Arnold Schwarzenegger
Governor

# CALIFORNIA REGIONAL WIND ENERGY FORECASTING SYSTEM DEVELOPMENT VOLUME 1: EXECUTIVE SUMMARY

PIER FINAL PROJECT REPORT

*Prepared For:*

**California Energy Commission**

Public Interest Energy Research Program

*Prepared By:*

***Electric Power Research Institute, Inc.***

ELECTRIC POWER RESEARCH INSTITUTE

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# EXECUTIVE SUMMARY

The rated capacity of wind generation in California is expected to grow rapidly in the future beyond the approximately 2100 megawatts (MW) in place at the end of 2005. The main drivers are the state's 20 percent Renewable Portfolio Standard requirement in 2010 and the low cost of wind energy relative to other renewable energy sources.

As wind is an intermittent generation resource and weather changes can cause large and rapid changes in output, system operators will need accurate and robust wind energy forecasting systems in the future. In response to this need, the California Energy Commission (Energy Commission) and the Electric Power Research Institute (EPRI) initiated the California Regional Wind Energy Forecasting System Development Project in 2003 to develop and test short- and intermediate-term (for example, next-hour and next-day) forecast algorithms with improved forecast accuracy relative to the results of a previous project completed in 2002.

Volume 1 of the final report is an executive summary of the research and results. It addresses development and testing of same-day and next-day wind forecasting algorithms, wind tunnel and empirical modeling of wind flow over the complex terrain at Altamont Pass, and development of the California Wind Generation Research Dataset (CARD). Volumes 2 through 4 present the detailed results.

## Results and Findings

The short-term forecast research developed and tested an artificial neural network (ANN) algorithm to generate five-minute/three-hour regional wind energy generation forecasts for the four largest California wind resource areas, updated every five minutes. The mean absolute errors of the ANN forecasts were lower than those of a simple persistence forecast algorithm after the first 15 to 20 minutes of the three-hour forecast time horizon.

The intermediate-term forecast research initially screened several forecast algorithm improvements to identify those that would yield the greatest reduction of mean absolute forecast error vs. the previous forecasting evaluation at the Altamont and San Gorgonio projects, completed in 2002. Relative to the previous California project, the mean absolute error of the wind energy forecasts decreased from 14.1percent to 11.9percent of rated capacity at Altamont and from 16.6percent to 13.0percent at San Gorgonio. The improved forecast algorithm was then tested at five wind projects in California.

Wind tunnel and numerical modeling of wind flow over the complex terrain at Altamont Pass showed significant variations of wind speeds and directions both between individual wind turbines and between the wind turbines and nearby meteorological towers (met tower). In addition, atmospheric stability appears to significantly affect the wind plant power curve, for example the relationship between the power output of a group of wind turbines and the wind speed measured at the met tower.

The California Wind Generation Research Dataset (CARD) provides one year of wind speed, direction, power density, and other parameters at multiple elevations over two 5-km grids, one in Northern California and one in Southern California. The database was generated using numerical weather data and a meso-scale weather model for the period July 1, 2004, through June 30, 2005.

## Challenges and Objectives

Electricity systems with significant intermittent wind capacity create a challenge to the system operator. Rapid changes of wind generation relative to load require rapid dispatching of generation and transmission resources to balance generation vs. load, regulate voltage and frequency, and maintain system performance within limits established by Control Performance Standards 1 and 2 (CPS1 and CPS2). This is especially true during periods when wind generation is fluctuating rapidly relative to system load, for example during passage of thunderstorms and weather fronts. Wind energy forecasts can help the system operator anticipate rapid changes of wind energy generation vs. load and make informed decisions. The objectives are to develop and demonstrate the capabilities of wind energy forecasting technology for both same-day and longer-term forecasts.

## Applications, Values, and Use

The improved wind energy forecasting algorithms developed in this project have already been incorporated into regional wind energy forecasting systems in California that generate daily forecasts for several wind projects in the state and for a large utility company. The results also provide the basis for collaborating with electricity grid operators to customize wind energy forecast system content, format, and method of delivery to meet the needs of the system operator, while continuing to develop and test further algorithm improvements.

## EPRI Perspective

Volume 1 of the final report from the California Regional Wind Energy Forecasting Development project provides an executive summary of the detailed research and results presented in Volumes 2 through 4. The topics addressed include the short-term and intermediate-term wind energy forecasting system development and testing and numerical modeling of wind flow over complex terrain (Volume 2), wind tunnel modeling of wind flow over complex terrain (Volume 3), and development of the California Wind Generation Research Dataset (CARD) (Volume 4). The results presented in this report and the companion volumes represent significant advances in both short-term and intermediate-term wind energy forecasting technology. It is anticipated that further improvements in forecast accuracy are possible by such measures as applying the full two-stage short-term forecast algorithm developed in the project, optimizing the use of real-time wind speed and direction data from upwind met towers, and ensemble forecasting. These improvements can be developed and tested in parallel with a field demo project to develop a wind forecast display for utility and system operators.

## Approach

Researchers developed and tested improved wind energy forecasting technology for both the next-hour and next-day time frames and for both wind resource areas and individual wind plants; conducted wind tunnel and numerical modeling of wind flow over complex terrain; and developed the California Wind Generation Research Dataset (CARD) to provide a resource for future study of wind energy generation and forecasting in California. In each case, real-time and historical wind resource and energy generation data were collected and used to train and then test the forecast system performance. The forecast performance metric was the mean and mean absolute error of the forecasts vs. the observed data for each case.

# ABSTRACT

The rated capacity of wind generation in California is expected to grow rapidly in the future beyond the approximately 2100 megawatts in place at the end of 2005. The main drivers are the state's 20 percent Renewable Portfolio Standard Requirement in 2010 and the low cost of wind energy relative to other renewable energy sources.

As wind is an intermittent generation resource and weather changes can cause large and rapid changes in output, system operators will need accurate and robust wind energy forecasting systems in the future. In response to this need, the California Energy Commission (Energy Commission) and Electric Power Research Institute (EPRI) initiated the California Regional Wind Energy Forecasting System Development Project in 2003 to develop and test short- and intermediate-term (for example next-hour and next-day) forecast algorithms with improved forecast accuracy relative to the results of a previous project completed in 2002.

Volume 1 of the final report is an executive summary of the research and results. It addresses development and testing of same-day and next-day wind forecasting algorithms, wind tunnel and empirical modeling of wind flow over the complex terrain at Altamont Pass, and development of the California Wind Generation Research Dataset (CARD). Volumes 2 through 4 present the detailed results.

The short-term forecast algorithm used an artificial neural network (ANN) algorithm trained using five-minute time series data for wind energy deliveries to the grid in each of the five wind resource regions, provided by the CA ISO. Testing showed the ANN forecast algorithm reduces forecast error vs. persistence. Further testing of the algorithm is needed to assess the impact of adding real-time wind speed and direction data and rapid-update weather forecast data to the inputs to the ANN forecast algorithm on forecast performance.

Development of the intermediate-term forecast algorithm assessed the impacts of several algorithm changes on forecast performance relative to the results of the first California forecasting project completed in 2002. Of the five changes tested, using improved water surface temperature data, segmented wind plant power curves, more sophisticated model operating statistics (MOS), and ensemble forecasting gave the greatest improvement.

Wind tunnel and numerical modeling of wind flow over the complex terrain at Altamont Pass showed significant variations of wind speeds and directions both between individual wind turbines and between the wind turbines and nearby meteorological towers. In addition, atmospheric stability appears to significantly affect the wind plant power curve, for example the relationship between the power output of a group of wind turbines and the wind speed measured at the meteorological tower.

The California Wind Generation Research Dataset (CARD) provides one year of wind speed, direction, power density, and other parameters at multiple elevations over two 5-km grids, one in Northern California and one in Southern California. The database was generated using numerical weather data and a meso-scale weather model for the period July 1, 2004, through June 30, 2005.

**Keywords**
Wind, Power generation, Wind energy forecasting, Meso-scale weather models, Artificial neural networks, Screening multiple linear regression

# ACKNOWLEDGEMENTS

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# 1
# INTRODUCTION

California has good potential for developing new wind generation capacity beyond the approximately 2100 MW of rated capacity in place at the end of 2005 (American Wind Energy Association, 2006). California's Renewables Portfolio Standard, which calls for 20% renewables in the generation mix by the end of 2010, is expected to result in a large increase of the installed wind capacity in the state. Most of the current capacity is located in the five principal wind resource areas of the state (Solano, Altamont, Pacheco, Tehachapi, and San Gorgonio), shown in Figure 1-1. The new capacity is expected to be installed in these and other promising California wind resource areas in northern and southern California.

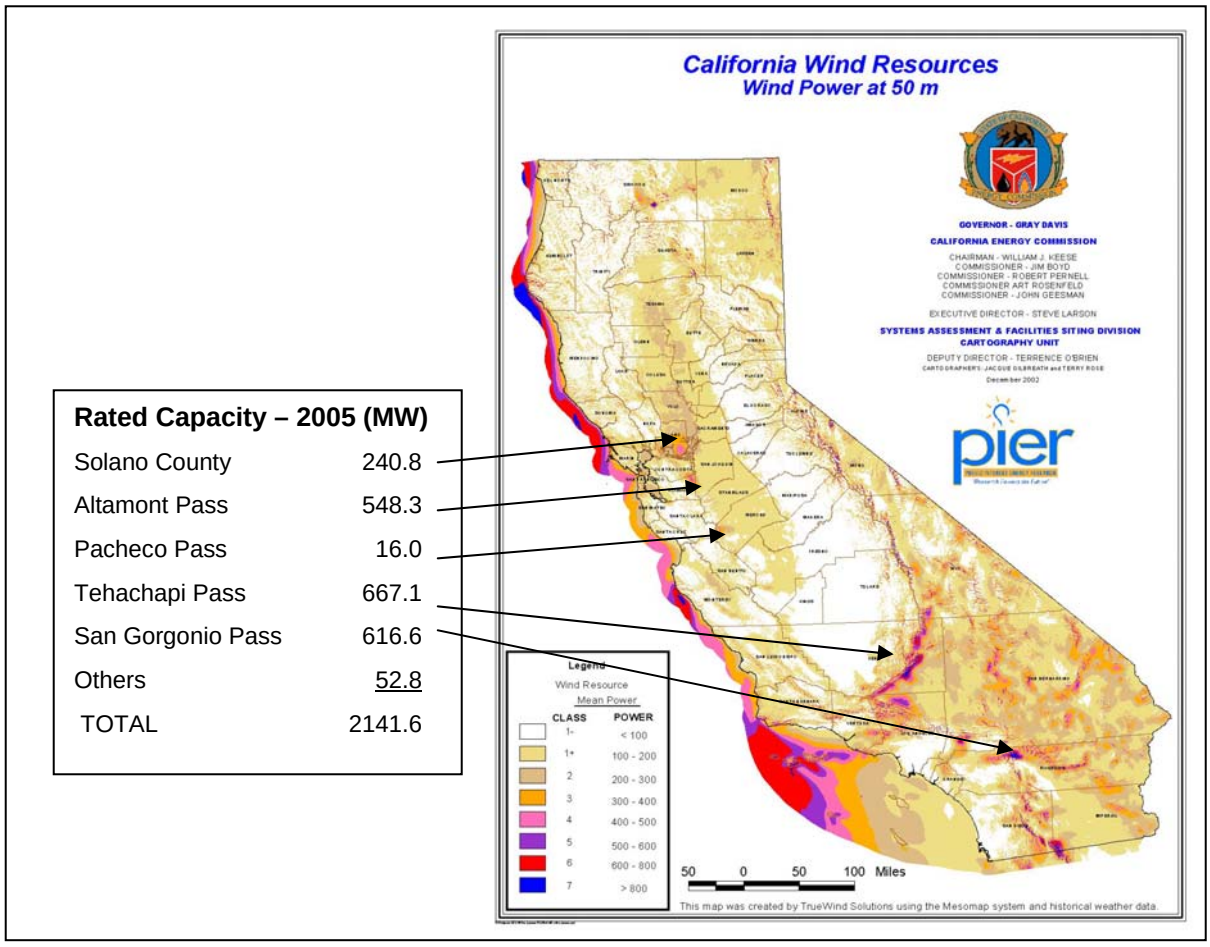


**Figure 1-1 California Mean Wind Power Map at 50-m Elevation and 2005 Rated Capacity of Wind Generation at Principal Wind Resource Areas (California Energy Commission, 2006)**

Because wind generation is an intermittent resource and large concentrations of wind generation can affect electricity grid operations and reserve requirements, development of accurate wind energy forecasting tools will become an increasingly critical need for managing wind and other intermittent generation resources connected to the California grid. Accurate next-hour and next-day forecasts will make it possible to optimize the response to rapid changes in wind generation to balance load and supply reserve and regulation resources to the grid.

## Previous Energy Commission-EPRI Wind Energy Forecasting Project, 2001-2003

In 2002, the California Energy Commission (Energy Commission) and EPRI completed testing two forecasting systems at Altamont and at San Gorgonio (Energy Commission and EPRI, 2003a and 2003b; EPRI, 2003). Two wind energy forecasting system developers, Risoe National Laboratory and TrueWind Solutions, applied their meteorology-based, meso-scale modeling algorithms to generate twice-daily, 48-hour forecasts of hourly wind speed and energy generation, during a 12-month period.

The host wind projects were the 90-MW Wind Power Partners/WindWorks project, operated by PowerWorks at Altamont Pass, and the 66.6-MW Mountain View 1 and 2 wind project, operated by Seawest at San Gorgonio Pass. Based on the monthly and annual mean absolute errors (MAE) of the forecast vs. observed data, the Risoe and TrueWind forecasts performed better than simple persistence and climatology forecasts. However, the forecast errors were still significant, indicating that additional research is needed to incorporate improved forecast technology and forecast performance.

## Current Energy Commission-EPRI Regional Wind Energy Forecasting Project, 2004-2005

In 2004, the Energy Commission, EPRI, and CA ISO initiated a new 18-month project to build on the first project and develop and test improved wind energy forecast algorithms for both short-term forecasts (regional five-minute forecasts over three hours) and intermediate-term forecasts (hourly wind plant forecasts over 48 hours) in the principal wind resource areas of the state. The project was completed during December 2005. The results are presented in the four-volume report, *California Regional Wind Energy Forecasting System Development and Testing* (Energy Commission and EPRI, 2006a, 2006b, 2006c, and 2006d).

This report, *California Regional Wind Energy Forecasting System Development – Volume 1: Executive Summary*, summarizes the objectives, scope, key results, and recommendations of the project.

The other volumes are *Volume 2: Wind Energy Forecasting System Development and Testing and Numerical Modeling of Wind Flow over Complex Terrain*; *Volume 3: Wind Tunnel Modeling of Wind Flow over Complex Terrain*; and *Volume 4: California Wind Generation Research Dataset (CARD)* (Energy Commission and EPRI, 2006b, 2006c, and 2006d).

## Objectives and Scope

The overall project objectives include both economic and technical goals.

The overall economic goals are:

- Support the California Independent System Operator's (CA ISO) development of a viable competitive market for intermittent wind resources.

- Pave the way for increasing market penetration of renewable resources.

The overall technical goals are:

- Leverage the experiences gained under the prior forecasting efforts to improve forecast accuracy

- Provide capability to generate accurate forecasts for both short-term and longer-term forecast timeframes.

The specific objectives include:

- Develop and test short-term forecasting algorithms with higher accuracy than persistence forecasts to provide real-time forecasting capability and support system real-time updates to meet dispatching needs.

- Determine the sources of forecast error and assess methods to reduce errors for both next-hour and next-day forecasts, e.g. improved input data, finer grid sizes in meso-scale models, and improved statistical models for short-term forecasting and model operating statistics.

- Investigate wind flow and wind plant power curve variations over complex terrain via wind tunnel and numerical modeling.

The project scope includes:

- Generate real-time weather forecasts real time over a 4-km grid in both northern and southern California using the COAMPS meso-scale model.

- Develop and test wind energy forecast systems to provide forecasts for two "look-ahead" time horizons: (1) short-term forecasts of five-minute wind energy generation over a three-hour period to be issued every five minutes for the principal wind resource areas of the state (Solano, Altamont, Tehachapi, and San Gorgonio); and (2) intermediate-term forecasts of hourly wind generation over the a 48-hour period issued twice daily or every 12 hours for wind plants in each of the principal wind resource areas.

- Conduct numerical and wind tunnel modeling of wind flow and power density at each wind turbine location vs. wind speed at a reference meteorological tower to investigate the variation of wind flow and wind plant power curve with wind speed and direction, atmospheric stability, and other conditions.

- Generate the California Wind Generation Research Dataset (CARD), a data base of daily forecasts of hourly wind generation at multiple elevations over 5-km grids in northern and southern California.

The project was conducted over the eighteen-month period, July 2004 through December 2005.

## Project Participants and Tasks

The project participants included the California Energy Commission as program manager, EPRI as project manager, EPRI subcontractors AWS Truewind LLC, the University of California at Davis, and UC Davis subcontractor, Lawrence Livermore Laboratory; project advisors, CA ISO, National Renewable Energy Laboratory, Southern California Edison, and five wind plant operators who together with CA ISO also provided wind resource and power data for their respective wind projects, Sacramento Municipal Power District, PPM/High Winds, PowerWorks, Oak Creek Energy Systems, and BMR/Mountain View 1 & 2.

The project consisted of six major tasks: Task 1: Project Review and Reporting; Task 2: Wind Resource Data Collection and Analysis; Task 3: Rapid-Update Wind Speed and Direction Forecast Algorithm; Task 4: Regional Short-Term Wind Energy Forecasting System Development and Testing; Task 5: Long-Term Wind Energy Forecasting System Development and Testing; and Task 6: Wind Tunnel Testing Coupled with Advanced Numerical Model Data.

The project was conducted over the eighteen-month period, July 2004 through December 2005.

## Report Organization

This report consists of eight chapters, including Chapter 1, *Introduction*.

Chapter 2, *Wind Energy Forecasting Integration into Electricity Grid Operations*, addresses how additions of large amounts of intermittent wind generation affect electricity system operations; why wind energy forecasting is important for next-hour and next-day dispatching of system resources; and the content, format, and method of delivery of the forecasts that would be most useful to system operators.

Chapter 3, *Next-Hour Regional Wind Energy Forecasting System Development and Testing*, describes the conceptual design of a two-stage short-term forecasting algorithm, based on artificial neural networks, and application of a portion of the algorithm to generate five-minute forecasts over three hours for the principal California wind resource areas.

Chapter 4, *Next-Day Wind Plant Energy Forecasting System Development and Testing*, describes testing of various improvements in data, meso-scale models, and other features of the forecast system to assess the potential improvement in forecast performance vs. the earlier work and application of the resulting improved forecast system to five wind projects in the principal wind resource areas.

Chapter 5, *Numerical and Wind Tunnel Modeling of Wind Flow and Wind Plant Power Curves over Complex Terrain*, describes the parallel efforts by AWS Truewind and University of California at Davis to apply numerical and wind tunnel models to evaluate wind flow and variation of wind plant power curves with wind speed, atmospheric stability, and other conditions over the complex terrain at Altamont Pass.

Chapter 6, *High-Resolution Weather and Wind Forecasting*, describes the application of the COAMPS meso-scale model to generate real-time daily weather and wind forecasts over 4-km grids in northern and southern California.

Chapter 7, *California Wind Forecasting Research Dataset*, describes the CARD dataset of wind energy forecasts at multiple elevations over 5-km grids in northern and southern California, generated using NOAA-NCEP forecast data and AWS Truewind's MASS 6 model for the period July 1, 2004 through June 30, 2005.

Chapter 8, *Conclusions and Recommendations*, identifies the key advances made by the project, remaining issues that should be addressed in future work, and specific topics for further investigation.

Chapter 9 presents the references.

# 2
# WIND ENERGY FORECASTING INTEGRATION INTO ELECTRICITY GRID OPERATIONS

This section addresses the characteristics of wind generation; how wind generation affects electricity system operations; why wind energy forecasting is important for next-hour and next-day dispatching of system resources; and the content, format, and method of delivery of forecasts that would be most useful to system operators.

