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Short-term reforecasting of power output from a 48 MWe solar PV plant

Yinghao Chu, Bryan Urquhart, Seyyed M.I. Gohari, Hugo T.C. Pedro, Jan Kleissl, Carlos F.M. Coimbra *

Department of Mechanical and Aerospace Engineering, Jacobs School of Engineering, Center for Renewable Resource Integration, University of California, San Diego, 9500 Gilman Drive, La Jolla, CA 92093, USA

Department of Mechanical and Aerospace Engineering, Jacobs School of Engineering, Center for Energy Research, University of California, San Diego, 9500 Gilman Drive, La Jolla, CA 92093, USA

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Abstract

A smart, real-time reforecast method is applied to the intra-hour prediction of power generated by a 48 MWe photovoltaic (PV) plant. This reforecasting method is developed based on artificial neural network (ANN) optimization schemes and is employed to improve the performance of three baseline prediction models: (1) a physical deterministic model based on cloud tracking techniques; (2) an auto-regressive moving average (ARMA) model; and (3) a k-th Nearest Neighbor (kNN) model. Using the measured power data from the PV plant, the performance of all forecasts is assessed in terms of common error statistics (mean bias, mean absolute error and root mean square error) and forecast skill over the reference persistence model. With the reforecasting method, the forecast skills of the three baseline models are significantly increased for time horizons of 5, 10, and 15 min. This study demonstrates the effectiveness of the optimized reforecasting method in reducing learnable errors produced by a diverse set of forecast methodologies.

Keywords: Real-time reforecasting; Artificial neural networks; Genetic algorithm optimization; PV generation

1. Introduction

The importance of short-term solar forecasting systems for renewable integration has been discussed at length elsewhere (Lew et al., 2010; Inman et al., 2013). The variable nature of renewable power generation is an obstacle for achieving higher level of solar penetration into the power grid. Uncertainty in solar power generation caused by atmospheric processes adversely affects the stability of power grid and increases the capital and operational cost of reserves and ancillary generators. Smart generation control based on accurate generation forecasts is essential for integrating high level of cost-competitive solar power while maintaining a high level of grid stability (Hart et al., 2012; Inman et al., 2013). Motivated by the pressing need for more effective predictive ability for solar integration, different solar forecasting methodologies (physics-based, imaging, stochastic learning and regression models, etc.) have been developed for various temporal horizons ranging from minutes to several days (Kalogirou, 2001; Li et al., 2008; Bacher et al., 2009; Huang et al., 2010; Mellit and

* Corresponding author at: Department of Mechanical and Aerospace Engineering, Jacobs School of Engineering, Center for Renewable Resource Integration, University of California, San Diego, 9500 Gilman Drive, La Jolla, CA 92093, USA.

E-mail address: ccoimbra@ucsd.edu (C.F.M. Coimbra).

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Pavan, 2010; Hassanzadeh et al., 2010; Marquez and Coimbra, 2011; Pedro and Coimbra, 2012; Lave et al., 2012; Hart et al., 2012; Marquez and Coimbra, 2013a; Marquez et al., 2013; Inman et al., 2013; Quesada-Ruiz et al., 2014).

The performance of individual forecasting method can be further improved by real-time reforecasting, i.e., by adopting stochastic tools based on the analysis of the forecast and error time series. Reforecasting is mostly used in weather and climate forecasts to diagnose systematic bias, recognize model deficiencies, statistically correct forecast errors, and run data assimilation, thereby aiding in the calibration of forecasts and improving forecast skills and reliability (Carter et al., 1989; Kalnay et al., 1996; Krishnamurti et al., 1999; Rajagopalan et al., 2002; Hamill et al., 2004; Hamill et al., 2006; Whitaker et al., 2006; Wilks and Hamill, 2007). In this work, the application of re-forecasting advanced here is different than the one used for meteorological models. Reforecasting in meteorology is used over long periods of historical data to fine tune the parameters of deterministic models, while here the proposed reforecasting is a method to statistically improve predictive model in real-time using optimized stochastic learning techniques. In this work, the reforcasting operates as adaptive Model Output Statistics (MOS) enhancers for each of the baseline forecasting models.

