



The importance of forecasting regional wind power ramping: a case study for the UK

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The importance of forecasting regional wind power ramping: A case study for the UK

Daniel. R. Drew^{1,*}, Dirk. J. Cannon¹, Janet. F. Barlow¹, Phil. J. Coker² and Tom. Frame¹

¹ Department of Meteorology, University of Reading, Reading, UK

² School of Construction Management and Engineering, University of Reading, Reading, UK

* Author to whom correspondence should be addressed; E-Mail: d.r.drew@reading.ac.uk; Tel.: +44 (0)118 378 7696

Abstract

In recent years there has been a significant change in the distribution of wind farms in Great Britain, with a trend towards very large offshore farms clustered together in zones. However, there are concerns these clusters could produce large ramping events on time scales of less than 6 hours as local meteorological phenomena simultaneously impact the production of several farms. This paper presents generation data from the wind farms in the Thames Estuary (the largest cluster in the world) for 2014 and quantifies the high frequency power ramps. Based on a case study of a ramping event which occurred on 3rd November 2014, we show that due to the large capacity of the cluster, a localised ramp can have a significant impact on the cost of balancing the power system on a national level if it is not captured by the forecast of the system operator. The planned construction of larger offshore wind zones will exacerbate this problem. Consequently, there is a need for accurate regional wind power forecasts to minimise the costs of managing the system. This study shows that state-of-the-art high resolution forecast models have capacity to provide valuable information to mitigate this impact.

Keywords: Wind; energy; ramping; predictability; offshore

1.0 Introduction

In recent years there has been a significant growth in wind power in the UK. Between 2008 and 2014, the installed capacity of wind turbines increased from 2.9 GW to 12.4 GW and the proportion of electricity provided by wind power increased from 1.5% to 9.3% [1]. Much of this growth is the result of the development of offshore wind. Following the construction of the offshore wind farms in the second round of developments (started by the Crown Estate in 2003); the offshore capacity has risen to approximately 5 GW (40 % of total wind capacity). Much of this new capacity has been installed in a small number of very large wind farms which are located in clusters. For example, in the Thames Estuary alone there is approximately 1.7 GW of capacity [2]. This trend looks set to continue as the third round of offshore wind development in the UK, launched in 2009, identified 9 zones within which a number of individual wind farms could be located. Consequently, following the construction of the round 3 wind farms the majority of GB wind capacity would be located offshore in clusters of very large wind farms [3, 4].

Concentrating large amounts of capacity in a small number of wind farms in close proximity can lead to large regional ramps in generation on time scales of minutes to hours as the impact of local meteorological phenomena could simultaneously impact production in several sites. Drew et al [5] showed that on time scales of less than 6 hours, the ramps in generation of the cluster of wind farms in the Thames Estuary were larger than those of the more spatially dispersed onshore wind farms. Large fluctuations in power on short time scales have also been observed at the Horns Rev wind farm [6, 7].

43 Given the large capacity of the offshore wind farms, these fluctuations could present a challenge to
44 National Grid, the system operator responsible for ensuring a balance between supply and demand of
45 electricity, particularly if they are not accurately forecasted.

46 Making reliable forecasts of exactly where and when local ramping events will occur is a significant
47 challenge. Potter et al. [8] identified three types of errors; phase error, magnitude error and location
48 error. A phase error is defined as a ramping event which has the magnitude accurately predicted but
49 occurs at the wrong time. A magnitude error is defined as a ramping event that is forecasted to occur
50 at the correct time but with the wrong magnitude. A location error is defined as an error in the
51 geographical location of the meteorological feature which produces the ramping event.

52 The predictability of ramping events has been investigated using a range of methods. At relatively
53 short lead times (minutes to hours), forecasts can be made using simple statistical methods such as
54 ARMA (auto-regressive moving average) [9] or more complicated data-driven methods such as
55 artificial neural networks (ANN) [10, 11]. Forecasts for the next few hours up to several days ahead
56 rely on numerical weather prediction (NWP) models [12, 13, 14]. NWP model forecasts are initialised
57 from analyses, which represent the observed state of the atmosphere on a three-dimensional grid by
58 blending observational data with an earlier forecast. A forecast of the future state of the atmosphere is
59 then made by mathematically modelling the dynamics and other physical processes.

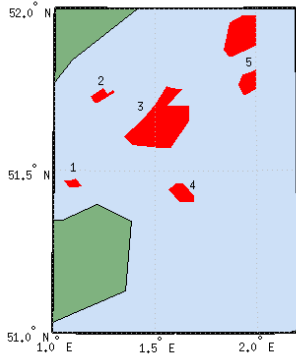
60 Due to its chaotic nature, the state of the atmosphere at a future time is sensitive to small errors at the
61 start of the forecast. Consequently, there is uncertainty in NWP model forecasts, which grows with
62 increasing lead time. To determine this uncertainty the NWP model can be run a number of different
63 times from slightly different starting conditions (designed to represent the uncertainty in the initial
64 state of the atmosphere) and the complete set of forecasts is known as an ensemble. By using this
65 approach the individual ensemble members can be analysed to get a better idea of which possible
66 weather events may occur. Cannon et al [15] showed that using an ensemble of NWP forecasts of GB-
67 aggregated wind power does have an improved skill of ramp forecasting relative to climatology up to
68 a lead time of 7 days. On smaller spatial scales, Bossavy et al [13] showed that conditioning
69 probability forecasts by the number of NWP ensemble members forecasting a ramp can improve the
70 reliability of the forecast for a multi megawatt wind farm in the South of France.