## How Wind Generation Affects Electricity Grid Operations

Wind generation exhibits both short- and longer-term fluctuations over periods from seconds to longer periods due the intermittent nature of wind. Figure 3-1 illustrates the fluctuations of one-minute wind power delivered to the California grid during a single 24-hour period on a summer day in California (CA ISO, 2005). The chart presents both aggregated wind power data for the state and data for each of the five wind resource areas (Solano, Altamont, Pacheco, Tehachapi, and San Gorgonio). Experience in Germany, where more than 15,000 MW of wind generation is in place, indicates that very large changes in wind output can occur in minutes as weather fronts pass through (E.ON Netz, 2004).

The California diurnal wind generation profile in Figure 2-1 is typical of a summer day in the areas affected by the coastal marine-layer. Wind speed and generation build during the afternoon as the marine-layer spreads from the high-pressure region over the cool Pacific Ocean to the low-pressure regions over the hot interior valleys. It then reaches a peak in early evening, and begins to fall off during the early morning hours reaching a minimum between about 10:00 am and 2:00 pm.

Unfortunately, the diurnal patterns of wind power and system load do not match well. This is especially true during the evening, when system load decreases while wind generation is reaching its peak. The system operator or balancing authority must reduce other generation to balance generation and load using decremental bids (800 MW in the example). In the morning, when load is building and wind generation diminishes to its minimum, the reverse situation exists. The system operator must dispatch additional generation or non-spinning reserve to balance the system (1000 MW in the example).

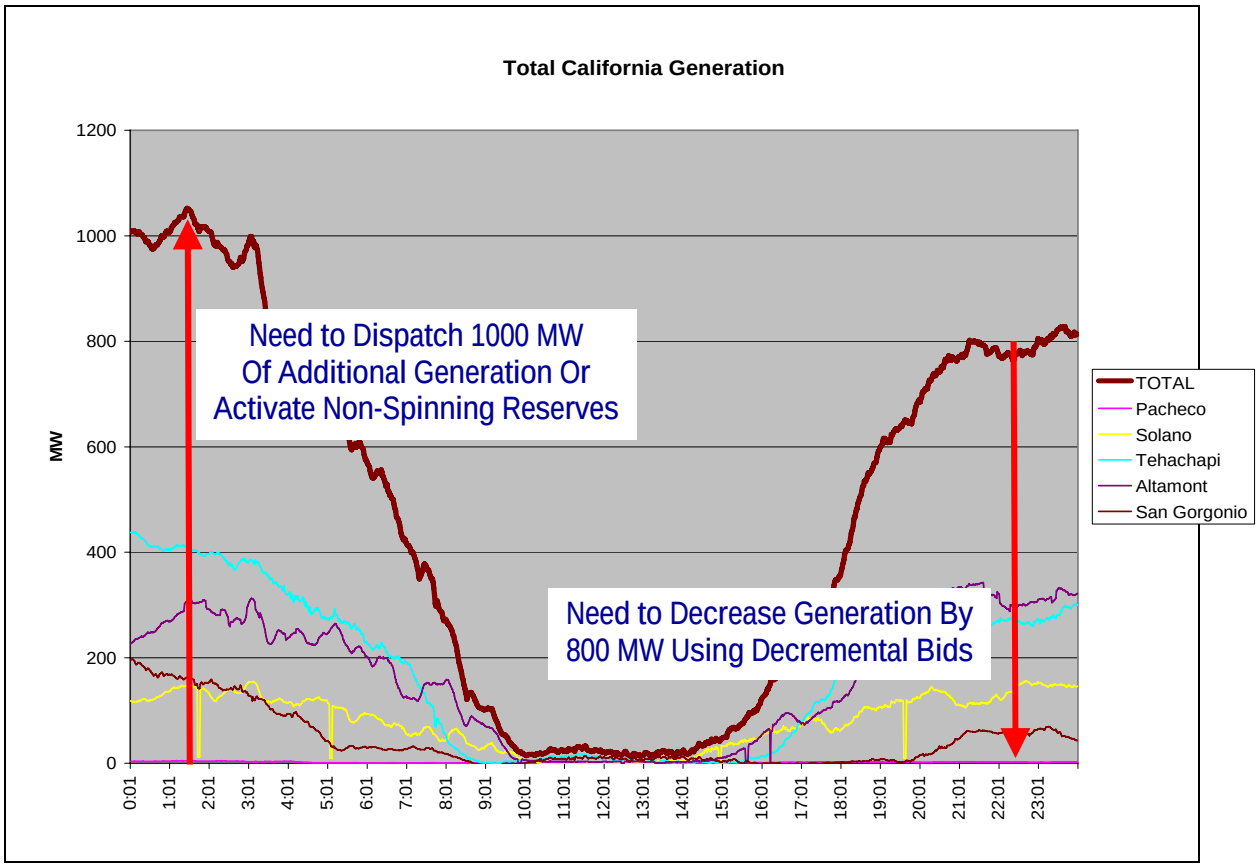


**Figure 2-1 Typical Variation of Total and Regional One-Minute Wind Generation in California on a Summer Day (CA ISO, March 2005)**

## System Operators and Balancing Authorities

System operators are often single utilities responsible for operating the generation, transmission, and distribution system of single and sometimes multiple control areas. Balancing authorities like CA ISO and other regional transmission operators (RTOs) balance the generation and transmission resources for a group of control areas covering large regions. Each control area is responsible for maintaining the Area Control Error (ACE) within two ranges, referred to as CPS1 and CPS2. ACE is an algebraic function of the average deviations vs. schedule of generation, load, frequency, and net interchanges with other control areas.

Figure 2-2 illustrates the principal objectives of area and regional control operators, which are to operate transmission within thermal limits, maintain voltage within voltage stability limits, observe transient stability limits, and balance generation against load. In addition, the regional balancing authority balances the overall generation load, maintains scheduled interchanges, and supports interconnection frequency.

In order to meet these objectives, the operator is responsible for scheduling generation and transmission resources for both day-ahead and hour-ahead periods, load following, and system voltage and frequency regulation to balance generation and load and meet other objectives.

Figure 2-3 illustrates the duration of system load vs. upward and downward regulation; day-ahead, hour-ahead, incremental and decremental scheduling; and five-minute-dispatch of generation resources.

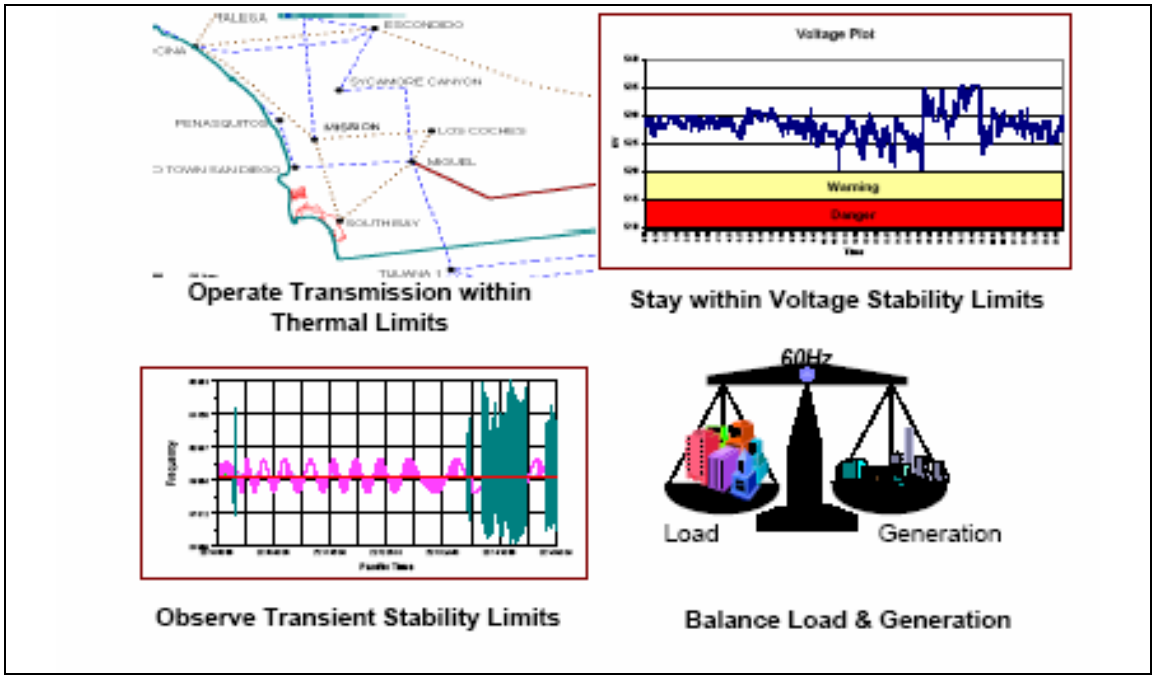


**Figure 2-2 Control Area Objectives Focus on Balancing Load & Interchange vs. Generation (CA ISO, 2005)**

The system impacts include unit commitments and scheduling, voltage regulation/reactive power control, reserve margins for security and reliability, transmission bottlenecks during windy periods, frequency control and regulating reserves, and load following and energy balancing.

The magnitudes of the impacts can vary over wide ranges and depend on several important factors, including percentage penetration of rated wind capacity in the generation mix, geographical dispersion of wind capacity, diurnal and seasonal correlations between wind generation and system load, penetrations and types of other generation resources in the mix, presence of hydro, pumped storage hydro, and peaking capacity in the mix, and adequacy of transmission resources to transmit wind energy during periods of peak generation to the population centers.

## Importance of Wind Energy Forecasting

Wind energy forecasting is one of several mitigation measures available to reduce the impacts of wind on power system operation and control (EPRI, 2003c, 2004a, 2005a, and 2005b). Others include power electronics and line compensation to absorb short-term fluctuations and control

power factor; integration with hydroelectric generation and energy storage; and transmission upgrades to relieve bottlenecks during windy periods; and wind energy forecasting.

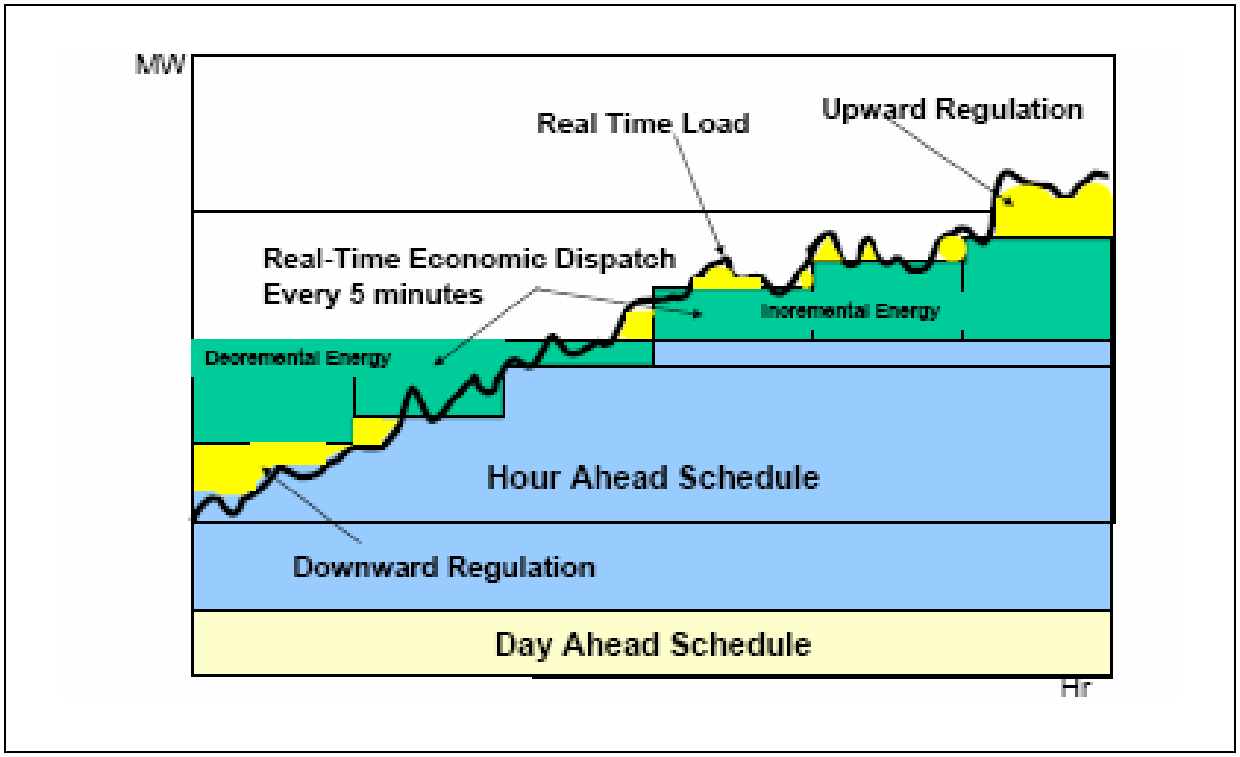


**Figure 2-3 Balancing Authority Balances Generation Resources vs. Real-Time Load (CA ISO, 2005)**

In combination with load forecasting, wind energy forecasting can support optimal dispatching of intermediate and peaking generation, including hydro, fossil, and other dispatchable generating units; dispatching of transmission resources; scheduling next-hour and next-day wind energy deliveries to the grid; markets for green power and green certificate trading; and other uses. The ongoing CA ISO Participating Intermittent Resources Program (PIRP) provides hourly forecasts of next-hour and next-day wind generation to participating wind plant operators for use in scheduling next-hour wind energy deliveries to the California grid (CA ISO, 2005).

## Forecasting Wind Generation Ramp Rates

Forecasting of wind generation ramp rates will be particularly important if the rated wind capacity in the Tehachapi Mountains increases as forecast by about 4000 MW, from 600 MW now to 4500 MW in the future. For example, Figure 2-4 shows the hourly wind generation and ramp rates for April 8, 2005, adjusted from 609 to 4500 MW rated wind capacity at Tehachapi (CA ISO, 2005). During the 24-hour period, wind generation varies between zero and 4500 MW and the ramp rate exceeds minus 1000 MW/hr during two hours, and reaches plus or minus 600

MW/hr during 11 of the 24 hours. The two minus-1000 MW/hr ramps occur at 7:00 and 8:00 AM, precisely at the time when load is building rapidly.

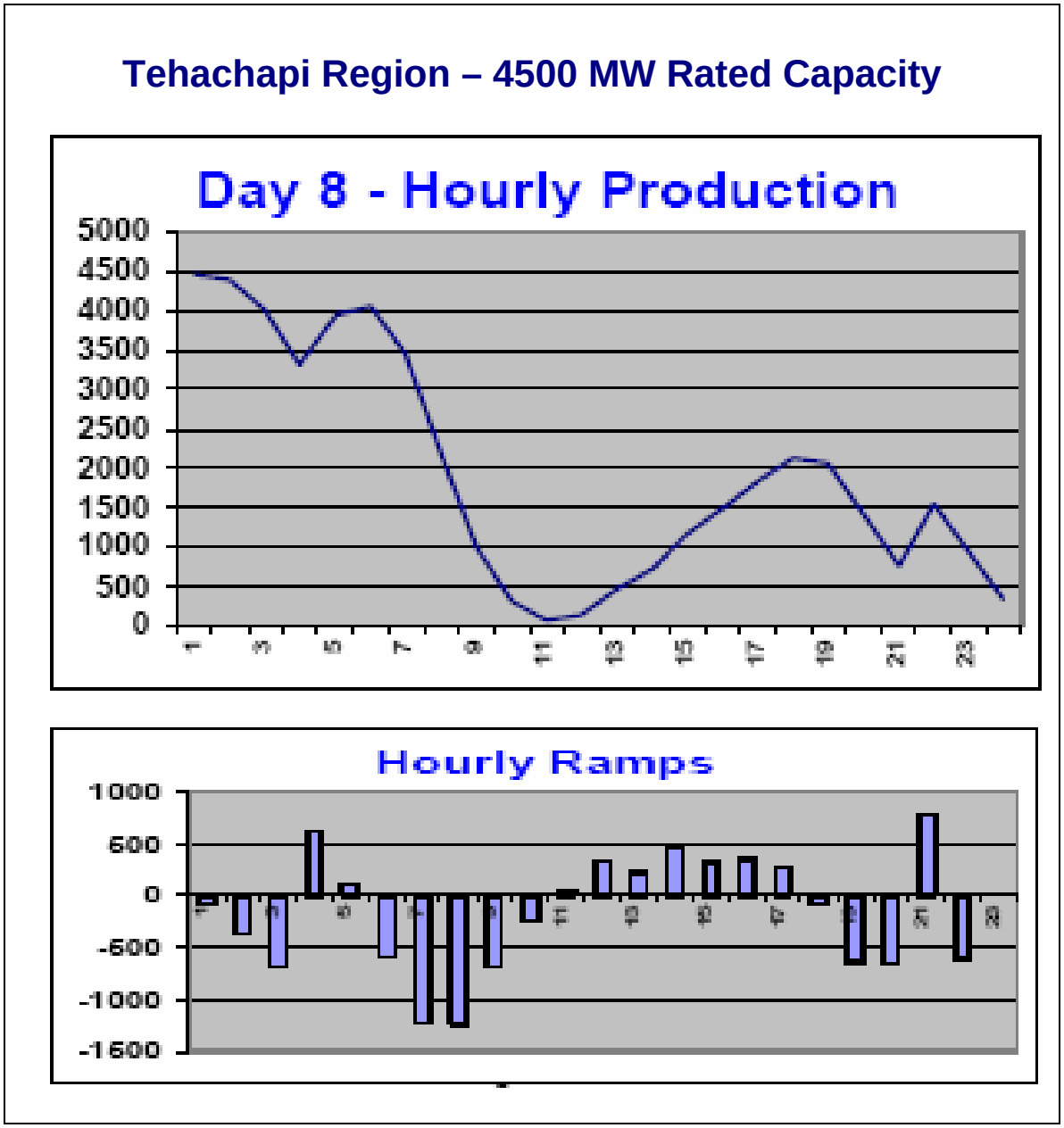


**Figure 2-4 Hourly Wind Generation (MW) and Ramp Rates (MW/hr) at Tehachapi for April 8, 2005, Adjusted to 4500 MW Rated Capacity (CA ISO, 2005)**

As a result of the above and other internal studies, CA ISO has concluded that it is important to accelerate development and validation of wind energy forecast tools now so that they are ready to use when the wind generation capacity in the state grows to a level that reaches two to four times the current 2100-MW level (CA ISO, 2005).

## Customizing Wind Energy Forecasts for System Operators

Even the most accurate next-hour and next-day wind energy forecasts for a region will be almost useless to the system operator if they are delivered, for example, as simple tables of wind speed and wind energy generation forecasts vs. time, without additional information that directly addresses the needs of the operator with regard to content, format, and method of delivery.

For example, other forecast information and data may at times be of greater interest to the system operator than the actual wind speed and energy forecast, e.g. the forecast ramp rate of regional wind generation, the impact of forecast errors on control area CPS1 and CPS2 compliance, and the cumulative monthly imbalance of scheduled vs. delivered wind energy.

Figure 2-5 presents an example of a web-page display developed by AWS Truewind during the development of the intermediate-term forecasting system described in Section 3. It displays the most recent 48-hour forecast of hourly wind generation, in this case for a specific wind project, together with the observed wind generation for the site through the most recent hour, plus forecast performance metrics for various time periods through the present.

Examples of other information that could be provided in such a graphical display include the relative confidence in forecast accuracy based on weather conditions; range of uncertainty of forecast vs. time superimposed on forecast chart; archived data and charts containing previous forecasts, forecast performance statistics and other information; and customized forecast and other information, such as next-hour and next-day ramp rates of regional wind generation.

## Conclusions

Wind energy forecasting will become especially important to control area operators and balancing authorities like the CA ISO in the future as wind generation concentrated in single regions reaches thousands of megawatts. Accurate forecasting systems are needed to generate both next-hour and next-day and longer forecasts for several reasons:

- Provide early warning of high hourly ramp rates of wind generation for planning both same and next day dispatching of generation and transmission resources.
- Support markets for ancillary services to support intermittent wind generation.
- Support issuing accurate dispatch notices to quick-start generators
- Support scheduling of next-hour and next-day deliveries of wind energy to the system.

Development and validation of the forecasting algorithms needed to meet the needs of the control area operators and balancing authorities should begin now.

The system operators should be actively involved in the development and testing of the algorithms to ensure that their needs are met.

