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Stochastic optimization model to study the operational impacts of high wind penetrations in Ireland

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Abstract—**A stochastic mixed integer linear optimization scheduling model minimizing system operation costs and treating load and wind power production as stochastic inputs is presented. The schedules are updated in a rolling manner as more up to date information becomes available. This is a fundamental change relative to day-ahead unit commitment approaches. The need for reserves dependent on forecast horizon and share of wind power has been estimated with a statistical model combining load and wind power forecast errors with scenarios of forced outages. The model is used to study operational impacts of future high wind penetrations for the island of Ireland. Results show that at least 6000 MW of wind (34 % of energy demand) can be integrated into the island of Ireland without significant curtailment and reliability problems.**

Index Terms—**Wind power, unit commitment and dispatch, reserves, forecast errors, energy policy.**

NOMENCLATURE

Indices:

i, I	Unit, set of units
I_r	Set units in region r
I_r^{Stor}	Set of electricity storages in region r
I_r^{FAST}	Set of units with start-up time < 1 hour
$r, \bar{r}, R$	Region, neighbouring region. set of regions
s, S	Stochastic scenario , set of scenarios
t, t^l, t^{End}, T	Time step, first time step in optimisation period, last time step, set of time steps
T^{Day}	Set of time steps of day-ahead forecast horizon

Variables:

$K_{i,s,t}^{Sto}$	Storage level [MWh]
$P_{i,t}^{Day}$	Day-ahead scheduled power generation [MWh/h]

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$P_{i,s,t}^{+}$	Up regulation power generation [MWh/h]
$P_{i,s,t}^{-}$	Down regulation power generation [MWh/h]
$P_{r,s,t}^{-,W}$	Wind curtailment [MWh/h]
$P_{i,s,t}^{Onl,RP}$	Replacement reserves by online units [MW]
$P_{i,s,t}^{Off,RP}$	Replacement reserves by offline units [MW]
$P_{r,t}^{Sp,W}$	Incremental spinning reserves by wind power [MW]
$P_{i,s,t}^{Sp,+}$	Incremental spinning reserves by units [MW]
$Q_{r,t}^{DAY}$	Slack day-ahead electricity balance [MWh/h]
$Q_{r,s,t}^{INT}$	Slack intra-day electricity balance [MWh/h]
$Q_{r,s,t}^{SPIN}$	Slack spinning reserve requirements [MW]
$Q_{r,s,t}^{RP}$	Slack replacement reserve requirements [MW]
$R_{r,\bar{r},t}^{Day}$	Day-ahead scheduled electricity exchange [MWh/h]
$R_{r,\bar{r},s,t}^{+}$	Up regulation electricity exchange [MWh/h]
$R_{r,\bar{r},s,t}^{-}$	Down regulation electricity exchange [MWh/h]
$R_{r,\bar{r},s,t}^{RP}$	Provision of replacement reserves by electricity import [MW]
$V_{i,s,t}^{Onl}$	Unit online (binary variable)
$V_{i,0}^{Onl}$	Online status of unit at the beginning of the planning period
$W_{i,t}^{Day}$	Day-ahead scheduled loading of electricity storages [MWh/h]
$W_{i,s,t}^{+}$	Up regulation loading of electricity storages [MWh/h]
$W_{i,s,t}^{-}$	Down regulation loading electricity storages [MWh/h]
$W_{i,s,t}^{Sp,+}$	Incremental spinning reserves by storages [MW]
$W_{i,s,t}^{RP}$	Provision of replacement reserves by storages [MW]

Parameters:

η_i^{Sto}	Storage loading loss
π_s	Probability of scenario s
$c_{r,\bar{r}}^{Loss}$	Transmission loss between regions
cap_i^{Max}	Maximal capacity [MW]
cap_i^{Min}	Minimal capacity [MW]
$cap_{r,\bar{r}}^{T,Max}$	Maximal transmission capacity [MW]

$c_i^{Operation}(\cdot)$	Operation cost function of unit [€]
$c_i^{Opp}(\cdot)$	Opportunity cost function for online units and storages [Euro]
$c_i^{Start-up}(\cdot)$	Start-up cost function of unit [Euro]
$d_{r,t}^{Exp}$	Expected electricity load forecast [MWh/h]
$d_{r,s,t}^{Upd}$	Updated electricity load forecast [MWh/h]
$d_{r,s,t}^{Sp,+}$	Demand for incremental spinning reserves [MW]
$d_{r,s,t}^{RP}$	Demand for replacement reserve [MW]
l^L	Penalty slack day-ahead and intraday electricity balances [€/MWh]
l^{RP}	Penalty slack replacement reserves [Euro/MW]
l^{Sp}	Penalty slack spinning reserves [Euro/MW]
$p_{r,t}^{ExpW}$	Expected wind power production forecast [MWh/h]
$p_{r,s,t}^{UpdW}$	Updated wind power production forecast [MWh/h]
ru_i	Ramp-up rate of unit i [MWh/h]
sp_i	Incremental spinning reserve capability [MW]
su_i	Start-up ramp rate of unit i [MWh/h]
t_i^{SU}	Start-up time of unit i [h]
u_i^0	Number of hours the unit i has been online prior to the start of the planning period [h]
ut_i	Minimum up time of unit i [h]

I. INTRODUCTION

THE share of wind power capacity installed is increasing throughout the world. Wind energy is expected to contribute to the emission reduction targets given in the EU [1]. It is further expected that there will be a decrease in system operation costs i.e. excluding capital costs, because less conventional fuel needs to be consumed to cover the electrical demand. However, wind power production is subject to high variability and limited predictability. Control of wind power is limited to curtailing it. Hence, the integration of wind power has impacts on the operation of electrical power systems. To maintain the reliability of the power system to cover the load, conventional units have to be operated more flexibly. This implies more frequent part-load operation with reduced efficiencies and additional start-ups of conventional power plants leading to increased wear and tear [2]. In addition, an increased provision and use of reserve power is required [3], [4]. Moreover, if wind power is concentrated in regions with favorable wind conditions that are remote of load centers, increased wind power generation may lead to bottlenecks in existing transmission networks [5].

The evaluation of the impacts of increasing wind power on costs and system performance is important to assist policy makers and industry in setting wind power targets. Therefore, the optimal unit commitment and dispatch of conventional power plants, explicitly taking into account the variable and partly predictable characteristics of wind power generation, needs to be determined. The standard approach to determining the optimal power plant unit commitment and dispatch is represented by mixed-integer optimization models minimizing the operational costs of a power system subject to constraints [6]. Due to the stochastic nature of the wind power, this standard approach is not sufficient here. The approaches described for example in [7] - [9] are only capable of assessing the operational impacts of wind power variability. Yet, for systems with high wind power penetration, the analysis has to further account for the uncertainness of wind power production due to forecast errors in an optimal manner. In [10], the expected value of wind power forecasts is considered. The methodology in [11] calculates the wind power generation "at risk", which estimates the wind power production with a confidence interval. A more appropriate approach to account for the uncertain forecast error and its distribution is the application of stochastic programming [12], [13].

