Final Report

California Renewable Energy Forecasting, Resource Data and Mapping

Appendix B

Wind Energy Forecasting: A Review of State-of-the-Art and Recommendations for Better Forecasts

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Abstract

Wind energy in the United States has increased dramatically over the last decade. The rapid growth in installed wind power capacity has led to an increased interest in wind energy forecasting. This report discusses the importance of forecasting for wind power industry and reviews state-of-the-art methodologies for forecasting wind energy and output ramp rates. This report also discusses available data sources for validation and calibration and makes recommendations on best practices for wind forecasting and on future research.

Keywords: wind, energy, renewable, forecast, NWP, modeling, ramp rate, data sources

Summary

In this CEC-funded effort, work has been conducted with focuses on: 1) surveying industry to explore major stakeholders' forecasting needs for wind energy, 2) reviewing state-of-the-art methodologies for forecasting wind energy and output ramp rates, 3) reviewing data sources for validation and calibration, and 4) making recommendations on best practices of wind forecasting and future research.

Below are the key findings and recommendations:

- The rapid growth in installed wind power capacity has led to an increased interest in wind energy forecasting. More and more utilities and ISOs are adopting, or planning to adopt, central wind forecasting systems as a means of more effectively integrating greater amounts of wind power.
- Currently major stakeholders in California (PG&E, SMUD, CAISO, SCE) use both hour ahead (HA) forecasts and day ahead (DA) in their daily business (for power generation scheduling, power trading, system operating, etc). There is an emerging interest in intra-hour forecasting from a few parties.
- There exist two approaches to the short-term wind power forecasting: physical approach and statistical approach. In some cases, a combination of both is used. Most forecast models employ numerical weather prediction (NWP) models to improve forecast accuracy.
- The accuracy of the forecasts from a wind forecasting model depends on a number of factors, such as wind farm terrain topology, surface roughness, weather regime, wind pattern, forecast horizon, etc. For a specific wind forecasting project, comparison of different models needs to be carried out in order to find the "best" forecasting model or combination of models.
- The quality and availability of data are critical to successful wind forecasts. It is recommended to fund and support work focusing on better understanding the data impacts, improving data acquisition and transmission, promoting data sharing, and developing new technologies in meteorological measurements.
- There are limited studies on ramp forecasting. More efforts need to be taken to improve ramp rate forecasting. When forecasting ramp rates, it is important to define the aspects of ramping that have the highest priority such as ramp time start, ramp rate or magnitude. The CAISO and other system operators should work with forecasters to determine how to ask for and evaluate ramp rate forecasting.
- Wind data are recorded and stored by a variety of entities in California, including CAISO, IOUs and munis, Wind Plant Owners, Wind Developers, NOAA and NWS, and a few other organizations and government agencies. Most data have restricted availability/accessibility, inconsistent data quality, and insufficient sampling frequency.
- Additional recommended future research include: new technologies in meteorological measurements, turbine icing forecasting, and studies on atmospheric boundary layer profiles.
- Currently the penetration level of wind energy in communities and buildings is extremely low. Current industry does not see any need for distribution level wind forecasting.

1 Introduction

The United States is reforming its energy mix and developing diverse sources of clean, renewable energy to overcome emerging challenges such as increasing energy prices, supply uncertainties, and environmental concerns. Wind energy is one of the renewable energy sources that has seen rapid growth over the last decade. According to AWEA's 2010 report, nearly 10,000 MW of wind came online in the United States in 2009, bringing the total US installed wind capacity to over 35,000 MW. This represents nearly a twelve-fold increase in wind capacity in 2000.

1.1 20% Wind Energy by 2030

In 2006, President Bush emphasized the nation's need for greater energy efficiency and a more diversified energy portfolio, which led to a collaborative effort to explore a modeled energy scenario in which wind provides 20% of US electricity by 2030 (DOE Report, 2008). In its Annual Energy Outlook 2007, the US Energy Information Administration (EIA) estimates that US electricity demand will grow by 39% from 2005 to 2030, reaching 5.8 billion megawatt-hours (MWh) by 2030. To meet 20% of that demand, US wind power capacity would have to reach more than 300 gigawatts (GW) or 300,000 megawatts (MW). This growth represents an increase of more than 290 GW within 23 years. The 20% Wind Scenario also estimates that the installation rate of wind power would need to increase from installing 3 GW per year in 2006 to more than 16 GW per year by 2018 and to continue at roughly that rate through 2030.

1.2 Wind Forecasting Applications

The rapid growth in installed wind power capacity has led to an increased interest in wind power forecasting. Historically, given its variable nature, wind generation has been taken on an as-available basis, where wind simply "shows up" and grid operators take whatever measures necessary to accommodate it, mainly reducing the output of other committed generation. At low wind penetrations, such actions are reasonable. However, at higher levels of wind penetration, uncertainty surrounding the amount of wind energy that can be expected becomes more problematic. In addition, there are costs associated with having excess units online, as well as from reduced unit efficiency and increased operations and maintenance. Improved wind power forecasting can reduce these costs (NERC Report, 2009).

Various parties, such as system operators, utilities, project developers, and wind farm owners, can benefit from wind forecasting. For system operators, wind forecasts allow them to predict and manage the variability in wind power to balance supply and demand on regional or national grid system. Moreover, knowing in advance when expected surges in cheap and clean wind energy production will occur could allow for grid operators to reduce costs through the power-down of more expensive natural gas-fired plants. Having recognized the importance of wind forecasting, the following system operators have implemented central wind forecasting as of May, 2010: the California Independent System Operator (CAISO), the Midwest Independent System Operator (MISO), the New York Independent System Operator (NYISO), the Electric Reliability Council of Texas (ERCOT), and the Pennsylvania-Jersey-Maryland

Interconnection (PJM). The Alberta Electric System Operator (AESO) and the Ontario Independent Electric System Operator (IESO) also have plans to implement central wind power forecasting in 2010.

CAISO was the first ISO to implement centralized wind power forecasting in North America in June 2004. Its program is known as the Participating Intermittent Resource Program (PIRP). Intermittent generators that participate in PIRP pay CAISO a $0.10 per megawatt-hour (MWh) fee, agree to stay in PIRP for one year, install CAISO's telemetry equipment, schedule consistently with the CAISO's forecast of wind generation, and do not make advance energy bids into the California market. The positive and negative imbalance associated with wind power generators are netted out monthly, with any remaining imbalances paid or charged at a monthly weighted Locational Marginal Price (LMP). CAISO uses both day ahead (DA) forecasts and hour ahead (HA) forecasts in its daily operations. The DA forecasts are submitted at 5:30am prior to the operating day, which cover each of the 24 hours of the operating day on an hourly basis. The HA forecasts are submitted 105 minutes prior to each operating hour. It also provides an advisory forecast for the 7 hours after the operating hour. Recently, CAISO has shown an interest in intra-hour forecasts as well as three-day ahead forecasts (Blatchford, 2010).

Energy providers and utilities can benefit from wind power forecasts. Imbalance charges imposed on energy providers that result from deviations in scheduled output will increase energy providers' operating costs. Wind power forecasts can help to minimize these penalties. Wind power forecasts can also reduce the significant opportunity costs of being too conservative in bidding output into a forward market, due to uncertainty of availability. In California, two major utilities - Southern California Edison (SCE) and Pacific Energy and Electricity (PG&E) - have both integrated wind power forecasts into their daily business.

SCE serves a 50,000-square-mile area of California and reached a record peak demand of 23,303 MW on August 31, 2007. SCE considers its available generating capacity data to be confidential, but has reported its 1,073 MW of installed wind capacity. Although SCE is a participating transmission owner in CAISO, it has its own wind forecasting system and does not participate in PIRP. SCE started creating power generation profiles for wind in 1998. At that time, daily wind power profiles were simply derived from two years of historical power data using the Least Square Fit (LSF) method. The forecasting results were not satisfactory. In November of 2000, SCE hired AWS Truewind as their wind power forecast vendor. Since then, SEC uses AWS Truewind's wind forecasts for scheduling wind generation, and pays for the wind power forecasting service internally. Currently, AWS Truewind sends HA forecasts to SCE twice a day, once at 5:00am and once at 5:00pm. The forecasts predict the energy output for the next seven days. SCE also uses 90-day ahead forecasts for power trading. SCE also thinks intra-hour forecasting is beneficial for real-time power trading (Gilman, 2010).

PG&E currently uses next-day and two-day forecasts in its power generation scheduling. PG&E suggests providing, in addition to HA and DA forecasts, 15 min ~ 2 hour forecasts to facilitate ancillary services (Klingler, 2010).

Wind project developers can take advantages of wind forecasting. The suitability of a wind energy project depends on a large number of factors. For wind energy development, the meteorological conditions at the site are of the utmost importance, since wind acts as the fuel in wind energy projects. Even though this fuel is free, no amount of money can buy additional fuel once a project is built. Project siting is therefore the single most important, controllable factor in determining whether a wind project will be economically viable or not.

Since direct observations of wind speed are only made at a limited number of sites, a comprehensive dataset based on observations alone is impossible. Instead, computer models that simulate the dynamics of the atmosphere (Numerical Weather Prediction models, or NWPs) can provide important spatial and temporal information on the wind resources at a site. Proper assessment techniques using NWP modeling can provide valuable information on the expected diurnal and seasonal load for a project as well as a long-term evaluation of the site's potential.

Wind power forecasting can be applied to save costs when wind farm owners/operators need to schedule wind project maintenance and construction. Wind projects often require that turbines be taken down during the commissioning of new turbines. This can take hours to weeks depending in part on the weather. Precipitation, high winds and extreme temperatures need to be avoided for obvious reasons. Without accurate forecasting information, the chances of idling a mobilized work crew and necessary equipment (such as large cranes) increases. The associated costs can exceed $100,000 per day (Lerner and Garvert, 2009). By not taking advantage of the right weather conditions for construction, operations, and maintenance, overall project costs increase as deadlines are not met, plant generation is diminished, and resultant production revenues from Green Tags or Production Tax Credits are lost.

1.3 Structure of This Report

In the rest part of this report, we present a review of state-of-the-art methodologies for forecasting wind energy and output ramp rates in Sections 2 and 3. Section 4 focuses on discussing available data sources for validation and calibration. The last section of this report, Section 5, provides recommendations on best practices for wind forecasting and on future research.

2 Wind Forecasting Methodologies

A wind power forecast is an estimate of the expected power production of one or more wind turbines (or wind farms) in the near future (from a few minutes to several days). This estimate is usually generated using one or a combination of *wind forecast models*. A wind forecast model is a computer program that uses various inputs to produce wind power output for future times. The complexity of the wind forecast models can range from very simple to very complex. For example, one of the simplest models is the *persistence* model. In this model, the forecast for all times ahead is set to the value it has now. The persistence model performs surprisingly well for very short forecast horizons (up to six hours) and it has become the benchmark that all other forecast models have to beat. Compared to the persistence model, modern wind forecast models are notably more complex. These modern forecast models are often called *wind forecast systems* by their developers, probably due to their complexity. For example, AWS Truewind's eWind system involves using a combination of *physics-based models* (such as Mesoscale Atmospheric Simulation System (MASS), Weather Research and Forecasting (WRF), and Mesoscale Model Version 5 (MM5), *statistical models* (such as Screening Multiple Linear Regression (SMLR) and Artificial Neural Network (ANN), and *plant output models*.

This section focuses on operational and commercial wind forecast systems that are generally of medium to high complexity. For more information on wind forecast models, please refer to review papers by Giebel (Giebel, 2003) and by Monteiro (Monteiro et al, 2009).

2.1 Forecast System Introduction

A wind forecast model or wind forecast system can be considered as a "black-box". This "black-box" takes various data as inputs and generates wind power production forecasts as outputs. Depending on the complexity of the forecast model or forecast system, the number of inputs can be either small or large. For example, the persistence model mentioned above only needs one input: current power generation. AWS Truewind's eWind forecast system, on the other hand, operates upon a wide range of input data such as online meteorological data (wind speed, wind direction, temperature, pressure, etc.) measured by on-site and off-site met towers, online power production data provided by wind farm owners, historical power production data of a wind farm, and turbine availability data for a wind farm.

2.1.1 Physical Approach and Statistical Approach

Wind forecast models or wind forecast systems ("black-boxes") can be categorized according to their approaches to producing the wind power prediction. There exist two approaches to wind power forecasts: *physical approach* and *statistical approach*. In some forecast systems, a combination of both is used. Figure 1 illustrates different approaches used for wind power forecasting (WPF).

