Wind Power for Utility Applications

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A Primer on Wind Power for Utility Applications

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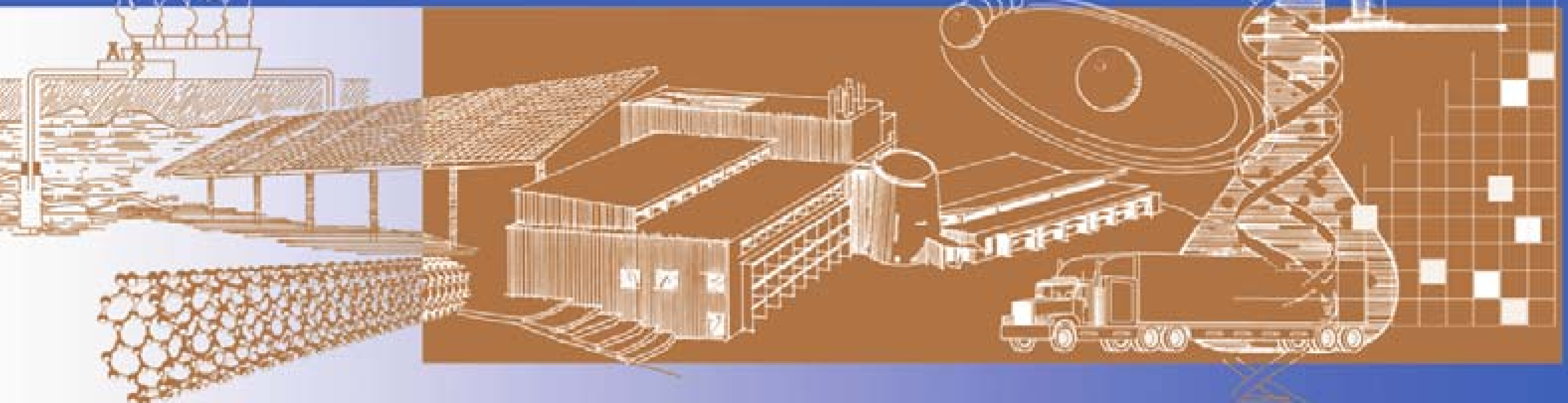

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1. Introduction

In the past 20 years, U.S. wind power capacity has increased continuously. With the federal tax credit and the emerging green market, total installed wind power capacity in the United States exceeds 6,000 megawatts (MW). However, the industry still faces many market barriers, some of which stem from utilities' lack of experience with the technology. The effects of wind power fluctuations on power system operations have increasingly concerned many electric utilities and wind power developers.

Large-scale installation of wind power is being scrutinized more because of its unique characteristics. Wind power output varies with wind speed. A single wind power plant may have many relatively small induction generators that behave differently than conventional central-station power plants with large synchronous generators. Utility system operators and planners need to understand the effects of fluctuating wind power on system regulation and stability. Without high-frequency wind power data and realistic wind power plant models to analyze the problem, utilities often rely on conservative assumptions and worst-case scenarios to make engineering decisions.

To remedy the situation, the National Renewable Energy Laboratory (NREL) has undertaken a project to record long-term, high-resolution (1-hertz [Hz]) wind power output data from large wind power plants in various regions. The objective is to systematically collect actual wind power data from large commercial wind power plants so that wind power fluctuations, their frequency distribution, the effects of spatial diversity, and the ancillary services of large commercial wind power plants can be analyzed. It also aims to provide the industry with nonproprietary wind power data in different wind regimes for system planning and operating impact studies.

Under NREL's wind power plant monitoring project, data are being collected at seven locations. The locations and total installed capacity of the monitored plants are listed here. Figure 1-1 shows the locations of wind power plants.

The power data are recorded at 1 Hz. One-minute average wind speeds at hub height are also recorded from an on-site meteorological tower at the southwest Minnesota (SW Minn.) wind power plant. From the recorded 1-second and 1-minute data series, 1-minute, 10-minute, and 1-hour time-series wind power and wind speed data are compiled for analysis.

The industry has used a large amount of data collected for various system integration studies. Links to some of the reports are listed in the Appendix. This report will summarize the results of data analysis performed at NREL and discuss the wind power characteristics related to power system operation and planning. The goal is to help utility planners and operators who have not had experience with wind power in their systems to better understand wind power plant behavior.

Figure 1-1. Locations of monitored wind power plants

2. Statistics of Wind Time-Series Data

Wind blows because of the atmospheric pressure differences across the surface of the earth. Uneven heating of the earth's surface by the sun and heat transferred by the ocean currents create the pressure differences. Close to the ground, the air movement is also affected by the characteristics of the earth's surface. The result of all of these factors is that wind varies all the time—in both speed and direction. For wind generation, speed is of particular interest because it has the most direct impact on the wind power plant behavior. This chapter will review the statistics of wind speed time-series and explain the variations of wind speed on different time scales.

This report focuses on the behavior of large wind plant output, so it will only briefly discuss those wind attributes that directly affect short-term wind power fluctuations. The wind speed attributes of interest are average, standard deviation, step changes, and ramping rates over different time scales. The following example illustrates these attributes.

Figure 2-1 plots wind speed time-series for several time steps: 1-second (1800 data points), 1-minute (1440 data points), 10-minute (1440 data points), and 1-hour (720 data points). These wind speed traces are very similar except for the 1-second wind speed series. The 1-second data series appears to be "smoother" than the other three time series because the wind speed changes in such a short time interval are small. The step change (the speed differences between consecutive time steps) statistics of these four time series will confirm the observation. Table 2-1 lists the standard deviation values of wind speed step changes of these four time series. Average step change values for these four time series are very small and are not included in the table. The variance of 1-second wind speed step changes is one magnitude smaller than that from the time series of longer time steps. This means that 1-second wind power step changes should also be small.

Table 2-1. Standard Deviation of Wind Speed Step Changes

	1-second	1-minute	10-minute	1-hour
Step Change Standard Deviation (m/sec)	0.07	0.55	0.53	0.88

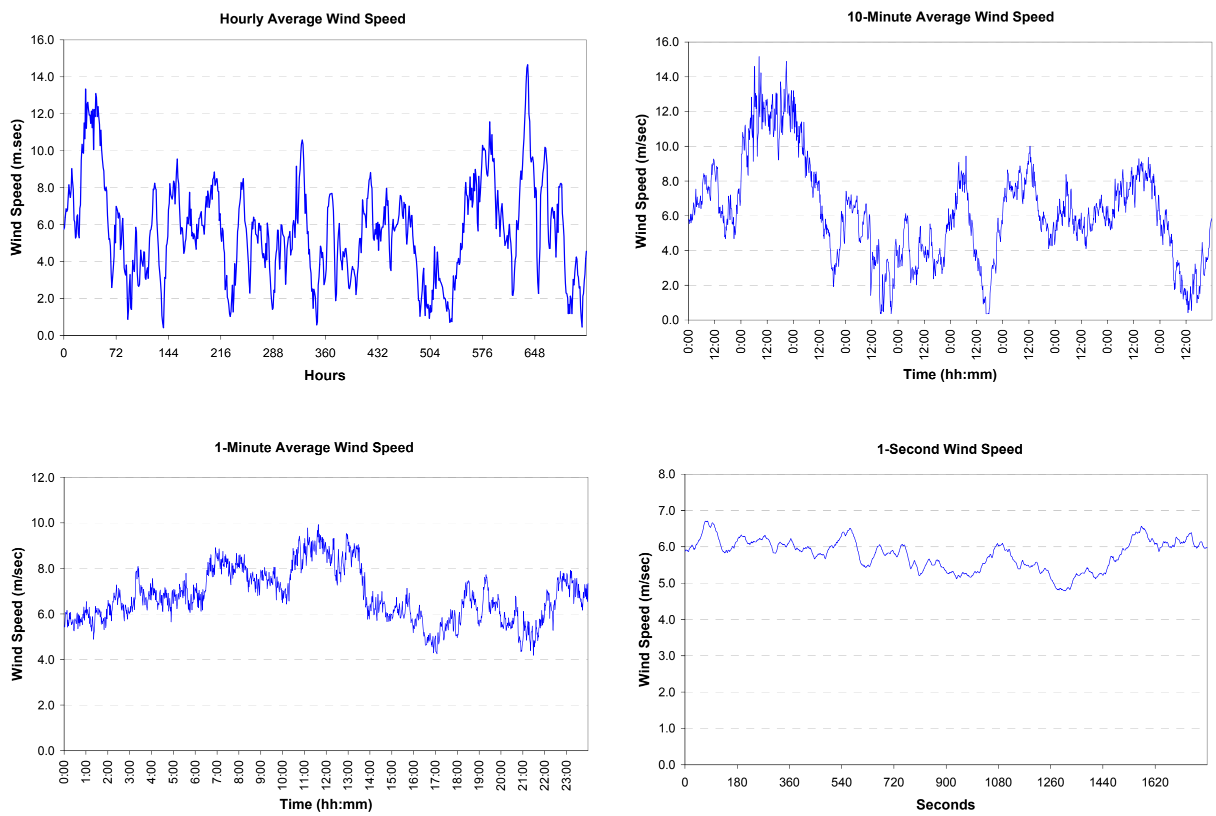


Figure 2-1. Sample wind speed profiles at different time intervals

Table 2-2 lists the average wind speed and its standard deviation values for a month calculated from four time series. Average wind speeds for these four time series are the same with only slightly different standard deviations. The average wind speed and its standard deviation values are specific to a site and the time intervals in which the data are collected. These statistics are not sensitive to the actual time steps of the data series. In addition, wind speed has significant seasonal and yearly variations. To accurately estimate power generation potential of a site, long-term measurement of wind speed at the proposed turbine hub height is needed.

Table 2-2. Sample Monthly Average Wind Speed

	1-second	1-minute	10-minute	1-hour
Average Wind Speed (m/sec)	5.69	5.69	5.69	5.69
Standard Deviation (m/sec)	2.80	2.77	2.72	2.68

3. Statistics of Wind Power Time-Series Data

With wind speed fluctuating all the time, the power generated by a single turbine or the entire wind farm is expected to also vary continuously. Figure 3-1 shows the 3-second output power series from a single turbine during a 1-hour period. Figure 3-2 shows 1-minute average power from the same turbine for a 24-hour period.

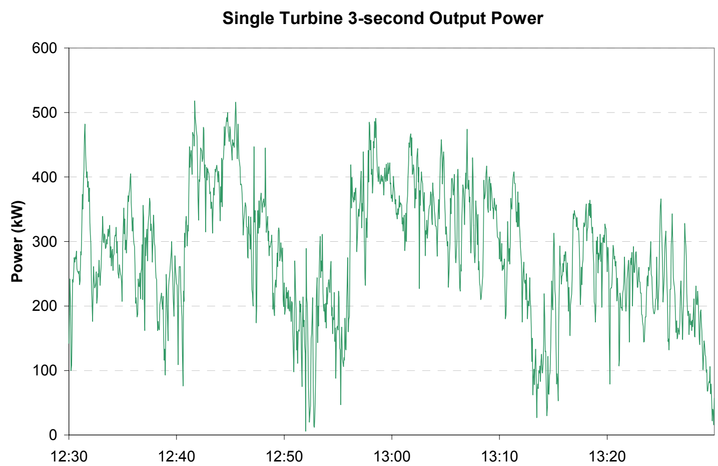


Figure 3-1. Single turbine output (3-second)

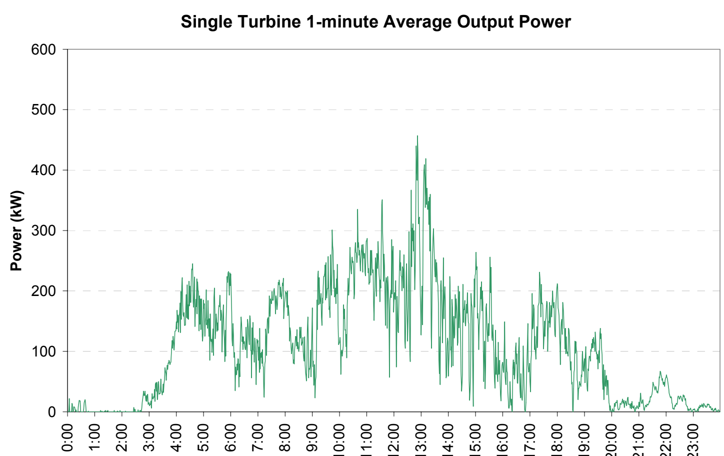


Figure 3-2. Single turbine output (1-minute average)

These two wind power profiles look similar despite the fact that one depicts 3-second instantaneous values over 1 hour and the other depicts 1-minute average values over a day.

During the 1-hour period, the average wind power is 280 kW (with a standard deviation of 100 kW). During the 24-hour period, the average wind power is 139 kW (with a standard deviation of 82 kW). Compared to the wind speed variations during the same periods, the variability of power output is less than the variability of wind speed. Table 3-1 shows the coefficient of variance (COV, or standard deviation divided by average) for the wind speed, wind speed cubed, and wind power.[1] It can be seen that the COV of wind power series is less than that of wind speed cubed. The reason the COV of 1-minute average power and 1-minute average wind speed are the same is the zero and very low output values in the power data series (but not in the wind speed data series) that skew the series statistics. If the zero and low power (less than 10 kW) values are eliminated from the computation of COV, the COV for wind speed cubed and wind power would be 0.38 and 0.34, as shown in the row labeled modified 1-minute series.

Table 3-1. COV of Wind Speed, Wind Speed Cubed, and Wind Power

	Wind Speed	Wind Speed Cubed	Wind Power
3-second series	0.17	0.46	0.36
1-minute series	0.21	0.59	0.59
1-minute series (modified)	0.12	0.38	0.34

Wind farms consist of tens and even hundreds of turbines. The combined output of all turbines shows less variability than a single turbine because of spatial diversity of wind resources. Even with a well-defined weather front moving over the wind farm, not all wind turbines within the wind farm will experience the same wind condition. Figures 3-3 and 3-4 plot 3-second and 1-minute outputs of the single turbine and of the combined output of 11 turbines at the same site.

