Final Report

California Renewable Energy Forecasting, Resource Data and Mapping

Executive Summary

Regents of the University of California

Basic Ordering Agreement

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Objectives, Organization, and Acknowledgements:

Objectives: This report is an account of work addressing the following task objectives:

- Review and evaluate current knowledge and models for forecasting wind, solar thermal and photovoltaic generation resources, and recommend ways in which forecasting can be enhanced.

- Review and evaluate maps and databases locating geothermal, wind and solar thermal resources, and maps and databases of transmission lines and loads in the LA Basin and the Salton Trough.

Project Organization and Acknowledgements: The authors and contributors thank the California Energy Commission and its Public Interest Energy Research Program for initiating, identifying objectives and funding the work presented in this report. The project scope was organized according objectives and team expertise. Thus, Parts 1 and 2 of Task 1 were complete by the California Solar Energy Collaborative (CSEC) and the California Wind Energy Collaborative (CWEC) respectively. Task 2 was a joint effort coordinated by the California Geothermal Energy Collaborative with contributions from CSEC and CWEC. Other valuable contributions to the project are acknowledged as follows:

Task 1: California Renewable Energy Forecasting, Resource Data and Mapping, Part 1 of 2: Solar Forecasting: The California Solar Energy Collaborative team is grateful to Bill Mahoney (NCAR), James Blatchford (CAISO), Phil de Mello (UC Davis) for their input.

Task 1: California Renewable Energy Forecasting, Resource Data and Mapping, Part 2 of 2: Wind Data Forecasting and Mapping: The California Wind Energy Collaborative team thanks the following people for their input: Jim Blatchford (CAISO), Phil de Mello (UC Davis), Bill Mahoney (NCAR), Barry Gilman (SCE), Jim Molesworth (enXco), Andrew Klingler (PG&E), and Buck Cutting (SMUD).

Task 2: California Renewable Energy Forecasting, Resource Data and Mapping, Identification of Areas within the Los Angeles Basin and Salton Trough with Potential for Integrated Renewable Energy Projects: Jacque Gilbreath and Terry L. Rose of the California Energy Commission's Cartography Unit of the Siting, Transmission and Environmental Protection Division provided the base maps used to construct Figures 10 and 13, and their support is gratefully acknowledged. The California Geothermal Energy Collaborative team also thanks Chris Silva for his work in support of the data retrieval and organization effort. Conversations with Pablo Gutierrez, Prab Sethi and Gail Wiggett of the California Energy Commission substantially improved the presentation and analysis.

Executive Summary

INTRODUCTION

Renewable Energy Data Milestones and Questions

This report summarizes a short term project responding to California renewable energy data milestones identified in Energy Commission renewable energy technology roadmaps and in the California Renewable Energy Collaborative strategic plan. Specific milestones include:

- **Increased Data Integration and Dissemination:** "A historical, real-time and forecasted data portal is established and accepted by industry that expands tiered access to data for a mix of private and public use. The portal would have flexible architecture designed for new data inputs in the future." (high priority/long term)[1]

[1] Roadmap for Utility-Scale Renewable Energy, Navigant Consulting, September 30, 2009

- **Improved Sensor Deployment Plan:** "A plan for optimizing the state-wide deployment of met towers and other resourcing-monitoring sensors has been developed." (high priority/mid-term)[1]
- **Data Access:** "Establish a database and related web-portal that would allow easy access to updated resource assessments. Key the database so that site-specific data can be readily accessed. Assure that the available data are regularly updated and vetted within the geothermal community." [2]

The work reflected in this report provides initial answers to some important questions, including the following:

Solar and Wind Forecasting Data Needs

- What is the current state of the art in wind forecasting in support of California grid operations, including commercial software offerings, sources of real time wind data available and being to calibrate day-ahead and hour-ahead forecasts, and forecasting applications in development that will be deployed by CAISO and the state's transmission operators?
- How can the accuracy and coverage of forecasting capabilities in current use be improved by deploying additional sensors and capabilities for analytical interpretation of real time energy production data?
- What data sources are available to support day-ahead and hour-ahead forecasting of solar power plant performance, and what is the current state of the art in solar power plant operation using such data sources to dispatch thermal energy storage and predict ramping and variability of utility scale PV plant output?
- What data needs exist or will exist for solar forecasting services in the context of smart grid operation, and how can real time production data from rooftop systems be used in production forecasting at all deployment scales, i.e. building, community and utility?

Resource Data for Integrated Renewable Energy Systems

- Based on mapping of available and relevant data, what potential exists for geothermal energy production at oil and gas wells in the LA Basin?
- Based on mapping of oil, gas and geothermal wells and power plants, what potential exists for building, community and utility scale geothermal energy applications in the Salton Sea Trough?
- What GIS mapping resources exist for solar radiation in the LA Basin and Salton Sea Trough, and what upgrades are feasible in the short term?
- What GIS mapping resources exist for wind resources in the LA Basin and Salton Sea Trough, and what upgrades are feasible in the short term?
- What GIS maps are available that show transmission, distribution and related facilities in the LA Basis and Salton Sea Trough, and how can these maps be best adapted for use in concert with RE resource maps?
- Where in the LA Basin and Salton Sea Trough are large concentrations of residential, commercial or industrial load within five miles of potential integrated renewable energy systems sites, and is the current electricity delivery infrastructure capable of delivering renewable energy from these sites to the nearby load concentrations?

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[2] California Renewable Energy Collaborative Strategic Plan and Organizational Structure, June 2009, page 17

- What opportunities and barriers to hybrid RE system deployment in the LA Basin and Salton Sea Trough can be inferred from available GIS mapping information?

The above questions reflect the intended use of California state-wide solar and wind forecasting data in balancing electricity supply and demand on a state-wide basis. They also reflect awareness that regional and local balancing requires both historical resource information as well as data that can be processed and used in near term resource forecasting. Attempting to develop such information and data to the required degree of refinement on a state-wide basis was outside the team's capacity and schedule, so efforts were focused on a geographic zone having good resource quality and diversity as well as strategic importance to the reliable operation of the California's electricity grid.

BACKGROUND AND RECOMMENDATIONS

Renewable Energy Resource and Forecasting and Mapping - Background

Regarding forecasting of variable resources, wind forecasting has quickly evolved as a service offered to transmission system operators by multiple vendors globally. The California Independent System Operator is one such customer. As the dialog between vendors and their ISO customers continues, wind forecasting services will evolve to be more accurate and include more predictive features, e.g. unusual weather conditions that result in abnormal wind delivery profiles, e.g. strong winds that require taking wind plants off line. It is likely that wind and solar forecast offerings will be integrated as well.

Because the solar energy deployment in California will encompass building scale, community scale as well as utility scale PV generation, as well as solar thermal power plants with and without thermal energy storage, solar forecasting services and customers will likely be more diverse and sophisticated than for wind alone. It is easy, for example, to imagine ways in which the evolving “smart grid” will be able to deliver solar forecasting information to communities and buildings for purposes of regulating demand in anticipation of solar generation patterns in the context of real time pricing by local electricity distribution companies.

It is equally easy to imagine solar and wind forecasts being integrated to determine the best strategy for thermal storage charge and discharge and the appropriate price signals to the operators of solar power plants that include storage capacity.

It is important for RD&D programs like PIER to envision such emerging technical integration solutions in order to fund the data collection and public access databases that will be needed to fully optimize California electric system operations and minimize end user costs overall.

Regarding mapping in support of integrated systems development, the LA Basin represents a resource context in which electric transmission and distribution infrastructure is pervasive, and circuits are loaded according to utility customer demand. In this context the time variability of the local renewable resource mix would be of prime interest, because it would affect local reliability and power flows. These considerations, along with local demand forecasts would determine the extent to which new investment in transmission and distribution infrastructure could be avoided.

Another consideration for the LA Basin is the fact that it represents a major load center with constraints on the capacity of its transmission gateways. In other words, during high demand periods, there is a limit on the capacity to feed electricity into the area from the state-wide grid. The existence of renewable generation sources in the Basin would mitigate this limit and possibly result in avoided costs of increasing gateway transmission capacity.

The Salton Sea Trough area represents a resource context in which deploying additional renewable resources may require additional transmission upgrades or even new corridors. Cost of service impacts of such investments would be minimized to the extent incremental and existing transmission capacity could be operated with less variability and higher utilization factors. This would require adjusting the mix of renewable and energy storage systems in the resource area for least combined generation and transmission cost.

Finally, development of integrated renewable energy resources in the Salton Sea Trough area may require greater attention to environmental factors than development in areas with high human population densities. The extent to which multiple resources could be converted on the same generation plant site would tend to reduce environmental impacts for a given amount of energy supply. Shared site infrastructure could represent an economic opportunity as well. For example, solar and wind arrays could at least conceptually share electricity collection and interconnection infrastructure.

Definitive determinations on the matters discussed above are beyond the scope of the present effort but can be addressed in future case studies.

Renewable Energy Resource and Forecasting and Mapping - Recommendations

The work reported here is foundational to longer term efforts to address the above questions more fully and in greater depth. Core efforts were significantly constrained by a four month period of performance, following which a six month no cost extension allowed for some refinements. A major recommendation is that efforts to address the above questions be re-initiated by research teams having a longer period of performance. Their charter should include efforts to apply resource information, including maps and real time forecasts to practical problems facing both project developers and energy system operators. Validation of the accessibility and practical use of information and data resources should be part of any effort to develop such resources.

Solar Forecasting State of the Art - Background

As solar thermal and photovoltaic (PV) generation begins to have a larger role in electrical generation in California, the California Independent System Operators needs to accommodate their variable nature in its forecasting and dispatching. Likewise, solar power plant operators and net metered utility customers using solar PV will have uses for forecasting information.

Load forecasts have been an integral part of managing electric energy markets and infrastructure for many decades. Consequently, experiences, regulations, and planning by utilities and independent system operators (ISO) are the dominant consideration for this report. Furthermore the rules established by ISOs will impact the economic value of forecasting to other stakeholders such as owner-operators. Consequently, in the near-term the primary stakeholder to be considered for forecasting needs and plans is the California Independent System Operators. Secondary stakeholders are utilities who will see greater distributed PV penetration on their urban distribution feeders. Currently on a few utilities have mechanisms in place to use solar forecasts for local automated response to voltage fluctuations caused by solar production.

The market need for better solar power integration and planning tools have been widely recognized (e.g. DOE FOA 0085, CEC PON 08-11, CSI RD&D Round 1). CAISO uses the following forecasts: The day ahead (DA) forecast is submitted at 0530 prior to the operating day, which begins at midnight on the day of submission and covers (on an hourly basis) each of the 24 hours of that operating day. Therefore, the day ahead forecast is provided 18.5 to 42.5 hours prior to the forecasted operating day. The vast majority of conventional generation is scheduled in the DA market. The hour ahead (HA) forecast is submitted 105 minutes prior to each operating hour. It also provides an advisory forecast for the 7 hours after the operating hour. CAISO also is studying in intra-hour forecasts on 5 minute intervals. FERC has issued a Notice of Proposed Rulemaking requiring public utility transmission providers to offer all customers the opportunity to schedule transmission service every 15 minutes, and requiring providers with variable renewables on their systems to use power production forecasting.

Currently, under the CAISO Participating Intermittent Resources Program (PIRP), a participating intermittent resource receives special settlement treatment that nets output deviations over a month's period if the resource's scheduling coordinator submits hour ahead forecasts developed by a forecast service provider for that operating hour (de Mello and Blatchford, personal communication, 2010). Although the PIRP program does not require them, in practice DA forecasts are provided under the same contract. Wind units may participate in

DA market however no special settlement treatments apply. Forecasts are integrated in CAISO planning, but there is no financial incentive to the forecast providers for accurate forecasts.

At some point PIRP may be modified and renewable generators will be required to participate in parts of the regular DA and HA markets. In that case some of the economic benefit and interest in forecasting would shift to the owner-operators of renewable power plants which would dramatically change the marketplace for renewable forecasting. An example of such a system is the Spanish 'premium tariff' for the regulation of renewable energy which allows operators of power plants to participate directly on the electricity market instead of reverting to flat-rate prices. The premium tariff option motivates operators of renewable energy plants to increasingly act like managers of conventional plants, selling electricity at the liberalized market. Just like a normal market participant, the operator places bids in advance on the DA market and is obliged to fulfill them. Thus there is the need for operators of renewable energy plants to be able to provide predictable and "dispatchable"energy in the profitable premium tariff.

Solar Forecasting State of the Art - Recommendations

- **Current Forecast Skills:**

Satellite and numerical weather prediction (NWP) are currently the best tools for hour ahead (HA) and day ahead (DA) forecasts, respectively. Efforts are underway by solar forecasters and NOAA to improve mesoscale NWP for the HA market.

Further research should be conducted on the forecast skills of the low hanging fruit - operational NWP models - for California. The applicability of mesoscale NWP to locally enhance forecast skill should also be quantified. This research would enable wind forecast providers to adapt their existing products for the solar forecasting market and quantify the potential success of such an approach.

Support should be provided to the California ISO to conduct a 12 months forecast 'competition' to evaluate forecast skills of forecast providers and maturity of different approaches. Careful design of such a study is critical and stakeholders should be consulted in the planning stage.

- **Expanding ground measurements:**

Ground measurements of global horizontal irradiance and direct normal incident irradiance for concentrating plants should be (and currently are) required by the California ISO for utility scale solar farms. To improve HA and intra-hour forecasts statewide, more ground data are necessary. The most economical approach would be to require or incentivize 3rd party data providers / aggregators to share PV output and radiometer data in real time with the ISO, utilities, and forecast providers. Models should be developed to derive solar irradiance values from such ground PV data. The advent of smart meters that can monitor residential PV outputs provides an additional avenue to implement this strategy. Also, research on sky imager deployments in areas with high PV penetration should be pursued.

- **DNI Forecasts:**

Research on radiative transfer in the atmosphere related to direct normal incident (DNI) forecasts is necessary. These forecasts should evaluate the effects of cirrus clouds, forest fire smoke, dust storms, and urban aerosol air pollution transport on concentrating solar power plants in California.

Please refer to the report "Appendix 1 – Current State of the Art in Solar Forecasting," for a full review of solar power forecasting and more detailed recommendations.

Wind Forecasting State of the Art – Background

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

Wind Forecasting State of the Art – Findings and Recommendations

- The rapid growth in installed wind power capacity has led to an increased interest in wind power forecasting. More and more utilities and ISOs are adopting, or planning to adopt, central wind forecasting systems as a means of more effectively integrating greater amounts of wind energy.
- Currently major stakeholders in California (PG&E, SMUD, California ISO, SCE) use both hour ahead (HA) forecasts and day ahead (DA) in their daily business (for power generation scheduling, power trading, system operating, etc). There is an emerging interest in intra-hour forecasting from a few parties.
- There exist two approaches to the short-term wind power forecasting: physical approach and statistical approach. In some cases, a combination of both is used. Most forecast models employ numerical weather prediction (NWP) models to improve forecast accuracy.
- The accuracy of the forecasts from a wind forecasting model depends on a number of factors, such as wind plant terrain topology, surface roughness, weather regime, wind pattern, forecast horizon, etc. For a specific wind forecasting project, comparison of different models needs to be carried out in order to find the "best" forecasting model or combination of models.
- The quality and availability of data are critical to successful wind forecasts. It is recommended to fund and support work focusing on better understanding the data impacts, improving data acquisition and transmission, promoting data sharing, and developing new technologies in meteorological measurements.
- There are limited studies on ramp forecasting. More efforts need to be taken to improve ramp rate forecasting. When forecasting ramp rates, it is important to define the aspects of ramping that have the highest priority such as ramp time start, ramp rate or magnitude. The CAISO and other system operators should work with forecasters to determine how to ask for and evaluate ramp rate forecasting.
- Wind data are recorded and stored by a variety of entities in California, including the California ISO, IOUs and munis, wind plant owners, wind developers, NOAA and NWS, and a few other organizations and government agencies. Most data have restricted availability/accessibility, inconsistent data quality, and insufficient sampling frequency.

