Presented at the

International Wind Forecasting Workshop

Portland, OR

July 24-25, 2008

An Overview of AWS Truewind's Approach and Experience in Providing Wind Power Production Forecasting Services to Utilities and Balancing Authorities in North America

John W. Zack, Ph. D.

Principal and Director of Forecasting

AWS Truewind, LLC

185 Jordan Rd

Troy, NY 12180 USA

jzack@awstruewind.com

© 2007 AWS Truewind, LLC

Outline

- AWS Truewind's wind power production forecast system: eWind
- The Nature of the Forecasting Challenge
- Overview of Forecast Performance and associated Issues
- Forecasting R&D and the Future of Forecasting

© 2007 AWS Truewind, LLC

AWS Truewind

AWS Truewind (AWST)

Headquarters: Albany, NY, USA

- Mapping
- Energy Assessment
- Project Engineering
- Performance Evaluation
- Forecasting

- **Mapping and Project Development**
  - **Utilizes AWST's resource assessment tools: MesoMap and SiteWind**
  - **Constructed regional wind maps for over 25 countries and 50 states and regions**
  - **Been involved in over 20,000 MW of project development**
- **Forecasting**
  - **Based on AWST's multi-model forecast system: eWind**
  - **Currently contracted to provide forecasts for nearly 6,500 MW**
  - **Selected as forecast provider to several major grid operators: CAISO, ERCOT, NYISO**
- **European Applications through Meteosim Truewind partnership**
  - **Headquarters in Barcelona, Spain**

© 2007 AWS Truewind, LLC

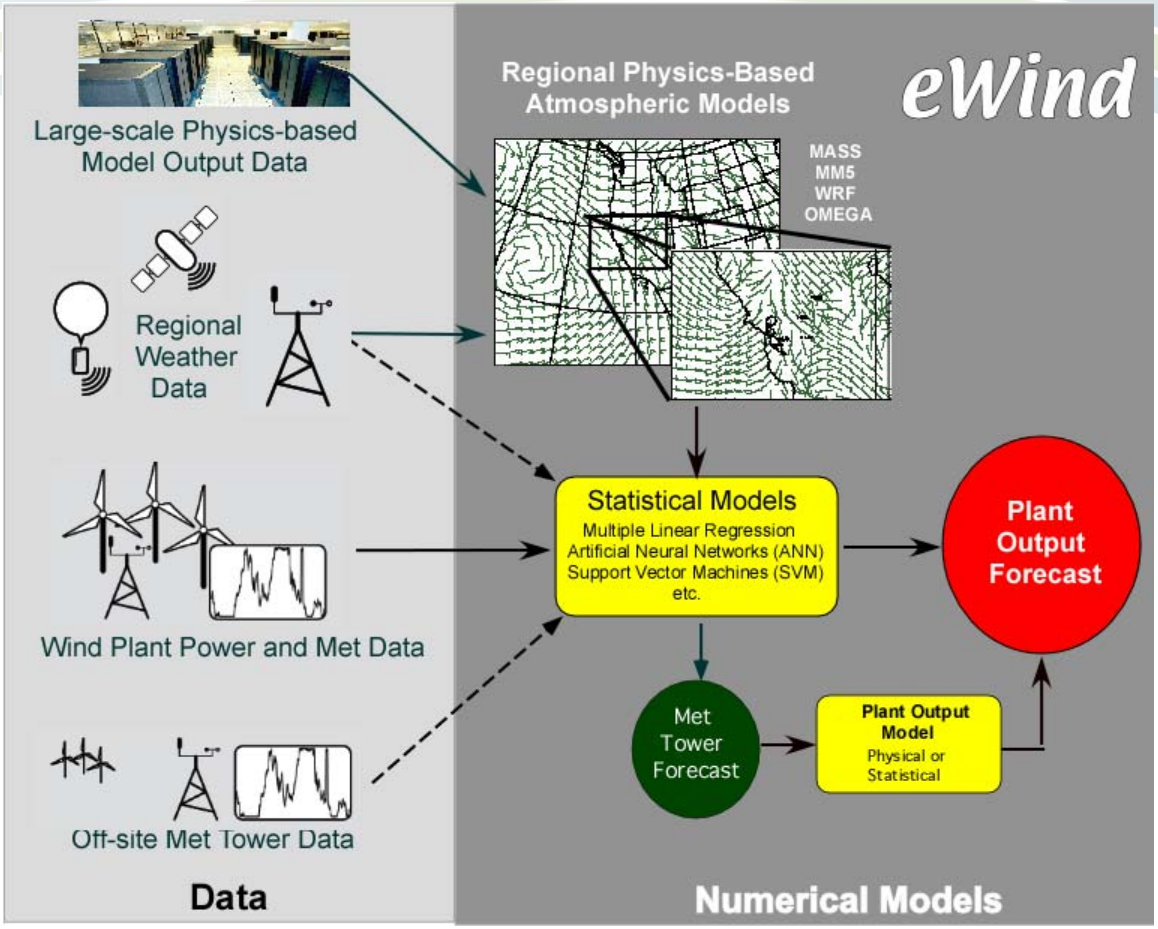
Forecast Production at AWST

- System-level overview of eWind
- Description of forecast system components
- Typical system configurations
- Types of forecast products

© 2007 AWS Truewind, LLC

AWST's Forecast System: eWind

- A combination of physics-based (NWP) and statistical models
- Uses a diverse set of input data with widely varying characteristics
- Forecast ensembles (sets of forecasts) are used to improve deterministic forecasts and estimate uncertainty
- Importance of specific models and data types vary with look-ahead period

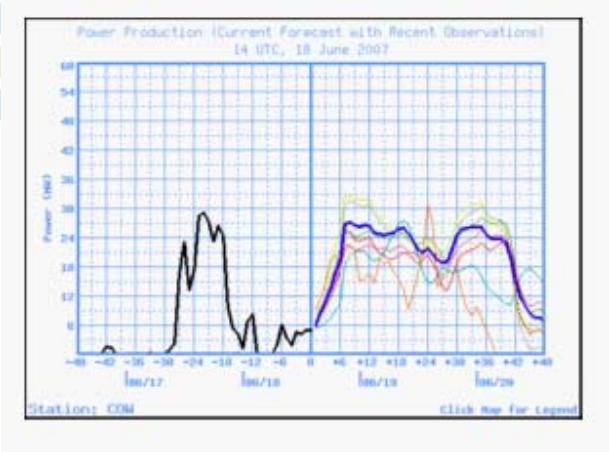


© 2007 AWS Truewind, LLC

Forecast Ensembles

AWS Truewind

- **Uncertainty present in any forecast method due to**
  - **Input data**
  - **Model type**
  - **Model configuration**



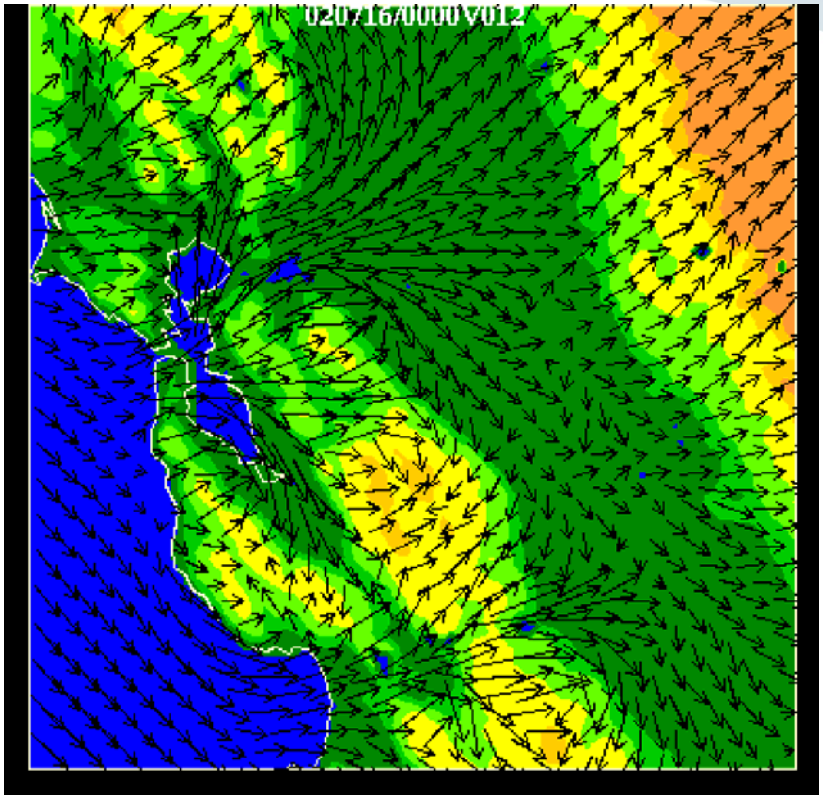
- **Approach: perturb input data and model parameters within their range of uncertainty and produce a set of forecasts**
- **Benefits**
  - **Ensemble composite is often the best performing forecast**
    - Even better performance is sometimes possible by weighting members according to recent performance or regime-based performance
  - **Spread of ensemble provides a case-specific measure of uncertainty**

