Impact of Operational Flexibility on Generation Planning

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***Abstract*—Recent work on operational flexibility—a power system's ability to respond to variations in demand and supply—has focused on evaluating the impact of large penetration of renewable generation on existing power systems. Operational flexibility is equally important for long-term capacity expansion planning. Future systems with larger shares of renewable generation, and/or carbon emission limits, will require flexible generation mixes. Flexibility is rarely fully considered in capacity planning models because of the computational demands of including mixed integer unit commitment within capacity expansion. We present a computationally efficient unit commitment/maintenance/capacity planning formulation that includes the critical operating constraints. An example of capacity planning for Texas in 2035 with hypothetical RPS and carbon policies shows how considering flexibility results in different capacity and energy mixes and emissions, and that the omission of flexibility can lead to a system that is unable to simultaneously meet demand, carbon, and RPS requirements.**

***Index Terms*—Flexibility, Capacity Expansion, Renewables, Unit Commitment, Integer Programming, Carbon Policy**

I. Introduction

GENERATION expansion planning choses investments in new generation units to meet load growth and replace retiring units. There is a long tradition of using optimization techniques to minimize total investment and operations costs during generation expansion planning [1]–[3]. Such centralized planning has been and continues to be used by vertically integrated utilities in regulated systems. In addition, there is renewed interest in "indicative planning" [4] to inform policy and regulatory decisions regarding carbon emissions, renewable portfolio standards, energy market design, and wide-area transmission planning. Examples of recent innovations in generation expansion include the combination of modern heuristic optimization with traditional approaches [5], [6], the effects of market power on capacity decisions in a liberalized markets using equilibrium methods [7], the impacts of risk aversion on market agents [8], stochastic transmission planning with generation planning as a subproblem [9], and transmission planning with generation planning and operations in liberalized markets [10], [11].

Analyses of policies to reduce emissions or encourage renewable generation are a particularly important application of generation expansion models, especially in light of the large number of studies (e.g., [12], [13]) that purport to inform the optimal mix of technologies, including for the electric sector, based on high-level models that lack many critical characteristics and constraints of real power systems. A key omitted characteristic in the majority of planning models is operational flexibility or the ability to adapt to rapid changes in net load resulting from renewable generation variability. Several reports have stressed the importance of including flexibility explicitly within planning [14]–[16].

Unit commitment (UC) formulations have seen significant improvements to represent these new sources of variability and to assess the flexibility of a given capacity mix (e.g., [17]–[19]). Because the UC problem itself is a large mixed integer problem and difficult to solve in its own right, embedding it as a subproblem within generation expansion presents computational challenges. Instead, generation expansion formulations typically represent annual demand with a small number of representative, non-chronological load blocks. This simplification ignores operational flexibility by implicitly relying on the fact that, historically, demand varied smoothly and predictably at a rate slower than the response time of most power plants. Interactions among intermittent renewables, demand-side resources, and storage occur at faster operating timescales, requiring sequential energy and demand variations, their weather dependent correlation [20], [21], and operating constraints for the complementary thermal generation (e.g. ramping, startup) [22], [23]. Neglecting these faster dynamics and constraints within longer term planning may misrepresent the true cost and performance of a particular generation mix and result in capacity mixes that are suboptimal or infeasible.

A few previous studies have also proposed methods for incorporating operational flexibility within capacity planning. These studies either rely on heuristics that give low-resolution approximations or reduce the problem size in order to keep the problem computationally tractable. One approach has been to develop generation mixes with conventional expansion models, and then perform flexibility assessment using detailed simulations (e.g.[21], [24]), but this approach does not produce a capacity mix informed by the hourly-scale constraints. Rosekrans et al. [25] use an iterative non-optimal heuristic to estimate unit commitment and reserves. Shortt and O'Malley [26] present a heuristic algorithm to estimate cycling behavior that divides all generation units into two groups. De Jonghe, et al. [27], [28] also present an approximate method that includes some key flexibility constraints, such as operating reserves and ramping within an LP formulation. This is an improvement over models that ignore chronology, but because each technology acts as a single, minimally constrained unit it cannot model startups, minimum up/downtimes, and may misrepresent reserve availability. Shortt et al. [29] compare

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optimal generation investments from unit-commitment versus dispatch-only operations models, but this method exhaustively tests all capacity combinations, which becomes computationally prohibitive for larger systems or higher resolution in unit sizes. In contrast, Ma et al [30] explicitly formulate a model with UC and capacity investment decisions using a priority list to reduce computational demands. However, they use four representative weeks of load and wind and the relatively small IEEE RTS-96 system with 26 existing units and only a small number of candidate new units. Similarly, Pudjianto et al [31] formulate a capacity expansion model with embedded unit commitment and trasmission constraints, but apply it to choosing optimal storage capacity for a given capacity scenario, and provide no methodology for managing the computational burden of applying this formulation to large systems. Finally, while the studies cited here consider the flexibility in the context of renewable generation, none of them consider the role of flexibility when renewable generation is coupled with carbon emission constraint. The interaction of variable renewables and a carbon emission limit is likely to put even more strain on the system in terms of flexibility. Carbon limits introduce a further computational challenge due to the linking across all model periods.

We present a generation expansion formulation with explicitly embedded mixed integer UC for a full 8760 hour profile of load and demand, which is solved as a single MILP optimization. Our approach builds on an integer clustering approach to UC ([32]–[34]) that has been demonstrated to closely approximate the main results of a traditional binary UC model in orders of magnitude less computation time. Here, we extend this integer-based clustering approach to include investment and maintenance decisions for each unit. Rather than sacrificing resolution in the size of the system modeled or the temporal resolution, we simplify by assuming that units within each category (e.g., all natural gas combined cycle units) have identical characteristics. This enables tractably designing full-scale systems with a wide range of candidate unit types. Because our objective is to model strategic long-term capacity planning, the majority of the units for a future year do not yet exist and the omission of heterogeneity among units of a similar type is reasonable.

Our contributions are to:

- Introduce a practical method for performing capacity expansion with embedded unit commitment and maintenance that can solve a full year (or more) of 8760 hours, with large numbers of individual units (hundreds), and can consider not only large penetration of renewables but also carbon emissions constraints or prices; and
- Demonstrate with this approach that 1) renewable-driven operational flexibility changes the optimal capacity and energy mixes, 2) that these changes are a function of the carbon policy, not simply the amount of renewables in the system, and 3) that ignoring flexibility may lead to large emission errors or infeasible generation mixes.

The remainder of this paper is as follows. Section II presents the model formulation. We present the test system and assumptions in Section III. Section IV gives numerical results for an example policy scenario at one RPS target and carbon price. The impact of emissions limits and RPS levels are described in Section V. Section VI concludes.