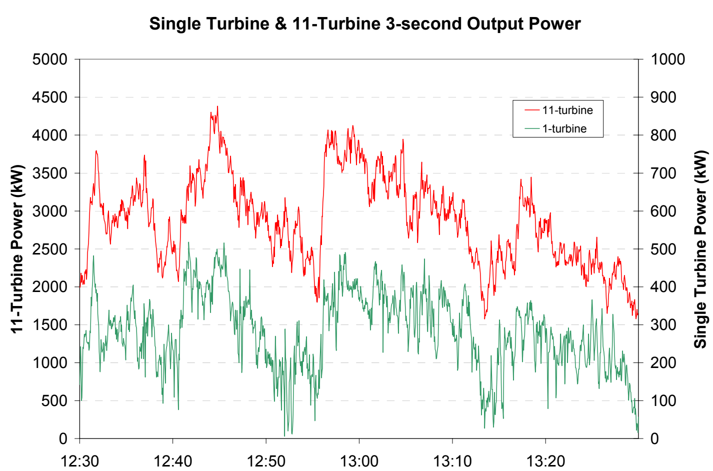


Figure 3-3. Three-second output of a single turbine and 11 turbines

[1] COV of wind speed cubed is used because available wind power is proportional to the wind speed cubed.

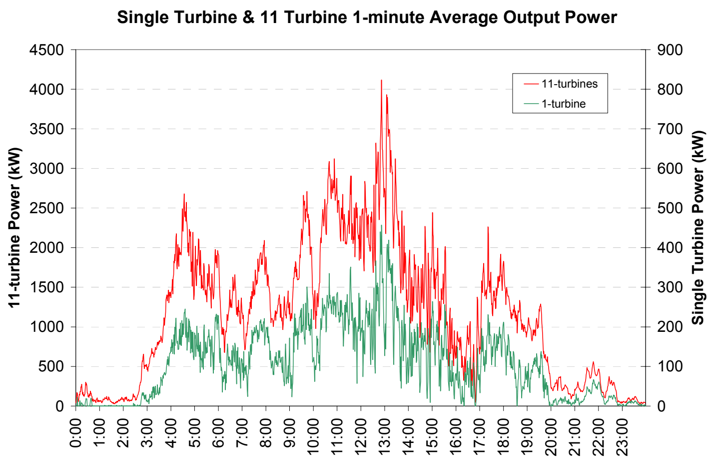


Figure 3-4. One-minute average power of a single turbine and 11 turbines

Although the combined output of 11 turbines tracks the output of a single turbine closely, the smoothing of the overall output is still evident. During the 1-hour period, the peak output of a single turbine in Figures 3-1 and 3-3 is 518 kW, but the combined output of 11 turbines only has a peak of 4,383 kW, or 23% lower than 5,698 kW (11 x 518 kW if all 11 turbines reached the same peak output at the same instant). For the 24-hour period, peak 1-minute average power for the single turbine is 457 kW and 4,116 kW for 11 turbines. Peak outputs of the single turbine and the 11-turbine string occur at different time. Table 3-2 lists individual peak outputs of the 11 turbines and the combined output of all 11 turbines. This phenomenon is very similar to the behaviors of individual loads, which also show the strong effect of noncoincidence.

Table 3-2. Individual Turbine Peaks and Peak of Combined Output

Turbine ID	3-second peak (kW)	1-minute peak (kW)
#1	510	376
#2	525	434
#3	530	442
#4	517	430
#5	491	423
#6	330	252
#7	505	375
#8	518	457
#9	523	464
#10	486	453
#11	521	423
ALL	4,383	4,116

The COV of the combined output series is lower than the COV of the single-turbine output power series. Table 3-3 shows standard deviation values (σ) and COV of the 3-second and 1-minute power series for a single turbine and 11 turbines. It also shows these values as percentage of the turbine and total capacity. This observation suggests that scaling up output of a single turbine to simulate output of a large wind farm will distort the true characteristics of wind power. The scaling process exaggerates the variability of wind power because it does not account for the wind resource diversity within the wind farm. This will be discussed in more detail later.

Table 3-3. Output Variability of Single Turbine and 11 Turbines

	3-sec Data Series			1-min Data Series		
	σ (kW)	(% of capacity)	COV	σ (kW)	(% of capacity)	COV
Single turbine	100	18%	0.36	82	15%	0.59
11 turbines	588	10%	0.20	727	12%	0.48

3.1 Fluctuations of Wind Power

For a better gauge of the wind power fluctuations, wind power level step change values are examined at different time steps. The step changes are power level differences between two consecutive time steps. Because wind power level is not expected to change the same amount in the same direction for every time step, the step change values establish the boundaries of wind power ramping (rate of changes) behavior. Figure 3-5 is an example of 1-second wind power series in a 20-minute interval and its step change series.

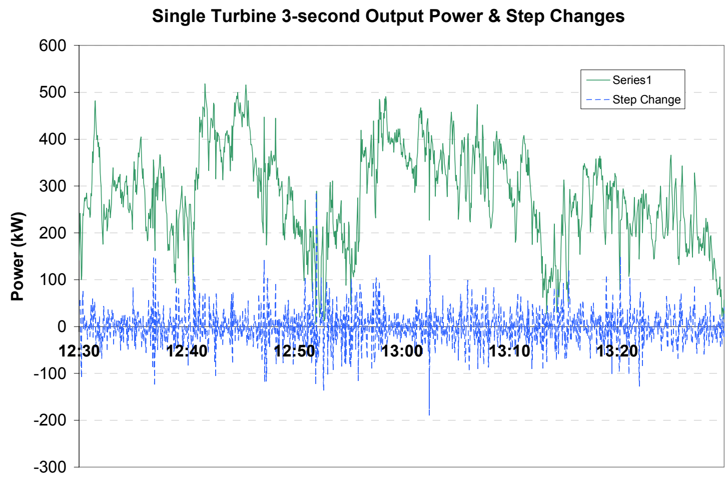


Figure 3-5. Single turbine output power and step changes

The average value of wind power step changes during this hour is zero. This is expected because this power series starts and ends at about the same level, and therefore, positive step changes are offset by negative step changes during this period. In fact, given enough time, the average step change values of a wind power series of short time step are always zero or very small. Short-term wind power fluctuations are random. The positive and negative steps are about evenly distributed. The standard deviation value of step changes during this hour is 39 kW (or 7% of the turbine capacity). The maximum step changes values are 283 kW increase and –188 kW decrease, or about 51% and 34% of the single turbine capacity, respectively.

Figure 3-6 shows the 11-tubine output and its step change series. It is obvious that step changes of the combined output are relatively small compared to the single-turbine output step changes. For the 11-turbine output step changes, its standard deviation value is 118 kW (or 2% of the total capacity). The maximum step changes are 427 kW increase and –421 kW decrease. They are higher than the extreme values of the single turbine output, but when expressed in terms of the total capacity, it is only about 7% of the combined capacity. This result demonstrates that the aggregation effect of wind turbines on the wind power is very significant, proving again the spatial diversity of wind resources. It also shows that short-term wind power fluctuations are relatively small.

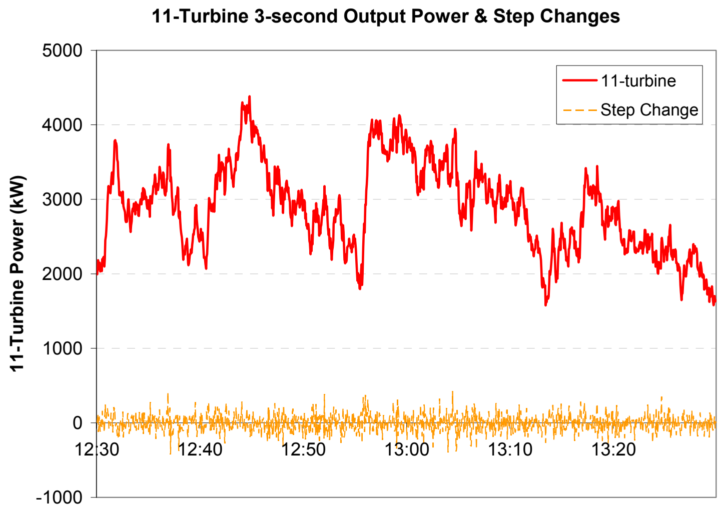


Figure 3-6. Eleven-turbine output power and step changes

The effect of aggregating more turbines on the combined output is also evident on a much larger scale. The following data collected over 1 year illustrate the effect: 1-second wind power data from a 14-turbine string and a 138-turbine wind farm and combined wind power output data from several wind farms with more than 200 wind turbines[2]. From the 1-second wind power data series, 1-minute, 10-minute, and 1-hour average wind power data series are assembled, and their step changes statistics are calculated. Figure 3-7 is an example of the profiles of 1-minute average wind power of these three data series.

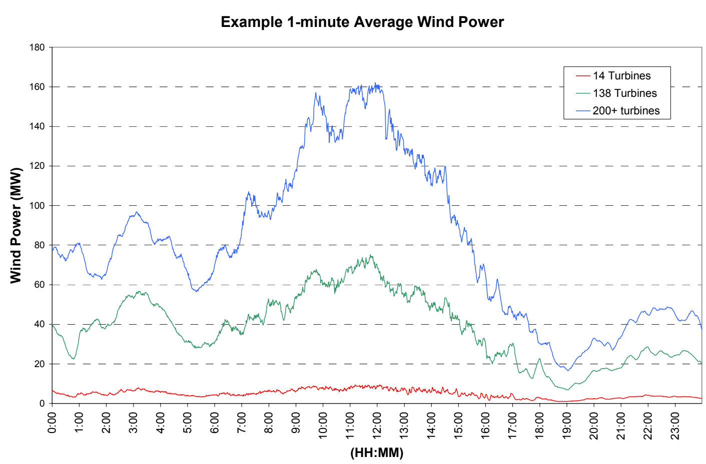


Figure 3-7. Output profiles of 138-turbine wind farm and 14-turbine cluster

[2] The 14-turbine string is part of the 138-turbine wind farm. The 138-turbine wind farm is one of the wind farms whose outputs make up the combined wind power data. Nameplate capacities for these three wind installations are 10.5 MW, 103.5 MW, and 242 MW. All wind farms are within the Buffalo Ridge region of southwest Minnesota.

The average values of wind power step for any long time series are always very small because over time, the positive steps (amount of increasing wind power) tend to be balanced by the negative steps (amount of decreasing wind power). For a better picture of wind power step changes at different time steps, the average magnitude (absolute value) of step change values is calculated instead. Table 3-4 lists the average magnitude and the standard deviation (σ) values of wind power step changes from these three wind installations for different time steps. Also listed in the table are these values expressed in terms of the respective generating capacities to show their relative values.

Table 3-4. Wind Power Step Change Average Magnitude and Standard Deviation Values

		14 turbines		61 turbines		138 turbines		250+ turbines	
		(kW)	(%)	(kW)	(%)	(kW)	(%)	(kW)	(%)
1-second									
	Average	41	0.4	172	0.2	148	0.1	189	0.1
	Std Deviation	56	0.5	203	0.3	203	0.2	257	0.1
1-minute									
	Average	130	1.2	612	0.8	494	0.5	730	0.3
	Std Deviation	225	2.1	1,038	1.3	849	0.8	1,486	0.6
10-minute									
	Average	329	3.1	1,658	2.1	2,243	2.2	3,713	1.5
	Std Deviation	548	5.2	2,750	3.5	3,810	3.7	6,418	2.7
1-hour									
	Average	736	7.0	3,732	4.7	6,582	6.4	12,755	5.3
	Std Deviation	1,124	10.7	5,932	7.5	10,032	9.7	19,213	7.9

The effect of aggregation on wind power fluctuations can easily be seen from the statistics of wind power step changes. It is immediately clear that as the size of wind power generating capacity increases (with more wind turbines in the wind farm), the magnitude of step changes does not increase proportionally. And as a percentage of the total generating capacity, the magnitude of step change actually decreases when output from more turbines is included. As more and more wind generating capacities are installed, their combined output becomes less and less variable.

Another way to show the effect of turbine aggregation is to scale up the output from a small group to match the output from a large group and compare their step change statistics. Table 3-5 is an example of such an analysis. The output from the 14-turbine string was multiplied by factors of about 9.6 and 22.3[3] to make it the same as the output of the 138-turbine wind farm and the combined output of 250+ turbines. Compared to the actual fluctuations of outputs from large wind farms, the scaled-up wind power outputs would have fluctuations that are several times larger, especially for shorter time steps. For example, scaling 1-minute data from 14 turbines to match 138 turbines results in an average step size of 1,286 kW from the scaling, compared to 494 kW from the actual 138 turbines. When 1-minute data are scaled to match 250+ turbines, the scaled average is 2,870 kW compared to 730 kW calculated from the actual recorded values of the Buffalo Ridge substation. Similar increase to the standard deviation of step changes can also be observed. With 1-minute data, scaling output of 14 turbines to match that of 138 turbines results in a scaled standard deviation of 2,218 kW, compared to actual standard deviation of 849 kW. When we observe the impact of scaling up to 250 turbines, we see that the scaled standard deviation is 5,144 kW, compared to the actual value of 1,486 kW. This analysis shows that it is

[3] This factor changes with time steps as peak average outputs between small and large wind farms do not maintain the same ratio across the four time steps.

not advisable to simply multiply the output of one turbine or a group of turbines to simulate the total output of a larger wind power plant. The simple scaling operation will exaggerate the fluctuations of wind power and make fluctuation characteristics worse than the actual performance.

