Title	Impact of Wind Forecast Error Statistics Upon Unit Commitment
Authors(s)	Lowery, Colm, O'Malley, Mark
Publication date	2012-10
Publication information	Lowery, Colm, and Mark O'Malley. "Impact of Wind Forecast Error Statistics Upon Unit Commitment." Institute of Electrical and Electronics Engineers, October 2012. https://doi.org/10.1109/TSTE.2012.2210150.
Publisher	Institute of Electrical and Electronics Engineers
Item record/more information	http://hdl.handle.net/10197/4735
Publisher's statement	© 2012 IEEE.
Publisher's version (DOI)	10.1109/TSTE.2012.2210150

Impact of Wind Forecast Error Statistics upon Unit Commitment

Colm Lowery and Mark O'Malley, *Fellow, IEEE,*

***Abstract*—Driven by a trend towards renewable forms of generation, in particular wind, the nature of power system operation is changing. Systems with high wind penetrations should be capable of managing the uncertainty contained within the wind power forecasts. Stochastic unit commitment with rolling planning and input scenarios, based on wind forecasts, is one way of achieving this. Here a scenario tree tool is developed which allows forecast error statistics to be altered and facilitates the study of how these statistics impact on unit commitment and system operation. It is shown the largest individual impact on system operation is from the inclusion of variance and that variance, kurtosis and skewness together produced the error information with the lowest system cost. Similar impacts for inaccurate error statistics are observed but generalisation of these results will need more studies on a range of test systems.**

***Index Terms*—Power generation, Stochastic systems, Power engineering and energy, Wind power generation**

NOMENCLATURE

S_n	set of μ_t, M_1, M_2,M_1 and $AC_{\tau,j}$
$S_{T,n}$	the desired values of S_n
$S_{S,n}$	the sampled values of S_n
W_n	optimisation weights assigned to S_n.
$x_{t,j}$	values for scenario j during time step t.
$P_{t,j}$	scenario probabilities for time step t
M_l	the lth Moment at time t
$AC_{\tau,j}$	autocorrelation at timelag τ for scenario j
μ_t	mean of the scenario set at time t
μ_k	mean of the scenario k
τ	the time lag of the autocorrelation.
N	max forecast horizon
sc	the set of scenarios
t	forecast hour within the tree up to N
j	index of a given scenario
jk	indices of scenarios branching from scenario j

I. INTRODUCTION

THE nature of power system operation is changing worldwide. Plans are in place to increase the proportion of demand met through wind power throughout the European Continent [1], Ireland [2], Great Britain [3] and the United States [4]. In Europe, for example, this change is driven by EU policy which aims to reduce CO_2 emissions and dependency on imported fuel. Primarily this policy encourages the growth of renewable generation including wind power [5]. It is expected that this increase in renewable generation will displace conventional generation - causing a decrease in system operation costs as less conventional fuel is consumed in meeting system demand.

However, displacing conventional generation with non-synchronous renewable generation is creating new system operation challenges. As wind is by its nature variable and cannot be forecast with perfect accuracy, additional reserve must be carried and conventional units must be operated in a more flexible, adaptable manner - leading to reduced efficiency through partial loading and an increase in the number of start-ups required for conventional power plants [6]. For high wind penetrations the uncertainty associated with wind forecasting error will impact upon the reliability, efficiency and economic performance of unit commitment [7].

Ideally the system will be scheduled in such a way that the expected value of the operating costs is minimised given the uncertainty of wind generation and the constraints upon the system. This can be approximated by treating unit commitment as a stochastic problem where the distribution of possible wind generation is represented by a number of probability weighed time series scenarios. In many forms of stochastic unit commitment, the operational cost of a unit commitment is evaluated for each of these scenario tree branches, similar to deterministic treatments of wind generation [8]. However, it is the expected cost of the entire scenario tree which is the objective to be minimized for the unit commitment.

The WILMAR project developed a stochastic unit commitment scheduling model to analyse the integration of wind power in a large liberalised electricity system [9]. This model has previously been used to study the benefits of stochastic treatment of wind uncertainty over deterministic treatments as well as the impact of accounting for more of the wind uncertainty by increasing the frequency of rolling planning [10]. In addition it has been used to assess the impact of increasing quantities of uncertain wind generation upon the cycling experienced by base-loaded units [6].

While stochastic treatments of wind uncertainty have previously been investigated, the contribution to solution quality of specific statistical properties of forecast error have not been considered. These properties are available from analysis of the error between historical forecasts and realised data. In ideal circumstances, a system operator will have the necessary

This work was conducted in the Electricity Research Centre, University College Dublin, Ireland, which is supported by the Commission for Energy Regulation, Bord Gais Energy, Bord na Mona Energy, Cylon Controls, Eir-Grid, the Electric Power Research Institute (EPRI), ESB Energy International, ESB Energy Solutions, ESB Networks, Gaelectric, Siemens, SSE Renewables, and Viridian Power & Energy. This publication has emanated from research conducted with the financial support of Science Foundation Irehowever land under Grant Number 06/CP/E005.

C. Lowery and M. O'Malley are with the School of Electrical, Electronic, and Communications Engineering, University College Dublin, Dublin 4, Ireland (e-mail: Colm.Lowery@ucdconnect.ie; mark.omalley@ucd.ie)

information prioritised in the form best suited for decision making. In practice, and in many prior studies quantification of forecast error has often been limited to simple statistical properties such as variance and mean error and an assumed Gaussian distribution [11]. This neglects statistical properties such as the skewness and excess kurtosis (peakedness) which could change the shape of the error distribution significantly [12], [13]. In practical terms, excluding these terms could underestimate the number of extreme events which will occur, or the likelihood of any forecast under or overestimating available wind power. The system may therefore be inadequately prepared for the realised wind, carrying insufficient reserves and the reliability may be impacted.

