Forecasting solar radiation and farm power using combined seasonality and autoregressive model

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The most common approach to solar energy forecasting is to use a clear sky radiation model to create a clear sky index time series using multiplicative deseasoning transformation and develop a forecasting tool for the deseasoned series. The output of the forecasting tool is retransformed to include seasonality. An alternative method used by the present authors is to characterise the seasonality with a Fourier series and the deseasoned series with an autoregressive model, developed on a training set to use in forecasting future output. From working on a project on solar farm output forecasting, a clear sky related output model seemed useful in certain circumstances. We describe the use of the clear sky model, coupled with additive deseasoning to forecast the output of solar farms. If one used the clear sky index approach, one would have to use a power conversion model to transform to the farm output forecast. We discuss how to switch between our standard and clear sky output models.

Background

Boland (2008) describes the process for using Fourier series to typify the seasonality of solar radiation using empirical modelling of the radiation time series. In essence, the Fourier series defines the solar climate for a particular location. The departures from this climate series, the residual series, comprise the weather fluctuations. This residual series has been modelled as an autoregression process as shown in Equation 1

$$r_t = \alpha_1 r_{t-1} + \alpha_2 r_{t-2} + \cdots + \alpha_p r_{t-p} + z_t \quad (1)$$

where z_t is the noise term. Typically, only two or three autoregressive terms are needed for hourly data and up to five for minutely data. Call the combination of the Fourier series and this model **Mod1.** Typically**,** the noise terms are assumed to be white noise, independent and identically distributed. Although this is not the case for solar radiation and solar farm power, the ramifications of this assumption are not discussed here, as it is important for probabilistic forecasting which is not the subject of this paper.

Methods

We use the method detailed above to forecast solar farm output to comply with the requirements of the Australian Renewable Energy Agency (ARENA) project *Solar Power Ensemble Forecaster*. The forecast is made for the power output at a time at the start of a five minute interval, performed seven minutes before the start of that interval. We have also developed a method to specifically cater for clear sky days. Many researchers have used a physically based clear sky model to typify the theoretical maximum solar radiation at any time in the year. They then divide this into the global horizontal irradiation (GHI) to create a clear sky index, which they then apply an autoregressive or artificial neural network model to in order to complete the construction of a forecasting tool. When forecasting solar farm power output, there are reasons this is not the most suitable approach. First is that solar farms usually have an excessively large number of solar panels, making the field capacity greater than that of the inverters, meaning that the daily amplitude of the output is essentially the same year round, limited by the inverters capacity and negating the need for some components of the clear sky model. Second, as the focus is on forecasting solar power output, not the radiation input, we would have to use a power conversion model to obtain that.

As an alternative, we have developed an empirical clear sky model for solar power output. This model takes the maximum value of the power output for each minute of the day, using typically 30 days of historical data. This empirical clear sky power output is then smoothed using a Fourier series. The difference between this and the power output is then modelled using an autoregressive process estimation. Call this combination **Mod2**.

From our research, **Mod1** (Figure 1) performs better on days with intermittent radiation and **Mod2** (Figure 2) is the best for clear days. In Figure 1, **Mod2** tends to overshoot after a drop, while in Figure 2, **Mod1** is unable to reach the peaks. In the ARENA project, these two approaches are blended with various other approaches including using sky cameras, satellite images, and even smart persistence, to enhance the forecasting of the output.

