Public Interest Energy Research (PIER) Program

FINAL PROJECT REPORT

CALIFORNIA RENEWABLE ENERGY FORECASTING, RESOURCE DATA, AND MAPPING

Prepared for: California Energy Commission

Prepared by: Regents of the University of California

OCTOBER 2012

CEC-500-2014-026

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Contract Number: 500-99-013

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ACKNOWLEDGEMENTS

The authors and contributors thank the California Energy Commission and its Public Interest Energy Research Program for initiating and identifying objectives and funding the work presented in this report. The project scope was organized according to objectives and team expertise. Thus, the California Solar Energy Center (CSEC) and the California Wind Energy Center (CWEC) completed Chapters 1 and 2, respectively. Chapters 3 and 4 were a joint effort coordinated by the California Geothermal Energy Center 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 Center team is grateful to Bill Mahoney (National Center for Atmospheric Research [NCAR]), James Blatchford (California Independent System Operator [California ISO]), Phil de Mello (UC Davis), Gerry Braun (UC Davis), Ronnie Holland for their help and input.

Task 1: California Renewable Energy Forecasting, Resource Data and Mapping, Part 2 of 2: Wind Data Forecasting and Mapping: The California Wind Energy Center team thanks the following people for their help and input: Jim Blatchford (California ISO), Phil de Mello (UC Davis), Bill Mahoney (National Center for Atmospheric Research [NCAR]), Barry Gilman (Southern California Edison [SCE]), Jim Molesworth (enXco), Andrew Klingler (Pacific Gas and Electric [PG&E]), Buck Cutting (Sacramento Municipal Utility District [SMUD]), Gerry Braun (UC Davis), and Ronnie Holland.

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, and their support is gratefully acknowledged. The California Geothermal Energy Center 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. Chapter 4 of this report benefited from critical reviews by Paul Brophy and Toni Boyd. Their comments are gratefully acknowledged.

PREFACE

The California Energy Commission Public Interest Energy Research (PIER) Program supports public interest energy research and development that will help improve the quality of life in California by bringing environmentally safe, affordable, and reliable energy services and products to the marketplace.

The PIER Program conducts public interest research, development, and demonstration (RD&D) projects to benefit California.

The PIER Program strives to conduct the most promising public interest energy research by partnering with RD&D entities, including individuals, businesses, utilities, and public or private research institutions.

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- Renewable Energy Technologies
- Transportation

California Renewable Energy Forecasting, Resource Data and Mapping is the final report for the California Renewable Energy Forecasting, Resource Data and Mapping project (Contract Number 500-99-013, Work Authorization Number BOA-99-248-R) conducted by University of California, Davis and San Diego. The information from this project contributes to PIER's Energy-Related Environmental Research Program.

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ABSTRACT

As wind and solar thermal and photovoltaic generation begin to have a larger role in electrical generation in California, the California Independent System Operator needs to accommodate their intermittent nature in its forecasting and dispatching activities. This project reviewed and evaluated the current state of knowledge and models for forecasting solar resources and considers options for improving forecasts through RD&D and additional measurements.

Satellite and numerical weather predictions have been shown to be the best tools for hour-ahead and day-ahead forecasts. However, solar forecast performance has yet to be evaluated for California, where the coastal microclimate may present a significant challenge. To validate and calibrate such forecasts, a combined real-time production database for all metered photovoltaic systems is deemed to be the most spatially dense and economical set of "measurements." A research roadmap for improving the forecasts of direct normal irradiance (the amount of solar radiation from the direction of the sun) is provided.

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 the wind power industry and reviews state-of-the-art methods for forecasting wind energy and output ramp rates. Available data sources for validation and calibration are presented, and recommendations are offered regarding the best practices for wind forecasting and future research needs.

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. This study benefits California ratepayers by providing information on key sources of clean renewable energy with the potential for significant human health benefits, environmental benefits, and cost savings.

Keywords: California Energy Commission, Geothermal, Solar, Wind, Forecasting, Dispatching, California ISO, Los Angeles Basin, Salton Trough, solar thermal, photovoltaic systems, energy, renewable, forecast, modeling, wind, energy, renewable, forecast, numerical wind prediction, NWP, modeling, ramp rate, data sources

Please use the following citation for this report:

Glassley, William, Jan Kleissl, C.P. "Case" van Dam, Henry Shiu, Junhui Huang. (University of California). 2011. ***California Renewable Energy Forecasting, Resource Data and Mapping.*** California Energy Commission. Publication number: CEC-500-2014-026.

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EXECUTIVE SUMMARY

Introduction

This research is intended to address the current state of forecasting for both solar and wind resources, and provide a preliminary assessment of geothermal resources in the Los Angeles Basin and Salton Trough that are co-located with solar energy.

The first component of this project provides a summary of the state of solar and wind forecasting. The information gathered under this project includes the types of forecasting and models that are used to predict solar and wind resources, how they are used, and the data and research that is needed to further improve forecasting. Solar and wind forecasting models will help integration of these renewable resources into California's power grid.

The second component of this project was intended to provide an initial assessment of renewable resources in the Los Angeles Basin and Salton Trough/Imperial Valley, an area that holds promise for integrating geothermal resources with both solar and wind. Although there are significant renewable resources in this area, they are unevenly distributed. This study examined published reports, maps, and databases to determine the extent of these resources, and to establish how well these resources aligned with each other and with transmission lines.

Background and Recommendations

Solar and Wind Forecasting —Background

As wind, solar thermal, and photovoltaic (PV) generation begins to have a larger role in electrical generation in California, the California Independent System Operators (ISO) needs to accommodate their variable nature in its forecasting and dispatching activities. In the future, the California ISO may also shift some of the economic costs of forecast errors to wind and solar power plant operators and net metered utility customers using solar PV, who will then have needs for forecasting information.

A wind or solar power forecast is an estimate of the expected power production of one or more wind turbines, wind plants, or solar 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 and solar power forecast models*. A power forecast model is a computer program that uses various inputs to produce wind or solar power output for future times. The complexity of the wind or solar 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. Because the persistence model performs surprisingly well for very short forecast horizons (up to a few hours), it is the benchmark that all other forecast models are compared against. Compared to the persistence model, modern wind and solar power forecast models are notably more complex. These modern forecast models are often called *power forecast systems* by their developers since they contain a combination of *physics-based models* (such as Weather Research and Forecasting (WRF)), *statistical models* (such as Screening Multiple Linear Regression (SMLR) and Artificial Neural Network (ANN)), and *plant output models*.

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 ISOs are the dominant consideration for this report. Furthermore, the rules established by the California ISO will impact the economic value of forecasting to other stakeholders such as owner-operators. The California ISO currently uses day ahead and hour ahead forecasts. The day ahead forecast is submitted at 05:30 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 day ahead market. The hour ahead forecast is submitted 105 minutes prior to each operating hour. It also provides an advisory forecast for the 7 hours after the operating hour. The California ISO is also studying intra-hour forecasts on 5 minute intervals.

Currently, under the California ISO 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). Wind units may participate in day ahead market; however, no special settlement treatments apply. Forecasts are integrated into California ISO planning, but there is no financial incentive to the forecast providers for accurate forecasts.

Future modifications in rules and tariffs may cause some of the economic benefit and interest in forecasting to shift to the owner-operators of renewable power plants which would dramatically change the marketplace for renewables forecasting. An example of such a system is the Spanish 'premium tariff' which allows operators of renewable power plants to participate directly in 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 power plants, selling electricity at the liberalized market rates. Thus, there is the need for operators of renewable energy plants to be able to provide energy that can be predicted and dispatched in the profitable premium tariff market.

Solar Forecasting State of the Art—Conclusions and Recommendations

Current Forecast Skills

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

Further research should be conducted on the forecast skills of operational numerical weather prediction models for California. The applicability of mesoscale numerical weather prediction to locally enhance forecast skills 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 hourly ahead and intra-hour forecasts statewide, more ground data are necessary. The most economical approach would be to require or incentivize third 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. Also, research on sky imager deployments in areas with high PV penetration should be pursued.

Direct Normal Incident (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.

"Chapter 1: Solar Forecasting State of the Art" presents a full review of solar power forecasting and more detailed recommendations.

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 (Pacific Gas and Electric [PG&E], Sacramento Municipal Utility District [SMUD], California ISO, Southern California Edison Company [SCE]) use both hour ahead and day ahead forecasts 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 are two approaches to short-term wind power forecasting: the physical approach and the statistical approach. In some cases, a combination of both is used. Most forecast models employ numerical weather prediction models to improve forecast accuracy.
- The accuracy of forecasts from a wind forecasting model depends on a number of factors, such as wind plant terrain topology, surface roughness, weather conditions, wind pattern, forecast horizon, etc. For a specific wind forecasting project, a comparison of different models needs to be carried out 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.
- Wind data are recorded and stored by a variety of entities in California, including the California ISO, independent operator utilities (IOU), municipal operator utilities (MOU), wind plant owners, wind developers, NOAA, National Weather Service (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 includes: new technologies in meteorological measurements, turbine icing forecasting, and studies on atmospheric boundary layer profiles.
- There are limited studies on power 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 California ISO and other system operators should work with forecasters to define power ramp events and to evaluate ramp rate forecasting.
- 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.

"Chapter 2: Wind Forecasting State of the Art" presents a full review of wind power forecasting and more detailed recommendations.

Resource Mapping: Los Angeles Basin and Salton Sea Trough—Background

The Los Angeles Basin and the Salton Trough contain substantial geothermal resources as well as wind and solar thermal resources. This project reviewed maps and databases locating these resources, and the maps and databases of transmission lines and loads. These maps and databases were evaluated and recommendations were made for their enhancement. This review can be used to identify promising locations for integration of renewable projects that include geothermal resources.

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 methods 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. The authors considered a pool to be a potential geothermal resource if the pool had temperatures exceeding 91°C. Such pools were also characterized as "geopressured" if the pressure in the pool exceeded 10 percent of the nominal hydrostatic pressure. The identified pools were then mapped with respect to already characterized solar and wind resources. The results indicate 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 one 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: Los Angeles 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 near three geothermal pools in Los Angeles County and warrant consideration for generation purposes at a local urban feeder scale.

The authors recommend a 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. “Chapter 3:

"Resource Mapping of Co-Located Geothermal Resources in the Los Angeles Basin" presents 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. "Chapter 4: Resource Mapping of Co-Located Geothermal Resources in the Salton Trough" presents documentation and discussion of supporting analysis.

CHAPTER 1:
Solar Forecasting State of the Art

1.1 Overview

This project was comprised of two components. The first task is related to forecasting and dispatching intermittent renewable resources. The second task concerns identifying additional geothermal resources in the Los Angeles Basin and Salton Trough, particularly those resources that can be co-located with other wind and/or solar resources. Table 1 lists the tasks that are addressed in this portion of the project.

Table 1. Task 1 Elements

Part 1 Task Elements
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.
2. Summarize and assess sources of real time wind and solar data used to calibrate day-ahead and hour-ahead forecasts.
3. Review data on actual and forecast wind and solar thermal plant output ramp rates.
4.-6: Recommendations for expanded sensor deployment and data collection. Recommendations for forecasting at high renewable penetration levels.

1.2 Solar Forecasting

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 portion of the project reviews and evaluates current knowledge and models for forecasting solar resources and considers options for improving forecasts through research and measurements.

1.3 Solar Forecasting Needs, Market Connection, and Stakeholders

This section reviews and evaluates current knowledge and models for forecasting solar resources, and recommends ways in which forecasting can be improved. .

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 only 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. 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 2). 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 reduce DNI by up to 30percent 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** (such as 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 2).

Table 2: Quantities Relevant to Solar Forecasting, 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 temperature, wind	low	high
Direct Normal Incident (DNI)	Concentrating Solar Power	Clouds, aerosols, water vapor	medium	Low

1.3.1 Solar Forecasting Methodologies

1.3.1.1. 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 1, Figures 1 and 2d):

- 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 (now cast) up to 15-30 minutes. by applying image processing and cloud tracking techniques to sky photographs (Fig. 1c). 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. 1b) 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 (such as 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 3. 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. 1c)	30 sec	10s to 100 meters	2-5 mile radius	10s of minutes	Short-term ramps, regulation
GOES satellite imagery (Fig. 1b)	15 min	1 km	US	5 hours	Load following
NAM weather model (Fig. 1a)	1 hour	12 km	US	10 days	Unit commitment

Figures 1 a-c: Solar Forecasting Imagery Maps

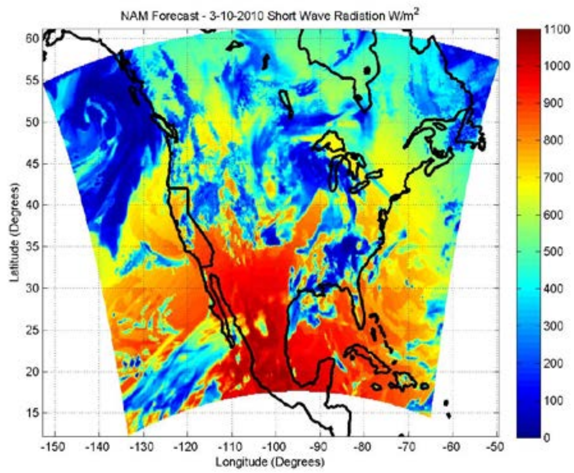


Figure 1a: Map of the forecast GHI [W m^{-2}, color bar] in March 2010 at midday from the North American Mesoscale model (NAM).

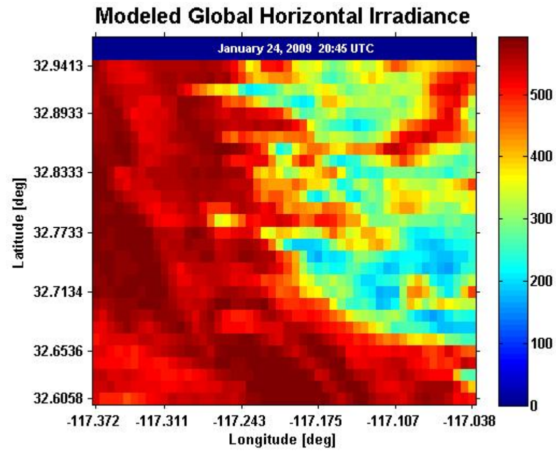


Figure 1b: Map of the forecast GHI [W m^{-2}, color bar] for San Diego on January 24, 2009 at 1245 PST using the GOES-SUNY satellite model.

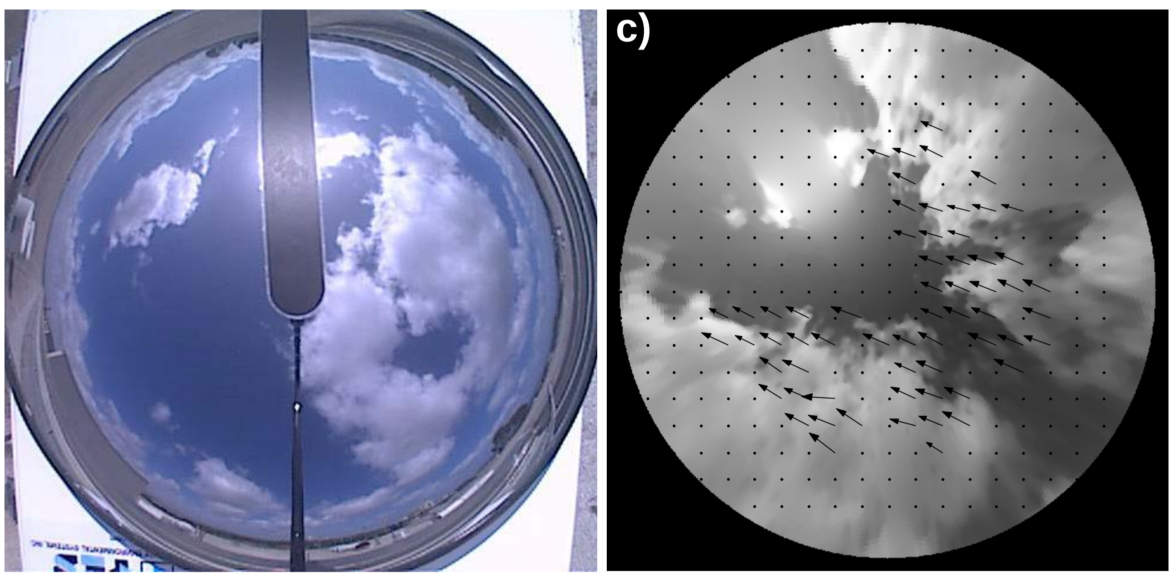


Figure 1c: Cloud motion vectors (right) and sky image (left) at the UC San Diego campus on August 19, 2009 at 1431 PDT.

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), auto regression 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 (such as 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.

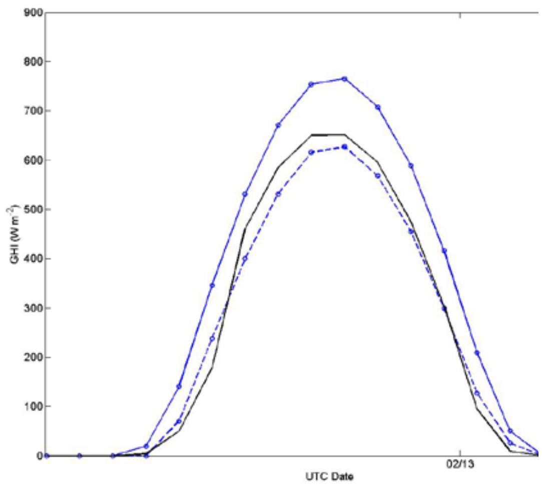
1.3.2. Evaluation of Numerical Weather Prediction Solar Forecasts in California

The authors 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 a more accurate forecast in clear sky conditions than in overcast conditions (Figure 2b). 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. 2c). On average, these bias errors can exceed 25percent. 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 (Figure 2b). The RMSE for the corrected forecasts ranges from 25percent under very cloudy conditions to 8percent under clear conditions.