This paper examines the influence of these forecast statistics on the performance of a unit commitment in order to understand the priority of information required for a good decision to be made and the degree to which inaccuracy in error quantification alters the quality of the unit commitment. Section II describes the methodology with an emphasis upon the Scenario Tree Tool (STT) created for this paper to generate trees conforming to the cases studied. Section III describes the test system and outlines the simulation set and the cases examined. Section IV presents the results in terms of expected costs, unit operation and the performance of the schedules and Section V summarises the conclusions from these results.

II. Methodology

Here a Scenario Tree Tool (STT) is developed which allows forecast error statistics to be altered and facilitates the study of how these statistics impact on the outcomes of the WILMAR scheduling model.

Prior to this study, WILMAR has used scenarios generated using Monte Carlo simulations of wind error methods based upon an Auto Regressive Moving Average (1,1) model (ARMA(1,1)) [14]. Specifically, the wind forecast error was based upon the assumption of a Gaussian distribution of wind speed error [15] with standard deviation dependent upon the forecast horizon. These wind speed error scenarios are added to the wind speed forecasts, converted to wind power and scaled taking account of the spatial correlations of the wind power forecast [16]. These scenarios are then reduced in number and branched through the use of scenario reduction techniques based upon Euclidean distances between scenario pairs [17], [18].

Due to the requirement for direct control of the statistical properties, ARMA series/scenario reduction methodologies were not considered suitable for this study. A new STT was designed using a methodology based upon a moment matching technique where each time period, within a tree, has a defined variance, skewness and kurtosis. These statistics together with the autocorrelations of the scenario determine the values of the scenarios at that time period. While alternative heuristic methodologies have been proposed for deriving a scenario tree that matches specific moments [19], this study is based upon a nonlinear optimisation moment matching method [20], [21].

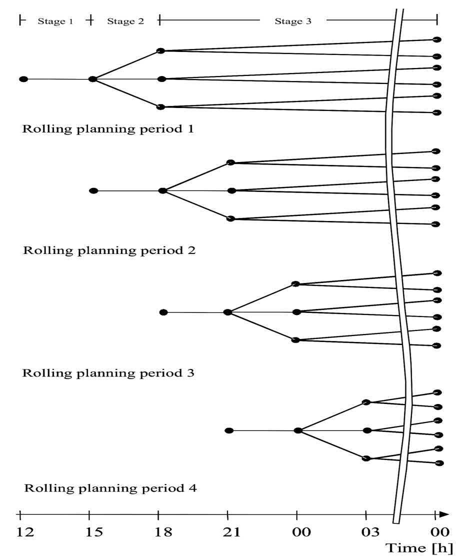

Fig. 1. Illustration of rolling planning Scenario Trees

A. The Scenario Tree Tool

In power plant scheduling, decisions must be made on both information known with certainty and uncertain information which must be forecasted. In stochastic unit commitments, wind forecasts, demand forecasts and their forecast error can be accounted for by representative branching trees consisting of probability weighed scenarios for available wind generation (Fig. 1). The number of scenarios has been restricted to minimise dimensionality in the unit commitment solution, while retaining accuracy in the specified statistical information. For computational reasons, the first stage of these trees is assumed to be known with perfect certainty.

Each scenario in the tree consists of an assigned probability and two time series values - one for load and one for wind. Each of these time series can be represented as a forecast time series, common to all scenarios within the tree, and an error time series which, together with the error time series of the other scenarios, represents the error distribution of the forecast.

The scenario tree generation is itself divided into three parts. The first step in generating the trees optimises the values of the time series contained within each individual stage of the scenario tree according to moment matching. The second part groups scenarios, with similar or complementary autocorrelations, to optimise the structure of scenario branching between stages. The third part consists of the reserve and forced outage calculations necessary for the WILMAR model.

1) Moment Matching: For each stage in the tree, a nonlinear optimization was used to produce a matrix of scenarios consisting of wind, demand and probability values matching the specified statistics as closely as possible. In addition, stages which have already been determined are used to provide additional autocorrelation information for subsequent stages.

In each stage, the optimisation acts to minimize the following loss function (1) using the values of $x_{j,t}$, the matrix of individual scenario values, and P_j, the probability of a scenarios occurrence, for the stage while meeting the constraints

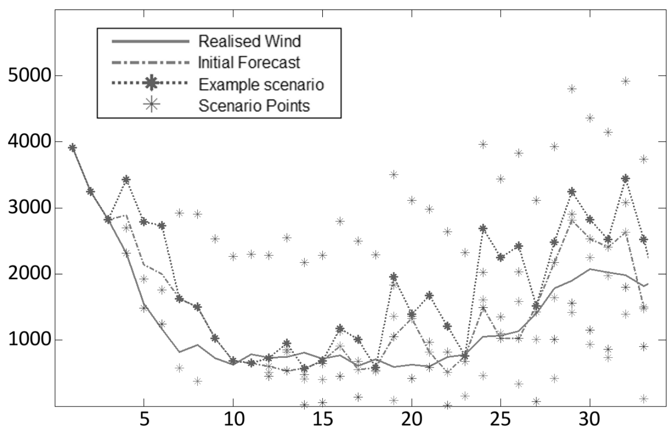

Fig. 2. Example output of the scenario tree. * marks points contained in a scenario, while the dashed line represents the original forecast, the dotted line represents an example scenario and the full line represents the realised value of wind to provide context