71 Here we present a case study to investigate the impact of the high frequency ramping of a cluster of
72 offshore wind farms on the national level power system (in terms of balancing costs), if it is not
73 forecasted by the system operator. We then explore the effectiveness of state-of-the-art high
74 resolution NWP models of forecasting events of this nature.

75 To achieve the aims of this study a wide range of data have been used. The first section presents the
76 generation characteristics of the cluster of wind farms in the Thames Estuary (currently the largest
77 cluster of offshore wind farms in the world) for 2014 and quantifies the power ramps on time scales of
78 less than 6 hours. The second section investigates the ramping event which occurred on 3rd November
79 2014 in more detail, highlighting the impact on the national level power system using data on volume
80 of imbalance and balancing prices. The final section investigates whether state-of-the-art high
81 resolution forecast models are able to capture ramping events of this nature, and if so, at what forecast
82 lead time.

83 2.0 Method

84 This study focuses on the wind farms located in the Thames Estuary, approximately 100-200 km east
85 of London, UK. This is the largest of the offshore clusters consisting of 5 individual farms (full details
86 of the wind farms are given in *Table 1* and *Figure 1*) with a total capacity of 1.7 GW, which equates
87 to approximately 14% of the installed wind capacity in the UK. The aggregated power output from all
88 wind farms in the cluster at 5 min resolution for the whole of 2014 has been obtained (data coverage
89 >99%).



	Farm	Size (MW)	Turbines
1	Kentish Flats	90	Vesta V90-3MW
2	Gunfleet Sands	172	Siemens SWT-3.6-107
3	London Array	630	Siemens SWT-3.6-120
4	Thanet	300	Vesta V90-3MW
5	Greater Gabbard	504	Siemens SWT-3.6-107

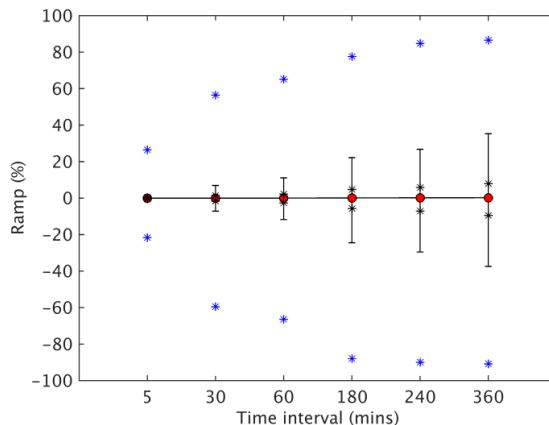
Table 1 Details of the wind farms in the Thames estuary

90
91 **Figure 1** Location of the wind farms in the Thames estuary

92 The generation data were analysed to assess the high frequency ramping events during 2014. The
93 definition of a wind power ramp typically refers to the change in power output over a defined time
94 scale, usually seconds to minutes [16, 17] or hours [18, 19]. In this study a ramp, R , is defined as the
95 change in output of the cluster (expressed in the form of capacity factor, CF) over a given time
96 interval, Δt (as shown in equation 1).

97
$$R = CF(t + \Delta t) - CF(t)$$

98 Figure 2 shows the magnitude of the ramps for a range of different time intervals. As shown in Drew
99 et al [5], the distribution of the ramps for all time windows is approximately Gaussian with median
100 values close to zero and similar frequencies of positive and negative fluctuations. As expected, the
101 magnitude of the ramps increases with the time interval. For example, when the time window is 5
102 minutes ($\Delta t = 5$ mins), the largest fluctuation was 26.5% in comparison to 88% when the time window
103 is 180 minutes ($\Delta t = 180$ mins). In general, the majority of the ramping events are relatively small, for
104 the longest time window considered ($\Delta t = 360$ mins), 90% of the ramps lie within the range -37% to
105 35%. However, a small number of very large ramping events also occurred. For example, the
106 maximum ramp over a time window of 60 mins was 66%, this equates to a change in power output of
107 1.1 GW, which could make balancing the power network problematic if not well forecast.
108 One of the largest ramp-up events occurred on 3rd November 2014 (67% in a period of 2 hours and
109 45 minutes). This was immediately followed by one of the largest ramp-down events (73% in a period
110 of 1 hour and 50 minutes). This day is therefore used as a case study to consider the potential impact
111 of high frequency local ramping events on the power system and to investigate whether high
112 resolution meteorological forecast models can capture events of this nature.



113
114 **Figure 2** The magnitude of the ramps of the Thames Estuary wind farms in 2014 (expressed in the form of a change
115 in capacity factor) for a range of time intervals. The red circles show the median, the black stars give the
116 interquartile range, the whiskers represent the range between the 5th and 95th percentile and the blue stars indicate
117 the minimum and maximum values.

