

Title	Quantifying the value of improved wind energy forecasts in a pool-based electricity market
Authors	McGarrigle, Edward V.; Leahy, Paul G.
Publication date	2015-08
Original Citation	McGarrigle, Edward V.; Leahy, Paul G. (2015) 'Quantifying the value of improved wind energy forecasts in a pool-based electricity market'. <i>Renewable Energy</i> , 80 (8):517-524.
Type of publication	Article (peer-reviewed)
Link to publisher's version	<a href="http://www.sciencedirect.com/science/article/pii/S0960148115001135">http://www.sciencedirect.com/science/article/pii/S0960148115001135</a> - 10.1016/j.renene.2015.02.023
Rights	Copyright © 2015 Elsevier Inc. All rights reserved. NOTICE: this is the author's version of a work that was accepted for publication in <i>Renewable Energy</i> . Changes resulting from the publishing process, such as peer review, editing, corrections, structural formatting, and other quality control mechanisms may not be reflected in this document. Changes may have been made to this work since it was submitted for publication. A definitive version was subsequently published in <i>Renewable Energy</i> [Volume 80, August 2015, Pages 517–524] <a href="http://dx.doi.org/10.1016/j.renene.2015.02.023">http://dx.doi.org/10.1016/j.renene.2015.02.023</a>
Download date	2023-06-10 08:43:02
Item downloaded from	<a href="http://hdl.handle.net/10468/1792">http://hdl.handle.net/10468/1792</a>



# UCC

**University College Cork, Ireland**  
Coláiste na hOllscoile Corcaigh

# Quantifying the value of improved wind energy forecasts in a pool-based electricity market

E. V. Mc Garrigle<sup>a,\*</sup>, P. G. Leahy<sup>a,b</sup>

<sup>a</sup>*School of Engineering, University College Cork, College Road, Cork, Ireland.*

<sup>b</sup>*Environmental Research Institute, University College Cork, Lee Road, Cork, Ireland.*

---

## Abstract

This work illustrates the influence of wind forecast errors on system costs, wind curtailment and generator dispatch in a system with high wind penetration. Realistic wind forecasts of different specified accuracy levels are created using an auto-regressive moving average model and these are then used in the creation of day-ahead unit commitment schedules. The schedules are generated for a model of the 2020 Irish electricity system with 33% wind penetration using both stochastic and deterministic approaches. Improvements in wind forecast accuracy are demonstrated to deliver: (i) clear savings in total system costs for deterministic and, to a lesser extent, stochastic scheduling; (ii) a decrease in the level of wind curtailment, with close agreement between stochastic and deterministic scheduling; and (iii) a decrease in the dispatch of open cycle gas turbine generation, evident with deterministic, and to a lesser extent, with stochastic scheduling.

*Keywords:*

---

\*Corresponding author, Tel.: +353 21 490 3767

*Email address:* e.mcgarrrigle@umail.ucc.ie (E. V. Mc Garrigle)

1 **1. Introduction**

2 Wind power is given priority dispatch over the conventional, non-renewable  
3 sources of generation in most electricity markets. For this reason Transmis-  
4 sion System Operators (TSOs) may view wind generation as a negative load.  
5 As forecasts of wind generation and system demand are required for schedul-  
6 ing generator dispatch, wind power forecast inaccuracy can be viewed as  
7 a component of the net system load forecast inaccuracy. In systems with  
8 high wind penetrations, load forecasts are more accurate than wind power  
9 forecasts [1], therefore it is wind power forecasts that are the largest source  
10 of uncertainty in terms of net system demand requirements. Furthermore,  
11 wind generation, unlike conventional forms of generation, has little control-  
12 lable variability in its output, with the exception of wind curtailment, and to  
13 compound the issue, this variability has a low degree of predictability with  
14 very large instantaneous errors in forecasts occurring frequently. There is,  
15 therefore, a considerable uncertainty associated with wind generation fore-  
16 casting, with root mean squared errors of up to 20% for 24-hour ahead pre-  
17 dictions reported [2].

18 The Republic of Ireland (ROI) and Northern Ireland (NI) have agreed  
19 to generate 40% of electricity from renewable sources in response to the  
20 ambitious renewable energy targets set by the European Union for its member

21 states [3, 4, 5]. Due to this, a large amount of wind capacity will be added  
22 to the system which will result in a large proportion (in excess of 30%) of  
23 All-island of Ireland (AI)<sup>1</sup> electricity generation coming from a single source  
24 that is dependent on instantaneous weather conditions across the region.

### 25 *1.1. Forecasting*

26 Wind forecasting is important for the efficient running of the AI electricity  
27 system as the scheduling of large generators takes place one day in advance of  
28 dispatch[6]. In the event of the wind forecast being inaccurate, the day-ahead  
29 unit commitment (DA UC) schedule will mistakenly commit too little or too  
30 much capacity from cheaper large generators, resulting in additional costs  
31 due to such generators being run at reduced efficiency levels or by bringing  
32 on additional, more expensive, open cycle gas turbines (OCGTs) to make up  
33 the system demand requirement. It is viewed that the improvement of wind  
34 forecasts has potential benefits for TSOs, wind farm operators in deregulated  
35 electricity markets, non-wind generation operators in the same markets and  
36 electricity traders [2]. It is recognised by the TSO's that improving the  
37 accuracy of wind power forecasts, particularly the 48 hour ahead forecast  
38 used in optimising the DA UC schedule, is worth investing in [7] and it has  
39 been stated that increasing the penetration of wind in the AI system may be  
40 achieved by improvements in the accuracy of wind power forecasting [8].

---

<sup>1</sup>All-island of Ireland (AI), consisting of Northern Ireland (United Kingdom) and the Republic of Ireland.

41 Previous works have used different methods to simulate wind forecasts for  
42 use in UC and economic dispatch studies of electricity systems. For example,  
43 auto-regressive moving average (ARMA) methods were used in [9] to create  
44 12-36 hour ahead wind generation forecast time series with a mean absolute  
45 error (MAE) of 7.8%, and in [10, 11, 12] where the Wilmar planning tool  
46 was used to develop wind forecast scenarios for the AI system. The use of  
47 ARMA in the simulation of wind forecasts was first documented by [13]. The  
48 method used in [14] forms the basis of the ARMA component of the wind  
49 power forecast error model used in this paper.

50 It has been shown in previous work that, in the presence of wind forecast  
51 errors, stochastic scheduling approaches perform better than deterministic  
52 approaches [10, 15, 16]. Stochastic methods have been used in a number  
53 of other studies to determine the effects of wind forecast uncertainty on  
54 electricity systems [11, 17, 18] .

### 55 *1.2. Wind forecasting effects on systems*

56 Rogers et al. [19] acknowledged that one of the greatest challenges as-  
57 sociated with the integration of wind generation will be formulating the DA  
58 UC schedule, due to the limited accuracy of wind forecasts. The authors of  
59 that study stated that errors in wind forecasts must be taken into account  
60 when the DA UC schedule is created in advance.

