

Impact of Unit Commitment Constraints on Generation Expansion Planning with Renewables

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Abstract—Growing use of renewables pushes thermal generators against operating constraints – e.g. ramping, minimum output, and operating reserves – that are traditionally ignored in expansion planning models. We show how including such unit-commitment-derived details can significantly change energy production and optimal capacity mix. We introduce a method for efficiently combining unit commitment and generation expansion planning into a single mixed-integer optimization model. Our formulation groups generators into categories allowing integer commitment states from zero to the installed capacity. This formulation scales well, runs much faster (e.g. 5000x) than individual plant binary decisions, and makes the combined model computationally tractable for large systems (hundreds of generators) at hourly time resolutions (8760 hours) using modern solvers on a personal computer. We show that ignoring these constraints during planning can result in a sub-optimal capacity mix with significantly higher operating costs (17%) and carbon emissions (39%) and/or the inability to meet emissions targets.

Index Terms—Power generation planning, Wind energy, Integer linear programming, Power system analysis computing, Carbon tax, Power generation dispatch, Power system modeling, Unit commitment

I. INTRODUCTION

ENVIRONMENTAL, technical, economic, and political factors are driving a worldwide transition to advanced electric power systems, increasingly characterized by

- Intermittent renewable generation e.g. wind and solar photovoltaic [1],
- Distributed, demand-side resources e.g. high-performance buildings, distributed generation, and demand response [2], [3], and
- Novel storage technologies e.g. electric drive vehicles and thermal storage [4]–[6].

These technologies introduce new dynamics across multiple timescales, forcing power systems planners and policy makers to revisit the longstanding question of how much operational detail must be captured to adequately assess long-term planning options.

In this paper we focus on the dynamic impacts of wind when planning a traditional thermal power system. Such models are directly useful to utilities contemplating the best strategy to integrate renewables. Moreover, market-based system operators, utility regulators, and policy makers can also use the approach during indicative planning [7] to determine policies and incentives required to achieve regulatory goals such as carbon emission targets.

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As described in the next section, the models historically used for such analysis rely on highly simplified approximations for operations costs that ignore details such as plant startups, minimum loads, operating reserves, and ramping limits. Within the power systems modeling hierarchy, these details are typically reserved for unit commitment models that are run a few hours or days ahead of actual operation to determine which power plants to turn on and when. Historically in capacity planning these details have successfully been largely ignored because of highly predictable and fairly slow time dynamics of historic load patterns. However, with increased quantities of renewables, the net load required to be met by traditional power plants is less predictable with faster time dynamics potentially requiring considering these details within planning models.

In this paper, we first describe a modeling approach that makes capturing this level of detail tractable within capacity planning models and then explore its use for some example problems.

II. INTEGRATED UNIT COMMITMENT AND GENERATION EXPANSION PLANNING MODEL

This section describes the mathematical formulation of the integrated unit commitment (UC) and generation expansion planning (GEP) models. We begin with an introduction to these basic problems in isolation, introduce a key unifying framework, and then describe the combined model. Each of these models builds on the simple concept of economic dispatch and can be characterized as a mixed-integer optimization problem as described below. In this paper, we ignore transmission effects and treat all generation and demand as occurring at a single node.

A. Basic Economic Dispatch

In its simplest form, economic dispatch attempts to find the minimum cost instantaneous power output levels from a set of generators to meet demand. The dispatch problem can be formulated as a simple optimization problem:

$$\min \sum_{g \in G_{avail}} \sum_{t \in T} P_{g,t} c_g^{var} \quad (1)$$

where we minimize the total variable operations costs, computed as the sum of generation unit power output, $P_{g,t}$, times corresponding variable (marginal) cost per MWh, c_g^{var} for all available generators, g , over all time periods, t . This variable cost, c_g^{var} , includes fuel costs, carbon costs, and variable

operations and maintenance (O&M). The minimization is subject to:

$$\sum_{g \in G_{avail}} P_{g,t} = D_t \quad \forall t \in T \quad (2)$$

$$p_g^{min} \leq P_{g,t} \leq p_g^{max} \quad \forall t \in T, g \in G_{avail} \quad (3)$$

The sum of supply equaling demand, D_t , and power output falling between the generation minimum, p_g^{min} , and maximum, p_g^{max} , output levels.