(2, 3, 4) given the stages and branch connections that have already been defined:

$$\sum_{n=1}^{S} W_n(S_{S,n} - S_{T,n})^2 \tag{1}$$

$$\sum P_{jk,t} = P_{j,t-1} \tag{2}$$

$$\sum P_t = 1 \tag{3}$$

$$P_{jk,t} > 0 \tag{4}$$

The individual components of the loss function (1) are calculated using the below formulas

$$M_l = \sum_{j=1}^{sc} P_j(x_{j,t} - \mu_t)^l \tag{5}$$

$$AC_{\tau,j} = \sum_{i=1}^{N-\tau} \frac{(x_{i,j} - \mu_k)(x_{i+\tau,j} - \mu_j)}{\sum_{k=1}^{N}(x_{k,j} - \mu_j)^2} \tag{6}$$

2) Scenario Grouping: The scenario stages produced by moment matching are divided into groupings according to the branching of the scenario tree and the similarity of their autocorrelations. This is done to ensure that when joined to the relevant scenario in the preceding stage the autocorrelation of each branch of the tree is consistent across the stage boundaries. This prevents the creation of suboptimal scenario branching as a result of joining two disparate scenarios. Scenario ordering is determined by finding the ordering which minimises the difference in autocorrelation and the Euclidean distance between the initial values of each grouping.

These groupings and scenarios are then used in the optimisation of any subsequent moment matching steps to provide consistent autocorrelations for each scenario throughout the tree stages. An example of the output of this stage can be seen in Fig.2

3) Forced Outages, and Reserve: In addition to the scenario trees for demand and wind forecasts, the scenario tree tool can also produce a time series of forced outages for the conventional units, and estimates the reserve targets required by the scheduling model.

The time series of forced outages for each conventional unit are simulated using semi-markov chains [22], where the failure and repair rates are expressed by the mean time to failure and the mean time to repair. The methodology used in this study is unchanged from that presented in the All Island Grid Study (AIGS) [23]. Similarly, short term spinning reserve is estimated from the largest infeed to the system and forecasted wind using the methodology presented in the AIGS [11].

Replacement reserve is estimated for each individual scenario branch of wind and demand within the tree and is calculated using a similar methodology to that presented in the AIGS [23]. However, the AIGS used methods assuming prior scenario reduction, which calculate reserve from the 90th percentile of the undreduced set of scenarios used to generate the scenario tree. This method can therefore not be used with the new STT as it uses moment matching. Instead, the reserve is calculated from the 90th percentile of a distribution based upon the average variation of wind and demand error represented by those scenarios.

B. The Scheduling Model

The WILMAR model was initially developed to study the integration of wind into the Nordic system [24]. As part of the All Island Grid Study (AIGS), this model was adapted to examine the Irish system [23]. A full description of the model itself was recently published [25].

WILMAR's scheduling model uses stochastic mixed integer optimisation to minimise the operational costs of meeting expected demand and reserve targets subject to constraints. These constraints include constraints upon unit operation such as startup time, minimum up and down times and minimum/maximum generation, as well as constraints upon interconnection and penalties for failing to meet demand and reserve targets.

In the scheduling model, unit scheduling is performed at noon of every simulated day for the following 36 hours. Subsequent rolling planning rescheduling, where unit commitment is reoptimised after every three hours (see Fig. 1), takes into account this initial day-ahead schedule. However, it allows for revision of the schedule to account for changing availability and accuracy of information as the forecast horizon shrinks. For example, this revised information might include previously unforseen changes to unit availability (forced outages) and forecasts (wind and demand). For each subsequent roll forward, the system is planned until midnight the following day. As a result, there are eight optimizations in each day and the planning period becomes shorter for each planning loop until noon the next day when the 36 hour forecast begins again.

This model is implemented in Generic Algebraic Modelling System (GAMS) and solved using the *CPLEX12* mixed integer programming solver. It should be noted that the current form of the scheduling model has been used extensively by prior work

TABLE I
TYPES OF UNIT IN PLANT PORTFOLIO USED IN STUDY

Type of unit	**No.**	**Capacity (MW)**	**Fuel (€/GJ)**
Coal	5	1257	1.75
Mid-merit Gas & Peakers	19	1646	6.46
Base-loaded Gas	12	4114	5.91
Inflexible baseload	3	345	3.71
Base RE	1	360	2.78
Hydro	1	216	-
Pumped Storage	4	292	-
Tidal	-	200	-
Wind Power	-	6000	-

[6], [10]. This paper is concerned with using the WILMAR scheduling model in conjunction with the STT to examine the operational impacts of wind forecast error statistics.

C. Computational information

The *fminsearch* unconstrained nonlinear solver was used to derive the Scenario Tree Tool output trees and the *CPLEX12* mixed integer solver was used to solve the scheduling model. These solvers were used on a computer with an *Intel Xeon* W3520 2.67 GHz processor with 12 GB of RAM. The STT and the scheduling model (at a duality gap of 0.1%) took approximately 24 hrs to solve for each individual simulation.

III. TEST SYSTEM AND SIMULATION CASES

A. Test system

The WILMAR scheduling model was run for a year of demand and wind data produced by the Scenario Tree Tool representing a a possible portfolio for the year 2020. Altered error information required for each simulated case was appended to the forecasts based on those used for the AIGS study. The test system is based upon portfolio 5 of the All Island Grid Study [26]. The quantity of total renewables in this portfolio amounts to 42% of energy demand, including 6000MW of installed wind (34.3% of energy demand). It also contains 8300MW of conventional generation (Table I). Mid-merit gas includes open cycle gas turbines (OCGT), aero-derivative gas turbines (ADGT) and peaking units. Base RE consists of renewable generation capable of contributing to base load such as biomas, biogas, sewage gas or landfill gas plants. Base-loaded gas consists of combined cycle gas turbine (CCGT) units, while inflexible baseload plant refers to peat-fired plants and are classified as inflexible due to requiring greater than one hour to start. Table II shows the startup time for the various types of conventional plant on the system.