61 On examination of the literature, to the authors knowledge, there has  
62 been no systematic attempt to estimate the effects of realistic, incremental

63 improvements of wind forecast accuracy on electricity system scheduling. A  
64 number of studies have estimated the effects of wind forecasts on electricity  
65 systems containing significant penetrations of wind energy [10, 11, 12, 15, 17,  
66 20, 21, 22] however these studies compare a single forecast scenario against  
67 the 'perfect foresight' scenario. It was attempted in [23] to quantify the effects  
68 of variance and skewness of wind forecast error. While it is noted that these  
69 works focus on several different electricity systems with varying penetrations  
70 of wind energy, they all share some common conclusions, such as negligible  
71 wind curtailment. On comparison of the works above there are differences  
72 reported in the savings of total system costs ranging from 0.02% to 1.2%  
73 when accounting for the difference between actual wind forecast errors and  
74 perfect foresight.

75 The work presented in this paper differs from the aforementioned studies  
76 in comparing how the DA UC schedules are used, as large generators were  
77 not relaxed in [15, 18] and these studies did not simulate over a full year.  
78 It has also been shown in [24] that using shorter time steps in the schedul-  
79 ing simulation results in higher system costs, due to the higher accuracy of  
80 modelling, although this work assumed perfect foresight for wind forecasts.

### 81 *1.3. Reserve provision*

82 Previous works have looked at the effect of wind forecasting on system  
83 reserve provision [9, 10, 11, 20, 21, 25]. It has been shown that increasing in-  
84 stalled wind capacity increases replacement reserve requirements [11, 20, 22].

85 In [11] it is shown that there are only small changes in spinning reserve re-  
86 quirements for different installed wind capacities and therefore changes in  
87 wind forecast accuracy should have a negligible effect on spinning reserve  
88 capacities overall. However, the latter study does show large increases in the  
89 requirement for replacement reserve as the forecast horizon is extended and  
90 this could also be interpreted as an increase in replacement reserve necessary  
91 with decreasing wind forecast accuracy. From this it can be assumed that  
92 wind forecast accuracy will have small effects in terms of spinning reserve and  
93 therefore spinning reserve will not be considered for the purpose of this study.  
94 It is recognised however that wind forecast accuracy will have an effect on  
95 the provision of replacement reserve. Replacement reserve is provided over  
96 the time frame of 20 minutes to four hours [26]. This results in replacement  
97 reserve mainly being provided by off-line OCGTs. To help mitigate the ef-  
98 fects of not explicitly considering replacement reserve provision the published  
99 AI operational constraints [27] include a constraint that 400MW of OCGT  
100 capacity must not be scheduled any one time in order to act as replacement  
101 reserve.

## 102 **2. The Model**

103 The model implemented here attempts to replicate the running of the  
104 Irish Single Electricity Market (SEM)<sup>2</sup>. Six wind forecast accuracy scenarios

---

<sup>2</sup>The SEM area consists of Northern Ireland (part of the UK) and the Republic of Ireland.

105 are used to illustrate the effects of wind forecast errors on the system. The  
 106 first scenario has a 0 MAE% forecast error i.e. the assumption of perfect  
 107 foresight. The other five wind forecast accuracy scenarios have reducing wind  
 108 forecast accuracy of 2, 4, 6, 8 and 10% MAE. The system is modelled using  
 109 both stochastic and deterministic approaches under all of these accuracy  
 110 scenarios. There are ten model runs of each of the five 2-10% MAE wind  
 111 forecast accuracy scenarios and a single run of the perfect foresight scenario.  
 112 This results in 51 model runs each for both the stochastic and deterministic  
 113 scheduling methods. The results to be presented within each non-zero MAE  
 114 scenario will be averages based on forecasts from the ten wind forecast runs.

115 The power systems simulation tool PLEXOS® [28] was used in this study.  
 116 This software is widely used for the simulation of mixed integer unit com-  
 117 mitment/economic dispatch problems (e.g. [29, 30]). Version 6.208 (R08)  
 118 of PLEXOS® was run on a Dell Precision T7500 with a Intel® Xeon®  
 119 CPU of six X5650 cores. The XpressMP solver was used at a relative gap of  
 120 0.5 for the DA model and 0.05 for the RT model with each stochastic and  
 121 deterministic model run taking an average of 16 and 2 hours respectively.

Table 1: Scheduling time-line.

<b>Time</b>	<b>Event</b>
12.00hr d-1	Wind forecasts are submitted to System Operator
16.00hr d-1	DA UC schedule is created and submitted to generators
06.00hr d	DA UC schedule commences
05.30hr d+1	DA UC schedule ends
06.00hr d+1	Lookahead period for model optimisation begins
11.30hr d+1	Lookahead period for model optimisation ends



122 *2.1. Scheduling*

123 The model is run on the forecast simulation year of 2020. To accurately  
124 take account of the forecast errors and forced outages that occur on the  
125 system and to help replicate the running of the SEM [6], two separate models  
126 run in step with each other using an interleaved optimisation tool which is  
127 described in more detail in [31]. It was assumed that the scheduling times  
128 are as shown in Table 1 which are taken from [6, 32, 33, 34]. From this,  
129 the assumption was made that an 18-42hr point wind forecast would best  
130 represent the forecast on which the Irish TSOs<sup>3</sup> base the DA UC schedule.

131 *2.1.1. Day-ahead model*

132 The day-ahead (DA) model's only function is to create the DA UC sched-  
133 ule for generators and interconnectors. These schedules are created based on  
134 the data available on the day prior to dispatch. This necessitates the use  
135 of wind forecasts and also means that forced outages cannot be taken into  
136 account. The DA UC schedule fixes large generators to be on-line with spec-  
137 ified start times and lengths of generation. At the end of the DA simulation  
138 day  $d_1$  the DA UC, interconnector and generation schedules are passed for-  
139 ward to the real-time (RT) model to be included in the RT run of the same  
140 simulation day  $d_1$ . For the deterministic optimisation of the system schedule,  
141 the DA model receives only the median wind forecast. Therefore, in the de-

---

<sup>3</sup>The SEM contains two TSOs, EirGrid in the Republic of Ireland and the System Operator for Northern Ireland (SONI)

142 deterministic case, the DA model has no capability to evaluate the associated  
143 wind forecast uncertainty.

