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Grid-level valuation and impact of large-scale energy storage deployments

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Grid-level valuation and impact of large-scale energy storage deployments

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Committee in charge:

Assistant Professor Duncan S Callaway, Chair
Professor Daniel M Kammen
Professor Shmuel S Oren

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Abstract

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Electric power systems are currently facing substantial changes in their operating frameworks on a wide variety of fronts. With increasing deployment of grid-connected wind and solar generators, power system operators are concerned that the challenge of following variable generator outputs may degrade system reliability. Additionally, as temperature changes associated with climate change increase, the magnitudes and frequencies of peak loads will correspondingly grow, thus compounding the variability problems introduced by intermittent generation. The fossil fuels that are currently used to run most of the system are changing in cost as new methods are developed to extract them, even as new policies are being proposed that restrict or tax carbon emissions. Additionally, much of the current electricity system infrastructure is nearing the end of its life, and will soon need to be decommissioned or replaced.

Energy storage has been proposed in several different venues as a solution to many of these problems. If energy storage can be deployed appropriately, it is possible that variability could be reduced, fossil fuel dependency could be lessened, and additional investments in new plants to handle increased demand could be avoided. Though these benefits could be large, the benefits to adding storage to the current grid have not been fully characterized.

We seek to better characterize the potential for storage to change overall grid operations. To do this, we use a 240-bus model based on the US Western Interconnection. In this model, we first optimally locate storage devices in the network and then dispatch them along with conventional power generation units by using a unit commitment model with DC load flow. Storage in the model can provide frequency regulation, load following, and arbitrage for each hour of a study year, and we investigate a range of scenarios for fuel price and renewables penetration. We use this model to investigate the demand curves for added storage and added TCL aggregations that function as thermal storage, as well as the extent to which carbon taxes may have an effect on the overall benefits that storage may provide. We find that storage and demand response are most valuable operationally and economically when they are providing high power services like frequency regulation and demand response. We

also show that the relationship between carbon taxes and the benefits that energy storage resources could provide is not linear.

To my wonderful husband, Ben Preskill,

who encouraged me, fed me, and loved me through this whole process

and to my late father, Gordon Good,

who always believed I could do anything, even if it seemed impossible, and who would happily have read every one of the following words.

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Chapter 1

Introduction

1.1 Overview

Energy storage is increasingly being considered for deployment on the electricity grid. While many possible functions for grid-connected storage have been identified, the overall value of storage performing one or more of these functions has not been fully characterized. Further, storage has often been identified as a technology that has the potential to reduce overall greenhouse gas emissions and enable renewables, but the extent to which storage can do this is still being assessed. Carbon taxes also have an important role to play in reducing greenhouse gas emissions, but they have not been studied in conjunction with storage. Finally, it has been suggested that energy storage services can be provided through demand response by aggregating thermostatically controlled loads and controlling their operating temperatures such that they act as thermal storage when desired. The grid-level benefits of such a strategy have not been fully assessed.

My research focuses on characterizing the value of increasing the energy storage capability of the current grid in California and WECC, using existing market structures to assess and compensate idealized storage devices. Through this research, I attempt to place bounds on the amount of energy storage that will reduce overall system operation costs in California and WECC wide, determine the extent to which future system changes might cause the bounds I assess to move, and characterize the extent to which storage compensation and total system value are decoupled. I test the hypothesis that large-scale storage penetration is necessarily going to decrease greenhouse gas emissions on a system-wide basis, and confirm that, under certain system conditions, storage does indeed lead to an increase in emissions. I also explore the extent to which carbon prices affect system benefit from storage, revenue potential for storage, and carbon emissions of the underlying system when storage is present. Finally, I explore the extent to which TCL aggregations, which operate like storage devices with time-varying power and energy constraints, can compare to storage in terms of system benefit.

1.2 Context and Motivation

The electric power system in the United States is facing a myriad of systemic changes that have the potential to disrupt current business operations. Renewable energy systems are increasingly being deployed across the country, and with the addition of their low-cost power comes a potential decrease in system reliability due to intermittency. As climate change progresses, peak loads are expected to become higher and more frequent, and the overall variability of the load to be met is expected to increase. The fossil fuels that are currently used to run most of the system are increasing in cost, and it is likely that they will become even more expensive as state, federal, and international bodies continue to implement policies that aim to reduce carbon emissions. Additionally, much of the current electricity system infrastructure is nearing the end of its life, and will need to be decommissioned or replaced.

Energy storage is currently being considered as one potential solution to many of these current and predicted problems. Additionally, energy storage capabilities have been implicated in a variety of proposed scenarios for future grid evolution [64] [45]. Depending on the type of storage technology, energy storage has the potential to reduce peak loads, decrease the need for conventional ancillary services, postpone infrastructure investment, provide ramp support for renewables, and increase system reliability [22]. At present, energy storage resources are limited, coming primarily from hydropower and having produced only 5.9% of the net electricity generated in 2008 [36]. Compressed air energy storage (CAES), sodium sulfur batteries, fly wheels, and lithium ion batteries are also being built out, but their portion of current storage capacity is much smaller than the portion held by pumped hydro storage [22]. It is likely that the buildout of these newer technologies will depend on the potential for storage to provide value to the current electricity system.

In light of these observations about storage and its potential for improvements to the overall grid, several policy decisions have been put into place. Assembly Bill 2514 (AB 2514), passed in 2010 and amended in 2012, directed the California Public Utilities Commission (CPUC) to adopt recommendations for increasing the current penetration of storage on the grid. In 2013, CPUC issued a decision in compliance with AB 2514 that requires all California utilities (Pacific Gas and Electric Company, Southern California Edison Company and San Diego Gas & Electric Company) to procure 1325 MW of storage by 2020, with installations required no later than 2024. The decision also establishes a target for community choice aggregators and electric service providers to procure energy storage equal to one percent of their annual 2020 peak load in the same time frame. These entities must file Tier 2 Advice Letters demonstrating their compliance every two years, starting in 2016 [14].

This decision does not address the duration of the required storage. There are many possible ways to achieve 1.325 GW of additional storage capacity, using a variety of technologies, from low energy capacity (e.g., lithiium-ion batteries) to high energy capacity (e.g., pumped hydro storage). This also means that the added storage could participate in a variety of markets, and that the storage capacity procured will not be earmarked for any particular function. Because storage devices can cover such a broad swath of functionality, future policy decisions that improve on AB 2514 may need further tailoring to ensure optimal future system buildouts of storage.

The rulemaking for AB2514 also cites Assembly Bill 32 (AB 32), the Global Warming Solutions Act, which aims to reduce overall emissions in California to 1990 levels by 2020 [6]. This means that AB2514 is making the implicit assumption that increasing storage penetrations will necessarily decrease carbon emissions. Unfortunately, this assumption is not borne out in the literature. [13] shows that storage actually increases carbon emissions in ERCOT, and [31] shows this more broadly for the US.

1.3 Research Questions and Approaches

Characterizing the value of storage at a system-wide level

The value of storage performing particular electricity system functions has been addressed in the literature. Sioshansi et. al. investigate the value of the energy arbitrage function of storage, and demonstrate that the value of energy arbitrage decreases as the total capacity of storage on the system is increased [56]. Drury, Denholm, and Sioshansi look at the revenue potential for CAES operators, if they participate in additional markets in addition to the energy market [20]. Eyer and Corey discuss 26 different value sources for storage, and benefit ranges in $/kW for each source [24], and the Electric Power Research Institute discusses benefits of various technology options in a 2010 white paper [22]. In summary, energy storage is increasingly being considered for deployment on the electricity grid, because of its potential to benefit the system in several ways, including but not limited to the following list of major storage benefits.

1. **Load Leveling/Arbitrage:** By charging when demand is low and discharging when demand is high, storage can reduce peak loads and reduce overall ramping throughout the day.

2. **Reserves:** Storage devices can be used to provide regulation, load following, spinning, and nonspinning reserves with differing energy/power ratios.

3. **Reduced transmission congestion:** By strategically placing storage devices, transmission congestion can be reduced by using storage to provide power during high-congestion times, and charging during low-congestion times.

4. **Power quality improvement:** Storage devices can be used to reduce voltage sag, undervoltage, and short interruptions in power supply.

5. **Enables Renewables:** In addition to improving power quality issues with intermittent generation sources, storage devices can be used to increase the predictability of the energy sourced from renewables.

6. **Reduces Spilling:** By charging when generation on the system is greater than demand, storage devices can reduce spilling of unused power.

7. **Reduces Carbon Emissions:** By enabling intermittent renewables and reducing the need for inefficient peaker plants, storage has the potential to reduce the overall carbon emissions of system operation.

8. **Delayed Investments:** Peaker plants, transmission lines, and transformers all need to be replaced or augmented as they wear out and system demand increases. If storage is used to reduce transmission congestion, level peak load, and improve power quality, these investments can be delayed, and in some cases may not be necessary.

While many possible functions for grid-connected storage have been identified, the overall value of storage performing one or more of these functions has not been fully characterized. It is also possible that there are some synergies between these categories where opportunities for storage are as yet undiscovered.

1.4 Carbon taxes and their potential effects on energy storage deployment

If storage is able to reduce spillage, decrease use of peaker plants, and enable the use of renewables, there exists some potential for storage technologies to reduce the use of carbon in a system overall. However, it is also possible that a system with carbon-intense baseload power and peakers that are less carbon intense, that storage could actually increase the carbon intensity of overall system operations, by charging storage devices using high-carbon baseload, and then discharging them at times when lower carbon peaker plants would have been in use. Effectively, this allows high carbon baseload power to be used in situations when it otherwise would not be, like those that call for fast-ramping or more capacity than currently exists on the system as baseload. This effect has been demonstrated in Carson and Novan, 2013 [13] and Hittinger et. al, 2015 [31], as well as Preskill, 2015 [52].

When carbon emissions go up due to a particular policy action or industrial innovation, it is becoming standard practice for policy makers and scholars to endeavor to balance out the increase in emissions with a decrease elsewhere, if it is not possible to prevent the increase altogether. A general strategy for reducing carbon emissions is pricing carbon, thus "internalizing the externality" [63]. Many researchers have employed prices or taxes on carbon as a way to drive down the rate of investment in fossil fuels, as well as incorporate the social costs of carbon into their models (see [7], [45], [50], and [29], among others). Because storage is not a generator of energy on its own, and instead operates as an arbitrage provider in energy markets, the effect of carbon taxes on any possible increases in emissions due to storage is not straightforward.

1.5 The storage-like behavior of aggregations of TCLs

As WECC increasingly moves toward a grid system with high-penetration renewables, larger ramping capabilities will become necessary to meet load in all hours reliably. This is particularly evidenced in the "duck chart," as discussed by CAISO, which indicates that by 2020, almost 14000 MW will be needed for ramp over a mere three hours in the evening [48]. This occurs as a result of peak demand in the evening overlapping with a sudden cut in solar generation as the sun sets. In large part due to this phenomenon, the California Independent System Operator has been developing a flexible ramping product, with the capability to handle multiple sources of variability that fall between the 15-minute real time unit commitment (RTUC) window and the 5-minute real time dispatch (RTD) window [66]. Storage could be a good resource for meeting such large ramping requirements, particularly high power, low duration storage, since the evening ramp is large, but relatively short.

One potential source for this type of storage resource is aggregations of thermostatically-controlled loads (TCLs). TCL aggregations are a good candidate, because they have high power capabilities relative to their energy storage potential. Mathieu et. al. (2013) describe the mechanism by which TCL aggregations might work in detail [42]. When large numbers of TCLs are operating such that they are within their deadband (meaning that the temperature is not so extreme that the TCL must be entirely off, or constantly on), it is possible to control them such that they continue to operate within their deadband, but the sum of their outputs follows an exogenous signal, rather than simply going up and down with the mean temperature.

1.6 Overview of the Thesis

Chapter 2 characterizes the value of storage in WECC by iteratively adding storage capacity to the grid and allowing it to provide a variety of services, including energy arbitrage, regulation, and load following. It also describes the model used for the rest of the work in detail. In Chapter 3, I use the model from Chapter 2 to show the effects of a carbon tax on the emissions that can be attributed to added storage. I also discuss the implications for storage revenues of a carbon tax, and argue that a high tax on carbon (greater than \$100/ton CO_2 is necessary to ensure that incentives for storage and benefits for the electricity system are aligned. In Chapter 4, I use the model from Chapter 2 to explore the differences between traditional storage and thermal storage implemented as aggregations of TCLs with time varying energy and power constraints.

Chapter 2

How much energy storage do modern power systems need?

2.1 Abstract

The central question we seek to address in this paper is: How rapidly do the operating cost benefits of grid-scale energy storage decline as installed storage capacity increases? We use a 240-bus model based on the US Western Interconnection, first optimally locating storage in the network and then dispatching it in a unit commitment model with DC load flow. The model uses storage to provide frequency regulation, load following, and arbitrage for each hour of a study year, and we investigate a range of scenarios for fuel price and renewables penetration. We find that value from long-term energy shifting is negligible at all penetrations we investigate, but also that displacing fossil-fueled generators from providing reserves is initially very valuable. However, in most scenarios the value is negligible beyond 10 GWh of storage, or the equivalent of roughly 6 minutes of average demand in the system. Above penetrations of 4-8 GWh, storage operating cost benefits are less than estimated capacity values for storage. We also show that storage has the potential to increase overall carbon emissions in the electricity sector, even when it is not providing significant amounts of arbitrage and is preferentially providing regulation and load following services.

2.2 Introduction

Energy storage is an important part of a variety of proposed scenarios for future grid evolution [64, 45, 51, 15, 34, 33]. Depending on the type of storage technology, energy storage has the potential to reduce peak loads, decrease the need for conventional ancillary services, postpone infrastructure investment, provide ramp support for renewables, and increase system reliability [22, 24]. At present, energy storage resources are limited, coming primarily from hydropower [36]. In the near term, the buildout of newer technologies – including compressed air energy storage (CAES), sodium sulfur batteries, fly wheels, and lithium ion batteries – will depend on the potential for storage to provide value to the current electricity system.

The most obvious use for storage devices is energy arbitrage, where storage devices are charged when prices (or system loads in regions without a real time energy price) are low, and then discharged when prices (or system loads) are high. Several papers have investigated the potential for energy storage to provide arbitrage services in various systems, e.g.[38], [31], [8]. However as the total capacity of storage on the system grows, or if the average spread of energy prices decreases with the addition of high-penetration renewables, the arbitrage value of storage could decline [28, 56, 30]. Some recent work suggests that revenue from arbitrage does not grow for storage capacities in excess of 5 hours [8].

As an alternative, several papers investigate the potential for storage to provide reserves. [20] find that providing reserves in addition to arbitrage services can net an additional $13-51/kW-yr in revenues for storage devices. [28] studied the impact of a range of storage technologies in a unit commitment model that included reserve constraints, and although they did not directly report on the value of providing reserves at different penetration levels, they did find that the operating benefits of storage technologies other than CAES do not justify their economic costs. [60] and [55] also demonstrate that there are benefits to providing reserves services using storage devices. Additionally, [9] show that regulation is the more valuable service to provide over arbitrage. In combination with Bradbury et. al.'s exploration of the relationship between revenue from arbitrage and duration, these results strongly suggest that optimizing storage device deployment for reserves over arbitrage will maximally add value.

[18] also raise the possibility that there is value to colocating storage with intermittent renewables, but while they demonstrate the value for individual producers by increasing the proportion of their power they are able to sell over a constrained network, they also indicate that the overall system benefits of storage are maximized when storage is operating according to system-wide price signals, rather than according to an individual generator's needs. Nevertheless, the location of storage is still important in a congested network, as the congestion relief provided by storage can allow power to flow from remote locations to demand centers.

However, these papers shed little light on how these relationships will evolve as we install increasing quantities of storage on the grid. Services valuable at low penetrations of storage are likely to be less valuable on the margin at higher penetrations. This paper builds on these earlier investigations by examining how rapidly the operating cost benefits – including reserve provision *and* arbitrage – of grid-scale energy storage decline as the quantity installed increases. To answer this question we simulate storage operation over a year at different levels of renewable generation, fuel prices and quantities of storage added. We use a model that iteratively adds storage capacity to a 240-bus model, choosing buses that maximize locational value. The model then uses the added resources to provide frequency regulation, load following, and arbitrage for each hour of the year. The choice of which services to provide is determined endogenously, based on the most valuable actions and the current operating constraints of the system. The model is based on a previously published model of the US Western Interconnection (WECC) [53], however our central objective is to make broad conclusions about how storage value depends on a variety of factors, rather than to precisely capture the specific value of storage in the WECC context.

As with earlier studies that include reserves, we find that storage value does not come from multi-hour energy shifting, but instead from displacing fossil-fueled generators from providing reserves; as such systems with higher requirements for regulation and load following provide more opportunity for storage value. However we find that the operating cost benefits due to storage decline very quickly with increasing penetrations: In most scenarios the value is negligible beyond 10 GWh of storage, or the equivalent of roughly 6 minutes of average demand in the system. We also find that, above penetrations of 4-8 GWh, storage operating cost benefits are less than hypothetical capacity values for storage – this suggests that capacity value will dominate investment decisions above those penetrations. In the long run, if penetrations of wind and solar grow even further and power system fuel mixes evolve to accommodate those changes, energy storage could play a more important role in diurnal (or longer) energy shifting, as in [43]. However our results suggest that in the short run energy storage has relatively little value at the transmission level.

While operating cost benefits are small, we do show that storage has the potential to *increase* overall carbon emissions in the electricity sector, even when it is not providing significant amounts of arbitrage and is preferentially providing regulation and load following services. These carbon increases continue beyond the point where storage provides significant operating cost benefits, meaning that even if the primary economic driver for building storage is capacity value, its day-to-day operations could be detrimental to system-wide carbon emissions. The carbon emissions increase is greatest in a high renewables / low gas price scenario, which is consistent with the most likely future conditions in light of energy futures prices and renewables capacity expansion rates.

2.3 Methods

Model and Solution Method

The model used for this analysis is an hourly unit commitment model of the Western Interconnection (also referred to as the Western Electricity Coordinating Council, or WECC). The model is formulated as a mixed-integer linear program that minimizes system operating costs subject to constraints on generator operation, storage device operation, DC power flow, and reserve requirements, which include both a short-duration regulation service, and a longer-duration load-following service. It is solved using a branch-and-cut algorithm that is implemented using the CPLEX 12.5 C++ library. Values and data sources for any constants in the following section are described in more detail in Section 2.3.

Objective Function

The objective function minimizes total system operating costs over the set $\mathcal{G}$ of generators on the system and the set of time periods modeled, $\mathcal{T}$, as follows:

$$\min \sum_{g\in\mathcal{G}}\sum_{t\in\mathcal{T}} \Gamma_g q_{gt} + SU_g s_{gt}, \tag{2.1}$$

where q_{gt} is a decision variable denoting the level of output for generator g in time period t and s_{gt} is a decision variable denoting whether or not generator g started up in hour t. Both Γ_g, the marginal cost for running generator g, and SU_g, the startup cost for generator g, depend on the fuel price F_g for generator g. Explicitly, $\Gamma_g = F_g * HR_g + O_g$, where HR_g and O_g are respectively the heat rate for generator g and the variable operations and maintenance cost for generator g.[1] We define startup cost as $SU_g = SE_g * F_g + SA_g$, where SE_g is the energy required to start generator g, and SA_g is the fixed cost component of starting generator g.

Generator Constraints

In each time period, each generator g in the model can supply regulation up, r^u_{gt} and regulation down, r^d_{gt} as well as load following up, lf^u_{gt} and load following down, lf^d_{gt}, in addition to the energy supplied, q_{gt}. These terms are related by the following two constraints:

$$q_{gt} + r^u_{gt} + lf^u_{gt} \leq \overline{Q}_g u_{gt} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T}, \tag{2.2}$$
$$q_{gt} - r^d_{gt} - lf^d_{gt} \geq \underline{Q}_g u_{gt} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T}, \tag{2.3}$$

where u_{gt} is a binary decision variable denoting whether or not generator g is operating in time period t, and $\overline{Q}_g$ and $\underline{Q}_g$ are the maximum and minimum generation limits, respectively, for generator g. Each of the ancillary service variables must also be less than their respective limits for each generator:

$$0 \leq r^u_{gt} \leq RU_g u_{gt} \qquad \forall g \in G, t \in T \tag{2.4}$$
$$0 \leq r^d_{gt} \leq RD_g u_{gt} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{2.5}$$
$$0 \leq lf^u_{gt} \leq LFU_g u_{gt} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{2.6}$$
$$0 \leq lf^d_{gt} \leq LFD_g u_{gt} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{2.7}$$

Between hours, generators are subject to ramp rate constraints:

$$R^-_g \leq q_{gt} - q_{g,t-1} - r^d_{gt} - lf^d_{gt} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{2.8}$$
$$R^+_g \geq q_{gt} - q_{g,t-1} + r^u_{gt} + lf^u_{gt} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{2.9}$$

[1]For simplicity we assume heat rate is constant across each generator's output range

Continuous startup variables for generators are used with binary operating variables and minimum up and down times in the manner described by [49]:

$$\sum_{k=t-UT_g+1}^{t} s_{gk} \leq u_{gt} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{2.10}$$

$$\sum_{k=t+1}^{t+DT_g} s_{gk} \leq 1 - u_{gt} \qquad g \in \mathcal{G}, t \in \mathcal{T} \tag{2.11}$$

$$s_{gt} \geq u_{gt} - u_{g,t-1} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{2.12}$$

$$0 \leq s_{gt} \leq 1 \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{2.13}$$

$$u_{gt} \in \{0, 1\} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T}. \tag{2.14}$$

Storage Constraints

We model energy arbitrage in each storage device as scheduled consumption or supply of energy in hourly blocks. We also model the commitment of storage capacity to provide regulation and load following reserves and enforce constraints on reserves that avoid "double counting" capacity, i.e. if capacity is committed to providing reserves it cannot also be used for arbitrage.

