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A unit commitment study of the application of energy storage toward the integration of renewable generation

Chioke Harris,[1,a)] Jeremy P. Meyers,[1,2] and Michael E. Webber[1,3]
[1]*Mechanical Engineering, The University of Texas at Austin, Austin, Texas 78712, USA*
[2]*Center for Electrochemistry, The University of Texas at Austin, Austin, Texas 78712, USA*
[3]*Center for International Energy and Environmental Policy, The University of Texas at Austin, Austin, Texas 78712, USA*

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To examine the potential benefits of energy storage in the electric grid, a generalized unit commitment model of thermal generating units and energy storage facilities is developed. Three different storage scenarios were tested—two without limits to total storage assignment and one with a constrained maximum storage portfolio. Given a generation fleet based on the City of Austin's renewable energy deployment plans, results from the unlimited energy storage deployment scenarios studied show that if capital costs are ignored, large quantities of seasonal storage are preferred. This operational approach enables storage of plentiful wind generation during winter months that can then be dispatched during high cost peak periods in the summer. These two scenarios yielded $70 million and $94 million in yearly operational cost savings but would cost hundreds of billions to implement. Conversely, yearly cost reductions of $40 million can be achieved with one compressed air energy storage facility and a small set of electrochemical storage devices totaling 13 GWh of capacity. Similarly sized storage fleets with capital costs, service lifetimes, and financing consistent with these operational cost savings can yield significant operational benefit by avoiding dispatch of expensive peaking generators and improving utilization of renewable generation throughout the year. Further study using a modified unit commitment model can help to clarify optimal storage portfolios, reveal appropriate market participation approaches, and determine the optimal siting of storage within the grid. © *2012 American Institute of Physics*. [doi:10.1063/1.3683529]

I. INTRODUCTION

Alongside the introduction of "smart grid" technologies, many states plan to significantly expand the portion of their total electricity generation from wind, solar photovoltaics, and concentrating solar power.[1] Renewable power sources offer domestic energy security and reduced carbon emissions, but these generators, especially wind facilities, have highly variable outputs and are typically sited where the relevant resource is most available, creating capacity constraints and additional reliability challenges.[2] This intermittency, as well as unpredictable customer demand, is currently managed by operating primary fossil fuel generators at part-load to provide frequency regulation capacity and spinning reserves, with fleets of fast-response gas turbines or diesel generators to relieve these providers if long-duration support is needed. These reserve generation, or ancillary service (AS), requirements could instead be met by energy storage, which offers lower marginal costs, protection from volatile fuel prices, greater system resiliency, and zero emissions. Given the complexity and requirements of the electric grid, it is not obvious if energy storage will be able to deliver these benefits without incurring prohibitive capital expenses.

[a)]Electronic mail: chioke@utexas.edu.

Since significant benefits could be obtained with the availability of energy storage as a component of the electric grid, the literature includes a multitude of approaches that attempt to assess and quantify these benefits. Not only are there many approaches applied to the study of grid-scale energy storage, but these various methods explicitly capture different storage operational modes. Eyer *et al*. catalog that the primary services energy storage could provide on the grid.[3] They define 13 modes in three groups: "grid system applications," "end-use applications," and "renewables applications." Sullivan *et al*.,[4] Sioshansi and Denholm,[5] Walawalkar *et al*.,[6] and many others discuss the benefits of using storage for many of these modes. The work presented here considers storage for market arbitrage and renewables integration. The storage types appropriate for diurnal and multi-day storage could also provide shorter time scale ancillary services. It is possible, however, that other storage technologies not explored in detail here could be better suited to those services. Unit commitment model formulations are well-suited to the operational modes and time scales studied here. While the storage modeling framework used here can be applied to shorter time scale studies to examine storage for ancillary services, because of the difficultly of estimating future ancillary service capacity prices and deployments, similar to many other authors, we refrain from attempting to model them explicitly.

Many studies have focused on a specific operational mode and energy storage technology, typically because it is assumed to be the lowest cost or most readily available option for a given region and regional geography. Benitez *et al*.[7] examined pumped hydroelectric storage as part of a study of the costs of wind integration. Though the authors found that hydroelectric storage lowered the cost of integrating large quantities of wind generation, they did not address the capital costs of such a system. Tuohy and O'Malley[8] included these costs and found that pumped hydroelectric storage was only beneficial when CO_2 emission prices are high. Given that pumped hydroelectric storage is only available in limited areas where geography permits, Greenblatt *et al*.[9] and Fertig and Apt[10] examined the placement of compressed-air energy storage with respect to wind generation sites in transmission constrained systems. Geology suitable for compressed air energy storage exists in most states outside California, Nevada, and the southeast.[9] Both studies found limited circumstances where storage might offer net benefits, though both studies also limited storage to wind generation only. Conversely, Lu *et al*.[11] and Lund *et al*.[12] examined optimal energy storage bidding strategies for participation in electricity markets in the absence of transmission constraints. Such strategies are likely important given that suboptimal participation strategies, subject to the quality of available price and demand forecasts, might have a significant impact on storage revenues.

Conveniently, examination of a single storage type, as in the aforementioned studies, ensures a tractable model. It is possible that the predetermination of the energy storage type, its costs, and its capabilities outside the optimization framework yields suboptimal results. Though these studies often employ optimization methods, without exploration of the effect of energy storage preselection, it is difficult to assess the optimality of the results.

To avoid these risks, several studies have examined multiple storage types. Such studies can determine not only storage value, but also the relative importance of storage parameters with respect to the objective, typically operating costs or total system costs, as selected by the authors. Barton and Infield[13] used a probabilistic approach to determine whether energy storage could increase acceptable renewable penetration levels without adding to total system costs. Though their results suggest that at short time scales, small quantities of energy storage might be beneficial, not all benefits associated with available energy storage were captured in their probabilistic approach. Walawalkar *et al*.[6] examined four types of energy storage to determine where regulation and arbitrage opportunities might exist in a given electricity market. Sioshansi and Denholm[5] study an arbitrary energy storage device to determine the relative importance of several storage parameters, but they note that their results are subject to several limitations. Both Sioshansi and Denholm and Walawalkar *et al*. modeled storage as a price taker (as do Lu *et al*., Lund *et al*., and others), leading to an overestimation of the value of storage, since the interaction of storage with the system will necessarily decrease prices during high price periods and increase prices during low price periods, reducing revenues.[5] Further, to more closely approximate real markets, where future prices or load cannot be known, Sioshansi and Denholm allowed only two-week price foresight. This approach does offer some realism by limiting foresight and thus reducing predicted revenues, but it also limits the potential for storage operation planning beyond a two week horizon. This limitation excludes results that might suggest longer term storage.

In light of previous results in the literature, the model developed in this work seeks to avoid the revenue overestimation associated with modeling storage as a price taker, limit storage type predetermination, avoid constraining storage to only output from specific generators, and avoid specifying the operational mode of any energy storage selected such that the "optimal" result is constrained by these predefined inputs. This model co-optimizes the operation of energy storage with thermal electricity generator commitment and dispatch, rather than focusing on specific operational strategies or the profit-maximizing operation of the energy storage system as an independent participant in an electricity market. This integrated approach can yield operational approaches suitable for both independent storage operators and vertically integrated utilities. To examine the potential benefits of energy storage, a unit commitment model that includes energy storage devices is developed. This modeling approach yields a structure that can be adapted to a variety of thermal generator and storage constraints as well as any coherent set of generators and demand. This approach can also be adapted to any region of study and for any type(s) of energy storage.

