Recent Trends in Variable Generation Forecasting and Its Value to the Power System

Kirsten D. Orwig, Mark L. Ahlstrom, *Senior Member, IEEE*, Venkat Banunarayanan, Justin Sharp, James M. Wilczak, Jeffrey Freedman, Sue Ellen Haupt, Joel Cline, Obadiah Bartholomy, Hendrik F. Hamann, Bri-Mathias Hodge, *Member, IEEE*, Catherine Finley, Dora Nakafuji, *Member, IEEE*, Jack L. Peterson, David Maggio, *Member, IEEE*, and Melinda Marquis

***Abstract*—The rapid deployment of wind and solar energy generation systems has resulted in a need to better understand, predict, and manage variable generation. The uncertainty around wind and solar power forecasts is still viewed by the power industry as being quite high, and many barriers to forecast adoption by power system operators still remain. In response, the U.S. Department of Energy has sponsored, in partnership with the National Oceanic and Atmospheric Administration, public, private, and academic organizations, two projects to advance wind and solar power forecasts. Additionally, several utilities and grid operators have recognized the value of adopting variable generation forecasting and have taken great strides to enhance their usage of forecasting. In parallel, power system markets and operations are evolving to integrate greater amounts of variable generation. This paper will discuss the recent trends in wind and solar power forecasting technologies in the U.S., the role of forecasting in an evolving power system framework, and the benefits to intended forecast users.**

***Index Terms*—Forecasting, large-scale integration, market design, power-system reliability, renewable energy, solar energy, variable generation, wind energy.**

Manuscript received September 15, 2014; accepted September 21, 2014. Date of publication December 23, 2014; date of current version June 17, 2015. Paper no. TSTE-00476-2014.

K. D. Orwig was with the National Renewable Energy Laboratory (NREL), Golden, CO 80401 USA. She is now with Swiss Re America, Armonk, NY 10504 USA (e-mail: kirsten_orwig@swissre.com).

M. L. Ahlstrom is with the WindLogics, St. Paul, MN 55108 USA (e-mail: mark@windlogics.com).

V. Banunarayanan is with the ICF International and Department of Energy (DOE), Washington, DC 20585 USA (e-mail: venkat.banunarayanan@icfi.com).

J. Sharp is with Sharply Focused, Portland, OR 97232 USA (e-mail: justin@sharply-focused.com).

J. M. Wilczak and M. Marquis are with the National Oceanic and Atmospheric Administration (NOAA), Boulder, CO 80305 USA (e-mail: james.m.wilczak@noaa.gov; melinda.marquis@noaa.gov).

J. Freedman is with the Atmospheric Sciences Research Center, SUNY, Albany, NY 12203 USA (e-mail: jfreedman@albany.edu).

S. E. Haupt is with the National Center for Atmospheric Research (NCAR), Boulder, CO 80301 USA (e-mail: haupt@ucar.edu).

J. Cline is with the Department of Energy (DOE), Washington, DC 20585 USA (e-mail: joel.cline@ee.doe.gov).

O. Bartholomy is with the Sacramento Municipal Utility District (SMUD), Sacramento, CA 95817 USA (e-mail: obartho@smud.org).

H. F. Hamann is with IBM, Yorktown Heights, NY 10598 USA (e-mail: hendrikh@us.ibm.com).

B.-M. Hodge is with the National Renewable Energy Laboratory (NREL), Golden, CO 80401 USA (e-mail: bri.mathias.hodge@nrel.gov).

C. Finley is with WindLogics, Grand Rapids, MN 55744 USA (e-mail: catherine.finley@windlogics.com).

D. Nakafuji is with the Hawaiian Electric Company (HECO), Honolulu, HI 96813 USA (e-mail: dora.nakafuji@heco.com).

J. L. Peterson is with Southern California Edison (SCE), Rosemead, CA 91770 USA (e-mail: jack.peterson@sce.com).

D. Maggio is with the Electric Reliability Council of Texas (ERCOT), Taylor, TX 76574 USA (e-mail: david.maggio@ercot.com).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TSTE.2014.2366118

I. Introduction

VARIABLE generation poses a challenge to power systems that traditionally have operated under deterministic rules. There are a number of variable generation management and mitigation strategies [1]–[5] and forecasting is generally seen as low-hanging fruit to facilitate the integration of higher penetrations of variable generation into existing power system architecture [6]. However, the uncertainty and inaccuracy of variable generation forecasts remain obstacles for users. As Jones [3] states, “94% of grid operators say that integrating a significant amount of wind [power] will largely depend on the accuracy of the wind power forecast.” The greater the uncertainty between the forecasted and actual values, the less confident operators will be in relying on forecasts for maintaining system reliability, especially in high-penetration scenarios. Here, we define high penetration as a threshold of wind and solar power generation that begins to affect power-system operations. This level will be different for each system depending on operational practices, generation mix, inherent flexibility, and market rules. Not only does the variable nature of the atmosphere (e.g., wind, temperature, and irradiance) impact the power output from wind and solar power generators, but it is also a factor in determining the load, which together account for the variability that must be balanced by the power system.

Integrating high penetrations of variable generation is quickly becoming a reality for many utilities, balancing authorities (BA), and Independent System Operators (ISO) throughout the United States. As of 2012, nine states obtain more than 10% of their electricity from wind energy [7]. Additionally, with widespread adoption of state renewable portfolio standards (RPS), reduction in the cost of energy, and growing concerns about climate change, a rapidly expanding fleet of utility-scale wind and solar power systems are being incorporated into the grid. The number of systems above 20 MW is increasing dramatically, which will affect electric power system planning and operations processes. Also, there is increasing interaction between the distribution and transmission systems with the advent of roof-top solar, demand-side strategies, electric vehicles, more affordable storage, distributed generation, and multimegawatt power plants on distribution feeders.

Several papers have been published overviewing wind and solar power forecasting technologies [8]–[17]. This paper is intended to present recent advancements through large-scale research programs, including trends in forecast adoption and market evolution within the U.S. power system.

II. Recent Technology Advancements

Numerical weather prediction (NWP) is a major component of wind and solar power forecasting. The National Oceanic and Atmospheric Administration (NOAA) generates many of the NWP products used as inputs to the wind and solar power products created by forecast providers. The U.S. Department of Energy (DOE) and NOAA both recognize that improvements to NWP models will benefit renewable energy forecasting applications, and these agencies have established a Memorandum of Understanding to further cross-agency collaboration in part to assess and develop "new methodologies for weather-dependent and oceanic renewable energy resource forecasting" and "support advanced forecasting methods..." [18]. Thus DOE, in partnership with NOAA, has funded two major studies to advance renewable energy forecasting capabilities. These two studies, the Wind Forecasting Improvement Project (WFIP) [19] [20] and the Improving the Accuracy of Solar Forecasting Project, are intended to make substantial enhancements to NWP physics, data assimilation, model grid resolution, and output parameters that will benefit renewable energy applications. While NWP is typically a foundational input to variable generation forecasting technologies, the forecast process is often augmented by complex statistical algorithms and coupled modeling systems as discussed in the following sections.

A. DOE/NOAA Wind Forecasting Improvement Project

The skill of NWP in predicting winds within the atmospheric boundary layer is key to the accuracy of wind-power forecasts. Prior to WFIP's commencement, forecast errors were on the order of 10–30% (by energy) for intraday to day-ahead forecasts for individual wind plants and 6–18% (by energy) for a region of aggregated plants [21]. Historically, wind-speed forecast errors of 1–2 m/s were acceptable to most users of NWP forecasts. However, since wind power is a function of wind speed cubed, these relatively small errors in wind speed produce significant wind power forecast errors between turbine cut-in and rated wind speeds.