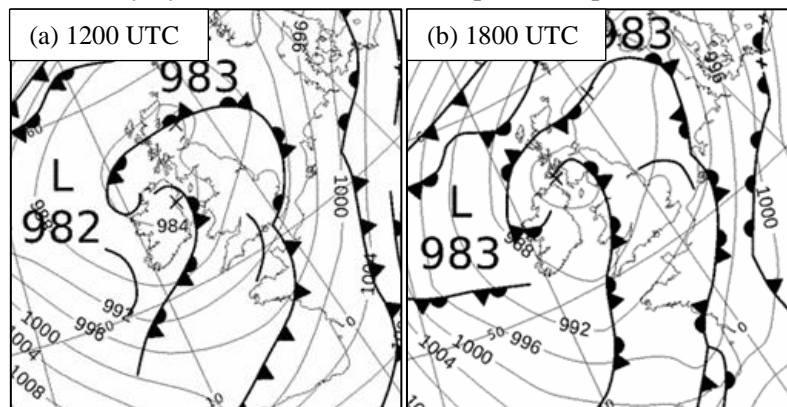
118 Two different high resolution models developed by the UK Met Office have been considered; (1) the
 119 deterministic UK model (UKV) which has a high resolution inner domain of 1.5 km (2) Met Office
 120 Global and Regional Ensemble Prediction System (MOGREPS) which produces a forecast on a
 121 resolution of approximately 2.2 km using 11 ensemble members and a control forecast (see Table 2
 122 for further details). This study also considers the GB-aggregated hourly wind power forecast produced
 123 by National Grid, which is updated 4 times per day and published via the Elexon Portal [20]. This
 124 forecast was not produced using data from either of the UK Met Office models considered in this
 125 study.
 126

	UKV	MOGREPS UK ensemble
Resolution	1.5 km	2.2 km
Forecast length	36 hours	36 hours
Run times	0300, 0900, 1500, 2100	0300, 0900, 1500, 2100
Members	Deterministic	12

127 **Table 2** Details of the Met Office forecast models used in this study

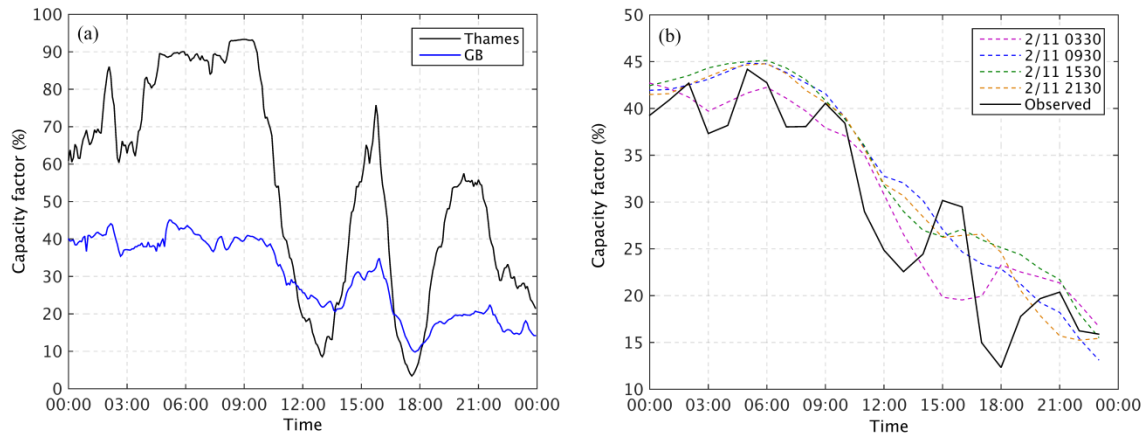
128 3.0 Ramping case study: 3rd November 2014

129 On the morning of 3rd November 2014 an occluded weather front moved across the South East of
 130 England which led to high wind speeds and heavy rainfall in the Thames Estuary (see figure 3). After
 131 the front moved eastwards away from the cluster of farms, their wind generation reduced
 132 dramatically, falling from 93.2% of capacity at 09:25 to only 8.6% at 13:00 (see Figure 4a).
 133 Following this, a trough moved across the region which corresponds with an increase in wind power
 134 generation and by 15:45 the output was back up to 76% at 15:45, however this ramp had a short
 135 duration and by 17:35 the output had reduced to only 3% (see Figure 4). The ramping event between
 136 13:00 and 17:35 equates to an increase in power output of 1.1 GW within 2 hours and 45 minutes,
 137 followed almost immediately by a 1.24 GW reduction in power output within 1 hour and 50 minutes.



138
 139 **Figure 3** Met Office analysis charts for 12:00UTC (left) and 18:00UTC (right) on 3rd November 2014

140 Due to large proportion of the national wind capacity located in the Thames Estuary, the ramping
 141 event is clearly observed in the GB-aggregated wind generation (Figure 4a). Between 13:40 and 15:55
 142 wind generation increased from 1.7 GW (capacity factor of 20%) to 2.9 GW (capacity factor of 35%)
 143 before reducing down to 0.8 GW (capacity factor of 10%) at 17:45. This indicates that the ramping
 144 event was highly localised to the Thames Estuary and therefore related to a meteorological feature
 145 with a relatively small spatial extent. Figure 4(b) shows the National Grid forecast for 3/11/2014 for a
 146 range of lead times. In general, the forecast accurately captures the overall trend of the generation for
 147 all lead times, but the ramping event is not predicted in any of the forecasts. We speculate that this
 148 may be due to a smoothing effect caused by ensemble averaging; however full details of the forecast
 149 are not available.