II. METHODOLOGY

While unit commitment is a well-established method for modeling electric power generation systems[14] and provides a suitable foundation for modeling future scenarios, some limitations arise when examining energy storage. The ability of a unit commitment model to predict the operation of some future generation assets or the impact of a change in market rules is dependent on the selection of an appropriate model and time step length. If careful consideration is not given at this stage, the model's results might give a solution implied by the selected time scales. While this problem might appear easily avoided by using appropriately short time steps, computational constraints might limit the feasible number of time steps if the model length is many orders of magnitude larger than the step. At the same time, some models might require long time horizons to capture variations in demand or renewable resource availability over seasonal time scales. In the case of modeling energy storage, time steps at least 5 min long can reveal seasonal storage commitment decisions, which are of significant interest. Unfortunately, this resolution precludes simultaneous study of energy storage as an ancillary service provider.

The City of Austin serves as the test region for the development of this model. Through an intellectual partnership with Austin Energy, the local municipal utility, data about historical dispatch and power plant operational characteristics have been made available. Beyond these data, Austin Energy serves as an appropriate initial case for model testing because the utility, in conjunction with the city, has committed to an ambitious schedule of obtaining 30%–35% of their electricity from renewable sources by 2020.[15] More than 70% of the renewable generation contracted to meet this target will be from wind energy, meaning that by 2020, more than 20% of Austin Energy's generation will be from wind.[15] Additionally, the City of Austin is pursuing aggressive goals for the integration of electric vehicles (EVs) with smart grid technology to enable smart charging and vehicle-to-grid (V2G) programs.

Given these deployment plans, energy storage could provide significant operational value to Austin Energy by firming and shaping renewable generation and providing lower marginal cost generation during peak hours. The unit commitment model developed in this work is designed to determine the optimal level of energy storage to yield these benefits.

A. Objective function and costs

The mixed-integer programs (MIPs) used here have marginal cost minimization objective functions. The objective function, Eq. (1), includes ongoing fuel, operation, and maintenance costs (mc_g), indexed by the set of generators g, as well as startup costs ($s_{g,t}$), indexed over all discrete time steps t as well. Variable $x_{g,t}$ denotes the dispatched generation from each facility in MW. Estimated startup costs are calculated by Eq. (2) and include increased maintenance costs and reduced heat rates associated with low initial operating levels. Equation (2) is modified to exclude negative values, as detailed further in Appendix A 1

$$z = \sum_{g,t} mc_g \, x_{g,t} + \sum_{g,t} s_{g,t}, \tag{1}$$

$$s_{g,t} = startcost_g (y_{g,t} - y_{g,t-1}). \tag{2}$$

In some of the results, energy storage is selected from a portfolio of storage types, requiring additional terms in the objective. For each storage device in the set *type*, Eq. (3) includes these additional terms: fixed yearly maintenance costs ($fixcost_{type}$) and marginal costs ($varcost_{type}$) associated with fuel for expansion turbines in a compressed air energy storage (CAES) facility. Variable $out_{type,t}$ denotes energy discharged from a particular storage type in every time step t and parameter $inlimit_{type}$, multiplied by the number (n_{type}) of that type of storage selected, indicates the maximum charge rate for that storage type. The scalar 0.25 has the unit hours per period and ensures that the first term has the unit dollars, since variable $out_{type,t}$ has a value for every 15 min period. The value 35 040 on the second term divides the length of the model ($card_t$) by the length of a year to calculate the total fixed marginal costs for the modeled period

$$\ldots + \sum_{type,t} (0.25 \; out_{type,t} \; varcost_{type}) + \sum_{type} \left(n_{type} \; inlimit_{type} \; fixcost_{type} \frac{card_t}{35040} \right). \tag{3}$$

Further details about the objective function formulation are in Appendix A 1.

Including capital costs in the objective function could improve storage portfolio allocation by directly capturing the primary costs associated with storage. Facility capital costs would not, however, typically be included in bids in an electricity market. Introducing capital costs to a model concerned with unit commitment might distort dispatch decisions. Further, including storage capital costs would require knowledge about capital costs and financing of existing plants owned by Austin Energy. Since these data are not available, instead of including capital costs explicitly, we can evaluate the capital cost and payback period for the installation of a storage asset selected by the model and compare that to the dispatch cost reduction it yields.

Current estimated capital costs associated with storage types available to the model are in Table I. These capital costs are used for comparison with cost savings in the results. The indicated capacity-cost ratio provides a total cost per unit capacity point of comparison between storage types, where CAES serves as the ratio baseline. Plug-in hybrid electric vehicles (PHEVs) are modeled as having no capital or operating costs borne by the utility, which assumes that customers will receive no remuneration from the utility for the use of their battery. While this arrangement is unlikely, it is outside the scope of this study to explore payment strategies for PHEVs. Future prices for other storage types could decrease due to economies of scale associated with mass production or improved manufacturing techniques, or increase due to demand for active materials or construction materials, thus capital costs are also excluded on the basis of unknown future storage prices. It should be noted that there exist manifold research, development, and commercialization programs devoted to grid-scale storage

TABLE I. Estimated capital costs for selected storage devices.[16]

Type	Price (\$/MWh)	Price (\$/MW)	Lifetime (years)	Capacity-cost ratio
NaS battery	196 000	1 862 000	10	9.8
Vanadium FB	236 000	2 691 000	20	12
PHEVs	0	0	10	—
CAES	21 830	750 000	25	1

technologies, which could reduce capital costs. As such, these results can continue to be instructive even as capital costs change.

B. Thermal generator constraints

Constraints governing the operation of thermal generators are important to ensure that results that satisfy the objective are consistent with real system limitations. The model's structure is based on MIP constraints proposed by Baldick[17] and Tuohy *et al.*,[18] with an emphasis on capturing those most important to sensible generator dispatch.[14] Thermal generator constraints include up and down ramp rates (MW/min), minimum startup and shutdown levels (MW), generator nameplate capacity (MW), startup costs, and minimum spinning reserves. The equations that define these constraints are detailed further in Appendix A 2. Minimum generator up- and down-times are neglected in this model, since the inclusion of startup costs in the objective function should prevent repeated on/off cycling of all generators except simple-cycle gas turbines, which are designed for frequent startup and shutdown. Electrical system constraints such as reactive power and voltage regulation and support are ignored. Many authors neglect these constraints with no apparent detriment to commitment and dispatch decisions.[17] Forced and scheduled generator outages are also ignored, which will yield overprediction of the dispatch of some generators during some periods, but these should largely balance through the year as all units compensate for other generator outages. Also, all renewables are indicated as having zero marginal costs. This simplification of costs was done in an attempt to ensure that all available renewable generation will be dispatched, since Austin Energy currently procures all its renewable generation through forward contracts with third-party power producers. It is known that many of these generators have extremely high marginal costs, but contractual purchasing agreements make the cost irrelevant to economic dispatch. These costs are estimated based on Refs. 19–23 and do not reflect actual marginal or startup costs.

C. Modeling future scenarios

Austin Energy's renewable generating fleet is planned to grow significantly by 2020.[15] Energy storage is likely to have the greatest benefit after this growth in installed wind capacity, so this future scenario has been modeled. Austin Energy has estimated that their peak requirements will increase by 238 MW from 2008 to 2020, assuming demand-side management (DSM) efforts successfully prevent 700 MW of demand growth in the intervening years.[15] Load (D) data provided by Austin Energy for 2008 were scaled to fit the 2020 scenario by maintaining the load profile, but normalizing for increased peak demand with Eq. (4).

$$D_{2020} = D_{2008} + 238\frac{D_{2008}}{D_{max,2008}}. \tag{4}$$

Using a similar approach to demand scaling, wind and solar availability were scaled based on anticipated increases in installed capacity between 2008 and 2020. Existing wind generation data provided by Austin Energy from their contracted facilities were aggregated and scaled up to the anticipated 846 MW of peak generation available in 2020. Since wind generation rarely reaches its peak capacity, 2008 wind output was scaled according to its 2008 percentage of peak—if in some time period in 2008 wind output was 137 MW, or 50% of peak, then in 2020, that value was scaled to 50% of 846 MW, or 423 MW. It is currently unknown whether, as more wind generation is installed, variability will scale directly as assumed here or be reduced due to geographic wind turbine diversification or other factors.

