Solar Industry

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Latest Solar Forecasting Tools Help Operators Maintain Grid Stability

New technologies can determine where clouds lurk - and when they will threaten system output.

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Over the next several years, the U.S. will experience considerable growth in the installation of residential and commercial solar energy systems. However, for many of these installations, the temporal and spatial variability of the solar resource can be considerable due to cloud cover influenced by terrain and local circulations. Detailed knowledge of local and regional electrical grids' sensitivity to variable solar generation is crucial.

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System operators need foreknowledge of imminent changes in solar energy output and the potential for large-scale ramp events occurring on short time scales. As the U.S.' solar generating capacity grows - as does the capacity of other variable resources, such as wind - the existing operating and planning paradigms are insufficient for operators to manage power distribution for their respective grids.

Therefore, forecasting tools will need to be developed to enable the variability of solar power production to be more effectively and economically managed on multiple time scales. These tools will facilitate a higher level of solar power production on the grid while maintaining distribution reliability.

The dominant factor causing variability in solar power production is the variability of solar irradiance. For example, steep power ramps can be caused by the shadows of relatively fast-moving, low-level cumulus or stratocumulus clouds. Temperature is also a factor for most types of solar generation technology. In addition, different types of solar generation technology have different sensitivities to the direct and diffuse components of solar radiation.

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However, variations in the global horizontal irradiance (GHI) are typically responsible for a large portion of the variability in the output of a solar generation facility. Accurate prediction of GHI is the key to reliable forecasts of solar energy output.

In some cases, a sufficiently dense network of instruments is needed to develop a robust statistical description of cloud shadows crossing a prospective solar array. Therefore, a project site may have to be instrumented to capture the fine-scale temporal and spatial variability of the cloud-light environment. The amount of irradiance reaching the earth's surface is controlled by two factors:

- **The variation in the sun's angle due to changes in the time of day or time of year.** This accounts for a substantial portion of the variability, but it is highly predictable from earth-sun geometry.
- **The transparency of the atmosphere (its optical depth).** This is affected principally by the amount and size of liquid water or ice particles (i.e., clouds), variations in water vapor content, and the amount and size of suspended solid particles, such as dust.

A robust integrated solar forecast system must be able to accurately predict the evolution of the sky-light environment as it is influenced by changes in the atmosphere's optical depth.

Forecast approaches

Cloud prediction is also complicated by the fact that clouds occur on a wide range of spatial and temporal scales, at different levels of the atmosphere, with variable water or ice content. For example, individual cumulus clouds can be hundreds of meters in size and may have a typical lifecycle of less than one hour.

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On the other hand, clouds associated with large-scale storm systems may extend over 1,000 km and have a lifecycle of several days. Smaller-scale cloud features may be embedded within larger-scale systems. Therefore, the challenge associated with predicting solar irradiance at the surface of the earth depends on the space and time scales that are of interest for specific applications.

Generally, there are three approaches necessary to ensure the temporal continuity of a complete solar energy forecasting system: sky imagery cloud motion vector analysis and extrapolation, satellite-based cloud motion vector analysis and extrapolation, and Numerical Weather Prediction (NWP) forecasts of cloud cover and the partitioning of the irradiance components. Complementing the forecast system is ground-based and satellite remote sensing instrumentation, as well as plant output used for forecast system initialization and validation.

The sky imagery analysis and extrapolation approach consists of four components: acquisition of a whole (hemispheric) sky image in the vicinity of the forecast site, using a device such as a Total Sky Imager; analysis of sky image data to identify cloud features and estimate cloud motion using successive images; use of cloud location and motion vector data for short-term deterministic or probabilistic cloud-cover forecasting; and use of the cloud-cover forecast to predict irradiance and solar power production at the generation site.

The sky imagery cloud motion vector analysis and extrapolation method has the advantage of using very detailed information about the extent, structure and motion of existing clouds in the vicinity of the solar generation facility at the time the forecast is made. These data are acquired at high frequencies (15 seconds to one minute) and can be used to generate very short-term (minutes ahead) predictions of future cloud patterns in the vicinity of the plant.

However, the approach does not account for cloud development and dissipation or significant changes in cloud geometry. The extrapolation of the cloud patterns is also limited to the spatial scale defined by the field of view of the sky imager (usually 10 km to 20 km). It is possible to extend the spatial scale by using multiple imagers at different locations.

The existence of multiple cloud layers with different characteristic motion vectors can also pose a problem for this approach, because clouds at upper levels may be partially obscured by clouds at lower levels. These factors generally limit the usefulness of this approach to look-ahead periods of less than one hour.

The actual look-ahead time for which this method has significant skill will depend upon the speed of cloud movement relative to the imager field of view and rate at which the cloud field is departing from the evolution defined by the cloud motion vectors (e.g., development and dissipation).

