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Development of an Equivalent Wind Plant Power-Curve

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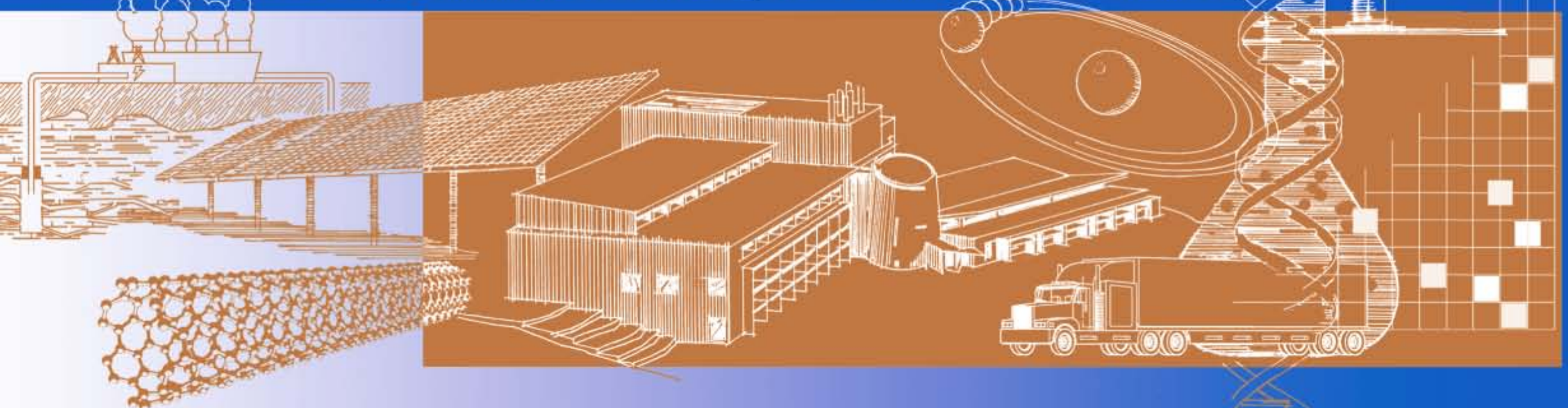

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Development of an Equivalent Wind Plant Power-Curve

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Abstract

Wind turbine manufacturers publish and certify power curves for their turbines. These turbine power curves are used for planning purposes and estimating total wind power production. When a wind plant consisting of many turbines connects to the utility grid and starts operation, the focus shifts to the entire plant's performance. An equivalent wind plant power-curve becomes highly desirable and useful in predicting plant output for a given wind forecast. The National Renewable Energy Laboratory (NREL) has worked with a utility to collect detailed data from a large wind power plant to develop such an equivalent power curve. This paper will (1) summarize available data, methodology, and the results of this work; (2) discuss the validation process; and (3) explore the applicability of such an approach on other wind power plants without detailed data.

Performance of a single wind turbine can be characterized by a power curve − a graphical representation of the turbine electric power output as a function of the hub-height wind speed. With such a curve, turbine power output and energy production can be predicted without detailed knowledge of turbine operations and its control schemes. An equivalent power curve for the entire plant can serve the same purpose for plant and system operators to predict the plant output for a given wind speed. However, unlike the single-turbine power curve, a single curve cannot capture all the nuances of a wind plant consisting of tens or even hundreds of turbines. A model consisting of a set of power curves is required to fully characterize the complex input/output relationship of a wind plant to account for the effects of different wind directions, local terrain, and asymmetric turbine layout in a wind plant. NREL has obtained data from a large wind plant for the development of such a model. The data include plant output, wind speed, and direction from meteorological towers, and nacelle anemometer readings and power output from each turbine. From this extensive dataset, the distributions of wind speed and power production of all turbines are analyzed over a wide range of wind speeds. From these distributions, a model is constructed to generate an equivalent power curve for the plant.

1. Introduction

The National Renewable Energy Laboratory (NREL) has collaborated with a utility to analyze the performance of a large wind power plant using measured power and meteorological data. The objective is to develop models, such as a power curve or a set of power curves, so that the wind plant performance can be characterized with a few measured or predicted input variables such as wind speeds and directions.

Performance of a single wind turbine can be characterized by a power curve − a graphical representation of the turbine electric power output as a function of the hub-height wind speed. With such a curve, the turbine power output and energy production can be predicted without detailed knowledge of a turbine and its components. Turbine manufacturers provide measured power curves for turbines based on industry standard IEC 61400-12-1.[1] Figure 1 below is an example of a power curve of a wind turbine with active power control[2].

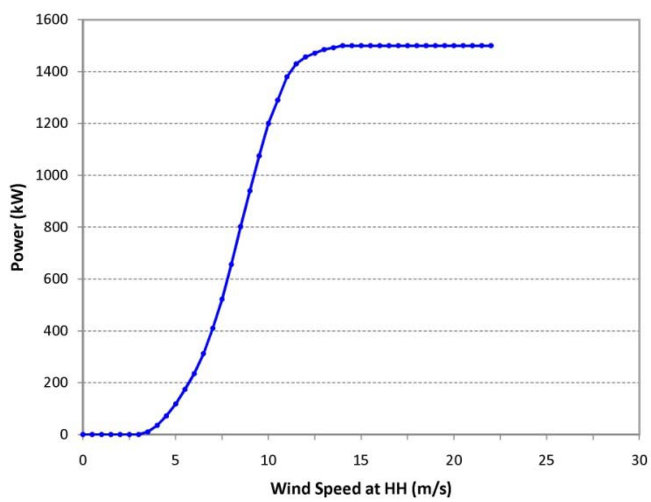

Figure 1 −Turbine power curves.

There are three key points on this curve: (1) cut-in speed below which the turbine will not produce power; (2) rated speed at which the rated power of the turbine is produced; and (3) cut-off speed beyond which the turbine is not allowed to deliver power. A wind power plant normally consists of many turbines with identical power curves and therefore an equivalent power curve for the entire plant is expected to take a similar shape. However, the aggregated curve will be dependent on the impacts of local terrain, wind direction, turbine wakes, and other factors. Such a curve, if it can be developed, can help plant and system operators predict the plant output for a given wind speed which takes into account these pertinent factors. The task is to construct an equivalent wind power curve for the entire wind plant.

The wind plant analyzed for this report is located in northeast Colorado. It consists of two types of turbines totaling 274. The turbines are spread across an area of approximately 17 km by 17 km. The plant electric collection system uses standard 34.5-kV underground cables to connect turbine strings and feed the power to a substation. There are two meteorological (MET) towers at this site. Figure 2 is a site map

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[1] IEC 61400-12-1 Wind Turbines – Part 12-1: Power Performance Measurements of Electricity Producing wind Turbines; first edition 2005-12.

[2] GE Wind Energy (2009) "1.5 MW Wind Turbine." http://www.gepower.com/prod_serv/products/wind_turbines/en/download/GEA14954C15-MW-Broch.pdf

of the wind plant showing the relative distances between turbines (blue dots and yellow dots) and MET towers (red dots).[3] The turbines are at two hub heights − 80 m and 69 m. The turbines are generally lined up in rows which are perpendicular to the prevailing wind direction (northwest) at the site. The average distance between turbines in the same row is about 320 m, or roughly 5 rotor diameters. The distances between rows range from about 530 m to more than 8,900 m. The two MET towers (designated A09 and H06) measure wind speed (in m/s) and direction (from 0° to 359°) at 80 m (designated H1) and 50 m (designated H2) at MET tower A09 and at 69 m (H1), and 50 m (H2) at MET tower H06. In addition, barometric pressure (in mBar) and temperature (in °C) are measured at both MET towers.

