

In short: Irradiance Forecasting with cloud motion vectors

Aus NREL: "Best Practice Handbook for the Collection and Use of Solar Resource Data for Solar Energy Applications"
ab S. 187 (resp. 168) Kapitel 7.2.1

7.2.1 Irradiance Forecasting With Cloud Motion Vectors

For short-term horizons, the temporal change in cloud patterns is strongly governed by horizontal advection, with the shape of clouds often remaining rather stable. Techniques detecting clouds and cloud motion in sufficient detail therefore provide valuable information for irradiance forecasting in the corresponding time scales. Evidently, the performance of this forecasting method is degraded when local cloud formation and dissipation processes, such as strong thermal convection, are dominant over cloud advection. The following basic steps comprise forecasting based on cloud motion vectors:

- Images with cloud information ("cloud images") are derived from satellite or groundbased sky-imager measurements
- Assuming stable cloud structures and optical properties for the considered temporal and spatial scales, cloud motion vectors (CMV) are determined by identifying matching cloud structures in consecutive "cloud images"
- To predict future cloud conditions, the calculated motion vectors are applied to the latest available "cloud image"—i.e., cloud motion is extrapolated using the additional assumption of persistent cloud speeds and velocity
- Forecasts of site-specific solar irradiance are inferred from the predicted "cloud images."

7.2.1.1 Forecasting Using Ground-Based Sky Imagers

Solar irradiance forecasts in the subhourly range with very high temporal and spatial resolutions can be derived from ground-based sky images. In particular, they have the potential for capturing sudden changes in irradiance, often referred to as ramps, on a temporal scale of minutes or even less (see Figure 7-4). Cloud fields may be resolved in high detail, allowing partial cloud cover on large PV installations to be modeled and forecasted (see Figure 7-2). **Maximum possible forecast horizons strongly depend on cloud conditions—i.e., cloud height and velocity.** They are limited by the time the monitored cloud scene has passed the location or area of interest, typically up to **15 minutes to 30** minutes ahead.

Short-term irradiance forecasting based on ground-based sky imagers is a rather new research field; a review of the state of the art is given in Urquhart et al. (2013). Currently, there is no defined standard for sky-imaging hardware, camera calibration, or image processing techniques. Systems in use range from commercially available low-cost web-cam-based sky cameras to high-quality prototype systems developed at research institutes. These use digital cameras with **charge-coupled device chips** and large fish-eye lenses for photography and industry applications—for example, the sky imaging systems specifically designed for solar energy purposes at the University of California at San Diego (Urquhart et al. 2014).

Cloud detection from sky-imager pictures is performed by evaluating different image properties. The red-to-blue ratio (RBR, Figure 7-2, middle right) is a main indicator for clouds because of different spectral-scattering properties of clouds (high RBR) and clear sky (low RBR) (Shields, Johnson, and Koehler

1993; Long and DeLuise 1998). Pixel intensities (Figure 7-2, middle left) are also related to cloud cover and may be exploited as an additional feature for cloud detection.

Binary cloud decision maps (Figure 7-2, top right) can be derived on the basis of **threshold** procedures—for example, by evaluating the RBR in relation to a **clear-sky library** (Chow et al. 2011) to **account for nonuniform clear-sky signal over sky hemisphere in dependence on the position of the sun**. Cloud detection is particularly difficult in the circumsolar region because of saturated pixel information with high RBR values not only for cloudy but also for clear conditions. Gauchet et al. (2012) consider the circumsolar area and the solar disk separately with an image segmentation approach, distinguishing also clear **skies, bright, and dark clouds**. Ghonima et al. (2012) propose a method to differentiate between thin and thick clouds for various atmospheric conditions using a clear-sky library. Additional information on the cloud type in the monitored scene, which also gives an indication on cloud optical thickness and **cloud height**, can be obtained by a **cloud classification algorithm** (for example, Heinle, Macke, and Srivastav 2010).

