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Accommodating Variability in Generation Planning

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***Abstract*—Many of the most commonly used generation planning models have been formulated in a way that neglects the chronological sequence of demand and the mixed-integer nature of generating units. The generator schedules assumed by these models are inaccurate and become increasingly divorced from real schedules with increasing variability. This paper seeks to characterize and quantify the limitations of these models over a broad set of input parameters. For an illustrative set of test systems, wind capacities and generator types, annual system costs are determined for all combinations of generating units using a unit-commitment model, which captures the chronological behavior of units and a dispatch model which does not. It is seen that the relative performance of the dispatch model is highly system specific but generally degrades with increasing variability. The difference in cost estimates between the models is decomposed into start costs, starts avoidance and average cost estimation error. The impact on least-cost portfolios is shown and finally sensitivities are performed with the addition of hydro and nuclear power to assess their impact.**

***Index Terms*—Power Generation Planning, Wind Power Generation**

I. Nomenclature

C_{avg}	Average cost (per MWh)
C_{incr}	Incremental cost (per MWh)
C_{noload}	No-load cost (per hour)
C_{start}	Cost of starting unit type
E_{inflow}	Hourly reservoir water inflow (MWh)
E_{mid}	Bi-daily reservoir contents (MWh)
f_{obj}	Annual generation costs (objective function)
G	Hourly generation costs
I	Installed flexible generation (MW)
I_{hydro}	Installed hydro capacity (MW)
N	Number of inflexible generators ($integer$)
P_{dem}	System electrical demand (MW)
P_{max}	Maximum unit production (MW)
P_{min}	Minimum unit production (MW)
P_{res}	Minimum total reserve (MW)
P_{wind}	Available wind production (MW)
R_{max}	Maximum hourly unit ramp (MW/hr)
$t \in T$	Time-steps
T_{bi}	Set of first hours of every 2nd day
$u_{fl} \in U_{fl}$	Flexible generation types
$u_{in} \in U_{in}$	Inflexible unit types
$u_N \in U_N$	Inflexible units
V_{curt}	Decision variable: Wind curtailment (MW)
V_{gen}	Decision variable: Electrical output (MW)
V_{hydro}	Decision variable: Hydro elec. output (MW)
V_{online}	Decision variable: Unit online status ($binary$)
V_{water}	Decision variable: Reservoir contents (MWh)
V_{spill}	Decision variable: Reservoir spill (MWh)
V_{start}	Decision variable: Unit start ($binary$)

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II. Introduction

THE impact of system variability has been receiving increasing attention from market participants, regulators, system operators and planners, largely due to increasing wind and solar penetrations in certain systems [1], [2]. Production from these sources generally takes priority in dispatch, leaving conventional generators to meet the residual, i.e. net-demand. A change in the pattern of net-demand may render an existing portfolio economically sub-optimal, by for example inducing costly cycling behavior [3] or may substantially increase the probability of a shortfall in generator ramping availability [1], [4].

For many systems, there is already a significant amount of variability in system demand. Utilities that own and operate all of the units on a system can account for this by selecting units that are suited to their duty-cycle. However, in liberalized markets the translation process between what is needed and what is built is not usually as straight forward, so even in the absence of variable sources, generation portfolios ill-suited to the needs of the system may evolve [5]. This emphasizes the role of generation planning models in informing the design of effective market rules and incentives, but also in the need to actually have models that can satisfactorily account for variability.

The variability in system demand can be broadly segmented by time-scale and frequency of occurrence. While systems vary markedly in terms of their patterns of demand, there will typically be a seasonal variability, owing largely to levels of sunlight and temperature; a fall in demand at weekends and finally the diurnal, or within-day cycle. As the diurnal pattern is most frequent, it will also tend to have the greatest impact on plant cycling.

The types of units on a system will also influence how well it can respond to variability, particularly in terms of unit starts. A unit should start if it will be online long enough to recoup the cost of starting by replacing the fuel use of more costly units. It is for this reason that start costs of a unit must be considered relative to the fuel cost difference between the unit and other competing units. The number of starts for a particular unit is also driven indirectly by how often it is shut down, which itself is driven by the start costs, part-load efficiencies and turn-down ratios (maximum to minimum output ratios) of all available units. Generation planning models, for example [6]–[10], will often implicitly assume that these factors have an insignificant overall impact and thus that conventional generation technologies can be characterized solely by the installed capacity and average production cost of each. It will be shown here that these methods can underestimate production costs by a significant amount, in particular for increasing variability, whilst favoring plant portfolios with an excessive number of high start-cost units.

These models (referred to as *probabilistic production cost models* in [11]) assume that the temporal sequence of demand has an insignificant effect on the overall cost of generation. Often making use of load duration curves, which are system demand time-series sorted in descending order, or aggregated versions of these, the models know only the frequency (in the statistical sense) and magnitude of system demand. Thus temporal constraints cannot be specified in the problem. The extent to which these limitations are significant is case-specific but crucially, there are such a large number of causal influences on the optimal unit-commitment that it may not be possible to pre-suppose whether this method of estimating production costs would be sufficiently accurate without having first scheduled the system in a more robust manner.

These models were originally formulated at a time when computational power was limited [12] so a computationally intensive simulation of the scheduling of units would have been impractical. The dimensionality arising from longer-term features of the problem, e.g., fuel price uncertainty or the number of potential unit combinations, often motivates a greater attention to higher level concerns, relegating the production cost modeling to a more simple treatment. In order to inform decisions that define or incentivize the evolution of generation portfolios, the multi-layered nature of generation planning should be captured; but in the absence of a relatively accurate production costs model at the core, the results of the overall model will not be robust. Beyond the scope of power systems, multi-sector models exist, which consider energy use in transport and heating as well as electricity production, however, these generally do not utilize unit-commitment in their formulation of the electricity sector [13]–[17]. While some make use of chronological time-series data, this is only to permit coordination within and between sectors, e.g. gas supply to the electricity sector, power plant heat to the residential sector etc. These linear programs ignore the mixed-integer, chronology-dependent nature of unit behavior. In some instances, power systems operations models utilizing unit-commitment have been applied in generation planning. Two significant examples of models which have this capability are the WILMAR model [18] which simulates the stochastic nature of wind power with scenario trees and BALMOREL [19], a combined heating-electricity-transport model for the Baltic Sea Region. Planning models utilizing unit-commitment are ideal where the number of input sets to be studied is small relative the computational power available, but are less useful for higher levels of dimensionality. It should be noted that the inclusion of stochasticity can increase the computation time by an order of magnitude.

The impact of variability, particularly with reference to wind power, has been studied and documented extensively in recent years [20]–[22] by considering systems with and without variable generation. This paper seeks to determine the relative importance of utilizing unit-commitment in the planning of generation on systems with varying amounts of variability, both from variable generation and existing demand variability.