Results obtained with stochastic programming are robust with respect to multiple possible realizations of wind power, not only for the expected value. This is crucial since the necessary inclusion of inter-temporal constraints into power plant scheduling models, for example describing start-up times, requires the determination of the unit commitment before the exact realization of the uncertain wind power becomes known. Hence, the importance of stochastic optimization increases with the presence of inter-temporal constraints. Stochastic modelling has been used in the past for unit commitment models to consider the uncertainty of parameters like fuel and electricity market prices, hydro inflow or demand. The reviews in [14], [15] give a broad overview of existing approaches and applications. Recently, stochastic programming was applied to the joint optimization of pumped-storage units and wind generation for bidding into electricity markets [16]. However, this approach does not take into account the impacts on the conventional power system. A short-term forward electricity market-clearing problem with stochastic security taking wind power generation into account is presented in [17]. In [18] an algorithm for calculating a day-ahead unit commitment schedule is presented taking iteratively network constraints into account and being robust towards wind power forecasts errors.

In this paper a stochastic mixed integer linear optimization scheduling model treating wind power forecasts and load forecasts as uncertain parameters is used to study the operational impacts of high wind penetrations on the power system of the island of Ireland. The model is unique in its combination of a scenario generation methodology, treatment of reserves and a rolling stochastic unit commitment and dispatch driven by updated forecasts. Compared to [17] and, [18] the unit commitment algorithm presented in this paper allows different unit commitment schedules for each set of wind power, load and replacement reserves forecasts as long as unit restrictions concerning such as start-up times are respected. More fundamentally, the unit commitment schedules are updated in a rolling manner as more up to date forecasts become available [19]. In section II the different parts of the planning tool are described. Section III describes the study model. Section IV presents the results and discussion

and Section V concludes.

II. THE PLANNING TOOL

On the island of Ireland (Northern Ireland (NI) and Republic of Ireland (RoI)), a particularly favorable regime for wind generation can be identified. To understand the technical and economic impacts of high levels of installed renewable generation, the governments of NI and RoI commissioned in cooperation with the Irish transmission system operators and energy regulators the All Island Grid Study analyzing wind power integration issues for the study year 2020.

The All Island power system (the power systems in RoI and NI) comprises a single synchronous power system with a present peak demand of approximately 7000 MW and 500 MW interconnection to the power system in Great Britain (GB). The modeling of the operation of this nearly isolated power system with high penetrations of wind power requires a detailed representation of the unit commitment including provision of reserves and forced and planned outages. The unit commitment and dispatch model which has been developed in the Willmar project [20], has many of the characteristics required. However, the model was extended and enhanced to conduct one of the work streams in the All Island Grid Study. In particular the integer decisions (on/off status of power plants) are modeled (i.e. mixed-integer-programming) and a detailed representation of reserves as a function of wind power is included. Furthermore in addition to wind uncertainty, load uncertainty and forced outages of power plants have also been modeled. Below a description of the extended Wilmar planning tool is given, which consists of two main components, the Scenario Tree Tool (STT) and the Scheduling Model (SM) [20].

A. Scenario Tree Tool

In order to schedule power plant operation, decisions have to be taken that consider both parameters known with certainty as well as the distribution of uncertain parameters for future hours. To represent the uncertainty, multi-stage scenario trees are applied, Fig. 1, generated by the STT. Future wind power and load outcomes and associated demand for replacement reserves (see Section II.C for treatment of individual reserve categories) are described with given probabilities of occurrence for the different paths of the scenario tree. The values within the root node (corresponding to the first three hours in every scenario tree in Fig. 1) of a scenario tree are assumed to be known with certainty. Furthermore the STT generates time series describing forced outages of conventional power plants.

The main input data for the Scenario Tree Tool is wind speed and/or wind power production data, electricity demand data, and data of outages and the mean time to repair of power plants. In order to consider the spatial distribution of future wind power capacity and the correlation of wind power production, the All Island power system is subdivided into 11 onshore and 10 offshore zones described with respective wind time series. Wind correlation effects within one zone are

considered by smoothing out the given wind time series according to [21]. The required set of scenarios is generated by Monte-Carlo-simulations of wind speed and load forecast error based on Auto Regressive Moving Average (1,1) (ARMA(1,1)) time series models [22]. They are applied to represent the statistical characteristics of wind speed and load forecast errors of the All Island power system, in particular the standard deviation in dependence of the forecast horizon [23]. It is assumed that the distribution of the wind speed error follows a Gaussian distribution [24]. Concerning wind speed forecast scenarios, spatial correlations of wind power forecast errors as observed in the All Island power system are explicitly taken into account. With decreasing distance between two wind power production sites, the correlation between wind power forecast errors increases. Additionally, the correlation increases with increasing forecast horizon. The representation of these characteristics is based on a Cholesky decomposition of the correlated Gaussian matrix considered by multidimensional ARMA time series [23].
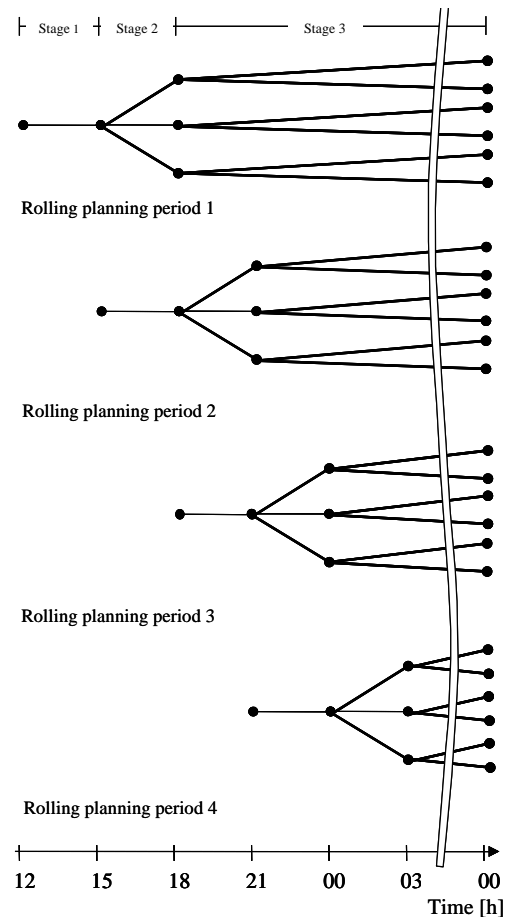

Fig. 1. Scenario trees and rolling planning covering half a day.

Many randomly drawn sample paths of the ARMA series represent multiple possible outcomes of forecasting errors. These sample paths of wind power prediction errors and load forecasts errors are added to historical time series of respectively wind power production and load time series scaled to match 2020 yearly wind power production and load

to generate wind power production and load scenarios. In order to describe the obtained distribution of these wind power and load scenarios with a reduced number of scenarios, a scenario reduction approach consisting of two steps following [25] is used. The number of scenarios is reduced by firstly determining the Euclidean distances between the individual forecast scenarios. One scenario of the scenario pair with the smallest Euclidean distance is deleted and the sum of the probabilities of both scenarios is allocated to the remaining scenario. This procedure is repeated until a predefined number of scenarios is achieved. Afterwards, based on the remaining scenarios that still form a one-stage tree, a multi-stage scenario tree is constructed by deleting inner forecasts and creating branching within the scenario tree.