144 The DA model for the stochastic optimisation of wind forecasts uses a  
145 scenario-wise decomposition method instead of the deterministic scheduling  
146 used in the RT model. This allows the DA model to evaluate different de-  
147 grees of wind power forecast error together with their associated probability  
148 of occurrence. Therefore it is a cost minimisation problem dependent on the  
149 probability of expected results. The model receives a wind power forecast  
150 file containing the median forecast (corresponding to 50% probability of ex-  
151 ceedence) and upper and lower quantiles of wind power forecast error with  
152 associated cumulative exceedance probabilities (5.0, 27.4, 72.6 and 95.0%),  
153 described in detail in Section 2.2. Each of the five wind forecast quantiles is  
154 used to create five separate “model samples”. From the five model samples a  
155 single set of DA UC decisions is optimised for each simulation day. The DA  
156 UC schedule is created from the economic dispatch minimisation from the  
157 likelihood of occurrences of the five separate “model samples”. This is done  
158 through the use of UC non-anticipativity penalty costs associated with all  
159 the scheduled large generators and interconnectors, making the UC schedule  
160 of these selected generators and interconnectors match across all five “model  
161 samples”. This set of DA UC decisions provides the lowest-cost solution in  
162 the DA model as the expected inputs of the RT model and therefore realis-  
163 tically reflects the probability of actual wind generation diverging from the  
164 forecast value between the DA and RT scheduling.

165 *2.1.2. Real-time model*

166 The purpose of the real-time (RT) model, which uses deterministic schedul-  
167 ing, is to reschedule the AI system within the constraints imposed by the DA  
168 UC schedule, in response to realised actual wind generation and forced out-  
169 ages. The RT model permits restricted rescheduling of generators committed  
170 in the DA UC schedule, as well as allowing all committed generators to alter  
171 their generation output within their operational limits. Partial rescheduling  
172 of large generators outside the UC schedule allows for more realistic simu-  
173 lation of open cycle gas turbine usage on the system where it was assumed  
174 that 200GWh of OCGT generation per annum would occur in the base case  
175 scenario of perfect wind foresight. This method of post unit-commitment  
176 relaxation (PUCR) is described in detail in [35]. At the end of the RT model  
177 run of the simulation day  $d_1$ , the initial conditions of all generators are sent  
178 back to the DA model to be included in the start of the DA run of the next  
179 simulation day  $d_2$ . The schedules of the interconnectors and some generators  
180 (hydro, waste, biomass and CHP) are created directly from the DA model  
181 and are fully fixed, with no possibility of relaxation by the RT model.

182 *2.1.3. Formal description of the RT and DA models*

183 The DA and RT models may be described by the following equations:

$$DA(d-1|d) = f(WF(d), IC_{info}, Model_{s,info}(d))$$

where  $d = 1$

$$DA(d-1|d) = f(WF(d), IC_{info}, RT.End_{syst,con}(d-1), Model_{s,info}(d)) \quad (1)$$

where  $d = 2, 3, 4, \dots, n$

$$RT(d|d) = f(WA(d), DA.UC_{puer}(d), DA.IC_{fix}(d), DA.Gen_{fix}(d), FO(d), Model_{s,info}(d)) \quad (2)$$

where  $d = 1, 2, 3, \dots, n$

$$Model_{s,info}(d) = Sys_{demand}(d), F_{cost}, OP_{const}, Gen_{const}, GB_{system,info}(d), Maint(d) \quad (3)$$

184 where:  $DA(d-1|d)$  refers to the DA model solved for day  $d$  on day  $d-1$ ;  
 185  $Model_{s,info}(d)$  is the system information given to both DA and RT mod-  
 186 els;  $Maint(d)$  is the maintenance schedule set for both DA and RT models;  
 187  $RT(d|d)$  refers to the RT model solved for day  $d$  on day  $d$ ;  $f(WF(d))$  is the  
 188 DA wind energy forecast and uncertainty quantiles time series;  $f(WA(d))$  is

189 the realised actual wind energy time series on day  $d$ ;  $IC_{info}$  is the intercon-  
 190 nector characteristics;  $RT.End_{syst,con}$  is the end system conditions from the  
 191 RT model, used for setting subsequent DA initial conditions;  $DA.UC_{puer}(d)$   
 192 is the DA UC schedule with post unit commitment relaxation;  $DA.IC_{fix}(d)$   
 193 is the fixed interconnector flow schedule from DA model;  $DA.Gen_{fix}(d)$  is  
 194 the fixed generator flows schedule on day  $d$  from DA model (hydro, waste,  
 195 biomass and CHP units);  $FO(d)$  indicates forced outages;  $Sysdemand(d)$  is  
 196 the system demand;  $OP_{const}$  represents the operational constraints;  $Genconst$   
 197 is the generator profile constraints, ensuring minimum capacity factors and  
 198 reducing ramp cycling (Hydro, Waste, Biomass, Peat and CHP units);  $F_{cost}$   
 199 is the fuel costs;  $GB_{systeminfo}$  is the Great Britain wind generation, system  
 200 demand and price settings;  $d$  is the day number in 2020; and  $n$  is the number  
 201 of simulation days (366 days in 2020).

## 202 2.2. Generating wind forecast data

203 The Irish TSO, EirGrid, publishes up to date wind generation and wind  
 204 forecast profiles online allowing wind forecast error time series to be cal-  
 205 culated in order to analyse the evolution of forecast error over time [36].  
 206 EirGrid also has published the annual MAE of forecasts of 0-48 hour lead  
 207 times for each of the years 2008-2010 showing the decrease in accuracy of  
 208 a forecast with increasing lead time [37]. A forecast with a 2-day horizon  
 209 is regularly published for NI and ROI by SEMO [38] but this is frequently  
 210 updated overwriting existing information so “pure” point forecasts are not

211 available from this source.

212 For this study it was necessary to synthesise wind power forecasts at  
 213 specified accuracy levels. From studying the literature it was decided that  
 214 the use of autoregressive moving average (ARMA) models would best repli-  
 215 cate wind power forecast errors. Using an ARMA model it is possible to  
 216 issue synthetic wind power forecast time series that are statistically similar  
 217 to real wind forecasts. An additional benefit of using ARMA models, which  
 218 is demonstrated here, is the ability to generate specific levels of errors and as-  
 219 sociated probabilities of occurrence with the generated wind power forecasts.  
 220 This gives much more detailed information for use in the DA UC economic  
 221 dispatch decisions.

