Post-processing COSMO output for improved wind forecasts

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1 Introduction

Ireland has a large number of wind farms, which have supplied an average of 15% of system demand over the last year, and have peaked to supply up to 50% of demand (EirGrid), as shown in figure 1. The amount of electricity delivered by wind farms is due to increase, with more wind farms under construction. The government has set an ambitious target of 40% of electricity to be supplied from renewables by 2020. The majority of this is due to come from wind energy.

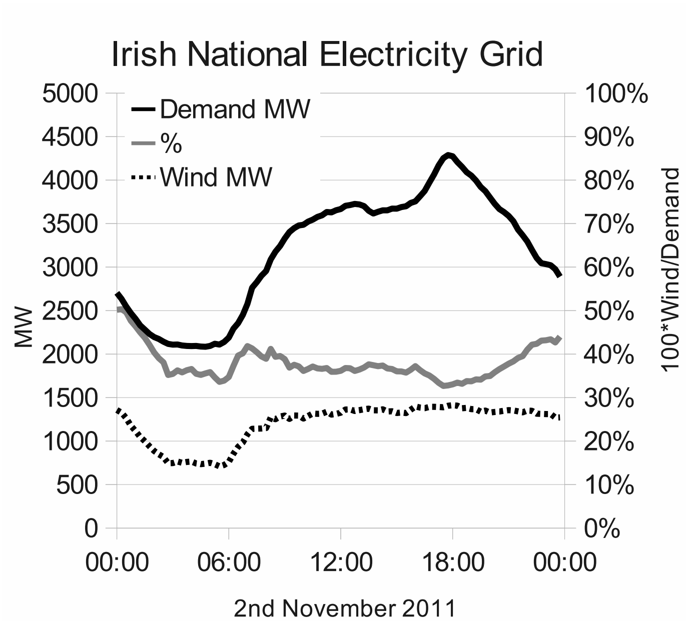

Figure 1: Total grid demand (MW), wind generation (MW), and percentage (100*wind/demand) for the Irish grid (data from EirGrid)

Although wind energy has the benefit of being environmentally friendly, it has the disadvantage of being difficult to integrate efficiently into the national electricity grid. Unlike traditional generators, the wind can not be turned on or off at will.

To help with this potentially costly problem of managing a large amount of wind energy on the grid, there is a keen interest in developing methods to accurately predict when the wind will blow, and how much electricity will be generated.

It is common practice for a forecast office to issue a forecast based, amongst other things, on the output of a numerical weather prediction model (like COSMO!). Even the best model, however, cannot produce a perfect forecast. Some of these forecast errors are difficult to overcome, but others may be due to some systematic process. It is these systematic errors that we hope to reduce by applying post-processing methods to COSMO.

2 Post-Processing Methods

We wanted to consider some simple methods for post-processing COSMO forecasts. Ideally, the methods should require only a short training period, so that they could adapt quickly to changes in COSMO (new versions), as well as changes to the observing networks (new and/or retired stations). The methods used were as follows:

- The **Kalman filter** (Crochet, 2004, Louka et al., 2008) and **Artificial Neural Networks (ANN)** (Salcedo-Sanz et al., 2009). We investigated how the methods used in these recent studies would improve our forecasts, and how they would compare to some simple methods.
- **Short-term bias-correction forecasts (STB)** simply calculated the average error (forecast speed minus observed speed) over the previous 30 days (called the training period), and applied this to the forecast. This, as with the other methods, was done separately for each station location.
- The **linear least-square corrected forecast (LLS)** calculated the linear expression that minimized the least-square-error of the fit between the forecast wind speed and the observed wind speed over the training period, and used this to correct the forecast.
- The **directional-bias forecast (DIR)** tried to take into account the fact that the wind speed error may be different in one direction than another. For example, a nearby hill that is not resolved by the model may act to reduce the wind speed for one direction, but increase it for another direction. The DIR forecast considered all of the wind speed errors and their corresponding wind directions over the training period. The errors were averaged in 30° bins by their directions, and the current forecast wind direction was then used to select the error correction to apply to the forecast wind speed, giving the DIR forecast wind speed.

3 Forecast and Verification

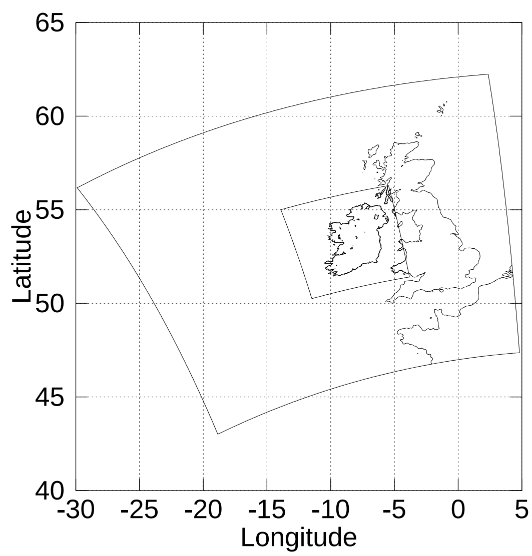

Figure 2: Domains for the 7 km and 3 km COSMO forecasts

We ran 48-hour COSMO forecasts at horizontal resolutions of 7 km and 3 km over a two year period (June 2008 to May 2010). The domains used are shown in figure 2. We used the ECMWF IFS T799L91, which has a horizontal grid spacing equivalent to 25 km, to drive the 7 km forecasts, which then drove the 3 km forecast.

We compared the 10 m wind to observations at 7 stations around Ireland. Using the simple skill scores of bias and root mean square error (RMSE) over the two year period, we found that the post-processing methods produced forecasts with better skill scores than the unprocessed COSMO model output. The LLS, DIR and ANN forecasts gave the best reductions in errors, but *no single method consistently outperformed the others*.

We decided, therefore, to investigate methods to combine the post-processed forecasts to produce a more accurate forecast. We did this using a simple method that assigned weights to each forecast based on its recent skill score, and combined the forecasts using these weights. This combined forecast produced skill scores that were *always equal to or better than* any of the input forecasts.

4 Summary and Outlook

Post-processing the COSMO model output reduces forecast error. Post-processing methods are adaptive, as they are always produced using data from the last 30 days. They are automatic, in that they need no tuning parameters. They are also very computationally efficient; all of the methods used here were run on a standard desktop computer.

By combining a stream of post-processing methods, a forecast can be produced that matches, or exceeds, the skill score of any of the input forecasts. More information on the methods used is available in Sweeney et al.(2011a, 2011b).

The next project we are working on involves taking these post-processing methods, and applying them to an ensemble of forecasts. Much work has already been done with ensembles in the COSMO community (Montani et al. 2010), and we hope that post-processing will be able to help reduce errors in probabilistic forecasts.

This research has a direct application in the wind energy community, as it allows cost/loss decision-making models to be run. These can be used by the electricity grid operator, for example, to decide how much money to spend on reserve capacity for a given time. They could also be used by wind farm operators, to allow them to decide on an optimal bid price for wind energy on an open market.

References

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