Unlike wind, where existing generation was scaled to fit future capacity, insufficient solar generation is currently in Austin Energy's fleet for similar assumptions to be made. Instead, data from the National Solar Radiation Database (NSRDB) were used to estimate future solar photovoltaic generation.[24,25] New Braunfels, TX (site 722416) was the closest NSRDB site to Austin Energy's planned solar photovoltaic facility in Webberville, TX. Hourly total solar insolation data from 2004 were converted to power output using planned peak capacity of 100 MW and an

TABLE II. For the purposes of this study, a small subset of storage types has been selected based on their suitability for daily storage.

Type	Round-trip efficiency	Typical size (MWh)	Maximum input (MW)	Maximum output (MW)	Charge ramp rate (MW/min)	Discharge ramp rate (MW/min)
NaS battery[16]	0.88	0.43	0.05	0.05	0.05	0.05
Vanadium FB[16]	0.85	100	10	10	0.5	0.5
PHEVs[26]	0.9	0.0116	0.01	0.01	0.005	0.005
CAES[27]	1.25[a]	10 000	270	200	20	270

[a]Heat is added, typically by burning natural gas, to raise the temperature of the outflow stream before expanding it in a turbine train, making the total energy extracted greater than that stored.[27]

assumed panel efficiency of 19%. Since data with a higher sampling rate were not available, it was assumed that solar radiation remained constant throughout each hour period in the model.

D. Energy storage

Energy storage was initially included in the model by simply adding another unit to the list of thermal generators in Austin Energy's fleet, where that generator had zero marginal costs and virtually unconstrained ramp rates and "nameplate capacity." This approach does not capture storage efficiency, but it also does not require a predetermination of available storage types. This zero-cost, 100% efficiency case provides an upper bound on the application of energy storage for arbitrage in Austin Energy's system. Subsequently, the model was revised to select the best type(s) from some set of possible storage devices. Because the size of the time steps in these models, storage will either be used for arbitrage or not selected; hence, the storage types provided to the model are those that are regionally appropriate and suitable for daily storage. Because of the topography of Texas, pumped hydroelectric storage is not included.

The parameters shown in Tables II and III detail the operating constraints on a typical energy storage unit—charge and discharge rates (MW), charge and discharge ramp rates (MW/min), fixed ($/MW-year) and variable marginal costs ($/MWh), round-trip efficiency, and total capacity (MWh). Each storage type shown in Tables II and III is detailed for a typical single unit. Constraint equations governing the operation of energy storage in the model are detailed in Appendix A 3.

It should be noted that the number of PHEVs are restricted to 12 000, which represents roughly 3% of the light-duty vehicles in the Austin Energy service area and is an approximation of an upper limit for PHEV market penetration in the region after slightly less than one decade of widespread commercial availability. PHEVs are modeled as available whenever the utility wants to use their stored electricity and their state of charge is assumed to be invariant except when dispatched. While these modeling simplifications are not entirely realistic, the details of V2G interactions of PHEVs are outside the scope of this study and neglecting them reduces computational requirements.

III. RESULTS AND DISCUSSION

Full-year model cases with and without storage are compared, including scenarios with discrete storage selection from the portfolio in Table II. These year-long models facilitate study of the hypothesis that seasonal storage might be able to provide additional dispatch improvements

TABLE III. Marginal costs for energy storage are also included in the discrete storage scenarios.

Type	Fixed marginal costs ($/MW-year)	Variable marginal costs ($/MWh)
NaS battery[16]	42 200	0
Vanadium FB[16]	56 100	0
PHEVs[26]	0	0
CAES[27]	108 000	1.5

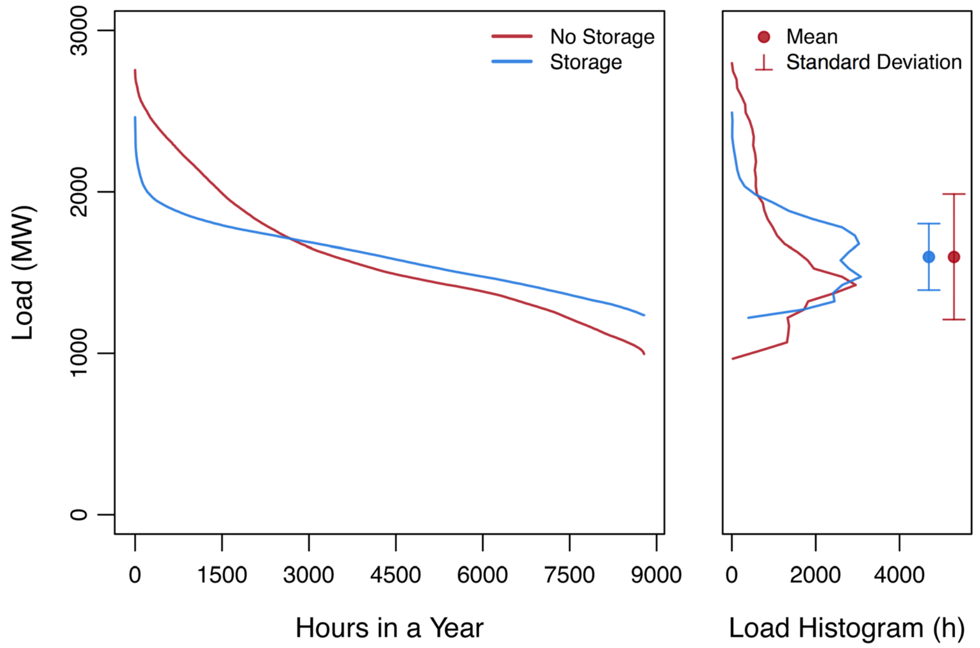

FIG. 1. Energy storage flattens demand significantly throughout the year, and as shown in the histogram in the right panel, storage thus reduces the number of hours of peak generation and the magnitude of peak requirements while also increasing demand during the lowest few hours of the year. Average load and standard deviation for each of these cases are summarized in Table VI.

and cost reductions over daily arbitrage. The impact of including round-trip efficiencies, marginal costs, and other storage constraints from Tables II and III on energy storage allocation is examined. The types of storage selected by the model and the effect of varying integer limits on energy storage allocation are also studied in the discrete storage selection scenario.

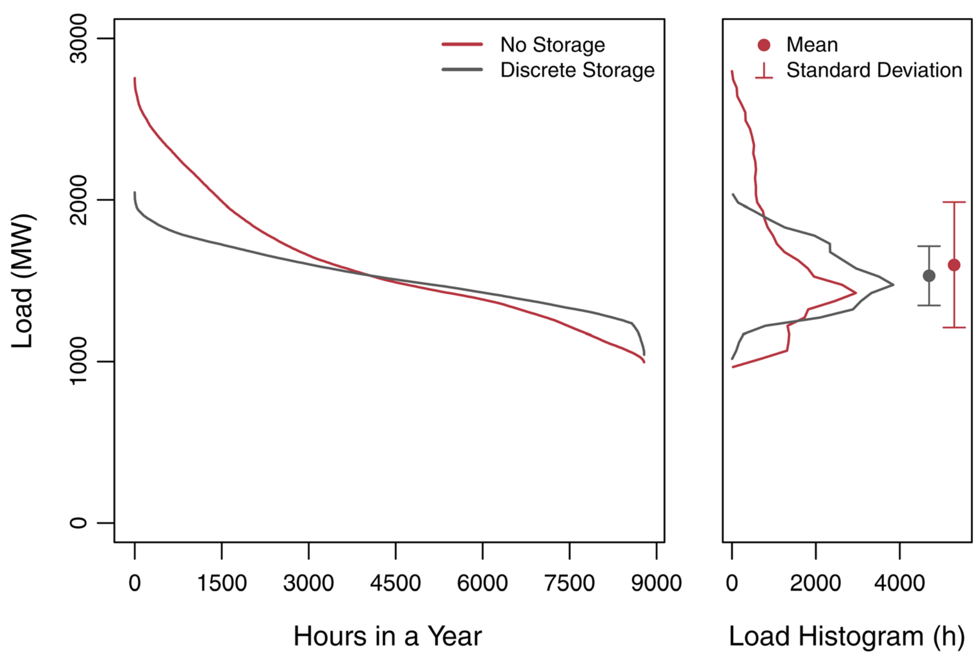

FIG. 2. With the presence of CAES, the discrete scenario results show not only a concentration of load levels to be served, as in Figure 1, but also a small overall reduction in load.

