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Short-term forecasting of solar irradiance without local telemetry: A generalized model using satellite data

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ABSTRACT

Due to the increasing integration of solar power into the electrical grid, forecasting short-term solar irradiance has become key for many applications, e.g. operational planning, power purchases, reserve activation, etc. In this context, as solar generators are geographically dispersed and ground measurements are not always easy to obtain, it is very important to have general models that can predict solar irradiance without the need of local data. In this paper, a model that can perform short-term forecasting of solar irradiance in any general location without the need of ground measurements is proposed. To do so, the model considers satellite-based measurements and weather-based forecasts, and employs a deep neural network structure that is able to generalize across locations; particularly, the network is trained only using a small subset of sites where ground data is available, and the model is able to generalize to a much larger number of locations where ground data does not exist. As a case study, 25 locations in The Netherlands are considered and the proposed model is compared against four local models that are individually trained for each location using ground measurements. Despite the general nature of the model, it is shown show that the proposed model is equal or better than the local models: when comparing the average performance across all the locations and prediction horizons, the proposed model obtains a 31.31% rRMSE (relative root mean square error) while the best local model achieves a 32.01% rRMSE.

1. Introduction

With the increasing integration of renewable sources into the electrical grid, accurate forecasting of renewable source generation has become one of the most important challenges across several applications. Among them, balancing the electrical grid via activation of reserves is arguably one of the most critical ones to ensure a stable system. In particular, due to their intermittent and unpredictable nature, the more renewables are integrated, the more complex the grid management becomes (Lara-Fanego et al., 2012; Voyant et al., 2017).

In this context, as solar energy is one of the most unpredictable renewable sources, the increasing use of solar power in recent years has led to an increasing interest in forecasting irradiance over short time horizons. In particular, in addition to activation of reserves to manage the grid stability, short-term forecasts of solar irradiance are paramount for operational planning, switching sources, programming backup, short-term power trading, peak load matching, scheduling of power systems, congestion management, and cost reduction (Hammer et al., 1999; Reikard, 2009; Voyant et al., 2017).

1.1. Solar irradiance forecasting

The forecasting of solar irradiance can be typically divided between methods for *global horizontal irradiance (GHI)* and methods for *direct normal irradiance (DNI)* (Law et al., 2014), with the latter being a component of the GHI (together with the diffuse solar irradiance). As in this work GHI is forecasted, Law et al. (2014) should be used for a complete review on methods for DNI. For the case of GHI, forecasting techniques are further categorized into two subfields according to the input data and the forecast horizon (Diagne et al., 2013; Voyant et al., 2017):

1. Time series models based on satellite images, measurements on the ground level, or sky images. These methods are usually suitable for short-term forecasts up to 4–6 h. Within this field, the literature can be further divided into three groups.
   (a) Classical statistical models like ARMA models (Ahmad et al., 2015), ARIMA models (Reikard, 2009), the CARDS model (Huang et al., 2013), or the Lasso model (Yang et al., 2015).

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Acronyms

ARX	Autoregressive with Exogenous Inputs
DL	Deep Learning
DNN	Deep Neural Network
ECMWF	European Center for Medium-Range Weather Forecasts
GBT	Gradient Boosting Trees
GHI	Global Horizontal Irradiance
KNMI	Royal Netherlands Meteorological Institute
NWP	Numerical Weather Prediction
rRMSE	Relative Root Mean Square Error
SICSS	Surface Insolation under Clear and Cloudy Skies
TPE	Tree-Structured Parzen Estimator

(b) Artificial intelligence models such as neural networks models (Mellit and Pavan, 2010; Lauret et al., 2015), support vector machines (Lauret et al., 2015), decision trees-based models (McCandless et al., 2015), or Gaussian models (Lauret et al., 2015).

(c) Cloud-moving vector models that use satellite images (Lorenz and Heinemann, 2012).

2. *Numerical weather prediction (NWP)* models that simulate weather conditions. These methods are suitable for longer forecast horizons, 4-6 h onward, time scales where they outperform the statistical models (Perez et al., 2010). As the goal of this work are short-term forecasts, Diagne et al. (2013) should be used for more complete review of NWP methods.

