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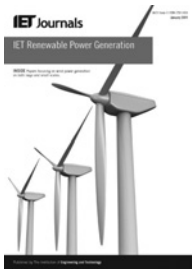

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Should unit commitment be endogenously included in wind power transmission planning optimisation models?

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Abstract: The historical time series data or Monte Carlo simulation approaches that are often used to represent wind power in transmission planning models will lead to large-scale optimisation problems. The complexity of such problems will be further compounded if advanced techniques for wind variability and wind forecast uncertainty management are also endogenously included, corresponding to a merging of the traditionally separate 'real-time operations' and 'long-term planning' analysis timeframes in power system analysis. A stochastic mixed-integer scheduling model is applied here to investigate the likely transmission planning model formulation impacts of advanced wind forecast techniques, and to determine whether any additional optimal transmission planning model precisions offered justify the associated very-large-scale computational burden. Results indicate that power-flow modelling is only significantly influenced in a small subset of the network branches associated with major interconnections and flexible/inflexible conventional generation locations. Model sensitivity analysis also suggests that even at high wind penetrations, such power-flow modelling differences may be overshadowed by the impact of general uncertainty in fuel price volatility and demand profile that is systemic to long-term planning problems. Such trade-offs have significant practical relevance to the many researchers currently investigating formulations of this class of optimisation problem.

1 Introduction

Increasing wind energy penetration is recognised as a key contributor to reducing carbon emissions and maintaining diversity of primary energy supply [1]. Detailed wind-integration studies have been carried out in many power systems [2–4], with transmission network limitations universally acknowledged as a significant challenge. Prudent allocation of new wind farm connection licences or optimal transmission development plans could be determined to accelerate wind connection to transmission networks.

Indeed there has been significant focus in recent times on the formulation of these types of wind and transmission planning optimisation models. For example, an optimal firm wind power connection model (i.e. no wind curtailment assumed) is proposed in [5], with corresponding optimal non-firm wind power connection models of varying levels of detail given in [6–8]. A market-equilibrium-constrained model is given in [9], while the model in [10] focuses on regional interconnection investments. An interesting model incorporating how independent generators might dynamically respond to transmission investments by the system operator (and vice versa) is given in [11], while the efforts of [12] focus on determining the optimal transfer capacity and wind curtailment trade-offs for a given transmission system location. The focus is not limited to onshore wind power connections either – an optimal offshore grid topology formulation is offered in [13] for example.

Transmission access study for large-scale centralised conventional generation was traditionally carried out either in a deterministic manner at onerous snapshot hours such as the 'winter-day-peak' and/or the 'summer-night-valley' of system load profile, or by using a sliced load-demand duration curve approach. In contrast, wind power is a low capacity factor, geographically distributed and statistically interdependent source of power generation. Clearly, transmission planning methods require suitable adaptation over a much broader number of study cases to incorporate such characteristics – some related modelling techniques have been studied in the recent literature as a result. For example, a random Monte-Carlo sampling approach to statistical dependency modelling using copula theory is outlined in [14], while noting that simple random sampling methods cannot recreate sequential hour-to-hour wind variability patterns. Basic auto-regressive moving-average sequential time series synthesis with statistical transformation methods has been reported in [15]. Wind production profiles based on historical data behaviour have also been widely applied in practice for wind-integration study [2]. A historical wind time series data approach is also presented for distribution system analysis in [16] for example. Although a practical drawback is that sometimes there may not be enough data available to give completely statistically robust conclusions, the benefit of using historical data is that any multivariate statistical and auto-correlative sequential dependencies are implicitly contained in the recorded data set, and can be easily incorporated to the optimal transmission planning model, if so desired.

Equally importantly however, the recent development of advanced unit commitment and reserve scheduling strategies to account for wind variability and forecast uncertainty through stochastic optimisation techniques [17–22] now necessitates a consideration of how the traditional separation of 'operations' timeframe and 'planning' timeframe power-flow assumptions may not be as distinct as often assumed in the past. Appropriate choice of model formulation for combined wind-generation/transmission optimisation studies such as in [5–13] therefore requires detailed consideration. If integer variables are retained to model the hourly unit commitment process, the problem complexity will be greatly increased. On the other hand, if the temporal link from hour-to-hour can be relaxed, then there will be significant implications for model formulation and solution approach [23, 24] as will be discussed further in later sections. In the past literature, unit commitment for wind variability (but not forecast uncertainty) issues has been included in [5, 8] but is rarely discussed in most other transmission planning works.

In any case, the wind generation/transmission optimisation problem must also be formulated with some consideration of long-term model parameter uncertainty. Although future customer demand growth and conventional plant fuel prices are always difficult to predict accurately, the impacts of electric transportation or smart-meter efficiency applications on the future power system load flow patterns are furthermore uncertain at this present time. The future location of new generation plants is also rather uncertain. Models incorporating short-term operations timeframe issues such as stochastic unit commitment, applied over the extended number of samples necessary to represent wind variance characteristics, and under a number of alternative long-term demand-profile/fuel-price uncertainty scenarios will require unprecedented computational efforts (for complexity and dimensionality reasons) to be solved for power system transmission networks of realistic size. The important question of whether stochastic unit commitment issues should in future be endogenously included in the optimal transmission planning model formulation has not yet been studied in detail, and is therefore the subject matter of this paper.