One WFIP hypothesis is that having a better representation of the boundary layer will improve NWP wind-speed predictions, and that this may be accomplished by initializing and bias correcting with additional ground-based observations including wind-profiling radars, SoDARs, LiDARs, surface flux stations, and industry-provided meteorological tower and turbine nacelle data [19]. Another hypothesis of WFIP is that better assimilation and postprocessing methodologies would also produce better weather forecasts. Additionally, NOAA's intraday to day-ahead NWP products are at temporal and spatial scales that are suboptimal for wind energy applications, so a major aspect of WFIP is to test and improve an experimental high-resolution rapid refresh (HRRR) model, which is using the additional observations and is updated hourly.

The WFIP forecasts and analyses were performed for two regions in the U.S., the Midcontinent ISO (MISO, formerly the Midwest ISO) and the Electric Reliability Council of Texas (ERCOT), with an emphasis on the short-term (0–6 h) time frame. The wind power forecasting techniques varied between the two study regions. The MISO study, led by WindLogics, uses three different NOAA NWP forecasts, the operational Rapid Update Cycle (RUC) [replaced by the Rapid Refresh (RAP)], an experimental RAP (ESRL), and the HRRR, which were each bias-corrected, run through a machine-learning process, and combined with a fourth NWP model, the North American Model (NAM), to create an ensemble forecast. This team evaluated the improvements at each step along the forecast process. The ERCOT study, led by AWS Truepower, used three NWP models, the Weather Research and Forecasting (WRF) system [22], the Mesoscale Atmospheric Simulation System (MASS) [23], and Advanced Regional Prediction System (ARPS) [24], [25], each with three different configurations, in addition to the HRRR for a total of ten NWP forecasts. Each forecast was bias-corrected and weighted to generate an ensemble wind-power forecast. This forecast was then compared with the baseline ERCOT Short-Term Wind Power Forecast (STWPF). More details of these forecasting systems can be found in a paper by Orwig et al. [19] and the respective final reports [62], [63].

The results demonstrate that methods undertaken to improve the forecasts have proven successful, particularly for shorter forecast horizons. Examples of the results are shown in Fig. 1.

B. DOE/NOAA Improving the Accuracy of Solar Forecasting Project

Solar power forecasting technologies are relatively less mature than those for wind power due to lower solar penetration levels and the difficulty of accurately predicting clouds in NWP models. Additionally, solar irradiance measurements are limited, and forecasters often have to rely on satellite data for verification. It is necessary to derive and predict several irradiance values including direct normal irradiance (DNI), diffuse irradiance, plane-of-array (POA) irradiance, and global horizontal irradiance (GHI) from satellite imagery [26]. These derivations, and predictions thereof, require knowledge of the aerosol optical depth (for which there are few observations), cloud heights and densities (which are difficult to derive from visible satellite imagery), as well as cloud dynamics and other factors. Also, the more advanced radiative transfer and cloud microphysics schemes necessary to accurately forecast irradiance dramatically increase the computational expense of the NWP models.

To achieve significant advances in solar irradiance and power forecasting, the DOE SunShot program funded the Improving the Accuracy of Solar Forecasting project, which began in early 2013. This project seeks to develop standardized metrics, baselines, and target values to measure forecast accuracy improvement (see Section II-E), and enhance forecasting technologies

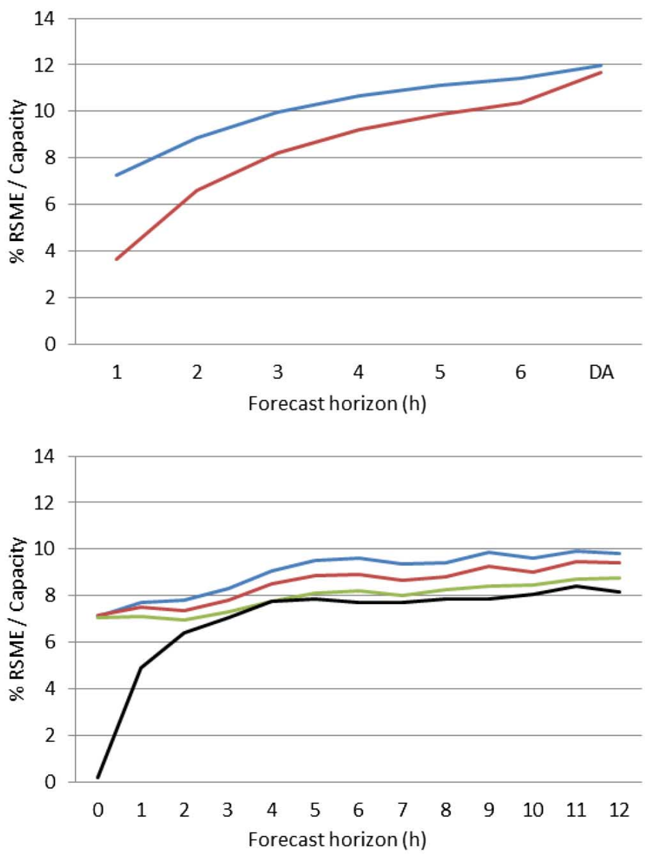

Fig. 1. Forecast errors for (top) current ERCOT STWPF (blue) and WFIP (red) forecasts for various forecast horizons in ERCOT from October 2011 to September 2012, and (bottom) raw NWP (blue), bias-corrected NWP (red), coupled machine learning/NWP (green), and ensemble of coupled machine learning/NWP forecasts (black) for the aggregate of NextEra wind plants in MISO from January to September 2012.

while integrating the forecasts into the control room. The two integrated teams of industry, public, and academic organizations are led by the National Center for Atmospheric Research (NCAR) and IBM Research, respectively. This project will be a collaborative effort, with DOE and NOAA providing a public platform for incorporating the resulting forecast advancements. The advancements will include: a new Weather Research and Forecasting Solar (WRF-Solar) model; an operationalized rapid update WRF (every 15 min); improved radiative transfer, cloud, and aerosol physics; incorporation of enhanced NOAA satellite imagery; and a "big data"-driven machine-learning multiscale forecasting platform.

Each of the teams will supply quasi-operational forecasts to their utility and BA partners for 1 year. This will allow for iterative improvement, as well as provide a sufficiently long time series to perform verification. A lasting impact of this solar-forecasting project will be wide dissemination of the results and an integrated evaluation that includes advances in NWP and statistical learning methods, and metrics to assess the forecast value.

C. Observation Systems for Very Short-Term Forecasting

Observation systems are another aspect of forecasting that have recently experienced an evolution in value. Meteorological observations devoted to variable generation projects were only considered useful for resource assessment purposes (and not economical to maintain once projects were built), but data from such stations are now integral to the system operations process. Several load-serving entities (LSE) and BAs currently obtain more detailed observational data from devoted networks and from within wind and solar power plants to augment and facilitate variable generation forecasts. The Hawaii Electric Company (HECO), for example, with support from DOE and the Electric Power Research Institute (EPRI) has strategically sited remote sensing equipment (multiple SoDARs, a scanning LiDAR, and a radiometer) to enhance deterministic and probabilistic forecasts, as well as ramp alerts [27], [28]. Also, Xcel Energy, HECO, and Southern California Edison (SCE) all require the measurement and provision of various meteorological parameters within their power-purchase agreements. In addition, all BA/ISOs with centralized forecasting systems [e.g., MISO, ERCOT, Bonneville Power Authority (BPA), New York ISO (NYISO), Pennsylvania-New Jersey-Maryland (PJM), ISO New England (ISONE), and California ISO (CAISO)] require that some data be provided from variable generation projects. Indeed, the Federal Energy Regulatory Commission (FERC) Order 764 [29] mandates provision of such data to BAs who perform centralized wind power forecasting.