Planned and forced outages are described for each individual power plant with an hourly time resolution. The occurrence of forced outages in a certain hour is simulated with Semi-Markov chains describing the alternating process between the availability and the unavailability state of a power plant [26], [27]. Failure and repair rates are thereby expressed with the mean time to failure and the mean time to repair [28].

B. Scheduling model

The scheduling problem is solved by minimizing the expected operational costs of meeting load and reserve demands subject to all modeled constraints taking into account all different paths of the scenario tree. The problem is formulated as a stochastic, mixed integer linear optimization problem eq. 1-19. In the root node of the tree, so-called here-and-now decisions have to be taken. For subsequent stages, a wait-and-see approach is applied for the decisions following one of the individual paths [12], [13]. The simultaneous anticipation of the several different possible outcomes at later stages has an impact on power plant scheduling in the earlier stages – e.g. more capacity with longer start-up times might be started up earlier to be able to cope in later stages with wind production below expectations.

To analyze system operation with large wind penetrations, it is important to use repeated, rolling planning to account for rescheduling when updated information becomes available, (e.g. new wind forecasts). In the first planning period starting at noon an optimal schedule is produced based on the most up to date forecast information, as generated with the Scenario Tree Tool, for the 36 hours from noon to the end of the following day. In the following planning periods, rescheduling is done intraday based on updated forecast information and existing schedules. Rescheduling is determined by recourse decisions that result in up- or down-regulation of the power plant dispatch and changes in the unit commitment planned in previous planning loops [29]. Fig. 1 shows the resulting planning process, with scenario trees for four planning loops, each three hours apart, covering half a day. Planning more often (e.g. every hour) would be favourable however this would dramatically increase the computation time. The final realized operation of the power system is represented by the values of the decision variables in stage 1 of every planning

period (see Fig. 1), i.e. they represent the final outcome of the rolling planning process.

$$
\min \left\{
\begin{aligned}
& \sum_{s\in S}\pi_S \sum_{t\in T}\sum_{i\in I} c_i^{Operation}(P_{i,t}^{Day}+P_{i,s,t}^{+}-P_{i,s,t}^{-})+ \\
& \sum_{s\in S}\pi_S \sum_{t\in T}\sum_{i\in I} c_i^{Start-up}(V_{i,s,t}^{Onl},V_{i,s,t-1}^{Onl}) \\
& -\sum_{s\in S}\pi_S \sum_{i\in I} c_{i,s,t^{End}}^{Opp}(V_{i,s,t^{End}}^{Onl},K_{i,s,t^{End}}^{Sto}) \\
& +\sum_{s\in S}\pi_S \sum_{t\in T}\sum_{r\in R}\left(l^L Q_{r,s,t}^{INT}+l^{SP}Q_{r,s,t}^{SPIN}+l^{RP}Q_{r,s,t}^{RP}\right) \\
& +\sum_{t\in T}\sum_{r\in R} l^L Q_{r,t}^{DAY}
\end{aligned}
\right. \tag{1}
$$

s.t.

$$
\sum_{i\in I_r}P_{i,t}^{Day}+p_{r,t}^{ExpW}+\sum_{\overline{r}\in R}((1-c_{r,\overline{r}}^{Loss})\cdot R_{r,\overline{r},t}^{Day})=\sum_{i\in I_r^{Stor}}W_{i,t}^{Day}+ \tag{2}
$$

$$
\sum_{\overline{r}\in R}R_{\overline{r},r,t}^{Day}+d_{r,t}^{Exp}-Q_{r,t}^{DAY}\quad\forall t\in T^{Day};r\in R
$$

$$
\sum_{i\in I_r}(P_{i,s,t}^{+}-P_{i,s,t}^{-})+\sum_{r\in R}((1-c_{r,\overline{r}}^{Loss})(R_{r,\overline{r},s,t}^{+}-R_{r,\overline{r},s,t}^{-}))
$$

$$
+\sum_{i\in I_r^{Stor}}(W_{i,s,t}^{-}-W_{i,s,t}^{+})-P_{r,s,t}^{-,W}=\sum_{r\in R}(R_{r,r,s,t}^{+}-R_{r,r,s,t}^{-})) \tag{3}
$$

$$
+p_{r,t}^{ExpW}-\left(p_{r,s,t}^{UpdW}-P_{r,t}^{SpW}\right)-\left(d_{r,t}^{Exp}-d_{r,s,t}^{Upd}\right)-Q_{r,s,t}^{INT}
$$

$$
\forall s\in S;t\in T;r\in R
$$

$$
\sum_{i\in I_r}P_{i,s,t}^{Sp,+}+\sum_{i\in I_r^{Stor}}W_{i,s,t}^{Sp,+}+P_{r,t}^{SpW}\geq d_{r,s,t}^{Sp,+}-Q_{r,s,t}^{SPIN} \tag{4}
$$

$$
\forall s\in S,t\in T;r\in R
$$

$$
\sum_{i\in I_r}P_{i,s,t}^{Onl,RP}+\sum_{i\in I_r^{FAST}}P_{i,s,t}^{Off,RP}+\sum_{i\in I_r^{Stor}}W_{i,s,t}^{RP}
$$

$$
+\sum_{\overline{r}\in R}((1-c_{r,\overline{r}}^{Loss})\cdot R_{r,\overline{r},s,t}^{RP}\geq\sum_{\overline{r}\in R}R_{\overline{r},r,s,t}^{RP}+d_{r,s,t}^{RP}-Q_{r,s,t}^{RP} \tag{5}
$$

$$
-\max\left\{0,p_{r,t}^{ExpW}-p_{r,s,t}^{UpdW}-\left(d_{r,t}^{Exp}-d_{r,s,t}^{Upd}\right)\right\}
$$

$$
\forall t\in T;s\in S;r\in R
$$

$$
P_{i,t}^{Day}+P_{i,s,t}^{+}-P_{i,s,t}^{-}+P_{i,s,t}^{Sp,+}+P_{i,s,t}^{Onl,RP}\leq V_{i,s,t}^{Onl}\cdot cap_i^{MAX} \tag{6}
$$

$$
\forall i\in I;s\in S;t\in T
$$

$$
P_{i,t}^{Day}+P_{i,s,t}^{+}-P_{i,s,t}^{-}\geq V_{i,s,t}^{Onl}\cdot cap_i^{Min}\quad\forall i\in I;s\in S;t\in T \tag{7}
$$

$$
P_{i,t}^{Day}+P_{i,s,t}^{+}-P_{i,s,t}^{-}+P_{i,s,t}^{Sp,+}+P_{i,s,t}^{Onl,RP}\leq
$$

$$
P_{i,t-1}^{Day}+P_{i,s,t-1}^{+}-P_{i,s,t-1}^{-}+V_{i,s,t}^{Onl}\cdot ru_i+su_i\left(V_{i,s,t}^{Onl}-V_{i,s,t-1}^{Onl}\right) \tag{8}
$$

$$
+cap_i^{Max}\left(1-V_{i,s,t}^{Onl}\right)\quad\forall i\in I;s\in S;t\in T
$$

