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

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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:

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Wind forecasting, Autoregressive moving average, Stochastic unit commitment, Wind curtailment, Power systems, Ireland.

1. Introduction

Wind power is given priority dispatch over the conventional, non-renewable sources of generation in most electricity markets. For this reason Transmission System Operators (TSOs) may view wind generation as a negative load. As forecasts of wind generation and system demand are required for scheduling generator dispatch, wind power forecast inaccuracy can be viewed as a component of the net system load forecast inaccuracy. In systems with high wind penetrations, load forecasts are more accurate than wind power forecasts [1], therefore it is wind power forecasts that are the largest source of uncertainty in terms of net system demand requirements. Furthermore, wind generation, unlike conventional forms of generation, has little controllable variability in its output, with the exception of wind curtailment, and to compound the issue, this variability has a low degree of predictability with very large instantaneous errors in forecasts occurring frequently. There is, therefore, a considerable uncertainly associated with wind generation forecasting, with root mean squared errors of up to 20% for 24-hour ahead predictions reported [2].

The Republic of Ireland (ROI) and Northern Ireland (NI) have agreed to generate 40% of electricity from renewable sources in response to the ambitious renewable energy targets set by the European Union for its member states [3, 4, 5]. Due to this, a large amount of wind capacity will be added to the system which will result in a large proportion (in excess of 30%) of All-island of Ireland (AI)[1] electricity generation coming from a single source that is dependent on instantaneous weather conditions across the region.

1.1. Forecasting

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

[1] All-island of Ireland (AI), consisting of Northern Ireland (United Kingdom) and the Republic of Ireland.

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

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

1.2. Wind forecasting effects on systems

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

On examination of the literature, to the authors knowledge, there has been no systematic attempt to estimate the effects of realistic, incremental improvements of wind forecast accuracy on electricity system scheduling. A number of studies have estimated the effects of wind forecasts on electricity systems containing significant penetrations of wind energy [10, 11, 12, 15, 17, 20, 21, 22] however these studies compare a single forecast scenario against the 'perfect foresight' scenario. It was attempted in [23] to quantify the effects of variance and skewness of wind forecast error. While it is noted that these works focus on several different electricity systems with varying penetrations of wind energy, they all share some common conclusions, such as negligible wind curtailment. On comparison of the works above there are differences reported in the savings of total system costs ranging from 0.02% to 1.2% when accounting for the difference between actual wind forecast errors and perfect foresight.

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

1.3. Reserve provision

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

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

2. The Model

The model implemented here attempts to replicate the running of the Irish Single Electricity Market (SEM) [2]. Six wind forecast accuracy scenarios

[2] The SEM area consists of Northern Ireland (part of the UK) and the Republic of Ireland.

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

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

Table 1: Scheduling time-line.

Time	**Event**
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

2.1. Scheduling

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

2.1.1. Day-ahead model

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

[3] The SEM contains two TSOs, EirGrid in the Republic of Ireland and the System Operator for Northern Ireland (SONI)

terministic case, the DA model has no capability to evaluate the associated wind forecast uncertainty.

The DA model for the stochastic optimisation of wind forecasts uses a scenario-wise decomposition method instead of the deterministic scheduling used in the RT model. This allows the DA model to evaluate different degrees of wind power forecast error together with their associated probability of occurrence. Therefore it is a cost minimisation problem dependent on the probability of expected results. The model receives a wind power forecast file containing the median forecast (corresponding to 50% probability of exceedence) and upper and lower quantiles of wind power forecast error with associated cumulative exceedance probabilities (5.0, 27.4, 72.6 and 95.0%), described in detail in Section 2.2. Each of the five wind forecast quantiles is used to create five separate "model samples". From the five model samples a single set of DA UC decisions is optimised for each simulation day. The DA UC schedule is created from the economic dispatch minimisation from the likelihood of occurrences of the five separate "model samples". This is done through the use of UC non-anticipativity penalty costs associated with all the scheduled large generators and interconnectors, making the UC schedule of these selected generators and interconnectors match across all five "model samples". This set of DA UC decisions provides the lowest-cost solution in the DA model as the expected inputs of the RT model and therefore realistically reflects the probability of actual wind generation diverging from the forecast value between the DA and RT scheduling.