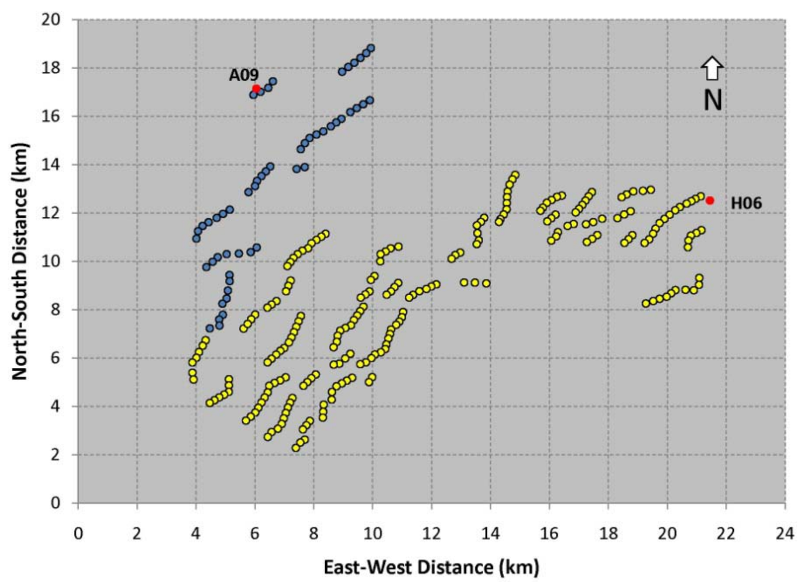

Figure 2 − Turbine and MET tower locations.

2. Available Data

The utility has installed a Plant Information (PI) system to collect detailed operating information of the wind plant. For each turbine, the collected data includes turbine status (availability and online status[4]), rotor speed (rpm), power output (kW), nacelle position (degree), and wind speed from the anemometer on top of the nacelle (m/s). The output of the entire plant is monitored by the utility's supervisory control and data acquisition (SCADA) system and transmitted to its PI system. Together with wind speed, direction, barometric pressure, and temperature data from the two MET towers, and with other diagnostic information of the plant, there are more than 2,500 data streams from the wind plant being collected and stored by the PI system. When storing raw data, the PI system uses a special compression algorithm to reduce the size of data files and minimize storage requirements. This technique results in a compressed data stream with unevenly spaced time intervals. Post-processing software enables users to extract and process the data in almost any fashion. The PI system began storing data in October 2008. Only individual turbine availability status (online or off-line), output power, nacelle wind speed, wind speed and direction from two MET towers, and metered total plant-output data from October 2008 to December

[3] Locations of turbines and MET towers are approximate, based on information from FAA obstructions database (https://oeaaa.faa.gov/oeaaa/external/searchAction.jsp?action=showSearchArchivesForm).

[4] A turbine can be available for generation but not online due to other conditions such as line outage.

2009 were extracted and processed for this report, and this period is referred to as the study period in the rest of this report. The calibration status of the instruments on the two MET towers is not known.

2.1 Data Quality Issues

The amount of available data offers a rare opportunity to look into the operations of a large wind power plant. These data make it possible to check the validity of data by simply cross-referencing many data points. For this task, the individual turbine-nacelle wind speed, output power, turbine availability, total metered plant-output power, and wind speed and direction readings from the two MET towers are of primary interest.

For turbine power curve measurements, the IEC standard recommends averaging the data over 10-minute periods. Following the IEC standard recommendation, all data from the PI system except for the individual turbine status data were averaged over 10-minute periods with the corresponding time stamps attached. The turbine availability status data are binary type (either 0 or 1). Instead of averaging, the turbine availability data are sampled (effectively taking a single snap-shot) every 10 minutes at the start of the 10-minute period. Because the raw PI data streams are not evenly spaced (i.e., the data are not stored in any fixed time intervals), one turbine availability status reading every 10 minutes may not represent the true turbine status during the entire 10 minutes. A turbine could be down at the beginning of the 10-minute period and returned to operation in the next minute (or vice versa), but the turbine availability status reading taken at the beginning would show the turbine was down (or up) for the entire 10-minute period. However, with 274 turbines in the plant, such errors were judged to be very small.

An initial preliminary data quality check was performed on the 10-minute average data streams to eliminate obvious data errors such as no data, constant values and negative values of barometric pressure readings, wind speed readings, and wind direction readings. This step eliminated about 6% of the available 10-minute data points. Figure 3 is a scatter plot of the metered plant output and H1 and H2 wind speeds from MET tower A09. Figure 4 is the same wind power scatter plot, but with H1 and H2 wind speeds from MET tower H06. The blue dots in both figures are H1 wind speeds and the red dots are H2 wind speeds.

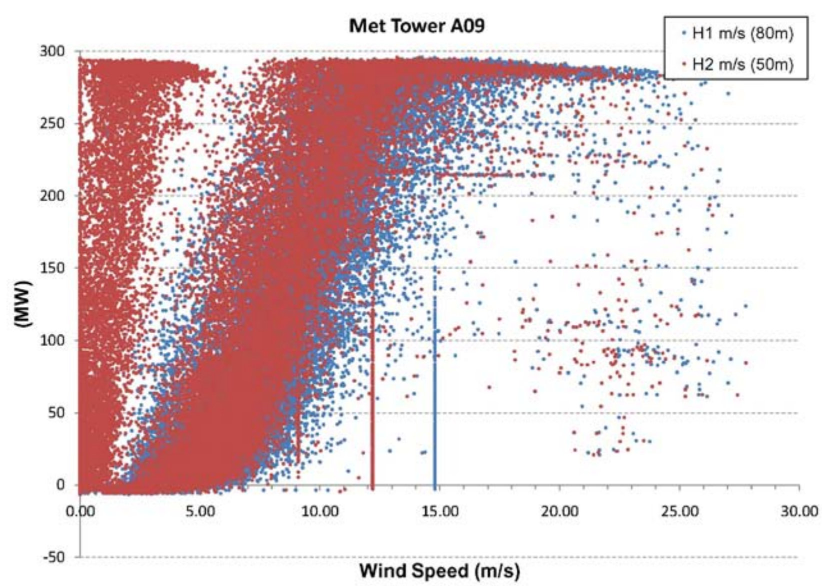

Figure 3 − Scatter plot of plant output and MET tower A09 wind speeds.

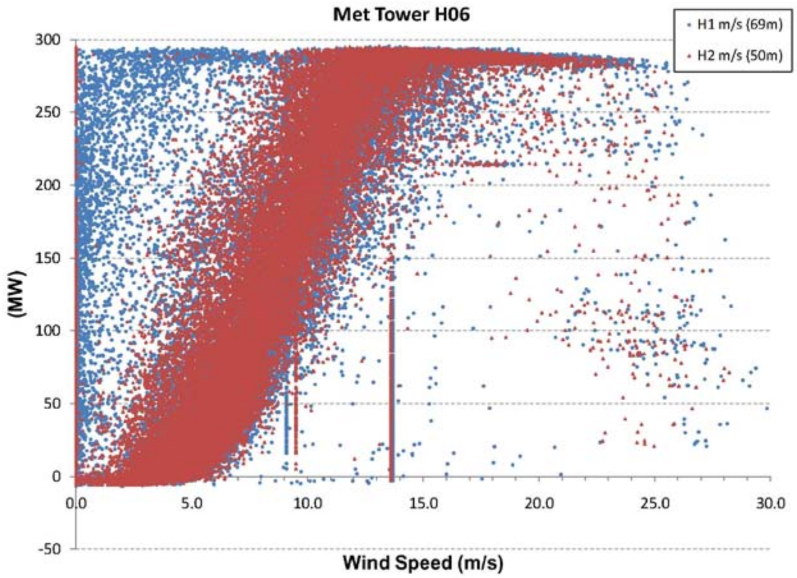

Figure 4 − Scatter plot of plant output and MET tower H06 wind speeds.

It's clear that the wind plant power curve may have a general shape that is similar to the power curve of a single turbine. It is also immediately clear from the two scatter plots that the 10-minute data streams need additional cleaning to get rid of some apparent outliers. For example, while the blue dots in Figure 3 are mostly found at the expected places, there are a large number of red dots in Figure 3 that appear to be out of place. The locations of red dots in Figure 3 suggests that the plant was producing power all the way to its rated capacity at zero or very low wind speeds measured at a height at or close to the turbine hub height. In Figure 4, the roles of H1 and H2 appear to be reversed with more blue dots seeming to be out of place. Wind shear may cause some shift in red and blue dots, but those in the upper left portion of the figures are clearly not correct. There are also blue and red dots that form several vertical traces in both plots. Those were caused by constant values from the MET towers over a long period. The horizontal traces in the plots were the results of plant output curtailment.