Figures 2a-d: Solar Forecast Correction Techniques for Varying Sky Conditions



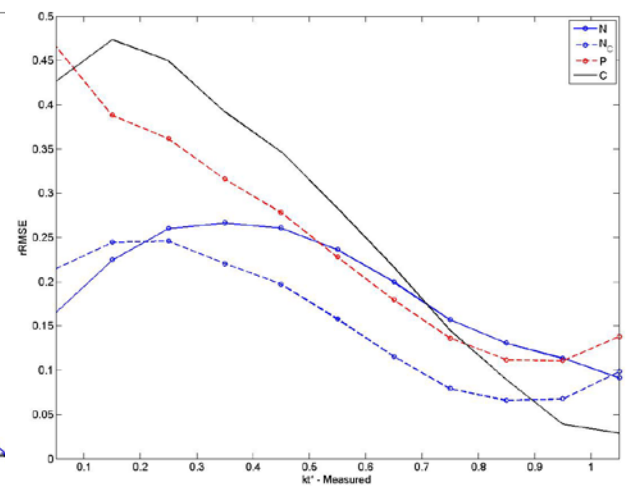


Fig. 2a: Camarillo, CA original NAM forecast N and MOS corrected N_C forecasts compared to CIMIS ground data on Feb 13, 2010. Blue: Original NAM forecast, dashed blue: bias corrected NAM forecast, black: CIMIS measurement. The MOS reduces forecast error by nearly 200 W m^{-2} at mid day.

Fig. 2b: 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.

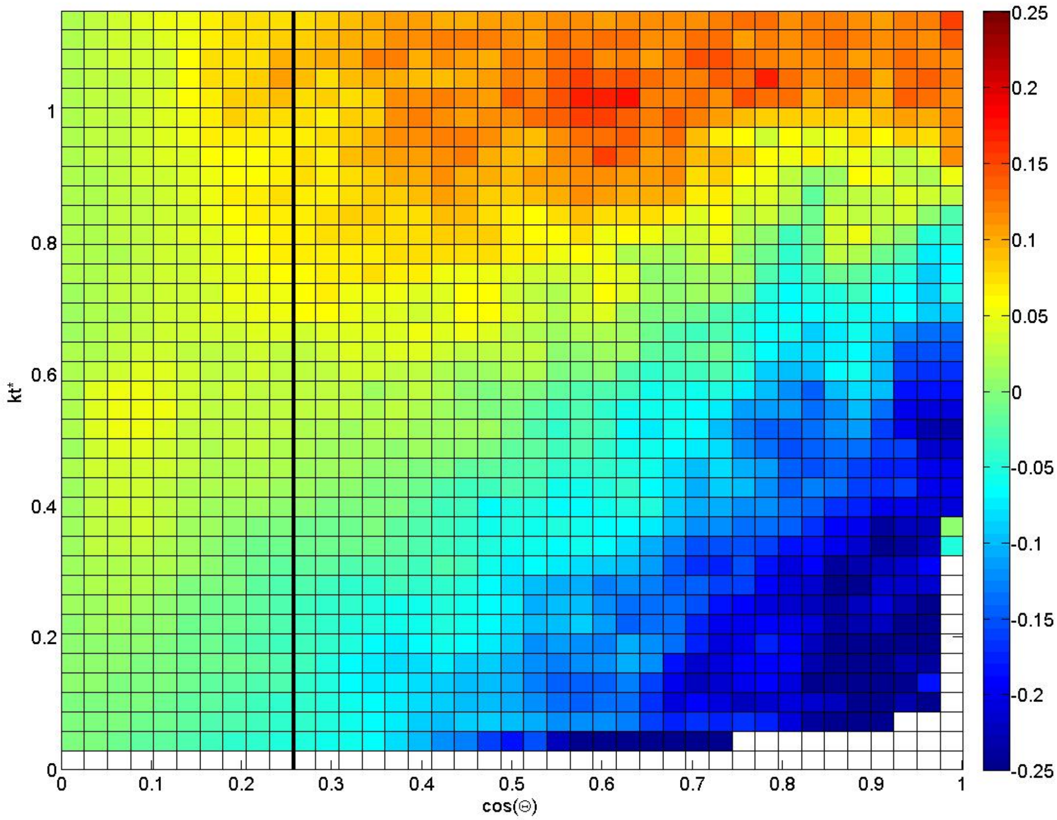


Figure 2c: Relative mean bias error [percent/100, color scale] of NAM forecast N as a function of solar zenith angle (θ) and forecasted clear sky index (kt*) from February to June 2010 compared to CIMIS measurements.

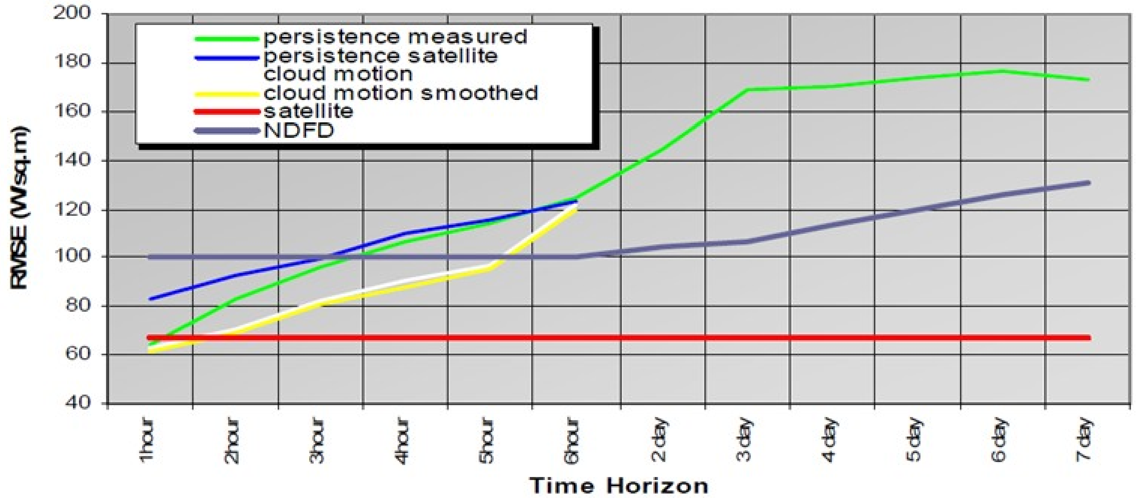


Fig. 2d: Root mean square error (RMSE) of different solar forecasting techniques obtained over a year at seven SURFRAD ground measurement sites (from Perez et al. 2010). The red line shows the satellite now cast for reference, i.e. the satellite 'forecast' for the time when the satellite image was taken. 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.

1.3.3. Literature Survey of Forecasting Applications

1.3.3.1.. Peer-Reviewed Research

Addendum 1 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. 2d) 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:

- Surprisingly, significant bias errors (such as 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.
- Only for clear sky conditions can accurate forecasts be obtained with as low as 6 percent RMSE.
- 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 percent 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.

- DNI forecasts are associated with about twice the RMSE than global horizontal irradiance (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).
- now casting 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.

1.3.4. 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. The authors 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 (such as 1–hour, 2-hours etc.) according to their relative performance in a relevant sample (such as 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 (such as 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 selfcalibrating 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 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 percent and an RMS error of 11 percent. Forecasting in a humid semi-tropical environment proved more difficult with a MAE of -7 percent (the model under predicts the observed) and an RMS error of 38 percent.

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 percent with 12 percent RMS error. Again the semi-tropical site proved more problematic with MAE of -8 percent and RMS errors near 25 percent.

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 (such as 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.

1.4 Summary of Recommendations for Improving Solar Forecasting

- **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.
- **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 independent system operators (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.

1.5 Data Sources for Validation and Calibration

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 4 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, and 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 is 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 third party installed irradiance sensors, but the data remain proprietary to the operator.

Table 4 Available Irradiance Measurements in California.

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

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.

1.6 Discussion

1.6.1 Evaluation of Forecast Accuracy

1.6.1.1 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.

1.6.1.2 Economics versus Irradiance

All forecast evaluations (see Addendum 1) calculate the forecast error in W m^{-2} or percent 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

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

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.

1.6.2 Single Site Versus Regional Forecasts

Solar forecast quality dramatically improves when several sites are aggregated over a region (such as 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 (such as the clouds responsible for these fluctuations are usually smaller than the distance between sites) aggregation of power output 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.

1.7. Solar Forecasting 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: Researchers (for example, NREL, NOAA, and Scripps Institution of Oceanography, and scientists with 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.[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: Researchers with experience and knowledge in solar modeling in collaboration with the CAISO.

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, the authors 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. For example, 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

[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."

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 third party data providers 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 4). 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.

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 demonstrate the potential and feasibility of such an approach to improve the accuracy of solar forecasting.

Also research on total sky imager (Figure 1c) 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: Researchers 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. Researchers, for example, NASA-NOAA-EPA has performed some work in this area (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 solar irradiance.

CHAPTER 2: Wind Forecasting State of the Art

2.1 Introduction

In this Energy Commission 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.

2.2 Overview

The key findings and recommendations regarding wind energy forecasting are:

- 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 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.

2.3 Wind Energy: Current State

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.

2.3.1 20 Percent 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 percent 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 percent from 2005 to 2030, reaching 5.8 billion megawatt-hours (MWh) by 2030. To meet 20 percent 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 percent 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.

2.3.2 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 Truepower (formerly Truewind) as their wind power forecast vendor. Since then, SEC uses AWS Truepower's wind forecasts for scheduling wind generation, and pays for the wind power forecasting service internally. Currently, AWS Truepower 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 site placement 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.

2.4 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 Truepower'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)(see bibliography).

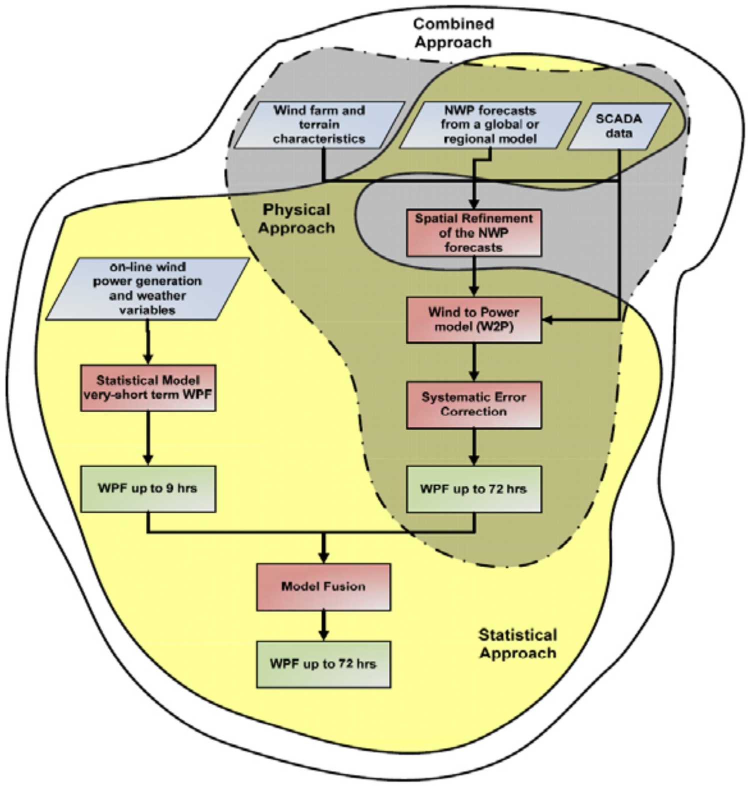
2.4.1 Forecast System Introduction

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 Trueopowers'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.

2.4.2 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 3 illustrates different approaches used for wind power forecasting (WPF).

Figure 3. There Exist Two Approaches to Wind Power Forecasting (WPF): Physical Approach and Statistical Approach.



Source: 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 (such as 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 Addendum 1 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.

2.5 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).

2.6 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.

2.7 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.

2.8 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.

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 4 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 **Error! Reference source not found.** 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 **Error! Reference source not found.**), 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.

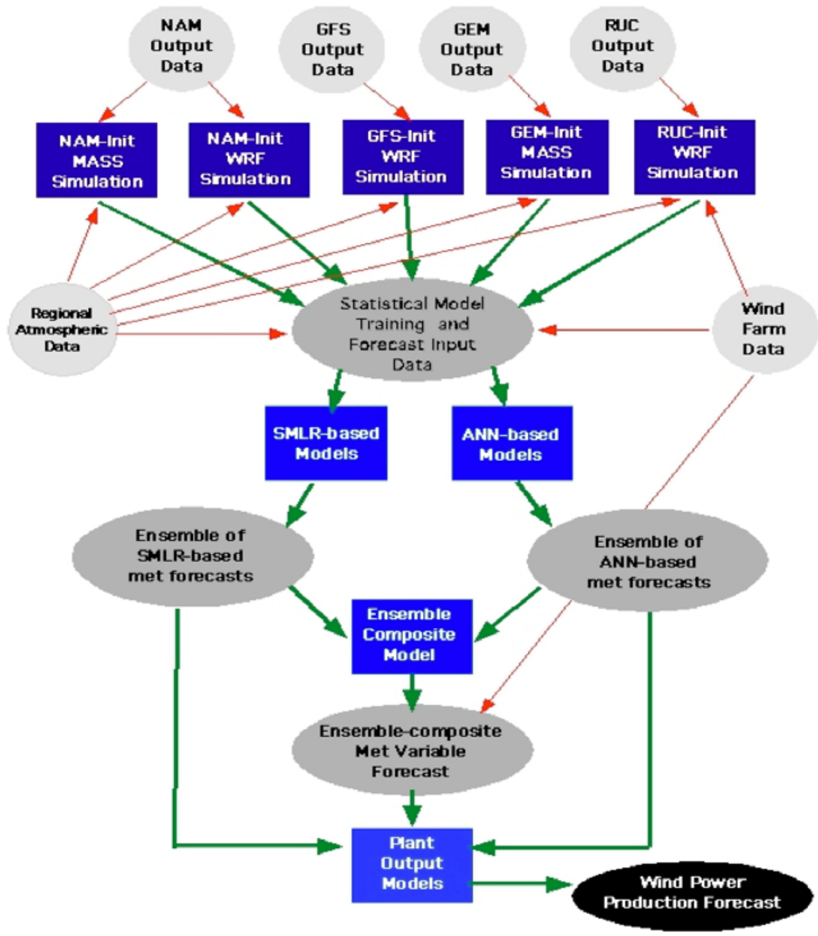
Garrad Hassan – GH Forecaster

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 4. Schematic of the Data Flow and Computational Process for the AWST eWind Forecast System Used for the Alberta Pilot Project



Source: from AWS Truewind, 2008

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.

National Center for Atmospheric Research – Now casting and DICast Systems

National Center for Atmospheric Research (NCAR) has spent more than 15 years developing and operationally deploying a short-term Now casting 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 now casts 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.

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.

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 percent 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 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.

2.9 Evaluation of Forecasting Systems

2.9.1 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.

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). The request for bids required that each 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.

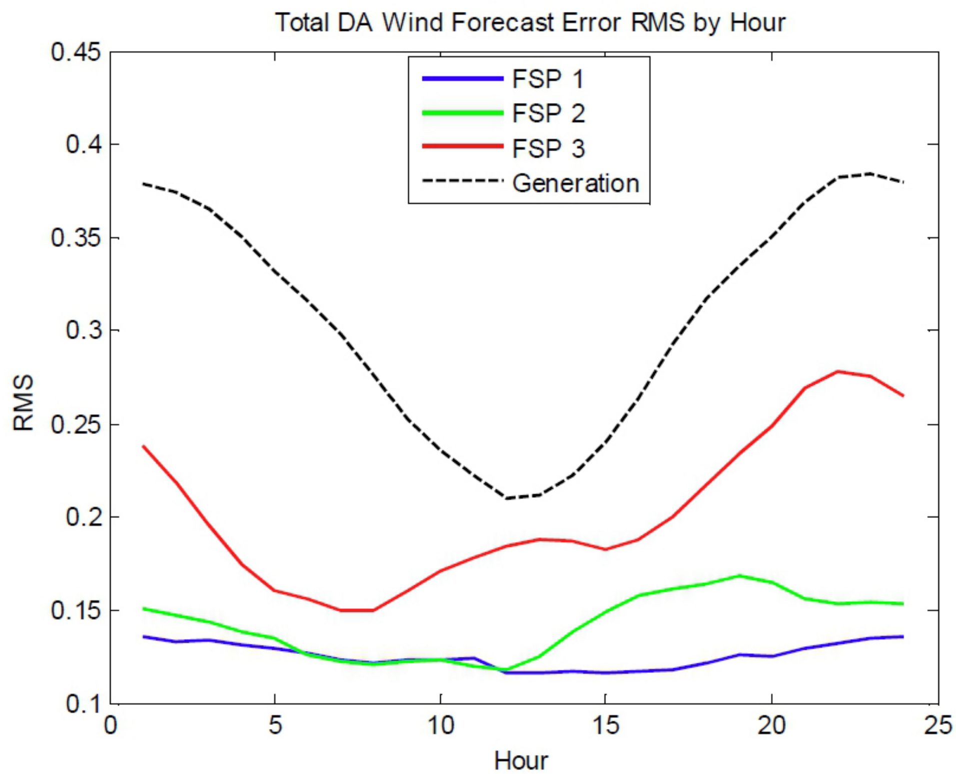
Here are the key findings of their analysis:

- Aggregate day ahead forecast error is less than 15 percent, calculated as the root mean square error (RMSE).
- Nearly 40 percent of the day ahead forecasts have an absolute error of less than 5 percent; over 60 percent of all day ahead forecasts have an absolute error of less than 10 percent; and over 75 percent of all day ahead forecasts have an absolute error of less than 15 percent.
- Aggregate hour ahead forecast error is less than 10 percent RMSE.
- Approximately 50 percent of the hour ahead forecasts have an absolute error of less than 5 percent; nearly 75 percent of the hour ahead forecasts have an absolute error of less than 10 percent; and nearly 90 percent of all hour ahead forecasts have an absolute error of less than 15 percent.
- 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 percent of total capacity and less than 20 percent of capacity.

- Data quality constitutes a critical factor in forecast accuracy.

Figure 5 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 percent to 17 percent. For Forecaster 3, the DA forecast RMSE ranges from 15 percent to 28 percent. 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.