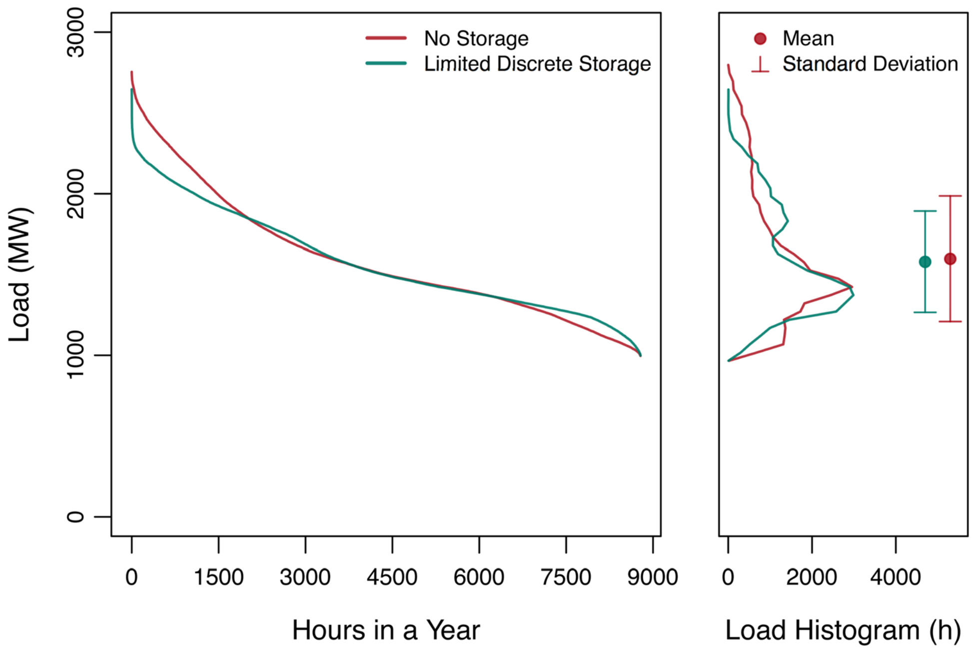

FIG. 3. With limited storage available, minimal reshaping of demand occurs, using storage to shift only the most expensive hours of the year, maximizing the benefit of what storage is available.

Figures 1–3 show load duration curves adjacent to histograms of the number of hours load is served. The histograms are divided into 50 MW increments for the entire load range. Bars to the right of the histogram show the mean and standard deviation of the two scenarios to further aid examination of the operational effects of storage. Together, these figures show how load is distributed throughout the year—either concentrated tightly around a few hundred megawatts that could be served by a relatively inflexible fleet of generators optimized for these load levels, or varying many hundreds of megawatts, requiring a wide range of flexible generating units to respond to varying levels of demand. Each figure compares a single storage case with the baseline case without storage.

Figure 1 illustrates the effect of energy storage availability. In this case, the quantity of storage available was not restricted. If storage is assigned without regard to cost or efficiency

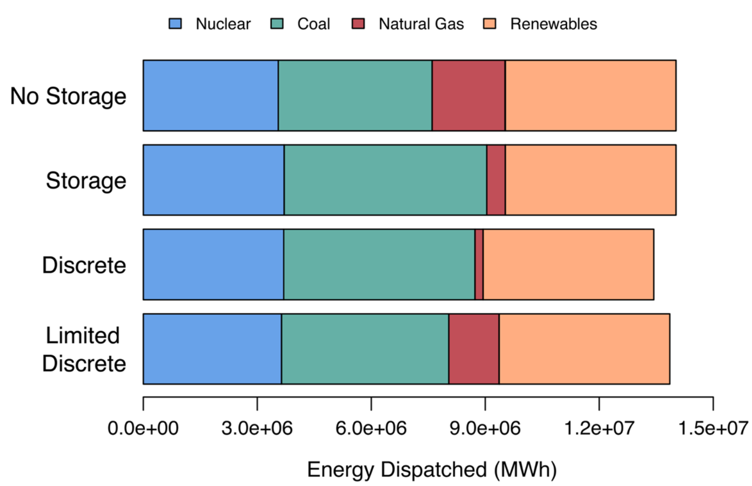

FIG. 4. As in earlier results, the availability of energy storage improves dispatch of inexpensive generators by shaping renewables availability.

TABLE IV. With low limits set for all available energy storage types, the optimal outcome still appears to be the maximum allowable storage.

	Integer limit (#)	Optimal portfolio (#)	Capacity (MWh)
NaS battery	5000	5000	2150
Vanadium FB	10	10	1000
PHEVs	0	0	0
CAES	1	1	10 000

constraints, average load does not change, but storage reduces the standard deviation of load from 383 MW to 202 MW. If storage efficiency were included and if it were not for energy additions from natural gas in expansion turbines at CAES facilities, the load average would increase. Concentrating load requirements into a narrow operating range allow sustained operation of the cheapest and most efficient plants while simultaneously maximizing the usefulness of renewable power generation, as indicated in Figure 4. This flattening of demand throughout the year is especially notable at the extremes, where maximum load is reduced by 291 MW and minimum load increased by 241 MW.

Comparing Figures 2 and 3, the discrete energy storage scenarios appear to serve less total load because some thermal generation has been replaced by stored energy returned to the grid from the CAES facility. The CAES facility modeled here uses natural gas as a secondary input to the outlet turbines, where the combustion of that natural gas to preheat the expanding air from the storage cavern increases the output energy such that efficiency of the plant appears to be greater than one. This additional electricity from the combustion of natural gas displaces other, more expensive generators.

The discrete energy storage case in Figure 2 captures the constraints that describe the operation of the selected energy storage types, yet it shows a similar result to the generic storage case. The presence of energy storage here yields the same narrowing of operating load requirements, but load is characterized by a lower average, since some additional generation is provided by natural gas combustion during the release of compressed air from the CAES storage cavern. This comparison also shows increases in minimum load and concomitant decreases in maximum

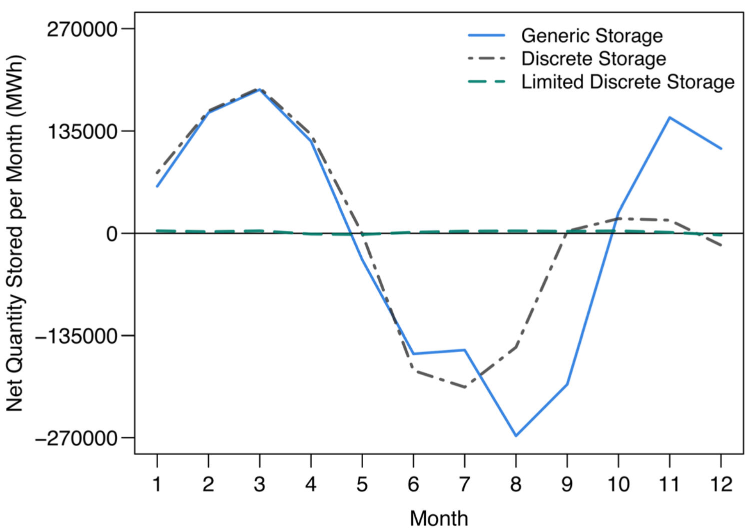

FIG. 5. While there is no clear bias towards storage in any one period when energy storage is limited, when quantities are unlimited, storage is concentrated primarily in the winter and spring months, when stored energy is the cheapest. It is likely that the difference between generic and discrete storage behavior in the final months of the year is a consequence of limiting constraints in the discrete storage scenario.

