Solar Energy 170 (2018) 924–939

Contents lists available at ScienceDirect

Solar Energy

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

Solar irradiance forecast using aerosols measurements: A data driven approach

Abdullah Alfadda*, Saifur Rahman, Manisa Pipattanasomporn

Virginia Tech – Advanced Research Institute, Arlington, VA 22203, USA

ARTICLE INFO

Keyword:
Machine learning
Multilayer perceptron
Solar energy
Solar power forecasting

ABSTRACT

The use of renewable energy resources has grown several fold in the last two decades. One of the main challenges is the uncertainty in their output power due to fluctuating meteorological conditions like sunshine intensity, cloud cover and humidity. In desert areas, another parameter that has a significant impact on solar irradiance is dust, which has been neglected in many studies. In this work, an hour-ahead solar irradiance forecasting model is proposed, this model utilizes both Aerosol Optical Depth (AOD) and the Angstrom Exponent data observed from a ground station at the previous hour. The proposed model was tested under different widely used data driven forecasting models, including Multilayer Perceptron (MLP), Support Vector Regression (SVR), k-nearest neighbors (kNN) and decision tree regression. Applying the MLP model using data from Saudi Arabia shows a root mean square average error of under 4% and forecast skill of over 42% for one-hour ahead forecast. The proposed forecasting model demonstrates a superior accuracy compared to other models when tested and verified under different feature selection schemes. The MLP model is especially applicable for desert areas under clear sky conditions, where dust storms are frequent and AOD in the air is high (>0.4).

1. Introduction

Renewable energy resources represent 24% of the total electrical energy generated worldwide as of 2016 (IEA, 2017), and the solar share is only 1.2%. Many countries around the world have plans to invest in large-scale renewable energy projects. However, the main issue with these resources is the uncertainty in their output power, which can result in an overall power grid instability. With respect to solar power, this can be caused by the fluctuation in many meteorological variables, such as cloud cover, temperature and wind speed. Thus, solar irradiance forecasting is of great importance for grid operators, allowing them to ensure the stability of the power grid, optimally set demand response schedules, economic dispatch and optimize power plant operations.

Saudi Arabia is one of the countries that have ambitious plans to decrease their dependence on oil and natural gas for energy production. In 2016 Saudi Arabia revealed that the country plans to produce 9.5 GW of energy from renewable resources by 2023 (Asif, 2016), with an initial target of 3.45 GW by 2020. The expected total electricity generation in the country will be around 95 GW by 2023 (Abdel Gelil et al., 2017). One main issue when installing solar Photovoltaics (PV) in desert areas like Saudi Arabia is the frequent occurrence of dust storms (Hassan et al., 2017). The dusty weather results in less accurate solar irradiance forecasts. Moreover, the overall PV module efficiency decreases due to dust accumulation over the module's surfaces. In Notaro et al. (2013) they provided a detailed dust assessment all over the country with trajectory analysis.

Solar irradiance is directly dependent on multiple weather factors, mainly cloud cover, humidity and visibility, besides other parameters, such as ground albedo. Thus, better forecasts of these weather factors would result in an improved solar irradiance model. However, in some areas that have low cloud cover, the solar forecasts would be more affected by the remaining factors. Moreover, areas like Arabian Peninsula and North Africa are exposed to frequent dust storms and high aerosols index all over the year. Thus, developing a solar irradiance forecasting model that incorporates the dust phenomena is of a great importance for such areas.

Some work has been carried out to investigate the relationship between the PV module efficiency and dust accumulation over PV panels (Sarver et al., 2013; Sulaiman et al., 2014). In Jiang et al. (2016), authors studied the optimum cleaning frequency for the PV module to improve module efficiency. In Alqatari et al. (2015) authors have compared the cost and performance of different PV cleaning techniques.