To this end, varying levels of operations timeframe scheduling complexity are applied to a test power system in this paper. A key issue explored is whether the additional computational rigor of endogenously including either a traditional deterministic unit commitment, or even an advanced stochastic unit commitment, in the optimal transmission planning model is likely to be justified, or whether a judiciously simplified operations timeframe model would be reasonably adequate with pragmatic acknowledgment of the general uncertainty in the long-term power system model itself. This hypothesis list is summarised in Table 1.

Section 2 outlines the operations timeframe complexity issues considered, whereas the test system is presented in Section 3. The results, and a contextual discussion of their implications for optimal wind transmission planning models, are outlined in Sections 4 and 5, respectively.

Table 1 Hypotheses under consideration

1 – Does the complexity of plant scheduling model applied for the system dispatch materially influence the annual power flows modelled?
2 – Are these differences, if any, relative in scale to other long-term uncertainty influences?
3 – Are there any implications for optimal transmission planning model formulation?

2 System power-flow modelling

2.1 *Impact of operations timeframe wind issues in long-term network planning timeframes*

The 'unit commitment' task could be described as how to optimally schedule the turning on and off of generators to meet variations in net electricity demand spanning timeframes of hours, days or weeks. The 'economic dispatch' task refers to the here-and-now decision of how to optimally decide the generation levels of generators that are already turned on. With significant wind capacity installed, more flexible and robust conventional plant commitment and dispatch schedules must be produced so that the system can balance with respect to the wind that actually occurs at the operations timeframe time-horizons of the near future.

Operations timeframe real-time wind forecast uncertainty can be represented with a spread of probability-weighted 'scenarios' [25]. Techniques such as 'rolling-planning' and stochastic mixed-integer programming (MIP) using probability-weighted wind forecast scenarios have been reported for generation production-cost analysis in the literature [17–20]. As the power production, and crucially for this paper, the transmission system load flow patterns, may now deviate somewhat from those modelled by a simple 'merit-order' (MO) based economic dispatch alone (which is generally assumed in most optimal transmission planning models [26]), then the relevance and merits of including the additional complexity in the long-term transmission planning model should now be assessed.

The power flow in each transmission network branch can be considered (in a first-order simplistic manner at least) as the superposition of individual power-flow 'contributions' from generator source nodes and customer demand sink locations. From a 'real-time' network operations timeframe perspective, any one of the wind forecast uncertainty scenarios could potentially occur for each stage of the 24–36–48 h scheduling horizon ahead [27]. Various alternative network congestion management plans would need to be prepared accordingly in advance [28]. From the transmission planning perspective however, only one of the wind power forecast uncertainty scenarios (that help define the forecast error probability) will actually occur at any given operations timeframe time-step and therefore result in a specifically wind-related power-flow contribution which the network design must accommodate – the other wind forecast scenarios that do not end up occurring (once real-time for that given forecast horizon actually arrives) will therefore not influence the power flows directly. Therefore if a historical wind power time series of a number of years' length is available to clarify the actual wind-power-flow contribution requirements in the transmission planning model, the wind-related operations timeframe power-flow contribution uncertainty in itself is (to a good approximation) not so relevant in the transmission planning timeframe. This is a key distinction between the implications of wind forecast uncertainty for the transmission network operations timeframe real-time and long-term planning problem contexts.

However, the generation unit commitment task must be carried out in the hours and days prior to real-time due to conventional plant inter-temporal constraint limitations (i.e. start-up times, minimum up/down times, ramp limits etc.), before the true resultant wind power production scenario is known. Therefore the specifically conventional-plant-related power-flow 'contributions' may indeed be influenced (in a manner distinct from a simpler MO approximation) by the choice of operations timeframe wind uncertainty management strategy. To a large extent, this specific issue is the basis for investigating whether or not the stochastic unit commitment model should be endogenously included in the optimal transmission planning model formulation.

2.2 Scheduling model power-flow investigations

The investigative approach carried out in this paper does not directly implement a transmission network optimisation model in itself. Instead, the power-flow modelling impacts of different operations timeframe wind forecast uncertainty management strategies are studied in detail for a given transmission network topology – this is a more practical approach that will allow the relevance of the various issues to be established without the necessity for a massive computational burden to be tackled.

Three different system operations timeframe wind management strategies are therefore investigated for the same fixed load and wind time series profiles (of one year's timeframe length) in each case:

1. MO economic dispatch applied only – without any start-up costs or inter-temporal unit commitment constraints linking the separate hours, and no account of wind forecast uncertainty, this option is analogous to studying the power-flow outcomes of a random Monte-Carlo (i.e. non-chronological) simulation such as in [14], and relates to the assumption used in most transmission planning analyses and optimisation algorithms [26].
2. Deterministic unit commitment applied with the simplifying assumption of perfect wind/load forecasting (DUC-PF) – this option includes a full MIP deterministic optimisation and allows a consideration of the effect of system operations timeframe variability alone on the network power-flow model – as was included by [5, 8].
3. Stochastic unit commitment (SUC) – using a wind forecast error scenario tree tool and a stochastic MIP optimisation model – this option allows a complete analysis of both operations timeframe variability and forecast uncertainty effects on transmission network power-flow modelling.