Energy in storage device m at time t, e_{mt} must be less than the capacity E_m of the storage device, where $\mathcal{M}$ is the set of all storage devices on the system:

$$0 \leq e_{mt} \leq E_m \quad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{2.15}$$

The charge and discharge rates for the storage device are also constrained by the power limits (P^{charge}, $P^{discharge}$) of the storage device:

$$0 \leq c_{mt} \leq P_m^{charge} \qquad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{2.16}$$

$$0 \leq d_{mt} \leq P_m^{discharge} \qquad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{2.17}$$

$$\tag{2.18}$$

All storage devices must also satisfy energy balance for scheduled arbitrage in all hours, such that

$$e_{mt} = e_{m,t-1} + \tau\beta_m c_{mt} - \frac{\tau}{\delta_m} d_{mt}, \tag{2.19}$$

where c_{mt} and d_{mt} are scheduled hourly charge and discharge rates, respectively, between hour $t-1$ and hour t, τ is the time period length in hours, and β and δ are the charging efficiency and discharging efficiency, respectively, of storage device m.

We enforce constraints to ensure that each battery is capable of serving the worst case reserve action in addition to delivering or consuming energy according to the arbitrage schedule. Discharging, regulation up, and load following up all require energy to leave the storage device, so the sum of the energy needed to provide each of those services (in the worst case where reserves are provided at the full contracted power for the total contracted duration) in hour t must be greater than the amount available at the beginning of the hour. Similarly, charging, regulation down, and load following down rely on headroom in the storage device, so their sum must be less than the head room available at the beginning of the hour. These constraints are represented as follows:

$$e_{m,t-1} \geq \frac{1}{\delta_m}\left(\tau d_{mt} + \tau^r r_{mt}^{us} + \tau^{lf} lf_{mt}^{us}\right), \tag{2.20}$$

$$E_m - e_{m,t-1} \geq \beta_m\left(\tau c_{mt} + \tau^r r_{mt}^{ds} + \tau^{lf} lf_{mt}^{ds}\right), \tag{2.21}$$

where τ^r is the length of time for which regulation must be provided in hours, τ^{lf} is the length of time for which load following must be provided in hours, and r_{mt}^{us}, r_{mt}^{ds}, lf_{mt}^{us}, and lf_{mt}^{ds} represent the power contributions of the storage device at node n to regulation up, regulation down, load following up, and load following down, respectively, in time period t (we will define these parameters in Section 2.3).

Network Constraints

We enforce nodal power balance constraints for hourly schedules with a linear DC load flow model:

$$\sum_{g\in G_n}(q_{gt}) + \sum_{m\in M_n}(c_{mt} - d_{mt}) + \sum_{i\in N} B_{ni}(\theta_{nt} - \theta_{it}) = L_{nt}, \tag{2.22}$$

where G_n is the subset of generators located at node n, M_n is the subset of generators located at node n, B_{ni} is the susceptance between node n and node i, θ_{nt} is the voltage angle at node n at time t, and L_{nt} is the load at node n at time t.

Also, the total load flow on line ij must be less than or equal to the maximum load flow allowed, $\overline{D}_{ij}$:

$$B_{ij}(\theta_{it} - \theta_{jt}) \leq \overline{D}_{ij} \tag{2.23}$$

Note that we do not model power flow associated with reserve actions; we assume that any line capacity violations that result from reserve actions are sufficiently small or short in duration that they can be tolerated by the system operator or, in the case of larger disturbances, that the system can be redispatched to resolve constraints. We assume these events are sufficiently rare that they can be neglected for our objective of quantifying the annual cost benefits of storage at the scale of the model.

Reserve Requirements

In each hour, minimum reserves of each type (regulation in up and down directions, load following in up and down directions) must be procured, corresponding to system needs. We model daily regulation up and down requirements as a proportion, ρ, of the peak load for the day added to a proportion, σ, of the total installed wind and solar capacity. We model load following up for each hour as a proportion, η, of the forecasted load plus a proportion, ν, of the forecasted wind and solar for the hour. We model the load following down requirement as a constant proportion of the renewables forecast. The following equations define these constraints explicitly, with $\overline{S}_n$ and $\overline{W}_n$ being the solar and wind capacities installed at node n, respectively, and S_{nt} and W_{nt} being the solar and wind forecasts at node n during time period t. To reduce complexity, we model total reserves constraints globally.

$$\sum_{g\in G}(r^u_{gt}) + \sum_{m\in M}(r^{us}_{mt}) \geq \rho\left(\max_{a\in T:t_{max}-a\geq t} L_{na}\right) + \sigma\left(\sum_{n\in N}(\overline{S}_n + \overline{W}_n)\right) \qquad \forall t \in \mathcal{T} \qquad (2.24)$$

$$\sum_{g\in G}(r^d_{gt}) + \sum_{m\in M}(r^{ds}_{mt}) \geq \rho\left(\max_{a\in T:t_{max}-a\geq t} L_{na}\right) + \sigma\left(\sum_{n\in N}(\overline{S}_n + \overline{W}_n)\right) \qquad \forall t \in \mathcal{T} \qquad (2.25)$$

$$\sum_{g\in G}(lf^u_{gt}) + \sum_{m\in M}(lf^{us}_{mt}) \geq \eta \sum_{n\ inN} L_{nt} + \nu \sum_{n\in N}(S_{nt} + W_{nt}) \qquad \forall t \in \mathcal{T} \qquad (2.26)$$

$$\sum_{g\in G}(lf^d_{gt}) + \sum_{m\in M}(lf^{ds}_{mt}) \geq \nu \sum_{n\in N}(S_{nt} + W_{nt}) \qquad \forall t \in \mathcal{T} \qquad (2.27)$$

Solution Method

We run the model iteratively for each of the days in a given year, passing the final storage levels, generator output levels for ramping, and generator operating and starting levels as constants denoting the starting levels for the next day. This corresponds to the following constraints, where the *prev* superscript denotes variables from the previous day's solve:

$$e_{n0} = e^{prev}_{n24} \qquad \forall g \in G \qquad (2.28)$$

$$u_{gb} = u^{prev}_{g,24+b} \qquad \forall g \in G, b \in (-DT_g + 1, ..., 0) \qquad (2.29)$$

$$s_{gb} = s^{prev}_{g,24+b} \qquad \forall g \in G, b \in (\min(-UT_g + 1, -DT_g + 1), ..., 0) \qquad (2.30)$$

Additionally, because it would otherwise be optimal to fully discharge storage devices at the end of each unit commitment modeling period, we also constrain the final storage levels and generator operating levels. To do this, we run a preliminary two-day unit commitment model with a four hour time step for the generator unit commitment variables, and save the generator and storage states at the end of the first day for use as constraints in a second run. In the second (final) run, we use single-day unit commitment in one hour increments with final storage charge levels and final generator operating states constrained to be equal to those saved from the first run (as in [55]). This corresponds to the following additional constraints for the first two-day unit commitment, where $T = \{t \in \mathbb{Z} : 1 \leq t \leq 48\}$

$$u_{gt} = u_{g,t-1} = u_{g,t-2} = u_{g,t-3} \ \forall g \in G, \{t \in T : t \mod 4 = 0\} \qquad (2.31)$$

We implement the model in C++ and solve it with CPLEX 12.5. We solve the first two-day unit commitment problem with a mip gap of 0.5%, and the second problem with a

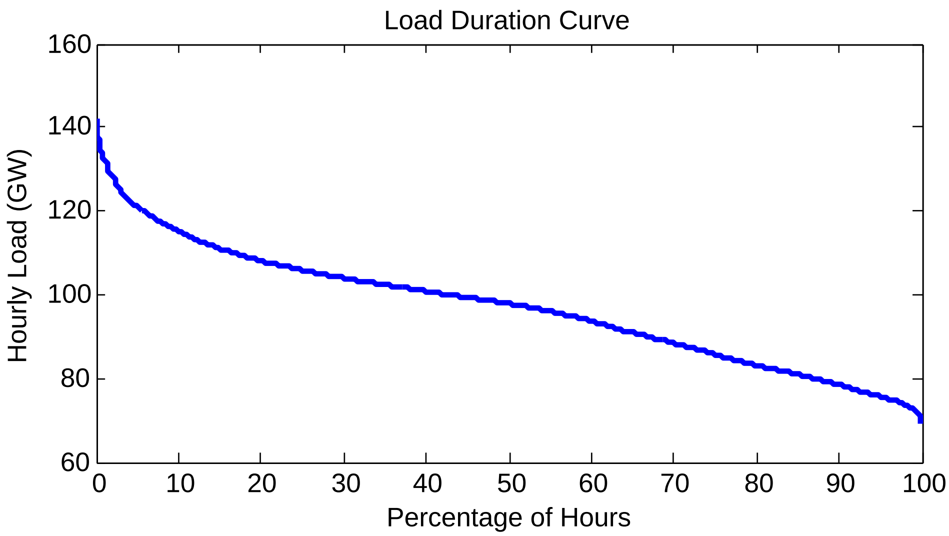

Figure 2.1: The load duration curve for the year of data modeled.

mip gap of 0.05%. The average time taken to solve these two problems and obtain results for an individual day was 72.4 seconds.

Data Inputs

The layout of the system network for the model is based on data for the 240-bus model created and published in association with a model developed at CAISO [53], hereafter the Price model. From this resource, we obtain susceptances B_{ij} and line limits $\overline{D}_{ij}$ for the network. The hourly load at each node, L_{nt}, also comes from the Price model, and is based on 2004 data. Though WECC infrastructure has evolved since that time[2], our objective in using the Price model is to capture the effect of storage operating over large scales, but not to precisely model the effect of storage on current infrastructure. However as we will discuss, we will investigate how storage additions impact system operations in different renewables penetration scenarios. Figure 2.1 shows the yearly load duration curve.

In total, the model commits and dispatches 185 generators, of which 38 are coal-fired, 135 are gas-fired, 4 are nuclear, and 8 are run on fuel oil. The model does not dispatch hydro, biomass, wind, solar, and geothermal plants; instead the production profiles and capacities for those generators originate in the Price model. The set of dispatched generators used is based on disaggregated generator data from the Price model, which are then modified such that generators with similar heat rates are aggregated together, and each node in the network

[2]In the time since the model was built, total demand has remained relatively flat [61] and generation capacity for all fuels but wind, solar and natural gas were virtually unchanged [21]. Gas capacity has grown significantly since 2004, however because total and peak demand remained flat this capacity has had relatively little impact on operations.

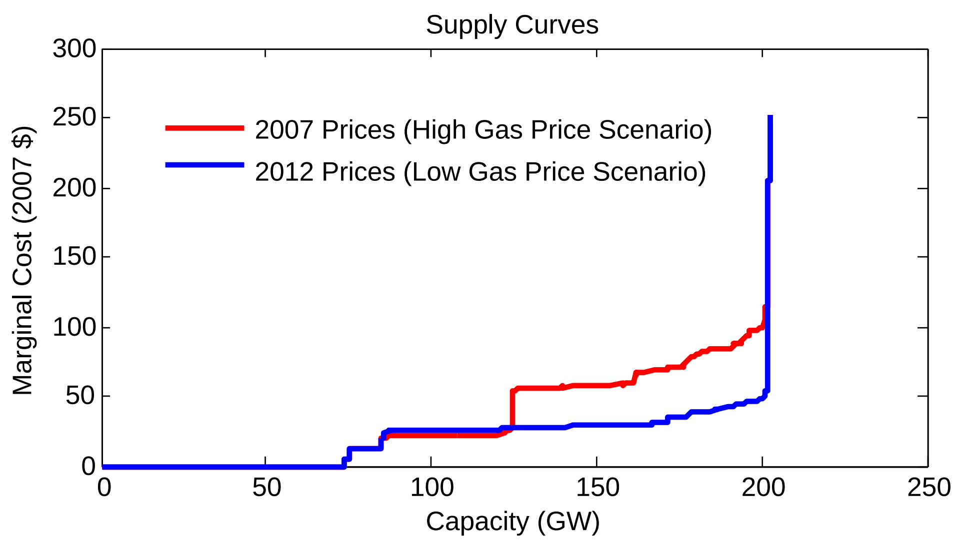

Figure 2.2: The supply curves for the set of generators modeled, in the low and high gas price scenarios. The supply curves in this graph are created for the low renewables scenarios; the high renewables scenarios have a larger region where the marginal cost is zero.

has only one generator with each heat rate, which reduces symmetry in the subsequent formulation. From the Price data we obtain heat rates and maximum operating capacities for each generator (HR_g, $\overline{Q}_g$). We obtain fuel prices F_g from EIA data corresponding to 2007 and 2013 ([57], [58]). Figure 2.2 shows how the heat rate curves for all generators with non-zero marginal cost on the system change with fuel prices.

We match the prime mover for a generator in the Price data, when available, to TEPPC generator category data from the 2009 TEPPC Study Program Results to obtain ramp limits (R_g^+, R_g^-), minimum up- and down-times (UT_g, DT_g), minimum operating capacities ($\underline{Q}_g$), start-up costs and startup energy required (SA_g, SE_g), and variable operations and maintenance costs (O_g). When only a fuel type, rather than a prime mover is available from the Price data, we chose the generator type from the TEPPC data with the heat rate that is the closest to the heat rate reported from the data in the Price model and use the corresponding figures.

In each hour, we enforce ancillary service constraints for regulation and load following. We model these on the requirements used in [51]. Total regulation in both directions must be greater than 1% of peak load ($\rho = 0.01$) in both directions. The Western Wind Integration Study indicates that 1% of peak is acceptable for regulation with respect to wind capacity, but does not investigate whether this also applies for additions of solar. To ensure that regulation needs are satisfied with the addition of both resources, we also add 1% of the installed wind and solar capacities to the regulation requirement in both directions ($\sigma = 0.01$). Total load following in the up direction must be greater than the sum of 3% of forecasted load and 5% of forecasted wind and solar ($\eta = 0.03$, $\nu = 0.05$), in accordance with the "3+5" rule. In accordance with the need for load following in the down direction as specified in [39], we also require an amount of reserve in the down direction equal to 5% of forecasted wind and solar.

The maximum regulation (RU_g, RD_g) and load following capabilities (LFU_g, LFD_g) of each generator are calculated based on the maximum generator movement in 10 minutes, using the one-minute ramp rate for the generator's prime mover [62]. Generator limits on ramps between hours were calculated based on maximum generator movement in 60 mins. [49]

In addition to the generators, the model also dispatches 4 pumped-hydro plants in all scenarios. The efficiencies and capabilities for the pumped hydro plants are taken from the Price model, and comprise 3.0 GW of power, with 201 GWh of total energy capacity.

We assume that storage efficiency is 90% on both charge (β_n) and discharge (δ_n) and a power:energy ratio of 4, such that $P_n^{discharge}/E_n = 4$. By choosing this ratio, we ensure that power constraints will bind for regulation, and energy constraints will bind for load following and arbitrage. Both pumped hydro and added storage can provide regulation and load-following, subject to constraints that require enough energy to be present in the battery (or energy capacity for charging in the case of down reserves) for provision of 15 minutes of regulation and 2 hours of load following (Eq. (4.15) and Eq. (4.16) with $\tau^r = 0.25$ hrs and $\tau^l = 2$ hrs) [55].

Placing Storage in the Model

We determined the locations for storage devices prior to running the unit-commitment model by slightly modifying the model. Specifically, we include decision variables denoting the total amount of energy storage capacity to be added at each node and, for each total storage quantity E_{tot} we investigate, we constrain the sum of storage capacity across all nodes such that $\sum_{\forall n} E_n \leq E_{tot}$. Because these added decision variables significantly increase the complexity of the model we made several modifications to limit computing time in the placement phase. First, we only run the model on the peak demand day. Second, because reserves are not a location-specific quantity in the model, we dropped reserve requirements from the objective function. Finally, we identified storage locations iteratively, i.e. after locating the smallest quantity of storage, we fix its location and identify the location of the next increment of storage, and so on. Because of these modifications to the model, added increments of storage are only optimal for energy arbitrage on the peak demand day. However, because the peak demand day is the most severely constrained and energy is the only quantity subject to nodal balance constraints, we assume that the identified locations are a decent proxy for the true optimal locations. In all scenarios, storage is preferentially located in San Diego before any other locations.

Scenarios

We explored four different scenarios that allowed us to explore the effects on the value of storage of high vs. low natural gas prices and high vs. low penetrations of renewables. First, we explored low and high natural gas prices. We used average fuel prices from recent years in which gas prices were relatively high (2007; the "high gas price" scenario, \$7.12/MMBtu for gas and \$1.77/MMBtu for coal, 2007 \$ [57]) and relatively low (2012; the "low gas price" scenario, \$3.17/MMBtu for gas and \$2.22/MMBtu for coal [58]). Figure 2.2 shows a supply curve for the generators and prices modeled. For each natural gas price, we also looked at a low-penetration renewables scenario and a high-penetration renewables scenario that meets California's RPS goals [53]. The low penetration scenario has 6.5 GW of wind and 0.5 GW of solar, whereas the high-penetration scenario has 24 GW of wind, and 7 GW of solar.[3] We also perform a low wind, high solar scenario high-penetration scenario where we scale solar profiles and wind profiles such that their respective installed capacities are reversed.

2.4 Results

Total Social Benefit from Storage

Figure 2.3 shows the total system cost savings for each of the four major scenarios as a function of storage energy added to the system. The range of benefits across scenarios is very large, and both renewables penetration levels and fuel prices have significant impact on the outcome, though for the scenarios we investigate fuel prices appear to matter more. Note that, because some capacity is allocated to regulation (requiring a 4C battery) and some to spinning reserve (requiring a 1/4C battery), we report results only in units of energy storage (GWh) on the x-axis, rather than units of power capacity. We also find that, for a given penetration of renewables, the specific mix of solar and wind has little impact (less than 4%) on savings attributable to storage (Figure 2.4). This is in contrast to other recent results that suggest storage is more important in systems with high solar versus high wind penetration (e.g. [43]). We attribute this difference to several observations: (1) our model optimizes only the *operation* of the system but not the mix of generation infrastructure as in [43] and (2) storage does relatively little net load shifting in our model and instead is allocated to the higher value ancillary services; we will discuss this more when we describe Fig. 2.9 below. Finally, we note that storage will be more important for load shifting at higher solar penetrations.

Figure 2.5 shows the marginal benefit for storage for a 20-year time horizon with a 7% discount rate, assuming identical cost savings each year (left vertical axis), and also for a single year (right vertical axis). The marginal benefit is computed as the ratio of the change in operating cost resulting from each incremental addition of storage to the size of the storage

[3] These scenarios are taken directly from the Price model; wind and solar capacity in WECC in the most recent available year (2013) were approximately 18 and 5 GW, respectively [21]

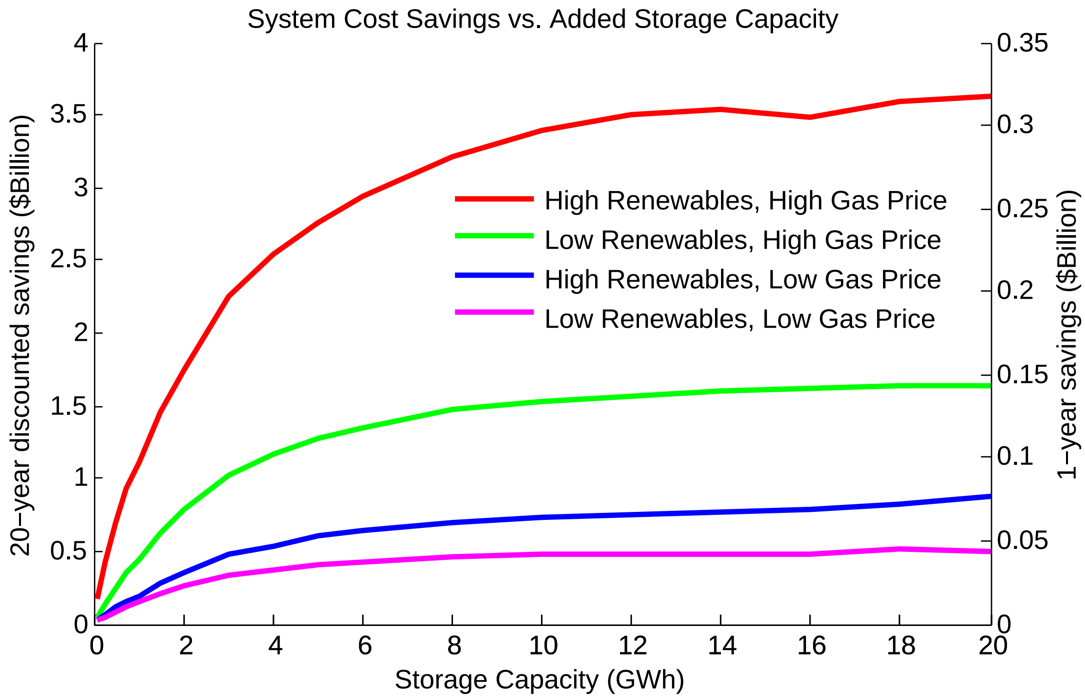

Figure 2.3: System cost savings as storage penetration is increased. System cost savings level out in each scenario, and by the time 20 GWh of additional storage are added, increasing the amount of storage on the system no longer produces significant savings.

increment. We see that the diversity in value of a small addition of storage capacity across scenarios is large, with the 20-year benefit ranging from $1800/kWh in the high gas price / high renewables scenario to about $200/kWh in both low gas price scenarios. Still, with small amounts of storage on the system, the marginal benefit of additional storage in every scenario is greater than the ARPA-E GRIDS target of $100/kWh [4] (depicted as a dashed line in Figure 2.5), suggesting that discounted system benefits would be greater than storage capital costs for storage technologies that meet this target.[4] The marginal benefit then drops off sharply, such that by the time 10 GWh of storage capacity have been added to the system,[5] the marginal benefit in all scenarios falls below $100/kWh. By the time 20 GWh of additional storage are added, increasing the amount of storage on the system no longer produces significant operating cost savings. We note that current battery costs are significantly higher than the ARPA-E target, however we do not consider those costs here because the industry is in a phase of rapid cost reduction and policies to support energy

[4]ARPA-E's target is for systems 1C systems, i.e. batteries that discharge their rated energy in 1 hour. Frequency regulation requires higher power rating (we assume 4C, or systems that discharge their rated energy in 1/4 hour), which would add to the cost of the technology, possibly significantly more. Therefore $100/kWh in our context should be taken as an especially low and aggressive target.