The system modelled has a peak demand of 9600 MW and a minimum demand of 3500 MW in 2020. Interconnection to Great Britain (GB) is assumed to be 1000 MW and the GB electricity system is modelled as large blocks of similar units. Wind provides approximately 12% of GB electricity demand. GB wind generation and demand are assumed to be forecast with perfect knowledge.

TABLE II
START-UP TIME FOR CONVENTIONAL UNITS USED

Type of unit	**Start-up time (hrs)**
Coal	4-5
Mid-merit Gas and Peaking units	< 1
Base-loaded Gas	2-4
Inflexible baseload	1-4

B. Simulation cases

Here, two cases of simulations were run. Case I seeks to answer which statistical properties of wind forecast error contribute meaningfully to the operation and performance of a power system. To examine this, three sets of scenario trees were created in which each possible combination of the statistical properties is accounted for, excepting the case where higher moments would be matched in the absence of the lower moments it depends upon. In each of these sets one or more of variance, skewness and kurtosis was excluded (by setting the relevant W_n to zero) from the optimisation criteria of the moment matching method (equation 1) meaning trees are only evaluated on matching the included moments. The details of this design can be found in Appendix I Table III and the scenario tree structure for this study can be found in Table V.

Case II examines the degree to which inaccuracy between the assumed values of the statistical properties of forecast error, and the true values for the forecast error, impact the operation and performance of the power system. Three values were considered for each property - an underestimated value (half the true value), an overestimated value (double the true value for all statistics) and the true value itself. In addition, due to its importance, four further simulations (paired with three preexisting simulations) were run for variance to examine the effect of its variation upon the unit commitment. The details of this factorial design and the additional variance runs can be found in Appendix I Table IV.

While it is necessary to include the autocorrelation of the scenarios in the optimisation in order to ensure the scenario trees presented to WILMAR exhibit realistic behaviour once added to the underlying forecast, this is a computational requirement to ensure the solution of the problem is meaningful. For this reason, the effect of the autocorrelation of forecast error has not been considered.

IV. RESULTS/DISCUSSION

Simulated results are examined to identify and quantify the influence of the statistics of forecast error on system cost, production of each unit type and the number of startups per unit type.

A. Case I: Exclusion of statistical information

1) Impact on system cost: Fig. 3 shows the change in system cost, when different combinations of variance, skewness and kurtosis are considered in the creation of the scenarios.

First, it is clear that the lowest system cost occurs for the M2,M3,M4 simulation. This is the expected result as this

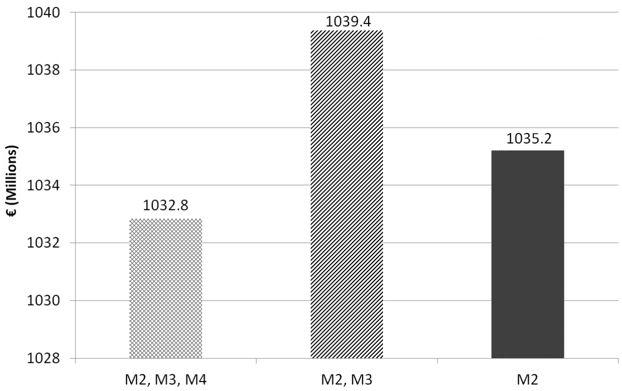

Fig. 3. System Cost for the three exclusions. The x-axis labels refer to which properties were included for each simulation. M2 being variance, M3 being skewness and M4 being kurtosis

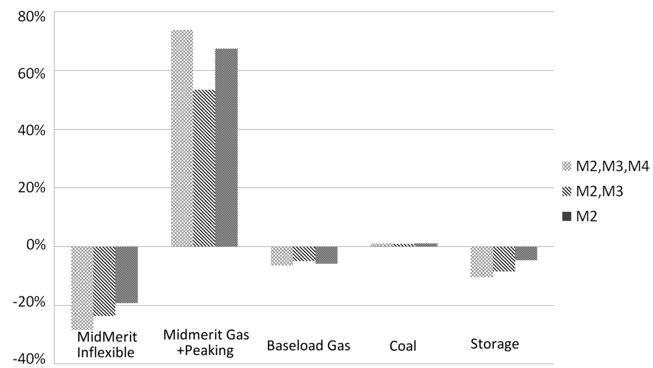

Fig. 4. Percentage change in production compared to perfect forecasting

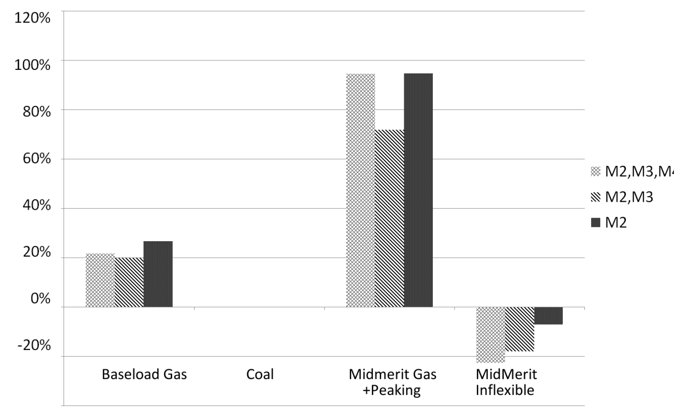

Fig. 5. Percentage change in unit startups by generator type compared to perfect forecasting

simulation contains the most information about the forecast error. However, the next lowest cost is variance by itself indicating that if skewness is considered in addition to variance, so must kurtosis be. It is likely that this is due to the interaction of skewness and kurtosis in determining the shape of the distribution. Skewness accounts for the likelihood of whether the forecast will over or under estimate the realised wind by changing the location of the distribution peak. As the addition of kurtosis alters the peakedness of the distribution of scenarios, describing the proportion contained within the peak and tails, it will alter the ratio of inflexible plant committed to better match the error characteristics of the forecast.

