NCAR’s Recent Advances in Wind Power Forecasting

Sue Ellen Haupt, Branko Kosovic, & Gerry Wiener
Xcel Energy Service Areas

About Xcel Energy

- Northern States Power Company - Minnesota
- Northern States Power Company - Wisconsin
- Public Service Company of Colorado
- Southwestern Public Service

5736 MW (wind) (highest in continental US)

Moving toward 40%

Obtain up to 60% of energy from wind at some times

Provides good geographical diversity for research and testing
Wind Power Forecasting Necessary for Effective Grid Integration

- Day Ahead forecasting – Energy trading and planning
- Short-term forecasting – Grid integration and stabilization

Thus, an effective forecasting system should target both.
Variable Energy Forecasting System

- **Natl Center Data**
  - HRR, NAM, GFS, RAP
  - GEM (Canada), ECMWF

- **WRF RTFDDA System**

- **Ensemble System**

- **Solar Energy Forecast**

- **Supplemental Wind Farm Data**
  - Met towers
  - Wind profiler
  - Surface Stations

- **Wind Farm Data**
  - Nacelle wind speed
  - Generator power
  - Node power
  - Availability

- **Dynamic, Integrated Forecast System (DICast®)**

- **VDRAS**
  - (nowcasting)

- **Expert System**
  - (nowcasting)

- **Extreme Weather Events**

- **Statistical Verification**

- **Wind to Energy Conversion Subsystem**

- **Probabilistic and Analog Forecast**

- **Potential Power Forecasting**

- **Data Mining for Load Estimation**

- **Operator GUI**

- **Meteorologist GUI**
  - WRF Model Output

- **Supplemental Wind Farm Data**
  - Met towers
  - Wind profiler
  - Surface Stations

Scientific Advances in Wind Power Forecasting
**DICast Integrator System**

Dynamic Integrated foreCast System

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**Wind speed example**

10-15% decrease in error
Observation-based power curves represent the site better than manufacturers’ power curves
WRF-Real Time 4D Data Assimilation (RTFDDA) Assimilates Wind Farm Data

- WRF RTFDDA exhibits exceptional capability for forecasting wind ramps in term of their timing, rates and magnitudes.
- Rapid cycling (hourly) WRF RTFDDA is recommended where 0 - 6h ahead wind ramp prediction is critical.
WRF- RTFDDA Improves Short Term Forecasts (0-9h)

95th% Confidence Intervals on pairwise differences (RTFDDA-Baseline)

Bold confident intervals means statistical significance

Dates: Feb 9 – Feb 24 – **SMALL SAMPLE**

MAE (m/s)

Lead Time (hr)

Baseline Better

RTFDDA Better
Wind Energy Ramp Event Nowcasting

VDRAS
Variational Doppler Radar Analysis System + Expert System (obs-based)
Observation-based Ramp Forecasting

10m Wind-Speed Observing Stations
Ramp Metrics calculated at each site using current wind-speed and previous 15min wind-speed

Wind Farm
18z Run
15min Fcst (valid 18:15z)

18:00z obs -> 18:15z fcst
17:45z obs -> 18:00z fcst
17:30z obs -> 17:45z fcst
17:15z obs -> 17:30z fcst
e tc

18:00z obs -> 18:45z fcst
17:45z obs -> 18:30z fcst
17:30z obs -> 18:15z fcst
17:15z obs -> 18:00z fcst
e tc

18:00z obs -> 19:00z fcst
17:45z obs -> 18:45z fcst
17:30z obs -> 18:30z fcst
17:15z obs -> 18:15z fcst
e tc

12km
DICast System Blends Output from Several Numerical Weather Prediction Models

Public Service of Southwestern Public Service Company
Total Power, 03/08 Ramp
Proabilistic Power Prediction With Analog Ensemble Method

- Normalized Power (Nameplate Capacity)
- Forecast Lead Time
- Deterministic forecast
- Observations
- Percentiles
Probabilistic Forecasting Using Analog Approach Compares Well with Deterministic DICast

AnEn (RMSE = 2.39 ms\(^{-1}\))
DICAST (RMSE = 2.34 ms\(^{-1}\))

**Lead Time (hours)**

**RMSE (ms\(^{-1}\))**

<table>
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<tr>
<th>Lead Time (hours)</th>
<th>Training (188-223 days)</th>
<th>Optimization (18 days)</th>
<th>Test (35 days)</th>
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Probabilistic Forecasting Using Analog Approach Compares Well with Deterministic DICast

- Training (188-223 days)
- Optimization (18 days)
- Test (35 days)
- Test (35 days)

AnEn (RMSE = 2.39 ms$^{-1}$)
DICAST (RMSE = 2.34 ms$^{-1}$)

AnEn (Corr = 0.70)
DICAST (Corr = 0.71)
Icing Forecasting System ExWx Provides Categorical Forecast of Icing

- Predicting wind turbine icing is critical for power trading on open market and short term load balancing.

- In order to successfully develop a robust wind turbine icing forecasting system, a truth dataset must be developed.

- Limited documentation of icing events and monitoring equipment make identifying icing after the fact difficult.

- Plus, there is a “Big Data” problem.
Datasets For Icing Forecast

Power Data

DICast Data
- Forecast Module A
- Forecast Module B
- Forecast Module C
- Forecast Module D
- Forecast Module N
- Integrator
- Post Processing
- Forecast Products

Sensor Data

NWS Data

http://www.newavionics.com/Images/9734_410x359.jpg

http://www.newavionics.com/Images/9734_410x359.jpg

NWS Forecast Zones
ExWx Uses WRF-RTFDDA and DICast Blended NWP Output to Compute Icing Potential

- **WRF icing potential**
  - Evaluates all WRF model levels < 1km
  - Combines model level height, model predicted supercooled liquid water, and temperature at each level using fuzzy logic maps (configurable)
  - Final potential at each WRF grid point is the maximum of the icing potential at each level < 1km

- **DICast icing potential**
  - Conditional probability of icing (CPOI) deterministic forecast from DICast
  - Combines five NWP model solutions
  - Typically one site per farm, more in some cases
Icing Forecasting System Provides Categorical Icing Forecast

- Note no missing data—wherever DICast was missing the WRF is used exclusively (and vice-versa)
- Threshold of 0.5 is configurable based on experience of operators
- Event well forecast by ExWx!!!

ExWx icing potential forecasts for all ExWx runs affecting the event window (8 hours centered on 00Z)

- Icing potential < 0.5 inside window
- Icing potential > 0.5 inside window
- Icing potential > 0.5 outside window
- Icing potential < 0.5 outside window
## Wind Power Forecasts

### Savings for Ratepayers

<table>
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<tr>
<th>Forecast MAE</th>
<th>Percentage Improvement</th>
<th>Savings</th>
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<tr>
<td>2009</td>
<td>2014*</td>
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<td>16.83%</td>
<td>10.10%</td>
<td>$49,000,000</td>
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Also: saved > 267,343 tons CO2 (2014)

Drake Bartlett, Xcel
CO-Labs - Governor’s Award 2014 for Sustainability
NCAR’s comprehensive variable power forecasting system integrates recent advances in forecasting at a range of time scales including:

- Ramp forecasts
- Probabilistic forecasting
- Forecasting of extreme events

Day-ahead forecasting system provides significant savings for ratepayers.

Effectiveness of a forecasting system for efficient integration of variable generation depends on the quality and quantity of data.

More data (amount, frequency) is better, however,…

First data from existing sources should be:
- Standardized
- Quality controlled
- Delivered in timely manner, and
- Archived for future use (e.g., training for machine learning algorithms).
Thank You!

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