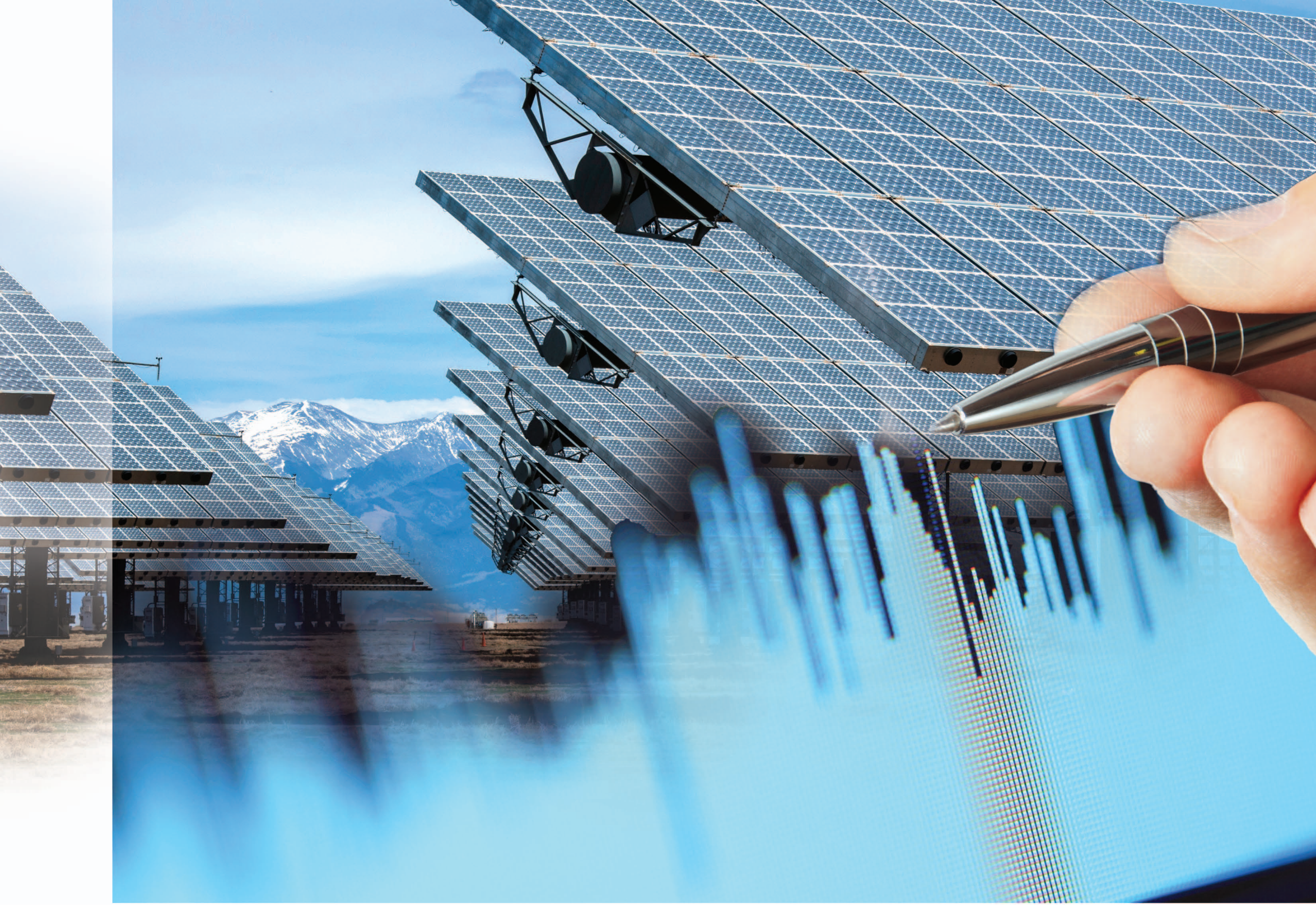

THE DEPLOYMENT OF SOLAR-BASED ELECTRICITY generation, especially in the form of photovoltaics (PVs), has increased markedly in recent years due to a wide range of factors including concerns over greenhouse gas emissions, supportive government policies, and lower equipment costs. Still, a number of challenges remain for reliable, efficient integration of solar energy. Chief among them will be developing new tools and practices that manage the variability and uncertainty of solar power.

Short-term uncertainty (up to a week ahead) can be managed with many possible solutions, such as increased demand-side participation, greater coordination to balance allocation among areas, and deploying more flexible—but often also more expensive—methodologies like energy storage. However, one of the most effective and economical ways to integrate solar, particularly at current penetration levels, is by forecasting the expected power output and using these forecasts to more reliably and efficiently operate the system.

Solar forecasts are already used by a variety of stakeholders in the power industry. System operators use solar forecasts to schedule generation, procure operating reserves, and ensure sufficient flexibility to manage changes in output. Market participants use forecasts to manage their generation portfolios: for example, in Germany, 38 GW of solar capacity is traded on the energy market—an amount that strongly impacts market prices so that even traders who do not sell solar energy use solar forecasts.

Previous issues of this magazine have provided an overview of wind forecasting, including the production of wind power forecasts and their end use. While similar to wind forecasting in many ways, solar forecasting has its own unique characteristics, which this article will explore. In particular,

Solar Forecasting

Digital Object Identifier 10.1109/MPE.2015.2461351
Date of publication: 20 October 2015

1540-7977/15©2015IEEE

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Methods, Challenges, and Performance

solar power forecasting can be differentiated from wind forecasting in that much of the variability and uncertainty is related to visible cloud movement. This can be forecast in the short term by technologies such as ground-based sky imaging and satellite imaging systems; these are described here, along with potential drawbacks related to cloud formation and dissipation.

The underlying "clear-sky" solar PV output is easily calculated based on the position of the solar panels relative to the sun, so the main challenges lie in predicting the actual irradiance at the solar panels given the influence of clouds, aerosols, and other atmospheric constituents, and also PV panel efficiency, which is temperature dependent. Adding to these challenges, large amounts of solar are being installed on the distribution system, often behind the meter (BTM), which means that transmission system operators see only load netted with the solar generation rather than the output of the solar system.