Many of the observed outliers are due to problems with the MET tower anemometers, while other outliers may not be an error. For example, the turbines may not experience the same wind conditions as indicated by the MET tower readings. Turbine availability status data also have data quality issues. If a turbine is producing power with an availability status of 0, there is obviously a conflict. However, the opposite condition of no power from a turbine with an availability status of 1 (and above cut-in wind speed at the hub height) is difficult to validate. Validity of other situations such as a rapid change in total numbers of available turbines in consecutive 10-minute periods is also harder to determine. However, a more rigorous quality check on the data was needed to address these issues. The first step was to remove data points that coincided with fewer than 272 turbines available for generation. This is a somewhat arbitrary criterion and the remaining data have less than 1% uncertainty in output power.[5] This step removed 39% of the points from the data stream.

[5] If two turbines are not generating power, it will amount to 2/274=0.7% error.

The next step was to delete data points of very low wind speeds (less than 2.0 m/s) and positive output power. When turbines are producing power and nacelle anemometer readings are above the turbine cut-in wind speed, those low and zero wind speed readings from MET towers do not add useful information to the construction of wind plant power curves. Also deleted are data points with constant wind speed (and direction) over a long period (longer than 2 consecutive 10-minute periods). Those steps eliminated 38% of the available data points from the remaining data streams. The results are shown in the scatter plots in Figures 5 and 6.

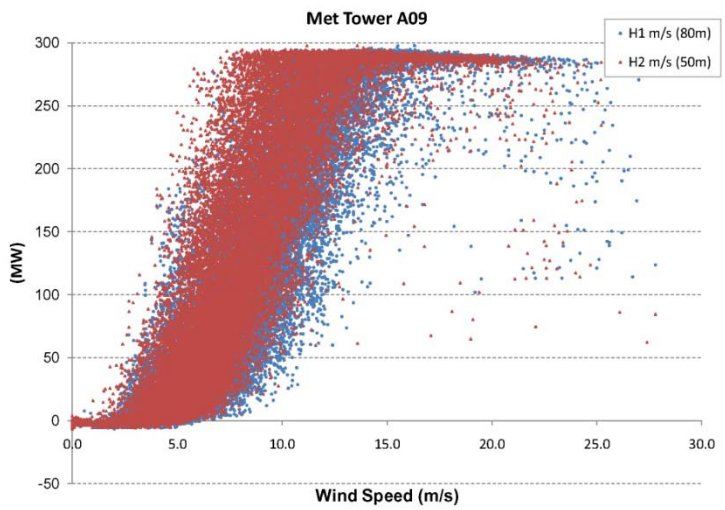

Figure 5 − Scatter plot of plant output and partial MET tower A09 wind speeds.

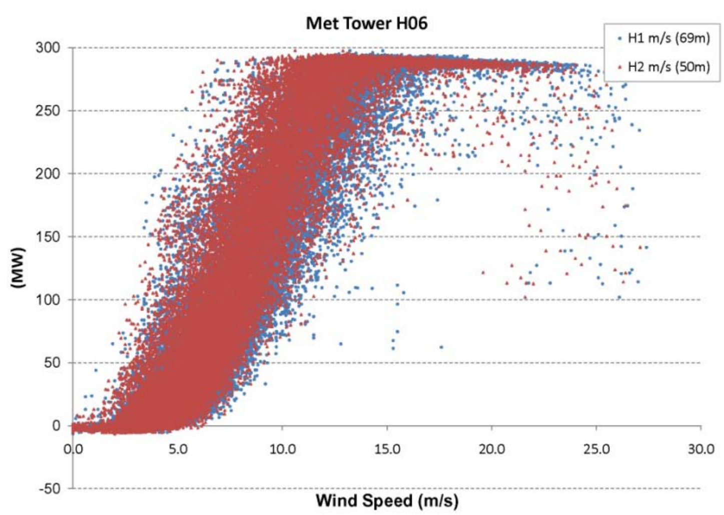

Figure 6 − Scatter plot of plant output and partial MET tower H06 wind speeds.

It should be clear after examining Figures 5 and 6 that the elimination of those "spurious" data points is somewhat arbitrary. With a large number of turbines over a large area, it is not easy to determine the validity of every data point. Some are easier to determine than others. For example, when total plant output is over 290 MW (very high), a wind speed reading of 0.5 m/s (very low) at 80 m above ground level (AGL) is clearly not right. However, as the power level decreases and wind speed reading increases, it becomes less and less certain if the data points represent the actual condition or not.

Figures 7 and 8 show the distribution of measured wind speeds before and after the "spurious" data points are eliminated. The probability densities were calculated with each wind speed data bin centered on multiples of 0.5 m/s and a bin width of 0.5 m/s. Figure 8 also plots the expected Weibull distribution of the measured wind speed time series (dashed lines) based on their average and standard deviation values.[6] You can see from Figure 8 that the cleaning process did not eliminate all of the questionable data points. There are still too many data points in the zero wind speed bin and the standard deviation values of the remaining wind speed data are relatively high. There are noticeable discrepancies between the actual distribution and theoretical Weibull distribution. One reason could be the calibration of anemometers. It is also clear that the "cleaning" process might leave too few data points to produce a smooth distribution curve. Longer data measurement periods may help resolve some of these questions, and further research on this issue is needed.

Table 1 lists the average and standard deviation values of the four measured wind speeds of both the raw dataset and the cleaned dataset. The statistics of the raw dataset strongly suggest that the quality of data from MET tower A09 is higher than that of MET tower H06. It shows wind speed readings from MET tower H06 at H2 height (50-m AGL) has higher average values than wind speed readings at H1 height (69-m AGL). The cleaned datasets reversed the situation and show wind speed readings at higher AGL with higher average values than wind speed readings at lower AGL. This is the expected result and it indicates that the data cleaning process was reasonable. Table 2 lists cross correlation among the four measured wind-speed data streams. The lower correlation coefficients between wind speed readings of the two MET towers are another indication of wind variability within this large wind plant.

Table 1 − Average and standard deviation of measured wind speeds in m/s.

	Raw Data		Cleaned Data	
	Average	**Std. Dev.**	**Average**	**Std. Dev.**
Met A09 H1 (80m)	8.9	4.5	8.5	4.2
Met A09 H2 (50m)	6.0	4.7	7.6	3.9
Met H06 H1 (69m)	7.2	5.7	8.3	4.6
Met H06 H2 (50m)	8.2	4.5	7.8	4.2

Table 2 − Cross correlation of measured wind-speed data streams.

	Met A09 H2	Met H06 H1	Met H06 H2
Met A09 H1	0.96	0.90	0.91
Met A09 H2		0.89	0.88
Met H06 H1			0.98

[6] Estimating k and c factors of a Weibull probability density function based on measured average wind speed and its standard deviation can be found in many wind energy textbooks. For example, J.F. Manwell, et.al. (2002) *Wind Energy Explained--Theory, Design and Application*, John Wiley & Sons, West Sussex, England.

