Optimal Interpolation of Satellite Derived Irradiance and Ground Data

Antonio T. Lorenzo*, Matthias Morzfeld†, William F. Holmgren‡, Alexander D. Cronin§

*College of Optical Sciences, University of Arizona, Tucson, AZ, 85721, United States
†Department of Mathematics, University of Arizona, Tucson, AZ, 85721, United States
‡Department of Atmospheric Sciences, University of Arizona, Tucson, AZ, 85721, United States
§Department of Physics, University of Arizona, Tucson, AZ, 85721, United States

***Abstract*—We describe how Bayesian data assimilation can be used to improve nowcasts of irradiance over small, city-scale, spatial areas. Specifically, we use optimal interpolation (OI) to improve satellite derived estimates of global horizontal irradiance (GHI) using ground truth data that was collected sparsely over Tucson, AZ. Our results show that the local data indeed improves the satellite derived estimates of GHI. A key to success with OI in this context is to prescribe correlations based on cloudiness, rather than spatially. OI can be used with a variety of data, e.g., rooftop photovoltaic production data or irradiance data, as well as with several different satellite derived irradiance models.**

***Index Terms*—data assimilation, optimal interpolation, remote sensing, solar irradiance**

I. Introduction

Accurate estimates of the global horizontal irradiance (GHI) are crucial to the deployment and grid integration of photovoltaic (PV) systems. Satellite derived GHI estimates are used to design and site PV power plants, to forecast the power output of a fleet of PV generators, and to provide electric utilities real-time estimates of the distributed generation (DG) or "behind the meter" generation of rooftop PV systems. Data assimilation provides a framework to combine the large area coverage of GHI estimates derived from satellite imagery with the more accurate data of ground sensors.

Previous work has also explored using data assimilation techniques to improve solar radiation estimates [1], [2]. We use optimal interpolation (OI), which can be thought of as a generalized least squares approach [3]. OI is a statistical method to combine prior information about some parameter (the background) with observations based on the errors and correlations in the background and observations. The background is computed from satellite estimates, the observations come from a mix of GHI sensors and rooftop PV systems. OI is also used by [2], where numerical weather prediction (NWP) solar radiation data are combined with ground sensors. A key difference and innovation in our paper is that correlations used for OI are prescribed based on differences in cloudiness between locations, rather than spatial distance.

Our paper is organized as follows. We describe OI in Sec. II and apply it to satellite GHI estimates in Sec. III. We discuss the results in Sec. IV and future work in Sec. V. Finally, a summary is provided in Sec. VI.

II. Optimal Interpolation Procedure

A. Method

We briefly describe the OI method; the derivation can be found in many data assimilation textbooks, e.g. [3]. The output of an OI routine (known as the analysis), $\hat{\mathbf{x}}$, is a vector of length N and is a weighted sum of the background (the prior information represented as an N vector), $\mathbf{x}_b$, and the measurements, $\mathbf{y}$ (M vector):

$$\hat{\mathbf{x}} = \mathbf{x}_b + \mathbf{W}(\mathbf{y} - \mathbf{H}\mathbf{x}_b). \quad (1)$$

In this study, $\mathbf{x}_b$ is composed of satellite derived clear-sky indices and $\mathbf{y}$ is composed of clear-sky indices from a number of ground irradiance sensors. The observation matrix, $\mathbf{H}$ ($M \times N$ matrix), maps points in the background space to points in observation space. We construct $\mathbf{H}$ using the nearest neighbor approach of selecting the background points that are closest to the observation locations. The weight matrix, $\mathbf{W}$ ($N \times M$ matrix), is constructed from the error covariance matrix of the background, $\mathbf{P}$ ($N \times N$ matrix), and the error covariance of the observations, $\mathbf{R}$ ($M \times M$ matrix) as

$$\mathbf{W} = \mathbf{P}\mathbf{H}^T(\mathbf{R} + \mathbf{H}\mathbf{P}\mathbf{H}^T)^{-1}. \quad (2)$$

We also compute the error covariance matrix of the analysis, $\hat{\mathbf{P}}$ ($N \times N$ matrix), as

$$\hat{\mathbf{P}} = (\mathbf{I} - \mathbf{W}\mathbf{H})\mathbf{P}, \quad (3)$$

where $\mathbf{I}$ is the $N \times N$ identity matrix.

An essential part of the OI routine is choosing appropriate error covariance matrices, $\mathbf{R}$ and $\mathbf{P}$. The standard method, that we also follow is to assume that the errors between sensors are uncorrelated so that $\mathbf{R}$ is a diagonal matrix. Each diagonal element of $\mathbf{R}$ is the variance of the observations at each location over a given period (in the results that follow we used the entire study period).

The method we use to obtain $\mathbf{P}$ is novel, in fact it is the primary difference between our work and [2]. First, we separate $\mathbf{P}$ into a correlation matrix $\mathbf{C}$ and diagonal variance matrix $\mathbf{D}$:

$$\mathbf{P} = \mathbf{D}^{1/2}\mathbf{C}\mathbf{D}^{1/2}. \quad (4)$$

We obtain $\mathbf{D}$ in a similar manner as $\mathbf{R}$: we take the variance of each pixel in the satellite image over some period of time.

Care must be taken when estimating the background correlation matrix $\mathbf{C}$. A standard method is to assume the correlation

978-1-5090-2724-8/16/$31.00 ©2016 IEEE