II. Model Development

A. Overview

This analysis extends the clustered unit commitment operations formulation presented in [33]–[35] to include maintenance scheduling and capacity planning in a single MILP optimization. We call our model framework the Modular Electricity Planning and Operations (MEPO) model. As described in [33], an efficient way to reduce the size of a problem with binary decisions and constraints (e.g., commitment state) is to combine similar generating units into clusters. This replaces the large set of binary commitment decisions, one for each unit, with a smaller set of integer commitment states, one for each cluster, representing the number of units of that type currently on-line. All of the other variables—such as power output level, reserves contribution, etc.—and constraints are then aggregated for the entire cluster. Within the cluster, however, the integer commitment variable still captures individual unit level relations. Computationally, the integer variables provide structure that both reduces the dimensionality of and guides the search through the combinatorial commitment state space by eliminating identical or very similar permutations of binary commitment decisions. In addition, clustering reduces the number of continuous equations and variables since all relations now apply over the smaller number of clusters rather than the full set of individual units.

With this approach, each of the discrete decision variables—commitment, maintenance, and investment—can be captured by a single integer variable for each generation type (cluster) with an intuitive relation shown graphically in Fig. 1.

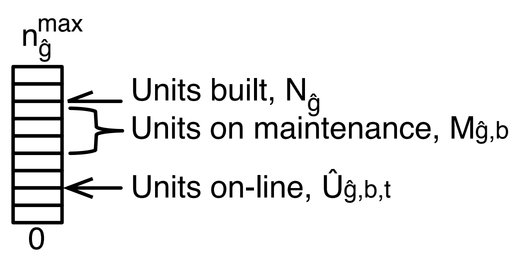

Fig. 1. Conceptual diagram of clustered capacity planning with integrated unit commitment and maintenance for a single type of unit at a single time.

The analysis here employs clustering by unit type only—all units with the same combination of fuel type and prime mover (e.g., coal steam, open cycle gas turbine, natural gas combined cycle) are combined into a single cluster. For heterogenous existing generating units, the representative unit for each cluster is assumed to have a nameplate capacity equal to the cluster average, and technical characteristics such as heat rate, ramp rates, minimum output, minimum up/down time, etc., are taken as the size-weighted average. This representative plant is effectively duplicated such that the number of units in the cluster, $n_{\hat{g}}$, matches the original number of individual units.

Mathematically, clustering is captured by the inequality:

$$0 \leq \hat{U}_{\hat{g},b,t} \leq N_{\hat{g}} - M_{\hat{g},b} \leq N_{\hat{g}} \leq n_{\hat{g}}^{max} \quad (1)$$
$$\hat{U}_{\hat{g},b,t}, M_{\hat{g},b}, N_{\hat{g}} \in \{0, 1, \ldots, n_{\hat{g}}^{max}\}$$

which requires that the number of committed units, $\hat{U}_{\hat{g},b,t}$ in technology cluster, $\hat{g}$, weekly time block, b, and hourly time step, t is less than the number of available units (not on maintenance), which is less than the total installed number of units, $N_{\hat{g}}$, which in turn is less than the maximum number of units (including units not yet built), $n_{\hat{g}}^{max}$. By definition, the number of available offline units equals $N_{\hat{g}}$ - $M_{\hat{g},b}$ - $\hat{U}_{\hat{g},b,t}$.

B. Objective

The least cost objective function is:

$$C^{\text{total}} = \min \sum_{\hat{g} \in \boldsymbol{G}} \Bigg(N_{\hat{g}} a_{\hat{g}}^{size} a_{\hat{g}}^{CRF} c_{\hat{g}}^{capital} + \sum_{b \in \mathbf{B}} \left[C_{\hat{g},b}^{\text{maint}} + l_b^{duration} \sum_{t \in \boldsymbol{T}} \left(C_{\hat{g},b,t}^{\text{var}} + C_{\hat{g},b,t}^{\text{start}} \right) \right] \Bigg) \quad (2)$$

1) Capital costs: are annualized based on the weighted average cost of capital (WACC) using a capital recovery factor [36]:

$$a_g^{CRF} = \frac{WACC}{1 - \left(\frac{1}{1+WACC}\right)^{a_g^{life}}} \quad (3)$$

2) Maintenance costs.: For each discrete maintenance decision, $M_{\hat{g},b}$, costs are computed based on a fixed fraction, $a_{\hat{g}}^{MaintFractOfO\&M}$, of the fixed O&M costs divided among the required weeks of maintenance $a_{\hat{g}}^{maint}$ as given by:

$$C_{\hat{g},b}^{\text{maint}} = M_{\hat{g},b} \frac{c_{\hat{g}}^{fixO\&M} a_{\hat{g}}^{MaintFractOfO\&M}}{a_{\hat{g}}^{maint}} l_b^{duration} \quad (4)$$

3) Variable costs,: $C_{g,t}^{\text{var}}$, include fuel costs, $c_{g,t}^{\text{fuel}}$, and variable operations and maintenance (O&M) costs, $c_g^{\text{varO\&M}}$:

$$C_{g,t}^{\text{var}} = \mathrm{F}_{g,t}(P_{g,t})\, c_g^{\text{fuel}} + P_{g,t} c_{g,t}^{\text{varO\&M}} \qquad P_{g,t} \geq 0, F_{g,t} \geq 0 \quad (5)$$

where $\mathrm{F}_{g,t}(P_{g,t})$ represents the heatrate function, here assumed to be affine.

4) Startup costs,: $C_{g,t}^{\text{start}}$, assume a constant fuel use per startup, f_g^{start} and include an additional fixed cost per start, $c_g^{\text{fix start}}$ for maintenance and personnel costs:

$$C_{g,t}^{\text{start}} = S_{g,t} \cdot \left(f_g^{\text{start}} c_g^{\text{fuel}} + c_g^{\text{fix start}} \right) \quad (6)$$

C. Operating constraints

This analysis uses the full unit commitment operations formulation presented in [33]–[35] which includes:

- System energy balance (supply=demand);
- Minimum & maximum output constraints on each unit;
- Inter-period ramping limits (up and down);
- Minimum up and down times; and
- Five classes of reserves: Primary up and down, Secondary up and down, and Quick Start.

The commitment state is represented with three integers following the results of Ostrowski, et al. [37].

D. Maintenance Constraints

To balance tractability and accuracy, we use a simplified maintenance formulation described below. As with unit commitment, clustering enables replacing individual unit maintenance decisions and schedules with a decision on the number of units in each cluster under maintenance for each time block.

1) Maintenance Sufficiency: ensures that each unit undergoes the required annual maintenance by constraining the sum-product of block duration, $l_b^{duration}$, and units on maintenance, $M_{\hat{g},b}$ to be greater than or equal to that required per unit, $a_{\hat{g}}^{maint}$, times the number units in the cluster, $n_{\hat{g}}$:

$$\sum_{b \in \mathcal{B}} M_{\hat{g},b} l_b^{duration} \geq a_{\hat{g}}^{maint} n_{\hat{g}} \quad (7)$$

where the block duration (in weeks) is given by $l_b^{duration}$.

