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Short term solar radiation forecasting: Island versus continental sites

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ABSTRACT

Due its intermittency, the large-scale integration of solar energy into electricity grids is an issue and more specifically in an insular context. Thus, forecasting the output of solar energy is a key feature to efficiently manage the supply-demand balance.

In this paper, three short term forecasting procedures are applied to island locations in order to see how they perform in situations that are potentially more volatile than continental locations. Two continental locations, one coastal and one inland are chosen for comparison. At the two time scales studied, ten minute and hourly, the island locations prove to be more difficult to forecast, as shown by larger forecast errors.

It is found that the three methods, one purely statistical combining Fourier series plus linear ARMA models, one combining clear sky index models plus neural net models, and a third using a clear sky index plus ARMA, give similar forecasting results.

It is also suggested that there is great potential of merging modelling approaches on different horizons.

1. Introduction

Unlike conventional power stations that can operate more or less continuously to meet demand, solar and wind technologies are inherently time-varying sources of energy on scales from minutes to seasons. Storage of large amounts of energy on-site is generally problematic. Thus the incorporation of solar energy sources into the electricity grid provides some new challenges in managing a stable energy supply, because 'back-up' energy from other sources needs to be found when solar production falls below anticipated levels or fails entirely (e.g., clouds moving across the solar farm). In such cases, the ability to accurately forecast the output of solar energy facilities is essential to ensuring that back-up sources are available to maintain supply in a cost-effective manner.

There are two aspects to solar energy forecasting, that of the expected level of energy, and also that of putting sensible error bounds on that forecast. In this paper, we will concentrate on the former, and in particular, that of the global horizontal irradiation (GHI). As stated in Ref. [1], *GHI forecasting approaches may be categorized according to the input data used which also determine the forecast horizon*. For periods of more than six hours, up to at most about seven days, numerical weather prediction models (NWP) would perform best, while for the very short term of a number of minutes to the range for NWP, statistical models appear to be superior [1]. On horizons longer than a week, it is probably the case that climatology would out perform any other method. Inman et al. [2] also examines the various approaches that one needs to consider on different time scales.

This work highlights solar forecasting in the case of islands, as compared to continental locations. Several previous works were related to solar forecasting in an insular context with techniques ranging from statistical models [3], sky imagery [4] to post-processing of numerical weather prediction model [5]. In Ref. [3], the focus was on insular sites only while in the present study, we assess the performance of the models in the case of continental sites as well. In addition, in this previous work, all models were based on the multiplicative approach as all of them used a clear sky model to remove the geometric course of the sun. In this submission, we propose to evaluate the additive approach used in the classical time series (CTS) method (see Section 3).

In this paper, we will focus on three approaches to the very short term forecasting task. One approach will be to use an additive method of characterising the seasonality, Fourier series, followed by the use of the Box-Jenkins method of determining an ARMA model for the residuals left after the seasonal component is

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removed. This is a simplification of the coupled autoregressive dynamical system model (CARDS) developed in Ref. [6], as globally this performs almost as well. The second approach involves a multiplicative approach to defining the seasonality using the Bird clear sky model [7]. The Clear Sky Index (CSI) is formed by dividing the measured GHI by the clear sky irradiance derived with the BIRD model. The resulting CSI is then modelled using an ANN. A variation on this approach involved using an ARMA model for the CSI.

Herein, we will focus on one step ahead forecasts, whereas future work will include forecasting for multiple steps ahead.

2. Data

We used data from a variety of locations, three in small islands, one on the coast of a large island and one inland. The latter two were to provide some comparison with the difficulties of forecasting solar radiation on small islands with strong prevailing winds and also, being tropical or sub-tropical, being prone to high degrees of convection. The three island locations are St. Pierre, Reunion Island, 55.49 East Longitude, −21.34 Latitude, Oahu, Hawaii, 158.08 West Longitude, 21.31 Latitude, and Fouillole, Guadeloupe, 61.52 West Longitude, 16.2 Latitude. The location on the coast of a large island is Adelaide, Australia, 138.60 East Longitude, −34.93 Latitude. The inland location is Las Vegas, USA, 115.14 West Longitude, 36.17 Latitude. For the majority of locations we had only one or two years os data available for this preliminary study. The exception is Adelaide, for which we had ten years, 1995–2004. See Fig. 1 for a summary of the data used for the study.