Table 3-5. Step Changes Statistics of Scaled-Up Wind Power Data

		14 turbines X 9.6		138 turbines (actual)		14 turbines X 22.3		250+turbines (actual)	
		(kW)	(%)	(kW)	(%)	(kW)	(%)	(kW)	(%)
1-second									
	Average	413	0.4	148	0.1	932	0.4	189	0.1
	Std Deviation	552	0.5	203	0.2	1,274	0.5	257	0.1
1-minute									
	Average	1,286	1.2	494	0.5	2,870	1.2	730	0.3
	Std Deviation	2,218	2.1	849	0.8	5,144	2.1	1,486	0.6
10-minute									
	Average	3,240	3.1	2,243	2.2	7,513	3.1	3,713	1.5
	Std Deviation	5,400	5.2	3,810	3.7	12,521	5.2	6,418	2.7
1-hour									
	Average	7,255	0.7	6,582	6.4	16,824	7.0	12,755	5.3
	Std Deviation	11,077	10.7	10,032	9.7	25,685	10.7	19,213	7.9

3.2 Distribution of Step Changes

The small standard deviation values of wind power step changes suggest that they are concentrated within narrow ranges. An example of step change distribution is given in Figure 3-8, which plots the relative frequencies of 1-second step changes for the outputs from 14-turbine, 138-turbine, and 250+-turbine wind installations. Although it is not easy to see, calculations show that practically all step changes for the 1-second time step are within ±3σ.

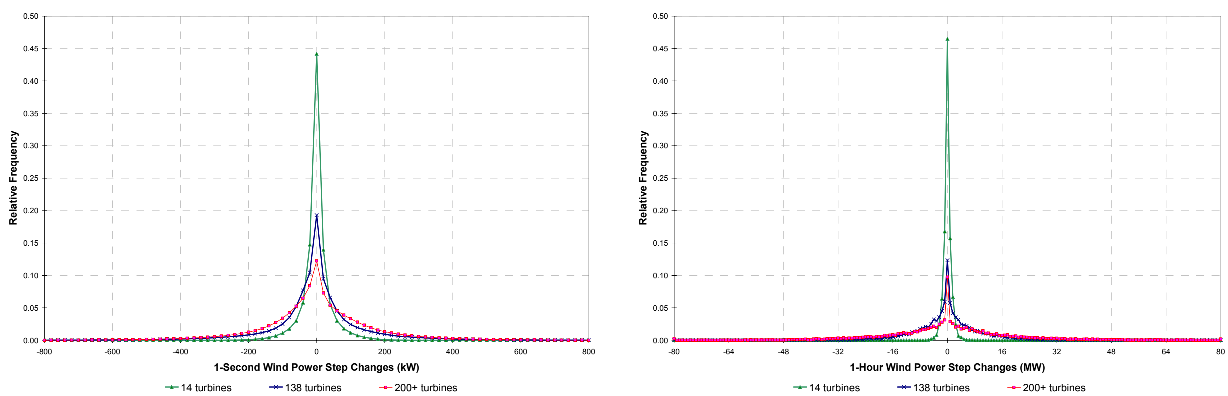


Figure 3-8. Example wind power step change distribution

More information on wind power step change distribution is given in Table 3-6, which lists the cumulative frequencies of wind power step changes in terms of its standard deviation values (σ). For the 138-turbine wind farm (total generating capacity 103.5 MW), 98.67% of the 1-minute step changes are within ±3σ (±2.6 MW), or about 2.5% of farm capacity. For hourly step changes, 98.34% of step changes are within ±3σ (±30 MW), or about 29% of farm capacity.

Table 3-6. Cumulative Frequency of Wind Power Step Changes

14 turbines				
	1-second (σ=42kW)	1-minute (σ=225kW)	10-minute (σ=548kW)	1-hour (σ=1.1MW)
±1σ	0.84862	0.85808	0.83122	0.78389
±2σ	0.94342	0.95387	0.95466	0.94628
±3σ	0.97876	0.98337	0.98447	0.98307
±5σ	0.99727	0.99715	0.99677	0.99831
> ±5σ	0.00273	0.00285	0.00323	0.00169
138 turbines				
	1-second (σ=154kW)	1-minute (σ=849kW)	10-minute (σ=3.8MW)	1-hour (σ=10.0MW)
±1σ	0.83681	0.83178	0.83543	0.78813
±2σ	0.93999	0.95598	0.95479	0.94462
±3σ	0.97842	0.98666	0.98365	0.98339
±5σ	0.99693	0.99795	0.99637	0.99823
> ±5σ	0.00307	0.00205	0.00363	0.00177
250+ turbines				
	1-second (σ=0.2MW)	1-minute (σ=1.5MW)	10-minute (σ=6.4MW)	1-hour (σ=19.2MW)
±1σ	0.84126	0.87624	0.84122	0.78629
±2σ	0.96155	0.97424	0.95850	0.94601
±3σ	0.99005	0.99253	0.98495	0.98419
±5σ	0.99896	0.99816	0.99583	0.99803
> ±5σ	0.00104	0.00184	0.00417	0.00197

The table also shows that extreme step changes (those step changes with magnitude greater than 5σ) increase as time step lengthens. It is expected because wind can experience bigger changes in longer time. For shorter time steps such as 1-second and 1-minute, the σ values are small; even for step changes at 5σ level, they are still only about 2% to 10% of the plant capacity. Further investigation suggests that none of the 1-second step change that exceeds 10% of plant capacity was wind speed related. For data series of longer time steps, it is not easy to determine the cause of large step changes. Many of these large changes were the results of abnormal network conditions such as forced outages within and outside of the wind farm. It is extremely unlikely that all of the turbines (or even a large number of turbines) in a large wind plant would develop a fault at the same time, causing a large power-level change.

3.3 Ramping Rates of Wind Power

Step change statistics define the outer boundary of the wind power fluctuations. The ramping (rate of change) of wind power level in a given time interval (e.g., 10 minutes or 1 hour) is also of interest to system operators. Wind power level changes continuously. For example, with a 1-second wind power data series, it is calculated that the average duration for wind power to keep increasing or decreasing is only 2.2 seconds (with a standard deviation of 44 seconds). With a 1-minute data series, the average duration is 2.4 minutes (standard deviation 8.4 minutes) before the wind power level changes its momentum (i.e., from increasing to decreasing, or vice versa).[4]

[4] Calculated from output power data of the 14-turbine string. For a 138-turbine wind farm, the average durations are 2.2 seconds (standard deviation 37 seconds) with 1-second data series and 2.8 minutes (standard deviation 7.3 minutes) with 1-minute data series.

To analyze the ramping behavior of wind power, the apparent rate of changes of wind power over a fixed time interval is calculated. In this report, the apparent rate of change is the slope of the straight line that fits the wind power data points in a 10-minute interval. Table 3-7 lists the resulting ramping statistics.

Table 3-7. Wind Power 10-Minute Ramping Characteristics

	Average		Standard Deviation		Max (+)		Max(–)	
	(kW/min)	(%/min)	(kW/min)	(%/min)	(MW/min)	(%/min)	(MW/min)	(%/min)
14-turbine	47	0.45%	78	0.74%	1.2	11%	–1.4	-13%
138-turbine	269	0.26%	465	0.45%	7.0	7%	–12.2	-12%
250+ turbine	438	0.18%	811	0.34%	11.3	5%	–29.0	-12%

The average and standard deviation values of 10-minute interval ramping rates for small and large wind farms are small. In terms of wind farm generating capacity, average ramping rates range from 0.45% per minute for a small wind installation to 0.18% per minute for a large wind installation. The maximum ramping rates, however, appear to be large. The maximum downward ramping rates for large wind farms exceed 12% of wind farm capacity per minute. To gain a better picture of wind power extreme ramping behavior, the distribution of all ramping rates are calculated (Table 3-8).

Table 3-8. Distribution of Wind Power 10-Minute Ramping Rates

	< ±1σ (78 kW/min)	< ±2σ (156 kW/min)	< ±3σ (234 kW/min)	< ±4σ (312 kW/min)	< ±5σ (390 kW/min)	> 5%/min (525 kW/min)
14-turbine	0.82476	0.95146	0.98305	0.99299	0.99673	0.00122 (64)
	< ±1σ (0.5 MW/min)	< ±2σ (1.0 MW/min)	< ±3σ (1.5 MW/min)	< ±4σ (2.0 MW/min)	< ±5σ (2.5 MW/min)	> 5%/min (5.2 MW/min)
138-turbine	0.84047	0.95742	0.98450	0.99304	0.99619	0.00040 (21)
	< ±1σ (0.8 MW/min)	< ±2σ (1.6 MW/min)	< ±3σ (2.4 MW/min)	< ±4σ (3.2 MW/min)	< ±5σ (4.0 MW/min)	> 5%/min (12.1 MW/min)
250+-turbine	0.86471	0.96779	0.98856	0.99438	0.99649	0.00044 (23)

It can be seen that high ramping events (wind power ramping faster than 5% of plant capacity per minute) decrease as the number of turbines in the wind installations increases. When the number of wind turbines increases (larger wind farms), the distribution of ramping rates becomes more tightly bundled (i.e., more smaller ramping values). The last column lists the relative frequencies and the actual numbers of occurrences (over 1 year) of large ramping rates that are over 5% of capacity per minute. Further examination of the data indicates that not all of those very large ramping rates (over 5% capacity per minute) are the results of wind speed changes. Fifty-one out of the 64 occurrences of over 5%/min ramping rates from the 14-turbine data series are wind-speed related.[5] For the 138-turbine data series, only 6 out of the 21 occurrences are wind-speed related; 3 are up ramping and 3 are down ramping. For the 250-plus-turbine wind data series, only 1 such occurrence (down ramping) can be related to wind speed change.

[5] A corresponding change of wind speed was observed during those events. The causes of other events of high ramping rates were not clear. Some pf them are the results of forced and scheduled outages and curtailment.

3.4 Correlation between Wind Farms

Despite their close proximity, instantaneous outputs from individual turbines of a large wind farm are not synchronized. Physical separations and differences of local terrains cause wind speeds at each turbine to vary. Output power from individual turbines will vary as each turbine is likely operating at different states (e.g., outputs from some turbines are increasing while others are decreasing). The diverse outputs from many turbines will make the aggregate output from large numbers of turbines less volatile, especially in short time frames. However, similar wind conditions will eventually sweep over the entire wind farm. During longer time frames, outputs of individual turbines or groups of turbines should be similar and are likely to move in the same directions. Table 3-9 gives an example of output correlation for wind power from individual turbines in a small wind farm.

The numbers in Table 3-9 are correlation coefficients of individual wind turbine output power step changes. The data used in the table are daily 3-second, 1-minute, 10-minute, and 1-hour output series from a 12-turbine string installed along a ridge line. The turbines are identified as #6 through #17 (data from turbine #11 are not available) in column and row headings in Table 3-9. For 3-second data series, it can be seen that even outputs from adjacent turbines have very poor correlation. When turbines are farther apart, their outputs actually move in opposite directions at the same time (numbers in parentheses denote negative correlation coefficients). As time interval increases, the outputs from those turbines are more in sync. The high correlation coefficients for the 1-hour data series suggest that hourly outputs from these turbines are practically in lockstep.

Large wind farms that are hundreds of kilometers apart experience significantly more spatial variations of wind resources, and their outputs should be less correlated than those among different turbine groups within a single plant. Their short time frame power fluctuations should be independent, and even their longer time frame power fluctuations are not expected to be correlated.

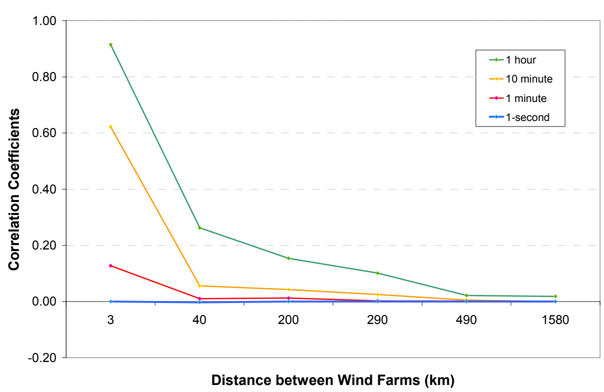


Figure 3-9. Wind power correlation as a function of distance

To examine the effect of separation on wind power output correlation, the correlation coefficients of output step changes from five wind farms for different time steps are calculated. Figure 3-9 plots the correlation coefficients vs. distances between wind farms. Wind power data from wind farms in the Midwest and Texas are used. The distances between these wind farms range from about 3 km (two turbine strings within the same wind farm) to about 1,580 km (between Midwest and Texas wind farms).