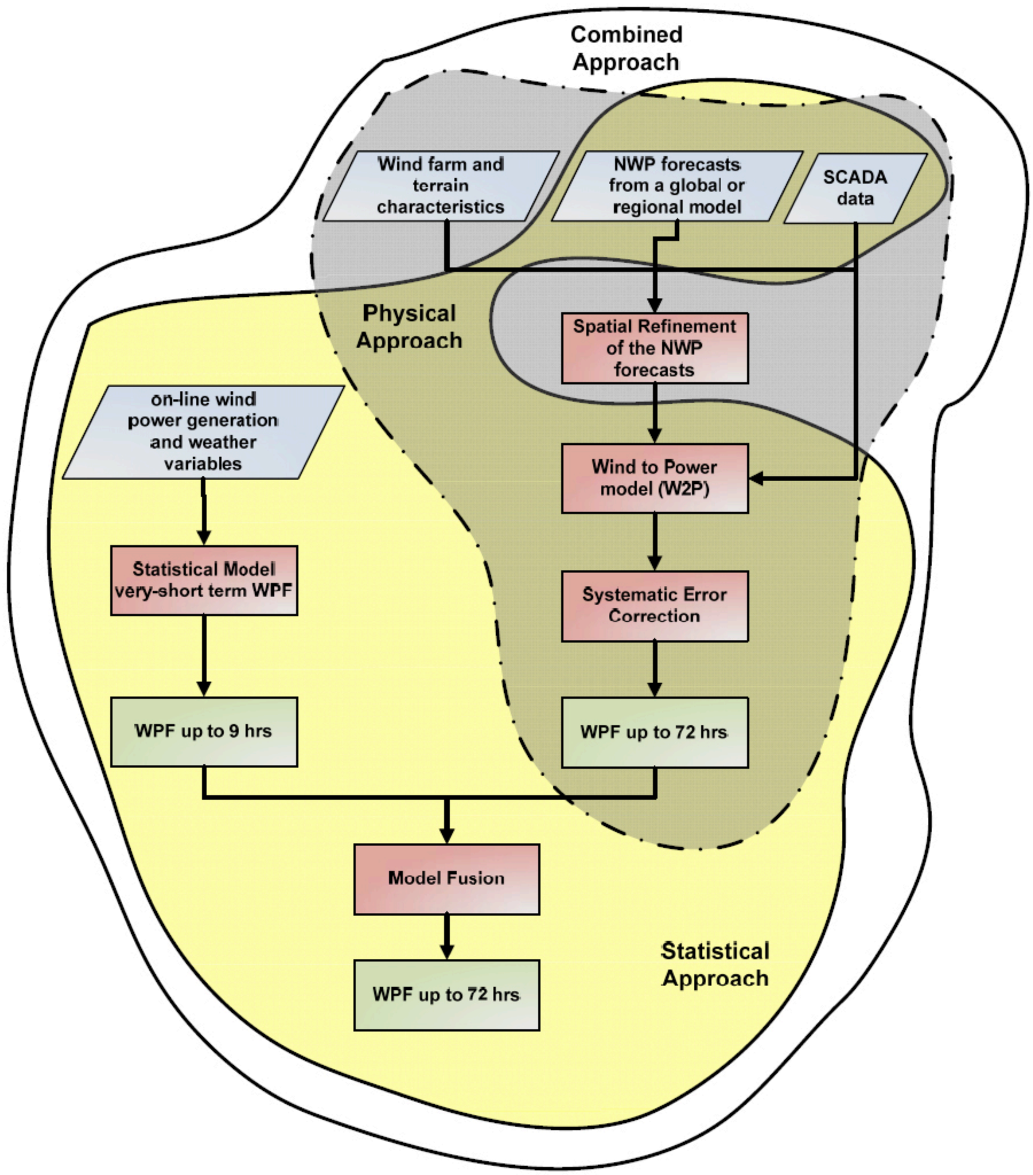

Figure 1. There exist two approaches to wind power forecasting (WPF): physical approach and statistical approach (from Monteiro et al, 2009).

In the physical approach, a wind forecast system tries to use physical considerations as long as possible to reach the best possible estimate of the local wind speed before using model output statistics (MOS) to reduce the remaining error. Wind forecast systems using physical approach usually take the output from external numerical weather prediction (NWP) models, which are run at the government forecast centers, and the raw regional atmospheric data as the inputs to run its own set of NWP models. These models employ higher horizontal and vertical resolution than the government center models and in some cases also include physics-based formulations that are more customized for low-level wind forecasting than those in the government center models.

The NWP models are formulated from the fundamental principles of physics (i.e. conservation of mass, momentum, and energy, and the equation of state for the constituents of air), which yields a set of differential equations that are typically solved on a three-dimensional grid. The size of the grid elements and the extent of the computational domain in these models determine the scales of atmospheric processes that can be simulated by a specific configuration of a model. Some commonly used NWP models include: North American Mesoscale (NAM), Global Forecast System (GFS), Rapid Update Cycle (RUC), Mesoscale Model Version 5 (MM5), Navy Operational Global Atmospheric Prediction System (NOGAPS), Coupled Ocean/Atmosphere Mesoscale Prediction System (COAMPS), etc. Please refer to Appendix A for more details on NWP models.

In the statistical approach, a wind forecast system uses statistical models to find relationships between a wealth of explanatory variables (including results from NWP models that are run at government forecast centers) and online measured power data. Usually, the statistical models are developed by employing one or more of several different statistical algorithms. The algorithms include techniques such as Screening Multiple Linear Regression (SMLR), Artificial Neural Networks (ANN), Support Vector Regression (SVR) as well as other methods such as fuzzy logic clustering that can be employed to pre-condition training samples to enable the training methods to find stronger empirical relationships. The statistical models can be used at any stage of the modeling, and often they combine various steps into one.

2.1.2 Forecast Stages

If the forecast system is formulated rather explicitly, as is typical for the physical approach, then the stages are: *downscaling*, *conversion to power*, and *upscaling*:

- **Downscaling**: At this stage, the wind speed and direction from the relevant NWP level is scaled to the hub height of the turbine. This usually involves a few steps. The first step is to find the best-performing NWP model(s). The next step is the so-called downscaling procedure. The physical approach uses a meso- or microscale model for the downscaling.
- **Conversion to Power**: The downscaling stage generates a wind speed and direction for the turbine hub height. This wind is then converted to power with a power curve. One can use either the manufacturer's power curve or the power curve derived from measured power output and wind speed and direction. The use of the manufacture's power curve is the easiest approach since it does not require any historical data. However, newer research has shown that it is more accurate to use the power curve derived from measured data (Garcia-Bustamante et al, 2009).
- **Upscaling**: Utilities usually want a prediction for the total area they service instead of a prediction for a single wind farm. Therefore, in this stage, the single result is upscaled to the area total. If all wind farms in an area would be predicted, this would involve a simple summation. However, since it is not practical to predict hundreds of wind farms, some representative farms were chosen to be the input data for an upscaling algorithm. Several publications studied the effects of the number and location of representative wind farms on the expected power output of a whole region. It is well documented in the literature that, by aggregating several wind farms over a wide area, weakly correlated forecast errors cancel out as a result of statistical effects (Monteiro et al, 2009).

2.1.3 Forecast Ensembles

In practice, an ensemble of forecasts is usually used rather than an individual forecast. It has been demonstrated that *forecast ensembles* can produce higher quality forecasts and forecast uncertainty estimates than any individual forecast in some applications (Sivillo, 1997).

The basic concept is that a set of forecasts is generated by perturbing the input data and the model configuration parameters within their respective ranges of uncertainty, producing a new forecast with the perturbed input data or model parameters. In theory, this provides a set of forecasts that bracket the ultimate realized value of the predicted variables. A composite of the set of forecasts typically provides an explicit prediction than any individual forecast and the dispersion of the ensemble provides information about the forecast uncertainty.

Since there is an enormous number of input data variables and model parameters, it is not practical to generate forecasts with all of the possible perturbations. Thus, in practice, one must select a subset of input data or model parameters to perturb to generate a forecast ensemble. The objective is to select the input data or model parameters that are responsible for most of the uncertainty in the forecast system. This can be quite difficult since the data or parameters responsible for the uncertainty typically will vary from one forecast cycle to another due to differences in weather regimes and other factors.

2.1.4 Forecast System Operations

The relative importance of the various inputs and models depends upon the look-ahead period of the forecast as well as other factors such as the characteristic weather regimes, surface properties in the vicinity of the wind farm and the amount and type of available data from the plant and other sources. The skill of short-term forecasts is typically more dependent upon the time series data from the wind plant as well as recent data from nearby off-site locations or nearby remote sensing systems (such as Doppler radars or wind profilers) and the performance of the statistical models. However, even 1 to 2 hour ahead forecasts can benefit from the intelligent use of output data from a customized high resolution NWP model.

The performance of day-ahead forecasts does not have much dependence on the current data from the wind plant or nearby locations. These forecasts are based predominantly on the output from the NWP models that has been adjusted by a MOS procedure to remove systematic errors that are common in the output of NWP models. Although current data from the wind plant is not crucial to day-ahead forecast performance, historical meteorological and plant production data is crucial to the successful utilization of the MOS procedure and the construction of high quality statistical plant output models.

2.2 Operational and Commercial Wind Forecast Systems

This section reviews major commercial wind forecasting systems currently in use. As stated in the previous section, modern advanced wind forecasting models fall into one of these three categories: physical approach, statistical approach, or hybrid approach (using both physical and statistical approaches). Almost all the forecasting systems use one or more NWP models to improve forecast accuracy.

2.2.1 AWS Truewind – eWind Forecasting System

AWS Truewind has been providing wind forecasting services through its eWind forecasting system to clients such as CAISO, FPL Energy, enXco, SCE, Shell energy, and International Energie. The eWind forecasting system employs physics-based numerical models and adaptive statistical techniques. Figure 2 shows a schematic overview of the eWind system used in the Alberta Pilot Project (AWS Truewind Report, 2008). In the Alberta Project, AWS Truewind utilized its eWind forecast system to produce 1 to 48 hour ahead forecasts of the wind power production for a total of 12 wind farms. The top row of circles in Figure 2 represents the output data from external NWP models that are run at government forecast centers. This data, along with the raw regional atmospheric data (light gray circle on the left side of Figure 2), are used to run eWind's own set of NWP models. These models employ higher horizontal and vertical resolution than the government center models and in some cases also include physics-based formulations that are more customized for low-level wind forecasting than those in the government center models. These models produce 3D forecasts of meteorological variables on a relatively high-resolution grid. The output from the physics-based simulations, as it becomes available from each physics-based model cycle, goes into a "potential predictor" database along with the raw regional atmospheric data and the Supervisory Control and Data Acquisition (SCADA) data from the wind farms.

The continuously updated composite NWP and observational database is used to train the statistical models to produce forecasts of atmospheric variables at the meteorological tower sites. An ensemble of these forecasts are produced by using two different statistical prediction procedures - Screening Multiple Linear Regression (SMLR) and Artificial Neural Network (ANN) - and a number of different training sample sizes, contents and stratification bins. The result of this process is an ensemble of forecasts for the atmospheric variables at the meteorological tower sites. This ensemble is converted into a single deterministic or probabilistic forecast for each variable and forecast hour by the ensemble composite model. This ANN-based model is trained on historical forecast performance data and essentially weights each forecast according to its recent performance or its performance in previous occurrences of the anticipated weather regime.

The hourly forecasts of atmospheric variables at the meteorological tower sites are converted to a power production forecast by "the plant output models". These models are typically trained with measured atmospheric variable and power production data although simulated atmospheric variable data may be used for those variables that cannot be computed with the available measured data. The output from the plant output models is a deterministic and probabilistic power production forecast for each forecast hour.

2.2.2 Garrad Hassan – GH Forecaster

Garrad Hassan (GH) has been predicting the long-term energy production of wind farms on a commercial basis for more than 18 years. As a natural extension to its long-term forecasting services, GH developed a method for the forecasting of the future energy production of wind farms over a time frame of a few hours to a few days and launched its "GH Forecaster" service around 2003.

The GH forecasting modeling method incorporates input data from a Numerical Weather Prediction (NWP) source of appropriate resolution, and from on-site data. The physical aspect of the modeling methodology is primarily provided by the NWP input. As of 2004, the results have been generated using NWP input from mesoscale models with a grid resolution of order of 12km. This input is enhanced through the application of multi-parameter statistical regression routines (Parkes and Tindal, 2009).

The generation of power output forecast within GH Forecaster is a two-stage process. The first stage is accurate modeling of the meteorological conditions. The meteorological model uses statistical regression to transform NWP model forecasts to site-specific ones. The second stage is transforming meteorological forecasts to forecasts of power output. This transformation is typically achieved via a wind farm power matrix, using multiple direction and wind speed bins to represent the power output of the wind farm. The process of generating the power matrix can be theoretical or based on measured data.