Section III of this paper introduces and defines the Unit-Commitment and Economic Dispatch (UCED) model and the Dispatch-Only (DO) model. The test systems used and the input parameter sets follow in Section IV. The results section (V) sets out how the models differ in terms of least-cost portfolios, generation costs estimates, unit starts and plant utilization. The difference in cost estimates by the models is explored by considering starts, starts avoidance and part-load operation. Additionally, some observations are drawn on the factors influencing computation time for the simulations. The paper closes with some conclusions in Section VI.

III. Methodology

The objective of this paper is to analyze how increasing variability influences optimal schedules and thus least-cost portfolios; and to infer the relative importance of accounting for hour-to-hour chronology and mixed-integer nature of units in generation planning models. First, several contrasting test systems were selected, and for a range of representative plant types, fuel prices and installed wind capacities, least-cost schedules were determined and compared for each possible plant combination using a typical UCED model and a basic DO model. Models that make use of unit-commitment produce more realistic schedules than models that do not, but at a computational cost. Unit-commitment, which accounts for the cost of unit starts, necessitates binary (online-offline) decision variable for each generating unit. Additionally, each unit's production will have an upper bound and can also have a lower bound greater than zero, which amounts to a mixed-integer representation of the generating units. In contrast, DO models have no binary online variables and so can be formulated as linear programs. The computational burden of mixed-integer programming for generator scheduling is high, and when taken in context of a broader generation planning methodology, may be excessive. However, under higher levels of variability, the influence of unit starts on least-cost schedules increases. Accordingly the implied schedules of DO models, which cannot account for starts, will become increasingly less plausible. Several alternative ad-hoc methods exist. For example, the commitment implied by a given dispatch can be determined and the relevant start costs and average production costs applied after. The cost of the schedule will be more accurate but the schedule will tend to be sub-optimal as the cost of starting and part-load inefficiencies will be not endogenous [23]. This alternative models have not been analyzed here.

The relative effectiveness of the models strongly depends on the installed generating units, the system demand profile and the quantity and characteristics of the installed variable generation. In order to assess the relative importance of these factors, the UCED model and the DO model are applied over a wide range of input parameters. Year-long, hourly schedules are determined for all combinations of a selection of plant types up to a specified total installed capacity. Each of these portfolio combinations is tested in a year-long simulation for a set of installed wind capacities and fuel prices, and on a selection of systems with strongly differing demand and wind characteristics.

Both models minimize system generation costs. Fixed costs, i.e. the cost of construction and fixed operations and maintenance, are added to the generation costs where the portfolios are compared in terms of total annual costs.

A. Unit-Commitment and Economic Dispatch (UCED) Model

In this model there are two sets of generators: flexible and inflexible unit groups. The inflexible units, U_n, include generators typically associated with baseload operation. This category of units are impacted most by variability and are thus afforded a full mixed-integer representation so that their operation can be accurately captured. Each inflexible unit has a variable for its online status and its level of production. Each inflexible unit group is defined by a minimum and maximum (P_{min} and P_{max}) production, cost of starting (C_{start}), no load cost (C_{noload}) and fixed incremental cost (C_{incr}). Flexible unit types, U_f, are those deemed to have sufficiently minor start costs and sufficiently high turn-down ratios such that their costs of production can be approximated as the product of their output and an average cost (C_{avg}) for each type. They have no online status and are thus not subject to start costs. As these units are typically relatively small and numerous, this approximation significantly reduces the number of computationally costly discrete variables. Since there isn't a binary online variable for each unit they can be aggregated into a single block of generation for each unit type.

The objective function (1) for this is the sum of generation costs, $G(t)$, for all of the time-steps in the scheduling horizon.

$$f_{obj} = \sum_{t \in T} G(t) \tag{1}$$

The generation costs, $G(t)$, for each time-step is given in (2) by the sum of costs for the inflexible units plus the sum of costs for the flexible generation types. The decision variables V_{start}, V_{online} and V_{gen} correspond respectively to whether the unit started, whether it was online, and its level of production for that hour.

$$\begin{aligned} G(t) = \quad & \sum_{u_N \in U_N} \Big(C_{start}(u_{in}) \cdot V_{start}(u_N, t) \\ & \quad + C_{noload}(u_{in}) \cdot V_{online}(u_N, t) \\ & \quad + C_{incr}(u_{in}) \cdot V_{gen}(u_N, t) \Big) \\ + \quad & \sum_{u_{fl} \in U_{fl}} \Big(C_{avg}(u_{fl}) \cdot V_{gen}(u_{fl}, t) \Big) \; \forall \, t \end{aligned} \tag{2}$$

Wind curtailment is modeled to capture instances where it would be necessary for the other constraints to be satisfied, or where it would reduce costs by avoiding starts. The load balance constraint that follows (3) defines that the total quantity of generation less wind curtailment (V_{curt}) must be equal the system demand, P_{dem}.

$$\begin{aligned} \sum_{u_N \in U_N} V_{gen}(u_N, t) + \sum_{u_{fl} \in U_{fl}} V_{gen}(u_{fl}, t) \\ + P_{wind}(t) - V_{curt}(t) = P_{dem}(t) \; \forall \, t \end{aligned} \tag{3}$$

Additionally, the level of wind curtailment cannot exceed the wind production for that time-step.

$$V_{curt}(t) \leq P_{wind}(t) \; \forall \, t \tag{4}$$

A spinning reserve target is defined, P_{res}, equalling the capacity of the largest installed unit for the given portfolio. Flexible generators are precluded from contributing to this target because they are not subject to a cost for being online and could therefore meet the entire target at no cost. This reflects real schedules, where spinning reserve will mostly be met by units analogous to inflexible generators as that will tend to be less costly. This constraint (5) also fulfills the system need for mechanical inertia by indirectly ensuring an appropriate minimum number of online inflexible units at all times [24].

$$\begin{aligned} P_{res} \leq \sum_{u_N \in U_N} \Big(V_{online}(u_N, t) \cdot P_{max}(u_{in}) \Big) - \\ \sum_{u_N \in U_N} \Big(V_{gen}(u_N, t) \Big) \; \forall \, t \end{aligned} \tag{5}$$

The production by any inflexible unit cannot exceed its maximum production, P_{max}, whereas production from any flexible unit group cannot exceed the installed capacity of that group, I:

$$\sum_{u_N \in U_N} V_{gen}(u_N, t) \leq P_{max}(u_N) \cdot N(u_{in}) \; \forall \, t \tag{6}$$

$$V_{gen}(u_{fl}, t) \leq I(u_{fl}) \; \forall \, t \tag{7}$$

The next two equations (8, 9) define the mixed-integer nature of the inflexible units whereby the units may be off, or online between their minimum and maximum output.

$$V_{gen}(u_N, t) \geq V_{online}(u_N, t) \cdot P_{min}(u_{in}) \; \forall \, t, u_N \tag{8}$$

$$V_{gen}(u_N, t) \leq V_{online}(u_N, t) \cdot P_{max}(u_{in}) \; \forall \, t, u_N \tag{9}$$