2) Contiguous Maintenance : ensures that once a unit begins maintenance, it remains off-line until the maintenance is complete. This constraint is analogous to the minimum up time constraint and is captured similarly using both a maintenance state equation (8), where $M_{\hat{g},b}^{begin}$ and $M_{\hat{g},b}^{end}$ represent the number of units in the cluster that begin and end maintenance respectively in time block b; and a minimum maintenance duration constraint (9):

$$\begin{aligned} M_{\hat{g},b} &= M_{\hat{g},b-1} + M_{\hat{g},b}^{begin} - M_{\hat{g},b}^{end} \\ with \quad & M_{\hat{g},b}, M_{\hat{g},b}^{begin}, M_{\hat{g},b}^{end} \in \{0, 1, \cdots, n_{\hat{g}}\} \end{aligned} \quad (8)$$

$$M_{\hat{g},b} \geq \sum_{b - a_g^{maint} \leq \beta \leq b} M_{\hat{g},\beta}^{begin} \quad (9)$$

As with commitment states, integer variables are used for the maintenance state variables to improve performance.

3) Crew limits : allow only a fraction, $w_{\hat{g}}^{maintfract}$, of each facility type to undergo maintenance at a time:

$$M_{\hat{g},b} < w_{\hat{g}}^{maintfract} n_{\hat{g}} \quad (10)$$

E. Planning Constraints

1) Retirement & existing generation : are captured by:

$$N_{\hat{g}} = \left\lfloor (1 - a_{\hat{g}}^{retire}) N_{\hat{g}}^{exist} \right\rfloor + N_{\hat{g}}^{new} \quad (11)$$

2) Renewable Portfolio Standards (RPS): require a minimum amount of energy, a^{RPS}, from renewable sources:

$$\sum_{g \in \mathbf{G}^{renew}} \sum_{t \in \mathbf{T}} 1 \cdot P_{g,t} \geq a^{RPS} \sum_{g \in \mathbf{G}} \sum_{t \in \mathbf{T}} 1 \cdot P_{g,t} \quad (12)$$

The set, $\mathbf{G}^{renew}$, only includes renewable sources. The factor 1 recognizes the need for unit conversion from power (e.g. GW) to energy (e.g. GWh).

III. Experimental Setup

We focus on a single future year, 2035, to represent a far enough future for significant retirements and that a broad range of RPS and emission policies are plausible.

A. Example Test System

Our test system is loosely based on ERCOT, which covers the majority of Texas and has negligible power exchange with other systems. ERCOT had a 2007 peak load of 62GW [38] supplied by 92.5GW of generation capacity from 672 units [39]. We use a simplified baseline of ERCOT generators from 2007 by removing the following unit types: 1) Non-dispatchable combined heat and power facilities (15GW, 204 units); 2) Hydro (0.5GW, 41 units); 3) Uncommon fuel types (0.1GW, 72 units); and 4) Units smaller than 50MW (1GW, 56 units). Note that these simplification apply only to the existing units that are not retired, and not to the new units which are described below. In addition, combined cycle facilities were modeled as 36 groups instead of 115 separate combustion and steam turbines. This results in a total of 205 units (204 thermal plus a single wind unit). For our future planning year, we assume half of these existing units have retired. Generators are clustered by fuel and prime mover. Existing generators and candidate new generators are assumed to have different technical characteristics and clustered separately.

We use 2007 hourly demand and wind generation data [38] assuming aggressive energy efficiency has kept load growth to 0% with no load shape changes. To introduce maintenance, the 8760 hour demand time series is broken into 52 week-long blocks of 168 hours. This still simulates the full year at an hourly resolution; however, since $52wks \times 7days = 364days$, We remove December 31st and scale the operations costs up by a factor of $365/364 \approx 1.00275$.

For wind, we start with the 2010 installed capacity of 9.4GW, and assume 50% retirement by 2035 leaving 4.7GW of existing wind capacity. Since wind shedding is allowed, wind dispatch is treated as a decision variable.

For new generation investments, we consider wind and six types of new thermal units:

- *Wind:* Assumed to to follow the 2007 production profile with investments in 200 MW increments;
- *Coal-fired Steam:* Supercritical pulverized sub-bituminous units. These high capital cost, low variable cost plants have moderate efficiency and operational flexibility. High carbon intensity greatly increases the effective variable costs under carbon policies;
- *Coal with CCS:* Coal-fired steam with 90% post combustion Carbon Capture and Sequestration (CCS)CCS increases capital costs and decreases efficiency. Flexibility constraints are assumed to remain the same;
- *NGCC:* Natural gas-fired combined cycle units provide moderate to high operational flexibility. Their combination of high efficiency and lower carbon fuel (compared to coal) provide a moderate carbon intensity;
- *NGCC with CCS:* with a 90% post combustion CCS. CCS increases capital costs and reduces thermal efficiency. Flexibility is assumed to remain the same.
- *NGCT:* Natural gas-fired aero-derivative simple cycle combustion turbines have the lowest capital cost and the highest non-carbon operating costs. Their jet engine heritage also enables very high operational flexibility.
- *Nuclear:* Assumed to be generation III+ (Advanced) pressurized light water reactors. As built in the US, nuclear power plants have strict technical operating constraints making them the least flexible of all generation types[1].

We use new generator capital costs, O&M costs, and efficiencies (heatrates) from [40]; and generator unit commitment and other technical data from [41]. Existing plant-level heat rate and unit size data are taken from eGrid 2010 v1.1 [39]. Complete generator and clustering information can be found in [34]. Since only a single year of operations is considered, the capital investment costs are annualized using the capital recovery factor (3) assuming a 9% WACC [42].

Fuel costs are based on the Annual Energy Outlook 2013 [43] reference scenario projections for 2035. We also present results based on the "Low Coal Cost" scenario.

B. Summary of Reserve Assumptions

Although the test system is loosely based on ERCOT, for simplicity and data availability, we adopt reserve assumptions from CAISO, PJM, and WECC as detailed in [34]. Our assumptions are summarized in Table I.

TABLE I
ASSUMED RESERVE REQUIREMENTS

TYPE	REQUIREMENT	SOURCE
PRIMARY UP	$1\% \cdot L_t + 0.385\% \cdot I_{wind}$	PJM [44] + ERCOT wind [45]
PRIMARY DOWN	$1\% \cdot L_t + 0.321\% \cdot I_{wind}$	
SECONDARY UP†	$max(2.3GW, 3.3\% \cdot L_t + 7.95\% \cdot I_{wind} + 13.9\% \cdot P_{wind,t})$	2 largest gens. [45] or CAISO data+wind regressions [34]
SECONDARY DOWN	3.3% of load + 2% of wind capacity	CAISO data + wind regressions [34]
TERTIARY	1.28 GW	largest generator

†50% of Secondary allowed from off-line, quick start units (WECC [44])

Where L_t is the load at time t, and I_{wind} is the installed wind capacity. The reserve capabilities of generators are based on the 5 min and 10 min ramp rates for primary and secondary respectively. Only NGCT provides quick start reserves.