About eWind | Contact Info | My Weather | Projects | Logout

**Project Page**

**Project Information**

**Site Name:** Oak Creek (Day Ahead)

**Rated Capacity:** 34.5 MW

**Historical:** Graphs

Most Recent Forecast

**Recent Project Data**

**Observation Time:** 12:00 PPT 3 Jun 2005

**Next Update Time:** 14:00 PPT 3 Jun 2005

**Wind Speed:** 4.8 m/s

**Wind Direction:** 349 °

**Temperature:** 18.3 °C (65 °F)

**Plant Output :** 7.59 MW

**Wind Plant Output Forecast and Statistics (past 7 days)**

| Date | % BIAS | % MAE | RMSE | Avg % capacity |
|---|---|---|---|---|
| 07LT 3 Jun | -12.95 | 17.84 | 7.95 | 66.10 |

**Historical and Real-time eWind Forecast Data**

Historical Period: 24 hours ending 12PPT 3 Jun

Forecast Period: 35 hours beginning 12PPT 3 Jun

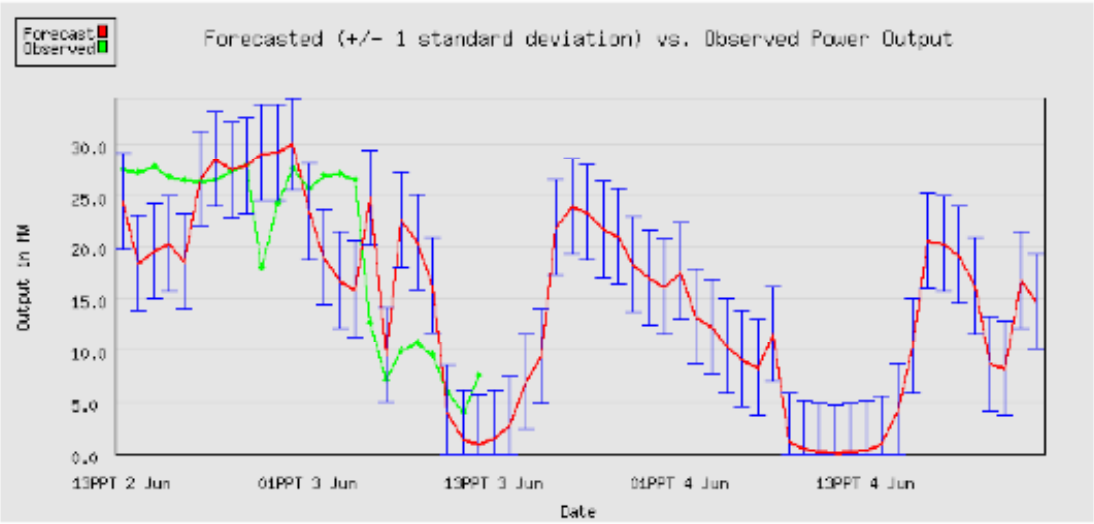


**Figure 2-5 Example Display of Real-Time Forecasts for Oak Creek Energy Systems Wind Project in Tehachapi, California (AWS Truewind, 2005)**

# 3
# NEXT-HOUR REGIONAL WIND ENERGY FORECASTING SYSTEM DEVELOPMENT AND TESTING

This section summarizes the conceptual design of a two-stage short-term forecasting algorithm, based on Artificial Neural Networks, and application of a portion of the algorithm to generate five-minute forecasts over three hours for the principal California wind resource areas. The detailed results are presented in (Energy Commission and EPRI, 2006b).

## Objectives and Scope

The overall goal of the "Next-Hour Regional Wind Energy Forecasting System Development and Testing" task was to produce an initial prototype of an integrated wind generation forecasting system that can provide short-term regional power production forecasts in California. The specific functional objective for this system is that it be capable of producing forecasts of the regional power production in five-minute intervals for the next three hours after forecast delivery. Thus each forecast should consist of predictions for the next 36 five-minute intervals. Furthermore, the system should be capable of producing an update every five minutes.

The short-term forecast system is intended to provide a low-cost regional wind generation forecasting tool to be used by Control Area Operators and Scheduling Coordinators at the CA ISO for more accurate and economical supplemental energy scheduling, real-time dispatch, load following and AGC control. The ultimate objective is to augment traditional short-term statistical forecasting techniques to include a consideration of local and regional atmospheric predictors of short-term changes in weather conditions. The intention is to develop a system that will generate regional power production forecasts even in the absence of site-specific monitored data by utilizing all of the available local and regional forecasted and observed weather data.

The work on this task was divided into two phases. The first phase designed a short-term forecast system based on a review of a variety of forecasting methods and AWS Truewind's experience with operational forecast systems and ongoing forecast system research and development for longer-term forecasts. The second phase implemented a portion of the system designed in the first phase and assessed its performance using five-minute regional wind power production data from the CA ISO system.

## Approach

The design process began with a comprehensive review of the key options for the forecast system with a focus on what data could be used as input into the system and which techniques could be used to produce the forecasts. It was recognized that zero- to three-hour forecasts in five-minute intervals will necessarily rely heavily upon statistical time series prediction tools, since it will not be possible to gather sufficient data to initialize a high resolution physics-based atmospheric model on the space and time scales required to make zero- to three-hour forecasts in five-minute intervals, nor would it be possible to execute such models quickly enough to have their output be useful in the forecast process. However, physics-based models run at moderately high resolution every few hours may provide some useful trend information for forecasts for the zero- to three-hour period. Therefore, the formulation of the forecast system began with a focus on statistical methods for time series prediction that could be employed in a short-term forecast system. The methods that were reviewed included classical time series prediction methods such as multiple linear regression and ARIMA as well as newer techniques based on recent advances in learning theory such as Artificial Neural Networks (ANN) and Support Vector Regression (SVR).

The information gathered during this review provided the basis for two major design decisions. First, it was decided that the ANN technique should be used as the primary tool for the statistical components of the forecast system. Second, it was decided that the system should not be based on a single forecast procedure that could be argued to be the best overall choice but instead should be based upon an ensemble of three forecast methods that have significantly different data utilization and model formulation characteristics. The concept is that each component of the system will have its strengths and that the composite of the forecasts produced by each of the component methods will yield better overall performance than using only one forecast procedure. In order to incorporate this ensemble approach, the design of the system included four forecast subsystems. Three of the subsystems produce quasi-independent preliminary power production predictions for all of the 36 five-minute intervals in the three-hour forecast window. The fourth subsystem blends the three separate preliminary forecasts into the final forecast by weighting each forecast in accordance with its performance characteristics (i.e. placing a greater weight on the forecast that is likely to do better under a specific set of conditions)

As noted previously, the design objective for the short-term forecast system was to go beyond the basic use of power production time series information from the individual wind resource regions, subregions or wind plants. In addition to the power production time series data, it is envisioned that the following information will also be used in the forecast system: (1) time series information of meteorological parameters from meteorological towers operated by wind generators or other members of the wind energy community; (2) meteorological data from surface weather observing sites operated by the National Weather Service and other organizations; (3) meteorological data from remote sensing systems such as wind profilers, Doppler radars and satellite-based sensors; and (4) short-term forecast data from high resolution atmospheric physics-based models run in a rapid update cycle mode (i.e. assimilation of new data and execution of short-term forecasts every few hours or possibly every hour).

## Forecast System Design

An initial forecast system design was formulated to address the previously noted design objectives. Figure 3-1 presents a schematic of the system. The circles represent input or output data, while the rectangles depict algorithms (i.e. numerical models) that operate on the data. The three columns of boxes that originate below the row of circles represent three forecast subsystems. The leftmost column is the autoregressive subsystem. This system generates a forecast based solely on the recent behavior (most recent level of production, trends, rate of change of trends etc.) of the production in the region (or wind plant). The second subsystem utilizes recent meteorological data within and in proximity to the region of interest. It finds and utilizes spatial and temporal meteorological relationships that have predictive value for the regional power production. The third (rightmost) subsystem constructs a regional power production forecast from the output of frequently updated very high resolution physics-based forecast simulations of the wind over the region of interest. Each of these subsystems supplies an independent forecast to the fourth subsystem, which constructs the final forecast by weighting each of the three input forecasts according to their recent performance characteristics.

Due to limitations in the availability of data and the resources available for this task, it was only possible to implement and test one of the three proposed subsystems. The implemented and tested subsystem was based on the approach that employed an ANN with autoregressive-type inputs from the time series of the regional power production. No meteorological data are used in this approach. The performance of this approach was evaluated with regional wind power production data for the year 2004 supplied by the CA ISO. CA ISO supplied data for the San Gorgonio, Tehachapi, Pacheco, Altamont and Solano regions.

## Results

After the forecast sensitivity experiments were completed, zero- to three-hour ANN-based forecasts in five-minute intervals were produced for four of the five regions for which data were available for the entire year of 2004. The one-year test indicated that the forecast performance was substantially different during the cold and warm seasons. This is not very surprising since the wind regimes in California are substantially different between the cold and warm seasons.

Figures 3-2 and 3-3 present the average mean absolute errors and skill scores (i.e. the percentage reduction in the mean absolute error) relative to a persistence forecast vs. look-ahead time for all four regions and for the warm and cold seasons. The two charts indicate that the reduction in MAE relative to a persistence forecast (i.e. the skill score) is much higher during the warm season than during the cold season. However, the actual MAE values are typically somewhat lower in the cold season.

This dichotomy between the MAE values and skill scores is mostly attributable to the fact that the cold season is characterized by a wind regime that consists of relatively long periods of light winds (often below the turbine start-up speeds) with little variability that are interrupted by short periods of high wind speeds with high variability. The short periods with high wind speeds are associated with storms that typically move into California from the Pacific Ocean, and the longer periods with light winds correspond to the quiescent period between storm events.

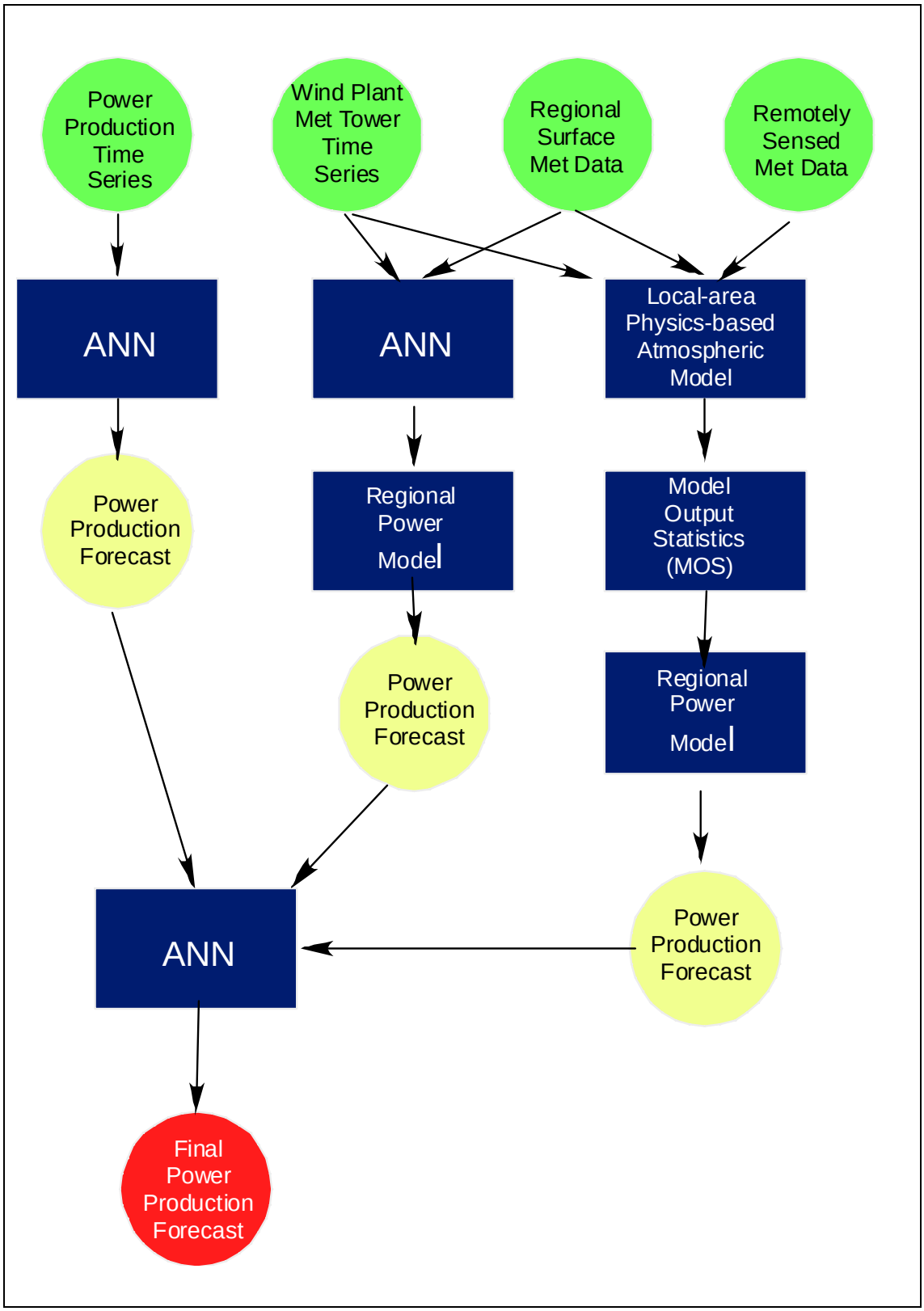


**Figure 3-1 Schematic of the proposed two-stage short-term (0 to 3 hour) forecast system**

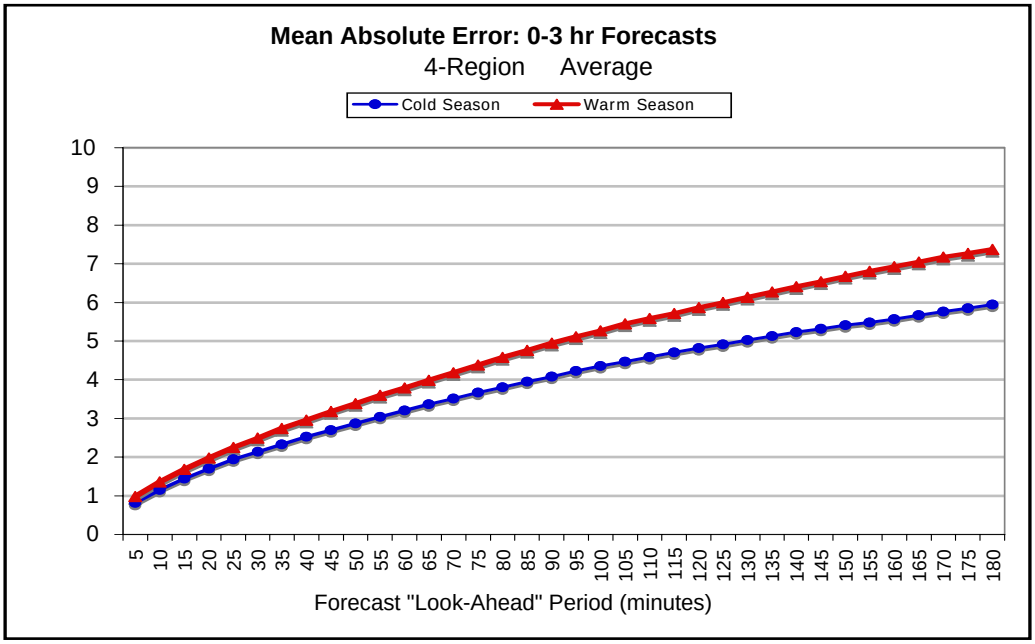


**Figure 3-2 Average regional power production forecast mean absolute error (% of capacity) vs. look-ahead period for the warm (May-Oct) and cold (Jan-Apr, Nov-Dec) season months of 2004 for ANN-based autoregressive (stage 1 – method 1) forecasts for the four largest California wind power production regions.**

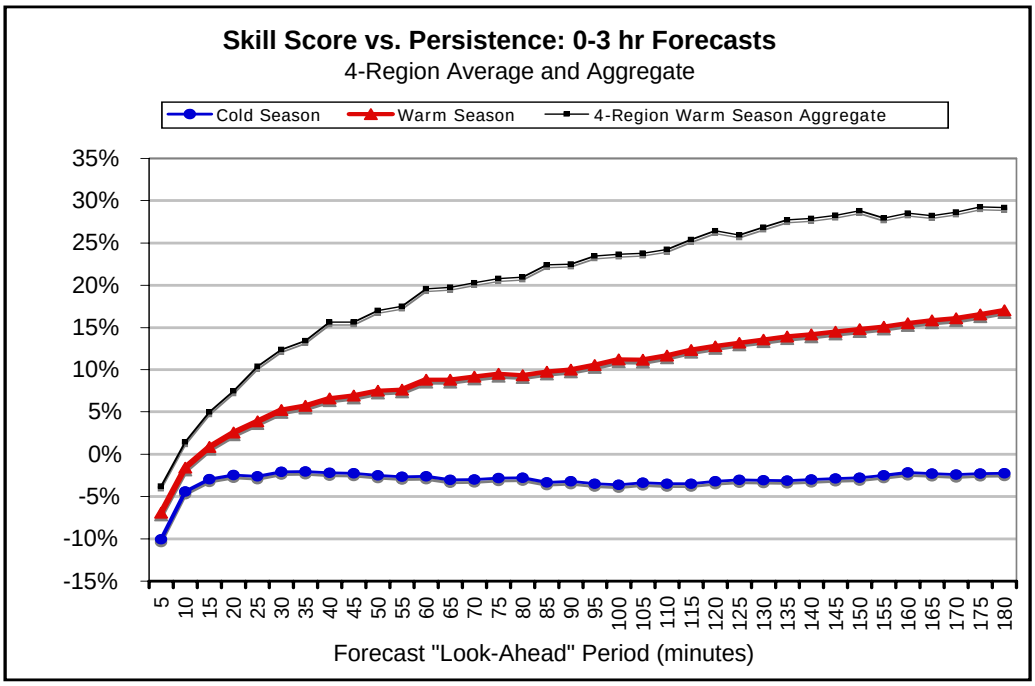


**Figure 3-3 Average regional power production forecast reduction in MAE relative to a persistence forecast (i.e. the skill score) vs. look-ahead period for the warm-season (May-October) and cold-season (November-April) months of 2004 and 2005 for ANN-based autoregressive (stage 1 – method 1) forecasts for the four largest California wind power production regions.**

A persistence forecast typically performs quite well during the light-wind periods since the power production is often zero for many consecutive hours during those periods. Persistence will perform poorly during the storm events, but unfortunately, a forecast system based solely upon time series of power production data will also perform poorly since the historical time series of data will not provide much information about approaching storm systems since storms are irregular events. It is necessary to utilize real-time meteorological data from a variety of regional sites and physics-based atmospheric model output data to obtain some predictive skill for these types of events. The use of these two additional forecasting resources is included in the short-term forecast system design. Since the overall level of power production is low during the cold season, the level of forecast performance is typically not as critical.

The high levels of production typically achieved during the warm season make it more critical for a forecast system to perform well during that portion of the year. As noted earlier, the MAE values of the autoregressive-type ANN forecast system component are typically slightly higher (as a % of capacity) in the warm season, and the skill scores are significantly higher. The average skill scores shown in Figure 3-4 indicate that a persistence forecast outperforms the autoregressive ANN-based forecast for the first two forecast intervals (0 to 10 minutes) for both seasons. However, the autoregressive forecasts outperform persistence by an increasing margin from the 15-minute mark through the end of the three-hour forecast period during the warm season. During this period, the average skill score relative to a persistence forecast rises from just above 0% to approximately 17%.

It should be noted that the skill scores in Figure 3-3 are unweighted mean values. The average skill score would be somewhat higher if a capacity-weighted average was employed, since the regions with lower capacity (e.g. Solano) tend to have lower skill scores. The performance of the forecasts for the aggregated power production for all four regions is substantially better than that of the average performance for the regions. During the warm season, the MAE for forecasts of the four-region aggregate power production is slightly under 0.5% for a five-minute forecast and rises to only about 4% for a three-hour ahead forecast of the five-minute power production. The warm season skill scores for the four-region aggregate forecast (Figure 3-3) are quite impressive. They rise from just under 0% for a five-minute ahead forecast to approximately 30% for a three-hour ahead forecast.

