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Adaptive postprocessing of short-term wind forecasts for energy applications

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Abstract

We present a new method to reduce the error in predicted wind speed, thus enabling better management of wind energy facilities. A numerical weather prediction model, COSMO, was used to produce 48 hour forecast data every day during 2008 at horizontal resolutions of 10km and 3km. A new adaptive statistical method is applied to the model output to improve forecast skill. The method applies corrective weights to a set of forecasts generated using several post-processing methods. The weights are calculated based on the recent skill of the different forecasts. The resulting forecast data is compared to observed data and skill scores are calculated to allow comparison between different postprocessing methods. The total RMSE performance of the composite forecast is superior to any of the individual methods.

keywords: wind forecast; wind energy; adaptive filtering; NWP; statistical postprocessing

1 Introduction

The European Union has endorsed a mandatory target of a 20% share of energy from renewable sources in overall Community energy consumption by 2020 [1], while the Irish Government has committed to delivering a significant

growth in renewable energy with a 2020 target of 33% of electricity consumption [2]. A large portion of the growth in renewable energy is expected to come from wind energy [3]. As wind energy becomes a larger proportion of overall energy supply, wind energy management will become a crucial issue. The available power of the wind varies with the cube of the wind speed. Current forecasts have wind speed errors of the order of 2 m/s, and this can cause substantial errors in the predicted amount of wind power.

It is difficult to store electricity, so wind power predictions are established as valuable tools to integrate wind energy into the electricity supply. The prediction of the power output of wind farms is mainly used for grid operation, power production scheduling and trading, and is mostly concerned with a time window of 48 hours.

Wind speed forecasting can be achieved using two approaches. The first uses past wind data, which can be obtained easily by wind farm operators on-site. Data may then be analysed with different statistical models. However, information about atmospheric dynamics is important for forecasts of the range considered here (48 hours), and so a good forecast model for this range must include meteorological models.

Most meteorological forecast systems use data from a global forecast model to drive a regional numerical weather prediction (NWP) model, which performs dynamical downscaling. One way to increase the skill of wind forecasts is to run the NWP model at a higher resolution. The value of running NWP models at higher horizontal resolutions is still an open question. A previous study [4] has suggested that increasing model resolution towards 10 km allows the definition of the major mesoscale topographic features of the region and their corresponding atmospheric circulations. Going to resolutions higher than $\simeq 10$ km may only show small improvements in verification statistics. An added problem with higher resolution forecasts is that position and/or timing errors in the forecasts will strongly affect traditional objective verification scores. A good way to improve on NWP data is to use it as input to a statistical downscaling process.

Landberg et al. [5] give an overview of the early (2003) methods used for short-term prediction of wind farm power output. Most prediction systems combined NWP model output, input of observations, and some further statistical method to produce the required output. They also raise the point that increasing skill in forecasting for wind energy has a beneficial commercial impact.

Costa et al. [6] wrote a later (2008) review of wind power short-term pre-

diction. Some methods have been developed for very short-term predictions, but not extended to time horizons useful for trading (≥ 48 hours). They noted that it is difficult to carry out a quantitative comparison between a large number of models and methods, as exactly the same data must be used by all models and methods. Researchers have come to different conclusions on the relative performance of forecasting methods, and indeed on the importance of different input parameters, local topography, and NWP settings in predicting wind power. They point out that it would be an advantage to all researchers in this area to adopt a standard for measurement of performance of models.

The research community is considering different ways to improve the wind forecast skill, such as running a collection of ensemble forecasts [7] or using statistical postprocessing. Calibrated ensemble forecasting has been used to predict the probability density function of generated wind power from one to ten days ahead at five UK wind farm locations [8]. It was found to outperform time series models and compared well with NWP models, although the advantage for short time-scales (< 48 hours) was less pronounced.

Limited area ensembles have been postprocessed using Bayesian model averaging to provide 48-hour probabilistic forecasts of wind speed [9]. This method produced higher skill scores than using the raw ensemble data. Running limited area ensembles requires considerable computational resources, however, which may not be practical.

A good description of the dynamical/statistical approach to forecasting is given by Salcedo-Sanz et al. [10], where a bank of neural networks was used for the final statistical downscaling process for a number of different model inputs. This was found to give better performance than using a single neural network, (as in [11]).