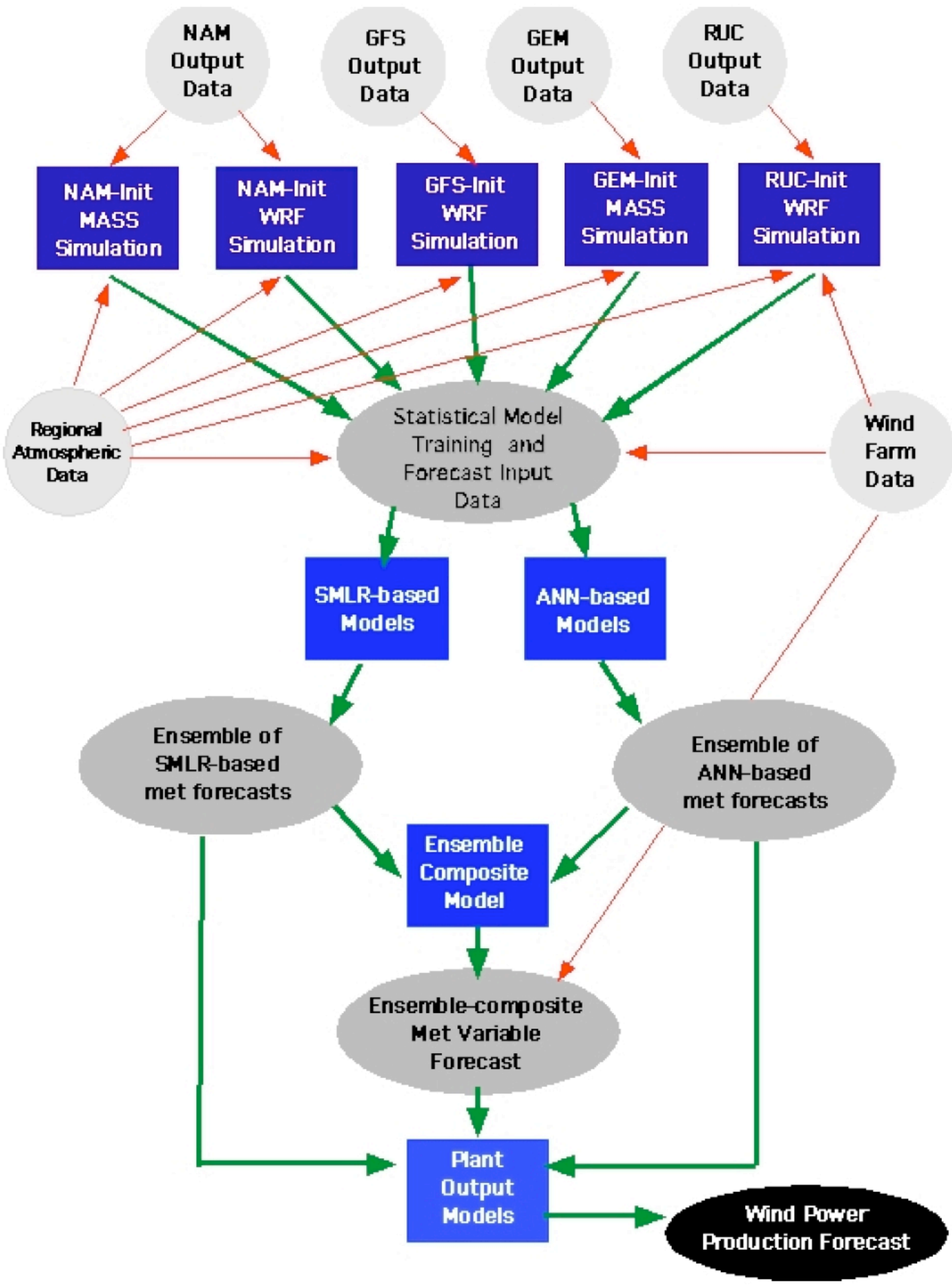

Figure 2. A schematic of the data flow and computational process for the AWST eWind forecast system used for the Alberta pilot project (from AWS Truewind, 2008).

2.2.3 3Tier – PowerSight Wind Forecasting System

3Tier is one of the major forecast providers in North America. The technical details of 3Tier's wind forecast system are not readily available. Therefore, the following introduction was taken from 3Tier's website.

3Tier's PowerSight wind forecasting system uses a combination of advanced statistical algorithms, mesoscale numerical weather prediction (NWP) models, self-learning artificial intelligence models, and publicly available weather forecasts, including data from the US National Weather Service (NWS) as well as other global weather forecast centers. PowerSight also incorporates the climatology and terrain for the project location using diurnal variability averages on a monthly time-scale. When historical met tower or power production data is available, PowerSight will apply model output statistics (MOS) to its atmospheric model simulations.

2.2.4 National Center for Atmospheric Research – Nowcasting and DICast Systems

National Center for Atmospheric Research (NCAR) has spent more than 15 years developing and operationally deploying a short-term Nowcasting system, which is based on a technology called Variational Doppler RADAR/LIDAR Data Assimilation System (VDRAS). This system uses available observational datasets (RADAR, surface station, satellite, LIDAR, and met tower) in real-time, analyzes the atmosphere using physical models, combines observational data with weather model output, and generates nowcasts out to 2 hours every 6-10 minutes. This capability is especially suited for wind energy ramp detection.

In 2009, in collaboration with Xcel Energy, NCAR implemented an operational Real-Time Four Dimensional Data Assimilation (RFDDA) system over the western and central states for supporting wind-power forecasting. This system contains three modeling domains with grid sizes of 30, 10, and 3.3 km. The 3.3 km domain covers the Rocky Mountains from New Mexico to Montana, the High Plains states, and more areas of the central plains. The system runs with a 3-hour cycle. In each cycle it produces 27-hour forecasts for the innermost domain and 72-hour forecasts for the two coarser domains. The real-time weather forecast maps and power-production forecasts for about 30 wind farms in Colorado, Minnesota, New Mexico and Texas are provided to Xcel operational centers. Currently NCAR is providing following forecasts to Xcel Energy: 1) 0~1/0~2 hour ramp rate forecasts, and 2) 0~72 hour wind energy output forecasts (this will be extended to 0~120 hour forecasting at the end of this year) (Mahoney, 2010).

NCAR has also been a leader in the development of intelligent weather prediction systems that blend data from numerical weather prediction (NWP) models, statistic datasets, real-time observations, and human intelligence to optimize forecasts at user-defined locations. The Dynamic Integrated Forecast System (DICast) is an example of this technology and it is used by several of the nation's largest private sector weather service companies. The DICast system can be used for predicting wind energy as it generates fine-tuned forecasts for specific user-defined locations.

2.2.5 Gamesa – Mega System

Spanish wind turbine manufacturer Gamesa launched an online weather forecasting service for wind farms through its Mega System in April, 2010 (Gamesa

Press Release, 2010). The Mega System was created based on Gamesa's years of experience in wind pattern forecasting and wind farm output modeling systems. The Mega System provides seven-day forecasts for hourly wind conditions and wind farm output.

According to Gamesa's April 20, 2010 press release, there are *Basic* and *Premium* versions of the Mega service. The *Basic* version provides forecasts to the wind farms five times a day. The forecasts include wind and electricity output patterns, and comparative analysis against hard data. The *Premium* version builds on the Basic version with hourly updates via a real-time connection to wind farm data.

2.2.6 Other Forecast Service Providers and Their Models

- Energy and Meteo Systems – Previento

  Previento is a wind power forecasting system developed by the German company Energy and Meteo Systems (Focken and Lange, 2008). It is capable of providing prediction of wind farm output power up to 4 days in advance and with a temporal resolution of up to 15 minutes. Energy and Meteo Systems has been delivering wind power forecasts to American grid operator Midwest ISO since August, 2008.

- WEPROG – MSEPS System

  The Multi-Scheme Ensemble Prediction System (MSEPS) is a wind power forecasting system developed by the Danish company Weather and Wind Energy PROGnosis (WEPROG) (Jorgensen and Mohrlen, 2008). The Alberta Electric System Operator (AESO) awarded a two-year contract to WEPROG to provide a centralized wind power forecast for Alberta in January, 2010.

- ARMINES – ARMINES Wind Power Prediction System (AWPPS)

  ARMINES and RAL have developed work on short-term wind power forecasting since 1993. In Project MORE-CARE, ARMINES developed models for the power output of a wind park for the next 48/72 hours based on both online SCADA and Numerical Weather Predictions. The developed forecasting system integrates:

  - Short-term models based on the statistical time-series approach able to predict efficiently wind power for horizons up to 10 hours ahead.
  - Longer-term models based on fuzzy neural networks able to predict the output of a wind farm up to 72 hours ahead. These models receive as input online SCADA data and numerical weather predictions.
  - Combined forecasts: such forecasts are produced from intelligent weighting of short-term and long-term forecasts for an optimal performance over the whole forecast horizon.

  The forecasting system developed by ARMINES is integrated in the MORE-CARE EMS software and is installed for online operation in the power systems of Crete and Madera.

- ISET – Wind Power Management System (WPMS)

  German research institute, Kassel Institute für Solare Energieversorgungstechnik (ISET), has worked with short-term forecasting since 2000, using the German Weather Service's DWD model and neural networks. Ernst and Rohrig reported in Norrkoping on the latest developments of ISET's WPMS (Durstewitz et al, 2001). They now predict for 95% of all wind power in Germany. In January 2009, ISET was transferred to the Fraunhofer-Gesellschaft and incorporated into the new Fraunhofer Institute for Wind Energy and Energy System Technology (IWES).

- Precision Wind – Precise Stream

  Precision Wind's forecast model is based on mesoscale/microscale atmospheric models (computational fluid dynamics techniques). The main feature is the ability to capture a full 17 km of vertical model depth as well as hundreds of km in the horizontal direction. The model uses three grids with different levels of horizontal resolution to define a large area around the site. The training method is a post-processing step that requires only three months' worth of data. Uncertainty estimation is also provided in the form of maximum and minimum wind generation values that vary according to current and forecasted weather conditions.

- WindLogics – WindLogics Wind Energy Forecast System

  WindLogics is a US company that provides services for utility-scale wind project development and grid integration. Its wind power forecast model uses Support Vector Machine (SVM) to convert wind speed to generation, and it is retrained every month in order to include new generation and weather data. It uses an ensemble of the National Centers for Environmental Prediction (NCEP), Rapid Update Cycle (RUC), North American Model (NAM), and the Global Forecast System (GFS) (WindLogics, 2008).

- AMI Environmental Inc. – Wind Energy Forecasting System

  AME Environmental (AMI) is a private technical research and engineering company with experience in interdisciplinary environmental programs. The AMI Wind Energy Forecasting System consists of four modules: 1) a mesoscale model called the Fifth Generation Mesoscale Model (MM5), 2) a diagnostic wind model, 3) an adaptive statistical model, and 4) the forecast access by users (Tran, 2004). AMI applied its wind forecasting system to a 12-month testing at a 75 MW wind plant in southwest Texas. Testing results indicate that the AMI forecasting system shows large improvement over both persistence and climatological skills.

- WSI – WindCast

  WSI's WindCast model delivers 7-day hourly predictions of wind power and speed for single wind farms. The forecasts can be updated seven times a day.

2.3 Evaluation of Forecasting Systems

2.3.1 Measures of Accuracy

Two common measures of accuracy are mean absolute error (MAE) and root-mean square error (RMSE). MAE is expressed as a percentage of the plant's rated capacity. RSME is expressed as the standard deviation of the forecast errors:

MAE=ce. The request for bids concluded in June 2009.

The request for bids required that teach forecast service provider submit forecasts from four selected wind farms, representing three of the major wind areas in California. These forecasts covered both day ahead and hour ahead time frames.

CAISO performed a detailed statistical analysis of the forecasts generated by three forecast service providers during the request for bids (RFB) period from July, 2008 through June, 2009 (Blatchford and de Mello, 2009). Here are the key findings of their analysis:

- Aggregate day ahead forecast error is less than 15%, calculated as the root mean square error (RMSE).
- Nearly 40% of the day ahead forecasts have an absolute error of less than 5%; over 60% of all day ahead forecasts have an absolute error of less than 10%; and over 75% of all day ahead forecasts have an absolute error of less than 15%.
- Aggregate hour ahead forecast error is less than 10% RMSE.