## Conclusions

The key results of the short-term forecast system development and testing are:

1. Review of statistical and physics-based forecast methods and analysis of the spatial and temporal characteristics of the wind speed and direction variability to provide the foundation for the design of a robust short-term forecasting system capable of producing forecasts of the 5-minute regional energy production for the next 3-hour period updated every 5 minutes;

2. Design of a two-stage forecast system with the first stage consisting of a mini-ensemble of three forecast methods that each produce an independent power production forecast,

and a second stage that weights each of the three forecasts from the first stage based on their recent performance to produce a single composite forecast and an estimate of forecast uncertainty; and

3. Initial testing of one of the three forecast methods (the autoregressive method) in the first-stage of the proposed forecast system with one year (2004) of regional wind power production data supplied by the CA ISO.

The main conclusions are:

1. The autoregressive component of the three-method first stage of the proposed forecast system produced a reduction in the regional power production forecast error of a persistence forecast for the warm season (May –October) that ranged from near 5 to 10% for the first 30 to 60 minutes of the 3-hr forecast period to the 15% to 20% range during the latter stages of the period; and
2. The autoregressive method showed no improvement over persistence for the cold season, but that is to be expected due to the character of the wind during the California cold season, and is one of the reasons for incorporating two other methods into the forecast system.

## Recommendations

The recommended next steps are:

1. Implement and evaluate the two other component forecast subsystems and the ensemble compositing subsystem that were not implemented in this project;

2. Implement and evaluate the performance of the entire forecast system for several months in different seasons for each of the wind resource areas in California; and

3. Test the system in an operational environment and obtain feedback from CA ISO personnel.

An alternative approach would be to test and implement the same subsystem tested in this project and then develop the other components while the single subsystem forecast system is in production. The results produced in this project suggest that this approach could yield a 5% to 20% improvement over a persistence forecast, especially during the warm season.

# 4
# NEXT-DAY WIND PLANT ENERGY FORECASTING SYSTEM DEVELOPMENT AND TESTING

This section summarizes testing of various improvements in data, physics-based atmospheric numerical models, and other features of the next-day forecast system and application of the resulting improved forecast system to five wind projects in the principal wind resource areas. The detailed results are presented in Section 4 of Volume 2 (Energy Commission and EPRI, 2006b).

## Objectives

There are two primary objectives to the "Next-day Wind Plant Energy Forecasting System Development and Testing" task. The first was to formulate and evaluate new forecast methods and datasets that have the potential to improve the forecast performance of next-day wind power production forecasts relative to the performance in the previous Energy Commission-EPRI wind energy forecasting project (Energy Commission and EPRI, 2003a and 2003b; EPRI, 2003). The second was to test the performance of the modified forecasting system over a one-year period for a set of California wind plants.

## Scope

The task was conducted in two phases: a screening phase in which a variety of potential forecast system improvements were tested using data from the previous project; and an evaluation phase in which forecasts were generated by a modified version of AWS Truewind's *eWind* forecast system and evaluated for a set of five participating California wind plants.

The screening phase of the project was built upon the data and results from the forecast evaluation experiment conducted during the 2001-2002 period as part of the previous Energy Commission-EPRI forecasting project (EPRI, 2003a, 2003b, and 2003c). In the previous project, 48-hour forecasts were generated for two California wind plants twice each day for a one year period (October 2001 to September 2002) by two forecast providers: AWS Truewind, LLC (AWST) and Risoe National Laboratory (Risoe) of Denmark. Each forecast provider generated and delivered two 48-hour forecasts per day of the hourly average power production (kW) and the average hourly wind speed (m/s) and direction for one meteorological tower for each wind plant. The morning forecast was delivered at 8:00 AM PST and the forecast period extended until the hour ending at 8:00 AM PST two days after the forecast was delivered. The evening forecast was delivered 12 hours later at 8:00 PM PST and its forecast period ended 12 hours after the end of the morning forecast.

It is important to note that these forecasts were generated in "next-day" mode. This means that the forecasts were produced without real-time data from the wind plants. Real-time data from the wind plants are very important for the performance of forecasts during approximately the first six to nine hours of the forecast period. However, real-time data from the plant have little impact on forecasts beyond this period.

The two wind plants that participated in the previous project were the Mountain View 1 and 2 wind plant in the San Gorgonio Pass of southern California and the PowerWorks plant located in the Altamont Pass. The rated capacities of the Mountain View and PowerWorks wind plants are 66.6 and 90 MW, respectively. The screening phase of the current project was designed to test potential improvements to the forecast system on the months in the earlier project that had the largest forecast errors.

The evaluation phase of the current task was designed to be similar in structure to that of the previous project. Forecasts of the hourly power production and wind speed for each of the next 48 hours for each participating wind plant were simulated for twice-daily delivery. The forecasts were generated by a modified version of AWS Truewind's *eWind* system that employed many of the system enhancements that were found to be useful in the screening phase of the project. However, the number of participating wind plants was expanded from two in the previous project to five in this project. Fortunately, the two plants that participated in the previous project also participated in the current project. This provided an opportunity to directly assess the change in forecast performance between the previous and current projects for the same wind plants. The evaluation metrics used in the current project were also kept the same as those used in the earlier project to facilitate comparison. These included, the mean error (ME), the mean absolute error as a percentage of installed rated capacity and also as a percentage of actual production, and the skill scores (i.e. the percentage reduction in MAE) relative to persistence and climatology forecasts.

## Phase 1: Screening of Improved Data and Forecast Methodologies

### *Approach*

The Phase 1 screening assessment of potential improvements in the input data and forecast methods was based on the measurement and forecast data from the previous Energy Commission-EPRI project for the Mountain View 1 and 2 and PowerWorks wind projects (EPRI, 2003a, 2003b, and 2003c).

It was not practical to execute a large number of forecast method experiments for the full 12 months of the previous forecast evaluation period for both wind plants. Therefore, it was decided to test each forecast system improvement using a three-month data sample for each of the two wind plants. The test months were selected independently for the PowerWorks and Mountain View plants. The main selection criteria were that (1) plant data were available for a large fraction of the hours in the months (i.e. low lost data rate); (2) the monthly forecast performance was worse than the annual average for the plant; and (3) the selected months should include a winter month, a summer month, and a transition season month.

Figure 4-1 is a schematic overview of the components of the *eWind* forecast system. The system consists of two major components: data and numerical models. There are three fundamental types of data used in the forecasting process: (1) regional weather data, which consists of data from a variety of sources including surface-based meteorological sensor arrays at airports, rawinsonde balloons and satellite-based sensors; (2) time series of power production and meteorological data from the wind plant; and (3) off-site local meteorological data. There are also three major types of numerical models used in the forecast system: (1) physics-based atmospheric models; (2) statistical prediction models and (3) a plant output model.

There is almost an infinite number of different configurations and new techniques that can be implemented within the general framework of the eWind system. Obviously, it was only possible to test a very small subset of the possible changes within the resource limitations of this project. The modifications tested within this task were based upon two criteria: (1) those that appeared to have the greatest promise of improving the forecasts; and (2) those that could be tested with the data available for this project and within the resource limitations of the project. Modifications were tested within the six focus areas listed in Table 4-1.

*Focus Area 1* addressed the input data used by the physics-based model. There are many emerging datasets that have the potential to improve the simulation of winds in physics-based models. This project evaluated the impact of using higher-resolution water surface temperatures from the current generation of satellite sensors.

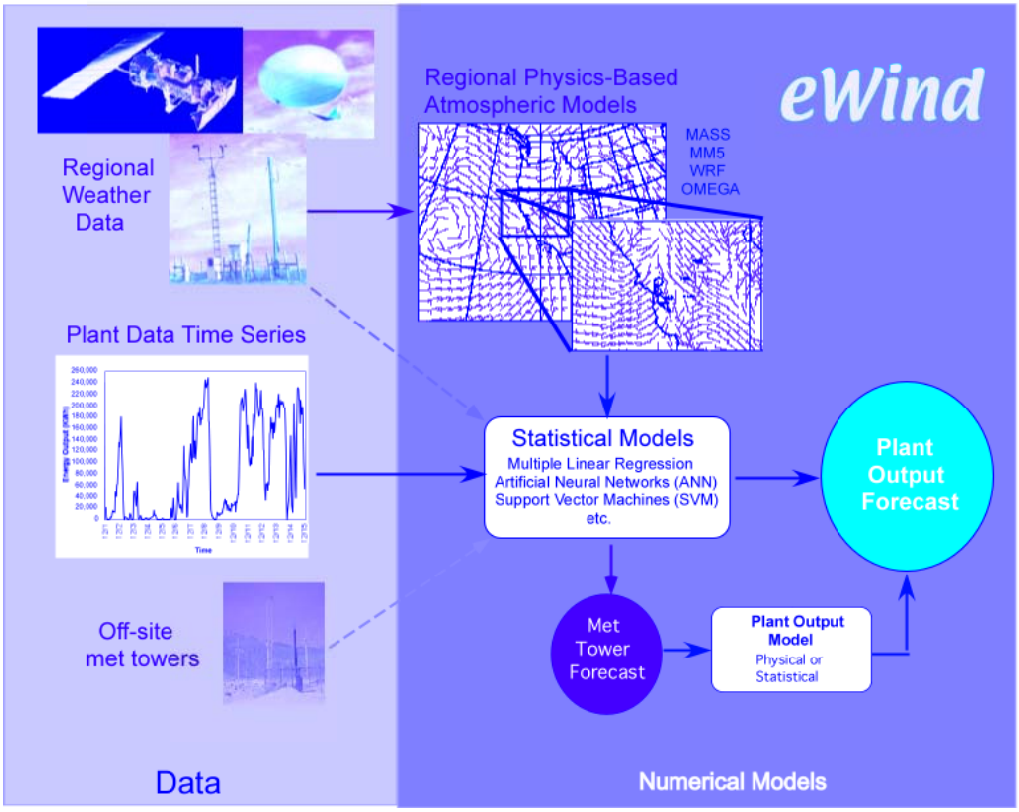


**Figure 4-1 A schematic depiction of the main components of the eWind forecast system.**

**Table 4-1 Focus areas and associated experiments**

| Focus Area | Experiments |
|---|---|
| 1. Additional or improved input data for the physics-based simulations | 4-km MODIS and Pathfinder Water Surface Temperature (WST) is used to initialize the physics-based model |
| 2. Higher resolution (i.e. smaller grid cells) for physics-based model | 4-km and 1-km physics-based simulations were executed |
| 3. "Next-generation" physics-based models | Forecast simulations were executed with the WRF model in place of the MASS model in the eWind system |
| 4. Advanced statistical models for MOS | Stratified multiple linear regression and artificial neural network methods were used for MOS in place of the screening multiple linear regression |
| 5. More sophisticated formulation for plant output model | Median-based power curve plus residual formulation was used |
| 6. Forecast Ensembles | An ensemble of MASS and WRF model forecasts was used in place of the single MASS forecast |

*Focus Area 2* assessed the impact of the resolution of the physics-based model grid. Smaller grid cells mean that the physics-based model can simulate smaller scale weather features that determine the evolution of the wind in the vicinity of the wind plant. The impact of utilizing a higher resolution grid for the physics-based model was evaluated.

*Focus Area 3* assessed the impact of employing a "next generation" physics-based atmospheric model in place of the MASS model currently used in the eWind system. The next generation model known as WRF was used to assess the impact of this potential improvement. The WRF model is an open-source community model being jointly developed by the National Center for Atmospheric Research (NCAR) and the U.S. National Weather Service.

*Focus Area 4* examined the impact of using more sophisticated statistical techniques for the Model Output Statistics (MOS) component of the forecast system.

*Focus Area 5* investigated the sensitivity of the forecast performance to the formulation of the plant scale power curve.

Finally, *Focus Area 6* examined the impact of employing a forecast based on a composite of several individual forecasts from different methods (i.e. an ensemble of forecasts).

### *Results*

Table 4-2 summarizes the impact of each of the forecast system modifications on the wind energy forecast performance. The MAE percentage reductions in Table 4-2 are the net reductions in the MAE for all six of the evaluation months (for both the Mountain View and PowerWorks wind plants) or as many months as were available for a particular experiment. For

**Table 4-2 Summary of the Improvements in the Power Production Forecast MAE associated with the Forecast System Modifications in each Focus Area.**

| Focus Area | Forecast System Modification | MAE Reduction (%) |
|---|---|---|
| 1 | MODIS and Pathfinder WST data (4 km)<br>BASELINE: NCEP OI WST (110 km) | 12.3% |
| 2 | 1 km physics-based model grid<br>BASELINE: 10 km physics-based model grid | -4.7% |
| 3 | WRF with 40 km grid as the physics-based model<br>BASELINE: MASS with 40 km grid | 4.0% |
| 4 | Stratified 2-stage SMLR scheme<br>BASELINE: Screening Multiple Linear Regression | 15.8% |
| 5 | Model deviations from power curve<br>BASELINE: Speed-based plant-scale power curve | 4.6% |
| 6 | Mean of an ensemble of forecasts<br>BASELINE: "Best" single forecast method | 0.8% |

a variety of reasons, the baseline method is not the same for each focus area. Therefore, Table 4-2 also notes the baseline method for each focus area.

The results indicate that the most significant improvements in forecast performance were associated with two of the six enhancements in Table 4-2. They are enhancements 1 and 4, which reduced mean absolute error by 12.3% and 15.8%, respectively. Enhancement 1 uses higher-resolution water surface temperature data derived from satellite-based sensors to initialize the surface temperature parameter in the physics-based model; and Enhancement 4 uses the stratified two-stage screening multiple linear regression (SMLR) approach to generate the MOS relationships in the forecast system. The other forecast system modifications yielded smaller or no improvements in forecast performance.

Interestingly, the use of higher-resolution grids in the physics-based model did not improve the ultimate wind speed or power production forecasts. Although the higher-resolution grids did improve the performance of the raw wind speed forecasts produced by the physics-based model, after applying the MOS procedure, the improvement in forecast performance was greatly diminished. That is, the MOS procedure and higher-resolution grid appear to contribute similar information and result in similar forecast performance improvements of the raw physics-based forecasts.

Another noteworthy observation is that the ensemble approach may have greater potential for improving forecast performance than indicated by this experiment. Others studies have shown that the ensemble approach tends to produce more significant forecast improvement with a larger set of ensemble members than used in the screening evaluation reported here. Note that the forecast evaluation phase reported in the next section did use a larger set of ensemble members.

## Phase 2: Evaluation of Improved Forecast Algorithm at Five Wind Projects

### *Approach*

Phase 2 assessed the performance of the modified forecast system for a set of California wind plants for a one-year evaluation period extending from July 1, 2004 to June 30, 2005.

Five wind plants agreed to provide power production and meteorological data for use in the generation and evaluation of power production and wind speed forecasts for their plants. The participating plants were: (1) the Mountain View plant, a 66.6 MW facility in the San Gorgonio Pass of southern California; (2) the Oak Creek plant, a 34.5 MW plant in the Tehachapi Pass, which is adjacent to the Mojave Desert; (3) the PowerWorks wind plant with a rated capacity of 90 MW in the Altamont Pass, which is located just to the east of the San Francisco Bay Area; (4) the 15.18 MW SMUD wind plant located in the Montezuma Hills in Solano County; and (5) the 162 MW High Winds Energy Center which is adjacent to the SMUD plant in Solano County.

The protocols for the forecast system test were the same as those used for the 2001-2002 evaluation period in the previous Energy Commission-EPRI project (EPRI, 2003a, 2003b, and 2003c): 48-hour forecasts of the hourly power production and wind speed were generated on a twice-daily cycle with scheduled delivery times of 8:00 AM and 8:00 PM PST each day. Three different physics-based models and four different Model Output Statistics (MOS) procedures were used to produce an ensemble of 12 different forecasts for each of the wind plants. This fairly large set of forecasts provided an opportunity to evaluate a number of different forecast methods as well as the performance of a forecast produced by averaging all 12 of the individual forecasts (an ensemble mean).

The forecasts were generated via a mixture of real-time and historical modes, although all forecasts only used data that were or would have been available to the forecast system in an operational real-time mode. In order to construct a more detailed evaluation of the forecast performance, a comprehensive analysis was only done for the forecasts generated during the morning forecast cycle (i.e. the forecasts scheduled for delivery at 8:00 AM each day).

The performance statistics indicate that the forecast performance differences between the morning and afternoon cycles were not significant and that all of the significant conclusions from the analysis of the performance of the morning forecast cycle would apply to the combined pool of both the afternoon and morning forecast cycles.

The potential number of forecast hours in the forecast evaluation pool was 17,520 (365 days x 48 forecast hours per day) for each wind plant and for the morning forecast cycle. Unfortunately, the actual number of hours in the verification pool varied, and in many cases was substantially less than the maximum possible number of forecast hours. The most common cause of missing hours was unavailable (or missing) observed data from the wind plants. The number of unavailable data varied substantially between the participating wind plants.

### *Results*

Table 4-3 presents the annual Mean Absolute Errors (MAE) and skill scores for all 48 forecast hours for both wind speed and power production forecasts for each of the five participating wind plants. The results shown in the table correspond to the best-performing forecast method for each wind plant over the entire one-year period.

For the Mountain View wind plant, the wind energy forecast MAE decreased from 16.6% of rated capacity in the previous project to 13.0%, and the wind speed MAE for the Catellus Tower decreased from 3.05 m/s to 2.65 m/s. In addition, the skill score vs. persistence increased from 37.5% to 40.5% and the skill score vs. climatology increased from 36.4% to 47.7%.

For the PowerWorks wind plant, the wind energy forecast MAE decreased from 14.1% of rated capacity to 11.9%, while the wind speed forecast MAE for PowerWorks Tower M438 decreased from 1.93 m/s to 1.78 m/s. In addition, the skill score of the power production forecasts vs. climatology increased from 30.9% to 38.9%. These statistics indicate that the forecast system enhancements substantially improved forecast performance relative to the previous project.

The average MAE of the power production forecasts for all five participating wind plants was 14.5% of installed capacity and 52.7% of the average production. The skill scores of the power production forecasts were 33.2% vs. persistence and 29.5% vs. climatology.

It should be noted that the skill scores relative to climatology are most likely too low. This is because no climatological data were available for three of the wind plants and the actual monthly mean wind energy generation for each hour of the day was assumed for the climatology value instead of independently-collected climatology data. Therefore, the forecast error of the resulting climatology forecast is lower than would be expected if actual climatology data had been used. The average mean absolute error of the wind speed forecast was 2.27 m/s, which is 34.1% of the average wind speed.

Two of the five participating plants (Mountain View and PowerWorks) also participated in the forecast evaluation experiment conducted in the previous Energy Commission-EPRI forecasting research project (Energy Commission and EPRI, 2003a and 2003b). This provided an opportunity to compare the results from this project to those obtained in the previous project.

**Table 4-3. Mean absolute errors and skill scores of the best-performing power production and wind speed forecast methods for each wind plant, 48-hour forecasts, and July 1, 2004 to June 30, 2005 forecast period**

| Site | Power Production Forecast MAE | | | | Wind Speed Forecast MAE | | | |
|---|---|---|---|---|---|---|---|---|
| | MAE % of Capcity | MAE % of Prod | Skill vs Persistence | Skill vs Climatology | MAE m/s | MAE % of Speed | Skill vs Persistence | Skill vs Climatology |
| Mountain View | 13.0% | 36.6% | 40.5% | 47.7% | 2.65 | 27.5% | 40.1% | 27.0% |
| Oak Creek | 15.0% | 57.1% | 33.2% | 27.1% | 2.03 | 40.6% | 32.8% | 43.8% |
| PowerWorks | 11.9% | 58.5% | 26.5% | 38.9% | 2.52 | 34.4% | 28.2% | 12.4% |
| SMUD | 16.0% | 60.8% | 37.1% | 16.1% | 1.98 | 35.9% | 31.3% | 10.9% |
| HighWinds | 16.8% | 50.7% | 28.6% | 17.5% | 2.16 | 31.9% | 27.1% | 9.9% |
| **Overall** | **14.5%** | **52.7%** | **33.2%** | **29.5%** | **2.27** | **34.1%** | **31.9%** | **20.8%** |

This comparison indicated that there was considerable improvement in almost all of the forecast performance statistics.

