Serving Northwest Loads with Columbia Basin Wind Turbine Generation

Chad Edinger and Kevin Tomovic, Fellow, IEEE

Abstract—Much of the public discussion and recent laws on renewable generation has focused on very broad issues of resources. But for smaller utilities and local regulators, determining regional resources ability to serve load may be difficult to resolve with such government mandates as renewable portfolio standards, particularly for wind generation. Wind is sporadic by nature and imposes a high level of uncertainty into utility operations. Moreover, wind has great seasonal and geographic dependencies that require intensive planning studies. This paper presents a simplified analysis for a utility in the Northwest United States to plan the amount of wind generation capacity that will be needed to meet state mandated renewable requirements reliably. Assumptions are proposed for converting existing wind speed data into a combined wind farm megawatt output. The model allows for analysis of wind turbine output from sites with relative geographic dispersion. Based on this output, the model allows for analysis of wind turbine output using appropriate statistical computations. The objective is to determine with acceptable certainty the wind generation a typical modest size utility will require to meet both theoretical goals and Washington State’s renewable portfolio standards.

Index Terms—Loss of Load Probability, Effective Load Carrying Capacity, Renewable Portfolio Standard, Wind Generation.

I. INTRODUCTION

WIND energy prediction and system integration for utilities with abundant resources and appropriate data is relatively straightforward at modest levels of penetration. A problem presents itself for a smaller electricity provider with no previous wind energy experience when it comes to performing an evaluation of the cyclical capacity of wind generation while at the same time meeting traditional planning criteria. This paper proposes two types of evaluation. The first is the comparison of generation cycles to load cycles for reliability purposes. This could be used in the case of a utility trying to add a generator to its existing mix. The second is an evaluation of the average load to average wind farm output to help the utility determine the amount of generation needed to meet renewable portfolio standard (RPS) requirements.

Washington state utilities are preparing for a large change in operations when the recently passed Initiative 937 takes effect. Beginning in the year 2012, utilities with over 25,000 customers in Washington will need to produce or purchase 3% of their electricity from a renewable resource, such as wind. The manner in which this 3% is measured is simplistic. The total load in 2010 and 2011 is added and averaged into a single year. Proof must be submitted to the state showing that in 2012 enough renewable energy contracts and or renewable energy credits have been purchased to cover at least 3% of this average load. In 2016, this number will increase to 9% and then finally to 15% in 2020 [1].

Specifically, this paper will investigate a plan for a medium sized Northwest utility either on its own, or as a member of a consortium, to install wind turbine generation to meet a portion of its load. The focus of this paper will be on the modeling of a wind resource for the utility using readily available data, determining how well those resources serve the utility’s load and to what extent those resources meet the Washington State RPS. Economic consequences and integration issues will be deferred to future work.

II. BACKGROUND

A. Effective Load Carrying Capacity

Valuing the capacity credit for wind generators varies from utility to utility and is subject to debate. The most commonly used measurement is capacity factor (CF). A wind turbine’s CF is defined by the output over a period of time divided by the capacity rating of the wind turbine. By summing all turbine outputs over the same period and dividing by the wind farm capacity over the period, one can obtain the capacity factor.

\[
CF = \frac{\sum_{i} OP_i}{\sum_{i} ROP_i}
\]  

(1)

where:

- \(OP_i\) is the output of \(i^{th}\) turbine;
- \(ROP_i\) is the rated output of \(i^{th}\) turbine;
- \(k\) is the total number of turbines within the wind farm;

Capacity factor is very much dependent on the time period over which it was measured. The longer the period of time the more accurate the evaluation of capacity. It appears though that many Northwest utilities use a single capacity factor for all wind generation projects [2-4]. Another method of valuing
the capacity of wind plants or other intermittent power plants is Effective Load Carrying Capacity (ELCC). The availability of the wind resource drives the ELCC value. As Milligan notes, the value of the ELCC may not match the annual CF and that ELCC is a more appropriate measure [5].

The first step in determining ELCC is calculating the Loss of Load Probability (LOLP). This is achieved by using a binomial distribution to calculate the probability of a single event [6]. By summing the probabilities of the outage combinations, one may calculate the cumulative probability that a maximum number of generators are unavailable [7].

\[
LOLP_i = \frac{n!}{i!(n-i)!} p^i (1-p)^{n-i}
\]

where:
- \( p \) is the forced outage rate;
- \( n \) is the number of generators available;
- \( i \) is the number of generators on outage;

When evaluating a renewable generator’s ELCC, the renewable under study is placed into a generation mix and LOLP is measured. The new LOLP is noted and the renewable is taken back out of the mix. It is then replaced in small increments by a benchmark generator until the LOLP is lowered to that which was achieved with the renewable [8]. Therefore, ELCC is a measure of the benchmark generation that is required to achieve the same level of LOLP as when the wind generator is connected.