Quantifying the benefit of additional observations can be difficult and may be quite specific to certain systems or regions. As mentioned earlier, the WFIP project is quantifying the value of additional observations for improving initial conditions of NWP models. The WFIP instrument suite provides information about a deep column of the atmosphere and hub-height data from the wind plants. The results from the MISO region showed an improvement in forecast accuracy of 2–5% of energy produced at each plant over the first 6 h of forecasts at most NextEra wind plants within the study area. The largest improvements were seen in the northern half of the study area, where the observation networks are very sparse compared to the southern portion of the study area. Additionally, the DOE Improving the Accuracy of Solar Forecasting project is developing very short-term forecasts utilizing sky imagers and other ground-based observations in addition to satellite imagery, which will be coupled with other intraday and day-ahead forecast systems. Also, the Sacramento Municipal Utility District (SMUD) has ongoing research to determine the value and spatial granularity necessary for producing accurate distributed PV production and forecast estimates using ground sensor data.

D. Advanced Statistical Methods and Forecasts

Statistical learning and optimization communities have grown significantly in the last decade as data availability and computing capabilities have substantially increased. The methods developed have evolved from foundational, theoretical, and computational roots and are now applied in a wide variety of fields including medical, biological, financial, engineering, security, video gaming, professional sports, and other industries. In renewable energy, recent developments include coupled systems that combine observations, NWP with improved data assimilation schemes, and advanced statistical models to improve forecast accuracy. These statistical models often include the use of artificial intelligence algorithms [30]–[36] and Kalman filtering [37], [38]. In general, these coupled models take historical and modeled information and optimize outcomes that "learn" as more information is provided to the system. These methods often lead to more accurate and precise forecasts. For example, in WFIP, forecasts generated with a coupled machine-learning/NWP system perform better overall than raw NWP forecasts, as shown in Fig. 1. The usage of these advanced techniques for forecasting has become much more acceptable and widespread in recent years.

E. Forecast Uncertainty and Performance Metrics

Currently, there is considerable debate in the industry regarding the best metrics for measuring the accuracy of forecasts. Recent research has better characterized forecast errors [39]–[42], but at present, there is no industry-wide standard performance metric. Also, work being performed under the DOE Improving the Accuracy of Solar Forecasting project has recently proposed a number of new metrics for evaluating solar power forecasting [43], with an emphasis on capturing the economic value of improvements to power system operators. These new forecasting metrics attempt to distinguish the most important improvements to the model, as well as prediction of power. The end goal is to build a value chain that quantifies the value of the forecast to the end user.

Statistical metrics are tested to ascertain how well they characterize the observed power production versus the forecasted power production. Another key component of this effort is to poll a wide variety of stakeholders and integrating their input into options tested by the team members. These metrics include Pearson's correlation coefficient, normalized RMSE, maximum absolute error (MaxAE), MAE, mean absolute percentage error (MAPE), mean bias error (MBE), standard deviation, kurtosis, skewness, Kolmogorov–Smirnov test Integral (KSI), and the integrated differences between cumulative distribution functions (OVER). Additionally, the metrics are evaluated as to their ability to represent the variability of solar power over a variety of time and geographic scales, and include the kernel density estimation (KDE). Key metrics for uncertainty quantification include the standard deviation and the Rényi entropy [41]. Heat maps and the swinging-door algorithm [44] will be used to quantify ramps at a variety of scales. Finally, economic metrics that also account for load forecast error will be used to assess the need and cost for flexibility reserves.

The sensitivity and performance of each of these metrics are another challenge that is being investigated using Support Vector Regression (SVR) and extended Fourier Amplitude Sensitivity Test (eFAST). The former has gained popularity in recent years in statistical learning and optimization communities and is being used to estimate metric performance via response surfaces that establish relationships between inputs and outputs. Meanwhile, eFAST is a variance-based sensitivity analysis approach that evaluates the impact of inputs on the outcome.

Results of this work, as discussed by Zhang et al. [40], showed that all of the metrics evaluated were successful in assessing forecast performance. All metrics were also found to be sensitive to uniform improvements to forecasts, while kurtosis, skewness, and Rényi entropy were also sensitive to ramp forecast improvements. Further work is underway to define forecast performance targets for specific utilities, BAs, and ISOs. Also, metric development and assessment for probabilistic forecasts are still needed.

There have been recent key advances in the presentation of uncertainty information in a manner that is clear and intuitive to system operators and allows the operators to gain additional trust in the forecasts. Ensemble and probabilistic forecasting methods are increasingly used because of their ability to better characterize the most likely power production, represent potential extreme scenarios, and provide a way to quantify the uncertainty [45]–[49]. The forecasts can be generated by running a variety of NWP models, running a single NWP with various physics configurations, or a combination thereof. They can also be coupled with aforementioned statistical models and ground-based observations to obtain power production estimates. The result is any number of power production forecast scenarios that can be blended to produce a "best guess" deterministic forecast based on the ensemble. Each of the ensemble members can be evaluated individually or collectively as well, to assess extreme scenarios, establish confidence intervals, or define probability distribution functions that describe the likelihood of different scenarios.

This ensemble approach, while providing valuable information, can be very computationally intensive. A similar yet more efficient approach that is emerging can identify analog conditions with a single deterministic forecast and use those to form an "analog ensemble" [37], [50]. This technique shows promise for improving upon deterministic forecasts while providing reliable forecast uncertainty information.

Incorporating easy-to-interpret probabilistic information into decision-making and energy management processes is one of the major barriers to the widespread adoption of probabilistic forecasts. ERCOT and HECO, for example, are working with AWS Truepower to implement a probabilistic ramp alert system, which is currently used primarily for situational awareness. Similarly, Xcel Energy is working with NCAR on such implementation. A more detailed discussion of this system follows in Section III-C.

III. Variable Generation Forecast Utilization

A. Value of Variable Generation Forecasts

The use and benefit of variable generation forecasts varies for each utility, ISO, and BA, so generalizations are difficult. Integration studies have historically shown that day-ahead forecasts can provide significant cost savings to grid operators under high-penetration scenarios [1]. On a system-by-system or intraday basis, it is less clear what the benefits are, broadly speaking. One of the goals of WFIP was to demonstrate the economic benefits of 0–6-h-ahead (HA) wind power forecasts for two grid operators, MISO and ERCOT. For places like Hawaii, where energy and fuel prices are directly correlated, the cost benefits can be quite significant with increasing fuel prices. As natural gas prices recover from historic lows, improved accuracy of forecasts can provide even more value in terms of system production cost savings.

It is important to point out that integration studies and WFIP assume that forecasts are optimally used within power system operations, which is a necessary assumption in the unit commitment modeling process. In reality, grid operators may not fully realize the full benefits, as modeled, from wind and solar power forecasts, much less from improved forecasts. This forecast usage optimization problem arises from barriers to forecast implementation within energy management systems (EMSs), and include cultural acceptance, forecast performance verification, and the interpretation of uncertainty. Efforts are currently underway to address these barriers and will be discussed further in the following sections.

B. Forecast Adoption

More and more LSEs and BAs are investigating and using variable generation forecasts to optimize their market and system operations. Porter and Rogers [51] published a survey of variable-generation forecast usage in the western U.S. After interviewing 11 BAs in 2011, they found that most of them use variable generation forecasts for intraday unit commitment, and half use them for determining reserve requirements. Most use wind power forecasts but few are using solar power forecasts due to the low solar penetration at the time of the survey. The authors also specify that generalizing forecast usage is difficult because of each BA's unique circumstances. For example, one BA has no load and uses wind forecasts for scheduling hourly sales, operating reserves, and generation outages, while another BA exports most of their wind power and uses the forecast for operational planning and hydropower dispatch.