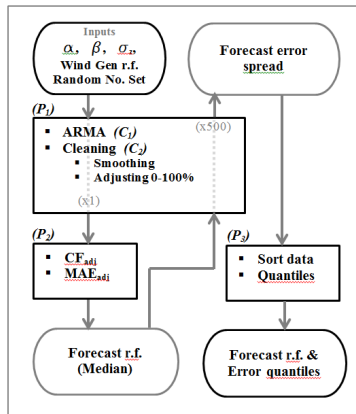


Figure 1: Flow chart describing the process of generating the wind forecast and associated error profiles

222 A code was developed in Matlab R2010b (Mathworks, USA) consisting  
 223 of three processes in order to realistically replicate the wind forecasts and

224 associated errors, illustrated in Fig. 1. The first step was to determine the  
225 parameters of the ARMA model  $\alpha$ ,  $\beta$  and  $\sigma_z$ . The parameter  $\beta$  was chosen  
226 first, this was determined from EirGrid’s reported wind forecast error time  
227 series [36]. It was determined through least-squares fitting that  $\beta = -0.1$  best  
228 replicated the actual error growth with forecast lead time when the ARMA  
229 model was run at a 30 minute time resolution. The target annual MAE  
230 levels for different lead times are shown in Fig. 2, based on [37], which the  
231 generated wind forecasts aimed to mimic. Using the first process,  $P_1$ , of the  
232 method illustrated in Fig. 1, the parameters  $\alpha$  and  $\beta$  were determined based  
233 on the 48 intervals (of 30 minutes each) of 367 days for 20 years, meaning the  
234 creation of 352,320 random numbers with a near-constant statistical spread  
235 between separate runs of  $P_1$ . For the parameter  $\alpha$ , a value of 0.99 was  
236 determined to give the best fit to the error growth profile shown in Fig. 2  
237 for the time period 18-42hrs for the chosen value of  $\beta$ . The last parameter  
238  $\sigma_z$  (0.390, 0.980, 1.550, 2.120, 2.695) was found to vary depending on the  
239 scenario of MAE (2, 4, 6, 8, 10% respectively).

240 The first process,  $P_1$  in Fig. 1, consists of two main components. This  
241 code is run twice, first to create the median wind forecast and then to create  
242 the forecast error spread. The forecast error spread is created from the me-  
243 dian wind forecast which is used as the base forecast from which a spread of  
244 500 randomised forecast time series are generated, shown in Fig. 3, using the  
245 same ARMA parameters used in the creation of the median wind forecast.  
246 The first component,  $C_1$  in Fig. 1, of  $P_1$  is an ARMA (Eqn. 4) model with

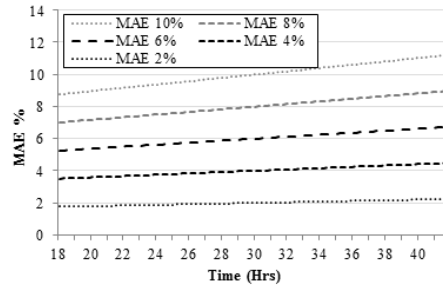


Figure 2: Forecast MAE over lead times of 18-42hrs, based on averages calculated over multiple issues of forecasts reported by EirGrid [37].

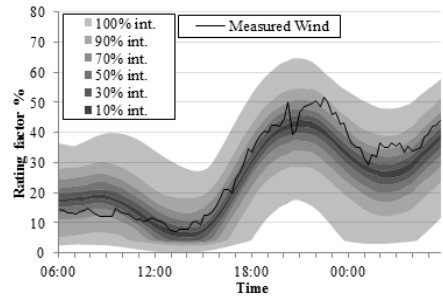


Figure 3: ARMA-generated DA interval wind forecast profile for the 6% MAE scenario and measured wind generation for the 2<sup>nd</sup> April of the test year.

247 three controlling parameters ( $\alpha$ ,  $\beta$  &  $\sigma_z$ ) which creates 96 half hour inter-  
 248 vals representing 0-48 hour point forecasts for the 366+1 days. The random  
 249 numbers produced have a mean of zero and a standard deviation of  $\sigma_z$  and  
 250 are normally distributed. This ARMA model was derived from that of [14],  
 251 and is represented by:

252



$$\begin{aligned}
Z(0) &= 0 \\
Z(t) &= \text{random numbers of standard deviation } \sigma_z \\
X(0) &= Z(0) \\
X(t) &= \alpha X(t-1) + Z(t) + \beta Z(t-1) \\
& \qquad \qquad \qquad (t=1,2,3,\dots,N)
\end{aligned} \tag{4}$$

253

254 where:  $\alpha$ ,  $\beta$  &  $\sigma_z$  are the ARMA controlling parameters;  $t$  = time step (in-  
255 tervals of 30 minute for 2 days);  $Z(t)$  = a random number for interval “ $t$ ”  
256 with a standard deviation of  $\sigma_z$ ;  $X(t)$  = the wind energy forecast error for  
257 interval “ $t$ ”;  $N$  = number of intervals in data.

258

259 The second, larger component,  $C_2$ , of the first process  $P_1$ , in Fig. 1, allows  
260 for the manipulation of the ARMA wind forecast into a more statistically  
261 representative time series. This takes the forecast error created by the first  
262 component and based on this, assesses the forecast error within the 18-42  
263 hour-ahead time window of interest determined from Table 1. The 367 “18-  
264 42 hour-ahead time windows of interest” are concatenated sequentially, one  
265 after another, making a complete wind forecast error time series. The wind  
266 forecast error is then added to the actual wind power generation time series,  
267 from ROI for the mean wind speed year of 2011 [36], giving the simulated  
268 wind power forecast time series.

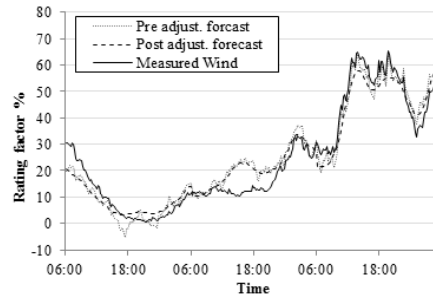


Figure 4: Wind forecast adjustment for the 6% MAE scenario and measured wind profile for the 21<sup>st</sup> to 23<sup>rd</sup> February of the test year.

269 The wind forecast must be adjusted as the generated values may some-  
 270 times fall outside the limits of 0-100% of installed wind capacity. Therefore,  
 271 using Eqn. 5 the assumption was made that all data under the percentage  
 272 rating factor ( $p$ ) would be adjusted upwards to avoid negative generation.  
 273 This was achieved by a linearly varying scaling factor with a value of 0 at the  
 274 minimum value of the wind forecast generation profile and a value of 1 at  $p$ ,  
 275 the results of which are shown in Fig. 4 where  $p$  was taken as five. Values  
 276 greater than 100%, due to their seldom occurrence, are simply set to 100%  
 277 rating factor.

278 In the creation of the predicted (median, 50%) wind forecast, an extra  
 279 adjustment ( $P_2$  in Fig. 1) is added, where the data is uniformly adjusted  
 280 by a multiplier to achieve the exact MAE% required. This is followed by an  
 281 adjustment to achieve the same annual capacity factor as the actual wind  
 282 generation. This is necessary as the limited number (367) of random forecast  
 283 series within a year does not always guarantee convergence precisely at the

284 desired value of the MAE. This also helps to reduce variations in the results  
 285 between runs in one MAE scenario. This adjustment is described by:

$$WF_{ad}(t) = |WF_{min}| \left( \frac{p - WF(t)}{p + |WF_{min}|} \right) \quad (5)$$

286 (t=1,2,3,...,N)

287 where:  $t$  indicates the time step (15 minute intervals for 367 days);  $WF(t)$  is  
 288 the set of wind forecasts issued at interval “ $t$ ”;  $WF_{min}$  is the minimum value  
 289 of the wind forecast set WF;  $WF_{ad}(t)$  is the adjusted set of wind forecast  
 290 issued at interval “ $t$ ”;  $N$  is the number of intervals in the data;  $p$  is the  
 291 percentage rating factor below which Eqn. 5 is applied.