[5]For context, at an average demand of 97.1 GW (the average for the dataset used here), 10 GWh of storage capacity could supply average demand in the model for 6 minutes and 11 seconds.

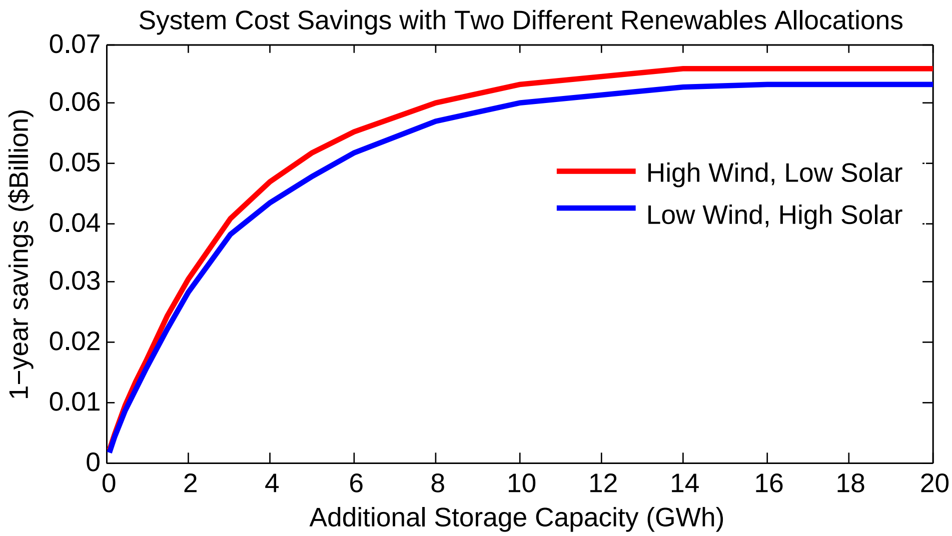

Figure 2.4: In this graphic, the renewable energy provided in the high renewables / low gas price scenario has been reallocated, such that about 66% of the total renewable energy comes from solar (the low wind / high solar scenario). The default case has been provided as the high wind / low solar scenario. The distribution of energy between wind and solar does not significantly affect the value provided by storage.

storage are likely to be based on the potential for cost:benefit ratios to be attractive in the future rather than today.

The most likely scenario for the future is one in which gas prices are low, and in these scenarios the $100/kWh break-even point allows no more than 4 GWh of energy storage capacity on the system before capital costs (at the $100/kWh target) are no longer recovered through system benefits. Capital costs depend strongly on technology type and power to energy ratio, and battery-only cost estimates (i.e. not including balance of system costs) currently span a very broad range [47], although many are working to develop storage devices that will meet the ARPA-E GRIDS target at scale [67, 44].

We can also compare these marginal benefits to the capacity value[6] that storage might provide. To do this, we divide the lowest cost of conventional generation capacity (we used the overnight cost for a combustion turbine, taken from [5] as $650/kW) by the number of hours storage would need to operate to be qualified as providing capacity value to the system (we assume 4 hours, based on recent requests for offers in California [54]). These parameters give an approximate storage capacity value of $160/kWh. In the low gas price scenarios, the marginal value of storage for providing arbitrage and ancillary services quickly falls below this number, suggesting that capacity payments will be an important factor for storage investment in these conditions. On the other hand, for the high gas price / high

[6]By *capacity value* we mean the amount of power a device can make available during peak load conditions.

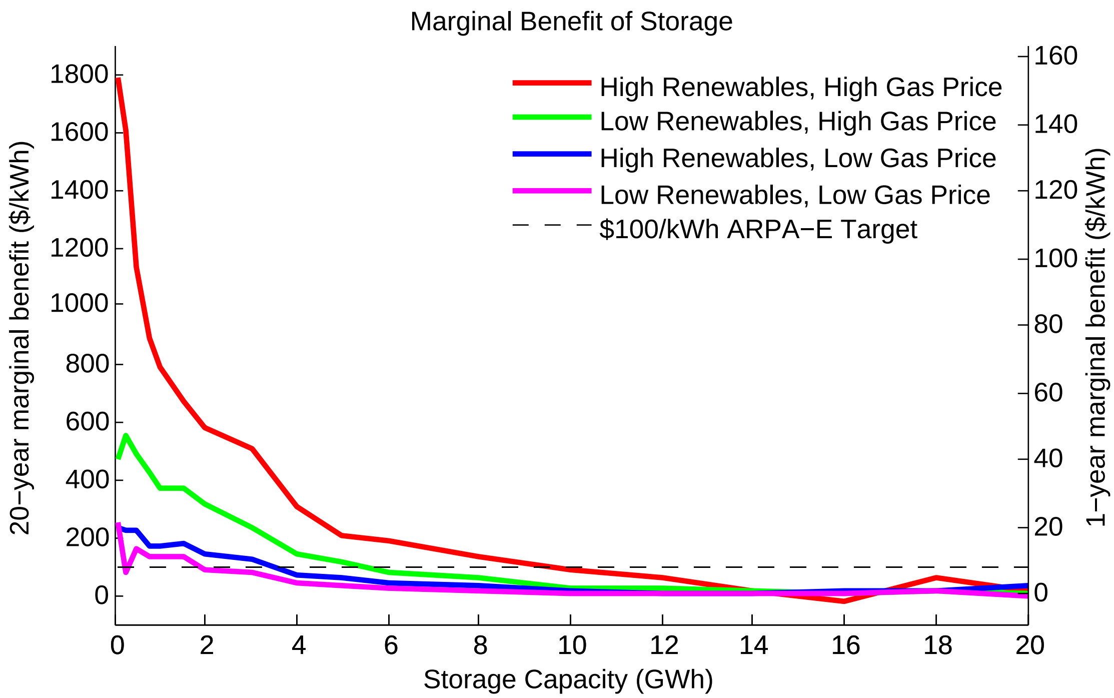

Figure 2.5: Marginal benefit of additional storage. In all scenarios, the benefit of adding an additional unit of storage decreases as the total amount of storage capacity on the system is increased.

renewables scenario, capacity payments may not drive investment in storage until higher penetrations (8-10 GWh across the system). Note that capacity value will be higher in "load pockets" with strong constraints on citing conventional generators (e.g. the Los Angeles basin); analysis of these conditions is outside the scope of this paper.

Figure 2.6 shows the proportions of various ancillary services requirements that are satisfied by storage. Because storage satisfies regulation up requirements first, these results indicate that regulation up is the most valuable service for storage to satisfy. The next most valuable services are load following up and regulation down, and finally load following down. With a higher gas price, more of the load following up requirement is satisfied by storage. While it might otherwise make sense to satisfy both load following up and regulation down services with the same storage device, in practice this will be undesirable, as regulation requires higher power capacity than load following, and a single storage device will likely be better suited for one or the other service. For investment purposes, it may be reasonable to invest first in high power, lower energy capacity storage devices that will supply regulation up and down, and then later install more moderate power devices with higher energy capacities that can satisfy load following requirements in both directions.

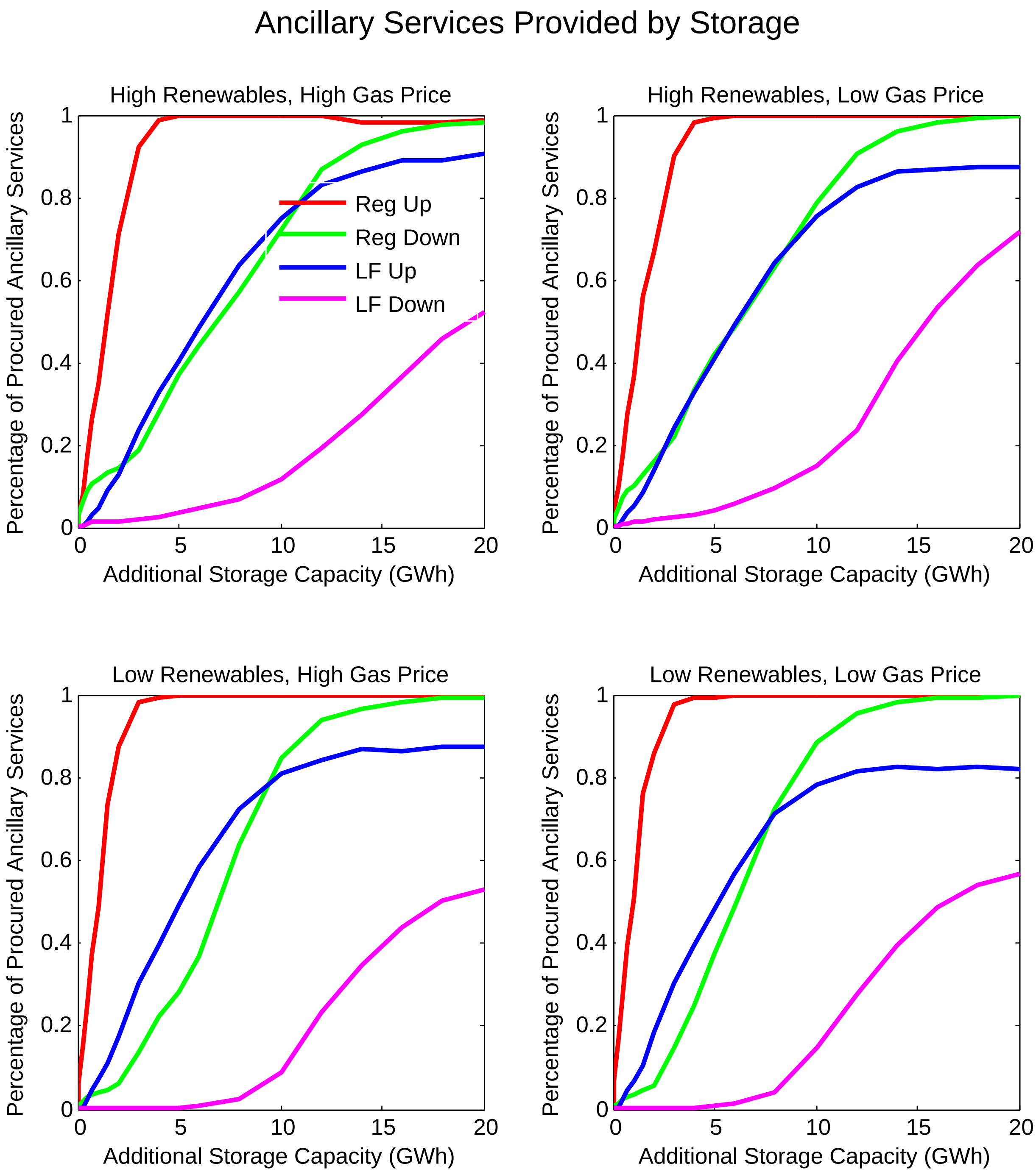

Figure 2.6: Proportions of ancillary services served by storage devices in various scenarios. In all scenarios, storage quickly moves to provide all required regulation up. Subsequently, storage emphasizes the provision of regulation down and load following up, and then finally begins to increase the proportion of load following down provided.

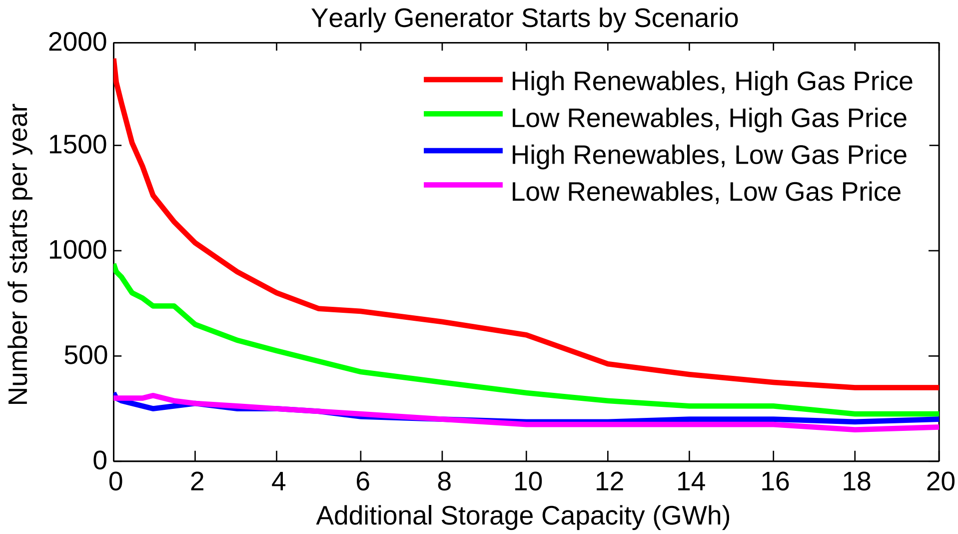

Figure 2.7: Number of generator starts per year. As the total amount of additional storage capacity on the system increases, the total number of generator starts decreases. The resulting reduction in startup costs paid contributes to the corresponding decreases in total system operating costs, as shown in Figure 2.3.

Figures 2.7 and 2.8 indicate that the number of generator starts and the cost due to generator starts both decrease in all scenarios as the amount of storage present in the system is increased. The savings due to reductions in generator starts is roughly 10 percent in the most impactful scenario (high renewables penetrations and high gas prices). With lower gas prices, the reduction in generator starts due to storage devices is much less dramatic than in the scenarios with higher gas prices. This is likely due to the fact that, in lower gas price scenarios, generators need to be turned off for a longer length of time to make incurring their startup costs economical.

Private and Market Benefits from Storage

In this section we investigate storage device profits and whether the system benefit from storage can be captured by independent storage operators. For energy market revenue, we assume each generator or storage device is paid the locational marginal price (LMP) for the node at which it is located. We obtain this price from the dual of the node balance constraint Eq. (4.30), which we will call λ_{nt}, where $n \in \mathcal{N}$ and $t \in \mathcal{T}$. Assuming a competitive market, we compute the market clearing price for each reserve market in each hour as the maximum opportunity cost (\$/MW) faced by a generator that is providing the corresponding resource in that hour. We will refer to these hourly prices as λ_t^{ru}, λ_t^{rd}, λ_t^{lfu}, and λ_t^{lfd} for regulation up, regulation down, load following up, and load following down, respectively. Only generators constrained by their maximum capacities (for generators providing up reserves) or minimum

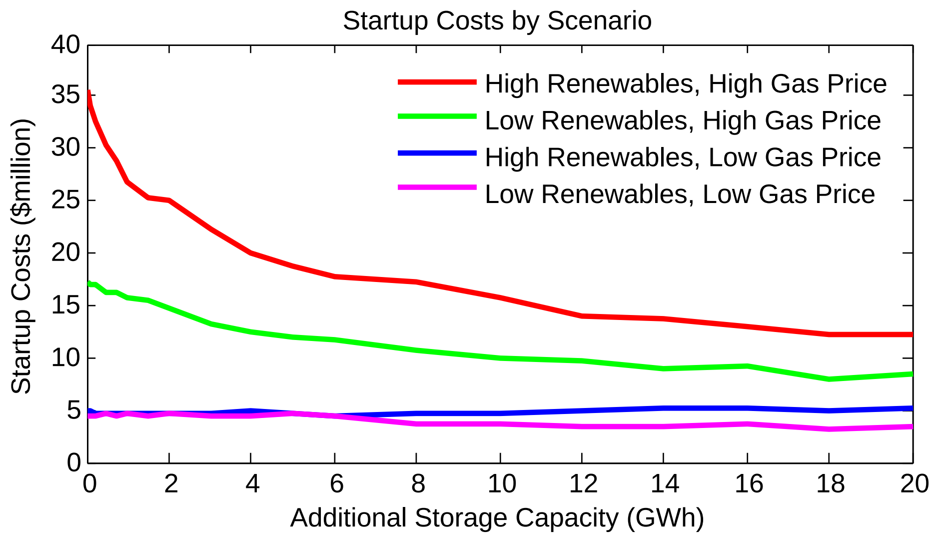

Figure 2.8: Cost of generator starts. As the total amount of additional storage capacity on the system increases, the total cost of generator starts decreases. The resulting reduction in startup costs paid contributes to the corresponding decreases in total system operating costs, as shown in Figure 2.3.

capacities (for generators providing down reserves) experience opportunity costs. Generators that have not committed their full, currently available capacities are indifferent to committing their capacities to one market versus another; they have available capacity to do both [65].

The gross profit, z_i, for a given storage device i over the entire year, then, is calculated as follows:

$$z_i = \sum_{t \in T} \left(\lambda_{it} d_{it} - \lambda_{it} c_{it} + \lambda_t^{ru} r_{it}^{us} + \lambda_t^{rd} r_{it}^{ds} + \lambda_t^{lfu} lf_{it}^{us} + \lambda_t^{lfd} lf_{it}^{ds} \right) \tag{2.32}$$

The total gross profit in the system, Z, is the sum of the z_i's over all storage devices in the system ($i \in \mathcal{S}$). Gross profit is calculated as the revenue received in the energy, regulation, and load following markets, less the cost to charge storage with energy purchased in the market. We do not include other costs or revenues in this metric (for example storage capital costs, taxes and depreciation, or tax incentives).

Figure 2.9 shows the changes in the value of the contribution to Z of reserves, load following, and energy arbitrage as additional storage devices are added to the system. The total revenue available is largest in the high renewables / high gas price case, when the reserve requirements are the largest due to the renewables, and the market clearing prices are set by generators with higher marginal fuel costs. The value to storage operators is coming from reserves more than arbitrage; in fact, as the total amount of storage on the system increases, storage operators lose money in the energy markets in favor of making capacity available for the more lucrative regulation and load following markets. Notably, while the regulation markets are the most lucrative initially, the revenue in these markets drops off quickly, and load following is the service that provides the most revenue over the largest range of installed storage capacities.

Figure 2.10 shows the marginal changes in Z as the total amount of storage in the system is increased. The total market revenue is largest in the high renewables / high gas price case, when the reserve requirements are the largest due to the renewables, and the market clearing prices are set by generators with higher marginal fuel costs due to the higher gas prices. Similar to the operating cost benefits, this metric also declines rapidly, and once the system has at least 10 GWh of capacity installed, the market revenue for energy and ancillary services available to storage operators becomes small and unlikely to cover storage capital costs on their own.

Figure 2.11 shows the ratio of the estimated market revenue (Z) for storage to its corresponding operating cost savings. In the figure, the ratio dips below one between 4 GWh and 6 GWh of storage capacity. This indicates that at this point, the system benefits from the presence of storage are no longer captured by storage operators through the markets modeled here. Primarily, these unaccounted for system benefits are realized as avoided starts when minimum up/down time constraints or ramp constraints would otherwise bind. Because storage operators are reliant on prices that are set by marginal costs of generators, storage operators are not able to realize the full value of their services, as the value of avoided starts is not reflected in the market clearing price for generation.

Carbon Emissions Due to Storage

As storage is added to the system, the carbon emissions associated with operating the system increase for most scenarios. Figure 2.12 shows that carbon dioxide emissions strictly increase in most scenarios as storage penetration increases. In the high renewables, high gas price scenario carbon dioxide emissions experience a slight decrease until 1 GWh of storage capacity is present, and then emissions begin to increase. This effect is driven by fuel switching (from gas to coal), as shown in Figure 2.13. When gas prices are low, there is less incentive to turn off gas plants to save money, since the savings from plant cycling is not enough to overcome large startup costs. This causes there to be more resources available on the system that can act as base load. The gas plants that are held on at their minimum capacities to avoid future startup costs are still more expensive to use on the margin than coal plants during operation, so coal plants are more frequently used at higher capacities.

It is particularly notable that the most significant emissions increases happen in the high renewables / low gas price scenario, which may well be the most likely in light of energy futures prices and renewables capacity growth rates. We will revisit this issue in the conclusions.