The stochastic programming methodology proposed in [18] for generation production costing studies (i.e. without study of transmission planning implications) is used for the SUC analysis of this paper. This is a stochastic mixed-integer hourly-resolution model of the operations timeframe unit commitment and economic dispatch problem, incorporating load and wind forecast uncertainty scenario trees, conventional generation forced outages, spinning and replacement reserve, fuel, carbon and start-up costs, and detailed conventional plant inter-temporal constraint limitations. Operations timeframe wind and load forecast uncertainty is updated with a rolling planning timeframe of 3-hourly periods, so that the system schedule is effectively re-planned eight times per day. The concise DUC-PF and SUC scheduling model formulations as applied here are thoroughly detailed with mathematical equations and so on in [18]. For very high wind penetration, additional constraints were also implemented, to ensure minimum number of large conventional plants remain online for inertial support reasons [29].

The generation power dispatch results can be taken from the three different scheduling investigations and subsequently input to a linear 'DC' network power-flow assessment [30]. Using histograms to compare the probability density functions (pdf) of yearly power flows in each transmission branch under the three different operational strategy modelling options allows a direct appreciation of the value of additional wind/transmission optimisation model complexity. Transmission network capacity limits are not enforced with an optimal power flow specification in these studies as the unconstrained power flow requirement of the network must be observed for planning purposes, and the power-flow pdf edges would be truncated at the network branch capacity levels otherwise. As the exact same wind and load time series are applied in the three scheduling approaches described above, then it follows from the nuanced reasoning of Section 2.1 that any differences between the power-flow pdfs will therefore be caused only by the differing generating patterns of conventional plant when both variability and forecast uncertainty are accounted for at the operations timeframe real-time stages.

2.3 Long-term uncertainty sensitivity analysis

Sensitivity analyses were also carried out using the SUC approach to understand the influence of long-term transmission planning model parameter uncertainty on the system power-flow model:

- *Case I* – Gas, oil and distillate fuel costs were scaled to 75 and 125% of their base case values to illustrate the impact of long-term fuel price volatility on network power-flow requirements.
- *Case II* – Load profiles were linearly scaled across the system to 105 and 95% of their base case patterns to investigate the influence of projected peak load growth uncertainty on network power-flow requirements.

The range of load profile and fuel price sensitivities arbitrarily chosen here is consistent with previously observed parameter deviations – for example, the customer electrical energy demand in the Republic of Ireland dropped by ~7% in the year 2008 alone because of unforeseen economic conditions [31], and significant gas price volatility is routinely observed in international commodity markets [32].

In isolation, it might be considered relatively trivial that these model uncertainties will influence the future system power-flow requirements in some way. However, the basis for including this aspect of the analysis is to allow a relative comparison of any differences in the estimated network power-flow requirements due to long-term model uncertainty with those resulting from different levels of operations timeframe unit scheduling complexity applied in Section 2.2, thus allowing a pragmatic consideration of the importance of including detailed operations timeframe issues endogenously in the long-term optimal transmission planning model itself.

3 Test system description

The test system used in the analyses of this paper is illustrated in Fig. 1. This has a 35-bus, 54-line network, denoted as 'Area 1' (based on a very simplified model of the Irish 'All-Island' 220/275/400 kV high-voltage transmission system). It contains a mixture of base-load and mid-merit fossil-fuel (coal and peat) steam turbine generation, combined-heat-and-power gas plants (CHP), combined-cycle gas turbines (CCGTs), higher-efficiency aero-derivative gas turbines (ADGTs), lower-efficiency open-cycle gas turbines (OCGTs), as well as a few gas/oil-distillate 'peaking' units, amounting to 10.4 GW conventional plant capacity overall. 500 MW of high-voltage DC (HVDC) interconnection capacity to a much larger separate power system denoted as 'Area 2' (based on an approximate model of the Great Britain generation portfolio) is available at both buses 12 and 34. Conventional plants in Area 2 are grouped approximately into multiple generation capacity blocks of similar plant-type, all connected at a single transmission node. Conventional plant performance data, seasonal natural gas fuel price variations, load profile, load magnitude (accounting for projected load growth to a maximum peak value of 9.61 GW), and the assumed load geographic distribution are consistent with [4]. Additional information on the test network branch reactance parameters (Table 4), the assumed system geographical load spread (Table 5), indicative conventional plant unit-commitment inter-temporal constraints (Table 6), and the conventional generation portfolio network locations (Table 7) as applied in this investigation are presented in the Appendix.