- Additional recommended future research include: new technologies in meteorological measurements, turbine icing forecasting, and studies on atmospheric boundary layer profiles.
- Currently the penetration level of wind energy in communities and buildings is low. Current industry does not see any need for distribution level wind forecasting.

Please refer to the report “Appendix 2 - Wind Power Forecasting: A Review of State-of-the-Art and Recommendations for Better Forecasts”, for a full review of wind power forecasting and more detailed recommendations.

Resource Mapping: LA Basin and Salton Sea Trough - Background

Renewable energy resources in Southern California are extensive but unevenly distributed. Two regions that hold promise for integrating renewable energy resources are the Los Angeles Basin and the Salton Trough/Imperial Valley.

Previous work had identified and quantified the power generating capacity of solar and wind technologies in the study areas. Although the geothermal resource in the Salton Sea/Imperial Valley region has been assessed, the geothermal resource in the Los Angeles Basin had not been previously estimated. Therefore, separate methodologies had to be developed for establishing the extent of co-located resources in the two regions.

The Los Angeles Basin geothermal resource was established by obtaining data from the California Division of Oil, Gas and Geothermal Resources database on oil pools in the Los Angeles Basin. We considered a pool a potential geothermal resource if the pool had temperatures exceeding 91ºC. Such pools were also characterized as "geopressured" if the pressure in the pool exceeded 10% of the nominal hydrostatic pressure. The identified pools were then mapped with respect to already characterized solar and wind resources. The results demonstrate that twelve pools in the Los Angeles Basin are likely geothermal resources. Of these twelve, five are located in close proximity to substantial wind resources. Although the solar potential is somewhat limited, there does exist substantial opportunity to locate rooftop solar PV technology in regions where geothermal pools exist, thus providing an opportunity for development of "micro-grid integrated systems". The most substantial wind and solar co-located resources are in the eastern part of the study region, where there are no geothermal resources. The existing transmission infrastructure in all but the eastern region is well developed and likely capable of supporting development of integrated systems without substantial infrastructure build-out. In the eastern part of the area, transmission corridors are well established, but they are localized.

Development of integrated systems in the Salton Sea/Imperial Valley region has good potential to succeed. There are fifteen geothermal power-generating facilities in the area, along with 1 solar power-generating facility. Comparison of geothermal and solar resource assessments indicates that substantial additional development could take place. The existence of a local transmission infrastructure that already accommodates these renewable energy resources suggests further development could occur on an as-needed basis. The wind resource in the area is also substantial, particularly in the eastern third of the region, and is co-located with the highest solar power density. Between the Salton Sea and the eastern highlands there exist numerous indications of geothermal resources, suggesting that this area may be appropriate for more detailed consideration for development of integrated systems.

Resource Mapping: LA Basin – Findings and Recommendations

Within the Los Angeles Basin twelve oil pools were identified that theoretically possess sufficient thermal energy to support power generation. Of these, four are located in proximity to significant wind resources such that co-located power generation facilities could be feasible. The existing transmission infrastructure appears to be suitable to allow relatively easy development of these resources, although no detailed analysis of this challenge was undertaken. Co-located wind and solar resources occur in south-western San Bernardino county and have the potential to be significant energy resources. Transmission infrastructure is sufficient to service a corridor through this area, but extensive infrastructure development might be required to access some of the most significant resource areas. Co-located geothermal resources and warehouse roof-top solar resources are significant in three geothermal pools in LA County and warrant consideration for generation purposes at a local urban feeder scale. The Salton Trough/Imperial Valley area has very extensive geothermal, solar and wind resources. The nature of the solar and geothermal resources could allow co-location of generating capacity throughout most of the area. The wind resource is mainly restricted to the eastern, mountainous portion of the study area. This resource is extensive and overlaps with the solar resource. Transmission infrastructure appears to be capable of accommodating build-out of generating capacity without the need for extensive construction of new transmission corridors within the Imperial Valley, particularly if co-located generating sites are carefully selected to maximize both access to transmission and coordination of resource development.

We recommend follow up effort to develop detailed resource assessments of the individual oil pools identified in the Los Angeles Basin area to establish the magnitude of each resource and its variability both with depth and with areal extent. The resource assessment should include the total resource reserve (that is, the amount of energy that is economically feasible to produce given existing technology) and the resource base (that is, the total amount of energy that is present, but which may not be technically or economically accessible given existing technology). Such an analysis should also identify the local loads that could be supplied by these resources, if developed from a "distributed generation" perspective, and determine the capacity of these resources to supply electrical power to the broader power grid.

Please refer to the report "Appendix 3 – "Identification of Areas in Southern California with Potential for Integrated Renewable Energy Projects, Part 1", for full documentation and discussion of supporting analysis.

Resource Mapping: Salton Sea Trough – Findings and Recommendations

The Salton Trough/Imperial Valley area has extensive geothermal, solar and wind resources. The nature of the solar and geothermal resources could allow co-location of generating capacity throughout most of the area. The wind resource is mainly restricted to the eastern, mountainous portion of the study area. This resource is extensive and overlaps with the solar resource. Transmission infrastructure appears to be capable of accommodating build-out of generating capacity without the need for extensive construction of new transmission corridors within the Imperial Valley, particularly if co-located generating sites are carefully selected to maximize both access to transmission and coordination of resource development. However, further analysis of this topic is required to establish rigorous caveats to this conclusion.

Please refer to the report "Appendix 4 – "Identification of Areas within Southern California with Potential for Integrated Renewable Energy Projects, Part 2", for documentation and discussion of supporting analysis.

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Appendix A

CURRENT STATE OF THE ART IN SOLAR FORECASTING

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Current State of the Art in Solar Forecasting

Jan Kleissl, University of California, San Diego

Abstract: As solar thermal and photovoltaic generation begin to have a larger role in electrical generation in California, the California Independent System Operators needs to accommodate their variable nature in its forecasting and dispatching. This project reviews and evaluates current knowledge and models for forecasting solar resources and considers options for improving forecasts through RD&D and additional measurements.
Satellite and numerical weather prediction (NWP) have been shown to be the best tools for hour ahead and day ahead forecasts at this time. However, NWP solar forecast performance has yet to be evaluated for California, where the coastal microclimate especially may present a significant challenge. To validate and calibrate such forecasts, an aggregated real-time production database for all metered PV systems is deemed to be the most spatially dense and economical set of "measurements." A research roadmap for improving Direct Normal Irradiance forecasts is provided.

Keywords: solar thermal, photovoltaic systems, energy, renewable, forecast, NWP, modeling

Overview: As solar thermal and photovoltaic (PV) penetration increases, the California Independent System Operators (CAISO) needs to accommodate their variable nature in its forecasting and dispatching. This project reviews and evaluates current knowledge and models for forecasting solar resources and considers options for improving forecasts through research and measurements.

Summary of recommendations (more detail is provided in section 4.3):

a) **Current Forecast Skills:** Satellite and numerical weather prediction (NWP) are currently the best tools for hour ahead (HA) and day ahead (DA) forecasts, respectively. Efforts are underway by solar forecasters and NOAA to improve mesoscale NWP for the HA market.
   - Further research should be conducted on the forecast skills of the low hanging fruit - operational NWP models - for California. The applicability of mesoscale NWP to locally enhance forecast skill should also be quantified. This research would enable wind forecast providers to adapt their existing products for the solar forecasting market and quantify the potential success of such an approach.
   - Support should be provided to CAISO to conduct a 12 months forecast 'competition' to evaluate forecast skills of forecast providers and maturity of different approaches. Careful design of such a study is critical and stakeholders should be consulted in the planning stage.

b) **Expanding ground measurements:** Ground measurements of global horizontal irradiance (GHI) (and direct normal incident irradiance (DNI) for concentrating plants) should be (and currently are) required by CAISO for utility scale solar farms. To improve HA and intra-hour forecasts statewide, more ground data are necessary. The most economical approach would be to require or incentivize 3rd party data providers / aggregators to share PV output and radiometer data in real time with the ISO, utilities, and forecast providers. Models should be developed to derive solar irradiance values from such ground PV data. The advent of smart meters that can monitor residential PV outputs provides an additional avenue to implement this strategy. Also, research on sky imager deployments in areas with high PV penetration should be pursued.

c) **DNI Forecasts:** Research on radiative transfer in the atmosphere related to direct normal incident (DNI) forecasts is necessary. These forecasts should evaluate the effects of cirrus clouds, forest fire smoke, dust storms, and urban aerosol air pollution transport on concentrating solar power plants in California.

Table of Contents

1. Solar Forecasting Needs, Market Connection and Stakeholders (Task 1.1)
This report reviews and evaluates current knowledge and models for forecasting solar resources, and recommends ways in which forecasting can be improved. Table S6 lists the tasks and corresponding sections in this report.

Table S6: List of tasks for POB248-D76 Task 1.

Task	Section
1.1. Review the current state of the art in wind and solar forecasting in support of California grid operations including a review of opaque and transparent commercial models	Sections 1 and 2. Table S2.
1.2. Summarize and assess sources of real time wind and solar data used to calibrate day-ahead and hour-ahead forecasts.	Section 3. Table S4.
1.3. Review data on actual and forecast wind and solar thermal plant output ramp rates.	Section 2.1. and Figs. S2a and S2b. Actual plant output could not be obtained.
1.4.-1.6: Recommendations for expanded sensor deployment and data collection. Recommendations for forecasting at high renewable penetration levels.	Section 4.

Load forecasts have been an integral part of managing electric energy markets and infrastructure for many decades. Consequently, experiences, regulations, and planning by utilities and independent system operators (ISO) are the dominant consideration for this report. Furthermore the rules established by ISOs will impact the economic value of forecasting to other stakeholders such as owner-operators. Consequently, in the near-term the primary stakeholder to be considered for forecasting needs and plans is the California Independent System Operators (CAISO). Secondary stakeholders are utilities who will see greater distributed PV penetration on their urban distribution feeders. Currently on a few utilities have mechanisms in place to use solar forecasts for local automated response to voltage fluctuations caused by solar production.

The market need for better solar power integration and planning tools have been widely recognized (e.g. DOE FOA 0085, CEC PON 08-11, CSI RD&D Round 1). CAISO uses the following forecasts: The day ahead (DA) forecast is submitted at 0530 prior to the operating day, which begins at midnight on the day of submission and covers (on an hourly basis) each of the 24 hours of that operating day. Therefore, the day ahead forecast is provided 18.5 to 42.5 hours prior to the forecasted operating day. The vast majority of conventional generation is scheduled in the DA market. The hour ahead (HA) forecast is submitted 105 minutes prior to each operating hour. It also provides an advisory forecast for the 7 hours after the operating hour. CAISO also is studying in intra-hour forecasts on 5 minute intervals. FERC has issued a Notice of Proposed Rulemaking requiring public utility transmission providers to offer all customers the opportunity to schedule transmission service every 15 minutes, and requiring providers with variable renewables on their systems to use power production forecasting.

Currently, under the CAISO **Participating Intermittent Resources Program (PIRP)**, a participating intermittent resource receives special settlement treatment that nets output deviations over a month's period if the resource's scheduling coordinator submits hour ahead forecasts developed by a forecast service provider for that operating hour (de Mello and Blatchford, personal communication, 2010). Although the PIRP program does not require them, in practice DA forecasts are provided under the same contract. Wind units may participate in DA market however no special settlement treatments apply. Forecasts are integrated in CAISO planning, but there is no financial incentive to the forecast providers for accurate forecasts.

At some point PIRP may be modified and renewable generators will be required to participate in parts of the regular DA and HA markets. In that case some of the economic benefit and interest in forecasting would shift to the owner-operators of renewable power plants which would dramatically change the marketplace for renewable forecasting. An example of such a system is the Spanish 'premium tariff' for the regulation of renewable energy which allows operators of power plants to participate directly on the electricity market instead of reverting to flat-rate prices. The premium tariff option motivates operators of renewable energy plants to increasingly act like managers of conventional plants, selling electricity at the liberalized market. Just like a normal market participant, the operator places bids in advance on the DA market and is obliged to fulfill them. Thus there is the need for operators of renewable energy plants to be able to provide predictable and dispatchable energy in the profitable premium tariff.

Wind forecasting has been important for severe weather events for decades and even wind forecasting for renewable energy is a fairly mature field with several major market players. While solar radiation forecasting is standard in numerical weather prediction (NWP, the sun's energy is the primary driver of all meteorological processes), the accuracy requirements on solar radiation forecasts per se were low and the priority was on forecasting rain and air temperature. Consequently there is significant potential for improvements of solar forecasts from NWP.

For solar forecasting different types of solar power systems need to be distinguished (Table S2). For **solar concentrating systems** (concentrating solar thermal or concentrating PV, CPV) the direct normal incident irradiance (DNI) must be forecast. Due to non-linear dependence of concentrating solar thermal efficiency on DNI and the controllability of power generation through thermal energy storage (if available), DNI forecasts are especially important for the management and operation of concentrating solar thermal power plants. Without detailed knowledge of solar thermal processes and controls, it is difficult for 3rd parties (solar forecast providers and CAISO) to independently forecast power plant output.

On the other hand, CPV production is highly correlated to DNI. DNI is impacted by phenomena that are very difficult to forecast such as cirrus clouds, wild fires, dust storms, and episodic air pollution events which can reduced DNI by up to 30% on otherwise cloud-free days. Water vapor, which is also an important determinant of DNI, is typically forecast to a high degree of accuracy through existing NWP. Major improvement in aerosol and satellite remote sensing are required to improve DNI forecasts.

For **non-concentrating systems** (i.e. most PV systems), primarily the global irradiance (GI = diffuse + DNI) on a tilted surface is required which is less sensitive to errors in DNI since a reduction in clear sky DNI usually results in an increase in the diffuse irradiance. Power output of PV systems is primarily a function of GHI. For higher accuracy, forecast of PV panel temperature are needed to account for the (weak) dependence of solar conversion efficiency on PV panel temperature (Table S2).

Table S2: Quantities relevant to solar forecasting. GI: global irradiance.

Forecast Quantity	Application	Primary Determinants	Importance to market	Current Forecast Skill
Global Irradiance	PV	Clouds, solar geometry	high	medium
Cell temperature	PV	GI, air	low	high

		temperature, wind		
Direct Normal Incident (DNI)	Concentrating Solar Power	Clouds, aerosols, water vapor	medium	Low

2. Solar Forecasting Methodologies (Task 1.1)

2.1. Forecasting Methods

The purpose of this section is to assess methodologies to forecast solar generation in California, to review best practices, and identify available data for validation and calibration of the forecasts.