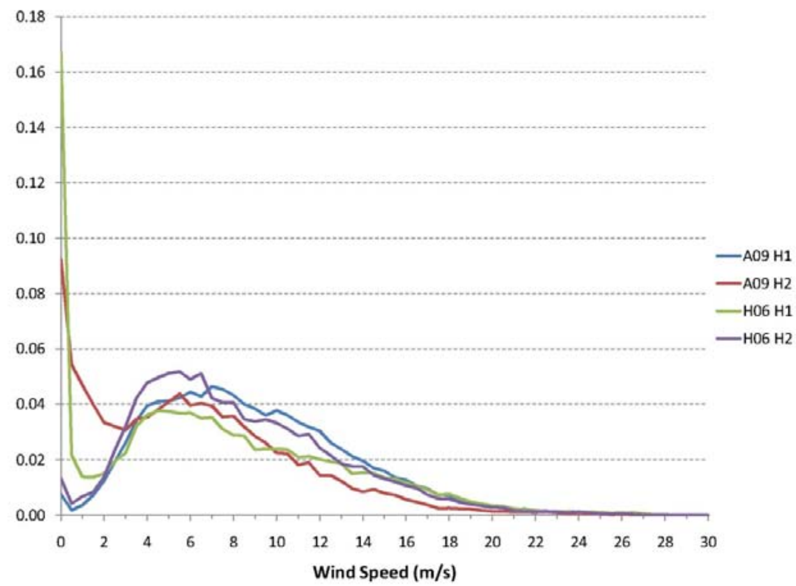

Figure 7 − Wind speed distribution (raw data).

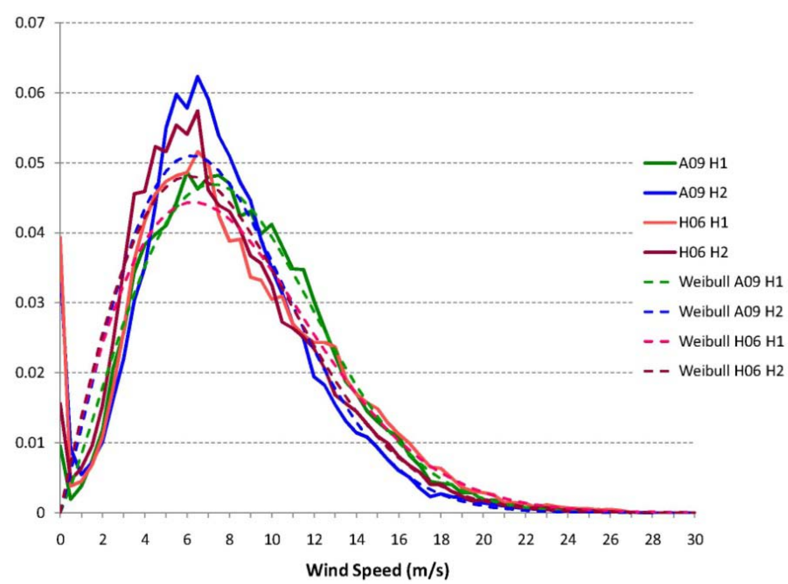

Figure 8 − Wind speed distribution ("cleaned" data).

Figure 9 shows the distribution of wind direction at this wind plant as measured by wind vanes on the MET towers. The prevailing wind direction during the period when data are available is northwest (between 293° and 338°). Wind blows from this sector more than 25% of the time.

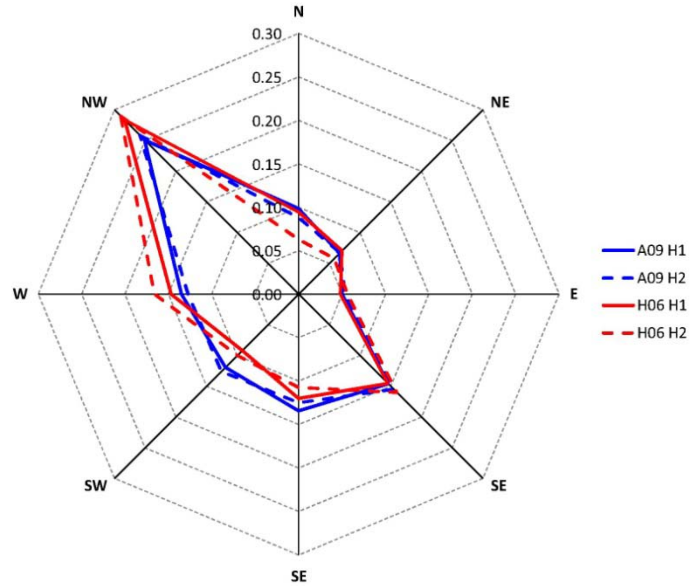

Figure 9 − Wind 'rose' diagram with MET tower data.

Table 3 summarizes the average wind speeds of the "cleaned" dataset for the eight wind sectors. The wind sectors are determined based on the direction readings at the same height as the wind speed readings of the respective MET tower, i.e., H1 directions for H1 the wind speeds. The table suggests that the quality of data from MET tower H06 is lower because it shows the average wind speeds at lower AGL were higher than average wind speeds at higher AGL for two out of the eight wind sectors. It is questionable that wind shear at this site has a negative value, especially in light of the MET tower A09 wind speed readings that show a positive wind shear.[7] This again points to the MET tower data quality issues such as measurement noise and tower shadow effects. For this reason, the initial analysis of the wind plant power curve is carried out by using wind speed and direction readings from MET tower A09 at H1 height.

Table 3 − Average wind speed (m/s) of 8 wind sectors.

	N	NE	E	SE	S	SW	W	NW
Met A H1	10.3	6.9	6.5	6.8	6.9	6.7	9.1	10.9
Met A H2	9.4	6.3	5.9	6.7	6.2	6.0	7.5	9.5
Met H H1	10.3	6.0	6.0	5.7	5.8	5.9	8.9	11.6
Met H H2	9.7	5.4	5.4	5.8	5.5	6.0	8.8	10.4

3. Equivalent Plant Power Curve

A single turbine power curve is determined by measuring the turbine output and inflow wind speed at the hub height. The location of wind measurement relative to the turbine is specified in IEC 61400-12-1. For an entire plant, there is no specification to determine a single representative wind speed that can characterize the wind condition of the plant. This is especially true at this wind power plant where turbines with two different hub heights are spread over a large area. The scatter plots of wind speed and wind plant output in Figures 5 and 6 suggest wind speed readings from either MET tower can be used to construct an equivalent power curve for the plant. The advantage of using the metered output of the entire

[7] One possible cause of the negative wind shear values is turbine wake effect. Turbines adjacent to MET tower H06 all have a hub height of 69 m. Wind speed readings at H1 height (69 m) may be affected more by the turbine wake effect than the wind speed reading at the lower H2 height (50 m).

plant to construct an equivalent power curve is that both array losses (due to wake effects) and electric collecting system losses are automatically included. There are different ways to use the data in Figures 5 and 6. Two of such are described below.

The most straightforward approach is curve fitting. Another approach is to use the method of the bins specified in IEC 61400-12-1. Basically, this method uses measured 10-minute average wind speeds (at the hub height) and plant output power. The 10-minute average wind speeds are separated into 0.5 m/s contiguous bins centered on multiples of 0.5 m/s (1.0 m/s, 1.5 m/s, 2.0 m/s, etc.). The mean value of power for each 0.5 m/s bin is then calculated and plotted against the mean wind speed of each bin. The wind direction is not considered because the time constant for a turbine to yaw and face the wind is much shorter than 10 minutes.

The results of these two approaches using H1 wind speeds of MET tower A09 are shown in Figure 10. It can be seen that these two approaches produce similar results. The jagged appearance of the method of the bins curve at high wind speeds manifests the challenge of modeling the wind power plant. When wind speed exceeds the turbine cut-off wind speed, the turbine will feather its blades and stop operation. It then monitors the wind speed and will not restart until the wind falls below the cut-off speed for at least 10 minutes.[8] For a single turbine, this hysteresis behavior does not distort its power curve because of the 10-minute averaging. For a large wind plant (such as with 274 turbines), individual turbine cut-in and cut-off instances during high wind periods appear to be random and the effect will show up in the power curve. Not having enough good data points at the high wind speed region can also be a cause of the jagged appearance of the equivalent power curve. The flat portion of the curve fitting trace is the result of truncating the third order polynomial curve after it starts bending downward beyond the inflection point (at above 15.0 m/s).