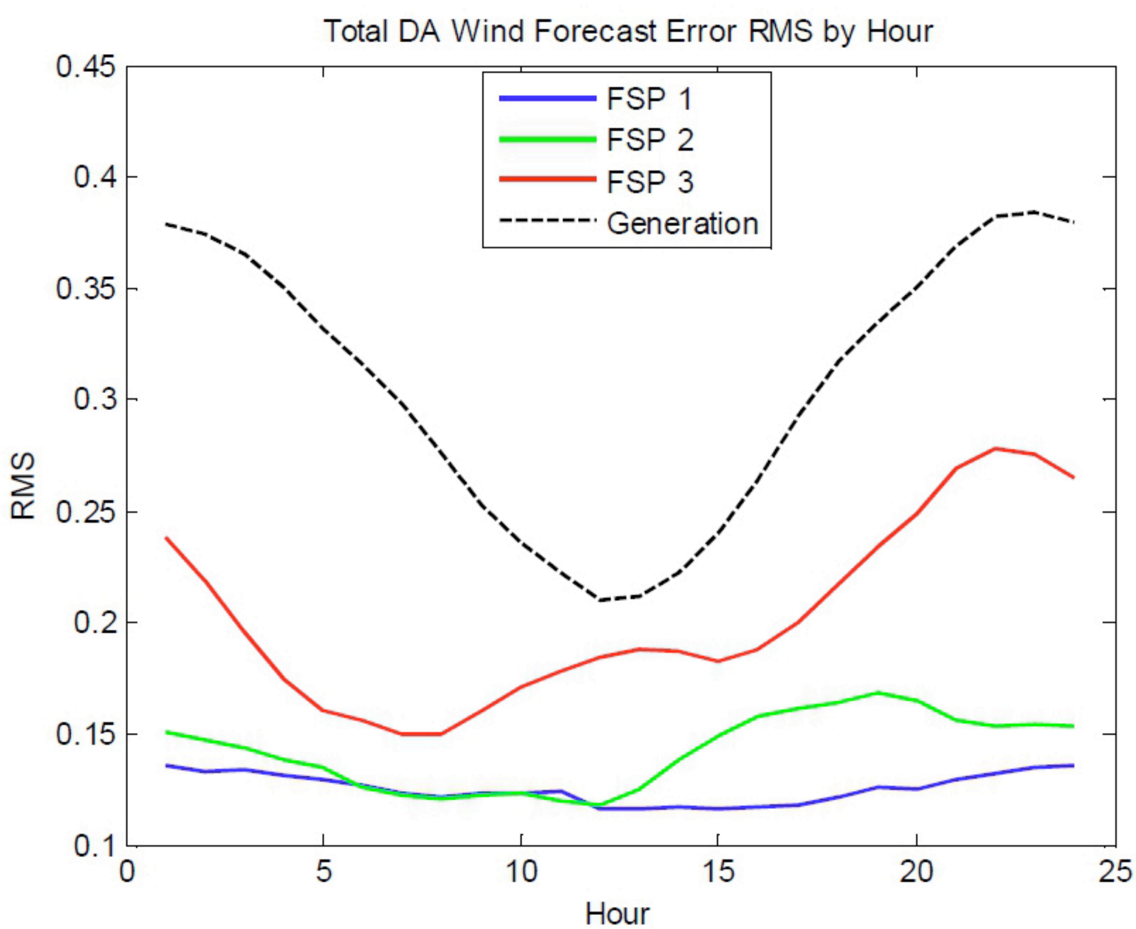

Figure 3. Total day ahead forecast RMSE by hour of day (from Blatchford and de Mello, 2009).

- Approximately 50% of the hour ahead forecasts have an absolute error of less than 5%; nearly 75% of the hour ahead forecasts have an absolute error of less than 10%; and nearly 90% of all hour ahead forecasts have an absolute error of less than 15%.
- Geographic diversity and aggregation of forecasts for individual wind facilities improve overall forecasting accuracy in both the day ahead and hour ahead time frames.
- Forecast performance is best at production levels greater than 80% of total capacity and less than 20% of capacity.
- Data quality constitutes a critical factor in forecast accuracy.

Figure 3 shows the total day ahead RMSE throughout the day and the average generation for each hour. It can be seen that for Forecaster 1 and Forecaster 2, the DA forecast RMSE ranges from 12% to 17%. For Forecaster 3, the DA forecast RMSE ranges from 15% to 28%. The forecast errors throughout the middle of the day seem to be generally smaller than the beginning and end of the day. This is likely due to the typical lower generation output during this time following the diurnal generation pattern.

Figure 4 is taken from CAISO's report and shows the weekly day ahead forecast RSME on a rolling basis. It can be seen that the overall pattern of root mean square error tends to track quite well between forecast providers with the exception of a few times of the year. This similar RSME trend among the forecast providers suggest that multiple forecast may not provide much additional value. This may also indicate that most forecast errors are rooted from the National Weather Service NWP output since all three forecasters use them as the input for their forecast models.

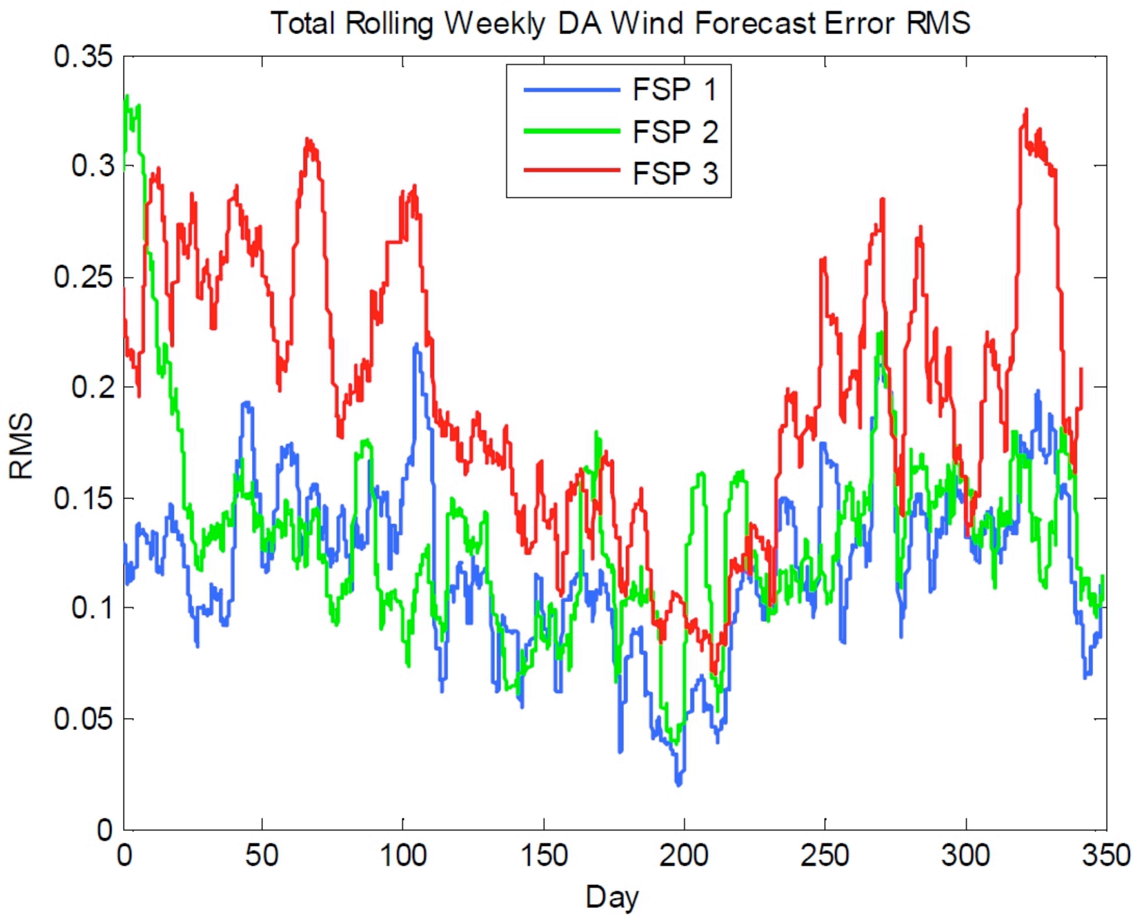

Figure 4. Rolling Weekly Day ahead Forecast RMSE (from Blatchford and de Mello, 2009).

2.3.2 Alberta Pilot Project

The Alberta Electric System Operator (AESO), in conjunction with the Alberta Energy Research Institute and the Alberta Department of Energy, initiated a wind power forecasting pilot project in the summer of 2006 (Industry Work Group, 2008). In the project, three very different forecasting methodologies were trialed. The forecasters selected were AWS Truewind from US, WEPROG from Denmark, and Energy & Meteo Systems from Germany.

The forecasters provided forecasts for 12 different wind power facilities (7 existing facilities and 5 future facilities) spread out across southern Alberta in four regions. From May 1, 2007 to May 1, 2008, forecasts were delivered each hour, predicting the next 48 hours. The forecasts included the hourly average, minimum and maximum of wind speed, wind power, and wind power ramp rates at each facility.

The project demonstrated that forecasting in Alberta appears more difficult than in other locations. This is primarily due to the extreme or variable weather patterns experienced in Alberta, such as Chinooks and complex terrain, being close to the Rocky Mountains.

In the very short term (up to 6 hours out), the forecasting models were comparable to persistence forecasts, where persistence assumes that conditions at the time of the forecast will not change. Beyond 6 hours, the forecast models outperformed persistence forecasts. As the time horizon increased, the accuracy of the forecasts decreased.

Figure 5 shows the total day ahead forecast RMSE for three forecasters that participated in the Alberta Pilot Project. The forecast RMSE increases as the forecast horizon increases, particularly for the first six forecast horizons. The forecast RMSE is in the range of 6% to 20% for the first six forecast horizons and 20% to 30% between the 7th and 48th forecast horizon.

The Albert Pilot Project aimed at identifying the best methodology to forecast wind power in Alberta. However, the most effective forecast of the three forecast methods and vendors trialed varied with the time horizon and weather pattern combination. While on forecaster performed well in one condition, they would perform less well in another, making it difficult to determine the better methodology.

In this project, all three forecast service providers used multiple Numerical Weather Prediction models to generate forecasts. Generally making use of various NWP models having different update cycles and update times should provide a more robust approach. This can also be beneficial as on NWP model might be better with certain weather regimes or in different time frames than another NWP model.

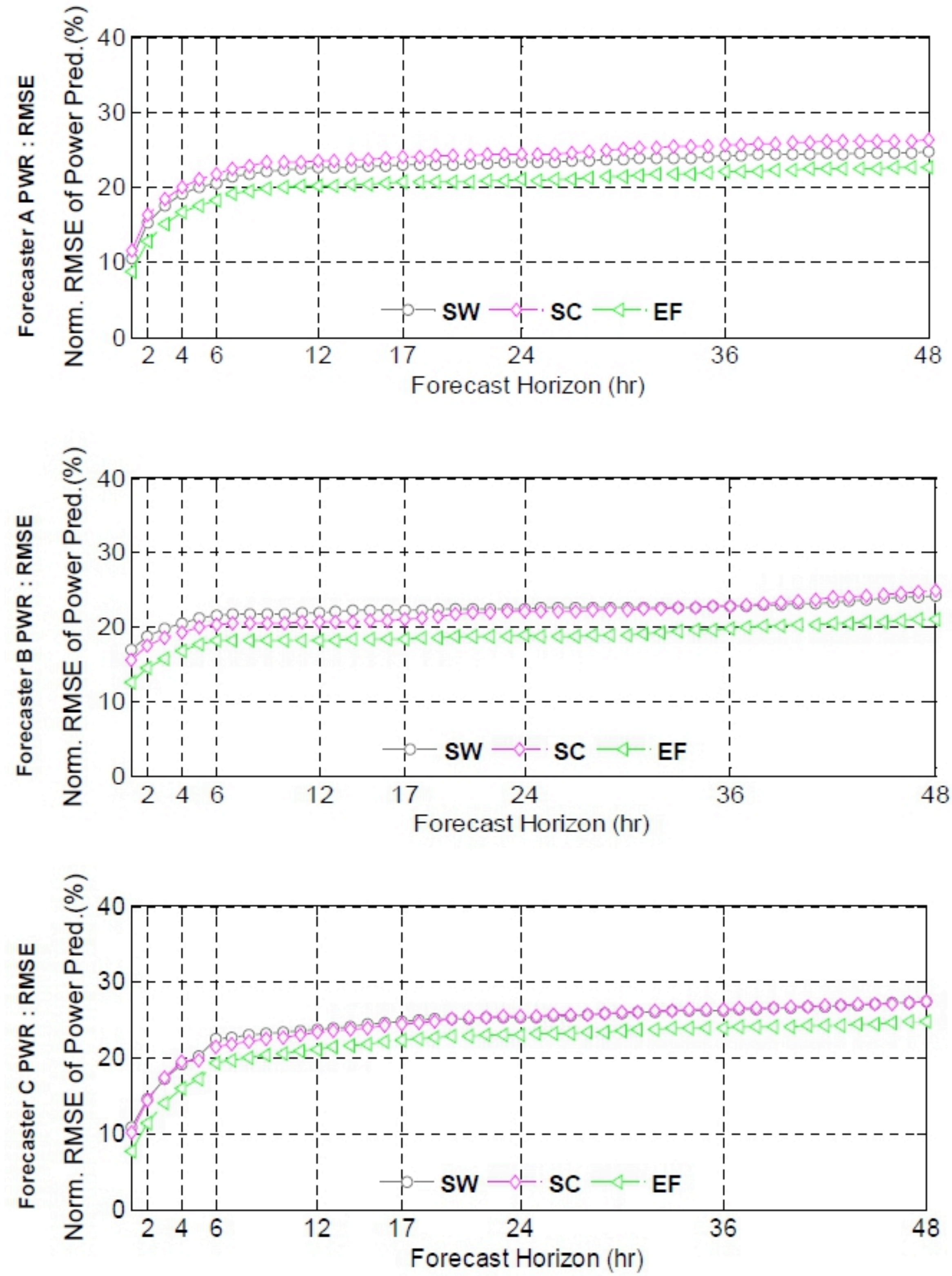

Figure 5. Total day ahead forecast RMSE for three forecasters as a function of forecast horizons (from McKay, 2008).