Model output statistics (MOS) is another popular technique for improving forecast skill from NWP data. MOS uses multiple linear regression to produce an improved forecast at specific locations by using model forecast variables and prior observations as predictors [12]. A recent study found that MOS performed better than a Kalman filter or 7-day bias removal [13]. However, MOS requires a rather long training dataset and therefore can be difficult to apply to modelling systems that undergo major changes and to observing networks and sites that lack a long and complete historical record.

The Kalman filter method [14] does not require a long training period, and has successfully been applied to NWP wind forecasts [13, 15]. The Kalman filter method consists of a set of mathematical equations that pro-

vides an efficient computational solution of the least squares method with minor computational cost and easy adaptation to any alteration of the observations. Louka et al. [16] applied non-linear Kalman filters using third-order polynomials to post-process NWP wind speed data. In all cases, the Kalman filter was found to produce better bias and RMSE scores than direct model output. They suggested that higher resolution NWP models may not be worth the additional computational expense as, in their case, the same skill could be achieved by applying the Kalman filter to lower resolution NWP models.

Many of the forecasting methods used for wind energy have used the same overall structure of the dynamical/statistical approach. A global model supplies data to drive a regional NWP model. The output from the regional NWP model is used as input to a statistical process. Different statistical processes can be used for the last step, as mentioned above.

The skill of forecast models, as calculated by validating the forecast variables against observations, is often compared to the skill of direct model output. However, even a simple process such as rolling bias correction may significantly improve forecast skill if the direct model output contains a bias. It seems that an important measure of performance is to compare the skill of the proposed method to both direct model output and bias-corrected model output. In this paper, we take such an approach. The skill scores of wind forecasts produced from raw model output are compared with those produced by rolling-bias and rolling-trend correction, and the Kalman filter (KAL) method. We then introduce a simple scheme to produce a composite wind forecast by *combining all available forecasts* with weights based on recent forecast skill.

Model data will be taken from an NWP run at 10 km and 3.3 km. This will enable the benefit of running at higher resolutions to be compared to the increase in skill obtained by statistical postprocessing. Traditional skill scores will be used to compare the resulting forecasts with observed hourly wind speeds at seven different synoptic stations over a full year.

Section 2 gives a brief description of the NWP model, describes the methods used to postprocess the forecast data, and the data verification methods used. Section 3 presents the results and compares the performance of the different forecast methods. Section 4 consists of the discussion and conclusions.

2 Methodology

2.1 The COSMO model

The COSMO-Model is a nonhydrostatic limited-area atmospheric prediction model. COSMO is based on the primitive thermo-hydrodynamical equations describing compressible flow in a moist atmosphere. The model equations are formulated in rotated geographical coordinates and a generalized terrain-following height coordinate. Many processes are taken into account by parameterization schemes. For more information about COSMO, refer to the COSMO web-site [17].

Data used to drive the COSMO model were taken from the ECMWF IFS *T_L799L91* deterministic forecast, which has a horizontal resolution equivalent to 25 km. The midnight analysis and forecast were retrieved each day, with boundary data available every 3 hours. COSMO was run without assimilation of additional observations.

The computational domains used for the 10 km and 3 km forecasts are shown in Fig. 1. The 10 km forecast used a rotated lat/lon grid of 0.09°, with 40 vertical levels and a timestep of 60 seconds. The output of the 10 km forecast was used to drive the 3 km forecast (one-way nesting). The 3 km forecast used a rotated lat/lon grid of 0.03°, with 50 vertical levels and a timestep of 20 seconds. Output data were saved every forecast hour from 00 to +48 hours.

2.2 Forecast verification

Hourly wind speed data were obtained from Met Éireann (the Irish National Meteorological Service) for seven different synoptic stations around Ireland, at the locations shown in Fig. 2. The wind speed data refers to the wind speed observed at a height of 10 metres above the ground. Hourly output data is also available from the COSMO models at a height of 10 m. However, the locations of the grid points used by the COSMO models may not coincide with the locations of the synoptic stations. Therefore, forecasts were produced for these seven locations by interpolating the 10 m wind speeds from the closest grid points. The forecast wind speeds could then be compared to the observed wind speeds. The skill scores used for the wind speed forecasts were the mean error (ME) and the root mean square error (RMSE).