2.1.2. Real-time model

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

2.1.3. Formal description of the RT and DA models

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

$$
\begin{aligned}
DA(d-1|d) &= f(WF(d),\ IC_{info},\ Model_{s,info}(d)) \\
& where\ d = 1 \\
DA(d-1|d) &= f(WF(d),\ IC_{info},\ RT.End_{syst,con}(d-1), \\
& \ Model_{s,info}(d)) \\
& where\ d = 2, 3, 4, \ldots, n
\end{aligned}
\tag{1}
$$

$$
\begin{aligned}
RT(d|d) = f(&WA(d),\ DA.UC_{pucr}(d),\ DA.IC_{fix}(d), \\
& DA.Gen_{fix}(d),\ FO(d),\ Model_{s,info}(d)) \\
& where\ d = 1, 2, 3, \ldots, n
\end{aligned}
\tag{2}
$$

$$
\begin{aligned}
Model_{s,info}(d) = &Sys_{demand}(d),\ F_{cost}, \\
& OP_{const},\ Gen_{const},\ GB_{sytem,info}(d), \\
& \ Maint(d)
\end{aligned}
\tag{3}
$$

where: $DA(d-1|d)$ refers to the DA model solved for day d on day $d-1$; $Model_{s,info}(d)$ is the system information given to both DA and RT models; $Maint(d)$ is the maintenance schedule set for both DA and RT models; $RT(d|d)$ refers to the RT model solved for day d on day d; $f(WF(d))$ is the DA wind energy forecast and uncertainty quantiles time series; $f(WA(d))$ is the realised actual wind energy time series on day d; IC_{info} is the interconnector characteristics; $RT.End_{syst,con}$ is the end system conditions from the RT model, used for setting subsequent DA initial conditions; $DA.UC_{pucr}(d)$ is the DA UC schedule with post unit commitment relaxation; $DA.IC_{fix}(d)$ is the fixed interconnector flow schedule from DA model; $DA.Gen_{fix}(d)$ is the fixed generator flows schedule on day d from DA model (hydro, waste, biomass and CHP units); $FO(d)$ indicates forced outages; $Sys_{demand}(d)$ is the system demand; OP_{const} represents the operational constraints; Gen_{const} is the generator profile constraints, ensuring minimum capacity factors and reducing ramp cycling (Hydro, Waste, Biomass, Peat and CHP units); F_{cost} is the fuel costs; $GB_{system\,info}$ is the Great Britain wind generation, system demand and price settings; d is the day number in 2020; and n is the number of simulation days (366 days in 2020).

2.2. Generating wind forecast data

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

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

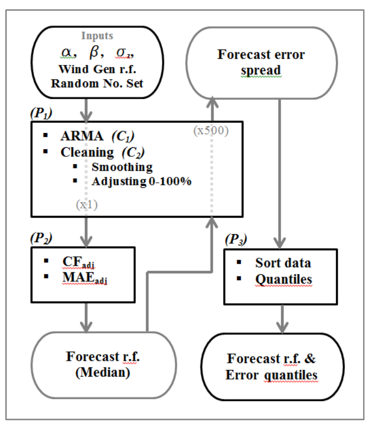

Figure 1: Flow chart describing the process of generating the wind forecast and associated error profiles

A code was developed in Matlab R2010b (Mathworks, USA) consisting of three processes in order to realistically replicate the wind forecasts and associated errors, illustrated in Fig. 1. The first step was to determine the parameters of the ARMA model α, β and σ_z. The parameter β was chosen first, this was determined from EirGrid's reported wind forecast error time series [36]. It was determined through least-squares fitting that β = -0.1 best replicated the actual error growth with forecast lead time when the ARMA model was run at a 30 minute time resolution. The target annual MAE levels for different lead times are shown in Fig. 2, based on [37], which the generated wind forecasts aimed to mimic. Using the first process, P_1, of the method illustrated in Fig. 1, the parameters α and β were determined based on the 48 intervals (of 30 minutes each) of 367 days for 20 years, meaning the creation of 352,320 random numbers with a near-constant statistical spread between separate runs of P_1. For the parameter α, a value of 0.99 was determined to give the best fit to the error growth profile shown in Fig. 2 for the time period 18-42hrs for the chosen value of β. The last parameter σ_z (0.390, 0.980, 1.550, 2.120, 2.695) was found to vary depending on the scenario of MAE (2, 4, 6, 8, 10% respectively).

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

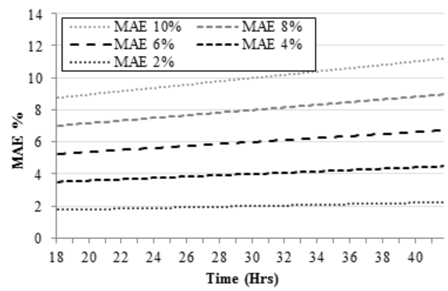

Figure 2: Forecast MAE over lead times of 18-42hrs, based on averages calculated over multiple issues of forecasts reported by EirGrid [37].