It can be shown that, except when p_g^{min} is binding, the optimal solution is simply to dispatch generators in increasing order of c_g^{var} , known as ‘‘merit order’’ dispatch.

B. Basic Generation Expansion Planning

1) *Mathematical model*: At its most basic, generation expansion planning attempts to minimize the combination of total fixed costs (investment, financing, O&M, etc.) plus operations costs as computed by economic dispatch. The resulting objective then adds a fixed cost term to (1) that includes the installed capacity, I_g (non-negative), times fixed cost, c_g^{fix} . To avoid complications with when plants run or not (see Unit Commitment below) the minimum output power is typically taken as zero ($p_g^{min} = 0$)

$$\min \sum_{g \in G} \left(\sum_{t \in T} P_{g,t} c_g^{var} + I_g c_g^{fix} \right) \quad (4)$$

In this formulation the generator items, g , can correspond to either individual generators or a grouping of similar generators, such as by fuel type. The corresponding installed capacity, I_g , will then correspond to either plant size or existing plus new capacity. As such, installed capacity, I_g equals p_g^{max} in (3). A simple extension captures the idea that power plants are lumpy (investments) by replacing installed capacity, I_g , with an integer number of plants, n_g , multiplied by the (average) size per plant, $p_g^{plantsize}$.

2) *Screening Curves*: It can be shown that these equations can be solved graphically using ‘‘screening curves’’ where each generator’s costs are plotted as straight lines of cost versus operating time with slope c_g^{var} , and intercept c_g^{fix} . The intersection of these lines correspond to the transition points where it is more cost effective to use a higher fixed cost generator due to savings in operating costs. These intersections can then be projected onto a cumulative distribution function, or ‘‘load duration curve’’ to determine the optimal capacity investment.

3) *Renewables in Capacity Planning*: For capacity planning with variable renewables, such as wind, the renewable output is typically subtracted from demand to produce the ‘‘net load,’’ which can then be used to compute the thermal generator requirements either numerically or with a net load duration curve as described above.

4) *Extensions and Limitations*: Significantly more sophisticated formulations looking at reliability, multiple time-periods, multi-criteria objectives, etc. have been developed; yet, despite its simplicity, the humble load duration curve (or its numeric equivalent) remains at the heart of most large capacity planning models including [8], [9].

In all cases, the major simplifying assumption of using a non-sequential formulation is that the inter-period dynamics and constraints can be ignored. This assumption seems to hold for systems where the generation flexibility is well matched to the time dynamics of the (net) load. This has historically been the case for thermally-dominated power systems with low quantities of variable renewables, but the sequential, inter-hour dynamics become increasingly important as the quantity of renewable generation rises. The following section on unit commitment modeling describes some of these additional operating constraints.

C. Basic Unit Commitment

1) *Mathematical Formulation*: The unit commitment problem expands on economic dispatch to consider which generators are actually turned on or ‘‘committed’’ and thus members of G_{avail} , as a subset of all generators G . This is obviously important when $p_g^{min} \neq 0$, as otherwise, all generators are running at all times. Mathematically, we introduce the binary commitment variable, $u_{g,t} \in 0, 1$, replace G_{avail} with G and modify (3) to be:

$$u_{g,t} p_g^{min} \leq P_{g,t} \leq u_{g,t} p_g^{max} \quad \forall t \in T, g \in G \quad (5)$$

Which implies that each generator is either off and outputting zero power, $u_{g,t} = 0$, or on and running within its operating limits, $u_{g,t} = 1$.

2) *Additional Unit Commitment Details*: A number of other considerations are typically included in the unit commitment problem including limitations on how fast thermal units can adjust their output power, known as ‘‘ramp limits’’

$$\begin{aligned} P_{g,t+1} - P_{g,t} &\leq \Delta p_g^{upmax} \\ P_{g,t-1} - P_{g,t} &\leq \Delta p_g^{downmax} \end{aligned} \quad \forall t \in T, g \in G \quad (6)$$

where Δp is the ramp limit up or down. Startup costs can be included by adding a startup cost term to the objective (1):

$$\min \left(\sum_{g \in G_{avail}} \sum_{t \in T} P_{g,t} c_g^{var} + \sum_{t \in T} S_{g,t} c_g^{start} \right) \quad (7)$$

and computing the startup events using a unit commitment state equation:

$$u_{g,t} = u_{g,t-1} + S_{g,t} - D_{g,t} \quad \forall t \in T, g \in G \quad (8)$$

Where $S_{g,t}$ represents the startup of a unit and $D_{g,t}$ represents the shut down.

