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Solar irradiance forecasting using spatial-temporal covariance structures and time-forward kriging

Dazhi Yang [a,*], Chaojun Gu [b], Zibo Dong [a], Panida Jirutitijaroen [b], Nan Chen [c], Wilfred M. Walsh [a]

[a] Solar Energy Research Institute of Singapore, National University of Singapore, Singapore S117574, Singapore
[b] Department of Electrical and Computer Engineering, National University of Singapore, Singapore
[c] Department of Industrial and System Engineering, National University of Singapore, Singapore

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ABSTRACT

Electricity power grid operations require information about demand and supply on a variety of time-scales and areas. The advent of significant generation contributions by time variable renewable energy sources means that forecasting methods are increasingly required. Some of the earliest requirements will be for spatial-temporal estimation of solar irradiance and the resulting photovoltaic-generated electricity. Accurate forecasts represent an important step towards building a smart grid for renewable energy driven cities or regions, and to this end we develop forecasting tools that use data from ground-based irradiance sensors.

Spatial-temporal datasets that enjoy the properties of stationarity, full symmetry and separability are in general more amenable to forecasting using time-forward kriging algorithms. Usually, none of these properties obtain in meteorological data such as wind velocity fields and solar irradiance distributions. In this paper, we construct a statistical forecast system to mitigate this problem. We first achieve temporal stationarity by detrending solar irradiance time series at individual monitoring stations. We then approximate spatial stationarity through deformations of the geographic coordinates. Various spatial-temporal variance-covariance structures are formed to explore full symmetry and separability. Finally, time-forward kriging is used to forecast the hourly spatial-temporal solar irradiance data from 10 Singapore weather stations. The aim of the proposed system is to forecast irradiance and PV electricity generation at arbitrary spatial locations within a monitored area.

1. Introduction

As solar photovoltaic electricity (PV) approaches price parity with grid electricity, the installed base of solar electricity systems increases at a fast pace. This creates challenges for electricity grid operators, as rapid changes in irradiance can potentially occur faster than grid reaction times. Forecasts can mitigate this problem, and the time-space distribution of solar irradiance contributes valuable information to solar energy planning and forecasting. Statistical methods are often used to perform the temporal and spatial estimates in situations where solar irradiance measurements are sparse [35].

Single station solar irradiance forecasts using statistical methods have been studied intensively in the past few decades. These include time series, autoregressive integrated moving average (ARIMA) analyses [27,29,34], artificial neural networks (ANN) multi-layer perceptron model [27,28,30], k-Nearest Neighbors' algorithm [30] and Bayesian inference [30]. Although the accuracies of these forecasting methods can be adequate, they do not provide spatial irradiance information. Thus in order to plan the electricity generation at power grid level, we require a large number of monitoring stations over the power grid area. The number of sensors is generally limited and their distribution is irregular. Thus, spatial-temporal estimation for solar irradiance is an important step towards the forecast required by renewable energy driven cities.

Temporal and spatial behaviors of solar irradiance are related through complex atmospheric mechanisms. Recent advances in space-time statistics [e.g. Refs. [8,11,25]] allow us to analyze such environmental processes not only in separate temporal and spatial domains but as a whole. Little work has been done on solar irradiance, although Gueymard and Wilcox [16] provide a study on long

* Corresponding author. Tel.: +65 9159 0888.
E-mail address: yangdazhi.nus@gmail.com (D. Yang).

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term (inter-annual) variability in global radiation. Most studies employ separate modeling despite aiming to study solar irradiance across time as well as space [e.g. Ref. [12]]. We aim to develop statistics that directly describe the spatial-temporal process. To facilitate our following discussion, we first introduce several statistics.

1.1. Some definitions

In statistics, covariance is a measure of the extent to which two random variables vary together. Very often, the covariance between two random variables can be modeled using a covariance function of space and time, the applications of which are widely seen in statistical planning and inference [e.g. Refs. [10,18]].

A random field at location $\mathbf{s}_i$ and time t_i is denoted as $Z(\mathbf{s}_i, t_i)$, $Z \in \mathbf{R}^{\mathbf{d}} \times \mathbf{R}$. We say the random field Z has separability if the covariance structure of Z can be separated into a purely spatial covariance structure and a purely temporal covariance structure:

$$\mathrm{cov}\{Z(\mathbf{s}_i, t_i), Z(\mathbf{s}_j, t_j)\} = \mathrm{cov}_S\{Z(\mathbf{s}_i), Z(\mathbf{s}_j)\} \cdot \mathrm{cov}_T\{Z(t_i), Z(t_j)\} \tag{1}$$

where the subscripts S and T are used to denote space and time respectively. However, most of the environmental data set cannot be assumed to be separable due to the complex time and space interactions. A more general class of spatial temporal processes are the fully symmetric processes. A random field is said to be fully symmetric if:

$$\mathrm{cov}\{Z(\mathbf{s}_i, t_i), Z(\mathbf{s}_j, t_j)\} = \mathrm{cov}\{Z(\mathbf{s}_i, t_j), Z(\mathbf{s}_j, t_i)\} \tag{2}$$

Examples of the above covariance functions appear in our case studies, below. Separability is a special case of full symmetry. Therefore when the covariance matrix is not fully symmetric, it cannot be separable.

