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Spatiotemporal interpolation and forecast of irradiance data using Kriging

Mohammad Jamaly*, Jan Kleissl

Center for Renewable Resources and Integration, Department of Mechanical and Aerospace Engineering, University of California, San Diego, La Jolla, CA 92093-0411, United States

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ABSTRACT

Solar power variability is a concern to grid operators as unanticipated changes in PV plant power output can strain the electric grid. The main cause of solar variability is clouds passing over PV modules. However, geographic diversity across a region leads to a reduction in the cloud-induced variability. In this paper, spatiotemporal correlations of irradiance data are analyzed and spatial and spatiotemporal ordinary Kriging methods are applied to model irradiation at an arbitrary point based on the given time series of irradiation at some observed locations. The correlations among the irradiances at observed locations are modeled by general parametric covariance functions. Besides the isotropic covariance function (which is independent of direction), a new non-separable anisotropic parametric covariance function is proposed to model the transient clouds. Also, a new approach is proposed to estimate the spatial and temporal decorrelation distances analytically using the applied parametric covariance functions, which reduce the size of the computations without loss in accuracy (parameter shrinkage). The analysis has been performed and the Kriging method is first validated by using two spatially and temporally resolved artificial irradiance datasets generated from Large Eddy Simulation. Then, the spatiotemporal Kriging method is applied on real irradiance and output power data in California (Sacramento and San Diego areas) where the cloud motion had to be estimated during the process using cross-correlation method (CCM). Results confirm that the anisotropic model is most accurate with an average normalized root mean squared error (nRMSE) of 7.92% representing a 66% relative improvement over the persistence model.

1. Introduction

1.1. Motivation

As demands for integration of large amounts of photovoltaic (PV) power plants into the electricity grid have increased recently, fully resolved (time steps on the order of seconds and spatial resolution on the order of 10 m) spatiotemporal irradiance data is needed. Simulations of solar power output for distribution feeder power flow studies (Nguyen and Kleissl, 2015) and short-term forecasting of power output from large power plants (Lipperheide et al., 2015) are some applications of such fully resolved irradiance data. Ground measurements of solar irradiance are sparse and continuous high quality measurements require more effort in maintenance and data quality control than common meteorological state variables (Vignola et al., 2013). On the other hand, temporal downscaling and spatial interpolation is usually required for satellite-derived irradiance data with coarse temporal resolution at 15–30 min and large pixel size (1 km or more). Therefore, an interpolation technique is required to provide such spatially and temporally resolved irradiance data at unobserved locations. While linear interpolation techniques may be appropriate to estimate the average annual solar resource at unobserved locations, they reduce the solar irradiation variance at unobserved locations and do not preserve correlation properties.

1.2. Kriging as a stochastic interpolation method

As an alternative to linear interpolation, a stochastic interpolation method (i.e., Kriging method) can be applied to high fidelity solar resource modeling at unobserved locations. The Kriging method is superior to deterministic interpolation techniques (which use only mathematical functions; e.g. Widen (2015)) since both analytical and statistical methods are applied to predict unknown values based on correlations in the irradiance data. Kriging methods have been shown to be the best linear unbiased prediction method in many fields of study. In the Kriging method, the mean and correlation properties of the irradiance data are preserved and an estimation of the error of the process (Kriging variance) is provided as a basis for stochastic simulation. The Kriging method can be applied to both ground measured as well as satellite-derived solar irradiance data for spatial interpolation,

* Corresponding author.
E-mail address: smjamaly@ucsd.edu (M. Jamaly).