2) Impact on system operation: The operation of the system changes dependent upon the manner in which uncertainty is treated. As the majority of uncertainty in wind occurs hour to hour, previous studies have suggested that the majority of changes in considering stochastic information should be expected to occur within the most flexible units - the midmerit gas and peakers [10]. Fig. 4 presents the percentage change in production for the three exclusion variants compared to the perfect forecast. As expected, the largest change in production is in the flexible mid merit gas and peaking units while inflexible coal (the longest required startup time) and expensive base-loaded gas (the most expensive of the inflexible units) are the most stable. In general, the increase in production from flexible units indicates the system having to respond to events which the modelled error statistics assumed to be unlikely and did not commit slow startup generators to be ready for.

It is notable that the highest use of flexible plant occurs in the case where kurtosis is represented. As kurtosis alters the degree of variance which is attributable to outlying events, including it within the model will decrease the amount of mid price mid flexibility units required by the system. With the removal of kurtosis, the inclusion of skewness decreases the amount of midmeritgas and peaking units used (the most expensive generation). However, it remains the highest system cost of the three versions despite including more information than the version modelling variance alone. As skewness determines the position of the peak, and hence the length of the balancing tail, it will increase the overcommital of expensive baseload gas by incorrectly estimating the number of outlier events contributing to the longer tail of scenarios it generates on one side.

Fig. 5 shows the percentage increase in startups compared to the case where wind is known with perfect foresight. As total system costs are optimised, as opposed to solely start up costs, the system will cycle units on and off when the forecast predicts it would save more by avoiding the cost of keeping the unit online when it is not required. It is clear that the number of unit starts is a function of forecast uncertainty and the manner in which error is accounted for. In particular, compared to perfect knowledge, the majority of unit types cycle more frequently for any of the stochastic errors represented. The exception to this being coal which maintains a steady number of starts for all cases. It is worth noting that the case where variance and skewness are represented without kurtosis (the highest system cost case) has less baseloadgas and midmeritgas/peaking unit start ups than the other two case. Combined with the increase in baseloadgas production and the decrease in midmeritgas/peaking unit production, it indicates baseloadgas units are being left running more frequently when it would be more efficient to use a more appropriate mixture of other generation types.

B. Case II: Inaccuracy of statistical information

This section examines the degree to which inaccuracy between the assumed values of forecast error and the true

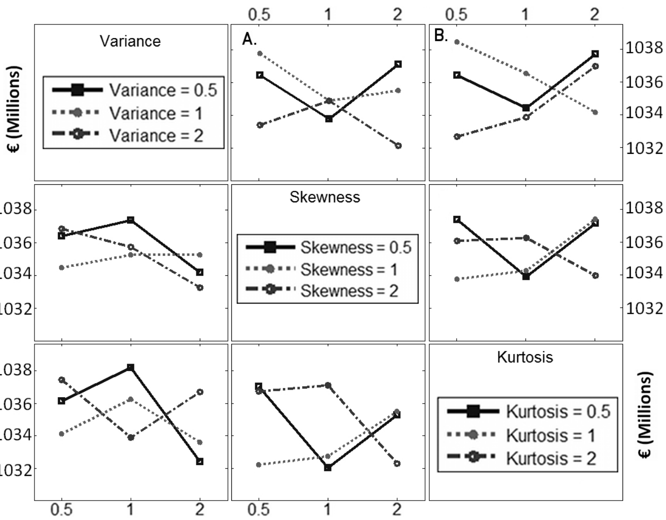

Fig. 6. Interaction Plot of System Cost for the inaccuracy design. X axis values correspond to inclusion of the variable in that column. Line style indicate the level the variable in that row. Whole lines indicate the low level (half normal value (0.5) or minus a half in the case of skewness(-0.5)), dashed line indicates the normal value(1), and the dashed and dotted line indicates double normal value(2)

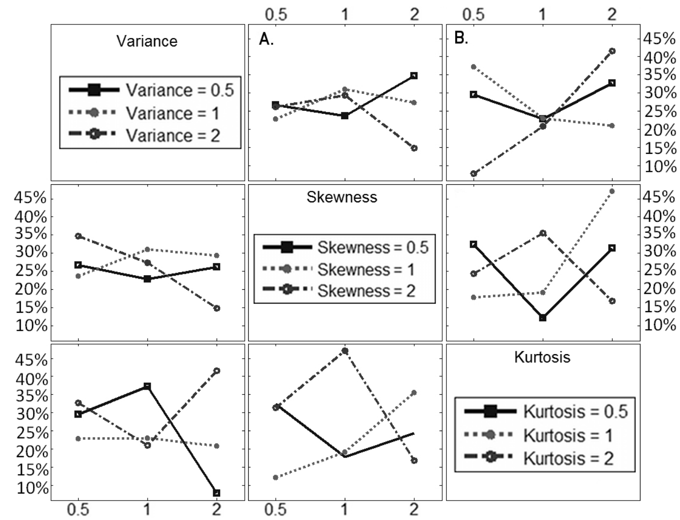

Fig. 7. Interaction Plot for percentage change in startups of Midmerit gas and peaking units compared to the perfect case for the inaccuracy case. X axis values correspond to inclusion of the variable in that column. Line style indicate the level the variable in that row. Whole lines indicate the low level (half normal value (0.5) or minus a half in the case of skewness(-0.5)), dashed line indicates the normal value(1), and the dashed and dotted line indicates double normal value(2)

values of forecast error impact the operation and performance of the power system. Three values were considered for each property - an underestimated value (half the true value, except in skewness where it is a negative half), an overestimated value (double the true value for all statistics) and the true value itself. In addition to this, a finer resolution sensitivity analysis has been performed for variance including each 25% increments between the underestimated value and the overestimated value for variance. For these, skewness and kurtosis were kept at their true value.