TABLE V. Comparing capital costs to annual savings for each of the storage scenarios suggests the limited storage portfolio provides the best economic basis for implementation.

Scenario	Allocated storage (MWh)	Capital cost ($million)[a]	Cost reduction ($million/year)
Storage	2.2e + 06	52 800[b]	75
Discrete storage	1.0e + 10	240 000 000	94
Limited storage	13 150	876	40

[a]Costs estimated based on $/MWh in Table I, not combined cost with $/MW.
[b]Capital cost estimated from portfolio costs from discrete storage case.

load compared to the generic storage scenario. As mentioned before, because of the way the system boundaries are drawn for this analysis, the use of CAES returns more electricity to the grid than stored, which depresses both the minimum and maximum loads, yielding a minimum load increase of only 46 MW and a peak decrease of 708 MW.

Since both the generic and discrete storage scenarios allocated significant quantities of storage, the integer limits on each storage type built into the discrete storage model were used to test the effect of a more limited portfolio of storage (Table IV). This portfolio was selected based on current high storage capital costs that have encouraged utilities to be initially conservative with energy storage deployment. With minimal storage available, the distribution of load throughout the year shown in Figure 3 is not as concentrated as it is for the unlimited[28] storage scenarios.

When storage availability is limited, it is still sufficient to address the highest cost hours of the year. Storage redistributes generation from lower cost periods to reduce dispatch requirements during peak hours. The total cost of this shifted generation, when including storage marginal costs, is significantly lower than that of peaking generators. With current capital costs, this result indicates that energy storage should be sized to address these highest cost hours first. If storage capital costs decrease with increased production volume in the future, further investment could be justified. The unlimited storage cases in Figures 1 and 2 suggest the ultimate opportunity for operating cost reductions, but these could only be realized with significantly lower storage capital costs. Regardless of the nature of the storage available, in all three scenarios, the magnitude of peak demand and the number of hours of high demand are reduced while simultaneously increasing load during the hours of lowest demand, flattening overall demand throughout the year. With less storage available, as in the limited discrete storage case, this effect is less pronounced, although still present.

Storage allocations in Figure 5 reveal that the dramatic load leveling that appears in the load duration curves of Figures 1 and 2 is achieved through extensive seasonal energy storage. From January through May, storage is filled and then throughout the summer, June through September, storage is fully depleted. Seasonal storage takes advantage of the cheapest power available in the year—inexpensive baseload generation and plentiful wind power during the cool fall, winter, and spring months when demand is relatively flat—and returns that power to the grid during the highest price peak demand periods in the hot summer months. This storage

TABLE VI. Comparing the effects of storage availability reveals that even limited storage can manage the highest cost hours of the year, though large quantities of seasonal storage has dramatic effects on dispatch throughout the year.

Scenario	Average load (MW)	Standard deviation (MW)	Δ Maximum load (MW)	Δ Minimum load (MW)	Allocated storage (MWh)
Without storage	1596	382			
Storage	1596	202	–291	241	2 218 745
Discrete storage	1530	181	–708	46	2 354 321
Limited discrete storage	1578	308	–108	2	13 150

TABLE VII. If possible, large quantities of energy storage will be allocated by the model, even when operating costs are included.

	Integer limit (#)	Optimal portfolio (#)	Capacity (MWh)
NaS battery	1 000 000	999 987	429 994
Vanadium FB	1 000 000	999 987	9.9e + 07
PHEVs	12 000	12 000	139.2
CAES	1 000 000	999 986	9.9e + 09

approach yields cost savings on the order of $100 million annually, as given in Table V. Totaling the energy storage allocated month after month in the unlimited storage scenarios, Table VII reveals that the storage required to achieve this dramatic load leveling and dispatch improvement is quite sizable. These costs are summarized in Table VI. While the operational benefits of seasonal storage are significant, the cost of such quantities of energy storage is prohibitive, based on the capital costs provided in Table I. In addition to the large storage capacities that are required to deploy seasonal storage, such a scenario requires the use of technologies that have extremely low self-discharge rates to ensure that energy stored during seasons with excess generation capacity can be used weeks or months later, creating an additional constraint on energy storage technologies to be used for such an application.

Based on the results from these year-long scenarios, seasonal storage is favored but prohibitively expensive, as shown in Table V. While this result is obviously implausible, the analysis reveals that, in general, storage offers value and increasing storage capacity offers increasing value, presumably until the variability in supply and demand across the day is completely flattened. If storage allocation is limited, the potential savings associated with storage are comparable to capital costs for those facilities because only the most expensive hours of dispatch in the year are addressed. The marginal benefit of additional storage is extremely limited, as evidenced by the unlimited storage scenarios that have many orders of magnitude, more storage capacity, and hence, much higher capital and marginal costs, but only two to three times greater yearly system operational cost savings. The payback period for the portfolio in the limited storage case is approximately 25 years, on the order of the lifetime of a CAES facility, while the larger storage scenarios require hundreds of years, well beyond the expected lifetimes of the equipment purchased.

Appropriate capital cost targets for energy storage are difficult to determine directly from these results, as they were not included in the optimization. If integer-limited storage cases were run with progressively increasing portfolio sizes, the marginal benefit of energy storage could be determined. These data could be found more efficiently, however, by directly capturing capital costs. Without these data, cost trends can still be drawn from existing results. In the limited storage allocation scenario, batteries account for 75% of the capital cost but provided less than 25% of total capacity, suggesting that costs for batteries will need to decline significantly before there is a cost basis for their implementation. Conversely, CAES has a definite economic basis for implementation given its ability to meet a variety of operational objectives, not the least of which is addressing the highest value added periods of the year. Comparing the cost of a CAES facility with those of the electrochemical storage options in Table I, electrochemical storage capital costs will need to decrease by about an order of magnitude to be competitive with CAES. Even at those prices, total feasible energy storage for a system the size of Austin Energy's would be limited to on the order of 10 000 MWh. Further study of CAES-only scenarios would provide a clearer sense of what the capacity threshold is for CAES implementation in a system like Austin Energy's. Additionally, as mentioned previously, capital costs are important for future models to develop greater confidence of what storage should be purchased.

IV. CONCLUSIONS

In the United States, through the implementation of state renewable portfolio standards (RPS) as well as federal production and investment tax credits, the installed base of renewable sources of electric power is growing rapidly. While this growth provides significant environmental benefits, the predictability and availability of these resources, especially wind energy, is limited. Wind generation thus requires an increasing number of peaking generators to provide support when wind is unavailable. Since many states have set aggressive RPS goals and in some regions, much of that renewable energy will come from wind turbines, addressing wind variability and availability is of increasing importance.

Energy storage improves the use of renewables by converting them into dispatchable resources available on-peak, increases the utilization of inexpensive, efficient baseload generators, and reduces the use of single-cycle gas turbines and older, more inefficient generators. These changes yield, over the study period, a significant reduction of the standard deviation of load, the magnitude of peak demand, and the number of extremely high demand hours. This flattening of load is achieved through extensive seasonal storage, where inexpensive renewable and baseload generation is stored during the winter months when demand is low and relatively flat and returned to the grid during the highest price peak hours during the summer months. Though seasonal arbitrage could be beneficial with much smaller systems, achieving these results requires quantities of energy storage that yield capital costs many orders of magnitude larger than the dispatch improvement provided.