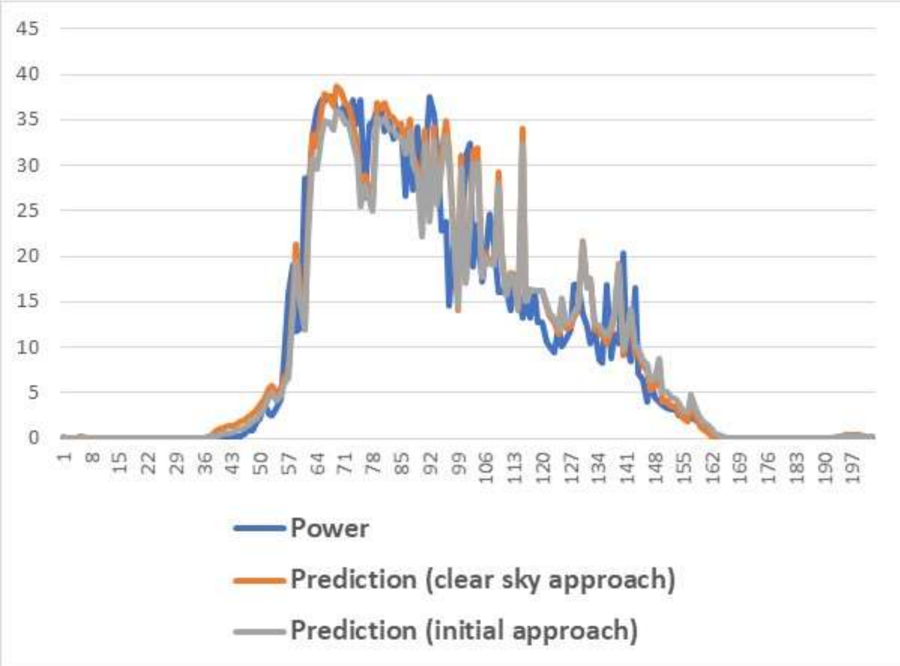

Figure 1. Forecast for an intermittent day

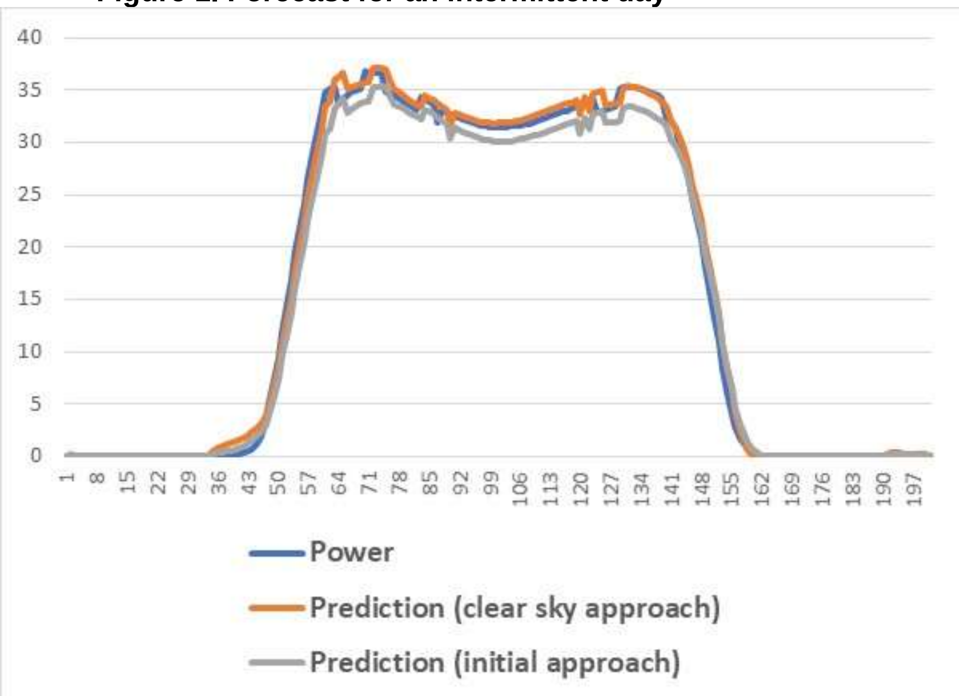

Figure 2. Forecast for a clear day

Presentation

We will elaborate on these findings and present results for several farms. We will also describe the use of the clear sky output model for GHI itself.

References

Boland J. (2008) Time series and statistical modelling of solar radiation, *Recent Advances in Solar Radiation Modelling*, Viorel Badescu (Ed.), Springer-Verlag, pp. 283-312.