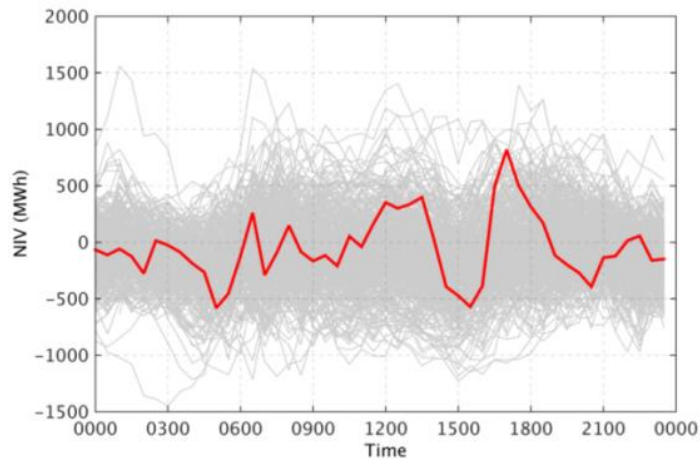
150
 151 **Figure 4 Wind power generation on the 3rd November 2014. (a) 5 minute mean generation of the Thames Estuary**
 152 **wind farms (black) and GB-aggregated (blue) (b) The hourly GB-aggregated generation and the National Grid wind**
 153 **power forecasts.**

154 **3.1 Impact on power system**

155 In the UK, the electricity market is based on 30 minute settlement periods. For each settlement period,
 156 suppliers and generators can contract volumes of electricity up to 1 hour prior to the delivery time
 157 (this cut-off is known as gate closure). At this point, large generating units, such as offshore wind
 158 farms must submit their expected generation, known as the final physical notification, (FPN).
 159 However, for each settlement period, a supplier might have incorrectly forecasted their demand or a
 160 supplier might not be able to generate the contracted amount and therefore there can be an imbalance
 161 between supply and demand. It is then the responsibility of the system operator (National Grid) to
 162 make the necessary actions to balance the system. This is achieved by using bids and offers in the
 163 balancing market. A bid is a proposal by a supplier to increase demand or a generator to reduce
 164 generation. An offer is a proposal by a generator to increase generation or a supplier to reduce
 165 demand.

166 For this case study, the final physical notifications of the wind farms in the Thames Estuary did not
 167 show the ramping event. Furthermore, it was not captured by the system operator's wind power
 168 forecast and therefore led to a large imbalance of the electricity network. As a result, National Grid
 169 was required to perform a number of actions in the balancing mechanism. The net imbalance volume
 170 (NIV) is the net of the buying and selling actions taken in the balancing mechanism. When NIV is
 171 positive it means that the system is short and therefore the system operator is accepting offers to
 172 increase generation. Conversely, when NIV is negative, the system is long and the system operator is
 173 accepting bids to reduce generation.

174 Figure 5 shows that in mid-afternoon (14:30 to 16:00) on 3/11/2014, the market was long, peaking at -
 175 570 MWh at 15:30. This is a result of the unexpected pick-up in the generation in the Thames
 176 Estuary. By 17:00, the generation had drastically reduced and the market was short by 820 MWh (the
 177 3rd largest negative imbalance for this time of day in 2014). This large imbalance coincided with
 178 winter darkness peak and therefore the electricity demand for this settlement period was very high,
 179 47.6 GW (in the top 2.5 percentile of half hourly demand in 2014). Consequently, there were fewer
 180 options, in terms of generation units, available to National Grid to balance the system. As a result,
 181 short term operating reserve (STOR) was deployed, which is expensive and therefore had implications
 182 on the system prices.

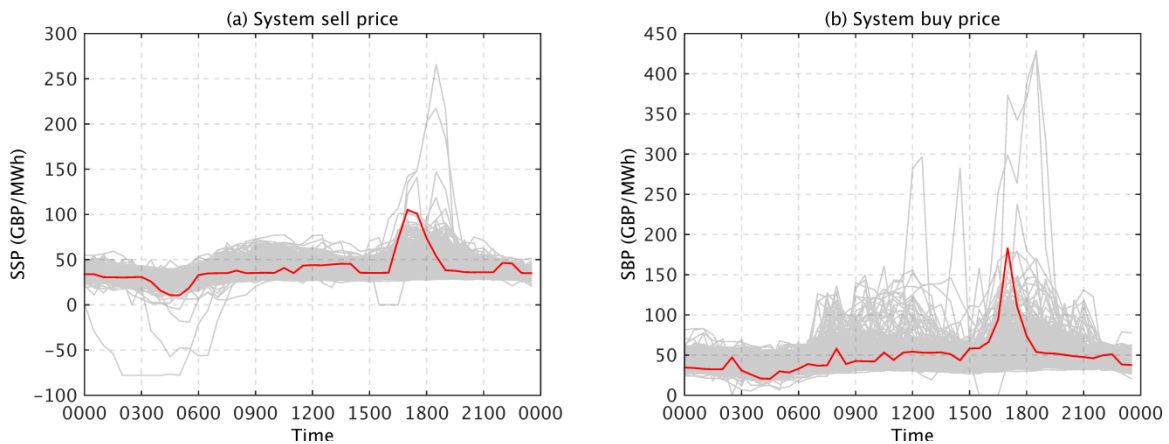


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Figure 5 The net imbalance volume (NIV) of the power system for each settlement period on the 3rd November 2014 (red). Also shown is NIV for every other day in 2014 (grey lines).

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In November 2014, the costs associated with balancing mechanism bids and offers were given by the system buy price (SBP) and system sell price (SSP). The SBP is the rate paid by a party with a net deficit of imbalance energy and the SSP is the rate paid to parties with a net surplus of imbalance energy. Figure 6 shows the ramping event had a significant impact on both the SSP and SBP. At 17:00, when the system had a large deficit, the SBP increased to £183 per MWh which was the third highest price in this settlement period during the year and 16th highest price for any settlement period in the year. SSP also increased to £105 per MWh, the 5th highest price for that period in 2014 and 19th highest for any settlement period during the year.



195
196
197

Figure 6 The system sell price (SSP) and system buy price (SBP) for each settlement period on the 3rd November 2014 (red). Also shown is the SSP and SBP for every other day in 2014 (grey lines).