## Variability of Power Generation Forecast Error

The forecast performance results raise a number of issues and questions about the nature of the variability in forecast performance. For example, the annual power-generation forecast MAE exhibits considerable variability between the wind plants, ranging from 11.9% of rated capacity at the PowerWorks plant to 16.8% at the High Winds plant.

Furthermore, the performance statistics indicate that the wind speed forecast MAEs are not highly correlated with the wind power production forecast MAEs. For example, the SMUD wind plant had the lowest wind speed MAE but the second highest power production MAE, while the Mountain View wind plant had the highest wind speed MAE but the second lowest wind energy forecast MAE. Clearly, the magnitude of the wind speed MAE is not the controlling factor for the wind power production MAE.

An obvious question is: what factors are responsible for this variability? It is clearly of critical importance to understand the factors that contribute to forecast performance variability in order to determine the direction of future efforts to improve forecast performance.

Therefore, a detailed analysis of the forecast errors for three wind plants was conducted. By eliminating the differences in wind speed errors between the wind plants, it was possible to gain considerable insight. This was done by assuming a constant two meter/sec wind speed error, randomly distributed between positive and negative deviations from the observed values for all hours of the year. The resulting wind energy forecast MAEs were 8.8% of rated capacity at the Mountain View 1 and 2 wind plant and 13.1% and 14.7% at the High Winds and SMUD wind plants, respectively. Thus, even with virtually identical overall wind speed error magnitudes, the wind power production MAEs still vary significantly between the wind plants.

The principal reason for the energy-forecast MAE variation between plants appears to be related to differences in the maximum slopes of the plant-scale power curves and the wind speed frequency distributions between the plants. Figure 4-2 shows empirical plant-scale power curves for each of the three wind plants. The general shapes of the curves imply that the sensitivity of wind energy forecast error to wind speed forecast error varies with wind speed. When the wind speed is in the range corresponding to the steeply-sloped middle section of the plant-scale power curve, the wind energy forecast error should be most-sensitive to wind speed forecast errors. Thus, the maximum wind energy forecast errors should occur at sites where the wind speed spends many hours in the middle range of the power curve.

However, the maximum slopes of the power curves also vary between the wind plants, and plants with higher maximum slopes should also exhibit higher wind energy forecast errors. The slopes are mostly determined by the correlation between the wind speeds at the individual wind turbine locations. This was verified by the “constant 2 m/s error experiment”. The SMUD wind plant with the steepest-slope power curve also exhibited the highest wind energy forecast MAE

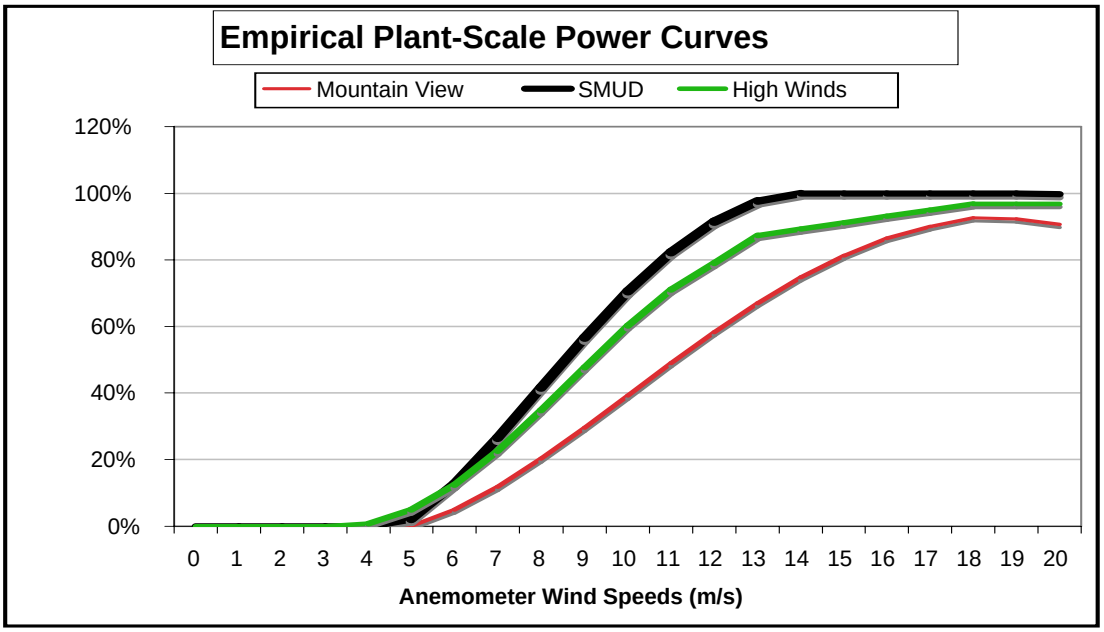


**Figure 4-2**
**Empirical median plant-scale power curves derived from measured wind energy generation and wind speed data for three of the participating wind plants**

when a constant wind speed forecast error of 2 m/s was assumed. The Mountain View plant with the lowest maximum power curve slope exhibited the lowest energy forecast MAE.

## Ensemble Forecasts

Applications and testing of composite forecasts based on an ensemble of individual forecast methods have demonstrated improved forecast performance in other meteorological forecast applications. In order to assess the potential of ensemble forecasting of wind power production, a composite forecast was generated from the ensemble of 12 individual forecasts that were generated in this project. The 12 individual forecasts consisted of four different MOS procedures applied to each of three physics-based models. The full suite of methods was only available for the four-month period extending from March 2005 through June 2005, so the evaluation of the ensemble approach was limited to that period.

Table 4-4 summarizes the wind speed and energy forecast MAEs for four combinations of power generation and wind speed forecasts from the 12-member ensemble. The first column of the power production and wind speed sections of the table lists the MAE of the ensemble-mean forecast. This forecast was constructed by calculating the average of all available members of the 12-member ensemble for each hour of every forecast cycle.

The next column to the right (labeled “Best Overall Method”) lists the MAE of the method that had the lowest MAE over the entire four-month period for each wind plant. This is the method that would typically be used in an operational forecast environment, since it would most likely be classified as the best method when reviewing performance statistics compiled over a long period.

**Table 4-4 Mean absolute errors of ensemble power production (% of rated capacity) and wind speed (m/s) forecasts for the five participating wind plants**

| Month | Power Production Forecast MAE | | | | Wind Speed Forecast MAE | | | |
|---|---|---|---|---|---|---|---|---|
| | Ensemble-12 Mean | Best Overall Method | Best Monthly Method | Average of MAEs | Ensemble-12 Mean | Best Overall Method | Best Monthly Method | Average of MAEs |
| Mountain View | 16.4% | 16.0% | 15.7% | 17.9% | 2.62 | 2.66 | 2.63 | 2.89 |
| Oak Creek | 18.9% | 17.3% | 17.3% | 20.7% | 2.07 | 2.14 | 2.05 | 2.25 |
| PowerWorks | 13.9% | 14.1% | 13.2% | 14.5% | 2.41 | 2.48 | 2.38 | 2.57 |
| SMUD | 17.1% | 17.4% | 17.3% | 18.6% | 1.82 | 1.87 | 1.80 | 1.94 |
| HighWinds | 18.4% | 18.3% | 17.6% | 19.3% | 1.95 | 2.02 | 1.95 | 2.11 |
| **4-months** | **17.0%** | **16.6%** | **16.2%** | **18.2%** | **2.17** | **2.24** | **2.16** | **2.35** |

Notes: The ensemble forecasts include: (1) averaging all the forecasts in a 12-member ensemble ("Ensemble-12 Mean"), (2) the individual method with the lowest MAE for the 4-month period ("Best Overall Method"), (3) a composite of the individual methods with lowest MAE in each month ("Best Monthly Method"); and (4) the average MAE of all 12 members of the ensemble ("Average of MAEs").

The next column to the right, labeled "Best Monthly Method," lists the composite MAE of the forecast created by taking the method with the lowest MAE for each of the four months. It would be difficult to use this approach in an operational environment, since one would have to identify which method was going to perform best for a particular month before the month began. However, it may be possible to develop an "intelligent ensemble composite" that varies the weight placed on different members of the ensemble in the ensemble-composite forecast as a function of parameters which indicate which ensemble members are likely to perform better for a particular forecast cycle. This is a possible area for future research.

The rightmost column, labeled "Average of MAEs," represents the average MAE of all 12 ensemble members. This is the forecast MAE that is most likely if one had no knowledge about the relative performance of the forecast methods and randomly selected a forecast method each day.

The results indicate that the performance of the ensemble mean forecast was substantially better for the wind speed forecasts than for the power production forecasts. For the wind speed forecasts, the ensemble-mean method clearly outperformed the best overall method. The five-plant average MAE for the ensemble-mean wind speed forecasts was 3.1% lower than the composite MAE of the best overall forecast for each wind plant. In fact, the MAE of the ensemble-mean was only very slightly higher than the MAE of the "Best Monthly Forecast". Furthermore, the ensemble-mean forecast had a lower MAE than the best overall method for all five of the wind plants. The ensemble-mean forecast also had an MAE that was almost 8% lower than that of the average MAE of all of the ensemble members.

However, the ensemble-mean power production forecast had a slightly higher four-month average MAE (17.0%) than the composite of the best overall method for each plant (16.6%). Much of the difference is attributable to very poor forecast performance for the Oak Creek plant, because one plant output model significantly outperformed all of the other types due to unusual systematic variations in the plant-scale power curve. Excluding the Oak Creek plant, the performance of the ensemble-mean power production forecast was about the same as that of the best overall method for each plant. This is still not as good as the performance of the ensemble-mean for the wind speed forecasts. The reason for this is not clear but may be related to the fact

that there was less diversity in plant output models than in other parts of the system. This will require further investigation.

These limited tests indicate that the ensemble approach appears to have at least modest potential to improve wind speed forecast performance.

The simple approach of constructing an average wind-speed forecast from all ensemble members could reduce wind speed MAE by 3% to 5% relative to the best overall forecast method. The improvement could increase if an intelligent ensemble composite can be constructed by weighting certain ensemble members more heavily when key parameters indicate they are more likely to produce better forecasts.

For power production forecasts, further refinements of the ensemble forecasting approach are needed. One possibility is to explore ways in which the uncertainty in the plant-scale power curve relationship can be addressed by the forecast ensemble. Another approach is to apply adjustments to the plant-scale power curve to account for variations in atmospheric stability. One way to do this would be to use rapid-update, high-resolution simulations of the wind flow field around the wind turbines to estimate deviations from a reference plant-scale power curve. The next section discusses an initial investigation of this concept.

## Conclusions

The results of the forecast experiments conducted in the screening phase indicated that:

1. The use of improved higher resolution water surface temperature values as input to the physics-based model and a more sophisticated statistical procedure in Model Output Statistics (MOS) component of the forecast system had the greatest positive impact on forecast performance;
2. The use of a higher resolution grid (i.e. smaller grid cells) for the physics-based model generally improved the performance of the raw physics-based model forecasts but did not significantly improve the performance of forecasts after the MOS procedure was applied;
3. The use of a next generation physics-based model (the WRF) and a more sophisticated plant output model yielded modest improvements in forecast performance in the experimental sample, but the significance of these improvements for a larger sample was questionable; and
4. Forecasts generated by computing the mean from an ensemble of two forecasts from different physics-based models produced an insignificant improvement in performance, but this disappointing performance may have been attributable to the small size and limited diversity of the ensemble in the screening phase of the project.

The results of the one-year forecast evaluation experiment indicated that:

1. The average mean absolute error (MAE) of the 48-hour power production forecasts was 14.5% of installed capacity and 52.7% of average production for the entire one-year period and the five participating wind plants;

2. The average MAE of the 48-hour wind speed forecasts was 2.27 m/s or 34.1% of the mean wind speed for the one-year period at the meteorological tower sites within each wind plant;

3. There was a considerable improvement in forecast performance between the forecast evaluation conducted in the previous Energy Commission-EPRI project (2001-02 period) and current project (2004-05 period) for the two wind projects that participated in both projects; the MAE of the annual power production forecast MAE decreased from 16.6% to 13.0% at the Mountain View 1 and 2 plant at San Gorgonio, and from 14.1% to 11.9% at the PowerWorks plant at Altamont Pass;

4. Ensemble forecasting yielded a 2% to 5% reduction in the MAE of the wind speed forecasts, but there was no significant improvement in the MAE of the power production forecasts.

5. The annual power production forecast MAEs varied significantly among the wind plants, ranging from 11.9% to 16.8%;

6. The annual power production MAE was not well-correlated with the wind speed forecast MAE, with low power production MAE values often occurring with high wind speed MAE values, and vise versa; and

7. A substantial portion of the power production forecast MAE variability is due to differences of the wind speed frequency distribution and the maximum slope of the wind plant-scale power curve.

8. In addition, the high-resolution wind flow simulations described in Section 5 indicate that atmospheric stability in the surface boundary layer affects the relationship of wind speeds and power generation between individual wind turbines and thus causes temporal variations in the plant-scale power curve. Thus, it may be possible to improve forecast performance by modeling the impact of anticipated changes in atmospheric stability on the plant-scale power curve.

## Recommendations

Although the current project made significant progress toward improving the accuracy of power production forecasts and the understanding of the characteristics of forecast errors, there are still many promising paths to pursue to further improve day-ahead power production forecast performance.

Ideally, the development of power production forecasting technology should be viewed as an ongoing cyclic process. The first step in each development cycle is a forecast evaluation experiment for a set of wind plants similar to the one performed in the second phase of this task. Next, the data from this evaluation experiment should be thoroughly analyzed to understand the error ranges and characteristics of the current state-of-the-art technology. The combination of an understanding of the error characteristics of the current state-of-the art forecast systems and

awareness of new data or modeling technology will enable modifications to the forecast system that can be tested in the evaluation phase of a new development cycle.

At present, the most promising opportunity for further improvement of forecast performance is the emergence of higher-resolution and more accurate measurements of atmospheric and ground and water surface variables by satellite-based and ground-based remote sensing systems. The challenge will be to effectively use the high volumes of data produced by these systems to obtain the maximum possible improvement in the performance of power production forecasts on the day-ahead or other look-ahead time scales. It is recommended that the next phase of wind energy forecasting research continue in California focus developing techniques to effectively utilize the next generation of remotely-sensed data.

# 5
# NUMERICAL AND WIND TUNNEL MODELING OF WIND FLOW AND PLANT-SCALE POWER CURVE OVER COMPLEX TERRAIN

This section summarizes the parallel efforts by AWS Truewind and University of California at Davis to improve the modeling of plant-scale power curves by utilizing numerical and wind tunnel models to evaluate wind flow, atmospheric stability, and other conditions over the complex terrain at Altamont Pass. The detailed numerical and wind-tunnel modeling results are presented in Section 6 of Volume 2 and Volume 3, respectively (Energy Commission and EPRI, 2006b and 2006c).

## Objectives

A significant source of uncertainty and error in wind power production forecasts is attributable to the scatter in the relationship between the average wind speed over a prescribed time interval (e.g. an hour) measured at one or more meteorological towers within a wind plant and the average plant power production over that interval. The data scatter indicate that, even with a perfect wind speed and direction forecast at the location of the meteorological tower(s), there will still be a substantial error in the power production forecasts.

Typically, given a perfect wind speed and direction forecast for the plant's meteorological towers, the energy forecast MAE is about 5% of rated capacity. This represents a substantial portion of the typical 15% to 20% MAE of state-of-the-art next-day energy forecasts. Some of the energy forecast error is related to non-meteorological factors such as variations in turbine availability and turbine performance. However, most of this error is attributable to the variation in wind speed and direction within the plant's domain, which frequently causes the wind speed experienced by each turbine to be different from that measured at the meteorological tower.

The objective of the wind flow modeling tasks is to improve the accuracy of plant-scale wind power production forecasts by constructing generic (i.e. not case specific) relationships between the wind speed and direction at a plant's meteorological tower and the wind speed and direction at each turbine location within the farm. The results presented here are based on both wind tunnel and very high-resolution physics-based numerical simulations of the wind flow within and in the vicinity of the wind plant for a representative sample of cases.

## Scope

The vision is that once relationships have been constructed, they can be used to estimate the wind speed at each turbine location from the measured or forecasted speed at the meteorological tower. The wind speed at each turbine location can then be used to calculate the power production of the turbine through the use of the manufacturer's power curve. Ultimately, the calculated power production for each turbine can be aggregated to yield a power production estimate for the entire wind plant.

The following sections present the research approach, results, and conclusions for the wind tunnel and numerical modeling research and the overall conclusions and recommendations.

## Wind Tunnel Modeling of Wind Flow over Complex Terrain

### *Approach*

Researchers at the University of California at Davis (UC Davis) used an atmospheric boundary layer wind tunnel (ABLWT) to model the air flow over the cluster of wind turbines associated with Tower M127 at the PowerWorks wind plant in the Altamont Pass of California. Figure 5-1 illustrates the terrain model of Altamont Pass used to measure wind power density at the met tower and wind turbine locations in the wind tunnel. The view is from the prevailing wind direction, west-southwest (240 degrees), toward east-northeast (60 degrees), and the highest terrain elevation is in the foreground.

The UC Davis group calculated the ratio of wind speeds at each turbine to the speed at the meteorological tower by measuring the simulated steady-state wind speed in the wind tunnel at the meteorological tower and each of 87 turbine locations. They calculated the wind speed ratios for four different wind directions by rotating the terrain model within the wind tunnel. The measurements were interpolated to create a database of relative winds for each turbine location over all wind directions. Given a wind speed and direction at the meteorological tower, this database can be used to extrapolate the wind speed at each turbine location. The turbine power curve supplied by the manufacturer is then applied at each turbine location to predict the power production of each turbine, which when summed, yields the total power prediction for the plant.

### *Results*

In addition to the plant power curve based on a database of wind-tunnel measurements, several other methods were developed for comparison purposes. A numerical simulation method that required minimal use of computational resources was developed at UC Davis to meet the goal of developing an "empirical" power curve that could be applied without requiring wind-tunnel measurements or computationally intensive numerical models. This method, called "Potential10," used ensembles of two-dimensional potential flow simulations at the turbine locations to develop a relative wind database equivalent to the one based on wind-tunnel measurements. Both the ABLWT and Potential10 methods can be applied with or without using the wind direction at the meteorological tower or a correction for air density. Finally, for the

ABLWT method, an "optimum" version was developed in which the method was "tuned" to minimize overall error. Additionally, two power curve methods were applied that used historical plant wind and power production data. The first used multiple linear regression (MLR) to fit a

**Figure 5-1 Terrain model of Altamont Pass used to measure wind power densities at the met tower and wind turbine locations vs. wind direction in the wind tunnel. View is from the prevailing wind direction, west-southwest (240°), toward the east northeast (60°). The highest elevation is in the foreground.**

power curve to the historical data, while the second used the medians of historical power production binned according to wind speed.

Each of the power curve methods was applied to predict the power production of the M127 turbine cluster based on the hourly observed Tower M127 wind speeds and directions between June 25, 2001 and June 11, 2005. Observations were excluded if the wind direction measurement appeared inaccurate. Table 5-1 presents the resulting mean errors (ME) and mean absolute errors (MAE) of the M127 power predictions (% of rated capacity) for the various plant power curve methods.

Generally, the ABLWT method outperformed the Potential10 method, mainly because the Potential10 method tends to over-predict power production over a broad range of wind speeds. It should be noted that the ABLWT method has been more extensively developed than the Potential10 method. Therefore, it may be possible to improve the Potential10 method by refining the model, especially the treatment of hill wake effects.

**Table 5-1 Mean error (ME) and mean absolute error (MAE) of UC Davis plant power curve methods. Values are percentage of wind farm capacity.**

| Prediction Method | ME | MAE |
|---|---|---|
| ABLWT (No Wind Direction) | 2.55 | 6.18 |
| ABLWT (w/ Wind Direction) | 2.06 | 5.96 |
| ABLWT (w/ Wind Direction and Density) | 1.89 | 6.01 |
| ABLWT (Optimum) | -0.38 | 5.80 |
| Potential10 (No Wind Direction) | 4.17 | 7.21 |
| Potential10 (w/ Wind Direction) | 3.10 | 6.77 |
| Potential10 (w/ Wind Direction and Density) | 2.92 | 6.74 |
| Median Historical Data Fit | 0.07 | 5.49 |
| MLR Historical Data Fit | -0.34 | 6.49 |

### *Conclusions*

The UC Davis plant power curve methods were all similar in overall accuracy. Perhaps the most significant finding is that the ABLWT and Potential10 methods were capable of predicting the wind farm power production to a similar degree of accuracy as the other methods, but do not require any historical data from the site for power curve development. This suggests that these methods may be especially useful for wind resource assessment and siting of turbines at proposed wind plant locations.

