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Forecasting solar radiation on an hourly time scale using a Coupled AutoRegressive and Dynamical System (CARDS) model

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Abstract

The trends of solar radiation are not easy to capture and become especially hard to predict when weather conditions change dramatically, such as with clouds blocking the sun. At present, the better performing methods to forecast solar radiation are time series methods, artificial neural networks and stochastic models. This paper will describe a new and efficient method capable of forecasting 1-h ahead solar radiation during cloudy days. The method combines an autoregressive (AR) model with a dynamical system model. In addition, the difference of solar radiation values at present and lag one time step is used as a correction to a predicted value, improving the forecasting accuracy by 30% compared to models without this correction.
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Keywords: Solar radiation forecasting; Time series method; Lucheroni model; Combination model; Fixed component; CARDS model

1. Introduction

When methods for forecasting solar radiation time series were first developed, the principal applications were for estimating performance of rooftop photovoltaic or hot water systems. If there were significant errors in the forecast, the consequences were not severe. In recent times there has been increasing development of larger solar installations, both large scale photovoltaic and also concentrated solar thermal. In order to first influence financial backers to participate in their development, and also to potentially compete in the electricity markets, better forecasting models are required than simple Box–Jenkins models, such as those outlined in Boland (2008). In this paper we explore a range of possible improvements in forecasting skill, and suggest a Combination model linking a standard autoregressive approach with a resonating model borrowed from work on dynamical systems, and also an additional component that greatly enhances forecasting ability.

There are many distinctive models for forecasting global solar radiation, such as those based on time series methods (Boland, 2008; Wu and Chan, 2011), Artificial Neural Networks (ANNs) (Mihalakakou et al., 2000; Tymvios et al., 2005; Cao and Lin, 2008; Mellit et al., 2010), satellite-derived cloud motion forecast models (Perez et al., 2010) and stochastic prediction models (Kaplanis and Kaplani, 2010) that use the volatility of the data over the whole time period. The inclusion of long-term volatility estimates into the design of stochastic prediction models leads to a method that works quite well overall (Kaplanis and Kaplani, 2010). However, predictions at individual points can actually be worse because of the inclusion of the stochastic component. In Gueymard (2000), instead of predictions for individual hourly periods for a specific day and

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year, ‘long-term’ distributions of daily irradiation are used to obtain the mean hourly distribution of global radiation over the average day of each average month. Some of these models work very effectively in normal weather conditions, but not as well in extreme weather situations. For example, the Autoregressive and Moving Average (ARMA) model, which is considered to be a stable model can produce a large error (Wu and Chan, 2011) in extreme conditions. Some ANN models have been found to produce less accurate solar radiation forecasts when the weather conditions changed dramatically (Mihalakakou et al., 2000). Even a hybrid model, such as an ARMA plus a Time Delay Neural Network (TDNN) (Wu and Chan, 2011), does not always improve the accuracy of solar radiation prediction in extreme weather. Note that Kostylev and Pavlovski (2011) have defined the benchmark to which one may compare the performance of a forecasting tool. They surveyed the literature on forecasting at various time scales, from a number of days, down to hourly forecasts. They found that the best performing model on an hourly time scale had an NRMSE of 16–17% for mostly clear days and 32% for mostly cloudy days.

In this paper, a new method for one-period ahead forecasting of global solar radiation is developed. That is, given the observed radiation F_t at time t, a forecast is made for F_{t+1}. The proposed method is based on a combination of autoregressive (AR) model and a dynamical system model. The dynamical system model considered here is the resonating model introduced in Lucheroni (2007), here termed the Lucheroni model, which is particularly well suited to high frequency data analysis, such as solar radiation. The resulting forecasting model is used to obtain 1-h ahead solar radiation forecasts for Mildura, a small town in western Victoria, Australia and its performance is assessed using a range of forecasting accuracy measures. Comparisons are also made with a number of other models using similar time scales available in the literature. In future work, other time scales will be considered as well. These will include half hour and 5-min time scales, which are the critical scales in the operation of the Australian electricity market.

The paper is organized as follows. Section 2 describes the data and Fourier series model of that data while gives the seasonal component, after the seasonal component is subtracted from the data, the residual time series is analyzed in Section 3. The Lucheroni model is described in Section 4 and the combination of AR and Lucheroni models in Section 5. Error analysis and comparison of these three models are given in Section 6. A new method to improve forecasting performance, based on a fixed component, is described and applied to the Combination model in Section 7. The result is the Coupled AutoRegressive Dynamical System (CARDS) model. Comparisons of the CARDS model with other models are made in Section 8. The final section is devoted to conclusions and a brief discussion of future work.

2. Determining the seasonality of a solar radiation series

The global solar radiation data used in the development of the prediction procedure is from Mildura, during the year 2000. Mildura is a small city in north western Victoria, Australia, Latitude 34°11′S, Longitude 142°09′E and the time zone is AEST (UTC+10). The data set consists of 8760 (24 × 365) hourly global radiation values in total. For the time period considered, 54% of days were sunny; the remaining days included cloudy periods. The average hourly global radiation was 488.62 W/m^2 and the maximum value was 1146 W/m^2.

When analysing a time series data set, the first step is to consider whether it contains a trend, or seasonality, or both. In this case, seasonality is the only significant feature of global solar radiation of the Mildura 2000 data, thus the first step is to deseason the data.

From Tolstov (1976), the Fourier series of a function S_t is given by

$$S_t = \frac{1}{2}a_0 + \sum_{n=1}^{\infty} a_n \cos(nt) + \sum_{n=1}^{\infty} b_n \sin(nt) \tag{1}$$

where

$$a_0 = \frac{1}{N}\sum_{k=1}^{2N} S_t \tag{2}$$

$$a_n = \frac{1}{N}\sum_{k=1}^{2N} S_t \cos\left(\frac{\pi nk}{Nt}\right), n = 0, 1, 2\cdots \tag{3}$$

$$b_n = \frac{1}{N}\sum_{k=1}^{2N} S_t \sin\left(\frac{\pi nk}{Nt}\right), n = 1, 2, 3\cdots \tag{4}$$

However, for the purposes of calculations, this model can be transformed into another form. Following Boland (1995, 2008), and using the results of Power Spectrum analysis, S_t can be written as:

$$S_t = \alpha_0 + \alpha_1 \cdot \cos\frac{2\pi t}{8760} + \beta_1 \cdot \sin\frac{2\pi t}{8760} + \alpha_2 \cdot \cos\frac{4\pi t}{8760} + \beta_2 \cdot \sin\frac{4\pi t}{8760} + \sum_{i=3}^{11}\sum_{n=1}^{3}\sum_{m=-1}^{1}\left(\alpha_i \cdot \cos\frac{2\pi(356n+m)t}{8760} + \beta_i \cdot \sin\frac{2\pi(365n+m)t}{8760}\right) \tag{5}$$

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_i, β_i 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 ($n = 2$, 3 as well as $n = 1$) and also the beat frequencies ($m = -1$, 1). The latter modulate the amplitude to fit the time of year, in other words describe the beating of the yearly and daily cycles.

Table 1 shows the frequency of yearly, twice yearly, daily and twice daily cycles, with percentage of variance

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