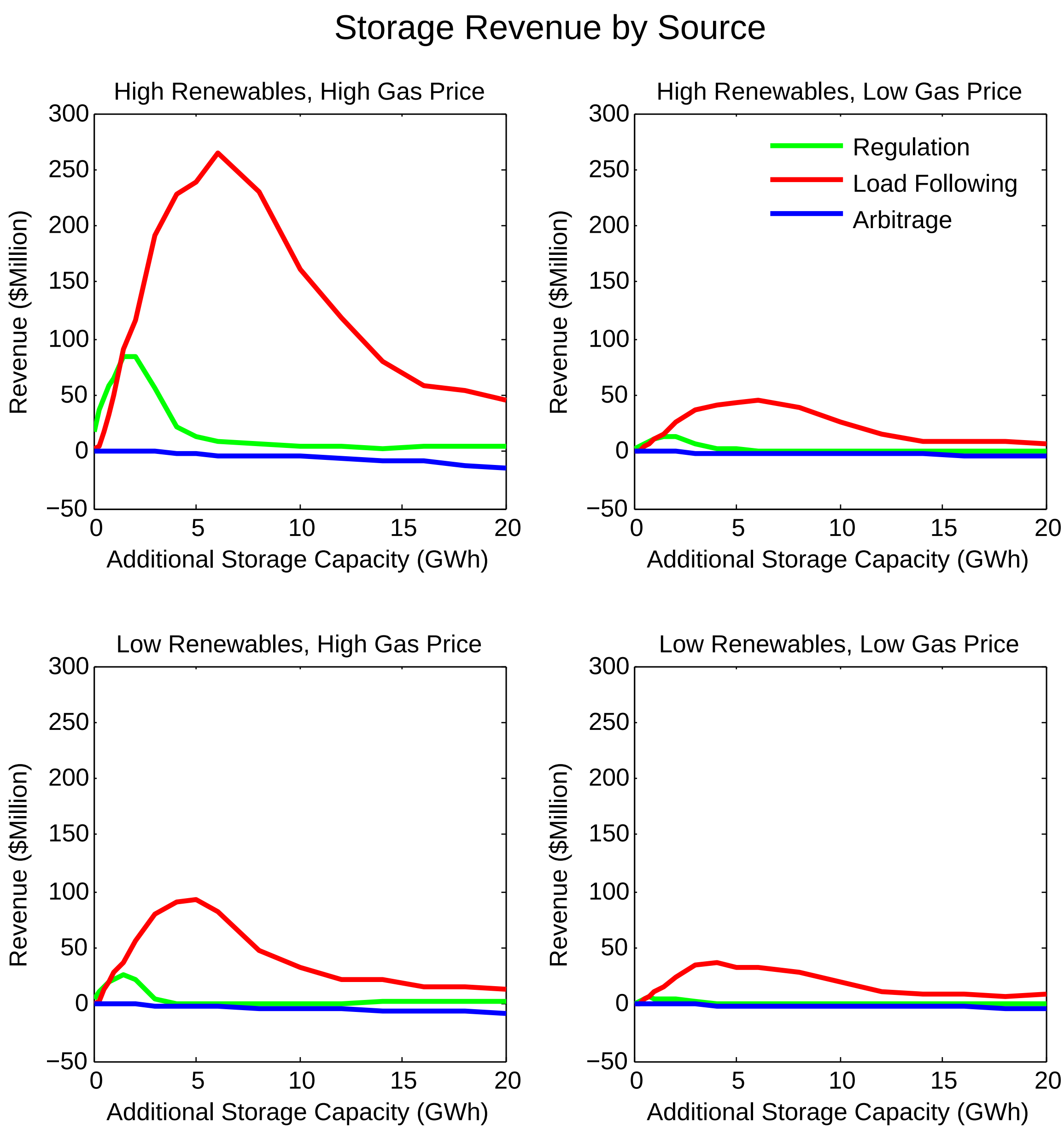

Figure 2.9: Revenue obtained by storage due to each service provided. Revenue is calculated by paying the storage devices the market clearing price for each service provided. In general, as storage is added to the system, the total revenue achieved by storage decreases. At very high penetrations, storage devices lose money in energy markets so that they may participate in the ancillary services markets.

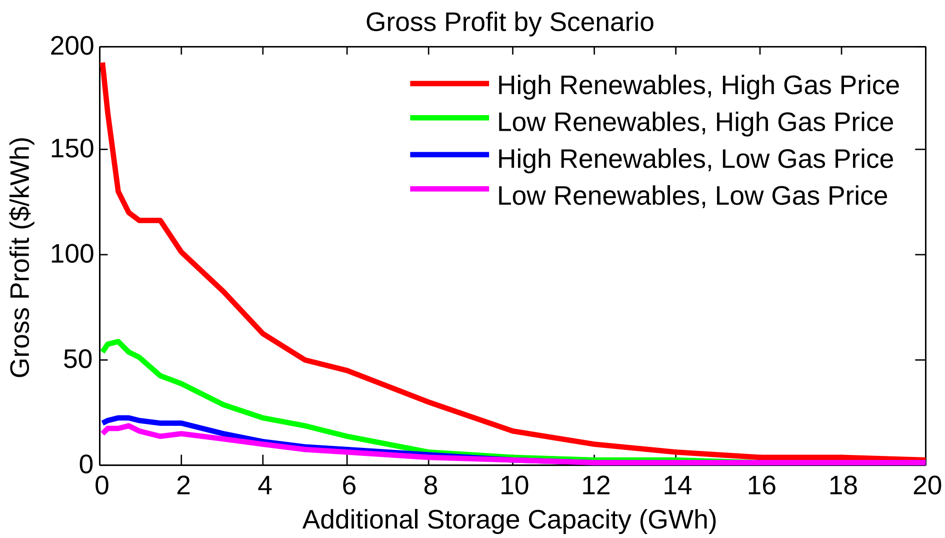

Figure 2.10: Gross profit, calculated as revenues less costs to charge, per kWh installed. As storage is added to the system, the gross profit seen by all storage operators decreases.

2.5 Discussion

We find that both fuel prices and renewables penetrations have a strong impact on the operational savings (see Figure 2.3), with fuel prices having a larger influence across the scenarios we investigated. This is driven in large part by the substantial difference in fuel prices in the 2007-2012 range we considered and particularly the large difference between the price of gas-fired peaker pants and coal-fired baseload plants (see the step change in marginal costs at 130 GW in the supply curve in Figure 2.2).

Having high concentrations of renewables also corresponds to important operating cost benefits for storage — savings from storage in high renewables situations is roughly double what it is in the low penetration scenarios we investigated. This is due to the increased reserve requirements. As we showed in Figure 2.9, in all scenarios the most valuable functions for storage to take over are reserve functions. We also note that operating cost benefits will further increase if one considers renewables penetrations beyond those we investigated; these benefits may eventually be comparable to the potential benefits at high gas prices. However we do not observe large differences in the benefits from storage when the renewables mix is mostly solar rather than mostly wind, because it is optimal to use storage primarily for reserves, rather than arbitrage services. This means that the timing of the resource is less important than its relative contribution to reserves requirements at the penetrations we investigated.

The observation that it is more valuable for storage devices to provide reserves than arbi-

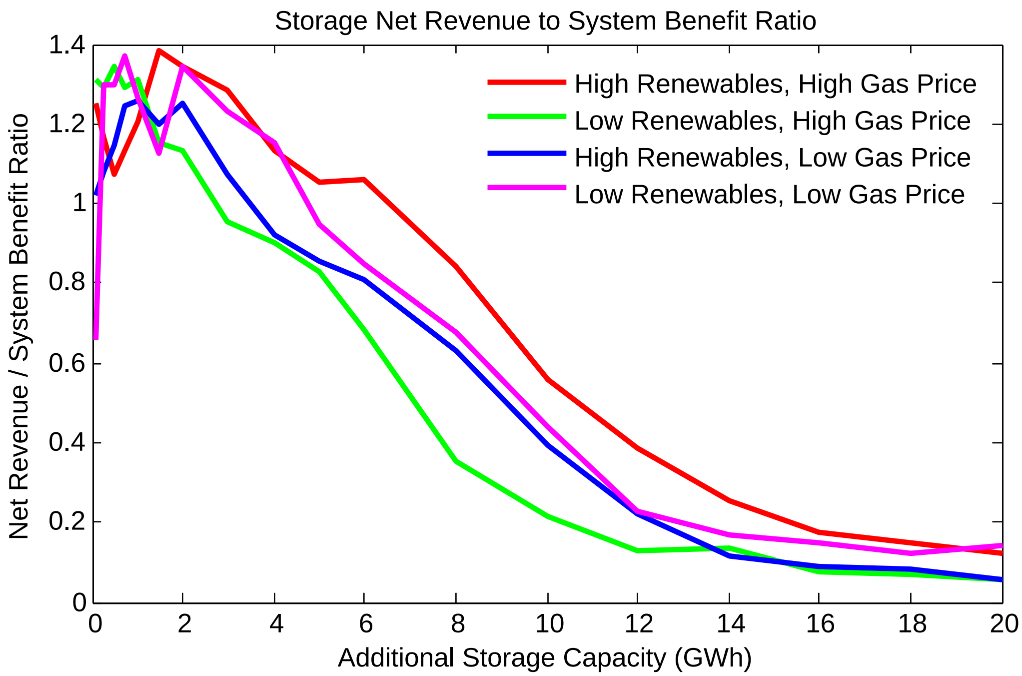

Figure 2.11: Ratio of net revenue obtained by storage to system benefit provided by storage, relative to the base case with no storage. Between 4 and 6 GWh of storage the ratio dips below 1, which indicates that the system benefits provided by storage operationally are no longer able to be captured by storage operators via modeled markets.

trage services is true from the perspectives of both storage operators and system operators. In all scenarios, regulation up is the most valuable service for storage to provide, followed by regulation down and load following up, and finally load following down. In general, load following provides the most revenue to storage operators, primarily because the market for load following is larger than the market for regulation. We also observe that the presence of storage has the potential to reduce both the total number and the overall cost of generator starts. These results echo [28], who also studied the impact of storage on unit commitment and reserve provision (though not for a range of storage penetration levels and with a focus on CAES), and found that low penetrations of storage appear to be the most sensible in the short run.

In combination, these factors indicate that storage is most beneficial in a system that has both large reserve requirements, as in the high renewables cases, and a large difference in marginal costs between low- and high-cost plants, as in the high gas price cases. While it is likely that renewables will encourage increases in reserve requirements in future systems, it is less likely that the spread in fossil fuel generation prices will stay large. With the recent decrease in natural gas prices due to hydraulic fracturing and horizontal drilling ("fracking"), the energy supply system has moved away from a price dichotomy that is advantageous for

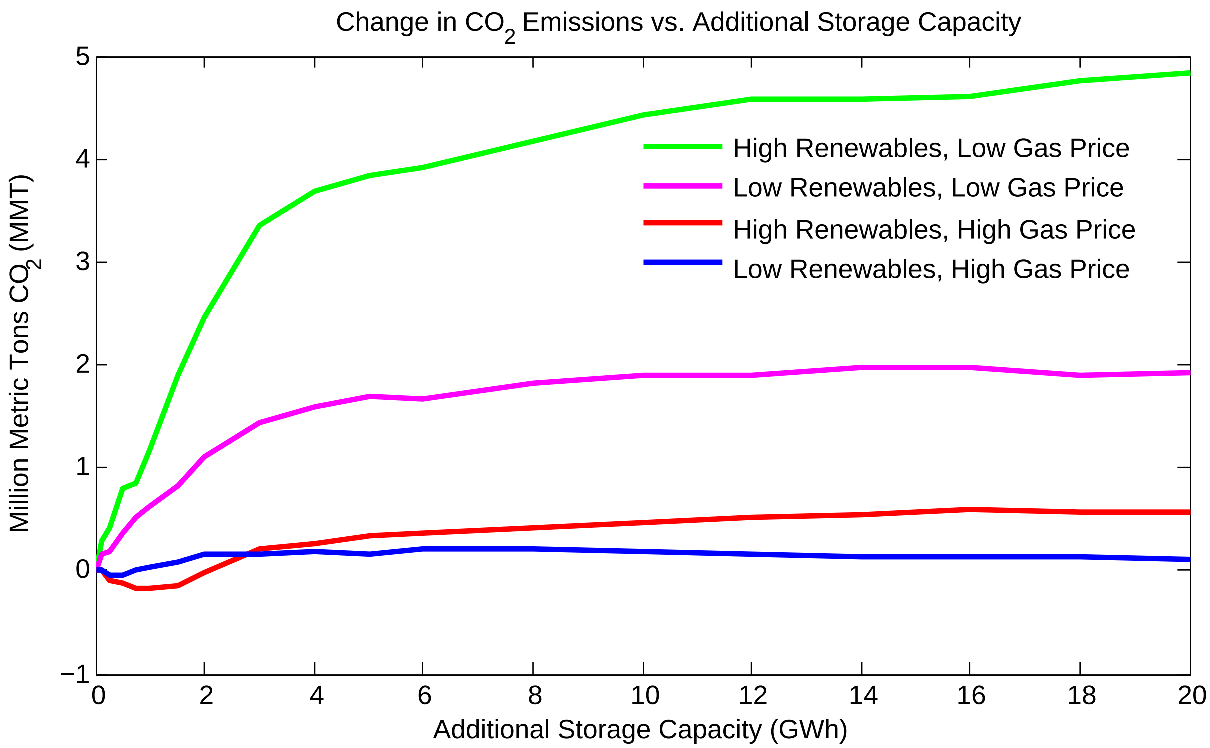

Figure 2.12: As storage is added to the system, the carbon dioxide released due to system operations increases. In 2005, WECC emissions were between 370 and 385 MMT [12].

storage, and is closer to a system in which storage has a smaller effect on the economics of operations[7]. In the scenarios with higher renewables penetrations and lower gas prices, the operating cost benefits achieved with storage are unlikely to justify capital cost expenditures on storage, even at aggressive capital cost estimates and low penetrations of storage. In these cases, it is very likely that the capacity value for storage will dominate any of the operational benefits we model here.

With respect to carbon emissions, the presence of storage on the system causes an increase in CO_2 emissions for all scenarios, except at very small storage penetrations in the high renewables / high gas case. This is due to increased usage of coal plants in lower demand, low price hours to charge storage devices. As long as the marginal price of electricity from gas exceeds that for coal (as it does in all scenarios we investigated), the cheapest times to charge storage devices will tend to be in hours when there are more coal plants on. This implied that the energy stored in and then delivered by the storage devices will be dirtier than the energy supplied without storage. Relative to system-wide emissions, the increases are small; around a 1.4% increase in emissions from the 2005 level. It is worth noting other recent work has come to similar conclusions but with different modeling assumptions; in [31],

[7]Of course, though it may seem unlikely, future prices could change just as suddenly as they did with the introduction of fracking, and we cannot rule out a future fuel price scenario that favors more energy storage.

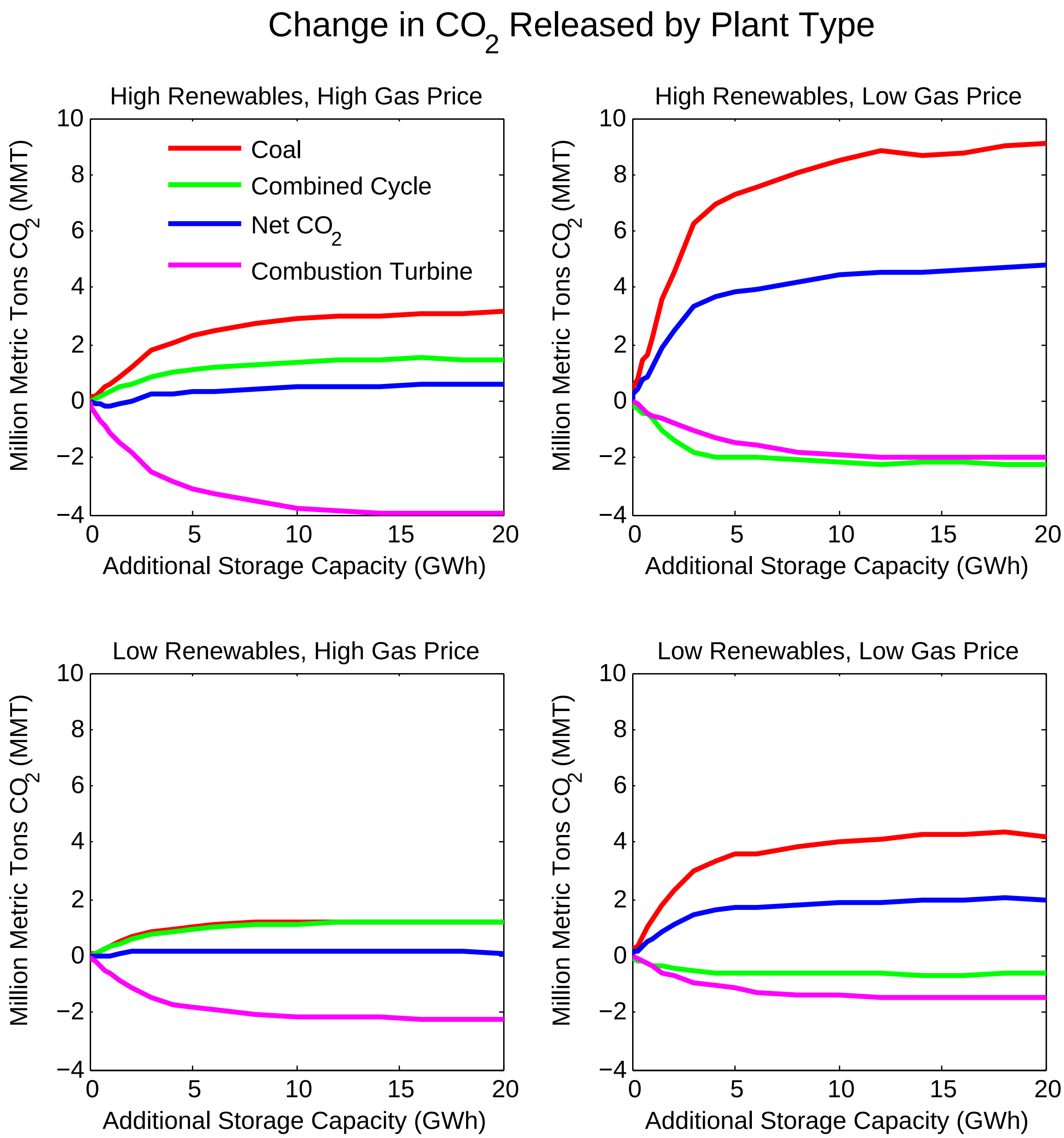

Figure 2.13: This figure shows the emissions sources broken out by scenario. From Figure 2.12, the largest increase in CO_2 emissions comes from a high renewables penetration and a low gas price. In all scenarios, as the amount of storage added is increased, emissions from coal plants rise. In cases with a high gas price, emissions from combined cycle plants also rise, but with a low gas price they fall. In all scenarios, emissions from combustion turbines fall as the penetration of storage devices increases.

the authors only examined bulk energy shifting, or arbitrage, but also found that storage increased carbon emissions.

Overall, the benefits from increasing the presence of storage decline rapidly as installed capacity increases. At 10 GWh of installed capacity, operating cost benefits for all but the high renewables / high gas price scenario are negligible. In the high renewables / high gas case, benefits at 10 GWh are less than $100/kWh; this is well below current prices but potentially achievable in the future if storage cost targets are met. However in most scenarios carbon intensity continues to increase beyond 10 GWh of installed capacity. This suggests that for the infrastructure we modeled – a simplified version of WECC – targets to install more than 10 GWh of energy storage are unlikely to be cost effective from an operating cost perspective in any near term future scenarios.

As we noted above the capacity value of storage (approximately $160/kWh assuming with 4 hour discharge capability storage could replace a $650/kW combustion turbine) could become a very important part of its value as operating cost benefits decline. If storage cost targets are met, capacity value alone could support significant expansion of storage capacity. In this case we expect that the operating cost benefits we observe would still be realized, except on the limited peak net demand days when storage capacity is required for system reliability.

2.6 Conclusions and Policy Implications

Though the operational value of storage is high at very low penetrations, our analysis indicates that at modest penetrations (10 GWh, or 6 minutes of average energy demand in the model) the operational value is unlikely to compensate for storage capital costs in the foreseeable future. To the extent storage is used to reduce operating costs, our analysis indicates that price arbitrage will be an insignificant factor, and that reserve provision will dominate. This suggests that operating cost savings on their own do not likely constitute a motivation for policies that incentivize storage installations, even if it is on the expectation that those policies will indirectly drive installed costs downward. However we note that reserve markets that capture the actual value of storage are in early stages; policy makers might consider initiatives to expand how much access storage owners have to reserve markets.

Our analysis also indicates that operating cost savings quickly fall below plausible storage capacity values, and therefore capacity value is likely to be a significant component of the total transmission-level benefits of storage. Indeed, if storage if cost targets are met, according to our calculations, generation capacity value alone justify the cost of storage. However we made a simple assumption that 4 hours of energy storage capability would be sufficient to reproduce peaker plant capacity. The total quantity of energy storage required for capacity value in practice could be more or less, depending on peak net load shapes but also the way storage is discharged in peak conditions. Because it is energy-limited, operators will likely discharge storage conservatively to ensure system reliability. If capacity value is to dominate operating cost benefits as a source of storage value, it will be important for storage owners, system operators, utilities and regulators to agree on best-practice discharge control algorithms in peak conditions.

We note, however, that our analysis did not investigate locational capacity value, both at the transmission level where "load pockets" can lead to very high local capacity costs and for distribution systems where substation and conductor capacity may require upgrades to manage peak load growth. These very important circumstances are beyond the scope of the present analysis; addressing them in detail would require detailed transmission models and circuit-level distribution capacity data.