Recorded historical wind power output from the Irish 'All-Island' power system, at hourly resolution over a time period of one year, was used for this study – this power output data were linearly scaled, depending on the total wind capacity level under investigation in Area 1. Equal wind capacity connection to buses 3, 5, 7, 9, 11, 13, 15, 17, 25 and 33 was investigated by linearly scaling this historical time series trend for each location. Up to 6 GW of installed wind capacity (corresponding to up to ∼34% annual wind energy penetration) was studied, with total capacity equally spread among the ten wind plant locations. The historical time series data are derived from the total aggregated wind power output in the Irish All-Island power system – as such the ten wind capacity locations will then have identical correlated output in this analysis. This is not significant however, as the issue under study is the impact of aggregated wind power output variability and uncertainty on unit commitment, and any modelling influences on transmission network flows that result from it. Furthermore, as explained in Section 2.2 above, the same wind time series are used in the three MO/DUC/SUC analyses, so the only differences observed in power-flow pdfs will be solely the impact of aggregated variability and uncertainty on transmission flows through changes in the generation scheduling process.

All model development was carried out in MATLAB [33], GAMS [34] or using the MATLAB/GAMS interface available at [35].

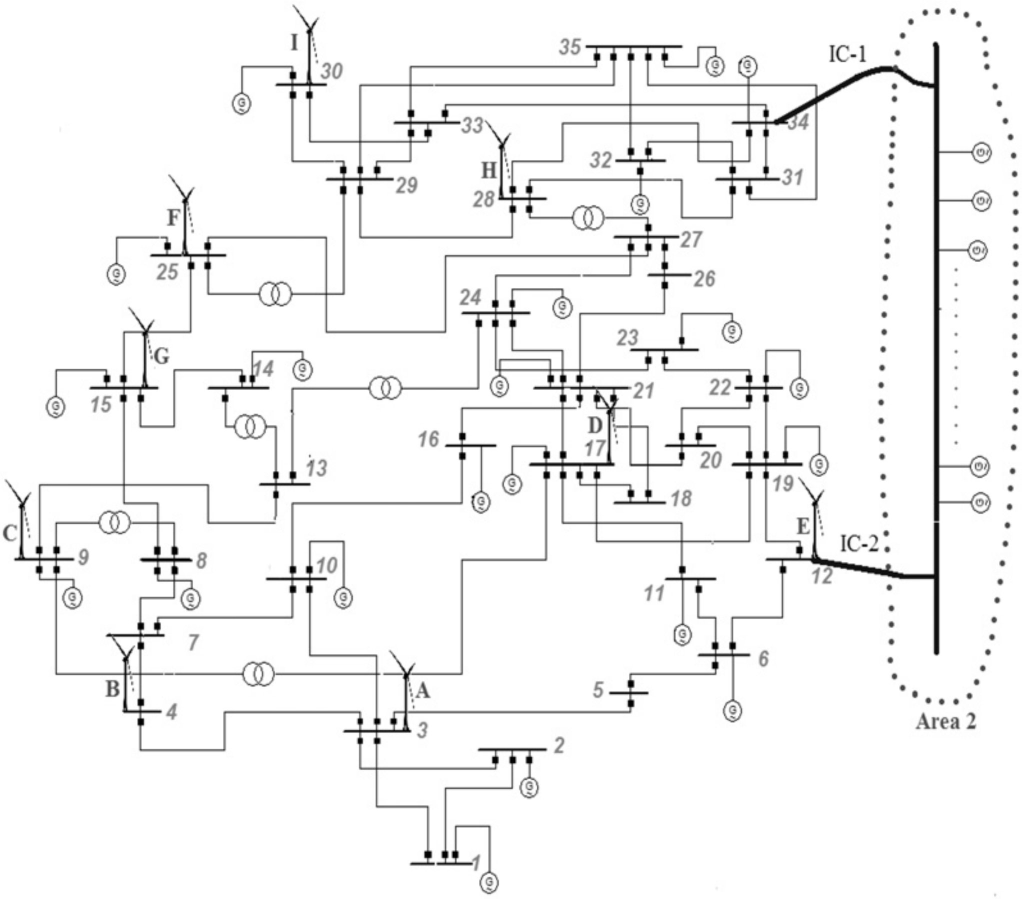

Fig. 1 *Test power system under investigation*

4 Results

4.1 Scheduling model plant capacity factor impact results

As illustrated in Table 2 (and consistent with other generation analysis studies) major system interconnection points and a few of the mid-merit conventional plants such as CCGTs and ADGTs will exhibit different capacity factors under the three different operations timeframe scheduling approaches – individual plant flexibility/inflexibility may require that it be brought online or kept offline (i.e. out-of-merit) for a particular operations timeframe situation. Base-load plants generally operate similarly across the three models. For the test power system in this paper, the large size of the Area 2 system with respect to Area 1 often results in the two HVDC interconnectors being used as sources/sinks for least-cost system variability and uncertainty management in Area 1 – hence the significant deviations in their usage. It should be noted that while generation capacity factors will merely influence the transmission network annual-average power-flow values, changes in their respective values suggest that the system is being dispatched slightly differently depending on the operations timeframe wind management strategy applied, and that more general differences in the line power-flow pdf extreme values (which are of primary importance for the network planning context of this paper) may also be evident.

