Forecasting Total Wind Power Generation on the Republic of Ireland Grid with a Multi-Scheme Ensemble Prediction System

S. Lang[1], C. Möhrlen[2], J. Jørgensen[2], B. Ó Gallachóir[1], E. McKeogh[1]

[1]Dept of Civil and Environmental Engineering, University College Cork, Ireland,
[2]WEPROG, Denmark
s.lang@ucc.ie, com@weprog.com

Abstract

A multi-scheme ensemble prediction system for Ireland, which allows forecasting of wind generation and provides a quantification of the forecast uncertainty by using a physically realistic ensemble spread, is described. Such a forecasting ability is critical to safe, efficient and economical operation of the power system, given the rapidly increasing wind penetration into the relatively small synchronous Irish system. Results presented indicate the forecast error for the aggregate wind capacity in Ireland (7 – 8%) is almost half that of a typical single-site forecast (which range from 10 – 16% over the 51 wind farms studied). Preliminary analysis of the aggregate forecasting error suggests a background error that is approximately half that of the average day-ahead forecast error, and which does not appear to originate from the numerical weather prediction (NWP) input, in contrast to the prevailing view that the NWP is the largest contributor to wind power prediction error.

1. Introduction

The ability to increase the penetration of wind energy generation onto the Irish power system is limited because of the relatively small size of the network and the weak interconnection to other synchronous power systems [2]. However, higher wind penetration is necessary for both economic and environmental reasons.

The power system in the Republic of Ireland (RoI) had by December 2005, a total of 496MW of wind power installed and a further 760MW with connection agreements [3]. The total installed generation capacity was over 6,400MW, with a maximum demand peak of >4,800MW and a minimum summer load of >2,000MW. Within a few years, therefore, it is possible that wind could contribute up to 65% of the summer valley. There is only weak interconnection with the Northern Ireland (NI) power system, which itself is only weakly connected to Scotland. The Single Electricity Market proposed for RoI and NI may pose further problems, as wind penetration in the north is also increasing rapidly [4].

If wind's penetration continues to increase at the pace seen in the past year (more than doubling the installed capacity in RoI, and with the current figure set to more than double by 2010), there are limited options available to maintain a secure grid and balance power effectively: Storage opportunities and stronger interconnection (N-S and E-W) are both important [5], as is a shift in the 'generation mix' to include a portfolio of generators with faster start-times and lower minimum loadings, in order to maximise wind's contribution and reduce reserve demand [6]. However, these measures will only be effective in the long-term.

Arguably the simplest and most cost-effective solution to the potential problems faced by rapidly increasing wind's penetration on the power systems of both RoI and NI, is the adoption of a flexible, informative and accurate 'All-Island' wind energy forecasting system. Such a system can also be fully implemented and exploited in the short-term, and does not require significant political decision-making.

2. Wind Power Forecasting Background

2.1 Forecasting Systems

There are a number of different types of wind power forecasting methods and systems currently in use and these were reviewed in [7]. Most of these systems are based on different combinations of persistence, statistical or physical models, and many rely on deterministic weather forecasts provided by national meteorological services, which do not tailor forecasts for the wind energy industry and whose requirements are in most cases quite different (e.g. for extreme weather forecasting).

2.2 Ensemble Prediction Systems

An ensemble prediction system (EPS) is one that produces a number of numerical weather forecasts, as opposed to a single, deterministic forecast. Ensemble forecasting has been developed in order to quantify forecast uncertainty and to improve the accuracy of deterministic forecasts.

Ensemble techniques have been employed for some time in operational medium-range weather forecasting systems [8]. Methods vary in how the ensembles are created, however, the dominant methods are the Ensemble Kalman Filter approach [9], and singular or breeding vectors [10, 11].

In addition to these, two other ensemble methods have been employed both for medium range weather forecasting, as well as for short-term wind power prediction:

- The multi-model approach, which uses NWP data from a number of meteorological centers in order to generate an ensemble [12].
- The multi-scheme approach, described here.

3. Methods

3.1 Multi-Scheme Ensemble Prediction of Weather

Multi-scheme ensemble prediction is a technique where different physical parameterizations, or schemes, are used to vary the formulation of the fast meteorological processes in the numerical weather prediction (NWP) model. One such multi-scheme ensemble prediction system (MS-EPS) is operated worldwide by Weprog (Denmark), and has been adapted for forecasting wind generation in Ireland. The MS-EPS is a limited-area NWP model which produces 75 different forecasts each model run [13]. An example output for the Ireland/UK area is shown below in Figure 1.

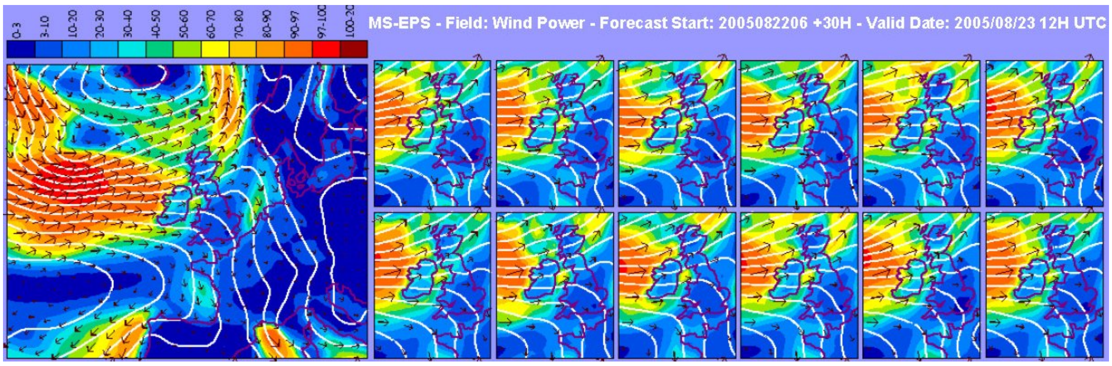


Fig. 1 – Example MS-EPS Output (Wind Power), showing Mean (left) and 12 Members

The 75 individual ‘members’ each differ in their formulation of the fast meteorological processes such as vertical diffusion and condensation. The focus is on varying the formulations of those processes in the NWP model that are most relevant for the simulation of fronts and the friction between the atmosphere and earth’s surface, and hence critical to short-range numerical weather prediction.

3.2 Wind-to-Power Prediction

3.2.1 Meteorological Parameters of Interest

Although turbine power output is solely influenced by the effective momentum flux through the rotor area, it may be of benefit to use multiple meteorological parameters in the computation of the power output. These include wind speed and direction, temperature, surface fluxes, precipitation, relative humidity, cloud cover and turbulent kinetic energy. These quantities are forecast by the MS-EPS and used outside the NWP in the wind-to-power conversion step.

3.2.2 Training

In order to calculate wind power from the above weather variables, two steps are carried out: A calibration, or 'training', step and a forecast step.

The training step involves comparing historical power production data from the wind farm(s) with forecast weather data and establishing the relationship between these two sets of data. At least 6 months of concurrent production and forecast data must be available for this method to be successful, although longer periods are preferred.
A power curve is computed for each ensemble member, using direction dependent power curves (to parameterise the obstacles and wake effects), because each member has its own error statistics. The individual members are trained to the same frequency distribution as the observed power measurements. The forecast horizon used in the training may be day-ahead or short-term. The choice depends on the priority of grid security versus RMS error.

After training of a forecasting system with historical production data, predictions can be made for the site or aggregate area, out to the horizon of the model.

3.2.3 Refinements to Wind-to-Power Prediction for Irish Conditions

In order to investigate the impact on the forecast error of converting from meteorological parameters to wind power, six different methods were investigated (Table 1).

Table 1. Wind-to-Power Prediction Methods

Method 1	Direction and time independent approach (simple sorting algorithm)
Method 2	Direction independent, least square minimized
Method 3	Direction dependency, all members with equal weight
Method 4	Direction dependency and individual member weight
Method 5	Direction dependency and individual member weight, in stability class
Method 6	Combination of methods 4 and 5, with all farms handled individually

Method 1: In this method the forecast wind speed data (from the ensemble mean) and the wind power observations are sorted by size. The two sorted data sets together form the power curve. The assumption behind this method is that the power curve is monotonic from 0 to full load and similar from cut-off to full load. This method was described in detail in [13].

Method 2: The wind speed data and corresponding wind power observations are sorted into wind speed bins of 1 m/s centred at 1, 2, 3... 30 m/sec. In each bin, a value is computed using a least square estimation. These values then form the power curve.

Method 3: The data is first sorted into 8 different wind directions (from the ensemble forecast mean), prior to sorting into wind speed bins of 1 m/sec as in Method 2. To ensure that there are sufficient data points in each direction sector, each bin has a window of 60 deg. (The method is only effective for data sets longer than a year.) All members have equal weighting.

Method 4: This is similar to Method 3, but with individual members (forecasts) assigned a weighting according to their overall statistics. The weight is independent of the wind speed, but dependent on the wind direction bins of the ensemble mean.

Method 5: This method uses the same algorithm as Method 3, but also assigns a stability (stable or unstable, based on the ensemble mean) to each individual member.

Method 6: This method combines method 4 and 5, i.e. sorting the data as time dependent, direction dependent and stability dependent, into 1m/sec bins and computing a value using a least square estimation. Then a weight coefficient is computed for each member (forecast) as a function of the predicted wind direction and stability at each point of the power curve.

Note, in Methods 4 – 6 the procedure was carried out for all ensemble members, whereas in Methods 1 – 3 the procedure was only applied to the ensemble mean. For Method 1-5, the training was carried out using the total wind power only. For Method 6 the training was carried out separately for each of the 51 wind farms.

3.3 Forecast Uncertainty

3.3.1 Varying Forecast Errors

Forecast quality of any prediction system can vary dramatically on a daily basis. This can be due to weather patterns, the non-linear nature of wind turbine power curves, as well as wind farm/turbine availability and operational characteristics of the wider electrical system.

Two approaches exist to quantify a forecast uncertainty: Typically, a static method is employed, which relies on the assumption that errors in forecast power are related to the non-linear turbine power curve, e.g. [14]. However, we have observed that low errors can occasionally result from wind speeds in the high wind ranges, and at other times high errors are observed in the low wind speed ranges. The multi-scheme ensemble method provides the wind power uncertainty dynamically, because it bases this on the weather uncertainty, and part of the forecast error is proportional to the spread in the ensemble.

3.3.2 Skill Measures for Assessing Forecasts

A number of error descriptors are commonly used in the evaluation of prediction systems, and these typically include the bias, Mean Absolute Error (MAE), standard deviation (SD) and the Root Mean Square Error (RMSE), usually normalised to the installed capacity of the wind farm or aggregate wind area.

3.4 Validation

3.4.1 NWP Validation

The MS-EPS is principally a numerical weather prediction system that provides an ensemble of weather forecasts. These forecasts are then used with a wind-to-power conversion tool to provide wind power forecasts. The validation of a number of meteorological outputs of the ensemble has been described in [15, 16], using meteorological observational data from Ireland and a number of other European countries. However, it is noted that there is no simple translation of forecast errors in meteorological parameters, such as 10m wind speed, to wind power prediction errors. It is therefore difficult (and questionable) to attempt to quantify the quality of any variables other than the trained power forecast.

3.4.2 Wind Power Forecast Validation

Following the single-site validation of the system using data from a single Irish site in complex terrain [13] and a preliminary validation using four months of production data (totals only) from 28 Irish wind farms [17], a testing and verification exercise was undertaken for the total aggregate wind capacity on the RoI grid, by individually training the model with power data for each wind farm connected in 2005.

Power production data for the whole year of 2005 were made available by Eirgrid. This was provided as individual wind farm production data (MW, in 15 minute time-steps) for each wind farm in operation by the end of the year. The installed wind capacity in RoI of 496MW at end of 2005 was made up of 51 wind farms (counting extensions to existing wind farms as new wind farms, in all but one case), for which locational and turbine type data was provided by Eirgrid in order to carry out full training of the model. Data from one wind farm was only available from October 2005, and this was therefore excluded from the following analysis.

The following procedure was then used to compare forecast power with observed power:

- The observed total power data from ESB were averaged to hourly values.

- Forecast power data from the MS-EPS for the period 1/1/05 – 31/12/05 were collated. These were the hourly forecasts produced at 00 UTC each day, for each of the 75 ensemble members, out to a horizon of 48 hours.
- Each ensemble member's forecast at 30m, 60m and 100m agl (model levels 32, 31 and 30) (u, v components for each hour) was interpolated to each wind farm site (or the estimated site location) from its location relative to the four closest grid points.
- Forecasted wind power outputs at one hour intervals, for each ensemble member, were produced for the aggregate wind generation on the Irish grid.
- The statistical 'best guess' of the forecast aggregate power for the 51 wind farms was calculated by combining the 75 ensemble members' power forecasts, using the probabilistic method described in [15].

4. Results and Discussion

4.1 Forecast errors

The forecast error results for each wind farm are illustrated in Fig. 3, by plotting against the measured load factor for the verification period. The wind farms are grouped together by size (installed capacity), and illustrate a weak relationship between forecast error and load factor: MAE tends to increase with increasing load factor, which is usually linked to the site mean average wind speed. However, there are a number of outlying wind farms that do not follow this and it is likely that more site-specific quantities – such as terrain complexity and meso-scale weather impacts – influence the skill of the forecasting system [18]. A summary of the results is given in Table 2. An example 48 hour forecast for the aggregate Irish wind capacity is shown below in Figure 2.

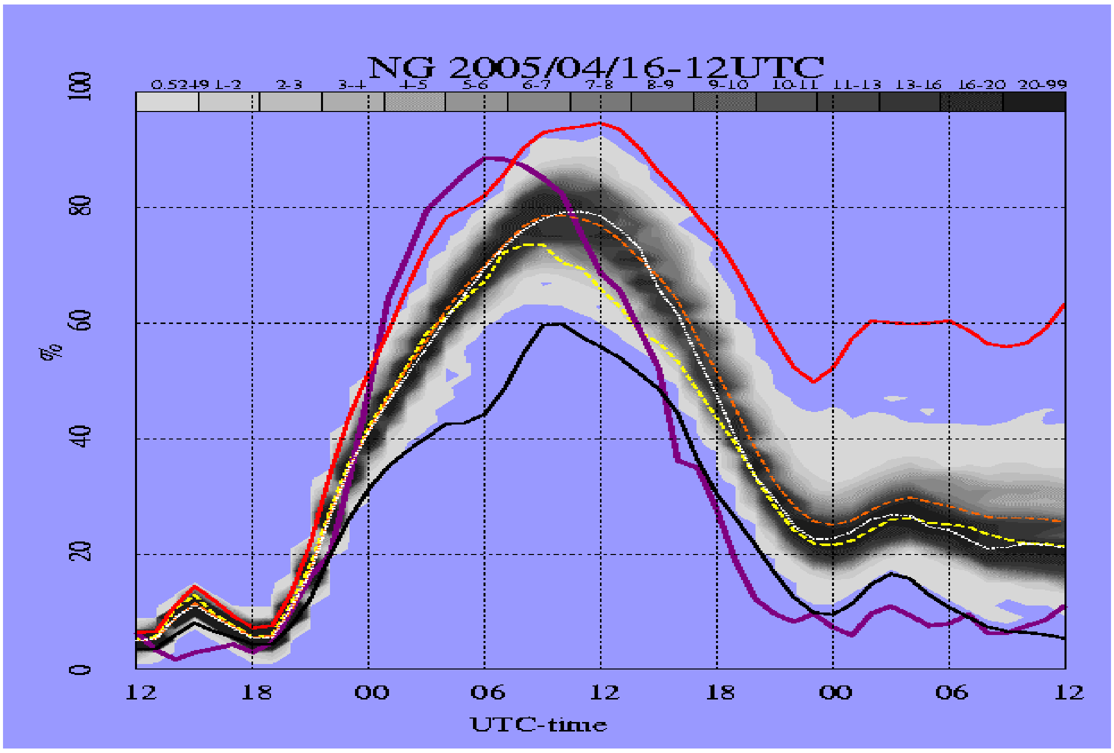


Fig. 2 – Example Aggregate Irish Wind Power Forecast

This is a time-varying probability density function (pdf) of the total wind power forecast on the Irish grid (shown as load factor, i.e. % of installed capacity operating). The grey regions represent low probability and the black represents the highest probability of occurrence. The black (lower) and red (upper) curves represent the ensemble max and mean and the orange the mean. The yellow & white are statistical 'best guesses', the latter being based on the probabilistic method described in [15]. The purple line is the actual power generation that occurred during this 48 hour period.

Normalising forecast error to the nameplate capacity also introduces an artificial variable, which is turbine model and manufacturer dependent, rather than relating to either forecast skill or average wind speed. Normalising the forecast error to average generated power provides a means of avoiding this – see Figure 4. The MAE results are then more strongly correlated with load factor (R^2 ~ 0.6 for all wind farms; and ~ 0.7 for the group with the largest sample size, i.e. those 0-5MW). Other alternatives may be to normalise to total swept area of the wind farm or the aggregate area, or to group together wind farms based on measures of terrain complexity, e.g. [18].

Table 2 - Forecast Results for Individual Irish Wind Farms, 2005[1]

	MAE (%)	*Bias (%)*	*RMSE (%)*	*R^2*
Wind Farm with Highest Forecast Error	16.0	-0.3	21.1	0.79
Wind Farm with Lowest Forecast Error	10.6	-0.3	14.6	0.83
Mean Forecast Error for all Wind Farms[2]	12.3	0.2	16.9	0.79

1. All error measures normalised to installed capacity of individual wind farm or aggregate area.
2. Mean of individual wind farm errors. Aggregate error is lower because there are both positive and negative biases in the individual wind farm data (see below).

Fig. 3 - Forecast Errors Normalised to Installed Capacity

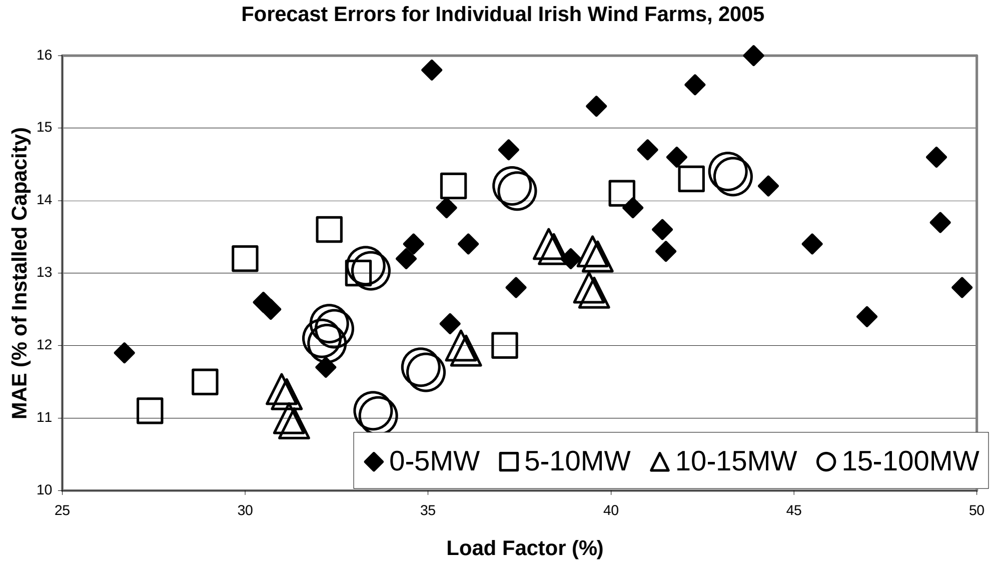
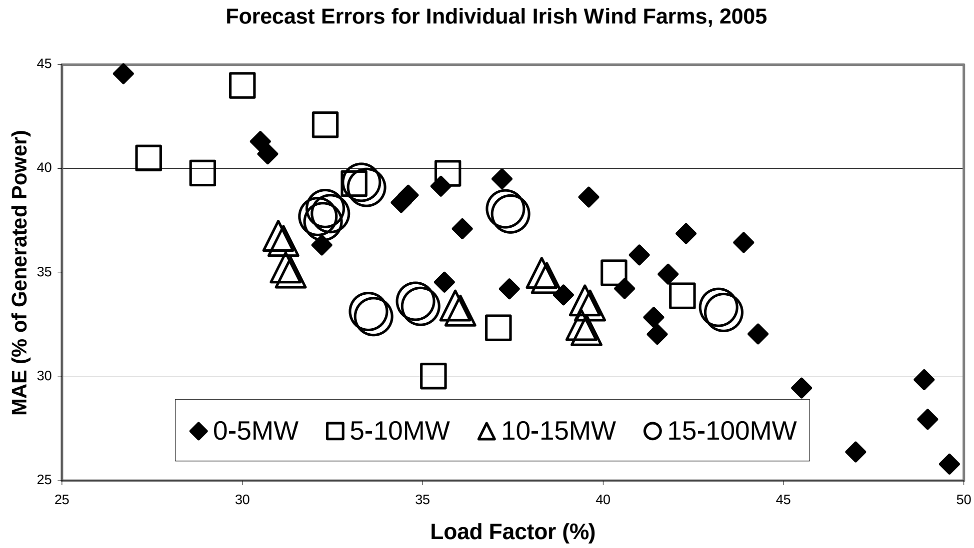


Fig. 4 - Forecast Errors Normalised to Generated Power



The total wind energy generation has also been calculated from the data: This amounted to 1.4TWh over 2005, excluding the wind farm not included in the analysis. Using the data illustrated in Fig. 3b above, we can calculate the error in forecast wind generation for each wind farm over the year by multiplying the nMAE (% of installed capacity) by the nameplate capacity, and then multiplying by 8760 (or the number of hours from commissioning, for those installed during 2005). Totalling these individual wind farm values gives about 0.3TWh, i.e. ~ 20% of the produced energy would have been incorrectly forecast, if these forecasts had been performed in real-time, and the individual values used to determine necessary reserve.

4.2 Wind-to-Power Prediction Methods

Below are the results of using different wind-to-power conversions methods.

Table 3 - Aggregate Forecast Results Using Different Wind-to-Power Methods

	MAE (%)	*Bias (%)*	*RMSE (%)*	R^2
Method 1	8.2	0.0	11.2	0.89
Method 2	8.1	-0.1	10.6	0.89
Method 3	7.5	-0.5	9.8	0.91
Method 4	7.1	0.2	9.4	0.92
Method 5	7.0	0.4	9.4	0.92
Method 6	6.8	0.3	9.3	0.92

These results suggest that there is only a small gain, in terms of error reduction, by adopting the more rigorous wind-to-power conversion methods 5 and 6.

4.3 Preliminary Error Decomposition

Preliminary analysis using Method 1 indicates an approximately linear error growth from 6% (nMAE) at 10 hour forecast length, to ~9.5% at 48 hours. This is typical of NWP forecast error growth. From 4 – 10 hours the error is greater, due to model 'spin-up', and observation 'nudging' is required in order to predict better in the ultra-short term.

Idealised extrapolation of the linear error growth from 10 hours to time = 0 suggest a background error that is not due to the NWP, but which contributes over half of the error for day-ahead forecasts.

These results indicate that the meso-scale weather error from the NWP model is a significant element of the error, but not necessarily the dominant one. This may contradict what the wind forecasting community has believed for a number of years, e.g. [7], including research at UCC, e.g. [19], which suggested that the largest error in wind power prediction was that due to the NWP model input.

5. Conclusions and Recommendations

The results confirm that the normalised error for day-ahead forecasts for the aggregate wind power in Ireland in 2005 was ~7 – 8% MAE, which is almost half of that which would result from summing individual wind farm forecast errors. These results agree with the preliminary results of aggregate forecasting on the Irish grid using the multi-scheme ensemble prediction method [17] and broadly agree with the findings of the International Energy Agency [2]. Preliminary decomposition of the aggregate forecast errors suggests these are not dominated by NWP error, and further work on errors and wind-to-power conversion methods is required.

The Transmission Grid Code in Ireland stipulates that all wind farms of capacity over 30MW must provide MW output forecasts 48 hours ahead on a half hourly basis [20]. Balancing costs will be much higher if treating these large wind farms in isolation. Recent work carried out on reserve requirement in Ireland [21] suggested that with a large wind capacity geographically dispersed, a sufficiently low aggregate forecast error will result in only minimal reserve demand. The ensemble prediction method presented here indicates that this aggregate forecasting error is now sufficiently low, and also allows quantification of the forecast uncertainty. This will allow calculation of the system balancing requirements due to wind, on a real-time forecast basis, further reducing the reserve demand and increasing the environmental benefit of the installed wind capacity. Work is currently underway to develop such a system for forecasting reserve demand in Ireland.

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