Wind Energy Forecasting: A Collaboration of the National Center for Atmospheric Research (NCAR) and Xcel Energy

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NREL is a national laboratory of the U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy, operated by the Alliance for Sustainable Energy, LLC.

Subcontract Report
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Introduction

At the end of 2010, Xcel Energy managed the output of 3372 megawatts of installed wind energy. The wind plants span three operating companies[1], serving customers in eight states[2], and three market structures[3]. The great majority of the wind energy is contracted through power purchase agreements (PPAs). The remainder is utility owned, Qualifying Facilities (QF), distributed resources (i.e., "behind the meter"), or merchant entities within Xcel Energy's Balancing Authority footprints. Regardless of the contractual or ownership arrangements, the output of the wind energy is balanced by Xcel Energy's generation resources that include fossil, nuclear, and hydro based facilities that are owned or contracted via PPAs. These facilities are committed and dispatched or bid into day-ahead and real-time markets by Xcel Energy's Commercial Operations department.

Wind energy complicates the short and long-term planning goals of least-cost, reliable operations. Due to the uncertainty of wind energy production, inherent suboptimal commitment and dispatch associated with imperfect wind forecasts drives up costs. For example, a gas combined cycle unit may be turned on, or committed, in anticipation of low winds. The reality is winds stayed high, forcing this unit and others to run, or be dispatched, to sub-optimal loading positions. In addition, commitment decisions are frequently irreversible due to minimum up and down time constraints. That is, a dispatcher lives with inefficient decisions made in prior periods. In general, uncertainty contributes to conservative operations – committing more units and keeping them on longer than may have been necessary for purposes of maintaining reliability. The downside is costs are higher. In organized electricity markets, units that are committed for reliability reasons are paid their offer price even when prevailing market prices are lower. Often, these uplift charges are allocated to market participants that caused the inefficient dispatch in the first place. Thus, wind energy facilities are burdened with their share of costs proportional to their forecast errors.

For Xcel Energy, wind energy uncertainty costs manifest depending on specific market structures. In the Public Service of Colorado (PSCo), inefficient commitment and dispatch caused by wind uncertainty increases fuel costs. Wind resources participating in the Midwest Independent System Operator (MISO) footprint make substantial payments in the real-time markets to true-up their day-ahead positions and are additionally burdened with deviation charges called a Revenue Sufficiency Guarantee (RSG) to cover out of market costs associated with operations. Southwest Public Service (SPS) wind plants cause both commitment inefficiencies and are charged Southwest Power Pool (SPP) imbalance payments due to wind uncertainty and variability.

Wind energy forecasting helps mitigate these costs. Wind integration studies for the PSCo and Northern States Power (NSP) operating companies have projected increasing costs as more wind is installed on the system due to forecast error [1][2]. It follows that reducing forecast error would reduce these costs. This is echoed by large scale studies in neighboring regions and states that have recommended adoption of state-of-the-art wind forecasting tools in day-ahead and real-time planning and operations [3][4]. Further, Xcel Energy concluded reduction of the normalized mean absolute error by one percent would have reduced costs in 2008 by over $1 million annually in PSCo alone [5]. The value of reducing forecast error prompted Xcel Energy to make substantial investments in wind energy forecasting research and development.

Wind energy variability, especially rapid changes in wind energy production, hereto called ramps events, are both a cost and reliability concern. A rapid ramp-up event requires conventional generators to turn down with comparable speed and vice versa for ramp-down events. Unfortunately, conventional generators have a finite

[1] Northern States Power (NSP), Public Service of Colorado (PSCo), and Southwestern Public Service (SPS)
[2] Colorado, Michigan, Minnesota, New Mexico, North Dakota, South Dakota, Texas, and Wisconsin
[3] Market participant in Southwest Power Pool (SPP) and Midwest Independent Transmission System Operator (MISO) and as a Balancing Authority engaged in bilateral transactions in the Western Electric Coordinating Council (WECC).

capacity to absorb wind ramp events at any one time. To better understand ramp event behavior, ramp events in PSCo and SPS were studied by the National Renewable Energy Laboratory (NREL). It was found that ramp events have seasonal and time-of-day patterns and can have a skewed distribution between up and down events [6].

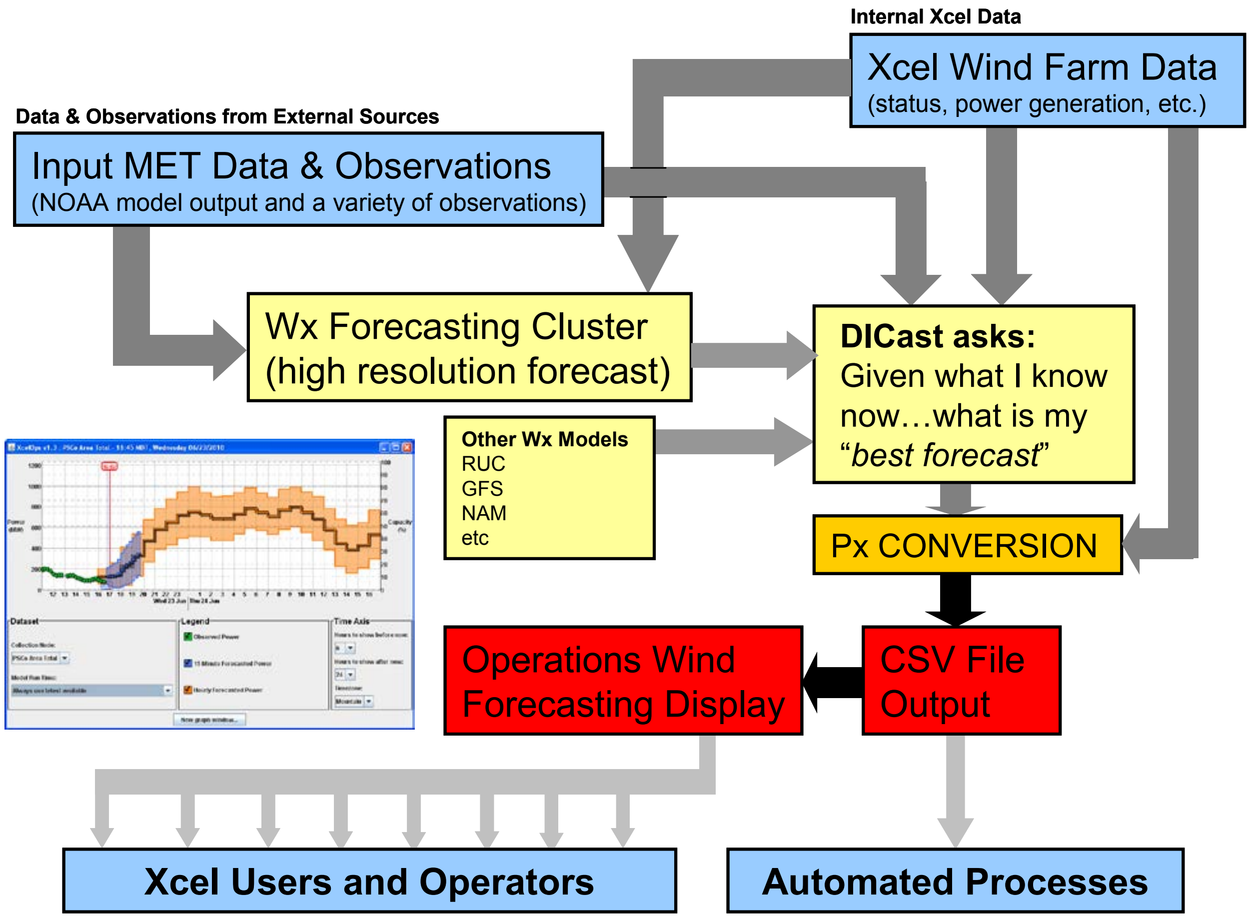
Frequently, there is poor to no notification of significant ramp events due to imprecise modeling of the underlying meteorological conditions. Large scale events, such as cold fronts, may be predicted by weather models, but the timing is frequently incorrect by tens of minutes to hours. Smaller scale events, such as strong outflows associated with convective activity, are frequently not forecasted at all. The uncertainty of timing and magnitude of wind ramp events requires operators to stage the balance portfolio conservatively despite wind ramps infrequent occurrence.

Xcel Energy contracted with the National Center for Atmospheric Research (NCAR) to develop a corporate-wide wind forecasting system. The program began in December 2008 with a period of performance of 18 months, ending in June 2010. A complete and stable system delivered in October 2009. The new forecasting system was adopted by Xcel Energy's Commercial Operations department for production purposes over the ensuing months. The system continued to be improved and refined through the period of performance. Since, it has continued to be the primary wind forecasting tool used at Xcel Energy. The focus of this report is the wind forecasting system developed during this contract period with results of performance through the end of 2010. The report is intentionally high-level, with technical details disseminated at various conferences and academic papers (see references).

Wind Forecasting System Overview

The Xcel Energy wind forecasting system consists of four parts (see Figure 1): Data Acquisition (blue), Wind Forecasting (yellow), Power Conversion (orange), and Output (red). Each component initializes the downstream process. A brief overview follows; standard meteorological data augmented by turbine-level nacelle wind speeds are fed to the weather forecasting cluster - a multi-processor computer system. The cluster utilizes the Real-Time Four Dimensional Data Assimilation (RTFDDA) process combined with a proprietary configuration of the Weather Research and Forecasting (WRF) model adapted for wind forecasting applications. The forecasted wind speed from the cluster, forecasted wind speed from publicly available weather models (together called the *foundation forecasts*), and nacelle wind speed gathered from the Xcel Energy wind plants are input into the Dynamic Integrated ForeCast (DICast). DICast generates a consensus wind speed forecast based on historic performance of the various forecasted data streams. The consensus forecast is sent to the power conversion module which converts wind speed to power using real-time power and wind speed data to initialize the calculation. Lastly, data are communicated to users via a CSV file and ultimately a forecast display for operators.

Figure 1 – Xcel Energy Wind Forecasting System.



The system produces two forecasts for each forecast node: a 72-hour forecast with hourly resolution updated every 15 minutes and a three-hour forecast with 15-minute resolution updated every 15 minutes. A *forecast node* is a group of turbines with a common point of interconnection – this is the most granular level of interest for operational purposes. There are 45 forecast nodes in the forecast system ranging from 2MW to 575MW. To contrast, the term *wind plant* is defined as a group of turbines under a common purchase power agreement, qualifying facility designation, or owned resource. While wind plants and point of interconnect (and thus forecast node) are frequently the same groups, sometimes wind plants cross multiple forecast nodes and multiple plants are behind one forecast node. Forecast nodes are then aggregated by Xcel Energy's three operating companies to give the system view most frequently used by operators.

This report discusses each of the four components (Data Acquisition, Wind Forecasting, Power Conversion, and Outputs) separately. A results section discusses year-over-year forecast improvements. For more information regarding the entire system, see [7].

Data Acquisition

A unique feature of the Xcel Energy wind forecasting system is the unprecedented acquisition of real-time turbine level data for use in a wind forecasting system. At the end of 2010, Xcel Energy was collecting power and meteorological data from 1929 turbines (74% of total), accounting for 2692 MW of generation (80% of total) on a sub-minute basis. In addition, static information, such as latitude, longitude, and hub height, was gathered from the counterparty or through the Federal Aviation Administration's Obstruction Evaluation/Airport Airspace Analysis (OE/AAA) database.[4]

The level of collected wind plant data determined the technique used to forecast power output of those turbines. Wind plants fell into three types of data detail. First, there are plants that had no turbine and nodal-level generation or meteorological data; we label these Level 1 wind plants. These include plants that were not included in the data gathering effort and are net metered − thereby conflating their output with load − or market participants within the Balancing Authority whereby nodal generation was unavailable due to the separation of transmission and marketing functions within Xcel Energy.[5] Second are wind plants with only total power output at the interconnection point (Level 2). These tend to be plants that were not included in the data gathering effort but are metered. These are plants that are technically incapable of providing real-time data and/or are small in installed power. For example, turbines built prior to 2003 tended to be technically incapable of providing data via the architected data collection system and plants less than 10MW were not pursued unless bundled together with other larger plants. Lastly, there are plants that provide turbine-level and nodal-level detail (Level 3). The last category makes up 80% of the installed generation (Table 1). Xcel Energy continues to pursue integration of real-time data in 2011.

