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Robust cloud motion estimation by spatio-temporal correlation analysis of irradiance data

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ABSTRACT

The main contributor to spatio-temporal variability in the solar resource is clouds passing over photovoltaic (PV) modules. Cloud velocity is a principal input to many short-term forecast and variability models. In this paper spatio-temporal correlations of irradiance data are analyzed to estimate cloud motion. The analysis is performed using two spatially and temporally resolved simulated irradiance datasets generated from large eddy simulation. Cloud motion is estimated using two different methods; the cross-correlation method (CCM) applied to two or a few consecutive time steps and cross-spectral analysis (CSA) where the cloud speed and direction are estimated by cross-spectral analysis of a longer time series. CSA is modified to estimate the cloud motion direction as the case with least variation for all the velocities in the cloud motion direction. To ensure reliable cloud motion estimation, quality control (QC) is added to the CSA and CCM analyses. The results show 33% (52°) and 21% (6°) improvement in the cloud motion speed (direction) estimation using the modified CSA and CCM over the original methods (without QC), respectively. In general, CCM results are accurate for all the different cloud cover fractions with average relative mean bias error (rMBE) of cloud speed and mean absolute error of cloud direction equal to 3% and 3°, respectively. For low cloud cover fractions, CSA estimates the cloud motion speed and direction with rMBE and mean absolute error equal to 10% and 11°, respectively. However, for high cloud cover fractions and unsteady cloud speed, CSA results are not reliable for 3–4 h time series; however, splitting the whole time series into shorter time intervals reduces the rMBE and mean absolute error to 15% and 16° respectively.

1. Introduction

1.1. Motivation

The power output from solar photovoltaic (PV) power plants is usually more variable than conventional power generation sources. Variability is the main challenge for integration of large amounts of PV power plants into the electricity grid (Marcos et al., 2011). The ability to forecast actual variability of solar distributed generation (DG) will allow grid operators to better accommodate the variable electricity generation for resource adequacy considerations, such as scheduling and dispatching of power.

Besides predictable solar variability according to diurnal and annual irradiance patterns, the main source of spatio-temporal variability in the solar resource is transient clouds and that variability is related to the cloud optical depth and speed. Cloud motion is the main input to most short-term solar variability and forecast models (Arias-Castro et al., 2014; Hoff and Perez, 2010; Lave and Kleissl, 2013; Chow et al., 2011; Marquez and Coimbra, 2013; Perez et al., 2012; Yang et al., 2014a, 2014b; Lorenzo et al., 2014). Therefore, cloud motion estimation has been extensively investigated recently (Bosch et al., 2013; Bosch and Kleissl, 2013; Fung et al., 2013; Huang et al., 2013; Quesada-Ruiz et al., 2014; Chow et al., 2015). Accurate cloud motion vectors are critical for solar forecast, interpolation, and variability analyses (Jamaly and Kleissl, 2017).

1.2. Cloud motion estimation

Vega-Riveros and Jabbour (1989) reviewed various techniques related to the motion analysis and detection. Motion analysis methods are either based on the direct numerical solution of the optical flow constraint equation (method of differentials) or correspondence-based approaches, where image features are identified and tracked to measure their displacement. These measurements are then used to calculate the displacement of the object as a whole. Estimating cloud motion for sky imaging and satellite data by solving the optical flow equation incurs

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less computational expense. However, it has many restrictions. Therefore, most of the methods for estimation of the Cloud Motion Vectors (CMVs) are developed using correspondence-based approaches. In general, CMVs are obtained by first locating salient image features such as brightness gradients, corners, cloud edges, or brightness temperature gradients (Bedka and Mecikalski, 2005; Menzel, 2001). Then, assuming the features do not change significantly over a short interval, CMVs are computed by tracking the features in successive images.

CMVs have been obtained using sky imaging devices (Marquez et al., 2013) for very short-term solar forecasts up to 20 min ahead. Moreover, CMVs have been estimated from satellite imagery (Perez and Hoff, 2013; Menzel, 2001; Hammer et al., 1999; Leese et al., 1971). Escrig et al. (2013) applied multispectral tests and binary cross-correlations for cloud motion estimation using geostationary satellite imagery. They applied coherence and quality control tests to the resulting motion vectors and proposed new thresholds for infrared and visible tests. Fuh and Maragos (1991) developed a model for estimating the displacement field in spatio-temporal image sequences that allows for affine cloud shape deformations. The model is based on the block matching method (which is based on the same principal as the cross-correlation method presented later) and parameters were found using a least-squares algorithm. Post-smoothing the velocity field via spatio-temporal vector median filtering almost always improves the performance of the matching algorithm. However, block matching has a higher computational complexity.