## Numerical Modeling of Wind Flow over Complex Terrain

### *Approach*

In this task, the same turbine/meteorological tower wind speed ratios, calculated in the boundary layer wind tunnel experiments, were inferred via a set of high-resolution, physics-based,

atmospheric numerical model simulations. The question is whether a numerical model can correctly simulate wind speed differences between individual turbines, and whether the simulated differences calculated from a few detailed simulations can improve the prediction of the plant power output over a longer period of time.

Version 6.4 of the Mesoscale Atmospheric Simulation System (MASS) was used to perform the simulations. MASS was originally developed in the 1980's (Kaplan *et al*. 1982) as a research model. It has since been used for a wide range of research and commercial applications and, in recent years, some of the model's databases and physical parameterizations have been optimized for a number of wind energy applications. MASS is a three-dimensional physics-based model which uses a set of mathematical equations to represent the basic physical principles of conservation of mass, momentum and energy and the equation of state for moist air.

## *Results*

The MASS model was used to generate six-hour simulations for each of ten cases distributed over three months (Dec 2001, May and July 2002), using a 100-meter grid centered over the M127 cluster of turbines at Altamont Pass. Thirty-three grid cells covered the turbine cluster, with one to five turbines falling within each grid cell. Most of the turbines are in locations with less favorable winds than the meteorological tower, i.e. terrain blocking and other effects will tend to reduce the wind speed ratios (turbine/meteorological tower) for most of the wind turbines to less than unity, especially under more stable atmospheric conditions.

### *Turbine Wind Speed Ratios*

Figure 5-2 shows the evolution of wind speed ratios for each of the 100-m cells that contain turbines in the M127 cluster over the six-hour simulation for 16 July 2002, one of the more stable cases. For cases with less atmospheric stability, there is much less variation between turbine locations, and the ratios are closer to one.

The ratio of the wind speed at each turbine location to the speed at M127 was calculated at each time and then averaged to yield a set of mean turbine wind speed ratios. These ratios were quite different from those obtained from the UC Davis boundary layer wind tunnel. The numerical simulation-derived ratios were used to infer the wind speeds at each turbine location from the wind speed at M127. The wind speeds were then used to calculate the power production of each turbine using the manufacturer's power curve, and the turbine power outputs were then added to yield the total M127 cluster power output.

Using two datasets of observed wind speeds covering either ten months or three years, this forecast method exhibited a mean absolute error (MAE) from 0.3% to 0.4% of rated capacity higher than those obtained using an empirical (statistical) plant-scale power curve, and 0.1% to 0.3% of rated capacity higher than those obtained using the wind tunnel method. The mean error (ME, bias) of the numerical simulation method however, was about 2% lower than those of the other two methods.

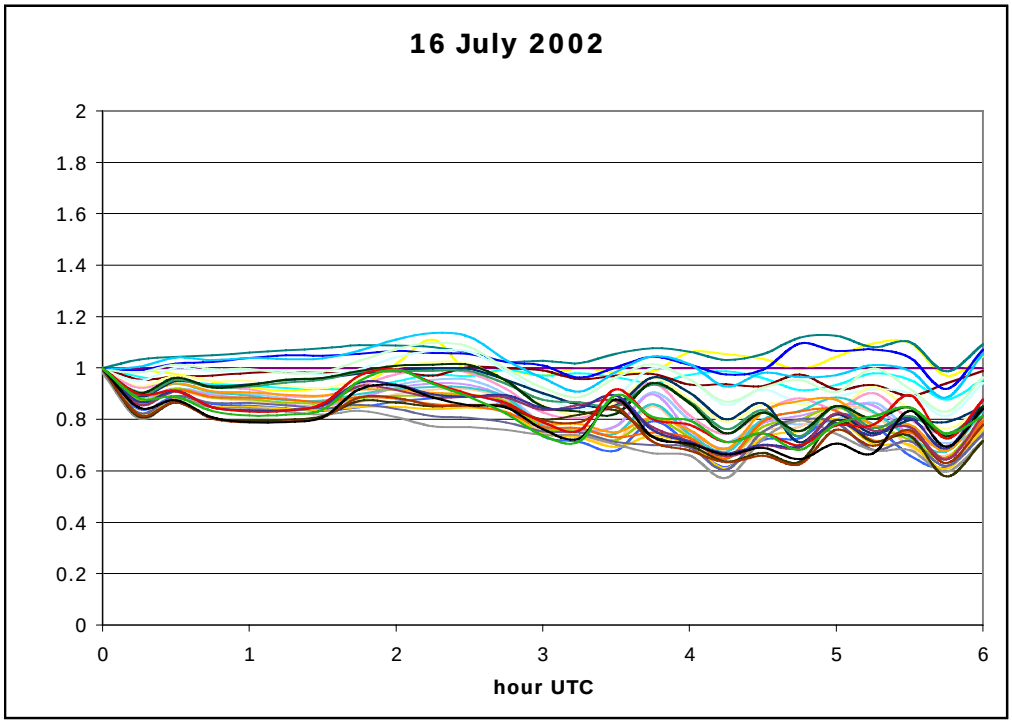


**Figure 5-2 Evolution of individual turbine wind speed ratios over the six-hour, 100-m simulation beginning at 0000 UTC 16 July 2002, Altamont Pass Turbine Cluster M127**

As shown in Figure 5-3, using ten months of forecast wind speeds, the MAEs of the three methods were almost indistinguishable.

### *Atmospheric Stability*

The ten simulated cases exhibited a wide range of atmospheric stabilities in the lowest few hundred meters of the atmosphere. The high wind speed cases in July exhibited relatively high atmospheric stability. Some of the December cases were also very stable, probably a result of the presence of a wintertime cold stable air mass and strong radiational cooling at the surface when skies were clear. One of the December cases and two of the May cases were much less stable and, under near-neutral stability, it would be expected that the numerical simulations would behave more like the neutral stability flow simulated in the wind tunnel.

Further investigation showed that forecast performance improved, by modifying the turbine wind speed ratios in a very simple way using a stability parameter calculated from the 100-m

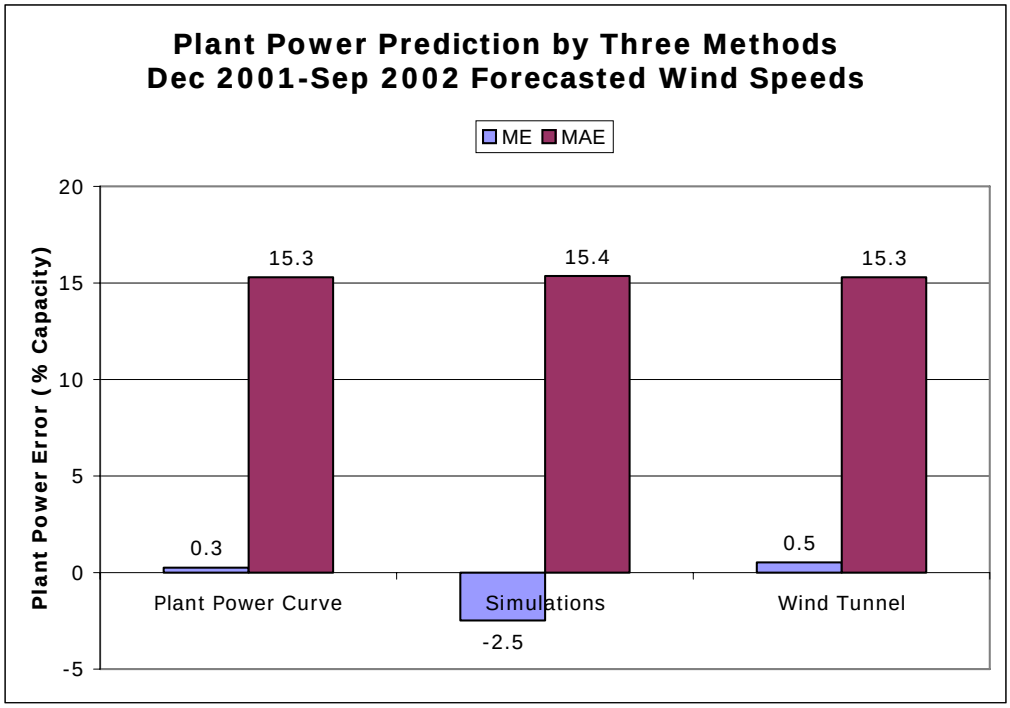


**Figure 5-3 Comparison of three methods of predicting the plant power output using forecasted M127 wind speeds from the December 2001 to September 2002 dataset.**

simulation data. As shown in Figure 5-4, the MAE of the stability-corrected power forecast was 1.3% of rated capacity lower than those of the statistical plant-scale power curve and wind tunnel methods, and the ME was 4% lower.

This encouraging result is tempered by the fact that the same stability correction didn't help when applied outside the time frame of the 100-m simulations. In that test, the stability at the meteorological tower was extracted from much coarser 8-km simulations. The lack of improvement suggested that the 8-km runs do not resolve the meteorology of the Altamont Pass well enough to provide a useful source of stability information.

One strategy would be to run operational simulations to as high a resolution as possible, perhaps at 2-km or 1-km resolution. The atmospheric stability estimates provided by these higher-resolution runs may be sufficiently dependable to apply a stability correction to the turbine wind speed ratios in order to improve forecast performance.

Another approach would be to apply the understanding of the effect of stability on the M127 wind speed-plant power relationship to improve the empirical plant power curve. Perhaps a set of stability classes could be defined, and an empirical plant power curve could be derived for each stability class.

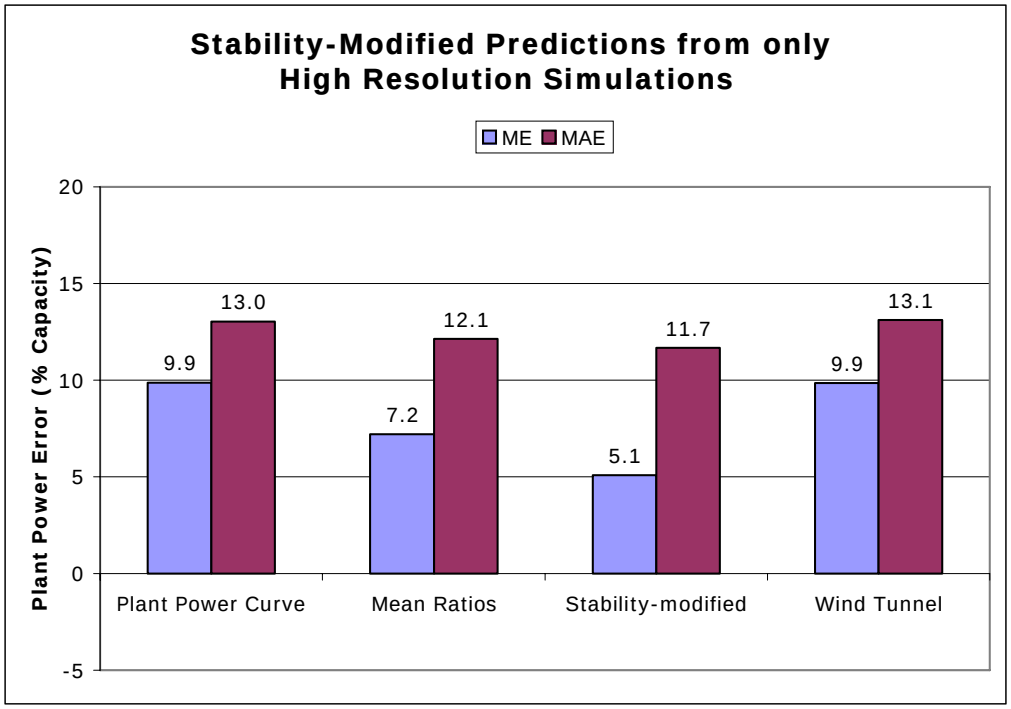


**Figure 5-4 Comparison of four methods of predicting the plant power output using observed M127 wind speeds from the ten 6-hr periods simulated by the high-resolution numerical model. "Mean Ratios" is the simulation method using wind speed ratios between the turbine locations and M127 that are averages over the ten cases with a range of stabilities. "Stability-modified" refers to predictions in which the turbine wind speed ratios were adjusted for the stability of each case.**

## *Conclusions*

In summary, the results from the very high-resolution numerical simulations of the wind flow in the Altamont Pass and their comparison to the results from the wind tunnel simulations indicate that:

1. The wind tunnel and numerical simulation wind speed ratios are substantially different, and the ratios derived from the numerical simulations are generally lower than those derived from the wind tunnel data;
2. Variations of the atmospheric boundary layer stability between the cases are the most likely cause of the differences between the wind speed ratios derived from the numerical and wind tunnel modeling. Only the numerical modeling considers atmospheric stability;
3. The met tower wind speed ratios exhibit substantial temporal variability on the time scales of hours as well as between days and seasons;
4. Forecasts using the numerical simulation and wind tunnel ratios achieved about the same level of performance, and the performance was not significantly different from forecasts employing the commonly-used empirical power curve method; and

5. The use of stability-modified wind speed ratios appears to offer some potential for improvement based on theoretical arguments and preliminary tests.

Recommendations for additional work on the impact of atmospheric stability include:

1. Investigate and find the best way to quantify atmospheric stability based on observations and high-resolution numerical simulations;

2. Determine whether a stability parameter can be generally employed to improve the power production predictions generated by a plant-scale power curve, given a measured wind speed and direction; and

3. Determine whether numerical simulations with relatively coarse grid resolution (one to four kilometers) can generate the critical atmospheric stability information needed to adjust the plant-scale power curve.

## Overall Conclusions and Recommendations

The similarity of the accuracy resulting from the various UC Davis plant power curve methods suggests that an overall accuracy limit is being approached, and that it will be difficult to achieve substantially better accuracy based on the wind speed and direction at a single point within complex terrain. This is because many factors such as atmospheric stability and local forcing conditions cannot be factored into any plant power curve based only on the wind speed and direction at a single location.

Future research should adapt the power curve methods addressed in this project to predict wind power output based on meteorological data from multiple local sites. Ideally, a wind tunnel test would be performed along with high resolution modeling to develop the plant-scale power curve using wind speed and direction measurements from the nacelle anemometer and vane and wind energy measurements for each individual wind turbine and wind speed and direction data from multiple meteorological towers.

The results from the high-resolution simulations clearly showed that the stability of the lower atmosphere has a significant effect on the spatial differences in wind speeds between turbines in the Altamont Pass M127 cluster and, therefore, on the relationship between the met tower wind speed and the wind plant power output. Although the stability routinely varies from day to day in a complex way (it’s not a simple seasonal effect), it is not used in any way to alter the plant-scale power curve and therefore the prediction of wind plant power generation.

# 6
# HIGH-RESOLUTION WEATHER AND WIND FLOW FORECASTING

This section describes high-resolution forecasting of the weather conditions in northern and southern California used to perform the numerical modeling described in the previous section. The detailed results are presented in Volume 2, Section 6 (EPRI-Energy Commission PIER, 2006b).

## Introduction

Accurate wind energy forecasting begins with an accurate forecast of the weather conditions in the region and accounts for local terrain, bodies of water, and other surface features that affect the wind speed and direction at the location of each wind turbine. The National Atmospheric Release Advisory Center (NARAC) at the Lawrence Livermore National Laboratory (LLNL) has the capability to generate accurate weather and wind speed and direction forecasts at very fine grid resolution using the latest meso-scale models. As a result, LLNL joined the project team to generate high-resolution wind speed and direction forecasts for use in the project.

The principal objectives of LLNL's involvement were to provide real-time wind speed and direction forecasts for use in development of improved wind energy forecasting algorithms and to support wind tunnel and numerical modeling of wind flow over complex terrain.

## COAMPS Model and Experiment Design

A modified version of the Naval Research Laboratory's (NRL's) three-dimensional Coupled Ocean/Atmosphere Mesoscale Prediction System (COAMPS), Version 2. 0. 15 was used in this study (Chin et al. 2000, 2001 and 2005). COAMPS consists of a data assimilation system, a nonhydrostatic atmospheric forecast model, and a hydrostatic ocean model.

In this study, we used only the data assimilation and the atmospheric model to provide real-time forecasts.

- The atmospheric forecast model is composed of a compressible form of the dynamics, nest-grid capability, and parameterizations of subgrid-scale turbulence, surface momentum and heat fluxes, explicit ice microphysics, subgrid-scale cumulus clouds, shortwave and longwave radiation, and urban canopy physics.

- The terrain-following vertical coordinate is also used to simulate airflow over an irregular surface. The model terrain is given from one-km resolution terrain database using Silhouette average method with filter.
- The model domain contains 31 grid points in the vertical direction, with the grid size varied to maximize resolution at lower levels. The vertical consists of nine grid points below 127-m elevation, with the grid spacings of 4, 4, 4, 6, 10, 16, 24, 34 and 50 meters, starting at ground level. The grid spacing aloft gradually increases to 800 m at 3.152-km altitude. Above this level, the grid size is uniformly set at 800 m up to 7.592-km altitude. Then, the grid size gradually increases to 5.0 km at 24.352-km altitude.
- In the horizontal direction, a total of three nested domains are used. Both zonal and meridianal coordinates have 61 grid points for all nested grids. A uniform grid size of 36 km is used for the outer coarse grid (nest_1), the grid sizes of the inner grids are each one third of the size of the previous grid, e.g. the middle grid size is 12 km (nest_2), and the inner grid size is 4 km (nest_3). with a constant size ratio of three to define the inner nest grids.
- The time series of the forecasts use time steps of 90 and 45 seconds for non-sound and sound wave calculations, respectively. The time steps for the finer-grid domains are reduced in proportion to the nest-grid size ratios.
- The rigid boundary condition is imposed at the vertical boundary. A sponge-damping layer is placed above 10.052 km to minimize the reflection of internal gravity waves off the rigid upper boundary. The Davies (1976) boundary condition is applied to the lateral boundaries with a nudging zone of seven grid points at each lateral boundary. A time filter with a coefficient of 0.2 is applied to control computational instability associated with the leapfrog time approximation in the model.

In this study, two watches of 48-h forecasts (00Z and 12 Z, respectively) are performed daily over California for a grid centered at the Altamont Pass and during the 12 months from July 2004 to June 2005. However, due to the size limit of huge forecast data storage, only the nested-grid data for the first week of each month are stored and used to assess the forecast errors with respect to the measurements at 11 available tower observations. Nonetheless, the yearly forecast data of the finest grids were stored at UC Davis for a separate study to evaluate the wind energy forecast errors. In this study, the forecast errors are measured by the mean absolute errors of the wind speed and direction forecast vs. the observed data for each forecast hour, which avoids the self-canceling effect of under-and over-prediction present in the mean forecast error.

## Results

Figure 6-1 shows the locations of the 11 meteorological towers used to estimate wind speed forecast errors and the resolution of the terrain elevation as a function of the four grid sizes tested in the evaluation (12, 4, 1.33, and 0.444 km). The mean absolute errors of forecast wind speed and direction were derived for each month using the forecast and observed data from 11 meteorological towers at Altamont Pass for each forecast hour throughout the 48-hour forecast period, and averaging over the available met towers and 14 weekly forecasts (two forecasts per day, seven days per week). Normally, the mean absolute errors were calculated using the

forecasts for the first week of each month. Occasionally, the forecast period was shifted several days to accommodate the availability of station measurements.