198 4.0 High Resolution Forecasts

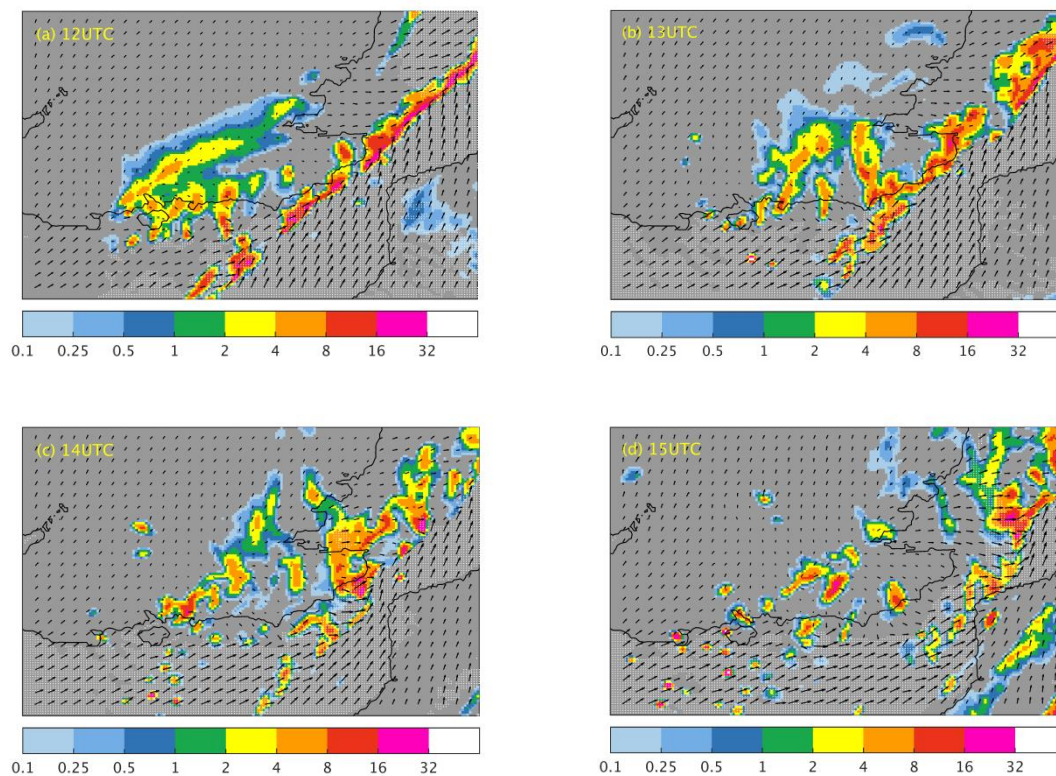
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The analysis in section 3 has shown that the recent trend for clustering large amounts of capacity in a relatively small area (e.g. Thames Estuary) can lead to large local power swings, which unless accurately forecast can have a significant impact on the cost of balancing the power system. This effect is likely to be exacerbated following the construction of the wind farms proposed as part of the next phase of offshore wind development in the UK. The aim of this section is to investigate whether state-of-the-art high resolution meteorological forecast models capture local ramping events, using the ramp on 3/11/2016 as a case study.

206 4.1 Meteorological conditions

207 The output from the high resolution models has been assessed to determine the meteorological
208 conditions on 3rd November 2014. Figure 7 shows the rainfall and wind from 12:00 and 15:00 UTC
209 derived by a single ensemble member of the MOGREPS forecast initialised at 09:00 UTC. The
210 figures clearly show the elevated wind speeds and heavy rainfall in the English Channel associated
211 with the main front which passed over the region earlier in the day. There is also a feature behind the
212 front with large amounts of rainfall which propagates from south west to north east along the front.
213 This is related to the trough marked on the analysis chart at 12 and 18 UTC (see Figure 3). The winds
214 associated with this feature are relatively low over land but pick up as it passes over the Thames
215 Estuary at 14:00 UTC.

216 Complete analysis of the dynamics of this feature is beyond the scope of this paper; however there are
217 several things of importance to consider. Firstly, the acceleration of the winds as the rainfall feature
218 passes from the land into the Thames estuary, which is possibly due to change in the surface
219 roughness. The most important thing to note is the way that the frontal region is comprised of small
220 scale banded structures with can lead to large local fluctuations in wind speed. The magnitude of the
221 uncertainty in the location and detailed structure of such banded features is larger than their spatial
222 scale meaning that ensemble mean forecasts will fail to capture them (this is explored detail in section
223 4.3).



225

226
227 **Figure 7 Instantaneous wind and Rainfall rate (mm hr⁻¹) from 12:00-16:00 UTC on 3rd November 2014 derived by**
228 **MOGREPS (ensemble member 4 from forecast initialised at 09:00 on 3rd November 2014).The white stippling shows**
229 **wind speeds at 10 m in excess of 10 ms⁻¹.**

