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Probabilistic Forecasting of Wind and Solar Farm Output

John Boland[1] and Sleiman Farah[1]

[1]Industrial AI, University of South Australia, Adelaide, Australia

Accurately forecasting the output of grid connected wind and solar systems is critical to increasing the overall penetration of renewables on the electrical network. This includes not only forecasting the expected level, but also putting error bounds on the forecast. The National Electricity Market (NEM) in Australia operates on a five-minute basis. We used statistical forecasting tools to generate forecasts with prediction intervals, trialing them on one wind and one solar farm. In classical time series forecasting, construction of prediction intervals is rudimentary if the error variance is constant - termed homoscedastic. But if the variance changes - either conditionally as with wind farms, or systematically because of diurnal effects as with solar farms - the task is much more complicated. The tools were trained on segments of historical data and then tested on data not used in the training. Results from the testing set showed good performance using metrics including coverage and Winkler score. The methods used can be adapted to various time scales for short term forecasting.

The classical time series model has the present value of the output written as a function of past values, including in the case of solar irradiance or power, some seasonal component, plus a noise term.

$$Y_t = f\left(S_t, R_{t-1}, \dots, R_{t-p}\right) + Z_t$$

In this, S_t is the seasonal component, and $R_t = Y_t - S_{t.}$ It is hoped that the noise terms Z_t are independent and identically distributed (i.i.d) - white noise. It is also hoped that the noise is normally distributed. But, for solar irradiance, wind speeds, and solar and wind farm output - none of these desires is fulfilled. This means that we must cater for the change in distribution or variance over time.

For wind farm output, there is conditional change of variance. If the noise were normally distributed, we could simply apply an ARCH or GARCH model to forecast the variance. Since the noise is highly skewed, we apply a normalising transformation and, as it turns out, using exponential smoothing forecasting for the variance works better. For the solar farms, the distribution changes over the day. So, we apply the following algorithm.

1. Since the noise distributions are not normal, one instead finds, for a 95% prediction interval, the 0.025 and 0.975 percentiles of the errors of the process and add them to the forecast.
2. Another complication - the error distributions change over the day. So, we perform this process separately for each hour of the day.

For the wind farm, the coverage percentages exceeded the expected by 2-3\% and widths as measured with the Winkler score were much better than a persistence forecast. For the solar farm, the coverage was almost exactly the expected and once again the widths were narrower than a smart persistence version.

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