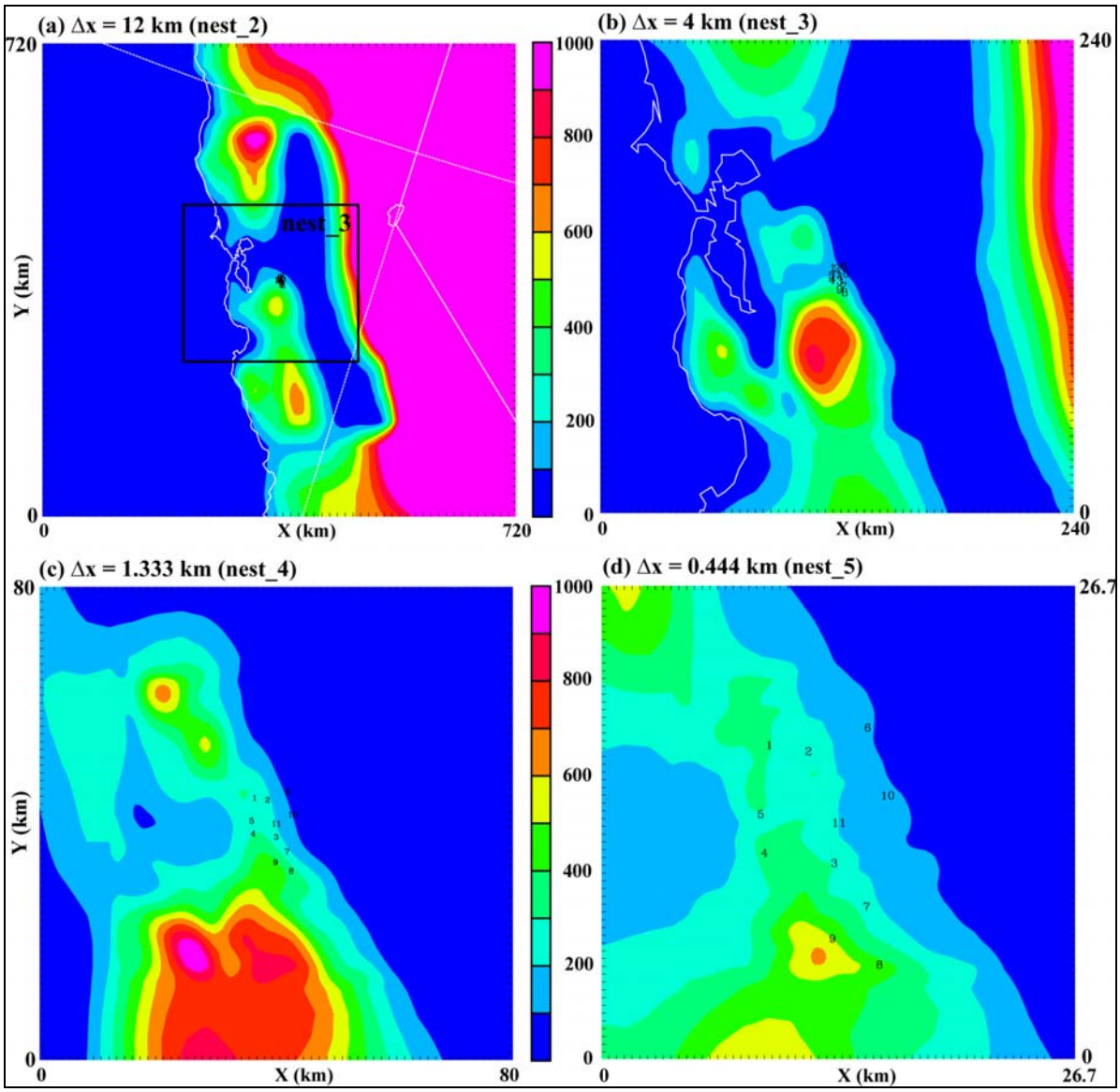


**Figure 6-1 Resolution of terrain elevation (meters) vs. grid size (km) of the nested domain: (a) Δx = 12 km (nest_2), (b) Δx = 4 km (nest_3), (c) Δx = 1.333 km (nest_4), and (4) Δx = 0.444 km (nest_5). The letters mark the locations of the met towers used in this study.**

As shown in Figure 6-2, for a warm month (June 2005), the wind speed forecast errors clearly exhibit dependence on grid resolution using the data from all stations (Figure 6-2a), but the wind direction error does not show the same dependence (Figure 6-2b). The observed station wind speed of the warm month sometimes reaches 20 m/s. The absolute error of forecast wind speed is about 6 m/s with the coarser grid resolution (36 km) and can decrease to 4 m/s in the higher resolution forecast (4 km). With the separation of UNC and REL stations, the impact of grid resolution on wind speed errors remains unchanged (Figs. 6-2c and 6-2e). In contrast, the wind

direction error is significantly reduced with increasing grid resolution using REL stations, while the error is fairly large at UNC stations and shows an opposite dependence on the grid resolution (Figures 6-2d and 6-2f).

In contrast, the forecast errors for a cold month (December 2004) in Figure 6-3 show much different patterns relative to those for the warm-months. Unlike the warm months, there is no clear dependence of forecast errors on grid resolution in the cold month, even with the separation of REL and UNC stations. In addition, the magnitude of wind speed errors is noticeably reduced in the cold month as a result of weaker winds (< 10 m/s, except for the storm periods). Although the resolution impact is weak during the cold months, the separation of UNC and REL stations still exhibits qualitative improvement in the forecast error for both wind speed and direction.

## Conclusions

The month-to-month variation of wind forecast errors clearly exhibits a semi-annual fluctuation with prominent dependence on the grid resolution in the warm months (i.e., strong wind power period) when the frontal activity is weak; the large forecast errors are systematically reduced with increasing grid resolution for both wind speed and direction. However, this dependence diminishes when synoptic-scale frontal activity prevails in the cold months.

The remaining question to be addressed from this research outcome is whether the grid resolution dependence would continue with decreasing grid size or if this dependence tendency converges at a certain grid size in the strong wind power period. Although the increasing grid resolution can resolve a better representation of model terrain geometry (magnitude and shape), further study of Silhouette terrain representation and the use of finer resolution terrain database are highly recommended to improve the forecast accuracy for the airflow over the complex terrain.

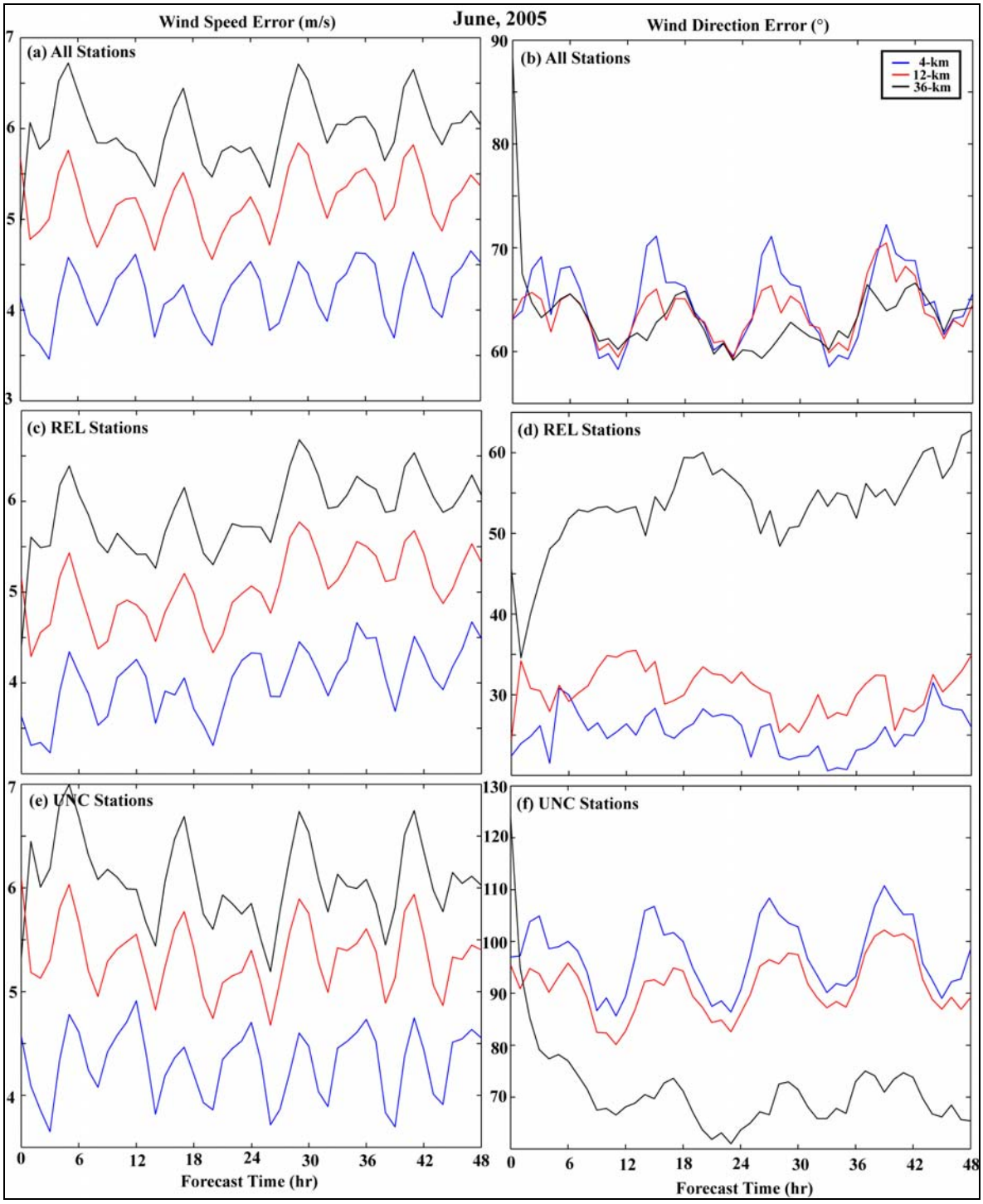


**Figure 6-2 Weekly mean absolute errors of NARAC forecasts averaged over the selected stations for June 1-7, 2005. The colored lines represent the results for different horizontal resolutions (36, 12, and 4km, respectively). The left panels present MAEs for wind speed forecasts, and the right panels for wind direction. The top panels (a and b) are the forecast errors using the measurements from all stations, the middle ones (c and d) using five reliable stations, and the bottom plots (e and f) using uncertain measurements from the remaining six stations.**

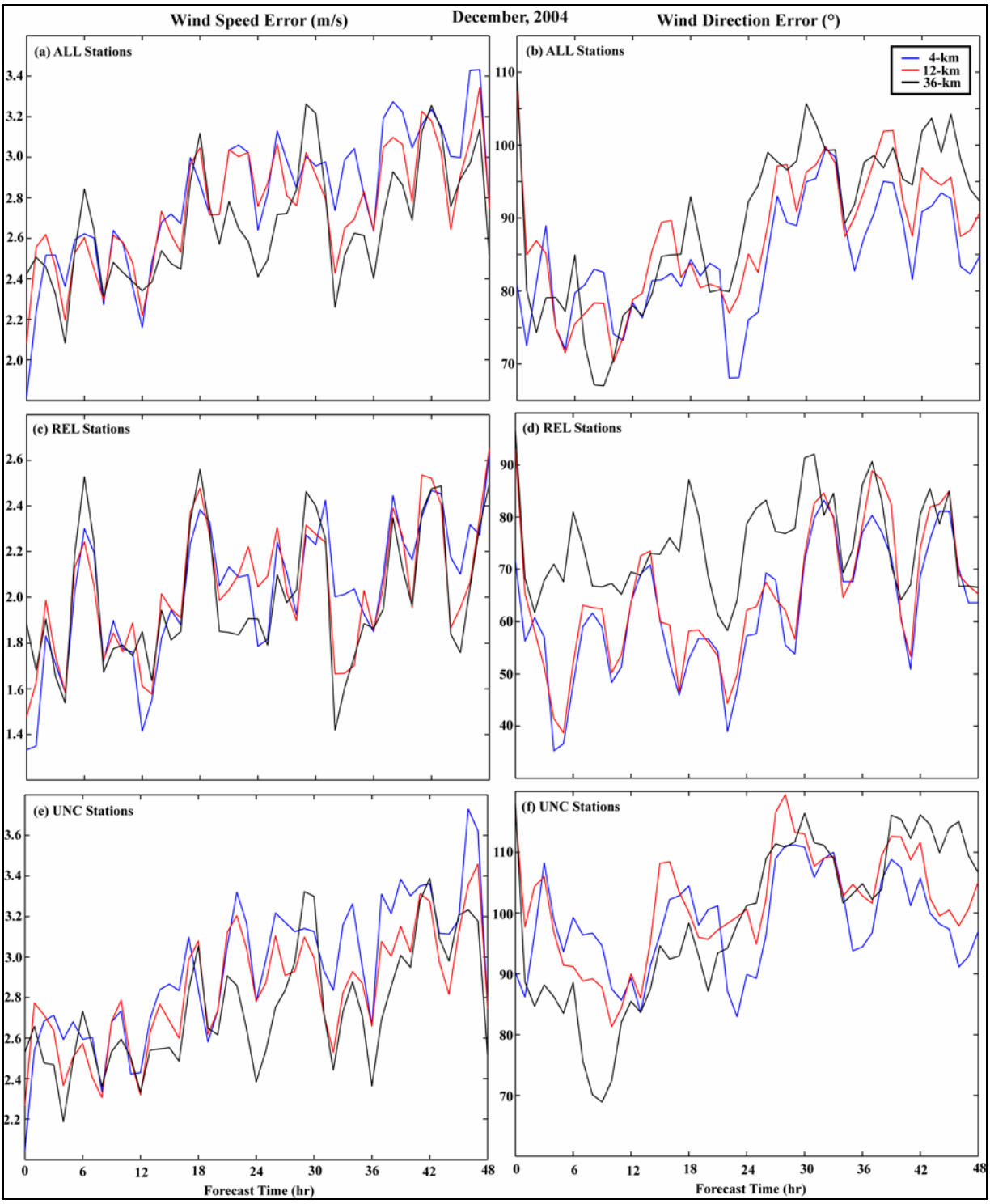


**Figure 6-3 Weekly mean absolute errors of NARAC wind speed (left) and wind direction (right) forecasts averaged over the selected stations for December 2004.**

# 7
# CALIFORNIA WIND GENERATION RESEARCH DATASET (CARD)

This section summarizes the *California Wind Generation Research Dataset* (CARD), a database containing wind resource and power density data at multiple elevations over 5-km grids in northern and southern California. The dataset was generated using NOAA-NCEP forecast data and AWS Truewind's MASS 6 model for the period July 1, 2004 through June 30, 2005. Volume 4 describes the CARD dataset in detail (Energy Commission and EPRI, 2006d).

## Objective

The concept of the California Wind Generation Research Dataset (CARD) was formulated in response to this need. The original vision was that the CARD database would consist of a wide variety of measurement data from both proprietary and public sources. It was envisioned that the database would consist of data from both in situ and remote-sensing measurement devices.

However, a number of issues arose with that version of the concept. First, much of the in situ data relevant to the wind industry are proprietary and access to the data typically comes with a variety of restrictions on the permitted uses and users. It would be difficult to include such data in a database while adhering to the restrictions.

Second, the data from different measurement systems often exhibit substantially different accuracy, scales of representativeness, and spatial and temporal coverage characteristics. Thus, it is often difficult to construct a composite representation of the behavior of the wind for a specific region (e.g. the area of a wind plant) from different sensors. The most common approach is for the user to ignore unfamiliar data types and rely on those that have characteristics that are familiar to the user.

Third, the spatial and temporal coverage provided by measurement data is typically characterized by large gaps for which no data are available due to the limitations of the measuring devices.

An approach that addresses many of these issues is to create a database of numerically-simulated data using a physics-based atmospheric model. Physics-based atmospheric models ingest data from a wide variety of atmospheric sensors and create a physically-consistent, three-dimensional dataset of all of the basic atmospheric variables.

It was decided to create the CARD database using the numerical simulation approach. The objectives were to design, create, and document the CARD database. The structure of the database was designed to take advantage of the physics-based numerical simulations that were

generated during the production of the one-year of day-ahead forecasts for the five participating wind plants, described earlier.

### Approach

The CARD dataset was generated using data from the numerical atmospheric simulations executed during the production of the one-year of 48-hour forecasts of hourly wind power production, described in Chapter 4. The forecasts were generated during the June 2004 to July 2005 period at five wind plants in California.

The algorithms used to generate the forecasts required generation of high-resolution physics-based simulations of the atmosphere over the regional area surrounding each wind plant. The outputs from these simulations were also used to create the CARD database.

The atmospheric model used to generate the simulations was Version 6 of the Mesoscale Atmospheric Simulation System (MASS) model. The MASS model was developed during the 1980s as part of NASA's research activities in the development of new remote sensing systems (Kaplan et al, 1982). The model has evolved over the ensuing 20 years by incorporating new representations of various physical processes as they became available. Version 5 of the MASS model was used to generate the forecast simulations for the previous Energy Commission-EPRI forecast evaluation project (EPRI, 2002).

The MASS 6 forecast simulations were generated on a nested grid system consisting of three grids. An outer grid of 100 by 80 grid cells with a cell size of 20 km was used to simulate the larger scale flow over the southwestern United States and the adjacent Pacific Ocean and Mexico. This grid is referred to as the "A" grid.

Two higher-resolution grids, designated the "B" and "C" grids, were nested inside of the A grid. Both of the high-resolution grids employed an 80 by 80 matrix of grid cells and a grid cell size of 5 km. The B grid was centered over the Bay Area of northern California, shown in Figure 7-1, and was used to generate forecast data for the PowerWorks, SMUD and High Winds wind plants. The C grid was centered over the area of southern California shown in Figure 7-2, and was used to generate forecast data for the Oak Creek and Mountain View wind plants.

The physics-based simulations were initialized twice per day. The initialization times were 0000 UTC (4:00 PM PST) and 1200 UTC (4:00 AM PST). The data required to specify the initial conditions and the lateral boundary conditions for the MASS model simulations were extracted from initialization analysis and forecast grid point data from NCEP's Global Forecast System (GFS).

The CARD data were extracted from hours 9 through 32 of the numerical simulations, initialized at 0000 UTC of each day. Since 0000 UTC corresponds to 4:00 PM PST, hour 9 of the simulation corresponds to the hour ending at 1:00 AM on the day after the initialization of the simulation, while hour 32 corresponds to the hour ending the following midnight. Thus, the database is a concatenation of the 24 hours of physics-based model output representing the period from hour 9 (1:00 AM) to hour 32 (midnight) of each day's numerical simulation.

## Results

The CARD dataset consists of two-dimensional fields of selected variables (i.e. grid point values) at one-hour intervals and at each grid point of the 5-km forecast grids over northern and southern California (Figures 7-1 and 7-2).

The database variables are wind direction (degrees), wind speed m/s), air density(kg/m$^2$) , temperature (C), water vapor mixing ratio (kg/kg) at height levels of 10, 30, 50, 70, 100, 300, 600 and 1000 meters above ground level, and the wind power density at 10, 30, 50 and 70 meters above ground level.

Figure 7-3 illustrates the directory structure of the CARD database. The top level of the directory structure is designated CALR1. There are two subdirectories within the CALR1 directory, one for the northern California B grid and one for the southern California C grid.

Each of the individual grid directories (B and C) contains 365 dated directories, an ASTAT directory, and a STATIC_DATA file.

There is one dated directory for each day of the one-year period from July 1, 2004 to June 30, 2005 (B and C grids). Each dated directory contains 24 individual data files, and each file contains grid point values of all database variables for one hour of the PST calendar day denoted by the directory name.

The naming convention of the dated directories is YYYYMMDDHH, where YYYY is the 4-digit year, MM is the 2-digit month, DD is the 2-digit day, and HH is the 2-digit UTC time of initialization of the model simulation that generated the data.

The ASTAT directory contains summary statistics files for each month of the year and for the year as a whole. Each summary statistics file provides monthly or annual statistical data, including the monthly or annual mean, maximum, minimum, and standard deviation of each database variable as well as the prevailing (most frequently occurring) wind direction at each elevation in the database .

The STATIC_DATA file contains two-dimensional arrays of the terrain elevation and latitude and longitude for each grid point.

## Conclusions

1. The CARD database can be used to simulate the hourly operation of a wind project at candidate sites, test wind energy forecasting methods, and conduct other wind power research and planning activities.

2. The wind resource and power density data in the CARD database represent simulated hourly conditions during the period July 1, 2004 through June 30, 2005, and should not be used to simulate long-term performance of a wind power plant over multiple years.