Table 1 – Summary of Data Granularity.

Type	Turbine Detail	Nodal Power	MW	% Total
Level 1	No	No	194	6%
Level 2	No	Yes	486	14%
Level 3	Yes	Yes	2692	80%
		Total	3372	

Data Requested

The data gathering effort was undertaken starting in October 2008 to gather real-time turbine-level data and meteorological data at the wind plant. Since the majority of Xcel Energy's wind energy is provided by counterparties through Power Purchase Agreements (PPAs), data needed to be separately negotiated and was acquired via each of the contractual counterparties.

Turbine Data

The requested data points changed over time as we refined our vocabulary. Ultimately, we settled on the following ten real-time data points:

1. Turbine Generation
2. Nacelle Wind Speed
3. Turbine Availability Status (or equivalent)
4. Generator Status (on/off-line)
5. Nacelle Position (relative to true north)
6. Wind Direction (relative to true north)
7. Yaw Error
8. Rotor RPM
9. Blade Pitch
10. Voltage

[4] Obstruction Evaluation/Airport Airspace Analysis (OE/AAA), https://oeaaa.faa.gov/oeaaa/external/portal.jsp
[5] FERC Order 880 separates the energy marketing and transmission functions in the utility sector. Since the wind forecasting tool is primarily used by Xcel Energy's energy marketing department, real-time output of other generators (like competing wind farms) within the Balancing Authority (BA) are restricted.

And the following static data points:

1. Latitude (NAD83)
2. Longitude (NAD83)
3. Hub Height (m)
4. Turbine Manufacturer and Model
5. Manufacturer's Power Curve

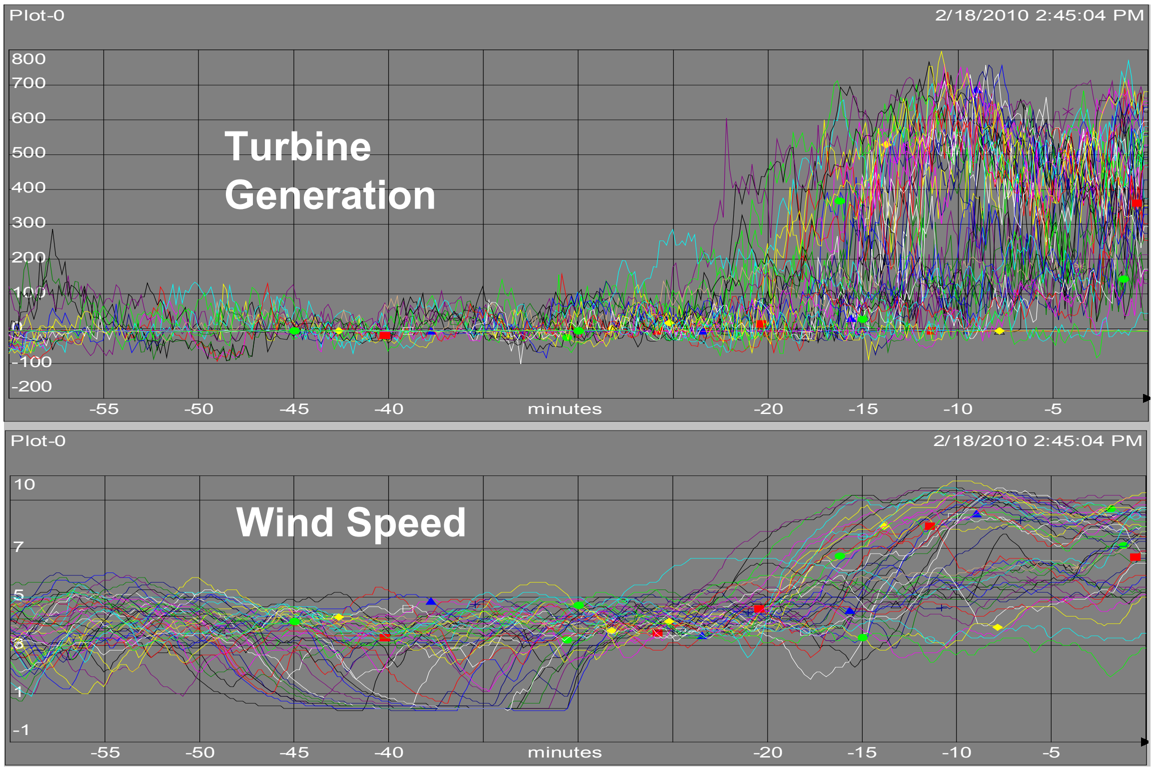
The first seven real-time data points were considered important for wind forecasting purposes. The remaining real-time data points were requested with the intention of possibly extending research at some future time.

While many points were requested, a subset of requested points was typically collected. Additionally, the requested dataset improved over time. For example, nacelle position is not a quality indicator of wind direction and had to be further refined to include *relative to true north* in the request. Wind direction and yaw error were added to the request after working with two wind plants. Even so, nacelle position relative to true north and wind direction are not typically part of the turbine system – i.e., they were never collected.[6] At a minimum, turbine generation, nacelle wind speed, and turbine availability status or equivalent were collected. In the case of turbine availability status, Xcel Energy translated numerous equivalent codes into a binary variable indicating the availability of the turbine.

Fortunately, the first three data points were the most useful for forecasting purposes. While wind direction was considered a critical meteorological data feed, and would be useful for future forecasting efforts, the teams quickly recalibrated data expectations to focus on the first three, most reliable data feeds. An example of the turbine generation and wind speed data for fifty turbines coincident with a slow-moving front is shown in Figure 2.

[6] It was later learned that nacelle position can be calibrated to true north – either by direct manipulation of the turbine system or through a calculated offset. It is a lesson learned that turbines are able to provide true north through coordinated activity or calculation, but is not part of the standard outputs available in the wind farm SCADA systems.

Figure 2 – Turbine Generation and Nacelle Wind Speed for Fifty Turbines.



The turbine data are used throughout the wind forecasting system to initialize the weather forecasting cluster, calibrate wind speed forecasts, initialize power conversion, and establish performance metrics.

Meteorological Tower Data

When available, meteorological tower data was gathered at the wind plant and communicated via OSISoft's PI system. Data requested included:

1. Wind Speed**
2. Wind Direction**
3. Temperature
4. Pressure
5. Air Density

**at all sensor heights

Meteorological tower data was infrequently available at wind plants. In many instances where data was available, the data quality was poor or incomplete due to broken or poorly maintained sensors.

Data Collection System

Xcel Energy gathers turbine-level data and meteorological data from Xcel Energy owned and contracted wind plants on a real-time basis. The data are collected and stored in numerous PI Systems[7]. A centralized PI System is placed outside the Xcel Energy corporate firewall (called the DMZ), thereby enabling easy

[7] The PI System is an energy industry-standard product produced by OSISoft (www.osisoft.com). The PI System stores and manages data intensive time-series data in an efficient, easy-to-use format.

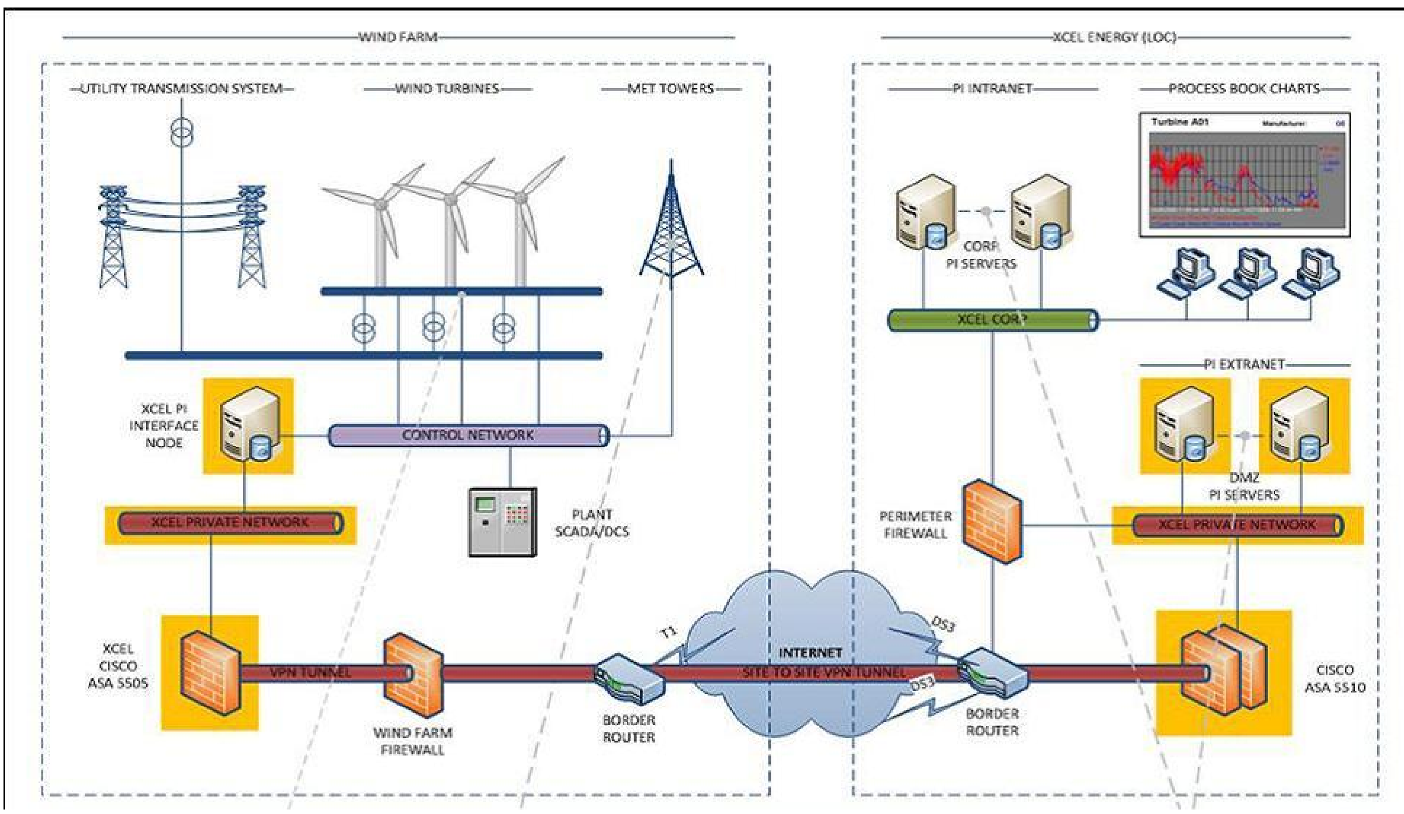
communication with outside counterparties. Data are retrieved from wind plants via one of two pathways which are described in detail in the next sections:

1. *Direct from the wind plant* - a direct feed from an Xcel Energy owned server installed at the wind plant.
2. *PI-to-PI Connection* - A PI-to-PI connection to a counterparty's PI System that already collects the required turbine-level and meteorological data.

Direct from the Wind Plant

Data are securely transmitted from the wind plant to Xcel Energy over the Internet (Figure 3). An Xcel PI Interface Node – a server connected to the wind plant supervisory control and data acquisition (SCADA) system – spools and translates turbine-level data into PI System format. The data are pushed across a Virtual Private Network (VPN) tunnel secured by two CISCO ASA 5505 devices with ready access to the Internet. Data are stored on the Xcel Energy PI DMZ System located outside the corporate firewall. Data are then spooled to the Corporate PI System server for long-term storage. New data on the PI DMZ System eventually overwrites the oldest data. The expected life of data is estimated to achieve steady state at approximately three months.

Figure 3 – Schematic of Turbine-Level Data Collection.