C. Implementation notes

The MEPO model is implemented in GAMS [46] and solved by CPLEX 12.3 [47]. All runs were conducted with a target MILP tolerance or "MIP gap" of 0.1%; however some model runs timed out after 60 hours for planning or 24 hours for operations-only. In such cases, MIP gaps $\leq$1.5% were considered solved. Larger MIP gaps were re-run using longer timeouts and/or the CPLEX parallel facilities. For units with minimum outputs <60MW—only NGCT—we use relaxed (non-integer) unit commitment variables to speed computation.

[1]Nuclear power is not inherently inflexible, as evidenced by the high-ramp rate designs of some nuclear power facilities in France. However, the re-engineering required further increases the already high capital costs, and has not yet been licensed in the US. Exploring the impacts of flexible nuclear is left as an area of future research, but the methods presented here are uniquely suited to assessing the trade-offs between cost and flexibility.

For these units, UC constraints–including startup and reserves–are still captured, but the corresponding commitment state can take a fractional value. Maintenance is included in all operations simulations and in MEPO-UC (see below) planning.

IV. Numeric Example

A. Example setup

We explore the capacity, energy, and carbon impacts of including operational flexibility in generation expansion planning for future RPS and carbon policies[2].

In our examples, we compare the expansion plans from two alternative versions of the MEPO model:

- *MEPO-MO:* Uses simple merit-order economic dispatch for operations and does not capture operational flexibility. Ignores inter-hour, reserve, and integer constraints; and
- *MEPO-UC:* Uses clustering to include UC operations and maintenance, including the full set of generator constraints described above, and thereby captures operational flexibility during planning.

Future year "actual" power system operations are then simulated for each generation plan including full clustered unit commitment as estimated using the operations-only mode of the MEPO-UC model (MEPO-UC-Ops). The "actual" operations for the MEPO-UC capacity mix are captured during the planning phase and not rerun. Therefore, only a single MEPO-UC model result is reported in the results[3]. In contrast, we report two alternative operations assumptions for the MEPO-MO capacity mix: The first is the "predicted" generation and emissions from the MEPO-MO planning model. The second assumes the capacity mix from the MEPO-MO plan is built, but the "actual" generation and emissions predictions are determined by the MEPO-UC-Ops simulation. The former assumption is consistent with long-term projections from simple policy models, while the latter assumption allows us to investigate the potential impacts of an inflexible capacity mix.

B. Capacity and Energy Mix

We first compare the results of the two planning models for a single policy scenario: a \$90/ton CO_2 tax and 20% RPS. Table II compares the resulting capacity and energy mixes from MEPO-MO to those from the flexibility-aware MEPO-UC model. The main differences between the capacity decisions are that the flexibility requirements lead MEPO-UC to invest in less nuclear generation and instead add significant NGCT. In addition, the MEPO-UC model recognizes the need to invest in additional wind capacity, since wind generation occasionally must be curtailed as a flexibility resource.

There are also widespread differences between the energy mix from MEPO-UC and that predicted by MEPO-MO,

[2]This section updates and expands earlier analysis in Palmintier & Webster (2011) [32]. Important changes include allowing non-served energy, revised operating reserves, an expanded generator set, and updated costs. The MEPO model now includes maintenance, minimum up and down time constraints, and many other enhancements.

[3]Further testing to compare the results to an independent commercial production cost tool represents an important area of future work. Such a tool was not available for this research.

TABLE II
Results Comparison for \$90/ton-20%RPS

	New Capacity (GW)		*Energy (TWh)*		
	MEPO-UC	MEPO-MO	MEPO-UC	MEPO-MO Predict	MEPO-MO Actual
Wind	26	22.3	67.5	61.9	46.3
Old NG-Steam			0.8	0.1	28
Old NG-CT			2.4	0	1.8
New NG-CT	8.4	0	5.7	0	0
Old NG-CCGT			28.3	11.3	28.3
New NG-CCGT	18	20.4	105	90.9	90.4
NG-CCGT w/ CCS	0	0	0	0	0
Old Coal SubBit.			2.2	0.2	12
Old Coal Lignite			3.9	1	13
New Coal	0	0	0	0	0
New Coal w/ CCS	0	0	0	0	0
New Nuclear	8.9	15.7	70.6	120.9	8.8
Old Nuclear			20.3	20.4	2.7
			Other Metrics		
Wind Shedding (TWh)			2.9	0	15.6
Non-Served Energy (GWh)			0.6	0	75399.8
Carbon Emissions (Mt CO2e)			58.9	36.9	89

largely driven by operational flexibility. As described below and hinted at in the "actual" MEPO-MO energy production, the additional NGCTs are critical to providing required operational flexibility. The MEPO-UC energy results also include more power generation by old coal facilities. This increase is necessary to comply with minimum uptime constraints on these coal units between daily peaks.

Furthermore, the MEPO-MO mix is so short on flexibility, that if its proposed mix were built and the 20% RPS and \$90/ton CO_2 policies were enforced, unacceptable quantities of non-served energy demand and of wind shedding would be required. Furthermore, the inflexible nuclear units are unable to cope with the high variability in net demand, instead remaining largely idle and forcing the old NG-Steam units to run regularly in an attempt to cover the lost generation.

To better illustrate the differences between the two models, Fig. 2 compares the *predicted* hourly operations for one week.

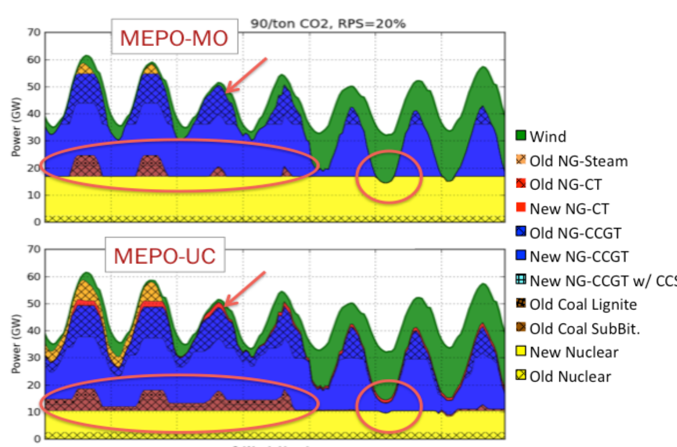

Fig. 2. Operations comparison for the week beginning August 14 as *predicted* using merit-order-based operations during planning (MEPO-MO, top) versus unit-commitment-based operations (MEPO-UC, bottom)