3) *Operating Reserves*: Since power generated on the grid must match demand instantaneously, a number of operating reserves are maintained by allowing room between generator output levels and corresponding limits to provide on-line capacity to quickly increase to make up for generation or transmission outages (spinning reserves), and to track quick changes in demand (regulating reserves up and down). In addition, some non-operating generation may be held in reserve to come on quickly following an outage for supplemental power

or to replace the spinning reserves. (quick start reserves). These may be introduced in the model using:

$$\sum_{g \in G} r_{g,t}^{type} = R_t^{type} \quad (9)$$

$$\forall t \in T, g \in G, type \in (spin, reg_{up}, reg_{down}, quick)$$

Where $r_{g,t}^{type}$ is the quantity (in capacity) of the corresponding *type* of reserve provided by generator g during time period t .

Each generator can provide different quantities (possibly zero) of each type of reserve. These constraints along with the need to adjust output levels to provide services can be captured by splitting the power limit constraint (5) to give:

$$\begin{aligned} u_{g,t} p_g^{min} &\leq P_{g,t} + r_{g,t}^{reg_{down}} \\ P_{g,t} + r_{g,t}^{reg_{up}} + r_{g,t}^{spin} &\leq u_{g,t} p_g^{max} \end{aligned} \quad (10)$$

$$\forall t \in T, g \in G$$

And adding an equation for quick start units from the pool of units which are currently not running and hence not committed:

$$r_{g,t}^{quick} \leq (\overline{u_{g,t}}) p_g^{plantsize} \quad \forall t \in T, g \in G \quad (11)$$

4) *Extensions and Limitations*: For large systems the combinatorial explosion of commitment states for each time period can quickly make the unit commitment problem difficult to solve, restricting most unit commitment implementations to a period of 24 to 176 hours (1-7 days). In some models, longer time periods are broken up into periods of this size and then iteratively simulated on a rolling horizon basis. [10], [11]

D. Combining Unit Commitment with Generation Expansion

Mathematically it is fairly straightforward to combine unit commitment and generation expansion models. To do so, we simply include all of the terms in the objectives from both models, (4) and (7) to create a combined objective:

$$\min \left(\sum_{g \in G} \left(\sum_{t \in T} P_{g,t} c_g^{var} + I_g c_g^{fix} \right) + \sum_{t \in T} S_{g,t} c_g^{start} \right) \quad (12)$$

and impose all of the constraints from the unit commitment problem: (6), (8), (9), (10), and (11).

In addition we can only turn on generators which have been built or invested in. Mathematically this adds the constraint:

$$u_{g,t} p_g^{plantsize} \leq I_g \quad \forall t \in T, g \in G \quad (13)$$

However, computationally, the problem quickly grows intractably large. The combinatorial explosion described above is compounded by a need to simultaneously capture long time horizons while also deciding among a space of investment options. For example, consider designing a power system from scratch with a maximum of 100 generators. There are $3^{100} = 5.1 \cdot 10^{47}$ possible configurations for each timestep – with 3 options: not-built, built and on, or built and off, for each generator. When used with full 8760 hourly operations the state space expands to $4.5 \cdot 10^{51}$ possible states, each with a linear programming (LP) subproblem. Below, we present an alternative formulation that reduces the dimensionality while solving the identical problem.

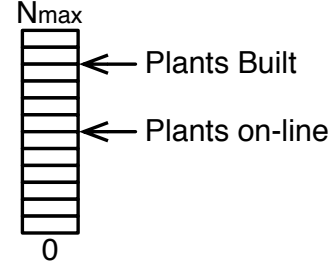


Fig. 1. Conceptual diagram of grouped integer unit Commitment for a single generator category. The number of plants on-line corresponds to the commitment state, $u_{g,t}$ which is \leq the number of plants built, N_g which is \leq to the maximum capacity for this category, N_g^{max} . This formulation results in a drastically smaller state space than considering build and commit decisions for each generator.