PI-to-PI Connection

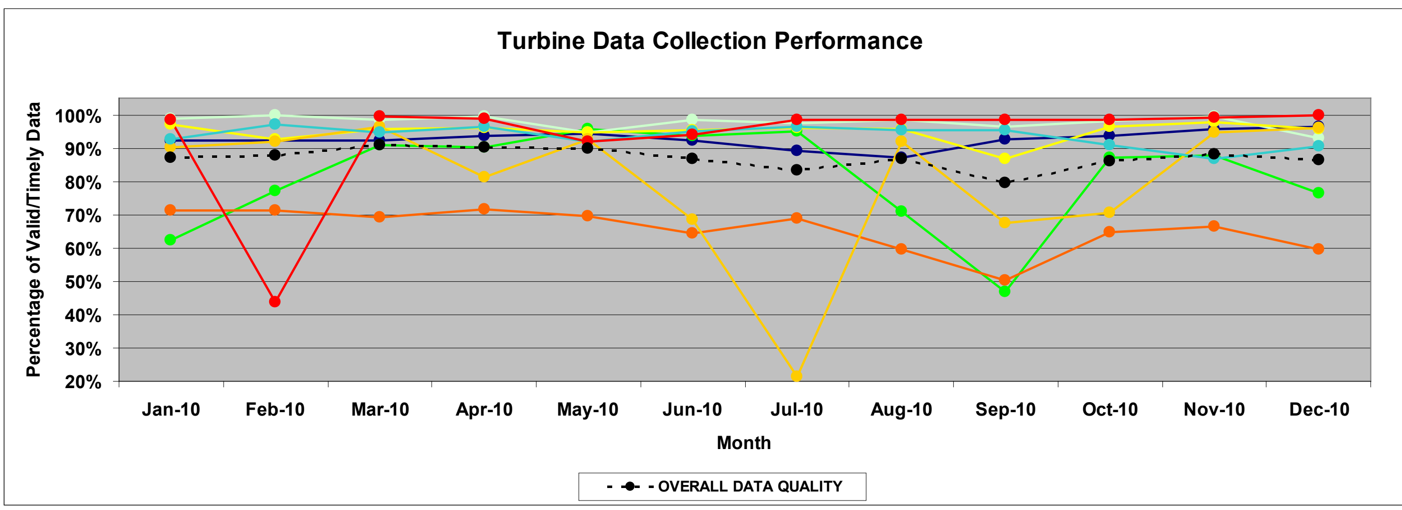
The second, more common method is a direct connection to another existing PI System. If the counterparty already has implemented a PI System solution, then a VPN tunnel is established between the counterparty's PI System and the PI DMZ System. Data are streamed across this PI-to-PI connection in real-time.

Data Quality

Timely, high quality data are a key part of the Xcel Energy wind forecasting system. To ensure quality, separate data quality calculations are performed on each set of turbine data. Range checks are performed on generation and wind speed data. For example, wind speeds are assumed to be positive and generation must be less than 120% of rated capacity. If the range check fails, the turbine data are flagged as bad. If the range check passes, then a time lag check is performed. If the last turbine-level data are greater than 5-minutes old, the data are flagged as bad. If the turbine passes all tests, the data quality passes as good. In addition to providing a real-time measure of data quality, performance can be measured as the percent of time the turbine had good data quality. Data are summarized by wind plant, counterparty, and operating company. Counterparties that drop in performance can be notified and mitigating action taken.

Data quality can be plotted historically by counterparty (see Figure 4), though counterparty names are excluded to protect their identity. Real-time data quality tended to perform around 90% overall with occasional degradation near 80%. Periodic data outages occurred, some lasting weeks. Since it is unrealistic to expect all data to flow all the time, a guide of 90% compliance was adopted at Xcel Energy – only counterparties that performed below 90% were informed of their performance. In rare occasions, technical problems associated with older wind plant technology caused a counterparty to be much below the target.

Figure 4 – Data Quality by Counterparty.



Wind Forecasting

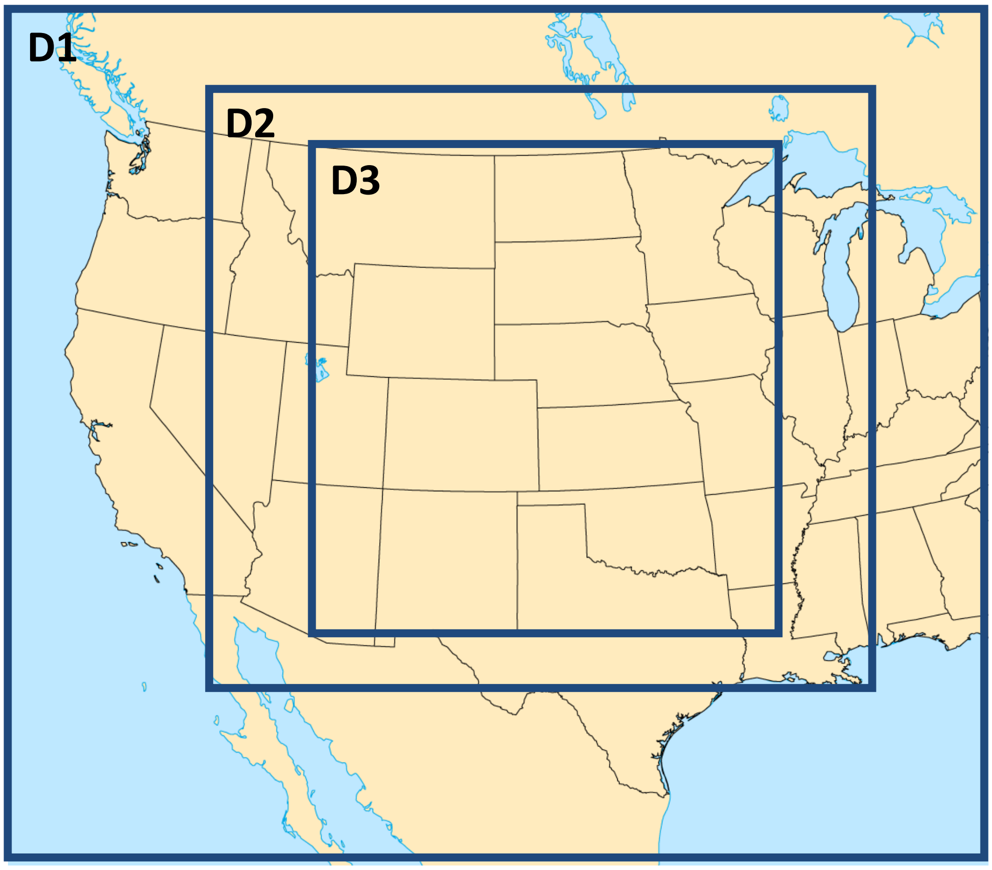
The Wind Forecasting component is the most complex function in the Xcel Energy wind forecasting system. This component consists of the forecasting cluster (RTFDDA-WRF), other public forecasting models, and the DICast systems.

Real-Time Four Dimensional Data Assimilation (RTFDDA)

The Real-time Four Dimensional Data Assimilation (RTFDDA) version of the Weather and Forecasting Mesoscale model (WRF) is a mesoscale numerical weather prediction model designed for high-resolution applications, featuring rapid forecast updates and continuous real-time assimilation of observed data. A customized version for Xcel Energy was optimized for wind energy applications. The model domain covers the entire western United States (D1 resolution = 30-km), with two nested domains (D2 resolution = 10-km; D3 resolution = 3-km) (see Figure 5). The model includes 41 vertical levels for all domains. D1 and D2 domains operate for the entire 72 hour forecast cycle with hourly outputs. The D3 domain is used for the first 24 hours of the forecast cycle, with 15 minute outputs. The model has a cold start once a week on Saturdays, with restarts every three hours (i.e., *warm starts*). The warm RTFDDA-WRF ingests new observations, including real-time nacelle wind speeds and meteorological tower information collected by Xcel Energy.

During forecast operation, model outputs − most importantly hub height wind speeds − are written in situ and passed to DICast for post-processing. Additionally, numerous meteorological displays are generated for use by staff meteorologists. The meteorological displays are discussed later in this paper.

Figure 5 – RTFDDA-WRF Model Domains.



The RTFDDA-WRF runs on 53 servers (49 x Dell PowerEdge 1950; 4 x Dell PowerEdge 2950) installed on two racks with 3 switches (2 x Dell Power Connect 5448 switch; 1 x Myrinet M3 E64 switch). It is referred to as the deterministic cluster, or XCEL-C1. For more information on the RTFDDA-WRF subsystem, please see [8].

Other Public Forecasting Models

Besides the RTFDDA-WRF, the Xcel Energy wind forecasting system utilizes other public forecasting models including:

1. North American Mesoscale model (NAM)
2. Global Forecast System (GFS)
3. Rapid Update Cycle (RUC)
4. MAV-MOS
5. MET-MOS
6. LAMP-MOS

These models are maintained for the public good by the National Center for Environmental Prediction (NCEP). Only the wind speeds from grids coincident with turbine locations are extracted. The ingest process must manage the various refresh times and forecasted time horizons of the various models in preparation for the DICast component.

Dynamic Integrated ForeCast (DICast)

The Dynamic Integrated ForeCast (DICast) system ingests RTFDDA-WRF model output, output from other public weather forecasting models (together called *foundation forecasts*), and nacelle wind speed observations to generate a *consensus forecast*. DICast performs a two-step optimization to generate the consensus forecast. In the first stage, DICast performs regression statistics to remove model bias from each of the foundation forecasts, better known as dynamic model output statistics (DMOS). The DMOS calculation is performed weekly with a training period over the last ninety days. In the second stage, DICast assigns weights to various adjusted foundation forecasts based on their recent performance. This calculation is performed daily using the last day's dataset as the training set. The weights are calculated for every forecasted time step, for every issue time, at every nacelle in the Xcel Energy service territories. While weights are equal at the initial condition, DICast changes weights daily to favor the better forecasts. Note that the maximum weight change is restricted to maintain stability. For turbines that have no real-time nacelle wind speed data, the weights never change from the initial conditions (i.e. the average of the foundation forecasts). The consensus forecast is the inner product of the DICast weights with the available adjusted foundation forecasts, divided by the sum of the weights of the available forecasts. The consensus forecast is a major input into the power conversion module.

DICast provides robustness by always producing a consensus forecast. If the real-time data ceases, DICast stops optimization and propagates the latest weights until such time that real-time data are reestablished. If a foundation forecast is missing, DICast will continue to optimize with the available forecasts. For more information on the DICast subsystem, please see [9]

Power Conversion

The power conversion algorithm depends on availability and granularity of real-time data. Three data detail categories were determined throughout the course of the project (see Table 1). In total, three power conversion algorithms were explored; two by NCAR − one for Level 1 and 2 plants and one for Level 3 plants − and four by NREL for Level 3 wind plants. The system ultimately employed NCAR's power conversion technique for Level 3 turbines.

Table 2 – Power Conversion Algorithms.

Count	Institution	Turbine Detail	Power Conversion
1	NCAR	Level 1 and 2	Manufacturer's Power Curve
2	NCAR	Level 3	Direct Estimate by Turbine by Plant
3	NREL	Level 3	Equivalent Power Curve
4	NREL	Level 3	Directional Equivalent Power Curve
5	NREL	Level 3	Direct Estimate by Turbine Type
6	NREL	Level 3	Neural Network

Level 1 and 2 Wind Plants

The manufacturer's power curve is used for power conversion for Level 1and 2 plants. This is a simple and rudimentary approach. There are many reasons more sophisticated models were not created. Level 1 and 2 wind plants make up a minority (less than 20%) of the total portfolio. Wind forecasting vendors have already developed sophisticated algorithms with limited real-time data. Further, Level 1 plants – especially third-parties within the Balancing Authority (BA) – may provide real-time data to Xcel Energy in the future either per a recent FERC Notice of Proposed Rulemaking (NOPR)[8] or through other commercial agreements. Level 2 plants tend to be older plants with incompatible SCADA systems for the data collection process that, as they

[8] November 18, 2010. FERC NOPR Docket No RM10-11-000 Integration of Variable energy Resources.

upgrade their systems, will become data-rich (Level 3). Future plants will be Level 3 plants because provisions in the PPA now require specific data to be provided. Thus, little effort was placed on improving techniques for Level 1 and 2 wind plants.