Another important property of spatial-temporal data is stationarity. We say a random field exhibits temporal stationary if the covariance function $\mathbb{C}$ is only a function of time separation τ, where $\tau = t_i - t_j$. A similar definition can be applied to spatial stationarity. A random field exhibits temporal stationary if the covariance function is only a function of spatial separation $\mathbf{h}$, where $\mathbf{h} = \mathbf{s}_i - \mathbf{s}_j$. We will show later that $\mathbf{h}$ does not necessarily represent the geographical distance between two observations. In mathematical form, spatial temporal stationarity is:

$$\mathrm{cov}\{Z(\mathbf{s}_i, t_i), Z(\mathbf{s}_j, t_j)\} = \mathbb{C}(\mathbf{h}, \tau) \tag{3}$$

Stationarity does not imply full symmetry nor separability. A special case of a separable stationary random field is represented by: $\mathrm{cov}\{Z(\mathbf{s}_i, t_i), Z(\mathbf{s}_j, t_j)\} = \mathbb{C}_S(\mathbf{h}) \cdot \mathbb{C}_T(\tau)$. Similarly, full symmetry can be defined as $\mathbb{C}(\mathbf{h}, \tau) = \mathbb{C}(\mathbf{h}, -\tau)$. Fig. 1 shows the Venn diagram for the three statistical properties.

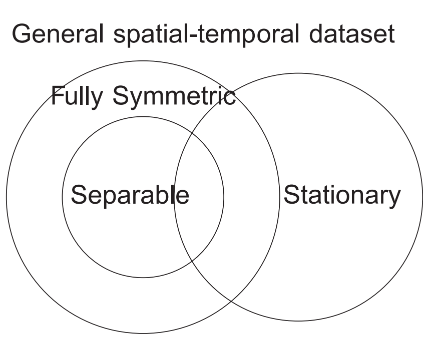

Fig. 1. Diagram illustration for stationarity, full symmetry and separability.

1.2. Anisotropy and time-forward kriging

The definitions introduced above indicate that using statistical prediction methods requires careful analytical description and analysis of a data set. Properties such as stationarity, separability and isotropy are frequently overlooked. For example, in geostatistics, 2D linear least squares estimation is often performed using kriging algorithms to construct 2D contour images, such as irradiance maps. Rehman and Ghori [33] plot monthly irradiance contours for Saudi Arabia; Righini et al. [35] develop contours for Argentina; Bland and Clayton [4] for Wisconsin and Bechini et al. [3] for northern Italy. These authors first identify a suitable variogram model (variance versus distance plot) for the region and then apply weighted spatial smoothing kriging techniques to perform the spatial prediction.

Spatial resolution, an important consideration in all spatial-temporal irradiance studies, is often limited by data sparsity. In the context of solar irradiance, it has been shown that the spatial correlation between two locations converges after the threshold distance [31]. The dependence metrics used in kriging, such as dispersion or correlation, must be carefully selected. Previous studies have applied kriging techniques to data from stations with large geographical separations. As a result, overestimates of the threshold distance occur, leading to information loss. Furthermore, many authors ignore the anisotropic nature of atmosphere processes by fitting isotropic variogram models. The large fitting errors typical in the literature imply uncertainties in their following analyses that render them too inaccurate for practical applications. It is likely that no isotropic variogram model can represent the anisotropic nature of the spatial variability of solar irradiance [36]. We show that even within a small island like Singapore (41.8 km ENE-WSW and 22.5 km SSE-NNW), whatever happens in the east is unlikely to cause any variability change in the west. We therefore aim to take anisotropy into consideration in this work.

In the rest of this paper, we construct a statistical forecast system. Temporal stationarity is an important feature of our models, and one that is readily derived by detrending solar irradiance time series at individual stations (Section 2). Spatial anisotropy is achieved through deformations of the geographic coordinates (Section 3). Various spatial-temporal variance-covariance structures are formed to further explore full symmetry and separability (Section 4). Finally, time-forward kriging is used (Section 5) to forecast the 5 min spatial-temporal solar irradiance data from 10 Singapore weather stations. Section 6 discusses three important observations, namely, perfect isotropic spatial-temporal process, the nature of variance-covariance structures and our forecasting results. Section 7 concludes the findings.

1.3. Data

Fig. 2 shows the geographical locations of 10 meteorological stations in Singapore. These stations are designed to perform monitoring of solar irradiance and control of PV systems to optimize their availability and reliability. Silicon sensors are employed at each station, with some also having pyranometers that measure diffuse and global irradiance. The silicon sensors are calibrated by the Fraunhofer Institute for Solar Energy Systems to achieve an uncertainty under 2%. The data used in this work is hourly data from these 10 stations from period 2012 November.

2. Temporal stationarity

We consider a time series (a sequence of observations taken sequentially in time) to be stationary if it has a constant mean level [6]. Both stationary and non-stationary time series forecasting