Examining capital cost estimates, daily arbitrage during summer months can provide sufficient dispatch improvement to justify the cost of a single CAES facility. This conclusion is consistent with results from the limited storage scenario, where 75% of total storage capacity but only 25% of the cost is from the single CAES facility permitted in the model. The marginal benefit of increased storage for price arbitrage diminishes rapidly once the highest cost hours during the summer months are managed with storage. Given this conclusion, there exist few, if any periods that are sufficiently expensive to justify the cost associated with electrochemical storage options. These conclusions are contingent on storage capital costs remaining constant in the future. Capital costs for electrochemical storage could, however, drop dramatically in the coming years. In the future, developing models that capture both the capital and operational cost impacts of energy storage might provide a clearer picture of the cost benefits, optimal quantities, and preferred types of storage.

Given the objective function applied here, the results are not focused on the optimal operation of the storage facility with respect to revenues or profits, but rather the effects that the availability of energy storage can have on thermal generator dispatch. For that reason, we have not included the profits of the energy storage device(s) and instead highlighted the operating cost reduction they can effect. Since capital costs are not included, and because the objective function minimizes operating costs rather than maximizing storage profits, net storage system revenues will likely approach zero. If the objective function were changed to maximize revenue for the energy storage assets, information would be required about not only the operating costs of each storage asset but also about the time-of-day pricing that is assessed by the utility to the independent storage operator for purchased electricity, which might not be identical to the market clearing price. Further, by combining energy storage types in the discrete storage simulations, it is possible that one storage facility can lose money over the course of the year but provides some other operational benefit, where the negative profit is covered by another storage device that has net positive profits.

Emissions are not addressed in these results since they are not included in the objective function. As energy storage is free to store any electricity generated, not just that from zero-emission generators, emissions are not necessarily reduced. The objective function applied here minimizes costs, which suggests that energy storage will be operated in a way that increases dispatch of lower cost generators and decreases dispatch of higher cost generators without regard to emissions. Thus, the dispatch of inexpensive baseload coal generation will be maximized. The results presented here thus reflect system-wide optimal operational approaches without the imposition of arbitrary constraints that define how storage is to be used or the specific performance capabilities that a predetermined storage type might offer. Further, our modeling approach avoids the assumption that storage is a price taker, which can artificially inflate storage benefits by neglecting the price leveling effect of energy storage for arbitrage. Existing

TABLE VIII. GAMS models are structured around controlling indices called "sets."

Index (Set)	Description
g	All generating units (Table XIII)
t	Model time periods in 15-min increments
type	Storage device type (Table II)

results provide specific storage price and performance requirements for operation within a utility's generating fleet and indicate that seasonal storage is an important operational mode in regions where renewable generation is readily available during extended periods of low electricity demand. In the future, this approach will be applied to study the relative importance of storage parameters and how system cost and performance requirements change if storage is an independent operator. With this model structure, it is also certainly possible to revise the objective function to reflect a utility that might want to operate an energy storage device such that it only stores zero emission renewable generation or minimizes total system emissions, though this might negatively impact revenues and limit the cost reductions that would otherwise justify an investment in energy storage.

From the results of the scenarios presented here, it appears that between 10 000 and 20 000 MWh of compressed air, energy storage or other similarly priced and equally capable storage technologies can improve renewable energy capacity factors and reduce peak generation requirements. Such a CAES facility would reduce yearly operational costs dramatically for a system like Austin Energy's. If market rules do not prohibit the use of energy storage for ancillary service provision and some small quantity of electrochemical energy storage is included as part of the CAES facility development, energy storage can provide low marginal cost ancillary services and participate in high value market arbitrage. If storage capital costs are reduced by several orders of magnitude, energy storage could be expanded to provide seasonal storage, favored by models that did not restrict energy storage allocation or capture facility costs. Seasonal storage would enable the capture of large quantities of renewables during the winter months when they are most available and further flatten apparent demand, improving the utilization of the lowest cost thermal generating facilities.

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TABLE IX. Model parameters define the operating constraints of all generators in Table XIII as well as time-dependent functions.

Parameter	Description
mc_g	Marginal costs for all generators *g* ($/MW)
$maxpower_g$	Generator nameplate (maximum) capacity (MW)
$minpower_g$	Minimum generator operating level (MW)
$rampup_g$	Ramp rate increase limit (MW/min)
$rampdown_g$	Ramp rate decrease limit (MW/min)
$startcost_g$	Startup costs for all generators *g* ($)
$demand_t$	Demand in each period (MW)
$wind_t$	Aggregated wind availability (deterministic) in each period (MW)[a]
$solar_t$	Solar availability (deterministic) in each period (MW)

[a]Wind availability is aggregated over all Austin Energy's contracted wind farms.

TABLE X. Model variables are combined with parameters to form the objective function and constraint equations.

Variable	Description
$spr_{g,t}$	Spinning reserve quantity provided by plant g in period t
$x_{g,t}$	Power generated by unit g in period t (MW)
$y_{g,t}$	Binary indicating if a unit g is on in period t
z	Objective function

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APPENDIX: MODEL

GAMS, used to implement the unit commitment models presented here, imposes a specific structure on them. In GAMS, governing sets, or variable and parameter indices, are declared first. Similar to most unit commitment models, only two primary indices are required—one for those parameters and variables that change for every generator g and one for those that vary throughout the modeled time t. Parameters—vectors of fixed values that typically describe components in the modeled system—are declared and assigned values. Finally, scalars and variables are declared and described. All of these components are then combined into equations that follow a form nearly identical to that presented in Appendix A 2. This approach creates a structure that can be conveniently represented, as shown in Tables VIII–XII. In all models presented here, only 15-min time steps are used.

These models were originally structured such that results for cases with and without storage were captured with one GAMS file. Since each variable must have a single index associated with it, structuring the model in this way led to many different variable names, making the code excessively long and difficult to follow. With added equations to capture more constraints, the model was transitioned to a structure where each version had only two indices.

The parameters in Table IX are almost entirely identical to the column headings in Tables XIII and XIV. Those parameters that vary with t: deterministic demand, wind, and solar availability, are added here. These parameters are fixed for the full model period, forcing all wind and solar generation to be dispatched. Thermal generators must respond to compensate for changes from these and other renewable generators, as they do in Austin Energy's current system.

In addition to the parameters in Table IX, two scalars are used in the model. The quantity of spinning reserve that must be held in the model, following the 90 MW guideline used by Austin Energy, is controlled by *resamt*. The marginal cost of the two nuclear generators, South Texas Project units 1 and 2, is adjusted by \$7/MWh using scalar *nukecdt* so that their marginal prices are

TABLE XI. For the discrete storage scenarios, additional parameters are required to enable constraints on their assignment and operation.

Parameter	Description
eff_{type}	Round-trip efficiency for all storage units of type *type*
$size_{type}$	Maximum capacity of one storage unit (MWh)
$inlimit_{type}$	Maximum charge rate (MW)
$outlimit_{type}$	Maximum discharge rate (MW)
chg_{type}	Maximum rate of change of charge rate (MW/min)
$dischg_{type}$	Maximum rate of change of discharge rate (MW/min)
$fixcost_{type}$	Fixed marginal costs (\$/MW-year)
$varcost_{type}$	Variable marginal costs (\$/MWh)

TABLE XII. Additional variables must be defined to constrain the selection and operation of energy storage in the discrete storage scenarios.