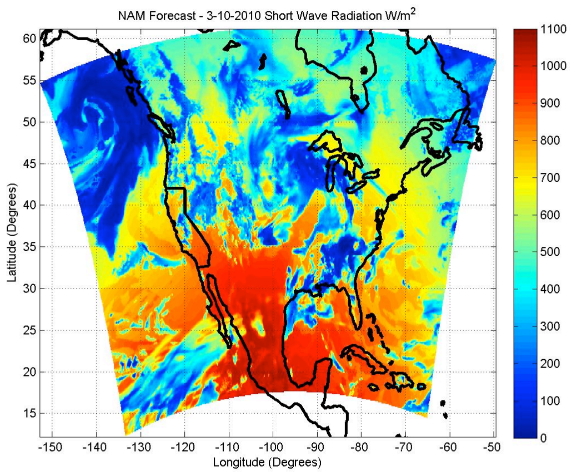
For solar forecasting very different methodologies are preferred depending on the forecast horizon (Table S1, Figures S1 and S2d):

- Persistence forecast is based on current or recent PV power plant or radiometer output and extrapolated to account for changing sun angles. Persistence forecasts accuracy decrease strongly with forecast duration as cloudiness changes from the current state.
- Total sky imagery can be used to forecast from real time (nowcast) up to 15-30 minutes. by applying image processing and cloud tracking techniques to sky photographs (Fig. S1c). The method assumes persistence in the opacity, direction, and velocity of movement of the clouds. Irradiance is predicted for the current cloud shadow and then the cloud shadow is moved forward in time based on cloud velocity and direction.
- For satellite imagery (Fig. S1b) the same methods as in total sky imagery are applied. Clouds reflect more light from earth into the satellite leading to detection and the ability to calculate the amount of light transmitted through the cloud (transmissivity = 1 – reflectivity – absorptivity). The lower spatial and temporal resolution causes satellite forecasts to be less accurate than sky imagery on intra-hour time scales. Satellite imagery is the best forecasting technique in the 1 to 5 hour forecast range. Classical satellite methods only use the visible channels (i.e. they only work in day time), which makes morning forecasts less accurate due to a lack of time history. To obtain accurate morning forecasts, it is important to integrate infra-red channels (which work day and night) into the satellite cloud motion forecasts (Perez, et al. 2010).
- NWP is the best forecasting technique for long time horizons of more than 5 hours. NWP models solar radiation as it propagates through the atmosphere including the cloud layers represented in the model. Operational National Weather Service models do not have the spatial or temporal resolution for accurate HA forecast. Consequently, NWP models are probabilistic because they infer local cloud formation (and indirectly transmitted radiation) through numerical dynamic modeling of the atmosphere. NWP models currently cannot predict the exact position of cloud fields affecting a given solar installation (Perez et al. 2009). High-resolution rapid-refresh NWP that are currently developed by NOAA and wind forecasters may be able to approach the resolution of satellite forecasts (1 km) within a few years and allow the application of high-frequency variability techniques (Mark Ahlstrom, Windlogics).

Table S1: Characteristics of solar forecasting techniques.

Technique	Sampling rate	Spatial resolution	Spatial extent	Suitable Forecast horizon	Application
Persistence	High	One point	One Point	Minutes	Baseline
Total Sky Imagery (Fig. S1c)	30 sec	10s to 100 meters	2-5 mile radius	10s of minutes	Short-term ramps, regulation
GOES satellite	15 min	1 km	US	5 hours	Load

imagery (Fig. S1b)					following
NAM weather model (Fig. S1a)	1 hour	12 km	US	10 days	Unit commitment



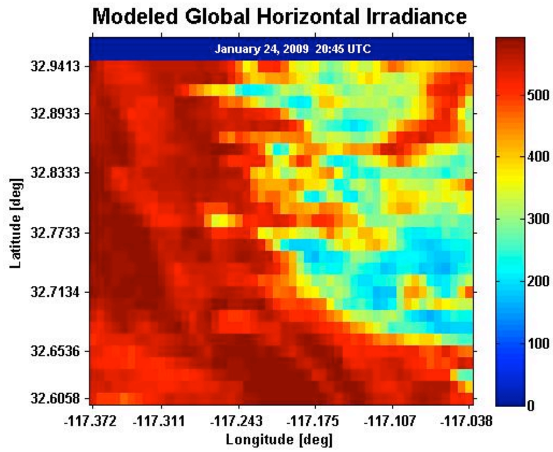


Figure S1a: Map of the forecast GHI [W m^{-2}, colorbar] in March 2010 at midday from the North American Mesoscale model (NAM).

Figure S1b: Map of the forecast GHI [W m^{-2}, colorbar] for San Diego on January 24, 2009 at 1245 PST using the GOES-SUNY satellite model.

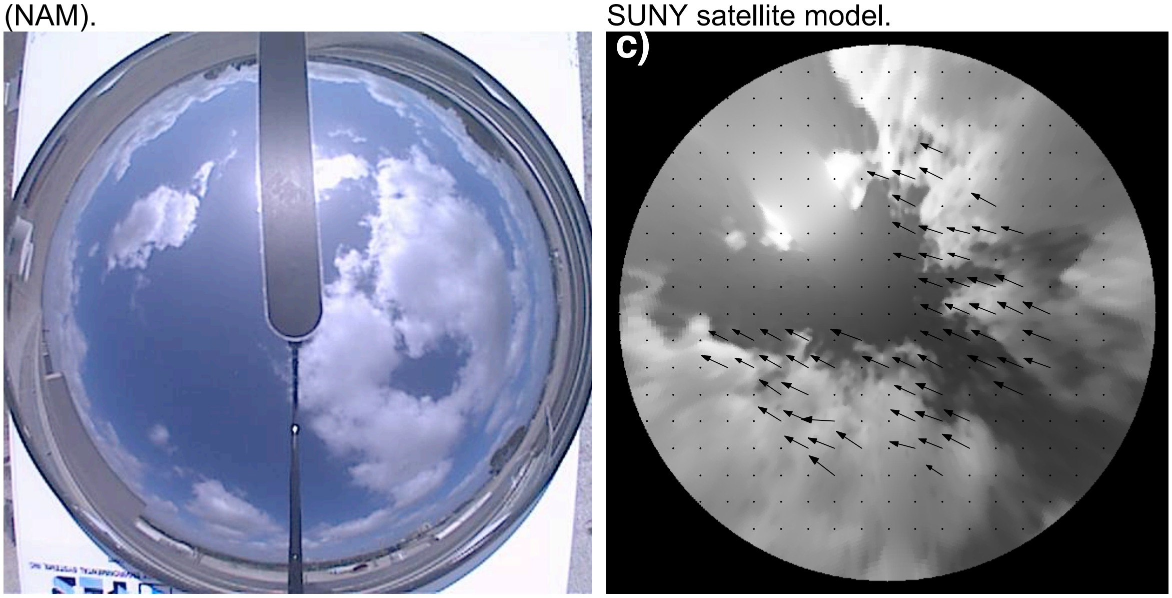


Figure S1c: Cloud motion vectors (right) and sky image (left) at the UC San Diego campus on August 19, 2009 at 1431 PDT.

Statistical methods can be applied to correct for known deficiencies of different forecasting methods through corrections for known model biases or automated learning techniques. Examples are modeled output statistics (MOS), autoregression techniques, and artificial neural network (ANN). For example, MOS uses statistical correlations between observed weather elements and climatological data, satellite retrievals, or modeled parameters to obtain localized statistical correction functions. This allows, for example, for the enhancement of low-resolution data by considering local effects (e.g. topographic shading) or for correcting systematic deviations of a numerical model, satellite retrievals, or ground sensors. A disadvantage of statistical methods is the large amount (typically at least one year) and accuracy of measurement data needed to develop statistical correlations separately for each location. This means that MOS-based forecasts are not immediately available for larger areas or for locations without prior measurements, such as most non-urban solar power plants in the California.

2.2. Evaluation of Numerical Weather Prediction Solar Forecasts in California

For Task 1.3 we conducted an analysis of the intra-day solar forecast skill of the current operational NWP model – the North American Mesoscale (NAM) model for February to June 2010 using California Irrigation Management Information System (CIMIS) GHI measurements. NAM provides hourly forecast up to 72 hours ahead on a 12 km grid within the Continental US.

A 24 hour persistence forecast was more accurate forecast in clear sky conditions than in overcast conditions (Fig. S2b). This indicates that clear conditions are persistent, but during times of transitional weather patterns P is inaccurate. Generally, P is an inaccurate method for more than 1 hour ahead forecasting and should be used only as a baseline forecast for comparison to more advanced techniques.

The original NAM forecast for GHI consistently over-predicts solar irradiation during clear sky situations, but under-predicts GHI for cloudy conditions (Fig. S2c). On average, these bias errors can exceed 25%. The consistent errors in NAM motivate application of a bias correction, termed model output statistics (MOS), as a function of solar zenith angle and clear sky index. Through the use of MOS, the bias error was eliminated and the root mean square error (RMSE) was significantly improved (Fig. S2b). The RMSE for the corrected forecasts ranges from 25% under very cloudy conditions to 8% under clear conditions.

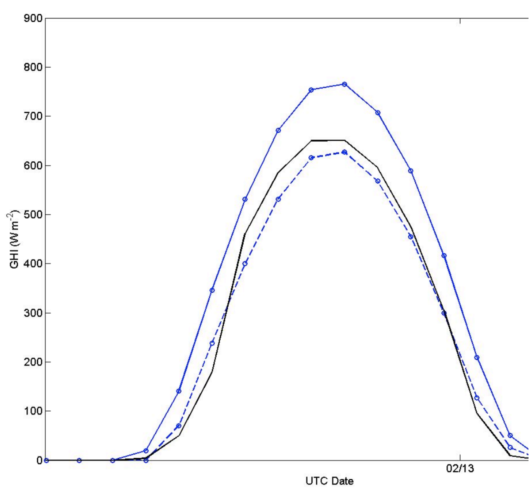


Fig. S2a: Camarillo, CA original NAM forecast N and MOS corrected N_C forecasts compared to CIMIS ground data on Feb 13, 2010. Blue: Original NAM forecast, dashed blue: bias corrected NAM forecast, black: CIMIS measurement. The MOS reduces forecast error by nearly 200 W m^{-2} at mid day.

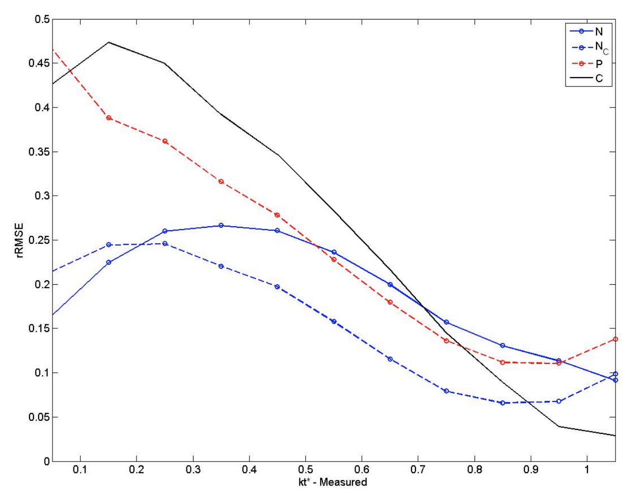


Fig. S2b: Relative root mean square error (y-axis, normalized by 1000 W m^{-2}) of different forecasts as a function of total cloud cover (x-axis) for February-June 2010 in California. Blue solid: original NAM model; blue dashed: bias corrected NAM model; red dashed: persistence forecast; black: clear sky forecast.

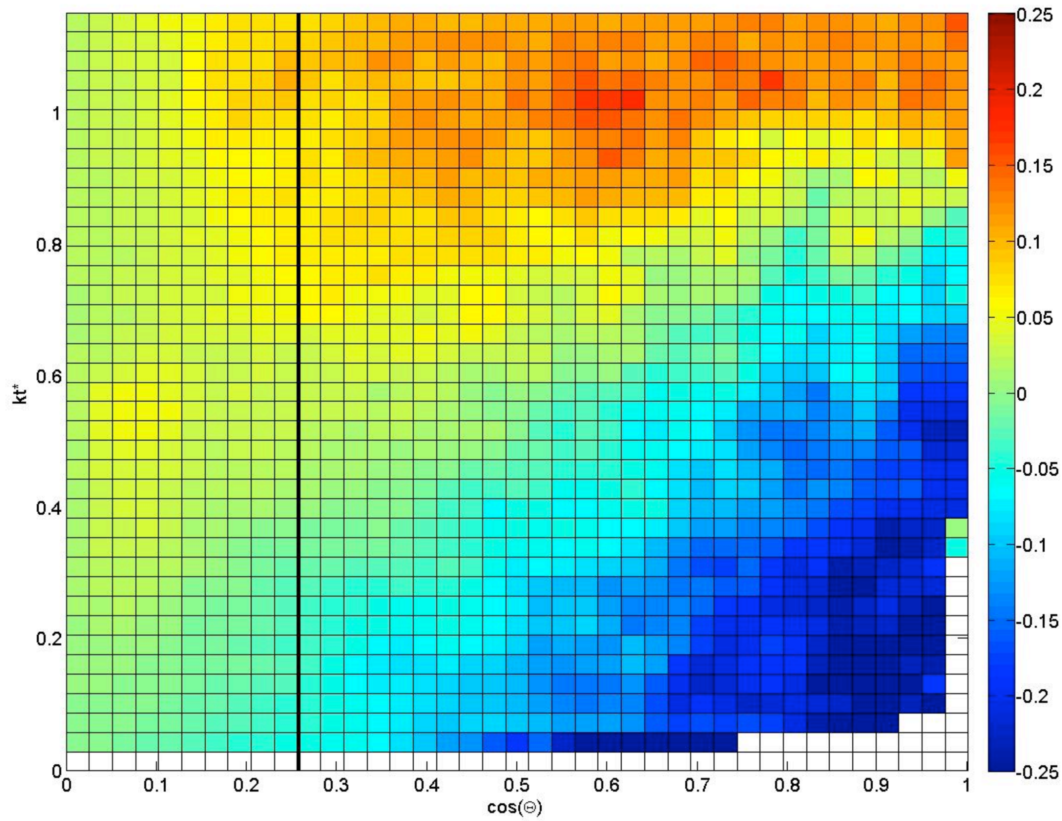


Figure S2c: Relative mean bias error [%/100, colorscale] of NAM forecast N as a function of solar zenith angle (θ) and forecasted clear sky index (kt*) from February to June 2010 compared to CIMIS measurements.