292 The third and final process in Fig. 1,  $P_3$ , creates the error quantiles. The  
 293 empirical error quantiles are taken from the sorted spread of wind forecast  
 294 time series created. The error quantiles were chosen at 5.0, 27.4, 50.0, 72.6  
 295 and 95.0% probabilities of occurrence, shown in Fig. 5, to best reflect the  
 296 statistical spread of the wind forecast errors. It should be noted that the  
 297 empirical quantiles method was chosen over distribution fitting as the error  
 298 distribution is not normal at rating factors less than 7% and greater than  
 299 93%, and due to the findings of [39] that it is a simplification to assume that  
 300 wind power forecast error is of a near-normal distribution.

### 301 *2.3. All-island system and constraints*

302 The AI system demand for 2020 was developed from 2012 AI data given  
 303 in [40]. The 30-minute resolution AI system demand time series, from a

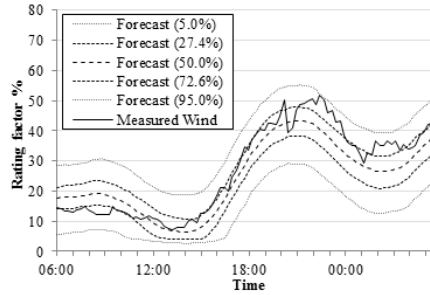


Figure 5: The five cumulative probability levels of DA wind forecast profile quantiles given to PLEXOS for the 6% MAE scenario and measured wind generation for the 2<sup>nd</sup> April of the test year.

304 peak demand of 6496MW and annual total energy requirement (TER) of  
 305 36.56TWh was manipulated to achieve a peak demand of 7317 MW and  
 306 TER of 39.85TWh in 2020 [41]. It is then scaled between the two nodes NI  
 307 and ROI at 0.252 and 0.748 respectively, based on the present-day ratio of  
 308 demand between the two nodes.

309 The generation portfolio is based on what is predicted to be present on  
 310 the AI electricity system in 2020 [41]. The generator specifications are taken  
 311 from [40]. Changes to the generation portfolio, not present in [40], for ROI  
 312 and NI include the removal of all oil-fired power stations in ROI along with  
 313 the units B4-6 in NI, and the addition of generators which are shown in Table  
 314 2.

315 Only one of the two the OCGTs, Cahir or Culleen, was retained due  
 316 to the recommendation to only include three of the four currently-planned  
 317 OCGTs in the model of [41]. The new peaker plants, aggregated generation  
 318 units (AGU) that mimic OCGT plants, and the new demand side units are

Table 2: Additions to the generation portfolio [41] not present in [40].

Generator name	Capacity (MW)
<b>ROI</b>	
Cahir or Culleen (OCGT)	98
NO1 (OCGT)	98
Caulstown (OCGT)	55
AE1 (DSU)	12
DAE (DSU)	29
Wind	3786
Dublin waste to energy	62
Small scale hydro	21
Biogas from landfill	43
Three biomass plants (CHP)	50 (x3)
<b>NI</b>	
Aggregated generation unit (AGU)	47
Wind	1278
NI waste to energy	17
Small scale hydro	4
Tidal	154
Biogas from landfill	23
Small scale biogas	30
Three biomass plants	15 (x3)
Small scale biomass	14

319 all based on the specifications of the modern OCGT in Kilroot (KGT3) due  
320 to it being most recent OCGT addition to the SEM. Small scale hydro, tidal,  
321 small biofuel energy plants have also been included in keeping with [41]. The  
322 non-wind priority dispatch plants were modelled with a zero generation cost  
323 in keeping with [42]. Fuel prices for 2020 were taken from [43]. The model  
324 also includes start-up costs and start-up fuel off-take which were taken from  
325 [44]. A carbon tax was included at €30 per tonne of CO<sub>2</sub>. Interconnection  
326 between the SEM and Great Britain (GB) is represented by the ROI-GB  
327 East West Interconnector (EWIC) at 500MW and Moyle between NI and

328 GB at 450MW in winter and 410MW in summer.

329 Operational constraints have a large effect on the results, particularly in  
330 terms of dispatch and wind curtailment [29]. The operational constraints  
331 applied here are based on [27], conservatively modified to reflect the changes  
332 that are likely occur by 2020, including increasing maximum flow between  
333 ROI and NI to 2000MW both ways, and raising the system-wide limit on  
334 non-synchronous sources to 70% of total generation and exports [29, 45].

### 335 3. Results

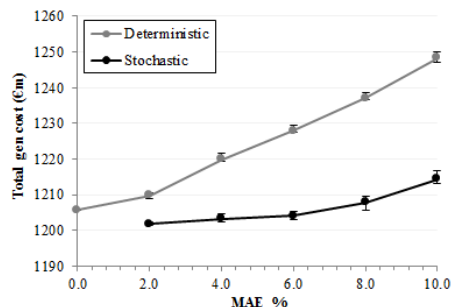


Figure 6: The mean total generation costs (€m) with standard deviation whiskers for both deterministic and stochastic modelling at different forecast accuracies (MAE%).

336 The results presented here are averaged over ten separate runs for each  
337 MAE scenario with standard deviations of the results shown only for total  
338 costs (Fig. 6). The key result of this work is the relationship between wind  
339 forecasting accuracy and total generation costs<sup>4</sup>. There is a clear trend of

---

<sup>4</sup>Total generation costs for AI refers only to cost of the conventional generation and does not include the cost of subsidies for renewables.

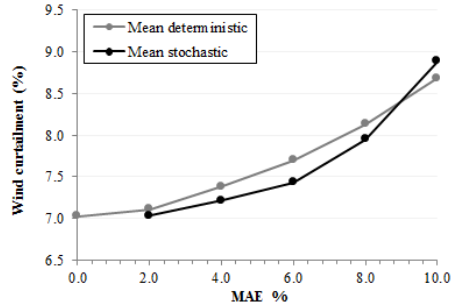


Figure 7: The mean percentage of wind curtailment for both deterministic and stochastic modelling at different forecast accuracies (MAE%).