Level 3 Wind Plants

The availability of real-time turbine-level data affords opportunities for novel power conversion methodologies. Both NCAR and NREL pursued power conversion methodologies. NREL developed four empirical power conversion methodologies for an entire wind plant, controlling for wind direction, temperature, pressure and wind speed from two sources: meteorological towers and nacelle wind speeds. NCAR developed a turbine specific methodology, empirically associating nacelle wind speed to turbine generation. The two methods are discussed below, followed by a discussion of their merits and pitfalls.

NREL: Four Empirical Methods

While output of a single wind turbine can be characterized by the manufacturer's power curve, an equivalent wind plant power-curve becomes highly desirable and useful in predicting an aggregated output for a given wind speed forecast. However, unlike the single-turbine power curve, it is difficult to capture all the nuances of a wind plant consisting of tens or even hundreds of turbines with a single curve. A model capable of fully characterizing 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 may consist of a set of curves or some other mathematical models. The wind speed information from on-site meteorological tower and metered plant output are used to construct an equivalent power curve for the entire plant. As expected, the resulting curve takes a similar shape of the single turbine power curve. Four empirical power curves were developed: equivalent power curve, directional equivalent power curve, direct estimate based on turbine type, and neural network.

The data used for this effort include 10-minute time series of average individual turbine generation, nacelle wind speed, total metered wind plant output, wind speed and direction from on-site meteorological (MET) towers, temperature and barometric pressure. Quantity and availability of these data vary significantly throughout the studying period. Consequently a large amount of effort is devoted to clean the data to arrive at consistent data streams.

Equivalent Power Curve

For a wind plant with hundreds of turbines, wind speed forecast for every turbine will be difficult to obtain. A more likely scenario is to have only one wind speed forecast for the entire plant site. In this project, the wind speed information from on-site MET tower and metered plant output are used to construct an equivalent power curve for the entire plant. As expected, the resulting curve takes a similar shape of the single-turbine power curve.

Directional Equivalent Power Curves

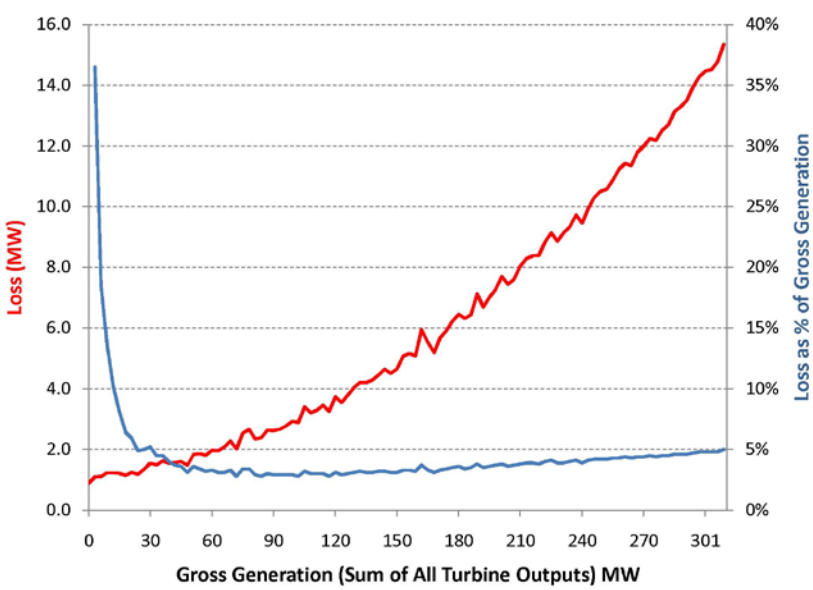
The asymmetric layout of turbines in wind plants indicates they are designed to minimize the wake effect of the site's prevailing wind direction. The data show the plant outputs vary with the directions of winds, and it suggests that a set of power curves, each associated with a specific wind sector may provide a better power conversion result. The wind resource data from the on-site MET tower were separated into eight wind sectors. The directional wind data along with their corresponding metered plant output are used to construct eight power curves for the wind plant. These eight directional power curves also resemble the single-turbine power curve. However, the differences between the equivalent power curves of the prevailing wind direction and the least frequent wind direction are significant.

Direct Estimate Based on Turbine Types

The specific wind plant for this project has two types of turbines – one with a hub-height of 80 m and the other 69 m – and thus two different turbine power curves. Another approach is to use wind information at the corresponding hub heights and the two turbine power curves to estimate the output of two groups of turbines directly. Outputs of one turbine from each group are estimated based on the hub-height wind speed forecast. Single turbine output is multiplied by the predicted numbers of on-line turbines for each group to calculate the group output.

If wind speed can be predicted for every turbine location within a wind plant, the power conversion process becomes a simple exercise of summing up all turbine outputs (obtained through manufacturer's turbine power curve) minus plant losses. Figure 6 below shows the wind plant loss curves from the available data.

Figure 6 - Wind Plant Loss Curves.



The plant output is the sum of two group outputs minus plant losses with the losses being estimated based on Figure 6.

Neural Network Model

Finally, the neural network technique is used to simulate the complex relationship between wind speeds, directions, temperature, and pressure and the wind plant output. In this report, the neural network is a straightforward feed-forward network with back-propagation using all available wind resource data and weather information from the on-site MET towers.

The results of these four approaches are compared by calculating the mean absolute error (MAE) between the predicted and actual wind plant outputs. Table 3 below lists MAE of all four approaches.

Table 3 – MAE of the Four Models.

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

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 because 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. 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 be required 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.

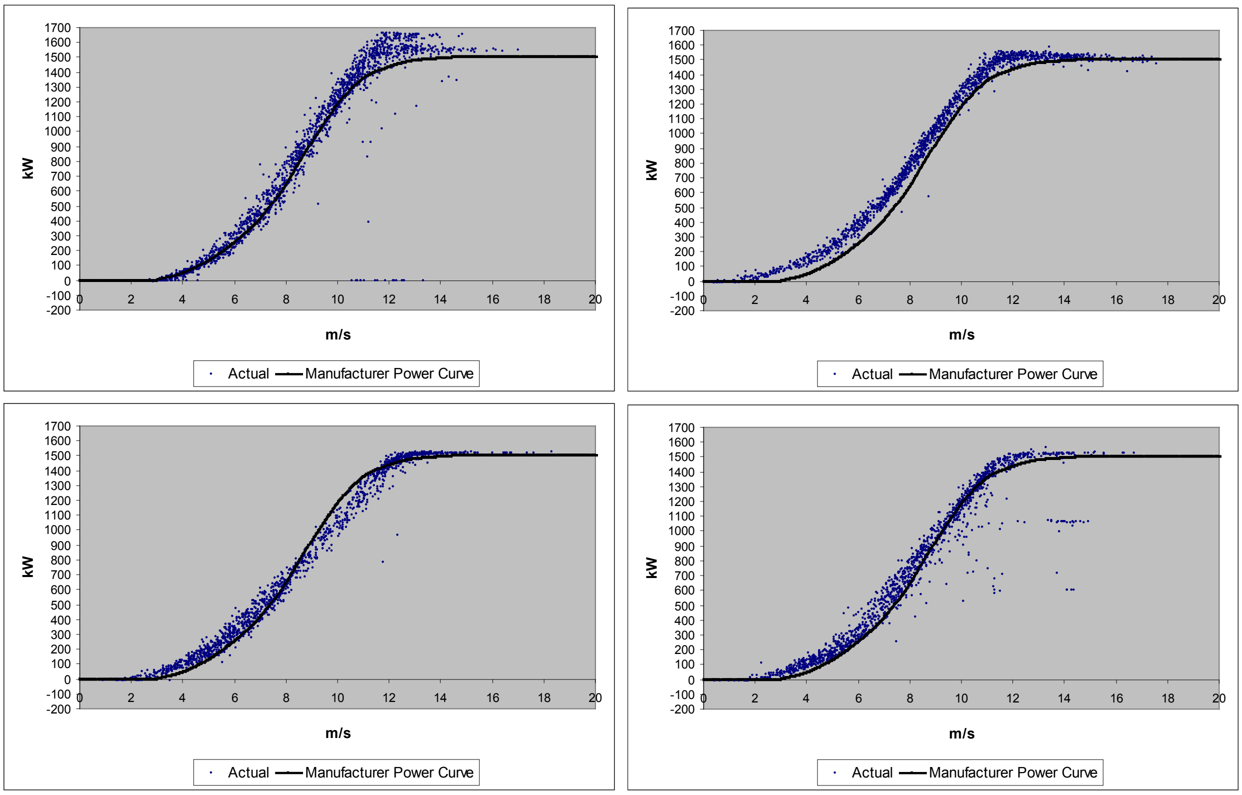
The direct estimate approach produces the best results compared to other approaches tested. This approach is straightforward and the concept behind it is simple. However, its success depends on the quality of turbine-level data.

A detailed description of NREL's estimation effort can be found at [10].

NCAR: Empirical by Turbine by Plant

Due to the availability of turbine-level data and the encouraging results of the NREL investigation, a turbine-level power curve methodology was implemented. An initial study was completed that demonstrated each turbine type within a plant behaved similarly given the paired wind speed and generation data. However, the behavior of the same turbine type over different plants was disparate (see Figure 7). The deviation from the manufacturer's power curve is also peculiar to each wind plant.

Figure 7 – Same Turbine Type at Four Different Wind Plants.



A representative turbine by turbine type by plant was selected for data mining. Wind speed and generation data was averaged over 15-minute intervals. The most predictive equation for current generation was derived from the previous generation and wind speed and the current wind speed. When forecasting, the forecasted wind speed is substituted for the current wind speed in a recursive equation (1a). The previous 15-minute observed power and wind speed initializes the equation (1b).

However, due to technical and operational vagaries, observed power and wind speed were not always available. In the absence of a valid observed power data point, an estimate is made using the observed wind speed and the manufacturer's power curve (1c). In lieu of any real-time data, the forecast wind speed is transformed to power through the manufacturer's power curve (1d).

Equation 1 – Empirical by Turbine

$$P_{t+1} = f\left(P_0, WS_0, WS_{t+1}\right) \qquad \text{(a)}$$

$$P_0 = P_{obs} \quad WS_0 = WS_{obs} \qquad \text{(b)}$$

$$P_0 = M\left(WS_{obs}\right) \quad WS_0 = WS_{obs} \qquad \text{(c)}$$

$$P_0 = M\left(WS_1\right) \quad WS_0 = WS_1 \qquad \text{(d)}$$

The forecasted power at the turbine-level is summed by connection node. The connection nodes are summed by operating company. This technique was internally referred to as the *sum-of-turbines* approach.

The sum-of-turbines approach has inherent flaws. As described in the above section, the losses between the turbine and the point of interconnect can be significant. These losses can be as large as 4-5% for plants with long radial transmission lines. Typically, wind plants are close to the point of interconnection making losses nominal, or the loss equation was estimated and applied outside the modeling environment. Second, the approach tended to assume full availability. Though, this can be mitigated by carefully choosing a training dataset with periods of maintenance, forced outages, and curtailments. If the training set included such periods, the data mining processes tended to derate the forecast-based current availability or curtailed output. This has a down side as derates tend to be propagated based on historic precedent and not current operational realities.

There are inherent benefits as well. The turbine-level datasets, when available, tended to be clean and usable with little data quality work. The method is simple. When connection nodes were expanded with new wind turbines, the turbine-level model could be added for the additional turbines, rather than retraining the entire connection node output.