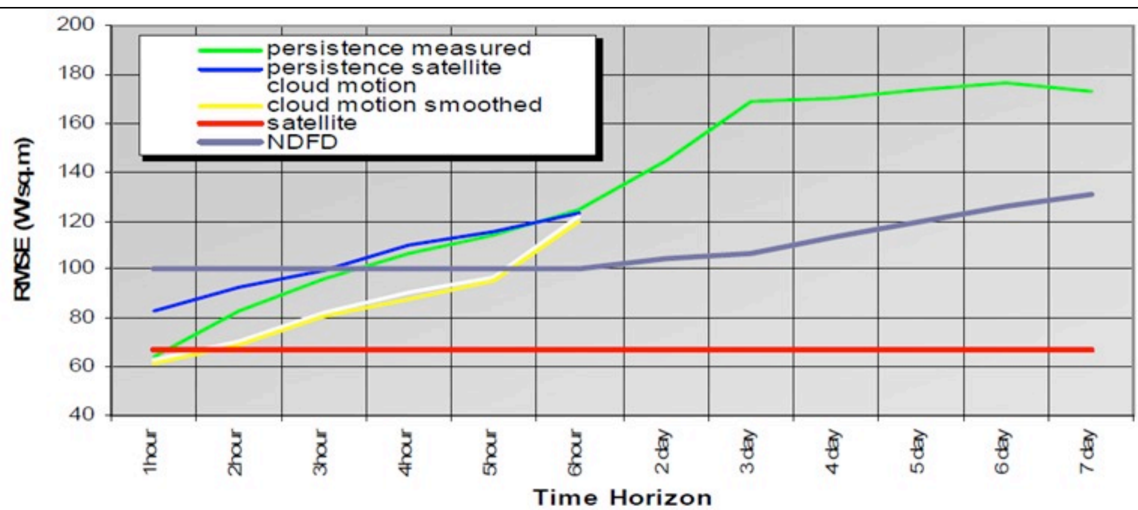


Fig. S2d: Root mean square error (RMSE) of different solar forecasting techniques obtained over a year at seven SURFRAD ground measurement sites (from Perez et al. 2010). The red line shows the satellite nowcast for reference, i.e. the satellite 'forecast' for the time when the satellite image was taken. Cloud motion forecasts derived from satellite (yellow and white lines) perform better than numerical weather prediction (NDFD) up to 5 hours ahead. Numerical weather prediction has similar accuracy for 1 hour to 3 days ahead.

2.3. Literature Survey of Forecasting Applications

2.3.1. Peer-reviewed research

Table A1 in the appendix provides an overview of studies validating solar forecasting methods. The most extensive body of research is from Germany by the groups of Prof. Heinemann at the University of Oldenburg and Dr. Schroedter-Homscheidt at the German Aerospace Agency. No studies exist that examine forecasts for California, partly because there is no high-quality SURFRAD measurement site in California for forecast validation. A comprehensive study of forecasts at seven SURFRAD sites in the US (Perez et al. 2010, Fig. S2d) is probably generally applicable to most inland areas of California. The coastal California meteorology poses unique challenges and forecast models will have to be independently validated there. Generally, published results of forecast error have to be examined with care. The forecast error strongly depends on the amount and variability of cloudiness, making comparison between studies performed in different seasons and climates difficult. Nevertheless, a few general **conclusions** can be drawn **from the literature survey:**

a. Surprisingly, significant bias errors (i.e. persistent high or low deviations) exist in NWP models. However, these errors could be corrected through MOS. NWP model errors should be carefully examined in California.
b. Only for clear sky conditions can accurate forecasts be obtained with as low as 6% RMSE.
c. For all conditions (cloudy and clear) all forecasts that are compared to ground data have RMSEs of at least 20% but as large as 40-80% for cloudy conditions. The main reason for these large errors is the difference in spatial scale between a satellite pixel or NWP model grid cell and the measurement station. Unless local techniques with a finer resolution are employed such as sky imagery, the forecast error will always be large, especially for sub-hourly intervals and cloudy conditions.
d. DNI forecasts are associated with about twice the RMSE than GHI forecasts.

The recommendations for the best solar forecasting approach are well summarized by Schroedter-Homscheidt et al. (2009), who propose to use

- deterministic NWP schemes in the day-ahead market with ensemble prediction technologies for GHI. Post-processing of NWP should be used to derive hourly DNI from NWP.
- aerosol optical depth modelling from air quality applications in the day-ahead prediction (for DNI).
- nowcasting of cloud fields and irradiance from satellites. Cloud motion vector forecasting including both visible and infrared channels should be used for the 1 to 5 hour forecast horizon (satellite-based aerosol added for DNI).
- ground measurements for intra-hour forecasts.

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Perez R., S. Kivalov, A. Zelenka, J. Schlemmer and K. Hemker Jr., Improving The Performance of Satellite-to-Irradiance Models using the Satellite’s Infrared Sensors. Proc., ASES Annual Conference, Phoenix, Arizona, 2010
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2.3.2. Solar forecast providers

For this section solar forecast providers were invited to describe their forecasting model, quantify forecast accuracy, and comment on research needs. Generally there are two camps of solar forecast providers. Especially established wind forecast providers apply techniques developed for wind forecasting to solar, which implies running dedicated mesoscale NWP together with machine learning (MOS, ANN) techniques to nudge the forecast to a particular site. Providers specializing in solar forecasts tend to use (government supplied) NWP data for DA forecasts, but use satellite cloud fields for intra-day or HA forecasts. **We believe that for HA forecasts in the coming 3 years the satellite-based method has the greatest maturity, highest spatial resolution, and accuracy. However, as NWP approaches smaller grid sizes and NWP and mesoscale models are improved to assimilate satellite data, NWP may become superior to satellite-based methods. For DA forecast NWP is and will always**

be the most promising forecasting method. A review of models from different providers follows (in alphabetical order):

3Tier does not provide details on solar forecasting capability on its website, but since it uses satellite-based technologies for its solar resource assessment it is likely to possess cloud forecasting capability. 3Tier was invited to comment, but has not responded.

AWS Truepower (AWST): "The production of forecasts in the AWST solar forecasting system is based on the dynamic weighting of an ensemble of forecasts generated by a combination of physics-based (also known as Numerical Weather Prediction (NWP)) models, advanced statistical procedures and cloud pattern tracking and extrapolation techniques. The individual members of the ensemble are weighted for each look-ahead time period (e.g. 1–hour, 2-hours etc.) according to their relative performance in a relevant sample (e.g. a rolling period prior to the forecast time or a set of cases that are similar to the current weather regime). The independent weighting for each look-ahead period allows the system to shift from heavy reliance on one method for a particular look-ahead interval to a heavy weighting of another method for a subsequent look-ahead interval according to the statistical performance characteristics of each method for each look-ahead interval. Currently, the AWST cloud pattern tracking procedure is under development and not yet used as part of the operational ensemble. AWST expects this approach to be added to its operational ensemble once development and testing is completed shortly.

The current operational version of the AWST's solar forecasting system consists of four major components. The first is the generation of a set of mesoscale NWP simulations using the MASS, WRF and ARPS models. These models are run from several sets of initialization and boundary conditions to generate an ensemble of mesoscale NWP forecasts. Most of the simulations employ the standard government-center 6-hour NWP update frequency. However, a small subset are operated in a rapid update cycle mode, which initializes a new simulation every 1 or 2 hours using the latest available data including synthetic moisture data inferred from cloud patterns in satellite images. This is intended to improve the short-term NWP prediction of cloud patterns and characteristics and is still being refined.

The second phase of the forecast production process employs statistical models such as multiple linear regression, Artificial Neural Networks (ANN) and support vector regression to create an ensemble of forecasts of irradiance and other relevant parameters (such as panel temperature). The input into these models includes the output from the NWP simulations, recent time series data from the forecast site and off-site locations and in the future the output from the cloud pattern tracking schemes. The statistical models serve to correct system errors in the NWP simulations as well as to adjust the NWP forecasts to account for recent trends revealed by the on-site or off-site measurement data. The output is an ensemble of forecasts for the site.

The third major component is the generation of a either a (1) deterministic forecast by statistically weighting members of the ensemble according to their performance in a relevant training sample or (2) a probabilistic forecast based on quantile regression using information about the dispersion of the forecasts in the ensemble and also trained on a relevant training sample.

The fourth component is the transformation of forecasted irradiance and other meteorological parameters to power output power output values by using a statistical or physics-based solar plant model. This can be done prior to or after the construction of the ensemble composite (i.e. applied to the individual members of the forecast ensemble or the ensemble composite predictions of the meteorological parameters)."

Provided by John Zack, AWS Truewind, john@meso.com

Clean Power Research offers the SolarAnywhere® solar resource assessment and solar forecasting service. Hourly GOES satellite images are processed using the most current algorithms developed and maintained by Dr. Richard Perez at the University at Albany (SUNY). The algorithm extracts cloud indices from the satellite's visible channel using a self-calibrating feedback process that is capable of adjusting for arbitrary ground surfaces. The cloud indices are used to modulate physically-based radiative transfer models describing localized clear sky climatology. Near term irradiance datasets are produced hourly and are accessible via the SolarAnywhere website or programmatically via web services.

SolarAnywhere provides hourly forecasts up to 7 days in advance using a cloud motion algorithm for short term forecasts and a NWP algorithm for longer term forecasts. The transition point between the short term and long term forecasts is automated in order to produce a unified dataset every hour containing 1 to 168 hours of forecast irradiance for each location. The accuracy of the forecast technique is reviewed in several papers Perez et al. (2009, 2010)

Clean Power Research and SUNY are in the process of increasing the spatial resolution from 10km to 1km and temporal resolution from one hour to one minute as part of the California Solar Initiative Advanced Modeling and Verification for High Penetration PV study. Other improvements in the near term include the imminent release of the v3.0 SUNY algorithm which will incorporate the four infra-red channels from the GOES satellites. Access to the new IR channels will enable early morning cloud motion forecasts during a time period that currently has an inadequate visual image history. Incorporation of the infra-red channels will achieve significant improvements in high albedo locations by enabling better differentiation between naturally highly reflective locations and intermittent snow cover.

Garrad Hassan is an established wind forecast provider. The entry into the solar market will likely be based off of existing NWP and mesoscale modeling capabilities. Garrad Hassan was invited to comment, but has not responded.

Green Power Labs (http://www.greenpowerlabs.com/services_forecasting.html) "provides solar radiation and power production monitoring and forecasting for utilities, independent system operators and solar power producers. The technology developed by Green Power Labs for broadband modeling of solar radiation at the Earth's surface is based on the analysis of GOES satellite visible spectrum images. The model software is implemented as plug-in for ESRI's ArcGIS9.3 suite.

Solar radiation monitoring is based on a physical model that relates the satellite-derived Earth-atmospheric reflectivity from the visible spectrum channel of the satellites to the transmissivity of the atmosphere. The model calculates the sun's position, air mass and extraterrestrial radiation and, in conjunction with digital databases of surface elevation, Linke turbidity data, produces estimates of clear-sky global radiation at the Earth's surface. The amount of solar radiation reflected by clouds is determined from the satellite-derived data. The resulting data of overcast global radiation at the Earth's surface are produced at a resolution of 1x1 km at the satellite's nadir, at 30 minute intervals. The SolarSatData results are adjusted to the site-specific conditions using World Meteorological Organization - grade weather monitoring stations initially set up at solar power generation sites.

Solar radiation forecasting works on a basis of physical relationship between cloud cover and solar radiation. The forecast system is based upon the cloud cover forecasts from two

Numerical Weather Prediction systems. These are the high resolution Nonhydrostatic Mesoscale Model (NAM) provided by the National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Prediction, covering North America and adjacent waters at 10 km resolution, and the Global Environmental Multiscale model provided by Environment Canada at 15 km resolution in its regional configuration. The solar radiation and solar energy generation system performance forecasts for the next 48 hours at hourly intervals are produced daily from the 00Z and 12Z runs and are made available online. GPLI solar radiation forecasts are well correlated with ground observations.

Solar power generation forecasting utilizes recognized models of solar power generation technologies. The service currently offers PV power generation forecasting for utility-scale and distributed systems as well as spatial aggregation of solar power generation in utility areas of service. ” (Tony Daye, Senior Manager, Green Power Labs Inc., tony.daye@greenpowerlabs.com)

Solarcasters (http://www.solarcasters.com/dayahead.htm, http://www.solarcasters.com/hourahead.htm, http://www.solarcasters.com/minuteahead.htm):
“offers a line of technical and engineering support services for utility-scale solar power generation. The line includes forecast services for the day-ahead (DA) and hour-ahead (HA) time frames. A service for forecasts in the 0-60 minute time frame is also under development.

SolarCasters DA forecasts predict irradiance and resulting power production in 3-hour average time blocks. Forecasts are made twice each day for the following 24-hour period (...). SolarCasters provides both irradiance forecasts and plant-specific power generation forecasts using its TRNSYS-based plant simulation software. Integration of these forecasts with electrical dispatch master controls systems from Siemens and GE is underway.

DA forecasts are based primarily on numerical weather prediction (NWP) with proprietary algorithms used to forecast cloud cover based on NWP results. The forecasts also use proprietary radiative transfer models to predict the irradiance reaching the ground. A proof-of-concept study at a desert location generated mean average errors (MAE) of around 1% and an RMS error of 11%. Forecasting in a humid semi-tropical environment proved more difficult with a MAE of -7% (the model under predicts the observed) and an RMS error of 38%.

HA forecasts predict 1-hour average power production for the 2-5 HA time frame and are generated using a series of proprietary algorithms based on analysis of satellite images, together with the SolarCasters radiative transfer modeling. The MAE at the desert site in this time period was typically 2% with 12% RMS error. Again the semi-tropical site proved more problematic with MAE of -8% and RMS errors near 25%.

The proof-of-concept studies were conducted on short time series and the results presented here may not be representative. All forecast results are expected to improve when site-specific corrections (MOS) derived from long-term observations are applied.

The forecast technology for the 0-60 minute time frame involves on-site imaging equipment and the use of geometric transforms to track and predict cloud-related transients affecting all or only a portion of a generating site. An X-band radar system for predicting cloud cover in this time frame has also been tested and may prove useful for the largest generating sites. Neither of these technologies has yet been subject to a proof-of-concept.”
Provided by: Steve Ihnen, CTO, SolarCasters, Inc., Redmond, WA 98052, o. (425) 736-4631, steve@solarcasters.com

Solardatawarehouse.com is an aggregator and data provider of solar irradiance data from 3600 stations throughout the US. Solardatawarehouse also offers a forecast product based on the dense ground measurements, airport METAR observations, and National Digital Forecast Database data. "The forecasting model has two separate components: One predicts solar radiation based on meteorological observations, while the second learns to recognize seasonal climate patterns at the site. Outputs from the two models are combined to forecast solar radiation one hour and three hours into the future. The models are adaptive and capable of self-learning based on the training data presented them." (James Hall – JHtech, (719) 748-5231, JamesHall@jhtech.com).

Windlogics has been developing expertise in solar resources and forecasting (e.g. Ahlstrom and Kankiewicz, Utility-scale PV variability workshop, 2009; Kankiewicz et al. American Solar Energy Society conference, 2010) and may be entering the market with new solar forecasting products soon.

3. Data Sources for validation and calibration (Task 1.2)

Solar forecasts from NWP or satellite models are of limited accuracy. Clouds are not resolved or modeled poorly in NWP. Satellites can observe large clouds directly, but they measure only the light *reflected* by clouds, atmosphere, and ground. Solar irradiance reaching the ground has to be modeled using various assumptions. Consequently, accurate data from ground stations is required to validate and calibrate NWP and satellite model forecasts.

