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RESEARCH ARTICLE

Adaptive post-processing of short-term wind forecasts for energy applications

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ABSTRACT

We present a new method of reducing 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 h forecast data every day in 2008 at horizontal resolutions of 10 and 3 km. A new adaptive statistical method was applied to the model output to improve the forecast skill. The method applied corrective weights to a set of forecasts generated using several post-processing methods. The weights were calculated based on the recent skill of the different forecasts. The resulting forecast data were compared with observed data, and skill scores were calculated to allow comparison between different post-processing methods. The total root mean square error performance of the composite forecast is superior to that of any of the individual methods. Copyright © 2010 John Wiley & Sons, Ltd.

KEYWORDS

wind forecast; wind energy; adaptive filtering; NWP; statistical post-processing

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1. INTRODUCTION

The European Union has endorsed a mandatory target of 20% share of energy from renewable sources in the 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 the overall energy supply, wind energy management will become a crucial issue. The available power of wind varies with the cube of the wind speed. Current forecasts have wind speed errors of the order of 2 m s^{-1}, 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 h.

Wind speed forecasting can be achieved using two approaches. The first uses past wind data, which can be obtained easily by wind farm operators onsite. The data may then be analysed with different statistical models. However, information about atmospheric dynamics is important for forecasts of the range considered here (48 h), 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] suggested that increasing model resolution towards 10 km allows the definition of the major meso-scale topographic features of the region and their corresponding atmospheric circulations. Going to resolutions higher than ≃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 NWP data is to use them 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 combine NWP model output, input of observations and some further statistical method to produce the required output. They also raise the point that increasing the skill in forecasting for wind energy has a beneficial commercial impact.

Costa *et al.*[6] wrote a later (2008) review on wind power short-term prediction. Some methods have been developed for very short-term predictions but not extended to time horizons useful for trading (≥48 h). Costa *et al.* note 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 post-processing. Calibrated ensemble forecasting has been used to predict the probability density function of generated wind power from 1 to 10 days ahead at five UK wind farm locations.[8] It was found to outperform time series models and compare well with NWP models, although the advantage for short time scales (<48 h) was less pronounced.

Limited-area ensembles have been post-processed using Bayesian model averaging to provide 48 h 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] who used a bank of neural networks 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 Ref. 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 performs better than a Kalman filter or 7 day bias removal.[13] However, MOS requires a rather long training data set 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] It consists of a set of mathematical equations that provides 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 root mean square error (RMSE) scores than using direct model output. Louka *et al.* suggest 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 earlier.

The skill of forecast models, as calculated by validating the forecast variables against observations, is often compared with the skill of direct model output. However, even a simple process such as rolling-bias correction may significantly improve the 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 with 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 NWP runs at 10 and 3.3 km. This will enable the benefit of running at higher resolutions to be compared with the increase in skill obtained by statistical post-processing. 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 and describes the methods used to post-process 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 non-hydrostatic 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 formu-

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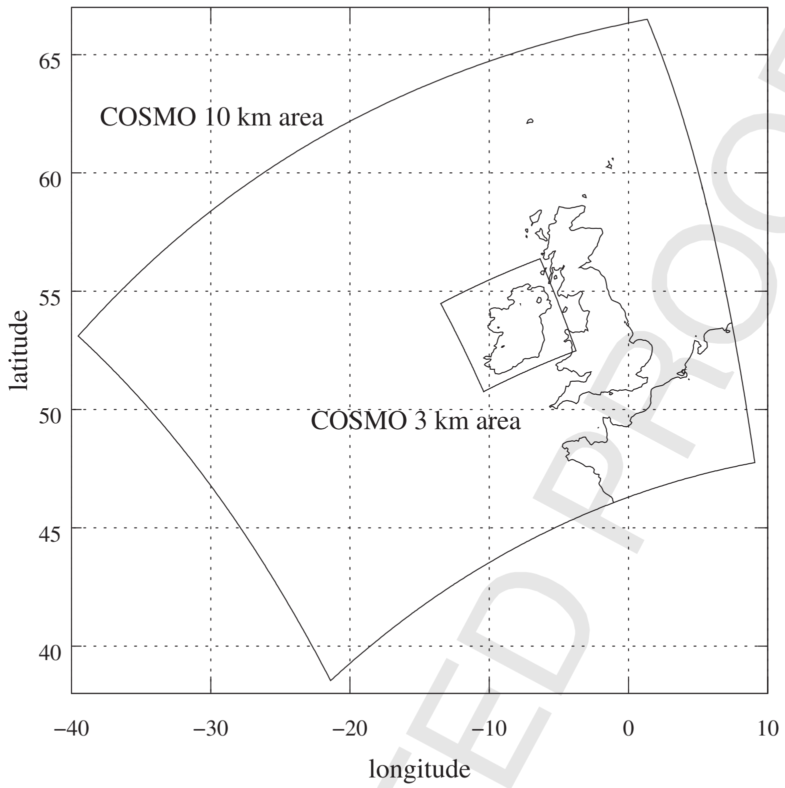

Figure 1. Computational domain for 10 and 3 km forecasts.

lated in rotated geographical coordinates and a generalized terrain following the height coordinate. Many processes are taken into account by parameterization schemes. For more information about COSMO, refer to the COSMO website.[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 h. COSMO was run without assimilation of additional observations.

The computational domains used for the 10 and 3 km forecasts are shown in Figure 1. The 10 km forecast used a rotated lat/lon grid of 0.09°, with 40 vertical levels and a time step of 60 s. 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 time step of 20 s. Output data were saved every forecast hour from 00 to +48 h.

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 Figure 2. The wind speed data refer to the wind speed observed at a height of 10 m above the ground. Hourly output data are 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 with the observed wind speeds. The skill scores used for the wind speed forecasts were the mean error (ME) and the RMSE.

