810 A Comparison of Turbine-based and Farm-based Methods for Converting Wind to Power

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1. Introduction

The National Center for Atmospheric Research (NCAR) is currently performing work that involves forecasting the power production at a variety of wind farms based on wind forecasts at each of the farms. This paper evaluates two different methods for forecasting power based on given wind forecasts.

The first method involves forecasting winds at each turbine at a given farm. The wind to power conversion is performed on a per-turbine basis and all of the resulting turbine power predictions are summed to produce an overall power forecast at the given farm. The second method involves utilizing a mean wind forecast for the entire farm. The wind to power conversion is performed by modeling farm power against the mean observed winds at a given farm. Finally, the mean wind forecasts are converted to farm power using the mean wind to farm power model.

This paper compares these two power prediction methods. It includes information on the wind forecasts, as well as the methodology of how the wind to power conversions are created using a data mining technique that utilizes turbine level wind observations, power observations and total farm power observations. This paper concludes with a comparison of the forecasting error and other qualities of these two power prediction methods.

2. Model Creation and Data

The observations used to create both the turbine-based and farm-based methods of converting wind to power were gathered from 17 different wind farms (or groups of farms whose power is collected in one point and are thus considered to be one farm) located in various regions across the United States, over approximately a two year period. For all of the farms considered, metered total farm power output was collected and is referred to as the farm's node power. Turbine level wind and power observations were collected from each turbine for a given farm as long as that turbine had the capability to report data. Both the farm node power and the turbine level wind and power data were collected as 15 minute averages. All of the turbines for all the farms considered had the capability to report turbine level data and thus these farms are referred to as data-rich. The wind observations from the turbines were gathered using a turbine's nacelle anemometer located at hub height behind the turbines blades.

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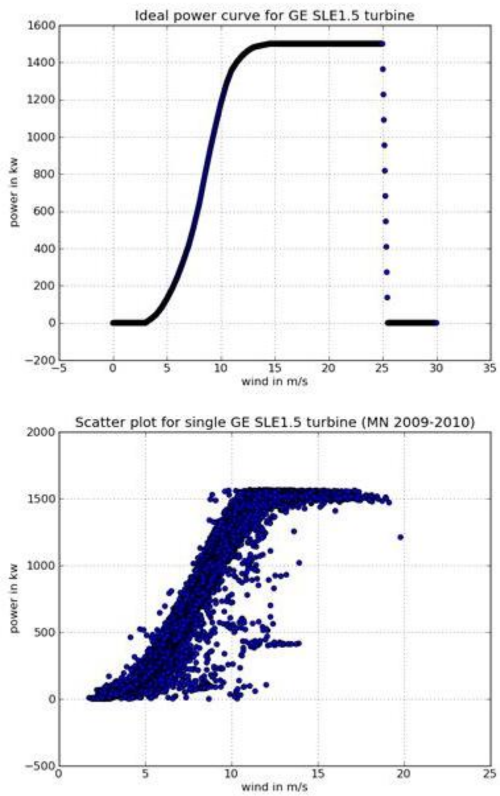

Figure 1: Manufacturer's power curve and data created power curve for one GE 1.5 sle turbine.

Although turbine manufacturers supply a power curve that can be used to convert wind to power, the observed turbine level wind and power data show that there is variability in the power output for any given wind speed. Figure 1 shows the manufacturer's power curve along with the power curve created by the observed wind and power from a GE 1.5 sle turbine. After investigating different techniques for modeling the relationship between observed turbine wind speed and power output it was determined that using a regression tree data mining algorithm that used the current observed wind speed, along with the previous observed wind speed and power output for a turbine minimized the error beyond other techniques (Wiener et al., 2011). Using this regression tree technique, the turbine-based models that convert wind to power were created by training on turbine level data from several turbines of the same type. For turbines of a specific type where no turbine level wind and power data was available, however, the manufacturer's power curve was used to do the wind to power conversion.

A similar approach was used to create the farm-based models. First, the turbine level wind data was used to create a turbine-capacity weighted average wind speed observation for each farm. This value takes into account that some farms have turbines with different capacities, giving a turbine's wind speed from a turbine with a larger capacity within a farm more weight in the average. Next, the models were created using the regression tree technique on a farm by farm basis, using the current average farm's wind as well as previous average wind and farm node power to forecast the current farm node power.