In this article we outline current methods used to produce solar PV power forecasts, focusing on aspects unique to solar forecasting. We also explore the nuances related to BTM solar forecasting and how these interact with load forecasting. In addition, we summarize the current performance of solar forecasting and then end by discussing improvements on the horizon that will increase operators' ability to accurately forecast solar PV generation.

Current Solar Forecasting Techniques

Forecasting solar output involves a variety of methods based on the time frame being forecast, the data available to the forecaster, and how the forecast is to be used. Past issues of the magazine have included articles on wind forecasting covering many basic forecasting techniques also important for solar (see the "For Further Reading" section). These methods, which are broadly categorized in Figure 1 according to the time horizon in which they generally show value, include numerical weather prediction (NWP) and the use of model output statistics, as well as statistical learning methods, climatology, and ensemble techniques that blend different kinds of forecasts.

To achieve the greatest accuracy, forecasters supply environmental inputs, such as irradiance and temperature, to models that transpose the irradiance into the incident plane of array (i.e., by taking the beam direction and solar panel orientation into account) and then convert the irradiance to power. Several methods can be used for this purpose; these are described below beginning with those that perform best on the shortest look-ahead time frames.

Time Series Prediction with Statistical Learning Methods

Direct observation of irradiance (such as from pyranometers or other measurement devices) can be used with time series statistical learning methods to project subsequent conditions. Historical records of site irradiance are used to train these prediction methods, while real-time measurements identify current condition on which to base the forecasts. Methods used include artificial neural networks, regression models, autoregressive models, support vector machines, and Markov chains, as well as composite methods, such as using genetic algorithms to optimize a neural network. These methods work best for the intrahour time horizon, but they may have some value out to two to three hours or more, especially when used in combination with other methods.

Sky Imagers

Sky imagers are digital cameras that produce high-quality images of the sky from horizon to horizon, which are used for detecting clouds, estimating cloud height above ground, and calculating cloud

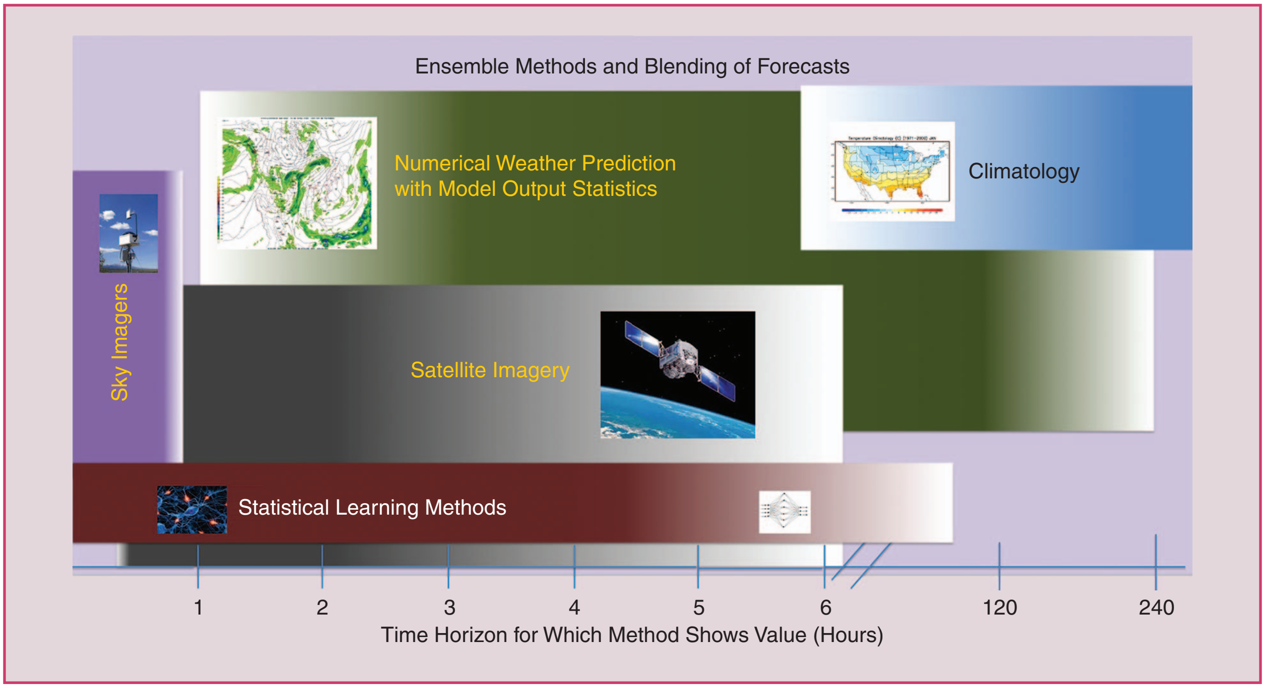

figure 1. An overview of solar forecasting methods, based on time horizon for which they show value.

motion. Clouds scatter some wavelengths of light more than they do others, and these can be used to categorize clouds as thick and thin as well as to differentiate them from aerosols or dust. Consecutive images can estimate cloud velocity and so can provide a very short-horizon forecast. If additional sky imagers are available, triangulation can provide information on cloud base and depth as well as differential advection speed at different cloud levels. Sky imagers are of significantly decreasing value beyond approximately a 30-min time frame; moreover, they are expensive to use relative to most other forms of very short-term prediction.

Satellite Imaging

Providing value for a longer look-ahead time frame, geostationary satellite data from networks such as the National Oceanic and Atmospheric Administration (NOAA) Geostationary Operational Environmental Satellite network for North and South America and the MeteoSat network for Europe, Africa, and central Asia supply information about cloud properties and movement. First, a physically driven model predicts clear-sky conditions at a specific site, using inputs like aerosol content, water vapor, elevation, and ozone. This modeled clear-sky irradiance is then modulated by estimated irradiance derived from satellite images. Sequential satellite images are combined to create cloud motion vector fields that can be used to predict future cloud locations. This technique has been shown to be effective in forecasting irradiance from one minute to as far as five hours ahead. However, it performs less effectively during conditions when clouds are rapidly forming or dissipating, such as convective and marine layer cloud regimes.