Output

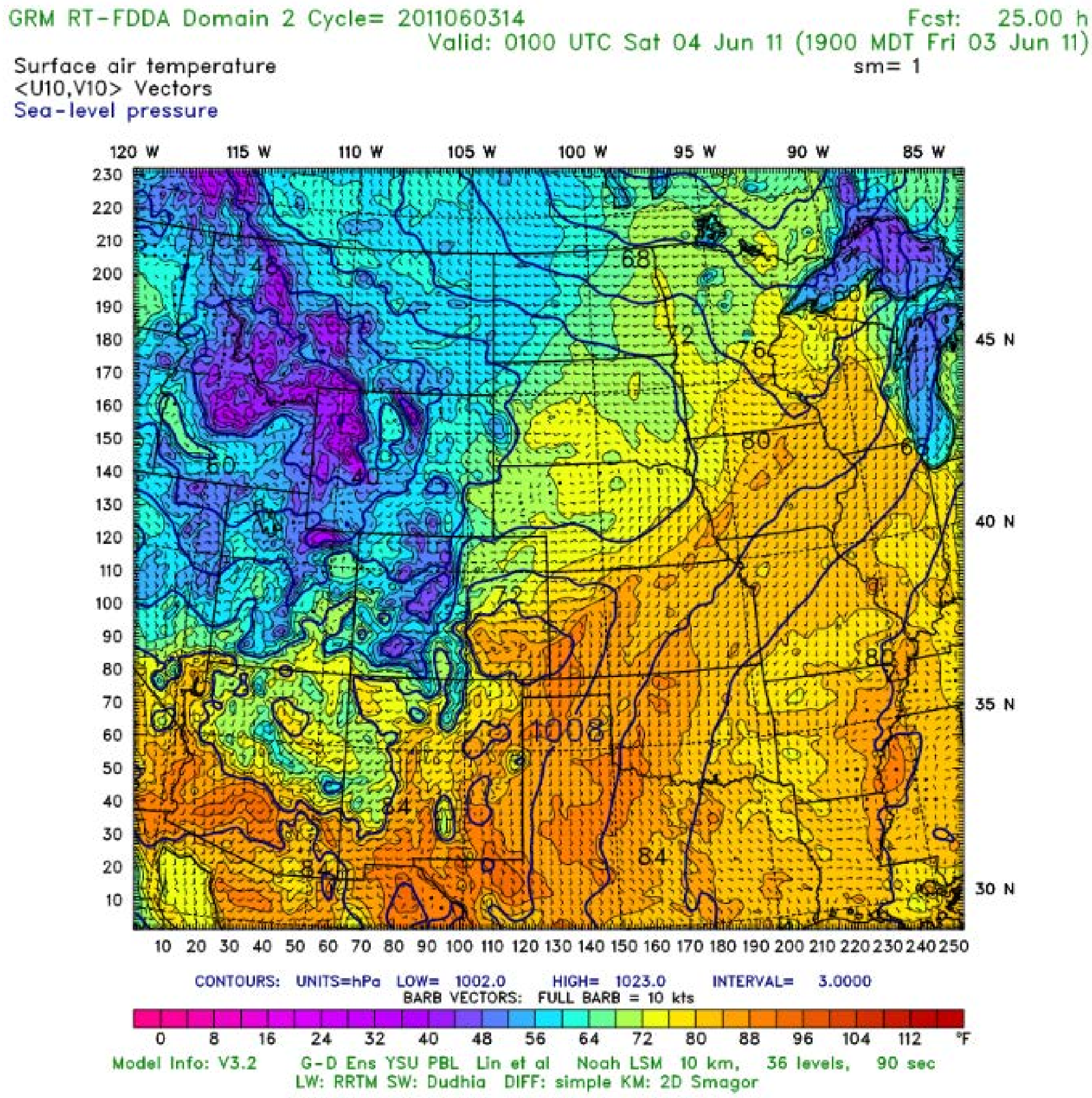
The Xcel Energy wind forecast system produces many weather related outputs including RTFDDA-WRF outputs, CSV files containing forecasted energy, and an Operator's graphical users interface (GUI) based on the CSV files.

Meteorological Outputs

The RTFDDA-WRF produces many weather related snapshots over the forecasted domains (D1 - 30-km; D2 - 10-km; D3 - 3-km) and forecast times. Xcel Energy meteorologists use these snapshots to better understand meteorological conditions to forecast wind and load, and characterize possible risks to day-ahead and real-time operations. The images are updated every 3-hrs and are archived for three days.

Figure 8 displays surface air temperature and wind vectors. It has a resolution of 10-km and is forecast hour 25 after the current hour. This one image contains a wealth of information about the pressure, temperatures, and winds at the surface. The images at different forecast steps can be invoked by rolling a mouse over a series of hyperlinks. This creates a "moving image" that gives meteorologists a quick overview of the forecast in both the geographic and time domains.

Figure 8 – Surface Air Temperature, Wind Vector; 10-km Domain; 25-hr Forecast.



Conditions of interest go beyond temperature and wind speeds. Figure 9 is an image of precipitable water for the 25-hour forecast. Precipitable water indicates the amount of moisture in a given environment. It indicates clouds and precipitation – or the likelihood thereof. It can help predict convective activity, identify fronts, and cyclones.

Figure 9 – Total Preciptable Water; 10-km Domain; 25-hr Forecast.

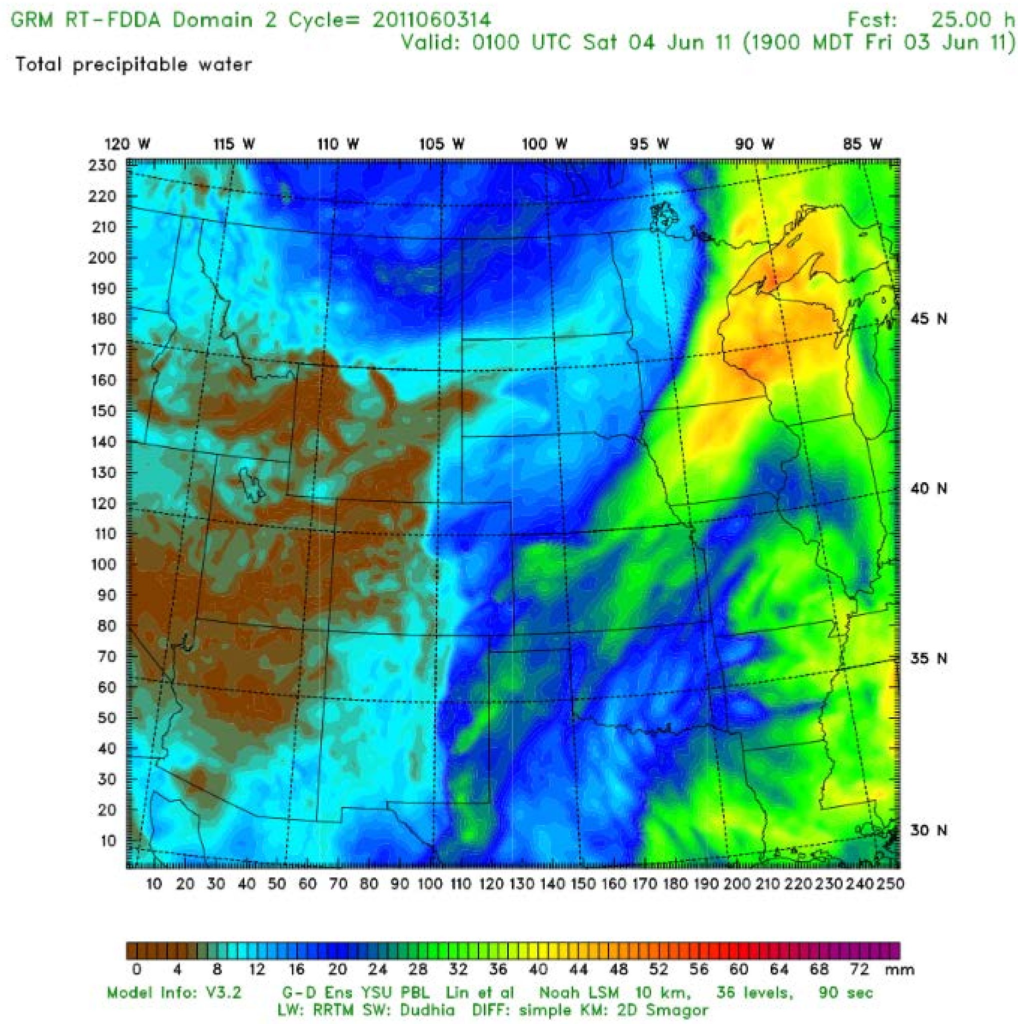


Figure 10 contains images of the 700 mb height, temperature, and winds. The first image has a coarser resolution (10-km grids). The second image is from the same 25-hour forecast, but the resolution is finer (3-km grids). The nested domain of the 3-km grid is smaller in the higher resolution map.

Figure 10 – 700mb Height Temperature and Wind Vectors; 10-km and 3-km Domain; 25-hr Forecast.

