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A suite of metrics for assessing the performance of solar power forecasting

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Abstract

Forecasting solar energy generation is a challenging task because of the variety of solar power systems and weather regimes encountered. Inaccurate forecasts can result in substantial economic losses and power system reliability issues. One of the key challenges is the unavailability of a consistent and robust set of metrics to measure the accuracy of a solar forecast. This paper presents a suite of generally applicable and value-based metrics for solar forecasting for a comprehensive set of scenarios (i.e., different time horizons, geographic locations, and applications) that were developed as part of the U.S. Department of Energy SunShot Initiative's efforts to improve the accuracy of solar forecasting. In addition, a comprehensive framework is developed to analyze the sensitivity of the proposed metrics to three types of solar forecasting improvements using a design-of-experiments methodology in conjunction with response surface, sensitivity analysis, and nonparametric statistical testing methods. The three types of forecasting improvements are (i) uniform forecasting improvements when there is not a ramp, (ii) ramp forecasting magnitude improvements, and (iii) ramp forecasting threshold changes. Day-ahead and 1-hour-ahead forecasts for both simulated and actual solar power plants are analyzed. The results show that the proposed metrics can efficiently evaluate the quality of solar forecasts and assess the economic and reliability impacts of improved solar forecasting. Sensitivity analysis results show that (i) all proposed metrics are suitable to show the changes in the accuracy of solar forecasts with uniform forecasting improvements, and (ii) the metrics of skewness, kurtosis, and Rényi entropy are specifically suitable to show the changes in the accuracy of solar forecasts with ramp forecasting improvements and a ramp forecasting threshold.
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Keywords: Grid integration; Nonparametric statistical testing; Solar power forecasting; Solar power ramps; Sensitivity analysis

1. Introduction

Solar power penetration in the United States is growing rapidly, and the SunShot Vision Study reported that solar power could provide as much as 14% of U.S. electricity demand by 2030 and 27% by 2050 (Margolis et al., 2012). At these high levels of solar energy penetration, solar power forecasting will become very important for electricity system operations. Solar forecasting is a challenging task, and solar power generation presents different challenges for transmission and distribution networks. On the transmission side, solar power takes the form of centralized solar power plants, a non-dispatchable component of the

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generation pool. On the distribution side, solar power is generated by a large number of distributed arrays installed on building rooftops and other sites. These arrays can alter traditional load patterns by offsetting electricity use behind the meter. Integrating large amounts of solar power into the grid can magnify the impact of steep ramps in solar power output, which poses challenges to system operators' ability to account for solar variability. Forecast inaccuracies of solar power generation can result in substantial economic losses and power system reliability issues because electric grid operators must continuously balance supply and demand.

1.1. Overview of solar forecasting

Solar power output is directly proportional to the magnitude of solar irradiance incident on the panels. To integrate high penetrations of solar energy generation, accurate solar forecasting is required in multiple spatial and temporal scales. Solar irradiance variations are caused primarily by cloud movement, cloud formation, and cloud dissipation. In the literature, researchers have developed a variety of methods for solar power forecasting, such as statistical approaches using historical data (Hammer et al., 1999; Sfetsos and Coonick, 2000; Paoli et al., 2010), the use of numerical weather prediction (NWP) models (Marquez and Coimbra, 2011; Mathiesen and Kleissl, 2011; Chen et al., 2011), tracking cloud movements from satellite images (Perez et al., 2007), and tracking cloud movements from direct ground observations using sky cameras (Perez et al., 2007; Chow et al., 2011; Marquez and Coimbra, 2013a). NWP models are the most popular method for forecasting solar irradiance several hours or days in advance. Mathiesen and Kleissl (2011) analyzed the global horizontal irradiance in the continental United States forecasted by three popular NWP models: the North American Model, the Global Forecast System, and the European Centre for Medium-Range Weather Forecasts. Chen et al. (2011) developed a statistical method for solar power forecasting based on artificial intelligence techniques. Crispim et al. (2008) used total sky imagers (TSI) to extract cloud features using a radial basis function neural network model for time horizons from 1 min to 60 min. Chow et al. (2011) also used TSI to forecast short-term global horizontal irradiance. The results suggested that TSI is useful for forecasting time horizons up to 15 min to 25 min-ahead. Marquez and Coimbra (2013a) presented a method using TSI images to forecast 1-min averaged direct normal irradiance at the ground level for time horizons between 3 min and 15 min. Lorenz et al. (2007) showed that cloud movement-based forecasts likely provide better results than NWP forecasts for forecast timescales of 3 h to 4 h or less; beyond that, NWP models tend to perform better. In summary, forecasting methods can be broadly characterized as physical or statistical. The physical approach uses NWP and PV models to generate solar power forecasts; whereas the statistical approach relies primarily on historical data to train models (Pelland et al., 2013). Recent solar forecasting studies (Chu et al., 2014; Quesada-Ruiz et al., 2014) integrated these two approaches by using both physical and historical data as inputs to train statistical models. A brief description of these solar forecasting methods is summarized in Table 1.

As solar penetration increases, considerable research is underway to improve the accuracy of solar forecasting models. In the United States, the Department of Energy's SunShot Initiative has created the solar forecasting accuracy improvement program to significantly improve the state of the art in solar forecasting.

1.2. Research motivation and objectives

A key gap in developing solar forecasting models is the unavailability of a consistent and robust set of metrics to measure and assess the improvement in forecasting accuracy, because different researchers use improvements described by different metrics as their own evaluation criteria. In addition, it is not clear that the traditional statistical metrics used to evaluate forecasts best represent the needs of power system operators. Because weather patterns and locational atmospheric conditions vary considerably both spatially and temporally, solar forecasting accuracy is dependent on geographic location and timescale of the data. Conventional measures of solar forecasting accuracy include root mean square error (RMSE), mean bias error (MBE), and mean absolute error (MAE). Marquez and Coimbra (2013b) proposed a metric for using the ratio of solar uncertainty to solar variability to compare different solar forecasting models. Espinar et al. (2009) proposed several metrics based on the Kolmogorov–Smirnov test

Table 1
Solar forecasting methodologies (Pelland et al., 2013).

	Methods	Description/comment	Forecast horizons
Physical approach	NWP models	NWP models are the most popular method for forecasting solar irradiance more than 6 h or days in advance	6 h to days ahead
	Total sky imagers (TSI)	TSIs are used to extract cloud features or to forecast short-term global horizontal irradiance	0–30 min ahead
Statistical approach	Statistical methods	Statistical methods were developed based on autoregressive or artificial intelligence techniques for short-term forecasts	0–6 h ahead
	Persistence forecasts	Persistence of cloudiness performs well for very-short-term forecasts	0–4 h ahead