Renewable Energy 86 (2016) 866–876

Contents lists available at ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

Day-ahead resource forecasting for concentrated solar power integration

Lukas Nonnenmacher, Amanpreet Kaur, Carlos F.M. Coimbra*

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

A R T I C L E I N F O

Article history:
Received 16 April 2015
Received in revised form
24 July 2015
Accepted 26 August 2015
Available online xxx

Keywords:
CSP Integration
Day-ahead forecasting
NWP based DNI forecasting
Solar variability
Solar uncertainty

A B S T R A C T

In this work, we validate and enhance previously proposed singe-input direct normal irradiance (DNI) models based on numerical weather prediction (NWP) for intra-week forecasts with over 200,000 hours of ground measurements for 8 locations. Short latency re-forecasting methods to enhance the deterministic forecast accuracies are presented and discussed. The basic forecast is applied to 15 additional locations in North America with satellite-derived DNI data. The basic model outperforms the persistence model at all 23 locations with a skill between 12.4% and 38.2%. The RMSE of the basic forecast is in the range of 204.9 $W\,m^{-2}$ to 309.9 $W\,m^{-2}$. The implementation of stochastic learning re-forecasting methods yields further reduction in error from 204.9 $W\,m^{-2}$ to 176.5 $W\,m^{-2}$. To a great extent, the errors are caused by inaccuracies in the NWP cloud prediction. Improved assessment of atmospheric turbidity has limited impact on reducing forecast errors. Our results suggest that NWP-based DNI forecasts are very capable of reducing power and net-load uncertainty introduced by concentrated solar power plants at all locations in North America. Operating reserves to balance uncertainty in day-ahead schedules can be reduced on average by an estimated 28.6% through the application of the basic forecast.

1. Introduction

Solar irradiance fluctuations are the biggest source of uncertainty for utility scale grid integration of solar power. The accurate prediction of solar irradiance on short- and long-term time horizons are among the most promising technologies to enable high solar power integration without jeopardizing grid reliability or increasing costs [1]. Previous studies mostly covered the prediction of global horizontal irradiance (GHI) due to the dominance of photovoltaic (PV) systems [2–7]. In recent years, concentrated solar power (CSP) technologies, solely relying on direct normal irradiance (DNI), reached market maturity, resulting in the installation of several operational large-scale CSP plants. Currently, the globally installed capacity is over 2500 MW with additional 2500 MW under construction and further 1400 MW under development [8]. Many of these projects do not facilitate the capability to store energy but are directly feeding electricity into the power gird. Hence, the power output of CSP plants without storage is non-dispatchable. Solar resource fluctuations on various time scales have a different impact on the operation of CSP and the power grid. This necessitates dispatchable resources and forecasting in the energy system to balance generation and demand in the grid. There are many benefits for day-ahead DNI forecasting: based on current market regulations in most countries, power producers have to schedule power production with the system operator, up to several days in advance (unit commitment). If storage is available, day-ahead DNI predictions can be used to increase revenue by dispatching energy to times of higher electricity prices [9,10]. It has been shown that (multiple) day-ahead DNI predictions can increase the revenue of CSP plants in Spain and the United States [9,11,12].

This study seeks to evaluate and optimize numerical weather prediction (NWP) based DNI forecasts, predicting hourly average values of DNI, 12–36 h ahead. This time horizon is important for day-ahead market participation [13] (e.g. in California, energy bids from renewable sources can be placed in the afternoon for the complete next day). The basic forecast model uses predicted cloud-cover from NWP (provided by the Regional Deterministic Prediction System (RDPS) of the Canadian Meteorological Centre) and the Ineichen clear-sky model as inputs. This combination of data and clear-sky model performed the best in our previous work [12]. The issued forecasts are evaluated at 8 locations in North America with

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

http://dx.doi.org/10.1016/j.renene.2015.08.068
0960-1481/

ground measurements for over 200,000 h. Additionally, the forecast has been applied to 15 locations with high and medium yearly DNI averages in the Southwestern United States with available satellite-derived DNI data. The Southwestern United States are of special interest due to the high deployment potential of the CSP technology [14]. Furthermore, we propose two strategies to optimize the forecasts: (1) Clear-sky model corrections. While clear-sky GHI mainly relies on the longitude, latitude and sun elevation angle, the DNI component of solar radiation additionally relies strongly on the transparency of the atmosphere. Two common measures of atmospheric clearness are the aerosol optical depth (AOD) and the Linke turbidity (LT). For an accurate prediction of DNI, the clearness of the atmosphere has to be measured or estimated. The basic forecast approach relies on a clear-sky model based on satellite-derived monthly turbidity averages. To show the impact of the clear-sky model, we deploy a second clear-sky model adaptive to daily turbidity conditions, based on a clear-sky recognition algorithm. (2) Re-forecasting methods are applied to enhance forecasts by extracting information of structured errors in a training set and applying the found model enhancements to the forecast. This adds to the efforts of previous studies to improve forecast accuracy by applying regression models (e.g. Refs. [15–18]).