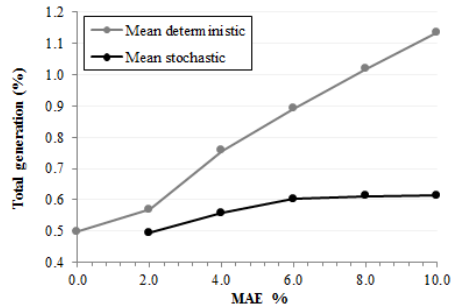


Figure 8: The mean OCGT generation as a percentage of total generation for both deterministic and stochastic modelling at different forecast accuracies (MAE%).

340 total generation costs reducing with improvements to wind forecasting ac-  
 341 curacy shown in Fig. 6. The figure also shows that the magnitude of the  
 342 savings is very dependent on the method of scheduling, be it deterministic  
 343 or stochastic. When using deterministic scheduling, total generation savings  
 344 show an almost linear relationship of € 5m (0.41%) per year for every per-  
 345 centage point reduction in forecast MAE from 10% to 2%. However, when  
 346 stochastic scheduling is employed, there is reduced advantage for improv-

347 ing wind forecast accuracy below 6% MAE, with savings of € 0.5m (0.04%)  
 348 per year for every percentage point decrease below this level. However, a  
 349 clear advantage of improving wind forecast accuracy from 10% to 6% MAE  
 350 remains, with € 2.5m (0.20%) savings per year for every percentage point  
 351 decrease in this range. The dependence of wind curtailment (Fig. 7) and  
 352 OCGT generation (Fig. 8) on wind forecast errors are also presented for  
 353 both scheduling methods.

Table 3: Mean number of OCGT start-ups, mean emissions intensity (kg/MWh), and mean of total generation (GWh) in the SEM for both deterministic and stochastic modelling at different forecast accuracies (MAE%).

	<b>Forecast scenario (MAE)</b>					
<b>OCGT</b>	<b>0%</b>	<b>2%</b>	<b>4%</b>	<b>6%</b>	<b>8%</b>	<b>10%</b>
Deterministic	381	528	617	704	792	892
Stochastic	-	433	457	451	445	439
<b>Emissions</b>	<b>0%</b>	<b>2%</b>	<b>4%</b>	<b>6%</b>	<b>8%</b>	<b>10%</b>
Deterministic	339.5	338.5	339.4	341.4	342.8	342.9
Stochastic	-	337.5	337.2	338.0	338.2	339.6
<b>Total generation</b>	<b>0%</b>	<b>2%</b>	<b>4%</b>	<b>6%</b>	<b>8%</b>	<b>10%</b>
Deterministic	40.22	40.48	40.49	40.46	40.48	40.51
Stochastic	-	40.38	40.30	40.18	40.05	39.88



Table 4: The mean percentage of total generation for the dispatch of generator technology type for deterministic modelling at different forecast accuracies (MAE%).

Generator type	Forecast scenario (MAE)					
	0%	2%	4%	6%	8%	10%
OCGT	0.50	0.57	0.76	0.89	1.02	1.14
CCGT	36.35	37.02	37.03	36.83	36.83	37.19
Steam Turbines	18.22	17.89	17.83	17.99	18.03	17.78
CHP and Waste	4.26	4.20	4.19	4.19	4.19	4.19
Wind	32.87	32.63	32.53	32.44	32.27	32.06
Other RES-E	7.79	7.68	7.67	7.66	7.66	7.65

Table 5: The mean percentage of total generation for the dispatch of generator technology type for stochastic modelling at different forecast accuracies (MAE%).

Generator type	Forecast scenario (MAE)					
	0%	2%	4%	6%	8%	10%
OCGT	-	0.49	0.56	0.60	0.61	0.61
CCGT	-	36.79	36.74	36.49	36.55	36.65
Steam Turbines	-	17.96	17.88	17.96	17.88	17.89
CHP and Waste	-	4.26	4.28	4.33	4.39	4.44
Wind	-	32.74	32.73	32.74	32.66	32.47
Other RES-E	-	7.77	7.81	7.86	7.91	7.95

#### 354 4. Discussion

355 The perfect foresight (0% MAE) scenario is only presented to illustrate  
356 a lower bound to system costs incurred due to wind forecasting errors. In  
357 reality, it is unlikely that wind forecast accuracy for this system could be im-  
358 proved beyond the 2-4% MAE range. It was apparent from the work carried  
359 out on creating the wind forecasts in Section 2.2 that the 2% MAE wind fore-  
360 cast very closely resembles the result of time-smoothing of the actual wind  
361 generation. Therefore this discussion will focus on comparing the changes

362 of effects on the AI electricity system from improvements in wind forecast-  
363 ing from 8% MAE, representative of the present-day accuracy of 7-9% MAE  
364 [37], to 4% MAE, assuming this to be a more realistic limit to possible future  
365 improvements.

366 It is important to note that there is some variation in the total AI gen-  
367 eration between all the scenarios which distort the results. These variations  
368 are shown in Table 3 and occur due to changes in the scheduling of the in-  
369 terconnectors and the use of pumped hydro energy storage plant in the RT  
370 model. Due to these variations it is necessary to scale all total cost data in  
371 Fig. 6 to allow for comparisons between the scenarios to be made.

372 Overall, the results show that taking account of probabilistic wind fore-  
373 casts by employing stochastic scheduling creates a much more efficient DA  
374 UC schedule than can be obtained from the deterministic approach. Chang-  
375 ing from deterministic to stochastic scheduling leads to a greater saving than  
376 a 4% improvement in wind forecasting accuracy from present-day levels.

#### 377 *4.1. Costs*

378 The results show that with improvements in wind forecast accuracy from  
379 8% to 4% MAE, there are considerable savings available in terms of total  
380 system costs. These savings amount to 0.50% and 1.64% respectively, de-  
381 pending on whether deterministic or stochastic scheduling is used. This is a  
382 respective saving for stochastic and deterministic scheduling of € 1.2m and  
383 € 4.5m per year for every percentage point decrease in forecast MAE between

384 8% and 4% MAE.

#### 385 *4.2. Dispatch of renewables*

386 With improvements in wind forecasts there is a reduction in the quantity  
387 of wind curtailment, shown in Fig. 7. There is very close agreement between  
388 the stochastic and deterministic scheduling for wind curtailment across the  
389 full range of scenarios and with the greatest reductions in wind curtailment  
390 occurring in the 10-4% range of MAE. There is a decrease in wind curtailment  
391 possible from 8% to 7.25% or 105 GWh in the 8% to 4% forecast MAE range.  
392 This result differs with work reviewed [10, 11, 12, 15, 17, 20, 21, 22] which  
393 finds that wind forecasting has a negligible effect on wind curtailment and  
394 continues to support the initial findings published in [29].