The distances from the station to the surrounding model grid points were

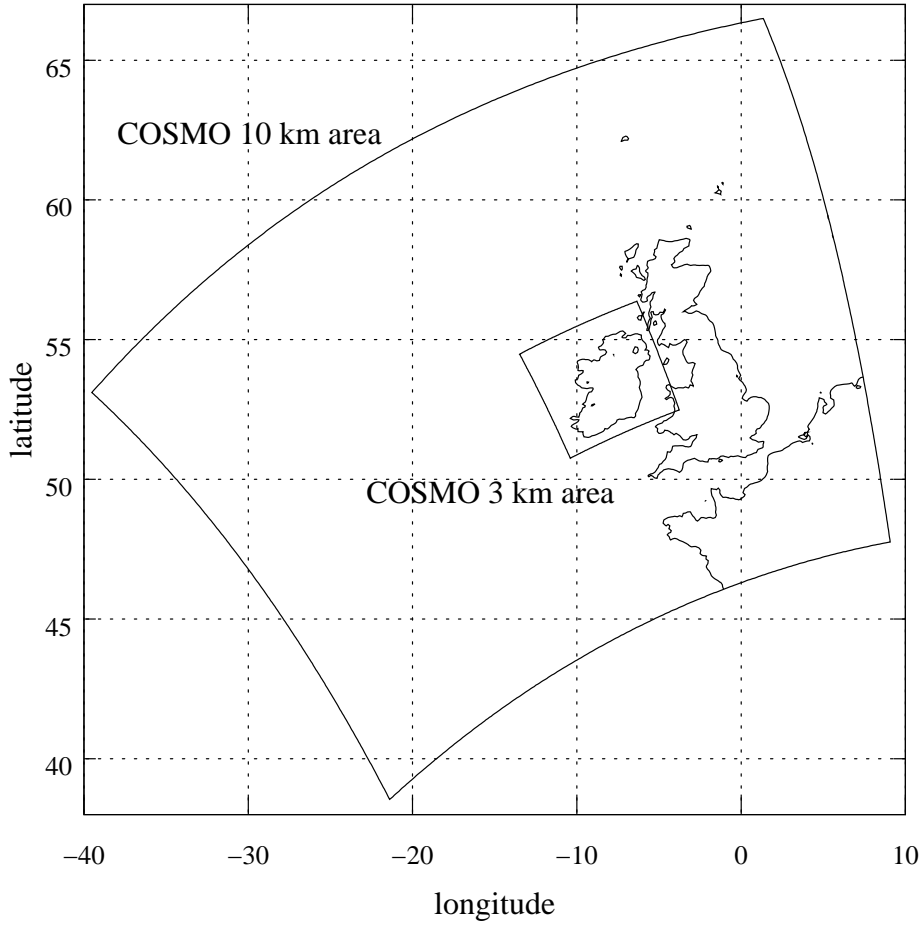


Figure 1: Computational domain for 10 km and 3 km forecasts.

	NWP resolution	closest point	3-point
Mean Error	10 km	2.099	1.946
	3 km	1.838	1.799
RMSE	10 km	2.502	2.351
	3 km	2.251	2.209

Table 1: Test scores for interpolating wind speeds

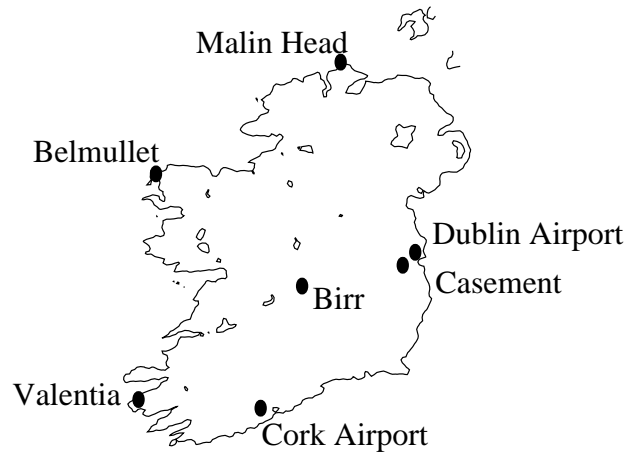


Figure 2: Synoptic stations used for forecast verification

calculated using latitude and longitude values. The interpolated wind speed could then be calculated using inverse distance weighting. Wind speeds were interpolated from the NWP model grid points to the station location in this way using the closest three model grid points. This interpolation method was compared to using only the closest model grid point over a test period of three months for the inland station located at Birr. Results showed that the 3-point interpolated wind speeds gave better values for mean error and RMSE than using the closest grid point alone, for both the 10 km and 3 km forecasts (Table 1). It is possible that different interpolation techniques may give better values for different stations, at different forecast resolutions. However, in this paper we try to adopt a uniform post-processing method for all forecast data, and so we have chosen to use the 3-point interpolated wind speeds for all stations and both forecast model resolutions.