B. Wind Turbine Output

To properly value the capacity of a given wind site, one must take many factors into consideration, including transmission constraints and load shapes. Barring the ability to build and gather output data from an actual wind turbine at a site, the most useful parameter is wind energy, usually measured in W/m². To determine this, prospectors of wind energy construct towers at possible sites to measure and record over a long period of time various parameters for the calculation of wind energy. The height of the tower from which the measurements are taken need to correlate to the hub height of the turbine model proposed for the site or data needs to be extrapolated so as to represent wind speed at the hub height. It is also important that measurements be taken over as long a period as possible to determine a baseline from which to evaluate and help determine cyclical behavior. Of course, greater data accuracy can also be achieved by constructing multiple towers over the proposed wind farm to account for variations caused by local terrain.

Since wind data is usually not available at the precise hub heights for a proposed turbine, the data is often extrapolated. Here, the 1/7 power law is used to extrapolate data to height. Similar methods have been employed in other studies using geographically dispersed wind monitoring sites [9-11].

\[
V_s = V_m \frac{H_s}{H_m}^\frac{7}{6}
\]

where:
- \( V_s \) is the velocity to be determined;
- \( V_m \) is the measured velocity;
- \( H_s \) is the height to be determined;
- \( H_m \) is the height of velocity measurement;

Given the wind speed data, one can determine the power output from simplified models, field tests or manufacturer data. Power output in this study is based on manufacturer data.

Figure 1 shows the generation output curve for the Vestas V80-2.0 MW turbine [12]. Note the importance of the cutout speed (55.92 mph for this turbine in Fig. 1) to prevent damage, which from an operation point of view, can act as a sudden generator outage. By using the manufacturer’s published curve, one can take into account the mechanical and electrical losses. This will leave only transformer and transmission losses unaccounted for, and both will be assumed negligible.

C. Statistical Comparisons across Sites

Wind generator performance is geographically dependent. A wind farm in the Northwest could have a capacity factor that is much less than a wind farm of equal capacity than say, in the Great Plains [13]. Having a diverse data set is beneficial because it is believed, and studies have shown, that having geographically dispersed wind sites enhance generator availability and reduce variability when combined to form a single source [9, 10, 14-16]. Optimally, wind sites need to be located as far apart as possible and in the windiest environments.

By calculating the correlation coefficient of the wind generator outputs, one my empirically value the diversity of a set of wind farms. The results should show a decreasing correlation as distance between sites increase. By lowering the correlation, the total output of the wind farms will become more reliable. Still, due to cost and transmission constraints, a limit on the value of geographic separation will become apparent. Though correlation does not guarantee a greater total output from the wind farms, it does allow for an indication of the variability of total output.

III. STUDY DATA

A. Wind Data

In Washington State, many of the prime wind sites reside along the Columbia River east of the Cascade Mountains, near Ellensburg, northeast of Walla Walla and along the state’s coastline [17]. Due to the remote nature of these wind sites from major load centers, transmission is of major concern.

BPA is a likely supplier of bulk transmission for Northwest utilities looking to build wind generation due to assets that
cover the region along the Columbia River in support of hydroelectric generation. This is in addition to the fact BPA already has over 1,500 MW of installed wind capacity in its control area [14]. Since 1978, the Energy Research Resource Library (ERRL) has been managed by Oregon State University for the Bonneville Power Administration’s Wind Forecasting Network [18]. All together BPA has eight different sites where data such as wind speed, wind direction, barometric pressure, and temperature have been recorded. This data was available for study at 10-minute intervals.

Based on data availability and transmission access, four of the eight sites were chosen - Sevenmile Hill, Goodnoe Hills, Kennewick, and Vansycle Ridge (see Fig. 2). Of these four sites, three are part of the Wind Forecasting Network and one, Vansycle, is at an existing wind farm. The distance from Sevenmile to Kennewick is 37.5 miles with the distances from Goodnoe to Kennewick and Kennewick to Vansycle being 72.3 and 23.6 miles respectively. Data was collected at 1-second intervals (except Vansycle which is 2-3 seconds) added together and averaged to form the 10-minute data. As for the wind data obtained from BPA, each site measured wind data at different heights. Sevenmile was measured at 100 ft, Goodnoe at 195 ft, Vansycle at 201 ft, and Kennewick at 86 ft. To be able to compare how the wind sites perform in relation to each other, and to accurately model turbine output, the wind speed at a common height was estimated.