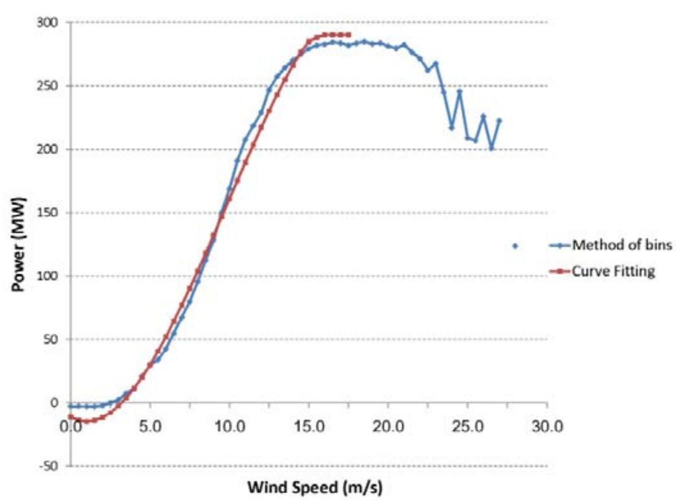

Figure 10 − Equivalent wind plant power curves using MET tower A09 H1 wind speed.

MET tower and metered plant output data from January and February 2010 were used to see if the equivalent power curve can be used to predict plant output that is close to the measured value. Using 10-minute average metered power and MET tower A09 H1 wind speeds, these two equivalent power curves yield mean absolute errors (MAE) of 26.4 MW (method of bins) and 28.0 MW (curve fitting), about 9% of the plant installed capacity. This is an expected outcome because data used to derive the equivalent power curves contain a wide range of power levels for any given wind speed value (Figures 5 and 6).

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[8] As conveyed through discussions with plant technicians.

The layout of turbines at this wind power plant indicates it is designed to take advantage of the prevailing winds from the northwest. It also suggests that wind from other directions may not produce as much power as the wind from the prevailing direction because of the wake effect. To see how wind directions affect the plant performance at this wind plant, individual turbine production is calculated for all eight wind sectors. The wind directions for this calculation are based on readings of wind vane on MET tower A09 at H1 height. The results reveal that the locations of turbines within a wind plant significantly affect its energy production. Figure 11 shows the turbine capacity factors for wind in the northwest sector (293° – 337°) during the study period. Figure 12 shows the turbine capacity factors for wind in the north sector for the same period (338° – 0° – 22°).[9]

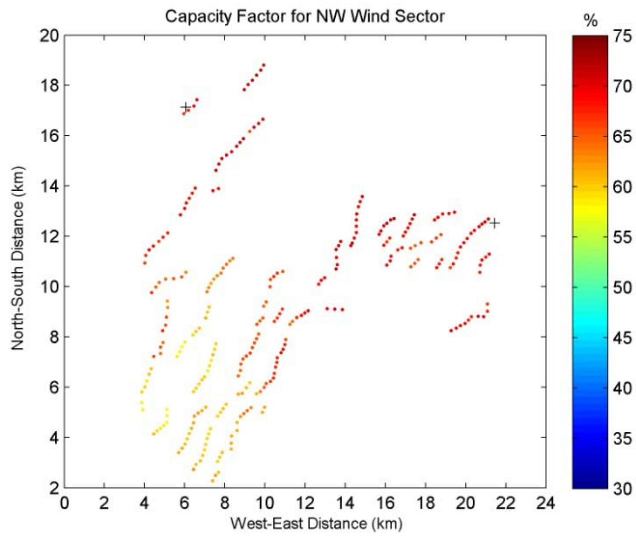

Figure 11 − Individual turbine capacity factors for northwest wind sector.

From Table 3, you can predict that in general the energy production at this wind plant will be higher when winds blow from the northwest sector because winds from this sector had the highest average wind speed. Figures 11 and 12 validate this prediction. On an annual basis, turbine capacity factors are much higher for northwest winds than for north winds. In fact, the highest capacity factor under north winds is lower than the lowest capacity factor under northwest winds. The obvious explanation is the fact that northwest winds were more energetic than north winds, but other factors may also play a role. In addition locations of the most productive turbines changed with the directions of winds. As expected, turbines having high capacity factors are located to the north and northwest sides of the wind plant for winds from the northwest sector. However turbines of high capacity factors under north winds are not located at the leading edge (relative to the wind direction) of the wind plant. For this sector, the higher capacity factor turbines are located on the southeastern fringe of the plant. Additionally, both Figures 11 and 12 show a group of turbines at the southwest portion of the plant with much lower capacity factors relative to other turbines in the plant. This observation is the case for all wind direction sectors, as shown in Figure 13. It's not clear why those turbines were not as productive as others in the plant.

[9] It should be noted that the individual capacity factors in Figures 11 and 12 were calculated with only the hours the winds were from a specific sector, not the annual capacity factors in the standard usage (i.e., calculated with 8,760 hours). The capacity factors values in those two figures should be viewed relatively to each other and are meant to show the significant differences in turbine performance when winds are from different directions.

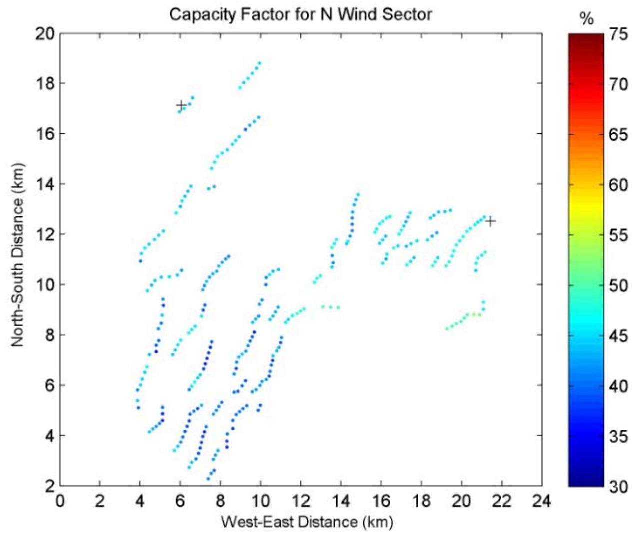

Figure 12 − Individual turbine capacity factors for north wind sector.

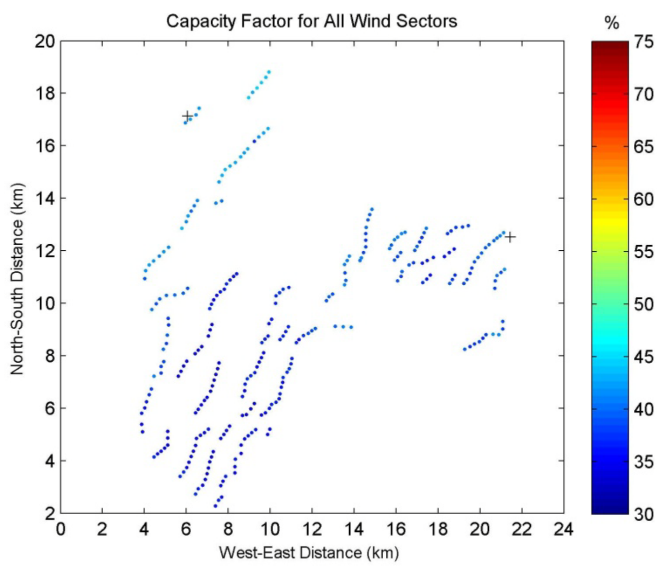

Figure 13 − Annual individual turbine capacity factor (all wind sectors).

3.1 Directional Equivalent Plant Power Curves

Differences in plant production under different wind directions do indicate that wind plant performance is also a function of wind direction. The next step is to construct directionally equivalent plant power curves. As in the previous discussion, wind speed and direction readings from MET tower A09 at H1 height are used. Figure 14 is a scatter plot of plant outputs and winds from the north and northwest sectors. The differences between the north wind data points and northwest wind data points are slight, but still noticeable. You can see that for the same wind speed value, the blue dots (northwest winds) tend to correspond to greater power than the red dots (north winds). The differences are more obvious in the scatter plot of plant outputs and winds from the southeast and southwest sectors shown in Figure 15.