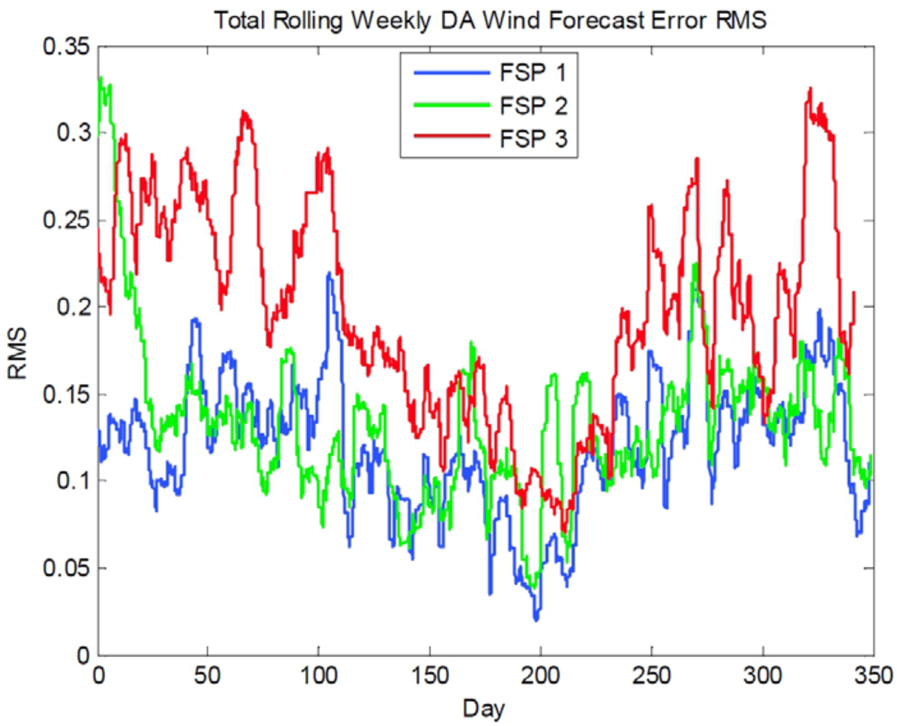
Figure 5. Total Day Ahead Forecast RMSE by Hour of Day



Source: from Blatchford and de Mello, 2009

Figure 6 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 forecasts 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 6. Rolling Weekly Day Ahead Forecast RMSE



Source: Blatchford and de Mello, 2009

2.9.2 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.

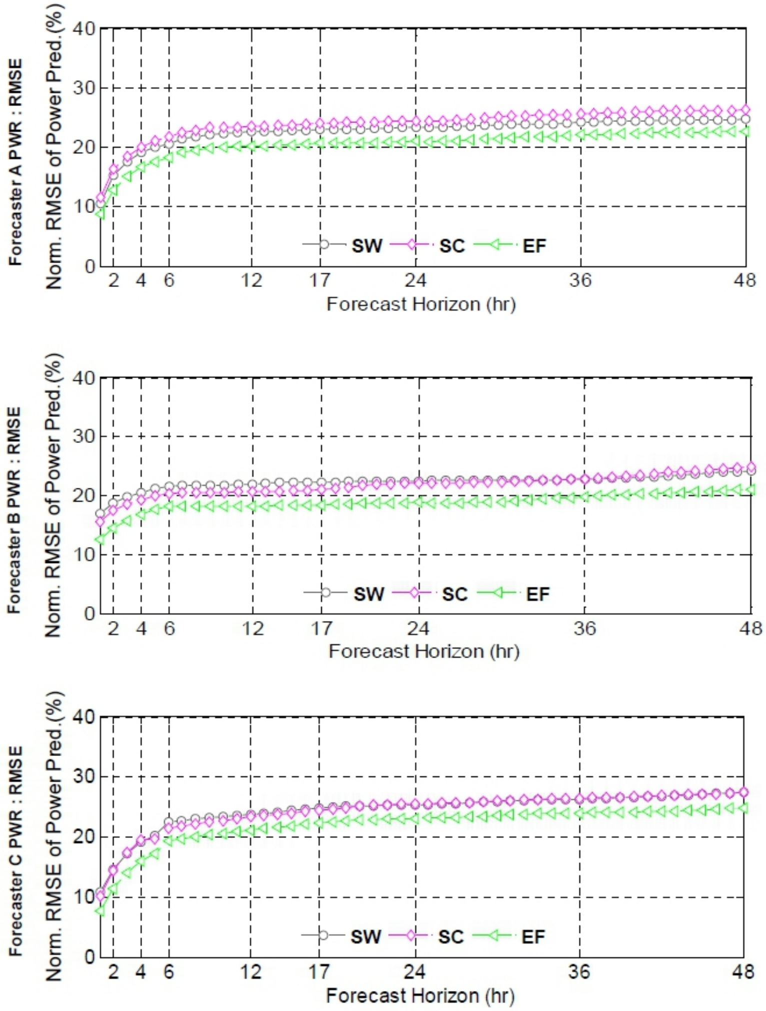
Figures 8a and 8b show forecasts based on different NWP models. In the top sub-figure, a ramp event was very well captured by Model 1. However, in certain weather situations such as small low pressure systems with fronts, Model 2 captures the sequence of events better than Model 1, as shown in the bottom sub-figure.

 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 percent to 20 percent for the first six forecast horizons and 20 percent to 30 percent 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.

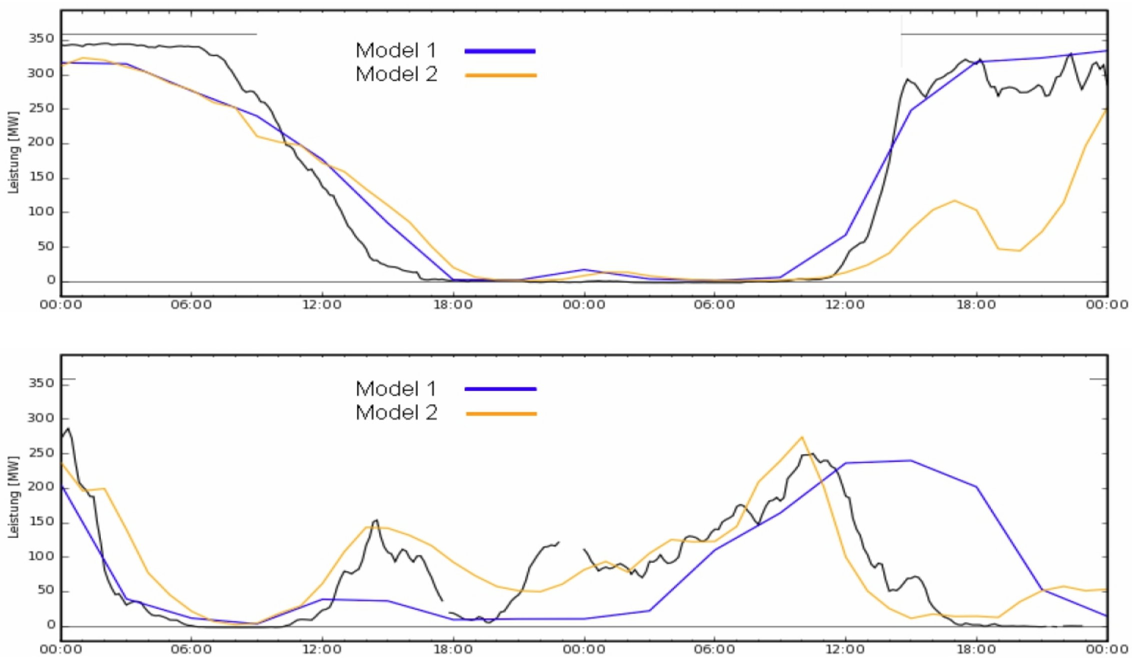
Figure 7. Total Day Ahead Forecast RMSE for Three Forecasters as a Function of Forecast Horizons



Source: McKay, 2008

Figures 8a and 8b show forecasts based on different NWP models. 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.

Figures 8 a, b: Two Sub-Figures Show the Individual Forecasts Based on Different NWP Models for Two Different Weather Situations



Sources: Figures 8a provided by Energy & Meteo Systems. Figure 8b Focken and Lange, 2008

2.9.3 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.

2.9.3.1 Frequency of Ramp Events and Definition of a Ramp Event

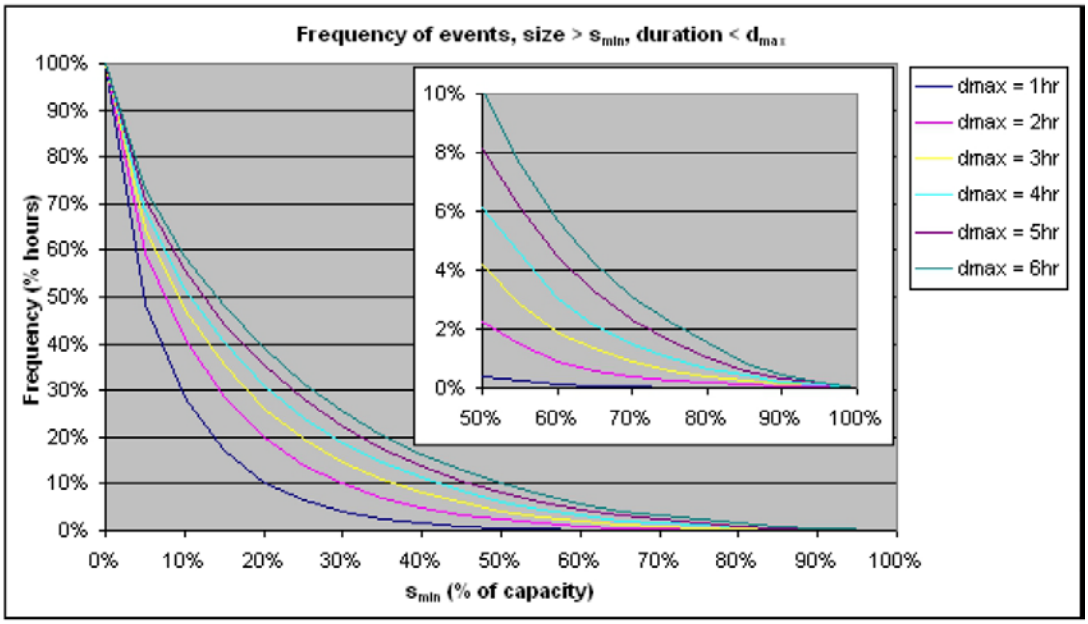
A change in power production can be defined by two parameters: the size of the ramp (the amount of change in power production that occurs, usually a percentage of the wind farm capacity), and the duration of time over which the change occurs. Ramp events of the greatest concern are characterized as having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

Figure **9** 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 percent of capacity. In Greaves' paper (Greaves et al, 2009), a ramp event was defined as having a change in power of 50 percent 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 9 that ramp events occur less than 6 percent of the time.

Figure 9. Frequency of Power Changes with Varying Size and Duration



Source: Greaves et al, 2009

2.9.3.2 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 percent. The ramp forecasts with a forecast horizon of 24 hours have a ramp capture rate of 59.1 percent. For portfolios of wind farms, the ramp capture rates are 50.0 percent and 42.9 percent, respectively.

Greaves (Greaves et al, 2009) also studied the effects of using a combination of different NWP models. Table 5 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 percent higher than the combination and the other NWP forecast.

Table 5: Ramp Capture Rate and Forecast Accuracies for Forecasts for a Single Wind Farm

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%

Source: Greaves Et Al, 2009

2.10 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.

2.11 Available Wind Data Sources

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.

CAISO PIRP

CAISO administers the Participating Intermittent Resource Program (PIRP), a voluntary program in which intermittent power plants (such as, 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,[3] 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.

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.

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.

[3] 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.

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.

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 (for example, 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.

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.

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.

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.

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.

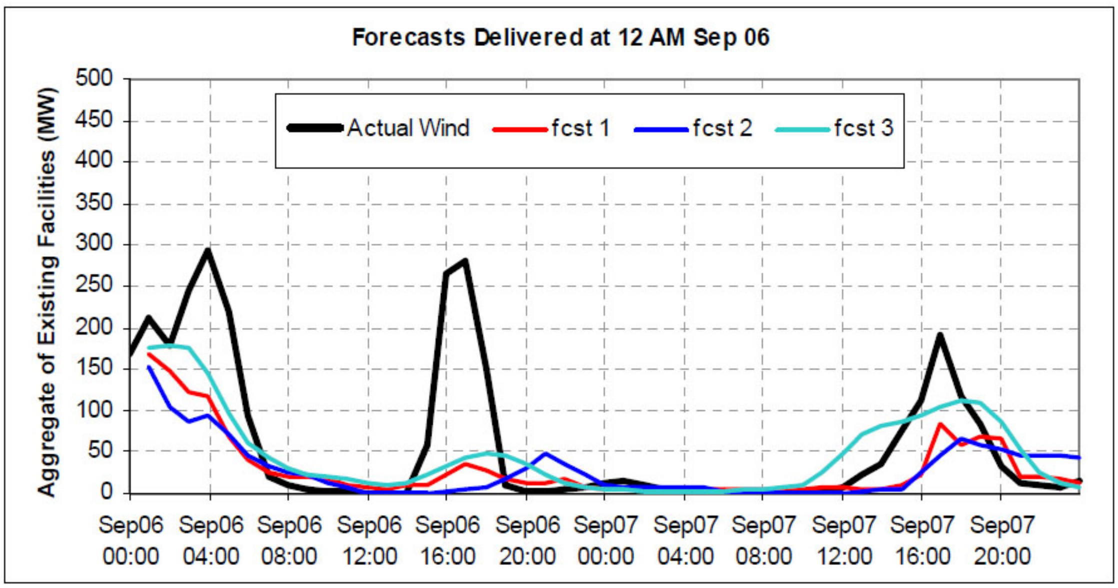
2.12 Recommendations

Best Practices in Forecasting

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 10. 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 10. Forecasting Models Trained to have Low Average Errors Missed Ramps on the Afternoon of September 6, 2007



Source: Industry Work Group, 2008

Improve Data Quality

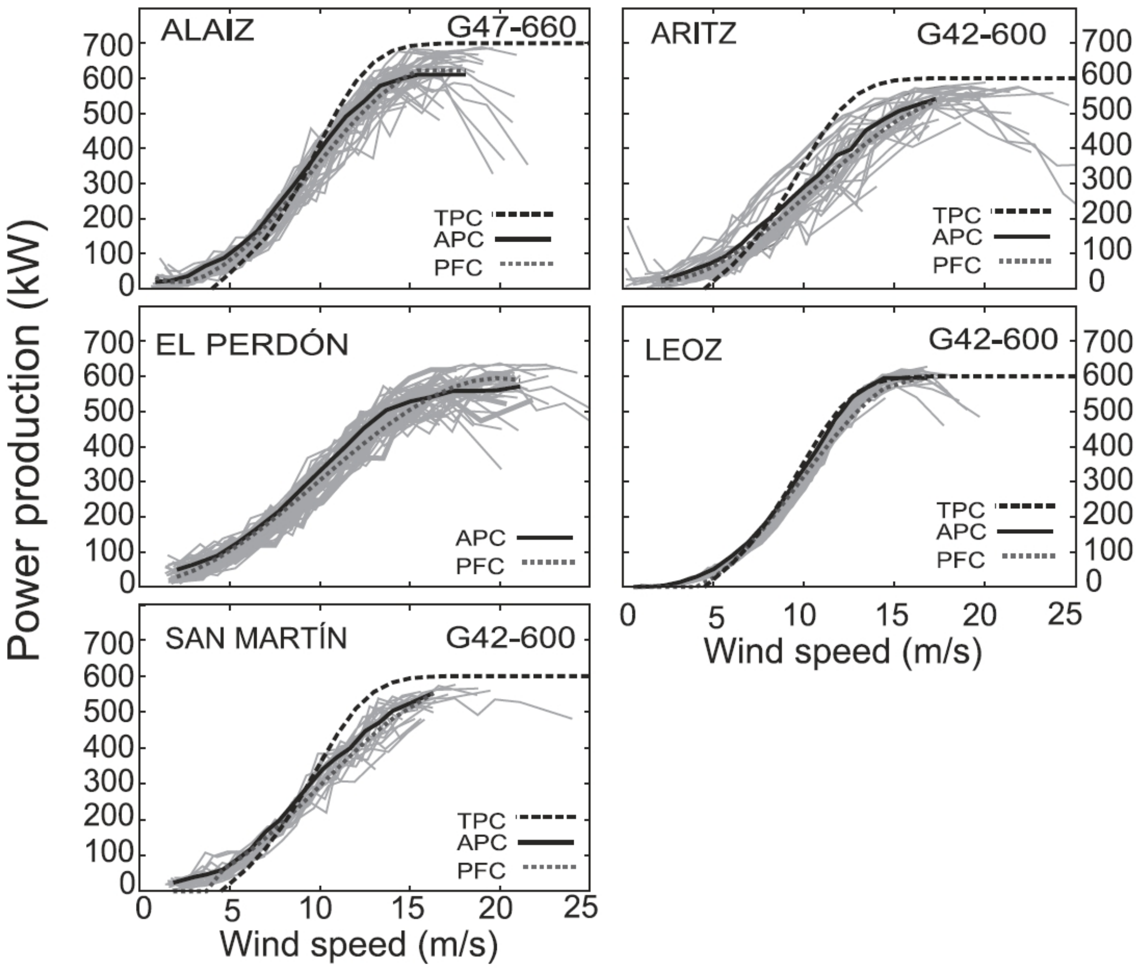
Forecasts rely on high quality data made available in a timely manner to the forecast providers for use within their models. Most stakeholders that we have talked with and literatures that we have reviewed emphasize the importance of high quality data to successful wind energy forecasting.

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 11 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 11. 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)



Source: Garcia-Bustamante et al, 2009

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.

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.

2.13 Data

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 12 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.