It is believed wind cycles can be seen most prevalently between seasons. Therefore, it is beneficial to isolate these variations and not rely solely on yearly comparisons. For the purpose of this paper, spring will be defined as March, April, and May; summer as June, July and August; and fall as September, October and November; and winter as December, January and February. The wind data analyzed spans from August 2002 through December 2006.

B. Load Data

To properly evaluate the value of a wind asset, one must also look at the load it serves. Electric loads are geographically dependent adding another level of complexity to finding the right combination of sites to serve a load. Wind speed’s contribution to generator capacity factor is only a portion of a proper evaluation of a site. Load data form a medium sized Washington utility was obtained from January 1, 2002 to December 31, 2006. The average load during this time was 545.6 MW with a peak demand of 962 MW and a minimum of 283 MW. The utility’s load is typical of a Western Washington load, which is winter peaking with a summer minimum.

In the Northwest, there exist three bilateral markets for purchasing electricity futures: a forward (month to 1 year), day ahead, and real time. Day ahead and real-time purchases are made in hourly blocks [19]. Due to the fact that Northwest utilities schedule for loads no shorter than on an hourly basis, it is beneficial to turn the wind data into hourly information. Therefore the same averaging is used for the hourly data as was used for the 10-minute data. Figure 3 above displays the load duration curve.

C. Turbine Data

The wind turbine used for modeling the wind farm output is the Vestas V80-2.0 MW turbine. This turbine was chosen due to the fact that a few of the larger, and more modern, wind farms in Washington use this type of turbine. The manufacturer of the wind turbine publishes a wind speed at the hub to generator output curve. Depending on the exact model, hub height variations come in 60, 67, 78, 85, and 100 m [12]. A hub height of 67m will be used due to the fact other Washington Utilities used this V-80 hub height at similar locations [20, 21].

Only one set of wind speed data for each site is recorded. Therefore, one can only precisely model four different wind turbines. The assumption will be made that if the modeled wind farms are equal in turbine count, the variations between the sites will correct for the linear scaling of the wind farm capacities. Given the typical size of a modern turbine located in the Northwest [19-24] and a conservative estimate of 20% capacity, the model will use a wind farm size based on 15% of the utility’s average hourly load. The reason for using 15% of
the utility’s average daily load is partly due to convenience, as a rough estimate is needed from which to start the model, and also due to the the Washington State RPS for the year 2020 requiring 15% of average load to be served by renewables. Using the Vestas V80-2MW model mentioned before, the total number of turbines at each site will number 50. This equates to a total nameplate capacity of 400 MW.

IV. ANALYSIS

A. Variability

Hourly wind turbine variations were determined for the sites based on wind speed and the manufacturer’s output curve as mentioned above. Table 1 shows the average hourly step change for each site based on the percentage of nameplate capacity, where SM refers to Sevenmile, GU to Goodnoe, VZ to Vansycle and KZ to Kennewick. Note that in the tables presented here that historic refers to all data collected for the site and due to data limits, only three years went into winter calculations. Table 2 shows all four wind sites combined. Only two step changes exceed the 5.3% found by Wan’s study [25] of 250+ turbine output from 3 different sites. The historic average found here, was 5.2099% of rated capacity. This holds in the model regardless of the number of turbines. One must ensure though, that each site maintains an equal number of turbines or else the variations of a single site will weigh the results. The benefits of diversity here are apparent.

The aggregate model, on average, has the least variation during the fall and the most during the spring. Table 3 below displays the standard deviation of these measurements. Winter shows the greatest standard deviation, with summer having the least. Due to the fact the utility is a winter peaking load, ideally the least deviation would occur during the winter period. Further analysis that includes the actual load is needed though, before any conclusions can be drawn.

B. Site Correlations

The wind farm correlations were next calculated and each site was compared. Table 4 displays the results of the calculations, which are relatively low. Recall the distances between SM and GU was 35.7 miles and between VZ and KZ which was 23.6 miles. The mean distance between these two groups was almost 100 miles. This helps explain the higher combined correlation between SM and GU, and between VZ and KZ. The lowest correlations across all seasons were between SM and KZ (107.9 miles). The largest distance was between SM and VZ (126.5 miles), which had a correlation coefficient that was the second lowest across all four seasons.

Winter consistently had the lowest correlation coefficient across the sites with the exception of Vansycle to Kennewick, which happens to also be the highest of all winter correlations. This is not too surprising given the fact it is the shortest distance between any two stations. The lowest correlations in effect show a greater independence of the wind sites during the winter. This bodes well for the utility, which sees the largest electrical loads during the winter season. Summer shows the largest correlation in every case but two, GU/KZ and VZ/KZ. These measurements help to show that correlations cannot be made simply by distance measurements, but that seasonal variations need to be taken into account.