1) *Grouped Integer Unit Commitment*: The key idea to making the combined capacity planning with unit commitment model tractable is to recognize that many types of power plants can be grouped into categories by similar characteristics. For planning purposes, this could even be coarse groupings by technology and fuel combination resulting in dramatic state space reductions. In the example above consider three groups of generators with 10, 20, and 70 units each. The number of possible states per time period is then reduced by forty orders of magnitude to $\prod \binom{N_g+2}{2} = \binom{12}{2} \binom{22}{2} \binom{72}{2} = 3.9 \cdot 10^7$ or equivalently $3.4 \cdot 10^{11}$ for a full 8760 hours of operations. This concept is shown graphically in Fig. 1.

Mathematically, most of our model remains largely unchanged, except to treat g as a category of generators and expand the range for both the commitment variable, $u_{g,t}$, and the number of power plants built within a category, n_g (equal to $I_g/p_g^{plantsize}$) to the set of non-negative integers, N_0 , capped by a maximum number of plants under consideration, N_g^{max} . This results in a new combined unit-commitment/capacity-expansion constraint in place of (13):

$$u_{g,t} \leq n_g \leq N_g^{max} \quad u_{g,t}, n_g \in \{0, 1, \dots, N_g^{max}\} \quad (14)$$

$$\forall t \in T, g \in G$$

It is also necessary to adjust the ramping limits to account for the fact that a new unit within the category may have started up (S) or shut down (D), and to account for how many plants are actually on-line. This modifies (6) to:

$$\begin{aligned} P_{g,t+1} - P_{g,t} &\leq u_{g,t} \Delta p_g^{upmax} + S_{g,t+1} * p_g^{plantsize} \\ P_{g,t-1} - P_{g,t} &\leq u_{g,t} \Delta p_g^{downmax} + D_{g,t} * p_g^{plantsize} \end{aligned}$$

$$\forall t \in T, g \in G \quad (15)$$

This formulation makes it both notationally and computationally efficient to combine unit commitment and capacity planning models. It can also boost efficiency for either capacity planning or unit commitment problems isolation.

Conceptually, this approach is similar to that of Sen & Kothari [12], who group units within a unit commitment only (no capacity expansion) model. However, their treatment assumes a binary commitment state with the entire block all on or all off, which though computationally helpful, is

less flexible than (14) which allows some of the generators within a group to run while others are off. This limitation is particularly challenging for startup costs and minimum output levels, since the minimum output with all generators running is much higher than if only a single generator was on-line. A simple extension treats groups of generators as a single large unit, with minimum output equal to that of a single generator. This approach avoids the minimum output problem but cannot adequately address startup costs or reserves. In a separate line of work, Garcia-Gonzalez, et al. [13] use an integer on/off state when modeling banks of identical hydro turbines for optimal combined bidding with wind, but the approach is not used within a larger unit commitment model. They also assume a fixed capacity. More recently, Shortt & O'Malley [14] highlight the importance of considering increased plant cycling during capacity planning with renewables. Their model combines generators into two groups using a merit-order-based unit commitment. Their resulting unit-commitment model relies on heuristics to capture cycling behavior that ignore many commitment configurations and simplify ramping and reserve constraints. They use a separate capacity planning model requiring an iterative solution algorithm and expert tweaking of initial guesses for tractable solution times.

E. Additional Considerations

1) *Renewable Portfolio Standard*: A renewable portfolio standard (RPS) can be added by ensuring that the power supplied by RPS-eligible generators, G_{RPS} exceeds the required percentage of total demand:

$$\frac{\sum_{t \in T} \sum_{g \in G_{RPS}} P_{g,t}}{\sum_{t \in T} D_t} \geq \text{RPS} \quad (16)$$

2) *Carbon Cost or Cap*: Carbon costs can be added as an additional term in the objective function (12) that adds up the emissions for each generator $E_{g,t}^{CO_2}$ and multiplies by the carbon price, c^{CO_2} :

$$\dots + \left(\sum_{t \in T} \sum_{g \in G} E_{g,t}^{CO_2} \right) c^{CO_2} \quad (17)$$

Alternatively, a carbon cap can be imposed as a constraint limiting total emissions to a maximum target:

$$\sum_{t \in T} \sum_{g \in G} E_{g,t}^{CO_2} \leq E_{limit}^{CO_2} \quad (18)$$

In which case, the corresponding (shadow) carbon price will be the corresponding dual variable.

