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Spatial-temporal forecasting of solar radiation

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ABSTRACT

We apply the CARDS solar forecasting tool, developed at the University of South Australia, to forecasting of solar radiation series at three sites in Guadeloupe in the Caribbean. After performing the model estimates at each individual site, forecast errors were tested for cross correlation. It was found that on an hourly time scale, there was small but significant correlation between sites, and this was taken into account in refining the forecast. Cross correlation was found to be insignificant at the ten minute time scale so this effect was not included in the forecasting. Also, the final error series in each case was tested for an ARCH effect, finding that to construct prediction intervals for the forecast a conditional heteroscedastic model had to be constructed for the variance. Note that cross correlation between sites has to be included for this procedure as well as in the forecasting of the radiation.

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1. Introduction

We will describe the multivariate forecasting of solar radiation using three sites at Guadeloupe, in the French West Indies. The goal is to see how much forecasting skill we can attain, when you have data from three partially correlated sites. For the first analysis, we will concentrate on hourly solar radiation data, and for the second, ten minute data. We use the eleven months February to December 2011, as this provided a time period for which valid data was available for all sites on both time scales. Note that in all the analysis herein, the units for solar radiation are W/m^2. We will follow the systematic procedure outlined in Ref. [1]. When analysing a time series data set, the first step is to consider whether it contains a trend, or seasonality, or both. Following Boland [2,3], 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 of Desirade, latitude 16.32° in Fig. 1. There are a number of interesting features to this power spectrum, particularly if you compare it with the power spectrum for a site at latitude −34.22°, Mildura, Australia, shown in Fig. 2. For Mildura, the annual cycle is more pronounced than for Desirade, and also there are two prominent spikes at 364 cycles/year and 366 cycles/year. As explained in Ref. [1], 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. Their relative absence for Desirade implies that the amplitude of the daily cycle does not change significantly during the year. As well as this, the lower power at the annual cycle shows that there is not as great a difference over the year in the mean daily solar radiation. These two conclusions are well illustrated by comparing the daily mean radiation over the year for Desirade, Fig. 3 and Mildura, Fig. 4. There is a much more pronounced difference between winter and summer for Mildura.

2. Forecasting tools

Several approaches have been developed for the forecasting of solar radiation on various time scales. A comprehensive review of recent articles can be seen in Refs. [4,5]. The approaches range from use of Artificial Neural Networks (ANN) using raw solar irradiance [6] to several methods utlizing first some type of seasonal adjustment. This seasonal adjustment is either in the form of multiplicative deseasoning such as using clearness index or a clear sky model, or additive deseasoning using Fourier series or wavelets. I shall comment on these various methods of seasonal adjustment, but first let us examine the range of forecasting tools subsequent to this process of the modelling. The tools range from ANN [6–8] and several other references, to Adaptive Autoregressive [9] to Exponential Smoothing [10]. As well as these single method approaches, several authors utilise what might be called hybrid models, like wavelets plus ANN [11–13], and the Coupled Autoregressive and Dynamical Systems (CARDS) model of the present author and colleagues [1]. This is not an exhaustive list but it gives the idea of the

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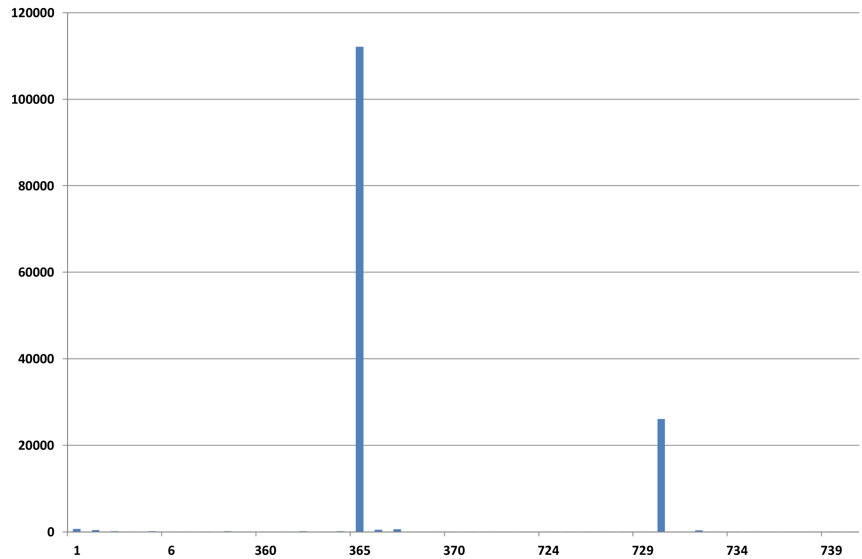