Figure 6 was provided by Energy & Meteo Systems. The two sub-figures show the individual forecasts based on different NWP models for two different weather situations. In the top sub-figure, a ramp event was very well captured by Model 1. However, in certain weather situations such as small low pressure systems with fronts, Model 2 captures the sequence of events better than Model 1, as shown in the bottom sub-figure.

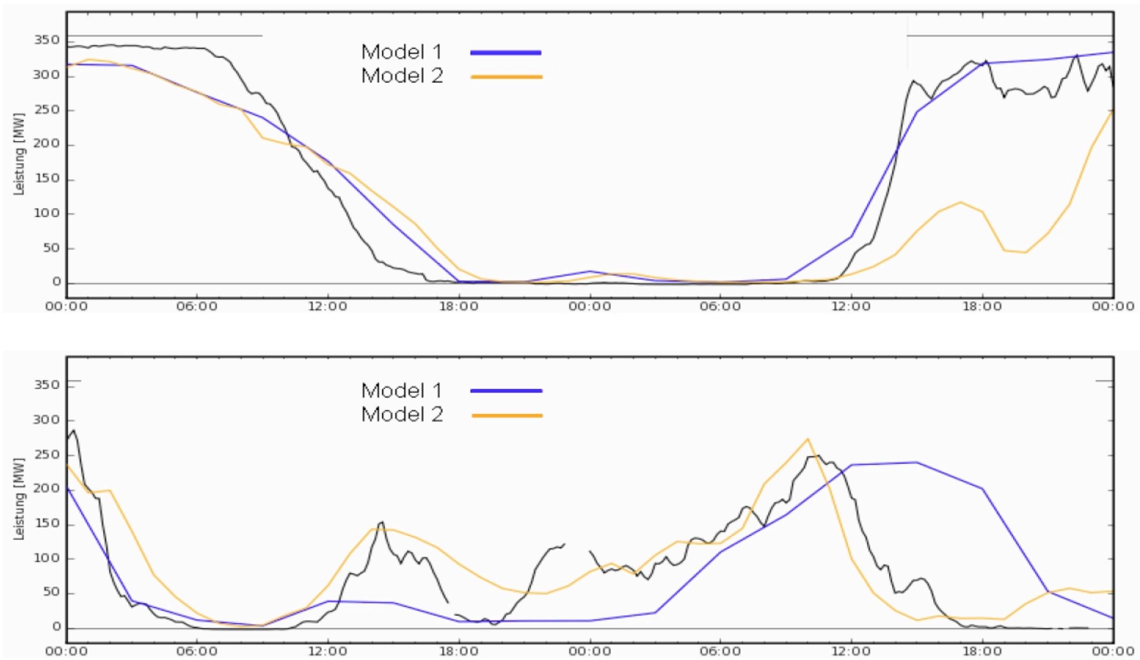

Figure 6. Individual forecasts based on two different NWP models for two different weather situations (from Focken and Lange, 2008).

3 Ramp Rate Forecasting

As the penetration of wind energy continues to increase around the world, the impact of wind energy on the management of electrical grids is becoming increasingly evident. The challenge for the grid operator of integrating wind energy, or for the energy trader to maximize the market value of the energy, is especially tough during periods of rapid change in wind farm production, or ramp events. This section will give an overview of efforts and studies on ramp rate forecasting.

3.1 Frequency of Ramp Events and Definition of a Ramp Event

A change in power production can be defined by two parameters: the size of the ramp (the amount of change in power production that occurs, usually a percentage of the wind farm capacity), and the duration of time over which the change occurs. Ramp events of the greatest concern are characterized as having large sizes and short durations.

Figure 7 is taken from a study by Greaves (Greaves et al, 2009) and shows the frequency of events with varying size and duration constraints using the measured data from a number of wind farms in the UK. It can be seen that the frequency of events decreases rapidly with increasing size and also decreases with decreasing duration.

Currently there is no strict definition of a ramp event, which poses some difficulty on assessing ramp events. In McKay's report (McKay, 2008), a ramp event was defined as a 1-hour change in power production of more than 20% of capacity. In Greaves' paper (Greaves et al, 2009), a ramp event was defined as having a change in power of 50% of capacity or more over a period of 4 hours or less. This definition of a ramp rate was also used in Zack (Zack, 2007). Using this definition, it can be seen from Figure 7 that ramp events occur less than 6% of the time.

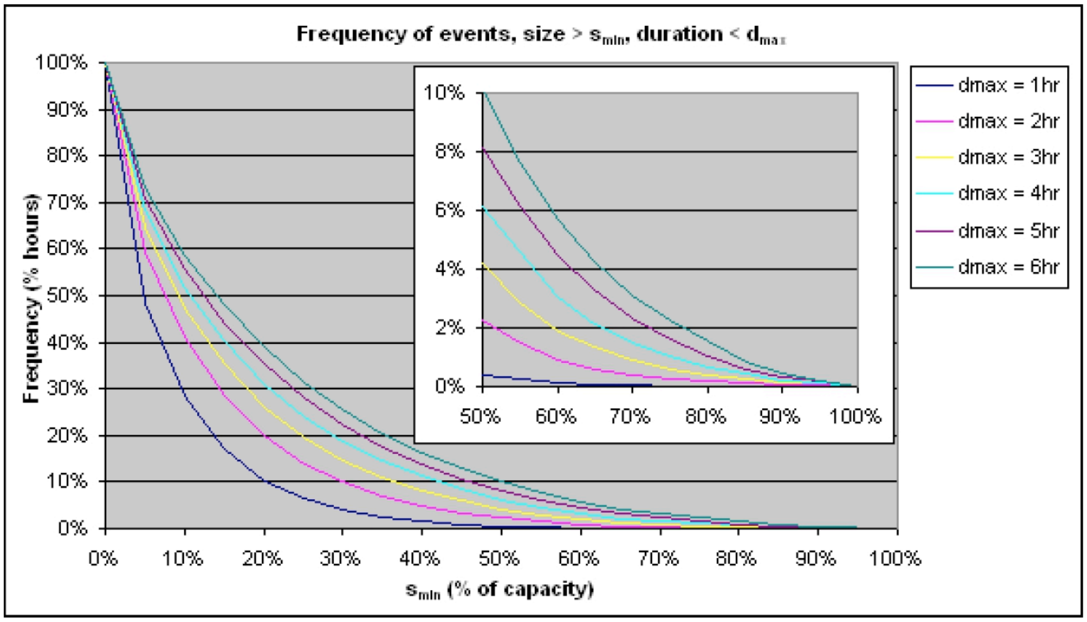

Figure 7. Frequency of power changes with varying size and duration (from Greaves et al, 2009).

3.2 Ramp Forecasting Research

There are limited studies and research on ramp rate forecasting. Kusiak (Kusiak et al, 2009) developed forecasting models for short- and long-term prediction of wind farm power built on weather forecasting data generated at different time scales and horizons. The wind farm power prediction models were built with five different data mining algorithms. It was found that the model generated by a neural network outperforms all other models for both short- and long-term forecasting. They also used their models to predict ramp rates.

Cutler (Cutler et al, 2009) discussed the advantages and disadvantages of time-series NWP forecasts. They developed a methodology to transform the wind speeds predicted at each grid point in a region around the wind farm location to an equivalent value that represents the surface roughness and terrain at the chosen single grid point for the wind farm site. The chosen-grid-equivalent wind speeds for the wind farm can then be transformed to available wind farm power. The result is a visually-based decision support tool which can help the forecast user to assess the possibilities of large, rapid changes in available wind power from wind farms.

In the Albert Pilot Project, the three participating forecast providers delivered wind energy output forecasts as well as ramp event forecasts to the system operator (Industry Work Group, 2008). The ramp event forecasts were assessed using an approach called Critical Success Index (CSI) (McKay, 2008). Using the CSI methodology it was found that none of the forecasters did well in predicting the ramp rates. Perhaps part of the reason was that forecast providers were not required to deliver ramp rate forecasts at the outset. Therefore, the forecasters trained their models to provide low long term error. If the forecasters were to focus on ramp rates, they could improve on ramping forecast accuracy.

Greaves (Greaves et al, 2009) conducted a study using Garrad Hassan's GH Forecaster system to forecast ramp events. Historical data from GH Forecaster services for forecast power and measured production were used to identify forecast and measured ramp events. A total of 18 wind farm sites were analyzed, among which 12 in the UK and 6 in the US. It was found that forecasts for portfolios of wind farms are generally more accurate than forecasts for individual wind farms, especially for large changes in power production. For individual UK sites, the ramp forecasts with a horizon of 3 hours have a ramp capture rate of 44.9%. The ramp forecasts with a fore cast horizon of 24 hours have a ramp capture rate of 59.1%. For portfolios of wind farms, the ramp capture rates are 50.0% and 42.9%, respectively.

Greaves (Greaves et al, 2009) also studied the effects of using a combination of different NWP models. Table 1 shows the ramp capture rate and forecast accuracies for forecasts for a single wind farm. By using current intelligent methods for the NWP combination the forecast accuracy is slightly better than that for either NWP forecast used on its own. However, the better NWP forecast has a ramp rate capture nearly 10% higher than the combination and the other NWP forecast.

Table 1. Ramp capture rate and forecast accuracies for forecasts for a single wind farm (from Greaves et al, 2009)

NWP source used	**NWP1**	**NWP2**	**Combined**
Number of true forecasts	78	97	80
Number of false forecasts	67	79	65
Number of missed ramps	127	108	125
Forecast accuracy (%)	53.8%	55.1%	55.2%
Ramp capture (%)	38.0%	47.3%	39.0%

4 Data Sources for Validation and Calibration

Wind data – either wind speed or power generation – are recorded and stored by a variety of entities. There are, however, a number of obstacles to employing these data for forecasting, particularly for grid integration applications. As discussed further below, the issues include:

- Restricted data availability/accessibility – Data accessibility can be restricted by confidentiality or because of difficulties with retrieving data from complex database systems.
- Data quality/errors – There are a wide variety of data quality issues. They are most likely to occur in data that are recorded without immediate application; in such cases, the data are often stored without any vetting.
- Insufficient sampling frequency – Wind data are often stored at 10-minute or hourly intervals. This is too slow for some forecasting analyses, particularly when dealing with ramps. Sampling frequency may be constrained by data telemetry or storage systems; even without such constraints, data are often stored at relatively low frequencies because there is no perceived need to save at a faster rate.

A number of wind data sources in California are detailed below.

4.1 Available Wind Data Sources

4.1.1 Generation Data in CAISO PI System

CAISO maintains the single largest warehouse of California wind power data in their PI data system. The PI System is a real-time data system from OSIsoft. CAISO also uses PI to store a vast amount of data on the California power grid, including power generation data for most of the power plants in California. Much of the power data are available at four-second sampling intervals. Presumably, some data are available at even faster rates, perhaps intra-second.

There are two significant issues with the PI data. First, much of the data are recorded, but never actually used. The data are therefore not vetted and may have data quality issues. Second, the data are bound by confidentiality; in general, CAISO cannot disclose data for any individual power plant. However, confidentiality can be satisfied by masking data through, for example, aggregation or normalization.

Shiu (Shiu et al, 2006) used various renewable generation data from the CAISO PI System. The data were one-minute averages. A lengthy discussion of the data and the problems they encountered obtaining and using the data are included in their report. Note that since the release of Shiu et al's study, CAISO has been called upon several more times for renewable generation data from PI. With the increased usage of the data, some of the issues identified by Shiu et al have been alleviated.

4.1.2 CAISO PIRP

CAISO administers the Participating Intermittent Resource Program (PIRP), a voluntary program in which intermittent power plants (i.e., solar and wind) are penalized for energy production deviations netted over a month. The deviations are based on forecasts provided by CAISO which, in turn, are partially based on meteorological data from the plant sites. CAISO records and stores the PIRP meteorological data.

Unlike the PI generation data[1], the PIRP data have immediate application with financial consequences. The data therefore have undergone some inspection and CAISO has actively taken steps to ensure their accuracy (Blatchford and Sahib, 2007). Like the PI generation data, the PIRP data are bound from release by confidentiality.