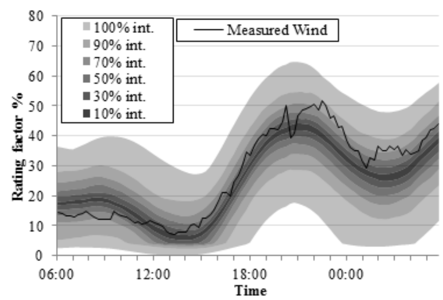

Figure 3: ARMA-generated DA interval wind forecast profile for the 6% MAE scenario and measured wind generation for the 2^{nd} April of the test year.

three controlling parameters (α, β & σ_z) which creates 96 half hour intervals representing 0-48 hour point forecasts for the 366+1 days. The random numbers produced have a mean of zero and a standard deviation of σ_z and are normally distributed. This ARMA model was derived from that of [14], and is represented by:

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

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

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

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

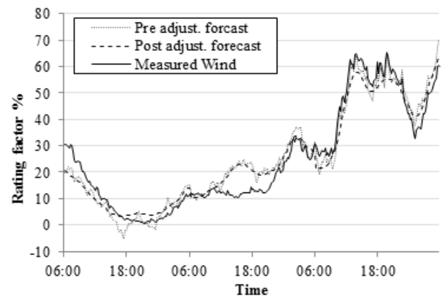

Figure 4: Wind forecast adjustment for the 6% MAE scenario and measured wind profile for the 21^{st} to 23^{rd} February of the test year.

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

In the creation of the predicted (median, 50%) wind forecast, an extra adjustment (P_2 in Fig. 1) is added, where the data is uniformly adjusted by a multiplier to achieve the exact MAE% required. This is followed by an adjustment to achieve the same annual capacity factor as the actual wind generation. This is necessary as the limited number (367) of random forecast series within a year does not always guarantee convergence precisely at the desired value of the MAE. This also helps to reduce variations in the results between runs in one MAE scenario. This adjustment is described by:

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

$$(\text{t}=1,2,3,\ldots,\text{N})$$

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

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

2.3. All-island system and constraints

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

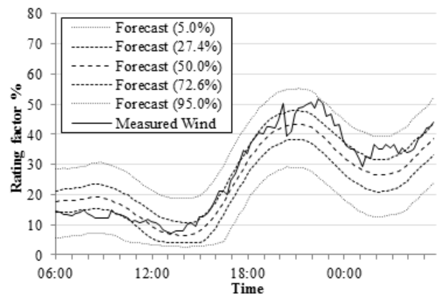

Figure 5: The five cumulative probability levels of DA wind forecast profile quantiles given to PLEXOS for the 6% MAE scenario and measured wind generation for the 2^{nd} April of the test year.

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

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

Only one of the two the OCGTs, Cahir or Culleen, was retained due to the recommendation to only include three of the four currently-planned OCGTs in the model of [41]. The new peaker plants, aggregated generation 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)**
ROI	
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)
NI	
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

all based on the specifications of the modern OCGT in Kilroot (KGT3) due to it being most recent OCGT addition to the SEM. Small scale hydro, tidal, small biofuel energy plants have also been included in keeping with [41]. The non-wind priority dispatch plants were modelled with a zero generation cost in keeping with [42]. Fuel prices for 2020 were taken from [43]. The model also includes start-up costs and start-up fuel off-take which were taken from [44]. A carbon tax was included at €30 per tonne of CO_2. Interconnection between the SEM and Great Britain (GB) is represented by the ROI-GB East West Interconnector (EWIC) at 500MW and Moyle between NI and

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

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

3. Results

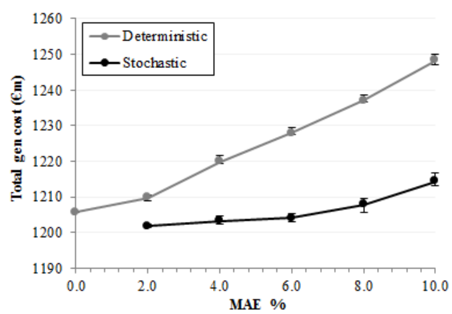

Figure 6: The mean total generation costs (€m) with standard deviation whiskers for both deterministic and stochastic modelling at different forecast accuracies (MAE%).

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

[4]Total generation costs for AI refers only to cost of the conventional generation and does not include the cost of subsidies for renewables.