3. Experiment

In an effort to compare the two forecast methods, each one was used to create farm level power forecasts for a four month period. The wind forecast used for both methods was taken from the NCAR forecasting system that uses several numerical prediction models, including the GFS, RUC, NAM, and WRF, and applies statistical dynamic MOS technology, DICast®, to formulate a tuned wind forecast at hub height for each turbine at every farm (Myers and Linden, 2011). These forecasts contain wind forecasts every 15 minutes out to 72 hours. Previous wind and power observations, along with the current wind forecast, either at the turbine level or wind speed averages at farm level, were used to create the first power forecast and then the model was applied recursively to create a forecast for every lead time. The farm-based method predicts the farm's node power directly, however, for the turbine-based method, all the turbine forecasts for a farm are summed to get the final farm node forecast.

4. Error Results

The metric used to evaluate each model's performance was a 30-day percent farm capacity mean absolute error or MAE. In general, initial results show lower MAE in the power forecast for short forecast lead times using the farm-based approach when compared to the turbine-based approach. As lead time increases, however, the two methods performance converges with some indication that the turbine-based approach may have slightly better performance. Plots of 30 day MAE over a three month period by lead time can be seen in Figure 2. Four different forecast lead time plots are shown. For this specific farm, the farm-based approach shows up to 1.5% improvement over the turbine-based approach for the short term forecasts. For longer lead times, such as twenty four hours, however, the turbine-based method shows similar, and up to 0.75% improvement, over the farm-based approach.

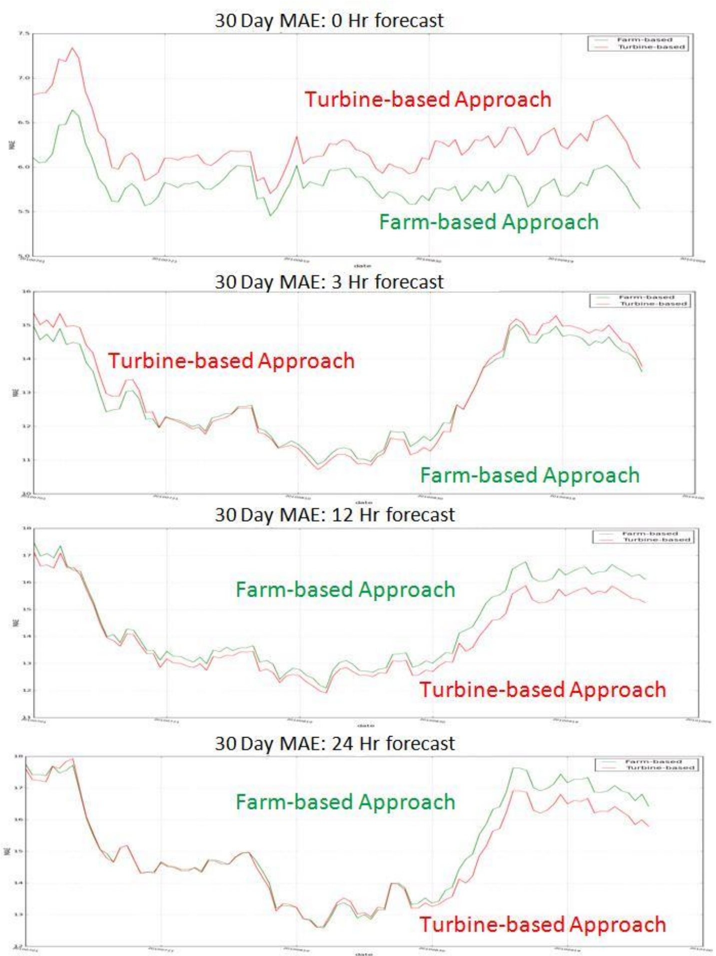

Figure 2: 30-day percent farm capacity MAE traces over a three month period for four forecast lead times

One difference in the error results of the two power forecast methods can be explained by the difference in power observations that each method is trained and scored on. In general, the sum of all the turbine power observations for a farm is greater than a farm's node power observations, therefore the two methods have a slightly different power target during training. Figure 3 illustrates this phenomenon showing farm power traces with both the observed farm-node power and sum of turbines power with the power forecast produced by each method. Here, both the observed and forecast power for the turbine-based method have larger values when compared to their farm-based counterparts. Since a farm's node power observations are what each method is scored against, the farm-based method has a slight advantage, especially in short term forecasts. One possible explanation as to why the turbine-based approach seems to have slightly improved error statistics over the farm-based approach for longer lead times is that the turbine-based approach will perform better when wind events are under forecast. As an example, it can be seen in Figure 3 that the wind trace plot shows the wind event was slightly under forecast and that the turbine-based power forecast is more in line with the farm nodes power observation.