4.1.3 Other CAISO Data Systems

CAISO displays the current amount of wind power generation feeding their control area at http://www.caiso.com/outlook/SystemStatus.html. It is updated every few minutes. Data for the preceding part of the day are shown graphically, but not quantitatively. Peak power generation and the total energy production of wind (and other renewables) of the previous day are reported at http://www.caiso.com/green/renewrpt/DailyRenewablesWatch.pdf.

CAISO also maintains the Open Access Same-time Information System (OASIS) at http://oasis.caiso.com/. OASIS is a publicly accessible system that reports real-time data on load, transmission, and various power and energy markets. OASIS does not contain any generation data, but its datasets may be useful to many grid integration analyses.

4.1.4 Utilities (IOUs and munis)

As the primary purchasers and resellers of bulk electricity, utilities – both the investor-owned utilities (IOUs) and municipal utilities (munis) – track power generation served within their territories. Wind power data is typically stored at relatively coarse sampling intervals – 10-minutes or greater. As these data are used directly for financial accounting, they are maintained at high quality and have been referred to – somewhat facetiously – as "correct by definition". Confidentiality is a significant barrier to accessing the data. Again, confidentiality can be satisfied through data masking.

Shiu et al obtained hourly data from PG&E and SCE, as detailed in their report. Separately, Shiu obtained ten-minute data from SMUD for a study of wind-grid integration (including ramps) and plant performance. Note that SMUD was also the owner of the wind plant studied and the contractee (client/recipient) of the study.

[1] Note that while we distinguish between CAISO's PI generation data and PIRP data, the PIRP data may very well also be stored in the PI System.

4.1.5 Wind Plant Owner/Operators

Owners/operators record and store data on their wind plants through SCADA (supervisory control and data acquisition) systems. Typically, SCADA data include turbine production, met data (including wind speed and direction) from individual nacelle met instruments, and met data from standalone met towers. The data are often little used except for rudimentary energy production calculations and cursory review of fault histories. They are commonly stored at 10-minute or slower intervals.

While some older SCADA systems were subject to a variety of data quality issues, modern systems are generally quite good. The data can be obtained and used only through arrangements with individual wind plant owners/operators.

4.1.6 Wind Plant Developers

Wind plant developers evaluate prospective sites with met towers of, typically, 50 m to 80 m height. The met data include wind speed, wind direction, standard deviation of wind speed (to quantify turbulence), temperature, and pressure (for air density). These parameters are measured at a range of heights and recorded at 10 minute intervals. The met towers are often remotely located and data must be either stored locally on flash cards or telemetered through limited bandwidth links (e.g., satellite). Faster data rates may therefore not be possible.

Developers generally guard their data very carefully, as they are the potential bases for very large investments. Once development for a site commences, the ownership of the data may shift to the plant owner/operator.

4.1.7 California Tall Tower Data

The California Energy Commission is conducting a tall met tower data campaign with a number of sites across the state. The data are intended for regional wind assessment, verification of numerically modeled wind maps, and generally for research to promote wind development in the state. The data recorded are similar to that of wind developers, discussed above. The data will be released to the public shortly.

4.1.8 NOAA and NWS

The National Weather Service (NWS) designed the National Digital Forecast Database (NDFD) to provide access to weather forecasts in digital form from a central location. As the foundation of the NWS Digital Services Program, NDFD consists of gridded forecasts of sensible weather elements (e. g., cloud cover, maximum temperature). NDFD contains a seamless mosaic of digital forecasts from NWS field offices working in collaboration with the National Centers for Environmental Prediction (NCEP). Currently, the NDFD contains data representing the following weather: 12-hour probability of precipitation, apparent temperature, dew point, hazards, maximum and minimum temperatures, quantitative precipitation amount, significant wave height, sky cover, snow amount, temperature, weather, wind direction, and wind speed. More elements will be added as development of the NDFD progresses.

NDFD data are available for projections at the following Coordinated Universal Times (UTC): 0000, 0300, 0600, 0900, 1200, 1500, 1800, and 2100. The elements in NDFD are available for the Contiguous United States (CONUS). A subset of NDFD elements is available for Puerto Rico/the Virgin Islands, Hawaii, Guam, and Alaska. Grids for the CONUS are currently available from NDFD at 5 km spatial resolution.

The spatial resolution for the grids for Hawaii and Guam is 2.5 km; for Puerto Rico/the Virgin Islands is 1.25 km; for Alaska, 6 km. For the North Pacific Ocean Domain the spatial resolution is 10 km. NWS plans to increase both spatial and temporal resolution in the future.

4.1.9 California Data Exchange Center (CDEC)

The California Data Exchange Center (CDEC) is not a single wind data source, but a centralized access point to a large number of public hydrological and meteorological datasets for California. CDEC is maintained by the Department of Water Resources and can be accessed at http://cdec.water.ca.gov/. It contains data from over a thousand remote stations and exchanges data with numerous federal and state agencies including the National Weather Service. However, note that much of the CDEC data is hydrological, not meteorological.

The wind data in CDEC are intended for applications such as fire management and general weather monitoring, not wind power analysis. In general, the anemometers feeding CDEC are at low heights and may be obstructed. Data should not be used without first surveying the source sensor installation. Seitzler [Seitzler, 2009] discuss the use of CDEC data for wind power applications and survey a number of sensors across California.

4.1.10 California Irrigation Management Information System (CIMIS)

The California Irrigation Management Information System (CIMIS) is a network of over 120 meteorological stations across the state. It is managed by the Department of Water Resources and its data are openly available at http://wwwcimis.water.ca.gov/. Wind and insolation data are recorded.

CIMIS anemometers are at a height of only two meters. While appropriate for irrigation management, the short height limits its utility for wind power analysis.

5 Recommendations

5.1 Best Practices in Forecasting

5.1.1 Well Defined Objectives

It is important for the forecast clients to consider factors such as how a wind power forecast will be used and what aspects of wind power a forecast should focus on. For example, the models trained to provide a low long term average error may not be suitable for short term system operations if the forecast methodology hedges against ramps or extremes, as shown in Figure 8. It has been demonstrated that without this focus, the nature of forecast error may be too broad for one single forecast to be optimal for multiple purposes such as real time operations, transmission scheduling and ancillary service forecasting (Industry Work Group, 2008).

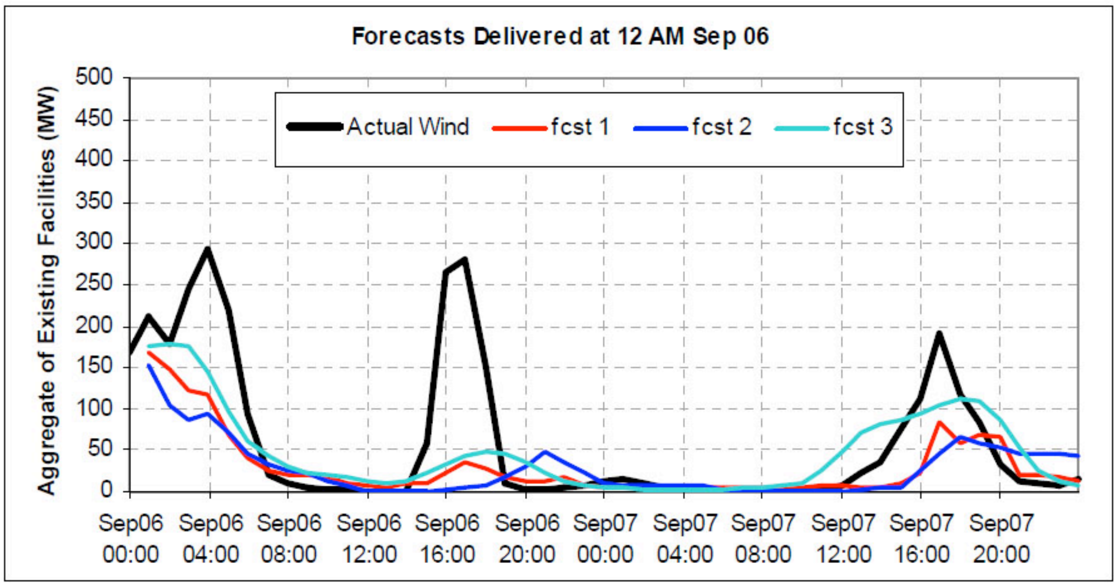

Figure 8. Forecasting models trained to have low average errors missed ramps on the afternoon of September 6, 2007 (from Industry Work Group, 2008).

5.1.2 Improve Data Quality

Forecasts rely on high quality data made available in a timely manner to the forecast providers for use within their models. Most stakeholders that we have talked with and literatures that we have reviewed emphasize the importance of high quality data to successful wind energy forecasting. Refer to Section 5.2 for more details.

5.1.3 Power Conversion

Research has shown that it is more accurate to use the power curve derived from measured data than to use the power curve provided by the turbine manufacturer. Garcia-Bustamante (Garcia-Bustamante et al, 2009) examined the effects of different power conversion models on estimated monthly energy output. Figure 9 shows the estimation of monthly energy output for five wind farms in Spain using three different power conversion models: Theoretical Power Curve (TPC), Average Power Curve (APC), and Polynomial Fit Curve (PFC). The TPC is the same as the manufacturer's power curve. The APC and PFC were power curves derived from measured wind and power data using two different methods. It can be seen that the TPC generally underestimates the power generated at the lower wind speeds whereas it tends to overestimate it for the higher wind speeds. A global overestimation of the final energy output should be expected from the TPC model. The APC and PFC are very similar and their estimations are very close to the measured energy output.

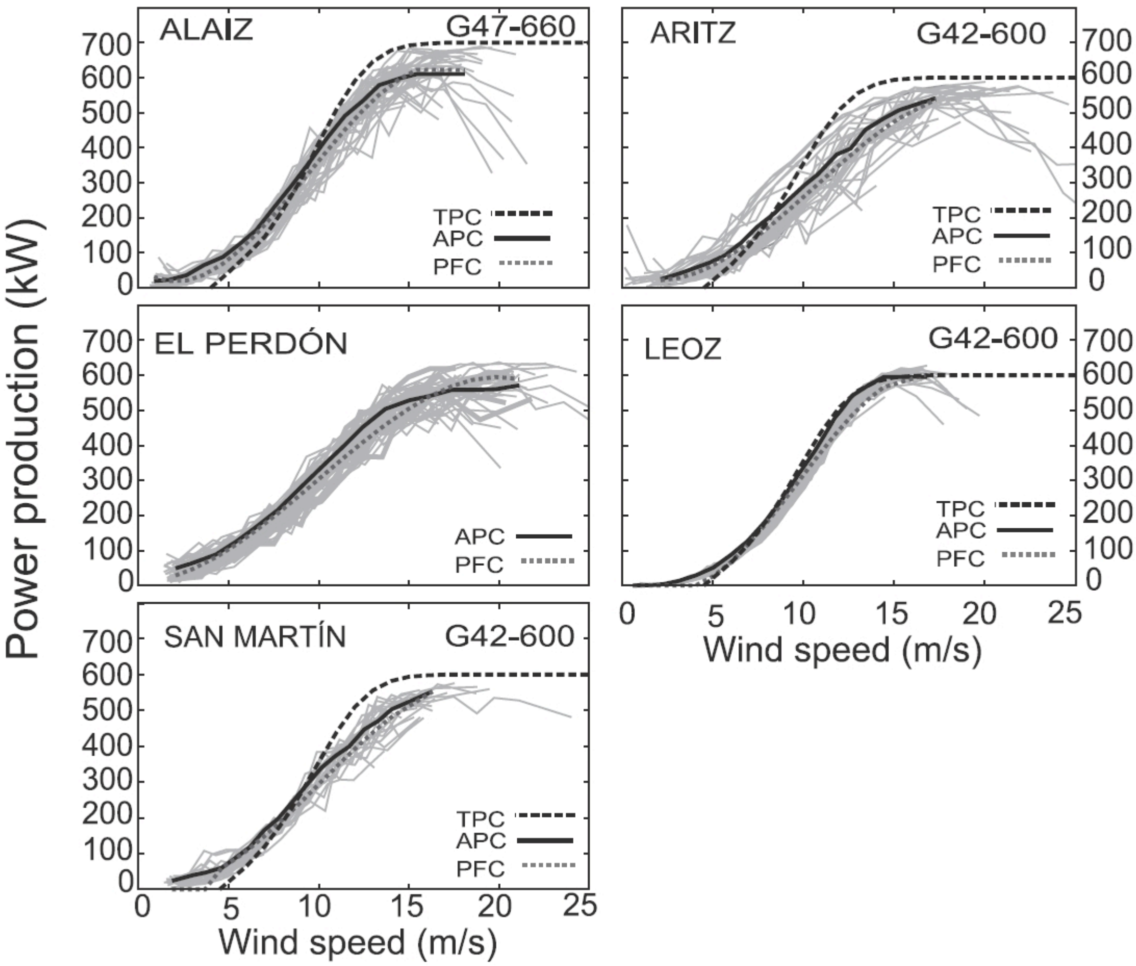

Figure 9. Estimation of monthly energy output for five wind farms in Spain using three different power conversion models: Theoretical Power Curve (TPC, dashed line), Average Power Conversion (APC, solid line), and Polynomial Fit Curve (PFC, points) (from Garcia-Bustamante et al, 2009).