In this example, demand peaks in the late afternoon before falling to a daily minimum in the early morning hours. In both models, most of this change is handled by ramping or cycling NGCC facilities, but there are important differences between the models' predicted dispatch patterns. In the MEPO-MO model, the older, less efficient NGCC facilities, shown with cross-hatching on a blue background, only run when the net load is greater than 33 GW. However, the MEPO-UC model accounts for the cost of each startup and instead keeps some of these older facilities running at/near their minimum output levels through the overnight low demand periods during the first four days. This increases carbon emissions (see below) because the older facilities are less efficient and hence burn more fuel than newer facilities. The need to keep coal plants running overnight is also clearly visible in the MEPO-UC results. Furthermore, during the last two demand troughs, very high wind output reduces the net load sufficiently that MEPO-MO model cycles all of the NGCC, while MEPO-UC keeps some of the new NGCC operating at all times. MEPO-UC also operates the highly flexible NGCT units to provide reserves during peak demand and high wind periods.

In general, our results are roughly consistent to some of the other studies that focused on flexibility in capacity expansion. In particular, [29], [30] also showed that in the presence of renewable generation, that unit commitment would shift the mix to include more flexible units. However because of the methods employed in those studies, the resolution was very limited in terms of the number of units, the number of technology types, and the number of potential capacity mixes considered. Furthermore those studies considered only flexibility when wind generation was included, but not the impact of a carbon emissions constraint. As shown in our results here, the combination of more renewables and tighter carbon caps increases the importance of considering flexibility.

In short, using a capacity expansion model such as MEPO-MO that neglects operational constraints on the unit level and hourly resolution can result in both investment and operations simulations that are unrealistic.

C. Carbon Emissions

The differences between predicted and actual energy mixes described above also result in large carbon emissions errors (Table II). In particular MEPO-MO underestimates CO_2 emissions by 35% compared to the more realistic MEPO-MO model mix, and by nearly 60% for its own generation mix. These large MEPO-MO carbon emission prediction errors highlight an important concern for long-term policy models that typically also use simplified operations: Ignoring operational flexibility (e.g. MEPO-MO) during planning for policy analysis can drastically underestimate the emissions that result from a given carbon tax. The reverse is also true: such models may drastically underestimate the carbon cost necessary to meet a given emissions target. In contrast, incorporating flexibility during planning (e.g. MEPO-UC) provides more accurate emissions (or carbon price) estimates.

D. RPS, Wind Shedding, and Reliability

With the MEPO-MO generation capacity mix, it is not possible to simultaneously meet demand and the RPS. In practice, the utility would keep the lights on and miss the RPS requirement, but for the sake of illustration, consider what would happen if the RPS were truly binding: To ensure a minimum fraction of renewable energy with the MEPO-MO mix, the total energy output would have to be reduced. This loss of load results from a causal chain that begins with insufficient operational flexibility (Fig. 3).

With insufficient highly flexible NGCTs to provide upward reserves for wind, the MEPO-MO capacity mix must provide reserves using NGCCs by reducing their output. The legacy NG-Steam and coal units are also brought on-line to help. However, these steam units have high minimum output levels and long minimum up/down times forcing them to run with significant power production during overnight low demand hours. This in turn, means that when high wind production coincides with these low demand periods, the significant minimum thermal output plus available wind power would be greater than demand. As a result, some of the available wind would be shed. This balances energy supply, but because MEPO-MO's wind capacity was built assuming all of the wind could be used, the wind shedding causes problems with the RPS. Since the RPS requires 20% of the annual energy to come from renewables (i.e., wind in this example) shedding some of the available wind means that the only ways to meet the RPS would to also reduce the total energy or build more capacity. Moreover, the lower total energy would cause a feedback loop that further squeezes the system's ability to simultaneously provide reserves, meet minimum output and up/down time constraints, and utilize available wind. This would result in further wind shedding and loss of load. While this downward spiral of loss-of-load ensued, MEPO-MO's nuclear generation capacity would go underutilized due to its low operational flexibility. Nuclear would no longer operate during many low demand hours because the minimum thermal outputs from the NGCC and steam units are already causing wind shedding. With its very long minimum cycle times nuclear would only provide output power during the few long-lasting periods of high demand and low wind.

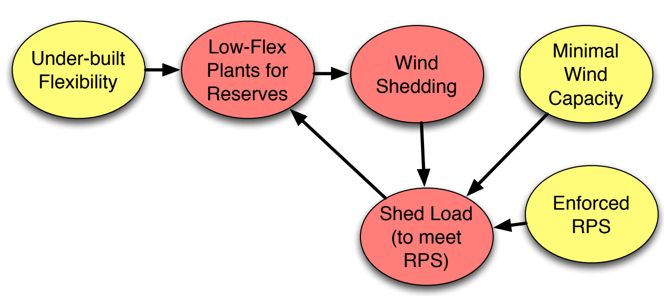

Fig. 3. Schematic description of the feedback loop that would lead to wind-shedding and load-shedding if an RPS was strictly enforced when flexibility is inadequate.

E. Sensitivity to Wind and Load Patterns

Wind patterns can vary significantly from year to year, making it important to examine multiple wind years in planning. Moreover, increasing wind capacity typically corresponds to reduced variability due to geographic diversity, resulting in higher capacity factors [48]. In this section, we consider the sensitivity to alternative wind patterns. Specifically we run the same \$90/ton 20% RPS scenario using historic ERCOT wind power time series from each year 2007-2010, and for the period of July 2011-June2012. During this time installed wind capacity grew steadily, more than doubling from 4.5GW in 2007 to 9.8GW in mid 2012, as seen in Table III.

The table also shows wind capacity factors ranged (non-monotonically) from 0.244 to 0.329 during the same periods. In all scenarios, we considered the same existing wind capacity of 4.7GW (after 50% retirement) used above and apply the normalized wind pattern from the corresponding year. In order to properly capture the weather dependent correlations between wind and demand, the corresponding historic demand data for each period was used, with its peak load scaled to match the baseline 2007 peak demand. As seen in Fig. 4, the alternative wind and load patterns resulted in differences in total new capacity, dominated by capacity factor driven differences in new wind capacity. However, the new thermal generation investment differences between MEPO-UC and MEPO-MO show strong, consistent patterns with those observed in the 2007 basecase and described in detail above. Specifically, all data years of the MEPO-UC build more flexible thermal generation mixes than the corresponding MEPO-MO mixes. All MEPO-UC new capacity investments shows very similar thermal mixes with reduced reliance on nuclear and increased investment in highly flexible NGCT.