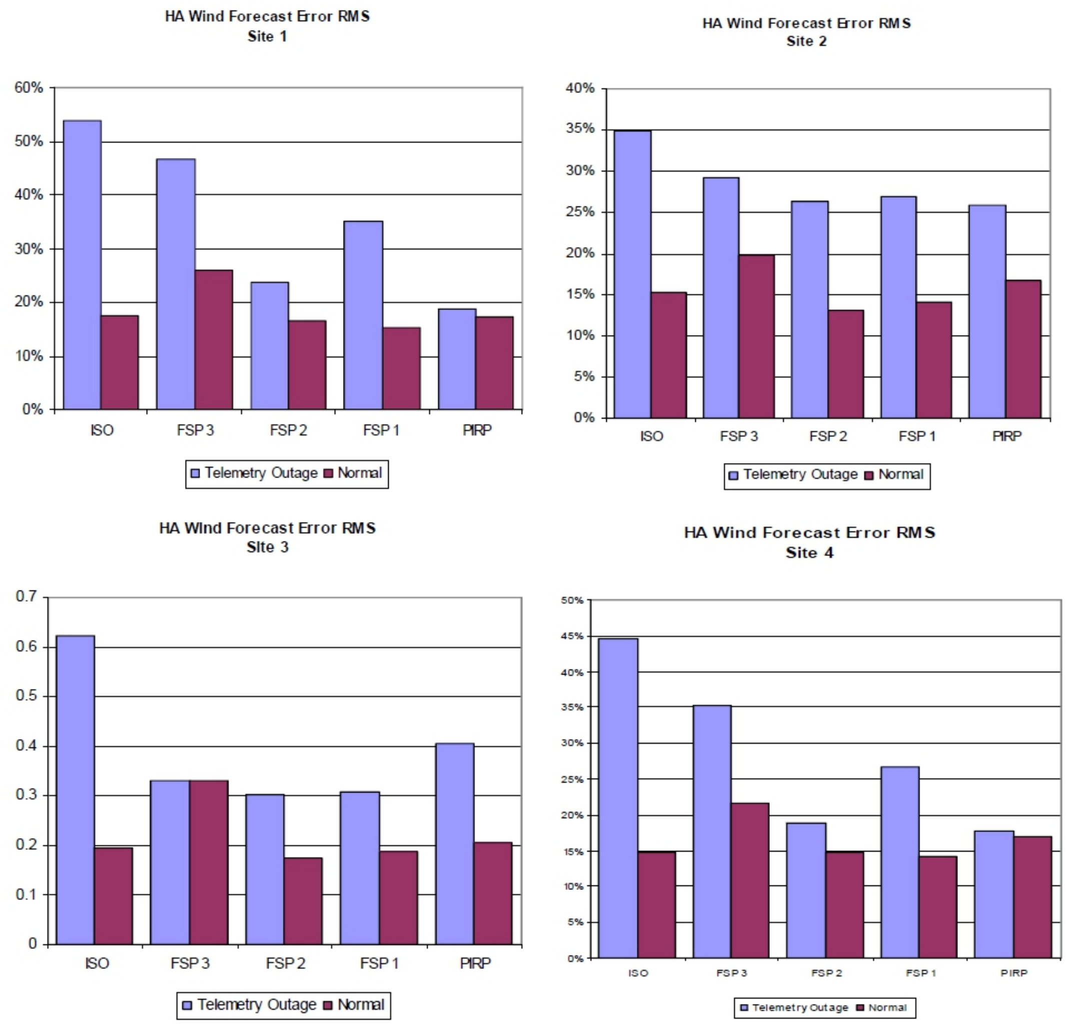
Data Validation and Filtering

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 12. Impact of Data Quality on Forecasts



Source: Blatchford and de Mello, 2009

2.14 Future Research

Data Acquisition and Transmission

Although it is well recognized that more sensors are needed 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?

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 efforts to improve accuracy.

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.

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.

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.

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.

CHAPTER 3: Resource Mapping of Co-Located Geothermal Resources in the Los Angeles Basin

3.1 Overview

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. The intent of this review is to identify promising locations for integrated renewable energy projects by identifying areas where geothermal, solar or wind resources occur in any combination in close proximity to each other and existing transmission infrastructure. We also considered resource variability, baseload capacity and correlation with load. 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. As a result, we developed separate methodologies for establishing the extent of co-located resources in the two regions.

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 resource 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. In the Salton Sea/Imperial Valley Region 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 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.

3.2 Introduction

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, both of which have substantial geothermal resources as well as wind and solar resources. The purpose of this project is to review maps and databases that allow determination of the magnitude of these resources, and establish the extent to which these renewable energy resources correlate with each other and with transmission lines and loads. The intent of this review is to identify promising locations for integrated renewable energy projects that include geothermal energy.

Power production from geothermal energy within the Salton Trough/Imperial Valley region has the potential to be the largest geothermal resource in the state. Current geothermal power production in that area exceeds 500 MWe, with a minimum projected production in excess of 2,500 MWe (GeothermEx, 2004). Other estimates suggest that the geothermal resource could exceed 40,000 MWe (Gawell, 2006) although these numbers remain highly uncertain. Although there are no other areas in Southern California where geothermal power production is occurring, recent technological improvements in so-called binary generating capability have made it possible to use fluids with temperatures as low as 91°C (195°F). Fluids extracted from oil and gas fields can reach such temperatures, thus potentially opening those regions to geothermal power generation. Since extensive oil and gas production has occurred in areas such as the Los Angeles Basin and Ventura County, it is conceivable that such areas may be candidates for geothermal power generation, at least at a modest scale.

California has the best combination of population density, solar resource, and transmission infrastructure to encourage expansion of solar power in the country. The global horizontal solar resource varies from annual averages of 4.1 kilowatt-hours per day per square meter (kWh/m^2/day) at the coastal border to Oregon to 4.9 kWh/m^2/day for most of coastal southern California to 5.8 kWh/m^2/day in the Imperial Valley and Mojave Desert. The latter area has one of the best resources of direct normal incident irradiance worldwide, allowing economical operation of concentrated solar power (CSP) plants. While the installed capacity has increased dramatically over the past years, the generation of solar power is still very small compared to the available resource or load. Through the California Solar Initiative, 653 MWp of solar PV have been installed since 2005 or is pending. Utility scale solar power is expanding rapidly, with both Pacific Gas and Electric (PG&E) and Southern California Edison (SCE) announcing plans for 100s of MW of new generation. Ignoring economic constraints, the technical PV potential on existing residential and commercial rooftops exceeds 74,000 MW of capacity. If CSP facilities are deployed only in those areas where the annual average direct-normal insolation exceeds 6 kWh/m^2/day, the CSP technical potential exceeds one million MW of capacity (Simons and McCabe, 2005).

There is tremendous supply of wind resources in California that can be harnessed to provide electricity for the state. California was the first U.S. state in which large wind farms were developed, beginning in the early 1980s. Through the end of 2009, the total installed wind power capacity in California has reached 2,794 MW, ranking No. 3 in the nation just behind Texas (9,410 MW) and Iowa (3,670 MW) (AWEA 2009 Year End Report). Currently utility-scale wind power generation facilities can be found in five major wind resource areas in California: Solano, Altamont, San Gorgonio, Tehachapi, and Pacheco. Three of these primary regions (Altamont, Tehachapi and San Gorgonio) account for nearly 95 percent of all commercial wind power generation in California (Yen-Nakafuji, 2005). Other areas that have abundant wind resources include Salton Sea/Imperial Valley, Shasta, and Lassen. In January, 2010, the Department of Energy's Wind Program and the National Renewable Energy Lab (NREL) published a new wind resource map for the state of California. The new wind resource map shows the predicted mean annual wind speeds at 80m height. This new wind map was created by AWS Truewind and verified by NREL. Using AWS Truewind's gross capacity factor data, NREL estimated the windy land area and wind energy potential in various capacity factor ranges. The total wind energy potential from development of the "available" windy land area in California was calculated to be 34,110 MW using a 30 percent capacity factor. With just over 2,790 MW currently captured and over 34,100 MW of "harnessable" energy at 80m, significant renewable wind energy remains untapped. With improved system designs, more detailed and accurate wind resource maps and reduced cost of wind turbines, California is trying to achieve a significant portion of the state's RPS goal of 20 percent renewable generation by 2017 just with wind power.

Co-locating renewable energy resources has the advantage of minimizing transmission requirements, coordinating power production to minimize variability, and reducing costs associated with permitting, land use and environmental impact. These elements in project development are particularly important for areas with high population density, such as the Los Angeles Basin. The purpose of this reconnaissance study was to determine whether there exist co-located geothermal, solar and wind resources in the Los Angeles Basin and the Salton Trough/Imperial Valley areas and, if so, whether the transmission infrastructure was sufficient to support their development with minimal additional construction. Such an evaluation can establish whether further consideration should be given to such resources.

The transmission infrastructure needs relevant for integrated systems are specific to the type, or category, of integrated system considered. In (i) a "**central station hybrid plant**". renewable resources share some on-site and interconnection resources or combine, in a single site, thermal (solar thermal or geothermal) resources that can be exploited by a single thermal power plant. Alternatively, a central station hybrid plant may combine resources in such a way that electric energy storage capacity can be shared. Another category of integrated systems is (ii) "**non-integrated utility scale distributed**

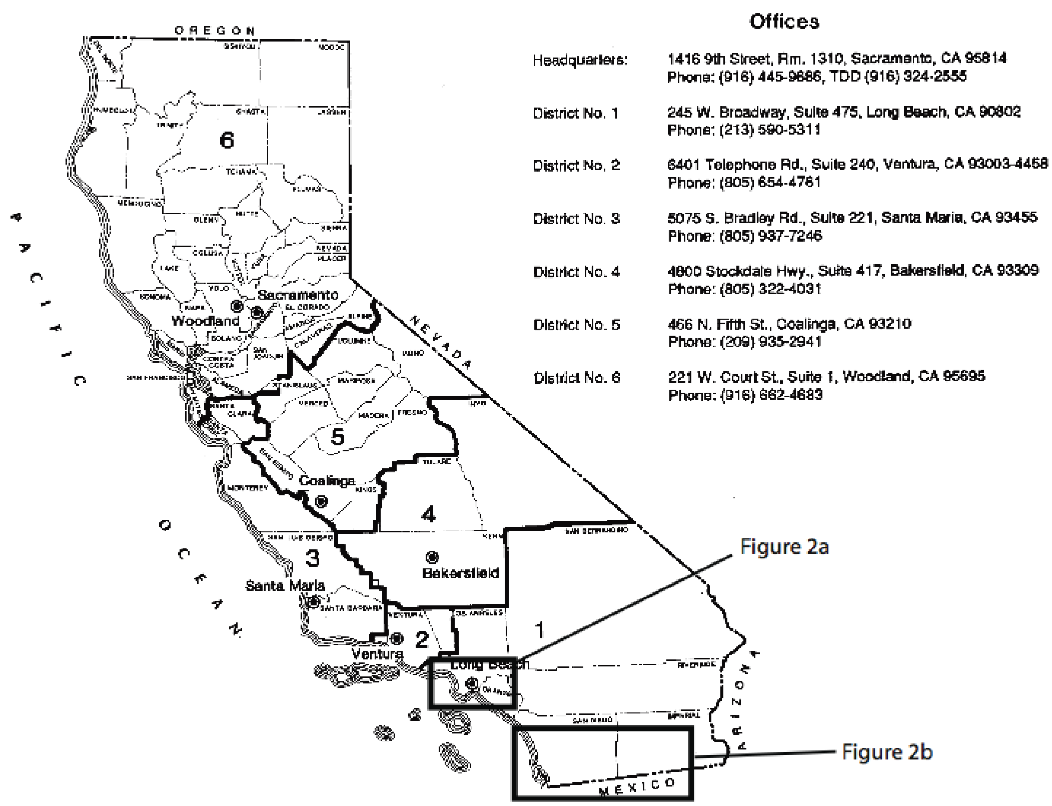
generation". In this case, generating capacity in the 1-20 MW range, supplied by a suite of technologies in proximity to each other, would allow local distribution of generated power. Such a system need not rely on a single substation for feed into the local grid, but rather a few substations could be utilized, as required by the generating technologies. (iii) In the **community-scale system** distribution is organized around a mix of in-community grid-tied resources and remote grid-tied resources. A modification of this concept is the "virtual power plant" (VPP) in which smart grid architecture is used to harmonize supply from diverse but geographically proximate sources, all feeding into the utility grid. Sources can be on buildings and feeding in at residential and commercial voltages, or feeding in at distribution feeder or sub-transmission voltages. Finally, in the "**micro-grid integrated system**" power generation and distribution is organized to serve a specific aggregated or distributed load based on supply that is dedicated to the load.

Each of these categories has different transmission architecture and requirements for co-location of resources. This report provides preliminary information useful for identifying where potential exists for these various integrated systems. Chapter 3 of this report describes the results obtained for the Los Angeles Basin area, while Chapter 4 describes the results for the Salton Trough/Imperial Valley area.

3.3 Methodology

The areas selected for study are shown in Figures 13 and 14. The areas were selected because they have the greatest concentration of diverse renewable energy resources within a restricted region. The boundaries for the Los Angeles Basin area were drawn such that the primary oil and gas fields would be included in the analysis. The boundaries for the Salton Trough/Imperial Valley area were drawn such that the areas that currently have operating geothermal power production were included.

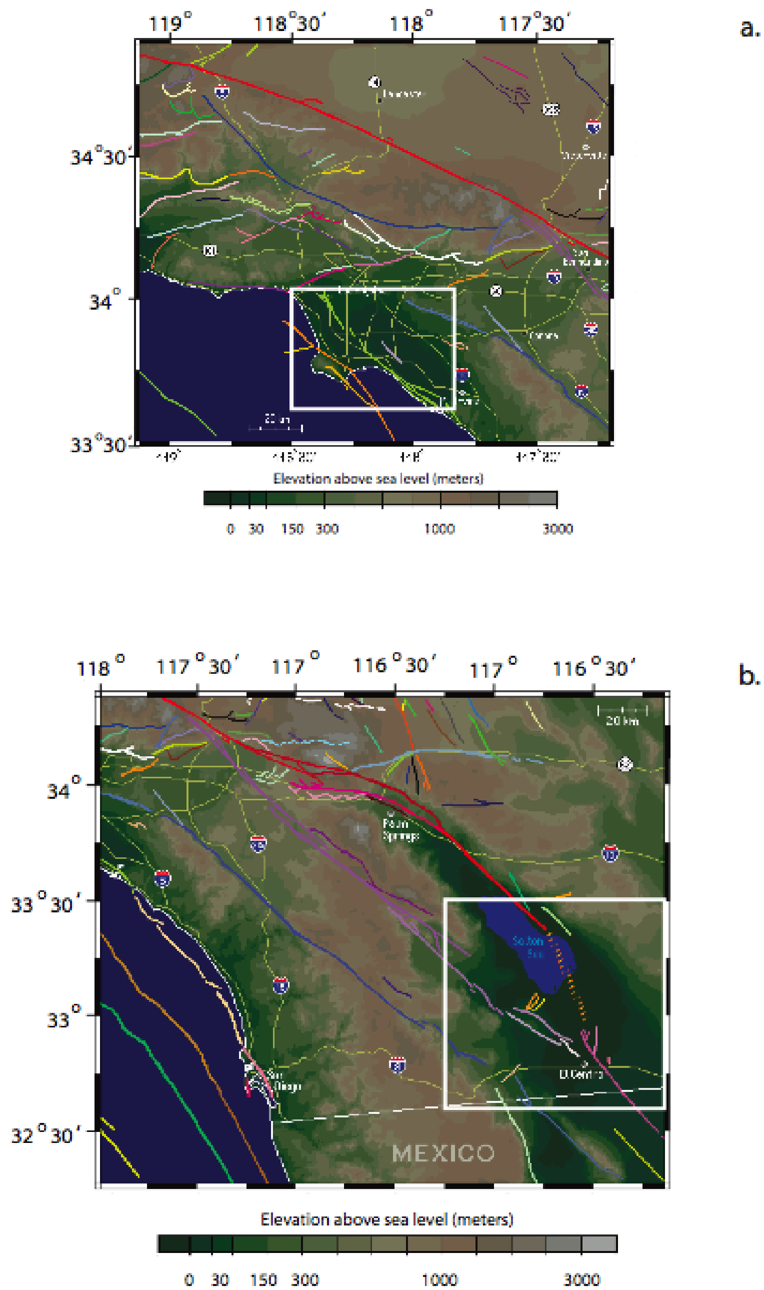
Figure 13. California Index Map Showing the Locations of the California Division of Oil, Gas and Geothermal Resources Districts and the District Office Contact Information



Note: The Los Angeles Basin and Salton Trough/Imperial Valley study areas are located within the District 1 region. The boxed areas labeled Figure 2a. And Figure 2b. Show the areas detailed in Figure 14.

To identify co-located resources and the respective transmission infrastructure, we obtained from the California Energy Commission's Cartography Unit of the Siting, Transmission and Environment Protection Division base maps showing the transmission infrastructure for the respective regions. That infrastructure includes substations, as well as transmission lines with the voltages indicated. Also included on the base maps were the mean seasonal (winter) wind speeds, at 50 meters, as recorded in the California Energy Commission database. We overlaid on these base maps the solar power density and the geothermal resource.

Figure 14. Regional Elevation and Geological Fault Locations for the Los Angeles Basin Area (a) and Salton Trough/Imperial Valley Area (b)



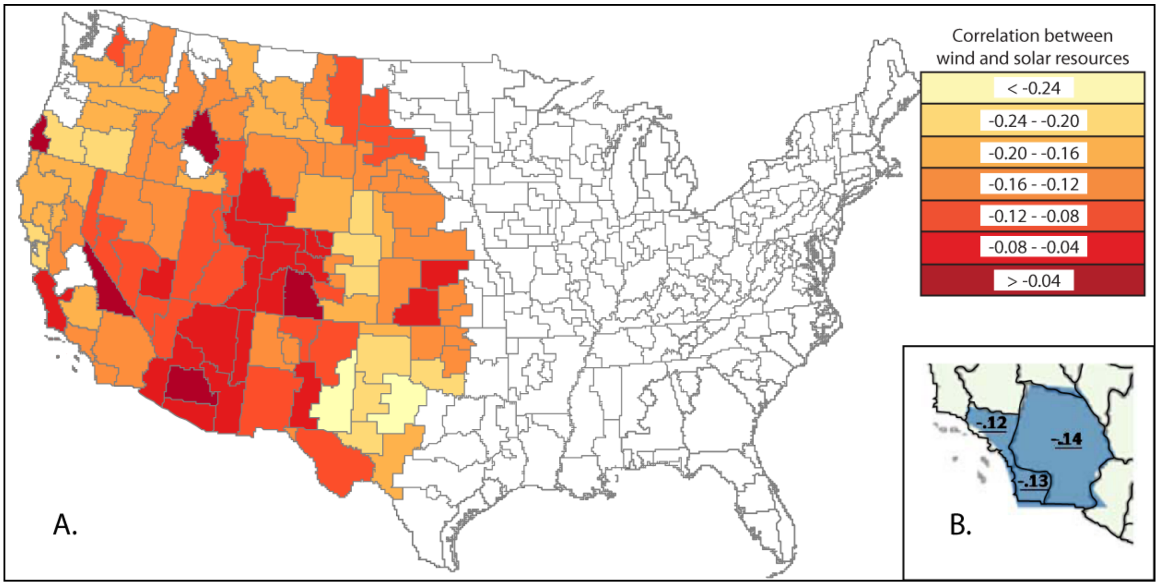
Note: The specific study areas considered in this report are delineated by the white boxes.