Transformation of the derived cloud maps to real-world coordinates requires information about **cloud height**, which together with the **position of the sun** determines the position of cloud shadows at the surface; therefore, it is essential for modeling and forecasting irradiance fields with high spatial resolutions. Note, however, that a single-point forecast for the position of the sky imager does not require information about cloud height but can be derived by simply evaluating the movement of cloudy pixels toward the pixel at the position of the sun. Different options to determine cloud height include ground-based observations, satellite methods, and the evaluation of sky-imager data. Most accurate information on cloud-base height is obtained from ceilometers (lidars), typically employed at airport weather stations. Cloud-top height retrieval from satellite images (see Chapter 4) gives spatially continuous information but shows larger uncertainties. **Different methods to determine cloud height using information from more than one sky imager are shortly introduced in Urquhart et al. (2013) and Prah et al. (2014).**

Detection of cloud motion is the next step to derive irradiance forecasts. Chow et al. (2011) identify cloud motion based on a normalized cross-correlation procedure—i.e., by **maximizing the cross-correlation** between shifted areas in two consecutive images. Alternatively, cloud movement may be analyzed by applying **optical flow** techniques (for example, as in Lucas and Kanade 1981 and Wood-Bradely, Zapata, and Pye 2012) to subsequent images (see Figure 7-3). The derived cloud motion vectors are then used to project the observed cloud scenes in the future.

Cloud shadows maps at the surface (see Figure 7-2, bottom) are produced by projecting the forecasted cloud scenes with their assigned height using information about the position of the sun. Finally, solar irradiance is estimated from these cloud shadow maps. **Without information about cloud optical properties and other atmospheric parameters, this is not a trivial task. Local irradiance or PV power measurements can be used to estimate irradiance or PV power for cloudy and clear skies.** Urquhart et al. (2013) analyze frequency distributions of PV power normalized to clear-sky conditions to determine a clear and a cloudy mode and to assign them to shaded and unshaded cells, respectively. Gauchet et al. 2012 propose the use of a regression model in combination with a clear-sky model to estimate the surface solar irradiance from segmented sky images with information about clear-sky, bright, and dark clouds; circumsolar area; and solar disk.

High-quality irradiance measurements are essential for further algorithm development. In particular, the analysis of irradiance fields with high spatial resolutions requires measurements from a dense network

of observation sites, such as the high-quality data set collected during the HOPE campaign (Macke and HOPE-Team, 2014] and Madhavan, Kalisch, and Macke 2014; Figure 7-2, bottom). Measurements with more than 90 photodiode pyranometers distributed throughout an area of 10 km by 10 km close to Jülich in Germany were taken from April to July 2013.

7.2.2 Satellite-Based Forecasts

Forecasts of several hours ahead require observations of cloud fields in large areas. For example, assuming a maximum cloud velocity of 160 km/h, a region of approximately 2,000 km by 2,000 km has to be covered to track arriving clouds 6 hours ahead. Satellite data with their broad coverage (see Section 4.4) are an appropriate source for these horizons.

Cloud and irradiance information from satellite images can be derived by a variety of methods, as presented in Chapter 4. In principle, all of them can be applied to satellite-based irradiance forecasting with cloud motion vectors. There are also many approaches to derive atmospheric cloud motion vectors, which are commonly used in operational weather forecasting to describe wind fields at upper levels in the atmosphere.

Satellite-based nowcasting schemes have been developed in recent years based on cloud motion vectors or sectoral cloud tracking (Hammer et al. 2003, Schroedter-Homscheidt et al. 2011). The satellite-based forecasting scheme from the University of Oldenburg in Germany (Lorenz, Heinemann, and Hammer 2004, Kühnert, Lorenz, and Heinemann 2013), described exemplarily here, uses images of the geostationary MSG satellites (See Chapter 4). The semiempirical HELIOSAT method (Hammer et al. 2003; see Chapter 4) is applied to obtain information about clouds and irradiance. A characteristic feature of the method is the dimensionless cloud index, which gives information about the cloud transmissivity.

Cloud motion vectors are derived by identifying corresponding cloud patterns in two consecutive images (see Figure 7-5). Rectangular areas, the “target areas,” are defined with a size of approximately 90 km by 90 km to be large enough to contain information about temporally stable cloud structures and small enough that cloud motion for this area can be described by a single vector. Mean square pixel differences between target areas in consecutive images (n_0 and $n-1$) are calculated for displacements in all directions (Figure 7-5a–c). The maximum possible displacement (“search area”) is determined by maximum wind speeds at typical cloud heights. The displacement that yields the minimum mean square pixel difference for a given target area is assigned as motion vector (Figure 7-5d). The derived motion vectors are applied to the cloud index image n_0 to predict future cloud conditions. A smoothing filter is applied to the predicted cloud index image to eliminate randomly varying small-scale structures that are hardly predictable. Finally, irradiance is derived from the predicted cloud index images using the HELIOSAT method.