The other main concern due to the presence of dust in the air is the increased uncertainty in solar radiation forecast. Moreover, the forecasted Aerosol Optical Depth (AOD) values are not fully correlated with

* Corresponding author.
E-mail address: alfadda@vt.edu (A. Alfadda).

https://doi.org/10.1016/j.solener.2018.05.089
Received 3 March 2018; Received in revised form 10 May 2018; Accepted 29 May 2018
0038-092X/

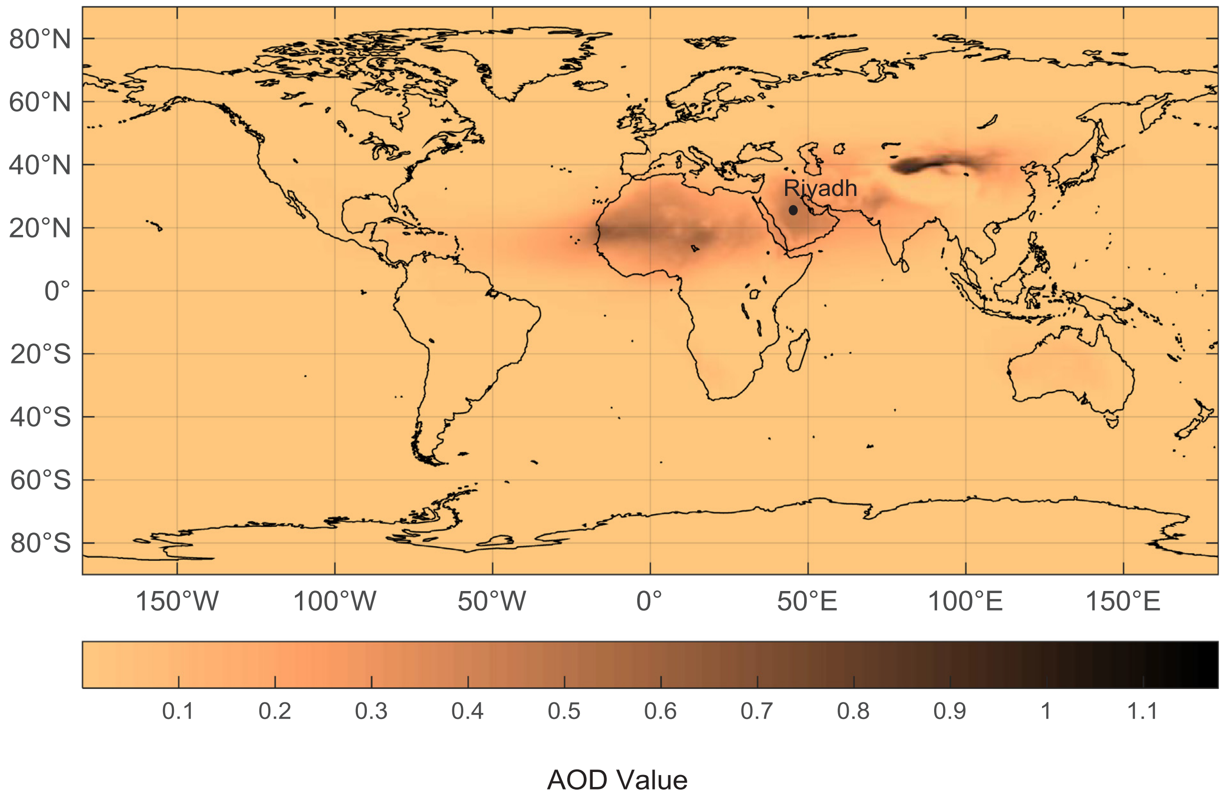

Fig. 1. Annual average AOD at 550 nm over the world for the year 2015 using CAMS dataset.

the ground-based AOD measurement. In Cesnulyte et al. (2014) authors compared AErosol RObotic NETwork (AERONET) data with European Center for Medium-Range Weather Forecasts (ECMWF) readings across multiple sites around the world, the average correlation coefficient found to be 0.77 for dust areas. Thus, uncertainty in forecasted AOD values would lead to a lower solar forecasting accuracy, especially in desert areas, where cloud-free environments are dominant and dust particles have frequent presence in the air.