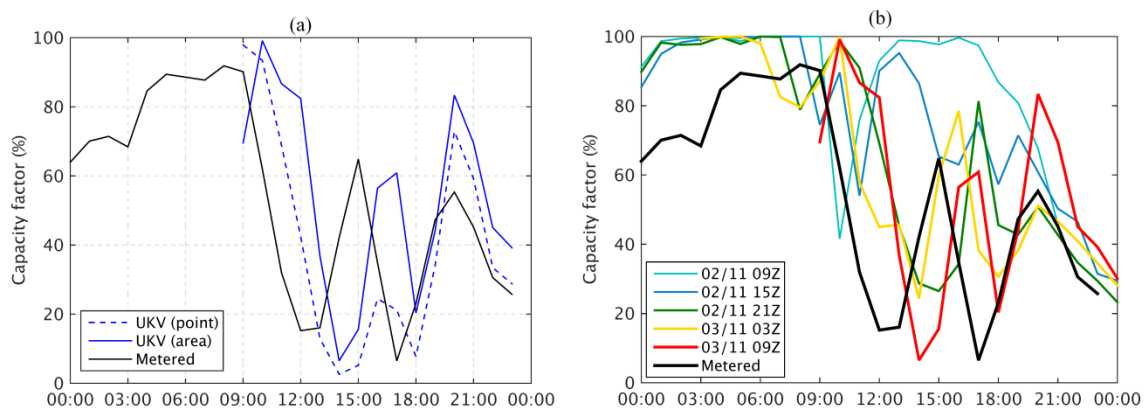
230 4.2 Deterministic Model (UKV) Results

231 The model forecasts have been obtained for a range of initialisation times (6 hourly intervals from
232 03:00 on 02/11/2014 to 09:00 on 03/11/2014). The generation of the cluster has been estimated by
233 applying the power curve produced by the turbine manufacturer to the model derived wind data
234 defined in two ways: (1) turbine location method: the wind speed from the model at the exact location

235 of each of the turbines (2) area maximum wind speed method: the maximum wind speed within a 10
 236 km radius of each of the turbines.

237 Figure 8a shows that using the wind speed at the exact location of the turbines ('point') produces an
 238 underestimate of the ramp in generation. Between 15:00 and 16:00 the capacity factor of the region
 239 increases by 19%, before reducing by 17% by 18:00 this equates to a magnitude error of 30%.
 240 However, using the maximum wind speed within a 10 km area of each of the turbines produces a
 241 clear, large mid-afternoon ramp up of 44% between 15:00 and 17:00 followed by a ramp down of
 242 40%. This reduces the magnitude error to only 8%, but there is still a 2 hour phase error in the
 243 forecast. This indicates that while the model was able to produce the band of post-frontal high wind
 244 speeds, it did not have the timing and position of the feature exactly correct.

245 By using the area maximum wind speed method to determine wind farm power output, there is an
 246 indication of a large ramp present in the forecast from the UKV 1.5 model out to a lead time of 24
 247 hours. Figure 8b shows that the forecast initialised at 15:00 on 02/11/2014 produces a ramp of 41%
 248 (magnitude error of 8%), however the ramp peaks at 1300UTC therefore there is a 2 hour phase error.
 249 As the forecast lead time decreases the representation of the ramp improves and by 03:00 on 3/11/14,
 250 the magnitude error is reduced to 5% but the phase error remains at 2 hours.



252
 253 **Figure 8 The hourly generation of the wind farms in the Thames Estuary compared to power forecast derived from**
 254 **the Met Office UKV1.5 model. (a) Comparison with power derived from the UKV wind speed (forecast initialised at**
 255 **03/11/2014 at 09:00) at the precise location of each turbine (point) and with the maximum wind speed within 10 km of**
 256 **each turbine (area). (b) Comparison with the wind power forecast for a range of lead times.**

257 4.3 Ensemble Model (MOGREPS) Results

258 For all forecast lead times, there is a large spread in the capacity factor across the 12 different
 259 ensemble members on the afternoon of 3/11/2014 (see Figure 9). It is clear from the figures that the
 260 ensemble mean grossly underestimates the variability in generation. This is due to the smoothing that
 261 occurs when averaging over the ensemble members and highlights the importance of considering the
 262 trajectory of individual ensemble members when estimating ramp events.

263 An assessment of the forecast of the different ensemble members has been made focussing on the
 264 period from 12:00 to 18:00 on 3/11/2014. To prevent large differences between successive forecasts,
 265 the forecasts from consecutive initialisation times are typically combined to produce a 24 member
 266 ensemble. For the forecast initialised at 09:00 and 15:00 on 02/11/2014 (27-21 hours prior to the
 267 ramp), the majority of the members have relatively high generation during the period; however 21%
 268 of members show a ramp with a magnitude of at least 20%. As the forecast lead time decreases the
 269 number of members predicting a ramp ($R > 20\%$) increases (see Table 3). For the forecast based on
 270 initialisation times of 03:00 and 09:00 UTC on 3/11/2014, there is a 75% probability of a ramp
 271 occurring (18 members forecast a ramp). Table 3 also shows that some ensemble members do predict
 272 a very large ramping event ($R > 40\%$) during the 3 hours either side of when the event occurred. For
 273 example, for the forecast at 12:00 on 02/11/2014 there is a 16.7% probability of a large ramp

274 (R>40%) occurring in this period. This increases to 33.3% for the forecast at 06:00 on 03/11/2014.
 275 However, the probabilities are significantly reduced when the time window is restricted to 1 hour
 276 either side of the event- indicating a phase error in the forecast.

277 For each ensemble member with a predicted ramp in the time window 12:00-18:00, the magnitude
 278 and phase error has been determined. In general, the magnitude of the ramps predicted by the
 279 individual ensemble members becomes more accurate as the lead time decreases. Figure 10 shows
 280 that the latest forecast (initialised at 09:00 on 3/11/2014) has 7 out of 12 members predicting a
 281 ramping event, with a range of magnitudes from 17-70%, but for two members the magnitude error is
 282 less than 5%. Figure 10 also shows that the magnitude error of the ramps predicted by the UKV1.5
 283 model is relatively low (less than 8%) for all lead times, this is lower than all but one ensemble
 284 member for the corresponding MOGREPS forecast. However, there is a consistent 2 hour phase error
 285 for all of the UKV forecasts.