4.2 Scheduling model power-flow impact results

The pdf of yearly line power flows from bus 12 to bus 19 is illustrated in Fig. 2 for 6 GW of wind capacity installed. As implied from Table 2, this transmission line (adjacent to the HVDC interconnection point to Area 2) exhibits a different spread of possible power flows, depending on the scheduling model complexity applied. For example, the DUC-PF model overestimates the maximum power-flow requirement by ~100 MW when compared to the MO or SUC results – transmission power-flow model differences have greatest significance if they occur at distribution tails, which influence most the system congestion and reliability indices. Similar differences (though less extreme) occur in

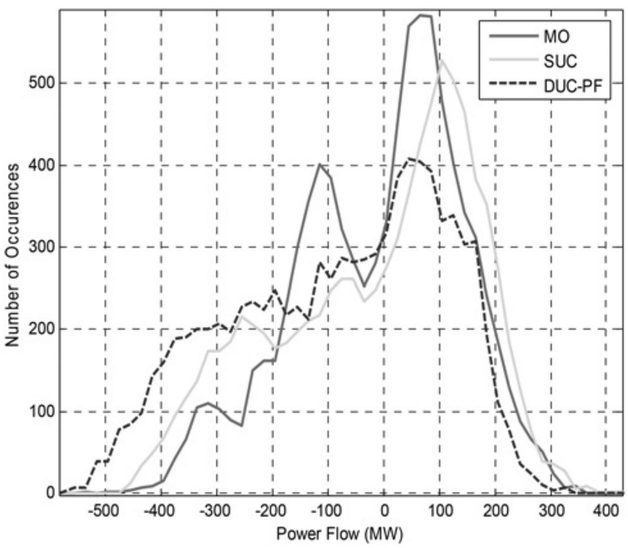

Fig. 2 *Power flow histograms for line adjacent to HVDC interconnection (lines from bus 12 to bus 19)*

Table 2 Plant capacity factors for different scheduling approaches – 6 GW installed wind

Unit type	MO, %	DUC-PF, %	SUC, %
Coal steam turbine	67.12	69.02	70.5
CCGT 1	79.76	79.06	77.13
CCGT 2	74.00	79.75	79.83
CCGT 3	42.34	47.04	43.1
ADGT 1	6.76	8.25	8.65
OCGT 1	0.73	2.48	2.97
HVDC Interconnector	30.26	9.6	29.02

lines adjacent to other conventional plants that are scheduled differently due to increased operations timeframe variability and uncertainty in the system – see the pdf of yearly line flows from bus 6 (the location of an ADGT plant) to bus 11 in Fig. 3. However, a reasonable majority of the transmission lines exhibit little or no difference in power flows, as illustrated by Fig. 4, implying there is no additional value obtained from the stochastic MIP scheduling model in their case. Furthermore, it is worth noting that power-flow modelling differences in a transmission line will have most significant influence on the solution of a network planning optimisation model only if that line is congested, which in practice may be the case for a limited subset of the network branches only.

4.3 Long-term planning model uncertainty sensitivities

4.3.1 Conventional plant fuel price uncertainty: The impact of the conventional plant fuel price volatility (as modelled in Case I) on the relative MO positions of typical base-load coal and CCGT generators is illustrated in Fig. 5. Natural gas fuel price can exhibit reasonably strong seasonal dependence due to increased space-heating demand in the colder winter months (in northern latitudes), with coal prices generally more stable throughout the year. As evidenced by Fig. 5 for the 'base-case' fuel price assumptions, the CCGT plant unit average energy costs

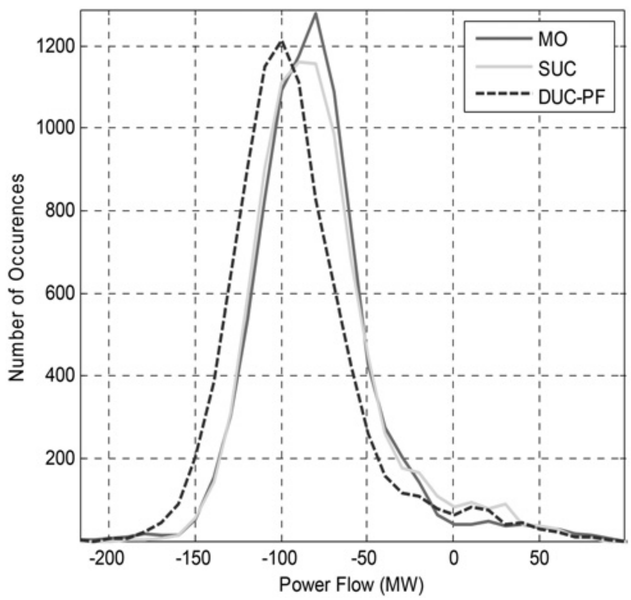

Fig. 3 *Power flow histograms for line adjacent to flexible ADGT plant location (lines from bus 6 to bus 11)*