3) *Maximum Startups*: In some situations, startup costs alone are insufficient to prevent excessive cycling of thermal power plants. Such cycling can cause premature wear on plant components, may exceed maintenance contract limits, or may simply be physically impossible (e.g. nuclear). To prevent excessive cycling, the maximum number of startups per time period, S_g^{max} , can be added as a constraint using:

$$\sum_{t \in T} S_{g,t} \leq S_g^{max} \quad \forall g \in G \quad (19)$$

III. NUMERIC EXPERIMENTS

A. Test System Description

1) *ERCOT Overview*: The test system used in numerical experiments is loosely based on the Electric Reliability Council of Texas (ERCOT) power system. The ERCOT system is largely electrically isolated from the rest of the United States power grid allowing us to ignore interchange with neighboring areas. It also has minimal hydropower, simplifying the model formulation and solution.

2) *Data and Assumptions*: Demand and wind generation data was taken from historic hourly ERCOT time series for 2009 to capture weather correlations. Both load and wind data were assumed to scale linearly. The ERCOT generation mix was estimated using historic bid data as described by Campbell [15].

Plant size and cost data were taken from the United States Energy Information Agency's (EIA) Annual Energy Outlook (AEO) 2010 table 8.2 [16]. Capital Costs were taken as total overnight costs (including contingency and optimism). Heat rates are the 2009 values from the same source assuming advanced nuclear (Nuke), new scrubbed coal (Coal), advanced gas/oil combined cycle (NG-CCGT), and advanced combustion turbines (NG-CT). Investment costs were annualized using a weighted average cost of capital (i.e. discount rate) of 10% using plant life estimates from [17]. Costs are in 2008 US dollars.

Fuel prices were taken from EIA AEO 2010 table 3 [16] except uranium-235 based on variable costs from [17] using fuel prices and heat rates from EIA AEO table 8.2 [16]. Fuel carbon intensities taken from EIA Reporting of Greenhouse Gases Program [18] assuming pipeline natural gas and subbituminous coal. Detailed operating constraints such as minimum outputs, ramp limits, and startup costs were estimated from typical plant performance data.

The planning reserve requirement was taken as 12.5% of the peak load and only counted for firm peak capacity. The firm peak capacity credit for Wind was taken as 10% of installed capacity. Operating reserve quantities were computed as a percentage of hourly load based on an analysis of CAISO 2006 ancillary services market as reported in [19].

3) *Computing Environment*: All tests were run on a single 64-bit core of a 2.4 GHz Intel Core 2 Duo processor using a custom, highly configurable model, "StaticCapPlan" written in GAMS [20] and solved using IBM ILOG CPLEX version 12.2. [21]

B. Computational Performance

The computational performance of the integer block unit commitment (UC) formulation was compared to the traditional binary individual UC model by optimizing a simple capacity expansion problem using each to estimate operating costs. For this experiment only, the operating time period was limited to a single week (167 sequential hours). As seen in Table I, the integer block was over 5000x times faster. Both formulations were run using discrete investment and unit commitment decisions, unit minimum output constraints, and startup costs until reaching a relative MIP tolerance of $\leq 0.02\%$.

TABLE I
SOLUTION TIME FOR CAPACITY PLANNING PROBLEM WITH DIFFERENT
UNIT COMMITMENT FORMULATIONS.

	Integer Block	Binary Individual
Solution Time (mm:ss.ss)*	00:00.57	56:55.22

*Comparison for 1 week (167 hr) of simulated operations.

The integer block unit commitment formulation and a full 8760 hours of annual operation were used for all other experiments.

C. Simple vs Detailed Operations

The least cost optimal expansion plans for the test system with 20% demand growth and a 20% RPS were computed for carbon prices of \$0, \$30, and \$45 per ton CO_2 . For each carbon price, two operations models were compared:

- a simple, non-sequential net load duration curve computed as a linear program, and
- detailed sequential operations using grouped integer unit commitment with integer decisions, reserves, startup costs, unit minimum outputs, and maximum startups.

Both models consider a full 8760 hours of operations in the simulation year.