Table 3-9. Individual Turbine Output Correlation Coefficients

3-second	#7	#8	#9	#10	#12	#13	#14	#15	#16	#17
#6	0.019	0.002	(0.014)	0.013	(0.027)	(0.002)	(0.002)	(0.009)	(0.009)	0.015
#7		0.000	0.012	(0.018)	(0.003)	0.016	(0.005)	(0.003)	(0.007)	(0.002)
#8			0.023	0.005	(0.018)	0.009	(0.006)	0.001	0.015	(0.001)
#9				0.042	(0.011)	(0.010)	(0.001)	0.007	(0.010)	0.008
#10					0.003	(0.008)	0.009	(0.002)	0.019	0.006
#12						0.014	0.001	0.013	(0.008)	(0.018)
#13							(0.023)	0.003	(0.010)	0.019
#14								0.012	0.011	(0.005)
#15									(0.018)	(0.012)
#16										(0.009)

1-minute	#7	#8	#9	#10	#12	#13	#14	#15	#16	#17
#6	0.492	0.188	0.055	0.043	0.053	0.071	0.055	0.014	0.012	(0.005)
#7		0.372	0.116	0.064	0.018	0.067	0.096	0.020	0.043	(0.001)
#8			0.459	0.285	0.102	0.111	0.141	0.112	0.072	0.008
#9				0.608	0.163	0.126	0.129	0.117	0.055	0.002
#10					0.164	0.108	0.114	0.124	0.016	0.013
#12						0.003	0.128	0.097	0.018	0.047
#13							0.195	0.109	0.152	0.092
#14								0.360	0.234	0.223
#15									0.501	0.300
#16										0.493

10-minute	#7	#8	#9	#10	#12	#13	#14	#15	#16	#17
#6	0.767	0.619	0.555	0.485	0.425	0.362	0.418	0.309	0.400	0.377
#7		0.842	0.659	0.558	0.423	0.373	0.462	0.357	0.493	0.502
#8			0.835	0.685	0.572	0.441	0.449	0.406	0.519	0.486
#9				0.903	0.671	0.443	0.568	0.530	0.571	0.514
#10					0.750	0.497	0.624	0.595	0.619	0.550
#12						0.538	0.578	0.570	0.597	0.433
#13							0.691	0.596	0.615	0.553
#14								0.769	0.716	0.666
#15									0.831	0.776
#16										0.848

1-hour	#7	#8	#9	#10	#12	#13	#14	#15	#16	#17
#6	0.953	0.915	0.922	0.918	0.889	0.794	0.910	0.940	0.940	0.916
#7		0.968	0.965	0.966	0.946	0.791	0.937	0.940	0.924	0.882
#8			0.993	0.992	0.972	0.802	0.947	0.942	0.918	0.881
#9				0.996	0.964	0.777	0.933	0.936	0.921	0.889
#10					0.966	0.787	0.938	0.943	0.921	0.885
#12						0.816	0.946	0.926	0.889	0.853
#13							0.856	0.885	0.882	0.839
#14								0.965	0.937	0.919
#15									0.987	0.967
#16										0.980

Figure 3-9 clearly displays the temporal and spatial relationships of wind power. For very short time intervals (1 second to 1 minute), power outputs from all wind farms are not correlated, regardless of the distances that separate them. As time interval increases, outputs from nearby wind installations begin to show higher and higher correlation while outputs from distant wind farms are still independent from each other. This implies that the combined power output of all wind farms should have a lower variability than either site on its own.

3.5 Aggregating Spatially Diverse Wind Plant Output

Wind power fluctuations are a function of wind speed variations, which are similar everywhere. Consequently wind power step change characteristics are very similar for wind farms from different regions. When the average and standard deviations of step changes are expressed in terms of wind farm generating capacity, they are remarkably close in value. Because the wind power step changes are random and independent, the combined wind power from more turbines and wind farms will be less volatile. Table 3-10 lists step change statistics (absolute average and standard deviation) from other large wind farms identified by the numbers of turbines and total nameplate capacity. Six wind farms are included in Table 3-10. The 138-turbine and 151-turbine wind farms are located in the Midwest. The distance between them is about 200 km. The next four wind farms are in Texas. The distances between these four wind farms range from 40 km to 490 km. The distances between wind farms in the Midwest and Texas range from 1,200 km to 1,590 km. The number in parentheses next to a quantity is its value expressed as a percentage of the wind farm generating capacity.

Table 3-10. Effect of Aggregating Wind Farms on Step Changes

	1-second		1-minute		10-minute		1-hour	
	Avg (kW)	Stdev (kW)	Avg (kW)	Stdev (kW)	Avg (MW)	Stdev (MW)	Avg (MW)	Stdev (MW)
138-turbine (104 MW)	87 (0.08)	154 (0.14)	481 (0.5)	657 (0.6)	2.2 (2.1)	2.9 (2.8)	6.7 (6.5)	7.7 (7.4)
151-turbine (113 MW)	66 (0.06)	121 (0.11)	457 (0.4)	748 (0.7)	2.2 (1.9)	3.2 (2.8)	6.6 (5.8)	7.8 (6.9)
2 combined (217 MW)	120 (0.06)	201 (0.09)	709 (0.3)	976 (0.5)	3.4 (1.6)	4.2 (1.9)	10.7 (4.9)	11.2 (5.2)
112-turbine (35 MW)	22 (0.06)	37 (0.11)	272 (0.8)	473 (1.4)	0.7 (2.1)	1.2 (3.4)	2.0 (5.7)	2.8 (8.0)
61-turbine (79 MW)	107 (0.13)	119 (0.15)	606 (0.8)	838 (1.1)	1.6 (2.1)	2.2 (2.8)	3.7 (4.7)	4.6 (5.8)
125-turbine (83 MW)	87 (0.11)	100 (0.12)	401 (0.5)	694 (0.8)	1.6 (1.9)	2.6 (3.2)	4.0 (4.8)	5.4 (6.5)
100-turbine (150 MW)	85 (0.06)	133 (0.09)	821 (0.5)	1194 (0.8)	3.2 (2.1)	4.7 (3.1)	9.1 (6.1)	11.7 (7.8)
4 combined (347 MW)	172 (0.05)	190 (0.05)	1241 (0.4)	1531 (0.4)	4.5 (1.3)	5.5 (1.6)	12.9 (3.7)	13.7 (4.0)
All combined (564 MW)	219 (0.04)	224 (0.04)	1508 (0.3)	1767 (0.3)	6.1 (1.1)	6.5 (1.2)	17.7 (3.1)	16.5 (2.9)

Two points are easily noticeable from Table 3-10. First, the step change statistics from the data series of the same time step are consistent for all wind farms. Second, large plants (with more turbines) tend to fluctuate less (relative to total installed capacity) in their outputs than do the smaller plants. When outputs from two or more wind farms are combined, the resulting power series are relatively less variable than individual wind farms. The average and standard deviation values of step changes as a percentage of total capacity are always smaller than individual wind farms. This relationship holds true for all wind farms. It appears that output fluctuations of wind power plants are determined more by the size of the plant. The types of turbines and locations of the plants have less influence.

Aggregating outputs of many turbines also reduces the ramping rates. Table 3-11 lists the statistics of 10-minute ramping rates for these wind farms and their combined outputs. It is very clear that large wind farms and aggregated wind power will have lower ramping rates (as a percentage of wind farm capacity). Aggregated wind power output also has less extreme ramping rates. For example, the output of all wind farms combined for this report (the last row of Table 3-

11) has an extreme ramping rate of about 15 MW/min, or about 2.7% of capacity (total) per minute—far less than the extreme ramping rates of 5% per minute seen from individual wind farms. In fact, the data show that there are only four occurrences of ramping rates exceeding 2.5%/min during a 12-month period.

Table 3-11. Effect of Aggregating Wind Farms on 10-Minute Ramping Rates

	Average		Standard Deviation		Max (+)	Max(–)
	(kW/min)	(%/min)	(kW/min)	(%/min)	(MW/min)	(MW/min)
138-turbine (104 MW)	269	0.26%	465	0.45%	7.0	–12.2
151-turbine (113 MW)	248	0.22%	429	0.39%	8.3	–12.9
2 combined (217 MW)	394	0.18%	635	0.29%	9.3	–12.9
112-turbine (35 MW)	100	0.29%	171	0.49%	3.5	–4.4
61-turbine (79 MW)	241	0.30%	402	0.51%	7.5	–5.7
125-turbine (83 MW)	212	0.26%	403	0.49%	8.8	–6.4
100-turbine (150 MW)	397	0.26%	713	0.48%	12.8	–15.6
4 combined (347 MW)	576	0.175	916	0.26%	12.0	–16.1
All combined (564 MW)	752	0.13%	1120	0.20%	15.0	–15.3

The result is significant to system planning and operating. As more and more wind generating plants over a wider area are integrated into the grid, spatial diversity of the wind resources will make the overall wind power much less volatile than the output from any individual wind farm. It also points out that when studying high wind power penetration scenarios, it is imperative to make sure the wind resource spatial diversity is considered in assembling the wind power series.

3.6 Rare Situations

The analyses of 1-second, 1-minute, and hourly wind power series show that the majority of wind power fluctuations are limited in narrow ranges and their average values are relatively small. However, with strong winds sweeping across the plant, the output power can increase quickly, as indicated by the extreme values of wind power step changes and ramping rates. If the ramping-up rate needs to be controlled during such an event, the plant operators can change the ramping-up rate by temporarily stopping some of the turbines.

Another concern about big wind power change is that power from large wind plants will drop from full capacity to zero very quickly. It has been surmised that during certain weather events, the continuously increasing wind speed will be over the turbine cut-off speed at some point and cause all the turbines to shut down after they have been operating at full capacity. Such an event may burden the power system considerably as it tries to bring up generation reserves to compensate for the sudden loss of a large amount of wind power. Grid disturbances or equipment malfunctions can certainly cause the entire wind power plant to trip off line in a very short time. However, other than such forced outage events, the data collected so far have not shown any evidence of high wind causing all turbines within a plant to reach cut-off state at the same time. High wind will exceed wind turbine cut-off speed and cause individual turbines to shut down, but not the entire wind power plant.

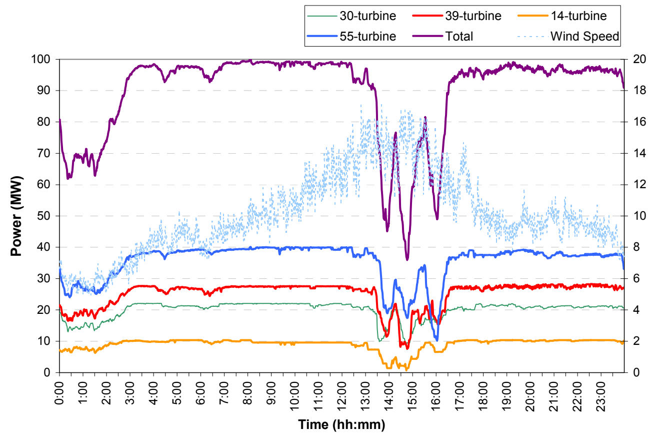


Figure 3-10. Example of wind power during high wind period

Figure 3-10 is an example of strong winds that exceeded turbine cut-off speed and caused output to drop. In Figure 3-10, 1-minute average powers from four turbine strings[6] and the total wind farm are plotted along with the reference wind speed at the site[7] for a 24-hour period. It shows that the plant had been generating at full capacity (about 100 MW) since 3:00 a.m. with continuously increasing wind. Shortly after 12:00 noon, the output power began to drop, and at about 15:00 when wind speed appeared to be at peak, the output power dropped to the lowest point for the day. After 15:00, wind speed began to decrease, but the output power of the wind plant began to increase (with some fluctuations closely related to the recorded wind speed). At about 17:00, the plant finally generated full power and remained at that level for the rest of the day.

The resolution in Figure 3-10 does not provide enough information about plant operations during a high-wind period. Figure 3-11 plots 1-second output power from the four turbine groups during the 3-hour period from 12:00 noon to 15:00. The step changes in the turbine group output traces are about 750 kW in magnitude (average) and within 2 seconds (2 data points). The fact that there are down-steps and up-steps during this period provides further evidence of wind diversities within the plant. These step changes show the shutdown of individual turbines during this high-wind period. They also show that all turbines do not shut down at the same instant, although some did appear to occur in rapid succession. The largest 1-second power drop during this 3-hour period was 1.4 MW (two turbines shut down at the same time), but the average ramping was only 293 kW/s (less than 0.3% of total capacity per second). Using 1-minute power data for this period, the average ramping rate was only 586 kW/min with the magnitude of the maximum ramping at 2.2 MW/min. Figure 3-10 offers clear evidence that output from a large plant does not drop from full power to zero rapidly because of a very strong wind that exceeds turbine cut-off wind speed. Physical separation and local terrain will cause variations in wind

[6] These four turbine strings of 14, 30, 39, and 5 turbines make up the wind farm. Output data from each string are recorded separately.

[7] The wind speeds were recorded by an anemometer mounted on a pole about 4 m above ground inside a fenced area. Although not hub-height wind speeds, they nevertheless give good indications of the wind conditions at the site.

speed at individual wind turbines, and therefore all turbines will not be at the same operating status.

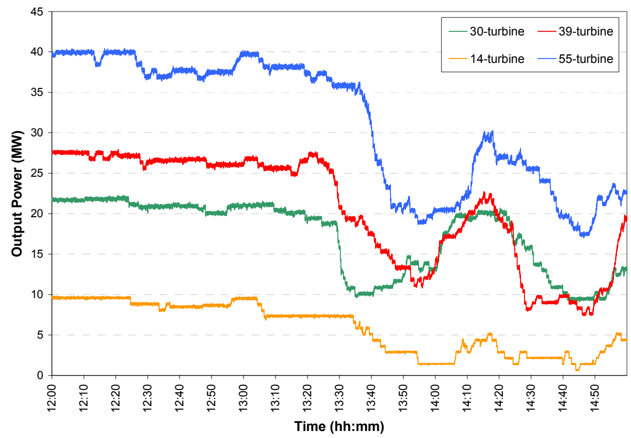


Figure 3-11. Detail of turbine cut-off with 1-second power data series

3.7 Generating Synthetic Wind Plant Output Time-Series

The intermittent nature of wind power and the limited control options on wind power plants make it difficult to study the wind power impact on system operations. The results will vary with each specific wind power used in the study. One of the accepted approaches to this problem is to perform a Monte Carlo type (probabilistic) simulation, in which a large number of wind power conditions are used. The statistics of all the results are then compiled and evaluated. For this method to be valid, a large number of independent wind power time series is required. With a large data requirement and the limited availability of actual wind power data series, it may be necessary to synthesize wind power data series for the probabilistic type of analysis.

A commonly used method for synthesizing wind power data series is the Markov method.[8] This method uses the probability distribution calculated from available actual wind power data series and a random number generator to create a new time series. A state transition matrix is first calculated from the available wind power time series. Table 3-12 is an example of a state transition matrix derived from hourly wind power data series. Only 10 states are used in Table 3-12 for clarity (they easily display on the page). The numbers in the matrix are probabilities that wind power will change from one hour to the next. For example, if the wind power for the current hour is at 30% of the wind farm capacity (within the range of 20% and 30%), the probability that it will stay at the same level is 0.4252 while the probability that it will jump to 70% is 0.0089. The probabilities across any row should add up to 1. A similar matrix can be constructed for other time series and with more states (power levels) for better resolution (e.g., 0.1% for 1-minute data series).