The extent of forecast usage has also evolved. Porter and Rogers [51] provide examples of how very simple forecasting systems were implemented initially, but now more sophisticated systems are used or being developed. Substantial advancements on this front have been made since the publication of this survey.

ERCOT currently contracts with AWS Truepower to produce an hourly wind power forecast, updated each hour for a rolling 48-h period. Forecasts are provided for individual wind power plants and for the whole service region. ERCOT primarily uses these forecasts for its day-ahead and intraday reliability unit commitment. Historical forecast errors from the previous month and same month of the previous year are one of the parameters used to determine nonspinning reserve requirements. In addition, the plant level forecasts are shared with the plant's scheduling agent so that the forecasts can be used in the decision-making processes. Aggregate wind power forecasts are also available on ERCOT's website for public access. Like many others, ERCOT has not yet invested in a centralized solar power forecast due to the relatively low penetration of solar plants in their system.

SCE has developed and been using different types of forecasts since the mid-1980s. SCE uses variable-generation forecasting in many aspects of the trading and energy operations timeline. These uses include situational awareness information, short- and long-term planning, trading position inputs, transmission position inputs, short-term position inputs, and after-the-fact data for analysis. All these uses filter down to more granular processing of the information depending on the particular needs of each group.

SMUD is taking measures to adopt solar power forecasting, as well as to provide feedback to forecast providers on areas of desired improvement. Throughout 2013, they have been working with four commercial solar power forecasters, Clean Power Research, Garrad Hassan, Green Power Labs, and AWS Truepower, to validate their forecast performance using an extensive network of 74 solar monitoring devices and 8 utility-scale PV systems. SMUD is evaluating spatial forecast accuracy and approaches to enhance temporal granularity and accuracy relative to predicting variability. SMUD is actively working with NCAR's team on the DOE-funded solar forecasting project to enhance forecast accuracy and appropriately value it. SMUD has incorporated solar forecasts into its Energy Trading platform to improve generator dispatch and procurement decisions.

Xcel Energy contracted with NCAR to develop a wind power forecasting system that has been licensed to Global Weather Corporation, and incorporated into Xcel Energy's operations [52], [53]. Xcel is also collaborating on solar power forecasts, both for their commercial sites and distributed solar systems.

HECO, in partnership with AWS Truepower and EPRI, has developed a real-time Solar and Wind Integrated Forecasting Tool (SWIFT) that is augmented by strategically sited remote sensing systems [54], [55]. SWIFT provides a short-term (6HA) forecast for wind and solar, updated every 15 min and a 48HA forecast for dispatch purposes. The probabilistic forecast also provides ramp alert statistics and probability of exceedance statistics to operators with an indication of how variable the wind or solar production is expected to be and to plan conventional generators accordingly. SWIFT is available through a web interface that provides a geographic view of the observed production by plant and substation-level forecasted production, wind vectors at 80 m, and the irradiance over the operational area (Fig. 2). SWIFT is being integrated into the real-time EMS environment as part of the High-Penetration PV Initiative (HiP-PV) in collaboration with the SMUD under the California Public Utility Commission (CPUC) California Solar Initiative [27] and DOE SunShot Program.

Other current efforts underway include the DOE SunShot SUNRISE project with HECO, San Diego Gas & Electric (SDG&E), CAISO, and SMUD to incorporate distributed and utility-scale solar forecasts into their EMS and Distribution Management Systems (DMS) [56]; and the Pacific Northwest National Laboratory (PNNL) project with the California Energy Commission (CEC), CAISO, AREVA, and the University of Washington to integrate wind power forecasts and their uncertainty into the AREVA and CAISO EMS [57].

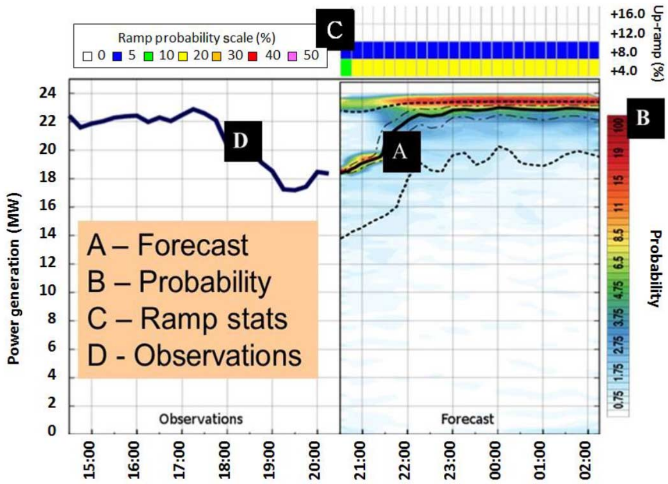

Fig. 2. SWIFT short-term wind forecasting screenshot with observations, forecast, ramp rate, and probability information.

C. Ramp Alert Systems

With higher penetrations of renewables on the grid, some LSEs and ISOs are implementing ramp alert systems. For example, ERCOT has contracted with AWS Truepower to develop and implement the ERCOT Large Ramp Alert System (ELRAS). ELRAS is a probabilistic ramp forecast updated every 15 min showing the likelihood of a ramp of a certain magnitude occurring within a range of time frames. Although ELRAS is not directly used by the commitment or dispatch applications at this time due to its probabilistic framework, the tool can significantly increase the level of situational awareness available to the operator by helping them to better gauge the level of risk that exists in the system. This risk can then be managed by taking into consideration additional factors, such as potential changes in energy consumption, reserves that can be deployed, and additional generators that may be available for commitment. As stochastic unit commitment and other related tools continue to evolve, there may be additional opportunities for the use of probabilistic forecast information.

Over the last several years, SCE has worked with many public, private, and academic organizations to develop ramp forecasting capabilities to be used as early warning and/or equipment deployment tools. Recent changes in market design in California, and perhaps even more so in other regions, may change the requirements and need for short-term ramp awareness.

D. Distributed Solar Power Forecasting

Distributed solar power has been increasing rapidly in some service areas, which has resulted in greater uncertainty in the load forecasts. For example, on a clear day in HECO, the load can be offset by 30% or more by behind-the-meter PV systems during certain times of the day [27]. SMUD and SCE have also observed load peak shaving. To provide more visibility to the value and variability of distributed resources, HECO recently made the Renewable Watch (REWatch) tool available for staff and the general public (Fig. 3). REWatch displays the amount of renewable generation and its impact on the system load. Additional details can be found on the HECO Company website (http://www.heco.com).

There is an increasing need to improve load forecasting capabilities that better incorporate distributed generation. Integrated solar forecasting has been an important component of the HECO efforts, demonstrated in recent SWIFT capabilities [54], [55] and scenario-based studies such as the Hawaii Solar Integration Study (HSIS) sponsored by DOE's SunShot initiative and the University of Hawaii's Hawaii Natural Energy Institute (HNEI) [58]. HECO and SMUD will continue to incorporate distributed solar forecasting and support EMS integration as part of the CPUC California Solar Initiative-sponsored HiP-PV Initiative [59]. Other utilities such as Xcel Energy are similarly working toward estimating the impact of distributed solar energy on their load and distribution system.

E. Power System Architecture and Forecasting

Utilities, ISOs, and BAs are beginning to recognize and take advantage of relationships between forecast error and forecast horizons, and between the magnitude of output variability and the length of the dispatch period. Several ISOs now integrate large amounts of wind power into their systems with little to no impact on operating costs or system reliability. Shorter dispatch intervals that incorporate both actual and forecast generation data, produced as close to the dispatch time as possible, are components to these successes. Dispatching generation (both conventional and variable) more dynamically can help mitigate the impacts of variable generation. Fig. 4 demonstrates how reducing the schedule interval by 50% affects the magnitude of the schedule error due to variability.