© 2007 AWS Truewind, LLC

Physics-based Models

(also known as Numerical Weather Prediction (NWP) Models)

- **Differential equations for basic physical principles are solved on a 3-D grid**
- **Must specify initial values of all variables for each grid cell**
- **Simulates the evolution of the atmosphere in a 3-D volume**
- **Many different models available**
  - MASS (AWST proprietary model)
  - WRF (new community model)
  - ARPS (university research model)
  - MM5 (old community model)
  - NAM, GFS (US government models)



© 2007 AWS Truewind, LLC

Role of Physics-Based (NWP) Models

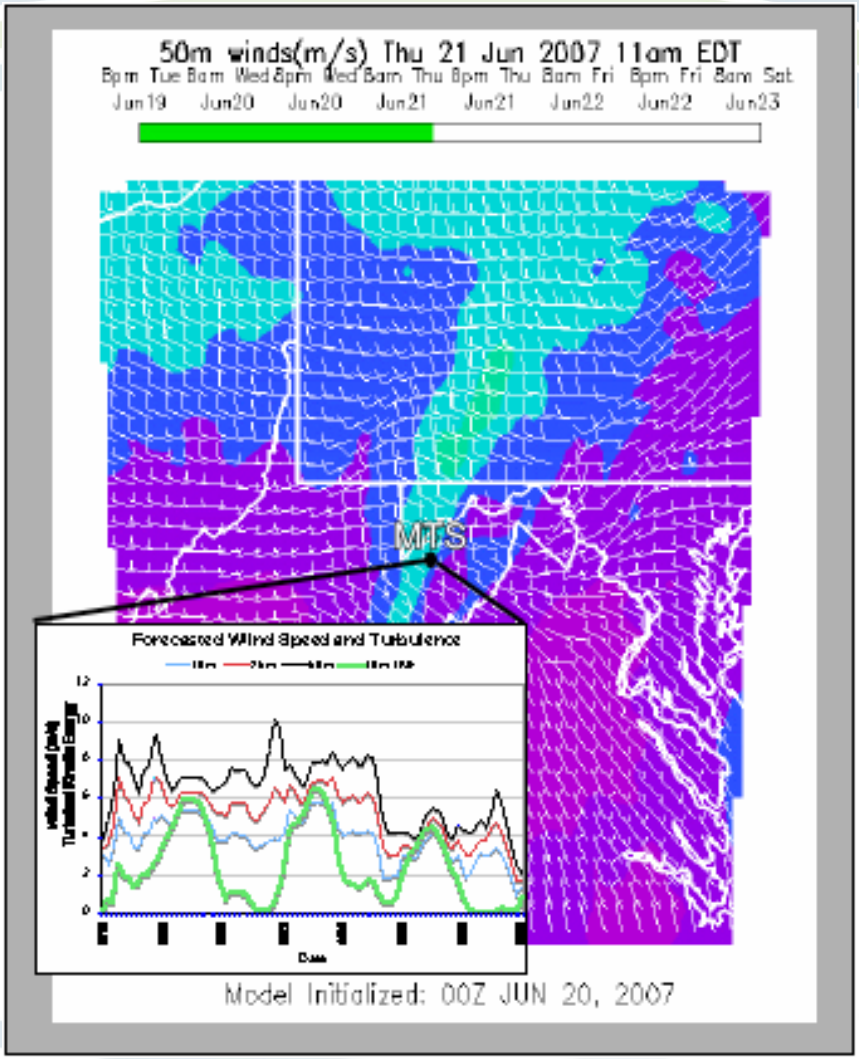
AWS Truewind

Question: Why run NWP models as part of a wind forecast system when you can get NWP model output data from government centers?

- Models can be configured or refined to optimize the forecast of near-surface winds
- Run with higher horizontal and vertical resolution
- Execute simulations more frequently
- Incorporate data not available to or used by government forecast centers
- Construct ensembles by executing runs with different model configurations and input datasets

Physics-based Models:
Typical eWind Configuration

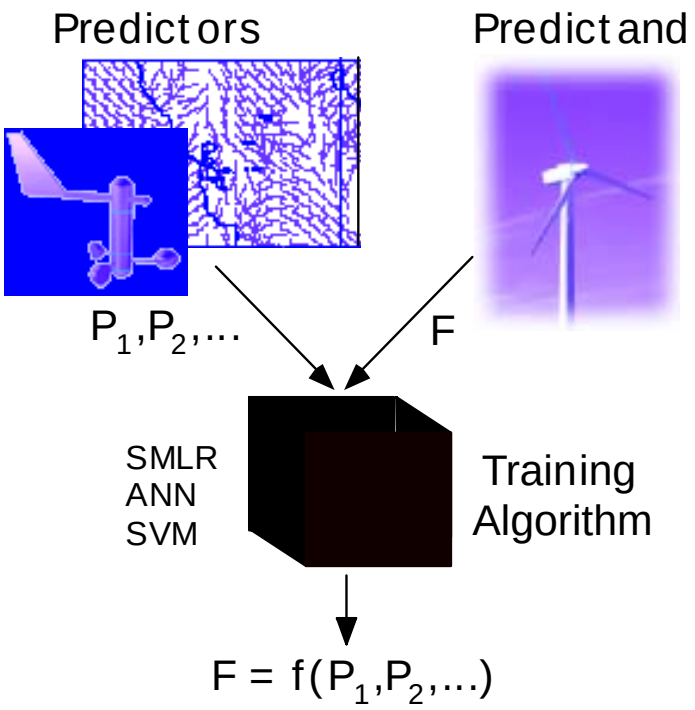
- Run ensemble of high resolution (~1 to 5 km grid cell sizes) NWP models
  - Multiple initializations
  - Several AWST models
    - MASS
    - WRF
    - ARPS
  - Up to 24 times per day
- Extract data for grid points near forecast location
- Use extracted data as input into statistical models



© 2007 AWS Truewind, LLC

Statistical Models

- **Empirical equations are derived from historical predictor and predictand data ("training sample")**
- **Current predictor data and empirical equations are then used to make forecasts**
- **Many different model-generating methods available**
  - Multiple linear regression
  - Artificial Neural Networks (ANN)
  - Support Vector Regression (SVR)
  - Time series (ARIMA, state space etc.)