Equation (10) defines a start, whereby a start will occur where V_{online} changes from zero to one from one time-step to the next. In all other combinations of the online variables V_{start} will take on zero, as taking on one would increase the value of the objective function.

$$V_{start}(u_N, t) \geq V_{online}(u_N, t) - V_{online}(u_N, t-1) \; \forall \, t, u_N \tag{10}$$

Equation (11) limits the maximum up-ramp for inflexible units to R_{max}.

$$V_{gen}(u_N, t+1) - V_{gen}(u_N, t) \leq R_{max}(u_N)\ \forall\, u_N, t \quad (11)$$

Rolling scheduling is employed, whereby the model is solved for the first 72 hours (the *forecast horizon*). The model then moves forward 48 hours (the *fixing horizon*) and is solved again for another 72 hours. This is repeated for the whole year. This sort of scheduling is preferable to solving for the whole year at once, as that would imply an unreasonable amount of foresight over wind and demand values. The length of the forecast and fixing horizons was chosen to be sufficiently long to accommodate units where many full-load hours of operation would be required to justify a start.

It was chosen not to include minimum up and down time constraints. The levels of start costs in the model are such that to justify a start, units have to be online for a duration exceeding typical minimum up times and would tend to only go offline for durations exceeding their minimum down times, as to do otherwise would incur a start cost that exceeds the saving from avoiding part-load operation.

B. *Dispatch-only (DO) Model*

The DO model differs in having a simpler representation of units and their behavior. The UCED model aggregates flexible generating types into blocks of generation. In this model, all generation is treated in this way. This means that there are no online status variables and thus no direct way of including unit start-ups. This essentially defines a linear dispatch model. The installed capacity of each generation type can be defined as a decision variable to determine the least-cost portfolio directly [25], however the objective of this paper is to assess the accuracy of this class of model in determining system costs across the portfolio space, so the installed capacities are defined as exogenous parameters.

$$f_{obj} = \sum_{t \in T} G(t) \quad (12)$$

$$G(t) = \sum_{u_{fl} \in U_{fl}} C_{avg}(u_{fl}) \cdot V_{gen}(u_{fl}, t)\ \forall\, t \quad (13)$$

$$\sum_{u_{fl} \in U_{fl}} V_{gen}(u_{fl}, t) + P_{wind}(t) = P_{dem}(t)\ \forall\, t \quad (14)$$

IV. Test Systems & Input Data

Three test systems are used: the electrical power systems of Finland [26] and Ireland [27] and the Electric Reliability Council of Texas (ERCOT), USA [28].

The systems differ strongly in terms of their characteristics relating to variability. Fig. 1 illustrates the level of pre-existing (demand) variability on each system and how it varies on a seasonal basis. For each day of the year, the diurnal range, i.e. the difference between the daily maximum and minimum demand, has been determined and the monthly average plotted as a percentage of the annual peak demand. The figure

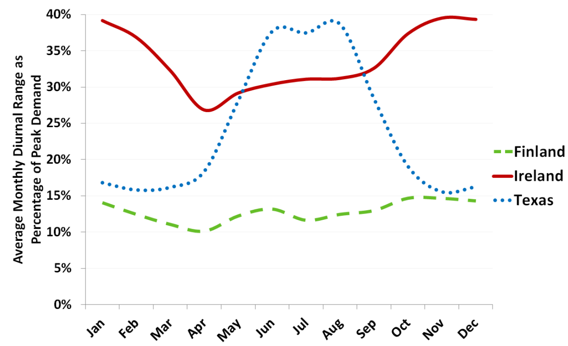


Fig. 1. Daily max. minus daily min. demand, averaged by month, as a percentage of annual peak demand for each system.

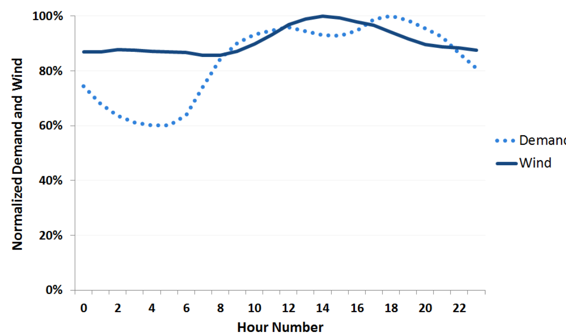


Fig. 2. Ireland (2008) - normalized hourly averages of system demand and wind production.

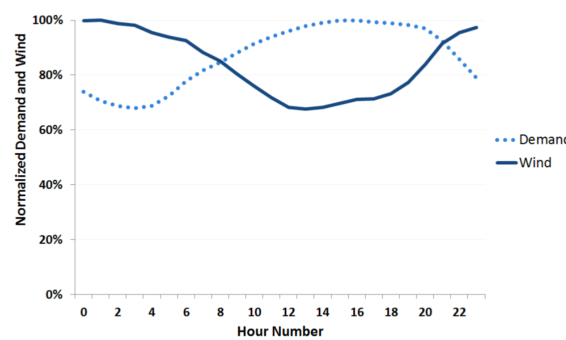


Fig. 3. Texas (2009) - normalized hourly averages of system demand and wind production.

indicates a modest degree of diurnal variability on the Finnish system, while in Ireland and Texas, diurnal variability is high and seasonal.

An interesting difference between the Texan and Irish system is the degree to which variable generation correlates with demand. Fig. 2 and 3 give the (normalized) average demand and wind for each hour of the day for the Irish and Texas systems. Wind generation and system demand are somewhat positively correlated on a time-of-day basis in the Irish system (Fig. 2), whereas they are highly negatively correlated in the Texan system (Fig. 3).

As the quantity of installed wind increases, the level of diurnal variability in each system increases, but to different degrees. For example, the average diurnal range (Fig. 4) on the Irish system is seen to be relatively less affected by increasing

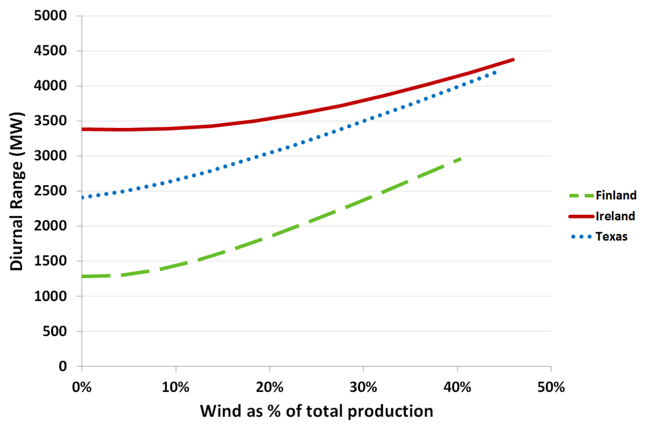


Fig. 4. Annual average diurnal range, i.e. daily max. minus daily min. net-demand, for increasing installed wind.

wind.