As seen in Fig 2, the new thermal capacity and energy mix for the \$0 per ton case are effectively identical, while the \$30 and \$45 per ton cases show a notable reduction in new nuclear capacity along with a corresponding reduction in nuclear fraction of generated energy using the detailed model. In both cases (existing) coal and natural gas combined cycle (CCGT) make up the missing energy. In all cases the existing fleet of generation was assumed still available. This existing capacity and the near constant new wind capacity (25.75GW \pm 0.25GW) are not shown.

D. Are these differences Real?

During testing, we noticed that only small differences in objective function distinguished similar system configurations and that in some cases, these differences were of similar magnitude as the relative Mixed Integer Programming tolerance, or “MIP gap.” To ensure that the reported results were real differences and not artifacts of the solution process, we ran the detailed unit commitment based model at a carbon price of \$45/ton with a set of largely fixed expansion plans. In each the number of new Nukes and CCGTs was fixed to form a three by three grid centered on the computed optimum. Each simulation corresponded to the permutations of \pm one Nuke and/or \pm two CCGT plants. The corresponding number of new CTs to build was determined by the model.

The worst absolute MIP gap for the objective function was \$3.7M, which is lower than the smallest observed difference with perturbed fixed capacities of \$6.5M, suggesting that the combined model is indeed converging on the actual optimum. Moreover, these differences are much smaller than the smallest difference (\$357M) between the detailed and simple operations runs depicted in in Fig 2 further suggesting the observed difference are indeed real.

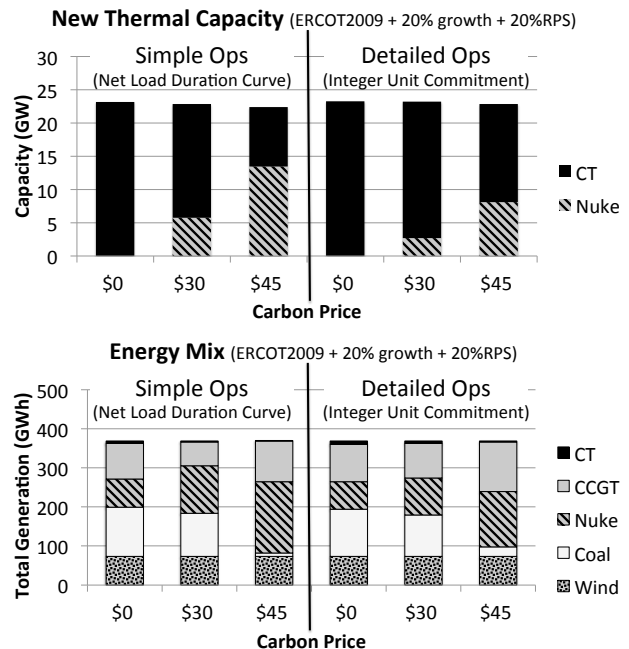


Fig. 2. Comparison of optimal least-cost expansion plans for different carbon costs using simple operations using (net) load duration curve vs detailed operations using grouped integer unit commitment. The unit commitment computation considers integer decisions, reserves, startup costs, unit minimum outputs, maximum startups. Both models consider all 8760 hours of operations based on 2009 historic demand, with 20% growth, and wind data, scaled to meet a 20% RPS. Note that only new thermal capacity is included. Existing generators and wind (constant across scenarios)

E. Impact on Carbon Cost and Emissions

Evaluating carbon policy and regulations provides one important application for long term planning models. Typically, such evaluations may be made for the electric power sector using simplified, load-duration-curve-based operations within a larger capacity planning model. To evaluate the impact of this simplification, we used the simplified model to determine capacity expansion investments necessary to meet an electric sector carbon cap of 44.5 Mt CO_2e with 20% load growth and a 20% RPS. Table II summarizes the resulting investment in new thermal capacity. The total cost (including annualized capital investment) for this run was just under \$38B of which \$12.6B was for operations.

The resulting mix was then scaled up to the next larger full sized plant and simulated using the detailed unit-commitment based model. No feasible (mixed-integer) solution could be found for this generation mix that simultaneously satisfied the carbon cap and renewable portfolio standards.