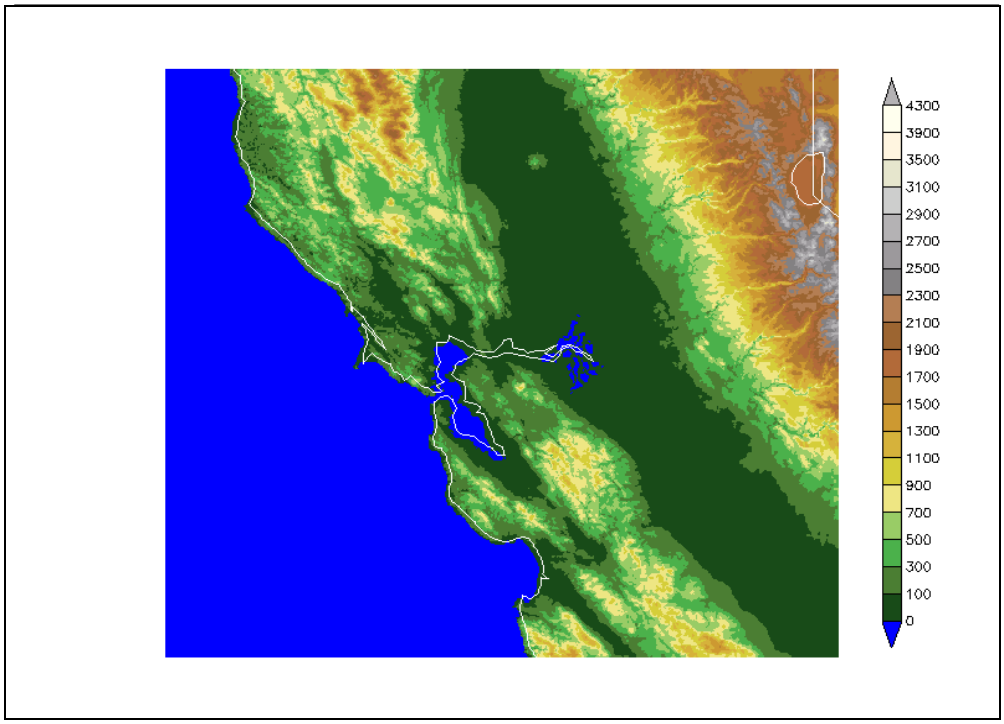


**Figure 7-1**
**The northern California geographical domain covered by the 80 X 80 matrix of 5-km grid cells used to produce the high-resolution MASS 6 simulations (B Grid)**

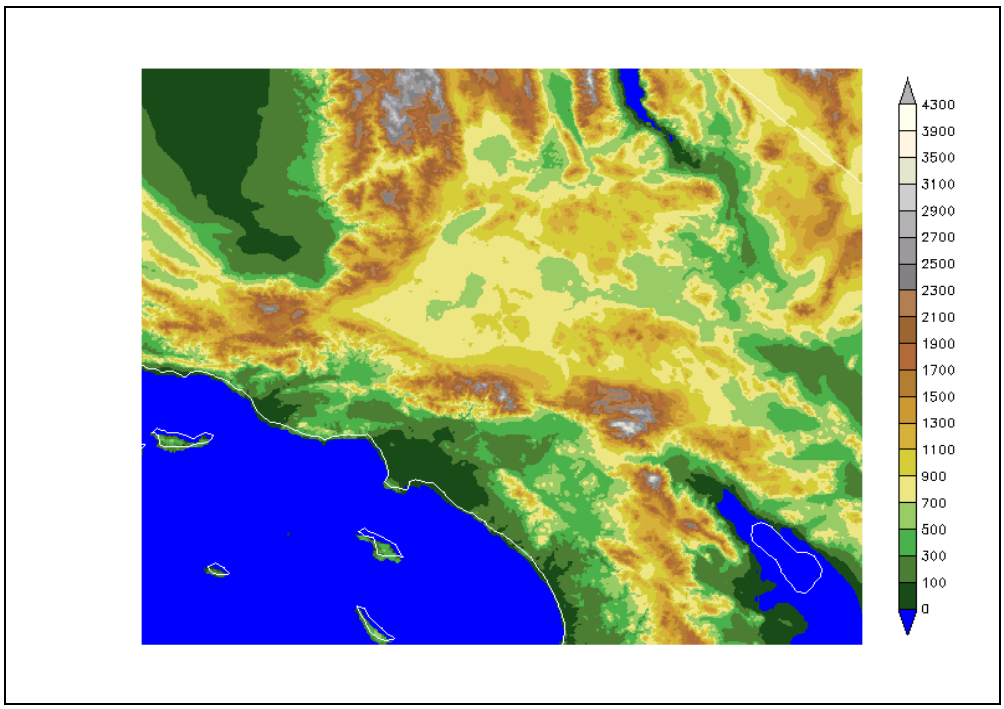


**Figure 7-2**
**The southern California geographical domain covered by the 80 X 80 matrix of 5-km grid cells used to produce the high-resolution MASS 6 simulations (C Grid)**

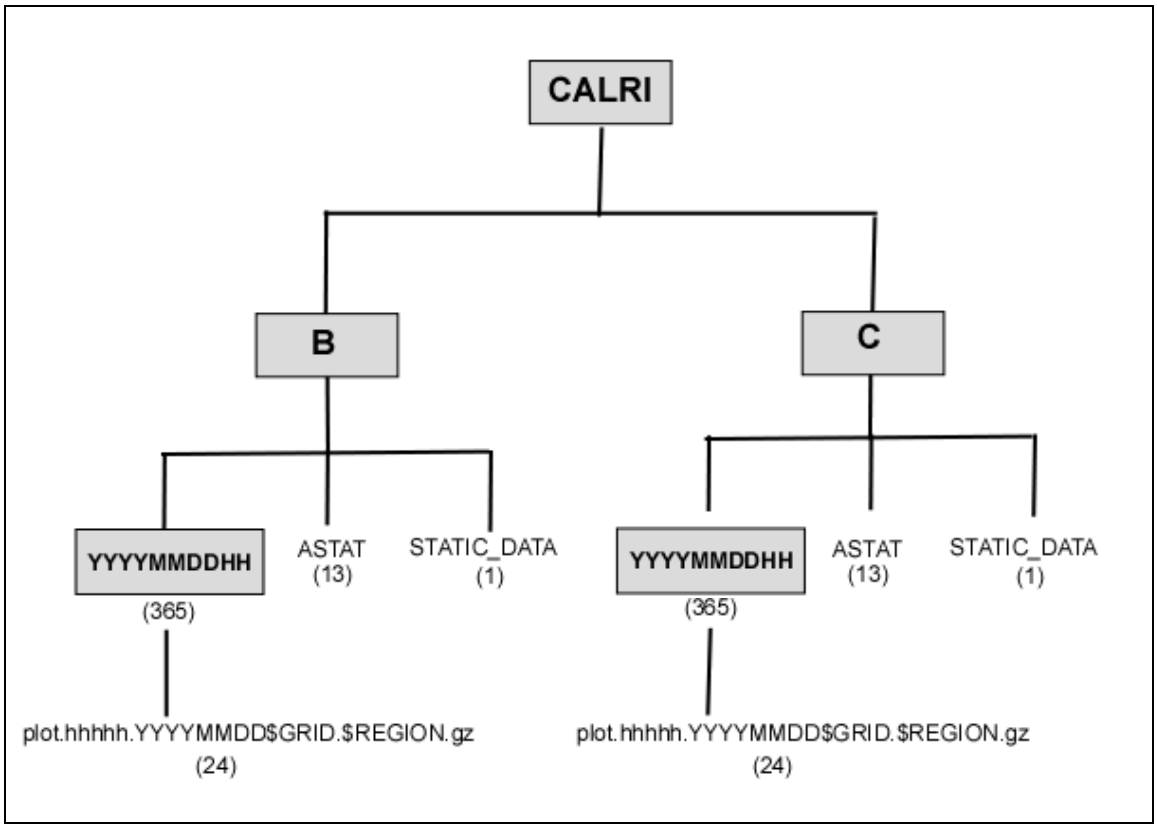


**Figure 7-3**
**The directory structure of the CARD database. The shaded boxes denote directories. Names not enclosed in boxes are files. The numbers in parentheses indicate the number of files or directories in each database element. See text for explanation of directory and file names.**

# 8
# CONCLUSIONS AND RECOMMENDATIONS

## Summary

The worldwide installed wind generation capacity increased by 25% and reached almost 60,000 MW worldwide during 2005. As wind capacity continues to grow and large regional concentrations of wind generation emerge, utilities and regional transmission organizations will increasingly need accurate same-day and next-day forecasts of wind energy generation to dispatch system generation and transmission resource and anticipate rapid changes of wind generation.

The project objectives were to summarize the status of wind energy forecasting, address the integration of wind energy forecasting into the utility and regional electricity system operations; and summarize the results of the California Energy Commission-EPRI Regional Wind Energy Forecasting System Development project completed in December 2005.

The Energy Commission-EPRI forecasting project developed and tested wind energy forecasting algorithms for both same-day and next-day hourly forecasts of wind speed and energy generation for the principal wind resource areas of California and for five wind plants. The report summarizes selected results including (1) development and testing of a next-hour regional forecasting algorithm based on a new two-stage, artificial-neural-network (ANN) algorithm; (2) enhancement and testing of the existing 48-hour forecast algorithm; (3) wind tunnel and high-resolution numerical modeling of wind flow over complex terrain and power generation of individual wind turbines; and (4) development of the *California Wind Generation Research Dataset* (CARD). The following sections summarize the project results.

### *Short-Term, Same-Day Forecasting*

The project team first developed a design concept for a two-stage forecast system for short-term, same-day forecasting based upon artificial neural network (ANN) techniques. The first stage consists of a mini-ensemble of three different forecast methods that exploit different input datasets and predictive tools. The second stage is composed of an artificial neural network that weights each of the three forecasts from the first stage according to their recent performance characteristics and creates an “optimal” composite forecast.

A limited version of the forecast system was tested using five-minute regional wind power generation data for 2004 provided by the CA ISO. The forecast system used only one of the three forecast methods in the first stage of the system, an autoregressive ANN technique, to forecast five-minute power generation over a moving three-hour forecast period.

The limited forecast system exhibited considerable skill (up to 20%) relative to persistence during the warm season, but virtually no skill during the cold season when the wind speeds are low most of the time. The lack of skill during the cold season was expected, and it is anticipated that the other two methods in the first stage of the system will provide most of the forecast skill during the cold season. The next step is to implement and test the entire two-stage forecast system.

## *Long-Term, Next-Day Forecasting*

The project team evaluated improvements of the existing 48-hour forecast algorithm used in the previous Energy Commission-EPRI project in two phases.

Phase 1 screened several potential input data and forecast model enhancements via a series of forecast experiments using wind resource and power production data for selected months from the previous Energy Commission-EPRI project (Energy Commission and EPRI, 2003a and 2003b).

Several of the enhancements resulted in significant improvement in forecast performance relative to the previous project, including the use of high-resolution surface water temperature data from satellite-based sensors and a more sophisticated statistical model to adjust the raw forecasts of the physics-based model.

Phase 2 incorporated several of the enhancements into a modified *eWind* forecast system and generated daily 48-hour forecasts of hourly wind speed and energy generation at each of five participating California wind plants for a one-year period. Two of the five participating plants also participated in the previous Energy Commission-EPRI forecasting project, the 66.6 MW Mountain View 1 and 2 project in San Gorgonio Pass and the 90 MW Wind Energy Partners/WindWorks project at Altamont Pass. The three other wind plants were located in the Solano (2) and Tehachapi wind resource areas.

The annual mean absolute error (MAE) of the 48-hour power generation forecasts was 14.5% of rated capacity and 52.7% of the actual wind generation for all five wind plants. The annual wind speed forecast MAE for the same plants and time periods was 2.27 m/s, which was 34.1% of the average speed.

In addition, generation of a composite forecast from an ensemble of forecast methods via a simple arithmetic average of the forecasts reduced the wind-speed forecast MAE by 2% to 5%. However, ensemble forecasting did not significantly reduce the power production forecast MAE. This may be related to a lack of diversity in how the wind speed forecasts were transformed to power production forecasts in the members of the ensemble. Most of the ensemble members used the same empirical power curve method and hence the power production forecast errors were highly correlated, which tends to reduce the benefits of the ensemble approach.

Another factor is that none of the forecast methods in the ensemble address the impact of atmospheric stability in the surface boundary layer on plant-scale wind flow and the variation of power generation between individual wind turbines, especially in complex terrain. The high-

resolution wind flow simulations showed that the variability of individual turbine power generation and therefore the plant-scale power curve are affected by whether the surface boundary layer is unstable, neutral, or stable as indicated by the vertical temperature profile.

The enhancements reduced the annual mean absolute errors of the wind power generation forecasts and provided significant insights into the characteristics and sources of the wind speed and power generation forecast errors. The results will help plan the direction of future research to improve day-ahead forecast performance.

### *Wind Tunnel and Numerical Modeling*

The project team applied two different approaches to very high-resolution modeling of wind flow and power generation in complex terrain. First, the atmospheric boundary layer wind tunnel at the University of California at Davis was used to simulate the variation of wind speeds at different turbine locations within the Altamont Pass M127 cluster. Second, high-resolution, physics-based, atmospheric numerical model simulations were used to simulate the same wind speed variations.

Both approaches were used to infer the wind speeds at individual turbine locations from the wind speed at the M127 meteorological tower, apply the turbine manufacturer's power curve to estimate the power production of each wind turbine, and aggregate the power production of the turbines to calculate the total hourly power output. The wind tunnel and numerical simulation methods each generated wind plant power forecasts that were very close to, but not quite as accurate as those generated by the widely-used empirical plant-scale power curve approach. This activity was assisted by high-resolution numerical weather forecasts provided by the National Atmospheric Release Advisory Center (NARAC) at the Lawrence Livermore National Laboratory (LLNL.

The numerical simulation results also indicate that atmospheric stability of the lower atmosphere significantly affects the relationship between the wind speeds at individual turbine locations. The use of an atmospheric stability parameter calculated from the high-resolution numerical simulations improved the accuracy of the wind plant power forecasts.

The importance of atmospheric stability suggests that additional research to incorporate atmospheric stability into the forecast models could further improve the accuracy of the next-day wind power production forecasts.

### *California Wind Generation Research Dataset (CARD)*

The project team developed the *California Wind Generation Research Database* (CARD). The CARD dataset contains one continuous year of hourly grid point data for a set of meteorological variables. The data are provided at multiple levels on two horizontal grids, each with a grid cell size of 5 km, one located in Northern California and one in Southern California. The dataset was generated for the period July 1, 2004 through June 30, 2005, using the MASS mesoscale model, and it is not based directly on measured data.

The database variables are wind direction (degrees), wind speed (m/s), air density(kg/m$^2$) , temperature (C), water vapor mixing ratio (kg/kg) at height levels of 10, 30, 50, 70, 100, 300, 600 and 1000 meters above ground level and the wind power density at 10, 30, 50 and 70 meters above ground level.

The CARD database can be used to simulate the hourly operation of a wind project at candidate sites, test wind energy forecasting methods, and conduct other wind power research and planning activities.

## Conclusions

Three factors shape the need for wind energy forecasting in California and other regions where wind generation is growing rapidly:

- The expected large additions of wind generation in California;
- The impacts of large regional concentrations of intermittent wind generation on wind generation ramp rates and electricity system operations and costs; and
- The resulting need for accurate same-day and next-day forecasts to forecast rapid ramp rates of wind generation and to support grid operations and wind energy markets

The California Regional Wind Energy Forecasting Project achieved all of its objectives and made significant advances in the following areas:

- *New Two-Stage Artificial Neural Network Forecast Algorithm:* The algorithm developed in the project has excellent potential for short-term wind power generation forecasting over the zero- to six- hour forecast time window. Since only a portion of the first stage was tested and it demonstrated improved forecast performance vs. persistence only during the warm season, additional testing of the full algorithm is needed for both the warm and cold seasons.
- *Enhancement of 48-Hour Forecast Algorithm*: The most promising enhancements include use of more sophisticated statistical methods in the MOS (Model Output Statistics) component of the forecast system, water temperature data available from satellite sensors; advanced statistical methods to adjust the raw physics-based forecasts, and ensemble forecasting using different combinations of meso-scale models, plant-scale power curve models, and statistical methods and averaging the resulting forecasts.
- *Ensemble Forecasting:* Ensemble forecasting improved 48-hour wind speed but not power generation forecast performance. Therefore, additional development and testing are needed, most likely to address the high sensitivity of power generation errors to wind speed forecast errors due to the shape of the plant-scale power curve and to account for atmospheric stability and other factors that affect the plant-scale power curve used in the forecast algorithm.

- *Wind Tunnel and High-Resolution Numerical Modeling of Wind Flow over Complex Terrain*: The forecast performance was similar for wind power production forecasts based on data from wind tunnel and high-resolution numerical modeling of wind flow over a portion of Altamont Pass. However, the variation of wind turbine/reference meteorological tower wind-speed ratios between individual wind turbines indicated by the wind tunnel and numerical model simulations were different, possibly due to the impact of atmospheric stability as discussed below.
- *Impact of Atmospheric Stability:* The most significant finding of the numerical modeling work is that atmospheric stability in the surface boundary layer affects the variations of wind turbine/reference meteorological tower wind-speed ratios between individual wind turbines. Initial testing of a simple algorithm that adjusts wind speed ratios for atmospheric stability yielded improved power generation forecast performance. Thus further development and testing is needed of both a plant-scale power curve algorithm that accounts for atmospheric stability and a rapid-update high-resolution meso-scale model to provide accurate estimates of atmospheric stability to the algorithm.
- *California Wind Generation Research Dataset* (CARD): The CARD database contains 8,760 hours of hourly wind speed, direction, wind power density, and other data at multiple levels over two 5-km grids in northern and southern California. It was generated via a numerical simulation of hourly weather conditions during the period July 1, 2004 through June 30 2005 and is not representative of long-term average data. CARD can be used to simulate the hourly operation of a wind project at candidate sites, test wind energy forecasting methods, and conduct other wind power research and planning activities.

## Recommendations

In order to provide accurate wind energy forecasting technology when it is needed within 5 to 10 years, it is strongly recommended that: (1) the California wind energy forecasting research program should continue with active participation by the California utilities and the CA ISO, California Energy Commission, and Electric Power Research Institute; and (2) the program should focus on two specific activities:

- Implement the same-day and next-day forecast algorithms developed in the Energy Commission-EPRI project via development of a real-time wind energy forecast workstation in collaboration with participating utilities, ISOs, and RTOs; and
- Continue to improve the forecast performance of both same-day and next-day forecast algorithms, especially with regard to accurately forecasting high hourly ramp rates of wind generation.

The recommended field implementation and research activities can be conducted in parallel:

### Field Implementation of Wind Forecast Workstation

1. Incorporate forecast algorithms from the California Regional Wind Energy Forecast System Development Project into a simplified forecast workstation to display real-time same-day and next-day forecasts, forecast performance statistics, and forecast confidence indicator.
2. Meet with utility, ISO, and RTO system operators to demonstrate workstation and invite input on forecast needs for responding to high wind ramp rates and other impacts.
3. Develop specifications for prototype wind forecast workstation in collaboration with system operators.
4. Develop, build, and test prototype forecast workstation; implement same-day and next-day forecast algorithm enhancements in the workstation as they become available.
5. Implement forecast improvements from research as they become available.

### Next-Hour and Same-Day Forecasting Research

1. Complete development and testing of the two-stage ANN regional forecast algorithm.
2. Focus development on improving forecast accuracy and providing accurate forecasts of high ramp rates over the three to six-hour time period.
3. Develop methodology for optimal placement of meteorological towers within and around each wind resource area.
4. Facilitate development, installation, and maintenance of a supplemental network of real-time meteorological towers at optimal locations within each wind resource area.
5. Develop and test rapid-update meteorological forecast model to support same day forecasting.

### Next-Day and Longer Forecasting Research

1. Continue research on use of remote-sensing data, enhancements of the mesoscale weather models, plant-scale power curves, statistical MOS, and ensemble forecast techniques to improve forecast performance.
2. Investigate the impacts of atmospheric stability in the surface boundary layer on the variability of turbine/met tower wind speed ratios.
3. Develop and test methodology to apply adjustment for atmospheric stability to turbine/met tower wind speed ratios and translate ratios into the plant-scale power curve.

4. Develop and test methodology to account for evaptranspiration of moisture from irrigated fields and other processes occurring at the air-land interface (i.e. the earth's surface).

# 9
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