In Table S4 sources of real time solar data are listed. Unlike for wind, there is an extreme shortage of publicly available ground based solar irradiance measurements. The following observations apply:

- There are only three stations in California (NOAA-ISIS at Hanford and NREL-MIDC in LA and Rancho Cordova) that provide publicly available, measured, real-time data. However, due to lack of funding and/or supervision even for these stations data quality is a concern (Manajit Sengupta, NREL, personal communication).
- The California Irrigation Management Information System (CIMIS) measurement network covers the entire state at decent resolution, but data are only available in hourly intervals and are only downloaded 1x / day in the evening making these data largely useless for solar forecasting applications.
- CAISO also presently has very little solar generation data, since many solar power plants have gas-fired backup generators which are not separately metered.
- GOES satellite data is currently the most promising resource due to real-time availability, large coverage, and decent accuracy.
- A powerful, but so far untapped resource are the more than 2000 metered PV systems around the state. Since PV power output is near linearly related to solar irradiance, these systems effectively act as distributed solar irradiance sensors. If the measurements could be linked to a national database in real-time, they would be a very valuable and economical resource for solar forecasting.

Also note, that recently NOAA and NREL (Michalsky et al. 2010) have proposed the upgrade of Climate Reference Network (CRN) to measure GHI, DNI, and DIF. However, with only 7 CRN stations in California these measurements would not be sufficient in their spatial density for California's solar forecasting needs. NOAA estimates that the cost of expanding the CRN network would be $1.5 M for the 7 sites in California. NREL also runs the SOLRMAP initiative to provide quality control for 3rd party installed irradiance sensors, but the data remain proprietary to the operator.

Table S4: Available irradiance measurements in California. ISIS: Integrated Surface Irradiance Study; CIMIS: California Irrigation Management Information System; ASOS: Automated Surface Observation System; PBI: Performance Based Incentive; MIDC: Measurement and Instrumentation Data Center.

Name	Type	Resolution / # of stations	Time step	Real Time?	Accuracy for GHI
GOES	Satellite	1 km	15 min	Yes	Low
NOAA ISIS	Ground GHI, DNI, DIF	1 (Hanford)	3 min	Yes	Medium – High
NREL MIDC	Ground GHI, DIF	2 (LA, Rancho Cordova)	1 min	Yes (30 min)	Medium – High
CIMIS	Ground GHI	134	1 h	No (1x / day download)	Medium
NOAA ASOS	Cloud height and density	82 (airports)	10 min	Yes	Low
CSI PBI	PV output, some GHI	>2070	15 min	No, NDA required[1]	Low
UCSD Sky Imager	Sky Image	50 m	30 sec	Yes	Low

4. Discussion

4.1. Evaluation of forecast accuracy

4.1.1. Error Metrics

Due to the binary nature of solar radiation (cloudy or clear) the choice of error metric is very important for the evaluation of solar forecast models. The root mean square error (RMSE) metric is problematic as it is dominated by large errors. Thus if a forecast model is usually correct but occasionally off by a large amount it may score worse than a model that is always slightly off but never way off. We recommend adding the mean absolute error (MAE) or mean absolute percentage error (MAPE) as a standard evaluation metric since it is less sensitive to large errors.

4.1.2. Economics versus Irradiance

All forecast evaluations (given for reference in Table A1) calculate the forecast error in W m^{-2} or % of solar irradiance. This has the advantage of comparability, but is not the most economically relevant metric. For example, a forecast error during peak load is likely both economically and operationally more significant than an error during off-peak times. To quantify the economic value of radiation forecasts and forecast errors we recommend that researchers use the CAISO OASIS site which continually updates prices in the HA and DA market.

4.2. Single site versus Regional Forecasts

Solar forecast quality dramatically improves when several sites are aggregated over a region (e.g. Lorenz et al. 2009), because average cloudiness in a region can be forecast more accurately than cloudiness at a particular site. Since shorter time-scale fluctuations in power output are uncorrelated across sites only a few miles apart (i.e. the clouds responsible for these fluctuations are usually smaller than the distance between sites) aggregation of power output

[1] May be available real-time in the future through smart meters.

from several sites mitigates the issue of large ramps over short time-scales. The larger the forecast region and the larger the number of sites within that region, the less important small scale variability becomes. For example, Mills and Wiser (2010) showed that 1 minute fluctuations are uncorrelated over distances as small as 20 km meaning that the relative variability standard deviation decreases with the square root of the number of sites – 4 sites means half the relative variability. They concluded that the increase in spinning reserve costs for solar are smaller than those for wind.

In the current market, prices are set at each node in the electric grid. Consequently, the economic value of forecasting is primarily in localized forecasting for a particular solar plant or an urban distribution feeder. However, for other applications such as congestion management and grid operation on larger scales, often aggregate or ensemble forecast are sufficient or desirable.

Likewise for solar forecasting in urban areas, the PV sites are distributed across different rooftops and aggregate forecasts are of greater relevance than forecasts for individual PV systems.

4.3. Recommendations

a) **Type of solar forecast:** GOES satellite and NWP data are the most accurate solar forecast sources for hour-ahead (HA) and day-ahead (DA) forecasts, respectively. An overwhelming body of research (Section 2.2) shows that solar forecast based on satellite models outperform NWP forecasts up to around 5 hours ahead. In turn, persistence forecasts give similar results as satellite forecast up to 1 hour ahead.

   Mesoscale Numerical Weather Prediction (NWP)
   Why: In the long term as computing power and models improve, NWP will be the most promising tool to forecast solar irradiance. This research would enable wind forecast providers to adapt their existing products to solar forecasting and quantify the potential improvement in accuracy.
   What to do: Research should be conducted on the forecast skills of operational numerical weather prediction models for California and the applicability of mesoscale meteorological models to locally enhance forecast skill.
   Who can do it: In collaboration with NREL (Bill Mahoney) and NOAA scientists (Stan Benjamin), California researchers should conduct modeling and evaluation studies for California. Scripps Institution of Oceanography researcher Masao Kanamitsu has significant experience in mesoscale meteorological modeling in California.

   Conduct a forecast competition: CAISO has successfully conducted a wind forecast competition in 2008/2009 and would like to repeat a similar project for solar forecasting. Any forecast providers could bid and provide forecasts for a few representative sites to the ISO for one year. The following parameters should be forecast: Global Horizontal Irradiance, Diffuse Horizontal Irradiance, Direct Normal Irradiance, Global (diffuse + direct) plane of array irradiance for fixed tilt PV, PV panel temperature for fixed tilt PV mounted onto a flat area, Global (diffuse + direct) irradiance for a two-dimensional tracking CSP plant. The California Solar Energy Collaborative (CSEC) could provide independent analysis of such a dataset for CAISO to evaluate operational forecast skill for different providers. Similar

to a previous study on wind forecasting, forecast providers would need to be reimbursed for these services by CAISO and their input to the design of such a study should be sought.[2]
Why: No peer-reviewed studies exist that evaluate solar forecast performance for California. With its unique microclimates California presents a significant challenge to forecast models.
What to do: Contact CAISO's James Blatchford as to the timeline and support required to conduct such a study.
Who can do it: CSEC has the experience, knowledge, and independence to work with CAISO in planning, execution, and analysis of such a study.

b) **Ground measurement networks:** More ground measurements of solar irradiance would improve HA and intra-hour forecasts. Ground measurements of GHI (and DNI for concentrating plants) should be (and currently are) required by CAISO for large solar farms (similar to wind measurements in the PIRP program). However, we believe that establishing and maintaining a separate dedicated network of solar irradiance sites in California would not be the most economical approach to improving forecast skill. High-quality irradiance sites are labor intensive to install and operate as most DNI sensors require daily cleaning. E.g. NOAA estimates that the cost of upgrading the Climate Reference Network to conform to solar resource and forecasting needs would be $1.5M for just 7 sites in California. Yet the high accuracy does not necessarily translate to reduced forecast error since clouds are spatially localized and their detection and prediction would require extremely dense networks. No peer-reviewed research study exists that shows advantages of non-local measurements networks for solar forecasting. However, if other energy meteorology networks were established (e.g. for wind forecasting for which the advantages of such networks are more obvious), it would be useful and economical to 'piggyback' off of these sites and install low-maintenance GHI silicon pyranometers.

The most economical approach to enhance ground measurements would be to require and/or incentive 3rd party data providers (e.g. SunPower, Energy Recommerce, Fat Spaniel) to share their data in real time with the ISO and/or solar forecast providers which – under NDAs – could operate a data warehouse for utilities, and forecast providers. The cost to sharing such data is minimal as the infrastructure is in place such as more than 2000 sensors, meters, telemetry, and databases (Table S4). The only change to the current mode of operation is that database access would be provided in real-time instead of sending monthly summaries to CSI as is done currently. This approach would be expected to cost a fraction of a new station network and could be operated by CAISO and the energy industry in an open market. The advent of smart meters that can monitor residential PV outputs provides an additional avenue to implement this strategy.

Why: There is a lack of solar irradiance measurements in California.
What to do: Research should be funded by the California Solar Initiative or PIER or both in collaboration to develop models to derive solar irradiance values from ground PV data and

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[2] John Zack from AWS Truepower comments that "A rigorous competitive evaluation of forecast providers is fundamentally a good idea to establish level of performance expectations and an estimate the variation in forecast performance among providers. However, it is important to realize that the information obtained from such a study will be limited by the design of the study. A particular method may perform very well for one objective but not as well for another. (e.g forecasting of routine events vs anomalous events) and some methods may perform much better if certain types of data are available but may not have any advantage if those data are not available. The danger is that conclusions derived from a specific set of forecast evaluation conditions will be extrapolated to general conclusions, which may to lead to erroneous decisions on how to best address other forecasting objectives. We have encountered this issue in many of our wind forecasting applications."

demonstrate the potential and feasibility of such an approach to improve the accuracy of solar forecasting.
Also research on total sky imager (Figure S1c) deployments in areas with high PV penetration should be pursued. Sky imagers can survey a large area from a single site. The reduced accuracy in the irradiance measures determined by a sky imager (compared to a pyranometer) will be more than overcome by the spatial density and cloud tracking capability of the observations.
Who can do it: Kleissl is conducting Total Sky Imager work at UC San Diego. For the data aggregation work, collaborators with a background in data assimilation would be useful.

c) **Forecast aerosol optical depth for DNI:** Depending on the expected market share of concentrating solar power (CSP) plants in California, research should be conducted on DNI forecasts examining the integration of aerosol models into weather forecast models. These forecasts should especially be able to consider cirrus clouds, forest fire smoke predictions, dust storms, and urban aerosol air pollution transport that may affect CSP in California.
Why: Aerosols can significantly decrease DNI which could impact CSP plants.
What to do: Evaluate satellite remote sensing products of aerosol optical depth and their assimilation into solar forecasting.
Who can do it: Since aerosols may not be detectable on the ground, satellite remote sensing techniques hold the most promise, especially if coupled with NWP. A joint NASA-NOAA-EPA effort seems to be the most advanced (http://www.star.nesdis.noaa.gov/smcd/spb/aq/). With the exception of work in Germany (Breitkreuz et al. 2009), prior AOD work is focused on air quality applications. Additional research is required to determine the skill in determining solar irradiance.

5. Glossary

The NREL '**Glossary of Solar Radiation Resource Terms'** defines the following:

AOD: Aerosol Optical Depth: AOD is the "extinction per unit path length due to aerosols alone". Extinction of solar radiation occurs due to water vapor, ozone, mixed gases, and 'equivalent extinction' represented by Rayleigh scattering of atmospheric molecules, and what is 'left over' is the aerosol extinction.

DIFF: Diffuse Sky Radiation (or Diffuse Horizontal Irradiance): The radiation component that strikes a point from the sky, excluding circumsolar radiation. In the absence of atmosphere, there should be almost no diffuse sky radiation. High values are produced by an unclear atmosphere or reflections from clouds.

DNI: Direct Normal Irradiance: Synonym for beam radiation, the amount of solar radiation from the direction of the sun.

GHI: Global Horizontal Irradiance: Total solar radiation; the sum of direct, diffuse, and ground-reflected radiation; however, because ground reflected radiation is usually insignificant compared to direct and diffuse, for all practical purposes global radiation is said to be the sum of direct and diffuse radiation only.

Irradiance: The rate at which radiant energy arrives at a specific area of surface during a specific time interval. This is known as radiant flux density. A typical unit is W/m^2.

MBE: Mean Bias Error: Metric to compare the b. MBE can be negative (forecast is too small, on average), zero (forecast has no bias), and positive (forecast is too large, on average).

Mesoscale: Scale of numerical weather prediction models with domain sizes on the order of 1000 km and grid cells on the order of 1 to 5 km. Mesoscale models provide more fine-grained information than macroscale models (which predict weather for the entire US or even the globe), but are limited in the area over which they forecast.

MOS: Model Output Statistics: Statistical method to correct model errors in postprocessing based on predetermined bias errors.

NWP: Numerical Weather Prediction: Weather forecasting using computer models.

PV: Photovoltaic: Technology for converting sunlight directly into electricity, usually with photovoltaic cells.

Pyranometer: An instrument with a hemispherical field of view, used for measuring total or global solar radiation, specifically global horizontal radiation; a pyranometer with a shadow band or shading disk blocking the direct beam measures the diffuse sky radiation, as is illustrated in the picture below. A picture of the Eppley PSP pyranometer is included in the PSP definition above.

RMSE: Root Mean Squared Error: Metric to compare forecasts to actual data.

Rotating Shadow Band Radiometer: An instrument that determines total solar radiation and diffuse sky radiation by periodically shading the total sky sensor from the sun with a rotating shadow band. Below is a picture of a rotating shadow band radiometer at the Solar Radiation Research Laboratory. The curved black shadowband at the right of the instrument is at rest; once every minute, it rotates 180° to obscure the sun for a few seconds, then returns to its resting position.

Scattered Radiation: Radiation that has been reflected from particles, disrupting the original direction of the beam

Silicon Sensor: A photovoltaic cell that is being used to measure solar irradiance. Because its spectral response is not as exact as that of thermopile instruments, it has a higher uncertainty.

Solar Concentrator: A solar collector that enhances solar energy by focusing it onto a smaller area through mirrored surfaces or lenses

Solar Thermal Electric: Technology for using the sun's energy to produce steam to run turbines that generate electricity.

Transmittance: The fraction or percent of a particular frequency or wavelength of electromagnetic radiation that passes through a substance without being absorbed or reflected.

Turbidity: A measure of the opacity of the atmosphere. A perfectly clear sky has a turbidity of 0, and a perfectly opaque sky has a turbidity of 1. Turbidity is affected by air molecules and aerosols.

Zenith Angle: The angle between the direction of interest (of the sun, for example) and the zenith (directly overhead).

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Appendix

Table A1: Review of studies for solar energy forecasting. Modica et al. (2010) showed first results for forecasts with sky imagery. NDFD: National Digital Forecast Database (National Weather Service, NOAA, Washington, DC); ECMWF: European Center for Medium-range Weather Forecasting; Meteosat: Geostationary european satellite.