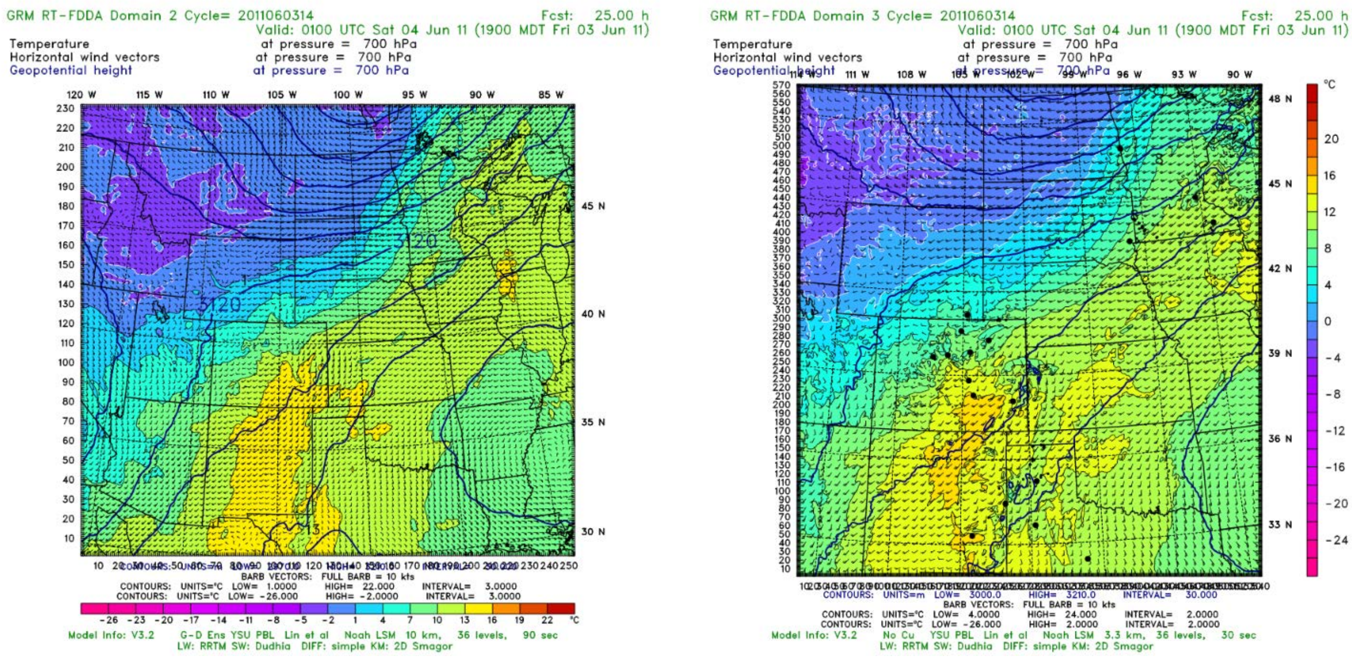
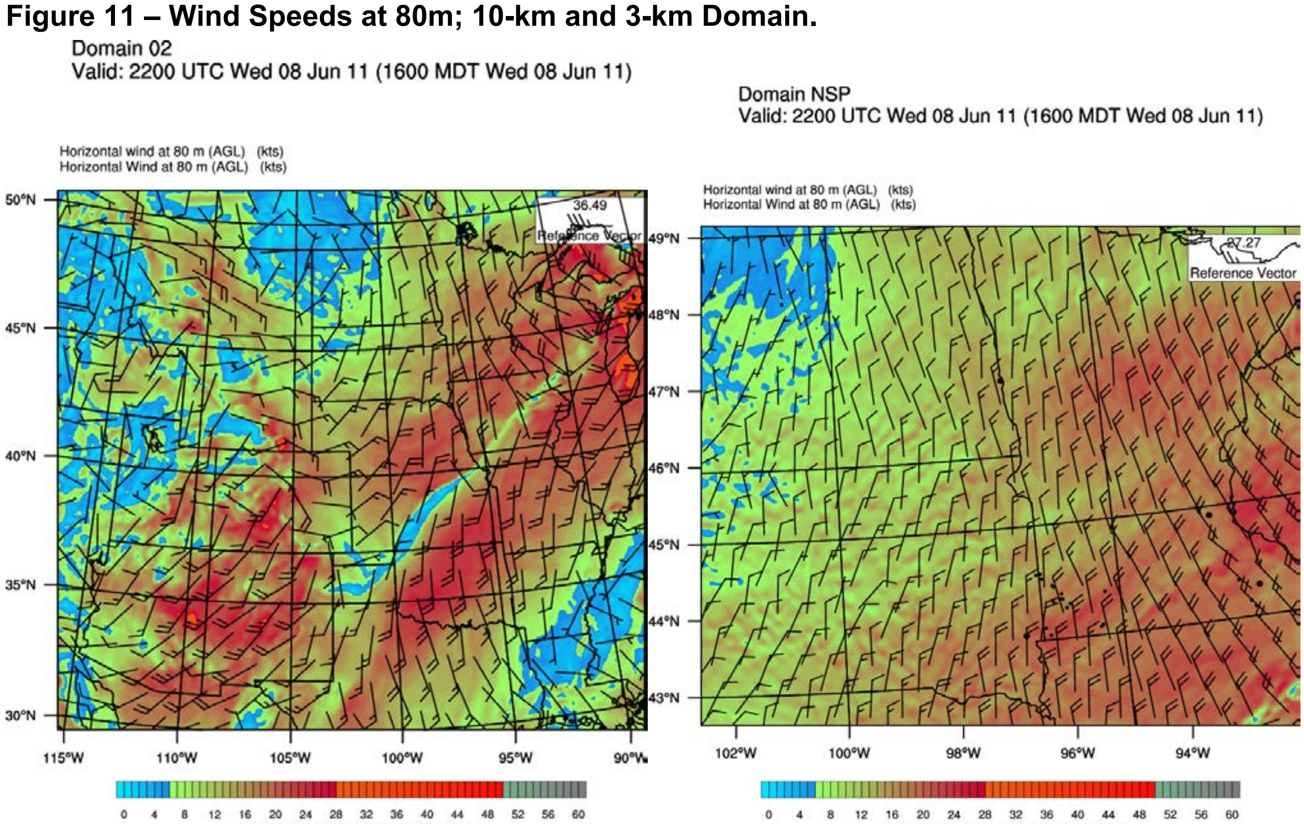
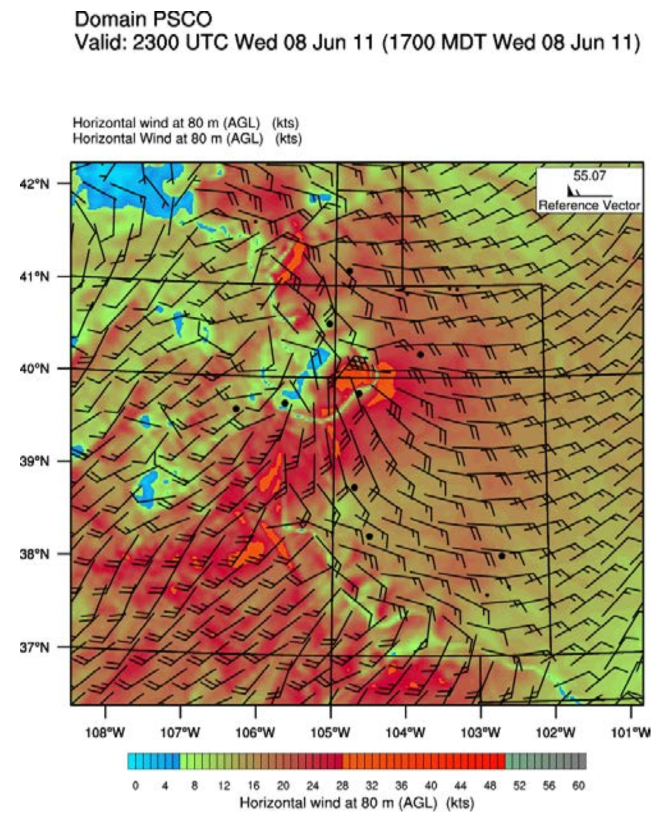
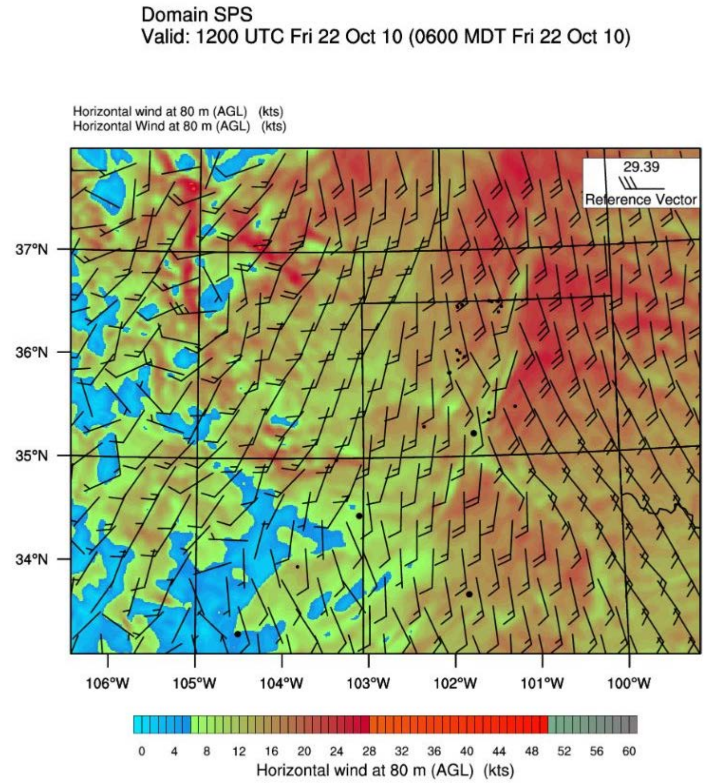


Figure 11 includes four images that indicate the wind speeds at 80 meters. The wind barbs indicate direction and speed while the color scheme indicates a finer resolution of wind speed. The first image is the full nested grid with 10-km grid spacing while the next three are the individual maps for each service territory at the 3-km grid spacing. Eighty meters was chosen because this is the dominant hub height for wind turbines in Xcel Energy's territory. These are superior to surface wind speeds, allowing meteorologists to view a slice of model output at the height of most significance over each of the service territories.

Figure 11 – Wind Speeds at 80m; 10-km and 3-km Domain.



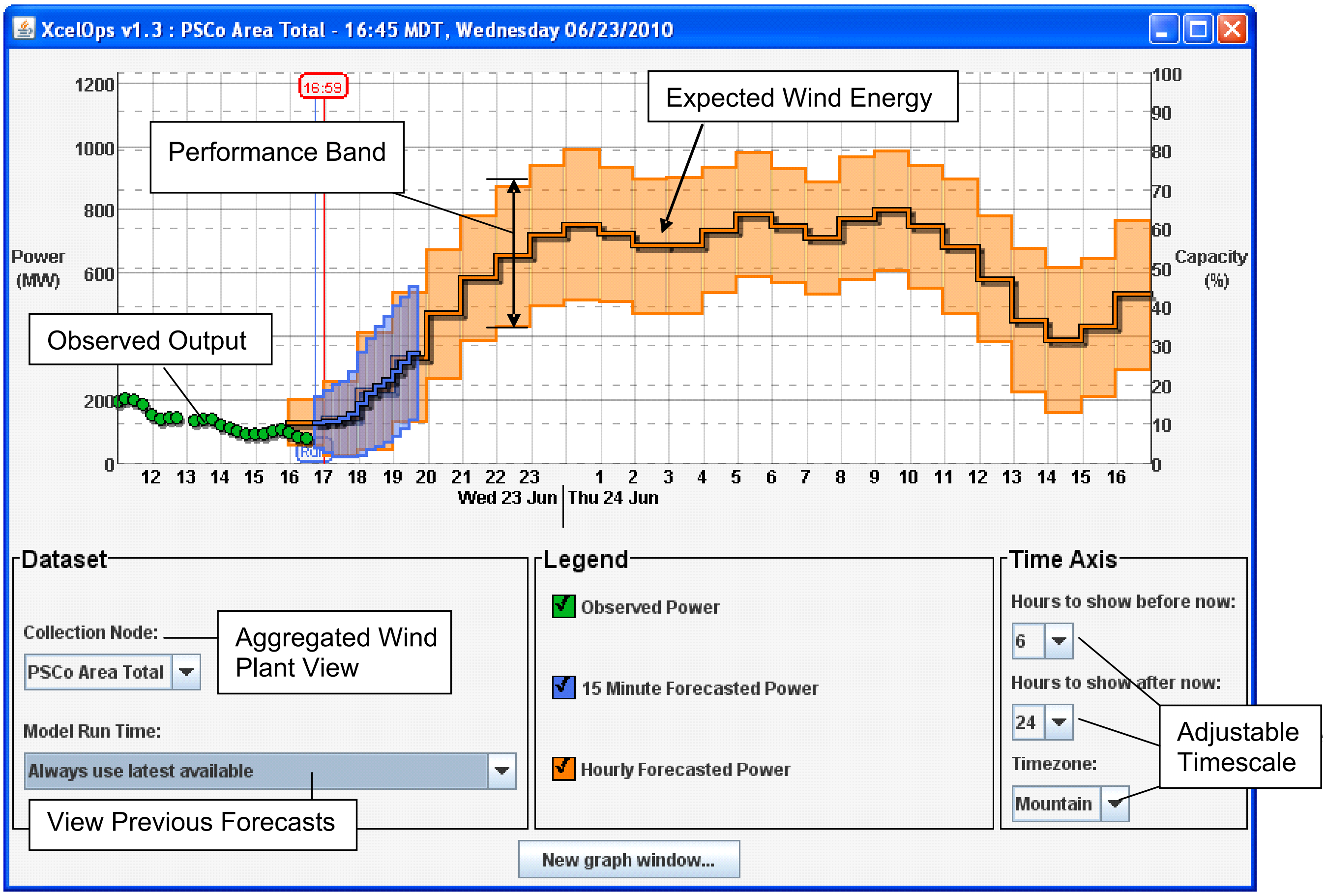




Operator's GUI

The Operator's GUI displays historic and forecasted energy time-series data with numerous drill down, look back, and configurable views. The observed output is displayed in a 15-minute average power time series to the left of the real-time line. Forecasted wind energy (both the 3hour/15minute and 72hour/hour forecasts) is shown to the right of the real-time line with a band indicating recent performance. The performance band is the 75% cumulative absolute error distribution over the last seven days above and below the expected forecast. The graph supports power (left) and percent capacity (right) on the y-axis. The time scale (x-axis) can be adjusted to accommodate different time zones and historic and forecasted time frames. Forecasts are rolled up to a system level view by the operating company. A user can drill down to every point of interconnection to view the observed and forecasted time-series data. Lastly, the user can look back at prior forecasts up to 72 hours in the past overlaid with observed data.

Figure 12 – Operator's GUI.