$$
\sum_{t=1}^{g_i}\left(1-V_{i,s,t}^{Onl}\right)=0\quad\forall i\in I;s\in S \tag{9}
$$

$$
\sum_{n=t}^{t+ut_i-1}V_{i,s,n}^{Onl}\geq ut_i\left(V_{i,s,t}^{Onl}-V_{i,s,t-1}^{Onl}\right) \tag{10}
$$

$$
\forall i\in I;s\in S;t=g_i+1\cdots t^{End}-ut_i+1
$$

where g_i is the number of initial time periods in each planning period that the unit has to be online. It is given by:

$$g_i = Min\left(T, \left[ut_i - u_i^0\right] V_{i,0}^{Onl}\right)$$

$$\sum_{n=t}^{t^{End}} \left[V_{i,s,n}^{Onl} - \left(V_{i,s,t}^{Onl} - V_{i,s,t-1}^{Onl} \right) \right] \geq 0 \tag{11}$$

$$\forall i \in I; s \in S; t = t^{End} - ut_i + 2 \cdots t^{End}$$

$$P_{i,s,t}^{Sp,+} \leq V_{i,s,t}^{Onl} \cdot sp_i \quad \forall i \in I; s \in S; t \in T \tag{12}$$

$$R_{r,r,t}^{Day} + R_{r,\bar{r},s,t}^{+} - R_{r,\bar{r},s,t}^{-} + R_{r,\bar{r},s,t}^{RP} \leq cap_{r,\bar{r}}^{T,Max} \tag{13}$$

$$\forall r, \bar{r} \in R; s \in S; t \in T$$

$$P_{i,t}^{Day} \leq cap_i^{MAX} \quad \forall i \in I; t \in T \tag{14}$$

$$W_{i,t}^{Day} \leq cap_i^{MAX} \quad \forall i \in I^{Sto}; t \in T \tag{15}$$

$$R_{r,\bar{r},t}^{Day} \leq cap_{r,\bar{r}}^{T,Max} \quad \forall r, \bar{r} \in R; t \in T \tag{16}$$

$$P_{r,s,t}^{-,W} + P_{r,t}^{SpW} \leq p_{r,s,t}^{UpdW} \quad \forall r \in R; s \in S; t \in T \tag{17}$$

$$V_{i,s',\tau}^{Onl} = V_{i,s,\tau}^{Onl} \quad \forall i \in I; s, s' \in S; \tau \text{ with } t^1 \leq \tau < t^1 + t_i^{SU} \tag{18}$$

$$K_{i,s,t}^{Sto} = K_{i,s,t-1}^{Sto} + \eta_i^{Sto}\left(W_{i,t}^{Day} + W_{i,s,t}^{+} - W_{i,s,t}^{-} \right)$$

$$- P_{i,t}^{Day} + P_{i,s,t}^{+} - P_{i,s,t}^{-} \quad \forall i \in I^{Sto}; s \in S; t \in T \tag{19}$$

The objective function of the model (eq. 1) includes operational costs consisting of fuel costs and costs of consuming CO_2 emission permits (line 1 in eq. 1), start-up costs including fuel consumption used for start-ups (line 2 in eq. 1), opportunity values of having online units and positive storage levels at the final time step of the scenario tree (line 3 in eq. 1), penalty costs of not fulfilling the electricity demand in the intra-day scheduling and the demand for spinning and replacement reserve (line 4 in eq. 1), and penalty costs of not fulfilling the demand in the day-ahead scheduling. Fuel consumption is calculated using piecewise linear fuel consumption curves. The opportunity value of online units at midnight (as the planning loops always ends at midnight) is set equal to the start-up costs of the unit. The opportunity value of having electricity stored at midnight is set equal to the marginal value of the balance equation of electricity storage at midnight in the previous planning loop.

System level constraints consist of regional electricity balance equations for day-ahead scheduling (eq. 2) using the average values of wind power and load in the scenario tree as the expected value forecasts of wind power and load, intra-day electricity balancing equations (eq. 3) where up and down regulation of power plants are used to cover deviations between average values and wind power and load forecasts in each path of the scenario tree, system spinning reserve requirements (eq. 4), replacement reserve requirements (eq. 5). Transmission losses between regions are allocated to the importing region as shown in eq. 2 and 3. Transmission and distribution losses within a region are assumed included in the electricity load. The demand for replacement reserve is reduced with the up-regulation already carried out by intra-day rescheduling (line 3 in eq. 5). Only input parameters are included in the max function hence usage of this function avoids non-linearity. Constraints on unit operation using binary variables following the approach of [30] and extended

to covering the stochastic optimization case have been included into the Wilmar planning tool. These constraints cover minimum and maximum stable operation levels (eq. 6) and (eq. 7), ramp-up and start-up ramp rates (eq. 8), minimum up times (eq. 9-11) and capability of providing spinning reserve (eq. 12). Eq. 9 ensures that a unit started up in a previous planning period stays online during the remaining hours of its minimum up time. Eq. 10 ensures that the minimum up time constraint is satisfied during all the possible sets of consecutive periods of size ut_i, and eq. 11 ensures that if a unit is started up ut_i hours or less before the planning period ends, it remains online until the end of the time span. A similar equation as eq. 7 constrains the ramp-down rate and similar equations as eq. 9-11 ensure minimum shut down times. Transmission restrictions between the Irish island and GB apply (eq. 13). Eqs. 14, 15 and 16 restrict the day-ahead quantities of respectively power production, loading of electricity storage and transmission to available capacities. Planned wind curtailment can not be larger than wind power forecasts (eq. 17).

Start-up times imply that the capacity online status of a unit in the first hours of a planning loop has to be decided in the previous planning loop, and therefore cannot be bigger than the capacity online found in the previous planning loop for the same hours. Furthermore assuming that the start-up process of a unit can not be interrupted, it is only possible to change unit commitment as a result of realisation of a certain load and wind power production scenario after the start-up time of the unit has passed (eq. 18). The modelling of unit start-up times is not as comprehensive as the model proposed in [31]. Restrictions ensuring energy balance in pumped hydro storage (eq. 19) and all units either pumping or generating are included (see [32] for full details). The scheduling model is implemented in General Algebraic Modeling System (GAMS) and solved using the CPLEX mixed integer programming (MIP) solver [33]. For a planning loop covering 36 hours, using scenario trees with 6 branches as shown in Fig. 1 and power plant portfolio 5 (see section III.A), the model consists of 137119 equations, 94873 continuous variables and 11487 discrete variables. It takes on average 1½ minute to be solved using a computer with an Intel Core2 Duo 3.0 GHz processor with 8GB of RAM running Microsoft Windows XP with 64 bit and the CPLEX MIP solver with a relative optimality criterion of 0.5.