Since no published evaluation of the geothermal potential for individual oil and gas fields exists in the Los Angeles Basin, we analyzed available well temperature and pressure data to estimate which oil and gas fields would be potentially suitable for geothermal power generation. For the Salton Trough/Imperial Valley region, geothermal resources have already been identified and exploited. In this instance, we focused on establishing the geographical relationship between the renewable resources.

When evaluating co-location of resources, account must be taken of the extent to which there may be variability in power production. Geothermal resources are a baseload energy resource, with capacity factors exceeding 90 percent. Wind and solar resources are variable, with capacity factors of 22 percent to 35 percent (IEPR, 2007). Variability of different, co-located renewable resources can be mitigated if their power production is anticorrelated. For example, since wind resources are large in the winter they are anticorrelated with reduced solar resources (due to low sun angles, shorter days, and winter storms), counterbalancing the seasonal solar variability of either resource. Mowers et al. (2010) have analyzed the correlation between concentrated solar power (CSP) and wind resources in the US (Figure 15). Figure 15 shows that wind and CSP resources are weakly anticorrelated in our area of interest. Consequently, a slight reduction in seasonal variability of an integrated wind and solar power plant could be expected.

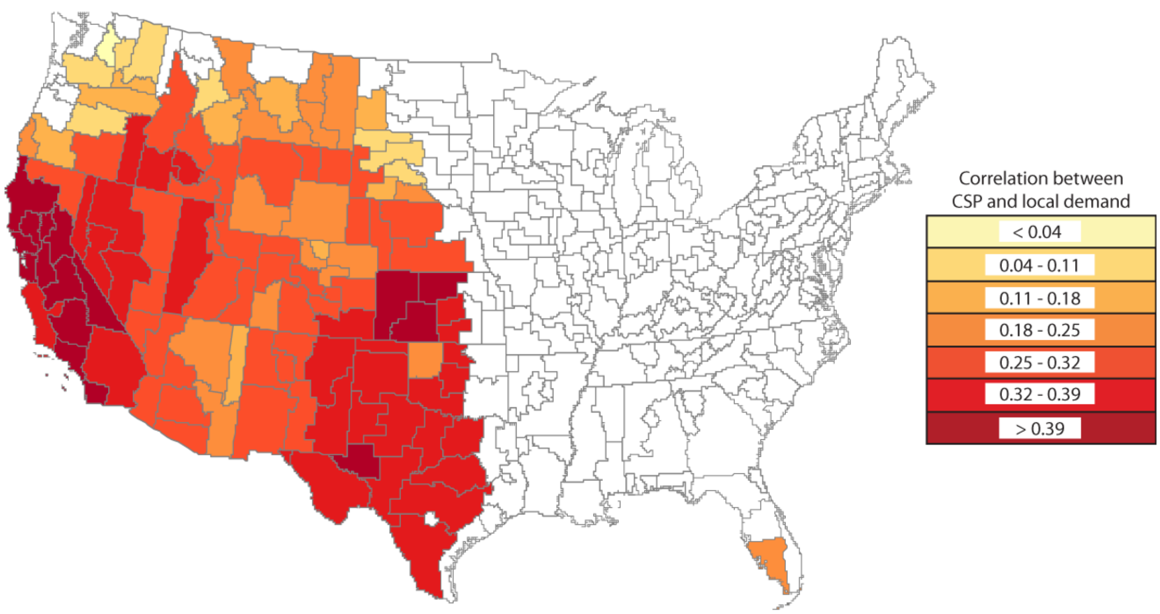
A second criterion for the value of renewable generation is the correlation with load. A renewable resource that is correlated to the load can be integrated into the grid at a high penetration level, since its generation can replace more expensive generation from peaker plants and can complement less expensive baseload renewable power plants. Figure 16 shows CSP generation is highly correlated with the load while Figure 17 shows that wind power generation is anticorrelated with load. Consequently, at high penetration, wind generation frequently would have to be 'dumped' while solar generation has the potential to replace peaker plants.

Figure 15. Correlation Coefficients Between Solar and Wind Resources.



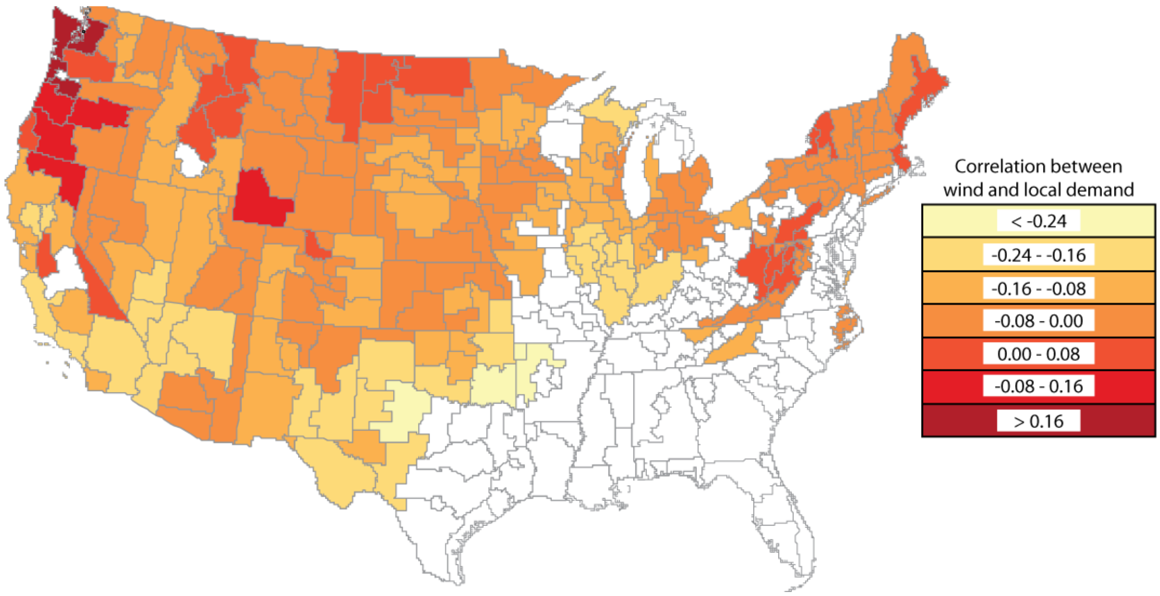
Note: Label A: correlation coefficients for the western half of US. Label B:correlation coefficient values for the regions of interest. Both LA and Imperial Valley wind resources are anticorrelated with solar resources, with a correlation coefficient of about -0.1. Source: Mowers et al, 2010.

Figure 16. Correlation of Concentrating Solar Power (CSP) with Local Demand



Note: Both the Los Angeles Basin and the Imperial Valley are correlated well with local demand with a correlation coefficient of about 0.4.

Figure 17. Correlation of Wind Resources with Local Demand



Note: Both the Los Angeles Basin and the Imperial Valley wind resources are anticorrelated with local demand with a correlation coefficient of about -0.2.

3.4 Los Angeles Basin Assessment

3.4.1 Solar Resource Assessment Methodology

The data used for the solar maps is the NSRDB-SUNY dataset, which is based on a model developed at the State University of New York - Albany (Perez et. al., 2002). The model uses visible images from Geostationary Operational Environmental Satellites (GOES) to develop estimates of the cloud index (CI) for each pixel. The CI is then used in a transmittance function that appropriately reduces the modeled clear sky irradiance for each pixel. The SUNY model also accounts for effects of atmospheric turbidity, ground snow cover, ground specular reflectance characteristics and individual pixel sun-satellite angle effects. Atmospheric turbidity is quantified in terms of the Linke Turbidity coefficient which is a function of monthly average atmospheric aerosol content, water vapor and ozone (Ineichen et. al., 2002). The model was run between 1998 and 2005 to generate hourly global horizontal irradiance (GHI), diffuse irradiance and direct irradiance values for the entire United States on a 0.1" node registered grid, corresponding to a grid spacing of about 10 km in California. This analysis used integrated hourly GHI values with an hour ending timestamp from the "Sglo" column in the NSRDB-SUNY database. These data are modeled from on the hour (for example 1200) irradiance "snap shots" derived from GOES visible images (Wilcox, 2007).

3.4.2 Geothermal Resource Assessment Methodology

Higgins (1981) qualitatively evaluated the potential of using waters from individual oil pools as sources of geothermal energy in the Ventura and Los Angeles Basins. His results indicated that 15 oil pools in the Los Angeles Basin had sufficient heat to be considered good to excellent resources. In 1991, the California Division of Oil, Gas and Geothermal Resources (DOGGR) published its California Oil and Gas Fields, Vol. II. report (1991) that expanded the available data for evaluating geothermal potential. In addition, significant changes in the technology employed for binary generation, as well as improved scientific understanding of geopressured resources in oil and gas fields have occurred. These historical developments, as well as interest in establishing a firm foundation for assessing the potential for co-locating renewable energy resources has motivated us to re-evaluate the geothermal resource potential in the Los Angeles Basin.

We obtained from the California Division of Oil, Gas and Geothermal Resources (DOGGR) the database of all wells within the District 1 area (Figure 1). That database, which contained the identification records for more than 31,400 wells, was downsized by extracting from it only those wells that fell within the boundaries of the Los Angeles Basin Study area. That resulted in a total of 29,156 wells. Within the time constraints of this study, it was evident that a thorough examination of that database to obtain temperature, depth and pressure information for the wells and their respective oilfields would not be possible. It was also evident that the well records in the DOGGR database did not include temperature measurements.

A modified search was then undertaken that relied on the California Oil and Gas Fields, Vol. II. report (1991). This approach emphasizes data on individual oil pools, as defined by the DOGGR. We consider for this study only those pools that are within Los Angeles County. The report contains, where available, temperature and pressure values at known depths in reservoirs for individual pools. Individual wells are not identified. We supplemented this information with that published by Higgins' (1981) reconnaissance report on the geothermal potential of Los Angeles County. The database compiled from these reports is presented in Addendum 1.

There are two geothermal resource types that may be useful for power generation in the Los Angeles Basin. Hydrothermal resources suitable for power generation are those resources that have fluid temperatures in excess of 91^{o}C (195^{o}F). This is the minimum temperature required for small-scale (approximately 250 kW) binary power systems (see specifications for the Pratt and Whitney "PureCycle Power System 280" and similar designs by Fuji Electric, Ormat, and Turbine Air Systems (TAS)). Note that the actual minimum temperature required for a given site and installation will depend on the cooling cycle temperature and other factors, and may be higher than the minimum 91 ^{o}C we used as our cut-off temperature for identifying potential resources.

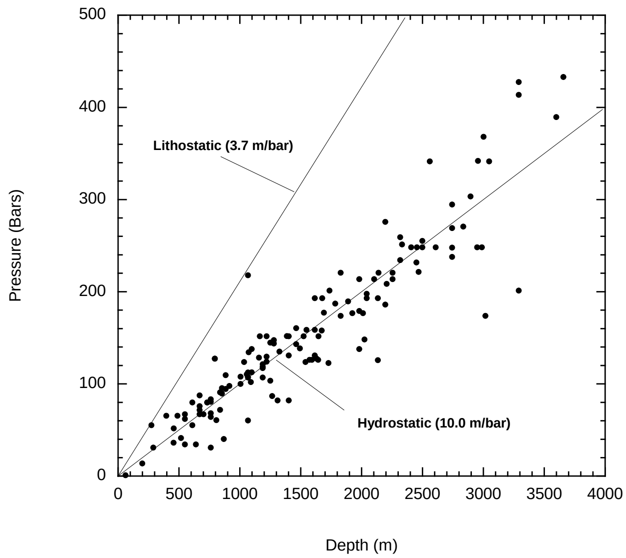
Geopressured reservoirs are another type of geothermal resource with the potential to generate electricity. In addition to elevated temperatures similar to those mentioned above, geopressured resources have fluid pressures that significantly exceed the pressure that would be imposed at the reservoir depth by a column of water extending from the ground surface to the reservoir depth. This so-called "hydrostatic" pressure is less than that which would be imposed by an equivalent column of rock (the so-called "lithostatic" pressure). Fluids located in geopressured resources have pressures that fall between hydrostatic and lithostatic values. As a result, tapping such reservoirs by drilling provides access to the gravitational potential of the fluid as the fluid spontaneously flows up the well under controlled conditions, thus adding a kinetic energy component to the geothermal resource. In addition, geopressured resources often have a natural gas-component, which, when combined with the thermal and kinetic energy such systems possess, makes them theoretically attractive energy resources.

We extracted from California Oil and Gas Fields, Vol. II (1991) all temperature, pressure and depth information for oil pools in Los Angeles County. Plotted in Figures 18 and 19, respectively, are all of the available pressure versus depth and temperature vs depth data. The reported temperatures are assumed to be equilibrated, at-depth temperatures.

As there is no rigorous definition of what the minimum over-pressure is for a resource to be classified as a geopressured system, we have taken an approach similar to that used by Sanyal et al (1993). They argued that a linear "best fit" to the measured pressure gradients observed in a region would likely define the local hydrostatic gradient. Geopressured systems would then be those systems that exceeded by a few percent the hydrostatic trend. Sanyal et al. (1993) determined a hydrostatic pressure gradient of 0.0996 bar/m (0.44 psi/ft) for the oil pools in the southern Sacramento Valley, which is close to the theoretical value of 0.10 bar/m, assuming a water density of 1.0 gm/cc. We have taken the approach of defining a geopressured pool as one for which the pressure exceeds by 10 percent the theoretical hydrostatic value and for which the temperature exceeds 91^{o}C. Applying this approach to the data for pools in the Los Angeles Basin, we obtain the results shown in Figure 20.

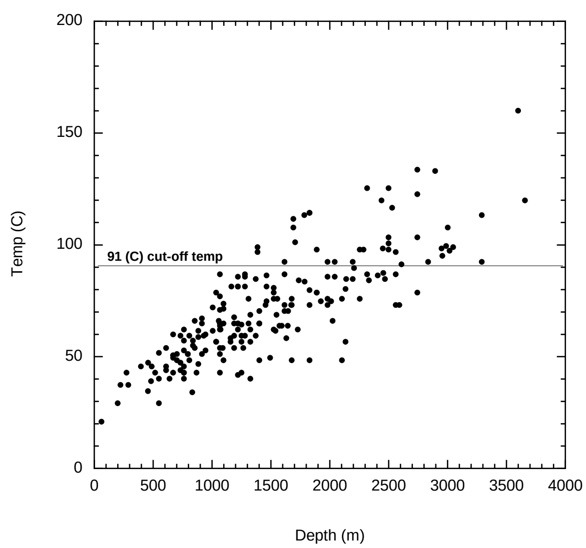
Table 6 summarizes the characteristics of the individual pools identified in Figure 20. Also indicated in Table 1 is the distance from the nearest substation to the mapped edge of the pool. For those cases where a zero distance is indicated, at least one substation is located within the footprint of the pool. We did not make an effort to determine whether there was suitable transmission infrastructure to accommodate the potential generating capacity of the geothermal resource or its co-located resources, due to the absence of sufficient time.

Figure 18. Pressure Versus Depth for Oil Pools in the Los Angeles Basin



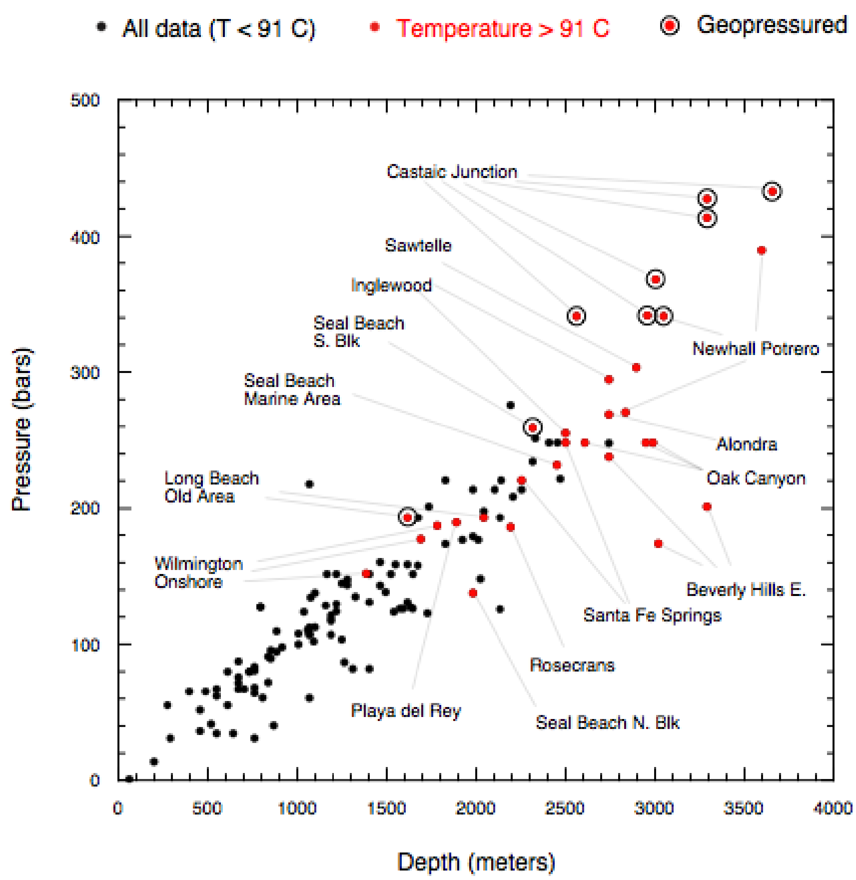
Note: The lines labeled "Hydrostatic" and "Lithostatic" define the theoretical trends for pure water and rock with a density of 2.7 gm/cc, respectively. Source: data from California Oil and Gas Fields Vol. II, 1991.

Figure 19. Temperature Versus. Depth for all Oil Pools in the Los Angeles Basin



Note: Above the line labeled "91 (C) cut-off temp" there is sufficient thermal energy to theoretically generate power using existing binary power plants, while below the line there is insufficient thermal energy. Source: As reported in the California Oil and Gas Fields Vol. II (1991) report.