For example, MISO now requires most wind power plants to submit updated schedules every 5 min, enabling them to dispatch generation that accounts for variations in wind generation on 5-min intervals. A similar approach has also been taken by ERCOT with its transition to 5-min real-time dispatch in late 2010. Real-time wind power plant capabilities are updated every couple of seconds based on conditions at the wind site. Information about the conventional generation plants is also updated with the same frequency. This process ensures that dispatch systems will always have current information regardless of when the dispatch solution is being executed. This approach has helped the system operator keep increases in reserves very modest despite continuing to see an increase in variable generation resources.

Enabling more dynamic dispatch capabilities takes advantage of the implicit nature of wind energy and weather, just as other scheduling practices, such as start-up costs and minimum run times, are used to reflect the implicit characteristics of thermal generators and fuel sources. Because wind power is relatively consistent over a period of up to 10–15 min, a persistence forecast at any given node will yield a small error relative to the overall generation of the system. Experiences in regions such as MISO and ERCOT that combine short-interval dispatch with very short-range forecasts (within 10 min of power flow) show that wind power plants can be fully incorporated into the real-time market. Once this happens, wind generators also have

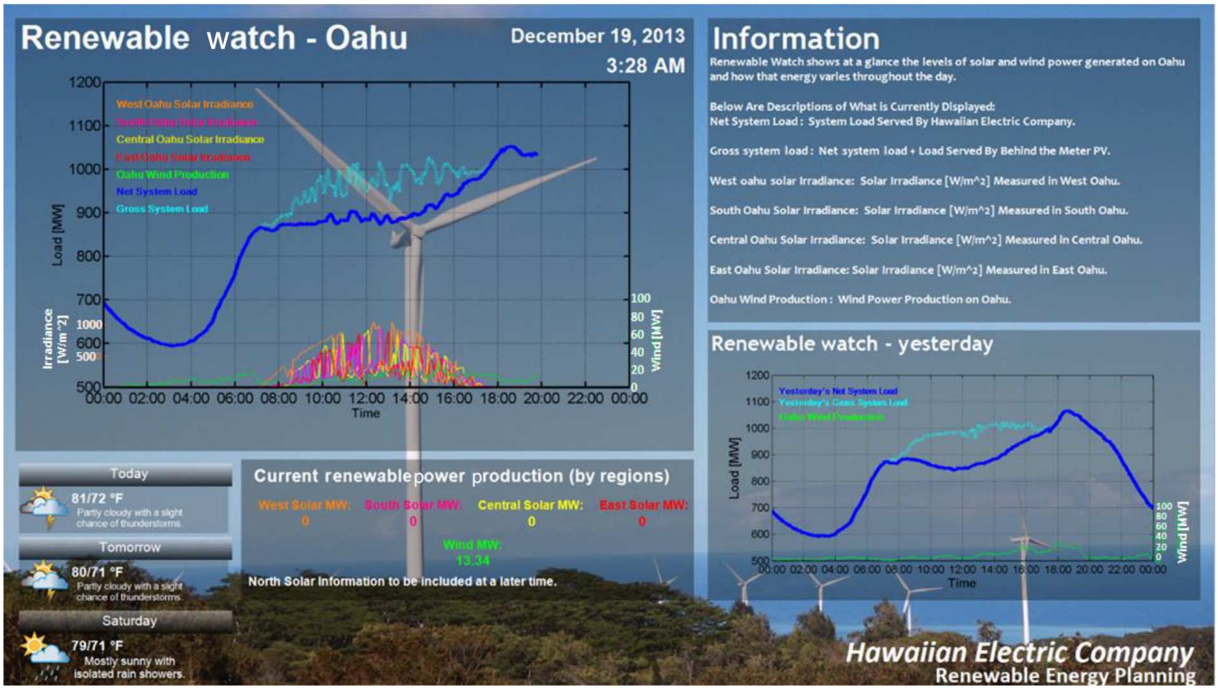

Fig. 3. Screenshot of HECO's REWatch display. Note the load ramps (light blue) in upper left chart due to behind-the-meter PV.

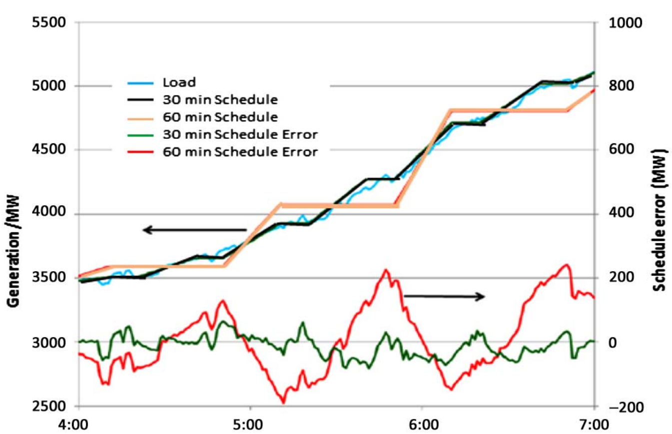

Fig. 4. Plot illustrating how schedule error of variable generation (or load) is a strong function of scheduling interval [60] (Courtesy: Kirby [61]).

more incentive to fully participate in the day-ahead or other intraday markets (if available). Market integration also provides virtual traders with the possibility to apply foresight of expected generation and load conditions to arbitrage opportunities. Thus, full market participation increases the value of wind power forecasts to utilities, market participants, and traders in these other timeframes and aids price convergence between day-ahead and real-time markets, which implies a more efficient and reliable market system. Further, this migration of value upstream from system operation necessitates improvements in both forecast skill and effective forecast communication.

Solar power, on the other hand, exhibits significant ramps and variability, even for behind-the-meter distributed roof-top systems for whole neighborhoods, within a 10–15 min period due to cloud shadowing. Therefore, persistence forecasts are much less reliable and additional aggregation, very short-term forecasts, or other mechanisms may be needed to reduce scheduling error. As noted earlier in this paper, research is ongoing into the use of instruments such as sky imagers and satellite imagery for very short-term solar forecasting systems. As with wind generation, geographic diversity will smooth some of the variability observed in the solar power output in many circumstances but not others (e.g., Hawaii).

The topic of market design is contentious at best. However, many systems are evolving to accommodate new generation sources. This evolution includes decision gates, closure times, and operating intervals that are more aligned with time periods that allow for a more efficient and reliable system based on the available generation mix and load requirements. Nodal markets, where each node has its own energy price, with frequent dispatch make it relatively easy to incorporate variable generation, and include NYISO, ISONE, MISO, ERCOT, and PJM. Zonal markets, where the energy prices are set over a large region, may have less transparency around the causes and locations of transmission congestion. However, these regions, such as in the European Union, may find reductions in scheduling error through aggregating portfolios of wind and solar energy offers into hourly markets or other methods. In the end, each system has its own unique way to manage variable generation. Ideally, mechanisms used should optimize system efficiency and reliability, and variable generation forecasting will continue to play a role in achieving this optimization.

IV. Concluding Remarks

Variable generation forecasting has seen major advancement in its science and application over the last several years. It is now a key component to the integration of large penetrations of wind (and eventually solar) power for many utilities, ISOs, and BAs. The forecasts and improvements thereof provide substantial economic and reliability benefits, in practice and in theory (i.e., power system modeling and simulation). However, there continue to be a number of barriers to the full adoption of variable generation forecasts in decision-making and energy management processes, thereby reducing the economic benefits realized. These barriers include cultural acceptance, forecast performance and verification, interpretation of uncertainty, and integration into EMSs, all of which are currently being addressed through various research efforts, as discussed in this paper.

In parallel to the advancement of variable generation forecasts, the power system operational architecture is evolving such that many systems now have real-time or near real-time markets or scheduling, where wind power is more reliably forecasted, and cost-effective now-casting solutions are available for solar power forecasts.