For the simulations, each system's demand time-series has been scaled to 10 GW peak to facilitate direct comparison. For each system, 11 wind scenarios are tested, from 0 to 10 GW in steps of 1 GW. The wind data used consists of year-long hourly percentage production time-series, i.e. total wind output from all grid-connected wind sites divided by the total installed capacity at each hour. For each scenario, these system percentage output series are scaled to the scenario's installed capacity to obtain total system wind time-series. For each system, the initial percentage output series is drawn from a large number of well-dispersed wind sites [29] so as to avoid over-stating the level of wind variability at high levels of scaling. Wind production at different locations will not be perfectly correlated, so as new dispersed wind sites are connected to a system, the frequency of very low and very high average levels of production should reduce. This beneficial geographic dispersion effect will tend to saturate beyond some level of dispersion. This level can be discerned by considering the statistical dispersion of normalized wind production as a function of the level of spatial dispersion of wind sites. Specific guidelines for assessing whether a data-set is sufficiently dispersed are given in [30].

All combinations of plant types (from Table I) totaling 11,800 MW were used, discarding only those portfolios with less than 1 GW of flexible generation, as it was assumed that such portfolios would have insufficient ramping capabilities. It was decided that wind generation could not contribute to the total capacity requirement. The wind generation would of course offer some capacity value, but its inclusion in the calculation of the total necessary capacity would make it impossible to compare portfolios with the same composition of conventional generation across levels of installed wind.

Table I details the parameters for the generation plant types considered: coal-fired steam turbine, Combined-Cycle Gas Turbine (CCGT) and Open-Cycle Gas Turbine generation (OCGT). Unit sizes are based on typical medium-sized units [31]. Fixed costs, which include fixed operations and maintenance costs are based on [32]. The ramp-up rate for coal is taken from the CAISO generation plant data set [33].

TABLE I
GENERATION UNIT PARAMETERS COMMON TO ALL RUNS

Technology	Type	Min. Output *MW*	Max. Output *MW*	Max Up Ramp *MW/hr*	Fixed Costs *€ per MW*
Inflexible	Coal	200	600	540	100,000
	CCGT	200	400		65,000
Flexible	OCGT				45,000

TABLE II
COST SET 1 (SOURCE: US EIA 2008)

Technology	Type	No load *€ per hr*	Incremental *€ per MWh*	Start *€ per start*	Average *€ per MWh*
Inflexible	Coal	485	12.7	200,000	13.5
	CCGT	1940	16.2	100,000	21.1
Flexible	OCGT		33.7		33.7

TABLE III
COST SET 2 (SOURCE: EEX 2010)

Technology	Type	No load *€ per hr*	Incremental *€ per MWh*	Start *€ per start*	Average *€ per MWh*
Inflexible	Coal	2500	65	50,000	69
	CCGT	4800	40	100,000	52
Flexible	OCGT		83		83

All ramp down rates are neglected as all units are assumed to be able to ramp-down their entire output within in hour while ramp-up rates are similarly neglected for CCGT and OCGT units.

The impact of chronology on least-cost schedules is substantially driven by the relative costs of generation available. In recognition of this, two cost sets are used as inputs (Tables II & III). In each case, the average cost applies only to the DO model whereas incremental costs, no load costs and start costs are only relevant to the UCED model. The average output of units is assumed to be equal to the rated output of units for the purposes of average cost calculation. The underlying thermal efficiencies used in calculating generation costs represent typical modern plants [31].

The fuel costs for the first set of inputs (Table II) is based on US Department of Energy data for fuel prices paid by electric power producers in 2008 [34], [35]. The net-generation cost from coal units is less than that for combined cycle generation, owing to pre-shale gas prices and non-application of any emissions charges. A broad range of estimates exists for the starts cost of large generating units [36]–[38]. In this first set, the coal generation has a larger start cost than the CCGT generation.

The fuel costs for the second set (Table III), derived from EEX 2010 spot prices [39] and including a €25 per tonne carbon tax, constitute substantially higher prices, in particular for coal. For the second set, a lower start cost is chosen for the coal-fired generation, though still within the range of estimated start costs cited previously.

The models were written in GAMS and solved using CPLEX12 on a small cluster utilizing 4 Intel i7 870 processors (totalling 32 logical cores) and 48 GB of memory. The optimality gap was 0.25%.

V. Results

The number of possible portfolios from the combination of discrete units from Table I, totaling 11.8 GW of installed capacity and subject to a minimum of 1 GW of flexible generation, equals 271. Each of these portfolios was tested for each of the 2 cost-sets, 11 levels of installed wind and 3 test systems. A total of 17,886 cases. There are many attributes other than cost that are of interest, such as project risk (and in turn cost of capital), market incentives, regulation and regulatory risk, fuel diversity and fuel diversification. Therefore the very least-cost portfolio may not be the most preferable. In recognition of this, the results have been averaged over the ten portfolios with lowest total costs, that is, including both generation and fixed costs, and for Fig. 6–9 are presented for increasing wind, which generally corresponds to increasing net-demand variability.

Fig. 5 illustrates the least-cost portfolio compositions for the highest wind case for the UCED model and the DO model. For both the models, the least-cost portfolios are largely driven by the interaction of fixed costs and fuel costs. However, under high variability, the DO model differs strongly from the UCED model and thus the least-cost portfolios diverge. The UCED model introduces starts, so it could be expected that the largest change would be a shift to the generation with lower start costs, in this case the open-cycle or combined-cycle generation. Instead, in cost-set 1 the most significant change is in the ratio of inflexible generation, where coal, the most expensive unit type to start, replaces CCGT units, which are half as costly to start (Table II). There are several factors contributing to this outcome. First, while coal units in cost-set 1 are more expensive to start, they also have significantly lower production costs in this cost-set than the CCGT units, so the minimum online duration to justify a start is lower. Second, coal-fired units are much less vulnerable to start-stop operation, owing to their superior turn-down ratio (Table I) meaning that large numbers of coal units can stay online during periods of low net-demand by ramping down their output. Finally, the UCED model has a spinning reserve constraint which forces part-load operation by inflexible units at times of high net-demand. The higher turn-down ratio of coal units allows them to turn down their output by a much larger degree than CCGT unit, thus offering more reserve per unit. Additionally, the lower no-load cost of coal units means that they are less costly to operate in this manner.