Numerical Weather Prediction

NWP systems have been the workhorse of forecasting applications for many years. Traditionally, these have performed best for the time horizon from six hours to two weeks; recently deployed rapid-update systems (such as the NOAA High-Resolution Rapid Refresh system) can provide value at shorter time scales. NWP methods have been well described in previous articles in relation to wind. These involve solving the Navier-Stokes equations to model the weather, combined with modules that compute other physical processes, such as radiative transfer, land surface effects, and cloud microphysics parameterization.

Historically, these models have been optimized for predicting variables such as temperature, humidity, probability of precipitation, and wind. Only recently has there been an emphasis on improving prediction of surface solar irradiance. Statistical learning methods are often used to correct for errors in the NWP model output and to blend output from multiple models in a process referred to as *model output statistics*. It is typical for such methods to improve upon the raw forecast of an NWP model by about 10–15%.

Ensemble Forecasting

Ensemble methods are important to deal with the uncertainty inherent to solar power forecasting, particularly during morning and evening ramps and with cloud cover and fog. An ensemble consists of a collection of forecasts and can represent the uncertainty in the calculation of the state of the atmosphere inherent in forecasting methods. Two major techniques are employed in creating an ensemble: the first adds perturbations to the initial state of a forecasting model, while the second uses different numerical models or physics schemes. Both provide insights into the likelihood of extreme events, such as ramps of solar output due to changes in cloud cover, fog, or other atmospheric features. Ensembles can be applied to any forecasting approach, although they are most well developed for NWP.

Ensemble forecasts for solar generation are used in power markets where the uncertainty of forecasting leads to price volatility. They may also be employed to help in determining reserves or scheduling generation. In such real-world applications, percentiles can be used to make the uncertainty visible and so more easily interpreted. Figure 2 shows how percentile "bands" change in size around a mean value (white line) and the true generation (black line). Percentiles represent a value below which the given percentage of the outcomes is expected to fall. For example, 10% of the outcomes should fall below the tenth percentile (P10) value, while 90% of the outcomes should fall below the 90th percentile (P90) value.

Distributed and Behind-the-Meter Solar PV Forecasting

A number of factors can impact how solar forecasts are developed and used, particularly when the solar generation is connected to the distribution network or is BTM:

- ✔ Whether the generation of a commercial or residential solar power system is recorded on its own or aggregated with customer load.
- ✔ Whether telemetered meter data is available in real time.
- ✔ Whether detailed static data (i.e., metadata) is available (the plant location, the PV geometry, nearby obstructions, hardware information, and the like).

At a large solar plant, meter data is typically available in near-real time and site metadata is generally known. For smaller distribution connected plants, dedicated meter data is usually recorded but is often not telemetered in real time. Metadata may be difficult to obtain as well. For BTM solar, real-time generator data is rarely known, meter data is often net of load, and metadata is difficult to obtain.

Therefore, distribution-connected PVs, in particular BTM PVs, can be more difficult to forecast. If detailed metadata is available, the data can be combined with irradiance and weather data, typically from satellite and/or NWP sources as described earlier. For example, information about all PV systems in the state of California is recorded and then combined with high-resolution irradiance values and weather predictions to forecast output for the entire state. Such a "bottom-up" approach is employed by the California Independent System Operator to predict the total contribution of BTM solar on their grid, as shown in Figure 3.

This approach can be quite cost-effective, particularly in areas having a large number of distributed PVs (California, for example, has more than 200,000 unique PV systems). It allows for wide-area aggregation to support independent system operators in utility-wide prediction and also for regional analysis, where distribution system operators and planners need to understand localized impacts. One potential benefit of this approach is that the particulars of each system are explicitly captured. For example, a PV system that is oriented toward the east will produce a different power curve than a south- or west-facing system, so the fleet composition will influence the resulting power profile for the overall system.

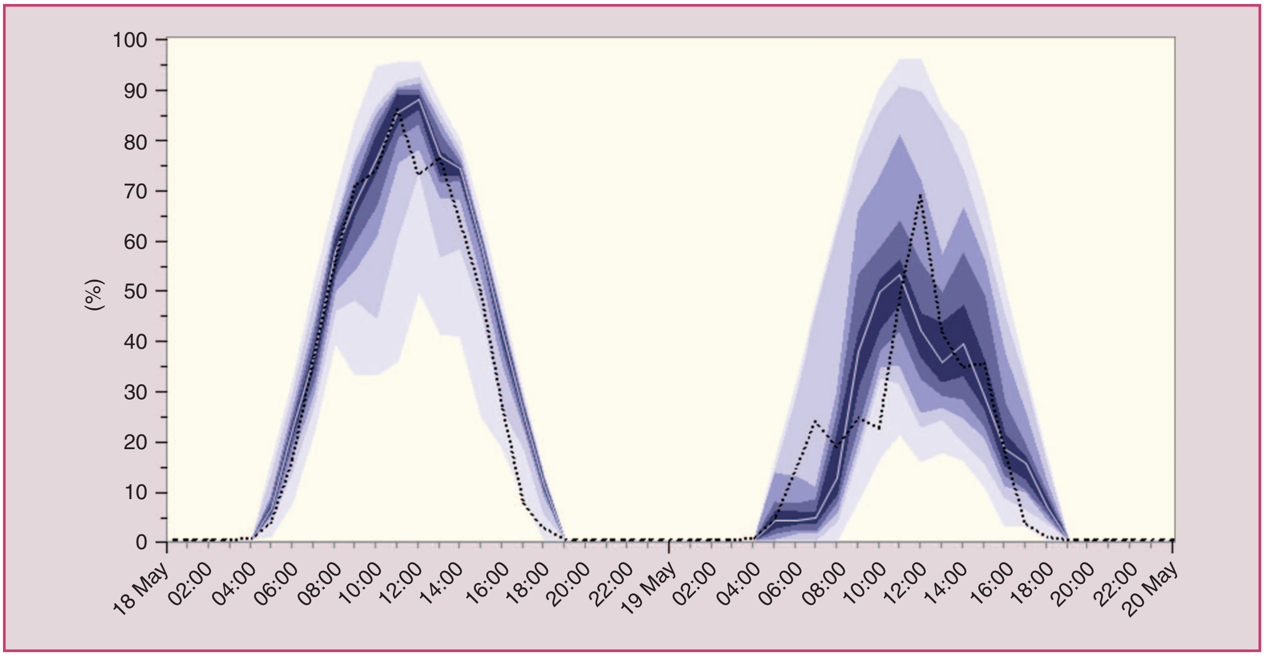

figure 2. An example of a two-day solar power forecast with nine percentiles (P10 through P90) and the actual measurements (black dotted line.)