Equivalent power curves of all eight wind sectors were constructed using the method of bins. The resulting curves are shown in Figure 16. This process separates the wind plant performance differences for eight wind sectors. Except for the northwest sector, the fit is noisy, especially at wind speeds greater than the turbine rated wind speed (the flat portion of the power curve). At high wind speeds, even the equivalent power curve of northwest wind sector is not smooth. Additional good data points at high wind periods may improve the fit. Figure 17 shows the directionally equivalent power curves using the curve fitting method with third- and fourth-order polynomials. This method produces smooth curves which also preserve the features shown in Figure 16.[10]

Both Figures 16 and 17 show that the plant outputs appear to vary significantly with winds from different directions. The data show that the plant output may differ as much as 100% for the same wind speed, but from different directions. For example, it's clear that the plant tends to produce less power for south-westerly winds between 6 m/s and 16 m/s than for northwesterly winds of similar speeds. Northeasterly winds also tend to generate less power at this plant than the northwesterly winds. Out of the three prevailing wind sectors, westerly wind produces the least amount of power compared to wind from the northwest and north sectors.

Testing of the equivalent power curves using January and February 2010 data show a MAE of 23.1 MW (or about 8% of plant capacity), which represents a slight improvement over the non-directional equivalent power curve. It's not clear if separating wind directions into finer wind sectors would improve the performance of the resulting equivalent power curves. The limitation is trying to use wind speed and direction readings from a single-point tower to represent the wind conditions for the entire wind power plant.

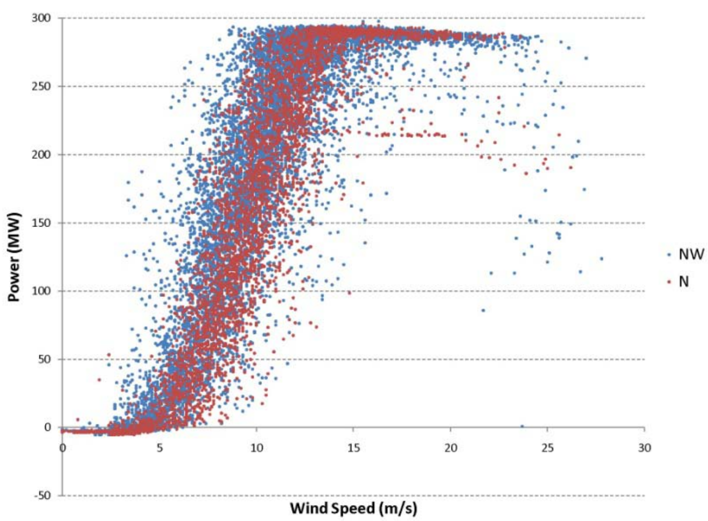

Figure 14 − Scatter plot of plant output and north and northwest winds.

[10] The portions of curves beyond inflection points at both low and high wind speeds are not shown.

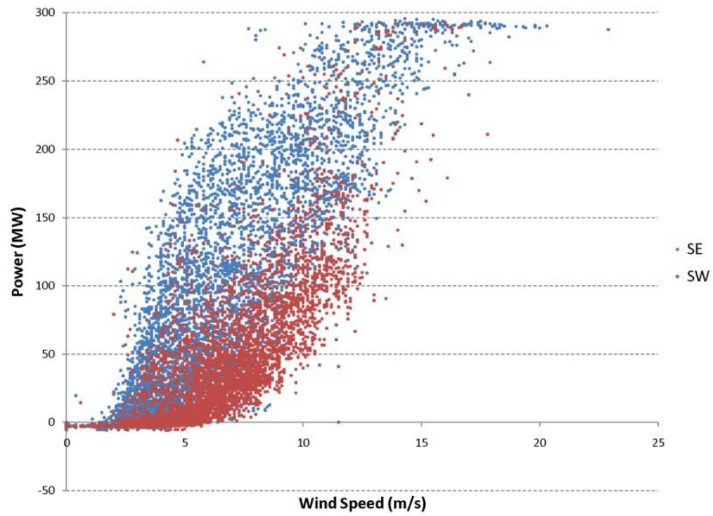

Figure 15 − Scatter plot of plant output and southeast and southwest winds.

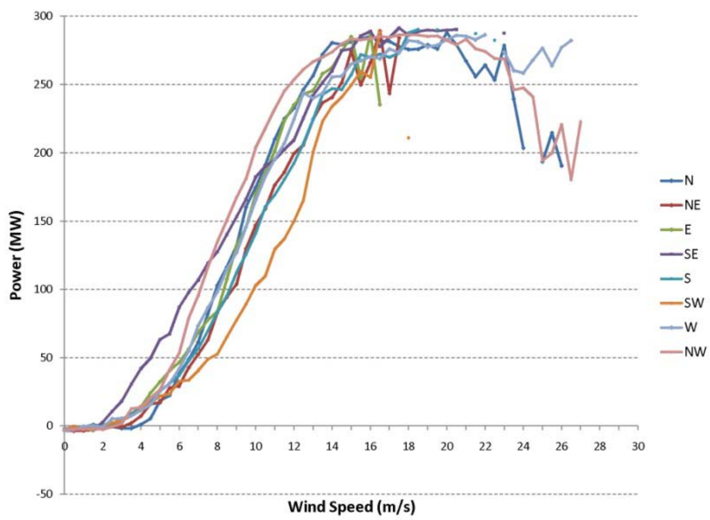

Figure 16 − Equivalent power curves (method of bins).

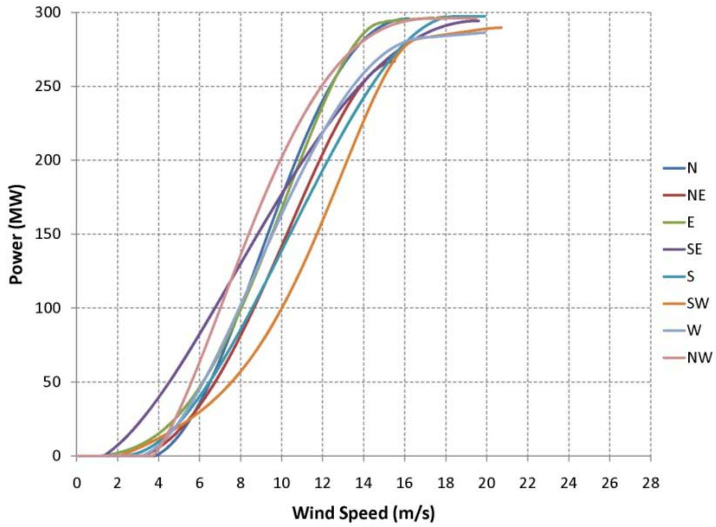

Figure 17 − Equivalent power curves (curve fitting).

4. Neural Network

The neural network technique has been used to perform complex functions for various applications.[11] It is a common practice in the industry to use neural networks to supplement other methods in converting the wind and weather data to power data from wind plants. The neural network approach is discussed here as an alternative to the equivalent power curve methods discussed in the last section. For this report, the neural network is a straightforward feed-forward network with back-propagation.[12] The same cleaned dataset used to develop the equivalent power curves was used to train and validate the neural network. All four wind speed and four wind direction readings from both MET towers at both H1 and H2 heights were used as input to the neural network. Additional data quality checks were performed to remove inconsistent data points. For example, if any of the eight data values is missing or in apparent error (negative or out of range), the whole group was discarded even though the other values were normal. This process eliminated another 5% of the available data points. The neural network was tested for its performance using the same 2010 January and February dataset as before.

With eight wind speed and direction streams as input to the neural network, the resulting model will yield a MAE of 18.5 MW (about 6% of the plant capacity) when tested against the 2010 January and February dataset. This represents another incremental improvement over the equivalent power curve method. However, it is expected that the neural network approach will produce better results because four times more information was used (four wind speeds and four wind directions as compared to one wind speed and one direction). Further inspection of the neural network prediction suggests that all of the large deviations between the predicted values and actual metered outputs were caused by data inconsistency among the 8 values, such as significant wind shear (large differences between wind speeds at H1 and H2 AGL) at the same tower or between towers A09 and H06. The behavior of the wind plant under high wind speed conditions has also produced large discrepancies between the neural network prediction and actual metered output. Figure 18 shows the scatter plots of metered plant outputs and wind speeds from both MET towers in January and February 2010. The many outliers in the plots represent the inconsistency of the data.