In cost-set 2, the combination of fixed costs and fuel prices heavily favors CCGT generation to the extent that increased variability does not lead to an increase in coal generation, which for this cost-set has lower start costs. The addition of a single coal plant to portfolios is also penalized as spinning reserve must increase in line with the increase in the size of the largest unit on the system. This explains the increase in CCGT for Finland, where the coal generation is amongst the least-cost portfolios for the DO model, whereas in the DO model, portfolios with larger quantities of CCGT but zero coal are lower cost as they avoid having to provide an extra $200MW$ of reserve. In Ireland and Texas there is a reduction in the optimal quantities of CCGT for the UCED model. This is expected and

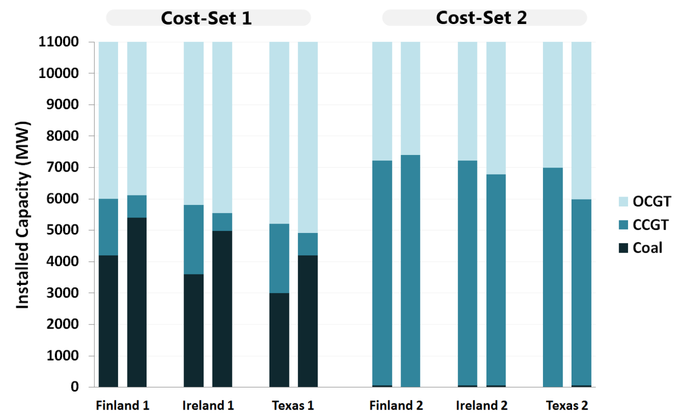


Fig. 5. High-wind (10 GW) portfolio compositions for cost-set 1 and 2. Averaged over ten lowest-cost portfolios. DO model estimates to left, UCED to right.

follows from the addition of start costs, reduced utilization (where starts are not justified) and part-load operation, which is particularly costly for CCGT units.

The difference between the models in terms of least-cost portfolios is driven by the degree of underestimation of generation costs by the DO model. The difference between the DO model estimate and the UCED model estimate will be expressed as a percentage and will be referred to as the level of error (15). It should be noted that the generation costs estimate produced by the UCED model is itself obviously subject to error.

$$error = \left(\frac{UCED - DO}{UCED}\right) \tag{15}$$

It can be seen (Fig. 6) that the level of error increases in wind at an increasing rate for all systems and cases. Broadly the level of error is somewhat higher in the Texan system than the Irish system, while the Finnish system exhibits markedly less error than both, especially for cost-set 2.

The sources of error in each case arise in three ways:

- Starts
- Starts avoidance
- Average Cost Estimation Error

Inflexible unit starts are shown in Fig. 7 for increasing quantities of wind. There is a much less fortuitous correlation of wind and demand in Texas system (Fig. 3), yet a greater number of starts is seen in the Irish system for all installed capacities of wind. This result is driven by the contrast in average minimum daily demand on the systems. In Ireland, the average minimum daily demand is approximately 60% of the average peak demand (Fig. 2), while in Texas, the same metric is approximately 70% (Fig. 3). Fig. 4 suggests that at greater levels of installed wind, the negative wind-demand correlation in Texan may have a stronger impact on starts, as the difference between the max. and min. net-demand in Texas starts to approach the levels observed in the Irish system. The Finnish system has a high number of starts relative to its level of error (Figures 6 & 7). Paradoxically, this can be partially explained by the high load factor on the Finnish system. The high load factor pushes up the capacity factor for potential

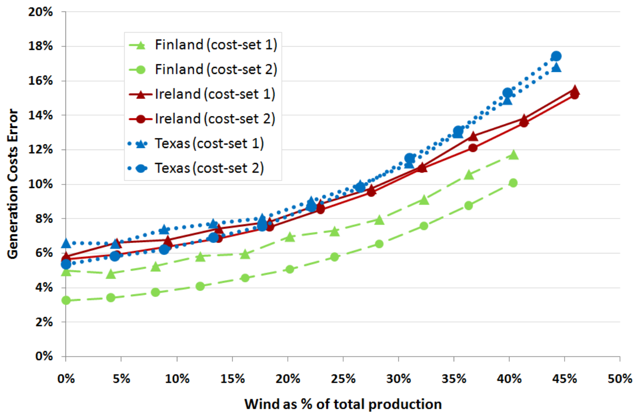


Fig. 6. Generation costs error for costs-sets 1 and 2, averaged over 10 portfolios with lowest total costs.

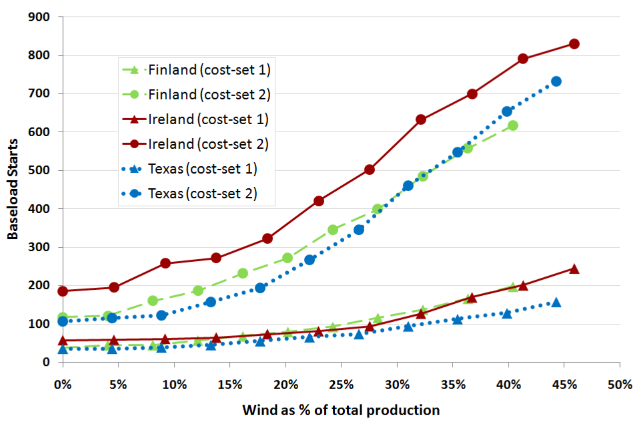


Fig. 7. Inflexible unit starts for costs-sets 1 and 2, averaged over 10 portfolios with lowest total costs.

units such that the higher fixed cost of CCGT units over OCGT capacity can be justified. The greater number of CCGT units (Fig. 5), which have a high minimum output (Table I), therefore results in an increase in starts and a reduction in starts avoidance.

Starts avoidance, the second source of error, refers to situations where an increase in system demand could be met by starting an inflexible unit, but is instead met by more flexible generation because the expected run-time for the inflexible unit would not be sufficiently long to economically justify a start. A consequence of the formulation of the DO model is that OCGT capacity will only be scheduled where the system demand exceeds the combined installed capacity of all generation with lower average costs (merit-order dispatch). OCGT capacity is therefore only used when there is no other alternative. The difference between the utilization of the OCGT capacity in the DO and UCED runs constitutes what might called the utilization error. A small portion of this will be attributable to the provision of reserve, arising in situations the inflexible units are forced to limit their output when they are nearly full loaded. Fig. 8 gives this quantity for all systems and cost sets. It is seen that the Finnish cases have the lowest quantity of starts avoidance, so even though there is a relatively large

TABLE IV
BREAK-EVEN HOURS BY UNIT TYPE & COST-SET

	Cost-set 1	Cost-set 2
Coal	16.5	6.0
CCGT	19.8	8.1

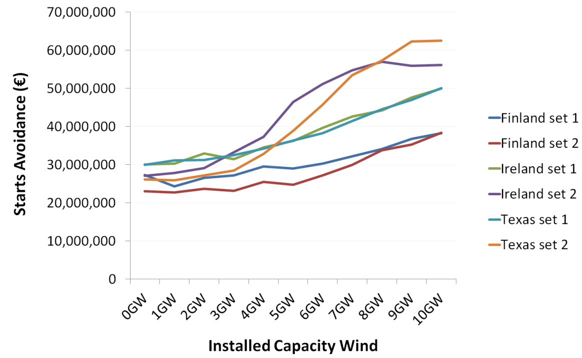


Fig. 8. Starts avoidance for all systems and cost sets – averaged over 10 portfolios with lowest total costs.

number of starts in the Finnish cases (Fig. 7), the level of error for Finland is significantly lower (Fig. 6). The quantity of starts avoidance depends on the duration of peaks in demand, which is affected by variable generation, but also on the cost of unit starts and the heat rates of the available generation. A means of combining the latter cost factors is to determine the number of hours of full-load operation required for an inflexible unit to justify a start. This quantity, referred to here as the quantity of *break-even hours* is equal to the cost of starting the inflexible unit divided by the difference in the cost of an hour of full-load operation, between the inflexible unit and the next-best flexible generation type. This can be used, for example, to determine which of two inflexible units is more likely to start, or how likely any flexible unit is likely to start given the relative costs. Table IV lists the number of break-even hours for each inflexible unit type and under each cost set. It is seen that the inflexible units in cost-set 1 will be subject to greater quantity of starts avoidance, as a greater number of online hours will be required to justify starting. In cost-set 1, even though the start cost of the coal generation is twice that of the combined-cycle generation, the CCGT units are less likely to start.