#### 395 *4.3. Dispatch of conventional generators*

396 Similar to the effects on total generation costs, the effects on generator  
397 technology dispatch from wind forecast inaccuracies is much more apparent  
398 in deterministic than in stochastic scheduling, this being evident in Tables 4  
399 & 5. It is shown in Fig. 8 that OCGT generation reduces almost linearly with  
400 wind forecast accuracy improvements when using the deterministic schedul-  
401 ing, with decreases in OCGT generation of 23% possible if wind forecast  
402 MAE is reduced from 8% to 4%. However while OCGT generation is also  
403 shown to reduce with wind forecast error under stochastic scheduling, this is  
404 to the lesser extent of 8%.

405 The trends in the number of OCGT start-ups shown in Table 3 very  
406 closely reflect the OCGT generation trends shown in Fig. 8. There is no  
407 noticeable change in the number of starts for the different wind forecast  
408 accuracies when using stochastic scheduling but when using deterministic  
409 scheduling there is an almost linear decrease in the number of OCGT start-  
410 ups required with improvements in the accuracy of wind forecasting.

411 There is no clear relationship evident in Tables 4 & 5 between the propor-  
412 tion of generation from CCGTs or steam turbines and improvements in wind  
413 forecast accuracy under either deterministic or stochastic scheduling. There  
414 is an apparent general trend of improvements in the carbon dioxide emission  
415 intensity with wind forecast improvements shown in Table 3, despite some  
416 variations occurring due to the sensitivity of CO<sub>2</sub> emissions to the coal-gas  
417 generation ratio.

## 418 **5. Conclusion**

419 The work presented here quantifies the value of wind forecast accuracy  
420 to an electricity system with high wind penetration, and in doing so helps  
421 to justify further investment in improving wind forecasting techniques. The  
422 results show that with a reduction in wind forecast errors from 8% MAE to  
423 4% MAE, there are available savings in terms of total system costs under  
424 both stochastic and deterministic scheduling of 0.50% and 1.64% respec-  
425 tively. Operational advantages also come from improved wind forecasts, as  
426 there is general agreement between stochastic and deterministic scheduling

427 in relation to wind curtailment, showing a reduction of 9% in wind curtail-  
428 ment. Improved wind forecasts also are shown to have an effect on OCGT  
429 scheduling with realistic possible decreases in OCGT generation of 23% us-  
430 ing deterministic scheduling and 8% using stochastic scheduling. From this,  
431 there are clear benefits in improving the quality of wind energy forecasts as  
432 it allows for more efficient use of non-wind generators and the transmission  
433 system.

434 This work also strongly highlights the benefit of creating the day-ahead  
435 unit commitment schedule from wind forecasts through stochastic scheduling  
436 rather than deterministic scheduling. This allows the uncertainty associated  
437 with wind forecasts to be accounted for in the UC process. At today's wind  
438 forecast accuracy levels, switching from a deterministic to stochastic schedul-  
439 ing would allow savings of 2.46% of total system costs in 2020.

#### 440 **Acknowledgements**

441 Edward Mc Garrigle was supported by an Embark Postgraduate Schol-  
442 arship awarded by the Irish Research Council. Paul Leahy is supported by  
443 the Stokes Lectureship scheme of Science Foundation Ireland. The support  
444 of Energy Exemplar through the academic licence for PLEXOS®, Dr. John  
445 Paul Deane of UCC and the EirGrid staff are gratefully acknowledged.

446 [1] V. Kurbatsky, N. Tomin, D. Sidorov, and V. Spiryaev, “Application  
447 of two stages adaptive neural network approach for short-term forecast

- 448 of electric power systems,” in *Environment and Electrical Engineering*  
449 *(EEEIC), 2011 10th International Conference on*, pp. 1 –4, May 2011.
- 450 [2] A. M. Foley, P. G. Leahy, A. Marvuglia, and E. J. McKeogh, “Cur-  
451 rent methods and advances in forecasting of wind power generation,”  
452 *Renewable Energy*, vol. 37, no. 1, pp. 1 – 8, 2012.
- 453 [3] “National Renewable Energy Action Plan,” tech. rep., Department of  
454 Communications, Energy and Natural Resources, 2010.
- 455 [4] “Northern Ireland Strategic Energy Framework,” tech. rep., UK, De-  
456 partment of Enterprise, Trade and Investment, 2010.
- 457 [5] The European Parliament, “DIRECTIVE 2009/28/EC on the promo-  
458 tion of the use of energy from renewable sources,” tech. rep., 2009.
- 459 [6] Poyry Energy Consulting, “Trading & Settlement Code, Helicopter  
460 Guide,” tech. rep., Commission for Energy Regulation (Republic of Ire-  
461 land) and Utility Regulator, Electricity, Gas, Water (Northern Ireland),  
462 2007.
- 463 [7] Commission for Energy Regulation and NIAUR, “Wind Generation in  
464 the SEM, Policy for Large-Scale, Intermittent Non-Diverse Generation.  
465 SEM/08/002,” 2008.
- 466 [8] S. Lang and E. McKeogh, “Verification of wind power forecasts provided  
467 in real-time to the Irish Transmission System Operator,” in *Power and*  
468 *Energy Society General Meeting, 2010 IEEE*, pp. 1 –6, July 2010.

- 469 [9] B. C. Ummels, M. Gibescu, E. Pelgrum, W. L. Kling, and A. J. Brand,  
470 “Impacts of wind power on thermal generation unit commitment and  
471 dispatch,” *IEEE Transactions On Energy Conversion*, vol. 22, pp. 44–  
472 51, Mar. 2007.
- 473 [10] A. Tuohy, P. Meibom, E. Denny, and M. O’Malley, “Unit Commitment  
474 for Systems With Significant Wind Penetration,” *Power Systems, IEEE  
475 Transactions on*, vol. 24, pp. 592–601, May 2009.
- 476 [11] P. Meibom, R. Barth, B. Hasche, H. Brand, C. Weber, and M. O’Malley,  
477 “Stochastic Optimization Model to Study the Operational Impacts of  
478 High Wind Penetrations in Ireland,” *Power Systems, IEEE Transactions  
479 on*, vol. 26, pp. 1367–1379, Aug. 2011.
- 480 [12] P. Meibom, “All Island Grid Study Workstream 2(b): Wind Variability  
481 Management Studies,” tech. rep., The Department of Communications,  
482 Energy and Natural Resources, (Republic of Ireland) and The Depart-  
483 ment of Enterprise, Trade and Investment (UK), 2007.
- 484 [13] B. G. Brown, R. W. Katz, and A. H. Murphy, “Time Series Models  
485 to Simulate and Forecast Wind Speed and Wind Power,” *Journal of  
486 Climate and Applied Meteorology*, vol. 23, pp. 1184–1195, 1984.
- 487 [14] L. Soder, “Simulation of wind speed forecast errors for operation plan-  
488 ning of multi-area power systems,” *2004 International Conference On  
489 Probabilistic Methods Applied To Power Systems*, pp. 723–728, 2004.