We found that storage operations can increase system-wide carbon emissions: by reducing the required number of generator starts and providing flexible reserves, storage makes additional room for coal in the dispatch order. It is important for regulators and system operators to consider policies and operating strategies that could be used to avoid this outcome. However we expect that those policies would limit the operating cost benefits to storage and, as a consequence, diminish the financial incentive for storage owners to expand installed capacity.

Chapter 3

Can carbon taxes incentivize energy storage investment?

Several recent papers have indicated that increased grid-scale storage resources have the potential to increase operational carbon emissions in the absence of carbon prices. Other papers have demonstrated that increased storage penetrations are necessary for high penetration renewables systems to continue to provide electricity reliably. We explore the extent to which a carbon price might influence storage-induced carbon emissions and storage-derived system cost benefits under different scenarios, including a variety of storage penetrations. We find that the relationship between carbon taxes and storage benefits is not linear, and in some cases taxes on carbon can reduce the desirability of storage services. If a primary goal for large-scale storage deployment is to reduce the long-term carbon impacts of the grid, then more attention should be paid to the overall mix of the system into which the storage capabilities are introduced. Increasing storage capacity is not an unequivocal path to carbon reductions when there are large gaps in marginal costs between low-cost coal and high-cost gas generation that storage can arbitrage. However, the likelihood of such an outcome increases with the addition of carbon taxes when the differences in marginal costs between gas- and coal-burning plants are smaller.

3.1 Introduction

Energy storage has been proposed as a vital component of the future of sustainable electricity generation, in which carbon emissions will be substantially reduced and eventually eliminated ([17], [43],). In California, Assembly Bill AB2514 aims to increase storage capacity on the grid [14]. AB2514 has the express purpose of decreasing emissions, citing as the impetus for its adoption Assembly Bill 32, the Global Warming Solutions Act, which aims to reduce statewide carbon emissions from all sources[6]. The bill does not specify the function that these resources should serve, but several papers have shown that energy storage is most beneficial economically in the current system as a provider of reserves or capacity value, rather than a provider of arbitrage ([8, 19, 52]). Other papers have shown that energy storage could increase carbon emissions rather than decrease them [13, 31, 52]. These raise some questions regarding the best use of storage resources on the grid, and suggest that policies calling for additional storage should be implemented in the face of this information.

As part of the transition to a lower carbon intensity, higher renewables grid, carbon pricing schemes will likely be deployed and large amounts of renewable generation will be built, in addition to any energy storage systems that are installed. Many existing and proposed policies that aim to reduce carbon overall rely on pricing carbon, either through cap and trade policies or through a carbon tax. These approaches both aim to economically incentivize reductions in carbon pollution by emitters. While they do have implementation differences, both types of policy can be used to achieve carbon reductions without appreciable differences in burden on various groups[27]. Both types of policy are often considered with the specific aim of equalizing the burden of carbon reductions across a sector or industry and "internalize the externality" [63]. Several studies use such mechanisms to appropriately price the externalities from fossil fuels, and reduce the overall contribution of electricity generation to climate change ([7], [45], [50], [29]).

Much thought has also been given to the impact of carbon taxes or cap-and-trade policies on revenues and profits for different types of plant operators, including both renewables and fossil fuel plants. [27] show that hits to revenues and profits for fossil fuel plants are similar under carbon taxes and cap-and-trade policies. [26] show that, under US-wide cap-and-trade policies, coal-fired generators show a reduction in profits, but non-coal fossil fuel generators and non fossil fuel generators show an increase in profits. [25] show that higher and more uncertain prices on carbon induce more investments in generators that have reduced emissions profiles. Overall, prices on carbon have been shown to decrease revenues and profits for fossil fuel generators, and incentivize investments in renewables instead. This is the same goal that has catalyzed interest in storage investment.

The literature is more sparse regarding the profits and revenues of storage operators under carbon taxes. Unlike renewables, which will be made more competitive via a carbon price, and fossil-fuel plants, whose marginal costs will be expected to increase under a carbon price, the impact of carbon prices on the revenue of storage is less clear. On the one hand, a carbon price could cause energy from peaker plants to be more expensive than energy from storage, thus increasing the revenue opportunities for storage units. On the other hand, storage may need to charge from a grid where prices have gone up due to increased taxes on generation, which will increase costs for storage.

Additionally, because the value of storage is dependent on the costs of the marginal generators in the hours storage devices are charging, the structure of the generator supply curve from which storage devices charge may have a large impact on the storage operations. Existing mechanisms that alter the generator supply curve may also alter the carbon reduction benefits that storage could otherwise provide via enabling renewables. Several papers have discussed possible future changes to the nature of current supply curves. In light of the recent reductions in natural gas prices, many have demonstrated that lower prices of natural gas can reduce overall emissions in various markets. [35] show that lower natural gas prices cause reductions in overall emissions by inducing fuel switching from coal to natural gas. [37] shows that the reduction in natural gas prices in 2008 caused a reduction in overall emissions of 8.76%, which was specifically driven by a switch from coal to natural gas. [16] demonstrates the relationship between carbon prices and the ratio of coal to gas price; in their model a carbon price of \$80/ton CO_2 is sufficient to cause marginal gas prices to be cheaper than coal. In such a scenario, the overall CO_2 emissions of the grid may change in a favorable direction without any additional investment in storage on the part of utilities or ISOs.

In this paper, we examine the impact of carbon pricing on energy storage, looking at both system-wide benefits and revenue to storage operators. We address these impacts in the context of the current system buildout of the western interconnection (WECC); this is not a planning model and so we do not consider potential future build decisions. In this case, we show that benefits due to storage vary greatly with respect to carbon price, and also do not vary in a linear way. We also investigate the impacts of added storage on grid-based carbon emissions, and find that storage has the potential to both increase and decrease carbon emissions on the grid, depending on carbon prices and fuel prices in the underlying system. We show that when there are large gaps in marginal operations costs between high cost natural gas and low cost coal-fired plants, there are no synergies between carbon taxes and additional storage capacity. When the gaps in marginal costs between these two types of plants are smaller, synergies between carbon taxes and additional storage capacity emerge.

3.2 Methods

Model Overview

We model the operational impacts of energy storage in a variety of different scenarios using an hourly unit commitment model that minimizes total system costs, including both startup and marginal costs, and that is subject to constraints on generator operation, storage device operation, DC power flow, and reserve requirements, which include both a short-duration regulation service, and a longer-duration load-following service. We solve the underlying model using a branch-and-cut algorithm that we implement using the CPLEX 12.5 C++ library. The underlying model is based on the Western Interconnection (also referred to as the Western Electricity Coordinating Council, or WECC). Results from the underlying model are described in [52].

Model Formulation

Objective Function

In the underlying model, we add storage capacity in increasing increments. We then use that storage, along with a set of thermal generators and forecasted wind and solar resources, to satisfy load at each node and a set of global regulation and load following requirements. We change the objective function of the model slightly to accommodate various carbon prices between \$0/ton CO_2 and \$200/ton CO_2. Having a price on carbon changes both the marginal generator operating costs and the generator start costs, because a certain proportion of both costs is dependent on fuel. The objective function is the same as in [52]:

$$\min \sum_{g\in\mathcal{G}} \sum_{t\in\mathcal{T}} \Gamma_g q_{gt} + SU_g s_{gt}, \tag{3.1}$$

where the sets $\mathcal{G}$ and $\mathcal{T}$ denote the sets of generators on the system and time periods modeled, the decision variable q_{gt} denotes the level of output for generator g in time period t, and the decision variable s_{gt} denotes whether or not generator g started up in hour t. Additionally, $\Gamma_g = F_g * HR_g + O_g$ and $SU_g = SE_g * F_g + SA_g$, and F_g, HR_g, O_g, SE_g, and SA_g are respectively the fuel cost for generator g, the heat rate for generator g, the variable operations and maintenance cost for generator g, the energy required to start generator g, and the fixed cost component of starting generator g.[1] To model different carbon tax amounts, we substitute $F_g * CP * EF_g$, for the fuel cost F_g in \$/MMBtu, where CP is the carbon price for the iteration in \$/ton CO_2 and EF_g is the emissions factor for the generator in tons CO_2/MMBtu. We obtain fuel prices F_g from EIA data corresponding to 2007 and 2013 [58]. We choose the emissions factors for generators, EF_g based on fuel type, and we obtain them from EPA. [23]Figure 3.3 shows how the heat rate curves for all generators with non-zero marginal cost on the system change with high versus low fuel prices and various carbon costs ranging from \$0/ton CO_2 to \$200/ton CO_2.

Generator Constraints

In each time period t, we allow each generator g to provide energy (q_{gt}), regulation up (r^u_{gt}), regulation down (r^d_{gt}), load following up (lf^u_{gt}), and load following down (lf^d_{gt}). We constrain these decision variables as follows:

$$q_{gt} + r^u_{gt} + lf^u_{gt} \leq \overline{Q}_g u_{gt} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T}, \tag{3.2}$$

$$q_{gt} - r^d_{gt} - lf^d_{gt} \geq \underline{Q}_g u_{gt} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T}, \tag{3.3}$$

where u_{gt} is a binary decision variable denoting whether or not generator g is operating in time period t, and $\overline{Q}_g$ and $\underline{Q}_g$ are the maximum and minimum generation limits, respectively, for generator g. Each of the ancillary service variables must also be less than their respective limits for each generator:

$$0 \leq r^u_{gt} \leq RU_g u_{gt} \qquad \forall g \in G, t \in T \tag{3.4}$$

$$0 \leq r^d_{gt} \leq RD_g u_{gt} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{3.5}$$

$$0 \leq lf^u_{gt} \leq LFU_g u_{gt} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{3.6}$$

$$0 \leq lf^d_{gt} \leq LFD_g u_{gt} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{3.7}$$

[1]For simplicity we assume heat rate is constant across each generator's output range

Between hours, generators are subject to ramp rate constraints:

$$R_g^- \leq q_{gt} - q_{g,t-1} - r_{gt}^d - lf_{gt}^d \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{3.8}$$

$$R_g^+ \geq q_{gt} - q_{g,t-1} + r_{gt}^u + lf_{gt}^u \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{3.9}$$

Continuous startup variables for generators are used with binary operating variables and minimum up and down times in the manner described by [49]:

$$\sum_{k=t-UT_g+1}^{t} s_{gk} \leq u_{gt} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{3.10}$$

$$\sum_{k=t+1}^{t+DT_g} s_{gk} \leq 1 - u_{gt} \qquad g \in \mathcal{G}, t \in \mathcal{T} \tag{3.11}$$

$$s_{gt} \geq u_{gt} - u_{g,t-1} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{3.12}$$

$$0 \leq s_{gt} \leq 1 \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{3.13}$$

$$u_{gt} \in \{0, 1\} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T}. \tag{3.14}$$

We obtain heat rates, and capacities (HR_g, $\overline{Q}_g$) from [53]. We also match the prime mover for generators in this dataset to TEPPC generator category data from the 2009 TEPPC Study Program Results to obtain ramp limits (R_g^+, R_g^-), minimum up- and downtimes (UT_g, DT_g), minimum operating capacities ($\underline{Q}_g$), start-up costs and startup energy required (SA_g, SE_g), and variable operations and maintenance costs (O_g). The maximum regulation (RU_g, RD_g) and load following capabilities (LFU_g, LFD_g) of each generator are calculated based on the maximum generator movement in 10 minutes, using the one-minute ramp rate for the generator's prime mover [62]. Generator limits on ramps between hours were calculated based on maximum generator movement in 60 mins. [49]

In total, the model commits and dispatches 185 generators, of which 38 are coal-fired, 135 are gas-fired, 4 are nuclear, and 8 are run on fuel oil. The model does not dispatch hydro, biomass, wind, solar, and geothermal plants; instead the production profiles and capacities for those generators originate in the Price model. Production profiles for wind and solar correspond to buildouts of 24 GW of wind capacity and 7 GW of solar capacity, which are slightly larger than recent buildouts were approximately 18 and 5 GW, respectively, in 2013 [21].The set of dispatched generators used is based on disaggregated generator data from the Price model, which are then modified such that generators with similar heat rates are aggregated together, and each node in the network has only one generator with each heat rate, which reduces symmetry in the subsequent formulation.

Storage Constraints

We model scheduled consumption or supply of energy from storage in hourly blocks. We also model the commitment of storage capacity to provide regulation and load following reserves on an hourly basis.

We require storage devices to adhere to physical constraints as follows. Energy in storage device m at time t, e_{mt} must be less than the capacity E_m of the storage device, where $\mathcal{M}$ is the set of all storage devices on the system:

$$0 \leq e_{mt} \leq E_m \quad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{3.15}$$

The charge and discharge rates for the storage device are also constrained by the power limits (P^{charge}, $P^{discharge}$) of the storage device:

$$0 \leq c_{mt} \leq P_m^{charge} \qquad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{3.16}$$

$$0 \leq d_{mt} \leq P_m^{discharge} \qquad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{3.17}$$

$$\tag{3.18}$$

These constraints ensure that every device is capable of serving the worst case reserve action for which they might be called, in addition to delivering or consuming energy according to the energy arbitrage schedule.

The following three constraints ensure that, at every time period, the available energy for arbitrage, regulation, and load following are all appropriately constrained by the current energy state of the storage devices.

$$e_{mt} = e_{m,t-1} + \tau\beta_m c_{mt} - \frac{\tau}{\delta_m} d_{mt}, \tag{3.19}$$

$$e_{m,t-1} \geq \frac{1}{\delta_m}\left(\tau d_{mt} + \tau^r r_{mt}^{us} + \tau^{lf} lf_{mt}^{us}\right) \tag{3.20}$$

$$E_m - e_{m,t-1} \geq \beta_m\left(\tau c_{mt} + \tau^r r_{mt}^{ds} + \tau^{lf} lf_{mt}^{ds}\right) \tag{3.21}$$

Here, r_{mt}^{us}, lf_{mt}^{us}, r_{mt}^{ds}, and lf_{mt}^{ds} are, respectively, the power contributions of storage device m to regulation up, regulation down, load following up, and load following down, respectively, in time period t. The constant τ is the time period length in hours, and τ^r is the length of time for which regulation must be provided in hours, τ^{lf} is the length of time for which load following must be provided in hours. β and δ are the charging efficiency and discharging efficiency, respectively, of storage device m. We assume that storage efficiency is 90% on both charge (β_n) and discharge (δ_n) and a power:energy ratio of 4, such that $P_n^{discharge}/E_n = 4$. By choosing this ratio, we ensure that power constraints will bind for regulation, and energy constraints will bind for load following and arbitrage. In addition to the added storage devices, the model also dispatches 4 pumped-hydro plants in all scenarios. The efficiencies and capabilities for the pumped hydro plants are taken from the Price model, and comprise 3.0 GW of power, with 201 GWh of total energy capacity. Both pumped hydro and added storage can provide regulation and load-following, subject to constraints that require enough energy to be present in the battery (or energy capacity for charging in the case of down reserves) for provision of 15 minutes of regulation and 2 hours of load following (Eq. (4.15) and Eq. (4.16) with $\tau^r = 0.25$ hrs and $\tau^l = 2$ hrs) [55].

Network Constraints

We enforce nodal power balance constraints for hourly schedules with a linear DC load flow model:

$$\sum_{g \in G_n}(q_{gt}) + \sum_{m \in M_n}(c_{mt} - d_{mt}) + \sum_{i \in N} B_{ni}(\theta_{nt} - \theta_{it}) = L_{nt}, \tag{3.22}$$

where G_n is the subset of generators located at node n, M_n is the subset of generators located at node n, B_{ni} is the susceptance between node n and node i, θ_{nt} is the voltage angle at node n at time t, and L_{nt} is the load at node n at time t.

Also, the total load flow on line ij must be less than or equal to the maximum load flow allowed, $\overline{D}_{ij}$:

$$B_{ij}(\theta_{it} - \theta_{jt}) \leq \overline{D}_{ij} \tag{3.23}$$

We assume that any line capacity violations that result from reserve actions are sufficiently small or short in duration that they can be tolerated by the system operator or that the system can be redispatched to resolve constraints. We also assume these events are sufficiently rare that they can be neglected for the purpose of quantifying the annual cost benefits of storage at the scale of the model.

The layout of the system network for the model is based on data for the 240-bus model created and published in association with a model developed at CAISO [53], hereafter the Price model. From this resource, we obtain susceptances B_{ij} and line limits $\overline{D}_{ij}$ for the network, as well as hourly loads L_{nt}.[2]

Reserve Requirements

We procure minimum reserves of each type (regulation in up and down directions, load following in up and down directions) in each hour. We model these on the requirements used in [51]. For regulation up and down requirements, we require in each hour a proportion, ρ, of the peak load for the day added to a proportion, σ, of the total installed wind and solar capacity. We model load following up for each hour as a proportion, η, of the forecasted load plus a proportion, ν, of the forecasted wind and solar for the hour. We model the load following down requirement as a constant proportion of the renewables forecast. Total regulation in both directions must be greater than 1% of peak load ($\rho = 0.01$). The Western Wind Integration Study indicates that 1% of peak is acceptable for regulation with respect to wind capacity, but does not investigate whether this also applies for additions of solar. To ensure that regulation needs are satisfied with the addition of both resources, we also add 1% of the installed wind and solar capacities to the regulation requirement in both directions ($\sigma = 0.01$). Total load following in the up direction must be greater than the sum of 3% of forecasted load and 5% of forecasted wind and solar ($\eta = 0.03$, $\nu = 0.05$), in accordance

[2]The [53] model is based on 2004 data. In the time since the model was built, total demand has remained relatively flat [61] and generation capacity for all fuels but wind, solar and natural gas were virtually unchanged [21]. Gas capacity has grown significantly since 2004, however because total and peak demand remained flat this capacity has had relatively little impact on operations.

with the "3+5" rule. In accordance with the need for load following in the down direction as specified in [39], we also require an amount of reserve in the down direction equal to 5% of forecasted wind and solar.

The following equations define these constraints explicitly, with $\overline{S}_n$ and $\overline{W}_n$ being the solar and wind capacities installed at node n, respectively, and S_{nt} and W_{nt} being the solar and wind forecasts at node n during time period t. To reduce complexity, we model total reserves constraints globally.

$$\sum_{g \in G}(r^u_{gt}) + \sum_{m \in M}(r^{us}_{mt}) \geq \rho \left(\max_{a \in T: t_{max} - a \geq t} L_{na} \right) + \sigma \left(\sum_{n \in N}(\overline{S}_n + \overline{W}_n) \right) \qquad \forall t \in \mathcal{T} \tag{3.24}$$

$$\sum_{g \in G}(r^d_{gt}) + \sum_{m \in M}(r^{ds}_{mt}) \geq \rho \left(\max_{a \in T: t_{max} - a \geq t} L_{na} \right) + \sigma \left(\sum_{n \in N}(\overline{S}_n + \overline{W}_n) \right) \qquad \forall t \in \mathcal{T} \tag{3.25}$$

$$\sum_{g \in G}(lf^u_{gt}) + \sum_{m \in M}(lf^{us}_{mt}) \geq \eta \sum_{n \ inN} L_{nt} + \nu \sum_{n \in N}(S_{nt} + W_{nt}) \qquad \forall t \in \mathcal{T} \tag{3.26}$$

$$\sum_{g \in G}(lf^d_{gt}) + \sum_{m \in M}(lf^{ds}_{mt}) \geq \nu \sum_{n \in N}(S_{nt} + W_{nt}) \qquad \forall t \in \mathcal{T} \tag{3.27}$$

Solution Method

As in [52], we run the model in series by passing the final storage levels, generator output levels for ramping, and generator operating and starting levels from the first day as constants that constrain the corresponding variables for the second day. This corresponds to the following constraints, where the *prev* superscript denotes variables from the previous day's solve:

$$e_{n0} = e^{prev}_{n24} \qquad \forall g \in \mathcal{G} \tag{3.28}$$

$$u_{gb} = u^{prev}_{g,24+b} \qquad \forall g \in \mathcal{G}, b \in (-DT_g + 1, ..., 0) \tag{3.29}$$

$$s_{gb} = s^{prev}_{g,24+b} \qquad \forall g \in \mathcal{G}, b \in (\min(-UT_g + 1, -DT_g + 1), ..., 0) \tag{3.30}$$

Additionally, because it would otherwise be optimal to fully discharge storage devices at the end of each unit commitment modeling period, we also constrain the final storage levels and generator operating levels. To do this, we run a preliminary two-day unit commitment model with a four hour time step for the generator unit commitment variables, and save the generator and storage states at the end of the first day for use as constraints in a second run. In the second (final) run, we use single-day unit commitment in one hour increments with final storage charge levels and final generator operating states constrained to be equal to those saved from the first run (as in [55]). This corresponds to the following additional constraints for the first two-day unit commitment, where $T = \{t \in \mathbb{Z} : 1 \leq t \leq 48\}$

$$u_{gt} = u_{g,t-1} = u_{g,t-2} = u_{g,t-3} \ \forall g \in G, \{t \in T : t \mod 4 = 0\} \tag{3.31}$$

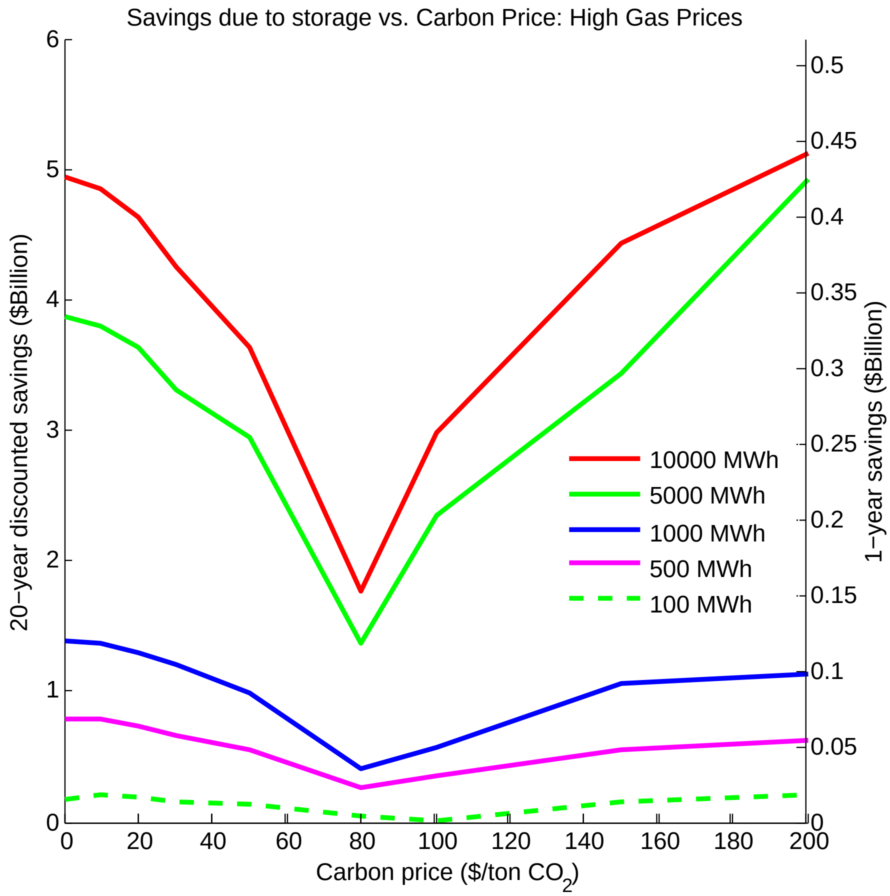

Figure 3.1: System cost savings at various storage penetrations as carbon tax is increased. At all storage penetrations, system cost savings due to added storage drop as carbon prices increase to $80/ton, and then increase again.