The third source of error, Average Cost Estimation Error (ACEE) arises from the fixed thermal efficiency of generators in the DO model. While the average efficiency can be set to reflect the average online output of generators, an appropriate value for this cannot be known without first undergoing a UCED. The average efficiency of a generator is a function of the average output of the generator during online hours, which itself is influenced by a collection of factors, including the costs of all available generators, net-demand over the period and net-demand uncertainty. The degree of part-load operation in this study, and thus the quantity of error associated with not accounting for part-load inefficiencies, can be seen in Fig. 9 which plots the average percentage output of inflexible units

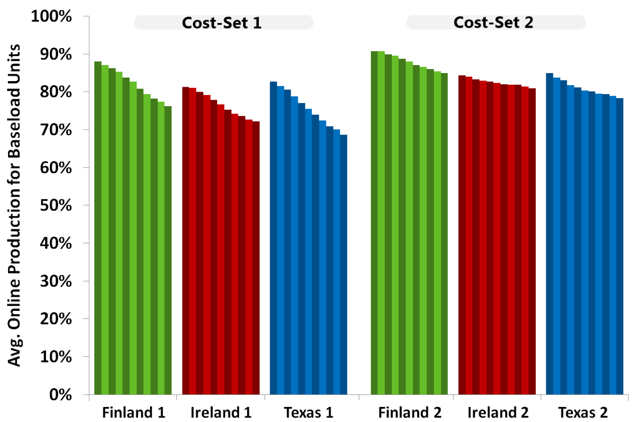


Fig. 9. Average production for online inflexible units for cost-set 1 and 2 – averaged over 10 portfolios with lowest total costs. Installed capacity of wind increases from left to right for each group of columns.

for periods where they are online. For cost-set 1 there is a much stronger decrease in average online output for increasing wind, than for cost-set 2. This leads from the greater quantity of coal generation across the lower cost portfolios for this cost-set. At low wind, the coal generation can maintain a high average online output. For higher levels of installed wind, the average online production from the coal generation can reduce, facilitated by the high turn-down ratio of coal units. This emphasizes the inability of DO models to account for the varying modes of operation of generation under differing demand scenarios. A value can be determined for ACEE for each inflexible generation type by calculating the difference in production costs using the assumed average cost and the actual average cost.

This can become substantially more problematic where these models are applied in capacity expansion. The assumed unit schedules from DO models are based on a merit-order of average costs. Where start costs are considerable, this merit-order approximation starts to break down for increasing variability. A plant with moderate average and fixed costs might be deemed to be the optimal expansion by the DO model, but if the plant type also required a significant number of hours to break-even for a start, its actual utilization may be considerably lower.

Addition of Nuclear & Hydro Power

Many systems have large existing installed capacities of nuclear or hydro power generation which have very differing characteristics to those included generation technologies considered so far. Hydro power when coupled with a reservoir, offers a time-shiftable form of generation, whereas nuclear power tends not to be load-following and thus requires greater flexibility from other plants on the system. To extend the analysis to include these forms of generation, several additional cases are considered and compared to the previous cases. The previous simulations are repeated with the addition of 2 GW of hydro power. They are then repeated with 2 GW of nuclear power, and finally with the addition of both 2 GW of nuclear and 2 GW of hydro power. A reduced set of installed wind capacities is used, from 0 to 10 GW in increments of 2 GW. The nuclear power is taken as a fixed output of 2 GW for simplicity. The hydro power is run-of-river with 24 full-load hours of storage. The reservoir inflow data [40] is for the combined hydro system of Finland for 2006 and has been scaled to provide 20% of annual demand in each system. A water-balance equation is added to both models (16). Hydro production is limited to the installed capacity of hydro (17) and reservoir levels are fixed at 48 hour intervals to 12 full-load hours as a proxy for valuing hours beyond the scheduling horizon (18). For brevity, a single cost-set (cost-set 2) was used for these nuclear-hydro sets. This amounted to 14,688 year-long simulations for each model.

$$V_{water}(t) - V_{water}(t-1) = E_{inflow} - V_{spill} - V_{hydro} \ \forall \ t \quad (16)$$