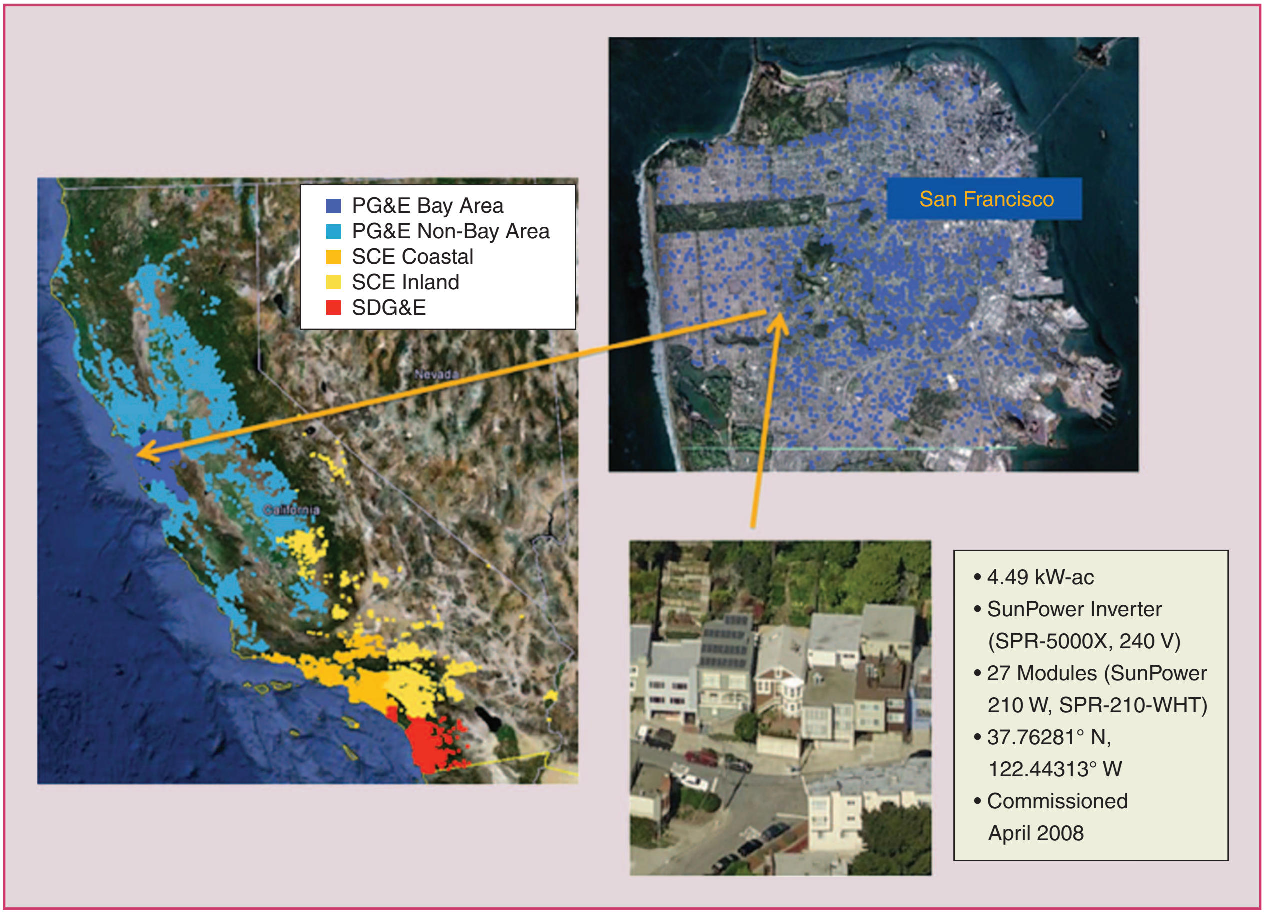

figure 3. Detailed site information and weather data, aggregated to fleet level, for the three major investor-owned utilities in California. (Courtesy of Clean Power Research.)

Challenges, however, do exist for this approach. While most hardware, location and orientation information is typically well documented, dynamic elements about each PV installation such as shading and hardware system availability will also impact the accuracy of the prediction. Suitable approaches are being developed to account for these impacts.

In applications where the objective is forecasting aggregated PV production or net load across a large system and/or where detailed data do not exist, other less detailed prediction methods can be deployed based on combinations of existing data, such as substation loads and regional meteorological data. This "top-down" approach has the advantage of limited data requirements. Whereas the bottom-up approach uses validated models applied to each system, the less detailed top-down approach requires comparisons to metered data on a statistically significant number of sites for benchmarking its overall accuracy. Challenges with this approach center on the representation of the statistical sample to adequately depict the total solar contribution. Ongoing research is focused on determining the detail of system data required based on the given PV penetration. It is important to recognize that different end users may have different requirements in terms of the amount of detail needed.

As an example, the forecasts for transmission system operators and distribution system operators in Germany are calibrated and evaluated against estimations of the solar production on a zip code level (Figure 4). Forecasts of aggregate BTM PV production are developed and validated based on the up-scaling of output from a select subset of representative PV sites. The real-time solar production is directly obtained from the solar inverters of these installations through companies that install PV modules and monitor their performance. This approach has two main advantages: first, the grid operator can predict solar output in real time, and, second, the forecasts can be optimized on a regional level.