[8] McNerney, G. and Veers, P., "A Markov Method for simulating Non-Gaussian Wind Speed Time Series," Sandia National Laboratory, SAND84-1277, January 1985.

Table 3-12. State Transition Matrix with Hourly Average Wind Power Data

	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
10%	0.8567	0.1199	0.0167	0.0043	0.0019	0.0005	0	0	0	0
20%	0.2196	0.4947	0.1975	0.0697	0.0115	0.0026	0.0018	0.0026	0	0
30%	0.0446	0.2418	0.4252	0.2091	0.0456	0.0228	0.0089	0.0020	0	0
40%	0.0051	0.0803	0.2764	0.3439	0.1771	0.0764	0.0306	0.0089	0.0013	0
50%	0.0033	0.0130	0.1317	0.2114	0.3171	0.1805	0.0959	0.0309	0.0130	0.0033
60%	0	0.0089	0.0302	0.1032	0.2402	0.3132	0.1833	0.0890	0.0249	0.0071
70%	0	0.0038	0.0076	0.0440	0.1033	0.2447	0.2849	0.2237	0.0803	0.0076
80%	0	0	0.0073	0.0054	0.0345	0.0726	0.2341	0.3593	0.2523	0.0345
90%	0	0	0	0.0026	0.0128	0.0217	0.0562	0.1801	0.6066	0.1201
100%	0	0	0	0	0	0.0028	0.0028	0.0212	0.1487	0.8244

With an initial state (power level) P_i, the next state P_j in the time series is created by first generating a random number r that is uniformly distributed between 0 and 1, then the next state j is such that $\sum_{j=0}^{j-1} s_{ij} \le r < \sum_{j=0}^{j} s_{ij}$, where s_{ij} is the probability (row i, column j) in the state transition matrix. Here is a numeric example: suppose the initial state is 50% and a random number is 0.473; using Table 3-12, the next state will be 50% ($\sum_{j=10}^{j=40} s_{50j} \le 0.473 < \sum_{j=10}^{j=50} s_{50j}$). The same process is repeated until the end of the desired time series.

With different initial states and random number series, any number of wind power time series can be synthesized. The resulting time series will have average and standard deviation values that are similar to the original data series used to construct the state transition matrix. Figure 3-12 shows the probability distribution of actual hourly wind power series (8,760 data points) and the synthesized hourly time series (87,600 data points).

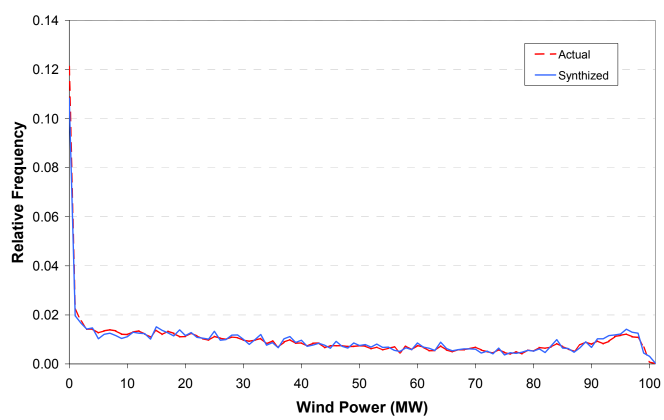


Figure 3-12. Probability distribution of actual and synthesized wind power series

Several issues with this method require additional attention. First and most critical, the process of assembling state transition matrix destroys the chronological information of the actual wind power time series. For example, if the actual wind power output exhibits a diurnal or seasonal pattern, the synthesizing process will not be able to capture any of it. If it is determined that the wind resources have distinguishable diurnal or seasonal patterns, additional state transition matrices will need to be constructed, and the process of synthesizing wind power series becomes time-dependent. Second, the step change and ramping statistics of the resulting data series are only representative to the periods when actual data are available to compute the state transition matrix. Unless very long series are produced, the synthesized series may miss few but significant extreme conditions that can occur. Third, the total energy of the synthesized time series may not match the desired level. If total energy is important to the study, an additional process needs to be performed (carefully) to reconcile the differences. And finally, the computational effort increases significantly when a finer resolution of states is desired.

There is another approach to produce a time series of output power from many wind power plants within a large area. This approach has been used in a study sponsored by the Utility Wind Interest Group (UWIG).[9] Using sophisticated meteorological models and historical meteorological data, it can re-create the weather conditions for the region of interest and for the selected period. The wind speed time series are then extracted from the model and converted to wind power time series. This method has several advantages. Outputs from any number of wind power plants can be produced at high resolution. It re-creates the weather conditions that drove the wind turbines, and as a result, produces realistic wind power time series. It does not depend on probability to capture extreme wind conditions, which may not be representative of the actual situations. However, this approach required substantial computational resources.

4. Statistics of Utility Load Data

Utility system load generally has a well-defined and predictable daily pattern because it corresponds to a daily cycle of routine human activities. However, this predictable pattern does not mean the utility load is deterministic at any given moment. Utility load is the aggregation of electricity usages by all of its customers. Fluctuations of any single load are usually random process (e.g., turning an appliance or a building air conditioning system on and off). Despite a clear daily profile, short time frame load changes are still random. Figure 4-1 is a sample of high-resolution utility daily load (4-second data rate) for three consecutive days. The overall daily profile is almost identical. It is also clear that from one time step to the next (4-second interval in this graph), the load can experience large and random changes. The utility load can also differ significantly from one day to the next at the same hour and the same minute (over 400 MW in this example). Seventeen days of 4-second high-resolution load data of Xcel Energy are available (April 12 to April 28, 2004).

Table 4-1 lists the step change statistics of utility load during the 17-day period for different time scales. Also included in the table are step change statistics of wind power recorded at Buffalo Ridge substation (total 240 MW wind generating capacity) during the same 17 days. The variance (standard deviation value of step changes) of wind power is about one or two magnitudes smaller than the variance of load. This is expected because wind power is much smaller than the load (The peak load during this period is 6,011 MW, and the peak wind output is 185 MW). However, when both are expressed in terms of their respective peak values, the differences become less dramatic. The 4-second and 1-minute step changes for the load and wind power are comparable when they are expressed as a percentage of their respective peak values. Higher variability of wind power begins to show only in a longer time frame. The average

[9] EnerNex Corp. and Wind Logics, Inc. (2004). Wind Integration Study – Final Report. Xcel Energy and the Minnesota Department of Commerce

magnitude of hourly wind power step changed is 7.1% of its peak value while the average magnitude of hourly load step changes is only 2.5% of the peak load.

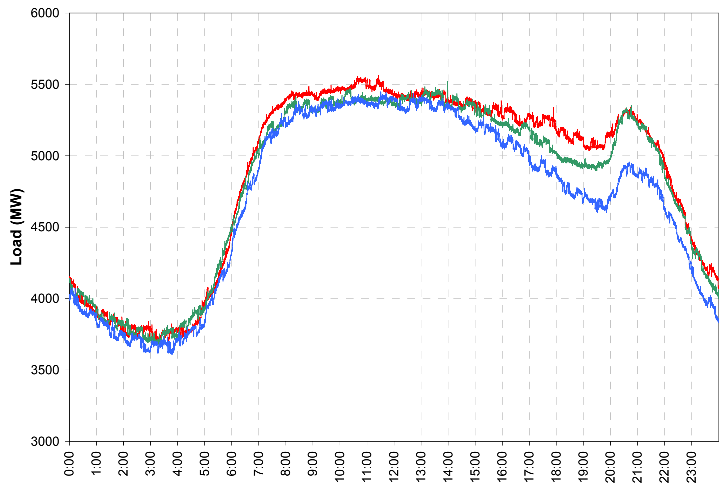


Figure 4-1. Sample of 3-day high-resolution (4-second) utility load data from Xcel

Figure 4-2 shows the distribution of load and wind power step changes for the four time steps whose standard deviation values are listed in Table 4-1 (4-second, 1-minute, 10-minute, and 1-hour). The hourly load and wind step change distribution plots are based on 3 years of hourly data. It can be seen that in general, the short-time changes of load are confined in a narrower range than that of the wind power, but the situation reverses in a longer-time frame. For example, 84% of 4-second load step changes are within ±1σ (±10.8 MW), and only 80% of the wind power step changes are within ±1σ (±0.3 MW). However, while 80% of hourly wind power step changes are within ±1σ (±18.6 MW), only 71% of hourly load step changes are within ±1σ (±218.2 MW). It can also be observed that about 99% of all wind power and load step changes are within their respective ±3σ ranges.

Table 4-1. Variance of Load and Wind Power in Different Time Scales

	Load Step Changes				Wind Power Step Changes			
	Avg (MW)	% of peak	Stdev (MW)	% of peak	Avg (MW)	% of peak	Stdev (MW)	% of peak
4-second	6.6	0.1	10.8	0.2	0.2	0.1	0.3	0.2
1-minute	8.8	0.1	19.2	0.3	0.8	0.4	1.4	0.8
10-minute	35.1	0.6	48.0	0.8	4.0	2.1	6.3	3.4
1-hour	152.4	2.5	218.2	3.7	13.2	7.1	18.7	10.1

To see how much step changes can be expected, the absolute value of step changes similar to those shown in Section 2 is computed for load and wind power for different time intervals, and the results are listed in Table 4-2. It can be seen that in 4 seconds, the average difference for load is 6.6 MW, or 0.1% of its peak. It is very similar to that of wind power changes in 4 seconds (0.2 MW, or 0.1% of its peak).

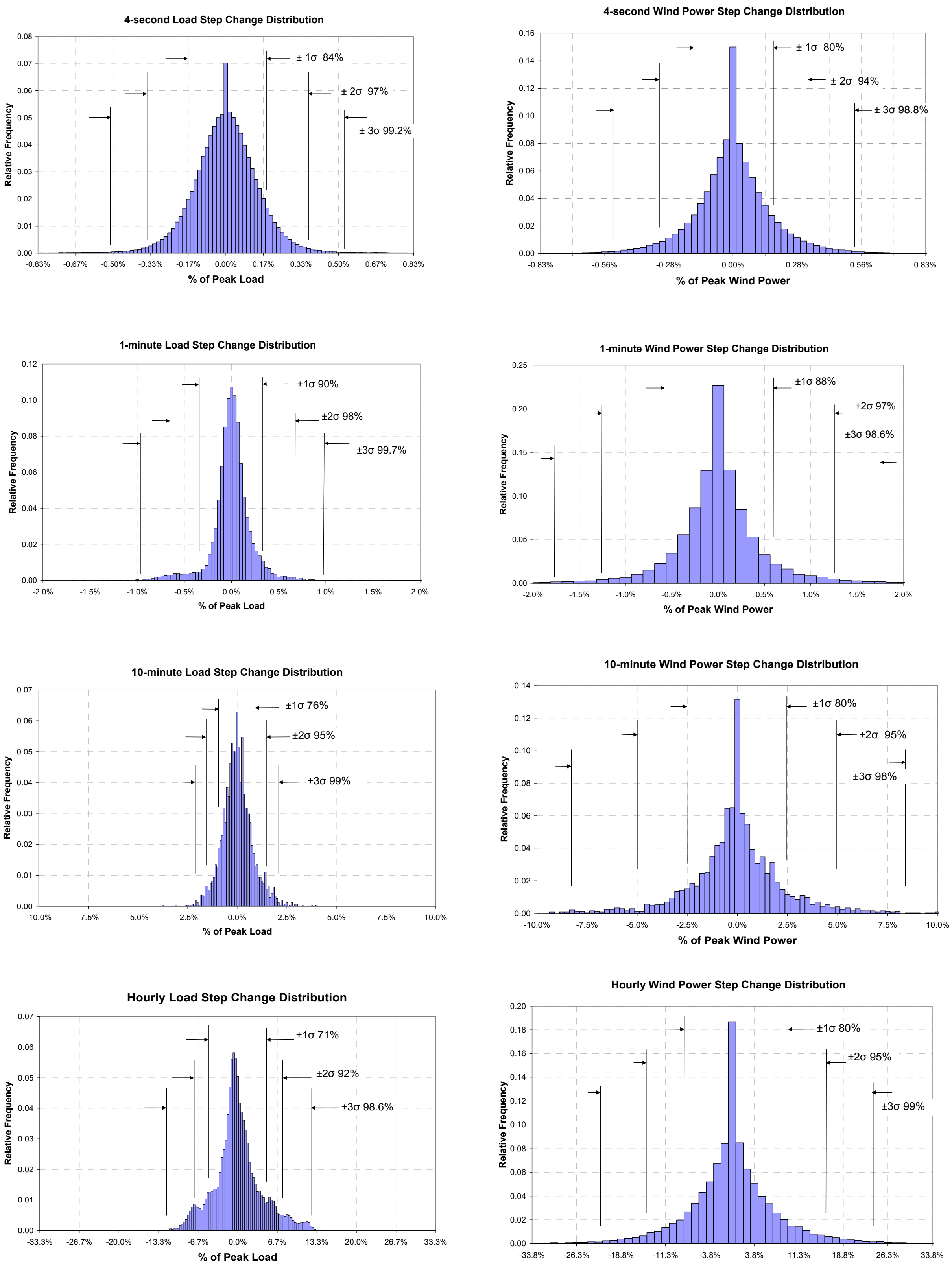


Figure 4-2. Distribution of load and wind power step changes

Table 4-2. Average of Absolute Load and Wind Power Step Changes

	Load Step Changes		Wind Power Step Changes	
	Average (MW)	% of peak	Average (MW)	% of peak
4-second	6.6	0.1%	0.2	0.1%
1-minute	8.8	0.1%	0.8	0.4%
10-minute	35.1	0.6%	4.0	2.1%
1-hour	177.1	2.9%	12.1	6.5%

The reason the average values of step changes for all time steps are zero or very small is also clear from Figure 4-2. These distribution plots are all symmetric: the numbers of positive and negative steps are about equal, and therefore their averages are about zero. The exception is the long-term hourly load step changes. Although the average values of long-term hourly step changes are still very small, the numbers of positive load step changes are less than the numbers of negative step changes. The daily load profiles of Figure 4-1 explained the slightly skewed hourly load step change distribution plot. Figure 4-1 shows that the morning load pick-ups are at a higher rate (steeper slope) than the evening load drop-off. It takes fewer time steps to reach daily peak load than the time for the load to decrease from its peak to its daily low.