286
 287
 288

Forecast	P(R>20%, t±3)	P(R>20%, t±1)	P(R>40%, t±3)	P(R>40%, t±1)
02/11/2014 12:00	20.8	20.8	4.2	4.2
02/11/2014 18:00	25.0	16.7	12.5	4.2
03/11/2014 00:00	45.8	20.8	20.8	4.2
03/11/2014 06:00	62.5	29.2	33.3	12.5

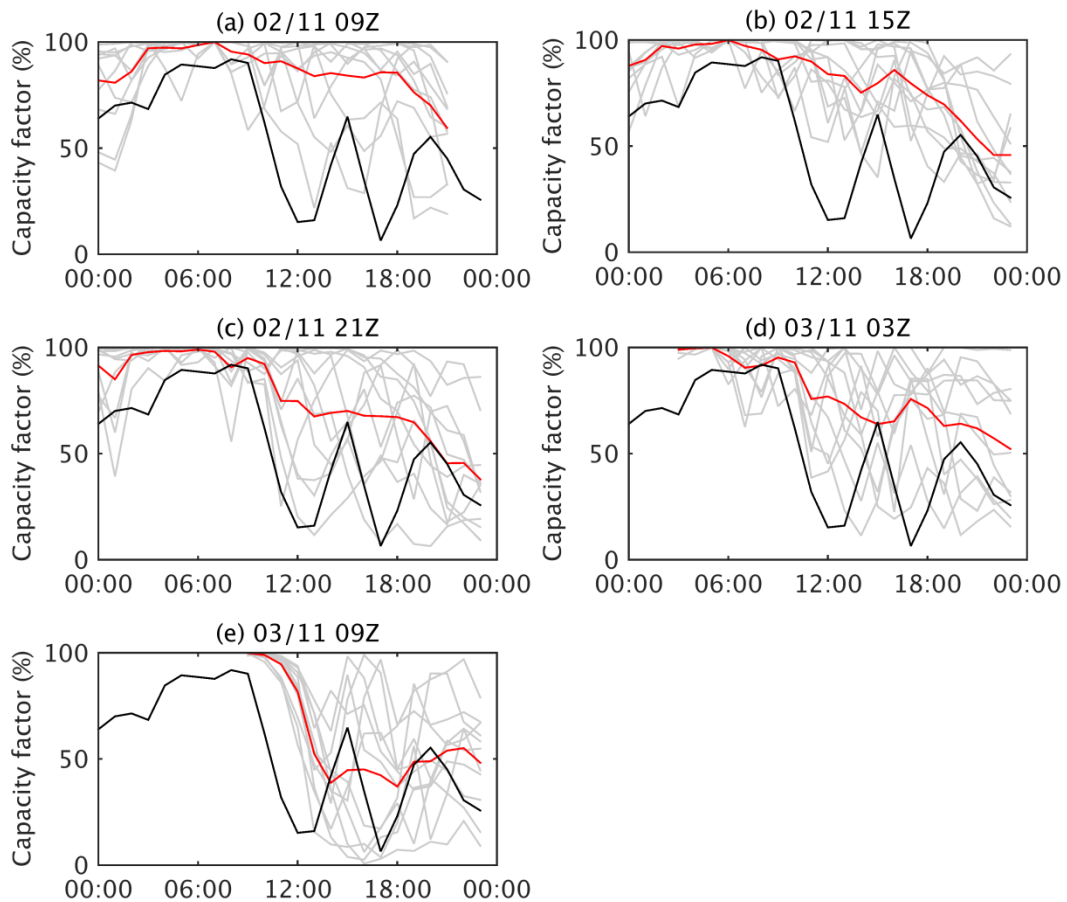
289 **Table 3 Probability of a ramping event (defined by the size R>20% and R>40%) occurring within t±1 and t±3 hours**
 290 **of the observed ramping event based on the MOGREPS forecast.**

291 4.4 Discussion

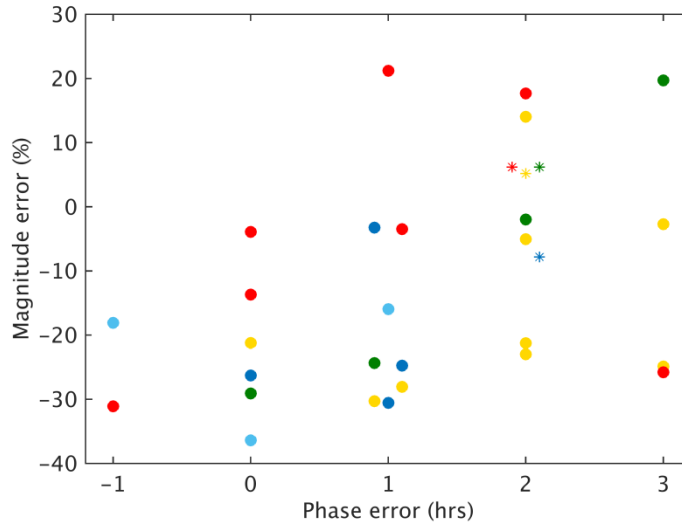
292 Analysis of the meteorological conditions on 3rd November 2014 has shown that the ramping event
 293 was caused by a trough which formed behind a large weather front. The trough was a relatively small
 294 feature (spatial extent of approximately 100-150 km) and therefore the ramping was localised to the
 295 wind farms in the Thames Estuary. The size of the feature presents a series of challenges to
 296 forecasting ramping events of this nature. Firstly, uncertainty in its location can have a significant
 297 impact on the predicted wind generation. For example, the high resolution deterministic forecast
 298 predicted the presence of the trough at a lead time of 24 hours, however as the feature is not predicted
 299 in exactly the right location there is a large error in the predicted wind power of the cluster. This error
 300 can be reduced by estimating the power output using the maximum wind speed within a given area of
 301 the turbines rather than the wind speed at the exact location of each turbine. Secondly, the size of the
 302 feature also means that it is unlikely to be captured in a wind power forecast which uses the ensemble
 303 mean. As shown in section 4.3, individual ensemble members capture the feature but in slightly
 304 different locations, so the mean smears out the increased generation.

