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Short-term solar irradiation forecasting based on Dynamic Harmonic Regression

Juan R. Trapero [a,*], Nikolaos Kourentzes [b], A. Martin [a]

[a] Universidad de Castilla-La Mancha, Departamento de Administracion de Empresas, Ciudad Real 13071, Spain
[b] Lancaster University, Department of Management Science, LA1 4YX, UK

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ABSTRACT

Solar power generation is a crucial research area for countries that have high dependency on fossil energy sources and is gaining prominence with the current shift to renewable sources of energy. In order to integrate the electricity generated by solar energy into the grid, solar irradiation must be reasonably well forecasted, where deviations of the forecasted value from the actual measured value involve significant costs. The present paper proposes a univariate Dynamic Harmonic Regression model set up in a State Space framework for short-term (1–24 h) solar irradiation forecasting. Time series hourly aggregated as the Global Horizontal Irradiation and the Direct Normal Irradiation will be used to illustrate the proposed approach. This method provides a fast automatic identification and estimation procedure based on the frequency domain. Furthermore, the recursive algorithms applied offer adaptive predictions. The good forecasting performance is illustrated with solar irradiance measurements collected from ground-based weather stations located in Spain. The results show that the Dynamic Harmonic Regression achieves the lowest relative Root Mean Squared Error; about 30% and 47% for the Global and Direct irradiation components, respectively, for a forecast horizon of 24 h ahead.

1. Introduction

The increasing investment in renewable energy is essential to guarantee immediate answers to both the high and fluctuating prices of crude oil and the energy supplies diversification. In some countries like Spain, solar power generation is becoming a research area of paramount importance. In this sense, reliable short-term forecast information of the solar radiation components is required to achieve an efficient use of fluctuating energy output from PV (photovoltaic), CPV (concentrated-photovoltaic) and CSP (solar thermal power plants). In particular, GHI (Global Horizontal Irradiation) is important for photovoltaic applications, whereas DNI (Direct Normal Irradiation) is required for Concentrated Solar Power applications, and this is often done through forecasting methodologies.

Electricity companies and transmission systems operators need to know the expected load profiles 24 h in advance, where forecast errors in the fluctuating input from solar systems can lead to significant costs. Krass et al. [1] carried out a simulation study to quantify the costs of forecasting deviations for a concentrating solar power system in the Spanish electricity market, where improved forecasting techniques reduced the penalties compared to the persistence case by 47.6%.

The diversity of solar radiation forecasting methodologies can be classified according to the input data and the objective forecasting horizon [2]. For instance, NWP (Numerical Weather Prediction) models, which are based on physical laws of motion and conservation of energy that govern the atmospheric air flow, are operationally used to forecast the evolution of the atmosphere from about 6 h onward. Although NWP models are powerful tools to forecast solar radiation at places where ground data are not available, many near-surface physical processes occur within a single grid box and are too complex to be represented and solved by equations. Thus, NWP models cannot successfully resolve local processes smaller than the model resolution.

Satellite-derived solar radiation images are a useful tool for quantifying solar irradiation at ground surface for large areas, but they need to set an accurate radiance value under clear sky conditions and under dense cloudiness from every pixel and every image [3].

* Corresponding author.
E-mail addresses: juanramon.trapero@uclm.es (J.R. Trapero), n.kourentzes@lancaster.ac.uk (N. Kourentzes), amartingarcia77@gmail.com (A. Martin).

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Ground-based observations, such as sky imaging techniques, are used to fill the intra-hour and sub-kilometer forecasting gap of NWP models regarding cloud cover over solar power plants. Nonetheless, operational forecast horizons are limited to very short-term, ranging from 5 to 25 min ahead [4].

These limitations have placed time series analysis as the dominant methodology for short-term forecasting horizons from 5 min up to 6 h [5]. Common features of solar radiation time series as intermittence, high sampling frequency and non-stationarity have contributed to the proliferation of multiple statistical forecasting techniques. A recent state of the art review can be found in Ref. [2]. In general terms, two main modeling approaches are identified depending on how the method deals with non stationarity, i.e., trend and seasonality. On the one hand, a deterministic approach based on solar geometry is used to remove the observed seasonality by means of the clearness index (k) defined as the ratio of irradiance at ground level with respect to extraterrestrial irradiance [6]. If additional information on atmospheric conditions is available, clear sky models can be used to estimate the global irradiance in clear sky conditions [7]. Then, the clear-sky index (k^*) can be calculated as the ratio of irradiance at ground level to clear-sky irradiance. However, some authors argue that such indices are mostly random and thus, they are not adequate for learning algorithms [8]. From the authors point of view, the adequacy of using indices rather than solar irradiance time series requires further research, and so far, both alternatives are valid. However, in this work, we opt for using solar irradiance time series to make sure that all the forecast errors come from the forecasting technique and they are not the result of modeling errors when estimating the indices.