We implement the model in C++ and solve it with CPLEX 12.5. We solve the first two-day unit commitment problem with a mip gap of 0.5%, and the second problem with a mip gap of 0.05%. The average time taken to solve these two problems and obtain results for an individual day was 72.4 seconds.

3.3 Results

Figures 3.1 and 3.2 show the system cost savings due to storage as carbon prices increase with 2007 (high natural gas prices) and 2012 (low natural gas) fuel prices, respectively. We show two axes for each graph. The right-hand axis shows the single-year results from our

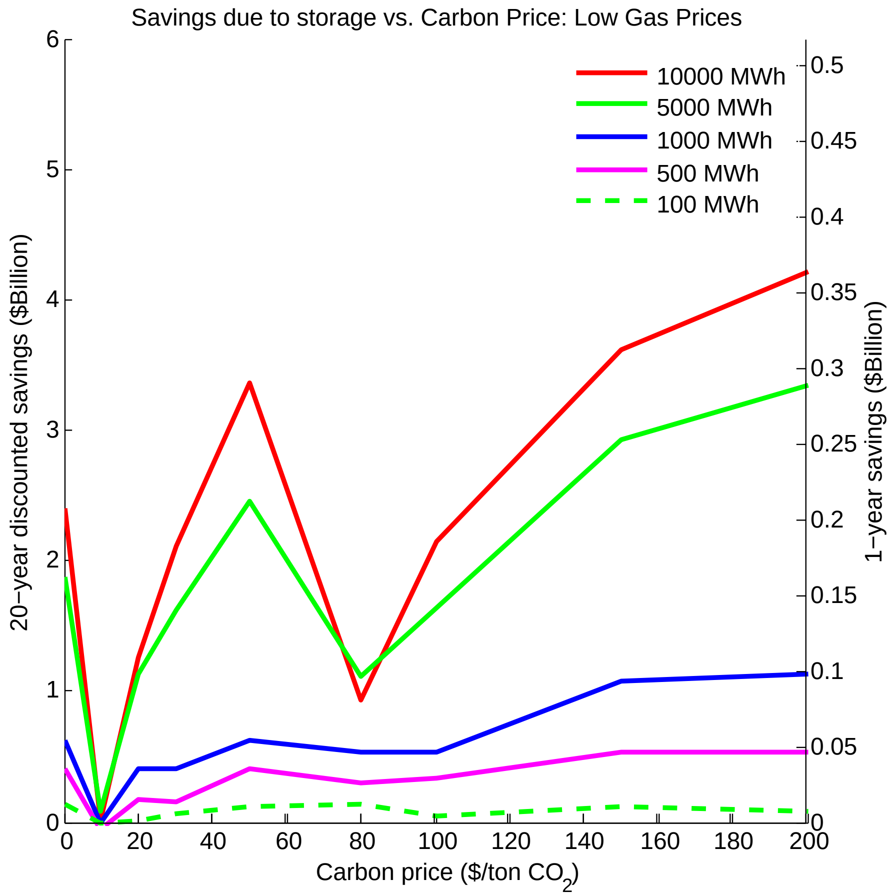

Figure 3.2: System cost savings at various storage penetrations as carbon tax is increased. At all storage penetrations, system cost savings due to added storage drop as carbon prices increase to $80/ton, and then increase again.

model. The left-hand axis shows the expected total savings over 20 years, assuming a 7% discount rate and that the savings achieved during the single year of savings modeled is consistently achieved for the duration of the 20-year time horizon.

In both fuel price scenarios, we show that additional storage capabilities result in system cost savings, regardless of the current price of carbon. We can understand these results by examining the generator supply curves from which storage devices are charging. When there is no price on carbon and gas prices are high, there is a large jump in the generator supply curve (see Figure 3.3). A similar jump occurs when gas prices are low and carbon prices reach $50/ton CO_2. These jumps are where storage is truly valuable, because storage provides value when it can arbitrage jumps in marginal costs in the energy and ancillary services markets.

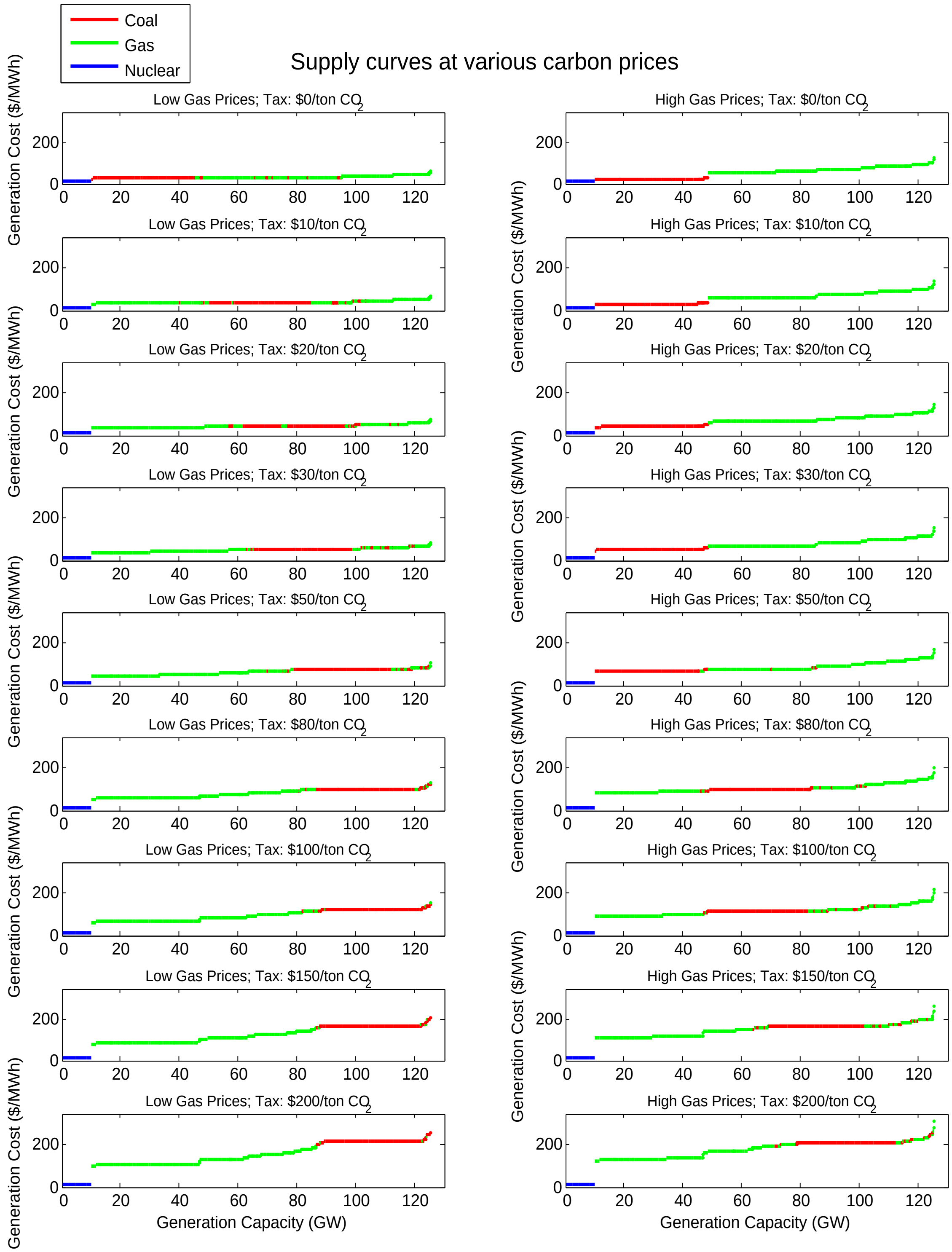

Figure 3.3: Generator supply curves at various carbon prices.

As carbon prices increase from \$0/ton CO_2, the corresponding generator supply curves become flatter, and the jumps in marginal costs between gas and coal generators decrease. This means that the opportunity for storage to contribute to system cost savings is reduced as carbon prices are increased, because the value of trading a kWh stored in a cheaper hour for either energy or ancillary services in a more expensive hour is not as high. We see this phenomenon occurring in Figure 3.1 over a large range of carbon prices, between \$0/ton CO_2 and \$80/ton CO_2. In this high gas price case, the spread between marginal gas and coal costs is large, and only closes after a large marginal cost change, brought about by prices on carbon. We also see a drop in storage value as storage prices increase in the low gas price case, between \$0/ton CO_2 and \$10/ton CO_2, and then again between \$50/ton CO_2 and \$80/ton CO_2. Overall, the sharp drops in savings occur when the mix of generators on the margin experiences a large fuel type shift from high cost to lower cost generators. The marginal generator for these runs is, on average, the one providing the 80th GW of power. In Figure 3.3, we can see that the energy mix near 80 GW switches from mostly gas to mostly coal for the high gas price cases at roughly \$80/ton CO_2. This is the point where storage value goes from decreasing with carbon tax size to increasing with the size of the carbon tax. For the low gas price case, the energy mix near 80 GW experiences a switch from gas to coal at \$10/ton CO_2. As with the \$80/ton point for the high gas price scenario, we see storage value go from decreasing w/ tax to increasing w/ tax at this value. The low gas price scenario also experiences another fuel switch from coal back to gas as the last few gas plants to be more expensive than coal plants finally become cheaper when the carbon price increases from \$50/ton CO_2 to \$80/ton CO_2. When this occurs, the generators on the margin switch from burning coal at a carbon price of \$50/ton CO_2 to burning gas at a carbon price of \$80/ton CO_2. The overall value of storage in the system then decreases, because gas plants have shorter minimum run times than coal plants once started, and storage has fewer opportunities to relieve these constraints.

We show the overall change in CO_2 emissions, relative to the no storage case, resulting from the addition of storage at various carbon prices for the high gas price case in Figure 3.4 and for the low gas price case in Figure 3.5. In the high gas price case, we observe an overall rise in CO_2 emissions relative to the no storage case when carbon prices are less than \$80/ton CO_2. In the low gas price case, we observe an initial increase in emissions followed quickly by a sharp drop in emissions, and then a reduction to zero change in overall emissions as taxes on emissions increase.

We also show that the emissions due to starts of different types of generators follow an inverse pattern to that of emissions due to energy generation. In Figure 3.6, we see that, for all storage penetrations with high gas prices, the emissions due to coal generator starts are initially curtailed as we first start adding a carbon tax. The relationship is different when gas prices are low; emissions due to gas generator starts rise, but emissions due to coal generator starts also rise for some penetrations of storage. In Figure 3.7, emissions due to gas and coal generation are more obviously inverses in every storage penetration scenario, but their behavior under high gas prices versus low gas prices is much different. In both gas price regimes, \$80/ton CO_2 is a key inflection point, where gas generation begins to provide

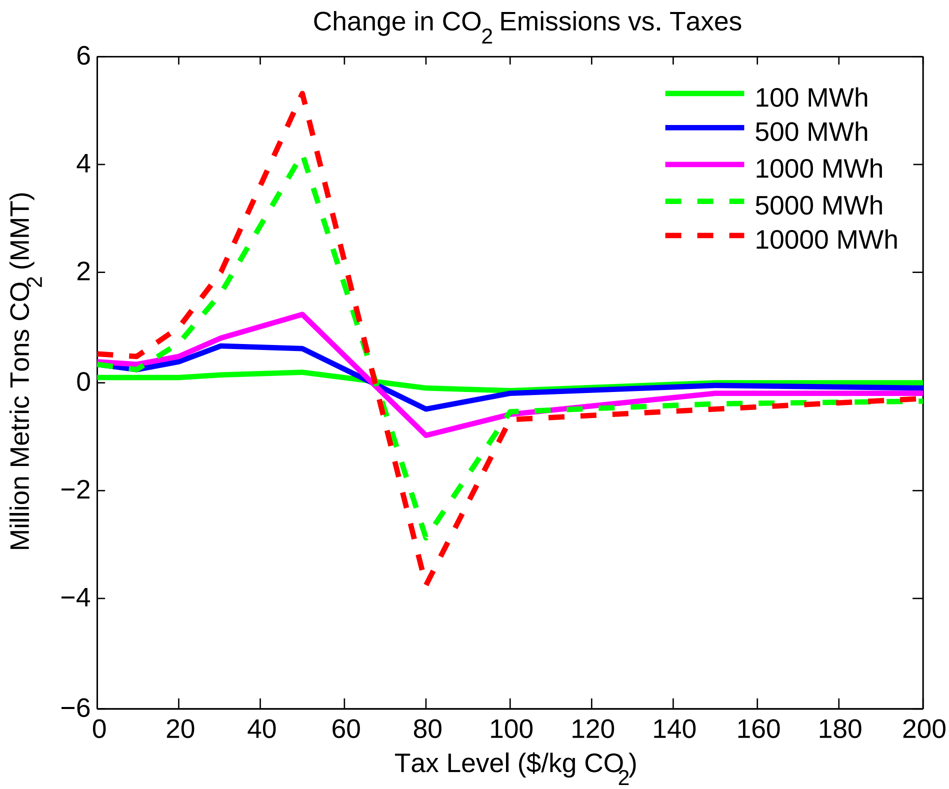

Figure 3.4: High gas prices: System cost savings at various storage penetrations as carbon tax is increased. At all storage penetrations, system cost savings due to added storage drop as carbon prices increase to \$80/ton, and then increase again.

emissions instead of coal. This is in line with [16], who show that \$80/ton CO_2 is the price at which fuel switching from coal to gas is instigated.

We also explore the gross profits seen by storage operators as carbon taxes increase from \$0/ton CO_2. We calculate these using the following equation:

$$Z = \sum_{m \in \mathcal{M}} \sum_{t \in \mathcal{T}} \left(\lambda_{mt} d_{mt} - \lambda_{mt} c_{mt} + \lambda_t^{ru} r_{mt}^{us} + \lambda_t^{rd} r_{mt}^{ds} + \lambda_t^{lfu} lf_{mt}^{us} + \lambda_t^{lfd} lf_{mt}^{ds} \right), \tag{3.32}$$

where λ_{mt}, λ_{mt}^{ru}, λ_{mt}^{rd}, λ_{mt}^{lfu}, and λ_{mt}^{lfd} are the energy, regulation up, regulation down, load following up, and load following down prices seen, respectively, by storage device m in hour t. We calculate λ_{mt} as the dual of the node balance constraint Eq. (4.30), and we calculate the prices in the reserve markets as the maximum opportunity cost faced by a generator providing that specific reserve service. These calculations assume that generators are bidding their marginal costs, and are not exercising market power.

Figures 3.8 and 3.9 show the gross profits seen by storage devices in our model at high gas prices and low gas prices, respectively. We calculate gross profits as the sum of the

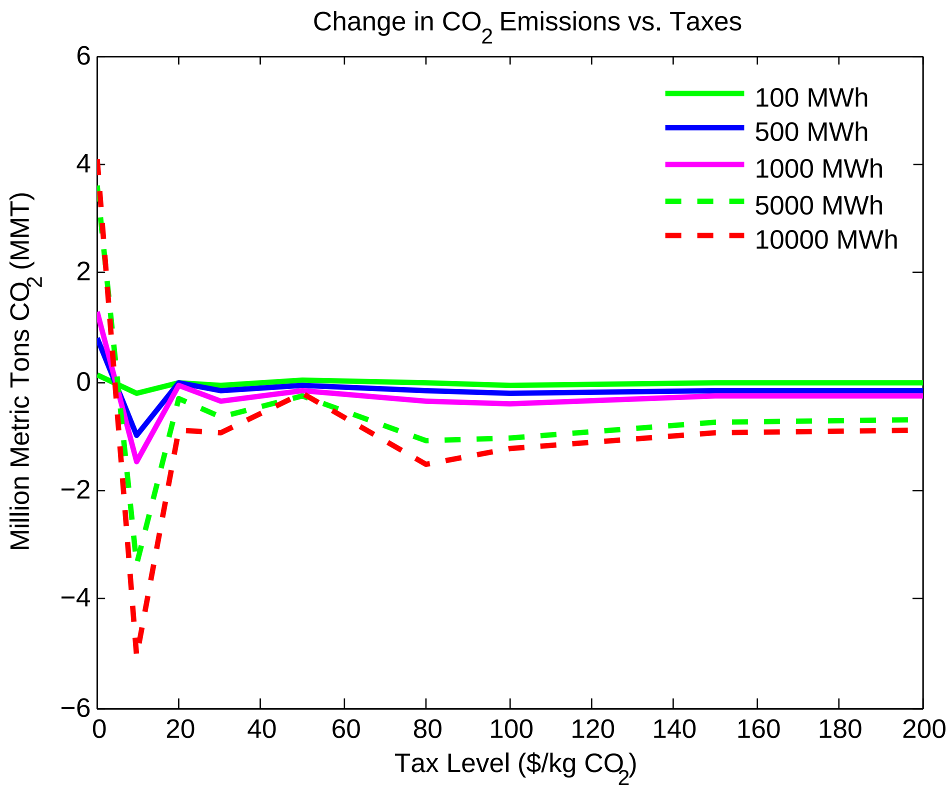

Figure 3.5: Low gas prices: System cost savings at various storage penetrations as carbon tax is increased. At all storage penetrations, system cost savings due to added storage drop as carbon prices increase to $80/ton, and then increase again.

revenues made in regulation, load following, and energy markets, less the cost to charge the storage devices. In these figures we show that in both high and low gas scenarios, the profits to storage operators decrease slightly when carbon prices are relatively low ($0–$50/ton CO_2), and then proceed to increase more strongly when carbon prices are higher (greater than $50/ton CO_2). It should also be noted that the order of lines on this graph does not follow a strict order based on the magnitude of storage capacity on the system, such that the gross profit that an additional kWh of storage capacity will see is greater with 500 MWh of storage on the system than with 5000 MWh of storage on the system. This is corroborated in [52], which also shows the decrease in value to additional units of storage as total storage penetration is increased.