In conclusion, the value of variable generation forecasting is very system-dependent. Some systems will find more benefit from short-term intraday forecasts, while other systems will obtain greater value in day-ahead or ramp-alert systems. There are a variety of approaches and solutions that each LSE or BA can use to tailor the way they utilize variable-generation forecasting to efficiently and reliably integrate those generation resources into their systems.

REFERENCES

[1] J. DeCesaro, K. Porter, and M. Milligan, "Wind energy and power system operations: A review of wind integration studies to date," *Electr. J.*, vol. 22, pp. 34–43, 2009.

[2] E. A. DeMeo, W. Grant, M. R. Milligan, and M. J. Schuerger, "Wind plant integration," *IEEE Power Energy Mag.*, vol. 3, no. 6, pp. 38–46, Oct. 2005.

[3] L. E. Jones, *Strategies and Decision Support Systems for Integrating Variable Energy Resources in Control Centers for Reliable Grid Operations*. Washington, DC, USA: Alstom Grid Inc., 2011.

[4] NERC, "Special report: Accomodating high levels of variable generation," North Amer. Electr. Rel. Corp., Princeton, NJ, USA, 2009 [Online]. Available: http://www.nerc.com/files/ivgtf_report_041609.pdf.

[5] J. C. Smith, M. R. Milligan, E. A. DeMeo, and B. Parsons, "Utility wind integration and operating impact state of the art," *IEEE Trans. Power Syst.*, vol. 22, no. 3, pp. 900–908, Jul. 2007.

[6] M. Ahlstrom, L. Jones, R. Zavodil, and W. Grant, "The future of wind forecasting and utility operations," *IEEE Power Energy Mag.*, vol. 3, no. 6, pp. 57–64, Oct. 2005.

[7] American Wind Energy Association, "U.S. wind industry annual market report year ending 2012," Amer. Wind Energy Assoc., Washington, DC, USA, 2013 [Online]. Available: http://awea.files.cms-plus. com/images/AWEA_USWindIndustryAnnualMarketReport 2012_ ExecutiveSummary(2).pdf.

[8] C. Chow *et al.*, "Intra-hour forecasting with a total sky imager at the UC San Diego solar energy testbed," *Solar Energy*, vol. 85, pp. 2881–2893, 2011.

[9] L. Landberg, G. Giebel, H. A. Nielsen, and T. Nielsen, "Short-term prediction—An overview," *Wind Energy*, vol. 85, pp. 273–280, 2003.

[10] M. Lei, L. Shiyan, J. Chuanwen, L. Hongling, and Z. Yan, "A review on the forecasting of wind speed and generated power," *Renew. Sustain. Energy Rev.*, vol. 19, pp. 915–920, 2009.

[11] E. Lorenz, J. Hurka, D. Heinemann, and H. Beyer, "Irradiance forecasting for the power prediction of grid-connected photovoltaic systems," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 2, no. 1, pp. 2–10, Apr. 2009.

[12] P. Mathiesen and J. Kleissel, "Evaluation of numerical weather prediction for intra-day solar forecasting in the continental United State," *Solar Energy*, vol. 85, pp. 967–977, 2011.

[13] C. Monteiro *et al.*, "Wind power forecasting: State-of-the-art 2009," Argonne National Lab., Lemont, IL, USA, ANL/DIS-10-1, 2009.

[14] J. Remund, R. Perez, and E. Lorenz, "Comparison of solar radiation forecasts for the USA," in *Proc. 23rd Eur. PV Conf.*, Valencia, Spain, 2008, pp. 1–3.

[15] E. Lorenz *et al.*, "Benchmarking of different approaches for forecast solar irradiance," in *Proc. 24th Eur. Conf. PV*, Hamburg, Germany, 2009, pp. 1–10.

[16] S. Soman, H. Zareipour, O. Malik, and P. Mandal, "A review of wind power and wind speed forecasting methods with different time horizons," in *Proc. North Amer. Power Symp.*, Arlington, TX, USA, 2010, pp. 1–8.

[17] Y.-K. Wu, "A literature review of wind forecasting technology in the World," in *Proc. IEEE Power Tech.*, Lausanne, Switzerland, 2007, pp. 504–509.

[18] U.S. DOE Office of Energy Efficiency and Renewable Energy and U.S. DOC National Oceanic and Atmospheric Administration, *Memorandum of Understanding on Weather-Dependent and Oceanic Renewable Energy Resources*, 2011.

[19] K. D. Orwig *et al.*, "Enhanced short-term wind power forecasting and value to grid operations: The wind forecasting improvement project (WFIP)," in *Proc. 11th Int. Workshop Large-Scale Integr. Wind Power Power Syst.*, Lisbon, Portugal, 2012, pp. 1–6.

[20] J. Wilczak *et al.*, "Enhancing short-term wind energy forecasting for improved utility operations: The wind forecast improvement project (WFIP)," in *Proc. 92nd AMS Annu. Meet.; 3rd Conf. Weather Clim. New Energy Econ.*, New Orleans, LA, USA, 2012.

[21] K. Porter and J. Rogers, "Status of centralized wind power forecasting in North America," National Renewable Energy Lab., Golden, CO, USA, Tech. Rep. NREL/SR-550-47853, 2010.

[22] W. C. Skamarock *et al.*, "A description of the advanced research WRF version 2," National Center for Atmospheric Research, Boulder, CO, USA, NCAR Tech. Notes 468+STR, 2005.

[23] J. Manobianco, J. W. Zack, and G. E. Taylor, "Workstation-based real-time mesoscale modeling designed for weather support to operations at the Kennedy space center and cape canaveral air station," *Bull. Amer. Meteorol. Soc.*, vol. 77, pp. 653–672, 1996.

[24] M. Xue, K. Droegemeier, and V. Wong, "The advanced regional prediction system (ARPS)—A multi-scale nonhydrostatic atmospheric simulation and prediction model, Part I: Model dynamics and verification," *Meteorol. Atmosp. Phys.*, vol. 75, pp. 161–193, 2000.

[25] M. Xue *et al.*, "The advanced regional prediction system (ARPS)—A multi-scale nonhydrostatic atmospheric simulation and prediction model, Part II: Model physics and applications," *Meteorol. Atmosp. Phys.*, vol. 76, pp. 143–165, 2001.

[26] R. Perez *et al.*, "A new operational model for satellite-derived irradiances: Description and validation," *Solar Energy*, vol. 73, pp. 307–317, 2002.

[27] D. Nakafuji, "Developing real-time solar & wind integrated forecasting technology (SWIFT) for Hawaii," Presented at UVIG Forecasting Workshop, Salt Lake City, UT, USA, 2013.

[28] J. Zack, "WindNET phase 1, final report," US Department of Energy, Washington, DC, USA, Tech. Rep. DOE/EE0001379–3, 2012.

[29] US Federal Energy Regulatory Commission, *Integration of Variable Energy Resources*, 2012, Docket No. RM10-11-000, Order No. 764.

[30] T. Barbounis, J. B. Thocharis, M. C. Alexiadis, and P. S. Dokopulos, "Long-term wind speed and power forecasting using local recurrent neural network models," *IEEE Trans. Energy Convers.*, vol. 21, no. 1, pp. 273–284, Feb. 2006.

[31] J. Catalao, H. Pousinho, and V. Mendes, "An artificial neural network approach for short-term wind power forecasting in Portugal," in *Proc. 15th Int. Conf. Intell. Syst. Appl. Power Syst.*, Curitiba, Brazil, 2009, pp. 1–5.

[32] R. Jursa and K. Rohrig, "Short-term wind power forecasting using evolutionary algorithms for the automated specification of artificial intelligence models," *Int. J. Forecast.*, vol. 24, pp. 694–709, 2008.