5.1.4 Learning by Doing

Forecast experience matters. As many research and project indicated, knowledge of the wind regimes and the regime-specific forecast model error patterns can often result in better forecast performance. Thus there is no substitute for learning by doing.

5.1.5 Collaboration with NWS, NOAA, and NCAR to Improve NWP Models

The National Weather Service (NWS) and National Oceanographic and Atmospheric Administration (NOAA) provide the numerical weather prediction (NWP) models tuned to providing temperature and rain forecasts for the entire US. These models are the baseline inputs to the forecasters' wind and solar predictions. Balancing authorities that are integrating intermittent renewable resources should coordinate efforts to tailor models for wind and solar forecasting.

There have been continuous efforts to improve NWP models used in wind and solar forecasting. For example, significant numerical model development is conducted at the National Center for Atmospheric Research (NCAR) with contributions from the research community. NCAR tests new model capabilities for NWS/NOAA before they become operational enhancements. It is recommended to collaborate with NWS, NOAA, and NCAR on improving current NWP models and developing higher-resolution NWP models to improve wind power forecast accuracy.

5.2 Data

5.2.1 Data Impacts on Forecasts

Most stakeholders that we have talked with and literatures that we have reviewed emphasize the importance of high quality data to successful wind energy forecasting. For example, to meet their increasing needs for real-time meteorological data, SCE and AWS Truewind worked together to put up 12 new meteorological stations in SCE's service areas (6 in Palm Springs and 6 in Tehachapi) since 2002. The real-time meteorological data (wind speed, wind direction, temperature, pressure, etc.) measured from these 12 met towers have been used as input to AWS Truewind's eWind forecasting system since then.

Blatchford and de Mello pointed out in the CAISO's report that the data quality from the wind sites including the meteorological, megawatt production, and megawatt availability impacts the forecast quality. Figure 10 shows how the hour ahead forecast root mean square error (RMSE) is impacted when the real-time megawatt production telemetry is improperly reporting. For all forecast providers the forecast error during periods of errant data is significantly higher than under normal circumstances.

5.2.2 Data Validation and Filtering

To obtain high quality data, it is recommended that dataset providers and forecast service providers work closely to create well-defined data formats, establish reliable, secure, and fast data transmission methods, and apply QA/QC measures to the data. The recommended QA/QC measures include:

- Reviewing instruments orientation and calibration reports and correcting the data accordingly when necessary.
- Flagging data with abnormal wind speeds or power and/or standard deviations and filtering them out if they fall outside of a certain range.
- Screening the data for icing events or any other anomalies that may have not been caught in the screening-out criteria and filtering them out.
- Comparing wind speed data from different anemometer levels and from adjacent sites looking for discrepancies that are then filtered when necessary.
- Other site specific QA/QC procedures.

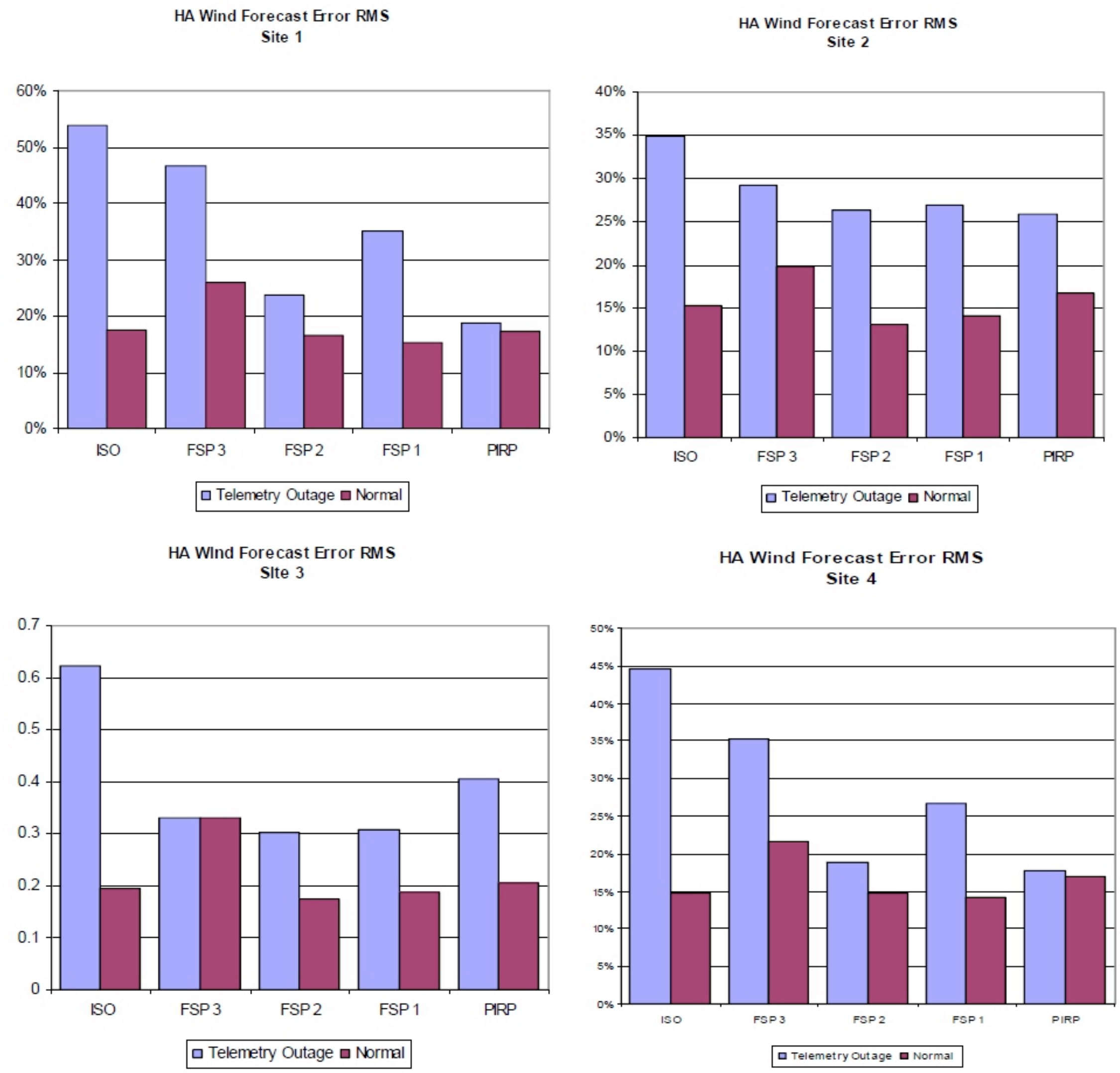

Figure 10. Impact of data quality on forecasts (from Blatchford and de Mello, 2009).

5.3 Future Research

5.3.1 Data Acquisition and Transmission

Although it is well recognized that more sensors are needed in order to obtain more real-time data, many questions remain. These questions to be addressed in future research:

- What are current and emerging technologies for meteorological measurements? What are their advantages/disadvantages?
- How many met towers/sensors are needed for a single wind farm?
- Where should new met towers/sensors in a wind farm be placed? What are the impacts of terrain topology on the forecast accuracy?
- How high should the new met towers be?
- How does the sampling frequency affect forecast results?

- How to securely, reliably and promptly transmit measured data? What protocols and formats should be used for data transmission?

5.3.2 Sources of Error

While the magnitude of the errors associated with forecasting is now well understood, the source of these errors is mostly unknown. Possible sources include NWP model output, meteorological tower location, anemometer sensors, wind power conversion models, turbine availability data, etc. If the sources of the errors can be determined, this information can focus effort to improve accuracy.

5.3.3 Ramp Rate Forecasting

Most wind energy prediction systems have focused on next day optimization. Research is needed to fully assess the best techniques or combination of techniques (for example, blending of rapid cycle NWP with statistical techniques) needed to fully address ramp events.

It is also important to define the aspects of ramping that have the highest priority such as ramp time start, ramp rate or magnitude. The CAISO and other system operators should work with forecasters to determine how to ask for and evaluate ramp rate forecasting.

5.3.4 Improving Icing Forecasts

Turbine icing is likely not a problem in California. However, in northern states where temperatures can drop below freezing point in winter, icing on wind turbines can dramatically affect their efficiency. Improved understanding of turbine icing is critical for the accurate prediction of wind energy.

A great deal of icing research and development has been performed over decades for aircraft icing and other structural icing. These capabilities should be analyzed to determine their applicability for turbine icing.

5.3.5 New Technologies

The authors recommend future research on new technologies in meteorological measurements, such as vertical RADAR and LIDAR.

Light Detection and Ranging (LIDAR) is an active remote sensing technology that measures properties of scattered light to find range and/or other information of a distant target. The major advantages of LIDAR over the traditional cup anemometers include: 1) LIDAR is a remote sensing technology, meaning LIDAR devices can be setup, operated and maintained at the ground level, and 2) LIDAR is capable of in-plane scanning, meaning it can measure wind speed and direction in a plane while cup anemometers can only measure wind speed at a point. The major disadvantage of LIDAR is its cost. LIDAR holds promise for detection and forecasting ramp events but more research is needed to prove this concept.

Several companies develop wind sensing devices based on LIDAR technology. British company QinetiQ has developed ZephIR LIDAR wind profiler, which is capable of measuring wind speed, wind direction, and turbulence for heights ranging from 10 m ~ 200 m. US company Catch the Wind Inc. also developed Vindicator Wind Sensor System based on LIDAR technology.

5.3.6 Atmospheric Boundary Layer Profiles

The authors recommend future research related to atmospheric boundary layer profiles. A boundary layer profile is the vertical distribution of wind velocity at a given location. It is affected by the surface roughness, temperature, turbulence, and many other factors.

The boundary layer profiles influence both the power production and the mechanical loads on the wind turbines. Knowledge of the wind characteristics across the blade span has a big impact on turbine efficiency (hence power production). The lack of a precise knowledge of atmospheric boundary layer profiles has negative impacts on the NWP models, especially in the downscaling step, resulting in less accurate forecasts.

References

[1] 3Tier Inc., "Wind Products – Operations and Optimization", 3Tier Website (http://www.3tier.com/en/products/wind/)

[2] AWS Truewind Inc., "Final Report for the Alberta Forecasting Pilot Project", Alberta Pilot Project, June 2008

[3] Blatchford, J., Harmon, D., and Sahib, R., "PIRP Data Transfer Analysis and Recommendations for the CAISO", September, 2007

[4] Blatchford, J. and de Mello, P., "Analysis of June 2008 – June 2009 Forecast Service Provider RFB Performance", California ISO Report, August 2009

[5] Blatchford, J., personal communication, 2010

[6] Cutler, N. J., Outhred, H. R., MacGill, I. F., and Kay, M. J., "Characterizing Future Large, Rapid Changes in Aggregated Wind Power using Numerical Weather Prediction Spatial Fields", Wind Energy, Vol. 12, 2009

[7] Durstewitz, M., Ensslin, C., Hahn, B., Hopper-Kipper, M., "Annual Evaluation of the Scientific Measurement and Evaluation Programme (WMEP)", Kassel, 2001

[8] Focken, U. and Lange, M., "Final Report: Wind Power Forecasting Pilot Project in Alberta, Canada", May 2008

[9] Gamesa, "Gamesa Launches an Online Weather Forecasting Service for Wind Farms", Gamesa Press Release, 2010

[10] Garcia-Bustamante, E., Gonzalez-Rouco, J. F., Jimenez, P. A., and etc., "A Comparison of Methodologies for Monthly Wind Energy Estimation", Wind Energy, Vol. 12, 2009

[11] Giebel, G, "On the Benefits of Distributed Generation of Wind Energy in Europe", Ph. D. Thesis from the Carl von Ossietzky Universität, VDI Verlag 2001

[12] Giebel, G., "The State-Of-The-Art in Short-Term Prediction of Wind Power – A Literature Overview", Project ANEMOS, 2003

[13] Gilman, B., personal communication, 2010

[14] Gow, G., "An Adaptive Approach to Short-Term Wind Forecasting", AWEA 2003

[15] Greaves, B., Collines, J., Parkes, J., and Tindal, A, "Temporal Forecast Uncertainty for Ramp Events", EWEC2009

[16] Industry Word Group, "Wind Power Forecasting Pilot Project", Alberta Pilot Project, 2008

[17] Jorgensen, J. U. and Mohrlen, C., "AESO Wind Power Forecasting Pilot Project Final Project Report", May 2008

[18] Kariniotakis, G., Position Paper on JOULE Project, JOR3-CT96-0119, 1997

[19] Klingler, A., personal communication, 2010

[20] Kusiak, A., Zheng, H., and Song, Z., "Wind Farm Power Prediction: A Data-Mining Approach", Wind energy, Vol. 12, 2009

[21] Landberg, L. and Watson, S. J., "Short-Term Prediction of Local Wind Conditions", Boundary Layer Meteorology, 1994

[22] Lerner, J. and Garvert, M., "The Role and Importance Forecasting Plays for Wind Power Industry", RMEL Electric Energy, Spring 2009

[23] Mahoney, B., personal communication, 2010

[24] McKay, D. C., "Wind Power Forecasting Pilot Project Part B: The Quantitative Analysis Final Report", Alberta Pilot Project, August 2008

[25] Monteiro, C., Bessa, R., Miranda, V., Botterud, A., Wang, J., and Conzelmann, G., "A Quick Guide to Wind Power Forecasting: State-of-the-Art 2009", ANL/DIS-10-2, November, 2009

[26] NERC, "Accommodating High Levels of Variable Generation", North American Electric Reliability Corporation Report, 2009

[27] Parkes, J. and Tindal, A., "Forecasting Short-Term Wind Farm Production in Complex Terrain", EWEC 2004

[28] Porter, K. and Rogers, J., "Status of Centralized Wind Power Forecasting in North America", NREL Report, NREL/SR-550-47853, 2010

[29[Seitzler, M. and Jackson, K., "Assessment of Selected Stations from the CDEC Database for Renewable Energy," CWEC report, 2009 (in print).