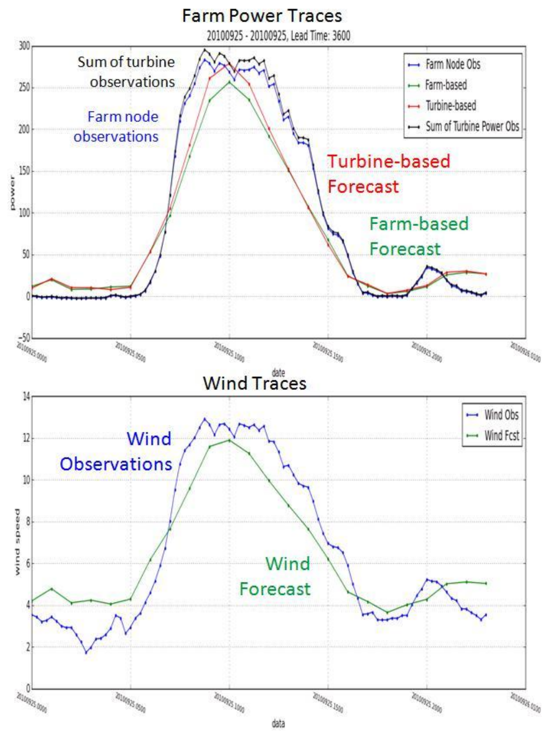

Figure 3: Power and Wind traces for both observations and forecasts over a 24 hour period

5. Quality Control Issues

One issue that arose in the power forecast from the farm-based method was 'spike' forecasts. These forecasts would deviate from nearby forecasts and did not relate well or track the wind forecasts over the forecast period. As an example, figure 4 shows power traces for a 12 hour lead time forecast showing both the observed farm node power and the power forecasts from each approach. Here the spike in the farm-based method is extreme and does not relate to the wind forecast shown in the lower plot of the figure. These spikes were due to quality control issues in the farm-based training data. Figure 5 shows the training data that was used to create a farm-based model that resulted in a spike forecast for this example farm. This 'spike' phenomenon was seen across almost all of the forecasts created from the farm-based models but was not seen in the power forecasts created from the turbine-based models.

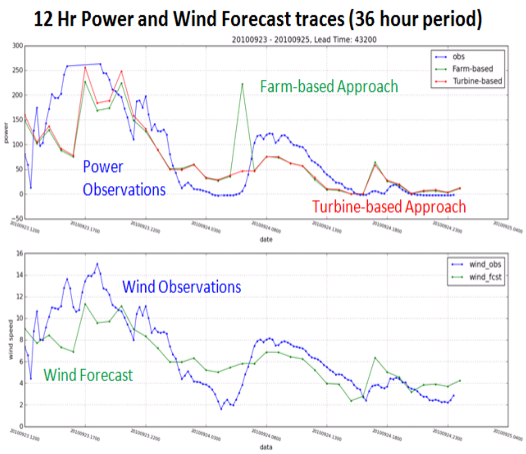

Figure 4: Power and Wind traces for both observations and forecasts for a 12 hour lead time forecast over a 36 hour period. Here the farm-based approach exhits a spike forecast that is not in line with the wind forecast.