305 Despite the relatively small size of the feature, the high resolution deterministic model was able to
 306 forecast the ramping event at a lead time of 24 hours but with a phase error of -2 hours and a
 307 magnitude error of -8%. When the lead time reduced to 12 hours, the magnitude of the ramp was
 308 accurately forecast to within 5% but the phase error remained at 2 hours (but opposite sign). In
 309 addition, a number of ensemble members also predicted a ramp up to 36 hours in advance. For lead
 310 times from 36 down to 6 hours there was a large spread in the ensemble members for the period
 311 during which the ramping occurred, indicating large uncertainty in the predicted wind generation.
 312 Access to such forecasts would have allowed National Grid to have prepared for the ramping event in
 313 advance, reducing the number of transactions required in the balancing mechanism and ultimately the
 314 cost of electricity.

315 While the NWP models were shown to be of benefit for this particular, high-impact case study,
316 further work is required to place the performance of the models in to context. The skill of the models
317 at predicting local ramping events could be determined over a long time period (large number of
318 ramping events) and compared to that of a low resolution global NWP model. This would quantify the
319 benefit of high resolution models and determine the bounds of predictability of local ramping events.
320



321
322 **Figure 9** The wind power forecast for the Thames Estuary wind farms derived from the MOGREPS model output for
323 a range of forecast lead times. The figure shows the forecast derived from each ensemble member (grey lines) as well
324 as the ensemble mean (red lines) and is compared to the measured hourly output (black).



325
 326 **Figure 10** The magnitude error (expressed in the form of capacity factor) and phase error of the ramps predicted by
 327 the individual MOGREPS ensemble members (circles) and the UKV1.5 forecast (stars). Data is shown for the range
 328 of lead times. 02/11 at 09:00Z (light blue), 02/11 at 15:00Z (dark blue), 02/11 at 21:00Z (green), 03/11 at 03:00Z
 329 (yellow) and 03/11 at 09:00Z (red).

330 5.0 Conclusions

331 In recent years there has been a significant change in the distribution of wind farms in Great Britain,
 332 with a trend towards very large offshore wind farms clustered together in several zones. This study
 333 has shown these clusters can experience large ramping events on time scales of less than 6 hours as
 334 the impact of local meteorological phenomena on the power production is strong. For example, for the
 335 wind farms in the Thames Estuary, 10% of the ramps over a 6 hour time window were in excess of
 336 30% of the total capacity. Due to the large capacity of the farms, these wind power fluctuations can
 337 present challenges for the system operator in maintaining the balance between supply and demand on
 338 a national scale.

339 A case study of the wind farms in the Thames Estuary has shown the implications of an unpredicted
 340 local ramping event on the cost of balancing the power system. On 3rd November 2014, there was an
 341 increase in power output of 1.1 GW within 2 hours and 45 minutes, followed almost immediately by a
 342 1.2 GW reduction in output within 1 hour and 50 minutes. As this event was not captured by the
 343 forecast used by the system operator the market was long by 570 MWh at 15:30 (due to the
 344 unexpected pick-up in the generation in the Thames Estuary) and then short by 820 MWh at 17:00 as
 345 the generation had drastically reduced. The large imbalance coincided with a period of very high
 346 demand and therefore there were fewer generation units available to help the system operator to
 347 balance the system. Consequently, expensive short term operating reserve was deployed which led to
 348 a spike in the system buy price of 183 per MWh which was the 16th highest price during the year.

349 The construction of even larger offshore wind zones, outlined in Round 3 of the UK's offshore wind
 350 development would exacerbate this problem. Furthermore, a number of other nations are seeking to
 351 dramatically increase their own offshore wind capacity. Consequently, there is a need for accurate
 352 regional wind power forecasts to minimise the costs of managing the system. In recent years a number
 353 of state-of-the-art high resolution forecast models have been developed. For this case study, these
 354 models were able to capture the meteorological feature which caused the localised ramping at a lead
 355 time of up to 24 hours and therefore the use of these forecasts would have been of benefit to the
 356 system operator. As system operators continue to seek to improve their forecasting of weather
 357 dependent renewable generation, the new forecast models should be considered. However, further

358 work is required to determine how well the model captures the high frequency ramping for a larger
359 number of events.

360

361 This study has also shown that careful interpretation of the forecast is required. For example, due to
362 possible errors in the position of small scale meteorological features in the models, a wind power
363 forecast derived from the predicted wind speeds at the exact location of each turbine can contain large
364 errors. It is therefore recommended that wind power estimates are based on the maximum wind speed
365 within a given area of the turbines. In addition, the ensemble mean power forecast is not suitable
366 when considering ramping events due to the smoothing that occurs when averaging over the ensemble
367 members. This highlights the importance of considering the trajectory of individual ensemble
368 members when estimating ramp events as well as the information about forecast uncertainty that they
369 provide.

370

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