Comparisons between such estimations and metered data show a very strong correlation. Essential to this approach is consideration in the selection of representative sites, for which sufficiently granular and reliable production data must be available. Further, real-time telemetry is required if these sites serve as the basis for *nowcasting* (i.e., within horizons of one hour or less). The approach offers a good example of the data and telemetry requirements that will be important for system operators, distribution utilities, and others to consider in their planning and interconnection processes.

Current Experience and Performance of Solar Forecasting

A key question for operators and other end users is "how well do solar forecasts perform?" The answer depends on a number of factors, many of which are also relevant for wind forecasting. For example, any forecast performance metric should be tied to the end-use application's sensitivity to forecast error. However, many users (system operators, traders, utilities, etc.) may not have a quantitative understanding of their sensitivity to forecast error and the related value of the forecast. Therefore, a standard set of widely used metrics is typically employed. Standardized metrics facilitate the comparison of solar forecasts, but they may not accurately inform a specific user as to which forecasts provide the most value for their specific application.

Currently, the three most widely used metrics for assessing deterministic point forecasts are mean (bias) error, mean absolute error (MAE), and root mean square error (RMSE). These metrics may be applied using different approaches. The most widely used approach, as followed here, is to express the metrics as a percentage of the installed capacity over all daylight hours. Other approaches calculate the percentage change in these metrics relative to a reference forecast (persistence or climatology) or as a percentage of average actual production over the evaluation period. There is also a movement toward comparisons using "smart persistence," which assumes that relevant conditions such as cloud cover and temperature remain the same but includes the underlying variation due to changing solar angle in the baseline.

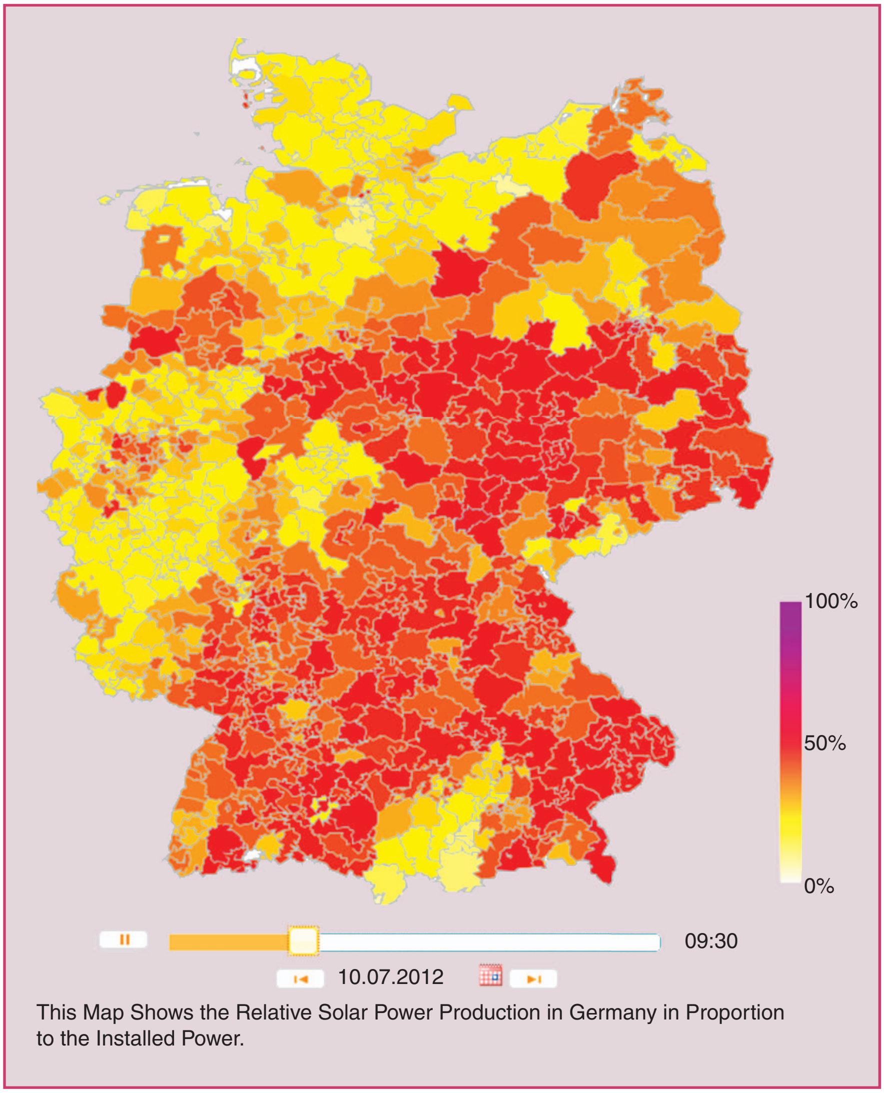

figure 4. The real-time estimation of the solar power production on a zip code level in Germany based on online data from inverters. (Source: energy & meteo systems.)

These metrics are simple to compute but one still needs to interpret the resulting metric values. Forecast performance is impacted by many factors, as described below.

1) **Look-Ahead Time.** One of the most intuitive factors that impacts forecast performance is the forecast look-ahead time (also known as the forecast time horizon or lead time). Figure 5 shows an example development of the forecast error (error growth) over a forecast horizon of 85 h. The figure depicts the MAE over two years for the aggregate solar generation in Spain, although the pattern is somewhat typical for both individual facilities and aggregates of facilities. The MAE rises rapidly over the first few hours after the issue time. After about six hours, the rate of error growth decreases substantially. It can also be seen that forecasting performance improves with further forecast system development in the region, as 2014 shows a significantly lower error rate than 2013 does.