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Nomenclature

AST	anisotropic spatiotemporal
C	covariance function
C_S	spatial covariance function
C_T	temporal covariance function
CCM	cross-correlation method
CGILS	CFMIP-GCSS intercomparison of Large-Eddy and Single-Column models
CSA	cross-spectral analysis
GHI	global horizontal irradiance
$I_{S=0}$	Dirac delta function
IST	isotropic spatiotemporal
L	total number of bins of distances in the domain
LES	Large Eddy Simulation
LOSO	leave-one-site-out
LOSOE	LOSO using the entire time series
LOSOP	LOSO using past data
LOTO	leave-one-time-step-out
LOTOE	LOTO using the entire time series
LOTOP	LOTO using past data
LWP	liquid water path
$N(h(l),u)$	number of pairs in each bin and time lag of the semivariogram
P_{CSI}	measured CSI PV power output
$P_{max,day}$	PV output expected for a day with clear condition
PV	photovoltaic
QC	quality control
RICO	rain in cumulus over the ocean
SDG&E	San Diego Gas & Electric
SMUD	Sacramento municipality utility distract
SP	spatial
SR	skill ratio
Z_0^*	irradiance estimate at an arbitrary location (x_0) and time (t_0)
Z_{ij}	observed irradiance at location (x_i) and time (t_j)
a	a coefficient of the parametric semivariogram function
c	a coefficient of the parametric semivariogram function
h_1	distance component in along-wind direction
h_2	distance component in cross-wind direction
h_c	spatial decorrelation distance
$h(l)$	number of bins in empirical semivariogram
kt	clear-sky index
kt_{CSI}	kt for measured CSI power output
kt_{SMUD}	kt for measured SMUD GHI data
m	number of time steps of time series
max_t	maximum time lags between irradiance at site pairs
nRMSE	normalized root mean squared error
u	time lag in parametric covariance function
u_c	temporal decorrelation length
v	cloud motion speed
wl,u	weights function in weighted least squares (WLS) method
WLS	weighted least squares
α	a coefficient of the parametric semivariogram function
β	separable factor in the spatiotemporal covariance function
γ	prametric semivariogram function
γ_{ik}^{jl}	γ for $\lvert i\text{-}k\rvert$ spatial and $\lvert j\text{-}l\rvert$ temporal lag, respectively
$\hat{\gamma}$	empirical semivariogram function
γ_{AI}	anisotropic semivariogram function
γ_{FS}	isotropic semivariogram function
γ_{LGR}	Lagrangian semivariogram function
Γ	spatiotemporal semivariogram matrix
δ	a coefficient of the parametric semivariogram function
ζ	a coefficient of the parametric semivariogram function
λ_{ij}	weights of the Kriging method
μ	Lagrange multiplier
ν_S	nugget effects of the parametric semivariogram function
ρ	parameter for convex combination model of anisotropic semivariogram function
σ^2	variance of the spatiotemporal process
σ^2_{OK}	Kriging variance
φ	general form of functions for stationary non-separable parametric covariance function
ω	general form of functions for stationary non-separable parametric covariance function

temporal downscaling, or forecast of the irradiance data. A literature review of state-of-the-art spatiotemporal Kriging methods is provided in Perez et al. (2016). According to Perez et al. (2016), various forms of the spatiotemporal Kriging are used in solar engineering: simple Kriging assumes that the mean of the process across space and time is known. Otherwise, ordinary Kriging (assuming unknown but constant mean) and universal Kriging (assuming the unknown mean is a known function of co-variates, e.g., latitude, longitude) can be used. In this paper, the spatial and spatiotemporal ordinary Kriging method is applied to estimate irradiation at an arbitrary point.

In the Kriging method, irradiance correlations are modeled by a parametric spatiotemporal covariance function and parameters are calculated empirically (Zimmerman and Stein, 2010; Zimmerman, 1989) based on some simplifications and assumptions including stationarity, separability, and isotropy. In a temporal (or spatial) stationary process, the mean and other statistical properties of solar radiation is constant over time (or space) and the covariance function is a function of time lags (or distance between locations) only; spatiotemporal stationarity of solar radiation is achieved if the process is stationary both spatially and temporally. In a separable covariance function, the spatial solar radiation variation is independent of its temporal variation. Gneiting (2002) and Gneiting et al. (2007) demonstrated special requirements for covariance functions and showed that the geostatistical covariance functions cannot be considered separable (especially for meteorological data such as wind velocity fields or solar irradiance data). In isotropic covariance functions, the covariance in solar radiation does not depend on direction.

1.3. Application of Kriging to irradiance data

Since the main source of spatiotemporal variability in irradiance data are transient clouds, to increase the performance of the Kriging method, anisotropic covariance functions are required to model transient clouds in the domain of investigation. Gneiting et al. (2007) considered a physically motivated directional dependence of the covariance (Lagrangian covariance function): introducing anisotropy according to the velocity vector of the flow, the covariance is a function of (x-vt) where x, v, and t represent space, velocity vector, and time, respectively. Adjusting an isotropic covariance function by a Lagrangian covariance function has been shown to improve forecast of meteorological data including wind velocity (Gneiting et al., 2007) and solar irradiance data (Aryaputera et al., 2015). Schlather (2010) developed a general form of the Lagrangian covariance by considering a variable velocity vector with a multivariate normal distribution. The Lagrangian covariance function is applied in many solar irradiance studies to account for anisotropy due to cloud motion (Lonij et al., 2013; Inoue et al., 2012; Shinozaki et al., 2014). Yang et al. (2013), on the other hand, achieved spatial stationarity and isotropy through deformations of the geographical space based on the two-step method developed by Sampson and Guttorp (1992).