Figure 4-2 also suggests that the differences between short-term fluctuations of utility load and wind power are minor. Occurrences of extreme step change values are the major differences between the distributions of load and wind power step changes. Table 4-3 lists the cumulative frequencies of step changes less than $\pm 1\sigma$ and $\pm 3\sigma$. It also includes the relative frequencies of step changes greater than $\pm 5\sigma$. Higher portions of wind power fluctuations are within $\pm 1\sigma$, indicating wind power has more small step changes than load. However, the distribution of wind power step changes have longer tails. Over 99% of all load step changes are within $\pm 3\sigma$, but less for wind power step changes. The differences between load and wind power extreme step changes are significant, especially for hourly step changes. Available data show that wind power can start up and reach over 90% of its generating capacity in an hour, and wind power can also decrease such an amount in an hour because of wind speed changes. Load will not experience such a large change in normal conditions.[10]

Table 4-3. Relative Frequencies of Extreme Step Changes

	Load Step Changes			**Wind Power Step Changes**		
	$< \pm 1\sigma$	$< \pm 3\sigma$	$> \pm 5\sigma$	$< \pm 1\sigma$	$< \pm 3\sigma$	$> \pm 5\sigma$
4-second	0.83534	0.99185	0.00074	0.87206	0.99093	0.00108
1-minute	0.90418	0.99732	0.00118	0.87716	0.98615	0.00337
10-minute	0.76355	0.99117	0.00123	0.80200	0.98243	0.00245
1-hour	0.73601	0.99639	0.00005	0.79861	0.98597	0.00114

4.1 Correlation between Load and Wind Power Fluctuations

The electric system responds to the short-term load fluctuations by adjusting the outputs of some of its online generating units, which can change its output quickly and are under automatic generation control (AGC). This function, called regulation, helps a control area maintain its interchange schedule, support its system frequency, and balance its generation and load under

[10] Some large loads such as an arc furnace can change between no load and full load in minutes. For a control area, the aggregated load does not exhibit such a big change.

normal operations. For longer time frame load variations (hourly and daily load profiles), the system will adjust the set points of online generators and start up and shut down additional generators to meet the demand. This is called load following.

When wind power is added to a utility system control area, the system must respond to fluctuations of both system load and wind power. Determining how wind power will affect system regulation and load following performance requires detailed modeling (system load and generators) and complicated calculations. System generation mix and wind resources are all important factors affecting the outcome. A dedicated, system-specific study of wind power impact on system operations is beyond the scope of this report. However, by examining the correlation between load and wind power, it is possible to gauge the extent of the impact.[11]

Two types of correlation between load and wind power are of interest: the correlation between step changes of load and wind power and the correlation between overall load and wind power levels. Short-term fluctuations of load and wind power affect system regulation. A high positive correlation between load and wind power step changes (both load and wind power move in the same direction) means the wind power will aggravate the system regulation requirement while a high negative correlation (load and wind power move in opposite directions) will alleviate it. Generator output at a given time is affected by the load and the amount of wind power. If wind power is consistently high during high load periods (high positive correlation), the wind power will have high capacity value to the system because it reduces the generation capacity needed to meet the load. On the other hand, if wind power is low during high load periods (high negative correlation), the capacity value of wind power is small.

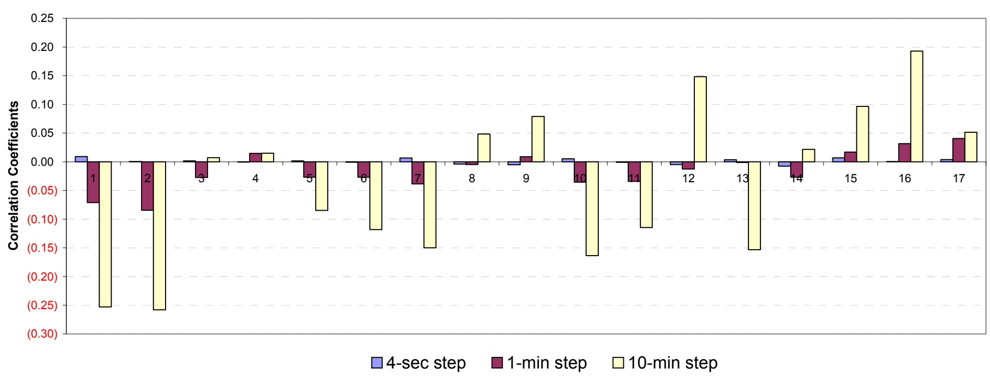


Figure 4-3. Correlation coefficients of daily load and wind power step changes

It has been shown that short-term power fluctuations from even adjacent wind turbines are not correlated. There is no reason for the short-term fluctuations of wind power and system load to be related. Available data show that indeed the load and wind power fluctuations are independent. Figure 4-3 plots the daily correlation coefficients between wind power step changes and load step changes during a 17-day period for three time steps: 4-second, 1-minute, and 10-minute.

[11] For example, Hirst, E. (2001). "Interaction of Wind Farms with bulk Power Operations and Markets" prepared for the Project for Sustainable FERC Energy Policy, September 2001.

Figure 4-4 plots the monthly correlation coefficients of hourly load and wind power and the monthly correlation coefficients of hourly load and wind power step changes.

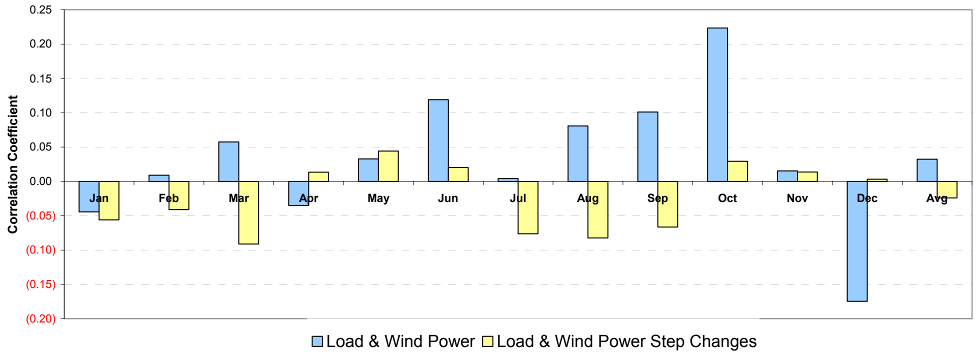


Figure 4-4. Correlation coefficients of monthly load and wind power and step changes

These correlation coefficients are small, especially for the 4-second time series. The correlation coefficients for the 10-minute time series are larger, but there is no clear pattern as to which direction they will move, indicating the relationship is not only weak but also random. The results for the 1-hour time series are similar. It is clear that for this case (Xcel Energy system load and wind power from a region within its control area), wind power impact on the system regulation and load following is symmetrical (i.e., the wind power may reduce regulation and load following requirements at one time and it will increase such requirements at the other).

To put the relationship between system load and wind power in better perspective, we need to take their sizes into consideration. Table 4-4 lists the step change standard deviation values of system load, wind power, and the net load (load minus wind power)[12] for the four time series.

Table 4-4. Variability of Load, Wind Power, and Net Load

Step Change Standard Deviations	Load (MW)	Wind Power (MW)	Net Load (MW)	% change
4-second	10.8	0.3	10.8	0.0%
1-minute	19.2	1.4	19.3	0.3%
10-minute	48.0	6.3	48.5	1.0%
1-hour	220.6	18.7	221.4	0.3%

Because of the low level of wind power (relative to the magnitude of system load), the variability of load before and after wind power is very small. System load variations overwhelm the wind power variations. These statistics do not imply that the impact of wind power on system regulation and load following is negligible. Wind power can experience more large magnitude step changes than load, and the system must cope with those large changes no matter how infrequently they occur. However, these statistics suggest that the impact should be very moderate.

[12] Here wind power is treated as a negative load because utilities generally do not dispatch wind generation. Whenever wind power is available, the rest of the control area generating units will see a reduced load.

5. Operational Impacts of Wind Power

The operational impacts of wind power actually cover concerns that span the entire range of time scales relevant to utility system operations. The issues range from long-term transmission and generation planning to progressively shorter time frame concerns such as annual and seasonal plant maintenance schedules, weekly unit commitment, hourly load following, minute-to-minute regulation, operating reserves, second-to-second frequency control, and sub-second system stability. Conventional utility planning and analytical tools have been adopted with wind power as an add-in to evaluating the impacts. Although the efforts have yielded valuable insight, many of those approaches are still too new to be established as standard utility practices.

In this section, wind power impacts to transmission planning, system reliability, and regulation are discussed. Through the description of current practices, issues related to the unique characteristics of wind power in analyzing system impacts will be highlighted.

5.1 Transmission System Planning

Conventional load flow analysis is the first step in the process of evaluating and planning the transmission system. This analysis is used to determine the maximum power output at the prospective wind power plant sites that can be accommodated by the existing transmission system and what additional facilities may be required. The process is straightforward, but careful considerations must be given to the selection of input data for the load flow program. Utilities usually construct load flow model based on summer and winter peak demand conditions when the majority of generators are producing full output and the transmission grid is stressed the most. This method is used so that fatal flaws of the transmission system can be more easily detected. However, the wind power plants may not produce full output during system peak demand periods. For example, Figure 5-1 shows the average hourly profile of utility system load and two Midwest wind power plants for the month of July. The average hourly load and wind power in the figure are normalized by their respective annual peak values so that they are shown on the same scale.

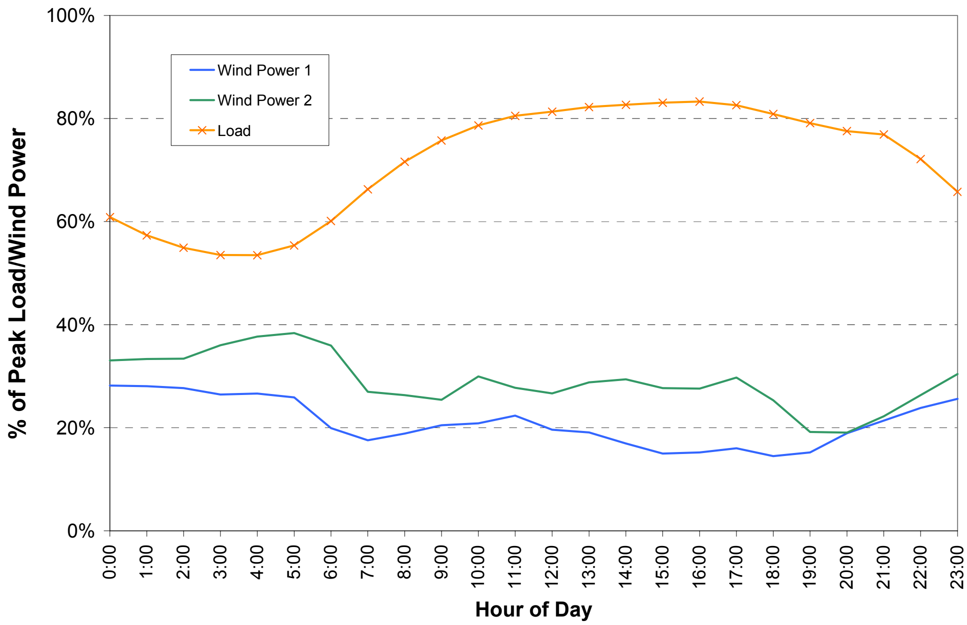


Figure 5-1. Average July daily load and wind power profile

The load profile has the familiar afternoon peak of a typical utility, but the wind power profiles show low output during afternoon and early evening hours. This type of wind power profile is not limited to wind power plants in the Midwest. The available data show that wind power plants in Texas, Oklahoma, and the Northwest also behave similarly. The wind resources are better in the winter season than in the summer season for the entire middle part of the continental United States. While utility system demand is near or at its annual peak during the afternoon hours, the wind power plants only generate at 30% or less of their annual peak output. Furthermore, available data show that wind power plants generate infrequently at peak level. Figure 5-2 is a sample of utility annual load duration curve and wind power annual hourly output duration curve. For the example in Figure 5-2, outputs of the wind power plant were over 90% of its annual peak only 8.5% of the time (744 hours). The time during which the load was over 90% of its annual peak value is even less (1.6% or 136 hours). The hours during which both system load and wind power are at their respective peak (or near peak) are very rare. In fact, for this particular example, it never occurred. For the Midwest wind power plants, peak production happens in the winter and spring (late October through early April), while the first 200 hours of system peak load occur in summer months (July, August, and September).