[11] Rabuñal, Juan R., and Julián Dorado. (2006) Artificial Neural Networks in Real-Life Applications. Idea Group Publishing, Hershey, PA.
[12] Implemented in the MatLab® Neural Network Toolbox™ 6.

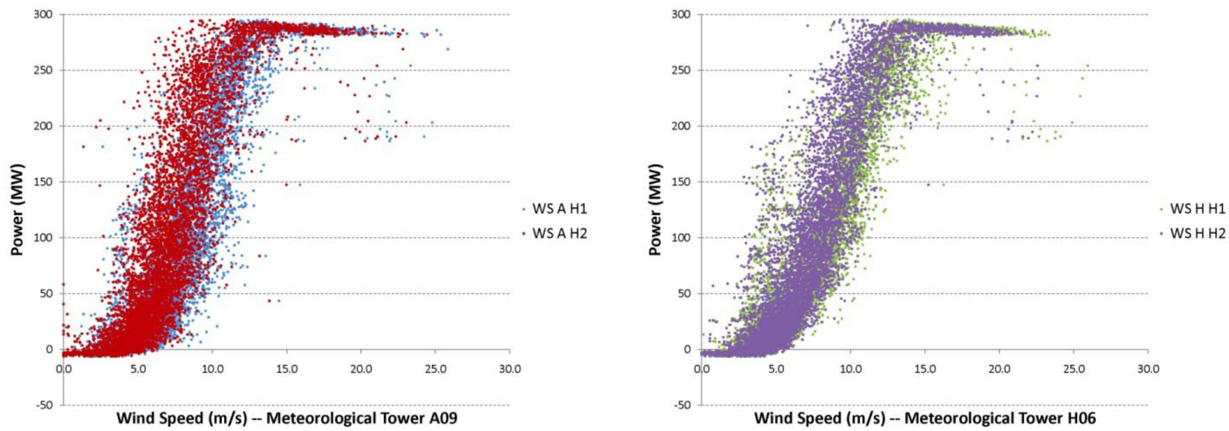

Figure 18 − Scatter plots of the wind power and wind speed during January and February 2010.

A second neural network was tested with two air density values as additional inputs.[13] However, this addition did not improve the performance of the resulting neural network. The reason may be that air density is much less variable over the year than wind speeds and directions. In fact, the coefficient of variation (CV) of air density (0.03) is one magnitude smaller than the CV of wind speeds (0.48-0.52). Output variability of the neural network model (the wind plant output) is dominated by the changes of wind speeds and direction. The addition of air density did not increase the amount of useful information significantly in the neural network model.

During the neural network training process, it also becomes evident that using the data of the entire study period is not necessary and will not improve its performance. Using data from windy months to train the neural network to predict the wind plant output during other windy months actually improves the model performance. For example, using data from October 2008 through December 2008 to train the model and then testing it against October 2009 through December 2009 will result in a MAE of 14 MW (less than 5% of the plant capacity). This outcome points to the need of further fine-tuning of the neural network.

Although the static, multilayered feed-forward network is capable of simulating the nonlinear power curve of a wind plant, a more complicated dynamic model may perform better. In a dynamic model the output depends on both current inputs to the network and the previous inputs and states of the network. This and other fine-tuning steps are subjects of ongoing investigation and results will be reported later.

5. Direct Estimate with Average Wind Speed

The performance of each individual turbine follows the turbine power curve, and the performance of a wind power plant is the sum of all individual turbine outputs. If wind speeds at each turbine are known, finding the plant output becomes a simple process of converting wind speed to power through the turbine power curve, and then addition. The electrical losses of the wind plant collection system will also need to

[13] The air density values were calculated using pressure and temperature readings from the MET towers and the following equation (1).

$$\rho = \frac{\mathrm{B}}{\mathrm{R_0} \cdot \mathrm{T}} \qquad (1)$$

where: ρ = 10-minute averaged air density, kg/m^3
B = measured air pressure averaged over 10 minutes, Pascals (= 100 * mBar)
R_0 = gas constant of dry air, J/(kg*K) (= 287.05)
T = measured temperature averaged over 10 minutes, K (= ° C + 273.15)

be accounted for to improve accuracy. However, direct measurement of wind speed at each turbine is impractical, and it is extremely demanding in terms of modeling effort and computational resource to forecast the wind speed at each turbine. An alternative is to find out the average wind speed at the wind plant and use the turbine power curve to convert it to power data. Multiplying this power by the numbers of online turbines and subtracting electrical collection system losses will provide a good estimate of the plant output. This process neglects turbine yaw errors (the deviation of turbine nacelle from the incoming wind direction). These errors are small when using 10-minute average data because the normal response time of the turbine yaw mechanism is less than 10 minutes.

The PI system at this wind plant records wind speed data from the anemometer on top of each turbine nacelle. The nacelle anemometer readings can be used as a substitute for actual wind speed at each turbine location. The problem with such substitution is that wind flow is disturbed by the blades and nacelle itself, so wind speed measured by the nacelle anemometer may not accurately represent free-stream wind speeds experienced by the blades. One previous study[14] on this subject, however, suggests that wind speed readings from nacelle anemometers can provide reasonably accurate approximations of incoming wind speeds as measured by upwind MET towers. The relationships between wind speeds at the nacelle anemometers and the upwind MET tower appear close to linear over most wind speeds, with the most variation at low (below cut-in) and high wind speeds (close to rated). For the purpose of estimating the plant output, which is the sum of all individual turbine outputs, averaged nacelle wind speeds (measured by nacelle anemometers) are deemed adequate to represent the wind conditions of the entire wind plant.

Average anemometer wind speeds for two types of turbines are calculated from the PI data separately because of their significant differences in hub heights. The average wind speeds need to be adjusted for local air density before being applied to turbine power curves for this wind plant because average elevation of the site is about 1,655 m. The following equation is used to adjust the wind speeds:

$$v = v_{10\mathrm{min}} \cdot \left(\frac{\rho_{10\mathrm{min}}}{\rho_0}\right)^{\frac{1}{3}} \qquad (2)$$

Where: v_{10min} is the 10-minute average nacelle wind speeds of all turbines
ρ_{10min} is the 10-minute average air density calculate from equation (1)
ρ_0 is the sea level air density (1.225 kb/m^3) referring to ISO standard atmosphere

A wind plant electric collection-system losses include power to the turbine control and monitoring systems, step-up transformer losses (no load and load losses), and cable conductor losses. Calculations of these losses in detail will be time consuming. It is not necessary here because the measured wind plant output and individual turbine outputs at this wind plant can be used to provide a very accurate estimate of these losses. The differences between the measured plant output and the sum of all individual turbine outputs (i.e., gross generation) are the losses. Figure 19 plots the losses as a function of the plant gross power generation. The gross generation is separated into 105 bins, each has a width of 3 MW. The losses are averaged within each bin and are plotted in Figure 19 in red. The losses are proportional to the current squared, and the quadratic nature of the loss curve is clearly seen in Figure 19. The blue line shows the losses as a percentage of the plant gross generation. The very high percentage at low gross generation is because there is about 1.1 MW of fixed losses (i.e., station power, transformer no load losses, etc.) at the plant. When the plant is generating at capacity, the losses are about 5% of the gross generation. It is expected that most wind power plants will have loss characteristics very similar to that shown in Figure

[14] Smith, B., Link, H., Randall, G, and McCoy, T. (2002) "Applicability of Nacelle Anemometer Measurements for Use in Turbine Power Performance Tests," AWEA WINDPOWER 2002, Portland, OR. NREL/CP-500-32494.

19 because distances between turbines in modern wind plants are very similar and the majority of plant electric collection systems use 34.5-kV underground cables.