2.3 Statistical postprocessing methods

Some simple postprocessing methods were applied to the raw model data for wind speed to see if this would improve the skill of the forecasts. The first method used was a short-term rolling-trend correction (STT). This method calculated the average error in forecast wind for each forecast hour over the previous 28 days. The forecast errors for the +25 to +48 section of the previous day's forecast cannot be calculated, as the observations are not yet available. These errors are set to equal the mean of the 0 to +24 errors.

STT results in a different error correction for each forecast hour, which is then applied to that day's forecast to produce the STT-corrected forecast.

The second method, the short-term rolling-bias correction (STB), worked in a similar way to the STT, except it only used the previous 3 days, and averaged over all forecast hours to produce a single error correction value, which was then applied to all forecast hours to produce the STB-corrected forecast for each day.

Finally, a simple Kalman filter was used to correct the forecast (KAL). The Kalman filter is described in papers such as [15], and only a brief overview is given here. Let X_t be a state vector, denoting the systematic part of the error of our NWP model at time t . We do not know X_t , and we base our initial guess on X_{t-1} , from the previous day:

$$X_{t-} = X_{t-1} \quad (1)$$

Let f_t be our NWP forecast for the variable of interest (wind speed) at time t . We write the predictor vector as: $H_t = [f_t \ 1]$. The Kalman-predicted wind speed is then given by:

$$\mu_t = H_t X_{t-} \quad (2)$$

Once an observation is made, the actual wind speed w_t is known, and the error in our prediction is calculated: $e_t = w_t - \mu_t$. The state vector X_t must now be updated. Following [18] we use a sliding window of width 7 days. We calculate the sample covariance V of e_t over the last 7 days. Similarly, we calculate the sample covariance matrix W of X_t over the last 7 days. We use W to give an initial estimate of the state variance matrix P :

$$P_{t-} = P_{t-1} + W \quad (3)$$

We now use P_{t-} and V to calculate the Kalman gain matrix:

$$K_t = P_{t-} H_t^T (H_t P_{t-} H_t^T + V)^{-1} \quad (4)$$

The Kalman gain determines how easily the filter will adjust to new conditions. Once we have K_t we can calculate an updated value for our state vector:

$$X_t = X_{t-} + K_t e_t \quad (5)$$

Finally, we update P :

$$P_t = (I - K_t H_t) P_{t-} \quad (6)$$

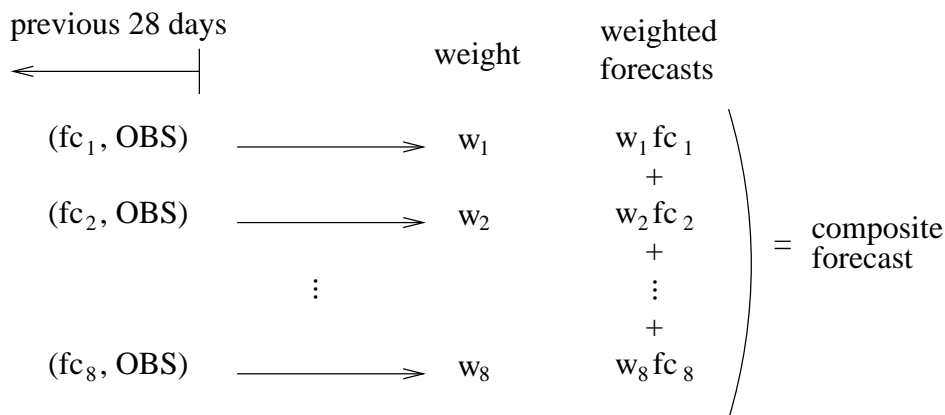


Figure 3: Producing the composite forecast

The initial values X_0 and P_0 must be set, and we use:

$$X_0 = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \quad P_0 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad (7)$$

These values do not seriously affect the results of the algorithm as they soon converge to their Kalman-estimated values. We now have a method for the recursive estimation of the state vector X_t .