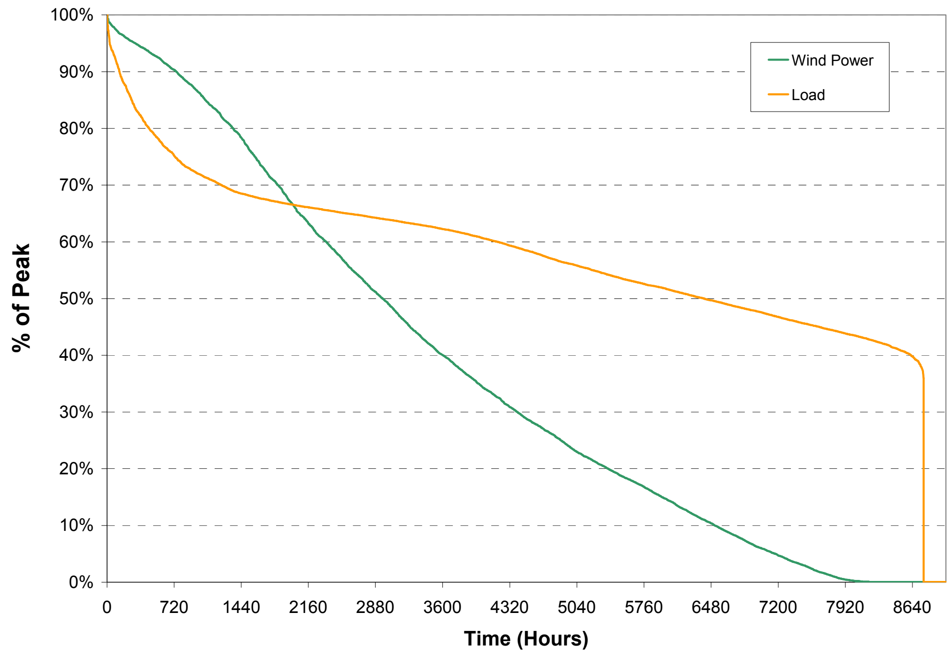


Figure 5-2. System load and wind power duration curves

It can be argued that using the utility system model of peak demand and wind power plant nameplate capacity in standard load flow analysis does not reflect the actual impact of wind power on the transmission system. A planning process with this approach will result in a very conservative system with large safety margins as far as wind power is concerned. A more realistic approach is to examine the long-term wind power data and determine the more likely wind power levels for the specific season.

5.2 System Reliability

The purpose of system reliability analysis with wind power is to determine the impact of wind power on the system's ability to maintain the desired reliability level. Various metrics gauge system reliability, and they are usually presented in terms of the probability that the planned total generating capacity will not be able to meet the projected system load. The most common measure is loss of load expectation (LOLE), expressed in days per year or days per 10 years. Utilities rely on sophisticated models and computer software to calculate reliability indices such as LOLE because of the complexity of multiple states associated with multiple generators and varying load levels. The effective load carrying capability of wind power is another index often calculated with the reliability model to see how wind power can contribute to meet the system demand.

Wind power can be included in the standard utility reliability models to calculate system reliability indices. The process is straightforward. Conventional power plants are usually represented in the model by multiple states (output levels), each associated with a forced outage rate (a probability). The forced outage rates for conventional power plants are derived from long-term plant statistics. However, this approach is not applicable to wind power. If a particular wind power plant is expected to have an annual capacity factor of 40%, it cannot be simply assigned a 60% forced output rate in the calculation process. The output of a wind power plant is not a simple binary process, and it is not totally random. Wind power has definite seasonal and sometimes diurnal patterns. Wind power plants having the same capacity factor but different daily and seasonal output profiles could have significantly different capacity values to a utility system. Treating wind power as conventional power plants in the model and assigning an equivalent forced outage rate to it do not capture the unique characteristics of wind power plants.

One approach is to use a wind power time series to modify system load; i.e., reducing system load by the wind power amount and calculating the reliability index. The change of system reliability indices before and after the introduction of wind power represents the capacity contribution from wind power. It is obvious that the results of such analyses depend heavily on the wind power data. Using different wind power time series that are representative of the yearly, seasonal, and diurnal variation of wind power, a wind power plant's contribution to system reliability index can be estimated. This approach can be time-consuming because a large number of simulation runs (Monte Carlo method) and long-term wind power data are needed to produce a reasonable estimate that captures the variation of wind power.

To remedy the shortcoming of the above conventional approach for not recognizing the probabilistic nature of the power variations from wind plants, an alternative has been proposed.[13] For wind power plants under consideration, an effective forced-outage rate for a selected time period is calculated. Depending on the seasonal and diurnal characteristics of wind regime, the length of the selected time period can be adjusted so that the calculated effective forced-outage rate is based on an appropriate time scale. Although this approach represents a significant improvement in computational efficiency over the Monte Carlo method, it still requires full-scale reliability simulations.

A less vigorous but faster way to estimate wind power capacity value for a system is to evaluate wind power production during a system peak demand period. While a detailed reliability model calculates system reliability indices with yearly load time series, the resulting system reliability indices are mainly influenced by the top 200 or so load hours of the year. For summer peaking utilities, these top 200 load hours almost exclusively occurred during the summer season. Analyzing wind power during the summer peak or wind peak demand season gives an approximation to the wind power capacity value. In actual application of this method, a daily window of several hours in the peak demand season is chosen and the wind power during these windows is averaged. A comprehensive wind power study for the state of New York found that this method could produce results close to that of a full-scale method[14] with the available wind power data.

It should be noted that this method provides approximate results because of the uncertainties of system load and wind power production. Although utilities recognize the conditions under which the system demand will peak (e.g., average daily temperature over 90°F five days in a row), they

[13] Milligan, M. (2001). "A Sliding Window Technique for Calculating System LOLP Contribution of Wind Power Plants," presented at the 2001 AWEA WindPower Conference, Washington, DC, June 4-7, 2001.
[14] The New York State Energy Research and Development Authority (2005). The Effect of Integrating Wind Power on Transmission System Planning, Reliability, and Operations Phase 2 Report: System Performance Evaluation.

still do not know in advance when such or other comparable conditions will occur. The approximation method can only provide an initial estimation of wind power potential. Analyses using standard reliability model are preferred, and long-term wind power data are needed to increase the confidence level of the results from either method.

5.3 Regulation

As discussed in Section 4, utility load changes continuously. Although utilities can predict the daily and seasonal load profiles fairly accurately, short-term (minutes and seconds) load changes are random and not predictable. Operation or control of the system requires that generators be dispatched and their outputs adjusted to maintain a balance of total generation (generally not controlled by utilities) and total load (most are under utility control) all the time. A small deviation of system frequency from the nominal 60 Hz is an indication of how well the system is operated or controlled. Control performance of each system is judged by the statistics of control area error (ACE), which must comply with North American Electric Reliability Council (NERC) standards CPS1 and CPS2.

Regulation in this report is the process of adjusting generators in response to shorter-term load changes (sub-hourly load fluctuations) while maintaining a near-constant 60-Hz system frequency. This function is performed automatically through the governor function of large generators and by the automatic generation control (AGC) subsystem of utility's Energy Management System (EMS). The generator's governor function responds to frequency changes immediately. AGC will adjust generator output set-points at a slower pace (every 4-6 seconds up to 2 minutes). Utilities normally reserve enough generator ramping capability under AGC to cope with the random load fluctuations.

When wind power is integrated into utility system's generation portfolio, its impact on system regulation needs to be analyzed through statistics derived from long-term data because of the stochastic nature of short-time frame wind power fluctuations and load changes. These data requirements have necessitated that analyses of wind generation impact on system regulation be performed in an after-the-fact fashion.[15] This is really not much different from the standard utility planning studies that are based on projected future load. Because wind power variations are within a narrow range and their long-term statistics property remain fairly constant, the analyses with historical data provide valuable insight on the effects, and the results serve as a good indicator to future performance.

The method for a statistical analysis of system regulation was explained by Hirst and Kirby.[16] It starts by decomposing high-resolution system load into three components: a base load component that is constant over the studying period, a ramping (trending) component during the period, and a randomly fluctuating component. A 4-second load time series for an hour is used as an example to illustrate the concept in Figure 5-3. The actual load (purple trace) during the hour is separated into a constant 4,400-MW base load (scale shown on the left side), a ramping component is a near-constant 9.6 MW/min (scale on the right side), and a fluctuation component

[15] Hirst, E. and Kirby, B. (1998). "Separating and Measuring the Regulation and Load Following Ancillary Service."
[16] Hirst, E. and Kirby, B. (2000). "What Is the Correct Time-Averaging Period for the Regulation Ancillary Service?"

varies between –24 MW to 43 MW (scale on the right side). The data in the figure satisfy the relation below.

Actual load = Base component + Ramping component + fluctuation component[17]

The system schedules enough generators on line to meet the base load. The ramping component is served by EMS load following function by gradually adjusting the set points of the generators. The fluctuation component is served by AGC, which changes generator output quickly.

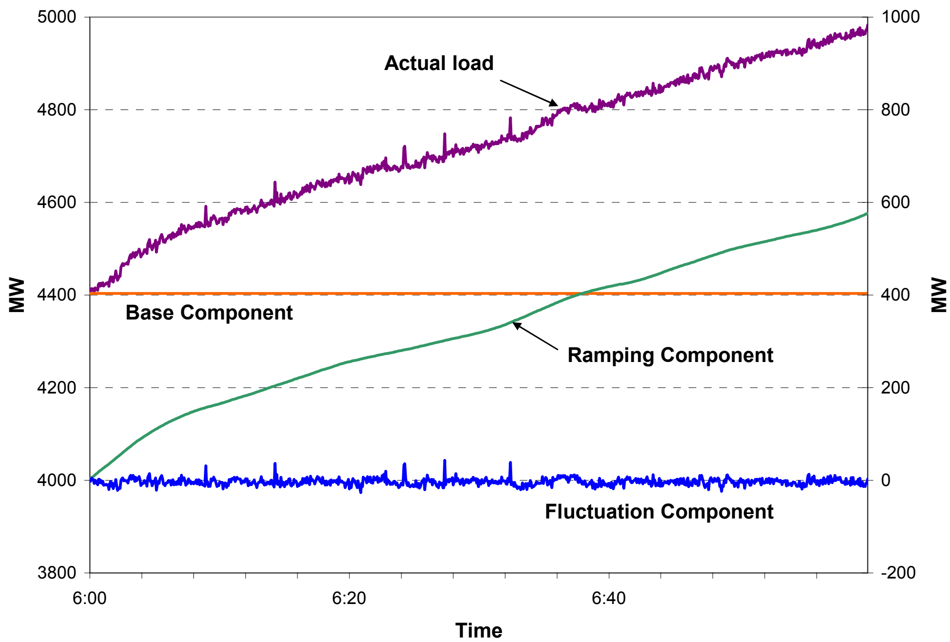


Figure 5-3. Components of system load

A properly applied decomposing process will result in a fluctuation component time series that has zero or very near zero average values, indicating the regulation is basically capacity service with no energy component. The standard deviation value of the time series can be related to the control area's regulation requirements. When wind power is added into the system, the same algorithm can be applied to a new load time series consisting of the differences of load and wind power (load minus wind power). The differences in standard deviation values between these two cases provide the information to estimate the wind power impact on regulations.

[17] The base component should be the average load during this period. In Figure 5-3 it is taken as minimum load value during the hour to make the trace easier to see. The ramping component is obtained by taking differences of actual load and base load through a low-pass filter. Careful consideration should be given to choose a proper cut-off frequency for the low-pass filter to be used. If the cut-off frequency is too high, then the ramping component will have too much of the fluctuation component. If the cut-off frequency is too low, then some of the ramping component (load following) will become part of the fluctuation component. When using a simple low-pass filter of rolling average, a window of 2 minutes (previous fifteen 4-second data points and fourteen 4-second data points after) appears to be adequate.

An example of the 4-second resolution load and wind power time series of 1 day is shown in Figure 5-4. Also shown in Figure 5-4 is the time series of net load (load minus wind power). Applying the above algorithm to the data, the standard deviation value of the fluctuation components are calculated and listed in Table 5-1. The example demonstrates that wind power affects the system regulation requirements slightly. Compared to the load fluctuation component, there is only a 0.8% increase in the net load fluctuation component (standard deviation). This is the expected result because short-term load variations and wind power variations have very low correlation (as shown in Section 4.1), especially for a system with a low penetration level of wind power (5,544 MW peak load and 145 MW peak wind power).