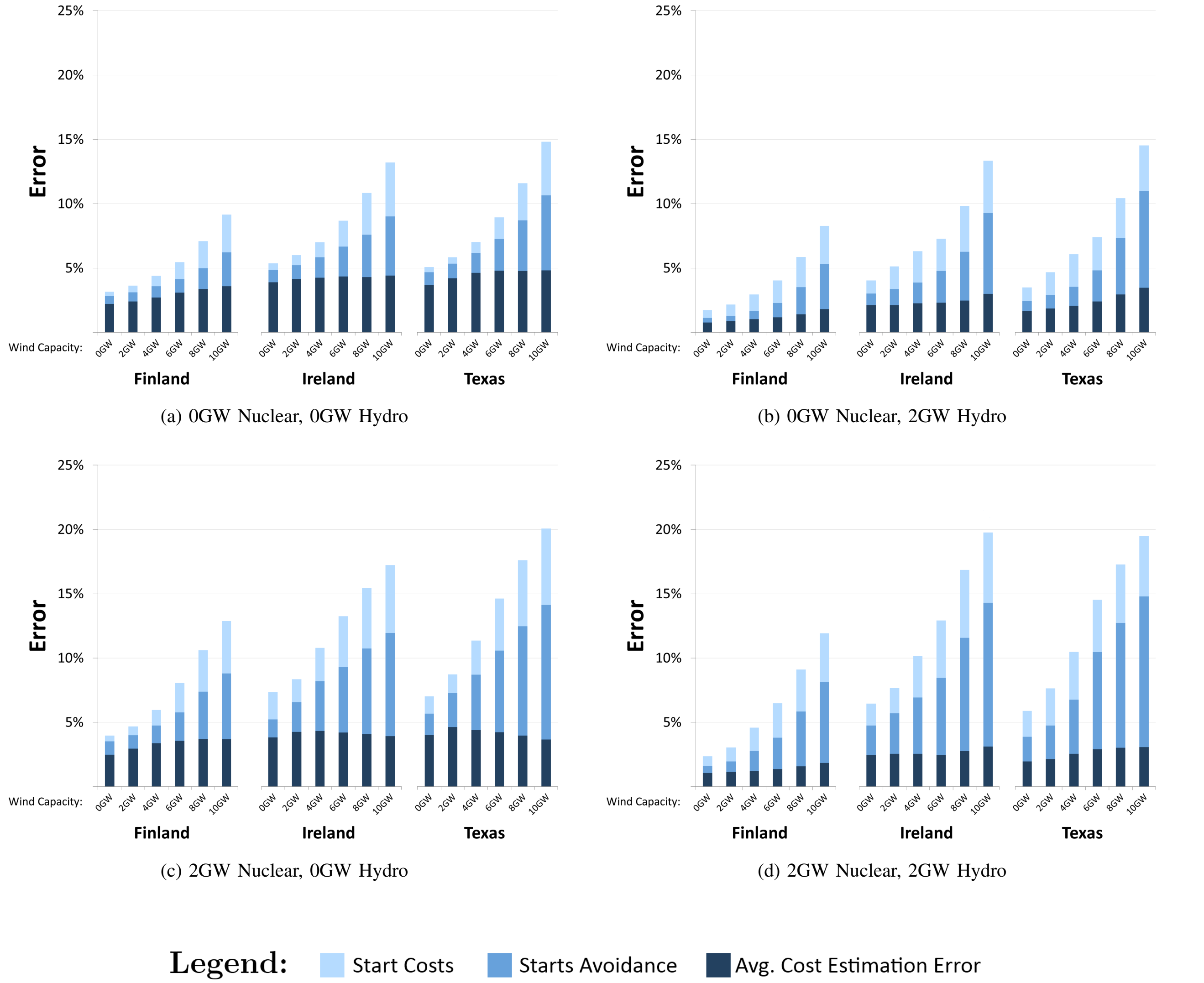
$$V_{hydro}(t) \leq I_{hydro} \ \forall \ t \quad (17)$$

$$V_{water}(t) = E_{mid} \ \forall \ t \in T_{bi} \quad (18)$$

Both nuclear and hydro power make a considerable impact on least-cost schedules as determined by both models, and in turn on the resulting least-cost portfolios. Figures 10a - 10d give the level of error between models, as decomposed into start costs, starts avoidance and average cost estimation error, for each system and installed capacity of wind. Fig. 11 gives the installed capacity of each generation type for increasing wind for both models, for each system and nuclear-hydro combination. This illustrates how nuclear and hydro power impact the relative performance of the models for increasing variability.

Without either hydro or nuclear power, ACEE is generally large and stable across wind capacities (Fig. 10a), whereas starts avoidance and start costs increase strongly, but from an initially low level. The increasing level of variability-related costs induces a reduction in the level of CCGT generation (Fig. 11a - 11c) as wind increases. The generally high level of CCGT, which is costly to part-load, is reflected in the large quantity of ACEE. The reducing quantity of CCGT at higher wind levels stabilizes the level of ACEE, which would otherwise increase. Starts and starts avoidance are generally more affected than ACEE by wind because as wind increases, it reduces net-demand non-uniformly. Units will tend to be forced offline more frequently, which induces future starts. Additionally, unit run-times will tend be cut short and thus less frequently justify starting, which increases starts avoidance.

The hydro generation offers a large quantity of energy that can only be stored in the short-term and since production by the flexible generators is small and rather seasonal, the hydro generation will tend to displace a large quantity of inflexible generation. Accordingly, a significant decrease in CCGT capacity is seen between the first and second rows of plots in Fig. 11. The Hydro generation will tend to produce more when net-demand is high so as to reduce CCGT part-load costs, which is seen in the general reduction in ACEE for all cases in Fig. 10b. As wind increases however, starts costs and starts avoidance increase. The hydro generation can only offer