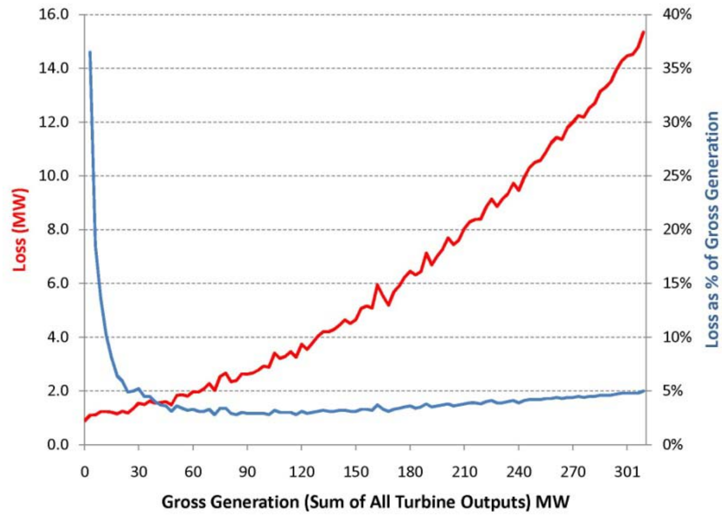

Figure 19 − Wind power plant loss curves.

When tested against the January and February 2010 dataset, the direct estimate method produced a MAE of 11.9 MW or about 4% of the plant nameplate capacity. It should not be a surprise that this approach produces the most accurate result of the four approaches discussed here. The amount of input data in this approach is the most among all four models. Table 4 lists the MAE of all five models.

Table 4 − MAE of the five models.

	Equivalent Power Curve (curve fitting)	Equivalent Power Curve (method of bins)	Directional Equivalent Power Curve	Neural Network	Direct Estimate
MAE (MW)	28.0	26.4	23.1	18.5	11.9
MAE (% of plant capacity)	9.3%	8.8%	7.7%	6.1%	4.0%

Figure 20 shows the distribution of errors produced by the four approaches.[15] Errors are shown as percentage of plant capacity and are plotted on a log scale. Except for the direct estimate method, errors from the other three methods appear to be evenly distributed around the zero value, indicating there is no bias with those approaches. The large errors can actually be traced back to the discrepancy of input data. For example the largest negative error (under-prediction) of -145 MW from the neural network model was produced during a 10-minute period when the MET tower wind speed readings were 6.6 m/s, 8.7 m/s, 6.2 m/s and 6.6 m/s (at MET tower A09 H1, MET tower A09 H2, MET tower H06 H1 and MET tower H06 H2) and the metered output was 219 MW. At a wind speed of 7 m/s, these turbines should produce around 20% of rated output, but the output of the entire wind plant was more than 72% of nameplate capacity. Not surprisingly, all other methods but the direct estimate produced very large errors for this time period. The direct estimate method based on average nacelle wind speeds of 11.4 m/s and 10.2 m/s during this time period resulted in a small error of -5 MW. The significant differences between the wind

[15] Error distribution of the curve fitting method is not shown to avoid clogging. Error distributions from curve fitting and the method of bins are very similar because the equivalent power curves from these two approaches are very close, as seen in Figure 10.

speeds indicated by the MET towers and turbine nacelle anemometer highlighted the data quality issue. Because wind speeds at lower AGL were higher than that at higher AGL also suggests some irregularity of the data. Such data inconsistency will affect model quality when used in constructing the model and skew the result, but it's not easily detected without more detailed information about the plant and its operations.

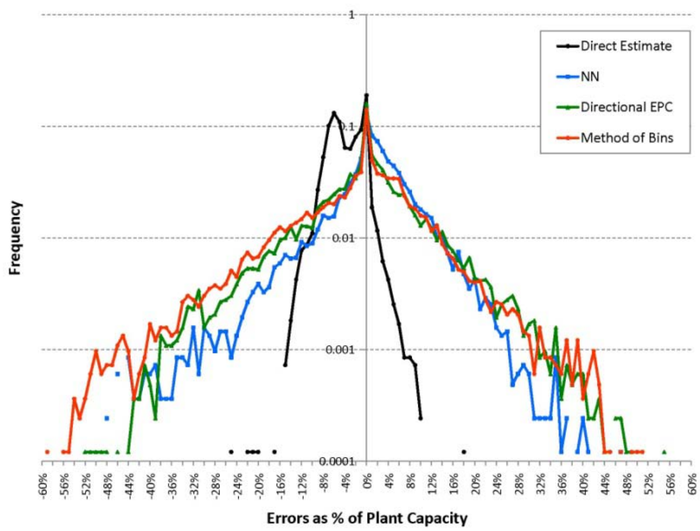

Figure 20 − Error distributions.

The error distribution plot of the direct estimate method is not symmetric around zero value. The prominent secondary peak at negative values indicates a tendency of under estimating the plant output. The reason could be that wind speed readings from nacelle anemometer are not the exact inflow wind speeds the turbines see. It suggests that the wind speeds registered by the nacelle anemometers are slightly lower than the incoming wind speeds before the blades. This bias could be corrected using longer term data.

6. Discussions and Conclusions

There are many issues with characterizing wind power plant operations with an equivalent power curve or a set of such curves, especially for large wind plants with many turbines spread over a wide area at different elevations. The problems arise from the fact that the output of a plant is influenced by many variables. Wind speed is the most critical variable in determining the plant output, but no single wind speed can adequately represent the wind conditions for the entire wind plant. Many wind speed values are required to characterize the plant operation. This point is clear by the wide spread of the wind plant output at any given wind speed shown in the scatter plots in this report. Depending on how the wind speed values are obtained, using them to characterize the plant operation can result in large uncertainty.

There are other variables besides wind speed that affect the plant performance and output levels. The results of directionally equivalent power curves demonstrated that separating the wind resource into major sectors marginally improves the representation. More data are required to reduce the noise in the resulting equivalent power curves. Finer wind sectors may incrementally improve the accuracy further, but also incurs the problem of determining the wind directions that are representative of the wind conditions for the entire wind plant.

The neural network technique appears to be well suited for the task of representing the complex relationship between input variables (wind speeds, direction, etc.) and plant output level. The reason that the neural network model did not perform significantly better than the equivalent power curves could be due to the input data quality. The locations of the two MET towers may not be optimal to characterize the wind conditions for the entire wind plant. A more rigorous quality check may need to be performed on all input data, although it is not clear how much improvement can be gained with additional cleaning of the input data. Using a more complex dynamic neural network model may offer greater performance improvement, especially during high wind periods. Individual wind turbines exhibit hysteresis behavior around cut-off wind speeds, and therefore individual turbine output is determined not only by current conditions of wind speed and direction, but depends on previous turbine states. A dynamic neural network model would be able to simulate this behavior.

The direct estimate approach requires the most amounts of input data, and produces the best results compared to other approaches tested. This approach is straightforward and the concept behind it is simple. However, its success depends on finding the average wind speed of the entire wind field in a wind power plant. At the wind plant, it turns out that average values of all nacelle anemometer readings provide very accurate estimates of the wind conditions for the entire wind plant. This method neglects the wind direction and yaw errors. It assumed that wind turbines will be turned into the wind within 10 minutes and the errors of neglecting wind direction and yaw errors are small compared to other uncertainties. If the average wind speed at a wind plant can be forecast with other methods or numerical models, the direct estimate approach can predict the plant output accurately, provided the numbers of online turbine are known in advance. Plant losses can be estimated from Figure 19, but actual wind plant data is still preferred to obtain a good estimate of the plant losses.

The direct estimate method should be very useful in practice because only one wind speed data stream (along with temperature and barometric pressure information to calculate air density values for further adjustment, if necessary) and numbers of turbines online are needed to estimate the plant output. For wind plants without reliable MET tower data streams, it is the only way to estimate plant output, and can produce very useful results.

Despite the fact that the collected data has significant quality issues, the importance of actual wind plant and turbine-level data should not be overlooked. Actual data provides a way to construct and validate wind plant models. Future work will include the development of more rigorous and systematic data quality checking processes because the analysis has shown that better data can significantly improve the performance of all models. Additional work might also include separating wind plant power curves by atmospheric stability or seasons or both.

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