Results

The NCAR forecasting system was integrated into day-ahead and real-time operations from November 2009 to April 2010. PSCo and NSP were integrated simultaneously first, with SPS' integration second. As such, a comparison of 2009 versus 2010 is largely a comparison of wind energy forecasts without and with the NCAR forecast system. Installed wind energy capacity did grow slightly over the comparison period, complicating a head-to-head comparison. To mitigate, installations at the very end of the study period, such as the installation of 200 MW Nobles Wind Plant in NSP in December 2010, are excluded from the error metrics. Remaining growth is only 233MW across all three systems (PSCo, 174 MW; SPS, 34.5 MW; NSP, 24.5 MW). Thus, error metrics are normalized by installed capacity hereto called the Mean Absolute Percent Error (MAPE). We focus on the day-ahead forecast.

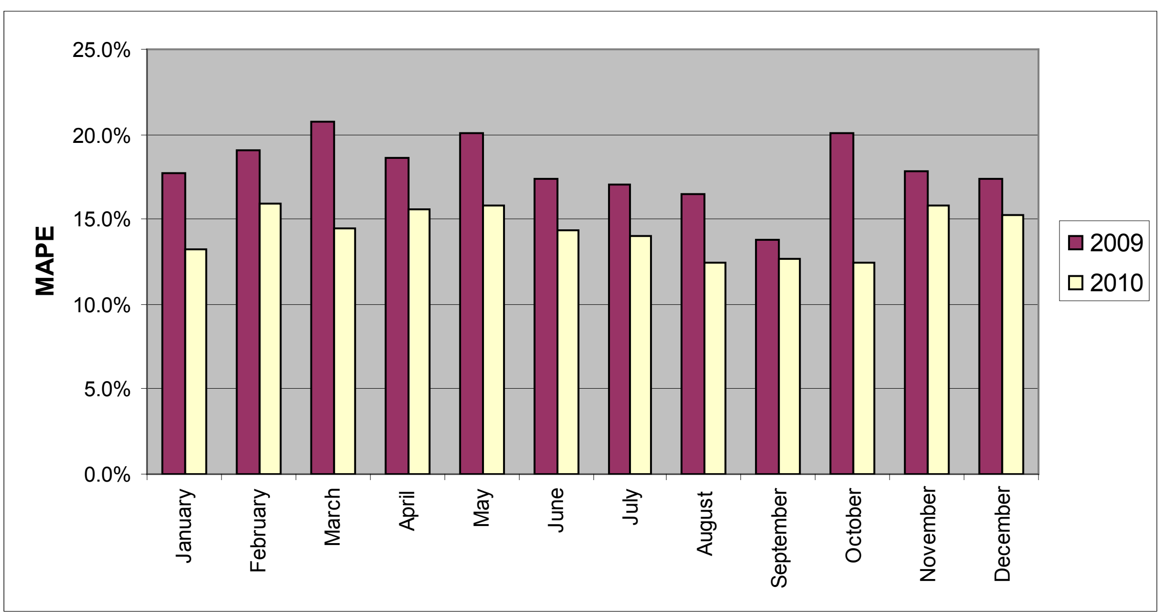
The day-ahead forecast is used in the day-ahead commitment process. This process has different forecast horizons depending on the market structure. For example, NSP bids into MISO's day-ahead market. MISO's day-ahead market operates everyday – Monday's bids and awards for Tuesday, and so on. In PSCo and SPS, the day-ahead commitment process is through the next business day – Monday for Tuesday, and so on, until Friday, which is a 3-day forecast through Monday. Forecasts extend longer for holidays. The implications of the day-ahead commitment process are many. Generators are informed of the intention to run the next day, natural gas nominations committed, and incremental and decremental prices are set up for day-ahead trading.

Prior to the NCAR forecasting system, Xcel Energy performed its own day-ahead forecast. Forecasted wind speeds were downloaded from the North American Mesoscale Model (NAM) as made available by

Pennsylvania State University's Bufkit Data Distribution System (BDDS)[9]. Since all NAM gridded output is unavailable through the BDDS, data soundings nearby major wind centers were used as proxies for a wind plant's wind speed forecast. The forecasted wind speed between 45m and 80m above ground level were used to approximate hub height wind speed. The manufacturer's power curve was used to transfer hub height wind speed to power output. The power output was scaled by the number of turbines at the wind plant and further adjusted for wind plant turbine availability.

The day-ahead forecast improved annually across all three systems. In Figure 13, PSCo saw reductions in error in every month, with a total reduction of from 18% (2009) to 14.3% (2010) – an absolute reduction of 3.7% - or a 20% decline in forecast error. Figure 14 demonstrates similar gains in NSP. Improvements were made every month except June and September. Annual forecast error was reduced by 3.5% from 15.65% (2009) to 12.2% (2010). SPS also demonstrated lower forecast errors (Figure 15). All months had lower forecast errors except February and March. Annual forecast error modestly reduced from 16.4% (2009) to 14.0% (2010) – an absolute reduction of 2.4% − or a 14.7% reduction. Note that SPS was the last system to fully integrate the NCAR modeling system. Also, improvements in the RTFDDA-WRF parameterization schemes implemented in June 2010 are believed to have contributed to further lowering the forecast errors. Overall, months with lower production (July through September) tend to have lower forecast errors. January and February 2010 in NSP and PSCo had unusually low capacity factors which contributed to the lower forecast errors. Lastly, icing events are not forecasted in the current system and contributed to large forecast errors.

Figure 13 – PSCo monthly day-ahead forecast error.



[9] More information regarding Pennsylvania State University's Bufkit Data Distrbution System can be found at http://www.meteo.psu.edu/bufkit/CONUS_NAM_12.html)

Figure 14 – NSP monthly day-ahead forecast error.

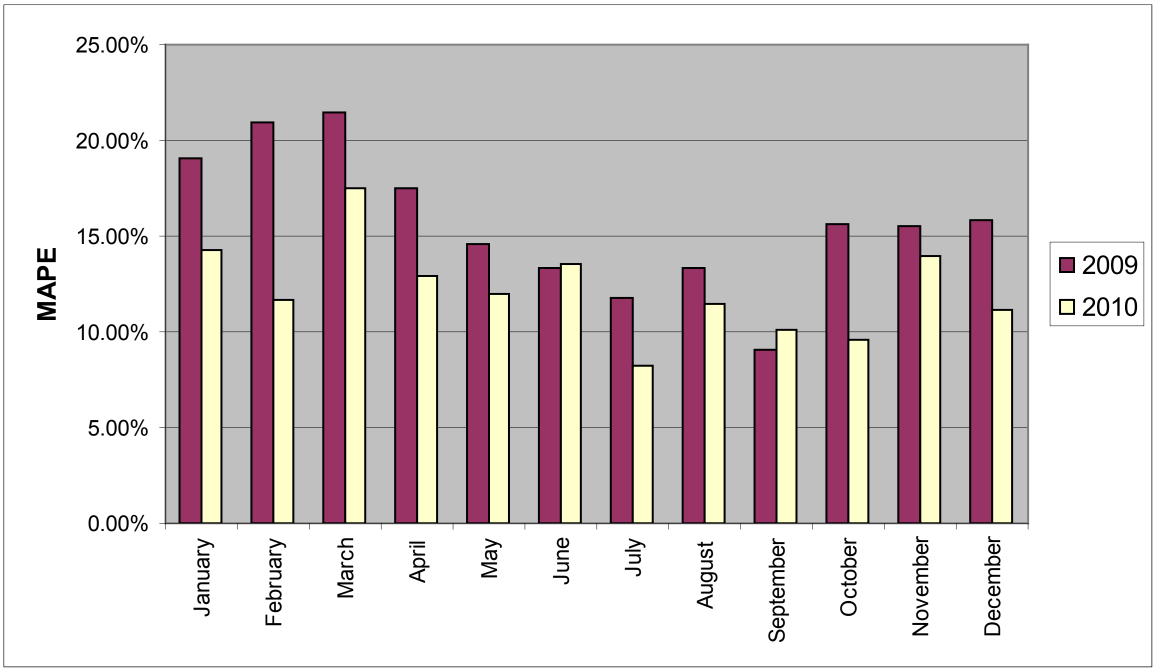
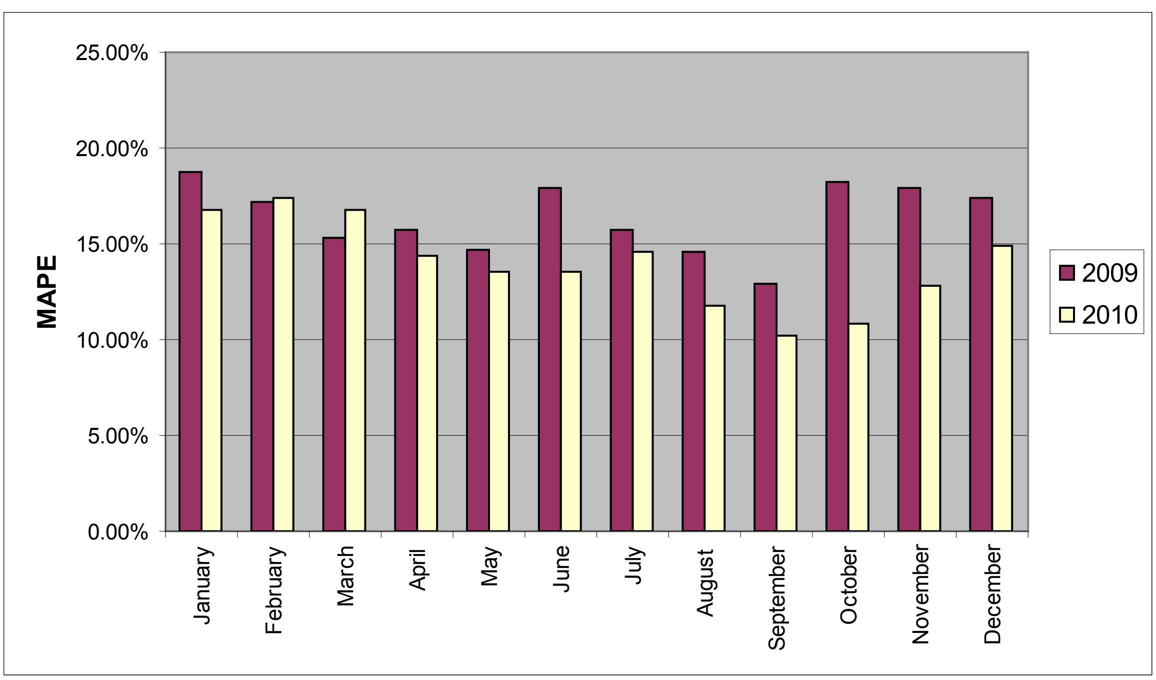


Figure 15 – SPS monthly day-ahead forecast error.



Ongoing Work

Since October of 2010, there have been a number of new developments in the forecast system. In particular, an NCAR mesoscale ensemble prediction model and the Canadian Global Environmental Multiscale (GEM) model from the Canadian Meteorological Centre (CMC) have been incorporated into the Xcel Energy forecasting system and are providing improved guidance. The GEM model inclusion involved accessing GEM model output and then subsequent incorporation into the DICast system. The mesoscale ensemble prediction model involved new model development and is discussed in more detail below.

High-resolution Mesoscale Ensemble Prediction Model (EPM)

It is known that atmospheric processes are chaotic in nature. This implies that even small errors in the model initial conditions combined with the imperfections inherent in the NWP model formulations, such as truncation errors and approximations in model dynamics and physics, can lead to a wind forecast with large errors for certain weather regimes. Thus, probabilistic wind prediction approaches are necessary for guiding wind power applications. Ensemble prediction is at present a practical approach for producing such probabilistic predictions. An innovative mesoscale Ensemble Real-Time Four Dimensional Data Assimilation (E-RTFDDA) and forecasting system that was developed at NCAR (Liu et al., 2008c, 2009, 2010, Pace et al., 2010) was used as the basis for incorporating this ensemble prediction capability into the Xcel forecasting system.