Farnebäck (2003) developed a method for motion estimation based on a two-frame algorithm. The first step is to approximate each neighborhood of both frames by quadratic polynomials. Then, a method to estimate displacement fields from the polynomial expansion coefficients was derived. The main weakness of the algorithm is the assumption of a slowly varying displacement field, causing discontinuities to be smoothed out. Hammer et al. (1999) developed a statistical method based on conditional probabilities to compute CMVs and predict solar radiation up to 2 h ahead. Lorenz et al. (2004) used a similar method (applying extrapolation of motion assuming persistence of cloud speed, size, and shape) to obtain solar radiation forecasts up to 6 h ahead. For longer forecast time horizons, non-linearities in atmospheric motion and cloud formation and evaporation cause Numerical Weather Prediction (NWP) models to outperform satellite-based CMV forecasts (Perez et al., 2012). Arking et al. (1978) applied Fourier phase difference technique which allows motion estimates to be made for individual spatial frequencies related to cloud pattern dimensions. However in the presence of mixtures of motions, changes in cloud shape and edge effects, the cross-correlation scheme yields a more reliable estimate of cloud motion than the phase difference technique.

Since CMV estimation by either sky imaging, satellite data, or NWP lack granularity and computational efficiency, local ground measurements of cloud speed are advantageous for short-term solar variability and solar forecasting (Bosch et al., 2013). Bosch and Kleissl (2013) showed that cloud motion can be detected from spatio-temporal irradiance or power measurements across a utility-scale PV plant from the timing of cloud arrival at three different points.

1.3. The proposed method

Prior methods using ground data were predicated upon sparse data. The analysis in this paper is motivated by the increased availability of dense PV power output observations in urban areas with spatial resolution on the order of 100 s of meters. Actual PV power output can be converted to clear sky index (see e.g. Engerer and Mills, 2014) and then cloud motion could be estimated just like if the PV system was an irradiance sensor. Therefore the success of two algorithms in detecting cloud motion is estimated from simulated dense ground data: cross-spectral analysis (CSA) and the cross-correlation method (CCM). In CSA, the cloud speed and direction are estimated by cross-spectral analysis of the irradiance data at some given locations (sites) through the domain (Inoue et al., 2012; Shinozaki et al., 2014). The CSA method suggested by Inoue et al. (2012) and Shinozaki et al. (2014) is restricted by the spatial arrangement of the sites such that the cloud direction may be inaccurate if there are only a few distinct relative angles between the pairs of the chosen sites. To remove the restriction, a new CSA approach for cloud motion direction is proposed by selecting the direction with least variation for all the velocities in the cloud motion direction.

In CCM, the cloud motion is estimated by comparing correlation between spatial irradiance data at two or more time steps (Hamill and Nehrkorn, 1993). The CCM suggested by Hamill and Nehrkorn (1993) is generalized for cloud movement estimation using unstructured ground measured data. Moreover, to compare the consistency of the method when applied to different scales, CCM is applied by considering the whole domain as well as smaller subdomains. Also, to ensure reliable cloud motion estimation, quality control (QC) is added to the CSA and CCM analyses including removing conditions with low variability and less correlated sites.

The algorithms are tested only on simulated ground data, which is advantageous because the true cloud speed is known. In real datasets the true cloud speed is unknown and such data suffer from spatial heterogeneity in surface and atmospheric conditions that manifests in spatial differences in cloud motion vectors. Such heterogeneities can be avoided in a simulated dataset and the cloud motion estimation results are therefore expected to be more generalizable. In Jamaly and Kleissl (2017) the CSA and CCM methods are applied to real data for spatio-temporal interpolation or forecast of solar irradiance.

The datasets are described in Section 2. The cloud speed methodology is described in Section 3. Results of the estimation of the cloud motion are presented in Sections 4 and 5 concludes the paper.

2. Dataset

The analysis has been performed using two spatially and temporally resolved simulated irradiance datasets generated from large eddy simulation (LES). LES is a three-dimensional computational fluid mechanics technique that numerically integrates the Navier-Stokes equations. The momentum, temperature, and moisture transport is simulated at each grid point. High spatial and temporal resolution allows simulating the large turbulent motions in the atmospheric boundary layer explicitly and LES therefore produces more accurate wind, temperature, moisture, and cloud fields than other techniques. Periodic boundary conditions in the horizontal directions are used to represent an infinitely long, homogeneous domain that allows atmospheric turbulence to develop in a realistic manner. LES is forced by a geostrophic wind at the top of the domain. Surface fluxes of heat and water largely determine the relative humidity in the boundary layer and whether clouds will form. We apply the well-validated UCLA-LES using the same settings as Ghonima et al. (2016). Simulated datasets are considered since LES wind vectors at the average cloud height can be considered as the reference cloud motion.

2.1. RICO simulation

In the first simulation, a spatial domain of 2540 m × 2540 m (128 × 128 grid points) with boundary and initial conditions from the rain in cumulus over the ocean (RICO) field study (vanZanten et al., 2011) centered at 18.0°N, 61.8°W is setup. The simulation is performed up to 4000 m height resolved by 100 grid points. The precipitating RICO case with boundary layer moisture in the initial profile equal to 12.35 g/kg is simulated. Following 4 h of spinup, 10 s liquid water path (LWP) aggregated from cloud base to cloud top is output over a 30 min interval. Also, a representative wind speed vector is output at each time step; the two velocity components are $u(x, y, z_c, t)$ and $v(x, y, z_c, t)$, where z_c is average cloud height. The wind velocity is considered as the reference cloud motion and compared against estimated cloud motion in Section 4.