The distances from the station to the surrounding model grid points were 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 with using only the closest model grid point over a test period of 3 months for the inland station located at Birr. Results showed that the three-point interpolated wind speeds gave better values for ME and RMSE than using the closest grid point alone for both the 10 and 3 km forecasts (Table I). It is possible that different interpolation techniques may give better values for different stations at different forecast resolutions. However, in this paper, we

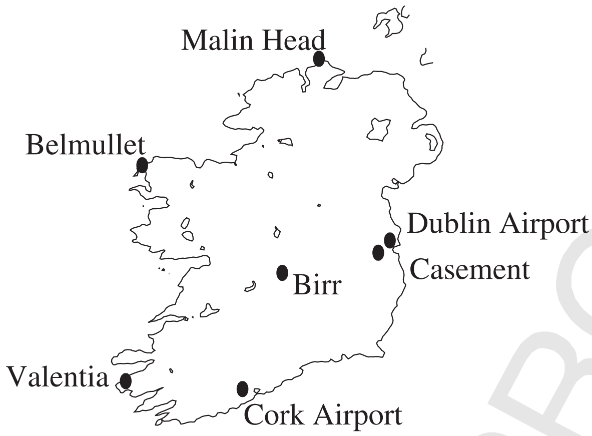

Figure 2. Synoptic stations used for forecast verification.

Table I. Test scores for interpolating wind speeds.

NWP resolution (km)	Closest point	Three-point
ME		
10	2.099	1.946
3	1.838	1.799
RMSE		
10	2.502	2.351
3	2.251	2.209

try to adopt a uniform post-processing method for all forecast data, and so we have chosen to use the three-point interpolated wind speeds for all stations and both forecast model resolutions.

2.3. Statistical post-processing methods

Some simple post-processing 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 were not yet available. These errors were set to equal the mean of the 0 to +24 errors. STT resulted in a different error correction for each forecast hour, which was 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 Ref. 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:

$$X_{t-} = X_{t-1} \tag{1}$$

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

$$\mu_t = H_t X_{t-} \tag{2}$$

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 Ref. 18, we use a sliding window with a width of 7 days. We cal-

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culate the sample covariance V of e_t over the past 7 days. Similarly, we calculate the sample covariance matrix W of X_t over the past 7 days. We use W to give an initial estimate of the state variance matrix P:

$$P_{t-} = P_{t-1} + W \tag{3}$$

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

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

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:

$$X_t = X_{t-} + K_t e_t. \tag{5}$$

Finally, we update P:

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

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

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

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 and 3 km and each raw forecast is post-processed 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 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 equation (8). The composite forecast (*COM*) is given by the sum of the weighted forecasts. Figure 3 gives an outline of this process.

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

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 carried out 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 MEs, 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 was applied to all available forecast data. In this paper, we 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.

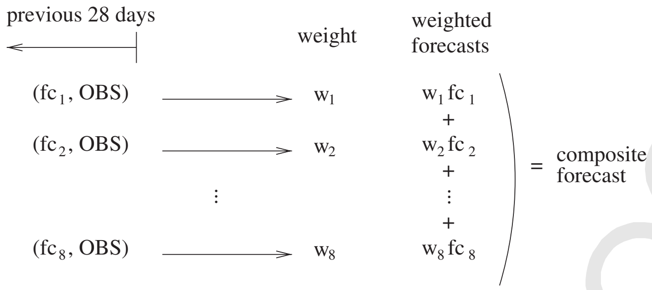

Figure 3. Producing the composite forecast.

Table II. 10 km forecast wind speed ME (m s^{-1}).

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 III. 3 km forecast wind speed ME (m s^{-1}).

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

3. RESULTS

A 48 h 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 ME is reduced at all stations by all post-processing methods, as shown in Table II (the best score is shown in bold type). However, the lowest ME was produced by different post-processing methods at different stations. STT performed best at two stations, STB was best at another two and KAL was best for the remaining three.

Results for the 3 km forecast also show that post-processing reduced ME at all stations (Table III). Again, no single method produced 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 was not always the method that produced the lowest ME for the 3 km forecast. The lowest ME was given by a different post-processing method for 3 km than 10 km at three of the seven stations. Furthermore, the higher resolution forecasts did not always produce lower ME scores. At two of the stations, the 3 km forecast produced a slightly worse ME than the 10 km forecast.

The RMSE was also calculated for each station for each forecast resolution. Results are shown in Tables IV and V. 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 STB giving the best RMSE at one station each.

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

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Table IV. 10 km forecast wind speed RMSE (m s^{-1}).

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 V. 3 km forecast wind speed RMSE (m s^{-1}).

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 VI. Raw and COM forecast wind speed ME (m s^{-1}).

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 VII. Raw and COM forecast wind speed RMSE (m s^{-1}).

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**

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 VI shows the ME of the COM forecast alongside the ME of the raw 10 and 3 km forecasts. The composite forecast had lower ME scores than the raw forecasts at all stations except Casement 3 km but did not produce ME scores as low as the best of all other forecasts. Table VII shows the RMSE of the COM forecast alongside the RMSE of the raw 10 and 3 km forecasts. Not only did COM result in better RMSE scores than either of the raw forecasts. It produced RMSE scores that were 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 VIII for all of the forecast methods. This shows that the total RMSE performance of the COM forecast was superior to any of the other forecast methods.

Table VIII. Average of the RMSE scores at all seven stations (m s^{-1}).

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**

4. DISCUSSION AND CONCLUSION

A set of 48 h wind forecasts was produced for every day in 2008 at horizontal resolutions of 10 and 3 km. The raw model data were post-processed 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). The ME and RMSE 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. Post-processing almost always increased the 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. It 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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