1) Impact on system performance: In Fig.6, the interaction between kurtosis, skewness and variance can be seen in terms of system cost. In these interaction plots (Fig.6,Fig.7), the subplots of interest have been marked as A (skewness and variance) and B (kurtosis and variance).

Three distinct patterns can be seen for the distinct values of kurtosis and variance (Fig.6.B). In the simulations where variance is overestimated, the minimum cost comes from an understimation of kurtosis, suggesting an increase in the general spread of scenarios and reducing the number of extreme events, and peaking around the forecast, will provide a lower cost unit commitment. In the cases where variance is underestimated, underestimating or overestimating kurtosis shows an increase in cost. As kurtosis increases the number of extreme deviations in addition to increasing the degree of peaking or clustering of values around the mode, it suggests that inaccuracy in kurtosis will exacerbate the effects of inaccurate variance by increasing the dependence on flexible units (when overestimated) or by overcommitting inflexible units (when underestimated). In contrast, overestimating kurtosis in the case when variance is accurate appears to reduce system costs, by reducing the use of slower units to cover the midrange of the error between the extreme values and the peak. As the error range is accurately covered by the variance, the additional use of flexible units is compensated for by leaving fewer units committed unnecessarily. It is also worth noting that the cost for low and high levels of variance are similar for normal and high levels of kurtosis. However, a portion of this may be attributable to the number of scenarios used in the construction of the tree (see section IV.C).

In the interactions of variance and skewness (Fig.6.A), it can be seen that the maximum number of flexible unit starts for overestimated variance comes when it is paired with accurate skewness. In the other cases, the minima sit at that point. The high and low skewness values suggest incorrect over or underestimation of the realised value of wind relative to the forecast and benefit from the additional variance increasing the width of the skewed distribution and the degree to which it covers the area covered by the true degree of skew. In contrast, the true skewness will not benefit from the additional variance in this way. In the case where variance is reduced, the minimum occurs as expected at the accurate value of skewness. Inaccuracy in skewness exacerbates the impact of reducing variance by skewing the distribution further away from the expected realised value.

2) Impact on system operation: In Fig. 7, the interaction plot for the percentage change in midmerit gas and peaking unit startups can be seen. Considering the variance/kurtosis interactions (Fig.7.B), the number of flexible unit starts required is consistent across all values of variance for the accurate value of kurtosis. In addition, overestimating kurtosis leads to an increase in the number of starts of flexible units. For overestimated variance, more flexible units are required as kurtosis is increased. The number of extreme events modelled increases necessitating an increase in the use of fast start units. This is consistent with what is expected, and is visible when variance is overestimated as the increased uncertainty

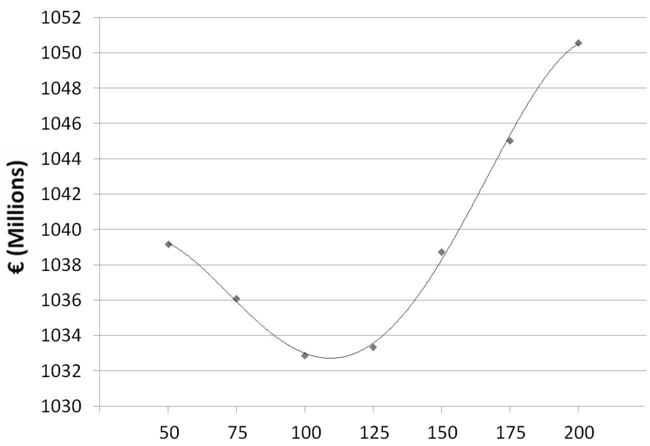

Fig. 8. System Cost as a function of percent of true variance represented. Minimum system cost occurs at 100% which represents the accurate value of variance

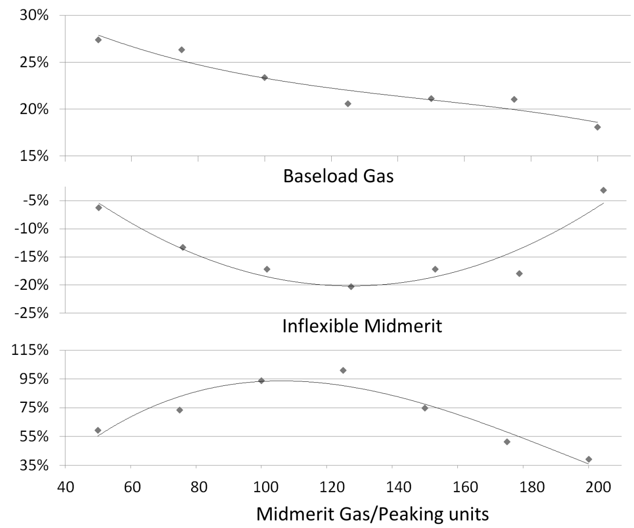

Fig. 9. Percentage change in unit startups compared to perfect knowledge as a function of percent of variance represented. Baseload gas is used less as variance increases while midmerit gas/peaking unit starts increase with accurate information while inflexible midmerit starts decrease

would emphasise the use of additional inflexible units, while increasing kurtosis will reduce the proportion of the scenarios for which inflexible units are required. In the cases where variance is not overestimated, decreasing kurtosis may decrease the coverage of unexpected events which would otherwise be accounted for.