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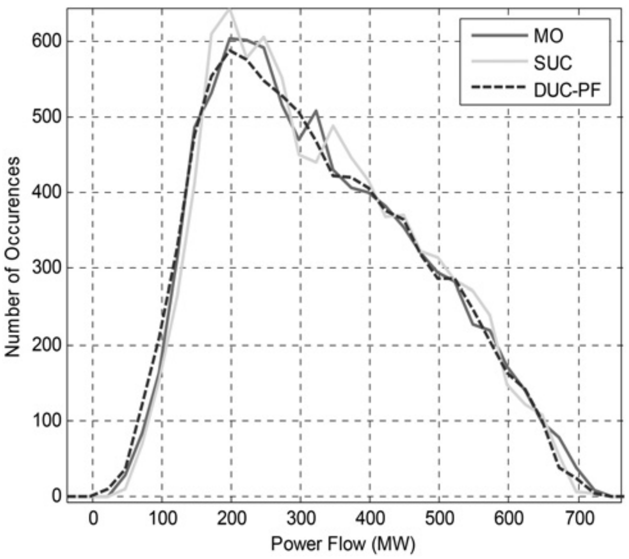

Fig. 4 *Sample power flow histogram from elsewhere in the system (lines from bus 17 to bus 21)*

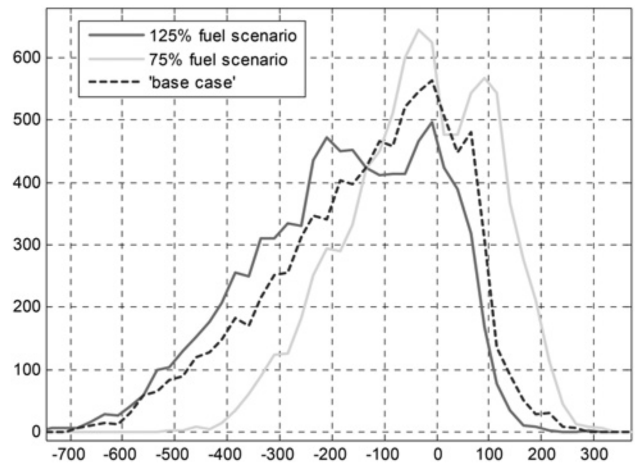

Fig. 6 *Sample pdf of line flows under the influence of fossil fuel price uncertainty (Case I, lines from bus 23 to bus 24)*

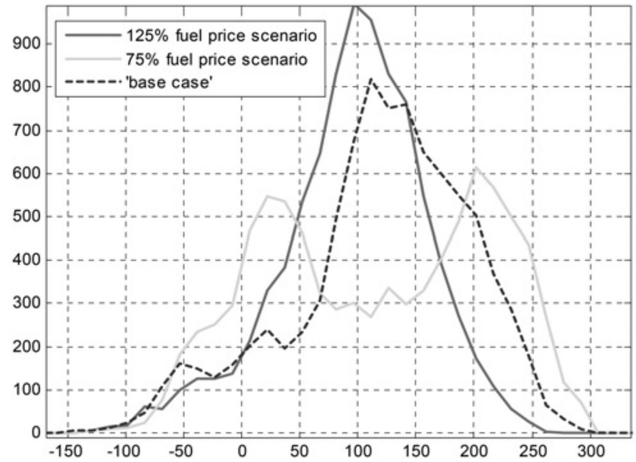

Fig. 7 *Sample pdf of line flows under the influence of fossil fuel price uncertainty (Case I, lines from bus 28 to bus 31)*

may become cheaper than those of the coal plants in the summer months, and thus replace them in the merit order. With the respective 75 or 125% average trend shifting sensitivities applied in Case I, however, the coal plants are either more expensive or less expensive for the full 12 months of the year (all other parameters kept fixed). Such merit order position uncertainty will have significant impact on the system dispatch patterns, and thus the unconstrained network power flows. This is evidenced by the considerable deviations in Fig. 6 for the power-flow modelling in the network branch from bus 23 to bus 24, and from bus 28 to 31 in Fig. 7. The power-flow pdf differences in Figs. 6–7 due to such long-term model uncertainty are clearly of similar or greater magnitude than those resulting from alternative operations timeframe wind management strategies as evident in Figs. 2 and 3. Analysis of the pdfs of other line flows in the test system suggests that the impact of fuel price uncertainty is furthermore much more widespread in the network, and thus may overshadow the power-flow modelling effects of operations timeframe wind management strategy.