C. Treatment of reserves

The demand for different categories of reserves as well as the provision of these reserves by suitable power plants has to be considered. In the grid code of the Republic of Ireland a number of reserve categories are defined [34]. These reserve categories may be subdivided into two groups: (a) spinning reserves with short activation times that can be provided typically by synchronised i.e. spinning units or tripping of pumps in a pumped storage station and (b) slower, replacement reserves which can be provided by both synchronised and offline units. The scheduling model considers these two types of reserve, spinning and replacement in eq. 4 and 5 respectively. Spinning reserves are modelled by one reserve category corresponding to tertiary operating

reserve band 1 (TR1) as defined in the Irish grid code [34] with a time frame of 90 seconds to five minutes. The demand for spinning reserves in the model is equal to the largest production plus spinning reserve provision from a single unit as planned in the previous planning loop, in combination with an additional demand to cover fast decreases of the current wind power production over the TR1 time frame as described in [3].

Reserve categories with activation times longer than five minutes are represented by replacement reserves. They can be provided by online power plants and offline power plants that are able to start up in time to provide the reserves in the hour in question. For a given forecast horizon specific distributions of wind power forecasts, load forecasts and forecast of forced outages will result in a specific demand for reserves needed to handle the estimated possible deviation. Therefore for each scenario and for each hour in the planning horizon there are replacement reserve targets. The targets are determined with the Scenario Tree Tool on the basis of a comparison of the hourly power balance considering perfect forecasts and no forced outages with the power balance considering scenarios of wind and load forecast errors as well as forced outages. A percentile of the deviation between the compared power balances has to be covered by replacement reserves, see section V.

The contribution from an individual power plant to reserve is restricted by its technical capability within the time frame of interest and its planned dispatch. By curtailment of the current wind power production, wind power plants are also able to contribute to positive spinning reserves. The model includes this possibility in the optimization by a variable determining the percentage of the lowest wind power production forecast being dispatched down to provide reserve from the wind turbines (see eq. 3 and 4). This variable is reoptimised in every planning loop, so the realized spinning reserves from wind power are based on up to 3 hour ahead wind power forecasts. The lowest wind power forecast in combination with reoptimisation every 3 hours is chosen to ensure that the wind power plants should be able to provide the amount of reserve. It was included in the model to analyse how often it was optimal to use such a strategy, however it would need to be tested via field tests to ensure its validity.

Demand for negative reserves (down regulation capabilities) is caused by wind productions being higher and/or load being lower than expected. Negative reserves can be provided by all power plants, including wind generators, subject to current unit commitment, dispatch and the technical capabilities.

Penalties for not fulfilling load and reserve demands are such that load is met before the demand for spinning reserves, and the demand for spinning reserve is met before the demand for replacement reserves, i.e. $l^L > l^{SP} > l^{RP}$ in eq. 1.

III. THE MODEL

A. *The Irish model*

Three different levels of renewable power production are

represented in five power plant portfolios enabling analysis of the economic and technical impacts of increasing the share of renewable energy (mainly wind) in the All Island power system for the study year of 2020.

By combining scenarios for forced outages of plants, wind power production and load, the LOLE (Loss of load expectation) of each portfolio is calculated. The capacity balances of the portfolios were calibrated to give a LOLE of 8 hours per year. Table I gives details of installed capacities for each portfolio.

Portfolio 1 (P1) has 2000 MW of wind power, portfolio 2, 3 & 4 (P2, P3 & P4) each have 4000 MW of wind power but with different thermal plant mixes and portfolio 5 (P5) has 6000 MW of wind power. Therefore the portfolios facilitated the study of increasing levels of wind power (i.e. P1, P2-P4, P5) and of different thermal plant mixes (i.e. P2, P3 & P4). Power plant portfolio P4 has a high share of base load plants (coal fired thermal plants and natural gas fired Combined Cycle Gas Turbines (CCGTs)), P3 has a high share of more flexible plants Open Cycle Gas Turbines (OCGTs) and Aero Derivative Gas Turbines (ADGTs)) and P2 a mix of CCGT, OCGT and ADGT. Thus, comparing portfolios P2, P3 and P4 allows evaluation of the impact of the structure of conventional power plant portfolio when renewable energy is integrated.

Apart from power exchange with Great Britain (GB), network issues were not taken into account.

TABLE I
INSTALLED CAPACITIES OF POWER PLANTS [MW] IN EACH PORTFOLIO.

	P1	P2	P3	P4	P5
Coal	1257	1257	1257	2420	1257
Peat	346	346	346	346	346
OCGTs	1838	1217	2356	699	1217
ADGTs	89	535	535	0	111
CCGTs	4424	4330	3130	4330	4330
Hydropower	216	216	216	216	216
Pumped hydro	292	292	292	292	292
Base Renewables	182	182	182	182	360
Tidal stream	72	72	72	72	200
Wind power	2000	4000	4000	4000	6000
Installed capacity excl. wind & tidal	8644	8374	8314	8484	8128
Peak load	9619	9619	9619	9619	9619

B. *The GB model*

The interconnectors between the island of Ireland and GB will influence both the day-ahead scheduling and the provision of reserve power in the island of Ireland. Consistent with existing and planned interconnection 1000 MW (two 500 MW HVDC) of transmission capacity is assumed, which due to the small size of the All-Island power system will have a

significant impact on scheduling of Irish units. The GB power system is represented in an aggregated way by seven groups of power plants shown in Table II. The conventional plants are not subject to any inter-temporal restrictions. This representation underestimates the costs connected to providing flexibility in the GB system. Hence to avoid overestimating the capability of the interconnectors to handle wind power variability and unpredictability, the usage of the transmission capacity was assumed to be determined in the day-ahead scheduling process, i.e. no rescheduling of the power transmission due to wind power forecast errors or outages was allowed (R^+ and R^- fixed to zero in eq. 3 and 13). It was assumed that the interconnectors provide 50MW each of spinning reserve in every hour during the year. This is consistent with the present-day usage of the existing 500MW Moyle interconnector between Northern Ireland and Scotland. Consequently the import capability into the All Island power system was reduced to 900 MW.

The wind power production in GB is deterministic and follows a fixed hourly time series taken from historical data for the Irish wind power production shifted one hour in time. The one hour time lag is based on the average distance between Northern Ireland and Scotland and average wind speeds in Ireland. By using correlated time series for wind power production in the All Island power system and GB, it is to some extent taken into account that export possibilities in high wind situations in the All Island power system probably will be limited by also having high wind situations in GB at the same time.

TABLE II
INSTALLED CAPACITIES OF PLANT TYPES IN GB.

Plant type	Nuc-lear	Coal	CCGT	OCGT	Oil	Hydro	Wind
Capacity [MW]	9556	28865	35800	589	2990	1166	14000

C. CO_2 and fuel price assumptions

TABLE III
FUEL PRICES [€/GJ]

Fuel	Great Britain	Northern Ireland	Republic of Ireland
Coal	1.75	2.11	1.75
Gas oil	9.64	8.33	9.64
Light oil	5.22	4.83	5.22
Natural gas base load	5.62	5.91	5.91
Natural gas mid-merit	5.81	6.12	6.12
Nuclear	0.4	-	-
Peat	-	3.71	3.71

A CO_2 price of 30 €/Ton was assumed and fuel price assumptions are given in Table III. The study used a monthly varying natural gas price with Table III giving the yearly average price. The natural gas price is slightly higher for power plants having lower utilization times (named mid-merit) in comparison to base load plants.