Figure 20. Pressure Versus Depth for All Oil Pools in the Los Angeles Basin



NOTE: Pools for which the temperature exceeds 91°C are shown in red. Pools for which the temperature exceeds 91°C and the pressure exceeds 10% of hydrostatic (such as, geopressured pools) are shown as circled red points. The names of the high temperature (>91°C) and geopressured pools are shown, linked to their respective data points.

The geographic locations of pools labeled in Figure 20 (such as, those that have geothermal power generation potential) are identified in Figure 21, along with the other developed oil and gas fields in the Los Angeles Basin. Of the approximately sixty identified oil pools in the Los Angeles Basin area, twelve meet the minimum requirements for geothermal power generation potential. In the remainder of this report, these pools are collectively characterized as the "geothermal pools".

It should be noted that the magnitude of the resource available in these "geothermal pools" is strongly affected by the subsurface temperature distribution and the processes by which it is controlled. As a preliminary, qualitative evaluation of the resource magnitude, we have computed the apparent geothermal gradient and plotted it versus depth (Fig. 22). Such a graph provides a means of identifying those areas where heat flow may be elevated, thus suggesting a subsurface thermal energy resource. As is clear in the figure, the "geothermal pools" consistently are those that fall at the high end of the observed range, at any given depth. Since all but one of the "geothermal pools" fall along a broad NW-SE trend, it would appear that deep-seated geological processes are controlling the geographical distribution of subsurface heat, which would suggest there may be an important thermal resource along this regional trend.

Table 6 Minimum (Min.) and Maximum (Max.) Temperatures (^{o}c) for Oil Pools In Los Angeles County that have Geothermal Potential.

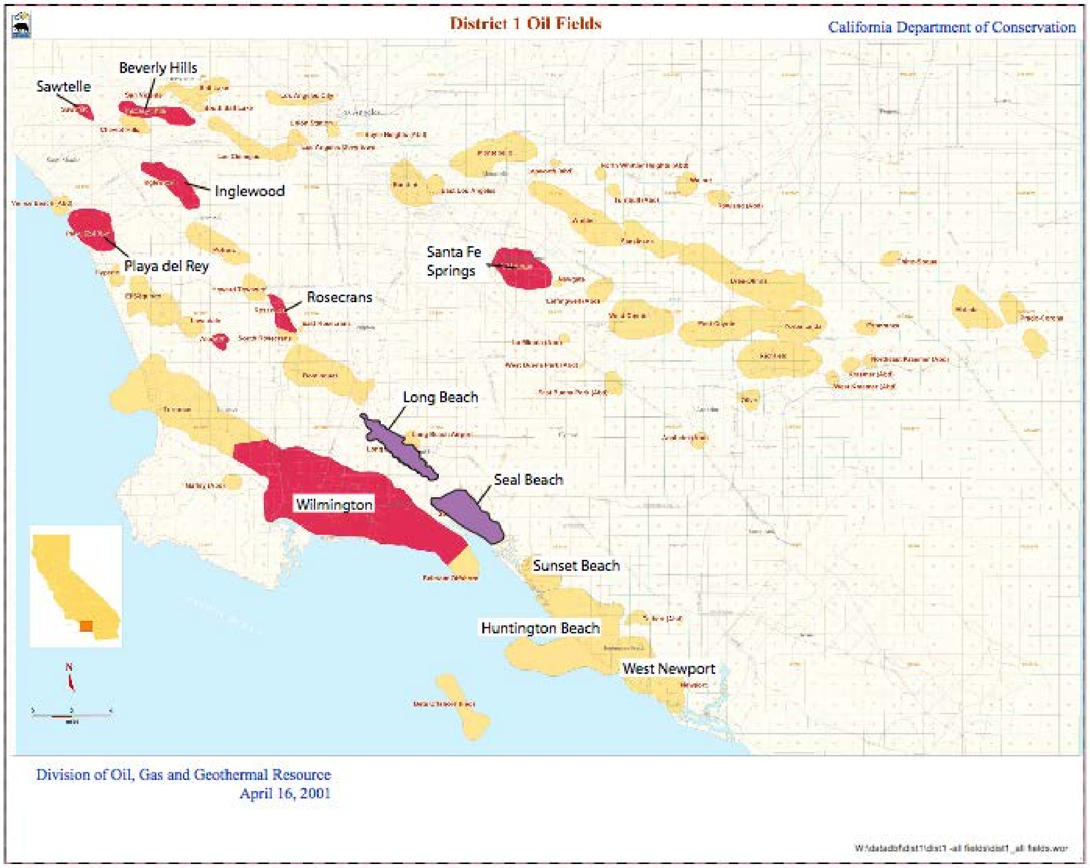
Name	Min. T (^{o}C)	Max. T (^{o}C)	Geopressured?	Substation (km)
Castaic Junction*	97	120	Y	
Newhall Potrero*	76	160	Y/N	
Sawtelle		133	N	1.0
Alondra		134	N	0.5
Inglewood	37	101	N	0
Seal Beach (S. Blk.)	64	125	Y	0
Seal Beach (Marine)	73	98	N	0
Santa Fe Springs	54	103	N	0
Oak Canyon*	55	100	N	
Beverley Hills East	86	103	N	0.5
Long Beach (Old Area)	44	92	Y/N	0
Playa del Rey		98	N	1.0
Wilmington (On Shore)	51	113	N	0
Rosecrans	84	98	N	0
Seal Beach (N. Blk.)	51	92	N	0

Note 1: * Resources that are within Los Angeles County but outside (north) of the study area.

Note 2: Pools that have pressures 10% above the theoretical hydrostatic pressure are also indicated (Y). Instances in which only a maximum temperature is shown indicate that only one temperature has been reported for the pool. Instances where the geopressured columns includes 'Y/N' indicates that only some wells within the pool show geopressure potential.

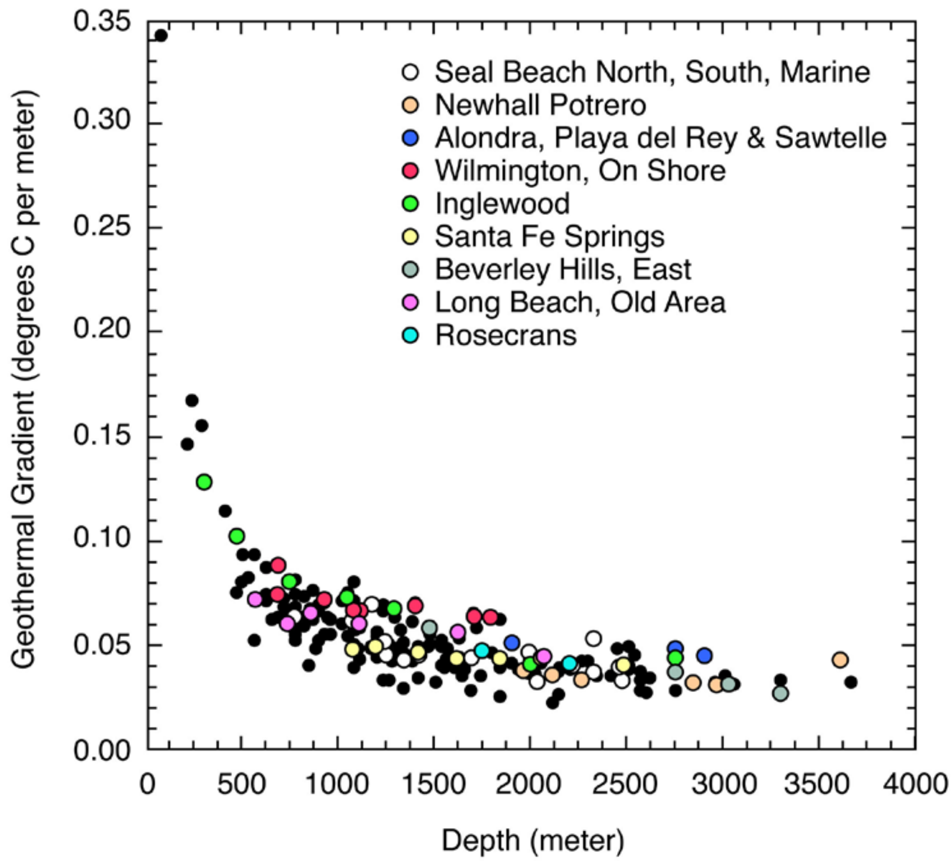
Sources: Data are from Higgins (1981) and California Oil and Gas, Vol. II (1991). Distance to the nearest substation (based on maps provided by the Cartography Unit of the Siting, Transmission and Environment Protection Division of the California Energy Commission) are also indicated.

Figure 21. Location of Oil Pools in the Los Angeles Basin



Note: Red pools have temperatures that are potentially high enough for binary geothermal power generation. Purple pools have temperature greater than 91°c and have pressures in some portions of the pool sufficiently above hydrostatic that they may be designated as geopressured.

Figure 22. Computed Geothermal Gradients Versus Depth for all Data Points in Appendix C



Note: The gradient was computed as the observed temperature divided by the depth and plotted at that depth. Note that this method implicitly assumes the surface datum to be zero C. This approach results in a slightly elevated computed gradient, compared with the actual geothermal gradient. This approach was chosen to facilitate comparisons between sites over a broad region where the actual surface temperature varies considerably due to contrasts in the local weather pattern (marine versus desert).

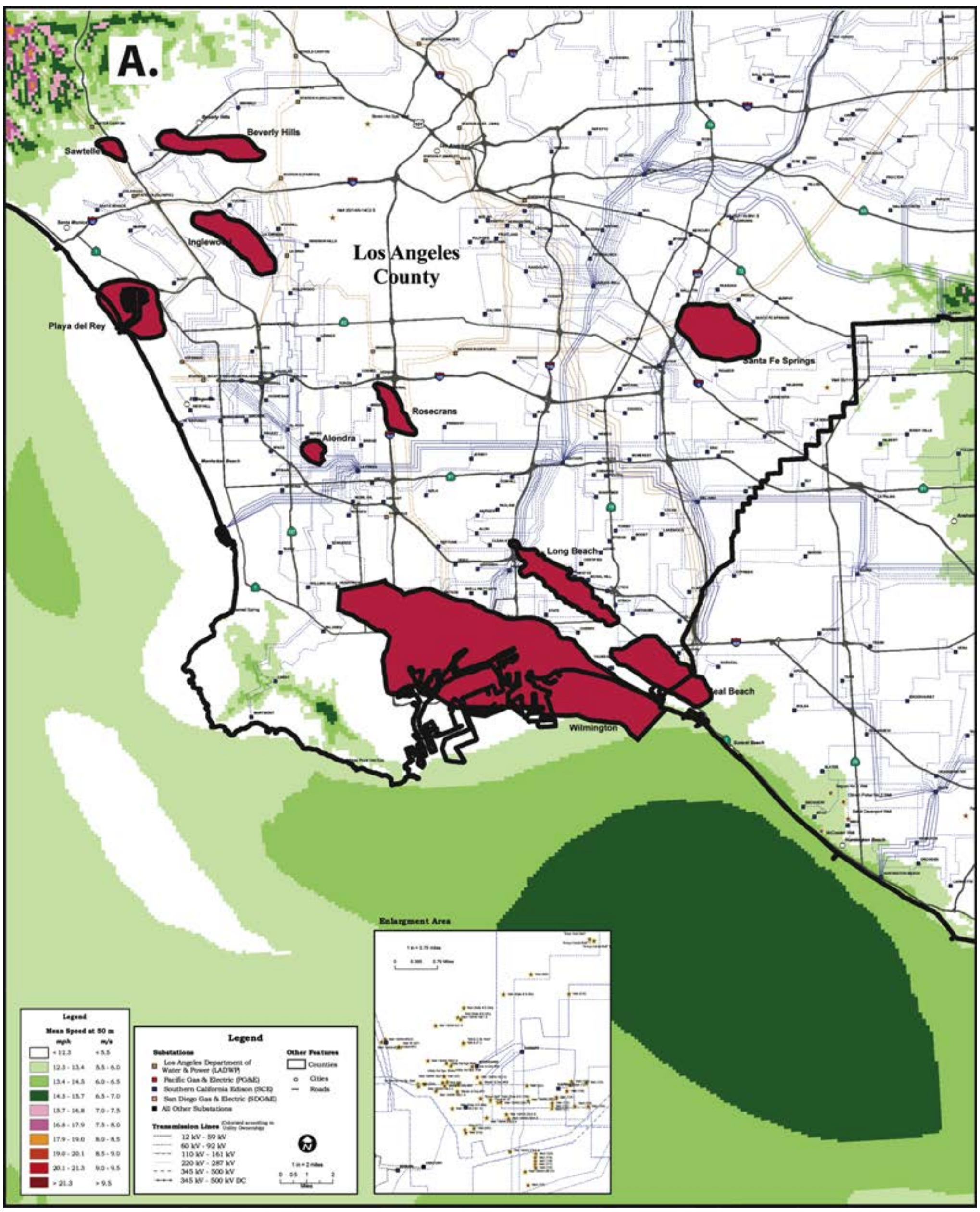
3.4.3 Co-Location of Resources

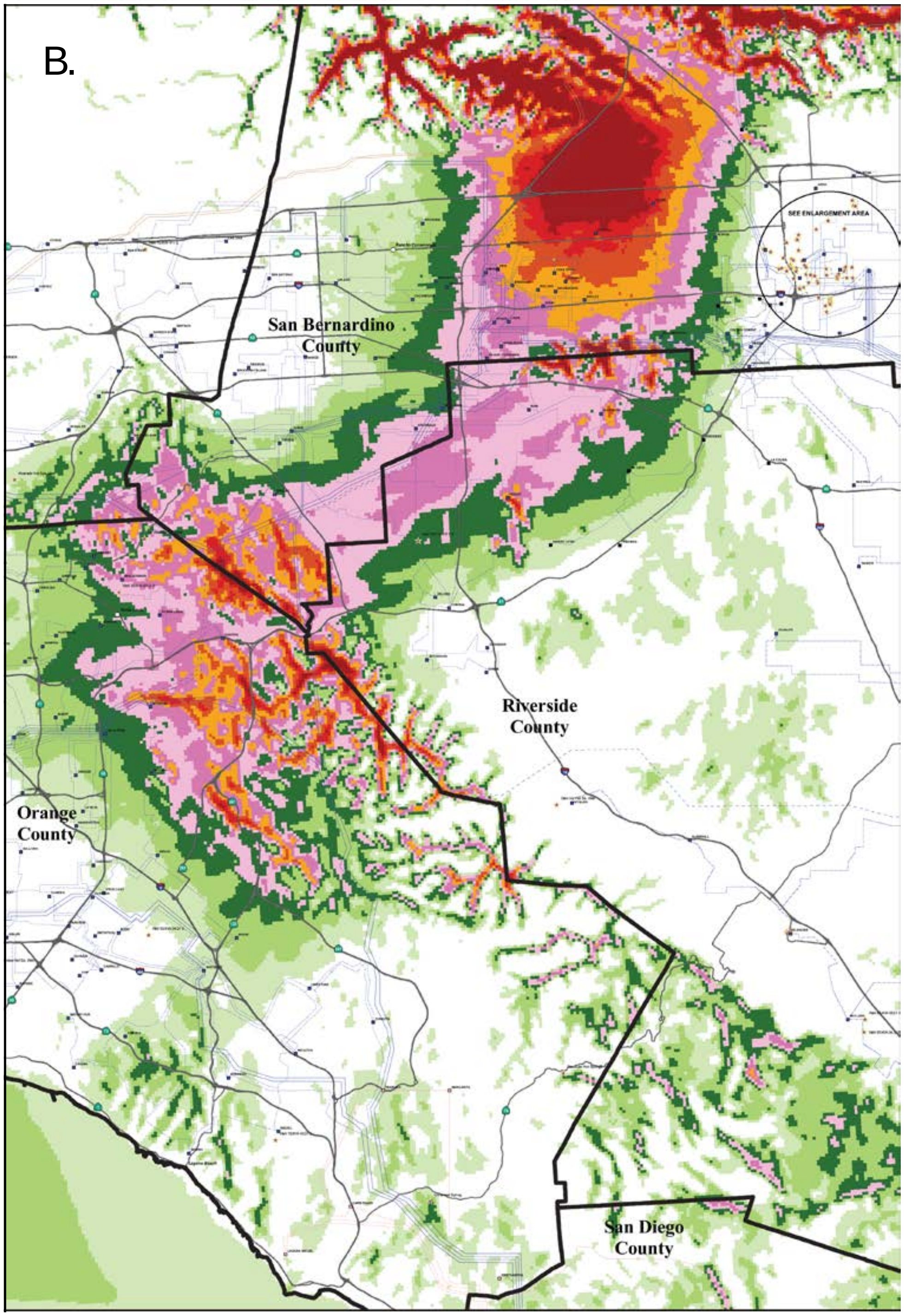
Shown in Figure 23 are the ten geothermal pools, superimposed on a map that displays the mean winter wind speed at 50 meters, as recorded in the CEC database. The winter season was selected for comparison since the other seasons have significantly lower wind speeds in all locations. Also shown in the figure are all transmission lines and substations.

The June global horizontal incident (GHI) solar power density, along with the locations of the geothermal pools, is shown in Figure 24. The June data were selected for depiction because they closely mimic the annual pattern for solar power density, while also providing an indication of the highest mean values.

Comparison of Figures 22and 23 documents that the geothermal and wind resources are restricted to specific geographical sites or areas whereas the solar resource is more evenly distributed throughout the Los Angeles Basin, varying less than 30 percent between the coast and the inland areas. Hence, from the perspective of evaluating co-location of resources, the primary constraint is the restricted geographical distribution of geothermal and wind resources.

Figure 23. Geothermal and Wind Resources Throughout the Western (A.) and Eastern (B.) Greater Los Angeles Basin Area





Note: The geothermal pools (red areas outlined in black) only occur in the western section, as shown. The legends in A. also apply to B. The mean winter wind speed at 50 meters is color-contoured (wind scale in shown in A.). Also shown in both figures is the transmission infrastructure. The locations of substations are accurate to within 0.5 km, while the transmission line locations are shown schematically.

The closest, co-located geothermal and wind resources are in the northwestern coastal area, where the Sawtelle and Beverley Hills pools reside just south and southeast of a region with mean winter wind speeds exceeding 16 mph (Figure 23A). There is also a close spatial relationship between the most southern geothermal pools (Wilmington and Seal Beach) and the large area of modest (14.5 to 15.7 mph) wind speeds offshore to the south.