3.4 Discussion

These results indicate a clear nonlinearity in the relationship between a change in carbon price and the potential benefits of increased storage capacity. Storage has been identified as a key component in many carbon reduction plans, but the interaction between storage and

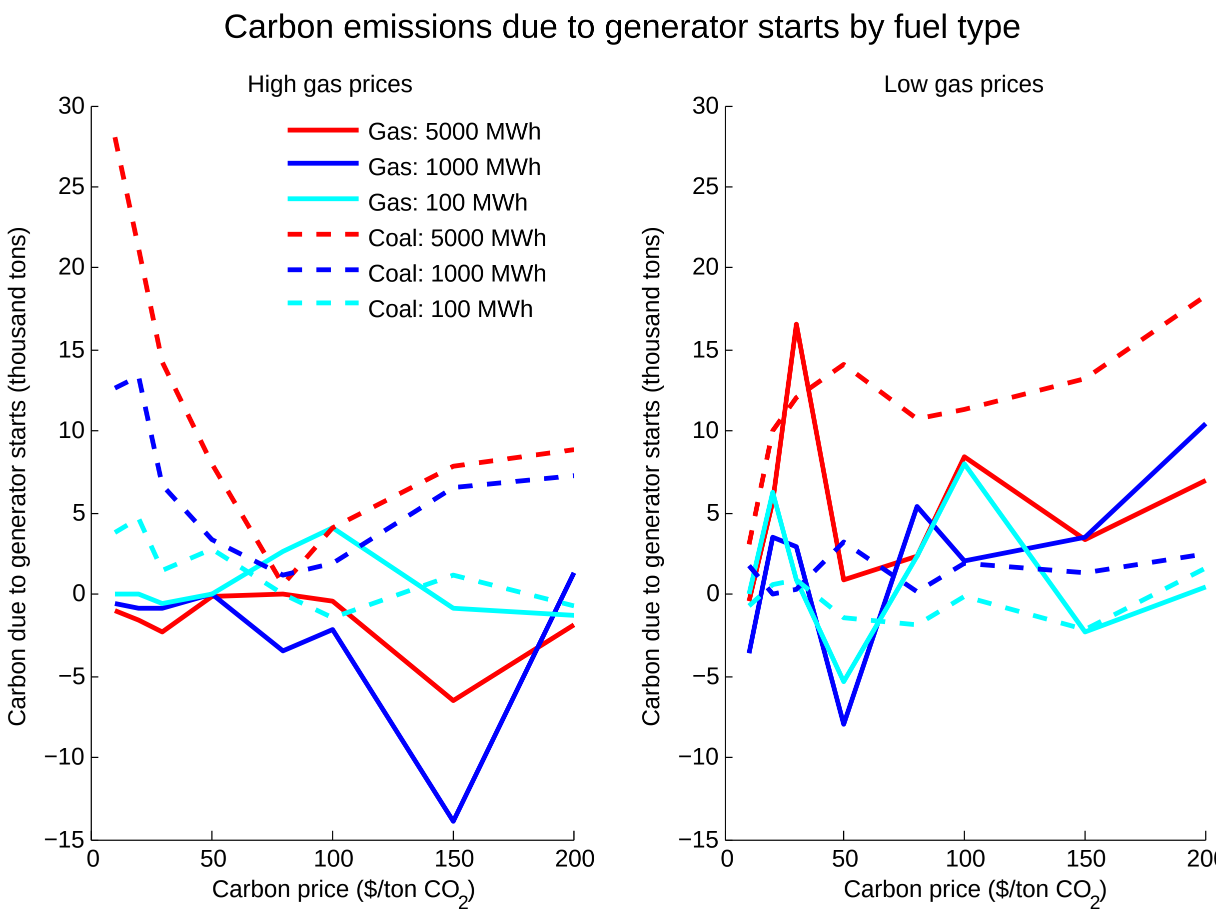

Figure 3.6: Emissions from generator starts broken down by fuel type: The relationship between emissions from coal starts and gas starts as a function of carbon price follows a different pattern than the relationship between overall emissions and carbon price; however, emissions due to energy generation is the key driver of emissions, rather than generator starts.

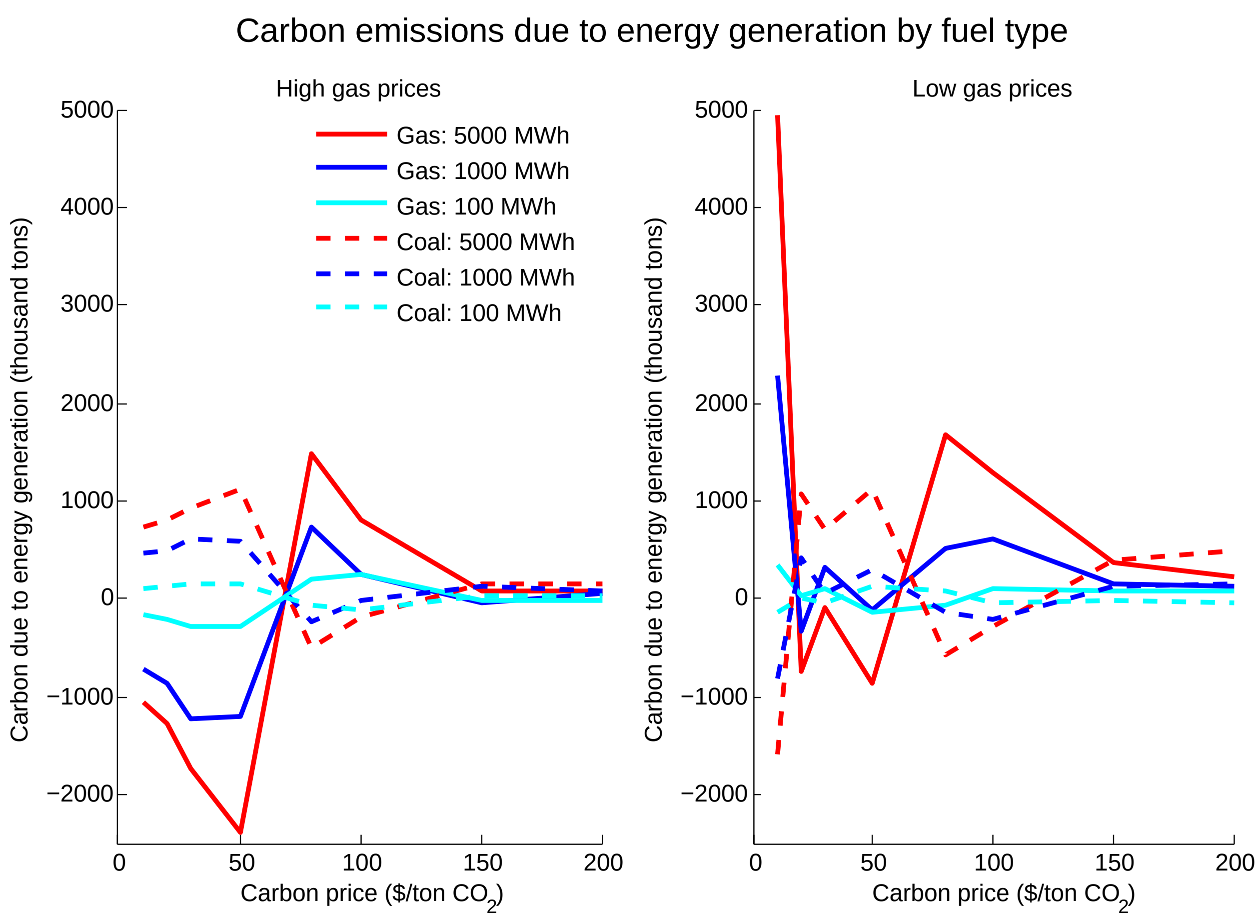

Figure 3.7: Emissions from energy generation broken down by fuel type:The relationship between emissions from coal and gas due to energy generation follows a different pattern than the relationship between overall emissions and carbon price; however, emissions due to energy generation is the key driver of emissions, rather than generator starts.

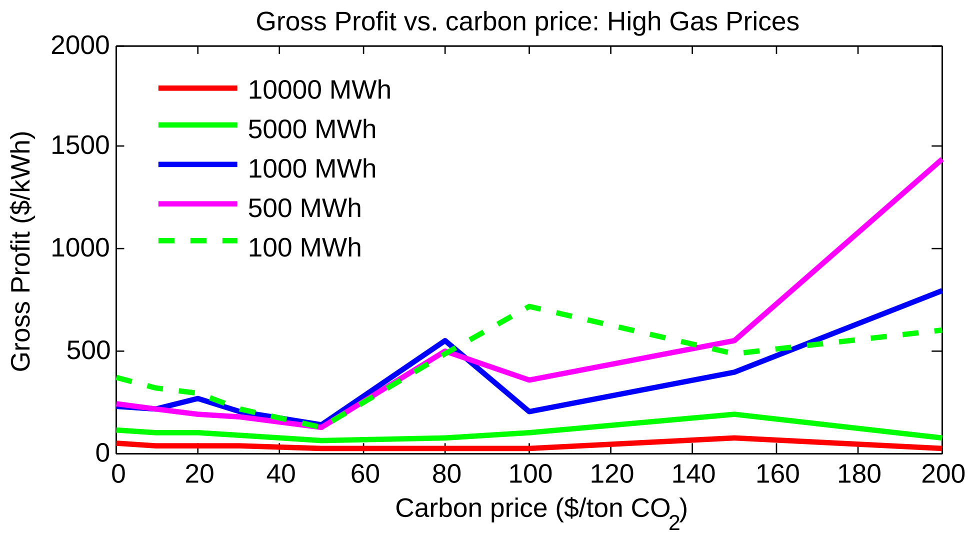

Figure 3.8: Gross profit seen by storage operators in a system with high gas prices under various carbon price regimes. At low carbon prices, storage operators achieve small profits that decrease as taxes increase. As carbon taxes increase past \$80/ton CO_2, storage profits begin to increase.

carbon price on the operating margin has not been specifically considered. We have shown that this relationship is not straightforward and depends on the particular supply curve in the system to which storage is added. At two different sets of fuel prices, we observe an initial reduction followed by an increase in the value of storage to a grid system as the overall price of carbon emissions is change from \$0/ton CO_2 to \$200/ton CO_2 (see Figures 3.1 and 3.2).

Further, we show that the actual contribution of energy storage devices to carbon reductions is not straightforward, and can depend on carbon price. In Figures 3.4 and 3.5, we show that, in the presence of additions to storage, carbon emissions and carbon taxes do not have a linear relationship. With more storage on the system, this effect is more pronounced. This is because adding a tax on carbon changes the supply curve from which storage is charging in fundamental ways, such that dirtier, more carbon intensive coal plants are equivalent in price to less carbon intensive gas plants. Storage tends to charge using power produced by plants that are lower on the supply curve and discharge to replace more expensive power from higher on the supply curve. When carbon taxes are high enough, storage can charge from gas plants and displace coal power that has become more expensive. When gas prices are already high and carbon taxes are low, the gap between the marginal costs of coal and gas is large. While a tax on carbon emissions serves to reduce the size of this gap, the coal

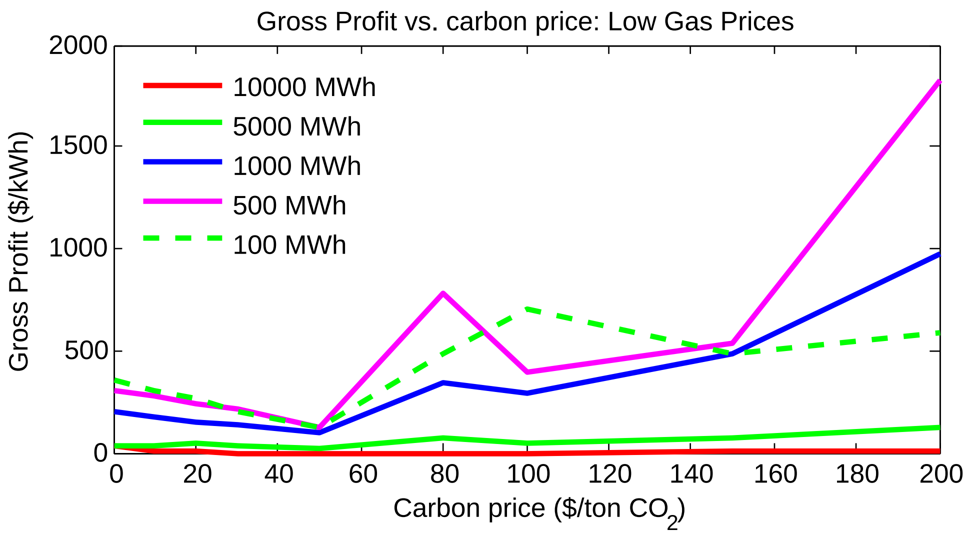

Figure 3.9: Gross profit seen by storage operators in a system with low gas prices under various carbon price regimes. At low carbon prices, storage operators achieve small profits that decrease as taxes increase. As carbon taxes increase past $80/ton CO_2, storage profits begin to increase.

plants below said gap must still operate to satisfy load, and they are still cheaper than gas plants. As storage capacity is increased, the overall use of baseload coal also increases due to storage charging[52]. At $80/ton CO_2, fuel switching from coal as baseload to gas as baseload begins to occur (see Figure 3.7), which causes emissions attributable to storage to drop rather than rise, as they do with a lower price on carbon.

The implications for the operational phase of energy storage life cycle emissions are therefore strongly dependent on the system in which storage is operating, and the taxes on carbon that already exist in the system. In both the high and low gas scenarios we explore, we observe that avoided carbon goes to zero as carbon taxes increase. When carbon taxes are high, the marginal costs of high carbon intensity plants increase, so that they operate in fewer hours. This means that at the highest carbon prices, the difference in carbon emissions between high and low cost generators gets smaller. As the overall energy mix gets cleaner and renewables penetrations increase due to policy changes such as AB32 and RPS, energy storage will no longer be able to trade high emissions energy for low emissions energy–all energy will be coming from low emissions sources. For this reason, any storage emissions reductions will decline as the energy mix gets cleaner, and the potential for storage to assist in direct operational emissions reductions may be limited.

Crucially, the value of storage to a future system with lower carbon intensity is path-dependent: if the system has been decarbonized by disincentivizing carbon emissions through taxes the value of storage will be different than if the system has been decarbonized through another method that does not significantly change the overall system supply curve and the relationships between baseload and peaker plants running on coal vs. gas (e.g. a method that implements wide ranging energy efficiency measures on the demand side would reduce carbon emissions overall by decreasing load, but the relationships between types of plants on the system supply curve would not change appreciably). A carbon tax is not guaranteed to incentivize investment in storage. The system in which storage investment is being considered may be primed to reduce the overall benefits of additional storage when a carbon tax is added, particularly if the price on carbon is not high enough to drive storage profits.

In some cases, the benefits to the system of additional storage capacity are reflected in the profits achieved by storage operators; however, in this case, the overall benefit that storage provides to the system grid-wide is not always a good proxy for estimating the incentive (e.g. revenue, profit, etc.) for storage operators to participate in energy markets. We show in Figures 3.8 and 3.9 that storage profits first dip slightly and then grow more strongly as carbon prices increase, but the benefits system wide do not show a similar pattern. From the results we present, it is reasonable to conclude that a carbon tax does not provide a straightforward incentive for storage penetrations to be increased through market dynamics alone. If fuel prices combined with carbon prices are such that storage operators find themselves entering the market near the nadir for benefits (as shown most clearly in Figure 3.1), they may be disinclined to do so. Even more starkly, a storage operator who finds it economically beneficial to operate at a carbon price of \$50/ton may no longer at a carbon price of \$80/ton, and may cease to operate. If such a storage device is contributing to overall carbon emissions reductions, and ceases to provide these when an increase in carbon price occurs, then the expected decrease in emissions that should otherwise coincide with an increase in carbon tax may not in fact be realized.

To avoid misalignment of storage incentives benefits to the grid, and benefits due to reductions in carbon, our results indicate that a carbon price of greater than \$80/ton CO_2 is necessary. It is only after this point that all of these incentives line up, and storage operators gain profit while providing a net reduction in carbon emissions as well as an overall reduction in system costs. Additionally, a carbon tax is most synergistic with storage capacity when gas prices are lower relative to coal prices. This means that as fracking contributes to lower gas prices, policy makers and storage device owners should be in agreement about adding a carbon tax to the system. \$80/ ton CO_2 is much larger than the current market clearing price of the Regional Greenhouse Gas Initiave (RGGI), at \$5.50/ton CO_2. \$80/ ton CO_2 is also on the larger side of estimates of the social cost of carbon, but not substantially so; the PAGE09 model gives an estimate of \$106/ton CO_2[32], the RICE model gives an estimate of \$59/ton CO_2[46], and the Anthoff model gives an estimate of \$51/ton CO_2[2].

In this paper, we are not considering the potential for storage to reduce emissions by reducing inefficient energy production during fast ramping. This is an area of great potential for fast-responding storage, because storage can be charged using energy from slow responding plants that are used for baseload, and that energy can then be used to provide ramp services. We are also not considering the potential for energy storage to reduce uncertainty or volatility in wind and solar power production. This is also a potential source of storage-driven emissions reductions in the overall electricity system.

3.5 Conclusions and Policy Implications

We demonstrate that carbon taxes affect the benefits that storage can provide. When carbon taxes increase, the effect on storage operation is dependent on the existing mix of generators on the system. Systems with a large gap in marginal cost between cheaper, higher emissions generators that burn coal and more expensive, lower emissions plants that burn gas will not tend to favor storage when the gap in marginal costs is reduced by a carbon tax. In these types of systems, there are no compelling synergies between policies that increase storage and policies that increase carbon taxes. In systems that, at the initialization of a carbon tax, have a smaller initial gap in marginal costs between natural gas plants and coal plants the synergies are stronger, and storage will be more beneficial when a carbon tax is also added. This suggests that we should consider a carbon tax under the current fracking-enabled natural gas price regime so that additional deployments of storage can be in the interests of storage operators as well as policy makers endeavoring to deploy storage in an effort to reduce carbon emissions. To properly align incentives for utilities, storage producers, and society, our results indicate that a carbon tax greater than \$80/ton CO_2 is necessary to ensure that storage operators are adequately incentivized, and any carbon emissions that result from storage operation are minimized. While \$80/ton CO_2 is higher than the current market clearing price of RGGI, it is within estimates in the literature of the social cost of carbon.

Others in the literature have demonstrated that carbon emissions have the potential to go up overall when storage is added to the current system ([52],[31]), and our results support this. We also show, however, that changes in carbon taxes can mitigate this effect when fuel prices for natural gas are low relative to coal. At present, current policies in California (AB2514[1]) and US-wide (the STORAGE Act[59]) regarding storage do not sufficiently consider the impacts of storage on carbon emissions, nor do they try to explicitly reduce this impact. Storage will be strongly beneficial in providing ramp and reserve capabilities to a system with higher requirements for these services due to the increased deployment of renewables. If policy makers are interested in having storage provide these kinds of services in a high renewables future, it is to their benefit to implement a carbon tax in the near term. This will incentivize storage capacity to be built out now, such that it will be available to support renewables in the future.

Chapter 4

Using TCLs as a grid-level resource

4.1 Abstract

As the energy grid evolves away from fossil fuel-driven baseload peaker plants and towards a system with a higher concentration of renewables and a stronger focus on efficiency, new engineering solutions for managing such systems are being considered. Thermostatically controlled loads (TCLs) could potentially be used to arbitrage electricity prices or provide ancillary services through non-disruptive load control. Non-disruptive load control allows management of TCLs in a manner similar to storage devices. We investigate the potential systemwide benefits of large populations of centrally-managed TCLs, and compare this to the benefits and operational impacts of storage devices.

4.2 Introduction

Demand response has been demonstrated to provide system benefits similar to storage, particularly with respect to handling variability associated with intermittent renewables, such as wind and solar [11]. Demand response acts in a similar manner as storage, given that demand that is curtailed is frequently shifted to another, less constrained, time of the day or year. Unlike storage, there is no round-trip efficiency loss, but many currently-in-use demand response programs have other restrictions, limiting the frequency that the resource can be called to curtail. Because demand response and storage work in similar ways, their use may be a bit in competition.

One particular application of demand response technologies that has been considered is the aggregation and control of the setpoints of thermostatically controlled loads [10]. By directing individual loads to turn on or off when they might not otherwise do so, we can raise or lower their net power consumption on the grid, while keeping the individual loads operating within their temperature dead bands. [42] demonstrate how to do this with state estimation techniques. These techniques allow for management of large quantities of TCLs without needing to know the exact state of each TCL individually. Millions of TCLs may be necessary to provide a substantial benefit, so these techniques reduce the required infrastructure that would otherwise be necessary to implement such a solution.

Flexible ramping products are being considered to address the "duck curve" in the electricity generation profile [66]. This curve originates as solar penetrations increase, because the evening ramp occurs as solar production winds down for the day and the electricity system needs to deal with the resulting larger ramp. Energy storage has been considered as a way to deal with this ramping need, but there is still some debate in the literature over whether or not bulk energy storage will be cost competitive enough to provide this service. Unlike dedicated energy storage, such as lithium-ion batteries, compressed air energy storage, or fly wheels, TCL aggregations may be more competitive in the market because their capital costs will be lower. TCLs will require a sensor network and software integration, but they will not need the kind of large-scale hardware that utility-scale storage would need, so the lifecycle emissions costs of such a solution could be expected to be lower as well.

In this paper, we model the potential operational benefits that could be achieved using TCL aggregations to provide storage services, including reserve services as well as energy arbitrage. We also investigate the extent to which dedicated energy storage and aggregations of TCLs might overlap, and the relative magnitudes of the two products' potential revenues and system benefits. We are interested in the overall effect of TCL aggregations, were they to participate in the market in a manner similar to a single large-scale storage device. For this reason, we are modeling their effects on an hourly basis. There may be other benefits that TCL aggregations could provide on a subhourly basis which we are not addressing.

4.3 Methods

Model Overview

We model demand response services from a large population of TCLs as if they were a smaller number of energy storage devices with constraints on their operation that are based on hourly varying temperatures. We then use these devices with time-varying energy parameters in an hourly unit commitment model that minimizes total system costs, subject to constraints on generator operation, storage device operation, DC power flow, and reserve requirements, which include both a short-duration regulation service, and a longer-duration load-following service. We do not pay demand response devices for their energy, although they do make revenue if they can divert their energy charging into lower cost hours. We solve the underlying model using a branch-and-cut algorithm that we implement using the CPLEX 12.5 C++ library. The underlying unit commitment model is based on the Western Interconnection (also referred to as the Western Electricity Coordinating Council, or WECC). Results from the underlying model are described in [52].

