Short Range Weather Forecasts for Energy

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Outline

- Stakeholder Needs
- Ingredients
- Forecasting Across Scales
  - Numerical Weather Prediction
  - Data Assimilation
  - Nowcasting (Minutes to Hours)
  - Blending
  - Power Conversion
  - Uncertainty Quantification
  - Extreme Events
- Assessment
- Valuation

Examples:
- Solar Power Forecasting
- Wind Power Forecasting

Theme: Smartly blending data, dynamics, physics, and statistical learning methods
Assessing Stakeholder Needs
Industry Needs for Renewable Energy Forecasts

- Need to predict POWER based on met variables
  - 80-m wind speed
  - Surface irradiance – GHI, DNI, DIF
- Time frames for prediction
  - Long range – weeks – maintenance and distribution
  - Medium range – days – hourly day ahead trading
  - Nowcast range – hours – 15-min grid integration
  - Very short range – seconds to minutes – voltage control
Value Chain:
What is the value of solar power forecasting?

Weather Monitoring
Observation Modelling Forecasting Dissemination & Communication Perception Interpretation Uses / Decision Making

Outcomes Economic & social values

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Weather Monitoring Observation Modelling Forecasting Dissemination & Communication Perception Interpretation Uses / Decision Making

Outcomes Economic & social values
Meteorological Prediction:

Adapted from Ravela, 2008
Auligne, 2014

- Physical approach
Meeting the Needs:
Seamless Approach to Solar Power Forecasting

Prediction Across Timescales
Forecasting System

Prediction Across Timescales

Numerical Weather Prediction
- HRRR
- WRF-Solar
- GFS
- Other

Statistical Prediction
- Satellite Cloud Advection
- Total Sky Imaging
- WRF-Based Nowcasting

DICast Integrator

Final Blending

Probabilistic Solar Power Forecast
- Analog Ensemble
- Power Conversion
Atmospheric Modeling
Numerical Weather Prediction

- Dynamics
- Physics
- Quality Assurance
- Sensitivity to Initial Conditions
- Preprocessing – Needs for Assimilation
- Postprocessing – Blending Information
- Validation
Numerical methods treat this as an initial value problem
- Discretize in space
- Integrate in time
- Constrained by continuity
- Related by state eqn

Nonlinearities make it difficult

\[
\frac{\partial \vec{v}}{\partial t} + \vec{v} \cdot \nabla \vec{v} = -\frac{1}{\rho} \nabla P + g - \nu \nabla^2 \vec{v}
\]

\[
\frac{\partial \rho}{\partial t} + \nabla \cdot (\rho \vec{v}) = 0
\]

\[P = \rho RT\]
- Various processes that we can’t resolve
- Thus, parameterize given
  - Knowledge of physical process
  - Empirics
  - Constants and tuning

AJ Deng, Dave Stauffer
WRF (Weather Research & Forecasting) Model Physics

- Turbulence/Diffusion (diff_opt, km_opt)
- Radiation
  - Longwave (ra_lw_physics)
  - Shortwave (ra_sw_physics)
- Surface
  - Surface layer (sf_sfclay_physics)
  - Land/water surface (sf_surface_physics)
- PBL (bl_physics)
- Cumulus parameterization (cu_physics)
- Microphysics (mp_physics)
Figure 4. Average rainfall rate, for a spring-season convective event (a), based on observations (OBS) and for five simulations that used different treatments for the convection - four different parameterizations, and no parameterization (EX). Also depicted is the rainfall rate bias score averaged for three warm-season convective events (b), again for each of the four parameterizations and for the use of no parameterization. The four convective parameterizations were the Grell (GR), Kain-Fritsch (KF), Betts-Miller (BM), and Anthes-Kuo (AK) schemes. Adapted from Wang and Seaman (1997).
Value of high-resolution regional model

Resolution: 0.0 km

Resolution: 2.4 km
Snowpack in Central Rockies: too little at high elevation and melts three months too early at coarse resolution

April 15 snapshot of snow pack at two model resolutions (Simulation of 2007-2008 water year)
QUALITY ASSURANCE IN ATMOSPHERIC MODELING

by Thomas T. Warner

The rapid growth in the number of atmospheric model users in motivation for reviewing best practices in atmospheric modeling and emphasizing the scientific and technical preparation that is necessary to use the modeling tools effectively.