TABLE III
ERCOT INSTALLED WIND AND CAPACITY FACTORS

Year	Installed MW	Capacity Factor
2007	4541	0.263
2008	8111	0.296
2009	8962	0.244
2010	9430	0.303
Jul2011-Jun2012	9838	0.329

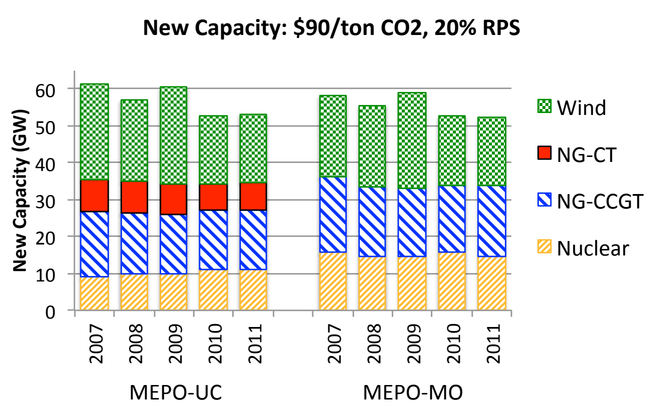

Fig. 4. Variation in optimal new capacity between 2007 baseline and alternate wind and load data years. Changing capacity wind capacity factors drives variations in total wind investment; however, the underlying flexibility differences between the MEPO-UC and MEPO-MO models remain unchanged. No new capacity was built for Coal, Coal with CCS, or NG-CCGT with CCS.

V. When Can Operational Flexibility Impact Planning?

This section explores a wide range of RPS and carbon targets to map out under what policy scenarios operational flexibility plays a critical role in system planning and emission estimates. We compare MEPO-MO and MEPO-UC results for these combinations of RPS and carbon limits under two fuel price scenarios.

Our policy dimensions serve as a proxy for the two sides of the operationally flexibility balance: carbon policy can restrict available flexibility by encouraging low carbon, but inflexible, generation; and renewables can require increased flexibility. Specifically we compare all combinations of four RPS levels–0%, 20%, 40%, and 60%–with four carbon emission limits–No limit, 141 Mt, 94 Mt, 47 Mt. These emissions limits were chosen to approximate 100%, 75%, 50%, and 25% of baseline (no carbon policy, no RPS) emissions. Note that for the 0% RPS case, we explicitly removed all of the wind, including 4.72GW of wind (50% non-retired of 2010 capacity of 9.4GW) included as existing in all other scenarios. In addition to providing more even steps for the renewable targets, these cases also show the impacts of capturing operational flexibility for flexibility limited systems–such as those encouraged by strict carbon limits–even without the increased variability of renewable generation.

To demonstrate the impacts of including hourly operational constraints, we compare the capacity investment decisions from the two models in Table IV. The color shading highlights increasing (none<yellow<red) absolute difference between the MEPO-MO and the MEPO-UC models. The errors from omitting operational constraints are smallest for weak carbon emission limits (bottom two rows) and low penetration of wind (two left columns). This is perhaps not surprising because the merit order approach to capacity expansion has long been used successfully in the absence of CO_2 limits and RPSs. However, as we plan for future conditions that could include more stringent limits on CO_2 and larger penetrations of renewables, the errors from the traditional approach become quite large.

As described above, the MEPO-UC results also recognize the need to overbuild wind capacity to allow for wind shedding as a source of flexibility. As seen in Table V the required amount of shedding is a strong function of the wind penetration. At 40% and 60% wind, considerable quantities of wind are shed with the flexibility assumptions used in this analysis. In practice this shedding could be considerably reduced with additional flexible units, by revisiting the reserve requirements, and/or through the use of storage. In the 20% wind cases, all but the most stringent carbon limit had modest wind curtailment $< 0.5\%$. The higher curtailment for the 47Mt, 20% case partially results from a further increase in wind capacity above that required by the RPS to supply 22% (after curtailment) as a way to reduce CO2 emissions.

TABLE IV
NEW CAPACITY BUILT FOR A RANGE OF RPS AND CARBON POLICIES (2035 REFERENCE CASE)

New Capacity (GW) for AEO 2035 Reference Fuel Prices

		No Wind		20% Wind		40% Wind		60% Wind	
		MO	UC	MO	UC	MO	UC	MO	UC
47Mt CO2 limit	Wind	0*	0*	17.5	21.3	47.2	50.9	110	159
	Coal	-	-	-	-	-	-	-	-
	NG-CC	17.6	10.4	24.0	12.4	27.6	14.4	22.0	18.8
	NG-GT	-	5.7	-	8.6	7.8	17.0	34.9	30.5
	Nuke	19.0	21.2	11.2	8.9	-	-	-	-
	NG-CC+CCS	0.4	-	0.4	5.4	5.4	9.2	-	2.3
94 Mt CO2 limit	Wind	0*	0*	17.5	17.5	47.2	50.9	110	159
	Coal	-	-	-	-	-	-	-	-
	NG-CC	31.6	27.2	27.2	27.2	21.6	18.0	16.4	11.2
	NG-GT	-	3.4	6.5	6.5	14.1	17.4	35.1	35.1
	Nuke	3.4	4.5	-	-	-	-	-	-
	NG-CC+CCS	-	-	-	-	-	-	-	-
141 Mt CO2 limit	Wind	0*	0*	17.5	17.5	47.2	50.9	110	159
	Coal	-	-	-	-	-	-	-	-
	NG-CC	29.2	27.6	24.0	22.0	20.8	17.6	16.4	10.8
	NG-GT	2.9	4.4	9.7	11.6	14.7	17.4	34.2	34.7
	Nuke	-	-	-	-	-	-	-	-
	NG-CC+CCS	-	-	-	-	-	-	-	-
No CO2 limit	Wind	0*	0*	17.5	17.5	47.2	50.9	110	159
	Coal	-	-	-	-	-	-	-	-
	NG-CC	28.4	27.2	24.0	22.8	20.8	17.6	16.4	13.6
	NG-GT	3.8	4.8	9.7	10.7	15.1	17.9	36.8	34.2
	Nuke	-	-	-	-	-	-	-	-
	NG-CC+CCS	-	-	-	-	-	-	-	-

*No Wind: Removed 4.72GW of existing, non-retired wind capacity

TABLE VI
NEW CAPACITY BUILT FOR A RANGE OF RPS AND CARBON POLICIES (2035 LOW COAL PRICE)