In particular, a 30-member E-RTFDDA system was implemented for wind power prediction. This system produces 6-hour analyses and 48-hour forecasts using 4 forecast cycles a day. Because the ensemble model requires significantly more computing power than a single model, the XCEL ensemble system contains only two domains, consisting of a coarse domain covering the same area of the deterministic forecast system's Domain 1 (cf. Figure 5) and a fine mesh domain that is the same as the deterministic forecast system's Domain 3, but at 10-km grid intervals (see Figure 16). A preliminary suite of probabilistic wind products was produced and provided to users by means of web pages. The suite includes ensemble mean, spread, spaghetti maps, meteograms, wind roses, likelihood-of-ramp event magnitudes and timing, and exceedance probabilities for given wind thresholds. The real-time E-RTFDDA wind predictions for 10 major wind plants located in different geographical regions across Colorado, Minnesota, New Mexico and northern Texas are now being generated and provided to the DICast post-processing system to improve wind power forecast accuracy and for estimation of forecast uncertainty.

Figure 16 – E-RTFDDA Model Domains.

Analog-Based Kalman Filter Bias Correction Algorithm (AnKF)

To deal with the bias of the mean and the spread of E-RTFDDA forecasts, an analog-based Kalman filter bias correction algorithm (AnKF) (e.g., Homleid, 1995, Delle Monache et al., 2006, 2008, 2010) was implemented for bias correction of E-RTFDDA wind predictions at the wind plants. For post-processing the E-RTFDDA forecasts at wind plants, the hub-height wind predictions of each ensemble member are first processed with the AnKF scheme for bias correction. Then the NCAR quantile regression (QR) calibration technique (Hopson et al. 2010) is employed to calibrate the hub-height wind prediction of E-RTFDDA at the wind plants using the AnKF output. The QR algorithm has been formulated using a step-wise forward selection framework. Model selection for each quantile relies on both the QR cost function and the binomial distribution, leading to ensemble forecasts with both good reliability and sharpness. In addition, a second pass is performed to re-calibrate over separate intervals of self-diagnosed forecast instability, leading to a calibrated ensemble forecast with an informative skill-spread relationship.

Wind Ramp Prediction

A difficult issue for wind power forecasting is consistently and accurately predicting wind power ramps (Ela and Kemper 2009). Although the core wind/power forecasting system described above has skill foreseeing power ramps generated from large-scale weather events (e.g., cold fronts), there is a need to fine-tune this capability to accurately predict the time, magnitude, and duration of intermediate and smaller-scale events including thunderstorm outflows. To that end, a short-term (0-6 hour) ramp forecasting subsystem is in the process of being incorporated into the overall wind/power prediction system. This ramp detection subsystem involves two additional components to the existing system: the four dimensional Variational Doppler Radar Analysis System (VDRAS) and an observational-based system that analyzes publically available meteorological data in the vicinity of the wind plant. At the same time, ongoing research and development efforts are being pursued to improve the identification of ramp events within WRF-RTFDDA and the Ensemble RTFDDA systems.

Wind Ramp Nowcasting Using VDRAS

VDRAS assimilates radar reflectivity and radial velocity data into a numerical cloud-scale model and produces high-resolution boundary layer wind fields (Sun and Crook 1997). Case studies are being conducted to evaluate and verify VDRAS performance for wind ramp 'now-casting'. A preliminary study of two cases over northern Colorado has shown that the frequently updated (18-minute) VDRAS wind analysis reveals wind ramps that were approaching the wind plants, suggesting that VDRAS could be a useful tool for generating a 0-2 hour warning of ramp events. Verification of the VDRAS analysis against turbine hub height wind measurements showed close agreement for the two cases studied. More cases will be evaluated and verified. Zero to 2-hour now-casting algorithms will be developed and tested in the near future.

Observation-based Ramp Forecast Techniques

A short-term ramp forecast expert system was developed that uses publicly available observational data in eight concentric rings centered on the wind plant with 50-km spacing. The current configuration is built to predict weather patterns advancing from the northwest, the predominant direction for synoptic patterns in this region. This rule-based expert system searches for wind ramp signatures in upstream observations and uses these observations to infer the time and magnitude of the wind ramp that is expected to affect the wind plant. For each site and each historical hour, a ramp metric is computed using the current hour and the previous hour's observations. The observed wind at 10 meters is extrapolated to hub height (80 meters) and changes in wind speed and direction are evaluated. The percentage of sites that indicate a ramp (defined here as a change of at least 25% of capacity) are tabulated. These percentages are averaged across rings for each lead time. A ramp indicator is computed that depends on a threshold of that average percentage. The expert system is applied for up to 6-hours lead time and results are displayed to advise system operators of imminent ramping events.

WRF-RTFDDA Ramp Studies

The high-resolution WRF-RTFDDA modeling system attempts to forecast wind ramps associated with different weather processes via a physical approach by incorporating high resolution terrain and land surface forcing, and regional and wind plant observations with 4-dimensional data assimilation into the full-physics WRF model. Studies are being conducted by employing a feature-based verification approach to assess the Xcel 3.3-km WRF RTFDDA wind ramp forecasts at four selected wind plants during the summer and winter seasons, and the initial result for the Cedar Creek wind plant in the northern Colorado with complex terrain indicates that the WRF-RTFDDA model captured 50–70% of the major ramps for 0 to12-hour forecasts. The model's ability to forecast these ramps degraded by 10–15% from 0 to 3-hour to 9 to 12-hour forecast ranges. Further studies to better identify and display the WRF RTFDDA ramp forecasts to Xcel Energy operators are being performed.

Part of the challenge for forecasting ramps is connected with the limited predictability of many mesoscale weather processes, such as convection and mountain waves over complex terrain. Ensemble forecasting systems, such as the Xcel Energy operational 10-km Ensemble RTFDDA system, provides a viable ability to address predictability issues by predicting the probabilities of the weather processes and associated wind ramps. Ongoing research is being performed to extract, derive and verify the probabilities of ramps in terms of their occurrences, timing, duration and magnitudes from the 30-member E-RTFDDA forecasts incorporating ensemble calibration approaches. The goal is to derive and present intuitive probabilistic forecast products signaling ramps for Xcel Energy operators. Finally, for future development guidance, NCAR is pursuing research to investigate the trade-off between finer-resolution deterministic forecasting and coarser-grid ensemble prediction, and then to optimize wind plant data assimilation for both approaches.

Conclusions

The Xcel Energy wind forecasting system has significantly reduced forecast error in all three systems. The day-ahead forecast errors were reduced by 22%, 20%, and 15% from 2009 to 2010 for NSP, PSCo, and SPS, respectively. The meteorological displays provide additional information to staff meteorologists specific to wind energy production with geographic focus in the wind producing regions. The turbine-level power conversion approach is reasonable, and possibly superior to other power conversion methods. None of the material gains would have been possible without substantial investment in real-time turbine-level power and wind speed data acquisition. Working with NCAR and NREL has proved a productive and worthwhile collaboration for Xcel Energy resulting in significant benefits for customers. Ongoing work has continued in this area with promise for further reductions in forecast error across all forecast time horizons.

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Conference Proceedings

The National Center for Atmospheric Research reported on their Wind Power Prediction research and development at the 91st Annual Meeting of the American Meteorology Society in January 2011. The topics ranged from numerical weather prediction through post-processing techniques to predict and calibrate wind turbine hub height winds and the resulting power output. The bulk of these papers were presented as part of the *Second Conference on Weather, Climate and the New Energy Economy,* but the team was also represented at several of the other conferences. These references go into more detail on the components of the forecasting system mentioned in this report. A list of these papers and links are provided below.

Second Conference on Weather, Climate and the New Energy Economy

"An overview of NCAR's advanced wind forecasting system for integrating wind resources into the new energy economy"
David B. Johnson, B. Mahoney, Y. Liu, G. Wiener, W. Myers, and K. Parks
http://ams.confex.com/ams/91Annual/webprogram/Paper186427.html

"Wind energy forecasting with the NCAR RTFDDA and ensemble RTFDDA systems"
Yubao Liu, W. Y. Y. Cheng, G. Roux, Y. Liu, L. Delle Monache, M. Pocernich, B. Kosovic, T. M. Hopson, A. Bourgeois, G. Wiener, T. Warner, B. Mahoney, and D. B. Johnson
http://ams.confex.com/ams/91Annual/webprogram/Paper186591.html

"*Kalman filter, analog and wavelet postprocessing in the NCAR-Xcel operational wind-energy forecasting system*"
Luca Delle Monache, A. Fournier, T. M. Hopson, Y. Liu, B. Mahoney, G. Roux, and T. Warner
http://ams.confex.com/ams/91Annual/webprogram/Paper186510.html

"Statistical Analysis of intra-farm microscale wind characteristics at selected Xcel wind farms"
Yuewei Liu, NCAR, Boulder, CO; and Y. Liu, W. Cheng, G. Wiener, B. Lambi, and B. Mahoney
http://ams.confex.com/ams/91Annual/webprogram/Paper186522.html

"Verification and analysis of hub-height wind forecasts from the NCAR-Xcel WRF-RTFDDA"
Gregory Roux, Y. Liu, M. J. Pocernich, W. Y. Y. Cheng, L. Delle Monache, A. Fournier, S. Linden, and W. Myers
http://ams.confex.com/ams/91Annual/webprogram/Paper186547.html

"A comparison of turbine-based and farm-based methods for converting wind to power"
Julia M. Pearson, G. Wiener, B. Lambi, and W. Myers
http://ams.confex.com/ams/91Annual/webprogram/Paper179783.html

"An evaluation of different data mining methods for forecasting wind farm power"
Gerry Wiener, J. M. Pearson, B. Lambi, and W. Myers
http://ams.confex.com/ams/91Annual/webprogram/Paper180009.html

"Improving the 0-3 hour wind forecast through wind farm data assimilation in the NCAR/ATEC WRF RTFDDA"
W. Y. Y. Cheng, Y. Liu, Y. Liu, B. Mahoney, M. Politovich, T. T. Warner, K. Parks, and J. Himelic
http://ams.confex.com/ams/91Annual/webprogram/Paper182487.html

"A rapid-updated wind analysis system based on mesoscale model, radar, and surface data for ramp-event wind energy forecasting"
Juanzhen Sun, Y. Zhang, G. Wiener, N. Oien, and W. Mahoney
http://ams.confex.com/ams/91Annual/webprogram/Paper182972.html

"An Investigation into the Spatiotemporal Scale of Two Wind Ramp Events in Northeastern Colorado"
Theresa A. Aguilar, Y. Liu, Y. Liu, and B. Mahoney
http://ams.confex.com/ams/91Annual/webprogram/Paper185976.html

Ninth Conference on Artificial Intelligence and its Applications to the Environmental Sciences

"A turbine hub height wind speed consensus forecasting system"
William Myers, and S. Linden
http://ams.confex.com/ams/91Annual/webprogram/Paper187355.html

Joint Session for the 24th Conference on Weather Analysis and Forecasting and the 20th Conference on Numerical Weather Prediction

"Kalman filter and analog schemes to postprocess numerical weather predictions"
Luca Delle Monache, T. Nipen, Y. Liu, G. Roux, R. B. Stull, T. T. Warner, and P. Childs
http://ams.confex.com/ams/91Annual/webprogram/Paper185473.html

"NCAR ensemble RTFDDA: real-time operational forecasting applications and new data assimilation developments"
Yubao Liu, T. Warner, S. Swerdlin, T. Betancourt, J. Knievel, B. Mahoney, J. Pace, D. Rostkier-Edelstein, N. A. Jacobs, P. Childs, and K. Parks
http://ams.confex.com/ams/91Annual/webprogram/Paper182108.html

"Sensitivity of WRF-RTFDDA model physics in weather forecasting applications: From synoptic scale to meso-gamma scale"
William Y. Y. Cheng, Y. Liu, Y. Zhang, Y. Liu, D. Rostkier-Edelstein, A. Pietrkovski, B. Mahoney, T. T. Warner, and S. Drobot
http://ams.confex.com/ams/91Annual/webprogram/Paper182629.html

15th Symposium on Integrated Observing and Assimilation Systems for the Atmosphere, Oceans and Land Surface

"The NCAR 4DREKF ensemble data assimilation and forecasting system"
Yubao Liu, L. Pan, Y. Wu, A. Bourgeois, T. Warner, S. Swerdlin, S. F. Halvorson, and J. Pace
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