The detailed model was then run for the same generation mix using the shadow carbon price determined by the simplified model (\$45/ton CO_2e) with no carbon cap. Table II shows that the resulting total carbon emissions for this case were 61.7 Mt CO_2e (39% higher). The corresponding operating costs were 17% higher at \$14.7B.

In contrast, two alternative expansion plans were created using the full, detailed operations model at design time, one corresponding the desired sector-wide carbon cap 44.5 Mt CO_2e and another corresponding to the (incorrectly) estimated

TABLE II
CARBON COST AND EMISSIONS TABLE

Design Model	Design Model Run Carbon			New Thermal Capacity			Detailed Operations Carbon			Total Cost
	Cap	Price	Emissions	NG-CT	NG-CCGT	Nuke	Cap	Price	Emissions	
	Mt CO _{2e}	\$/t CO _{2e}	Mt CO _{2e}	MW	MW	MW	Mt CO _{2e}	\$/t CO _{2e}	Mt CO _{2e}	\$millions
Simple	44.5	-	44.5	8906	0	13455	44.5		Infeasible ⁺	
Simple	-	\$45	44.5	8906	0	13455	-	\$45	61.7	40007
Detailed	44.5	-	44.5	4370	4000	13500	44.5	97.6 [†]	44.5	42576*
Detailed	-	45	68.6	14720	0	8100	-	45	68.6	38417

⁺Infeasible: unable to meet RPS and carbon cap with this mix, [†]shadow carbon price, *Includes carbon shadow price

corresponding carbon price of \$45/ton CO_2e . In both cases, feasible generation mixes were found. The actual carbon price required to meet the carbon cap was \$97.6/ton CO_2e , more than double that estimated with the simple model. In the carbon price based design, the resulting generation mix corresponded to a total cost of \$38.4B, only slightly higher than the (incorrect) baseline, but much lower than the baseline mix with realistic operations, \$40.0B.

IV. CONCLUSION AND FUTURE WORK

The results presented here suggest that incorporating detailed, unit-commitment-derived operations into capacity planning models can make important changes to the optimal generation mix by more accurately valuing operational flexibility. In one example, higher carbon prices (\$30 and \$45 /ton CO_2e) encouraged construction of large numbers of nuclear generators using a traditional capacity planning approach with simplified operations. However, when the same scenario was evaluated using a capacity planning model with integrated hourly unit commitment based operations, only about half as many nuclear facilities were built and instead, power was provided by running existing relatively more flexible natural gas combined cycle and coal plants more frequently. A second example simulated the use of a capacity planning model with simplified operations to determine the carbon price required to meet a sector-wide carbon cap. When the more realistic unit-commitment based operations are used instead within the capacity planning model, the actual required carbon price is found to be more than twice as high. Furthermore, if the expansion plan designed with the simpler model were actually built, it would not have enough flexibility to meet both the carbon cap and renewable portfolio standard.

To address the increased dimensionality of including unit-commitment-based operations within a capacity planning model, we propose and demonstrate a grouped integer unit commitment approach that groups similar power plants into categories while still maintaining the discrete unit-by-unit commitment states necessary to accurately model operating reserves, ramping, and startup constraints. This model formulation runs orders of magnitude faster than treating plants individually and easily integrates with a capacity planning model. This approach could also be used for other unit commitment applications where the assumption of similar operating characteristics within each group is an acceptable trade-off with the drastically reduced computation time.

This research suggests a number of lines of future inquiry. For example: How does the importance of capturing unit commitment details during capacity planning vary with power system configurations such as quantity of hydro power, quantity of existing flexible generation, RPS level, and inclusion of additional advanced technologies such as demand response and storage? How do the impacts of detailed operations compare and combine with uncertainty such as fuel prices or wind forecast errors? It would also be worthwhile to explore the impacts of operational detail within multi-stage planning models because key aspects of flexibility such as lead time and adaptability to uncertain future require modeling the ability to revisit decisions (recourse). In the multi-stage context, even our simplified unit commitment may still be intractably large, such that it will be important to first explore how much operational detail is enough, including which operating constraints are most important and is it necessary to capture all 8760 hours?