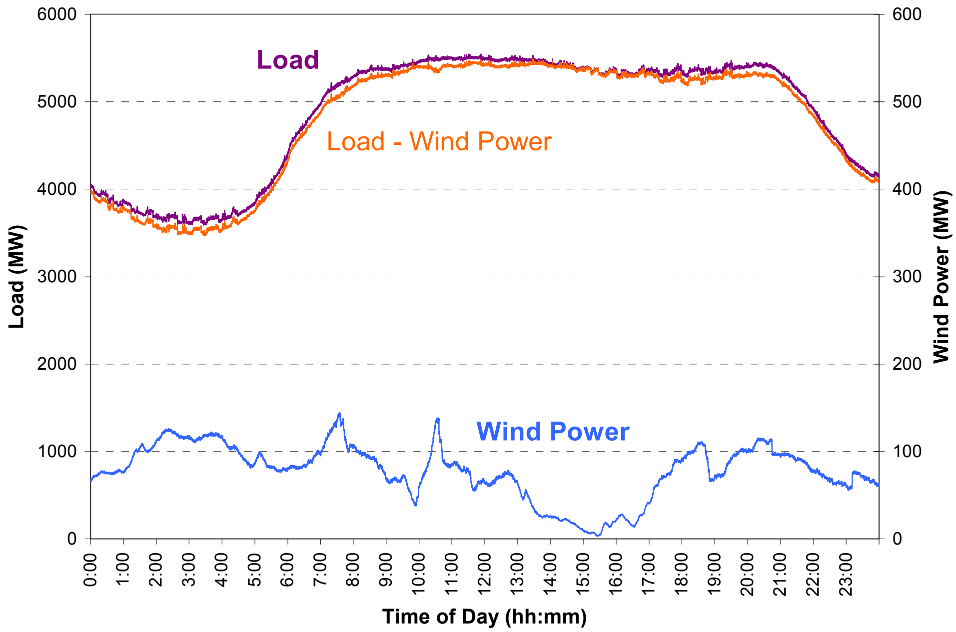


Figure 5-4. Daily 4-second load and wind power time series example

Table 5-1. Example of Wind Power Impact on System Regulations

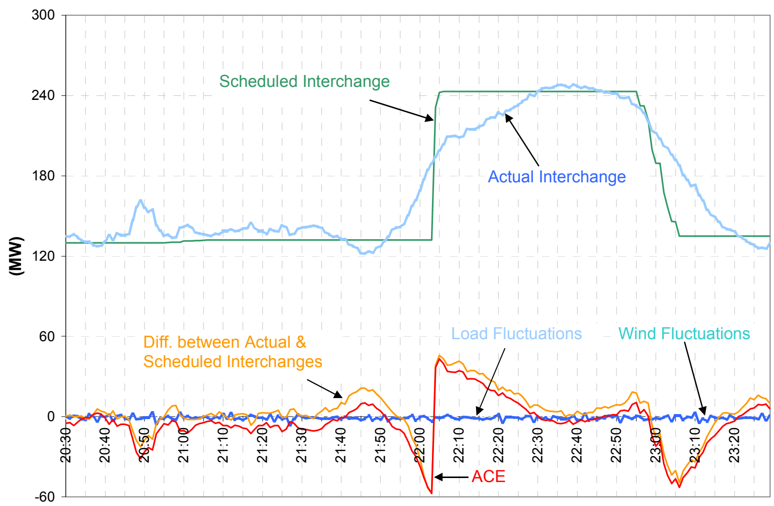
	Load Fluctuation	Wind Fluctuation	Net Load Fluctuation
Standard Dev. (MW)	9.99	0.77	10.07
3 x Standard Dev. (MW)	29.97	2.31	30.20
Maximum (+) (MW)	76.70	6.93	78.03
Maximum (–) (MW)	(58.60)	(8.35)	(58.41)
% within ±3σ	98.35	98.99	98.38

Results of this technique provide the range of regulation requirements when wind power is added into the system. It allows planners and operators to estimate wind power impact on system regulation requirements and make adjustments to operating procedures to integrate wind power into routine operations. However, it should be noted that although this gives a good indication of the system regulation requirements after wind power is added, the fluctuation component is not the real system ACE, and it does not show CPS1 and CPS2 compliance of the system. ACE is a function of system frequency[18] and the differences of scheduled and actual interchanges, but the

[18] More precisely, the combined frequency response of system load and generation.

above technique does not take frequency response of load and generation and interchange schedule into consideration.

Available data from one control area in Oklahoma show that at a low penetration level, the wind power fluctuations have minimal influence on ACE.[19] The correlation between system load changes and ACE is stronger than the correlation between wind power changes and ACE. This result suggests strongly that load fluctuations have a greater impact on system operations than do wind power fluctuations. Further examination of the data revealed that the majority of the large ACE values (positive and negative) have no relation to either system load changes or wind power changes. Large ACE values occurred during periods with large inter-hour interchange schedule changes. The available data have not shown that small short-term wind power fluctuations have any noticeable effect on ACE. Figure 5-5 is an example of such an event. It plots 1-minute actual and scheduled interchanges and their differences, 1-minute ACE values, and 1-minute step change values of wind power and system load. The figure clearly shows that



the ACE has no correlation with either load or wind fluctuations. The ACE tracks the differences between actual interchange and scheduled interchange and becomes very large during periods when the interchange schedule takes a large step change and the generators within the control area have not had time to bring the actual interchange to the new designated level.

Figure 5-5. Correlation between ACE and interchanges

Sudden changes of wind power do impact control area ACE behavior. However, other than forced and scheduled outages, wind power plants seldom experience sudden large changes (as discussed in Sections 3.2 and 3.2). CPS1 and CPS2 compliance are based on long-term ACE statistics. Infrequent large swings of wind power may not influence long-term CPS1 and CPS2 statistics very much. To study control area ACE performance after wind power is added to the system, the simulation software must simulate frequency characteristics of load and generation. It also must input a realistic interchange schedule. Commercial software can be used to simulate control area ACE behavior. This task is not commonly performed because many utilities only

[19] In this case the wind power is about 6% of the control area's peak summer demand. During periods of high winds and low loads, wind energy may represent 14% of the control area load.

have relatively small wind generation in their systems. As total wind generation capacity continues to increase and begins to impact grid operations in some areas, the need to better understand the ACE performance and CPS1 and CPS2 compliance will increase.

5.4 Summary

In general, wind power impact on system operations can be analyzed with standard utility software. Minor modifications of the procedure may be required to account for the unique characteristics of wind power. Some situations may require a new approach. A number of detailed studies have been performed. Because the utilities' experience with wind power is still limited (compared to operating experience with conventional power plants such as hydro and thermal units), trial and error seems to be a necessary process in developing robust techniques to analyze the interaction between wind power and system operations. However, one conclusion becomes clear from these studies: for low penetration of wind power in a utility system, the system appears to be capable of managing the impact of wind power.

At the same time, these studies point out the need to develop better models for wind power plants and collect long-term wind power data that capture the realistic behavior of a wind plant. This information establishes a planning boundary of expected performance under normal and rare conditions. Together with system data (load, generator output, frequency, interchange schedule, etc.) and valid wind plant models, an accurate account of the wind power impact on system operations can be obtained.

6. Conclusions

The analyses of large quantities of high-resolution wind power data series have demonstrated several important aspects of wind power.

1. Wind power fluctuations are concentrated within a narrow range. The average values of second-by-second changes of wind power are less than 0.1% of the wind power plant capacity. Maximum 1-second changes in power level are about 1% of the wind power plant capacity, and they occur infrequently. The average 1-minute step change of wind power is only about 0.3%~1.0% of the wind power plant capacity. Higher values are for smaller wind power plants and lower values are for larger wind power plants. Compared to the natural fluctuations of system loads, these short-term fluctuations are too small to have any impact on the system operations. The magnitudes of the largest 1-minute power level changes can reach 30% of the wind power plant capacity, but those extreme values appear to be caused by outages of the plant or the grid, and not the wind speed fluctuations.

   The short-term wind power data also highlight a unique attribute of wind power plants. Unlike other types of large power plants that can lose all generation capacity because of internal faults, malfunction of a single turbine will not cause all turbines in a wind power plant to trip off line at once. On this basis, the reliability of a wind power plant is actually higher than that of a large conventional power plant. The system can lose all the generation of a wind power plant when the line connecting to it trips because of a fault.

For 10-minute intervals, the average magnitudes of wind power step changes vary around 2% of the wind power plant capacity. For a 100-MW wind power plant, the average absolute values of 10-minute power level changes are around 2 MW. This value is smaller than the average magnitude of load forecasting errors expressed in terms of total system load.[20] More than 98% of all 10-minute step changes are within the range of $\pm 3\sigma$ (±11.4 MW or about ±11% of plant nameplate capacity). The data show that sizes of the wind power plants and turbine types have little effect on 10-minute step change statistics. The 10-minute interval maximum power level changes are only slightly bigger than the corresponding values of the 1-minute interval.

Wind power can change substantially in the hourly time frame, but even hourly step changes of wind power are still confined in a relatively narrow range. More than 98% of all hourly step changes are of a magnitude that is within the range of $\pm 3\sigma$ (±30 MW of ±29% of the plant nameplate capacity). The average magnitudes of hourly step changes are still relatively small, ranging from 4.5% to 6.4% of wind plant capacity. These percentage values are calculated with the name-plate capacity of the respective wind power plants. The differences in the average hourly step changes magnitudes expressed as a percentage of the wind plant capacity will be smaller if the actual achieved maximum power output is used to calculate the percentage values. It shows that the operations of wind power plants in different regions and with different types of turbines are very similar. The fluctuations are a function of short-term wind speed variations, and this wind characteristic is likely to be the same in all of the locations analyzed so far. Large wind power plants (with more turbines) tend to have fewer variations in their output.

2. The maximum magnitudes of hourly wind power level changes can be significant. With favorable wind, a wind power plant can start up and reach its full output in 1 hour. A wind power plant can shut down just as quickly. The largest monthly maximum hourly step changes are in the range of 80% of the wind plant capacity. Those large step changes were actually caused by outages outside of the wind power plants. Excluding the grid-outage-induced large step changes, the largest power level change of a wind power plant was about 70% of the wind plant capacity in 1 hour during a 12-month period. These changes occur infrequently. The step changes statistics show that even with the outages, wind power plants do not drop from full capacity to zero in a period of 1 hour or less. The rate of power increase of a wind power plant can be modified with a proper control strategy that limits the number of wind turbines that are allowed to start simultaneously. The rapid decrease of wind power is difficult to remedy. Better wind forecasting can help mitigate the impact on system operation.

3. Multiplying the output of single or small numbers of turbines to emulate the output of a large wind power plant does not provide realistic results. The output from a large wind power plant with many turbines will fluctuate less than the output from a single turbine or a small group of turbines. The spatial and temporal variations of wind speed within a large wind power plant make the combined output less variable. The effect of simple scaling up is equivalent to force the outputs of all turbines in a large wind power plant in sync, and it exaggerates the fluctuations of the output power. The actual data prove that such a practice, sometimes

[20] Hirst, E. "Integrating Wind Energy with the BPA Power System: Preliminary Study," September 2002.

performed out of necessity because of lack of actual data, is not advisable. It also emphasizes that one cannot simply extrapolate the data from a single anemometer to the wind power plant output because the resulting wind power plant output will have much worse fluctuation characteristics.

The approach of using meteorological models and archived weather data to simulate weather conditions and wind power may avoid these problems. If real wind power speed and power data are not available, the weather model can be used to produce realistic output power series from many wind power plants over a large area.

4. Wind power profiles are location specific. The data show that different regions have different daily, monthly, and seasonal wind power profiles. Wind power data from one region can be used to predict fluctuation behavior from second-to-second up to hourly, but they are not good indicators to daily and monthly performance of wind power plants in other regions. Utility system load follows predictable daily, weekly (weekdays and weekends), and seasonal (summer cooling, winter heating, on-peak, off-peak) patterns. With long-term wind power data, it is possible to assemble seasonal average output profiles for the region, but they may not be applicable to other regions. In addition, the available data do not show that wind power has any distinctive weekday and weekend profiles.

   Utility planners usually compile some representative load profiles for system analysis and planning. A different approach may be necessary with wind power. The stochastic nature of wind power series makes it difficult to compile representative daily or seasonal profiles for a specific region. The critical issue is that the wind power profiles capture the characteristic wind power variations. Again, this issue could be addressed with the weather model approach.

5. Capacity value or capacity credit of a generating plant to a utility power system is a very important measure in system planning and operation. There are different ways to assess the capacity credit of a power plant. For planning purposes, it is typically calculated using a reliability model that simulates the electricity production under various conditions. In operations, actual output from a power plant during system peak load period is sometimes used to represent the capacity credit. Long statistics of power plant output, especially hydro units, are often the basis for such methods. Regardless of what methods are used to assess the capacity credit of power plants, the results depend highly on the individual system characteristics such as load profiles, generation mix, and maintenance practice.

   Wind plant capacity credit can be calculated with standard utility methods. Researchers at NREL and other institutes studied this issue.[21] Their results show that despite the intermittent nature of wind, wind power can contribute to enhance the system reliability and thus has capacity value. However, wind power capacity credit is more site specific than conventional generating technologies. In addition to system attributes (load, generation mix, and other operating practices), the capacity credit of wind power also strongly depends on wind resources specific to the location of the wind power plant. Using wind resource data or wind

[21] Milligan, M.; Porter, K. (2005). Determining the Capacity Value of Wind: A Survey of Methods and Implementation; Preprint. 30 pp.; NREL Report No. CP-500-38062.

power data from other locations to assess wind power capacity credit introduces high uncertainty.

It is clear that the short-term fluctuations of a wind power plant are very small (about 0.1% of plant capacity for a 1-second data series and less than 1% for 1-minute data series). They are about the same percentage values as the system load variations. Ramping of wind power is also small. Average ramping rate for a wind farm is less than 0.5% of plant capacity per minute. In extremely rare situations, wind power can ramp 10% of its capacity per minute. The entire wind farm never shuts down simultaneously because of wind speed changes.

At low wind power penetration level, the load is much larger than the wind power, and its fluctuations dominate the short-time frame system regulation. For those systems, the small variations of short-time frame wind power are well within the range of normal system load variations. The addition of wind power may or may not appreciably increase system regulation duties, depending on the correlation between the wind fluctuations and load fluctuations. The impact of wind power on system operation becomes noticeable in a 10-minute or longer time frame. Wind power variations are higher than that of the load when both are expressed as a percentage of their respective capacity. Wind power also has a higher probability of large step change values in longer time intervals. If such large wind power fluctuations can be forecasted with confidence, it will be a tremendous help to system operators.

The data also suggest that output fluctuations are influenced mainly by the size of the wind power plants. Differences in turbine types and plant locations play much lesser roles in determining the step changes of wind power. For two wind power plants of the same installed capacity, their step change statistics will be very similar.

A corollary to the observed wind power temporal and spatial diversity is the cautionary note on the attempts to simply scale wind power up or down from available wind power data and wind speed data. The actual wind power data have shown that simply scaling the output of a small wind plant to match the expected output (either power or total energy) of a large wind power plant will exacerbate the fluctuation of wind power. Scaling down the output of a large wind power plant to match the expected output of a smaller wind power plant will have the opposite effect. Simply extrapolating from a single anemometer reading to the output of a wind power plant will produce an even worse effect. The resulting wind power profiles from either approach will not demonstrate the true behavior of the intended wind power plant.

With a multi-year high-resolution wind power data series, wind power plants can be analyzed with the conventional utility operating study models (chronological and probabilistic) to evaluate their capacity contribution and effect on system production cost. Additional wind power time series of desired variation characteristics can be generated by judicially applying the state transition matrix of available wind power data series or with the weather model approach.