3. Classical time series approach (CTS)

We will follow the systematic procedure outlined in Ref. [8]. When analysing a time series data set, the first step is to consider whether it contains a trend, or seasonality, or both. Following [9] [8], we construct the power spectrum which gives the power in the series at frequencies 1 to 731 cycles per year. We illustrate this for the site at latitude −34.22°, Mildura, Australia, shown in Fig. 2. For Mildura, the annual cycle is very pronounced, and also there are two prominent spikes at 364 cycles/year and 366 cycles/year. As explained in Refs. [8] [6], these are called either beat frequencies or sidebands. They describe the amplitude modulation, the change in the amplitude of the daily cycle to suit the time of year. Whenever there is a significant difference in the daily amplitude of the signal as the day of the year alters, the contribution at these frequencies must be included - see Fig. 3. It should be noted that in Ref. [10] it was shown that for a location at approximately 16° North latitude, they did not need to be included as the daily amplitude does not change significantly over the year.

3.1. Fourier Series model - additive seasonality approach

The power spectrum identifies which frequencies are significant contributors to what we will term the seasonality of the data. This seasonality is then well represented by a suitable Fourier series. Any insignificant frequencies will have a contribution to the series not far removed from zero. Equation (1) gives the Fourier series:

$$\begin{aligned} S_t = {} & \alpha_0 + \alpha_1 \cdot \cos\frac{2\pi t}{8760} + \beta_1 \cdot \sin\frac{2\pi t}{8760} + \alpha_2 \cdot \cos\frac{4\pi t}{8760} \\ & + \beta_2 \cdot \sin\frac{4\pi t}{8760} + \sum_{n=1}^{2}\sum_{m=-1}^{1}\left(\alpha_{nm}\cdot\cos\frac{2\pi(356n+m)t}{8760}\right. \\ & \left. + \beta_{nm}\cdot\sin\frac{2\pi(365n+m)t}{8760}\right) \end{aligned} \quad (1)$$

Here, α_0 is the mean of the data, α_1, β_1 are coefficients of the yearly cycle, α_2, β_2 of twice yearly and α_{nm}, β_{nm} are coefficients of the daily cycle and its harmonics and associated beat frequencies. An inspection of the power spectrum would show that we need to include the harmonics of the daily cycle ($n = 1, 2$) and also the beat frequencies ($m = -1, 1$). Fig. 4 shows an illustration of the Fourier series model of the data.

3.2. ARMA model

When the Fourier series contribution is subtracted from the data series, the residual series can be modelled with the coupled autoregressive and dynamical system approach, details of which are given in Ref. [6]. In this instance, we use a simpler but similarly effective procedure, that of a short lag autoregressive model. This simplification of the ARMA process is possible since in this instance, the moving average (MA) contribution is not significant.

The general form of an autoregressive process of order p, or $AR(p)$, is given by

$$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \ldots + \alpha_p X_{t-p} + Z_t. \quad (2)$$

This is like a multiple regression but X_t is regressed on past values of X_t, not on other predictor variables, hence the term autoregressive. In this, $Z(t)$ is white noise with variance σ_Z^2.

4. Multiplicative approach: use of a clear sky model

Conversely to the CTS approach, in the multiplicative approach, we use a clear sky model to remove the geometric course of the sun. As mentioned in the introduction, this approach leads to the use of the clear sky index (CSI) or k × defined by:

	Saint-Pierre Reunion	Fouillole Guadeloupe	Ohau Hawaii	Adelaide Australia	Nevada USA
Situation	Insular	Insular	Insular	Continental	Continental
Longitude	55.491°E	61.516°W	8.733°E	136.6°E	115.14°W
Latitude	21.34°S	16.264°N	41.917°N	34.93°S	36.17°N
Record time step	10 min. 1 hour	10 min. 1 hour	1 hour	1 hour	10 min. 1 hour
In sample period	1/01/2012 31/12/2012	1/01/2010 31/12/2010	18/03/2010 31/12/2010	1/01/2003 31/12/2003	1/01/2011 31/12/2011
Out sample period	1/01/2013 31/12/2013	1/01/2011 31/12/2011	1/01/2011 1/11/2011	1/01/2004 31/12/204	1/01/2012 31/12/2012

Fig. 1. Main characteristics of the measurement sets.