D. Data sources

Technology data for Irish power plants have been provided by the All Island Grid Study working group for existing power plants and by [9] for new plants. Historical wind time series and electricity load time series, appropriately scaled for the study year 2020 were provided by the Transmission System Operators of the RoI (EirGrid) and NI (SONI). The main source of GB data was [35]. Full details of data input can be found in [32]. To illustrate the flexibility of Irish thermal power plants, Table IV presents the range of unit data for the main plant types.

IV. RESULTS

Yearly simulation runs using the Wilmar planning tool were performed for the five portfolios with hourly resolution and rolling every three hours. To establish the credibility of the Wilmar planning tool, a comparison with the Irish industry standard deterministic unit commitment and dispatch tool, PLEXOS [36] was conducted. In order to compare, the Wilmar Planning tool was run using perfect foresight about wind power production and load i.e. not using stochastic optimisation. This is done by having only one scenario *s* in eq. 1-19 with load and wind power forecasts being perfect i.e. equal to realised values. Results from the two models were in good agreement. Calculation time for a yearly stochastic run of P5 consisting of 2924 planning periods and using a computer with an Intel Core2 Duo 3.0 GHz processor with 8GB of RAM running Microsoft Windows XP with 64 bit and the CPLEX MIP solver with a relative optimality criterion of 0.5% was 43 hours.

TABLE IV
RANGE OF VALUES USED FOR THERMAL POWER PLANTS IN IRELAND.

	Coal	Peat	OCGT/ ADGT	CCGT
Start-up time when hot [h]	2-5	1-4	0	1-2
Min. up time [h]	6-8	4-12	0-1	1-10
Min. down time [h]	4-8	0-2	0-1	1-8
Min. power output /Max. power output	0.32-0.5	0.34-0.44	0.1-0.17	0.48-0.58
Ramp rates up [% of max. power output per minute]	1.5-3.2	0.5-2.2	10.0-16.7	1.7-5.0
Eff. at min. power output/Max. eff.	0.81-0.95	0.89-0.93	0.41-0.43	0.84-0.93

A. Net load and demands for reserves

To illustrate the operational challenges posed by increased amounts of wind power production, the development of the net load and the demands for reserves is presented. The net load is defined as the realised electricity consumption minus the realised wind power production.
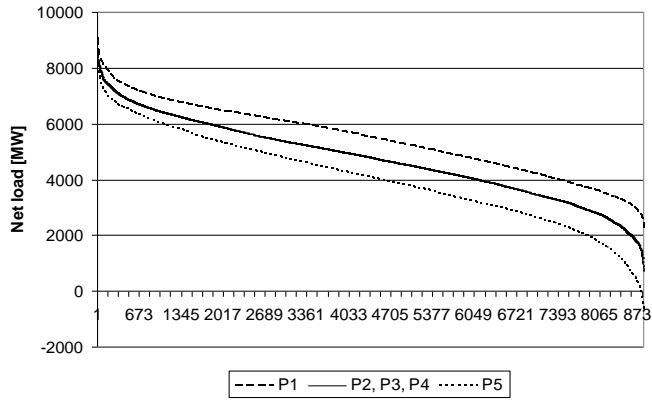
Fig. 2. Duration curves of the net load (load minus wind power production) in the All Island power system for all portfolios.

Fig. 2 shows the duration curves of the net load in the All Island power system. With increasing installed wind power capacity, the net load is generally decreased. In portfolio P5, the net load becomes negative for 48 hours.

Fig. 3 shows the effect of the power exchange with GB and usage of pumped hydro storage on the load to be covered by production from conventional plants in the All Island power system for P5. As the marginal production costs in GB are on average smaller than in the Irish power system, power imports dominate decreasing the net load in 6330 hours during the year. Power exports to GB and pumping are used in hours with low net load to avoid wind curtailment.
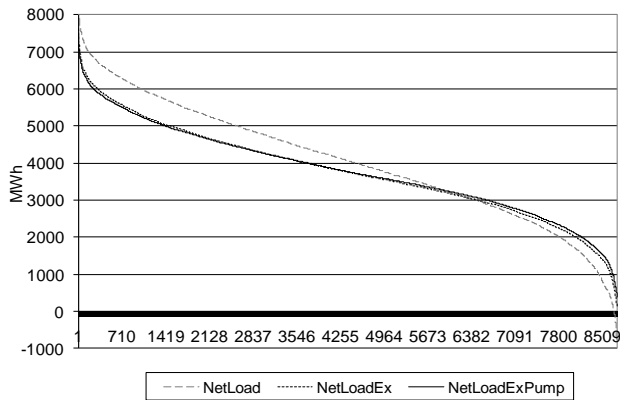
Fig. 3. Duration curves for P5 of the net load (NetLoad), net load minus net import (NetLoadEx), net load minus net import including usage of pumped hydro storage (NetLoadExPump) in the All Island power system.

A measure for the variability in the net load is the change in the net load from one hour to the next (here named delta net load). Table V gives statistical properties of delta net load with values expressed as a fraction of the peak load. Delta net load increases with increasing wind power capacity installed, thereby requiring more flexible operation from conventional power plants.

The demand for spinning reserves depends on the largest unit online and the wind power forecasts errors. The differences in the spinning reserve requirements between portfolios are relatively small with an average demand in the order of 475 MW and a variation between portfolios of

approximately 50 MW. This is due to the largest online unit having approximately the same size in all portfolios, and the influence of wind power forecast errors on spinning reserve requirements being small [3].

TABLE V
STATISTICAL PROPERTIES OF DELTA NET LOAD AS A RATIO OF PEAK LOAD.

	P1 [%]	P2, P3, P4 [%]	P5 [%]
Maximum	17	19	27
Minimum	-17	-25	-35
90% percentile	6	6	6
10% percentile	-5	-5	-6

Before determination of the demand for replacement reserves for power plant portfolios P1 – P5, the appropriate percentile of the total forecast error (wind, load & forced outages) to be covered by replacement reserves had to be determined. This was done by comparing different percentiles of total forecast error in the present Irish power system with the present requirements for replacement reserves. It was found that the 90th percentile corresponded to existing practice and this was used for the determination of the demand for replacement reserves.

The resulting average demand for replacement reserves dependent on the forecast hours for portfolios P1 – P5 is shown in Fig. 4. The demand for replacement reserves increases with increasing wind power capacity and forecast horizon. For longer forecast horizons of 16 hours and above, the demand for replacement reserves becomes approximately constant corresponding to wind power forecast errors not increasing for these forecast horizons.
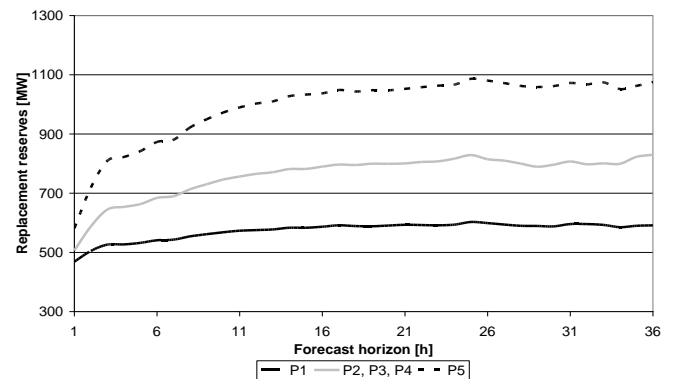

Fig. 4. Average demand for replacement reserves dependent on the forecast horizon for all portfolios given in MW. Demands for replacement reserves in portfolios P2, P3 and P4 are very similar due to the same wind power capacity considered.