In the case of the skewness interactions (Fig.7.A), the lowest number of required startups for the underestimated variance case is, as expected, when skewness is accurate. Inaccurate skewness will cause the assumed most frequent values of realised wind to be incorrect while reducing the variance will decrease the degree of cover from the implied error distribution, increasing the required use of flexible units. In contrast, where variance is overestimated, its maximum occurs at the accurate level of skewness. By overestimating variance, the underestimation and overestimation of skew reduce the number of flexible unit startups they require, due to having incorrect assumptions about the most likely value (mode of the error distribution) of realised wind compared to the forecast. In contrast, the case when skew is accurate does not gain this benefit. It is worth noting however that the majority of the values in the skew/variance interaction are small indicating that the effect skew has on the use of midmerit gas and peaking is relatively minor.

3) Sensitivity of cost and unit starts to variance accuracy: In fig. 8, the impact of accurate variance upon system cost can be seen. The minimum cost occurs at 100% indicating the correct estimate of variance decreases system cost. In addition, while a rapid increase in cost would be expected as the estimate declines in quality on either side of the 100% point, the system cost for a 25% overestimation of variance can be seen to be similar in magnitude to the accurate estimate. On either side of these points, a rapid increase in cost can be seen as the estimate declines in quality as expected suggesting that a tolerance exists for some overestimation in accounting for forecast error. This may be due to the influence of carrying replacement reserve upon system costs as increased variance will include additional replacement reserve while reduced variance will include less replacement reserve.

Fig. 9 similarly shows the impact of accuracy in variance upon the change in number of startups compared to the perfect knowledge case for baseload gas, inflexible midmerit and midmerit gas/peaking units. As the amount of variability assumed increases, regardless of accuracy, the use of baseload gas decreases. As baseload gas is the second least flexible category on the system and the largest non-wind generation type, it is to be expected that as the possible quantity of power to be generated conventionally becomes less definite, the amount of starts for baseload gas will decrease. In contrast, both midmerit gas/peaking units and inflexible midmerit startups appear to be strongly dependent upon the accuracy of variance with midmerit gas/peaking units experiencing a sharp increase in startups as variance accuracy increases and inflexible midmerit experiencing an inverse relationship - as accuracy increases the number of startups for inflexible midmerits decrease.

C. Modelling Assumptions and Impact on Results

In this study, several modelling assumptions have been made which should be born in mind when interpreting the results shown:

The duality gap used within the scheduling model was set at 0.1% due to computational limitations. As this value is calculated from the difference from a non-integer bounding value, the real precision of the model is considerably higher. Previous studies using this scheduling model indicate that the precision can be expected to be approximately a fifth the value suggested by the duality gap [10]. However, for this reason, care should be taken in interpreting the system cost results presented in this study.

The shape and dimensionality of the scenario tree was defined by the choice of scheduling model. While the number of scenarios available contain sufficient degrees of freedom to match the defined three moments, mean and autocorrelations given the guidelines in [20], prior work has suggested a higher number of scenarios would provide a stronger match [21]. The shortage of scenarios in stage two (3 scenarios) may impact upon some of the interactions of kurtosis and variance.

The results of this study are based upon a single high wind penetration test system. As multiple levels of wind penetration and different conventional portfolio compositions were not considered, the results of this study are specific to the given test system.

The WILMAR scheduling model uses reserve targets. As reserve serves to reduce the impact of errors in the wind or demand forecast and unit availability, the presence of reserve within the model will reduce the effect of altering the quality of the wind error information used by the system. However, the reserve in WILMAR is divided into spinning reserve determined by the N-1 criteria (the quantity of reserve necessary to keep running if the system lost the largest generator on the system), and the replacement reserve which is calculated from the error information of wind and load provided by the scenario tree. As the quantity of reserve used is linked to the forecast error presented, the reserve carried can be considered as a realistic factor in how these kinds of error would affect a unit commitment predicated on an incorrect evaluation of wind error.

V. Conclusion

This paper examines the impact of wind forecast error statistics upon unit commitment for a high wind penetration test system. As expected, variance has the most impact but the results also indicate that if skewness is included in the evaluation of error information, kurtosis should also be included to reduce system cost. The interactions of variance, skewness and kurtosis changes the utilisation and commitment of units. In particular, representation of variance, skewness and kurtosis can affect the dependency of commitment upon flexible units and the manner in which it is used. Additionally, accurate representation of wind error statistics and the manner in which such information is used can impact the optimal quantity of flexible plant within a given power system and hence the amount of reserve that it must carry. Further study on a range of different test systems is needed in order to fully understand and generalise the consequences of the observed impacts.

Appendix
Case I and II Designs

TABLE III
List of Moments included in each simulation in case I

Sim.	Variance on?	Skewness on?	Kurtosis on?
1	Yes	Yes	Yes
2	Yes	Yes	No
3	Yes	No	No

TABLE IV
Percentage of true value included in each simulation in case II

Sim.	Variance on?	Skewness on?	Kurtosis on?
1	50%	-50%	50%
2	50%	-50%	100%
3	50%	-50%	200%
4	50%	100%	50%
5	50%	100%	100%
6	50%	100%	200%
7	50%	200%	50%
8	50%	200%	100%
9	50%	200%	200%
10	100%	-50%	50%
11	100%	-50%	100%
12	100%	-50%	200%
13	100%	100%	50%
14	100%	100%	100%
15	100%	100%	200%
16	100%	200%	50%
17	100%	200%	100%
18	100%	200%	200%
19	200%	-50%	50%
20	200%	-50%	100%
21	200%	-50%	200%
22	200%	100%	50%
23	200%	100%	100%
24	200%	100%	200%
25	200%	200%	50%
26	200%	200%	100%
27	200%	200%	200%
V1	75%	100%	100%
V2	125%	100%	100%
V3	150%	100%	100%
V4	175%	100%	100%

References

[1] Pure Power: Wind energy targets for 2020 and 2030, EWEA, 2010 Available: http://www.ewea.org/

[2] Delivering a Sustainable Energy Future for Ireland, Government White Paper, 2007. Available: http://www.dcmnr.gov.ie.