On the other hand, the second approach consists of removing the trend and seasonality components to make the time series stationary. Typical deseasonalizing methods employed are: Fourier series [9,10], high order polynomial models [11], cosine function models [12], Gaussian models [13], and a seasonal-trend decomposition procedure [14]. Dong et al. [10] showed by using the KPSS (Kwiatkowski–Phillips–Schmidt–Shin) stationary statistical test that Fourier series had much higher probability of obtaining stationarity. Once the seasonality has been removed by the Fourier regression, the next step is to model the residuals by either autoregessive processes [9] or exponential smoothing algorithms [10].

This work investigates the forecasting performance of the DHR (Dynamic Harmonic Regression) model. The DHR is an extension of the typical harmonic regression, where the coefficients are time-varying instead of constant [15]. In other words, models described in Refs. [9] and [10] can be summarized in two steps. Firstly, they remove the seasonality by using a constant coefficients harmonic regression. Then, since the traditional harmonic regression may not capture the dynamics of the data, another step based on the residuals modeling is required to compensate potential biases on the harmonic regression constant coefficients. Note that these coefficients can be estimated by using typical least squares or maximum likelihood procedures. In turn, the DHR relaxes the assumption of constant coefficients integrating the processes of forecasting, interpolation and seasonal adjustments into a single recursive framework based on the Kalman Filter and the Fixed Interval Smoothing algorithms [16]. The DHR recursive nature allows to handle efficiently changes of amplitude and phase, as it commonly happens in the solar irradiation time series. Therefore, the use of DHR does not require a second residuals modeling step as it occurs in Refs. [9] and [10].

The DHR is a particularization of a more general type of models called UC (Unobserved Components) models based on the SS (State Space) framework. The literature on this topic is immense. The reader is referred to the seminal works by Refs. [15,17,18]. It should be noted that, although UC models have been initially proposed in solar irradiation forecasting in Ref. [5], the DHR model incorporates certain differences that can improve the forecasting accuracy of previous works. Essentially, unlike the UC model presented in Ref. [5] the DHR utilizes Fixed Interval Smoothing (in addition to Kalman Filter) and the estimation of model hyper-parameters is accomplished in the frequency domain. In this sense, the Fixed Interval Smoothing allows optimal signal extraction, smoothing and interpolation over gaps in the data. Furthermore, the hyper-parameter estimation in the frequency domain provides objective functions much better defined when the time series are clearly seasonal. In contrast, typical Maximum Likelihood estimation in the time domain may fail when the number of parameters to be estimated is high [15], as it happens in the present case study.

Although the DHR model has been successfully employed in other related applications as electricity price and load forecasting [19,20], this is the first time that this model is proposed to forecast solar irradiation. In order to illustrate the performance of the proposed model, hourly GHI (Global Horizontal Irradiation) and DNI (Direct Normal Irradiation) have been selected for this study.

The article is organized as follows: Section 2 describes the Dynamic Harmonic Regression. Section 3 introduces the benchmark models that are used to evaluate the performance of the DHR. Section 4 presents the case study which includes the description of the study area, the observational data and the experimental results. Finally, main conclusions are drawn in Section 5.

2. Dynamic Harmonic Regression

A DHR can be expressed as a UC model as in equation (1), where the GHI or DNI time series (y_t) is decomposed as the sum of a long term trend (T_t), a seasonal component (S_t) and an irregular component (e_t). The right expression in (1) is the equivalent harmonic regression with time-varying coefficients, where the trend T_t is associated with the frequency being set equal to zero ($k = 0$). The seasonal component S_t results from the addition of $P/2$ harmonics ($k = 1,2,\ldots,P/2$), where P is the fundamental period of the seasonal component, i.e. the number of observations per cycle. In our case study $P = 24$ since the data is hourly and there is a clear daily cycle. The irregular component e_t represents any stochastic and unpredictable temporal variations in y_t that have not been explained by all the other components. Finally, e_t is assumed to be a Gaussian random noise signal with zero mean and constant variance (σ^2).

$$y_t = T_t + S_t + e_t = \sum_{k=0}^{P/2}\left[a_{k,t}\cos(\omega_k t) + b_{k,t}\sin(\omega_k t)\right] + e_t \tag{1}$$

The model is completed when the dynamic behavior of the stochastic trend and seasonal subcomponents are specified. There is a wide range of options available in the literature to do this [17,18,21] and the ones favored here are explained briefly below.

Equation (2) shows the model for the trend. Formally it is usually called a LLT (Local Linear Trend), where $a^*_{0,t+1}$ stands for an additional unobserved state necessary for the specification of the trend T_t; and $w_{0,t}$ and $w^*_{0,t}$ are random Gaussian noises, independent of each other with zero mean and certain variances σ_0^2 and σ_0^{2*}, respectively.

$$\begin{pmatrix} a_{0,t+1} \\ a^*_{0,t+1} \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix}\begin{pmatrix} a_{0,t} \\ a^*_{0,t} \end{pmatrix} + \begin{pmatrix} w_{0,t} \\ w^*_{0,t} \end{pmatrix} \tag{2}$$

Each of the seasonal sub-components $a_{k,t}$ and $b_{k,t}$ ($k = 1,2,\ldots,P/2$) in equation (1) may be modeled as random walks, where $a^*_{k,t}$ is an additional state necessary to write the trigonometric