Variable	Description
$stored_{type,t}$	Energy stored in storage unit *type* at the end of period *t*
$in_{type,t}$	Input to storage *type* during period *t*
$out_{type,t}$	Output from storage *type* during period *t*
$str_{type,t}$	Spinning reserve provided by storage *type* during period *t*
n_{type}	Number of units of energy storage *type* available on the grid

below that of the cheapest generator indicated in Table XIII. The modification of the nuclear generators' marginal costs is to ensure that they are always fully dispatched and that, if necessary, dispatch of Fayette Power Project's generators is reduced first.

Variable $spr_{g,t}$ ensures that sufficient spinning reserve, governed by *resamt*, is always allocated. In the model, only Fayette units 1 and 2, South Texas Project units 1 and 2, Sand Hill unit 5 (combined-cycle), and Decker units 1 and 2 are permitted to provide spinning reserve. When storage is available, it is also permitted to provide spinning reserve. The dispatch of every plant g for all times t is assigned to the variable $x_{g,t}$, where in all periods that x is non-zero, $y_{g,t}$ must be equal to one, indicating that the plant is on. The variable z captures the value of the objective function and is passed to the solver for minimization.

As with thermal generators, constraints must be declared to govern the operation of each of the storage units of the set *type* based on parameters in Table XI. To capture round trip efficiency, withdrawals ($out_{type,t}$) from energy storage are measured separately from inflows ($in_{type,t}$). These variables are constrained by maximum withdrawals and inflows in every time period as well as ramp rates between periods. Additionally, the quantity stored, $stored_{type,t}$, at every time step t must be measured to ensure that total storage capacity for each unit is not exceeded. The storage unit performance characteristics given in Table II describes one characteristic unit of that storage type

TABLE XIII. Austin Energy's projected generating fleet in 2020 is comprised of a variety of thermal generating units as well as several types of renewables (PWR—pressurized water reactor; CC—combined-cycle; GT—gas turbine; NG—natural gas; and Pk—peaking).

Facility[15]	Fuel; type[15]	Max. load (MW)[15]	Min. load (MW)[b]	Max. ramp up (MW/min)[b]	Max. ramp down (MW/min)[b]
Fayette 1	Coal; steam	305	90	5	3
Fayette 2	Coal; steam	302	90	5	3
STP 1	Nuclear; PWR	211	37	2.3	7
STP 2	Nuclear; PWR	211	37	2.3	7
Sand Hill 5	NG; CC	512	120	15	15
Decker 1	NG; steam	327	45	4	4
Decker 2	NG; steam	414	55	4	4
Sand Hill Pk[a]	NG; GT	289	12	40	40
Decker Pk[a]	NG; GT	193	48	20	20
Wind		846	0	1000	1000
Landfill	Methane; CC	7.8	3	1	1
Biomass	Wood; steam	200	30	4	4
Solar PV		100	0	1000	1000

[a]These peaking facilities each have four generators, grouped here to reduce computation times; dispatch is not affected by this simplification.
[b]These data were provided by Austin Energy or estimated based on information from Austin Energy.

TABLE XIV. Startup and marginal costs.

Facility[15]	Startup cost ($)	Marginal cost ($/MWh)
Fayette 1	12 000	15.1
Fayette 2	12 000	15.2
STP 1	15 000	21.8
STP 2	15 000	21.8
Sand Hill 5	7500	54.2
Decker 1	10 000	95.6
Decker 2	10 000	97.7
Sand Hill Pk	250	113.9
Decker Pk	500	151.7

and n_{type}, an integer number of those units, might be used in the model. This integer is left to be assigned freely by the model to yield the optimal combination of storage types.

The model components—sets, parameters, and variables—are combined to form the governing equations for all of the scenarios tested. Below are the specific objective functions and constraint equations that provide realistic limits on the operation of thermal power plants and energy storage.

1. Objective functions

All models in this work share a common marginal cost minimization objective function equation. Equation (A1) includes marginal costs as well as other parameters included for control purposes

$$z = \sum_{g,t} mc_g x_{g,t} + \sum_{g,t} s_{g,t}. \tag{A1}$$

Equation (A1) captures major ongoing costs associated with thermal power generators—operating, fuel and maintenance costs (first term), and startup costs (second term). Marginal costs are given by Table XIII. Because renewable generation assets are assigned artificial marginal costs to ensure their dispatch, this objective does not strictly dispatch based on marginal costs. Each summation is over all terms in both sets g and t, or generators and time steps, respectively.

Startup costs are calculated using two equations, following the formulation of Carrión and Arroyo.[29] Equation (A2) calculates the startup cost values, where variable $s_{g,t}$ is positive for every startup, negative for every shutdown, and zero otherwise. To reflect real operations, where units would already be committed prior to the modeled period, startup costs are ignored in the first period to facilitate this initial commitment without penalty. Negative values that appear in the startup costs are removed from the $s_{g,t}$ matrix by Eq. (A3). The notation *foo.lo* indicates a GAMS-specific equation that sets the lower bound for a variable *foo*.

$$s_{g,t} = startcost_g(y_{g,t} - y_{g,t-1}), \tag{A2}$$

$$s.lo_{g,t} = 0. \tag{A3}$$

For models that include discrete storage selection, Eq. (A4) defines two additional terms that are appended to the objective given by Eq. (A1)

$$\ldots + \sum_{type,t}(0.25\, out_{type,t}\ varcost_{type}) + \sum_{type}\left(n_{type}\, inlimit_{type}\, fixcost_{type}\frac{card_t}{35040}\right). \tag{A4}$$

These terms calculate the variable (first term) and fixed (second term) marginal costs for those storage types employed in the model. The second term divides the length of the model ($card_t$) by the number of 15 min time steps in a 365 day year (35 040) to calculate total fixed marginal costs and correct for leap years.

2. Constraint equations

Each of the following equations simulates realistic physical constraints on generator operation. In all unit commitment systems, as in all real electricity generation and distribution systems, demand must be met at all times. Equation (A5) requires the model to dispatch generation to meet or exceed demand

$$\sum_{g} x_{g,t} - \sum_{type} in_{type,t} + \sum_{type}(out_{type,t} eff_{\text{type}}) \geq demand_t \qquad \forall\, t. \tag{A5}$$

The relation between dispatch ($x_{g,t}$) and demand ($demand_t$) implies that unit commitment could exceed demand, but because the objective to be minimized includes dispatch costs, demand will likely never be exceeded. Equation (A5) is dependent on the set t, thus, it is applied for all times t in the model formulation, as denoted by $\forall t$. Here, Eq. (A5) includes terms with the variables $in_{type,t}$ and $out_{type,t}$, which are only active in those models that have discrete storage selection. An alternate formulation could include a slack variable q on the left-hand side of the equation, allowing the model to not meet demand by assigning a positive value to q. The slack variable would appear in the objective function, multiplied by a large scalar value, penalizing the failure to meet demand. This approach could realistically represent the costs or penalties, if known, associated with blackouts or the use of resource entities. Correctly assigning the value of the penalty is crucial. If the penalty is too small, the model will pay it instead of dispatching any generators and if it is too large, it will never be used. This approach was avoided in the interest of determining unit commitment apart from the availability of demand as a resource.

For all generating units modeled, there exist minimum and maximum operating levels, applied to unit commitment variable $x_{g,t}$ with Eqs. (A6) and (A7)

$$x_{g,t} \geq y_{g,t}\, minpower_g \qquad \forall g, t. \tag{A6}$$

$$x_{g,t} + spr_{g,t}\Big|_{g<7} \leq y_{g,t} maxpower_g \qquad \forall g, t. \tag{A7}$$

These reflect real constraints on the rotating equipment of power plants, which can only generate electricity at a range of operating levels. Additionally, for those plants that are permitted to provide spinning reserve, indicated by the restriction on $spr_{g,t}$, they must not provide more spinning reserve than is possible given their nameplate capacity. Both equations apply for all units g during all periods t. To permit initial commitment at any allowable level between $minpower_g$ and $maxpower_g$ (or 0), these equations are not applied in the first time step t_o. Notably, units are not required to remain off for a specified amount of time through these or other constraint equations, as the penalty applied to generator startup in the objective function ensures, for the particular generating fleet and conditions modeled, that repeated unit startup and shutdown are avoided. Equations (A6) and (A7) also control the assignment of the commitment binary $y_{g,t}$, which indicates whether a unit g is operating in period t.