[3] Meeting the Energy Challenge, U.K. Government White Paper, 2007. Available: http://www.dti.gov.co.uk.

[4] Second Quarter 2011 Market Report, AWEA. [Online]. Available: http://www.awea. org/.

[5] Directive 2009/72/EC of the European Parliament. Available: http://eur-lex.europa.eu

[6] N. Troy, E. Denny, and M. OMalley, Base-load cycling on a system with significant wind penetration, IEEE Transactions on Power Systems, vol. 25, no. 2, pp. 10881097, 2010.

[7] I. Marti et al., Evaluation of Advanced Wind Power Forecasting Model Results of the Anemos Project, 2006. [Online]. Available: http://anemos.cma.fr.

TABLE V
STRUCTURE OF SCENARIO TREES WITHIN THE STUDY

Stage	No. of Scenarios	Start hour	End hour
Stage 1	1	1	3
Stage 2	3	4	6
Stage 3	6	7	36 (max.)

[8] S. Takriti, J. Birge, and E. Long, A stochastic model for the unit commitment problem, IEEE Trans. Power Syst., vol. 11, no. 3, pp. 14971508, 1996.
[9] Wind Power Integration in Liberalised Electricity Markets (WILMAR) Project. Available: http://www.wilmar.risoe.dk
[10] A. Tuohy, P. Meibom, E. Denny, and M. OMalley, Unit commitment for systems with significant wind penetration, IEEE Trans. Power Syst., vol. 24, no. 2, pp. 592601, May 2009.
[11] R. Doherty and M. OMalley, A new approach to quantify reserve demand in systems with significant installed wind capacity, IEEE Trans. Power Syst., vol. 20, pp. 587595, 2005.
[12] M. Lange, On the Uncertainty of Wind Power Predictions - Analysis of the Forecast Accuracy and Statistical Distribution of Errors, Journal of Solar Energy Engineering, vol. 127, pp. 177-184, 2005.
[13] B. Hodge and M. Milligan, Wind Power Forecasting Error Distributions over Multiple Timescales, NREL Report No. CP-5500-50614. Available: http://www.nrel.gov/
[14] R. Barth, L. Soder, C. Weber, H. Brand and D. Swider, Methodology of the Scenario Tree Tool, 2006. [Online] Available: http://www.wilmar.risoe.dk
[15] M. Lange and U. Focken, Physical approach to short-term wind power prediction. Springer. Berlin ,2006
[16] L. Sder, Simulation of wind speed forecast errors for operation planning of multi-area power systems, in Proc. 8th International Conference on Probabilistic Methods Applied to Power Systems, Ames, 2004.
[17] J. Dupacova, N. Grwe-Kuska, and W. Rmisch, Scenario reduction in stochastic programming - an approach using probability metrics, Math. Program., Ser. A 95, vol. 3, pp. 493-511, 2003.
[18] H. Heitsch and W. Roemisch. Scenario Reduction Algorithms in Stochastic Programming. Computational Applications and Optimization, 24(2-3):187206, 2003.
[19] K. Hoyland, M. Kaut, and S. W. Wallace. A Heuristic for Moment-Matching Scenario Generation. Computational Applications and Optimization, 24:169185, 2003.
[20] K. Hoyland and S. W. Wallace. Generating Scenario Trees for Multistage Decision Problems. Management Science, 47(2):295307, 2001.
[21] B. Hasche. Scenario Tree Generation for an Electricity Market Model. 2008., available: http://www.netmod.org/
[22] J. Valenzuela and M. Mazumdar, Monte-Carlo computation of power generation production costs under operating constraints, IEEE Trans. Power Syst., vol. 16, pp. 671677, 2001.
[23] P. Meibom, R. Barth, H. Brand, D. Swider, H. Ravn, and C.Weber, All Island Renewable Grid StudyWorkstream 2bWind Variability Management Studies, 2007. [Online]. Available: http://www.dcmnr.gov.ie.
[24] R. Barth, H. Brand, P. Meibom, and C.Weber, A stochastic unit commitment model for the evaluation of the impacts of the integration of large amounts of wind power, in Proc. 9th Int. Conf. Probabilistic Methods Applied to Power Systems, Stockholm, Sweden, 2006.
[25] Meibom, P., Barth, R., Hasche, B., Brand, H., Weber, C. and OMalley, M.J., Stochastic optimisation model to study the operational impacts of high wind penetrations in Ireland, IEEE Transactions on Power Systems, Vol. 26, pp. 1367 - 1379, 2011.
[26] High Level Assessment of Suitable Generation Portfolios for the All-Island System in 2020 All Island Renewable Grid StudyWorkstream 2A, 2006. [Online]. Available: http://www.dcmnr.gov.ie.

Colm Lowery received B.Sc.(Ing.) in Engineering with Management and M.Sc. degrees from Trinity College Dublin in 2007 and 2009. He is currently studying for a Ph.D. degree in the Electricity Research Centre, University College Dublin with research interests in the integration of wind energy in power systems.

Mark O'Malley received B.E. and Ph.D. degrees from University College Dublin in 1983 and 1987, respectively. He is the professor of Electrical Engineering in University College Dublin and is director of the Electricity Research Centre with research interests in power systems, control theory and biomedical engineering. He is a fellow of the IEEE.