C. Turbine Capacities

The capacity factors were next calculated. Each site’s capacity factor was derived with all sites acting as a single generator. Table 5 shows that the combined wind farm over the four seasons is 40.22% of rated output capacity. Sevenmile and Goodnoe show the greatest capacity factor in the summer and both were lowest in the winter. The combined value for Sevenmile shows the greatest capacity, while Goodnoe’s shows the least. Further east at Vansycle, the capacity factor is lowest in the fall and highest in the winter. Kennewick also experiences a sudden change where the spring is highest and the summer the lowest. In the case of all wind sites together, the peak is in the summer and the low is in the winter.

Note the majority of seasonally high correlations occurred during the summer, which has the highest capacity factor when all sites are considered. The opposite holds for the winter where a majority of the lowest seasonal correlations occurred, and winter had the lowest capacity factor. This leads to a result that shows seasons affect correlation and capacity. The data shows, by extension, that consistently higher summer winds have the greater correlation seen during the summer, between the wind farms.

Figure 4 shows the historical relative frequency of the output of all the wind farms together. When compared to Figure 5, one can see how geographic dispersion can create a more even wind resource output. The median output of all the wind farms together was 150.2 MW. Figure 5 shows that the individual wind farms, in this case Sevenmile, spends the
V. RELIABILITY OF SERVING LOAD

The next step is to analyze load data. The utility’s load is scaled to 15% to allow for hourly variations in load to be maintained while comparing RPS requirements. The historical data for the wind turbines included data from a shorter time period than the historical load data due to the fact that all load data is good and that generation data spanned over four different years. Still, all load data was used during the calculation of LOLP. Table 6 displays the seasonal variations in load. For the historical load, demand is never below 42.5 MW, never above 144.3 MW, and is below 79.4 MW half of the time. The wind farm output was found to be above 150.2 MW half of the time. Initially it seems the amount of generation needed to serve the utility’s load is over valued. The load for the winter season is relatively high, the spring season and fall seasons are intermediate and summer sees a relatively light load.

TABLE 5 WIND SITE CAPACITY FACTORS AS A PERCENTAGE OF RATED CAPACITY

<table>
<thead>
<tr>
<th></th>
<th>Winter</th>
<th>Spring</th>
<th>Summer</th>
<th>Fall</th>
<th>Historic</th>
</tr>
</thead>
<tbody>
<tr>
<td>SM</td>
<td>20.6%</td>
<td>41.2%</td>
<td>64.4%</td>
<td>35.5%</td>
<td>42.5%</td>
</tr>
<tr>
<td>GU</td>
<td>29.2%</td>
<td>38.1%</td>
<td>42.7%</td>
<td>30.6%</td>
<td>35.6%</td>
</tr>
<tr>
<td>VZ</td>
<td>43.3%</td>
<td>43.1%</td>
<td>40.1%</td>
<td>39.0%</td>
<td>41.0%</td>
</tr>
<tr>
<td>KZ</td>
<td>43.4%</td>
<td>48.3%</td>
<td>38.6%</td>
<td>39.8%</td>
<td>41.9%</td>
</tr>
<tr>
<td>All</td>
<td>34.1%</td>
<td>42.6%</td>
<td>46.4%</td>
<td>36.2%</td>
<td>40.2%</td>
</tr>
</tbody>
</table>

A. LOLP and ELCC Results

Next the LOLP was calculated using daily peak load versus
hourly wind farm output. The hourly LOLP (HLOLP) was then calculated to allow for a better understanding of how daily versus hourly load information impacts performance. There is no output for 1,847 hours out of the total 32,968 hours studied. This results in a minimum LOLP of 5.6% regardless of the wind farm size. In Table 7, one can see that the LOLP and HLOLP are the lowest during the summer season. This is the same season in which the correlation coefficient between load and generation displayed the largest negative value. This shows that although correlation can be worse during certain seasons, the generator’s ability to serve load can actually be better. This is mostly likely due to the average level of load during the season, with the intra-seasonal variations having the greater affect on LOLP levels.

The ELCC was calculated using the LOLP and HLOLP results. Since only a portion of the utility’s load is used for the study it would be plausible to use the LOLP of the wind generation, on its own, to find the capacity of a benchmark generator that would provide the same level. Using a benchmark forced outage rate of 5% and starting with a capacity of 80 MW the LOLP was calculated at 83.3%. Next 5 MW was added for a total of 85 MW and LOLP recalculated. This was repeated until the LOLP was below that of the renewable generator. The process was then repeated to calculate HLOLP. Figure 6 shows the results of the capacity additions relative to the wind farm LOLP and HLOLP.