A formal definition of quality assurance that is applicable to this discussion is as follows: the maintenance of a desired level of quality in a service or product, especially by means of inspection at every stage of the process of delivery or production. A brief description of quality assurance in the atmospheric modeling process can result from many causes. One is that some model users are less well trained and less experienced than others and lack an appreciation of the sensitivity of modeling processes in the numerous decisions that must be made when configuring a model for a particular application. Another is that demands for quick results can lead to less than thorough model setup and verification. A related factor is the availability of state-of-the-science community models: this represents a great potential benefit to the community, but there is the risk that the models will not be used wisely. This paper suggests ways in which the atmospheric modeling process and culture can be improved, and it is aimed especially at the many novice modelers who are using these tools. The recommendations apply to the use of models for operational forecasting of weather, for climate prediction, for research-oriented case studies, and for the generation of ensembles. Many of the suggestions are not new ones; they have appeared decades ago in references such as Arakawa (1983) and Keyser and Uccellini (1987). This paper merely collects the wisdom from these and other sources and includes some additional contemporary advice. Note that there is no attempt here to provide a complete list of references for the discussion; instead, the reader should refer to a text on numerical weather prediction (NWPs) for this information.

THE INCREASING USE OF ATMOSPHERIC MODELS...

In addition to the large operational forecasting centers, many universities, commercial organizations, and individual scientists now use models in real time for research, forecast training, and operational production.
WRF-Solar

CLOUD-RADIATION-AEROSOL INTERACTION

% Improvement over standard WRF

Courtesy: Pedro Jimenez
Fluid Flow is Sensitive to Initial Conditions

\[ \frac{\partial \vec{v}}{\partial t} + \vec{v} \nabla \vec{v} = -\frac{1}{\rho} \nabla P + g - \nu \nabla^2 \vec{v} \]

- Atmospheric flows display sensitivity to initial & boundary conditions and to physics parameterization
- Chaotic Attractor
- How do we stay on the correct trajectory?

Assimilation

Lorenz (1963)
Data Assimilation – incorporating observations into a model

- Surface observations
- Satellite observations
- Atmospheric profiles
- Radar observations
- Data from wind or solar farms
- Specialized data
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.

Courtesy: Yubao Liu
Application: Wind Energy Ramping
Real Time Four Dimensional Data Assimilation
RTFDDA

0-3 hour Wind Energy Predictions

00h to 03h fcst (Mean: 8.20; RMS: 2.80; MAE: 2.21; Bias: -0.71; Corr: 0.72)

W/O Farm DATA

Gain:
17% in RMS
20% in MAE
11% in Bias

With Farm DATA

Courtesy: Yubao Liu
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**

Lead Time (hr)

GFS  NAM  RTFDDA

Baseline Better

RTFDDA Better

Courtesy: Tara Jensen, Yubao Liu
8/03/09 771mw up-ramp from 20:10 - 22:10 followed by a 738mw down-ramp from 22:40 - 00:50

Wind Energy Ramp Event

800 MW increase then decrease over 4 hrs!
Dynamic Assimilation allows recovery of characteristics of realization

- Allows better prediction to meet user needs
- An effective way to deal with sensitivity to initial conditions

Courtesy: Jenny Sun
Application: Wind Energy Ramping
Variational Doppler Radar Analysis System (VDRAS)

Gust fronts approaching ‘wind plant’

Wind ramp event is imminent

Need to provide time-of-arrival and magnitude of wind energy ramp.

Courtesy: Jenny Sun

NCAR Auto-Nowcasting System
Wind Energy Ramp Event Nowcasting

VDRAS

Variational Doppler Radar Analysis System + Expert System (obs-based)

Courtesy: Jenny Sun
Nowcasting for Solar Energy

1. StatCast – regimes and data

2. TSICast - Total Sky Imaging

3. CIRACast – Satellite-based Cloud Advection

4. MADCast
   Multi-sensor Advective Diffusive WRF Nowcasting

5. WRF-SolarNowcasting
• Forecast Clear Sky Index
• Separate into:
  • Clear
  • Partly Cloudy
  • Cloudy

Tyler McCandless
Regime-Dependent Statcast

Identify Regimes (K-Means Clustering)

All Met Predictors
Cloud Predictors
Kt Predictors

Artificial Neural Network

Train/Test on each Regime Independently
Train/Test on All Data

Hierarchical Bayesian Prediction
Total Sky Imager Forecast

Image pyramid

Original

1st layer MV

2nd layer MV

Motion Vector

Motion Map

Recursion on gradient direction

In-Plane Solar Irradiance (cloudy day)

Solar Irradiance (W/m²)

Time (hours)

0:00 2:00 4:00 6:00 8:00 10:00 12:00 14:00 16:00 18:00 20:00 22:00 0:00

0 200 400 600 800 1000 1200 1400

6/19/12

Brookhaven NL
MADCast

Multi-sensor Advective Diffusive foreCast

Tom Auligne; Xu et al. (Adv. in Atmos. Sci. 2014)
Engineering the System

Diagram showing the flow of data from various models and integrators to power generation, with specific nodes such as GEM, NAM, HRRR, WRF-Solar, MADCast, StatCast, CIRACast, WRF-SolarNow, TSI Cast, Nowcast Integrator, and Obs. The diagram includes nodes for Hourly Avg Irradiance, 15-minute Irradiance, DNI, DIF, GHI, POA, and Power Module. The diagram also notes the need for sufficient training data for probabilistic power predictions.
Variable Energy Forecasting System

- **Natl Center Data**: HRRR, 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

CSV Data

35
Empirical Power Conversion Curves

Not Straightforward!

Anemometer defect

Wind deviation

Tower vibration

High wind speed cut-out

Ice accretion on blades

Other faults and downtime

Gerry Wiener
Observation-based power curves represent the site better than manufacturers’ power curves

Gerry Wiener
## Quantify Value - Metrics

<table>
<thead>
<tr>
<th>Model-Model Comparison</th>
<th>Economic Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Base</strong></td>
<td></td>
</tr>
<tr>
<td>• Mean Absolute Error</td>
<td>• Operating Reserves Analysis</td>
</tr>
<tr>
<td>• Root Mean Square Error</td>
<td>• Production Cost</td>
</tr>
<tr>
<td>• Distribution (Statistical Moments and Quantiles)</td>
<td></td>
</tr>
<tr>
<td>• Categorical Statistics for Events</td>
<td></td>
</tr>
<tr>
<td><strong>Enhanced</strong></td>
<td></td>
</tr>
<tr>
<td>• Maximum Absolute Error</td>
<td>• Cost of Ramp Forecasting</td>
</tr>
<tr>
<td>• Pearson's Correlation Coefficient</td>
<td></td>
</tr>
<tr>
<td>• Kolmogorov-Smirnov Integral</td>
<td></td>
</tr>
<tr>
<td>• Statistical Tests for Mean and Variance</td>
<td></td>
</tr>
<tr>
<td>• OVER Metric</td>
<td></td>
</tr>
<tr>
<td>• Renyi Entropy</td>
<td></td>
</tr>
<tr>
<td>• Brier Score incl. decomposition for probability forecasts</td>
<td></td>
</tr>
<tr>
<td>• Receiver Operating Characteristic (ROC) Curve</td>
<td></td>
</tr>
<tr>
<td>• Calibration Diagram</td>
<td></td>
</tr>
<tr>
<td>• Probability Interval Evaluation</td>
<td></td>
</tr>
<tr>
<td>• Frequency of Superior Performance</td>
<td></td>
</tr>
<tr>
<td>• Performance Diagram for Events</td>
<td></td>
</tr>
<tr>
<td>• Taylor Diagram for Errors</td>
<td></td>
</tr>
</tbody>
</table>

Tara Jensen
## Milestones Assessed

<table>
<thead>
<tr>
<th>Milestone</th>
<th>Metric</th>
<th>Success Value</th>
<th>Asses-</th>
<th>Measured Value</th>
<th>Goal Met?</th>
<th>Supporting Data (pg #)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Component Variable</td>
<td>Fst Type</td>
<td>Metirc</td>
<td>Eval Int.</td>
<td>Target Imp</td>
<td>% Above Success</td>
</tr>
<tr>
<td>3.1.1</td>
<td>StatCas t GH I</td>
<td>0-1hr</td>
<td>MA E</td>
<td>2 mo.</td>
<td>Part nr Sites</td>
<td>Eq / 20 %</td>
</tr>
<tr>
<td>3.1.1</td>
<td>StatCas t GH I</td>
<td>1-3hr</td>
<td>MA E</td>
<td>2 mo.</td>
<td>Part nr Sites</td>
<td>Eq / 20 %</td>
</tr>
<tr>
<td>3.1.2</td>
<td>TSICas t GH I</td>
<td>15min</td>
<td>MA E</td>
<td>2 mo.</td>
<td>All Part nr Sites</td>
<td>20 %</td>
</tr>
<tr>
<td>3.1.3a</td>
<td>CIRACast v0.1 GH I</td>
<td>0-1hr</td>
<td>MA E</td>
<td>4 mo.</td>
<td>Part nr Sites</td>
<td>Eq / 15 %</td>
</tr>
<tr>
<td>3.1.3a</td>
<td>CIRACast v0.1 GH I</td>
<td>1-3hr</td>
<td>MA E</td>
<td>4 mo.</td>
<td>Part nr Sites</td>
<td>Eq / 15 %</td>
</tr>
<tr>
<td>3.1.3b</td>
<td>MADCast v0.1 GH I</td>
<td>0-1hr</td>
<td>MA E</td>
<td>4 mo.</td>
<td>Part nr Sites</td>
<td>Eq / 15 %</td>
</tr>
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</table>
Recent emphasis in popular scientific literature to emphasize probabilistic approach

Nate Silver thinks meteorologists are ahead of the rest:
- Embrace uncertainty
- Quantify it
- This produces better deterministic forecasts as well
Ensemble Prediction
Probabilistic Power Prediction
With Analog Ensemble Method

- Normalized Power (Nameplate Capacity)
- Forecast Lead Time
- Deterministic forecast
- Observations
- Percentiles
What if we had only one member? Analog Prediction

Analog Ensemble Method

- Statistical learning method to calibrate model output and provide probabilistic information
- Based on observed past model-observation pairs
- Algorithm search for analogs and clusters them
- Shown to perform at least as well as full NWP ensemble systems

Luca Delle Monache & Stefano Allasandrini
Dynamic Integrated Forecast System (DICast)

Wind speed example 10-15% improvement over best model
DICast System Blends Output from Several Numerical Weather Prediction Models
Public Service of Southwestern Public Service Company
Total Power, 03/08 Ramp
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

Sensor Data

NWS Data

Primary

Secondary

Data Ingest

Integrator

Post Processing

Forecast Products

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

12/25/14

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

12/26/14
Valuation

Production Cost Modeling
- Accomplished by Utility Partners
  - Xcel
  - SMUD
  - SCE
  - NYISO
  - PG&E
- Upscaled by NCAR (Lazo)

Reserve Analysis
- Led by NREL
- Include data from utility partner analyses
Wind Power Forecasts Resulted in Savings for Ratepayers

<table>
<thead>
<tr>
<th>Forecasted MAE</th>
<th>Percentage Improvement</th>
<th>Savings</th>
</tr>
</thead>
<tbody>
<tr>
<td>2009 16.83%</td>
<td>2014* 10.10%</td>
<td>$49,000,000</td>
</tr>
</tbody>
</table>

*Data through November, 2014

Also: saved > 267,343 tons CO2 (2014)

Drake Bartlett, Xcel
Gridded Atmospheric Forecasts: GRAFS-Solar

NWP Models
- NAM
- GFS
- WRF-Solar
- GEM
- RAP/HRRR

Initial Grid
- Interpolated to 4 km
- CONUS Grid
- 1-Hour Averaging
- Archive data near observation sites

Observations
- SMUD
- MADIS
- OK Mesonet
- BNL
- SURFRAD
- Xcel
- DeSota
- ARM

Statistical Correction/Blending
- DICast Point Correction
- Gradient Boosted Regression Trees
- Cubist
- Random Forests
- Analog Ensemble

Output Products
- Maps of solar irradiance
- Single point forecasts
- % of clear sky irradiance
- Future:
  - Other met. variables

Future:
- Other met. variables
**Grid Forecast Timeseries: Sunny Day**

Forecast vs Obs of GHI fcst from 20141018 15z for site SMUD00067

DICast Correction
• A new forecast is generated every hour
• Individual images are generated for each lead-time
  – Currently hourly out to 60 hours.
AI methods at SMUD Sites
Summary

Theme: Smartly blending data, dynamics, physics, and statistical learning methods

• We need good models of the dynamics & physics
• We need high quality data to assimilate
• Statistical learning (artificial intelligence) can add value and help to determine the characteristics of the physics
• Specialized applications may require specialized forecasts
Questions