[33] M. Monfared, H. Rastegar, and H. M. Kojabadi, "A new strategy for wind speed forecasting using artificial intelligent methods," *Renew. Energy*, vol. 34, pp. 845–848, 2009.

[34] W. Myers, G. Wiener, S. Linden, and S. E. Haupt, "A consensus forecasting approach for improved turbine hub height wind speed predictions," in *Proc. WINDPOWER*, Anaheim, CA, USA, 2011, pp. 1–4.

[35] N. Sideratos, "An advanced statistical method for wind power forecasting," *IEEE Trans. Power Syst.*, vol. 22, no. 1, pp. 258–265, Jan. 2007.

[36] A. Yona, T. Senjyu, and T. Funabashi, "Application of recurrent neural network to short-term-ahead generating power forecasting for photovoltaic system," in *Proc. IEEE Power Eng. Soc. Gen. Meeting*, Tampa, FL, USA, 2007, pp. 1–6.

[37] L. Delle Monache, T. Nipen, Y. Liu, G. Roux, and R. Stull, "Kalman filter and analog schemes to postprocess numerical weather predictions," *Mon. Weather Rev.*, vol. 139, pp. 3554–3570, 2011.
[38] P. Louka *et al.*, "Improvements in wind speed forecasts for wind power prediction purposes using Kalman filtering," *J. Wind Eng. Ind. Aerodyn.*, vol. 96, pp. 2348–2362, 2008.
[39] R. Bessa *et al.*, "Quantile-copula density forecast for wind power uncertainty modeling," in *Proc. IEEE PowerTech*, Trondheim, Norway, 2011, pp. 1–8.
[40] H. Bludszuweit, J. Dominguez-Navarro, and A. Llombart, "Statistical analysis of wind power forecast error," *IEEE Trans. Power Syst.*, vol. 23, no. 3, pp. 983–991, Jul. 2008.
[41] B.-M. Hodge, K. D. Orwig, and M. Milligan, "Examining information entropy approaches as wind power forecasting performance metrics," in *Proc. IEEE 12th Int. Conf. Probab. Methods Appl. Power Syst.*, Istanbul, Turkey, 2012, pp. 1–6.
[42] M. Lange, "On uncertainty of wind power predictions—Analysis of the forecast accuracy and statistical distribution of errors," *Trans. ASME-N-J. Solar Energy Eng.*, vol. 127, pp. 177–184, 2005.
[43] J. Zhang *et al.*, "Metrics for evaluating the accuracy of solar power forecasting," in *Proc. 3rd Int. Workshop Integr. Solar Power Power Syst.*, London, U.K., 2013, pp. 1–8.
[44] A. Florita, B.-M. Hodge, and K. Orwig, "Identifying wind and solar ramping events," in *Proc. IEEE 5th Green Technol. Conf.*, Denver, CO, USA, 2013, pp. 147–152.
[45] J. Juban, N. Siebert, and G. Kariniotakis, "Probabilistic short-term wind power forecasting for the optimal management of wind generation," in *Proc. IEEE PowerTech.*, Lausanne, Switzerland, 2007, pp. 683–688.
[46] H. Nielsen *et al.*, "From wind ensembles to probabilistic information about future wind power production—Results from an actual application," in *Proc. Int. Conf. Probab. Methods Appl. Power Syst.*, Stockholm, Sweden, 2006, pp. 1–8.
[47] P. Pinson, C. Chevallier, and G. Kariniotakis, "Trading wind generation from short-term probabilistic forecasts of wind power," *IEEE Trans. Power Syst.*, vol. 22, no. 3, pp. 1148–1156, Jul. 2007.
[48] P. Pinson, H. A. Nielsen, J. K. Moller, H. Madsen, and G. N. Kariniotakis, "Non-parametric probabilistic forecasts of wind power: Required properties and evaluation," *Wind Energy*, vol. 10, pp. 497–516, 2007.
[49] P. Pinson, H. Madsen, H. A. Nielsen, G. Papaefthymiou, and B. Klockl, "From probabilistic forecasts to statistical scenarios of short-term wind power production," *Wind Energy*, vol. 12, pp. 51–62, 2008.
[50] L. Delle Monache, F. Anthony Eckel, D. L. Rife, B. Nagarajan, and K. Searight, "Probabilistic weather prediction with an analog ensemble," *Mon. Weather Rev.*, vol. 141, pp. 3498–3516, 2013.
[51] K. Porter and J. Rogers, "Survey of variable generation forecasting in the west," National Renewable Energy Lab., Golden, CO, USA, Tech. Rep. NREL/SR-5500–54457, 2012.
[52] W. Mahoney *et al.*, "A wind power forecasting system to optimize grid integration," *IEEE Trans. Sustain. Energy*, vol. 3, no. 4, pp. 670–682, Sep. 2012.
[53] K. Parks, Y.-H. Wan, G. Wiener, and Y. Liu, "Wind energy forecasting: A collaboration of the National Center for Atmospheric Research (NCAR) and Xcel energy," National Renewable Energy Lab., Golden, CO, USA, Tech. Rep. NREL/SR-550–52233, 2011.
[54] J. Freedman, D. Nakafuji, J. Zack, K. Pennock, and J. Manobianco, "Operation, implementation, and evaluation of a solar and wind integration forecasting tool (SWIFT) in the Hawaiian Islands," in *Proc. AMS Annu. Meeting; 4th Conf. Weather Clim. New Energy Econ.*, Austin, TX, USA, 2013.
[55] D. Nakafuji, "Hawaii utility integration initiatives to enable wind (WindHUI)," US Department of Energy, Washington, DC, USA, Tech. Rep. DOE/EE0001379–1, 2012.
[56] DOE Solar Program, 2013, *SUNRISE Awardees* [Online]. Available: http://www1.eere.energy.gov/solar/sunshot/sunrise.html
[57] Y. V. Makarov *et al.*, "Wind energy management system integration project," Pacific Northwest National Lab., Richland, WA, USA, Tech. Rep. PNNL-19189, 2010.
[58] R. Piwko *et al.*, "Hawaii solar integration study: Solar modeling developments and study results," in *Proc. 11th Int. Workshop Large-Scale Integr. Wind Power Power Syst.*, Lisbon, Portugal, 2012, pp. 1–8.
[59] E. Sison-Lebrilla and D. Nakafuji, "HiP-PV: PV visualization and integration update," presented at DOE-CPUC High Penetration Solar Forum, San Diego, CA, USA, 2013 [Online]. Available: http://www1.eere.energy.gov/solar/pdfs/highpenforum2013_1_10_smud.pdf
[60] B. Kirby and T. Castille, *FY 2012-2013 Proposed Power and Transmission Rate Adjustments, Attachment 1: To Direct Testimony of the Northwest Wind Group (NG)*, BPA Docket no. BPA-12, BP-12-E-NG-02-AT01, 2011 [Online]. Available: https://www.bpa.gov/secure/Ratecase/openfile.aspx?fileName=BP-12-E-NG-02.pdf&contentType=application%2fpdf
[61] B. Kirby, personal correspondence on Dec. 8, 2013.
[62] J. Freedman *et al.*, "The Wind Forecast Improvement Project (WFIP): A Public/Private Partnership for Improving Short Term Wind Energy Forecasts and Quantifying the Benefits of Utility Operations—the Southern Study Area Final Report," US Dept. Energy, Washington, DC, USA, Tech. Rep. DE-EE0004420, 2014, pp. 1–110 [Online]. Available: http://energy.gov/sites/prod/files/2014/08/f18/Wind%20Forecast%20Improvement%20Project%20Southern%20Study%20Area%20Final%20Report.pdf
[63] W. James *et al.*, "The Wind Forecast Improvement Project (WFIP): A Public/Private Partnership for Improving Short Term Wind Energy Forecasts and Quantifying the Benefits of Utility Operations Final Report," US Dept. Energy, Washington, DC, USA, Tech. Rep. DE-EE0003080, 2014, pp. 1–162 [Online]. Available: http://energy.gov/sites/prod/files/2014/05/f15/wfipandnoaafinalreport.pdf

Kirsten D. Orwig received the M.S. degree in atmospheric science and the Ph.D. degree in wind science and engineering from Texas Tech University, Lubbock, TX, USA, in 2003 and 2010, respectively.

