Application of a Multi-Scheme Ensemble Prediction System for wind power forecasting in Ireland and comparison with validation results from Denmark and Germany

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Abstract:

A Multi-Scheme Ensemble Prediction System (MS-EPS) for short-range forecasting of wind power has been applied and tested at various sites and areas. The MS-EPS is the first short-range ensemble prediction system that has been used for wind power forecasting. The ensemble technique is ideal for tackling the problems associated with wind power prediction error, because it provides physically meaningful information on the uncertainty of each forecast. This is a useful and necessary tool in the decision making process for electrical system operators or energy traders and/or markets.

Forecasts with the MS-EPS system have been performed and analyzed at various locations over a four month winter period in 2005. Forecasts for a single wind farm in northwest Ireland indicate a Mean Absolute Error of installed capacity (nMAE) of 11.4%. Results from continental Europe were found to be 4.4% for Germany and 8.2% for Denmark when looking at the aggregated wind capacity. At the Horns Rev offshore wind farm, the nMAE was 14.5%. It is shown that the level of dispersion of wind power and the average load factor heavily influence the achievable accuracy of wind power prediction systems. The study also shows the wind power prediction error is reduced with a combination of increased wind farm dispersion and also increased number of wind farms. This result is an important finding for Ireland, where the electricity grid is operated with only weak interconnection to Northern Ireland and into Scotland, but where a high growth rate of wind power is expected in the coming years.

Keywords: wind power forecasting, ensemble prediction, forecast uncertainty

1. Introduction

1.1 Rationale

The energy sector in Europe is under strong pressure to install more renewables, and in particular wind power. The relatively low level of predictability of wind power is one of the main barriers to increasing wind energy penetration, as it increases the costs associated with operating reserves and balancing intermittent wind generation [1]. In addition to the anticipated cost savings, reliable wind power forecasting has been identified as a key to enabling high wind energy penetration and at the same time ensuring power system security and stability.

This is of particular importance to the Republic of Ireland, where, by June 2005, a total of 385MW of wind power had been installed and a further 623MW had connection agreements [2]. The electrical grid itself has a total installed generation capacity of over 6,000MW, with a maximum demand peak of >4,500MW and a summer valley of >1,600MW. It is only weakly connected with the electrical grid in Northern Ireland, which itself has only a weak interconnection with Scotland. It is imperative, therefore, that Ireland has the ability to forecast wind generation well [3, 4].

1.2 Wind Power Forecasting For Single Sites and Aggregated Areas

The aggregation of wind power over many sites reduces the error contribution from weather forecast phase errors, as discussed in detail recently by the International Energy Agency [1], from the point of view of management of intermittency of wind power. Because of this smoothing effect, area aggregation filters wind farm fluctuations and allows more wind power onto an electrical grid.

However, other studies have also indicated there is strong relationship between high average load factor and low predictability of wind power, e.g. [5, 6], and this becomes increasingly important with the installation of very large capacity wind farms, both onshore and offshore. This study was therefore formulated to investigate the effects that dispersed large-scale wind power in Ireland would have on prediction error and forecast uncertainty, by analyzing wind power forecast errors from an Irish onshore wind farm, a Danish offshore wind farm and two aggregate areas of large wind capacity (Germany and Denmark).

2. Wind Power Forecasting Using Ensemble Prediction

2.1 Wind Power Forecasting Methods

The different types of wind power forecasting methods and systems currently in use worldwide were summarised by Giebel [7], who also noted that the greatest error in wind forecasting models is that associated with the numerical weather prediction (NWP). Many models rely on deterministic weather forecasts, usually provided by national meteorological services. The research programme at UCC has therefore concentrated on the numerical weather prediction modelling, e.g. [8], which has distinguished the research from other approaches [9].

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 techniques have been employed for some time in operational medium-range weather forecasting systems [10]. Three approaches dominate the field:

1. Ensemble Kalman Filter (EnKF) approach [11, 12, 13]
2. Singular vector (SV) approach [14, 15, 16]
3. Breeding approach [17, 18, 19, 20, 21]

Strauss et al [22] reported that for such forecasting, the spread of the ensemble is sufficient to cover uncertainties due to inaccuracies in the initial conditions and those due to model imprecision.

There are two other ensemble methods, the multi-model approach [23, 24, 25, 26, 27, 28] and the multi-scheme approach. These are discussed and tested in several studies of their feasibility, e.g. [27, 29, 30, 31, 32, 5]. Of the latter type, to the authors' knowledge, there is only one short-range ensemble prediction system operational worldwide at present: the 75 member Multi-Scheme Ensemble Prediction System (MS-EPS), developed and operated by WEPROG, in parallel with forecasting research at University College Cork in Ireland.

2.3 The MS-EPS Forecasting System

The MS-EPS is a limited area ensemble prediction system using 75 different NWP model parameterisations. These individual 'schemes' each differ in their formulation of the fast meteorological processes: advection, 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. A recent study by Meng et al [32], found that a combination of different parameterisation schemes has the potential to provide better background error covariance estimation and smaller ensemble bias.

Using an EPS for wind power prediction is fundamentally different from using one consisting of a few deterministic weather prediction systems. A wind power prediction module (WPPM) has therefore been developed to take advantage of the MS-EPS ensemble. This wind power prediction method (described below) is different from traditional power prediction tools, because it is designed to provide an objective uncertainty of the power forecasts due to the weather uncertainty.

The MS-EPS system has been in operational use since 2003 and is currently used for forecasting approximately 20GW of wind power. Parallel to basic research on the multi-scheme ensemble approach in 2001-2002 [5], an operational ensemble prediction system, the MS-EPS, was developed by WEPROG and first launched at the transmission system operator Energinet.dk in 2003 [33, 34, 35]. It has also been tested in other research projects in Germany, France and Denmark in 2003-2005 [6]. Various other research activities are dealing with further testing and development of the MS-EPS system, e.g. [36, 37, 38].

2.4 Wind Power Prediction

The Wind Power Prediction Module (WPPM) consists of a power curve generation step and a forecast step. A power curve is computed for each ensemble member, because each member has its own error statistics. The individual members are trained to the same frequency distribution as the observed power measurements. The ensemble should therefore resemble the observed load pattern of the turbines, and produce a realistic probability distribution in the forecasting output.

This goal cannot be achieved with a least squares estimated power curve, because such a power curve is influenced by prediction failures and produces an imbalance of idle and full load hours. The least squares method is therefore incompatible with the idea of using an ensemble prediction method, particularly with regards to risk assessment. The statistically best or most accurate prediction would be achieved using a least squares estimation method of every member, but the outcome would approach the climatic wind generation at high levels of uncertainty, which is of course undesirable.

What is employed instead is an estimation method, which produces 75 power curves, each estimated to give the correct number of idle, full load and cut-off hours. The method consists of the following steps:

4. Determination of the number of idle, full-load and cut-off hours in the training period.
5. Application of a time filter to the measurements and forecasts to ensure similar variance levels.
6. Determination of the wind speed with maximum load or the mean wind speed of the full load interval.
7. Splitting of measurement and forecast data sets into a lower and upper power curve domain, in which the differential coefficient of the power curve does not change sign.
8. Sorting of the power measurements and wind speed forecasts numerically in each domain, as two time-series.
9. Generation of pairs of wind speed forecasts and power measurements.
10. Formation of a monotonic increasing power curve as a function of wind speed in the lower domain from cut-in wind speed.
11. Formulation of a monotonic decreasing power curve as a function of wind speed from full load until cut-off wind speed.

The two domains will naturally not be strictly monotonic, but the width of the constant boundary values is determined by the number of idle and cut-off hours.

The justification for the numerical sorting process is that small meteorological phase errors cannot be prevented. We assume that each ensemble member simulates the same weather that the wind farm experiences, but with small phase and amplitude errors. This is only true for large-scale atmospheric motions, so therefore it is crucial to apply a time filter to the wind power measurements, to ensure that the variance characteristics of the forecasts and measurements become identical. This filter is applied prior to splitting the data into the upper and lower domains.

The need and possibilities for direction dependency differ from wind farm to wind farm, but the above estimation method is usually applied to 8 directions. Bilinear interpolation is then used in the forecast step to predict the power from each directional power curve, valid for each ensemble forecast.

This estimation method is not exact, but it has useful capabilities:

- The ensemble forecasts do not need to be of a specific resolution to resemble the measured and time-filtered features.
- Higher resolution is always beneficial, because the time filter may then allow shorter waves.
- The time scale of the forecasted events will be similar to that of the time-filtered measurements.
- Each ensemble member's bias characteristics are built into the power curves.
- The predicted wind power follows the wind speed with a smooth function.

The major difference to a least squares method is therefore that this approach can produce full load correctly, if a majority of ensemble members predict a wind speed that corresponds to full load. The transformation of wind to power assumes that the weather forecast is exact and the uncertainty lies in the ensemble of the forecasts. Thus, the mean of the ensemble members in uncertain weather conditions is quite similar to that of the least squares estimation method valid for a single forecast, whereas in predictable weather the ensemble mean is capable of predicting full load.

3. Validation of the MS-EPS

3.1 Error Measurement

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) [7].

These standard error descriptors are commonly given as a percentage of the installed capacity of the wind farm or group of wind farms for which the prediction system is forecasting. Sometimes, however, errors are given as percentages of actual generation or of the mean generation, or in absolute terms.

Quoting an error as a percentage of actual generation misrepresents the forecast error by suggesting very large errors for low wind generation and giving no credit for correct forecasting of these events. In terms of a forecasting system, the correct prediction of zero generation is as important as prediction in the steep part of the power curve or at full load. This is because at the basis of the application of a forecasting system is the requirement to be able to accurately schedule reserve plant on the grid and maximise the CO_2 benefit of high wind penetration.

The most useful measure of a prediction system is therefore considered to be the mean absolute error over all forecasts and the forecast range considered, for the validation period for which observed and predicted data exists. This is then normalised to the installed capacity of the wind farm or wind farms (P_{inst}), for which the observed data relates to, giving a normalised mean absolute error:

$$\text{nMAE} = \frac{\sum \left| P_f - P_o \right|}{c \cdot P_{inst}}$$

where P_f and P_o are the forecast and observed power, and the summation is over the number of time steps (c) for which both forecasts and observations exist.

Using the nMAE measure allows comparison of different prediction systems, by using forecast power from the different systems, and the same observed power data for the wind farm or aggregate area of wind farms. It is important however, that the same forecast range and horizon are used when making such comparisons. A protocol for standardizing the evaluation of short-term wind power prediction models has been suggested by Madsen et al [39].

Definitions used in the following validation and error analysis of the MS-EPS have been described in more detail by Lang [38].

3.2 Irish Results

Power production data (15 minute values) were obtained from the TSO in Ireland, ESB National Grid, for the Golagh wind farm in Co. Donegal, northwest Ireland, for the period 02/01/2005 – 01/05/2005. This site comprises 25 Vestas V42 turbines, each of 600kW rated capacity, with a total wind farm capacity of 15.0MW. Elevation is about 370m above sea level and the RIX measure of terrain complexity is 7.3, indicating semi-complex terrain [40].

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

1. The observed power data was averaged to hourly values in order to compare with the MS-EPS output.
2. Data output from the MS-EPS for the period 2nd January – 1st May 2005 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, i.e. 0, 1, 2, 3… to 48 hours.
3. For the period in question, each ensemble member's forecast of wind (u, v components for each hour) was interpolated to the wind farm site from its location relative to the four closest grid points (45km resolution).
4. Power curve training was carried out using the one hour smoothed data and each ensemble member's wind speed and direction data for year 2004 using 1,2,3... to 24 hour forecasts. This training produces time independent, direction dependent power curves for each of the 75 ensemble members.
5. Forecasted wind power output at one hour intervals, for each ensemble member, was produced for Golagh wind farm using the ensemble wind output and the trained power curves.
6. The statistical best guess of the forecast power was calculated using the probabilistic method described below.
7. Observed power, EPS mean, maximum, minimum, and the best guess, were plotted for the 00 UTC model run, for the hourly forecasts out to the 48 hour horizon.

A typical example of the output is shown in Figure 1a. This shows the 00 UTC model run for the first day of the validation period (2nd Jan 2005), with forecasted wind power out to 48 hours ahead. Vertical axis is the load factor (0-100% of installed capacity) and the horizontal axis is the time of day.

The ensemble members' probabilistic distribution is shown by the grey and black contours, or envelope. The darker areas of the envelope represent the highest values of the probability density function (grouping of most ensemble members). The weighted mean forecast power, or statistical 'best guess', is calculated using a probabilistic multi-trend (pmt) filter, which produces the statistically most accurate forecasts [5].

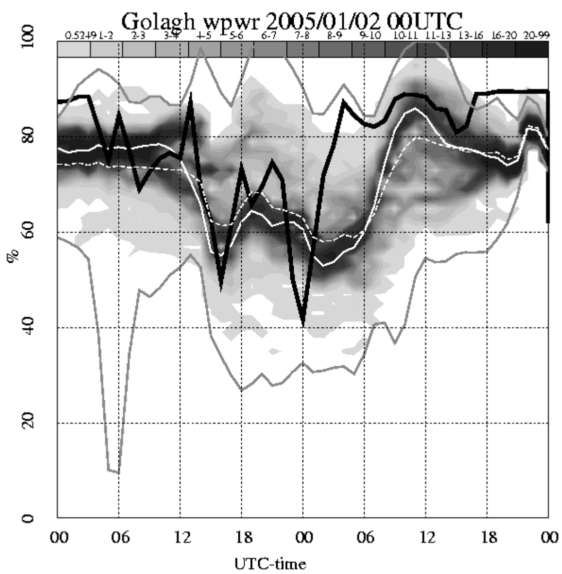
Figure 1b shows the same ensemble distribution, with the raw 15 minute observed power data.

3.3 Fluctuations in Observed Power

Even with observed wind farm data smoothed to one hour values (Fig. 1a), the observed power (black full line) on most days is fluctuating around the ensemble with an amplitude much higher than the EPS spread itself. The ensemble is calculated using a 45x45 km resolution, with wind speeds averaged over 20 minutes, which smoothes out forecasted variations. The ensemble spread is therefore not designed to predict fluctuations in power output of a single wind farm. The model wind is an area-average based on interpolation between the nearest four grid points, and assumes homogenous conditions with constant roughness.

This level of 'noise' in the observed power data is similar to that observed at the 160MW Horns Rev offshore wind farm [33]. These effects, both at an on-shore wind farm in northwest Ireland and an off-shore wind farm in the North Sea, may be due to mesoscale Atlantic weather. Due to computational constraints, they are, therefore, not easily predicted with the model resolution employed in most Numerical Weather Prediction models, where the grid size is usually much larger than the wind farm extent.

Phase errors and unpredictable noise in power output also interact strongly. Their effects are more pronounced when observing individual wind farms, as opposed to observations of aggregated, dispersed sites. The reason for the higher errors at single farms is mostly due to local effects not being smoothed out, the greater significance mesoscale weather has on the overall error, and wake effects [41].



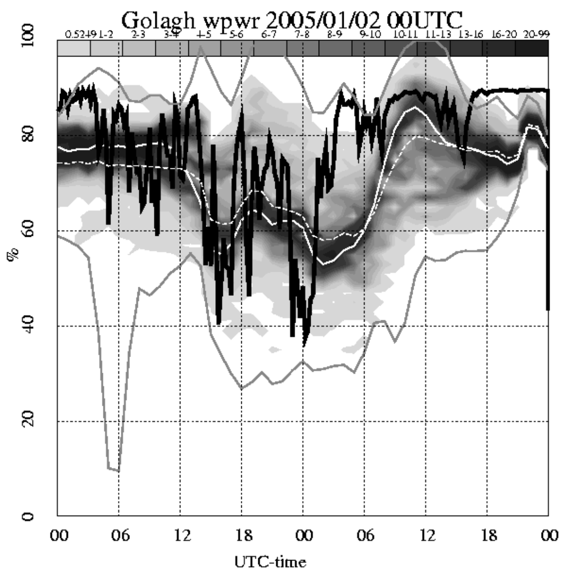


Figure 1. MS-EPS 0-48 hour Wind Power Forecast for Golagh on the 2nd January 2005. The black line is the observed power, smoothed to hourly values on the upper figure, and the raw 15min averages below. The grey lines are the EPS maximum and the EPS minimum, the white dashed is the average of all members (in power), and the white solid line is the weighted mean, or statistical 'best guess' forecast.

3.4 Error and Quality of the Irish results

The forecast quality of the Golagh wind farm has been verified for a four month period (2/01/2005 – 01/05/2005). All statistics of wind power forecasts have been computed with model wind speeds at 30m agl, using 24-48 hour forecasts for each day's 00 UTC model run. The results indicate that persistence forecasts for single sites in complex terrain, with relatively strong variations in wind speed over an hour, provide little value to a grid operator: The normalised mean absolute error (nMAE) for persistence over the validation period was 28.5% and the standard deviation (SD) was 37%.

Standard statistical parameters have also been computed for each of the individual months, using the same technique. These results are tabulated below, along with the overall statistics, and show that the forecast quality changes marginally from month to month on all parameters, with only January being significantly different.

Table 1: Variation of forecast quality at Golagh wind farm for individual months in early 2005 and overall average. Statistics have been generated for the 24-48 hour wind power forecasts (30m agl model wind speed). Mean wind speed (v_{avg}) in ms^{-1}. All error descriptors are in %, normalised to the installed wind farm capacity.

2005	Bias	nMAE	SD	r^2	v_{avg}
Jan	-2.3	13.8	19.4	0.76	12.9
Feb	-2.6	10.8	14.4	0.85	9.6
Mar	-1.2	9.8	13.7	0.87	9.2
Apr	0.6	11.0	14.3	0.81	8.4
AVG	-1.4	11.4	15.7	0.84	10.1

Figure 2 illustrates the behaviour of the forecast error over the forecast length. There is an apparent cycle in the error; however, on further investigation, it was noted that the higher error at certain forecast hours was due to events in January only, during which time the average wind speed was very high, and the load factor was twice that of the other months. In such conditions, one unpredicted cut-off error gives a contribution of almost 1% to the error statistics, accumulated over the four months.

Because of the varying error pattern throughout the forecast length, a linear regression of the error was added, in order to level out the random error pattern. It is random, because numerically large errors take place during intervals of a few hours and dominate the accumulated error statistics.

The linear regression was performed for the mean of the ensemble, the statistical best guess and the best ensemble member. The regression represents the slope of the nMAE (a = 0.075 – 0.085). The inherent error in the forecast is quite significant (9.3% - 9.5%), in comparison to the error growth over the forecast length, which is less than half the inherent error.

One way of reducing the error in the beginning of the forecast is by using on-line observations. However, this is only likely to reduce the error in the first 0-6 hours. The inherent error, due to mesoscale effects and the local effects at the wind farm, will remain relatively high.

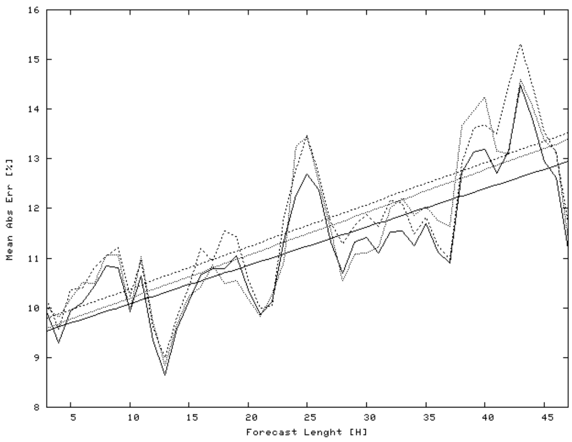


Figure 2. MS-EPS error data for Golagh Wind Farm, Ireland: Mean absolute error (MAE) and fitted regression lines for the statistical best guess (solid), the mean (dashed) and the best member (dotted) of the ensemble, for the 0-48h forecasts in the period 2nd January – 1st May 2005.

3.5 Comparison with Danish and German Results

A comparison was made between the Golagh results, and MS-EPS forecast results for the Horns Rev offshore wind farm (Denmark) and two areas with large aggregate wind capacity (Germany and western Denmark).

All wind power was computed with the same method (Section 2.4), trained with the same weather forecast data set and using the same model wind speed (100m agl). Although the statistics showed better results for Golagh wind farm when computing the wind power using the 30m model wind speed, the wind speed at 100m represents a better average overall, especially for the aggregate areas.

Table 2 shows forecasting results using the MS-EPS for the German and western Denmark aggregated areas, the Horns Rev 160MW offshore wind farm and the Golagh wind farm in Ireland. In Table 3 we present the validation results for each individual month at these four locations. The statistics shown represent hourly forecasts for the 24 – 48 hour (day-ahead) horizon, computed from 00 UTC model runs each day during the validation period. Table 4 provides the frequency distribution of the errors for each site/area.

Table 2. MS-EPS validation results for Denmark & Germany, compared with Golagh, Ireland. (45km model resolution and 100m model wind speed level. Validation period 2/1/05-1/5/05, except Horns Rev 1/1/05-1/5/05. LF is average load factor.)

Area / Site	*Germany*	*Denmark West*	*Golagh*	*Horns Rev*
No. wind farms	60 (850MW)	168 (655MW)	1 (15MW)	1 (160MW)
Scaled to:	17GW	2.5GW	15MW	160MW
LF	23.6%	28.3%	35-55%	35-55%
nMAE	4.4%	8.2%	12.5%	14.5%
SD	6.4%	12.1%	17.8%	20.7%

Table 3. MS-EPS Monthly Validation Results

Area / Site	*Germany*	*Denmark West*	*Golagh*	*Horns Rev*
Wind speed (100m agl)				
Jan	10.9	12.9	12.9	13.6
Feb	8.6	10.6	9.6	10.7
Mar	8.0	8.1	9.2	9.3
Apr	6.6	8.2	8.4	8.7
AVG	8.5	9.9	10.1	10.6
Bias (%)				
Jan	0.6	2.0	2.4	4.4
Feb	1.6	2.4	0.1	2.6
Mar	-1.8	-3.3	1.9	-1.2
Apr	0.3	-0.4	0.2	3.8
AVG	0.1	0.1	1.2	2.3
nMAE (%)				
Jan	5.1	9.9	14.1	13.2
Feb	4.9	7.6	12.5	14.5
Mar	4.0	8.4	11.7	14.7
Apr	3.5	6.7	11.6	15.7
AVG	4.4	8.2	12.5	14.5

The wind power in the German area, with an installed capacity of 17GW, was computed by up-scaling from the 60 representative wind farms that are used in real-time operation by the four TSOs in Germany. The wind power in Denmark, with an installed capacity of 2500MW, was up-scaled from the 168 representative wind farms that are used in real-time operation by Energinet.dk, for the western part of Denmark.

The Danish and German wind speed values are approximated by an area integral representing the installed capacity as accurately as possible in a grid of 0.45° resolution. 166 grid boxes in total form the integral of the wind speed computation in Germany and 27 points in Denmark. The coefficients in the finite integral were determined by the WEPROG authors, whereas the up-scaling of the measurements were determined by the relevant TSOs, using unpublished techniques.

The wind speed for a single point is interpolated using bi-linear interpolation in the Arakawa C model grid [42]. For the model resolution utilized in this study (0.45°), this results in an area of dependency of approximately 150km^2.

In this part of the study the intention was to estimate the effect of dispersion and the impact of integrating a large number of wind turbines into an electrical grid. The objective was not, therefore, to present optimal scores for the aggregate areas, but rather to provide scores that could be compared to the single sites (Horns Rev and Golagh).

Table 4. Frequency distribution of MS-EPS forecast error for each validation site/area shown in Table 2. (First column gives upper and lower boundary of error interval.)

Error Interval %	*Germany*	*Denmark West*	*Golagh*	*Horns Rev*
0 – 1	19.0	13.3	9.5	7.9
1 – 2	39.6	26.6	18.9	16.4
2 – 4	29.1	27.1	21.2	23.9
4 – 9	10.0	19.2	22.2	19.4
9 – 16	1.6	8.2	14.3	13.9
16 – 25	0.5	3.9	7.5	9.2
25 – 36	0.0	1.3	4.3	5.5
36 – 49	0.1	0.2	1.6	2.7
49 – 64	0.0	0.2	0.5	0.7
64 – 81	0.0	0.0	0.1	0.4

3.6 Discussion

The results show that the average wind speed is significantly different and higher in January at all four locations. In Germany the average wind speed drops continuously towards spring to a relatively low average wind speed. This effect is not as pronounced in Denmark. The nMAE error for Denmark is about twice that for Germany, even though the average Danish wind speed is only about 16% higher.

The errors for the area integrated power predictions are quite different to those for the single wind farms. Even though the precise load factors of the single wind farms are confidential, it can be seen in Table 2 that the average load factor is up to 2 times higher at single sites – at locations with good wind resources – than in the aggregated German area. This difference in load factors is even more pronounced in summer time, one reason for choosing a winter period (when errors are highest) for validation.

The results indicate that the average wind speeds at Golagh and Horns Rev are only 20% and 25% higher, respectively, than in Germany over these months, whereas the nMAE errors for the two single sites are about three times higher than in Germany. The German error level appears low in comparison to the single site errors, although it is higher in absolute MW terms, because of the higher aggregate wind capacity.

High power production is associated with periods of high wind speeds and significant movement of air masses. With less changeable weather, prediction does not in general fail if there is little synoptic forcing.

In Germany and Denmark, most wind turbines are dispersed in small clusters, mainly due to the historical development of wind energy. The weather and the wind resources are, however, quite different in the two countries, even though they are connected. Denmark has a long coastline, compared to the size of the country, and is exposed to the North Sea and hence more changeable weather.

Another contributor to the higher aggregate error in Denmark, compared to Germany, is that western Denmark has a local maximum of installed wind power on the west coast, and it has been shown that the error for these coastal sites is approximately 30% higher than that for non-coastal regions [37].

Despite these coastal effects, geographical dispersion of wind turbines in Denmark has been shown to lead to a lower aggregated forecasting error, and therefore it is likely that similar dispersion of wind turbines in Ireland would also lead to a lower aggregated forecasting error.

However, the best wind resources in Ireland are located at remote sites, where grid connection can add a significant cost to a wind farm. Larger wind farms are therefore becoming more attractive economically, even though they are likely to cause reduced wind power predictability, due to their fluctuations in power output. Balancing costs will therefore be much higher than those required with a large wind capacity geographically dispersed.

The alternative to this is to develop storage systems to absorb such noise in the areas with significant wind power. We believe ensemble prediction will make it possible to forecast when such noise will occur, and also the amplitude, but not the exact phase of such waves.

The comparisons made here have been tailored to verify the influence of the location with respect to the wind resource, average load factor and the distribution of the installed capacity, when evaluating the predictability of power generated from wind. The results shown here and those of others, e.g. [4, 6], suggest that the need for greater dispersion, with regards wind power deployment, is underestimated in most countries' development plans.

4. Conclusions

The relatively low level of predictability of wind power is one of the main barriers to increasing wind energy penetration, as it increases the costs associated with operating reserves and balancing intermittent wind generation. Reliable wind power forecasting is therefore vital for both economical and environmental reasons. It also aids in maintaining power system security and stability, particularly on island systems with weak interconnection to large neighbouring grids, such as in Ireland.

A multi-scheme ensemble prediction system (MS-EPS) has been applied to data from a wind farm in northwest Ireland (Golagh), and these results compared with those from the Danish offshore wind farm Horns Rev and area-aggregated wind power data from western Denmark and Germany.

Golagh and Horns Rev, with high load factors, have significant power output fluctuations and higher forecast errors than the aggregate areas. The forecast errors also increase with increasing load factor, due to increasing atypical weather events and higher average wind speeds.

The MS-EPS validation results, with nMAE ranging from 4.4% for Germany and 14.5% for Horns Rev offshore wind farm, are encouraging. However, they cannot be compared to other studies in this area, because the prediction accuracy is, as we have demonstrated and shown in Table 3, very dependent on the time of the year and the location of the wind farm. In the winter months we have shown a difference of 3% from month to month (e.g. January to February at Golagh). The average load of the wind farm or the aggregated area also has a significant impact on forecasting accuracy, because frequent cut-off wind speeds increase the forecast error.

We have shown that Germany has about half the forecast error of western Denmark. The average load factor in the northwest of Ireland is about twice the typical load factor in Denmark and the forecast error for a single site is about 50% higher. The single offshore site in Denmark has, however, about the same load but a greater error than the Irish wind farm.

This study therefore suggests that the Irish prediction error level would drop considerably if many more wind farms were installed, as well as being geographically dispersed.

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