B. Operational costs and CO_2 emissions

The share of the renewable power production (mainly wind power) of the yearly electricity demand in the All Island power system rises from 16 % (11 % wind) in portfolio P1 to 42 % (34 % wind) in portfolio P5 (see Table VI). With increasing wind power capacity installed, yearly operation costs of the All Island power system are reduced for portfolios P1 – P5. P5 is the best portfolio in terms of operational costs

and CO_2 emissions. Comparing those portfolios with an equal wind power capacity installed (portfolio P2, P3, P4), portfolio P4 shows the lowest (base load gas and coal) and portfolio P3 (OCGT) the highest total operation costs.

The CO_2 emissions in the All Island power system tend to decrease with increasing wind power installed. However, portfolio P4 shows the highest sum of CO_2 emissions caused by the large share of coal plants in P4 relatively to the other portfolios. P2 with more base load gas (CCGTs) has lower CO_2 emissions than P3 with more mid merit gas (OCGTs). The net import into the All Island power system is significantly smaller in P4 relatively to P1, i.e. the effect of decreasing CO_2 emissions due to increased wind power production in P4 relatively to P1 is offset by the increased share of domestic power production in P4 on base load coal plants relatively to P1. Comparing P2, P3 and P4 with respect both to operational costs and CO_2 emissions, it is preferable to have a high share of base loaded gas units with low variable costs in the portfolio (i.e. P2) relative to many peak units (P3) or many coal units (P4).

TABLE VI
RENEWABLE ENERGY PRODUCTION, OPERATIONAL COSTS AND CO_2 EMISSIONS IN EACH PORTFOLIO FOR ALL ISLAND. COSTS AND CO_2 EMISSIONS RELATIVE TO P1 SHOWN IN PARANTHESIS.

	P1	P2	P3	P4	P5
Wind prod/yearly demand [%]	11	23	23	23	34
Renewable production / yearly demand [%]	16	27	27	27	42
Operational costs incl. payments related to power exchange with GB [MEuro]	2335 (1.00)	2003 (0.86)	2105 (0.90)	1897 (0.81)	1622 (0.69)
Resulting sum of CO_2 emissions [Mton]	20.1 (1.00)	17.6 (0.88)	18.4 (0.92)	21.8 (1.08)	15.4 (0.76)

C. Reliability in the All-Island power system

The comparison of the installed capacity in the All Island power system excluding the non-dispatchable power sources, wind and tidal, with the peak load shows that all portfolios require import from GB and/or production from non-dispatchable power sources in order to meet the load in peak load hours (see Table I).

TABLE VII
NUMBER OF HOURS WHERE LOAD, DEMAND FOR SPINNING RESERVE AND REPLACEMENT RESERVES ARE NOT MET.

Portfolio	Hours where load is not met	Hours where demand for spinning reserve is not met	Hours where demand for replacement reserve is not met due to lack of capacity
P1	0	5	95
P2	2	6	94
P3	0	0	98
P4	1	5	102
P5	1	3	82

Table VII shows the number of hours where load, demand for spinning reserves and demand for replacement reserves are not met in the model runs, i.e. number of hours where the slack variables in eq. 1, 2, 3, 4 were used. All portfolios show a higher reliability than the calculated LOLE of 8 hours. The small number of hours where load and spinning reserves are not met in P1-P5 indicates that the inclusion of replacement reserves in the model results in production plans being robust towards forecast errors and forced outages. Table VII further shows that in all portfolios the demand for replacement reserves is not fulfilled in approximately 100 hours per year due to lack of capacity. Hence, the power system would not be able to cover the 90th percentile of the total forecast errors that may occur during these hours. Demand for spinning reserves is fulfilled in nearly all hours during the year. P2 and P4 are slightly less reliable than P3 although they have a bit more dispatchable capacity installed (see Table I). This is due to P3 having a larger share of dispatchable capacity as fast responding and flexible OCGTs and ADGTs than P2 and P4.

D. Provision of reserves

One of the main sources of positive spinning reserve is pumped hydro storage which provides 70 MW from each pump unit when pumping. Coal fired units and newer CCGTs are other main sources of positive spinning reserves. The part load efficiencies of these units are high resulting in rather low costs of operating below rated output capacity. ADGTs also have high part-load efficiencies and are used especially in P3 due to the fewer base load units in this portfolio. Wind power is used more frequently to provide spinning reserve as wind power production increases (see Table VIII). P3 has a higher provision of spinning reserve from wind power than P2 and P4. Because curtailment of wind power is a relatively expensive way of providing spinning reserve, this indicates that providing spinning reserves is most costly in portfolio P3 with many OCGTs compared to portfolio P2 with CCGTs and portfolio P4 with CCGTs and coal power plants.

TABLE VIII
NUMBER OF HOURS WITH WIND POWER PROVIDING SPINNING RESERVE AND THE AVERAGE PROVISION OF SPINNING RESERVE FROM WIND POWER.

	P1	P2	P3	P4	P5
Duration [h]	0	17	62	4	239
Average/installed wind capacity [%]	0	0.4	0.4	0.1	0.4

Nearly the whole demand for replacement reserves is provided with offline units (mainly OCGTs and ADGTs) in all portfolios. In most hours the availability of replacement reserves is significantly higher than the demand for replacement reserves indicating that the marginal costs of providing replacement reserves are equal to zero in these hours. This is due to the OCGTs and ADGTs in many hours being offline irrespective of the demand for replacement reserves, because of their high marginal production costs.

E. Dispatch of thermal power plants

Fig. 5 shows the yearly electricity production by fuel type for the All Island power system. Generally, the bigger part of the electricity production in the All Island power system from conventional power plants is borne by coal fired plants and CCGTs. This is also reflected in comparable high capacity factors of these units. As expected P4 has a high production on coal compared to P2 and P3, and P3 has a relatively high production from OCGTs and ADGTs using mid-merit-gas. P2 has higher production on base-load-gas than P3 and P4 due to less coal than P4 and more CCGTs than P3. OCGTs and ADGTs generally show a small contribution to the electricity production.
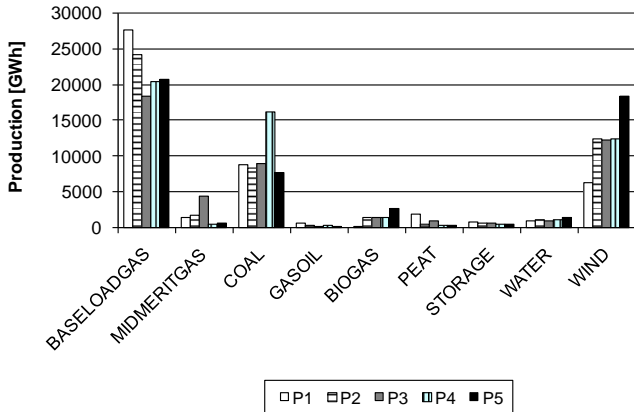
Fig. 5 Yearly electricity production distributed on fuel type for all portfolios in the All Island power system.