- 490 [15] J. Wang, A. Botterud, R. Bessa, H. Keko, L. Carvalho, D. Issicaba,  
491 J. Sumaili, and V. Miranda, “Wind power forecasting uncertainty and  
492 unit commitment,” *Applied Energy*, vol. 88, no. 11, pp. 4014 – 4023,  
493 2011.
- 494 [16] P. Pinson, “Wind Energy: Forecasting Challenges for its Operational  
495 Management,” *Statistical Science*, 2013.
- 496 [17] G. Liu and K. Tomsovic, “Quantifying Spinning Reserve in Systems  
497 With Significant Wind Power Penetration,” *Power Systems, IEEE  
498 Transactions on*, vol. 27, no. 4, pp. 2385–2393, 2012.
- 499 [18] A. Papavasiliou and S. S. Oren, “Multi-Area Stochastic Unit Commit-  
500 ment for High Wind Penetration in a Transmission Constrained Net-  
501 work,” 2012.
- 502 [19] A. Rogers, J. O’Sullivan, and I. Dudurych, “Operational tools and poli-  
503 cies for integrating large amounts of variable generation in Ireland and  
504 Northern Ireland,” in *Power and Energy Society General Meeting, 2011  
505 IEEE*, pp. 1 –6, July 2011.
- 506 [20] H. Holttinen, P. Meibom, A. Orths, B. Lange, M. O’Malley, J. O. Tande,  
507 A. Estanqueiro, E. Gomez, L. Sder, G. Strbac, J. C. Smith, and F. van  
508 Hulle, “Impacts of large amounts of wind power on design and operation  
509 of power systems, results of IEA collaboration,” *Wind Energy*, vol. 14,  
510 no. 2, pp. 179–192, 2011.



- 511 [21] M. Fripp, “Greenhouse gas emissions from operating reserves used to  
512 backup large-scale wind power,” *Environmental Science & Technology*,  
513 Nov 2011.
- 514 [22] “Operating Reserve Requirements as Wind Power Penetration Increases  
515 in the Irish Electricity System,” tech. rep., Sustainable Energy Ireland,  
516 2004.
- 517 [23] C. Lowery and M. O’Malley, “Impact of Wind Forecast Error Statistics  
518 Upon Unit Commitment,” *Sustainable Energy, IEEE Transactions on*,  
519 vol. 3, pp. 760–768, Oct 2012.
- 520 [24] J. Deane, G. Drayton, and B. Ó’Gallachóir, “The impact of sub-hourly  
521 modelling in power systems with significant levels of renewable genera-  
522 tion,” *Applied Energy*, vol. 113, no. 0, pp. 152 – 158, 2013.
- 523 [25] C. Weber, “Adequate intraday market design to enable the integration of  
524 wind energy into the European power systems,” *Energy Policy*, vol. 38,  
525 no. 7, pp. 3155 – 3163, 2010.
- 526 [26] EirGrid, “Grid Code, Version 3.5,” tech. rep., EirGrid, 2011.
- 527 [27] EirGrid and SONI, “Operational Constraints, Update 15th April 2013,”  
528 tech. rep., EirGrid and System Operator of Northern Ireland, (SONI),  
529 2013. <http://www.eirgrid.com/media/Operational>
- 530 [28] Energy Exemplar, “PLEXOS for Power Systems,” 2012.  
531 <http://www.energyexemplar.com/>.

- 532 [29] E. Mc Garrigle, J. Deane, and P. Leahy, “How much wind energy will be  
533 curtailed on the 2020 Irish power system?,” *Renewable Energy*, vol. 55,  
534 pp. 544 – 553, 2013.
- 535 [30] A. M. Foley, P. Leahy, and E. J. McKeogh, “Wind Energy Inte-  
536 gration and the Ireland-Wales Interconnector,” in *Proceedings IEEE-*  
537 *PES/IAS Conference on Sustainable Alternative Energy*, (Valencia,  
538 Spain), September 2009.
- 539 [31] E. McGarrigle and P. Leahy, “The value of accuracy in wind energy  
540 forecasts,” in *Environment and Electrical Engineering (EEEIC), 2013*  
541 *12th International Conference on*, pp. 529–533, 2013.
- 542 [32] “Generation Scheduling, Economic Dispatch and Unit Commitment,”  
543 tech. rep., Eirgrid, 2011.
- 544 [33] EirGrid, “Wind Forecasting and Dispatch,” tech. rep., EirGrid, 2011.
- 545 [34] P. O’Donnell and D. Garrett, “Wind Forecasting,” tech. rep., EirGrid  
546 and System Operator of Northern Ireland (SONI), 2011.
- 547 [35] E. V. Mc Garrigle and P. G. Leahy, “The effects of operational con-  
548 straints on the future Irish electricity system,” *IEEE Transactions on*  
549 *Sustainable Energy*, 2014. In Press.
- 550 [36] EirGrid, “Wind forecast and actual gener-  
551 ation time series files, publicly available.”  
552 <http://www.eirgrid.com/operations/systemperformancedata/windgeneration/>.

- 553 [37] EirGrid and SONI, “Ensuring a Secure, Reliable and Efficient  
554 Power System in a Changing Environment,” tech. rep., Eir-  
555 Grid and System Operator of Northern Ireland, (SONI), 2011.  
556 [http://www.eirgrid.com/media/Ensuring a Secure Reliable and Efficient Power System Report](http://www.eirgrid.com/media/Ensuring%20a%20Secure%20Reliable%20and%20Efficient%20Power%20System%20Report)
- 557 [38] “SEMO, Market data, Two day wind forecast.”
- 558 [39] H. Bludszuweit, J. Dominguez-Navarro, and A. Llombart, “Statistical  
559 Analysis of Wind Power Forecast Error,” *Power Systems, IEEE Trans-*  
560 *actions on*, vol. 23, no. 3, pp. 983–991, 2008.
- 561 [40] SEM-O, “Single Electricity Market Operator (SEM-O) forecast model  
562 of 2012-2013,” tech. rep., Commission for Energy Regulation (CER),  
563 2012.
- 564 [41] EirGrid and SONI, “All-Island Generation Capacity Statement 2013-  
565 2022,” tech. rep., EirGrid and System Operator of Northern Ireland,  
566 (SONI), 2012. <http://www.eirgrid.com/aboutus/publications/>.
- 567 [42] Commission for Energy Regulation and Utility Regulator, “Validation  
568 of Market Simulation Software in SEM to end 2013,” tech. rep., 2012.
- 569 [43] EirGrid, “Interconnection Economic Feasibility Report,” tech. rep., Eir-  
570 Grid, 2009.
- 571 [44] SEM-O, “Single Electricity Market Operator (SEM-O) Backcast Model  
572 2011,” tech. rep., Commission for Energy Regulation (CER), 2012.

573 [45] EirGrid and SONI, “All Island TSO Facilitation of Renewables Studies,”  
574 tech. rep., EirGrid and System Operator of Northern Ireland, (SONI),  
575 2011.