Study	Location	Quantity	Forecast Source	Averaging Interval	Time Horizon	Error Metric	Error Value	Comment
Schroedter et al(2009), Breitkreuz et al (2009)	121 sites in Europe	GHI	NWP (ECMWF)	1 h	1 - 72 h	RMSE MBE	10% (clear) – 40% (all) -10%	For clear-sky situations aerosol modeling significantly improves GHI and especially DNI irradiance forecasts relative to ECMWF. On the other hand, for cloudy conditions the AFSOL forecasts leads to significantly larger forecast errors.
		GHI	Aerosol + Mesoscale Model (AFSOL)	1 h	1 - 72 h	RMSE MBE	8% (clear) - 60% (all) 5% up to -25% (all)	
		GHI	Meteosat	1 h	1 - 72 h	RMSE MBE	6% (clear) – 22% (all) 0	I believe Meteosat was calibrated to data
		DNI	NWP	1 h	1 - 72 h	RMSE MBE	30% (clear) – 82% (all) -25% (clear) up to -35% (all)	Overall: 31.2% or 159 W m-2 -26.3% or -134 W m-2
		DNI	AFSOL	1 h	1 - 72 h	RMSE MBE	20% (clear) - 85% (all) 10% (clear) up to -15% (all)	18.8% or 96 W m-2 11.2% or 57 W m-2
		DNI	Meteosat	1 h	1 - 72 h	RMSE MBE	15% (clear) – 38% (all) <3%	15.6% or 80 W m-2 -1.7% or -9 W m-2
	Forecast length has a significant impact on forecast accuracy, as long as cloudy situations are included in the analysis: for the AFSOL system, this can be quantified by RMSEs of 49.7% for the first day, 62.4% for the second day, and 67.7% for the third day. When considering only cloud-free cases, forecast length has no effect on bias or RMSE for any of the model systems analyzed. Thus, it can be deduced that this error tendency is caused exclusively by difficulties in cloud forecasts that increase with growing forecast duration.							
Wittman (2008)	1 site in Spain, July 2003	GHI	NWP (ECMWF)	1 h	1 - 72 h	RMSE MBE	18.5% or 109 W m-2 -11.1% or -65.6 W m-2	Similar order but better results for clear skys only. AFSOL GHI on 5% RMSE.
		GHI	AFSOL	1 h	1 – 72	RMSE	25.1% or 148 W m-2	

					h	MBE	-2.2% or -12.7 W m-2	
		DNI	ECWMF	1 h	1 – 72 h	RMSE MBE	41.7% or 184.9 W m-2 -23.3% or -103.2 W m-2	
		DNI	AFSOL	1 h	1 – 72 h	RMSE MBE	47.0% or 208.6 W m-2 15.6% or 69.4 W m-2	
Lorenz et al. (2009)	Europe	GHI	ECMWF	1 h	3 h -	RMSE MBE	12% (clear) to 85% (cloudy) 0% (clear) to 25% (cloudy)	For both ECMWF and ECMWF + MOS: Day 1: RMSE = 35%, Day 2: RMSE = 40%, Day 3: RMSE = 55%.
			ECMWF + MOS	1 h		RMSE MBE	12% (clear) to 80% (cloudy) <5%	
	Study also shows confidence intervals for prediction. For ensembles distributed over a region of a size of 3o x 3o, the RMSE of the forecast is about half the RMSE of a single site. The RMSE is reduced to one third of the site-specific RMSE for regions of a size of about 8o x 8o.							
Perez et al. (2007)	Albany, NY	GHI	NDFD	3 h	3-72 h	RMSE MBE	32% (<4) to 40% (>26h) -10% (<4 h) to -4% (>26 h)	National Digital Forecast Database only output cloud cover
Hammer et al. (1999)	Central Europe, April - June	GHI	Meteosat - Heliosat	instantaneous	0.5 – 2 h	RMSE	18% for 30 minutes (vs 26% persistence), 22% for 1 h, 28% for 2 h, 38% for 3 h.	RMSE is satellite forecast versus satellite actual, i.e. no ground station data were used. Numbers were estimated from graphs. Filtering improves the forecast quality.
Bacher et al. (2009)	Denmark	P_{out}	Autoregressive models based on P_{out} (t-1) and NWP	1 h	1 h – 30 h	RMSE	40 - 100% (normalized by mean power) for same day, 5% - 13% (normalized by peak power) for next day	For horizons below 2-h solar power is the most important input, but for next day horizons no considerable improvement is achieved from using available values of solar power, so it is adequate just to use NWPs as input.
Hamill & Nehrkorn (1993)	Eastern 2/3 of US	Brightness	GOES cross-correlation	instantaneous	0.5 h – 2.5 h	RMSE	9% (0.5 h) to 18% (2.5 h) for fall, winter, spring. 11% to 25% for summer	RMSE is satellite forecast versus satellite actual in gray-shade values. Persistence was 12% to 21%. Using 500 mbar wind field nearly as good as crosscorrelation

								method. 11 km pixel resolution.
Heinemann (2006)	Germany Saarbruecken 8 Stations	GHI	Meteosat – Heliosat from Hammer et al. (1999)		0.5 h – 6 h	RMSE	25% (0h) to 42% (6 h) with motion & smoothing. 25% (0h) to 55% (6 h) with persistence	With increasing forecast the influence of smoothing becomes more important than the application of motion vector fields.. Variability in the cloud field has a strong effect on forecast RMSE.
	Same as above	GHI	MM5	1 h	1 h to 48 h	RMSE	with MOS: 33% for day 1 and 36% for day 2 with MM5: 52% for day 1, 55% for day 2	40 days in summer 2003
Jensenius (1981)			MOS on NWP			RMSE MBE	25% for 1 day 2% for 1 day	
Bofinger and Heilscher (2004)	32 sites in Germany		MOS on ECMWF			RMSE MBE	32% for hourly and 19% for daily. Persistence was 55% for hourly and 48% for daily. 2.9% for hourly and 2.8% for daily	1 year
	same		Meteosat - Heliosat	1 h		RMSE MBE	26% for hourly and 12% for daily 3% for hourly and daily	
Perez et al. (2009)	6 sites in US	GHI	Satellite	1 h	1 h to 6 h	RMSE MBE	53 to 64 Wm-2 (1h) to 100 to 133 Wm-2 (6h) (persistence: 53 to 65 Wm-2 (1h) to 108 to 125 Wm-2 (6h) -3 to 12 Wm-2 (1h) to -3 to -13Wm-2 (6 h) (persistence: 2 to 11 Wm-2 for 1h, 6 to -23 Wm-2 for 6h)	8/23/2008-1/31/2009. Persistence forecast included extrapolating measured irradiances using a constant GHI/GHIclear ratio. Forecast errors for Boulder, CO, are much higher due to local topography and are excluded.
	same	GHI	NDFD	1 h	1 (same day) to	RMSE MBE	75 to 114 Wm-2 (same day) to 97 to 146 Wm-2 (7 days) (persistence: 150 to 211	All NDFD forecasts originate at 11:00 GMT.

					7 days		Wm-2 (7 days)) -25 to 32 Wm-2 (same day) to -18 to 41 Wm-2 (7 days) (persistence: -8 to 10 Wm-2)	
	Cloud-motion forecasts are more accurate than NWP up to 4-5 hours ahead with a performance gain approaching nearly 40% for the 2-hour forecast. The forecasts also perform better than on-site measurement extrapolation with performance gain peaking at hour 4. NDFD overpredicts irradiance, even after it was adjusted empirically to prevent overprediction. Comparing range of mean monthly values within a 2^o by 2^o gridbox to absolute RMSE errors at the site shows that the RMSE errors are much smaller.							
Remund et al. (2008)	3 sites in CO, NV, MS	GHI	NDFD	1 h	1 day	RMSE MBE	18% (NV), 41% (CO), 36% (MS) 2% (NV), 3% (CO), -4% (MS)	April – September 2007. The breakeven of persistence is reached after 2-4 hours. The breakeven is dependent on the uncertainty. For ECMWF and NDFD this value is reached at 2 hours for GFS/WRF at 3 hours. The errors for same day and 2 day forecast are only marginally different from 1 day (shown on left).
			EMCWF V2			RMSE MBE	18% (NV), 40% (CO), 32% (MS) 3% (NV), 11% (CO), 6% (MS)	
			GFS/WRF			RMSE MBE	18% (NV), 50% (CO), 41% (MS) 2% (NV), 19% (CO), 18% (MS)	Also conducted Kolmogorov-Smirnov test.

Final Report

California Renewable Energy Forecasting, Resource Data and Mapping

Appendix B

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

Regents of the University of California

Basic Ordering Agreement

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

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Contents

Abstract

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

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

Summary

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

Below are the key findings and recommendations:

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

1 Introduction

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

1.1 20% Wind Energy by 2030

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

1.2 Wind Forecasting Applications

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

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

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

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

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

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

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

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

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

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

1.3 Structure of This Report

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

2 Wind Forecasting Methodologies

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

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

2.1 Forecast System Introduction

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

2.1.1 Physical Approach and Statistical Approach

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

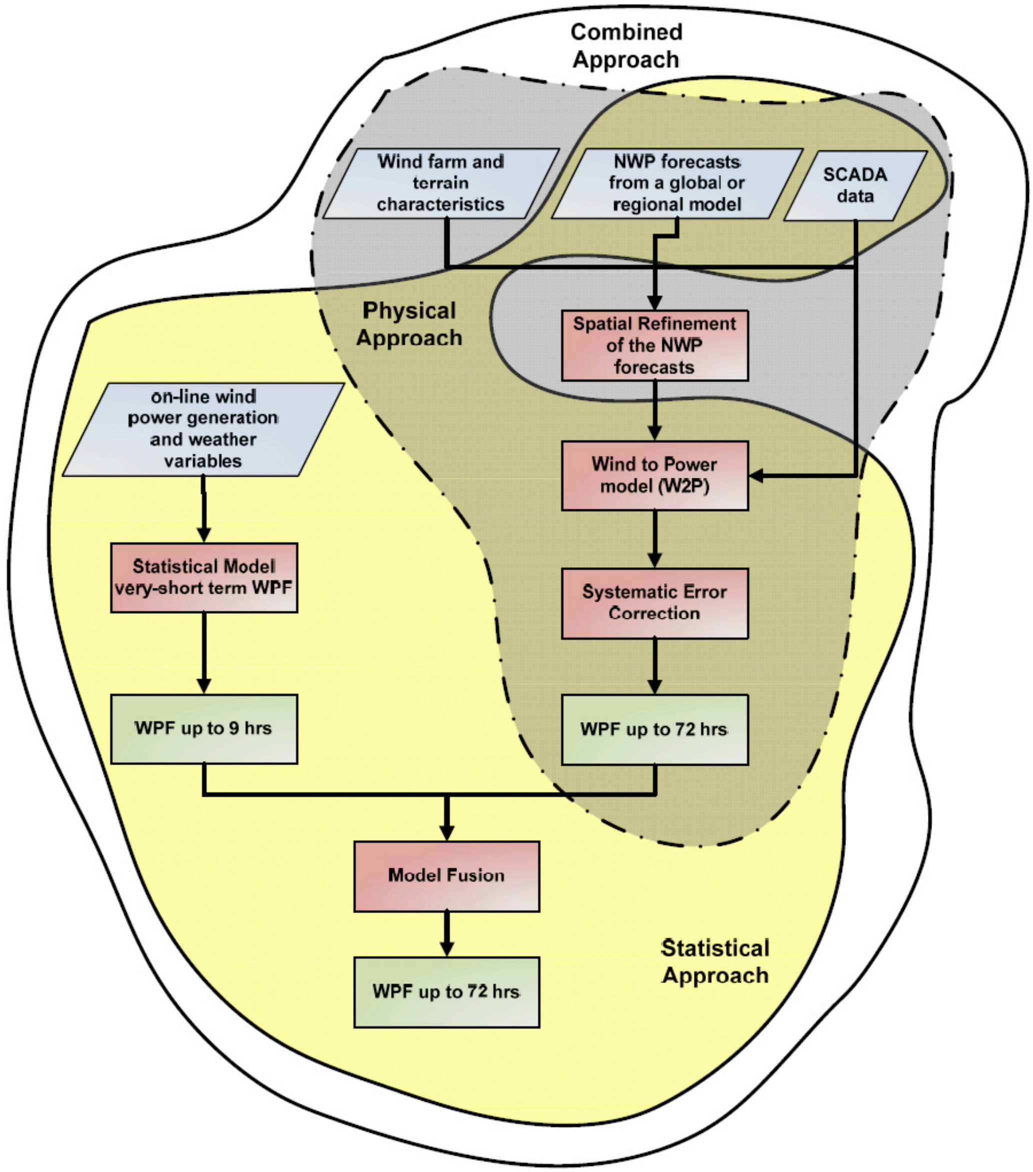

Figure 1. There exist two approaches to wind power forecasting (WPF): physical approach and statistical approach (from Monteiro et al, 2009).

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

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

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

2.1.2 Forecast Stages

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

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

2.1.3 Forecast Ensembles

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

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

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

2.1.4 Forecast System Operations

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

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

2.2 Operational and Commercial Wind Forecast Systems

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

2.2.1 AWS Truewind – eWind Forecasting System

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

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

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

2.2.2 Garrad Hassan – GH Forecaster

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

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

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

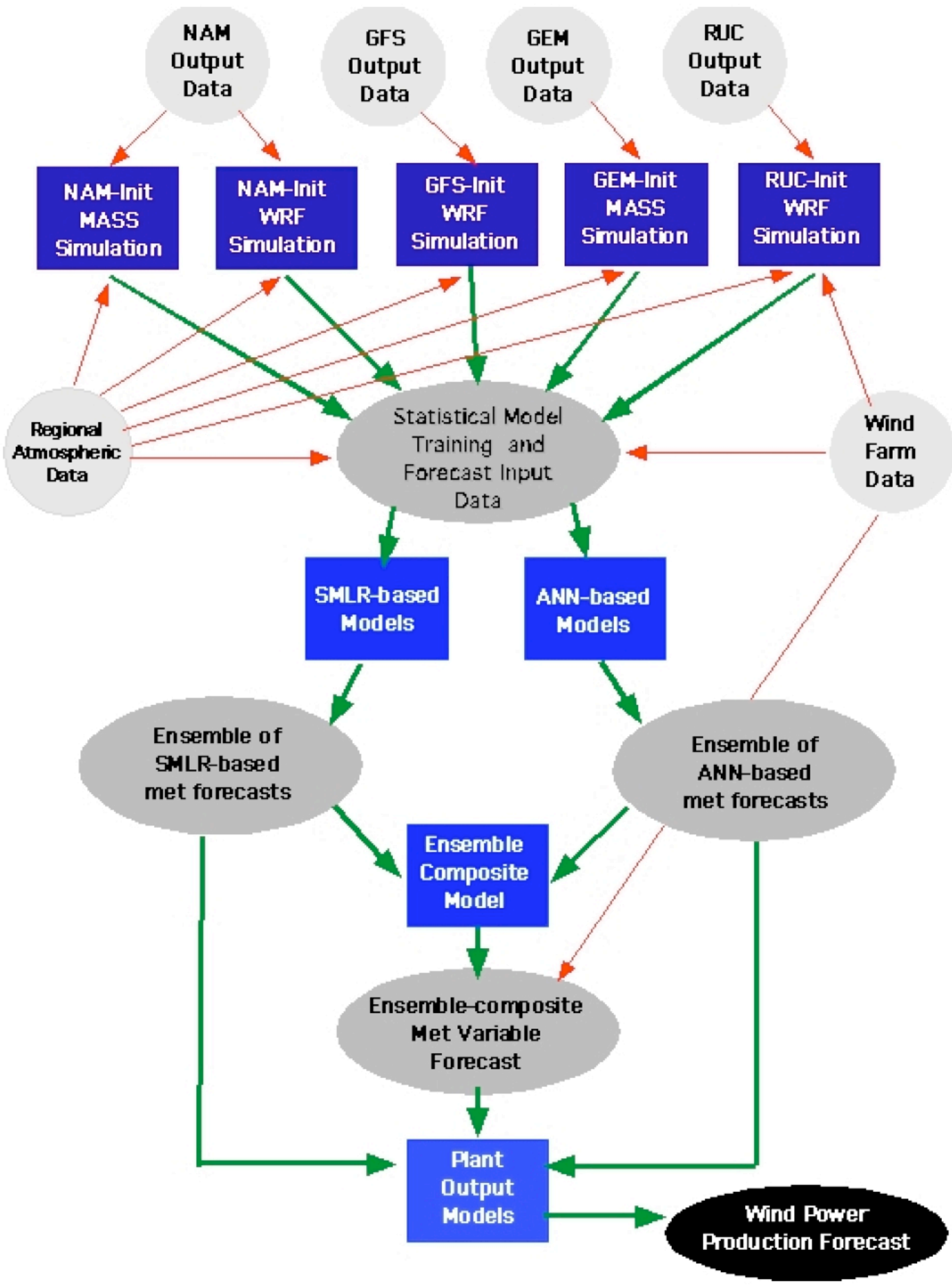

Figure 2. A schematic of the data flow and computational process for the AWST eWind forecast system used for the Alberta pilot project (from AWS Truewind, 2008).