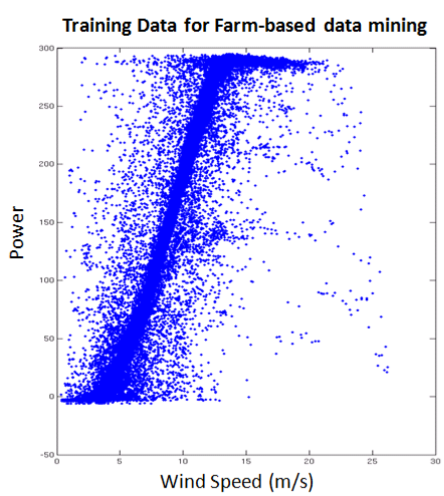

Figure 5: Farm-based training data for one farm. Data in the upper left of the plot is errouneous, leading to errors in the power forecasts for this method.

After quality controlling the data by eliminating farm node power observations that were not in line with the sum of all the turbine level power observations for the farm, the power curve used for training the farm-based models were considerably more distinct and clean. The quality controlled farm node power curve for the example farm is shown in figure 6. This process, along with quality control checks added to the power forecast procedure, eliminated the spike forecast phenomenon. A second run of the power forecast with the new farm-based models produced power forecast traces in line with the wind forecasts. (Figure 7).

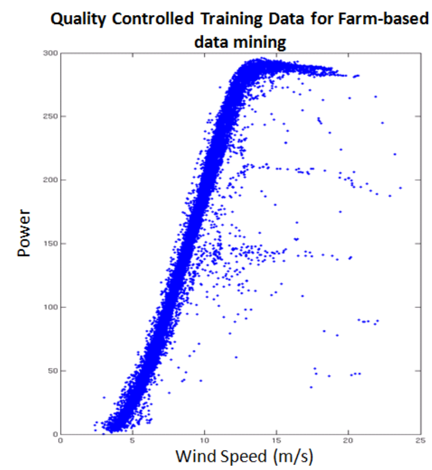

Figure 6: Training data for the farm shown in figure 5 after quality control.

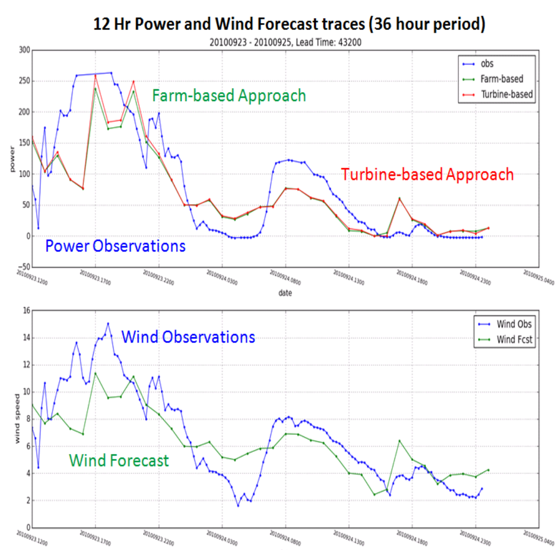

Figure 7: Wind and power traces as shown in figure 4 after quality control of the farm-based training data.

6. Other Considerations

While forecast error is an important metric when comparing these two approaches to forecasting power, other considerations need to be taken into account when setting up a forecast system. First, if forecasting for farms where not all of the turbines report turbine level data (data-mixed farms) or for farms where no turbines report turbine level data (data-poor farms) the farm-based approach is not feasible. In these instances, a turbine-based model created from turbines of the same type or a manufacturers power curve can be used on the turbine level to do the wind to power conversion. Also, if turbines are added to or taken away from a farm, the farm-based model becomes inaccurate. A new history of farm-node data would need to be collected in order to create a new farm-based model. For the turbine-based method, however, forecasts can begin or continue immediately since a turbine-based model or manufacturer's power curve can be added for that turbine in the forecast system immediately. Finally, a turbine-based method requires a more complex system since instead of forecasting a single wind and power value for a farm, the system may need to forecast wind and power for several hundred turbines for that farm.

7. Summary of findings

In general, the forecast error results of this study suggest that the farm-based method may perform slightly better for short term forecasts than the turbine-based method but that the two methods performance converges for longer lead time forecasts. Thus both methods can be used to make power forecasts. Forecast error alone, however, is not this only metric to consider since while both methods can be applied successfully, they have different strengths and weaknesses that may benefit different types of forecast systems. Farm-based methods have the advantage of reduced error for short term forecasts and of a simplified forecast system. Turbine methods are less sensitive to quality control issues and can be applied to all types of farms regardless of availability of turbine level data.

8. References

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