Fig. 6 shows that increased wind power production in P2, P4 and P5 relatively to P1 results in decreased production from conventional plants, and decreased net import from GB caused by the lower marginal production costs in Ireland. P3 with a high number of OCGTs has a higher marginal production cost and hence a slight increase in net import from GB.
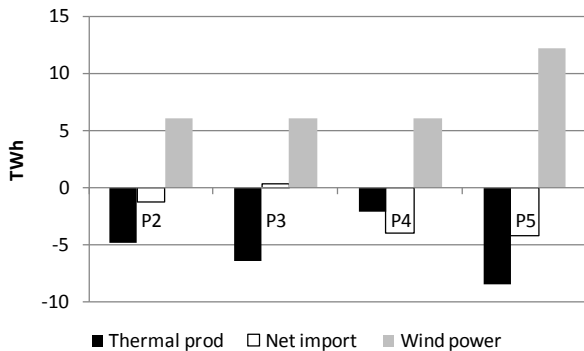

Fig. 6. Change in yearly production from thermal power plants in Ireland, net import from GB and wind power production for P2-P5 relatively to P1.

The average production efficiency for Irish power plants using the same type of fuel has been calculated for P2 and P5. The decrease in average production efficiency when

increasing wind power from P2 to P5 is 8% for gasoil and mid-merit-gas and below 0.5% for coal, base-load-gas and peat, which corresponds to an additional fuel consumption of 332 GWh. The increased fuel consumption due to increased part-load operation is therefore much smaller than the fuel savings due to increased wind power (6167 GWh).

Coal fired units and new CCGTs have low number of start-ups and high number of online hours during the year for portfolios P1 to P5 (see Fig. 7). The number of start-ups of these units increases in P2, P4 and P5 relatively to P1 due to increased wind power production. The large number of flexible OCGT units in P3 allows the coal units to operate with relatively low number of start-ups.
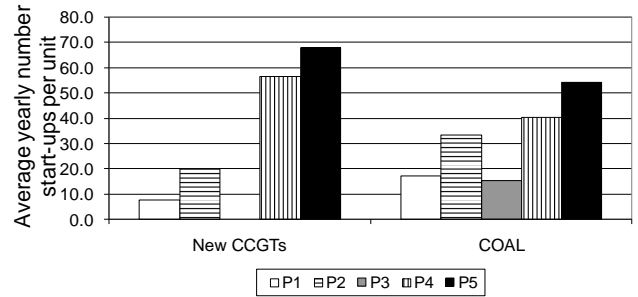

Fig. 7. Average yearly number of start-ups for new CCGTs and coal units in P1-P5. P3 does not have new CCGTs.

F. Wind curtailment

There is negligible wind curtailment for all wind power capacities (P1-P5). Curtailment occurs when there is too much wind and it is the most cost effective option to maintain supply demand balance ($P^{-,W}$ for wind in eq. 3). Wind is also curtailed in a limited number of cases to provide spinning reserves ($P^{Sp,W}$ in eq. 3 and 4). Operationally there may be a need to commit additional conventional power plants [37], [38] to provide reactive power and/or inertial response. These constraints, not implemented in this study, would increase the wind curtailment reported in this study due to the minimum stable operational limits.

G. Usage of pumped hydro storage

When analysing the yearly electricity production and consumption of the pump storage facility distributed on the hours during the day, it can be seen that pumping generally takes place during night and generation takes place during the peak load hours in the morning (hours 08-12) and in the afternoon (hours 16-19). No general change in the daily pattern of pumping and generation as a result of increasing wind power installed can be observed. This indicates that for the portfolios studied additional storage capacity may not be beneficial.

H. Improved wind and load forecasting

The economical benefits of improving the accuracy of wind power and load forecasts are identified by comparison of stochastic model runs treating wind power production and load as stochastic input parameters and of model runs treating wind power production and load as perfectly predictable. The

realised load and wind power production is the same both in stochastic and perfect forecast model runs. Determining the difference between the system operation costs gives the benefits of perfect forecasting (Table IX).

TABLE IX
COST REDUCTIONS DUE TO PERFECT FORECASTS OF WIND POWER AND LOAD.

	P1	P2	P3	P4	P5
Absolute cost reductions perfect forecast [MEuro]	1.0	7.3	4.3	11.3	18.5
Cost reductions relatively to Irish costs perfect forecast [%]	0.05	0.4	0.2	0.6	1.2

As the stochastic model takes updated wind and load forecasts into account every third hour, the cost reductions of going to perfect forecasts are small compared to the overall sum of operational costs, but still may account to several million Euros and increases with wind penetration. This is consistent with results reported in other studies [39]. The significant higher value of perfect foresight in P4 compared to P2, and the significant lower value of P3 compared to P2, shows the higher costs of rescheduling in the portfolio with relatively high share of base load plants, and likewise the lower rescheduling costs in portfolio with many OCGTs and ADGTs.

I. Further work

The stochastic, mixed integer optimization model developed takes a comprehensive approach to modeling wind integration. Several important issues that could impact on the results reported here have not been studied. Notably an improved consideration of grid constraints e.g. within the power network of the Irish island through the integration of load flow restrictions and voltage control is desirable. Additionally, the restrictions on the minimum number of conventional plants online, dynamics and operational issues at time resolutions smaller than one hour need further study. The cost impact of the cycling and additional starts of conventional plants and the impact on market prices and modeling of the GB system (in particular the wind correlation) are important topics that also need detailed analysis.

V. CONCLUSIONS

The article has presented a stochastic, mixed integer optimization model calculating cost efficient unit commitment and dispatch of power plants taking the demand for electricity and for power reserves into account. The model is unique in its combination of a short-term forecast scenario generation methodology, treatment of reserves and a rolling stochastic unit commitment and dispatch driven by updated forecasts.

The model has been used to study thoroughly the operational impacts of increased wind power production in the All Island power system. Five power plant portfolios in 2020 with three levels of wind power penetration have been investigated and results show that up to 6000 MW (Portfolio

5) of wind can be integrated into the island of Ireland system with no significant wind power curtailment and reliability problems occurring. Increased wind power production leads to less and more variable production on thermal power plants and increased power export to GB. Additional storage appears not to give any additional benefits. Improved forecasting leads to relatively small savings in system costs on a percentage basis but may still account for several million Euros. As expected the portfolio (P5) with highest amounts of wind has the lowest operational costs and CO_2 emissions of all portfolios while not impairing reliability. Comparing the portfolios with equal amounts of wind (4000 MW), with respect to operational costs it is preferable to have many coal units (P4) in the system, yet with respect to flexibility and CO_2 emissions it is advantageous to have a high share of base loaded gas units with low variable costs in the portfolio, i.e. P2 relative to many peak units (P3) or many coal units (P4).

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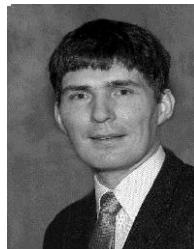
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