[30] Shiu, H., Milligan, M., Kirby, B., and Jackson, K., "California Renewables Portfolio Standard Renewable Generation Integration Cost Analysis", CEC-500-2006-024, March, 2006

[31] Sivillo, J., Ahlquist, J., and Toth, Z., "An Ensemble Forecasting Primer", Weather and Forecasting, Vol. 12, No. 4, December, 1997

[32] Tran, K., "Development and Testing of a Wind Energy Forecasting System", AMI Environmental Inc. publication, 2004

[33] University Corporation for Atmospheric Research, "Operational Models Matrix: Characteristics of NWP and Related Forecast Models", UCAR Website (http://www.meted.ucar.edu/nwp/pcu2/index.htm)

[34] US Department of Energy, "20% Wind Energy by 2030", DOE Report, 2008

[35] WindLogics, "Renewable Energy Research and Development Project (RD-57) – Final Report", October, 2008

[36] Zack, J., Bailey, B., and Brower, M., "Wind Energy Forecasting: The Economic Benefits of Accuracy", AWS Truewind Report, 2006

[37] Zack, J. W., "Optimization of Wind Power Production Forecast Performance during Critical Periods for Grid Management", EWEC 2007

Glossary

AESO	Alberta Electric System Operator
ANN	Artificial Neural Network
AWPPS	ARMINES Wind Power Prediction System
CAISO	California Independent System Operator
CDEC	California Data Exchange Center
CFD	Computational Fluid Dynamics
CIMIS	California Irrigation Management Information System
COAMPS	Coupled Ocean/Atmosphere Mesoscale Prediction System
CONUS	Contiguous United States
CSI	Critical Success Index
CWEC	California Wind Energy Collaborative
DA	Day Ahead (Forecast)
DICast	Dynamic Integrated Forecast System
EIA	Energy Information Administration
ERCOT	Electric Reliability Council of Texas
GDAS	Global Data Assimilation System
GEM	Global Environmental Multiscale
GFS	Global Forecast System
GSI	Gridpoint Statistical Interpolation
HA	Hour Ahead (Forecast)
IESO	Ontario Independent Electric System Operator
IOU	Investor-Owned Utility
ISET	Kassel Institute für Solare Energieversorgungstechnik
IWES	Fraunhofer Institute for Wind Energy and Energy System Technology
LIDAR	Light Detection and Ranging
LMP	Locational Marginal Price
LSF	Least Square Fit
MAE	Mean Absolute Error
MASS	Mesoscale Atmospheric Simulation System
Mesoscale	A term used in meteorology to describe weather systems with a scale between the storm scale and the synoptic scale. Horizontal dimensions generally range from around 5 km to 1,000 km.

Microscale	A term used in meteorology to describe weather systems with a scale smaller than mesoscale. Horizontal dimensions are about 1 km or less.
MISO	Midwest Independent System Operator
MM5	Mesoscale Model Version 5
MSEPS	Multi-Scheme Ensemble Prediction System
MOS	Model Output Statistics
MSEPS	Multi-Scheme Ensemble Prediction System
NAM	North American Model
NCAR	National Center for Atmospheric Research
NCEP	National Centers for Environmental Prediction
NDFD	National Digital Forecast Database
NMC	National Meteorological Center
NOAA	National Oceanographic and Atmospheric Administration
NOGAPS	Navy Operational Global Prediction System
NWP	Numerical Weather Prediction
NWS	National Weather Service
NYISO	New York Independent System Operator
OASIS	Open Access Same-time Information System
PG&E	Pacific Gas and Electric Company
PIRP	Participating Intermittent Resource Program
PJM	Pennsylvania-Jersey-Maryland Interconnection
RADAR	Radio Detection and Ranging
RLS	Recursive Least Square
RMSE	Root-Mean Square Error
RTFDDA	Real-Time Four-Dimensional Data Assimilation
RUC	Rapid Update Cycle
SCADA	Supervisory Control and Data Acquisition
SCE	Southern California Edison
SMLR	Screening Multiple Linear Regression
SMUD	Sacramento Municipal Utility District
SVM	Support Vector Machine
UCAR	University Corporation for Atmospheric Research
VDRAS	Variational Doppler RADAR/LIDAR Data Assimilation System
WEPROG	Weather and Wind Energy PROGnosis (Danish Company)
WPF	Wind Power Forecasting
WPMS	Wind Power Management System

WRF	Weather Research and Forecasting

Appendix A: Numerical Weather Prediction Models

Numerical Weather Prediction (NWP) models are complex computer programs that use current weather conditions as input into mathematical models of the atmosphere to produce meteorological information for future times at given positions and altitudes. The horizontal domain of a model is either *global*, covering the entire Earth, or *regional*, covering only part of the Earth. Regional models are also known as *limited-area* models.

The mathematical equations that NWP models use are nonlinear and are impossible to solve exactly. Therefore, numerical methods obtain approximate solutions. Different models use different solution methods. Some global models use spectral methods for the horizontal dimensions and finite difference methods for the vertical dimension, while other global models and regional models usually use finite difference methods in all three dimensions.

This appendix gives an introduction to major NWP models as well as a matrix that compares these models side by side. For more in-depth information, please refer to the NWP models page on UCAR's website.

A.1 Introduction to Major NWP Models

- Eta/NAM

  The Eta model is a grid point type regional model. Its horizontal resolution is 12 km and its vertical resolution is 60 layers. The Eta model was developed by Yugoslavian Zavisa Janjic and Fedor Mesinger in the 1970s for numerical weather prediction and a version became operational in Yugoslavia in 1978. In the mid-1980s, both modelers arrived at the National meteorological Center (now NCEP), where Janjic developed the core physics parameterizations. Further development has been a team effort involving numerous scientists, primarily at NCEP.

  The ETA model took on its new name as the North American Mesoscale (NAM) model in January 2005 with no model change at that time.

- GFS

  GFS stands for the Global Forecast System. The predecessor to the GFS was developed experimentally during the late 1970s and implemented as the global forecast model at the National Meteorological Center (NMC, now NCEP) in 1981. Since then, the GFS model has undergone a few major upgrades.

  Currently, the GFS is run four times a day (00 UTC, 06 UTC, 12 UTC, and 18 UTC) out to 384 hours. The initial forecast resolution was changed on May 31, 2005 to T574 (equivalent to about 27-km grid point resolution) with 64 levels out to 8 days. At later forecast times, the GFS has a resolution of T190 (equivalent to about 80-km resolution) and 64 levels beyond to day 16. All GFS runs get their initial conditions from the Gridpoint Statistical Interpolation (GSI) global data assimilation system (GDAS) as of May 1, 2007, which is updated continuously throughout the day.

- RUC

The Rapid Update Cycle (RUC) is an operational atmospheric prediction system that consists primarily of a numerical forecast model and an analysis system to initialize the model. The RUC was designed to provide accurate short-range (0- to 12-hour) numerical forecast guidance for weather-sensitive users. The RUC runs at the highest frequency of any forecast model at the National Centers for Environmental Prediction (NCEP), assimilating recent observations to provide very high frequency updates of current conditions and short-range forecasts.

The RUC is primarily used for 1) making short-range forecasts; 2) monitoring current conditions with hourly analyses; and 3) evaluating trends of longer-range models.

- MM5

The MM5 (Mesoscale Model, Version 5) is the fifth-generation mesoscale model developed by the National Center for Atmospheric Research (NCAR) and the Pennsylvania State University. The original version was built in the 1970s and has undergone improvements to evolve into the MM5 used today.

The MM5 is similar to other grid point models, such as Eta. However, there are two major differences: 1) since the MM5 is a mesoscale model, it runs at a finer resolution than most other models. Therefore, its output better depicts mesoscale features than regional models and global models; 2) The MM5 is a non-hydrostatic model, which means that it includes a prognostic equation for vertical motion. This enables it to directly include buoyancy processes and dynamic pressure perturbations.

The MM5 is the Air Force's fine-scale meteorological model of choice.

- NOGAPS

The NOGAPS (Navy Operational Global Prediction System) forecast model is a global model that is spectral in the horizontal and energy-conserving finite difference (sigma coordinate) in the vertical. The model top pressure is set at 1 hPa; however, the first velocity and temperature level is approximately 4 hPa. The variables used in dynamic formulations are vorticity and divergence, virtual potential temperature, specific humidity, surface pressure, skin temperature, and ground wetness.

In September 2002, NOGAPS 4.0 was increased in resolution from T159L24 to T259L30, an increase in equivalent grid point resolution from 0.75 to 0.5 degrees.

- COAMPS

The COAMPS (Coupled Ocean/Atmosphere Mesoscale Prediction System) forecast model is a non-hydrostatic regional model uses gridpoints in the horizontal and a terrain-following coordinate (sigma-Z) in the vertical. The model top height is set at 31.50 km (approximately 10 hPa).

In August, 2001, COAMPS was upgraded to version 3.0. The primary change was an increase in the number of vertical levels from 18 to 24. When COAMPS was further upgraded to version 3.1, the number of model levels was increase to 30.

The operational COAMPS 3.1 is run in nine different regions, usually with an 81-km outer nest and a 27-km inner nest (sometimes a third 9-km inner nest), except for SW Asia region, where triple nesting from 54-km to 18-km to 6-km is performed. The boundary conditions to the outer nest are provided by the global NOGAPS model, interpolated to COAMPS vertical resolution.

- GEM Regional/GEM Global

  GEM is an acronym that stands for Global Environmental Multiscale. GEM Regional is a short-range forecast model. It produces 48-hour forecasts twice daily (from 00 UTC and 12 UTC data). The model uses a 3D finite difference on an Arakawa-C staggered grid in the horizontal, and on an Arakawa-A grid in the vertical. The GEM regional model contains a high-resolution core covering North America and adjacent oceanic areas. The model executes on a 575x641 variable-resolution latitude-longitude global grid, of which 432x565 grid points are found in the uniform-resolution core.

  GEM global is a grid point model having uniform resolution in latitude (0.30 degree) and in longitude (0.45 degree). This mesh can be modified so that the resolution becomes variable in both directions. GEM global is a medium-range forecast model. It produces 240-hour forecasts at 00 UTC and 144-hour forecasts at 12 UTC.

The characteristics of the major operational NWP models can be found in Table A1.

Table A1. Major NWP Models - Model Structure and Dynamics

Module	Model Type	Vertical Coordinate System	Horizontal Resolution	Vertical Resolution	Domain
new NAM (WRF-NMM)	Grid Point, Non-Hydrostatic	Sigma-pressure hybrid	12 km	60 Layers	Regional
NAM (Eta)	Grid point	Eta	12 km	60 Layers	Regional
GFS	Spectral	Sigma-pressure hybrid	T574	64 Layers	Global
RUC	Grid Point	Hybrid Isentropic-Sigma	13 km	50 Layers	Regional
AFWA MM5	Grid Point	Non-hydrostatic Sigma	45 km, 15 km, and 5 km	42 Layers	Mesoscale
NOGAPS	Spectral	Hybrid Sigma/Pressure	T239, Physics, 55 km	30 Layers	Global
COAMPS	Grid Point, Non-Hydrostatic	Terrain-following Sigma	81 km (outer nest), 27 km (inner nest)	30 Levels	Regional
GEM Regional	Variable Resolution Grid Point	Generalized Sigma	15 km Regional Grid	58 Levels	Regional
GEM Global	Global Grid Point	Generalized Sigma		58 Levels	Global
ECMWF	Spectral, Semi-Lagrangian	Hybrid sigma-pressure	T1279	91 Layers	Global