In all statistical post-processing methods (STT, STB, KAL), the wind speed was constrained to be non-negative.

2.4 The Composite post-processing method, COM

If the model is run at 10 km and 3 km, and each raw forecast is postprocessed using three different methods, there will be eight different forecasts to choose from. If any one method consistently performed the best, we could simply choose that forecast and ignore the others. However, it is often the case that different methods attain the best skill scores at different times, and for different station locations. Therefore, we have produced a composite forecast that seeks to combine all available forecasts with weights based on their historical performance.

This is done by taking the absolute value of the mean wind speed error over the previous 28 days for each forecast method. This will result in eight error values, err_i , one for each of the eight available forecasts, fc_i . These

errors are used to calculate the weights to apply to each forecast, as described in equations (8). The composite forecast (*COM*) is given by the sum of the weighted forecasts. Figure 3 gives an outline of this process.

$$\begin{aligned}
 NUM &= \prod_{i=1}^8 err_i \\
 DEN &= \sum_{i=1}^8 \left(\frac{NUM}{err_i} \right) \\
 w_i &= \frac{NUM}{(err_i) DEN} \\
 COM &= \sum_{i=1}^8 w_i f c_i
 \end{aligned} \tag{8}$$

The weights used by the COM method are recalculated every day, thus enabling the method to adapt to changing synoptic conditions. We experimented with different sizes of sliding windows to use when calculating the weights. A test was done using window widths of 7, 14, 21 and 28 days. The COM method was tested using the whole year of data with each window width. All of the window widths produced very small overall mean errors, and the 28 day window was found to produce slightly better RMSE values. Therefore, we chose a window width of 28 days to use with the COM method in this paper.

It should be noted that the COM method is applied to all available forecast data. In this paper we have used three methods, STT, STB and KAL, to post-process NWP data supplied at two resolutions, but the method could just as easily include forecast data produced by any of the other methods mentioned in Section 1.

3 Results

A 48-hour forecast was run for each day in 2008. The first 28 days were used as a training period for the statistical post-processing methods, and skill scores were based on forecasts for the rest of the year. Results for the 10 km forecast show that mean error (ME) is reduced at all stations by all post-processing methods, as show in Table 2 (the best score is shown in **bold** type). However, the lowest ME is produced by different post-processing

Station	Raw	STT	STB	KAL
Belmullet	+1.877	-0.012	+0.030	+0.018
Birr	+1.827	+0.022	+0.047	+0.019
Casement	-0.461	+0.056	+0.028	+0.062
Cork Airport	+0.581	-0.001	+0.009	-0.003
Dublin Airport	-0.792	+0.032	+0.017	+0.001
Malin Head	-0.136	-0.033	+0.007	-0.032
Valentia	+2.110	+0.049	+0.043	+0.012

Table 2: 10 km forecast wind speed ME (m/s)

Station	Raw	STT	STB	KAL
Belmullet	+0.069	-0.027	-0.019	+0.001
Birr	+1.771	+0.012	+0.046	-0.001
Casement	+0.021	+0.006	+0.014	-0.001
Cork Airport	+0.406	-0.010	+0.005	+0.011
Dublin Airport	-1.262	+0.031	+0.013	+0.007
Malin Head	-1.847	-0.027	-0.010	-0.069
Valentia	+0.514	+0.026	-0.006	+0.018

Table 3: 3 km forecast wind speed ME (m/s)

methods at different stations. STT performs best at two stations, STB is best at another two, and KAL is best for the remaining three.

Results for the 3 km forecast also show that post-processing reduces ME at all stations (Table 3). Again, no single method produces the lowest ME at all stations, with KAL producing the lowest ME at four stations, and STB performing the best at the other three stations. It is interesting to note that the method that produced the lowest ME for the 10 km forecast is not always the method that produces the lowest ME for the 3 km forecast. The lowest ME is given by a different post-processing method for 3 km than 10 km at three of the seven stations. Furthermore, the higher-resolution forecasts do not always produce lower ME scores. At two of the stations, the 3 km forecast produces a slightly worse ME than the 10 km forecast.