2) **Variability in Solar Production.** In general terms, absolute forecast performance is impacted strongly by the amount of atmospheric-based variability in the solar power production. For example, the absolute level of cloud impact on solar irradiance is lower near sunrise or sunset, although the relative variation (the percentage of average irradiance change) may be much larger. Thus, variability in production and the magnitude of forecast errors tend to follow the diurnal cycle. This is illustrated in Figure 6 for a nontracking facility in Texas. The relationship between the diurnal

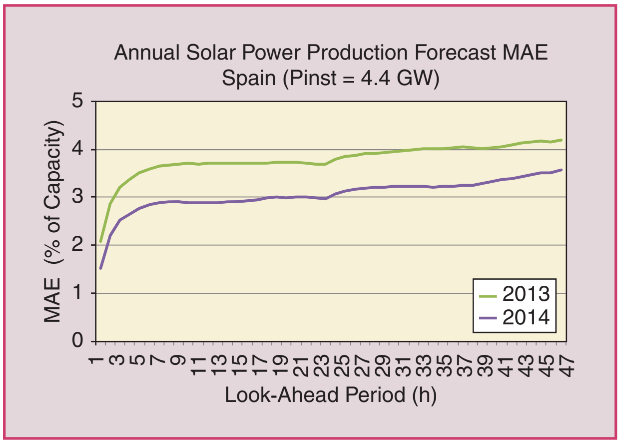

figure 5. Forecast performance over the look-ahead period of the forecast for aggregated 4.4 GW of PVs in Spain.

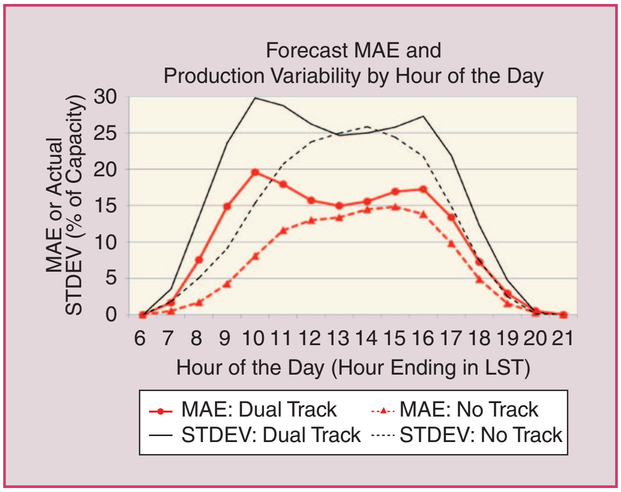

figure 6. Annual MAE versus variability (observed standard deviation) by hour of the day for a nontracking facility (red) and a nearby dual-axis tracking facility (black) in Texas.

cycle of variability and MAE is clearly evident in data presented in this chart.

3) **Specific Plant Attributes.** The various plant attributes of a solar generation facility are important as well, as Figure 6 also illustrates. The solid lines show the variability and MAE for a dual-axis tracking facility that is located close to (i.e., having very similar weather regimes) the facility without tracking, as represented by the dashed lines. The chart indicates that the variability and MAE for both facilities is similar at midday and near sunrise and sunset. However, the variability and MAE of the dual-axis tracker is substantially higher during the mid-morning and mid-afternoon hours. The impact of this pattern on the overall forecast MAE for the two sites is quite substantial.
4) **Spatial Scale.** A fourth factor that has a significant impact on forecast performance is the spatial scale of the generation. Due to the well-known aggregation effect, forecasts for geographically diverse aggregates of solar generation facilities have smaller errors than the forecasts for individual facilities in the aggregate. Local effects, which are more random and more difficult to forecast, tend to average away when we look at the aggregated forecast. A broad view of the effect of aggregation on the performance of day-ahead solar power production forecasts is depicted in Figure 7. This chart shows the annual MAE over all daylight hours for day-ahead forecasts for a broad spectrum, ranging from individual centralized facilities to regional and system-wide aggregates of centralized facilities and distributed generation. The power of the aggregation effect in reducing the absolute forecast errors is quite evident. Note that many factors impact forecast performance for a given entity of a specific size, such as the geographic diversity within the entity, the attributes of the facilities (e.g., tracking versus nontracking, and so forth), the amount of variability associated with local weather regimes, and the causes of the variability.
5) **Other Weather Phenomena.** While forecasting cloud cover is a predominant factor for solar forecasting ,there are some other phenomena that can have a similar impact on the predictability of PV generation, especially on day-ahead and longer time scales. These include fog, snow, and dust. An example of the impact of fog and snow on the performance of forecasts for a large aggregate of generation facilities in Germany is shown in Figure 8. The errors are much larger in the spring and fall when fog is a significant factor in power production variability.

Paths to Improved Solar Forecasting

Solar power forecasting is still a relatively new technology. Individual methods have deficiencies, such as the lack of attention that NWP models have traditionally paid to cloud cover variables and the relative immaturity of sky imaging techniques, while the blending of different forecasting techniques is still less than optimal. The fact that much PV generation is BTM means some of the data needed to set up models may not be available, and methods are still being developed to forecast this type of PV generation. Probabilistic forecasting techniques that could significantly improve on the representation of uncertainty are still being explored. Finally, ineffective communication of forecast information to the users and the lack of end use tools for using forecast information hinder the extraction of full value from forecasts.

A number of initiatives are currently underway in the United States and Europe to improve some of these key areas of solar power forecasting. These are covered in more detail in forums such as the Utility Variable Generation Integration Group's annual forecasting workshop and the energy track of the American Meteorological Society, but the following describes the major research areas, with specific examples:

Atmospheric Modeling Enhancement and Blending of Methods

The U.S. Department of Energy (DOE) is currently funding several efforts to improve the underlying models for solar forecasting under its SunShot initiative. This includes research by IBM on optimal blending of different models using machine-learning strategies and by the National Center for Atmospheric Research (NCAR) on combining individual models including sky imaging, satellite methods, and a solar-tuned NWP model to maximize the benefits of the individual methods. NOAA is adding various solar energy–related parameters, such as outgoing longwave radiation and incoming shortwave radiation, as well as direct and diffuse irradiance, to its hourly updated Rapid Refresh models. Efforts are also ongoing in Europe, including ones focusing on improving fog, snow, and dust representation in NWP models (for example, the MACCII project), and in academia, such as a University of Arizona project to develop a hybrid forecasting system at a high time resolution.