Typically, thermal power plants are constrained in their ability to change their power output level quickly. Additionally, when they turn on, they are not able to immediately provide generation up to their nameplate capacity.[30] For all time steps beyond the initial commitment period t_o, Eqs. (A8) and (A9) control unit commitment consistent with these limitations

$$x_{g,t} + spr_{g,t}|_{g<7} \leq x_{g,t-1} + 15 y_{g,t-1} rampup_g + (1 - y_{g,t-1}) minpower_g \qquad \forall g, t. \tag{A8}$$

$$x_{g,t-1} \leq x_{g,t} + 15 rampdown_g; y_{g,t} + (1 - y_{g,t}) minpower_g \qquad \forall g, t. \tag{A9}$$

As with Eqs. (A6) and (A7), Eqs. (A8) and (A9) are not applied until after t_o to allow initial commitment and dispatch, after which time any generator g can be committed to no more than its previous generation level plus its maximum ramp rate up, $rampup_g$, or less than its previous generation minus its maximum ramp rate down, $rampdown_g$. Additionally, spinning reserve from those plants that are permitted to provide it must not exceed the ramp up capability of that generator, as indicated in Eq. (A8). Ramp rates are specified in MW per minute, as in Table II, so those values are multiplied by 15 in Eqs. (A8) and (A9) to yield the ramp rate for each time step. Each of these equations applies to all generators g during all periods t.

For all generators that are permitted to provide spinning reserve, total reserve available for all times t must be greater than $resamt$ of 90 MW, the amount of reserve held by Austin Energy

$$\sum_{g} spr_{g,t}\Big|_{g<7} + \sum_{type}(str_{type,t}eff_{\text{type}})\Big|_{type\neq 3} \geq 90 \qquad \forall t. \tag{A10}$$

For scenarios with discrete storage selection, Eq. (A10) follows the form shown, including spinning reserve from thermal generators and available storage types except PHEVs. Where energy storage is treated similarly to other thermal generators, the str_{type} term is eliminated and the first term is expanded to include generic storage.

Because of Austin Energy's contractual arrangements with IPPs to furnish power from renewable power sources, these sources are modeled without marginal costs (Table XIII). As a result, regardless of the selected objective, all renewables will be fully dispatched by the model. Equations (A11)–(A13) further enforce this dispatch requirement by forcing the model to use all available renewable generation in all periods t

$$x_{g,t}\Big|_{g=10} = wind_t \qquad \forall t, \tag{A11}$$

$$x_{g,t}\Big|_{g=13} = solar_t \qquad \forall t, \tag{A12}$$

$$x_{g,t} = maxpower_g \qquad \forall g|_{g=11,12}, t. \tag{A13}$$

3. Storage-specific constraints

When storage is treated as simply an added on unit in the model with Austin Energy's existing thermal generation, only one additional equation is included in the model to control the assignment of $x_{g,t}$ for storage

$$\sum_{t} x_{storage,t} = 0. \tag{A14}$$

In the interest of constraining energy storage inflows and outflows as little as possible in any period t, only this constraint is applied. Equation (A14) requires that whatever is discharged from storage must be returned by the end of the modeled period, where round-trip efficiency of the transmission and energy storage system are assumed to be unity. As it is, this idealization precludes replication of model results with a real storage portfolio, which motivated expansion of the model.

To more realistically model energy storage in the unit commitment framework, additional equations for the model are developed using the parameters and variables from Tables XI and XII. These control the operation of storage to remain within the constraints presented in Table II. The major constraint equation controlling the use of energy storage defines the change in the quantity stored in each time step as the difference between the inputs and outputs in that period

$$stored_{type,t} = stored_{type,t-1} + in_{type,t} - out_{type,t} \qquad \forall type, t. \tag{A15}$$

Equation (A15) calculates the energy stored at the end of period t, $stored_{type,t}$, for all periods t and all storage units $type$. The variable $out_{type,t}$ measures the amount discharged from the storage device, where the amount delivered to the grid is $out_{type,t}$ multiplied by the round-trip efficiency eff_{type}. This multiplication is performed in the thermal generator Eq. (A5). Each of the variables represented in this equation capture totals for all n units of each type of storage selected in the results, which is distinctly different from storage unit parameters, which must be multiplied by n to determine actual operational constraints. Upper operational limits are controlled by

$$0.25 stored_{type,t} \leq size_{type} n_{type} \qquad \forall type, t, \tag{A16}$$

$$in_{type,t} \leq inlimit_{type} n_{type} \qquad \forall type, t, \tag{A17}$$

$$out_{type,t} + str_{type,t}\Big|_{type \neq 3} \leq outlimit_{type} n_{type} \qquad \forall type, t. \tag{A18}$$

Equation (A16) ensures that total energy stored (MWh) does not exceed the capacity of the storage unit at any point during the modeled time period. The coefficient 0.25 appended to variable $stored_{g,t}$ converts the right-hand side of the equation, which has units MW, to MWh of storage. Equations (A17) and (A18) control the maximum inflow and outflow for all storage devices selected by the model at all times t. In Eq. (A18), as in all equations where $str_{type,t}$ appears, spinning reserve from storage cannot be provided by PHEVs. In the model, this restriction is applied directly to the variable $str_{type,t}$ in the equation declaration.

In addition to limiting inflow and outflow for all storage types, the rate of change in these values must also be controlled

$$in_{type,t} - in_{type,t-1} \leq 15 chg_{type} n_{type} \qquad \forall type, t, \tag{A19}$$

$$in_{type,t} - in_{type,t-1} \geq 15 dischg_{type} n_{type} \qquad \forall type, t, \tag{A20}$$

$$out_{type,t} - out_{type,t-1} \leq 15 dischg_{type} n_{type} \qquad \forall type, t, \tag{A21}$$

$$out_{type,t} - out_{type,t-1} \geq 15 chg_{type} n_{type} \qquad \forall type, t. \tag{A22}$$

In a manner nearly identical to Eqs. (A8) and (A9) for thermal power plants, Eqs. (A19) and (A20) control ramp rates for inflows, while Eqs. (A21) and (A22) control ramp rates for outflows from all energy storage. These equations are formulated to limit the rates of change of inflows and outflows, such that increases in charge rates or decreases in discharge rates are changes in the same direction (more positive net flows) and are thus controlled by the storage parameter chg_{type}. Decreases in charge rates or increases in discharge rates reflect increasingly negative net flows and are controlled by the parameter $dischg_{type}$. The particular storage devices defined in Table II have ramp rates sufficient to ensure that the MW rating of the storage device will be the limiting variable for storage operation, but these equations are included in the interest of completeness.

Finally, regardless of ramp rates, a given energy storage $type$ cannot provide more reserve than is currently stored

$$str_{type,t} \leq stored_{type,t} \qquad \forall type\Big|_{type \neq 3}, t. \tag{A23}$$

Equation (A23) is entirely restricted to energy storage not provided from PHEVs because, as mentioned previously, they are not permitted to provide reserve since they cannot necessarily be expected to be plugged in when the utility wants to dispatch them. Other constraints to further limit PHEVs ability to provide storage would require predictions or estimates of owner behavior or desires. Further study of PHEV owner behavior is needed before they can be fully detailed in a unit commitment model. Further, it is unlikely that PHEVs will fit readily into a unit commitment framework since their availability will likely be non-optimal and subject to only limited control by the utility.

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