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An adaptive multi-modeling approach to solar nowcasting

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Abstract

The ability to forecast solar irradiance in near-real time (nowcasting) is crucial in managing the integration of solar energy in power grids. This paper focuses on minute-by-minute forecasts of the normalized clearness index, a measure of global horizontal irradiation, within a fifteen steps-ahead temporal horizon, using data collected with a radiometric station in Doha, Qatar, for the period January–December 2014. We describe a novel multi-modeling approach to solar forecasting that uses supervised classification of forecasting evaluation results from diverse stochastic models to select the best predictions, according to their expected superiority in terms of lower error rate. The hypothesis that such a multi-modeling approach rivals the performance of any single forecasting model is tested with reference to two autoregressive models, of order 3 and 11 respectively, a support vector regression model, and a persistence model which provide the baseline for solar prediction. The advantages of the proposed approach are demonstrated in an experimental evaluation where its application with these four models shows a relative skill score improvement of 44.92% over the baseline model, and 19.06% over the best performing model (autoregressive of order 11).

Keywords: Solar radiation forecasting; Normalized clearness index; Support vector regression; Autoregressive modeling

1. Introduction

The ability to forecast solar irradiance in near-real time, or "nowcasting", is crucial for network operators to guarantee power grid stability with specific reference to power plant operations, grid balancing, real-time unit dispatching, automatic generation control and trading (Inman et al., 2013). Solar irradiance is subject to sudden variation due to meteorological change (e.g., clouds, haze, dust storms). Sudden changes in solar irradiance can trigger unacceptable voltage and frequency deviations leading to grid instability, especially where solar energy penetration is high. Solar nowcasting can help solve this problem by providing insights about forthcoming changes in solar irradiance that can be used to optimize plant performance. As discussed in Hirsch et al. (2014), such an optimization can support diverse technical and economic goals. For example, knowledge about short-term electricity production from solar energy can help fine-tune electricity sales by providing a reliable match between announced and delivered electricity for solar plants that lack storage capacity. Combined knowledge about the electricity market and the short-term behavior of the solar plant can help plant operators formulate the optimal solution to meet a demand profile by mixing and matching storage and electricity co-generation strategies. From the viewpoint of power grid stability as a whole, the ability to forecast the individual

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production of each solar plant in the grid in the short term helps optimize usage of the power plant portfolio. Overall, solar nowcasting is increasingly becoming a focus of research in the area of operation, management and integration of solar power plants into the grid, and government agencies such as the European Commission are starting to make significant research investment in this area (DNICast, n.d.).

Existing approaches to solar forecasting can be broadly characterized as either physics-based or stochastic (Diagne et al., 2013; Inman et al., 2013). Physics-based approaches include techniques such as physical satellite models (Gautier et al., 1980; Möser and Raschke, 1984; Marullo et al., 1987; Dedieu et al., 1987), Numerical Weather Prediction (NWP) models (Yang et al., 2006; Yang et al., 2008; Benjamin et al., 2009), and local sensing models (Chow et al., 2011). Physical satellite and NWP models lack the spatial and temporal resolution needed for intra-hour forecasts (Inman et al., 2013). For example, even the NWP models with higher spatiotemporal resolution, e.g., the North American Mesoscale Forecast System (NAM, n.d.), are insufficient to resolve most clouds and any patterns for intra-hour timescales (Diagne et al., 2013). Local sensing instruments such as total sky imagers are now starting to provide adequate measurements to develop physics-based models for intra-hour forecasts (Chow et al., 2011). Overall, stochastic techniques have proved to be more effective than physics-based approaches for intra-hour solar forecasting (Diagne et al., 2013; Inman et al., 2013).

Various statistical and machine learning techniques have been used to forecast solar irradiance, including Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), Coupled Autoregressive and Dynamical System (CARDS), Artificial Neural Network (ANN), kNearest Neighbor (kNN), and Support Vector Regression (SVR) – see Mellit and Kalogirou (2008), Diagne et al. (2013), Pelland et al. (2013), Inman et al. (2013) and references therein. These algorithms have also been successfully improved through combination with data filtering techniques such as wavelet transforms (Mellit et al., 2006; Lyu et al., 2014).

However, while specific algorithms may overall outperform others, no single forecasting model can consistently provide superior forecasts in all solar radiation contexts, as discussed in Section 4 with reference to Fig. 2. The use of ensemble learning as a technique to select the best predictions from different models is well documented for NWP – see Delle Monache et al. (2013) and references therein – and has recently been applied to stochastic approaches to solar forecasting (Chaouachi et al., 2010; Mohammed et al., n.d.). In this paper, we explore a multi-modeling alternative approach to ensemble learning, where supervised classification of forecasting evaluation results is used to select the best predictions from diverse forecasting approaches, according to their expected superiority.

The paper is organized in five sections. First, we describe the data. Then, we discuss the forecasting algorithms used and the evaluation methodology adopted. Next, we present a comparative evaluation of forecasting results by model. Finally, we demonstrate how supervised classification helps predict the most appropriate model by time series data input, and show how these predictions can be used to develop a novel multi-modeling solar forecasting approach which rivals any single-model approach. We conclude with a few summary statements and some remarks about next steps.

2. Data

The Qatar Environment and Energy Research Institute (QEERI) has been operating a high precision solar radiation monitoring station since the end of November 2012 in Education City, Doha (25.33°N, 51.43°E) (Perez-Astudillo and Bachour, 2014). The station is equipped with a solar tracker that includes a sun sensor kit for improved tracking accuracy, and a shading ball assembly for diffuse measurements. Mounted on the sun tracker are one first class pyrheliometer for measuring Direct Normal Irradiance (DNI), and two secondary standard pyranometers (one of them shaded) for Global Horizontal Irradiance (GHI) and Diffuse Horizontal Irradiance (DHI) measurements. Both pyranometers are fitted with ventilation units. Data from the monitoring station are sampled every second and recorded as 1-min averages in Watt per square meter (W/m^2). Data quality checks following the Baseline Surface Radiation Network (BSRN) recommendations (Long and Dutton, 2002; McArthur, 1998) were applied. For the study described in this paper, we used a complete year of data collected as 1-min averages from 1 January 2014 to 31 December 2014. A full year of solar radiation data covers the full range of seasonal variation thus providing all the necessary atmospheric conditions to develop and test a solar forecasting model.

Measurements of solar irradiance in the plane of a photovoltaic (PV) array together with the temperature at the back of the PV modules are the main factors in determining PV output (Pelland et al., 2013). We direct our attention to GHI as it is the relevant solar irradiance measure for non-concentrating PV systems (Pelland et al., 2013), which represent the prevalent renewable energy technology foreseen for Qatar. To separate forecasting complexity into the prediction of solar geometry and the prediction of cloudiness and aerosol, we focus on the *clearness index* (K_T) as a GHI-based measure. K_T is calculated as the ratio of GHI to the incoming solar radiation on a horizontal surface at the top of the earth's atmosphere (Black et al., 1954; Duffie and Beckman, 1991). It characterizes the attenuating impact of the atmosphere on solar irradiance by specifying the proportion of extraterrestrial solar radiation that reaches the surface of the earth. To alleviate K_T's dependency on the zenith angle, which changes the traversed air mass during the course of a day, we select as forecasting