2.2.3 3Tier – PowerSight Wind Forecasting System

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

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

2.2.4 National Center for Atmospheric Research – Nowcasting and DICast Systems

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

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

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

2.2.5 Gamesa – Mega System

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

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

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

2.2.6 Other Forecast Service Providers and Their Models

- Energy and Meteo Systems – Previento

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

- WEPROG – MSEPS System

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

- ARMINES – ARMINES Wind Power Prediction System (AWPPS)

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

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

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

- ISET – Wind Power Management System (WPMS)

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

- Precision Wind – Precise Stream

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

- WindLogics – WindLogics Wind Energy Forecast System

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

- AMI Environmental Inc. – Wind Energy Forecasting System

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

- WSI – WindCast

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

2.3 Evaluation of Forecasting Systems

2.3.1 Measures of Accuracy

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

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

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

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

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

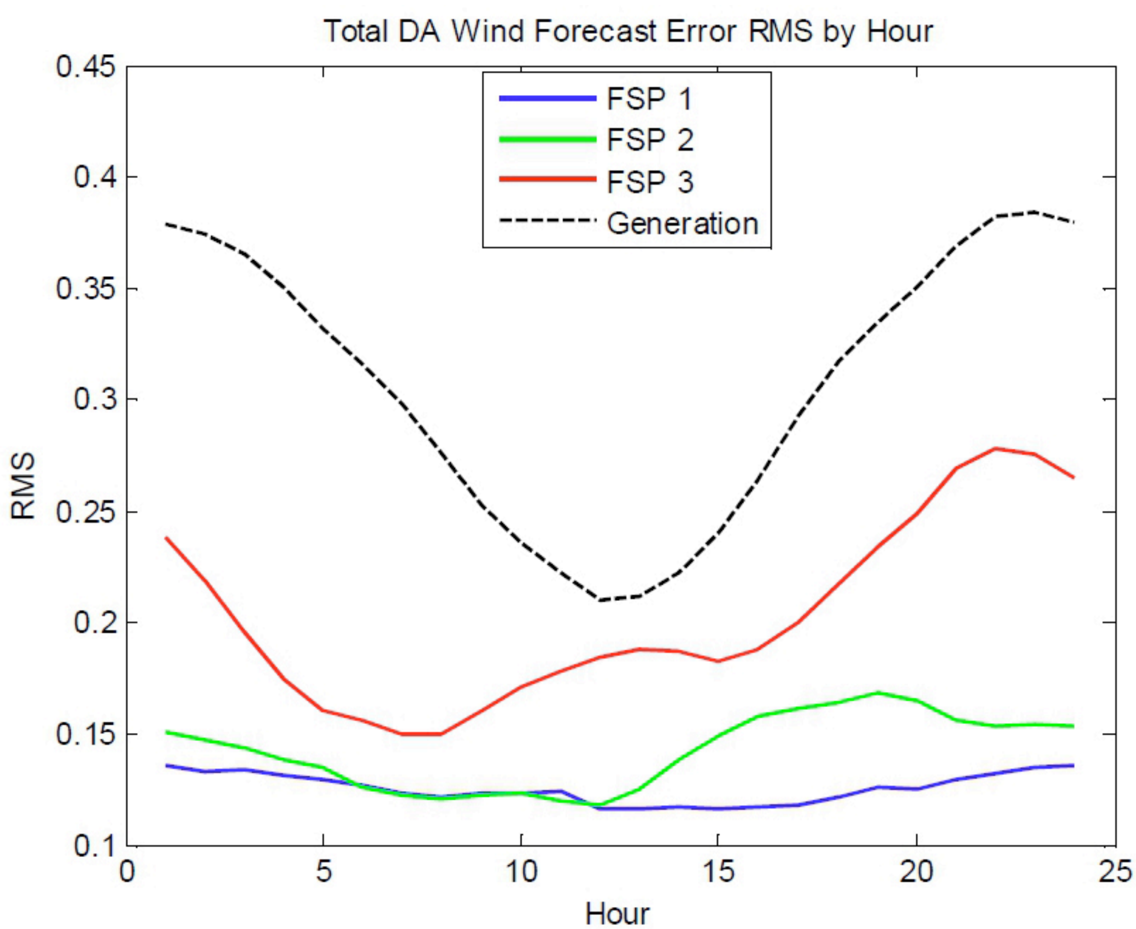

Figure 3. Total day ahead forecast RMSE by hour of day (from Blatchford and de Mello, 2009).

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

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

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

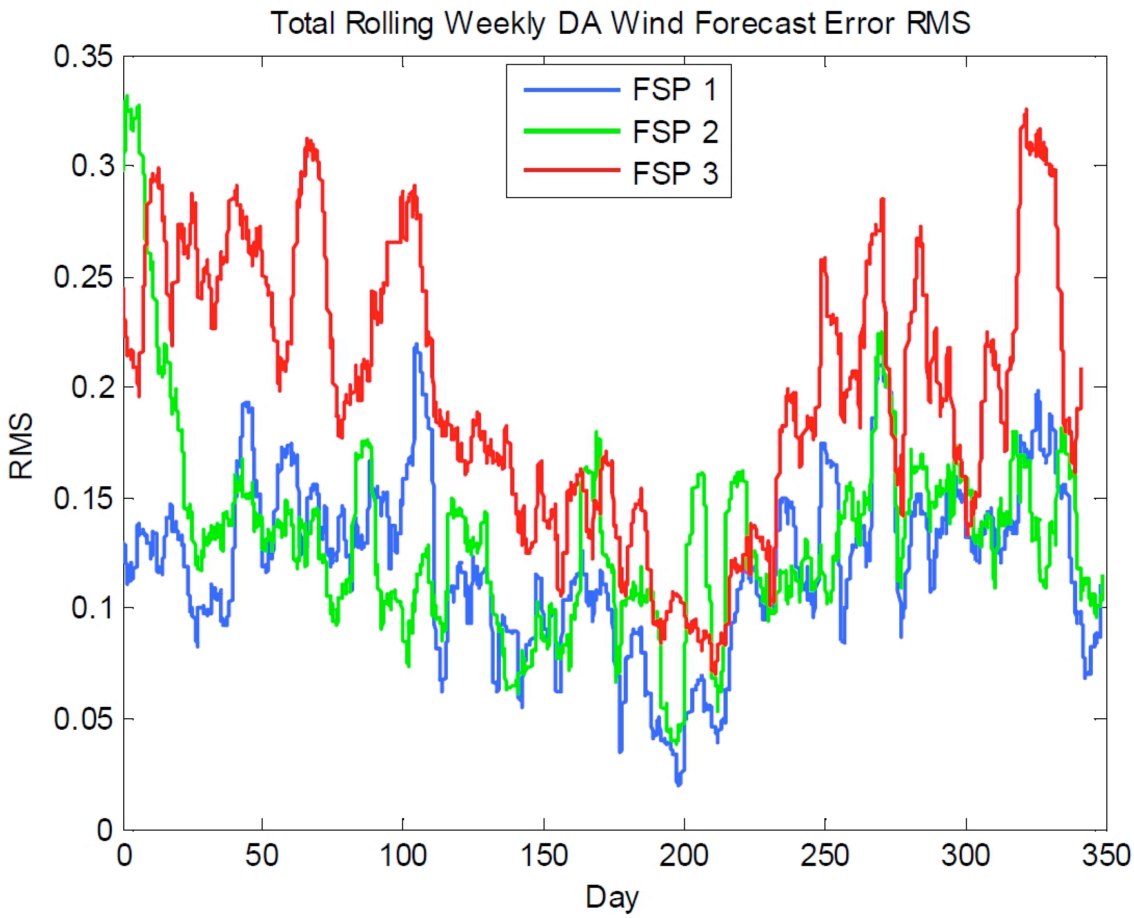

Figure 4. Rolling Weekly Day ahead Forecast RMSE (from Blatchford and de Mello, 2009).

2.3.2 Alberta Pilot Project

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

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

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

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

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

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

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

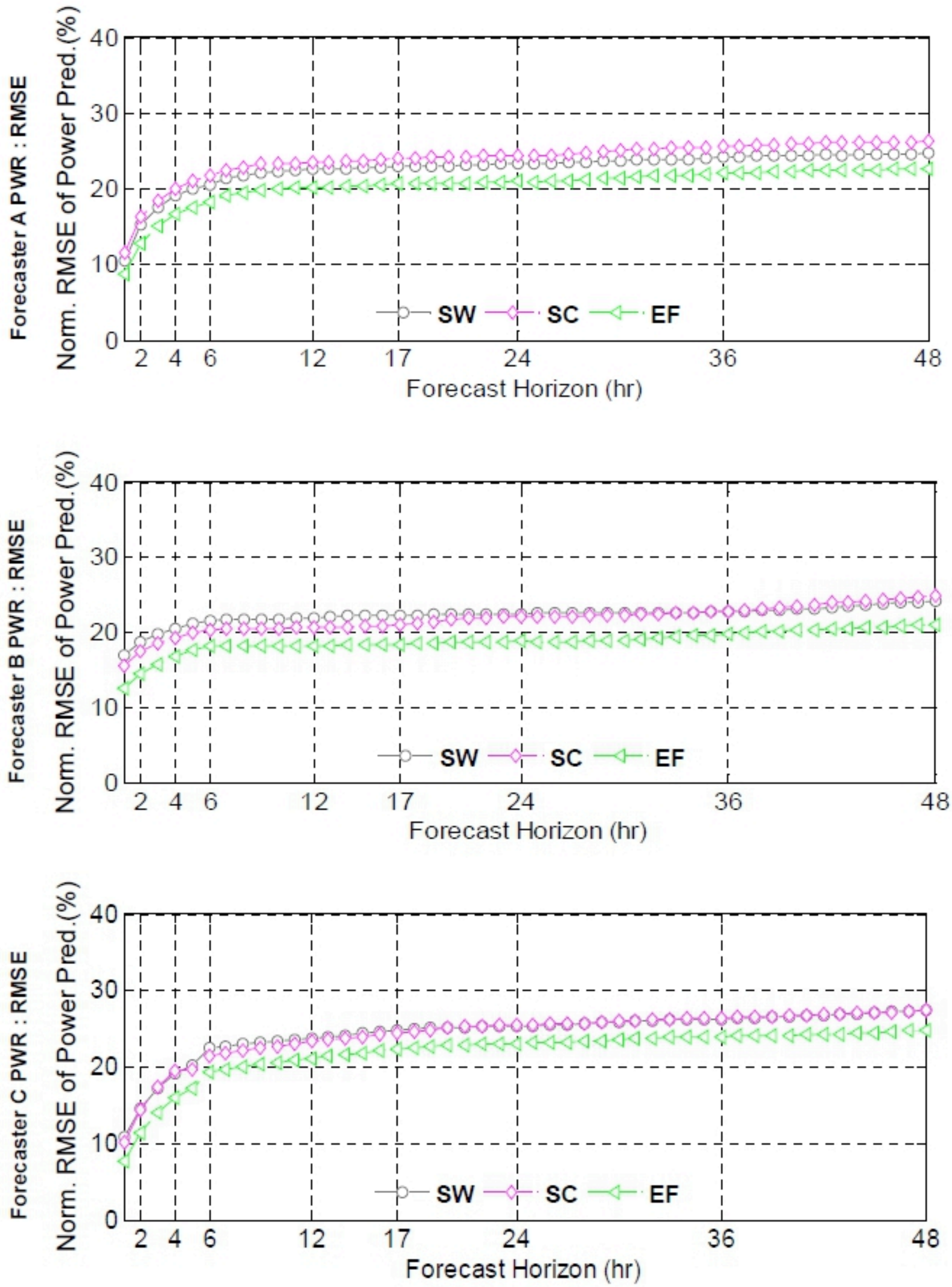

Figure 5. Total day ahead forecast RMSE for three forecasters as a function of forecast horizons (from McKay, 2008).

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

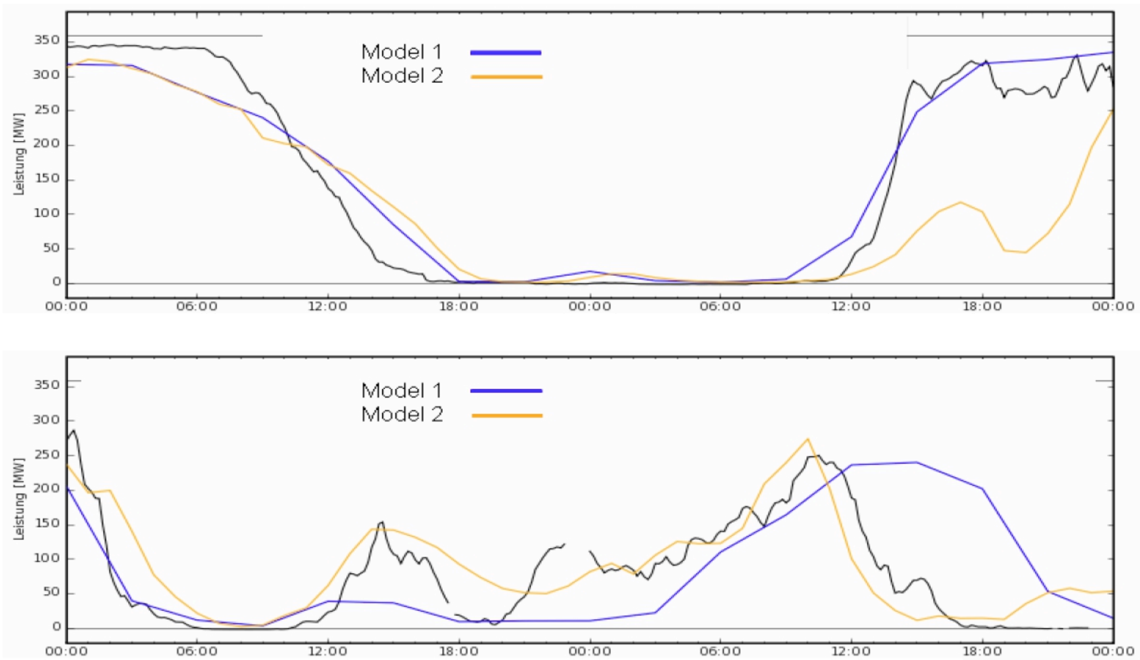

Figure 6. Individual forecasts based on two different NWP models for two different weather situations (from Focken and Lange, 2008).