REFERENCES

- [1] R. Wiser and G. Barbose, "Renewables portfolio standards in the united states - a status report with data through 2007," Lawrence Berkeley National Laboratory, Tech. Rep. LBNL-154E, Apr. 2008.
- [2] S. Borenstein, M. Jaske, and A. Rosenfeld, "Dynamic pricing, advanced metering and demand response in electricity markets," University of California Energy Institute-Center for the Study of Energy Markets, Working Paper CSEM WP 105, Oct. 2002. [Online]. Available: http://www.smartgridnews.com/artman/uploads/1/sgnr_2007_12012.pdf
- [3] A. B. Lovins, E. K. Datta, T. Feiler, K. R. Rabágo, J. N. Swisher, A. Lehmann, and K. Wicker, *Small is profitable: the hidden economic benefits of making electrical resources the right size*. Rocky Mountain Institute, 2002.
- [4] C. Bueno and J. Carta, "Wind powered pumped hydro storage systems, a means of increasing the penetration of renewable energy in the canary islands," *Renewable and Sustainable Energy Reviews*, vol. 10, no. 4, pp. 312–340, Aug. 2006.
- [5] W. Kempton and J. Tomic, "Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy," *Journal of Power Sources*, vol. 144, no. 1, pp. 280–294, Jun. 2005.
- [6] G. Zhou, M. Krarti, and G. P. Henze, "Parametric analysis of active and passive building thermal storage utilization," *Journal of Solar Energy Engineering*, vol. 127, no. 1, pp. 37–46, Feb. 2005, copyright 2005, IEE.
- [7] I. Pérez-Arriaga and P. Linares, "Markets vs. regulation: A role for indicative energy planning," *The Energy Journal*, vol. 29, no. Special Issue# 2, pp. 149–164, 2008.
- [8] T. L. Johnson, J. F. D. Carolis, C. L. Shay, D. H. Loughlin, C. L. Gage, and S. Vijay, "MARKAL scenario analyses of technology options for the electric sector: The impact on air quality," United States Environmental Protection Agency (EPA), Washington, D.C., Tech. Rep. EPA/600/R-06/114, 2006.

- [9] Electric Power Research Institute, "EGEAS: electric generation expansion analysis system, version 9.02B."
- [10] P. Meibom, H. V. Larsen, R. Barth, H. Brand, C. Weber, and O. Voll, "Wilmar joint market model, documentation," Risø National Laboratory, Roskilde, Denmark, Tech. Rep. Risø-R-1552(EN), Jan. 2006.
- [11] A. Ramos, L. Olmos, J. M. Latorre, and I. Pérez-Arriaga, "Modeling medium term hydroelectric system operation with large-scale penetration of intermittent generation," Sep. 2008.
- [12] S. Sen and D. P. Kothari, "An equivalencing technique for solving the Large-Scale thermal unit commitment problem," in *The Next Generation of Electric Power Unit Commitment Models*, B. F. Hobbs, M. H. Rothkopf, R. P. O'Neill, and H. po Chao, Eds. Boston: Kluwer Academic Publishers, 2002, pp. 211–225.
- [13] J. Garcia-Gonzalez, R. M. R. de la Muela, L. M. Santos, and A. M. Gonzalez, "Stochastic joint optimization of wind generation and Pumped-Storage units in an electricity market," *IEEE Transactions on Power Systems*, vol. 23, no. 2, pp. 460–468, 2008.
- [14] 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.
- [15] D. Campbell, "Cycling coal and gas: Challenges and implications," Aug. 2010. [Online]. Available: http://mydocs.epri.com/docs/SummerSeminar10/Presentations/3.3_Campbell_Luminant.pdf
- [16] Energy Information Administration, "Annual energy outlook 2010 early release," 2010. [Online]. Available: <http://www.eia.doe.gov/oiaf/aeo/>
- [17] Royal Academy of Engineering, *The cost of generating electricity*. London: Royal Academy of Engineering, 2004.
- [18] Energy Information Administration, "Voluntary reporting of greenhouse gases program fuel carbon dioxide emission coefficients." [Online]. Available: <http://www.eia.doe.gov/oiaf/1605/coefficients.html>
- [19] B. Palmintier, "It's not just the energy: Ancillary services and a peek behind the scenes for electric power systems," presented as MIT ESD.865 Guest Lecture, Cambridge, MA (USA), Sep. 2010.
- [20] GAMS Development Corporation, "General algebraic modeling system (GAMS)," 2010.
- [21] IBM ILOG. (2010) CPLEX optimizer.



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