Accordingly, reforecasting is applied for 3 distinct intra-hour forecast horizons (5, 10 and 15 min ahead) of power output for a photovoltaic power station in Boulder City, Nevada. The data used for model development and testing are discussed in Section 2. The three baseline forecasting models: a cloud tracking based deterministic model (Det), an Autoregressive and Moving Average model (ARMA), and a k-th Nearest Neighbor model (kNN) are described in Section 3. Section 3 also covers the smart reforecasting model, the GA optimization, and the statistical metrics for performance evaluation. Results and discussions are presented in Section 4. The main conclusions of this work are summarized in Section 5.

2. Data

Power output data is obtained from a 48 MW segment (approximately 1.3 km^2) of the Sempra Generation Copper Mountain solar power plant (114.993° W, 35.782° N, Fig. 1a). Cadmium telluride thin film panels are installed and fixed at an elevation angle of 25° with a due south azimuth. The generated power is collected by 96 inverters, and power output data is quality controlled by inspecting the output from each individual inverter.

Occasionally, the output measurements from a small subset of inverters are unavailable (less than 4 on a single day). As a result, the analyses and forecasts presented here are based on the average of available measurements. From Nov 1st to Dec 5th, 2011, the inverter-average power output are archived by a OSISoft PI Historian Server maintained by Sempra and transmitted to a similar server at the University of California, San Diego (UCSD). The sampling interval of the power output is thirty seconds.

Two Total Sky Imagers (TSIs, Fig. 1b) were installed by UCSD at the Copper Mountain solar power plant in July 2011 for automatic cloud observations. The TSI uses a spherical mirror to reflect the sky hemisphere into a downward pointing camera. Images are captured every 30 s at an effective resolution of 420×420 pixels. To reduce the intensity of reflected direct solar beam (i.e. the image of the sun itself), a strip of black rubber tape (a "shadowband") is affixed to the rotating mirror. The shadowband improves image quality and reduces potential sensor damage, but covers approximately 0.70 steradians of the sky hemisphere, which is about 14% of the image region used in the deterministic forecasting model (<80° zenith angle).

The power and imaging data (26,638 points each) are first paired and then split for model estimation and evaluation. The first 15,000 data points are used to estimate the parameters of the Det, ARMA, and kNN models. The remaining data are randomly divided into a learning subset and a testing subset (70% and 30%, respectively). The learning set (approximately 8000 data points) is used for

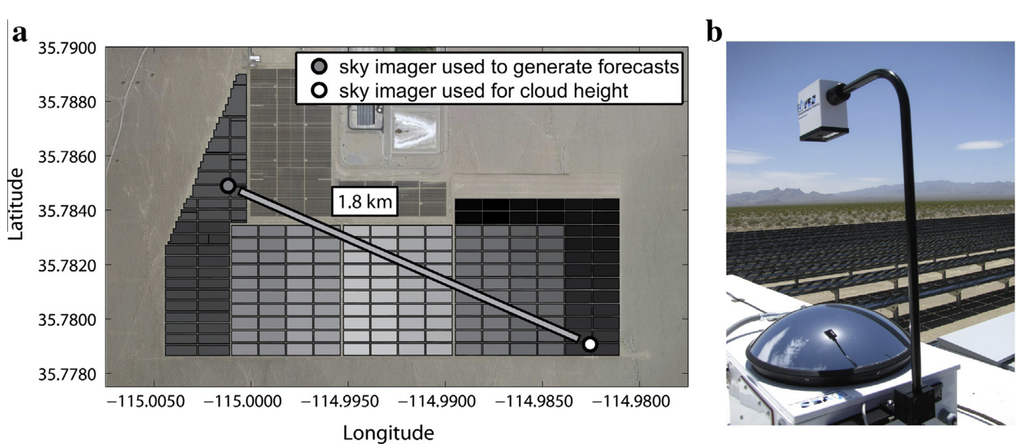

Fig. 1. (a) Schematic image of the analyzed solar power plant operated by Sempra Generation. The 48 MW subset of panels used in this work is indicated by the polygonal grayscale panel overlays. Each shade of gray is associated with one of the 96 inverters. The locations of the two sky imaging units used in the deterministic forecast are also denoted, along with the distance between them. (b) The Total Sky Imager (TSI) mounted on an inverter enclosure at the Copper Mountain plant.