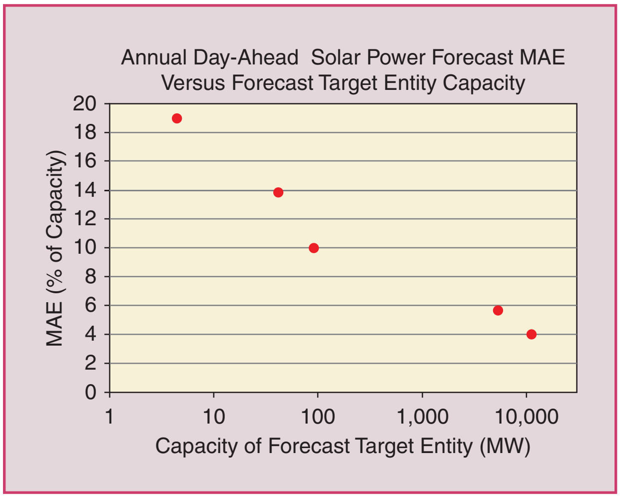

figure 7. The relationship of the annual day-ahead solar power forecast MAE (% of capacity) over all daylight hours to the installed capacity of the forecast target entity for a broad spectrum of entities (individual facility, regional, or system-wide aggregate).

Incorporation of BTM into Load Forecasting Methods

The load forecasting community is evaluating different ways of incorporating BTM PVs into existing load forecasts and the costs and benefits of using more detailed weather and PV system data, where available. In California, a number of government funded efforts are underway, using information about PV installations to predict the day-ahead and hour-ahead power output of the fleet. Clean Power Research has worked to integrate its solar forecasts into Itron's load forecasting tool, focusing on improvements to BTM forecast accuracy and integration of direct power prediction into the neural net load forecasting framework.

Cloud Propagation Techniques

Sky imaging and satellite-based cloud propagation methods are still at early stages of development, and several research groups are actively working to improve them. For instance, Colorado State University is developing a satellite-derived insolation

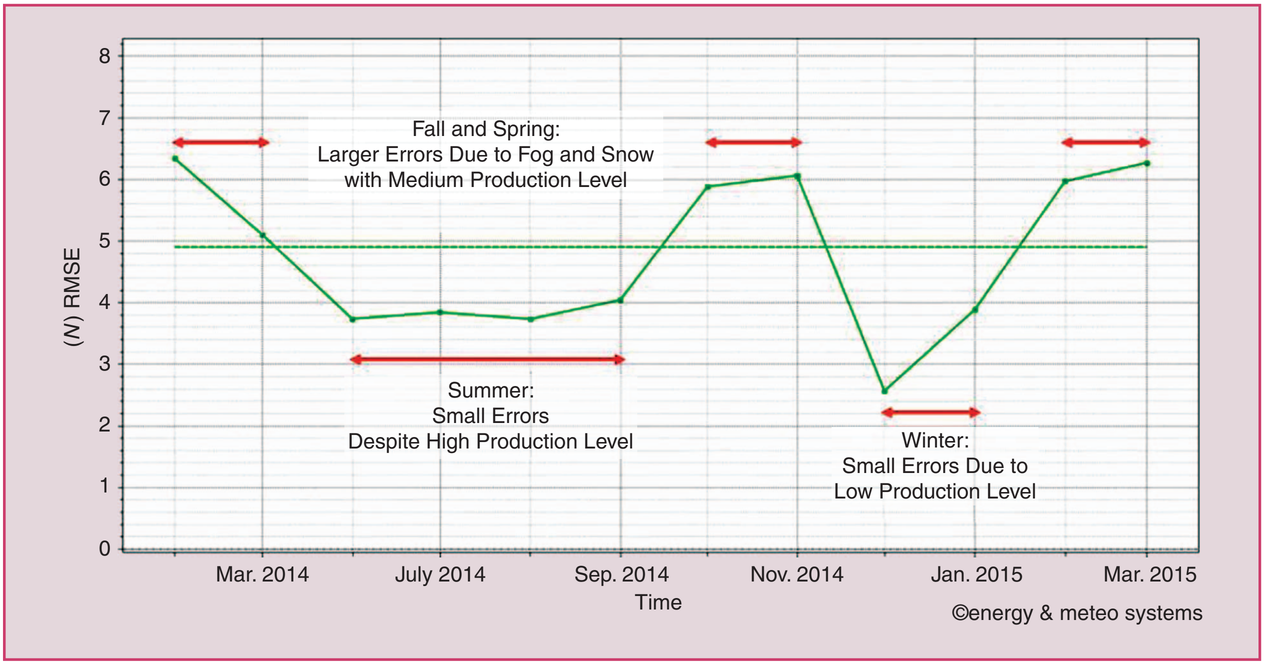

figure 8. A day-ahead forecast RMSE by month for distributed and centralized solar power in Germany, showing the impact of fog and snow.

> One of the most intuitive factors that impacts forecast performance is the forecast look-ahead time (also known as the forecast time horizon or lead time).

forecast in concert with colocated winds from an NWP model to capture the movement of clouds at different heights. In the NCAR SunShot project, a cloud nowcasting prototype based on multiple satellite infrared sensors and a simplified NWP model compares infrared radiance observations with their equivalents from a numerical model to develop a more accurate cloud profile that can be used with the other forecasting methods.

Probabilistic Forecasting

Ongoing research in this area includes improved probabilistic treatment of atmospheric physics models, as well as improved representation of uncertainties in cloud formation and decay. This will result in increased reliability and sharpness. One novel method is the analog ensemble approach, which, instead of generating multiple model forecasts, searches the past history for similar forecasts and makes corrections to the forecast according to the error in prior forecasts. The prior analogs become an ensemble that quantifies the uncertainty of the forecast.