Connection of potential generating facilities with the transmission infrastructure would likely require more development in the northern area due to the limited number of substations in that region compared to the southern area, where substations are common.

Wind and solar co-located resources have their most significant potential in the eastern part of the study area, where both resources have their greatest power densities. The nearest geothermal resource to this area is the Santa Fe Springs pool, which is more than 10 miles from the edge of the nearest concentrated wind resource. Much of the high wind area lacks adequate substation inter-connection infrastructure to support immediate generation development, but parts of the area are traversed by major transmission corridors that could readily support co-located generating facilities.

Figure 24. Location Of Geothermal Pools in the Los Angeles Basin (Red Areas Outlined in Black) and the June Solar Power Density

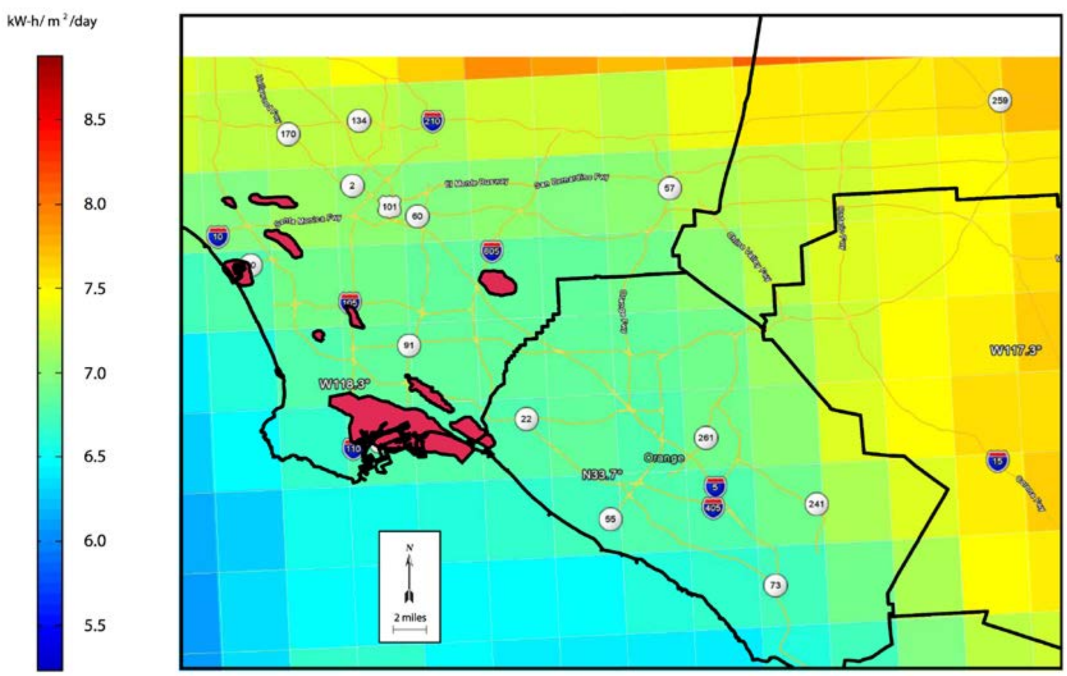
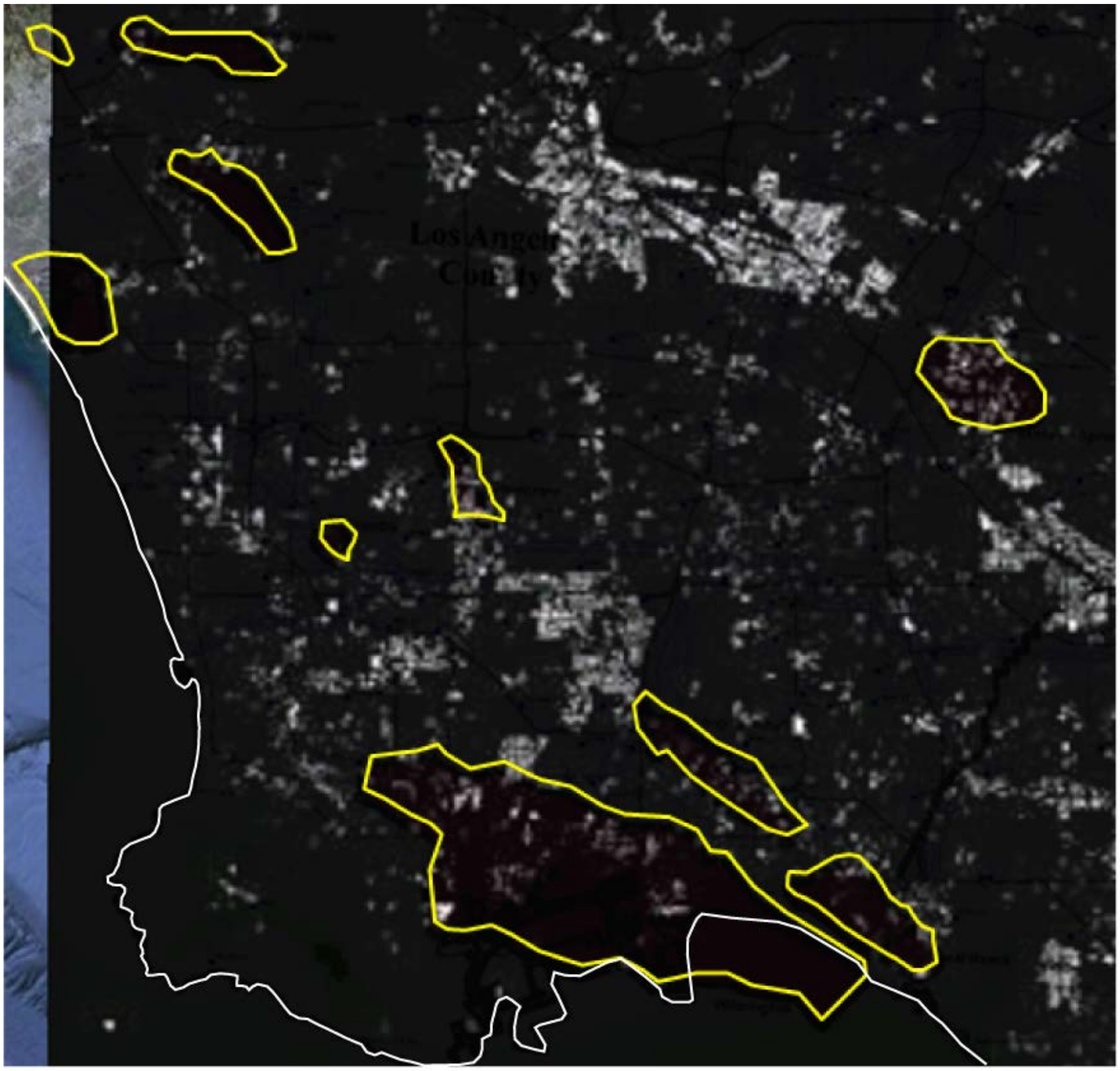


Figure 25: Overlay of Geothermal Resources (Yellow Border) and Solar Rooftop Potential (White) as Identified for ReDEC



Source: Black & Veatch, 2009

As noted in the introduction, power generation for local loads using co-located renewable resources can be an attractive use of renewable energy applications. In the Los Angeles Basin area, urban and industrial development is extensive, limiting the installation of solar power plants to rooftop systems. Warehouse rooftop spaces provide the best opportunities for installation of solar power plants due to large size leading to economies of scale, flat installation allowing optimal tilting of the panels, and industrial zoning simplifying permitting. to evaluate the possibility of utilizing co-located geothermal and solar resources for such applications, we considered the distribution of urban warehouse solar rooftop potential compiled by Black and Veatch (2009) and overlayed it on the geothermal resources (Fig. 25). With the exception of Alondra, Beverly Hills, and Sawtelle, the footprint of all geothermal pools closely coincides with significant solar warehouse roof space. The largest amount of warehouse roof space suitable for solar PV exists at the Rosecrans, Santa Fe springs, and Wilmington pools. These locations, therefore, have potential for "micro-grid integrated system" applications. Among these sites, the Santa Fe springs pool is the most promising site due to high density of warehouse roof space and larger solar resources than the Rosecrans and Wilmington pools. However, if other considerations rule out the Santa Fe springs resource, any of the other sites also provides significant warehouse rooftop space and solar resource potential.

CHAPTER 4: Salton Trough: Resource Mapping of Co-Located Geothermal Resources

4.1 Introduction

The approach taken to identify co-located renewable resources in the Salton Trough/Imperial Valley region is somewhat different from that used for the Los Angeles Basin described in Chapter 3. The different approach is due to the fact that geothermal and solar power generating facilities already are in place in the region, which immediately establishes that a transmission infrastructure has already been put in place that is potentially compatible with co-located renewable resources (Figure 25). In addition, the potential for solar generation is relatively uniform throughout the region - note, for example, that the July mean solar power density only varies between 7.4 and 7.8 kWh/m^2/day throughout the region (Figure 14). Moreover, although the existing geothermal power generating developments that are installed are localized (Figure 25), numerous studies (such as, Hulen, 2005; Williams et al., 2008) have concluded that the geothermal resource is likely to be broadly distributed throughout the area, in a manner not unlike that for the solar resource. Although estimates of the potential geothermal resource vary significantly, there is general agreement that the resource exceeds by at least a factor of three the existing, in-place generating capacity.

The wind resource, as in the Los Angeles Basin region, is most significant at higher elevations surrounding the Salton Trough/Imperial Valley (Figure 25). The wind resource is extensive, with many square miles of terrain over which mean wind speeds at 50 meters in the winter season are in the range of 18 to 20 mph or higher.

4.2 Co-Location of Resources

These observations suggest that co-located geothermal and solar resources are common and extensive in the Salton Trough/Imperial Valley area. A transmission infrastructure is already in place that services both geothermal and solar facilities. Build-out of this infrastructure to accommodate co-located generating facilities would be required if there were to be significant expansion of the solar and geothermal generating capacity.

Although wind resources are not located in close proximity to existing geothermal generating facilities, build-out of geothermal generating facilities near significant wind resource regions is not unreasonable, since there is a very broad distribution of geothermal resources in the area. This is particularly true along the eastern margin of the Salton Sea where numerous wells have been drilled and hot springs and mud pots exist. Direct overlap between significant solar and wind resources in the eastern part of the area makes co-location of generating capacity that utilizes all three resources a realistic possibility. If coordinated with further development of geothermal resources, these three renewable energy sources could be extensively developed in this area, particularly along the eastern margins of the Salton Trough/Imperial Valley area.

Figure 26. Geothermal Power Generation Facilities (Red Boxes) with Names Indicated, Solar Power Generating Site (Yellow Star) and Mean Winter Wind Velocity at 50 Meters (Contoured Colors) in the Salton Trough/Imperial Valley Area (Transmission infrastructure is also shown)

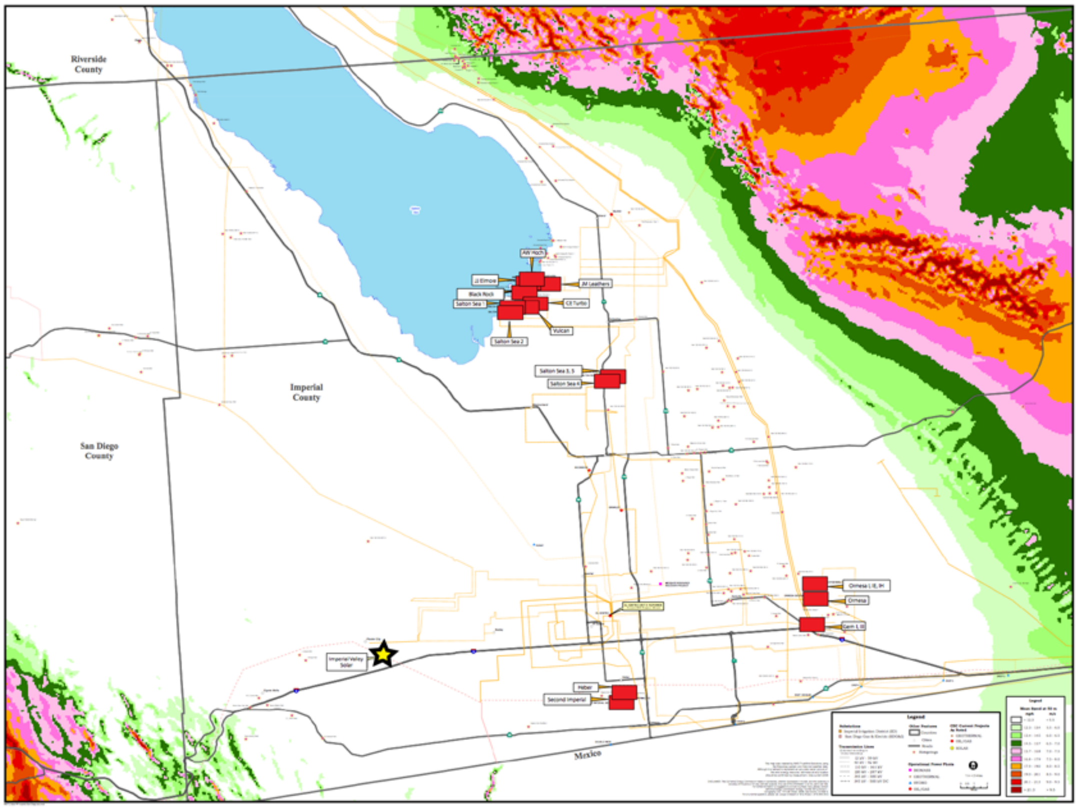
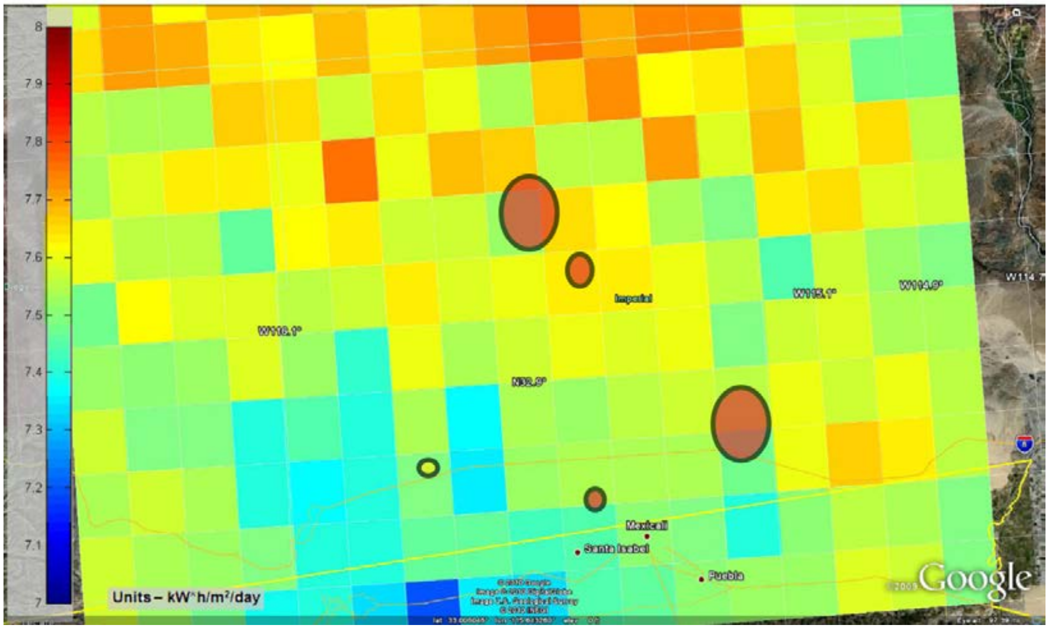


Figure 27. Generalized Locations of Geothermal (Transparent Red Ovals, Based On Generation Facilities Identified In Figure 25) and Solar (Transparent Yellow Oval), Superimposed on the Solar July Power Density Map for the Region



4.3 Conclusions

Co-located geothermal, solar and wind renewable energy resources that are sufficient for power generation occur within both the Los Angeles Basin and Salton Trough/Imperial Valley regions. 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. However, further analysis of this topic is required to establish rigorous caveats to this conclusion.

4.4 Recommendations

Further work is required in the following areas to allow rigorous evaluation of the potential for locating the various categories of integrated systems within the study areas:

- Conduct 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.

- Conduct detailed resource assessments of the roof-top solar PV potential in the Los Angeles Basin area. This resource assessment should consider the extent to which such resources are co-located with respect to the geothermal resource, and how these two resource types could be developed in a coordinated fashion to supply power for distributed, local loads. Such an analysis could be developed as a template for other urban settings in which co-located resources exist. Research into the optimal co-operation of solar and geothermal power plants given solar day-night and cloud-clear variability should be conducted to determine the extent to which geothermal power plants could be operated as backup to solar PV generation to facilitate high renewable penetration.

- For both regions considered in this study, the need exists for higher resolution (~10m) maps that would better delineate local variability of the resources. Knowledge regarding the variations in micro-climate and in the distribution of the geothermal energy in individual oil pools or in the subsurface around the Salton Sea could support much better description of where resource development could be economically undertaken. This information is also needed to prioritize development of transmission infrastructure and renewable energy generation capacity.

- Within the Salton Trough/Imperial Valley region, there is only one identified solar generating facility, but the resource is so extensive that further development of it is likely. Detailed analysis should be undertaken that would identify the best locations for further solar PV or solar thermal development, taking into account the existing and planned geothermal power generating capacity and the abundant wind resource in the eastern part of the study area.

- Transmission infrastructure in the Salton Trough/Imperial Valley region has been developed, in part, in response to geothermal power generating facilities. Further consideration should be given to future development of the infrastructure, from the perspective of co-locating renewable resources. This is particularly true along the eastern side of the Salton Sea, where the potential exists for extensive coordinated development of geothermal-solar-wind resources. Currently this area is not considered for future transmission infrastructure within the Renewable Energy Transmission Initiative (RETI, 2009). However, analysis of the co-located resources in this area may justify further consideration by RETI of this area.

GLOSSARY

Glossary List of Terms Related to Chapter 1

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 post processing 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 shadow band 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).