The SolarAnywhere short-term forecasting scheme (Perez et al. 2009, Perez and Hoff 2013) for the United States based on GOES satellite images (see Section 4.4.1) follows a similar approach to detect cloud motion and is also based on a semiempirical cloud index method (see Chapter 4). Another method presented in Schroedter-Homscheidt et al. (2011) discriminates the tracking of optically thin cirrus clouds from the tracking of optically thick cumulus or stratus clouds with respect to increased accuracy needs in direct irradiance nowcasting for concentrating technologies.

Müller and Remund (2013) propose a method that combines cloud index values retrieved from MSG satellites with wind fields from a NWP model. The wind fields are predicted with the WRF model (Skamarock et al. 2008) in hourly resolutions and applied to forward propagation of the observed cloud

patterns. Information about the height of the monitored clouds is necessary to determine the corresponding NWP model level. Müller and Remund (2013) assume fixed cloud heights for this purpose. An advantage of the application of NWP wind fields compared to satellite-derived cloud motion vectors is the potential to describe changes in the direction and speed of cloud movement during the extrapolation process.

A method for satellite-based short-term forecasting based on a physical cloud and irradiance retrieval scheme (see Chapter 4) is introduced by Miller et al. (2013). They process GOES satellite observations with the NOAA Pathfinder Atmospheres Extended (PATMOS-x) (Heidinger et al. 2014) retrieval package, a stand-alone radiative transfer code, and combine them with wind field data from the Global Forecast System (GFS) model. Cloud properties are retrieved with PATMOS-x in a first step. Next, the cloud fields are advected using GFS winds at the vertical level matching the cloud-top height as retrieved from PATMOS-x. Finally, solar irradiance at the surface is calculated with radiative transfer calculations using predicted cloud properties and additional atmospheric parameters.

7.2.3 Irradiance Forecasting with NWPs

NWP models are routinely operated by weather services to forecast the state of the atmosphere for several days ahead. Starting from initial conditions that are derived from worldwide observations, the temporal development of the atmospheric conditions is modeled by solving the basic equations describing the physical laws governing the atmosphere. This physical modeling is essential for any forecast more than several hours ahead. A comprehensive overview of NWP modeling is given in Kalnay (2003).

Global NWP models are applied to calculate the future state of the atmosphere for the complete Earth. To determine the initial state of a forecast, data assimilation tools (Jones and Fletcher 2013) are applied to make efficient use of worldwide meteorological observations, including measurement data from weather stations and buoys as well as satellite observations. The prognostic equations, describing the dynamics and physics of the atmosphere, are solved using numerical methods. These involve spatial and temporal discretization, in which the grid resolution is determined by the computational costs. Many physical processes occur on spatial scales much smaller than the grid size, including, for example, condensation, convection, turbulence, and scattering and absorption of radiation. The statistical effect of these unresolved processes on the mean flow is modeled with parameterizations of atmospheric physics. Today, the spatial resolution of global NWP models, run by approximately 15 weather services, is in the range of 16 km to 50 km; the temporal resolution of the model output is 1 hour, 3 hour, or 6 hour, limited by storage requirements.

Mesoscale or regional models covering only part of the Earth and taking initial and lateral boundary conditions from a global NWP model allow for downscaling to a finer grid. Weather services typically operate mesoscale models with a spatial resolution in the range of 3 km to 20 km and provide hourly forecasts, but also higher resolutions are feasible. The higher spatial resolution allows for an explicit modeling of small-scale atmospheric phenomena.

For irradiance forecasting, the parameterizations of radiation transfer and cloud properties are of special importance. Larson (2013) compares the respective model configurations with respect to GHI for four operational NWP models, including the integrated forecast system (IFS) of the European Center for Medium-Range Weather Forecasts and GFS run by NOAA. In particular, he discusses deep and shallow cumulus parameterizations, turbulent transport, stratiform microphysics and prognosed hydrometers,

cloud fraction and overlap assumptions, the description of aerosols, and the shortwave radiative transfer schemes. But he also emphasizes that “because of the strong feedback and interactions of physical processes in the atmosphere,” other processes may have a significant impact on irradiance forecasting.

Today, most NWP models offer GHI as direct model output, and some also provide forecasts of direct and diffuse irradiances. Although in principle direct model output can be used for solar energy application, in practice mostly an additional post-processing is applied to improve forecast accuracy (see Section 7.3.4).