Machine learning techniques have been widely used in solar irradiance forecasting. Artificial Neural Networks (ANNs) are the most widely used techniques for solar forecasting (Antonanzas et al., 2016), which have been applied to both short-term (Gutierrez-Corea et al., 2016) and long-term forecasting (Azadeh et al., 2009). ANN with more than one hidden layer is usually referred to as Multilayer Perceptron (MLP). k-Nearest Neighbors (kNN) has also been widely used in the literature, it has been applied to predict intra hour irradiances (Pedro and Coimbra, 2015a), and to generate probabilistic forecasts (Chu and Coimbra, 2017). Other machine learning methods have also been applied to solar forecasting, such as Support Vector Regression (SVR) (Belaid and Mellit, 2016), random forests (Ibrahim and Khatib, 2017) and Lasso (Yang et al., 2015). Machine learning techniques have also been used in solar forecasting with AOD as input, in Eissa et al. (2013) they used six thermal channels from SEVERI satellite images to predict the aerosols at 550 nm, then fed this prediction to ANN model to improve the Global Horizontal Irradiance (GHI), Direct Normal Irradiance (DNI) and Diffuse Horizontal Irradiance (DHI) forecasts.

Newer techniques such as deep learning has also been implemented in a number of time series forecasting models (Li et al., 2017; Qiu et al., 2014; Ryu et al., 2016), it has shown a superior accuracy compared to other machine learning methods. It was implemented to estimate the building energy consumption (Mocanu et al., 2016), predict the wind speed (Hu et al., 2016) and forecast the solar irradiance (Alzahrani et al., 2017). Convolutional version of deep learning has been implemented to predict the Photovoltaic output power (Wang et al., 2017) using both deterministic and probabilistic approaches. In Gensler et al. (2017) they implemented Long Short Term Memory (LSTM) version of deep learning to forecast the PV output power for the next day. Convolutional LSTM version was used to predict the short-term precipitation based on spatiotemporal data sequence (Shi et al., 2015). Spatiotemporal data were also studied using other methods such as Kriging (Jamaly and Kleissl, 2017) and applied to solar irradiance forecasting.

Solar forecasting time horizon can be categorized into short-term, medium-term and long-term forecasting. In the short-term forecasting the predicted solar irradiance value falls within the next few hours, multiple short-term models have been developed in the literature (Ghayekhloo et al., 2015; Pedro and Coimbra, 2015b; Rana et al., 2016). The medium-term forecasts generate predictions that cover the span of the next few days (Gulin et al., 2017; Pierro et al., 2016). Lastly, long-term forecasts predict the solar irradiance for the next few months to years (Ruiz-Arias et al., 2016a, 2016b).

The ground-based AOD measurement and angstrom exponent never been used altogether in the literature to construct an hour-ahead solar irradiance forecasting model. In this work, a data driven forecasting model under clear sky conditions with a large aerosol presence is proposed, utilizing both the ground-based AOD measurements observed at the last hour alongside the angstrom exponent and other weather parameters. All of the parameters are fed into the data driven solar forecasting model, which results in a more accurate (GHI/DNI/DHI) forecast for the next hour. The use of ground-based AOD measurements would result in a better AOD forecast accuracy for the next hour, and hence better (GHI/DNI/DHI) forecasting. The model was trained using hourly data collected from three different resources, i.e., King Abdullah City for Atomic and Renewable Energy (KACARE), Copernicus Atmosphere Monitoring Service (CAMS) and AERONET over the period of three years 2013–2015. The test site is in Riyadh, Saudi Arabia, chosen because it is frequently exposed to different degrees of dust storms over the year, ranging from mild to severe storms (Nabavi et al., 2016). Annual average AOD at 550 nm over the world for the year 2015 is shown in Fig. 1, as can been seen from Fig. 1 the test location reside in area where the average AOD is high. In Fig. 2 the annual average GHI over Saudi Arabia is shown.