© 2007 AWS Truewind, LLC

Role of Statistical Models in the eWind System

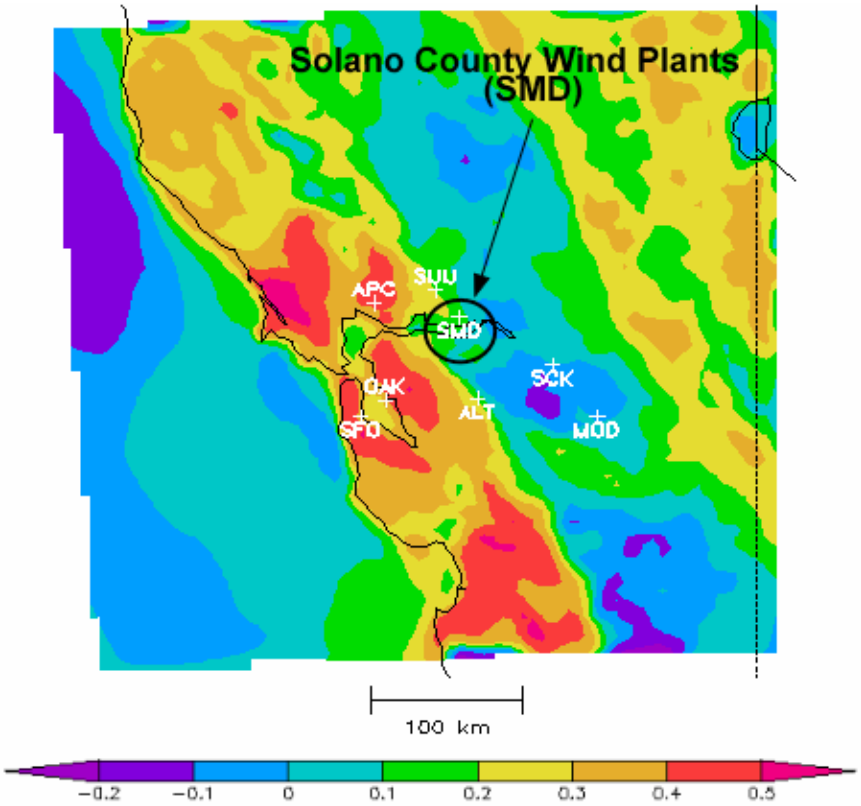
AWS Truewind

- **Transform grid point output of NWP models to site-specific forecasts for wind generation resources**
- **Correct systematic errors in the NWP forecasts**
  - What is the optimal way to do this? Regimes? Which regimes?
- **Incorporate observational data received after the initialization of most recent NWP model runs or that is not effectively included in NWP simulations**
  - Autoregressive relationships using recent plant data
  - Time-lagged relationships with off-site locations
- **Model the relationship between met variables and power production (implicit plant output model approach)**

Use of Offsite Data Sources for Short-Term Forecasting

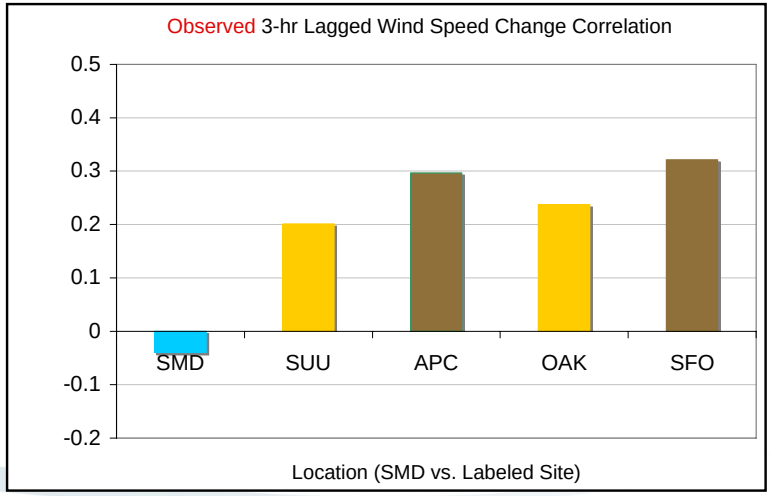
AWS Truewind

Numerical Simulations- June 2005



- Use numerical simulations to find time-lagged relationships with other locations for each forecast site
- Verify with obs data where possible
- Example: 3-hr lagged wind speed change correlations for the SMD site for June 2005

Anemometer Data - June 2005



© 2007 AWS Truewind, LLC

Statistical Models:
Typical eWind Configuration

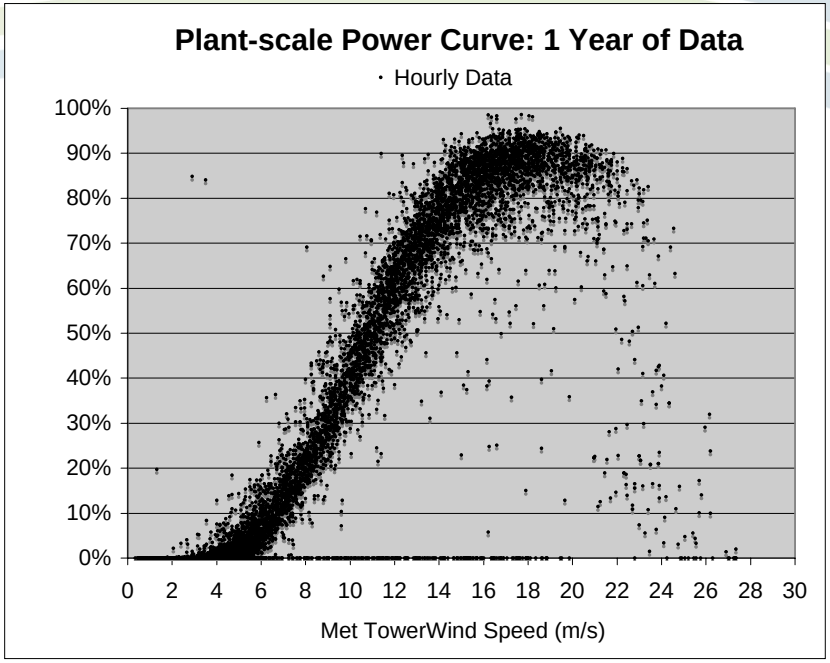
AWS Truewind

- **Run ensemble of statistical models for each set of physics-based model output and wind farm**
- **Latest observation data used for short-term (0-6 hr) forecasts**
  - **Multiple Training Samples**
    - Rolling previous 30 or 60-day trailing sample
    - Previous years of same season
  - **Suite of Statistical Methods**
    - Screening Multiple Linear Regression (SMLR)
    - Artificial Neural Networks (ANN)
  - **Multiple Regime Classification Schemes**
    - Key physical parameter (e.g. wind speed, stability etc.)
    - Large-scale weather regime (e.g. high pressure, nearby storms etc.)
- **Statistically combine output from statistical-NWP ensemble to get forecast (& uncertainty) of met variables**
- **Ensemble limited by size and quality of available data sample**

© 2007 AWS Truewind, LLC

Plant Output Models

- Relationship of met variables to power production
- Could be explicit or implicit
- Can be statistical or physics-based
- Often based on wind speed and direction but sometimes other variables are considered



Major Issue: amount, quality and representativeness of data from wind generation facility

© 2007 AWS Truewind, LLC

Plant Output Models:
Roles and Typical Configuration

AWS Truewind

- **Role of the Plant Output Model**
  - **Facility-scale variations in wind (among turbine sites)**
  - **Turbine layout effects (e.g. wake effects)**
  - **Operational factors (availability, turbine performance etc)**

- **Typical eWind Configuration**
  - **Small ensemble of statistical plant output models for each meteorological ensemble member**
    - Single parameter model (Wind speed vs power)
    - Multi-parameter (Multiple met variables vs power if data available)
    - Different training samples (recent 60 days, previous years etc.)
  - **Statistically combine individual power production forecasts into final deterministic or probabilistic forecast**

© 2007 AWS Truewind, LLC

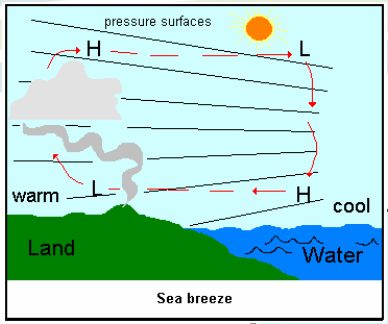
The Forecasting Challenge

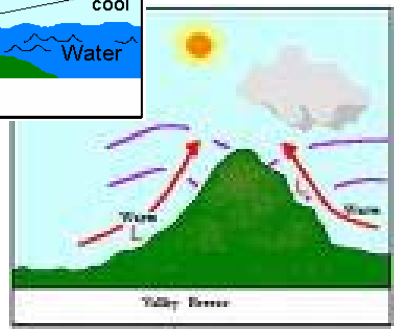
How the nature of the forecasting problem changes by time and space scale

© 2007 AWS Truewind, LLC

Hours-ahead Forecasts

- **Must forecast small scale weather features**
  - Large eddies, local-scale circulations
  - Rapidly-changing, short life-times
  - e.g. cloud features, mountain circulations, sea/land breezes
- **Typically poorly defined by current observing systems**