New Capacity (GW) for AEO 2035 Low Coal Price Fuel Scenario

		No Wind		20% Wind		40% Wind		60% Wind	
		MO	UC	MO	UC	MO	UC	MO	UC
47Mt CO2 limit	Wind	0*	0*	17.5	21.3	47.2	50.9	110	159
	Coal	-	-	-	-	-	-	-	-
	NG-CC	16.0	8.0	19.6	12.0	26.8	13.6	22.4	17.2
	NG-GT	0.4	6.3	3.8	8.4	7.1	14.9	33.4	30.7
	Nuke	20.1	22.4	12.3	11.2	4.5	-	-	-
	NG-CC+CCS	-	-	-	3.9	0.8	10.4	-	2.7
94 Mt CO2 limit	Wind	0*	0*	17.5	17.5	47.2	50.9	110	159
	Coal	-	-	-	-	-	-	-	-
	NG-CC	29.6	24.0	27.6	26.8	22.0	18.0	15.6	10.8
	NG-GT	-	3.6	6.3	7.1	13.9	17.4	35.9	35.5
	Nuke	3.4	5.6	-	-	-	-	-	-
	NG-CC+CCS	-	-	-	-	-	-	-	-
141 Mt CO2 limit	Wind	0*	0*	17.5	17.5	47.2	50.9	110	159
	Coal	-	-	2.6	0.7	-	-	-	-
	NG-CC	29.6	26.8	20.8	20.4	20.0	17.2	15.6	11.2
	NG-GT	2.9	4.4	10.1	12.4	15.1	17.6	35.7	34.9
	Nuke	-	1.1	-	-	-	-	-	-
	NG-CC+CCS	-	-	-	-	-	-	-	-
No CO2 limit	Wind	0*	0*	17.5	17.5	47.2	50.9	110	159
	Coal	16.3	14.3	2.6	-	-	-	-	-
	NG-CC	12.4	12.0	20.8	21.6	20.0	18.8	15.6	10.8
	NG-GT	3.4	5.7	10.3	12.0	17.4	18.3	35.7	35.3
	Nuke	-	-	-	-	-	-	-	-
	NG-CC+CCS	-	-	-	-	-	-	-	-

*No Wind: Removed 4.72GW of existing, non-retired wind capacity

TABLE V
WIND SHEDDING FOR THE 2035 REFERENCE CASE

	20% Wind	40% Wind	60% Wind
47Mt	4.0%	11%	52%
94 Mt	0.3%	11%	52%
141 Mt	0.5%	11%	52%
None	0.5%	11%	52%

Table VI shows that the capacity trends remain similar when using fuel prices from the the EIA low coal cost scenario. However, with reduced coal prices, the errors from ignoring flexibility are generally larger. Since coal and gas are the only fossil fuels used in this analysis, the low coal cost scenario is comparable to a high gas cost scenario.

VI. CONCLUSIONS

We have presented a new efficient method for performing capacity expansion with embedded unit commitment and maintenance constraints, using an integer-based clustering method. We have applied this model to an illustrative example of planning for ERCOT in 2035 under a carbon price and RPS. Comparing this model with hourly constraints to one without demonstrates the importance of capturing operational flexibility when assessing policy impacts for moderately strict carbon and renewable policies. In these examples using a capacity expansion model that ignores operational flexibility created large (35-60%) errors in the estimated carbon emissions for a $90/ton carbon tax with 20% renewables. In contrast, the planning model with UC is able to directly include the complex operating constraints important for flexibility constrained operations and produce realistic estimates for the emissions. A systematic sensitivity analysis over a range of carbon limits and RPS levels shows that the errors from ignoring flexibility will increase with tighter regulations. Further sensitivity analysis on wind patterns and fuel prices show these results are robust across a range of these parameters. Future work in explicitly considering these uncertainties within a stochastic optimization framework is encouraged. The integer clustering method described here could also be used for making such analysis tractable.

The precise scenarios for which operational flexibility impacts planning is highly system specific. A system with more flexible existing generation, such as extensive hydro, might be able to use standard merit order operations for a larger subset of cases. In contrast, systems with more inflexible legacy generators, including retirement rates lower than the 50% considered here, could require capturing operational flexibility for more, if not all scenarios. Moreover, when including candidate technologies that derive significant value from providing operational flexibility (e.g., storage, demand response, or flexibility-augmented thermal generation), operational flexibility must be considered in order to properly evaluate the benefits of the technologies. The techniques presented here could also be used in future research to value the option of paying additional capital cost to enable more operationally flexible nuclear and other thermal generation.

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References

[1] P. Massè and R. Gibrat, "Application of linear programming to investments in the electric power industry," *Management Science*, vol. 3, no. 2, pp. 149–166, Jan. 1957.

[2] C. D. Galloway and L. L. Garver, "Computer design of single area generation expansions," *IEEE Transactions on Power Apparatus and Systems*, vol. 83, no. 4, pp. 305 –311, Apr. 1964.

[3] B. F. Hobbs, "Optimization methods for electric utility resource planning," *European Journal of Operational Research*, vol. 83, no. 1, pp. 1–20, May 1995.

[4] I. Pérez-Arriaga and P. Linares, "Markets vs. regulation: A role for indicative energy planning," *The Energy Journal*, vol. 29, no. Special Issue# 2, p. 149–164, 2008.

[5] J. Sirikum, A. Techanitisawad, and V. Kachitvichyanukul, "A new efficient ga-benders' decomposition method: For power generation expansion planning with emission controls," *IEEE Transactions on Power Systems*, vol. 22, no. 3, pp. 1092–1100, Aug. 2007.

[6] F. Careri, C. Genesi, P. Marannino, M. Montagna, S. Rossi, and I. Siviero, "Generation expansion planning in the age of green economy," *IEEE Transactions on Power Systems*, vol. 26, no. 4, pp. 2214–2223, Nov. 2011.

[7] S. Wogrin, J. Barquin, and E. Centeno, "Capacity expansion equilibria in liberalized electricity markets: An epec approach," *IEEE Transactions on Power Systems*, vol. In Press, 2013.

[8] A. Ehrenmann and Y. Smeers, "Generation capacity expansion in a risky environment: A stochastic equilibrium analysis," *Operations Research*, vol. 59, no. 6, pp. 1332–1346, 2011.

[9] J. Roh, M. Shahidehpour, and L. Wu, "Market-based generation and transmission planning with uncertainties," *IEEE Transactions on Power Systems*, vol. 24, no. 3, pp. 1587–1598, Aug. 2009.

[10] D. Pozo, E. Sauma, and J. Contreras, "A three-level static milp model for generation and transmission expansion planning," *IEEE Transactions on Power Systems*, vol. 28, no. 1, pp. 202–210, Feb. 2013.

[11] P. Kaymaz, J. Valenzuela, and C. Park, "Transmission congestion and competition on power generation expansion," *IEEE Transactions on Power Systems*, vol. 22, no. 1, pp. 156–163, Feb. 2007.

[12] S. Paltsev, J. M. Reilly, H. D. Jacoby, and J. F. Morris, "The cost of climate policy in the united states," *Energy Economics*, vol. 31, p. S235–S243, 2009.