Integration into System Operations

While improving the underlying forecasts is important, it is also crucial that they are integrated into system operations so that operators can obtain the full value from the forecast. Many utilities now receive forecasts; however, most are still learning how to use them in their decision-making processes. There are significant efforts to integrate solar power forecasts more deeply into system operations. For example, Hawaiian Electric Company has supported the development of a Solar and Wind Integrated Forecast Tool, which is built on an optimized mix of various approaches described earlier and has deterministic and probabilistic elements as well as variability and ramp-rate predictions. Work is underway to integrate these forecast outputs directly into the energy management systems. The Red Eléctrica Control Centre of Renewable Energies in Spain, shown in Figure 9, can identify risks, anticipate the behavior of solar and wind, and compensate for their variability, without compromising the quality and security of supply.

Research on methods for using probabilistic forecasts to optimize system operations based on stochastic optimization techniques is being carried out in various institutions. For example, Sandia National Laboratories is developing a toolkit to demonstrate use of stochastic unit commitment, while the Electric Power Research Institute is investigating the use of probabilistic information to develop more intelligent operating reserve requirements. Power system operators and independent power producers could potentially see benefits by incorporating forecast uncertainty directly into their decision making.

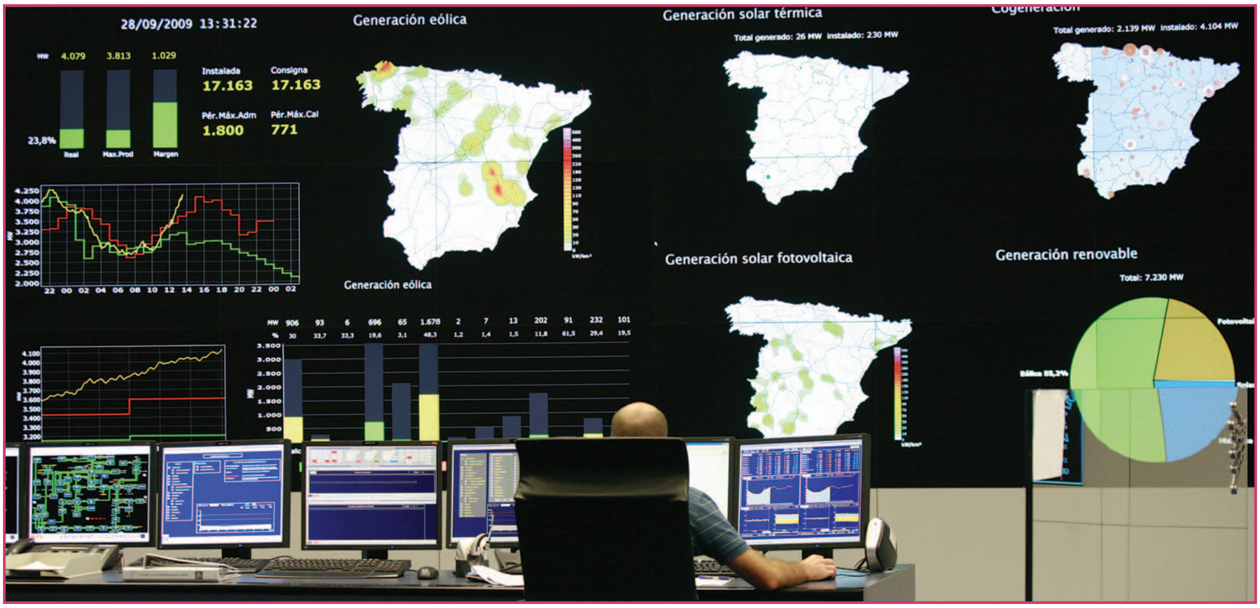

figure 9. Red Eléctrica Control Centre of Renewable Energies in Spain. (Courtesy of Red Electrica Espana.)

Finally, the need for an ability to evaluate forecasts on the basis of the value they provide is driving several research and development efforts. As shown earlier, there are a variety of metrics that can be used, and currently there is typically not a direct link between forecast performance metrics and the value a forecast provides. To this end, the DOE efforts mentioned earlier are developing and demonstrating a set of useful metrics for assessing performance of deterministic and probabilistic forecasts against both error-based metrics and metrics that link to the economic value of the forecast via production-cost modeling and reserve analysis.

Summary and Conclusions

Solar forecasting is one of the lowest cost methods of efficiently integrating solar energy. In this article, we have focused on the current state of solar forecasting and identified key issues related to its development and application. The process of solar forecasting for various time horizons, methods, and applications has many similarities to wind forecasting, but as solar output is strongly linked with cloud cover, there are other considerations and possibilities.

Most NWP models do not run at spatial resolutions that are high enough to explicitly model clouds and do not use detailed data about cloud cover and cloud formation when initializing. This means the first three to six hours of most current NWP models are not particularly useful for solar forecasting. As a result, methods such as sky imaging and satellite data have been used to predict near-term solar output, with some success. Additionally, increases in model resolution and more frequently updated models are helping advance forecasting of solar irradiance in NWP. Even with improved accuracy, it will still be important to quantify the uncertainty in the forecast to ensure efficient integration, and so we described various methods for quantifying uncertainty.

As performance is a key parameter to any new development, we demonstrated how accuracy can be measured and evaluated, with a focus on how the metrics can influence the end result. We showed some of the key factors driving uncertainty such as the look-ahead horizon, forecasting interval width, tracking systems, and system size. By considering these factors in plant design and electric system design we can reduce uncertainty and thus lower the cost to integrate solar energy.

BTM PV is likely to provide a large part of society's energy needs in the future. Both detailed bottom-up forecasting methods and aggregated top-down forecasting methods can be used to manage BTM solar generation. While detailed methods are likely to be more accurate, data is not always available, and certain applications may not require such a fine level of detail. With increasing penetration of BTM PV, data provision and availability will become increasingly important for successful forecasting and integration. This includes improved representation of static site data, but also, where possible, increased access to telemetered output data or historical meter data. Ongoing research focuses on all aspects of the value chain of forecasting, including not just improving the underlying forecasting methods and combining different forecasting techniques, but also on the ways that solar forecasts are valued and used in operations.

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