3 Ramp Rate Forecasting

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

3.1 Frequency of Ramp Events and Definition of a Ramp Event

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

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

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

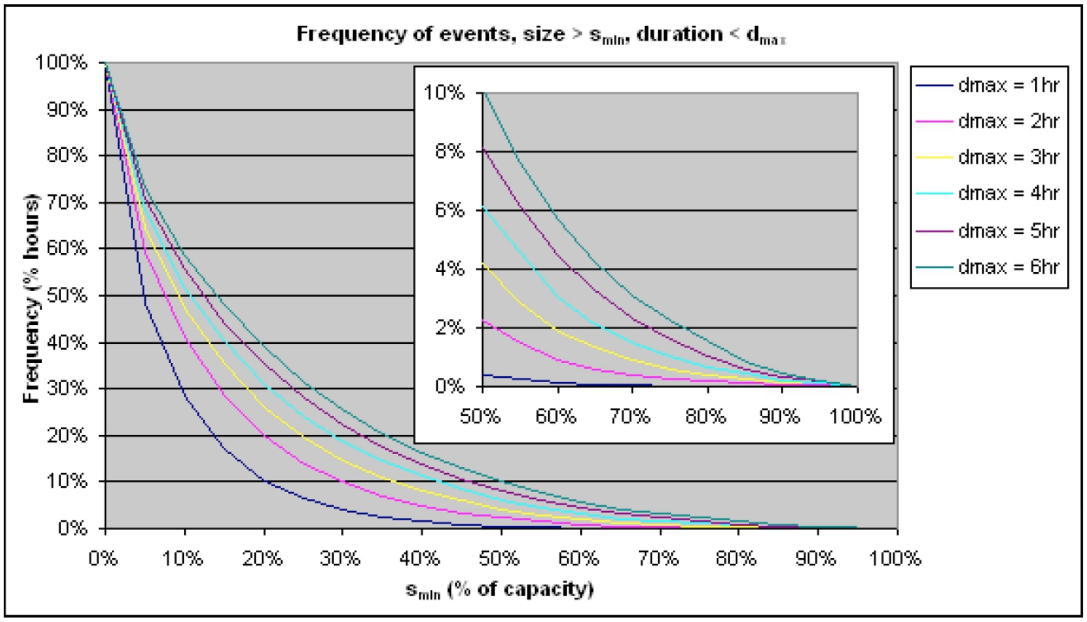

Figure 7. Frequency of power changes with varying size and duration (from Greaves et al, 2009).

3.2 Ramp Forecasting Research

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

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

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

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

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

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

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

4 Data Sources for Validation and Calibration

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

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

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

4.1 Available Wind Data Sources

4.1.1 Generation Data in CAISO PI System

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

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

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

4.1.2 CAISO PIRP

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

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

4.1.3 Other CAISO Data Systems

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

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

4.1.4 Utilities (IOUs and munis)

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

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

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

4.1.5 Wind Plant Owner/Operators

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

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

4.1.6 Wind Plant Developers

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

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

4.1.7 California Tall Tower Data

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

4.1.8 NOAA and NWS

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

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

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

4.1.9 California Data Exchange Center (CDEC)

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

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

4.1.10 California Irrigation Management Information System (CIMIS)

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

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

5 Recommendations

5.1 Best Practices in Forecasting

5.1.1 Well Defined Objectives

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

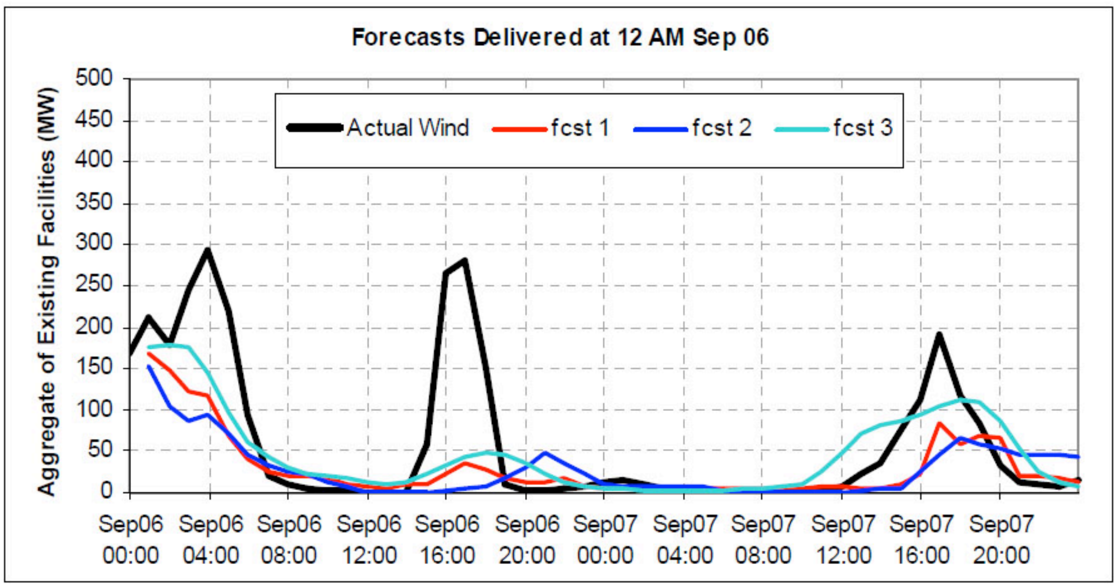

Figure 8. Forecasting models trained to have low average errors missed ramps on the afternoon of September 6, 2007 (from Industry Work Group, 2008).

5.1.2 Improve Data Quality

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

5.1.3 Power Conversion

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

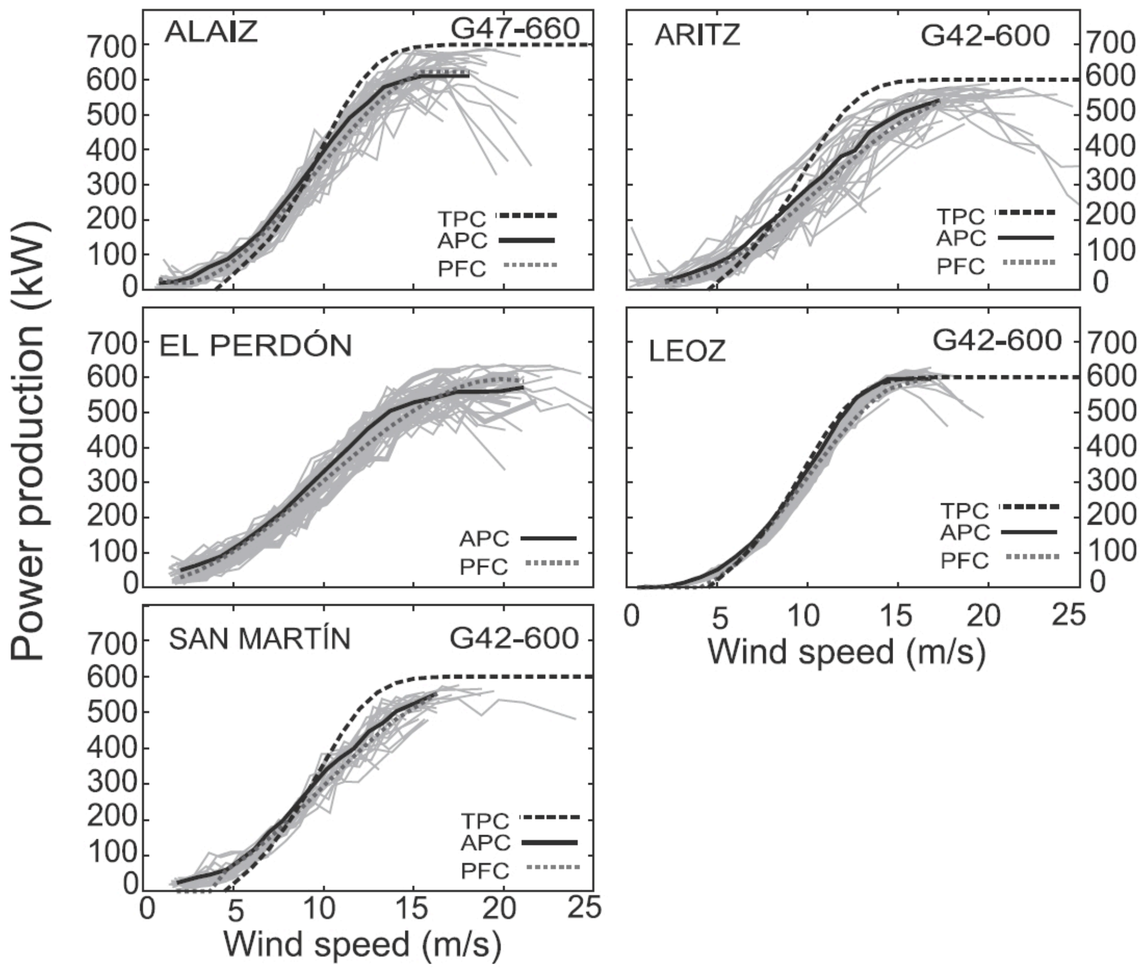

Figure 9. Estimation of monthly energy output for five wind farms in Spain using three different power conversion models: Theoretical Power Curve (TPC, dashed line), Average Power Conversion (APC, solid line), and Polynomial Fit Curve (PFC, points) (from Garcia-Bustamante et al, 2009).

5.1.4 Learning by Doing

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

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

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

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

5.2 Data

5.2.1 Data Impacts on Forecasts

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

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

5.2.2 Data Validation and Filtering

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

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

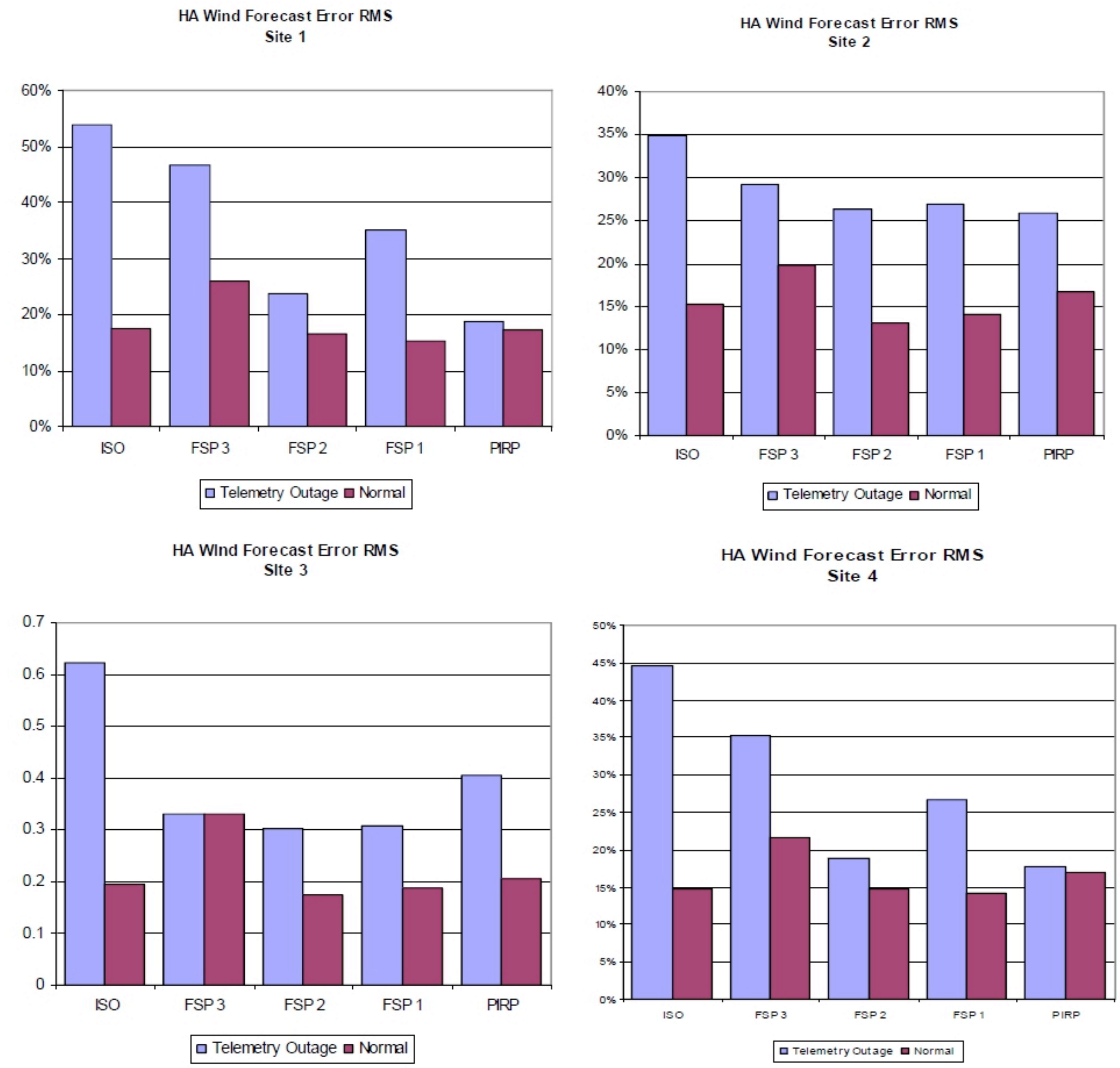

Figure 10. Impact of data quality on forecasts (from Blatchford and de Mello, 2009).

5.3 Future Research

5.3.1 Data Acquisition and Transmission

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

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

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

5.3.2 Sources of Error

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

5.3.3 Ramp Rate Forecasting

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

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

5.3.4 Improving Icing Forecasts

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

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

5.3.5 New Technologies

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

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

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

5.3.6 Atmospheric Boundary Layer Profiles

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

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

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Glossary

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

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

WRF	Weather Research and Forecasting

Appendix A: Numerical Weather Prediction Models

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

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

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

A.1 Introduction to Major NWP Models

- Eta/NAM

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

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

- GFS

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

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

- RUC

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

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

- MM5

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

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

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

- NOGAPS

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

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

- COAMPS

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

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

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

- GEM Regional/GEM Global

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

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

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

Table A1. Major NWP Models - Model Structure and Dynamics

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