[13] IPCC, *Climate Change 2007: Synthesis Report.*, Core Writting Team, R. K. Pachauri, and A. Reisinger, Eds. Geneva, Switzerland: Intergovernmental Panel on Climate Change [IPCC], 2007.

[14] North American Electric Reliability Corporation [NERC], "Accommodating high levels of variable generation," Princeton, NJ, Apr. 2009.

[15] IEA, "Empowering variable renewables: Options for flexible electricity systems," International Energy Agency, Paris, Tech. Rep., 2008.

[16] E. Lannoye, D. Flynn, and M. O'Malley, "The role of power system flexibility in generation planning," in *Proceedings of 2011 IEEE Power and Energy Society General Meeting*, Detroit, MI, Jul. 2011.

[17] J. Morales, A. Conejo, and J. Perez-Ruiz, "Economic valuation of reserves in power systems with high penetration of wind power," *IEEE Transactions on Power Systems*, vol. 24, no. 2, pp. 900–910, May 2009.

[18] P. Meibom, R. Barth, B. Hasche, H. Brand, C. Weber, and M. O'Malley, "Stochastic optimization model to study the operational impacts of high wind penetrations in ireland," *IEEE Transactions on Power Systems*, vol. 26, no. 3, pp. 1367–1379, Aug. 2011.

[19] J. Hargreaves and B. Hobbs, "Commitment and dispatch with uncertain wind generation by dynamic programming," *IEEE Transactions on Sustainable Energy*, vol. 3, no. 4, pp. 724–734, Oct. 2012.

[20] M. C. Caramanis, "Analysis of non-dispatchable options in the generation expansion plan," *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-102, no. 7, pp. 2098–2103, 1983.

[21] Enernex, "Eastern wind integration and transmission study," National Renewable Energy Laboratory (NREL), Tech. Rep. NREL/SR-550-47078, Jan. 2010.

[22] B. Kirby and M. Milligan, "Method and case study for estimating the ramping capability of a control area or balancing authority and implications for moderate or high wind penetration," National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/CP-500-38153, 2005.

[23] E. Ela and J. Kemper, "Wind plant ramping behavior," National Renewable Energy Laboratory (NREL), Golden, CO, Technical Report NREL/TP-550-46938, 2009.

[24] H. Chao, "NYISO reliability & economic planning process," Presented at FERC Technical Conference on Planning Models and Software, Washington, D.C., Jun. 2010.

[25] S. Rosekrans, D. Kirshner, and C. Marnay, "Issues in electricity planning with computer models: illustrations with elfin and WASP," *Utilities Policy*, vol. 7, no. 4, pp. 201–219, Feb. 1999.

[26] A. Shortt and M. O'Malley, "Impact of variable generation in generation resource planning models," in *Power and Energy Society General Meeting, 2010 IEEE*, 2010, pp. 1–6.

[27] C. De Jonghe, E. Delarue, R. Belmans, and W. D'haeseleer, "Determining optimal electricity technology mix with high level of wind power penetration," *Applied Energy*, vol. 88, no. 6, pp. 2231–2238, Jun. 2011.

[28] C. De Jonghe, B. Hobbs, and R. Belmans, "Optimal generation mix with short-term demand response and wind penetration," *IEEE Transactions on Power Systems*, vol. 27, no. 2, pp. 830 –839, May 2012.

[29] A. Shortt, J. Kiviluoma, and M. O'Malley, "Accommodating variability in generation planning," *IEEE Transactions on Power Systems*, vol. 28, no. 1, pp. 158–169, 2013.

[30] J. Ma, V. Silva, R. Belhomme, D. S. Kirschen, and L. Ochoa, "Evaluating and planning flexibility in sustainable power systems," *IEEE Transactions on Sustainable Energy*, vol. 4, no. 1, pp. 200–209, Jan. 2013.

[31] D. Pudjianto, M. Aunedi, P. Djapic, and G. Strbac, "Whole-systems assessment of the value of energy storage in low carbon electricity systems," *IEEE Transactions on Smart Grid*, pp. 1–12, 2013.

[32] B. Palmintier and M. Webster, "Impact of unit commitment constraints on generation expansion planning with renewables," in *Proceedings of 2011 IEEE Power and Energy Society General Meeting*. Detroit, MI: IEEE, July 2011.

[33] ——, "Heterogeneous unit clustering for efficient operational flexibility modeling," *IEEE Transactions on Power Systems*, In Press.

[34] B. Palmintier, "Incorporating operational flexibility into electric generation planning: Impacts and methods for system design and policy analysis," PhD Dissertation, Massachusetts Institute of Technology, Cambridge, MA, Feb. 2013.

[35] B. Palmintier and M. Webster, "Heterogeneous unit clustering for efficient operational flexibility modeling," MIT Engineering Systems Division, Cambridge, MA, ESD Working Paper ESD-WP-2013-04, 2013.

[36] G. M. Masters, *Renewable and Efficient Electric Power Systems*. Wiley-IEEE Press, 2004.

[37] J. Ostrowski, M. Anjos, and A. Vannelli, "Tight mixed integer linear programming formulations for the unit commitment problem," *IEEE Transactions on Power Systems*, vol. 27, no. 1, pp. 39–46, Feb. 2012.

[38] ERCOT, "2007 wind output," 2010. [Online]. Available: http://planning.ercot.com/data/hourly-windoutput/2007/

[39] US Environmental Protection Agency (EPA), "Emissions & generation resource integrated database (eGrid)," Dec. 2010.

[40] US Energy Information Administration [EIA], "Updated capital cost estimates for electricity generation plants (AEO 2011)," US Department of Energy, Washington, DC, Tech. Rep., Nov. 2010.

[41] Northwest Power and Conservation Council, "Appendix i: Generating resources - background information," in *Sixth Northwest Conservation and Electric Power Plan*, Feb. 2010.

[42] Electric Reliability Council of Texas [ERCOT], "Long-term system assessment for the ERCOT region," Tech. Rep., Dec. 2010.

[43] EIA, "Annual energy outlook 2013," *Report#: DOE/EIA-0383(2013)*.

[44] E. Ela, M. Milligan, and B. Kirby, "Operating reserves and variable generation," National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-5500-51978, Aug. 2011.

[45] GE Energy, "Analysis of wind generation impact on ERCOT ancillary services requirements," Tech. Rep., Mar. 2008.

[46] GAMS Development Corporation, "General algebraic modeling system (GAMS)," Computer Program, 2010.

[47] IBM ILOG, "CPLEX optimizer," Computer Program, 2010.

[48] M. Milligan, K. Porter, E. DeMeo, P. Denholm, H. Holttinen, B. Kirby, N. Miller, A. Mills, M. O'Malley, M. Schuerger, and L. Soder, "Wind power myths debunked," *IEEE Power and Energy Magazine*, vol. 7, no. 6, pp. 89 –99, Dec. 2009.