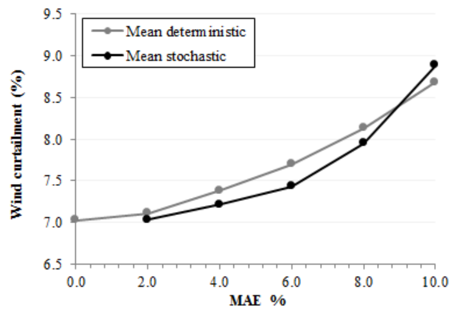

Figure 7: The mean percentage of wind curtailment for both deterministic and stochastic modelling at different forecast accuracies (MAE%).

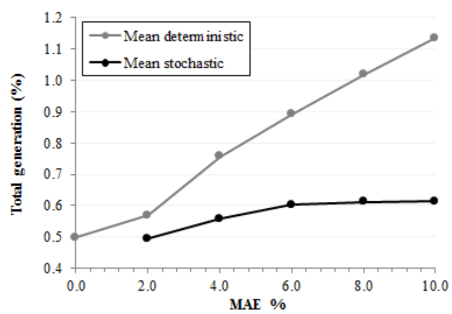

Figure 8: The mean OCGT generation as a percentage of total generation for both deterministic and stochastic modelling at different forecast accuracies (MAE%).

total generation costs reducing with improvements to wind forecasting accuracy shown in Fig. 6. The figure also shows that the magnitude of the savings is very dependent on the method of scheduling, be it deterministic or stochastic. When using deterministic scheduling, total generation savings show an almost linear relationship of €5m (0.41%) per year for every percentage point reduction in forecast MAE from 10% to 2%. However, when stochastic scheduling is employed, there is reduced advantage for improving wind forecast accuracy below 6% MAE, with savings of €0.5m (0.04%) per year for every percentage point decrease below this level. However, a clear advantage of improving wind forecast accuracy from 10% to 6% MAE remains, with €2.5m (0.20%) savings per year for every percentage point decrease in this range. The dependence of wind curtailment (Fig. 7) and OCGT generation (Fig. 8) on wind forecast errors are also presented for 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%).

	Forecast scenario (MAE)					
OCGT	**0%**	**2%**	**4%**	**6%**	**8%**	**10%**
Deterministic	381	528	617	704	792	892
Stochastic	-	433	457	451	445	439
Emissions	**0%**	**2%**	**4%**	**6%**	**8%**	**10%**
Deterministic	339.5	338.5	339.4	341.4	342.8	342.9
Stochastic	-	337.5	337.2	338.0	338.2	339.6
Total generation	**0%**	**2%**	**4%**	**6%**	**8%**	**10%**
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%).

	Forecast scenario (MAE)					
Generator type	**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%).

	Forecast scenario (MAE)					
Generator type	**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

4. Discussion

The perfect foresight (0% MAE) scenario is only presented to illustrate a lower bound to system costs incurred due to wind forecasting errors. In reality, it is unlikely that wind forecast accuracy for this system could be improved beyond the 2-4% MAE range. It was apparent from the work carried out on creating the wind forecasts in Section 2.2 that the 2% MAE wind forecast very closely resembles the result of time-smoothing of the actual wind generation. Therefore this discussion will focus on comparing the changes of effects on the AI electricity system from improvements in wind forecasting from 8% MAE, representative of the present-day accuracy of 7-9% MAE [37], to 4% MAE, assuming this to be a more realistic limit to possible future improvements.

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

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

4.1. Costs

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

8% and 4% MAE.

4.2. Dispatch of renewables

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

4.3. Dispatch of conventional generators

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

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

There is no clear relationship evident in Tables 4 & 5 between the proportion of generation from CCGTs or steam turbines and improvements in wind forecast accuracy under either deterministic or stochastic scheduling. There is an apparent general trend of improvements in the carbon dioxide emission intensity with wind forecast improvements shown in Table 3, despite some variations occurring due to the sensitivity of CO_2 emissions to the coal-gas generation ratio.

5. Conclusion

The work presented here quantifies the value of wind forecast accuracy to an electricity system with high wind penetration, and in doing so helps to justify further investment in improving wind forecasting techniques. The results show that with a reduction in wind forecast errors from 8% MAE to 4% MAE, there are available savings in terms of total system costs under both stochastic and deterministic scheduling of 0.50% and 1.64% respectively. Operational advantages also come from improved wind forecasts, as there is general agreement between stochastic and deterministic scheduling in relation to wind curtailment, showing a reduction of 9% in wind curtailment. Improved wind forecasts also are shown to have an effect on OCGT scheduling with realistic possible decreases in OCGT generation of 23% using deterministic scheduling and 8% using stochastic scheduling. From this, there are clear benefits in improving the quality of wind energy forecasts as it allows for more efficient use of non-wind generators and the transmission system.

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

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