Fig. 1. Power spectrum for hourly solar radiation for Desirade 2011 data.

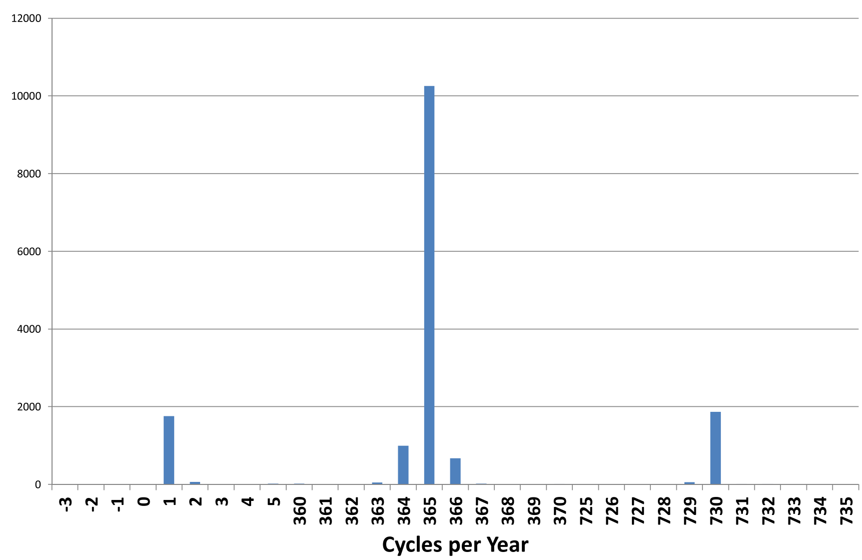

Fig. 2. Power spectrum for hourly solar radiation for Mildura data.

wide range of possible methods used for short term forecasting of solar radiation. I have not even delved into the more recent array of approaches utilising sky cameras and so forth.

I would now like to discuss in more detail the methods referred to above of dealing with the inherent seasonality in sub-daily solar radiation series, since the focus of this paper is forecasting on hourly and sub-hourly time scales. As mentioned, one approach has been to use multiplicative deseasoning in the form of dividing the solar radiation series by, in some cases, the clearness index [14–17]. Alternatively, numerous articles deal with dividing the solar radiation by some clear sky model to create a clear sky index [7,9]. It is useful to examine what type of situation is usually handled by implementing a multiplicative seasonal model. The multiplicative model is more prevalent with economic series since most seasonal economic series have seasonal variation which increases with the level of the series. One example is in the time series of tourist arrivals [18]. Interestingly, they deal with the seasonality by taking logarithms of the data. In fact, one researcher has done similar with solar data [19]. One could make an argument for using multiplicative deseasoning for solar data by using division with clearness index or a clear sky model as well, since the seasonality has a varying amplitude over the year. Note that, as will be shown below, using an additive Fourier series representation of the seasonality deals with this more effectively. If one does use multiplicative deseasoning, one could make a case for the use of the clearness index rather than a clear sky model, even though [20] discusses the use of both methods and goes for a clear sky index. I suggest that since Ineichen [21] feels it is necessary to examine the relative efficacy of numerous clear sky models, this points to using the clearness index being a better approach. This is because the clearness index approach utilises a variable calculated through astronomical formulae, rather than being the result of a model, with a number of inherent assumptions.

There are compelling arguments as to why an additive seasonal modelling process is preferable to a multiplicative one. This is especially true in the case of a Fourier series model. There are two

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