(a) 0GW Nuclear, 0GW Hydro

(b) 0GW Nuclear, 2GW Hydro

(c) 2GW Nuclear, 0GW Hydro

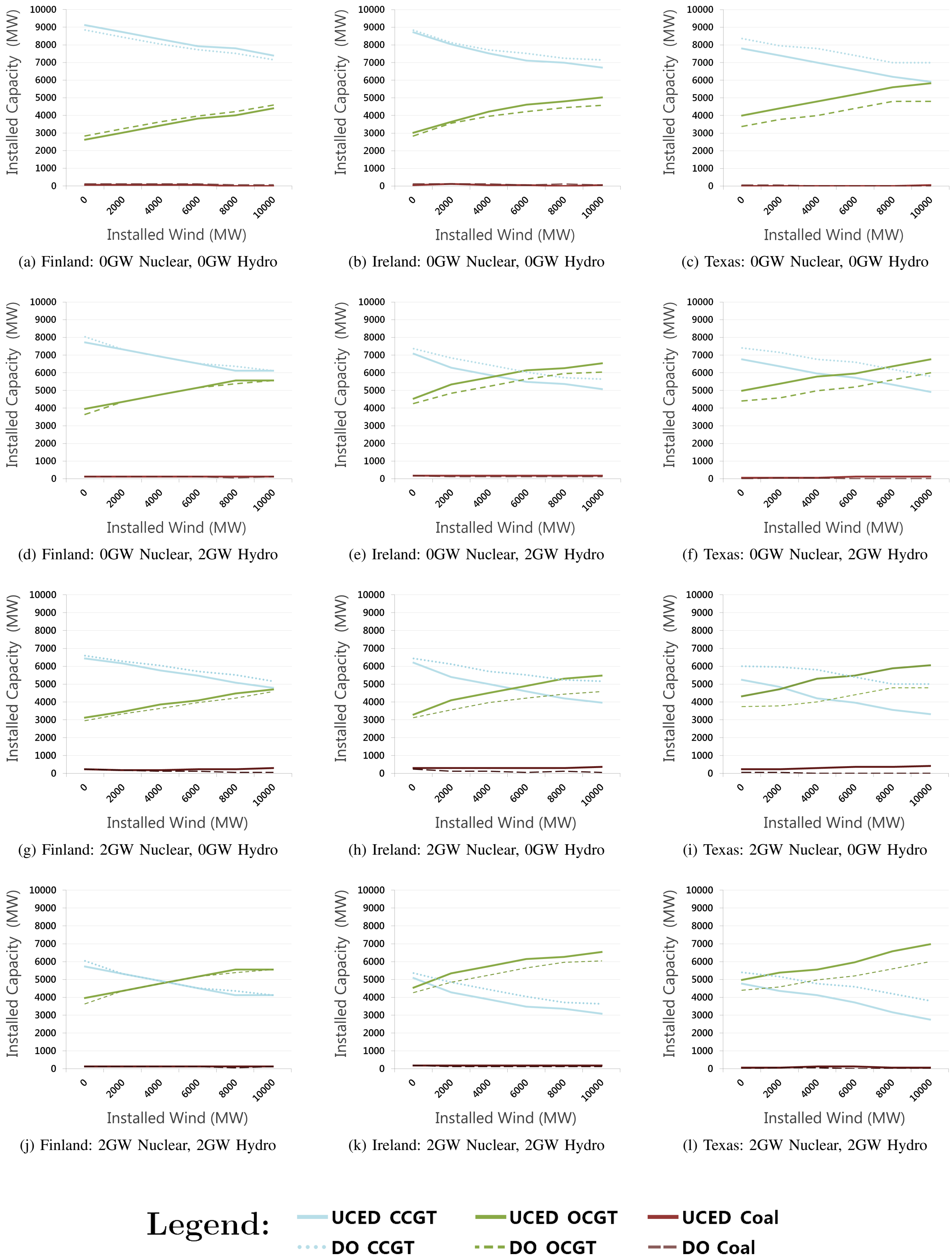
(d) 2GW Nuclear, 2GW Hydro

Fig. 10. Error broken down by Start Costs, Starts Avoidance & Average Cost Estimation Error for each system, wind capacity and nuclear-hydro combination.

production flexibility, not demand flexibility, so at times of high-wind it can only partially mitigate these particular error components.

Where the inflexible generators on a system have low turn-down ratios (high minimum outputs), they will often be exposed to stops and thus starts by the daily cycle of demand. The addition of nuclear is equivalent to reducing the net-demand by the capacity of the nuclear generation. The remaining demand to be met will be such that generators will have to ramp to lower levels of output and will more frequently be forced to go offline, which will increase starts. The mean online duration for inflexible units will also reduce as units operate over shorter, more frequent cycles. Where the online duration falls below the number of break-even hours, the units will be less likely to start. Figures 10c and 10d confirm large increases in both starts and starts avoidance seen for both levels of hydro and for all the systems as wind increases. The inclusion of hydro is seen to depress levels of ACEE (Fig. 10d) consistent with increased loading of the installed CCGT generation. Variability that would otherwise have been met by the CCGT units is now met by the hydro generation which is again producing more at times of high net-demand. Once again, the level of starts and starts avoidance increase markedly with wind since hydro can only offer production flexibility.

The impact of variability has been focussed on in this paper. However, wind power, the form of variable generation considered here, introduces a significant quantity of uncertainty. The primary consequence of uncertainty is seen in changes in the levels of the various categories of reserve, the most costly of which being spinning reserve. However, the uncertainty associated with losing large in-feeds already necessitates the provisioning of relatively large quantities of spinning reserve. Unit outages are relatively infrequent and load forecasts relatively good, so there tends to be a lot of unused spinning reserve available at any particular time. Therefore, the likelihood of losing a significant quantity of conventional generation at the same as making a large wind forecast error appears to be relatively small [41]. Translated



(a) Finland: 0GW Nuclear, 0GW Hydro
(b) Ireland: 0GW Nuclear, 0GW Hydro
(c) Texas: 0GW Nuclear, 0GW Hydro
(d) Finland: 0GW Nuclear, 2GW Hydro
(e) Ireland: 0GW Nuclear, 2GW Hydro
(f) Texas: 0GW Nuclear, 2GW Hydro
(g) Finland: 2GW Nuclear, 0GW Hydro
(h) Ireland: 2GW Nuclear, 0GW Hydro
(i) Texas: 2GW Nuclear, 0GW Hydro
(j) Finland: 2GW Nuclear, 2GW Hydro
(k) Ireland: 2GW Nuclear, 2GW Hydro
(l) Texas: 2GW Nuclear, 2GW Hydro

Fig. 11. Cost-set 2: Least-cost generation capacities for each system and each installed capacity of nuclear, hydro and wind.

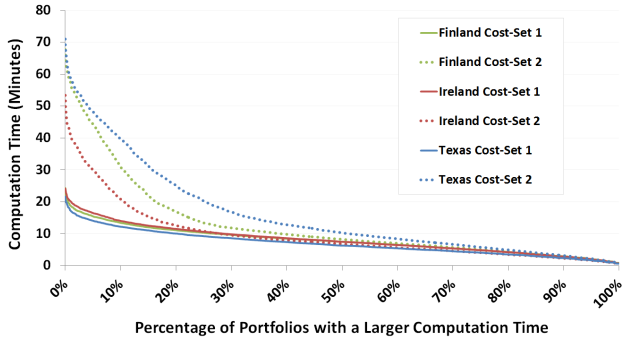


Fig. 12. Comparison of computation time between systems and cost-sets, for non-nuclear, non-hydro simulations.

into mathematical reasoning, the variance of the net uncertainty distribution is only increased slightly by the presence of wind generation uncertainty since the other components of uncertainty are significantly larger. Therefore, in the context of generation planning models, the extra model complexity and computational effort required to carry out a more detailed treatment of wind uncertainty is not justified.

In order to verify the validity of ignoring minimum up and down times for the cases studied, a program was written to analyze every schedule used in the results, to determine if these constraints would ever have been violated. No such cases were found. In certain circumstances however, in particular where units have long minimum up and down times, it may be necessary to include these constraints. An appropriate formulation can be found in [42].

Additionally, there are many constraints that are particular to individual systems that were not modeled here but may have a substantial impact on actual schedules and thus least-cost portfolios. For example, transmission networks may be insufficient for remote sources of variable generation, or for smaller systems, large quantities of variable production might result in too few online units, such that frequency stability becomes an issue. These situations will lead to curtailment and if such events are frequent, models may need to account for them through extra constraints.

Computation time varied considerably for the simulations undertaken. Portfolios with larger numbers of inflexible units, in particular those with lower turn-down ratios, took markedly longer to reach a solution. Secondly, the relative fuel costs of the plant types had a strong effect. For example, for cost-set 2 (Table III) the cost of CCGT and coal generation are relatively closer than for cost set 1 (Table II) which translated into much increased solution times (Fig. 12).

VI. Conclusions

The introduction of variable renewables will have consequences for the effectiveness of existing generation planning models. Where unit starts are not accounted for in the models, changes in how units will be committed and dispatched will not be anticipated and portfolios unsuited for variability will evolve. The outcomes are highly system specific. For high variability systems, the level of diurnality in demand can persist as the strongest driver of the unit-commitment, and thus the least-cost portfolios, for very high levels of variable generation. The overall monetary impact of starts can be split into start costs, starts avoidance–where utilization shifts from baseload to peaking generation–and lastly, the error associated with estimating the average costs of generating units. The introduction of hydro power served predominantly to mitigate average cost estimation error, while nuclear, like wind, had a strong upward influence on start costs and starts avoidance. The computational burden of the UCED model was found to be high and perhaps excessive for many applications. Less computationally costly approaches that can adequately account for the mixed-integer nature of generating units and chronology of net-demand may be needed in these cases.

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