This paper is structured as follows: Section 2 describes the origin of data and how it was obtained; Section 3 introduces the applied forecasting and optimization methods, including an approach for DNI clear-sky recognition and the re-forecast methods. Section 4 presents the results, the occurring errors and discusses implications of the day-ahead DNI forecast methodology. Conclusions are provided in Section 5.

2. Data

Publicly available data sets have been used where possible. DNI data from ground observatories are notoriously sparse due to costly instrumentation and high maintenance requirements. Time series of DNI ground data are available at 8 locations in the United States. Satellite models provide a tool to assess the DNI resource at locations without ground data. For all obtained data sets, night values were removed and time matching to Universal Coordinated Time (UTC) was applied. For figures, local time is used since it is more intuitive.

2.1. UCSD ground measurements

Ground DNI measurements have been obtained from the network of solar observatories deployed and maintained by the University of California, San Diego (UCSD) at four locations in California, namely Merced, Berkeley, Davis and San Diego. Data were acquired with MFR-7 instruments by Yankee Environmental Systems. The applied data quality control is described in Ref. [19]. Table 1 describes the solar observatories maintained by the Center for Energy Research at UCSD. The locations of these observatories are represented with blue markers in Fig. 1.

2.2. ISIS data

The Integrated Surface Irradiance Study (ISIS) network is part of a project to monitor surface radiation in the United States as part of a collaboration with the surface radiation budget measurement network (SURFRAD) from the National Oceanic and Atmospheric Administration (NOAA). The sampling rate of this data set is 3 min. Averages have been created where necessary. Details of this data set and the applied quality control are described in Ref. [20]. The ISIS network also acquires DNI data at Bismarck, North Dakota; Madison, Wisconsin; Seattle, Washington and Sterling, Virginia. These sets are not considered since CSP deployment in those regions is unlikely. Tallahassee, Florida was excluded due to a lack of usable data. Table 1 summarizes the ground data sets and Fig. 1 shows the locations.

Table 1
Observatories across the US with DNI ground instrumentation. The first four locations are installed and maintained by the University of California, San Diego. The other locations are part of the ISIS network, maintained by NOAA.

Location	Lat.	Long.	El.	Days
Data from UCSD:				
BER – Berkeley, CA	37.9	−122.3	97 m	876
DAV – Davis, CA	38.5	−121.7	19 m	821
MER – Merced, CA	37.4	−120.4	64 m	761
SAN – San Diego, CA	32.9	−117.2	101 m	619
Data from ISIS:				
ABQ – Albuquerque, NM	35.0	- 106.6	1617 m	1865
HAN – Hanford, CA	36.3	−119.6	73 m	861
OAK – Oak Ridge, TN	36.0	−84.3	334 m	202
SLC – Salt Lake City, UT	40.8	−112.0	1288 m	3090

2.3. Satellite-derived data

The national solar radiation database (NSRDB) contains meteorological and solar irradiance data, derived with the SUNY model from satellite images for approximately 1500 stations in the United States from 1998 to 2010 with hourly resolution. Data was downloaded from FTP servers operated by the National Renewable Energy Laboratory (NREL).

Additionally, data for 2012 has been provided from SolarAnywhere® deploying the SUNY v 2.4 model for the locations in Table 2 (public data set). The SUNY model was broadly verified and evaluated [19,21,22]. This data is used for all locations where no ground DNI data is available.

2.4. Cloud-cover predictions

Cloud-cover forecasts ($\widehat{cc}$), representing the spatial cloud-coverage of a grid element in percent, were obtained from RDPS. The RDPS is a NWP model developed and deployed by the Canadian Meteorological Centre. These data sets cover predictions for the 12-h to 36-h horizons in hourly increments, obtained from the daily NWP model run valid from 0:00 standard time (UTC). This input data delivered best performance in Ref. [12]. For the 8 locations with ground measurements, predicted cloud-cover data was available from January 2005 until the end of October 2014. Additionally, gridded data from the run valid from 0:00 UTC was available for the year 2012 for the Southwestern United States.

3. Methods

The following models have been previously proposed and are used. These basic models are the foundations for the optimized models shown in this section.

3.1. Persistence

A common baseline model to evaluate general performance, accuracy and skill of forecasts is the persistence model [11,15,23–25]. The persistence model is based on the assumption that the atmospheric conditions for a day are equal to the atmospheric conditions of the day before. In case of DNI, this means: