A 34-year simulation of wind generation potential for Ireland and the impact of large-scale atmospheric pressure patterns

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Abstract

To study climate-related aspects of power system operation with large volumes of wind generation, data with sufficiently wide temporal and spatial scope are required. The relative youth of the wind industry means that long-term data from real systems are not available. Here, a detailed aggregated wind power generation model is developed for the Republic of Ireland using MERRA reanalysis wind speed data and verified against measured wind production data for the period 2001-2014. The model is most successful in representing aggregate power output in the middle years of this period, after the total installed capacity had reached around 500MW. Variability on scales of greater than 6 hours is captured well by the model; one additional higher resolution wind dataset was found to improve the representation of higher frequency variability. Finally, the model is used to hindcast hypothetical aggregate wind production over the 34-year period 1980-2013, based on existing installed wind capacity. A relationship is found between several of the production characteristics, including capacity factor, ramping and persistence, and two large-scale atmospheric patterns – the North Atlantic Oscillation and the East Atlantic Pattern.

Keywords
Wind power; MERRA reanalysis; North Atlantic Oscillation; East Atlantic Pattern

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1. Background

'Generation potential models' have been used in a number of studies to model hypothetical wind power generation for a range of purposes. Where analysis of production characteristics in a high wind penetration scenario is required, a simple resampling or scaling of existing power production data is not appropriate, as the short time period available is likely to be affected by the temporal evolution of the wind industry (for example, improvements in reliability) and is therefore unlikely to capture the full effects of spatial variability and the locations of generation capacity. Sinden (2007) presented one of the earliest generation potential models for the UK using 10m wind speeds measured at 66 meteorological stations over a climatologically representative 34-year period. Having scaled surface wind speeds to hub height and converted these to potential power output using a turbine power curve, the author examined a number of characteristics of the hypothetical generation represented by these wind conditions. Pöyry (2009) followed this with a study of wind power variability for the UK and Ireland based on wind speeds measured at 36 meteorological station locations over a relatively short period of only 8 years, and using Monte-Carlo techniques to resample the data, created future scenarios with different installed capacities. Aguirre et al. (2009) used records for 7 years from 116 meteorological stations grouped into 16 regions of Great Britain (GB) to develop an estimated time series of aggregate wind power capacity factor. The influence of each region was weighted by its installed wind power capacity, and the model calibrated to match reported aggregate capacity factors. Sturt & Strbac (2013) expanded upon this dataset by using it to develop statistical time series models to create future scenarios, including adjustments to correct for different wind characteristics found offshore.

These studies, whilst valuable, did not account for the fact that wind measurement stations are not necessarily located close to or in similar topographical situations to the existing wind farms, and it is therefore possible that the actual spatial effects of wind variability may not be fully represented. In Ireland, the locations of the national meteorological measurement stations do not coincide particularly well with locations of wind generation (Figure 1). Kubik et al. (2011) showed that even using nearby meteorological measurement stations to estimate wind farm generation, whilst reasonably reflecting the long-term energy production, produces errors in the hourly power output. These authors discuss how this result has implications for using such methods to study temporally sensitive parts of the energy system, such as power flow and system balancing.

The process of meteorological reanalysis involves running numerical weather prediction models in 'hindcast' mode (i.e. for a historical period) whilst assimilating actual observations throughout the period to constrain the model and produce homogenous data that reflect the actual conditions. Typically, such datasets cover periods of 30-40 years (e.g. Rienecker *et al.* (2011)), with some covering over 100 years (e.g. Compo *et al.* (2011)). Long-term reanalyses products have recently been proven as a promising alternative to meteorological observations in reproducing both the long- and short-term characteristics of aggregate regional and national generation patterns in the UK and Sweden (Cannon et al., 2015; Kubik et al., 2013; OFGEM, 2013; Olauson et al., 2015), and even show reasonable performance at wind-farm level (Kubik et al., 2013; Staffell et al., 2014). A useful summary of the existing comparisons in the literature of reanalysis-based wind speed data against measured data is provided in Sharp et al. (2015). The authors found that the Climate Forecast System Reanalysis (CFSR) dataset could provide a representative view of UK wind climate, but also identified a lower skill at higher elevations. Aigner & Gjengedal (2011) discuss the differences between reanalysis- and measurement-based generation models for Germany and Denmark, with success of measurement-based models being related to the density of measurement stations available and topography.

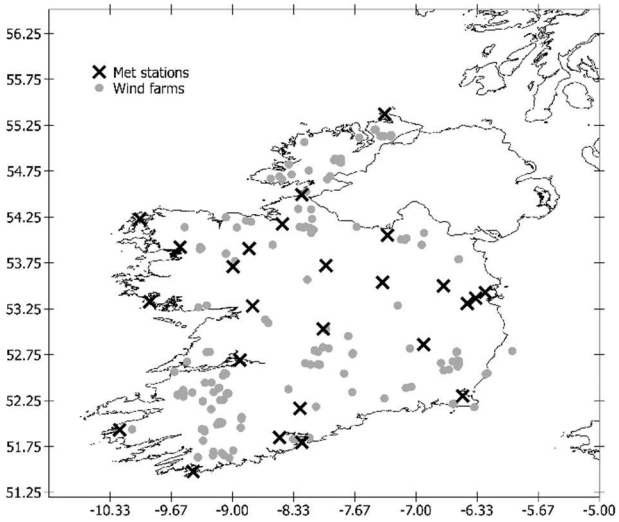

Figure 1 Locations of wind farms and met stations in Ireland

There is further potential in using downscaled reanalysis data, which should capture more of the local variations in wind climate (Cradden et al., 2014). This was demonstrated, for example, in Harrison et al. (2015) and Dunbar et al. (2015) where the Weather Research and Forecasting (WRF) mesoscale model driven by the National Centers for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) reanalysis was used to calculate capacity credit for wind power and arbitrage revenue from storage, respectively. The disadvantage of such high resolution datasets is that, aside from the resources required to produce them, they require significantly more storage and computational time when used to derive a generation model.

Based on comparison against real production data in the shorter term, reanalysis-based models, whether downscaled or not, offer the potential to examine the impact of longer-term climate variability on energy systems with a high contribution from wind generation. The World Meteorological Organisation (WMO) define 30 years as the period required to represent a 'climate normal', i.e. typical long-term average conditions (World Meteorological Organization, 2011), although some evidence would suggest that such periods do not capture the entire potential range of variability, e.g. Bett *et al.* (2013). The full impacts of spatial variability, including future planned generation sites, can also be studied using reanalysis models as they cover wide areas with equal density and temporal coherence. Additionally, such models can help to identify and analyse longer-term and wider-ranging climatic patterns influencing wind generation. For example, this approach would offer an alternative to the statistical wind data generation techniques used to examine the effects of the NAO in Brayshaw et al. (2011), Curtis et al. (2016) and Ely et al. (2013).

1.1. Objectives

Ireland is a relatively small but topographically complex country, and the wind industry has seen very rapid growth in recent years, from just over 100 MW of installed capacity at the end of 2001 to around 2200 MW by the end of 2014. Pöyry (2009) simulated Irish wind power generation but the study was based on meteorological stations unrelated to generator locations. Grünewald, McKenna, & Thomson (2015) used wind speeds at 10m above ground level (a.g.l.) from a reanalysis dataset to model power production for the whole of Ireland for the short period from 2009-2012, but employed a relatively simplistic height transformation and power conversion process, and generalised the locations by county. It is useful to determine whether a detailed reanalysis-based generation model can be used to provide an accurate representation of the aggregate wind power output for a region of this size over a long period of time.

In this study a detailed wind generation potential model is first developed for the Republic of Ireland for a 14 year period (2001-2014) based on MERRA reanalysis data (Rienecker et al., 2011). Wind farm locations, specifications and connection dates are input to the model and the output verified by comparison with the actual production as reported by the grid operator, EirGrid (EirGrid, 2015b). For a sample year within this period (2006), the output of the model based on reanalysis data is compared with output from the same model driven by two very high resolution wind speed datasets, which might be expected better to capture the complexities of the local wind climate.

Due to their ability to produce long time series, reanalysis-based models are well suited to applications involving understanding the impact of large-scale climate features on regional wind generation patterns. Having successfully verified for the 14 year period, the model is then used to generate a hypothetical 34-year time series of aggregate wind generation for Ireland based on the actual installed wind capacity as of October 2015. Aggregate generation output is then examined in relation to some atmospheric patterns, the NAO and the EA, to ascertain the influence of these features on generation characteristics.

2. Simulating and verifying Irish wind generation 2001-2014

The model estimates hourly aggregate wind power output for the Republic of Ireland from 2001-2014, based on the location, capacity, date of generation commencement, and hub heights of turbines at wind farms around the country. This is compared with a dataset provided by the system operator, EirGrid, consisting of hourly actual wind power production values for the same time period.

2.1. Wind farm data

The name, capacity and connection date of each wind farm was provided by the grid operators (EirGrid (2015a) and ESB Networks (2015)) correct as of October 2015. Further wind farm specifications were obtained from the Irish Wind Energy Association (IWEA) and the Sustainable Energy Authority Ireland (SEAI). The location information was gathered manually using online mapping services to identify those farms in existence before the last update of the satellite images (c. 2012/2013). For those developed after this time, the name of the wind farm locality was used to estimate its geographic coordinates within +/-10km. Given the use of relatively low-resolution (~50km) reanalysis wind speed data as input, location uncertainties can be considered to be negligible.

2.2. Wind data

The primary source of wind data used for this study is the MERRA reanalysis dataset (Rienecker et al., 2011), as used by Cannon et al., (2015), OFGEM (2013) and Staffell & Green (2014). MERRA includes hourly surface wind fields on a 0.5 x 0.667 degrees latitude/longitude grid, which equates to a spatial resolution of around 50 km x 50 km, and was chosen in preference to other large-scale reanalyses products due to its provision of wind fields at different heights above ground level. To establish wind speeds at turbine hub heights, we followed the method of Cannon et al. (2015). For each wind farm location, the wind speeds at 2, 10 and 50m above ground level (a.g.l) are interpolated from the surrounding grid cells using bilinear splines to the required latitude/longitude. A logarithmic fit is found for the values at the three heights at the interpolation point, and extrapolated to the required hub height, typically 60-80m.

For comparison, the model has been re-run for a single year (2006) using two alternative wind resource datasets. Firstly, UK Meteorological Office (UKMO) Virtual Met Mast (VMM) data were provided by the SEAI (Standen et al., 2013). These 2006 data consist of hourly time series on a 1 km grid (bi-linearly interpolated from the original 4 km model resolution) at 20, 30, 40, 50, 75, 100, 125

and 150m a.g.l. The VMM model uses a log-linear fit assumption from a baseline height to establish the winds at these levels, so the fit equation is approximated from the data and is used to interpolate to turbine hub height.

The second high-resolution dataset is that used by Dunbar et al. (2015) and Harrison et al. (2015), developed at the University of Edinburgh. These data, derived from the WRF mesoscale model, are on a regular 3km grid covering the UK and Ireland. The model outputs were provided for the year 2006 at 10, 80 and 100m above ground level. As the model itself does not assume a particular vertical profile, a logarithmic fit was used to provide an interpolation function for turbine heights between these values (no wind farm hub height was above 100m).

2.3. Power calculation

To convert turbine hub height wind speeds to wind power output, a 'power curve' is used.

For individual turbines, power curves are often provided by the manufacturer based on measured output data for given wind speeds. For a wind farm, the curve representing the aggregate output of a number of turbines will be slightly different (Hayes et al., 2011). To represent an entire national fleet, further adjustments may be required. Cannon et al. (2015) present a power curve based on a single turbine, but modified to fit GB aggregate output, and this is applied here. Other modifications can be introduced, particularly with respect to the cut-out region of the function (OFGEM, 2013). Selected results from model runs using alternative power curves are presented in the supplementary material.

3. Model verification

3.1. Comparison of general characteristics

Over the 14 year comparison period, the basic summary parameters based on hourly production in MW for the model output and actual production data are shown in Table 1.

Table 1 Basic statistics from actual and model data, all values in MW, except for coefficient of variation

Year	*Mean*		*Maximum*		*Standard deviation*		*Coefficient of variation*	
	Actual	*Model*	*Actual*	*Model*	*Actual*	*Model*	*Actual*	*Model*
2001	35	31	107	110	30	27	0.86	0.88
2002	46	39	119	121	33	31	0.72	0.80
2003	45	48	130	184	34	40	0.76	0.82
2004	57	79	278	295	49	65	0.86	0.82
2005	118	126	452	437	91	102	0.78	0.81
2006	178	185	643	606	142	150	0.80	0.81
2007	215	208	708	650	172	173	0.80	0.83
2008	262	278	888	835	197	207	0.75	0.75
2009	329	328	1050	1102	245	252	0.74	0.77
2010	297	311	1222	1230	250	273	0.84	0.88
2011	486	484	1468	1405	377	390	0.78	0.80
2012	467	473	1492	1505	336	365	0.72	0.77
2013	530	562	1760	1774	397	456	0.75	0.81
2014	577	639	1813	1975	455	535	0.79	0.84
Overall	**260**	**271**	**1813**	**1975**	**308**	**335**	**1.19**	**1.24**

The model successfully captures the basic production characteristics. There is evidence of underestimation of the mean and standard deviation of production in 2001/2002 where installed capacity was low, but the model overestimates the annual maxima until 2005.

Figure 2 compares the modelled monthly mean capacity factors and production values (MW) with the actual values. The capacity factor is effectively the capacity-normalised power production, allowing comparison of each year on an equal basis. After 2005, the monthly mean capacity factors are well reproduced by the model (Figure 2, upper panel), with overestimation in a few months. The correlation is strong, with the largest outliers in the early years (blue points in the upper right panel), indicating that the model is capable of representing the monthly average aggregate patterns in wind generation, but perhaps only after a certain minimum installed capacity has been attained. As only a small number of sites are included in these early years, biases resulting from the low spatial resolution of the MERRA wind speed data will be particularly obvious with this low degree of aggregation.

Analysis of the monthly production values provides further insight (Figure 2, lower panels). In the early years, when the power output is relatively small, the corresponding absolute errors in these years are also small compared with the later years. There is a growing tendency to overestimate production in some recent years (Figure 2, red and orange points in lower right panel), which may be indicative of curtailment, i.e. production is deliberately reduced by the operator. This operational strategy for managing large power input to networks has only become necessary in recent years as capacity has increased significantly.

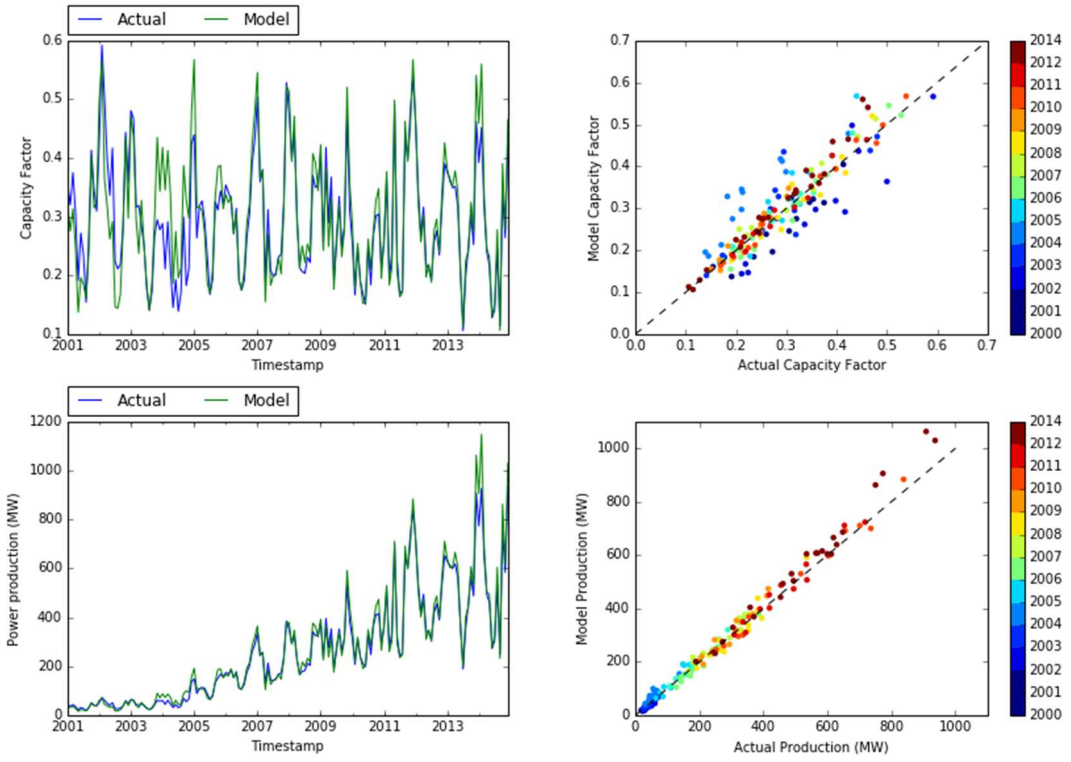

Figure 2 Monthly mean capacity factor (upper) and production values (lower) for the model calibration period (2001-2014). The correlation coefficient is 0.91 for monthly capacity factors and 0.99 for production.

A density plot of the actual and modelled hourly production values highlights a tendency for overestimation in the model, with the best fit line (heavily influenced by the higher number of occurrences in the 0-250 MW range) being slightly steeper than the ideal y=x line. Seasonal differences between model and actual capacity factor distributions are shown in the supplementary material.

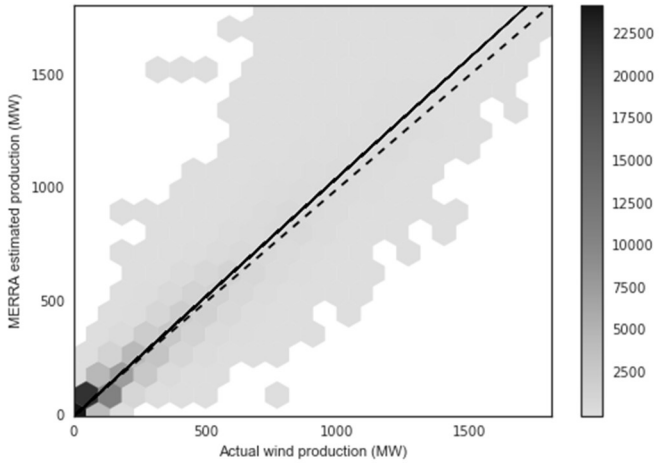

Figure 3 Density plot of modelled vs. actual hourly production. Dashed line is the y=x line, solid line is the best fit line.

3.2. Analysis of model error

The error statistics for each year are shown in Table 2, with the bias and RMSE given as percentages of the installed capacity (as per Kubik et al. (2011), Olauson & Bergkvist (2015)).

Table 2 Error statistics for each year (MERRA)

Year	*Correlation*	*Bias*	*RMSE*	*Scatter Index*
2001	0.88	3.46%	12.32%	0.42
2002	0.83	5.37%	16.29%	0.44
2003	0.87	-1.33%	11.73%	0.44
2004	0.88	-9.19%	15.74%	0.68
2005	0.91	-1.93%	10.76%	0.36
2006	0.95	-0.89%	8.24%	0.28
2007	0.95	0.93%	7.76%	0.25
2008	0.95	-1.86%	8.05%	0.26
2009	0.95	0.33%	7.84%	0.25
2010	0.95	-1.09%	6.40%	0.28
2011	0.96	0.10%	7.66%	0.23
2012	0.95	-0.35%	7.07%	0.24
2013	0.96	-1.71%	7.79%	0.27
2014	0.96	-2.94%	7.98%	0.29
Overall	**0.97**	**-0.79%**	**10.17%**	**0.33**

These statistics can be visualised using a normalised Taylor diagram (Figure 4). A detailed description of the diagram construction is given in Taylor (2005). Fundamentally, the closer the points to the 'reference' point, the better the model. The diagram visually reinforces the case that recent years are better represented by the model than the earlier years of the verification period.

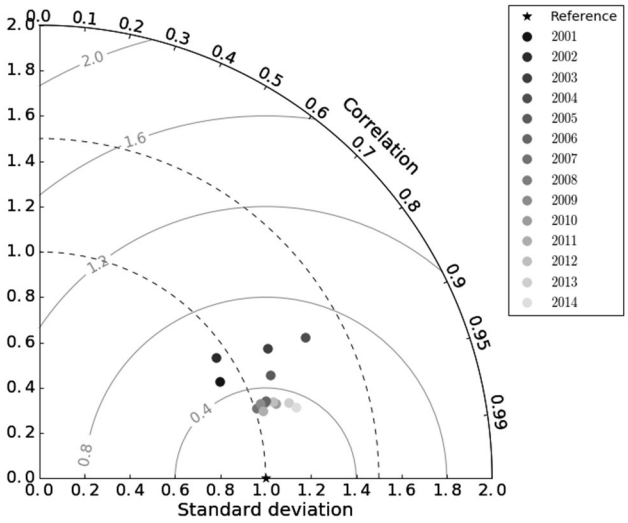

Figure 4 Taylor diagram - points for each year are plotted according to their relative standard deviation compared to the reference data (i.e. normalised, so the reference data has a standard deviation of 1) and the correlation between the time-series. Geometrically, the distance between the yearly points and the reference point is then the RMSE.

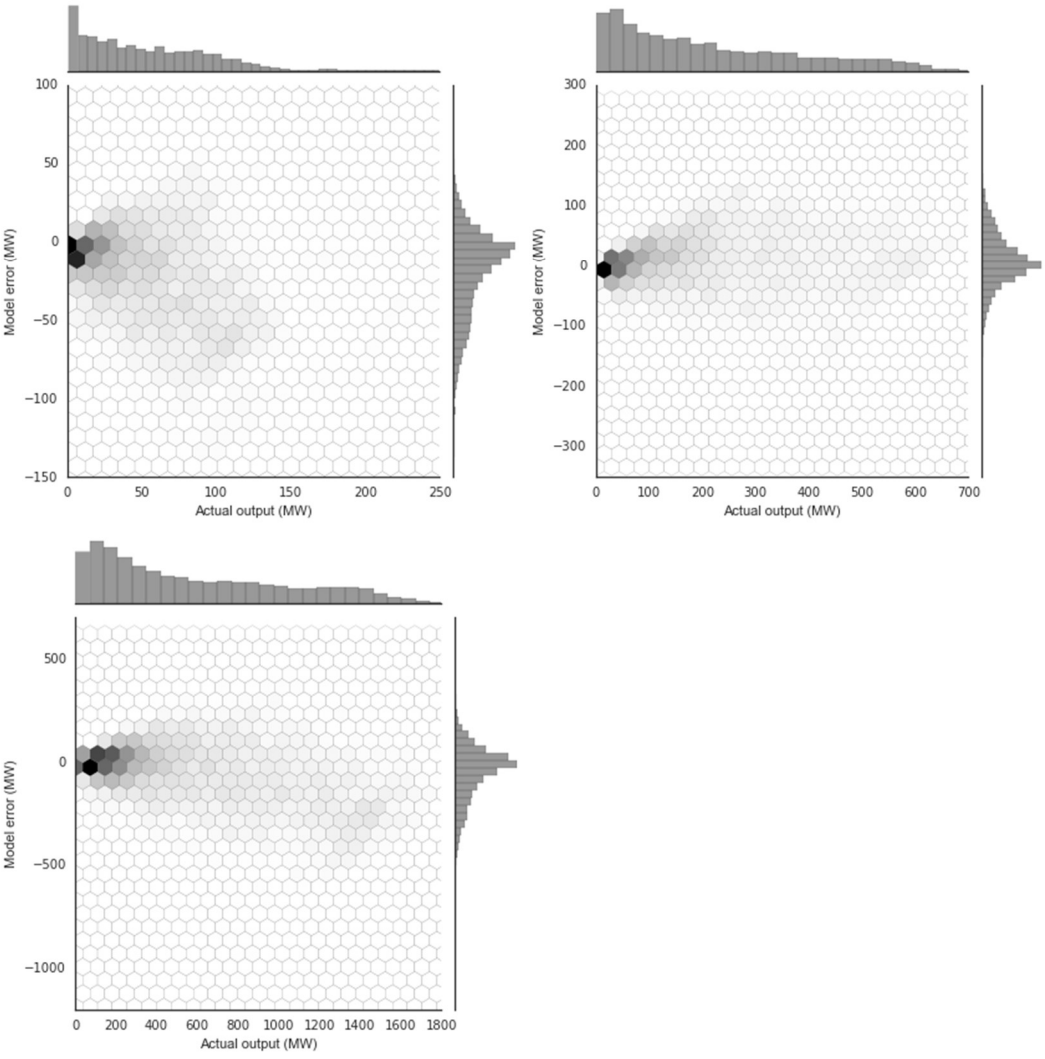

Figure 5 Model error vs. production for 2004 (top left), 2007 (top right) and 2014 (bottom left)

Scatter plots of the hourly errors (defined as 'Actual – Model') compared with the actual production for three of the years, 2004 (worst), 2007 (best) and 2014 (most recent), are shown in Figure 5. The model overestimates production throughout most of the analysis period, so that the error has a tendency to be negative. The year 2007, which performs well according to the previously described metrics but actually has a small positive bias, shows the most normal distribution of errors throughout the range of actual power production figures. In 2004 and 2014, the negative error increases with increasing generation. In 2004, this tendency may be due to biases in the wind speeds or lower than expected availability, but in 2014 is more likely to be related to curtailment.

3.3. Operational considerations

The power curve, as mentioned previously, has been created to be representative of national aggregate output for a given wind speed. Due to its empirical nature, it includes some operational factors that are present in the data used to derive it. No additional adjustments have been made to the model to account for specific operational practices such as maintenance (planned or unplanned), nor does the model consider performance issues resulting from early life start-up issues or long-term degradation in performance. The lack of operational considerations should lead to a tendency for the model to overestimate production.

At the beginning of the verification period, aside from the errors arising from the small degree of aggregation combined with low resolution wind speeds, there may be contributions from start-up date inconsistencies and unknown operational or reliability factors. From around the second half of 2003 until the end of 2005, the model produces the expected overestimates in many months. It is after this period, when total installed capacity reaches 500 MW, that the model estimates appear to be most accurate. Towards the latter end of the verification period, there is evidence that the capacity factor is being overestimated at the highest values. A probable operational contributor to these errors in recent years relates to the curtailment of wind generation by the network operator. Reasons for curtailment[1] are given in detail for the year 2014 in O'Sullivan et al. (2014). These include maintaining system stability, voltage control, and application of a feasible limit for absorbing non-synchronous power. Locally, wind output can also be curtailed due to local network faults and constraints.

An approximate time series of curtailed power was provided by the system operator, EirGrid, and made available for this study via the SEAI for 2012-2014. Reducing the model output by the percentage of power curtailed improves the RMSE by 0.75% (2012), 1.12% (2013) and 1.21% (2014), and very slightly improves the hourly correlations. This indicates that the presence of curtailment in the production data is a likely contributor to the additional model error in these years.

3.4. Using different wind resource data

Two sets of wind speed data with a significantly higher spatial resolution than MERRA were used to generate a year (2006) of aggregate production data. An identical power curve and set of wind farm information have been used. Due to their improved spatial resolution, both datasets might be expected to be more representative of the wind conditions at any one wind farm.

3.4.1. Wind speeds at 10m

It is difficult to validate the wind speeds from the datasets at turbine hub-height due to lack of wind speed measurements at these heights. Analysis of the 10m wind speeds from the three reanalyses compared to a set of 10m measured wind speeds in Ireland for the year 2006 is presented in the

[1] Curtailment is termed by the network operator as 'dispatch-down'; 'curtailment' is used to refer to a specific reason for dispatch-down

supplementary material. The results for MERRA are consistent with Cannon et al. (2015), with the low wind speeds tending to be higher than the measured, whilst at high measured speeds, MERRA appears to underestimate. Cannon et al. (2015) also found that changes in wind speeds over small time intervals were underestimated. In comparison with measured 10m wind speeds, the higher resolution WRF data performed better than MERRA, having higher correlations with hourly time series, and lower bias and RMSE. The VMM data have lower correlation with measurements, but have been extrapolated down to 10m from model output at higher levels so this may not provide a fair comparison.

Higher resolution models will be more sensitive to uncertainty in wind farm locations – the resolution of the alternative data is 1-3km, rather than ~50km with MERRA. In areas of complex terrain, this may lead to larger errors in the production estimates for individual wind farms.

3.4.2. Comparison of alternative models

A comparison of the data characteristics and error statistics for the one year of high-resolution datasets with those from the MERRA-based output is presented in Table 3. The correlation of the VMM data with actual output is lower than that achieved when the model is run using MERRA, and the scatter index and RMSE values from the VMM data are higher. The overall bias, however, is lowest, with the mean and standard deviation closer to the original data. In comparison, the WRF output has a similarly strong correlation with the actual power-generation data as the MERRA version. The mean is higher than the actual, close to the MERRA value, and the output has a similar bias. The WRF RMSE is the lowest. All models underestimate the maximum output to a similar degree.

For the year of comparison, Figure 6 shows the monthly average capacity factors and power production for the three models compared with the average recorded production for each month. All three models are most successful in spring (March, April, May), whilst for September-December, the VMM model is best. The WRF-based data tend to overestimate production in winter, and underestimate in summer.

Table 3 General characteristics of the model output and error statistics

	Mean	*Maximum*	*Standard deviation*	*Coefficient of Variation*
Actual	178	643	142	0.80
MERRA	185	606	150	0.81
VMM	177	605	143	0.81
WRF	184	607	143	0.78

	Correlation	*Bias*	*RMSE*	*Scatter Index*
MERRA	0.95	-0.89%	8.24%	0.28
VMM	0.91	0.24%	10.36%	0.35
WRF	0.95	-1.00%	7.3%	0.25

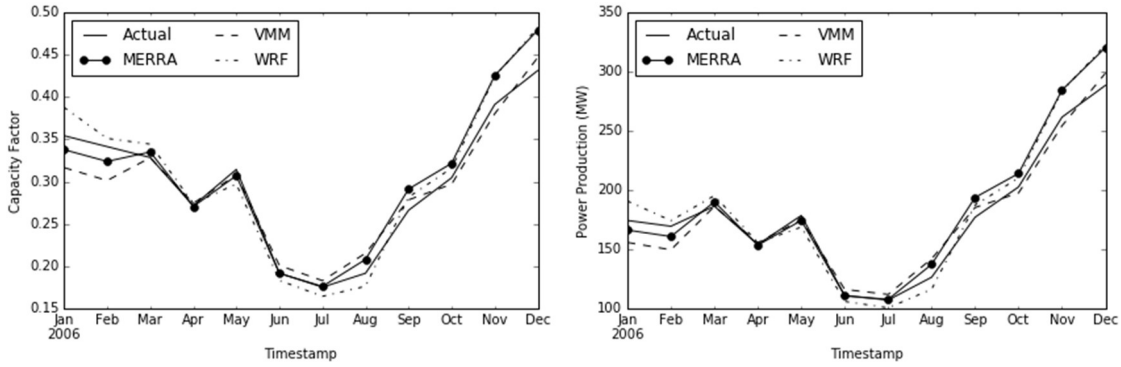

Figure 6 2006 Monthly capacity factor (left) and power production (MW, right) from the three models compared to actual

Considering the scatter plots of model error vs. actual production (Figure 7) the model errors all tend to approximate a 'normal' distribution. The distribution from the VMM-driven model shows the largest spread in the errors, with the MERRA and WRF versions slightly narrower in range.

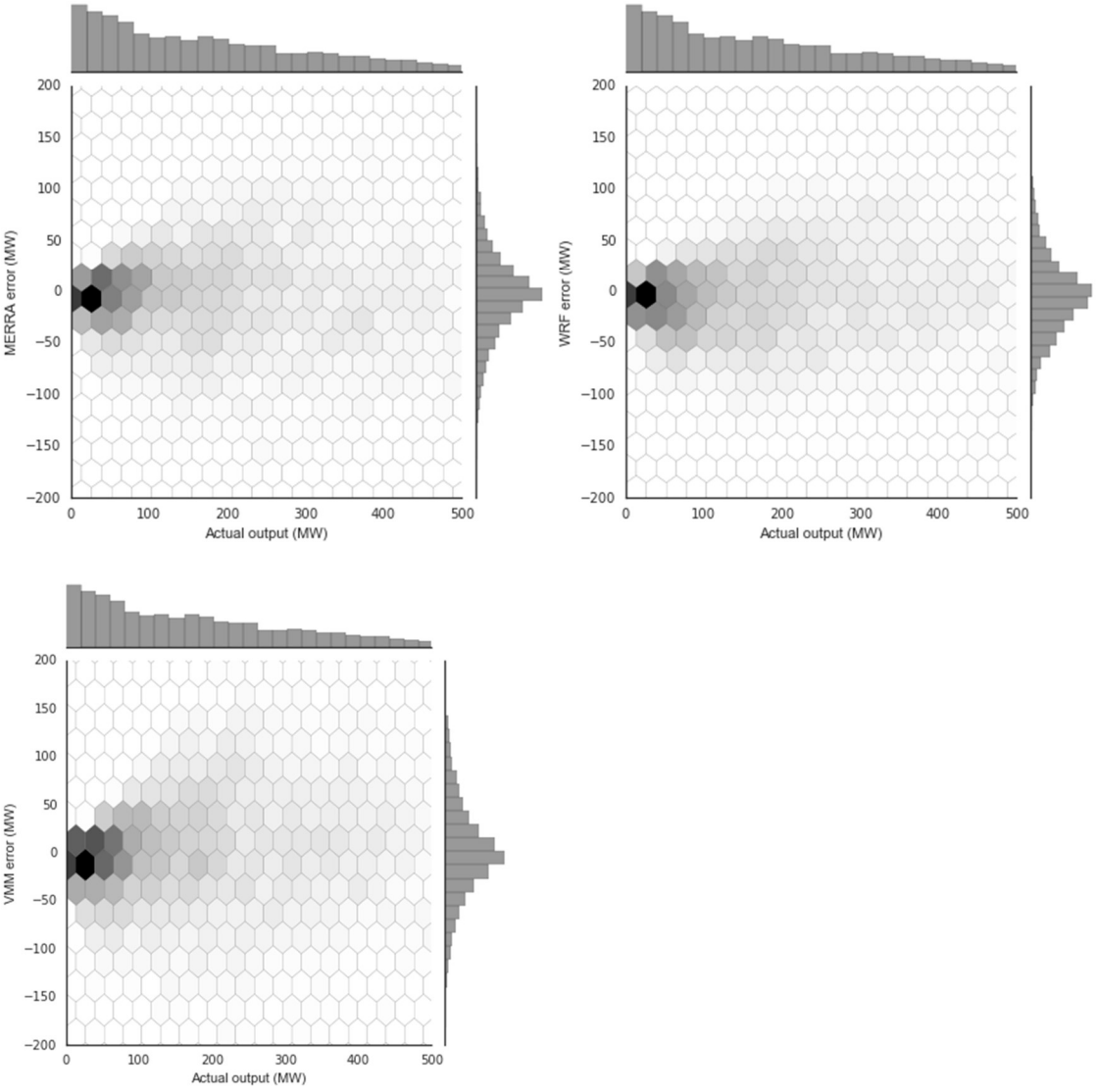

Figure 7 Comparison of model errors for 2006

3.4.3. Ramping events

Changes in capacity factors on the system hour-by-hour are particularly relevant to network and power system operations. A 'ramp' is defined for each hour, *t*, as the difference between capacity factor at time, t, and the capacity factor at time *t + horizon*. The cumulative frequency of ramps at a range of time horizons is shown in Figure 8. Similarly to Cannon et al. (2015), these plots represent the percentage of hours which precede a change in capacity factor (positive or negative) of at least a given size at the specified time horizons. The observed distributions are shown by solid lines, and the model distributions by dashed lines. For example, at a time horizon of 3 hours, the ramp that follows 10% of hours is actually around +/-14%, whilst the MERRA-driven model predicts this to be around +/-11%. Generally, at horizons of 1-3 hours for a given percentage of hours, the model produces ramps of a smaller magnitude than observed, but at 6 hours and beyond, the model ramping more closely matches reality.

The VMM data (Figure 8, left) offer an improvement in representing ramping events at shorter time horizons of 1, 3 and 6 hours, with the curve on the graph being slightly closer to that of the actual data compared with the MERRA curve. At 12 hours, both appear to have similar levels of difference to the real data. In the case of the model based on WRF (Figure 8, right), at all time horizons it underestimates the frequency of changes of a given magnitude. No difference was found between day-time and night-time ramping events.

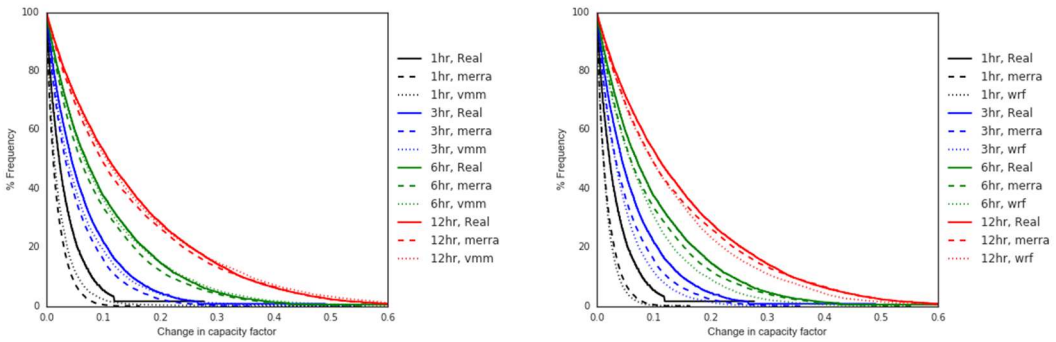

Figure 8 Model ramping compared with Actual. (Left) VMM and MERRA, (Right) WRF and MERRA.

In summary, when used in the generation model, the higher resolution data do not necessarily add skill to the model in all areas of assessment. While there is some improvement in predicting generation ramps at short time horizons using the VMM data, the correlation on an hourly basis using these data over the whole year is lower. The model output using WRF is comparable to that based on MERRA data, but it does not appear to capture the aggregate power ramping at short timescales. The end-use of the model output should be considered, therefore, when making a choice.

4. Application of model: Large-scale climate features and wind generation

The role of the North Atlantic Oscillation (NAO) has received some attention with regard to wind resources in recent years (e.g, Brayshaw et al. (2011); Ely et al. (2013)). Both studies used representations of local wind generation derived from a small number of meteorological measurements to establish correlations between hypothetical winter wind power output and the NAO index. Here, we use the MERRA-based wind generation model to consider the impact of the NAO on 34 years of simulated aggregate power output for the Republic of Ireland in winter, assuming the installed capacity as of 2014. Like most studies considering the NAO, the focus here is on the winter months of December, January and February, where the influence of the NAO on

surface weather variables is strongest and most consistent (e.g. (Hurrell, 1995). The capacity factors for all the December, January and February months have been extracted from the years 1980-2013 and compared with an NAO index for those months. A second index, the East Atlantic pattern (EA) that is captured by the 2nd principal component of sea-level atmospheric pressure variability in the region has been shown to modulate the influence of the NAO on winter weather conditions, including wind speeds, around Europe (Laia Comas-Bru et al., 2014), and is considered here alongside the NAO.[2] The NAO and EA indices used here are taken from Zubiate et al. (2016) and are based on a separate reanalysis dataset, ERA-Interim. It was shown in Comas-Bru *et al.* (2016), that the differences between NAO and EA indices from two different reanalyses products are small and here, as with Ely et al. (2013), it will not impact noticeably on the results of the analysis.

4.1. Monthly mean capacity factors

Figure 9 presents the relationship between the aggregate monthly mean capacity factor for the Republic of Ireland and the NAO and EA indices. The left-hand panel shows the empirical cumulative distribution for monthly mean capacity factor for the four sets of NAO and EA conditions. A Kolmogorov-Smirnoff two-sample test of significance is used to determine if the empirical probability density functions of the monthly mean capacity factors are significantly different in the EA+ or EA- state. The results suggest that the differences are significant when the NAO is both positive (p-value = 0.0009) and negative (p-value = 0.009), i.e. the likelihood of the differences being due to random error are less than 1% in both cases. It can be concluded that in those months where the NAO is negative and lower wind production is expected, that a concurrently negative EA may partly offset the effects of this.

The right hand panel of Figure 9 shows the individual capacity factors and the corresponding NAO/EA values, displaying the outliers more clearly including February 2010 when capacity factor was modelled at its minimum, 18%, and yet the EA was quite strongly negative. There is a corresponding opposite extreme case, January 1983, when the simulated capacity factor was 64%, but the EA was positive. Whilst the combinations of the two patterns do have an apparently significant effect on the probability distributions of capacity factors associated with each scenario, care is required when looking at individual results.

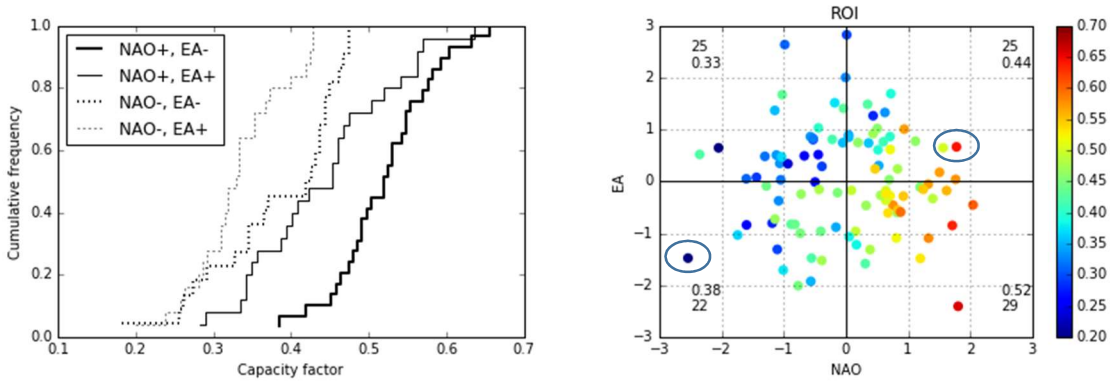

Figure 9 Influence of the NAO and EA on mean monthly aggregate wind generation capacity factors for December, January and February 1980-2013 in the Republic of Ireland. Left panel – cumulative frequency of capacity factors for each NAO/EA combination. Right panel – Individual monthly NAO/EA combinations, colour scale is the corresponding capacity factor. (Number of months represented by the number in the twenties, and mean capacity factor by the lower number.)

[2] It should be noted that the EA patterns discussed here follow the sign convention presented in (Laia Comas-Bru et al., 2014). Some other studies use the opposite.

4.2. Ramping events

The occurrence of large ramp events is one of the most problematic issues for network operators to manage, and it is possible that the frequency of such events is different depending on the prevailing NAO/EA combination. It was shown in an earlier section that the model is less successful at reproducing ramps at time horizons of around 1-3 hours, but improves in accuracy at longer time horizons, so only 6 hours and greater will be considered here.

The data are partitioned into four, depending on the NAO/EA combination for the winter month (DJF) in which each hour occurs, and the number of ramp events exceeding a specific size is calculated. The number of hours which precede these ramps is then converted to a percentage of the total hours in that NAO/EA state. The results are shown for ramps of greater than 20% at a 6 hour time horizon.

Table 4 Ramping events under NAO/EA combinations

State	*% of hours preceding a ramp >20% at 6-hour horizon*
NAO+	21%
NAO-	14%
NAO+ / EA+	18%
NAO+ / EA-	23%
NAO- / EA+	12%
NAO- / EA-	17%

The percentage occurrence of the specified ramps at 6 hours for NAO+ and NAO- conditions are 21% and 14% of hours respectively. A simultaneous EA- state increases the occurrence of these ramps compared to EA+ under both NAO states. This corresponds to the general increase in capacity factors under the same conditions. No difference was found between ramping during night or day time.

4.3. Persistence

A further feature of the large-scale atmospheric patterns worth considering is their influence on persistence. From the cumulative distribution, the 20th percentile aggregate capacity factor is around 13%, and the 80th percentile is around 74%. Figure 10 shows the number of periods when the capacity factor remained above 74% for more than 12 hours compared to the NAO, for each winter month in the 34-year period. There is a positive relationship (r-squared = 0.56), indicating that the more positive the NAO, the more likely there will be persistent periods of high aggregate output. The same relationship does not hold so strongly in the opposite case, i.e. there is only a weak

relationship between persistent low-wind conditions and the NAO index (r-squared = 0.29). The EA does not appear to have a discernible influence on persistence.

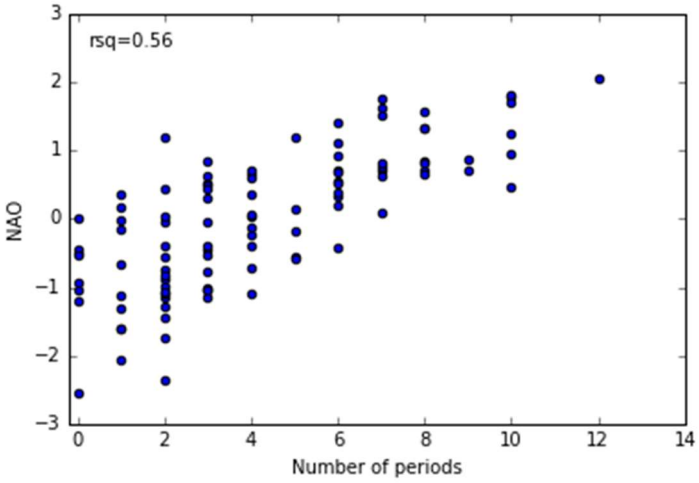

Figure 10 Monthly mean winter NAO vs. number of periods per month over 12 hours long where the capacity factor is above 74%. Each point represents an individual December, January or February.

5. Conclusions

This study presents a comparison of actual wind power generation output in Ireland with modelled generation using reanalysis wind speed data over a period of 14 years. It includes years when the wind industry was relatively young with a small number of wind farms, as well as more recent years with a well-established operational system. In general, based on comparison of basic statistics and error analysis, the model output driven by MERRA reanalysis data compares well with the real production data. The time series are strongly correlated and the errors approach a normal distribution. The model improves as the industry matures and installed capacity increases. A useful extension to the model would include development of a representation of operational characteristics, particularly curtailment, to be applied to the output to reproduce realistic scenarios for the most recent years.

In terms of capturing characteristics of generation that are of interest for energy systems analysis, the model represents the statistics such as monthly mean capacity factor well in most cases, and the distributions of hourly power output are close to the actual data. Representation of variability/ramping needs careful consideration and may be susceptible to error at small time horizons. Different input resource data has been shown potentially to improve the representation, but careful analysis is necessary to ensure the limitations are fully understood. An alternative would be to apply an additional higher frequency signal on top of the MERRA output to represent this variability statistically.

An application of the model in 'simulation mode' has been presented. It demonstrates that, based on the 2014 installed generation with no additional operational conditions applied, the NAO has a discernible effect on the distribution of winter mean monthly capacity factor in the Republic of Ireland, with negative NAO months tending to have lower capacity factors, on average. The impact of the EA is also significant, with EA- states causing a higher average capacity factor for a given NAO state. The combined NAO/EA states in which there are larger capacity factors correspond to more frequent occurrences of large ramps in capacity factor. More positive NAO states also lead to more frequent episodes with persistently high capacity factor events.

The relatively long 34-year time period of analysis based on current wind farm installations provides some confidence in the distributions of capacity factors for a given NAO/EA state and the likelihood of encountering large ramping events. Coupled with recent advances in predicting the NAO up to and including one year in advance (Dunstone et al., 2016; Scaife et al., 2014), this analysis informs system operators of the likely distribution of wind outputs in upcoming winter months.

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