4.3.2 Load profile uncertainty: The impact of customer demand profile peak uncertainty (Case II) on transmission power-flow modelling is illustrated using the pdf of power flows in the line from bus 27 to bus 28 in Fig. 8. Future peak customer demand projection errors will obviously affect the customer load bus injections themselves, but more importantly they will also significantly impact the usage of specific mid-merit and peaker conventional

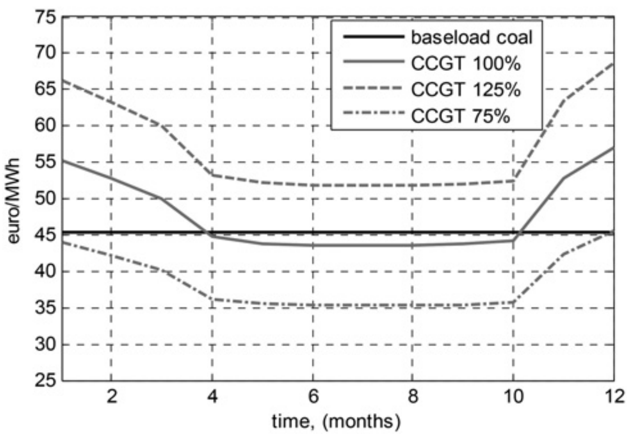

Fig. 5 *Seasonal baseload coal and CCGT average unit costs (Case I)*

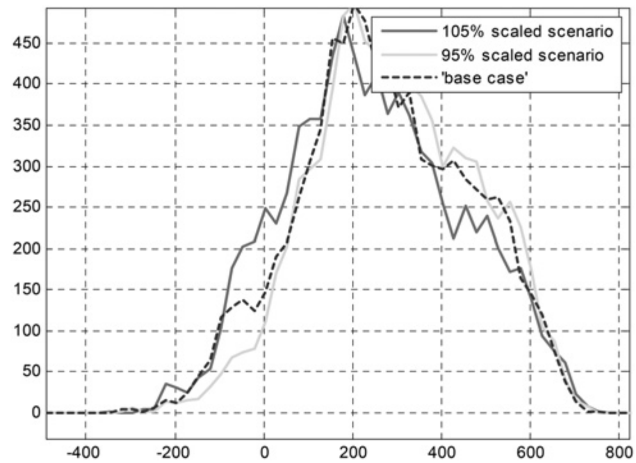

Fig. 8 *Sample pdf of line flows under the influence of peak customer demand uncertainty (Case II, line from bus 27 and 28)*

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generators and their resultant network power-flow injections. It was observed that the worst-case power-flow modelling impact of peak load demand profile uncertainty was generally of lesser absolute magnitude than that of the operations timeframe strategy model results in Section 4.2. Notably however, such distributed load profile related uncertainty impacted power-flow modelling in a greater number of lines throughout the system, whereas the detailed operations timeframe model power-flow differences are evident in the few lines associated with flexible/inflexible conventional plant and interconnection locations only.

5 Transmission optimisation model formulation impacts

A detailed consideration of the optimal transmission planning model implications of simplified operations timeframe assumptions has been outlined in this paper. Instead of attempting to solve the optimal transmission planning model itself, various levels of operations timeframe scheduling complexity were applied to a representative generation portfolio and a fixed network topology. This allowed a practical exposition of the major sensitivities without the need for excessive computational resources. Reasonably different network power flows were evident in specific parts of the test transmission network depending on the operations timeframe wind management strategy applied. However, these power-flow differences were contrasted with the impact of long-term load-profile/fuel-price parameter uncertainties using sensitivity analysis. In general, the network flow differences associated with the long-term uncertainty were more widespread throughout the test network, and (in the case of the fuel-price uncertainty) of much greater magnitude than those associated with the variations of operations timeframe strategy applied. This is important given that long-term fuel-price and load-profile parameters can in any case only be subjectively included in optimisation models due to their more general uncertainty. For example, it may difficult to objectively propose any particular probability weighting of the alternative gas-price scenarios in Fig. 5. Given the level of vague uncertainty in other influential optimal transmission planning model formulation parameters such as these, then for most power systems it might be unwise to insist on inclusion of comparatively excessive precision for the operations timeframe aspects.

Although a lack of flexibility in different systems' generation portfolios (e.g. pre-eminence of nuclear and/or base-load coal plants) could magnify the impacts of their operations timeframe wind variability and uncertainty patterns, the discussion in this paper should nonetheless be relevant to many diverse power systems. Power systems with larger demand levels than the test case presented here tend to have more base-load demand as a fraction of overall demand, and hence their individual generators traditionally used to serve this constant base-load, which might be larger and more inflexible. On the other hand, however, there will be more power plants to share the wind variability and uncertainty tracking in a larger system, which might lessen the effects of wind integration. Also, wind integration in larger power systems could be aided by the geographical or spatial smoothing of the wind power plant locations. Hence, the normalised variability and forecast uncertainty could be less than observable for the geographically-concentrated Irish All-Island power system used here. Precise extrapolation of the wind variability and uncertainty effects might be dependent on the system characteristics under consideration therefore.

It may be reasonable to conclude (see Table 3) for many power systems though, that the inclusion of stochastic mixed-integer unit commitment models endogenously within the optimal long-term transmission planning context will not give significant added value in proportion to their associated computational burden. The power-flow model differences shown in Section 4 should also be framed within the context of the computational requirements of the three distinct yearly simulation approaches – in the order of minutes for the MO approach, hours for the DUC model and more than 1.5 days for the SUC implementation on a contemporary desktop PC [18]. Note additionally that the time requirements to solve the optimal transmission planning model with endogenous inclusion of SUC would likely be much greater than reported for the analyses here, as the SUC-driven year-long network analysis task of this paper would essentially comprise a sub-problem stage of any optimal transmission planning decision evaluations.