As one can see, the effective load carrying capability of the wind farms based on LOLP is approximately 101 MW for the historical data. This is 60 MW lower than the 161 MW that would have been calculated at 0.4022 since load is factored in the ELCC calculation but not the capacity factor. Table 8 below shows the variations of ELCC over the seasons.

Table 9 illustrates the differences between ELCC values as the nameplate capacity of the wind farms are changed. Recall this model uses 200 wind turbines with an installed capacity of 400 MW. As you can see the amount of equivalent benchmark capacity that is obtained from increasing the size of the wind farms is minimal. Similarly, the amount of equivalent benchmark capacity decreases very little with large decreases in the number of turbines. It is surprising to note that the ELCC is actually highest in the winter. As shown in Table 7, the LOLP data set for the benchmark is actually much higher when compared to other seasons and the combined data. This shows that the higher load actually has a significant affect on the benchmark HLOLP and LOLP, which causes ELCC to increase.

B. Meeting RPS Requirements

Figure 7 shows that with a conservative 1.3% load growth, the utility would have to build 6 turbines at each site to achieve at least 3% of average load through 2016. In this case though, the utility could site all turbines in the most productive spot and perhaps decrease the total number needed. If the utility were to build out to meet I-937 requirements 30 years from now, 40 turbines at each site should provide sufficient average output.

VI. CONCLUSION

This paper has shown that modest levels of wind farm capacities appear to be able to meet the recent RPS in Washington State. These capacities also can add to reliability although not nearly as high as capacity factors might suggest.

The correlation between the wind sites showed that as distances increased, the correlation coefficient decreased supporting the value of dispersed locations. Total generation was measured and resulted in capacity factor of 40.22%. This high value may be attributed to an overly optimistic wind speed-to-turbine output curve published by the manufacturer, perhaps to the limited amount of time data has been collected at these sites as well as other considerations, such as, maintenance that would reduce output. Further analysis did show a seasonal capacity factor that was closer in value to those of studies conducted over limited time durations. In general, it can be said that winter has the lowest generating capacity and lowest wind site correlation coefficients. On the other hand summer, by and large, has the highest generating capacity and the highest correlation between sites.
A negative correlation coefficient between generation and the utility’s load was found. Other studies have found similar results but this should not preclude the Columbia River basin from being considered a valuable resource for reliability. Although the wind farms were used as the only generator in the generating mix, added value can be gleaned from the ELCC. The effective load carrying capacity measurements showed that the utility can expect more generating value from a wind resource during the winter months. Also shown was that as the wind farm size decreased, the greater the equivalent output as a percentage of nameplate capacity. This is valuable information to the utility in deciding how large of a wind farm to build without regard to reliability or RPS requirements.

Finally, the calculation of capacity a utility will need if they choose to meet renewable portfolio standard requirements via wind generation was performed. This was relatively easy to find if every megawatt generated is used to serve the utility’s load. However, the utility would still need forecasts of wind farm output so that it may plan other generators within the overall mix. Given that the example utility here supplies about 24% of its own electricity from hydroelectric under its direct control, results in some flexibility in controlling generation mix [26]. If the wind resource cannot be optimally integrated into the mix, a larger resource would be needed.

**ACKNOWLEDGEMENTS**

The authors appreciate the wind data provided by Energy Research Resource Library at Oregon State University.

**VII. REFERENCES**


BIographies

Chad Edinger received the B.S. and M.S degrees in electrical engineering from Washington State University, Pullman in 2003 and 2008. He is currently working for Tacoma Power's Operations and Trading group.

Kevin Tomsovic (F'07) received the B.S. degree in electrical engineering from Michigan Technological University, Houghton, in 1982 and the M.S. and Ph.D. degrees in electrical engineering from the University of Washington, Seattle, in 1984 and 1987, respectively. Currently, he is Head and CTI Professor of the Department of Electrical Engineering and Computer Science at University of Tennessee, Knoxville. Visiting University positions have included Boston University, Boston, MA; National Cheng Kung University, Tainan, Taiwan, R.O.C.; National Sun Yat-Sen University, Kaohsiung, Taiwan, R.O.C.; and the Royal Institute of Technology, Stockholm, Sweden. He was on the faculty of Washington State University from 1992-2008. He held the Advanced Technology for Electrical Energy Chair at Kumamoto University, Kumamoto, Japan, from 1999 to 2000 and was an NSF program director in the ECS division from 2004 to 2006.