GLOSSARY LIST OF ABBREVIATIONS

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
DNI	Direct Normal Incident
EIA	Energy Information Administration
ERCOT	Electric Reliability Council of Texas
GDAS	Global Data Assimilation System
GEM	Global Environmental Multiscale
GFS	Global Forecast System
GHI	Global Horizontal Irradiance
GI	Global Irradiance
GSI	Gridpoint Statistical Interpolation
HA	Hour Ahead (Forecast)
IESO	Ontario Independent Electric System Operator
IOU	Investor-Owned Utility
ISET	Kassel Institute für Solare Energieversorgungstechnik
ISO	Independent System Operators
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
PV	Photo Voltaic
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

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APPENDIX A:
Solar Energy Forecasting Tables Related to Chapter 1

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							

Study	Location	Quantity	Forecast Source	Averaging Interval	Time Horizon	Error Metric	Error Value	Comment
	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 skies only. AFSOL GHI on 5% RMSE.
		GHI	AFSOL	1 h	1 – 72 h	RMSE MBE	25.1% or 148 W m-2 -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

Study	Location	Quantity	Forecast Source	Averaging Interval	Time Horizon	Error Metric	Error Value	Comment
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 cross correlation 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.

Study	Location	Quantity	Forecast Source	Averaging Interval	Time Horizon	Error Metric	Error Value	Comment
	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.

Study	Location	Quantity	Forecast Source	Averaging Interval	Time Horizon	Error Metric	Error Value	Comment
	same	GHI	NDFD	1 h	1 (same day) to 7 days	RMSE MBE	75 to 114 Wm-2 (same day) to 97 to 146 Wm-2 (7 days) (persistence: 150 to 211 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)	All NDFD forecasts originate at 11:00 GMT.
	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 over predicts irradiance, even after it was adjusted empirically to prevent over prediction. 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%	Also conducted Kolmogorov-Smirnov test.

Study	Location	Quantity	Forecast Source	Averaging Interval	Time Horizon	Error Metric	Error Value	Comment
							(MS)	

APPENDIX B:
Numerical Weather Prediction Models Related to Chapters 3 and 4

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.

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 today 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 grid points 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 B-1.

Table B-1. 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

APPENDIX C:
Los Angeles County Oil Pools Related to Chapters 3 and 4

Table C-1. Los Angeles County oil pools. All data are from California Oil and Gas Fields, Vol. II (1991) unless marked by an asterisk (*), in which case the data are from Higgins (1981).

Oil Pool Name	Temp (F)	Depth (feet)	Pressure (psi)	Temp (C)	Depth (m)	Pressure (bars)	Geotherm. Gradient (°C/m)	Pool mean Geo. Gradient (°C/m)	Std. Dev.
Aliso Canyon	130	4150	1260	54	1265	87	0.043	0.037	0.0061
Aliso Canyon	144	5050	1795	62	1539	124	0.040		
Aliso Canyon	145	5673	1780	62	1729	123	0.036		
Aliso Canyon	175	9000	3595	79	2743	248	0.029		
Alondra	275	9000	3902	134	2743	269	0.049	0.049	
Anaheim (ABD)	105	4350		40	1326		0.030	0.030	
Bandini	140	4200		59	1280		0.046	0.0418	0.0038
Bandini	140	4500		59	1372		0.043		
Bandini	145	5000		62	1524		0.041		
Bandini	160	5300		70	1615		0.044		
Bandini	175	6200		79	1890		0.042		
Bandini	188	6500		86	1981		0.043		
Bandini	190	8400		87	2560		0.034		
Beverly Hills	110	2500	930	43	762	64	0.056	0.056	
Beverly Hills East Area	189	4800	2327	86	1463	160	0.059	0.039	0.0138
Beverly Hills East Area	220	9000	3450	103	2743	238	0.038		
Beverly Hills	209	9900	2523	97	3018	174	0.032		

East Area									
Beverly Hills East Area	200	10800	2920	92	3292	201	0.028		
Beverly Hills West Area	110	2500	990	43	762	68	0.056	0.056	
Beverly Hills West Area	195	4500							
Brea-Olinda	105	1800	900	40	549	62	0.073	0.053	0.0195
Brea-Olinda	108	4000	2200	42	1219	152	0.034		
Brea-Olinda	175	5000	2200	79	1524	152	0.052		
Cascade	94	2733		34	833		0.041	0.041	
Castaic Hills	100	730		37	223		0.168	0.168	
Castaic Junction	208	8400	4952	97	2560	341	0.038	0.034	0.0022
Castaic Junction	212	10000	4952	99	3048	341	0.032		
Castaic Junction	228	9850	5338	108	3002	368	0.036		
Castaic Junction	238	10800	6200	113	3292	427	0.034		
Castaic Junction	238	10800	6000	113	3292	414	0.034		
Castaic Junction	250	12000	6280	120	3658	433	0.033		
Cheviot Hills	180	4800		81	1463		0.056	0.053	0.0016
Cheviot Hills	260	8200		125	2499		0.050		
Coyote East	115	2500		46	762		0.060	0.053	0.0055
Coyote East	128	3100		53	945		0.056		
Coyote East	135	3400		57	1036		0.055		
Coyote East	150	4000		65	1219		0.053		
Coyote East	160	4600		70	1402		0.050		
Coyote East	165	5500		73	1676		0.044		
Cristianitos Creek	184	5860		84	1786		0.047	0.047	
Del Valle Main Area	165	6500	2600	73	1981	179	0.037	0.036	0.0006
Del Valle Main	185	7650	3645	84	2332	251	0.036		

Area									
Dominguez (from Higgins, 1981)	157	4350		69	1326		0.052	0.04825	0.0044
Dominguez (from Higgins, 1981)	165	4775		73	1455		0.050		
Dominguez (from Higgins, 1981)	170	5100		76	1554		0.049		
Dominguez (from Higgins, 1981)	175	6200		79	1890		0.042		
Howard Townsite (from Higgins, 1981)	210	8200		98	2499		0.039	0.039	
Honor Rancho	190	5300	1900	87	1615	131	0.054	0.054	
Huntington Beach Onshore Area	126	1800	975	52	549	67	0.094	0.0628	0.0182
Huntington Beach Onshore Area	122	2200	975	50	671	67	0.074		
Huntington Beach Onshore Area	125	2300	975	51	701	67	0.073		
Huntington Beach Onshore Area	130	3900	1550	54	1189	107	0.045		
Huntington Beach Onshore Area	150	4300	1190	65	1311	82	0.050		
Huntington Beach Onshore Area	150	4600	1190	65	1402	82	0.046		
Huntington Beach Onshore Area	170	4300		76	1311		0.058		

Inglewood	100	950	450	37	290	31	0.129	0.0773	0.0313
Inglewood	118	1500	750	47	457	52	0.103		
Inglewood	140	2400	1160	59	732	80	0.081		
Inglewood	175	3400	1795	79	1036	124	0.076		
Inglewood	188	4200	2140	86	1280	148	0.067		
Inglewood	255	9000	4275	123	2743	295	0.045		
Inglewood	215	8200	3700	101	2499	255	0.040		
Kraemer	118	2400		47	732		0.065	0.065	
Las Cienegas Fourth Ave. Area	190	3500	3160	87	1067	218	0.081	0.081	
Las Cienegas Good Shepherd	150	3900	1760	65	1189	121	0.055	0.055	
Las Cienegas Jefferson (from Higgins, 1981)	150	4000		65	1219		0.053	0.053	
Las Cienegas Murphy Area	128	2500	1170	53	762	81	0.069	0.06375	0.0057
Las Cienegas Murphy Area	136	2750	1320	57	838	91	0.068		
Las Cienegas Murphy Area	150	3500	1630	65	1067	112	0.061		
Las Cienegas Murphy Area	155	3900	1720	68	1189	119	0.057		
Lawndale (from Higgins, 1981)	250	8000		120	2438		0.049	0.049	
Long Beach Old Area	112	2000	1160	44	610	80	0.072	0.0593	0.0088
Long Beach Old Area	112	2400	1160	44	732	80	0.060		
Long Beach Old Area	130	2800	1300	54	853	90	0.063		
Long Beach Old Area	150	3600	2000	65	1097	138	0.059		

Long Beach Old Area	200	5300	2800	92	1615	193	0.057		
Long Beach Old Area	200	6700	2800	92	2042	193	0.045		
Long Beach Recreation Park Area	120	6000		48	1829		0.026	0.0245	0.0012
Long Beach Recreation Park Area	120	6900		48	2103		0.023		
Los Angeles Downtown	139	2900	1590	59	884	110	0.067	0.05975	0.0069
Los Angeles Downtown	141	3100		60	945		0.063		
Los Angeles Downtown	145	3500		62	1067		0.058		
Los Angeles Downtown	168	4800	2078	75	1463	143	0.051		
Los Angeles East Area	165	8400		73	2560		0.029	0.0285	0.0003
Los Angeles East Area	165	8500		73	2591		0.028		
Mahala Main Area	135	3800		57	1158		0.049	0.048	0.0010
Mahala Main Area	140	4100		59	1250		0.048		
Mahala Main Area	145	4350		62	1326		0.047		
Mahala West	145	4000	1800	62	1219	124	0.051	0.051	
Montebello	110	2200	1100	43	671	76	0.064	0.0575	0.0092
Montebello	130	3500	1550	54	1067	107	0.051		
Newgate (from Higgins, 1981)	244	8300		117	2530		0.046	0.046	
Newhall Tunnel Area	103	1581		39	482		0.081	0.081	
Newhall -	170	6500	3100	76	1981	214	0.038	0.036167	0.0044

Potrero									
Newhall - Potrero	170	6900	3100	76	2103	214	0.036		
Newhall - Potrero	170	7400	3100	76	2256	214	0.034		
Newhall - Potrero	200	9300	3925	92	2835	271	0.033		
Newhall - Potrero	205	9700	4959	95	2957	342	0.032		
Newhall - Potrero	323	11806	5650	160	3598	390	0.044		
Newport West	105	2500	450	40	762	31	0.053	0.04675	0.0056
Newport West	110	2850	585	43	869	40	0.049		
Newport West	110	3500	876	43	1067	60	0.040		
Newport West	165	5300	2300	73	1615	159	0.045		
Oak Canyon	132	2750	1043	55	838	72	0.066	0.0394	0.0088
Oak Canyon	148	5160	1830	64	1573	126	0.041		
Oak Canyon	148	5225	1830	64	1593	126	0.040		
Oak Canyon	148	5395	1830	64	1644	126	0.039		
Oak Canyon	168	6310	2565	75	1923	177	0.039		
Oak Canyon	168	6600	2565	75	2012	177	0.037		
Oak Canyon	178	7000	1825	80	2134	126	0.038		
Oak Canyon	189	7900	3600	86	2408	248	0.036		
Oak Canyon	191	8050	3600	87	2454	248	0.036		
Oak Canyon	198	8560	3600	91	2609	248	0.035		
Oak Canyon	211	9675	3600	98	2949	248	0.033		
Oak Canyon	213	9800	3600	100	2987	248	0.033		
Oat Mountain	135	7000	2800	57	2134	193	0.027	0.027	
Olive	122	4900	2010	50	1494	139	0.033	0.033	
Pacoima	165	6000	3200	73	1829	221	0.040	0.0395	0.0003
Pacoima	186	7200	4000	85	2195	276	0.039		

Playa del Rey Del Rey hills Area	210	6200	2750	98	1890	190	0.052	0.052	
Potrero East (from Higgins, 1981)	180			81					
Richfield	115	2000							
Richfield	117	2900	1371	47	884	95	0.053	0.05	0.0025
Richfield	125	3500	1559	51	1067	107	0.048		
Richfield	138	3800	1863	58	1158	128	0.050		
Richfield	186	7950							
Rosecrans	185	5700	2920	84	1737	201	0.048	0.044	0.0032
Rosecrans	200	7200	2700	92	2195	186	0.042		
Rosecrans South (from Higgins, 1981)	210	7500		98	2286		0.043		
Salt Lake	120	2650	880	48	808	61	0.060	0.06	
Salt Lake	123	2850							
Salt Lake	125								
Salt Lake	128	3300							
Salt Lake South	127	1000							
Salt Lake South	135	2500							
San Clemente	138	5350	1850	58	1631	128	0.036	0.036	
San Vicente	113	3200							
Sansinena Curtis Area	143	5100							
Sansinena East Area	144	3300	1450	62	1006	100	0.061	0.061	
Sansinena New England (from Higgins, 1981)	125	3000		51	914		0.056	0.056	
Santa Fe Springs	130	3580	1480	54	1091	102	0.049	0.04475	0.0033
Santa Fe Springs	140	3900	1700	59	1189	117	0.050		

Santa Fe Springs	150	4600	1900	65	1402	131	0.046		
Santa Fe Springs	160	5400	2200	70	1646	152	0.043		
Santa Fe Springs	177	6000	2520	80	1829	174	0.044		
Santa Fe Springs	188	6700	2870	86	2042	198	0.042		
Santa Fe Springs	210	7400	3200	98	2256	221	0.043		
Santa Fe Springs	220	8200	3600	103	2499	248	0.041		
San Vicente (from Higgins, 1981)	161	3500		71	1067		0.067	0.06	0.0099
San Vicente (from Higgins, 1981)	179	5000		81	1524		0.053		
Sawtelle	274	9500	4400	133	2896	303	0.046	0.046	
Seal Beach	125	2610	1850	51	796	128	0.064		
Seal Beach Alamitos Area	110	4100		43	1250		0.034	0.032667	0.0032
Seal Beach Alamitos Area	120	4600		48	1402		0.035		
Seal Beach Alamitos Area	120	5500		48	1676		0.029		
Seal Beach Marine Area	165	5490	2291	73	1673	158	0.044	0.041667	0.0021
Seal Beach Marine Area	195	7240	3026	90	2207	209	0.041		
Seal Beach Marine Area	211	8040	3362	98	2451	232	0.040		
Seal Beach North Block Area	125	2610	1850	51	796	128	0.064	0.05043	0.0150
Seal Beach North Block Area	135	4350	1960	57	1326	135	0.043		
Seal Beach North Block Area	152	3470	1600	66	1058	110	0.062		

Seal Beach North Block Area	180	3820	2200	81	1164	152	0.070		
Seal Beach North Block Area	200	6500	2000	92	1981	138	0.047		
Seal Beach North Block East Ext	152	6641	2150	66	2024	148	0.033		
Seal Beach North Block East Ext	186	8100	3215	85	2469	222	0.034		
Seal Beach South Block Area	149	4100	1500	64	1250	103	0.051	0.0465	0.0055
Seal Beach South Block Area	135	4100	2100	57	1250	145	0.045		
Seal Beach South Block Area	150	4600	2200	65	1402	152	0.046		
Seal Beach South Block Area	170	5500	2800	76	1676	193	0.045		
Seal Beach South Block Area	190	7600	3400	87	2316	234	0.038		
Seal Beach South Block Area	260	7600	3760	125	2316	259	0.054		
Torrance	152	2800	1385	66	853	95	0.077	0.0723	0.0045
Torrance	163	3300	1565	72	1006	108	0.072		
Torrance	190	4200	2087	87	1280	144	0.068		
Union Station	145	3520	1950	62	1073	134	0.058	0.04733	0.0095
Union Station	157	5080	2300	69	1548	159	0.044		
Union Station	186	7020	3200	85	2140	221	0.040		
Venice Beach	240	6000		114	1829		0.063	0.06433	0.0023

(from Higgins, 1981)									
Venice Beach (from Higgins, 1981)	180	4000		81	1219		0.067		
Venice Beach (from Higgins, 1981)	240	6000		114	1829		0.063		
Wayside Canyon	95	1495	525	35	456	36	0.076	0.076	
Whittier Central	115	1300	950	46	396	66	0.115	0.1045	0.0149
Whittier Central	115	1600	950	46	488	66	0.094		
Whittier La Habra Area	110	900	800	43	274	55	0.156	0.156	
Whittier Rideouts Area	120	2300		48	701		0.069	0.069	
Wilmington	145	2500	1210	62	762	83	0.082		
Wilmington Onshore	124	2200	1040	51	671	72	0.075	0.067321	0.0095
Wilmington Onshore	141	2200	1270	60	671	88	0.089		
Wilmington Onshore	150	3000	1420	65	914	98	0.071		
Wilmington Onshore	166	3600	1633	74	1097	113	0.067		
Wilmington Onshore	180	4000	1880	81	1219	130	0.067		
Wilmington Onshore	208	4550	2205	97	1387	152	0.070		
Wilmington Onshore	228	5550	2572	108	1692	177	0.064		
Wilmington Onshore	238	5850	2715	113	1783	187	0.064		
Wilmington (from Higgins, 1981)	120	3600		48	1097		0.044		

Wilmington (from Higgins, 1981)	130	2000	54	610	0.088
Wilmington (from Higgins, 1981)	140	3050	59	930	0.064
Wilmington (from Higgins, 1981)	135	3400	57	1036	0.055
Wilmington (from Higgins, 1981)	180	4200	81	1280	0.064
Wilmington (from Higgins, 1981)	170	5000	76	1524	0.050
Wilmington (from Higgins, 1981)	124	2200	51	671	0.075
Wilmington (from Higgins, 1981)	136	2500	57	762	0.075
Wilmington (from Higgins, 1981)	154	3000	67	914	0.073
Wilmington (from Higgins, 1981)	172	3500	77	1067	0.072
Wilmington (from Higgins, 1981)	188	4000	86	1219	0.070
Wilmington (from Higgins, 1981)	212	4550	99	1387	0.071
Wilmington (from Higgins, 1981)	235	5550	112	1692	0.066
Wilmington (from Higgins, 1981)	150		65		

Wilmington (from Higgins, 1981)	140	2650		59	808		0.074		
Wilmington (from Higgins, 1981)	144	2900		62	884		0.070		
Wilmington (from Higgins, 1981)	162	3600		72	1097		0.065		
Wilmington (from Higgins, 1981)	186	4500		85	1372		0.062		
Wilmington (from Higgins, 1981)	216	5600		101	1707		0.059		
Wilmington (from Higgins, 1981)	150	3500		65	1067		0.061		
Wilmington (from Higgins, 1981)	148	3500		64	1067		0.060		
Yorba Linda	70	200	15	21	61	1	0.343	0.12733	0.1107
Yorba Linda	85	650	200	29	198	14	0.147		
Yorba Linda	85	1800	500	29	549	34	0.053		
Yorba Linda	105	2100	500	40	640	34	0.063		
Yorba Linda	110	1700	600	43	518	41	0.083		
Yorba Linda	115	2000	800	46	610	55	0.075		