While the division in accuracy between NWP and time series models is given by the predictive horizon, establishing comparisons between time series models is more complex. In particular, while some authors have reported the superiority of statistical models over artificial intelligence methods (Reikard, 2009), others have obtained opposite results (Sfetsos and Coonick, 2000).

The input features typically used in the literature to predict solar irradiance vary widely, e.g. past irradiance values, satellite data, weather information, etc. In many cases, the inputs considered depend on the type of model used, e.g. cloud moving vector models require satellite images. While a detailed review on the different methods and input features is outside the scope of this paper, Diagne et al. (2013) is a good source for a more thorough analysis.

1.2. Motivation

To the best of our knowledge, due to the time series nature of the solar irradiance, the statistical and artificial intelligence methods proposed so far have considered past ground measurements of the solar irradiance as input regressors (Diagne et al., 2013). While this choice of inputs might be the most sensible selection to build time series models, it poses an important problem: local data is required at every site where a forecast is needed.

In particular, if the geographical dispersion of solar generators is considered, it becomes clear that forecasting solar irradiance is a problem that has to be resolved across multiple locations. If ground measurements of all these sites are required, the cost of forecasting irradiance can become very expensive. In addition to the cost, a second associated problem is the fact that obtaining local data is not always easy.

As a result, in order to obtain scalable solutions for solar irradiance forecasting, it is important to develop global models that can forecast without the need of local data. In this context, while current cloud-moving vectors might accomplish that, they are not always easy to deploy as they are complex forecasting techniques that involve several steps (Diagne et al., 2013).

1.3. Contributions and organization of the paper

In this paper, a novel forecasting technique is proposed that addresses the mentioned problem by providing a prediction model that, while being accurate and easy to deploy, forecasts solar irradiance without the need of local data. The prediction model is based on a *deep neural network (DNN)* that, using SEVIRI[1] satellite images and NWP forecasts, is as accurate as local time series models that consider ground measurements. Although the model uses satellite images just as cloud-moving vector models do, it is easier to deploy as it requires less complex computations. In addition, while obtaining satellite data might not be always easier or cheaper than installing local ground sensors, there are several locations where satellite data are available and the proposed model avoids going to the ground to install local measurements. An example of this is The Netherlands, where satellite data is provided by the national meteorological institute.

It is important to note that, to the best of our knowledge, the proposed method is the first of its class that tries to remove the dependence of local telemetry even for training. Particularly, while other methods from the literature successfully remove the local data dependence during forecasting, e.g. Larson and Coimbra (2018), they still require local telemetry at all sites of interest during training. While using local data in a small subsets of sites during training, the proposed model successfully predicts the irradiance in a much larger subset of locations without needing local telemetry from these sites at any stage of the estimation or the forecasting.

As a case study, 30 location in The Netherlands are considered and the model is estimated using 5 of these locations. Then, for the remaining 25 locations, the performance of the proposed estimated model is compared against individual time series models specifically trained for each site using ground data.

The remaining of the paper is organized as follows: Section 2 introduces the preliminary concepts considered in this work. Next, Section 3 presents the proposed general model for forecasting solar irradiance. Then, Section 4 introduces the case study and discusses the performance of the proposed model when compared with local models. Finally, Section 5 summarizes the main results and concludes the paper.

2. Preliminaries

In this section the concepts and algorithms that are used and/or modified in the paper are introduced.

2.1. Deep learning and DNNs

In the last decade, the field of neural networks has experienced several innovations that have lead to what is known as *deep learning (DL)* (Goodfellow et al., 2016). In particular, one of the traditional issues of neural networks had always been the large computational cost of training large models. However, that changed completely when (Hinton et al., 2006) showed that a deep belief network could be trained efficiently using an algorithm called greedy layer-wise pretraining. As related developments followed, researchers started to be able to efficiently train complex neural networks whose depth was not just limited to a single hidden layer (as in the traditional multilayer perceptron). As these new structures systemically showed better results and generalization capabilities, the field was renamed as deep learning to stress the importance of the depth in the achieved improvements

[1] The SEVIRI (Spinning Enhanced Visible and InfraRed Imager) is a measurement instrument of the METEOSAT satellite.