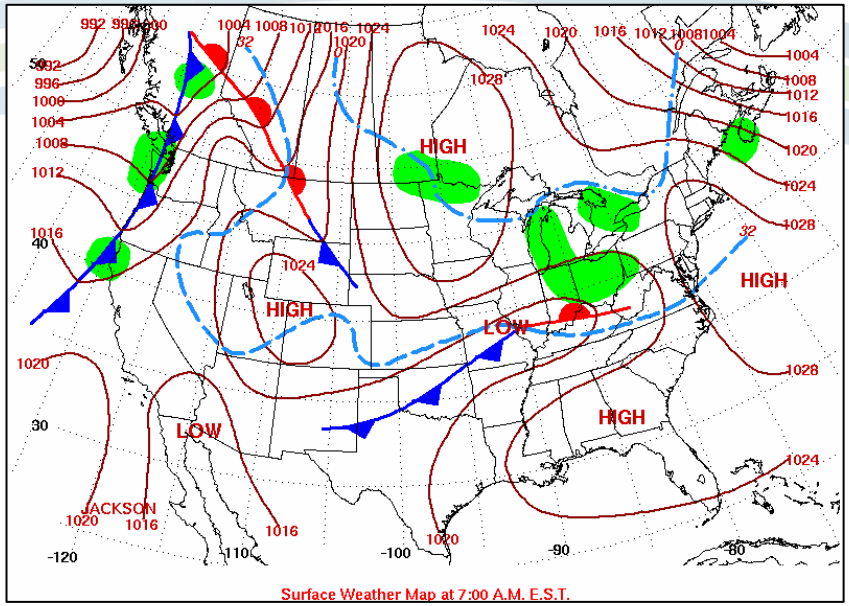


- **Tools:**
  - Difficult to use physics-based models
  - Autoregressive statistical models on wind farm time series data
  - Supplement with good off-site predictor data
- **Errors grow rapidly with increasing look-ahead time**

© 2007 AWS Truewind, LLC

Days Ahead Forecasts

- **Little skill in forecasting small-scale features**
- **Forecast skill mostly from medium and large scale weather systems**
- **Well-defined by current sensing networks**



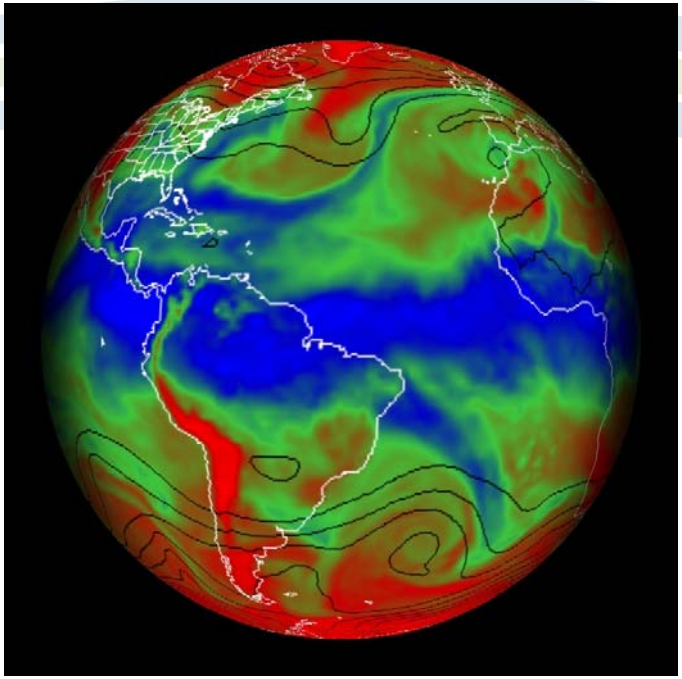
- **Tools:**
  - Physics-based model simulations
  - Statistical models used to adjust physics-based output (MOS)
  - Regional and continental scale weather data
- **Errors grow slowly with increasing look-ahead time**

© 2007 AWS Truewind, LLC

Weeks or Months Ahead

AWS Truewind

- **Very little skill in forecasting individual weather systems after about 10 days**
- **Forecast skill (if any) comes from predictions of weekly or monthly wind anomalies caused by global circulation anomalies**



- **Tools:**
  - Statistical relationships with global circulation indices
  - Anomalies in long-range physics-based model simulations
- **Predictive skill is limited to weekly or monthly averages**

© 2007 AWS Truewind, LLC

eWind Forecast Products

AWS Truewind

- **Deterministic Predictions**
  - Most likely MW production for a specific time interval (e.g. hourly)
  - Tuned to minimize a performance metric (e.g. RMSE etc.)
    - Often results in “hedging” for extreme event forecasts
- **Probabilistic Predictions**
  - Confidence Bands
  - Probability of Exceedance (POE) Values
- **Event Forecasts**
  - Probability of events in specific time windows
  - Most likely values of event parameters (amplitude, duration etc.)
  - Example: large up or down ramps
- **Situational Awareness**
  - Forecasts of significant weather regimes
    - Produce events (large errors, ramps etc.) that impact user’s applications
  - Geographic displays of wind patterns

© 2007 AWS Truewind, LLC

Forecast Performance

- Performance Assessment Issues
- Typical Ranges of Forecast Performance for Individual North American Wind Farms
- Factors that Impact Performance and Comparison of Forecast Performance

© 2007 AWS Truewind, LLC

Forecast Evaluation Issues

AWS Truewind

- **Type of forecast**
  - Deterministic vs probabilistic
- **Deterministic forecasts**
  - Many performance statistics: Net Deviation (Bias), MAE, RMSE etc.
  - Different aspects of performance can be measured
- **Probabilistic forecasts**
  - Error of a specific forecast can't be calculated
  - Reliability and sharpness are key concepts
- **What performance data are relevant to the user?**
  - Depends on user's "cost function" and application
- **Objective of the forecast**
  - Should evaluate what the forecast was intended to achieve
- **Forecast performance varies due to many factors**
  - Many beyond the control of a forecaster
  - Makes casual forecast performance comparisons very difficult

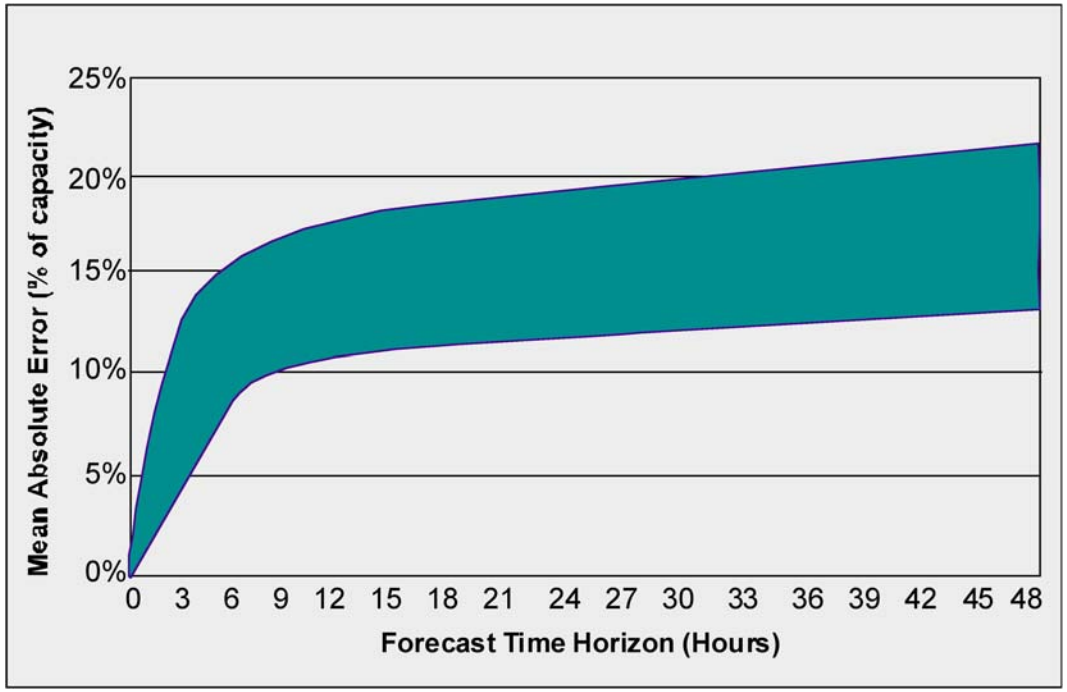
© 2007 AWS Truewind, LLC

Typical Range of Absolute Forecast Accuracy

(Individual wind farm - Forecast time step of 1 hour)