Satellite-based data

This method is conceptually similar to the sky image method, except the current cloud patterns are detected through the use of visible and/or infrared images from satellite-based sensors. Its advantage is that a much larger spatial scale of cloud patterns can be detected.

However, the spatial resolution of these images is much less (1 km to 4 km) than that of images produced by the ground-based sky imagers (tens of meters). Small clouds or small structures in larger-scale cloud features cannot be detected. In addition, the time frequency (approximately 30 minutes) of the images is lower than that of the sky imager, which means that the forecast cannot be updated as frequently.

The lack of high spatial and temporal resolution in satellite image data reduces the performance of the satellite-based approach relative to the sky imager method for forecast time frames of less than 1 hour. The much larger area of coverage means the motion of the cloud field can be projected forward over longer time periods; however, as with the sky imager approach, this method does not account for significant dissipation, development, or structural changes in the cloud patterns. Recent studies have suggested that this approach performs best in the one- to five-hour look-ahead time frame.

For longer time scales (three-plus hours to several days ahead), a third element of solar energy forecasting is the prediction of cloud coverage and characteristics (e.g., depth and liquid water content) with one or more NWP models.

An NWP model generates a detailed simulation of the atmosphere on a three-dimensional grid using equations for conservation of mass, momentum and energy. In order for the forecast simulation to be started, model-dependent variables (e.g., temperature, moisture and wind) must be specified for each grid cell.

Because measurements are not available at each grid cell location, many values must be inferred from available measurements. The process of estimating values where there is measurement uncertainty introduces some error in the initial state. This error can then propagate and grow during the simulation.

NWP models produce a three-dimensional grid point forecast of temperature, water vapor, cloud water and cloud ice. The existence of clouds in the simulation can be inferred from the presence of cloud water or ice at a grid point or from the grid cell relative humidity. With this information, NWP models can then make an explicit prediction of the total solar irradiance and its components.

NWP's uses

The strength of the NWP approach includes its ability to simulate cloud development, dissipation and structural changes, as well as cloud translation in the flow field. However, NWP models have two major limitations. The first is the typical size of their grid cells (usually 5 km to 10 km or more), which prohibits the representation of small-scale features such as cumulus clouds.

The second is that the models do not typically have an accurate representation of initial cloud patterns, because the state variables are derived from relatively sparse or lowresolution measurements. With these limitations, the NWP model cloud patterns are not very reliable for the first three hours after initialization, and the variability caused by sub-grid-size clouds is not well forecasted at any time scale.

These characteristics make NWP models a good tool for the production of solar irradiance forecasts on look-ahead time scales of three hours or more. As the length of the look-ahead period increases, NWP forecast errors grow, thereby limiting the practical usefulness of such forecasts for individual weather systems to about seven days.

In recent years, NWP models have been executed in a rapid update cycle mode in order to leverage data available at sub-hourly intervals and generate more frequent NWP forecasts. These types of model runs are often initialized every one or two hours and, thus, can be used as the basis for frequently updated solar irradiance forecasts. However, the models are still limited by grid cell size and inadequate representation of clouds at initialization time.

Statistical prediction

There are also several techniques available that can be used to improve the accuracy of solar irradiance and power forecasts. Two of these methods are ensemble forecasts and statistical methods.

With ensemble forecasts, multiple models can be run simultaneously from several sets of initialization and boundary conditions to generate an ensemble of mesoscale NWP forecasts. Most of the simulations employ the standard government-center six-hour NWP update frequency. But a small subset are operated in a rapid update cycle mode, which initializes a new simulation every one or two hours using the latest available data, including synthetic moisture data inferred from cloud patterns in satellite images.

This feature is intended to improve the short-term NWP prediction of cloud patterns and characteristics and is still being refined.

The forecasting process can also employ statistical models - such as multiple linear regression, Artificial Neural Networks and support vector regression - to create an ensemble of forecasts of irradiance and other relevant parameters (such as module temperature).

The input into these models includes the output from the NWP simulations, recent irradiance or power time series from the forecast site and off-site locations, as well as the output from cloud pattern tracking schemes. Statistical models can be used to correct system errors in the NWP simulations as well as to adjust the NWP forecasts to account for recent trends revealed by measurement data.

Separate statistical prediction equations can be used for each forecast look-ahead hour; thus, the statistical training schemes select the variables that have the greatest predictive information for each look-ahead hour. Typically, this approach emphasizes the recent performance of the collective PV systems and the solar resource data for shorter look-ahead periods (e.g., one to six hours) and puts more weight on the NWP data for longer forecast time horizons (i.e., greater than six hours ahead).

This approach produces a smooth transition from short-term to longer-term forecasts, even though the predictors change dramatically from the early to the later hours in the look-ahead period. The daily solar cycle, which changes seasonally, will also be an important predictor.

Several improvements are being made in integrating sky imagery, satellite irradiance and NWP models to improve solar forecasts. Ultimately, these improvements will make it possible to integrate ever-increasing amounts of solar energy onto the electrical grid.

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