She is an Atmospheric Perils Specialist with Swiss Re, Armonk, NY, USA. She was formerly an Engineer with NREL, Golden, CO, USA, leading wind and solar power forecasting.

Mark L. Ahlstrom (M'04–SM'12) received the B.S. degree in biochemistry and the M.S. degree in biomedical engineering from University of Wisconsin, Madison, WI, USA, in 1979 and 1981, respectively.

He is the CEO of WindLogics Inc., St. Paul, MN, USA, a leader in applied meteorology, wind energy analysis, wind forecasting, and integration.

Mr. Ahlstrom is a member of CIGRE.

Venkat Banunarayanan received the M.S. degree in electrical engineering from the University of Nevada, Las Vegas, NV, USA, in 1994, the Ph.D. degree in electrical engineering from North Carolina State University, Raleigh, NC, USA, in 1998, and the MBA degree in finance from the Union College, Schenectady, NY, USA, in 2010.

He is the Lead for Transmission and Solar Forecasting in the Solar Systems Integration Subprogram of the U.S. Department of Energy for the SunShot Initiative. He is also the Principal with ICF International, Washington, DC, USA.

Justin Sharp received the M.S. degree in meteorology from the Rutgers University, New Brunswick, NJ, USA, in 1997, and the M.S. and Ph.D. degrees in atmospheric science from the University of Washington, Seattle, WA, USA, in 2002 and 2005, respectively.

He is the Principal and Owner of Sharply Focused LLC, Portland, OR, USA, which bridges the gap between energy and meteorology. He was formerly Director of Meteorology with Iberdrola Renewables, Portland, OR, and a Forecast Meteorologist with Bonneville Power Authority, Portland, OR, USA.

James M. Wilczak received the B.A. degree in physics from the Kalamazoo College, Kalamazoo MI, USA, in 1976, and the M.S. and Ph.D. degrees in atmospheric science from the University of Washington, Seattle, WA, USA, in 1979 and 1982, respectively.

He is the Team Leader of the Boundary Layer Processes and Applications Group, ESRL, NOAA, Boulder, CO, USA, and the NOAA Technical Lead of the Wind Forecast Improvement Project.

Jeffrey Freedman received the B.S. degree in meteorology and oceanography from Polytechnic Institute of New York University, New York, NY, USA, in 1980, the J.D. degree in law from New York Law School, New York, NY, USA, in 1984, and the M.S. and Ph.D. degrees in atmospheric science from the State University of New York, Albany, NY, USA, in 1995 and 2000, respectively.

He is a Research Faculty with the Atmospheric Sciences Research Center, SUNY, Albany, NY, USA. He was formerly Lead Research Scientist with AWS Truepower, Albany, NY, USA, Principal with Atmospheric Information Services, a Postdoc with ASRC, Albany, NY, USA, and Assistant Counsel for New York City Department of Environmental Protection (DEP), NY, USA.

Sue Ellen Haupt received the B.S. degree in meteorology and marine science from the Penn State University, State College, PA, USA, in 1978, the M.S. degrees in engineering management and mechanical engineering from Worcester Polytechnic Institute, Worcester, MA, USA, in 1984, and the Ph.D. degree in atmospheric sciences from University of Michigan, Ann Arbor, MI, USA, in 1988.

She is the Director of the Weather Systems and Assessment Program with the National Center for Atmospheric Research (NCAR), Boulder, CO, USA. She was formerly Professor of Meteorology, Head of the Department of Atmospheric and Oceanic Physics, and Applied Research Laboratory, Penn State University, State College, PA, USA.

Joel Cline received the B.S. degree in meteorology and computer science from North Carolina State University, Raleigh, NC, USA, in 1984, and the M.S. degree in meteorology and physical oceanography from University of Miami, Miami, FL, USA, in 2003.

He is a Program Manager in the Wind and Water Power Program with the U.S. Department of Energy and leads the Wind Forecasting Improvement Project. He formerly held several roles within NOAA. He is a certified Project Manager (PMP 2013).

Obadiah Bartholomy received the B.S. degree in mechanical engineering from California Polytechnic State University, San Luis Obispo, CA, USA, in 2002, and M.S. degree in transportation technology and policy from University of California, Davis, CA, USA, in 2008.

He is Project Manager with Sacramento Municipal Utility District (SMUD) in the Energy Efficiency R&D Programs, Customer Advanced Technologies, and Climate Change Program.

Hendrik F. Hamann received the Ph.D. degree in natural sciences, in 1995.

He is the Manager and Research Staff Member with IBM Watson Research Center, Yorktown Heights, NY, USA. He was formerly with JILA, a joint research institute between NIST and University of Colorado.

Bri-Mathias Hodge (M’10) received the B.S. from Carnegie Mellon University, Pittsburgh, PA, USA, in 2004, the Dipl. Inj. from Åbo Akademi, Turku, Finland, and the Ph.D. degree in chemical engineering from the Purdue University, West Lafayette, IN, USA, 2005, and 2010, respectively.

He is a Senior Engineer with NREL, Golden, CO, USA. He was formerly a Postdoctoral Researcher with NREL.

Catherine Finley received B.S. degree in meteorology from Iowa State University, Ames, IA, USA, in 1988, the M.S. degree in atmospheric science from University of California, Davis, CA, USA, in 1990, and the Ph.D. degree in atmospheric science from Colorado State University, Fort Collins, CO, USA, in 1998.

She is a Senior Atmospheric Scientist with WindLogics, Inc., Grand Rapids, MN, USA. She was formerly an Associate Professor of Meteorology with University of Northern Colorado, Greely, CO, USA.

Dora Nakafuji (M’12) received the B.S. and M.S. degrees in aeronautical and mechanical engineering, in 1991 and 1994, respectively, and the Ph.D. degree in aeronautical and mechanical engineering from University of California, Davis, CA, USA, in 2001.

She is the Director of Renewable Energy for HECO and Adjunct Professor with the University of Hawaii at Manoa, Honolulu, HI, USA. She was formerly a Technical Lead with Wind Energy R&D, LLNL and Renewable Integration for the Public Interest Energy Research (PIER) program at the CEC.

Jack L. Peterson is the Trading and Energy Operations Support Manager with SCE, Rosemead, CA, USA. He was formerly with Union Pacific Resources in Oil and Gas E&P. His research interests include industrial automation and controls engineering, facilities construction and relocation, asset management, project management, and field supervision.

David Maggio (M’10) received the B.S. and M.S. degrees in electrical engineering from University of Illinois, Urbana-Champaign, IL, USA, in 2004 and 2006, respectively.

He is the Manager of Congestion Revenue Rights with ERCOT, Taylor, TX, USA, responsible for congestion revenue rights auctions, analyzing consistency across the various ERCOT markets, and related market rules development.

Melinda Marquis received the Ph.D. degree in organic chemistry from University of Colorado, Boulder, CO, USA, in 1995.

She is the Renewable Energy Project Manager with NOAA ESRL, Boulder, CO, USA. She was formerly Deputy Director for the IPCC Working Group I, and Leader of two NASA Earth-satellite missions with the National Snow and Ice Data Center.