- Chart depicts composite of annual MAEs of AWST forecasts for individual wind farms in North America

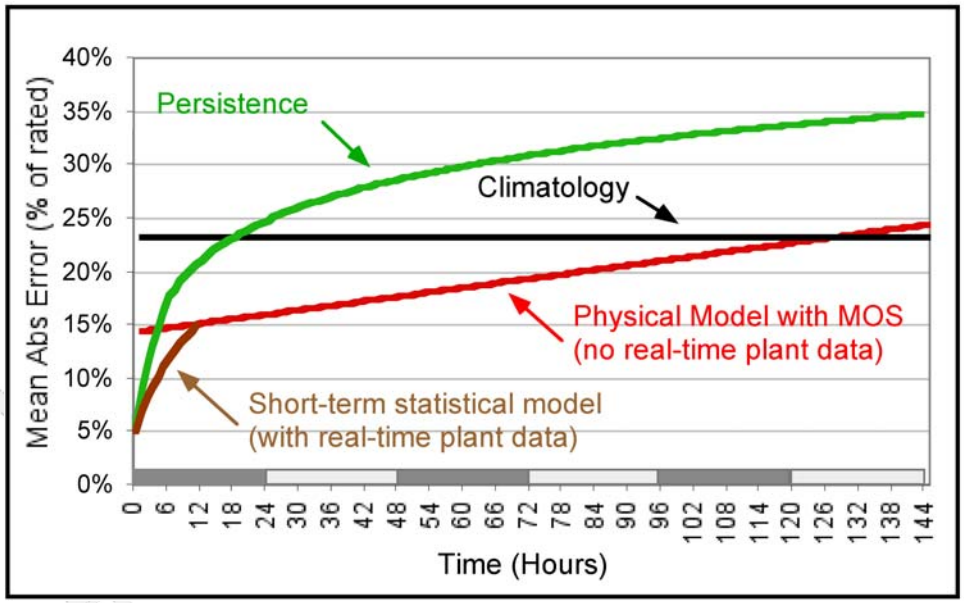
- Month to month variability at one site is often greater than site to site variability of annual MAE



© 2007 AWS Truewind, LLC

Typical Range of Relative Forecast Accuracy

(Individual wind farm - Forecast time step of 1 hour)



- **Physics-based models with statistical adjustment (with NO real-time plant data) outperform persistence and climatology from about 4 to 6 hours to about 5 to 7 days**

- **Short-term statistical predictions with real-time plant data outperform persistence and the "*adjusted physics-based forecasts without real-time plant data*" procedure from about 1 to 6 hours**

© 2007 AWS Truewind, LLC

Forecast performance factors

AWS Truewind

- Forecast time horizon (especially for short-term)
- Amount and diversity of regional aggregation
- Distribution of wind speeds relative to the power curve
- Type of wind and weather regime
  - Meteorological processes causing the wind variability
- Quality of generation & met data from the plant
- Shape of the plant-scale power curve
- Amount of variability in the wind resource
- Meteorological scales of wind variability
- Sensitivity of a forecast to initialization error

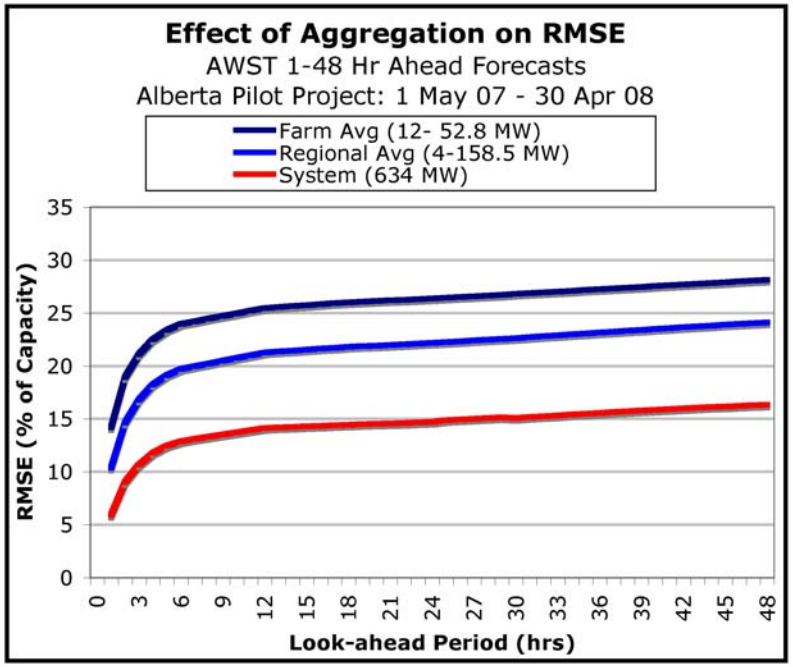
Plus other factors .....

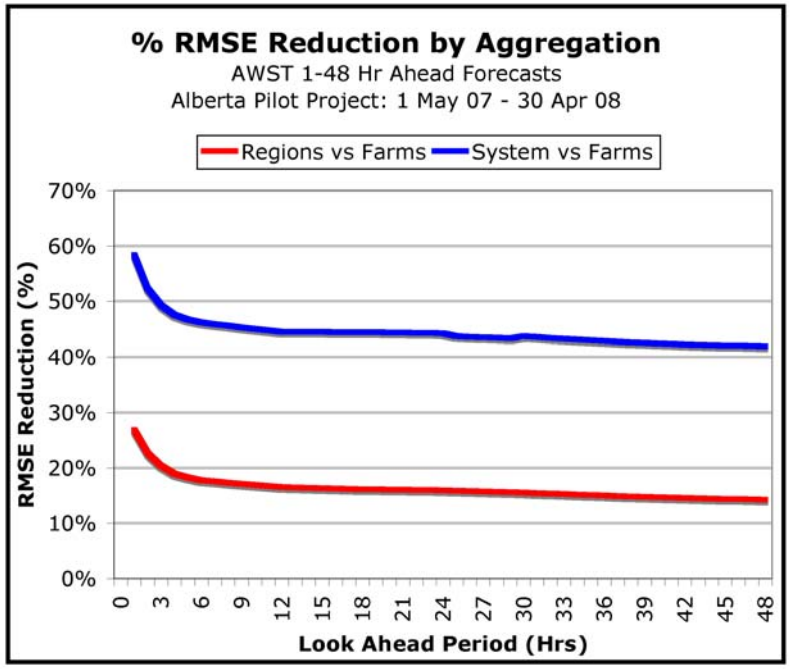
© 2007 AWS Truewind, LLC

Forecast Performance Factors:

Amount and Diversity of Regional Aggregation

- **Example #1: AESO's Wind Forecasting Pilot Project**
  - 1 year: May 2007-April 2008
  - 12 wind farms divided into 4 regions of 3 farms each
  - Hourly 1 to 48 hrs ahead forecasts for farms, regions and system
  - 3 forecast providers





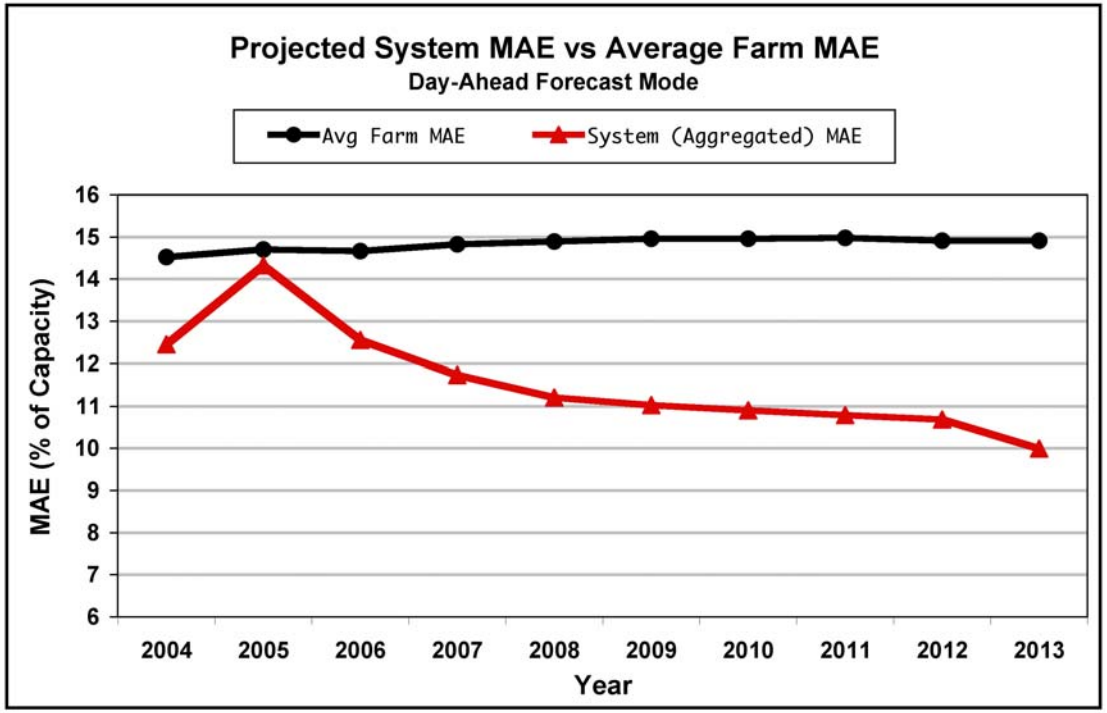
Forecast Performance Factors:

Amount and Diversity of Regional Aggregation

Example #2: New York

NY Wind Generation Growth Assumptions

Year	Plants	Capacity (MW)
2004	3	48
2005	4	348
2006	7	549
2007	12	960
2008	16	1,396
2009	20	1,750
2010	24	2,029
2011	28	2,264
2012	32	2,577
2013	36	3,348



Forecast MAE for system aggregated power production is sensitive to the number of wind plants and the inter-plant error correlations (related to the geographic dispersion of the plants and the spatial wind regime patterns)

© 2007 AWS Truewind, LLC

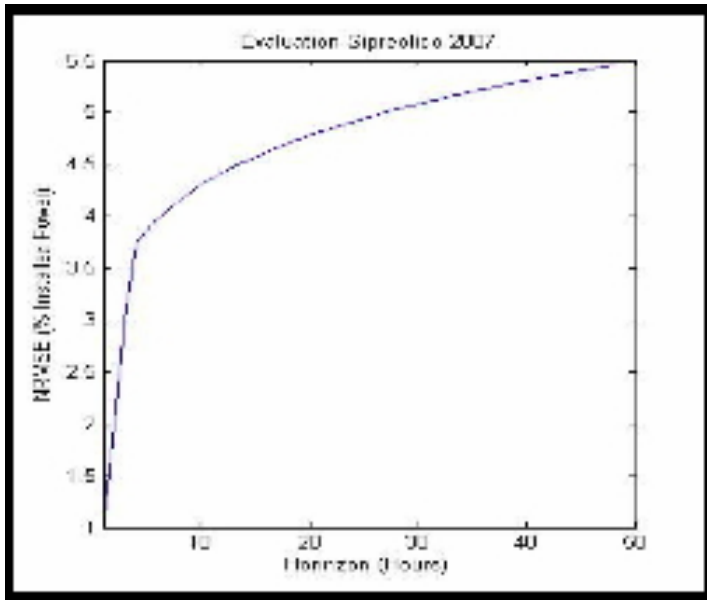
Impact of Aggregation on Performance Comparisons

AWS Truewind

- **Lack of a consideration of the impact of size and diversity of the generation resource leads to misconceptions about forecast performance**
- **Example: REE Visit Report. Is the accuracy of the reported REE/Sipreolico forecast system really phenomenal?**
- **The size and diversity of this aggregation is great so one would expect a huge aggregation effect vs a single wind park**

From the REE Visit Report:

"SIPREOLICO provides detailed hourly forecasts up to 48 hours updated every 15 minutes. The accuracy of the forecast is phenomenal: The forecast root mean square error for the 48-hour-ahead forecast is below 5.5% of the installed wind generation capacity. "

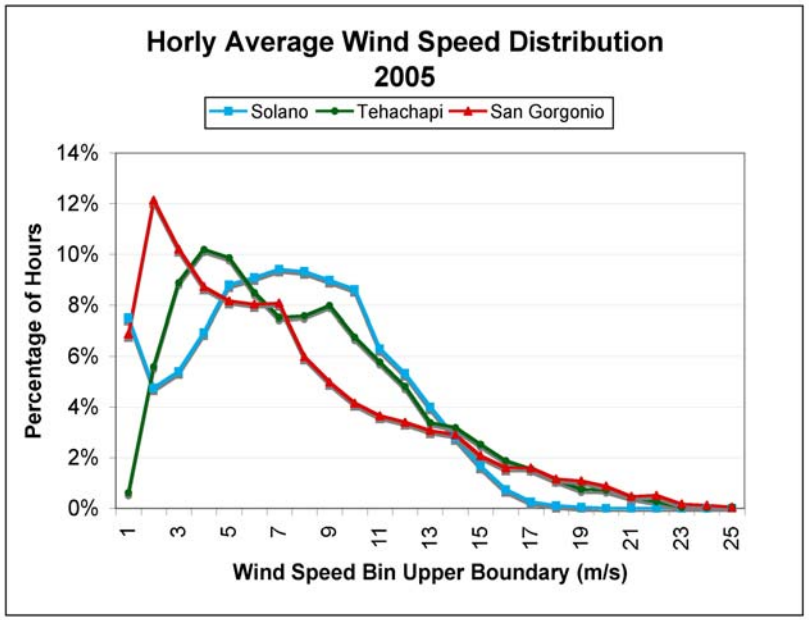


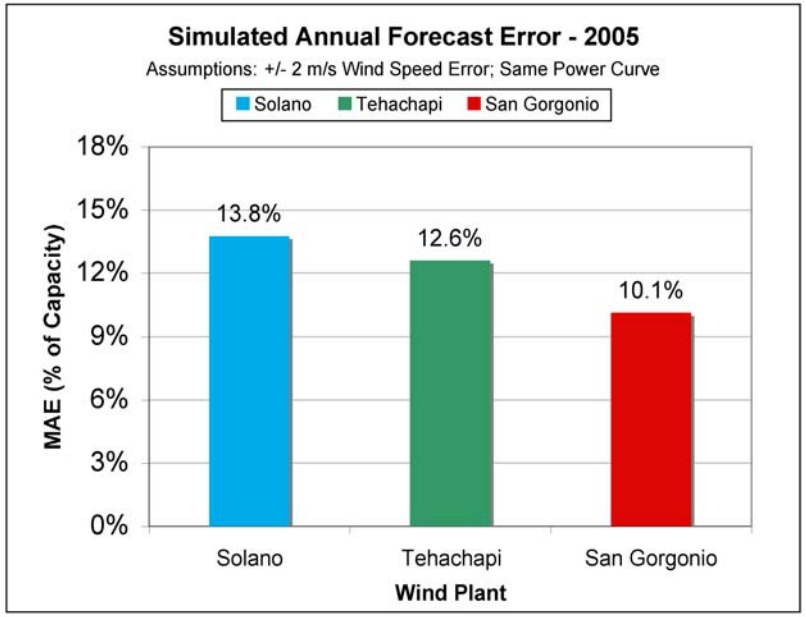
14,877 MW installed; 575 wind parks
~ 30 MW capacity/park
Peak Generation ~ 10,000 MW

Forecast Performance Factors:

Wind Speed Distribution

Experiment: Assume all hours over a 1-yr period have the same +/- 2 m/s error and the same plant-scale power curve





Slope of plant-scale power curve varies (related to correlations in wind speeds among turbines); therefore the sensitivity to wind speed forecast error varies

© 2007 AWS Truewind, LLC

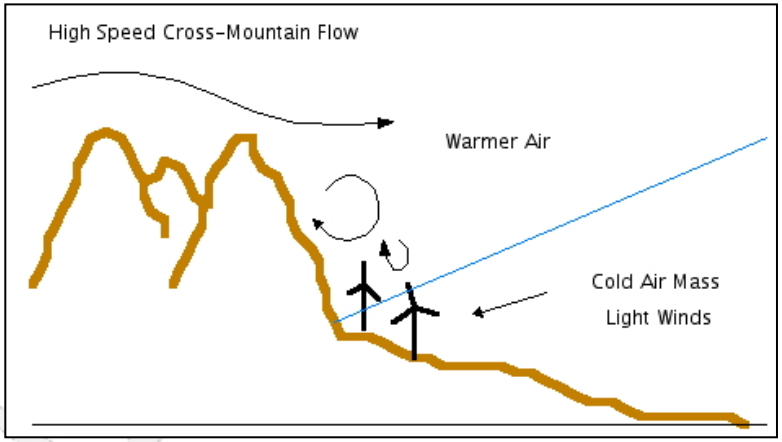
Forecast Performance Factors:

Weather Regimes

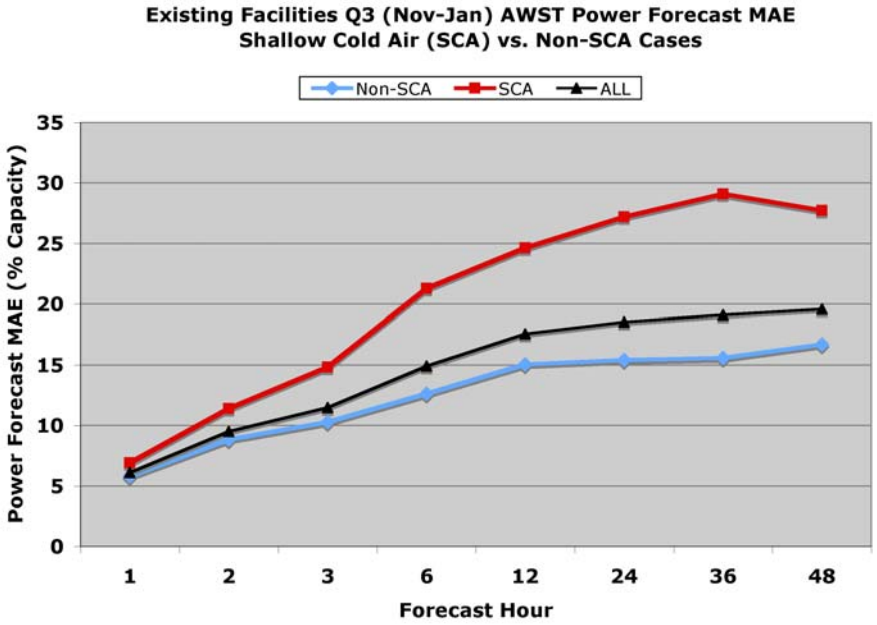
AWS Truewind

Example: power production forecasts during AESO's Alberta Pilot Project

- Significant winter wind regimes in Alberta were identified for the 2007-08 season
- Forecast performance was analyzed by regime



Shallow cold air (SCA) regime occurs when slowly moving cold air from the N or E undercuts a warmer air mass typically characterized by strong W or SW winds



Power production forecast error was much larger for the SCA regime than the non-SCA cases primarily because the characteristics of NWP forecast errors were quite different in SCA and non-SCA regimes

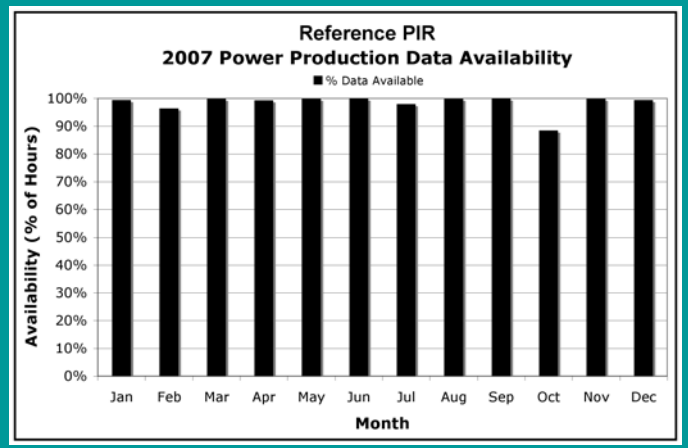
© 2007 AWS Truewind, LLC

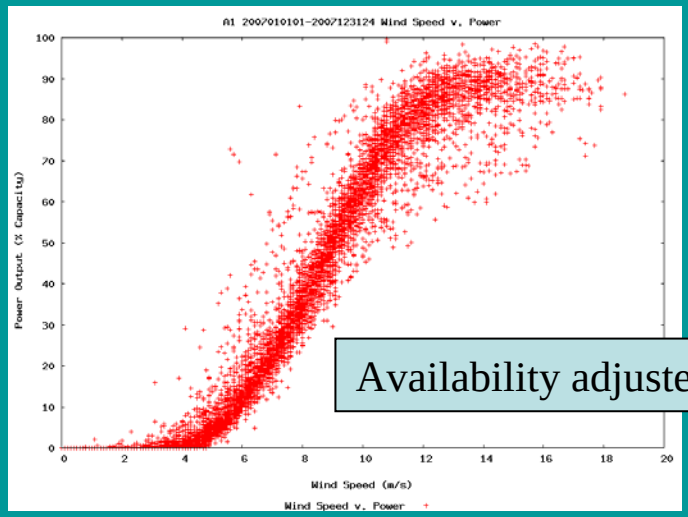
Forecast Performance Factors:

Quality of Wind Generation Resource Data

AWS Truewind

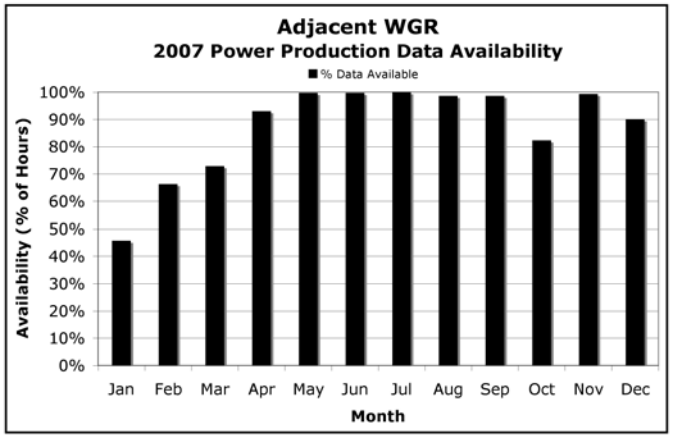
Reference WGR

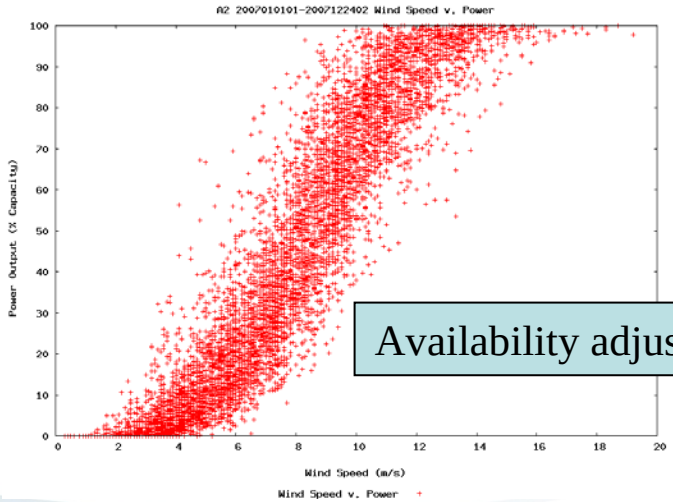




Availability adjusted

Adjacent WGR





Availability adjusted

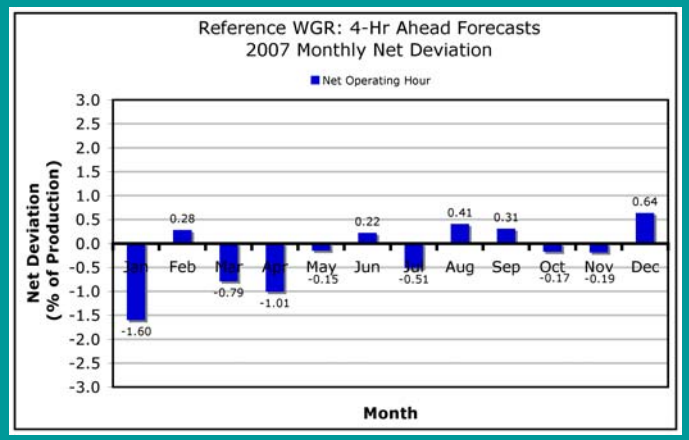
Forecast Performance Factors:

Quality of Wind Generation Resource Data

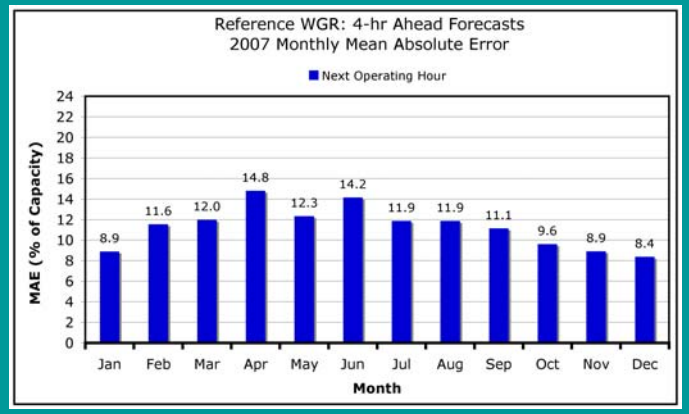
AWS Truewind

Reference WGR

Median Net Monthly Deviation: 0.36%

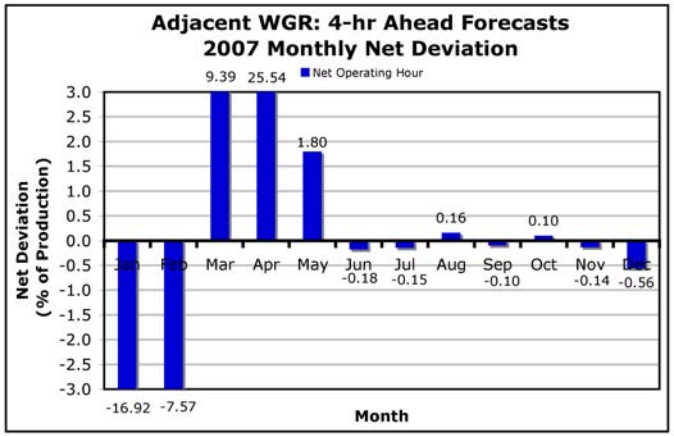


Annual MAE: 11.3%

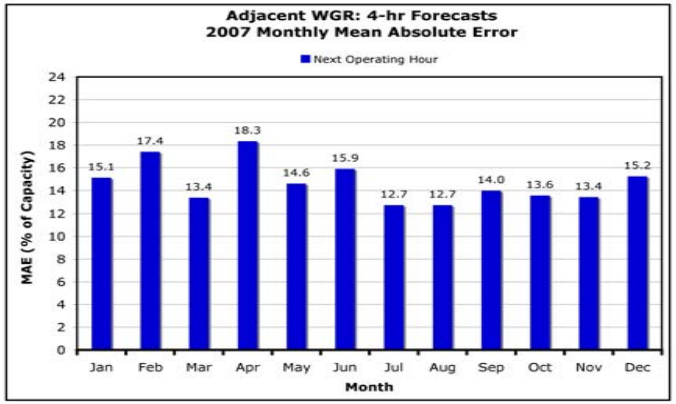


Adjacent WGR

Median Net Monthly Deviation: 0.37%



Annual MAE: 14.6%



Forecasting the Future of Forecasting

- How will forecasting technology and performance evolve over the next few years?
- What forecasting R&D is currently in progress at AWS Truewind?

© 2007 AWS Truewind, LLC

How will forecasts be improved?
(Top Three List)

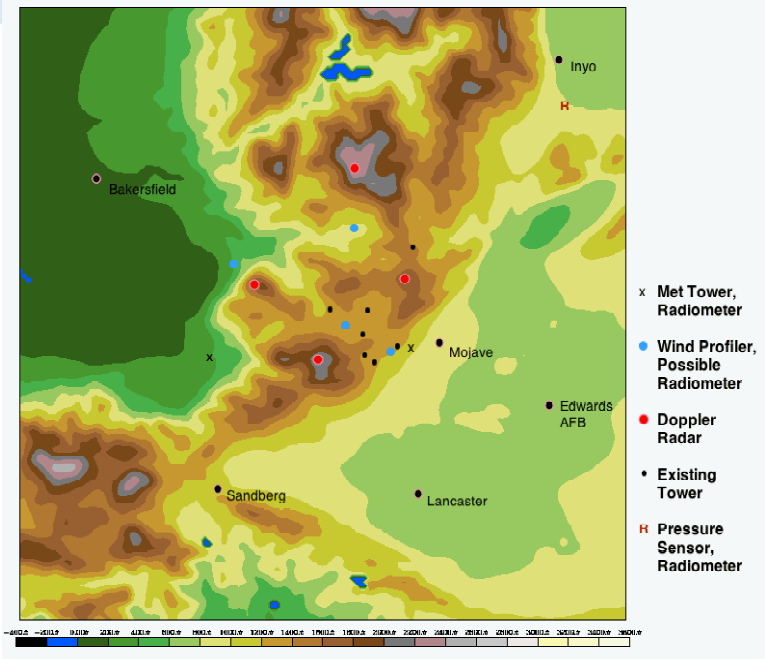
AWS Truewind

- **(3) Improved physics-based/statistical models**
  - Improved physics-based modeling of sub-grid and surface processes
  - Better data assimilation techniques for physics-based models
  - Learning theory advances: how to extract more relevant info from data
- **(2) More effective use of models**
  - Enabled by more computational power
  - Higher resolution, more frequent physics-based model runs
  - More sophisticated use of ensemble forecasting
  - Use of more advanced statistical models and training methods
- **(1) More/better data**
  - Expanded availability and use of "off-site" data in the vicinity of wind plants, especially from remote sensors
  - A leap in quality/quantity of satellite-based sensor data

© 2007 AWS Truewind, LLC

Forecasting R&D Initiatives at AWS Truewind

- **Focus on Short-Term Forecasting**
  - Explore new remote sensing technology to get 3-D Data
  - Time-lagged 3-D spatial correlations
  - Rapid NWP Update Cycle
- **Ramp Forecasting**
  - Develop tools for short-term forecasts
  - Optimal extraction of ramp event info from NWP data
  - Effective communication of ramp forecast info
- **Regime-based Statistical Procedures**
  - Optimal ways to identify systematic NWP errors
- **Effective Forecast Customization and Utilization**
  - Best way to display forecast info for each type of user application



Summary of Key Points

AWS Truewind

- **AWS Truewind: Multi-model Ensemble Approach**
  - Execute several NWP models including AWST's custom-developed model
  - Diverse ensemble with NWP, statistical and plant output model components
  - Forecasts from an optimized weighting of ensemble members
- **Customized regime-based statistical methods reduce error based on knowledge of local weather regimes**
  - Local knowledge and experience can be added to an automated system
- **Relative performance of different approaches is very uncertain**
  - Most casual forecast performance comparisons are questionable
  - Performance varies due to a number of factors that complicate comparisons
  - Forecast systems are also optimized for different objectives for different applications
- **Alberta Pilot Project suggests that North American and European forecaster providers perform comparably when all non-forecaster factors are equalized**
- **AWST has an extensive ongoing forecasting R&D program**
  - Supported by internal and some external funding
  - Focus on short-range (0-6 hrs) and ramp Forecasting
  - Extensive use of rapid update NWP and new remote sensing technology

© 2007 AWS Truewind, LLC