Of course, this is not to say that operations timeframe issues should be completely ignored in the transmission planning task. Indeed, there is a great discussion on both the power system research and industrial communities at present about the fact that short-term operations timeframe and long-term planning timeframe assumptions may need to be somewhat more consistent in future [36]. In that sense, the discussion outcomes of this paper do not preclude the fact that post-optimal solutions from simplified transmission optimisation models could be 'sanity-checked' with a fully rigorous and detailed operations timeframe analysis to ensure that critical aspects of system economics and/or reliability are not unduly degraded by necessary optimisation model formulation trade-offs. In future, this may provide a pragmatic approach to merging any overlapping operations timeframe and planning concerns, which by their distinct timeframes, must generally focus on quite distinct issues.

Although there are obvious computational advantages to excluding the many integer variables that would be necessary to endogenously include the unit commitment issues for the transmission optimisation model, there are also potentially very important implications for the approach required to model the characteristics of spatially distributed wind power resources. In power systems that are not significantly dominated by hydroelectricity and/or other energy-limited storage resources, then if a unit-commitment is not included, the requirement to maintain the chronological hour-to-hour sequence of wind power variations can be relaxed. This allows model compression techniques to focus on the combination of historically recorded wind power data-points from temporally separate hours, using probability-discretisation [37] and/or scenario reduction [23] (and chapter 7 of [24]) methods. When such model compression approaches can be combined with

Table 3 Main conclusions from hypotheses considerations

1 – Scheduling model complexity influences transmission system planning issues at a limited number of transmission network paths
2 – Influence of long-term uncertainty will tend to be more consistently critical than short-term operations timeframe complexity issues
3 – Optimal transmission planning model formulation significantly impacted – both in model formulation/compression, and indeed solution approach

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standard decomposition techniques and/or advanced parallel processing solution methods, the implications of the model formulation choices outlined in this paper are magnified significantly.

Although the analysis presented here does not include any specific analytical or algorithmic innovations in itself (instead focusing on judicious application of various generation-production-costing models in a refined transmission planning context), the gravity of the arguments outlined in this paper will have profound relevance to the many researchers around the world currently investigating the formulation of the optimal wind power and power system expansion planning model.

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8 Appendix

See Tables 4–7.

Table 4 Test power system network branch information

From-to bus	X_L (100 MVA base)	From–to bus	X_L (100 MVA base)
1–2	0.02	18–21	0.044
1–3	0.02	19–20	0.01
2–3	0.011	19–22	0.01
3–4	0.039	20–21	0.01
3–5	0.075	20–22	0.01
3–10	0.073	21–24	0.02
4–7	0.084	21–26	0.038
5–6	0.02	22–23	0.003
6–11	0.06	23–24	0.008
6–12	0.076	24–27	0.053
7–8	0.007	25–27	0.095
7–10	0.061	25–29	0.025
8–9	0.042	26–27	0.03
8–15	0.077	27–28	0.025
9–13	0.023	28–29	0.011
9–17	0.079	28–31	0.0185
10–16	0.08	28–34	0.036
11–17	0.051	29–30	0.011
12–19	0.046	29–33	0.0135
13–14	0.04	29–35	0.0282
13–24	0.046	30–33	0.02
14–15	0.029	31–32	0.005
15–25	0.076	31–34	0.0294
16–21	0.094	31–35	0.02
17–18	0.022	32–35	0.0196
17–19	0.036	33–34	0.0065
17–21	0.016	33–35	0.0198

Table 5 Maximum bus load values

Bus	$\text{Load}_{(MW)}$	Bus	$\text{Load}_{(MW)}$
1	312.9	19	621.2
2	013.8	20	618.1
3	400.3	21	408.0
4	108.9	22	1010.8
5	392.7	23	107.4
6	050.5	24	0
7	196.3	25	432.5
8	0	26	400.3
9	131.9	27	391.1
10	339.0	28	521.5
11	155.4	29	184.1
12	257.7	30	457.1
13	026.8	31	397.3
14	0	32	306.8
15	480.1	33	222.4
16	335.9	34	0
17	092.0	35	247.0
18	0		

Table 6 Typical unit commitment inter-temporal constraints applied

Unit type	Start-up time, h	Min up/down time, h
coal	4–5	1–8
peat	1–5	1–6
CCGT	1–4	1–4
CHP	4	4
OCGT/ADGT/Peaker	<1	<1

Table 7 Conventional generation portfolio information

Unit type	Number of units	Bus locations	Average fuel price, €/GJ	Total capacity, MW
coal	5	9, 34	1.75	1257
peat	3	11	3.71	345
base renewables	1	16	2.78	182
CCGT	11	8, 14, 19, 22, 23, 24, 30	5.91	5890
CHP	2	10	5.91	166
ADGT	7	1, 6, 8	6.46	735
OCGT	14	2, 15, 21, 22, 30, 32, 34, 35	6.46	1442
peakers	8	11, 25	8.33	383

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