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Nonparametric short-term probabilistic forecasting for solar radiation

Adrian Grantham [a], Yulia R. Gel [b], John Boland [a,*]

[a] University of South Australia, Mawson Lakes Boulevard, Mawson Lakes, SA 5095, Australia
[b] University of Texas at Dallas, 800 West Campbell Road, Richardson, TX 75080, USA

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Abstract

The current deep concerns on energy independence and global society's security at the face of climate change have empowered the new "green energy" paradigm and led to a rapid development of new methodology for modeling sustainable energy resources. However, clean renewables such as wind and solar energies are inherently intermittent, and their integration into a electric power grid require accurate and reliable estimation of uncertainties. And, if probabilistic forecasting of wind power is generally well developed, probabilistic forecasting of solar power is still in its infancy. In this paper we propose a new data-driven method for constructing a full predictive density of solar radiance based on a nonparametric bootstrap. We illustrate utility of the new bootstrapped statistical ensembles for probabilistic one-hour ahead forecasting in Mildura, Australia. We show that the new approach delivers sharp and calibrated ensembles of one-hour forecasts, and is computationally inexpensive and easily tractable.

Keywords: Global horizontal irradiance; Probabilistic forecasting; Sustainable energy; Bootstrap; Map of sun positions

1. Introduction

As it has been emphasized at the most recent 2015 Paris Climate Conference (COP21), at the face of increasingly dramatic impact of global warming on our ecosystem, "green power" resources such as wind, sunlight, wave and tides that quickly replenish themselves are now broadly recognized as the critical path toward future sustainability and reducing the environmental footprint. Many countries have accelerated their climate and energy policies with an aim to minimize the greenhouse gas emissions and pollution. For instance, the Australian Government has set a target for reducing greenhouse gas emissions by 26–28% below 2005 levels by 2030 (Commonwealth of Australia, 2015) while China commits to cap rising emissions by 2030 (Change Authority, 2015). The European Union commits to reduce emissions of at least 40% below 1990 levels by 2030, and similar initiatives are announced by the US and Brazil at the recent joint summit in June 2015. However, one of the key obstacles on the way of efficient and reliable integration of renewable energy into electric power systems is its natural intermittency and volatility, or as The New York Times mentioned, "the dirty secret of clean energy is that while generating it is getting easier, moving it to market is not" (Wald, 2008). This in turn has boosted a substantial interest in developing new methods for modeling clean energy resources and, particularly, in statistical procedures that construct a full predictive density of "green power" at various forecasting horizons, and thus allow to assess a wide range of uncertainties and facilitate decision-making. However, the vast majority of such methods focus on

* Corresponding author.
E-mail addresses: adrian.grantham@unisa.edu.au (A. Grantham), ygl@utdallas.edu (Y.R. Gel), john.boland@unisa.edu.au (J. Boland).

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probabilistic wind power forecasting (see, for example, reviews by Chen et al. (2013), Pinson (2013), Gneiting and Katzfuss (2014), De Greve et al. (2014), Erdem et al. (2014), Zhang et al. (2014), Wan et al. (2013), Zamo et al. (2014), and references therein), while systematic addressing uncertainty in solar energy prediction remains largely unexplored. For instance, recently Zhang et al. (2015) evaluate utility of various metrics for classification of uncertainties in a solar irradiation forecast but do not discuss methodology for constructing a full predictive density. Zamo et al. (2014) study probabilistic forecasting of photovoltaic (PV) electricity production based on an ensemble output from a numerical weather prediction (NWP) model. A related work of Ngoko et al. (2014) deals with synthetic generation of solar radiation sequences, thus implicitly using similar tools to those needed for prediction interval construction. Most recently, Boland and Soubdhan (2015) employs Autoregressive Conditional Heteroscedastic (ARCH) techniques to construct parametric prediction intervals for hourly and ten minute solar forecasts based on a normal distribution.

Nonparametric probabilistic forecasting for solar PV power has been recently examined by Golestaneh et al. (2016) and Le Cadre et al. (2015). Pinson and Kariniotakis (2010) propose to generate prediction intervals for wind power using a nonparametric approach called adaptive resampling. Similarly to our method for constructing a full predictive density (see Section 4), the approach of Pinson and Kariniotakis (2010) places errors into bins based on influential variables, for example predicted power level, in order to deal with the variation in variance of wind power at different power ranges. Recently, Gel et al. (2016) consider a nonparametric sieve bootstrap for generating probabilistic forecasts of wind speed.

This paper breaks through the current practice of point forecasting of solar radiance and proposes a new computationally efficient and data-driven method for constructing a full nonparametric predictive density for short term forecasting of solar radiation, using nonparametric bootstrap and a map of sun positions. What we demonstrate here is probabilistic forecasting of solar radiation on an hourly basis but the proposed methodology can be altered to cater for any predictive horizon from five minute to a few hours. Our study is primarily motivated by a project run by the Australian National Electricity Market (NEM), where dispatch decisions are made every five minutes and market clearing takes place on a half hour basis. Moreover, one of the authors (Boland) is part of a team developing the Australian Solar Energy Forecasting System (ASEFS) for the Australian Energy Market Operator (AEMO) which aims to enhance integration of solar energy generation at *all scales* into the Australian national grid. One of the primary ASEFS goals is to develop an operational system that employs forecasting techniques for all the AEMO-required forecasting time frames, which range from five minutes to two years. The new statistical procedures for probabilistic forecasting of solar power that we propose in this paper are thus expected to be implemented for operational use by AEMO. In view of the results on utility of a nonparametric sieve bootstrap (Bühlmann, 2002, 1997; Alonso et al., 2002; Chen et al., 2011), the bootstrap methodology proposed in this paper is expected to be applicable to a broad range of other time scales and forecasting horizons for global horizontal irradiation as well as for generating a full predictive density for PV output.

The paper is organized as follows. Description of the solar irradiation data is given in Section 2. Section 3 details a model for point forecasting. In Section 4 we present the new bootstrap methodology for probabilistic forecasting of solar irradiation. We evaluate the new probabilistic forecasting methodology in Section 5. The paper is concluded by discussion and future work in Section 6.

2. Data description

The solar irradiation data used in this study are recorded in Mildura, Australia (Latitude 34.11° S, Longitude 142.09° E). A map of Australia with Mildura's location is shown in Fig. 1. According to the Köppen-Geiger climate classification system (Peel et al., 2007), Mildura's climate is classified as semi-arid with hot summers and cool winters.

The data set consists of 87,600 ($10 \times 365 \times 24$) hourly global horizontal irradiation (GHI) values from 1995 to 2004 with units of watts per square meter, Wh m^{-2}. The first eight years of data is used to generate the forecasting and prediction interval model (i.e., in-sample) and the last two years is used for out-of-sample testing. Observations on February 29 in leap years are omitted. The average GHI value is 443.71 Wh m^{-2} (where the sun elevation is greater than zero degrees) and the maximum value is 1263 Wh m^{-2}.

Fig. 1. Mildura (The Wireless Institute of Australia, 2015).