The root mean square error (RMSE) was also calculated for each station, for each forecast resolution. Results are shown in Table 4 and Table 5. Post-processing resulted in lower RMSE scores at all stations for the 10 km forecasts, with KAL performing best at five of the stations, and STT and

Station	Raw	STT	STB	KAL
Belmullet	2.664	1.881	1.947	1.786
Birr	2.229	1.382	1.438	1.019
Casement	1.611	1.574	1.565	1.606
Cork Airport	1.490	1.405	1.421	1.345
Dublin Airport	1.651	1.471	1.495	1.523
Malin Head	2.051	2.034	2.062	1.978
Valentia	2.635	1.620	1.687	1.425

Table 4: 10 km forecast wind speed RMSE (m/s)

Station	Raw	STT	STB	KAL
Belmullet	1.778	1.745	1.776	1.796
Birr	2.199	1.409	1.441	1.007
Casement	1.346	1.356	1.388	1.390
Cork Airport	1.423	1.391	1.393	1.365
Dublin Airport	1.898	1.500	1.519	1.555
Malin Head	2.648	1.989	2.055	2.084
Valentia	1.528	1.459	1.453	1.469

Table 5: 3 km forecast wind speed RMSE (m/s)

Station	Raw 10 km	Raw 3 km	COM
Belmullet	+1.877	+0.069	+0.038
Birr	+1.827	+1.771	+0.057
Casement	-0.461	+0.021	+0.035
Cork Airport	+0.581	+0.406	+0.027
Dublin Airport	-0.792	-1.262	-0.001
Malin Head	-0.136	-1.847	-0.026
Valentia	+2.110	+0.514	+0.028

Table 6: Raw and COM forecast wind speed ME (m/s)

Station	Raw 10 km	Raw 3 km	COM
Belmullet	2.664	1.778	1.682
Birr	2.229	2.199	1.088
Casement	1.611	1.346	1.334
Cork Airport	1.490	1.423	1.307
Dublin Airport	1.651	1.898	1.405
Malin Head	2.051	2.648	1.907
Valentia	2.635	1.528	1.393

Table 7: Raw and COM forecast wind speed RMSE (m/s)

STB giving the best RMSE at one station each.

For the 3km forecasts, raw model data was best for one station, STB for one station, KAL for two stations, and STT for three stations. The best 3km RMSE scores outperformed the best 10km RMSE scores at only four of the seven stations, while the method that produced the best RMSE score for the 10km forecast was different to the best method for the 3km forecast at four of the seven stations.

3.1 Composite Forecasts, COM

A composite forecast was also produced by combining forecasts with weights calculated from their historical errors (COM), as described in Section 2.4. Table 6 shows the mean error of the COM forecast alongside the ME of the raw 10 km and 3 km forecasts. The composite forecast has lower ME scores than the raw forecasts at all stations except Casement 3 km, but does not produce ME scores as low as the best of all other forecasts. Table 7 shows the

Forecast Method	Average RMSE
Raw 10 km	2.0474
STT 10 km	1.6237
STB 10 km	1.6594
KAL 10 km	1.5260
Raw 3 km	1.8316
STT 3 km	1.5497
STB 3 km	1.5751
KAL 3 km	1.5238
COM	1.4450

Table 8: Average of the RMSE scores at all seven stations (m/s)

RMSE of the COM forecast alongside the RMSE of the raw 10 km and 3 km forecasts. Not only does COM result in better RMSE scores than either of the raw forecasts, it produces RMSE scores which are better than any of its eight constituent forecasts for six of the seven stations. The average of the RMSE scores at all seven stations is shown in Table 8 for all of the forecast methods. This shows that the total RMSE performance of the COM forecast is superior to any of the other forecast methods.

4 Discussion and Conclusion

A set of 48 hour wind forecasts was produced for every day in 2008 at horizontal resolutions of 10 km and 3 km. The raw model data were postprocessed using traditional rolling-bias correction (STB), rolling-trend correction (STT), and a Kalman filter (KAL). A new adaptive statistical method was applied to all available forecasts to produce a composite forecast (COM). Mean error and root mean square error scores were calculated for all forecast data.

Running the NWP model at 3 km did not always result in a better wind forecast than that produced at a 10 km horizontal resolution. Postprocessing almost always increased forecast skill. The total RMSE performance of the COM forecast was better than any of the other individual forecast methods.

The COM method is easy to implement, and has a very small computational cost. The COM method is fully automatic, and forecast streams can be added or removed as required, once they have been available for a short

training period.

Future work is underway in producing an improved Kalman filter method, which takes wind direction as well as speed into account. It is hoped that this will allow a further increase in skill for wind speed forecasts.

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