Aggregation of controlled TCL population as a single storage device with time-varying energy storage constraints

Aggregations of thermostatically controlled loads can be conceptualized as storage devices with time-varying parameters, because they can be controlled to operate such that their combined output is beneficial to system operators. "Charging" such a device amounts to having more devices on at a given temperature than would otherwise be expected, and "discharging" one corresponds to fewer loads in the "on" state.

To obtain the time-varying parameters that characterize our aggregated devices, we model the controlled TCL population using the analytical method described by [41]. Without control, the TCLs have a total power trajectory, or baseline aggregation, $B_{agg,j}$ in every hour j. With control, the TCL population can be operated at a higher total power, $P_{max,j}$, or a lower total power, $P_{min,j}$, depending on what is necessary for the overall system. In every hour, the power output of the aggregated device, $P_{agg,j}$ must be between $P_{min,j}$ and $P_{max,j}$. The amount stored, then, into the aggregate "device" is as follows:

$$S_{j+1} = S_j + (P_{agg,j} - B_{agg,j}\Delta T), \tag{4.1}$$

where ΔT is the length of the time period, in this case one hour. The total energy stored into the device cannot exceed $S_{max,j}$.

Each of the parameters $B_{agg,j}$, $P_{max,j}$, $P_{min,j}$, and $S_{max,j}$ depend on the temperature in hour j, as well as the various other parameters of the individual TCLs on the system. The parameters are calculated as follows:

$$\begin{aligned} B_{agg,j} &= \sum_{i=1}^{N_j} P^i D_j^i, && (4.2) \\ P_{max,j} &= \sum_{i=1}^{N_j} P^i, && (4.3) \\ P_{min,j} &= 0, && (4.4) \\ S_{max,j} &= \sum_{i=1}^{N_j} P^i h_{p,j}^i \left(1 - D_j^i\right), && (4.5) \\ & && (4.6) \end{aligned}$$

where N_j is the number of devices available in time period j, P^i is the rated power of device i, and h_p is the amount of time taken to traverse the entire deadband. We use a distribution of 1000 air conditioner TCLs, and the typical values used by [40]. For temperature data, we use hourly climate normals from the weather station at the Los Angeles Airport for the year 2010 [3]. Additionally, we locate the aggregation at a node in the system in Los Angeles, so that the aggregation is experiencing load conditions most closely associated with the temperature data used.

Unit Committment Model

Objective Function

In the model we use for the overall electricity system, we add storage capacity in increasing increments corresponding to TCL aggregations of 1000 units each. We then use that aggregation, along with a set of thermal generators and forecasted wind and solar resources, to satisfy load at each node as well as a set of global regulation and load following requirements. The objective function is the same as in [52]:

$$\min \sum_{g \in \mathcal{G}} \sum_{t \in \mathcal{T}} \Gamma_g q_{gt} + SU_g s_{gt}, \tag{4.7}$$

where the sets $\mathcal{G}$ and $\mathcal{T}$ denote the sets of generators on the system and time periods modeled, the decision variable q_{gt} denotes the level of output for generator g in time period t, and the decision variable s_{gt} denotes whether or not generator g started up in hour t. Additionally, $\Gamma_g = F_g * HR_g + O_g$ and $SU_g = SE_g * F_g + SA_g$, and F_g, HR_g, O_g, SE_g, and SA_g are respectively the fuel cost for generator g, the heat rate for generator g, the variable operations and maintenance cost for generator g, the energy required to start generator g, and the fixed cost component of starting generator g.[1] We obtain fuel prices F_g from EIA data corresponding to 2013 [58]. We choose the emissions factors for generators, EF_g based on fuel type, and we obtain them from EPA. [23].

TCL Aggregation Constraints

We model scheduled consumption or supply of energy from aggregated TCLs in hourly blocks. We also model the commitment of storage capacity from the aggregated TCLs to provide regulation and load following reserves on an hourly basis. We assume that there is no cost to using the aggregations, outside of the cost of the energy they consume to operate outside of their expected trajectories.

As in 4.3, we require the TCL aggregations to adhere to limits, such that energy stored in aggregation m at time t, $P_{agg,mt}$ must be less than the capacity $S_{max,m}$ of the resulting aggregation. In the following constraints, $\mathcal{M}$ is the set of all storage devices on the system:

$$0 \leq S_{mt} \leq S_{max,mt} \quad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{4.8}$$

The charge and discharge rates for the storage device are also constrained by the power limits for the aggregation, which are specified as follows:

$$P_m^{charge} = P_{max,mt} - B_{agg,mt} \tag{4.9}$$
$$P_m^{discharge} = B_{agg,mt} - P_{min,mt} \tag{4.10}$$

[1]For simplicity we assume heat rate is constant across each generator's output range

The charging c_{mt} and discharging $d_m t$ behaviour of the aggregations are then power-constrained as follows:

$$0 \leq c_{mt} \leq P_m^{charge} \qquad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{4.11}$$
$$0 \leq d_{mt} \leq P_m^{discharge} \qquad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{4.12}$$
$$\tag{4.13}$$

The following three constraints ensure that, at every time period, the available energy for arbitrage, regulation, and load following are all appropriately constrained by the current energy state of the aggregation of TCLs. These constraints ensure that every device is capable of serving the worst case reserve action for which they might be called, in addition to delivering or consuming energy according to the energy arbitrage schedule.

$$e_{mt} = e_{m,t-1} + \tau \left(c_{mt} - d_{mt}\right), \tag{4.14}$$
$$e_{m,t-1} \geq \tau d_{mt} + \tau^r r_{mt}^{us} + \tau^{lf} lf_{mt}^{us} \tag{4.15}$$
$$E_m - e_{m,t-1} \geq \tau c_{mt} + \tau^r r_{mt}^{ds} + \tau^{lf} lf_{mt}^{ds} \tag{4.16}$$

Here, r_{mt}^{us}, lf_{mt}^{us}, r_{mt}^{ds}, and lf_{mt}^{ds} are, respectively, the power contributions of aggregation m to regulation up, regulation down, load following up, and load following down, respectively, in time period t, and e_{mt} is the amount of energy that we store into aggregation m at time t. The constant τ is the time period length in hours, and τ^r is the length of time for which regulation must be provided in hours, τ^{lf} is the length of time for which load following must be provided in hours.

In addition to the added TCL aggregations, the model also dispatches 4 pumped-hydro plants in all scenarios. These are modeled similarly to the TCL aggregations, but they have efficiencies of charge and discharge. The efficiencies and capabilities for the pumped hydro plants are taken from [53], and comprise 3.0 GW of power, with 201 GWh of total energy capacity. Both pumped hydro and TCL aggregations can provide regulation and load-following, subject to constraints that require sufficient energy and power capabilities for provision of 15 minutes of regulation and 2 hours of load following (Eq. (4.15) and Eq. (4.16) with $\tau^r = 0.25$ hrs and $\tau^l = 2$ hrs) [55].

Generator Constraints

In each time period t, we allow each generator g to provide energy (q_{gt}), regulation up (r_{gt}^u), regulation down (r_{gt}^d), load following up (lf_{gt}^u), and load following down (lf_{gt}^d). We constrain these decision variables as follows:

$$q_{gt} + r_{gt}^u + lf_{gt}^u \leq \overline{Q}_g u_{gt} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T}, \tag{4.17}$$
$$q_{gt} - r_{gt}^d - lf_{gt}^d \geq \underline{Q}_g u_{gt} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T}, \tag{4.18}$$

where u_{gt} is a binary decision variable denoting whether or not generator g is operating in time period t, and $\overline{Q}_g$ and $\underline{Q}_g$ are the maximum and minimum generation limits, respectively, for generator g. Each of the ancillary service variables must also be less than their respective limits for each generator:

$$0 \le r^u_{gt} \le RU_g u_{gt} \qquad \forall g \in G, t \in T \tag{4.19}$$

$$0 \le r^d_{gt} \le RD_g u_{gt} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{4.20}$$

$$0 \le lf^u_{gt} \le LFU_g u_{gt} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{4.21}$$

$$0 \le lf^d_{gt} \le LFD_g u_{gt} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{4.22}$$

Between hours, generators are subject to ramp rate constraints:

$$R^-_g \le q_{gt} - q_{g,t-1} - r^d_{gt} - lf^d_{gt} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{4.23}$$

$$R^+_g \ge q_{gt} - q_{g,t-1} + r^u_{gt} + lf^u_{gt} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{4.24}$$

Continuous startup variables for generators are used with binary operating variables and minimum up and down times in the manner described by [49]:

$$\sum_{k=t-UT_g+1}^{t} s_{gk} \le u_{gt} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{4.25}$$

$$\sum_{k=t+1}^{t+DT_g} s_{gk} \le 1 - u_{gt} \qquad g \in \mathcal{G}, t \in \mathcal{T} \tag{4.26}$$

$$s_{gt} \ge u_{gt} - u_{g,t-1} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{4.27}$$

$$0 \le s_{gt} \le 1 \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{4.28}$$

$$u_{gt} \in \{0, 1\} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T}. \tag{4.29}$$

We obtain heat rates, and capacities (HR_g, $\overline{Q}_g$) from [53]. We also match the prime mover for generators in this dataset to TEPPC generator category data from the 2009 TEPPC Study Program Results to obtain ramp limits (R^+_g, R^-_g), minimum up- and down-times (UT_g, DT_g), minimum operating capacities ($\underline{Q}_g$), start-up costs and startup energy required (SA_g, SE_g), and variable operations and maintenance costs (O_g). The maximum regulation (RU_g, RD_g) and load following capabilities (LFU_g, LFD_g) of each generator are calculated based on the maximum generator movement in 10 minutes, using the one-minute ramp rate for the generator's prime mover [62]. Generator limits on ramps between hours were calculated based on maximum generator movement in 60 mins. [49]

In total, the model commits and dispatches 185 generators, of which 38 are coal-fired, 135 are gas-fired, 4 are nuclear, and 8 are run on fuel oil. The model does not dispatch hydro, biomass, wind, solar, and geothermal plants; instead the production profiles and capacities for those generators originate in the Price model. The set of dispatched generators used is based on disaggregated generator data from the Price model, which are then modified such that generators with similar heat rates are aggregated together, and each node in the network has only one generator with each heat rate, which reduces symmetry in the subsequent formulation.

Network Constraints

We enforce nodal power balance constraints for hourly schedules with a linear DC load flow model:

$$\sum_{g \in G_n} (q_{gt}) + \sum_{m \in M_n} (c_{mt} - d_{mt}) + \sum_{i \in N} B_{ni}(\theta_{nt} - \theta_{it}) = L_{nt}, \tag{4.30}$$

where G_n is the subset of generators located at node n, M_n is the subset of generators located at node n, B_{ni} is the susceptance between node n and node i, θ_{nt} is the voltage angle at node n at time t, and L_{nt} is the load at node n at time t.

Also, the total load flow on line ij must be less than or equal to the maximum load flow allowed, $\overline{D}_{ij}$:

$$B_{ij}(\theta_{it} - \theta_{jt}) \leq \overline{D}_{ij} \tag{4.31}$$

We assume that any line capacity violations that result from reserve actions are sufficiently small or short in duration that they can be tolerated by the system operator or that the system can be redispatched to resolve constraints. We also assume these events are sufficiently rare that they can be neglected for the purpose of quantifying the annual cost benefits of TCL aggregations used as storage devices at the scale of the model.

The layout of the system network for the model is based on data for the 240-bus model created and published in association with the Price model developed at CAISO [53]. From this resource, we obtain susceptances B_{ij} and line limits $\overline{D}_{ij}$ for the network, as well as hourly loads L_{nt}.[2]

Reserve Requirements

We procure minimum reserves of each type (regulation in up and down directions, load following in up and down directions) in each hour. We model these on the requirements used in [51]. For regulation up and down requirements, we require in each hour a proportion, ρ, of the peak load for the day added to a proportion, σ, of the total installed wind and solar capacity. We model load following up for each hour as a proportion, η, of the forecasted load plus a proportion, ν, of the forecasted wind and solar for the hour. We model the load following down requirement as a constant proportion of the renewables forecast. Total regulation in both directions must be greater than 1% of peak load ($\rho = 0.01$). The Western Wind Integration Study indicates that 1% of peak is acceptable for regulation with respect to wind capacity, but does not investigate whether this also applies for additions of solar. To ensure that regulation needs are satisfied with the addition of both resources, we also add 1% of the installed wind and solar capacities to the regulation requirement in both directions ($\sigma = 0.01$). Total load following in the up direction must be greater than the sum of 3% of forecasted load and 5% of forecasted wind and solar ($\eta = 0.03$, $\nu = 0.05$), in accordance

[2] The [53] model is based on 2004 data. In the time since the model was built, total demand has remained relatively flat [61] and generation capacity for all fuels but wind, solar and natural gas were virtually unchanged [21]. Gas capacity has grown significantly since 2004, however because total and peak demand remained flat this capacity has had relatively little impact on operations.

with the "3+5" rule. In accordance with the need for load following in the down direction as specified in [39], we also require an amount of reserve in the down direction equal to 5% of forecasted wind and solar.

The following equations define these constraints explicitly, with $\overline{S}_n$ and $\overline{W}_n$ being the solar and wind capacities installed at node n, respectively, and S_{nt} and W_{nt} being the solar and wind forecasts at node n during time period t. To reduce complexity, we model total reserves constraints globally.

$$\sum_{g\in G}(r^{u}_{gt}) + \sum_{m\in M}(r^{us}_{mt}) \geq \rho\left(\max_{a\in T: t_{max}-a\geq t} L_{na}\right) + \sigma\left(\sum_{n\in N}(\overline{S}_n + \overline{W}_n)\right) \qquad \forall t\in\mathcal{T} \tag{4.32}$$

$$\sum_{g\in G}(r^{d}_{gt}) + \sum_{m\in M}(r^{ds}_{mt}) \geq \rho\left(\max_{a\in T: t_{max}-a\geq t} L_{na}\right) + \sigma\left(\sum_{n\in N}(\overline{S}_n + \overline{W}_n)\right) \qquad \forall t\in\mathcal{T} \tag{4.33}$$

$$\sum_{g\in G}(lf^{u}_{gt}) + \sum_{m\in M}(lf^{us}_{mt}) \geq \eta\sum_{n\ inN} L_{nt} + \nu\sum_{n\in N}(S_{nt} + W_{nt}) \qquad \forall t\in\mathcal{T} \tag{4.34}$$

$$\sum_{g\in G}(lf^{d}_{gt}) + \sum_{m\in M}(lf^{ds}_{mt}) \geq \nu\sum_{n\in N}(S_{nt} + W_{nt}) \qquad \forall t\in\mathcal{T} \tag{4.35}$$

Solution Method

As in [52], we run the model in series by passing the final stored energy levels for the aggregation, if any, and generator operating and starting levels from the first day as constants that constrain the corresponding variables for the second day. This corresponds to the following constraints, where the *prev* superscript denotes variables from the previous day's solve:

$$e_{n0} = e^{prev}_{n24} \qquad \forall g\in\mathcal{G} \tag{4.36}$$

$$u_{gb} = u^{prev}_{g,24+b} \qquad \forall g\in\mathcal{G}, b\in(-DT_g+1,...,0) \tag{4.37}$$

$$s_{gb} = s^{prev}_{g,24+b} \qquad \forall g\in\mathcal{G}, b\in(\min(-UT_g+1,-DT_g+1),...,0) \tag{4.38}$$

Additionally, because it would be optimal to fully discharge the energy stored in the allocations at the end of each unit commitment modeling period, we also constrain the final storage levels and generator operating levels. To do this, we run a preliminary two-day unit commitment model with a four hour time step for the generator unit commitment variables, and save the generator and stored energy states at the end of the first day for use as constraints in a second run. In the second (final) run, we use single-day unit commitment in one hour increments with final stored energy levels and final generator operating states constrained to be equal to those saved from the first run (as in [55]). This corresponds to the following additional constraints for the first two-day unit commitment, where $T = \{t\in\mathbb{Z} : 1\leq t\leq 48\}$

$$u_{gt} = u_{g,t-1} = u_{g,t-2} = u_{g,t-3}\ \forall g\in G, \{t\in T : t \mod 4 = 0\} \tag{4.39}$$

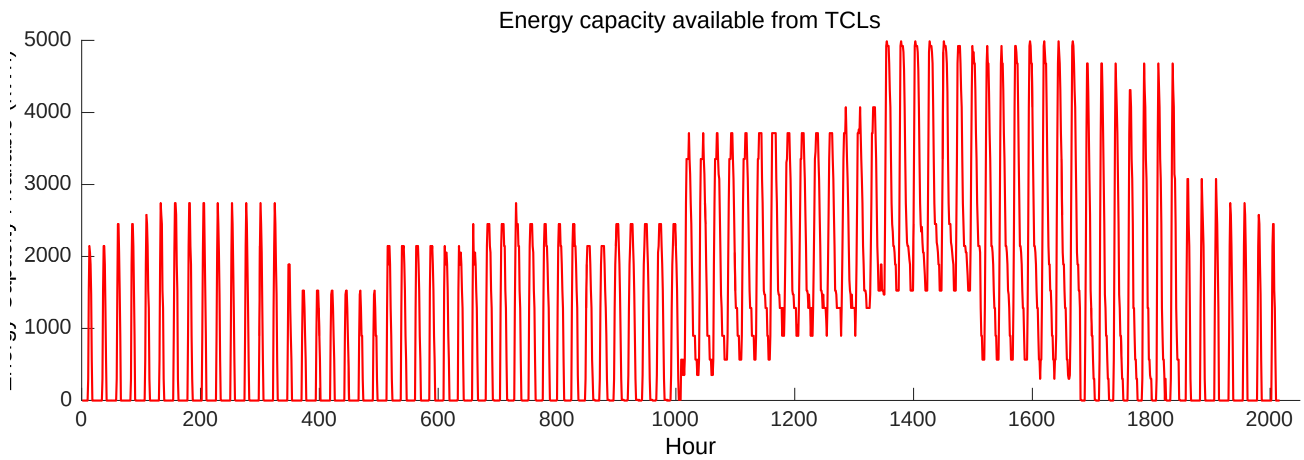

Figure 4.1: Energy available over the year with 20,000 TCLs on the system

In practice with air conditioners, most are only capable of being used to provide storage services at certain times of the year, when temperatures overnight are high enough that air conditioning loads are in an on state overnight (corresponding to temperatures above at least 64.7°F in the model.

We implement the model in C++ and solve it with CPLEX 12.5. We solve the first two-day unit commitment problem with a mip gap of 0.5%, and the second problem with a mip gap of 0.05%. The average time taken to solve these two problems and obtain results for an individual day was 68.3 seconds. To reduce the time taken to solve the problem, we run the model for a subset of days corresponding to the first week of each month in the data. We then scale the resulting costs accordingly such that they represent a full year of data.

4.4 Results

Figure 4.1 and Figure 4.2 show the energy available and the charge and discharge power available, respectively, over the time frame modeled. The x-axis for each graph numbers the hours modeled between 0 and 2016. This corresponds to the first week of every month in the dataset. From these figures it can be seen that on most days the energy and power available start and end at 0 kWh and 0 kW, respectively. This means that there are no opportunities on these days to carry over charge between days. Such opportunities are only available to air conditioners in the summer, when temperatures are sufficiently high to require air conditioning loads to operate overnight.

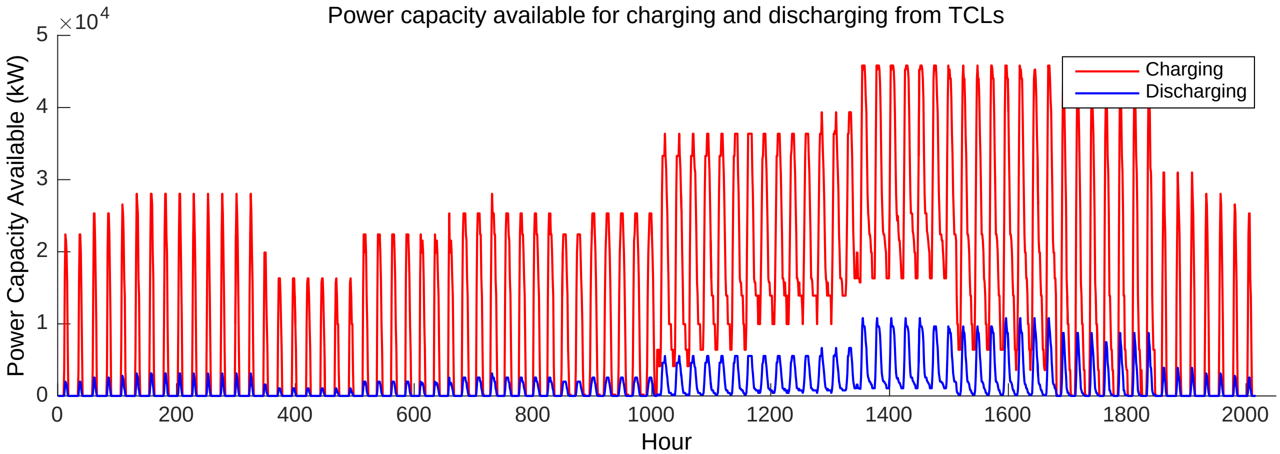

Figure 4.2: Power for charging and discharging over the course of the year with 20,000 TCLs on the system.

Figure 4.3 shows the total system cost savings due to the additions of TCL aggregations in 1000 TCL increments. There is an initial sharp rise in savings, which then levels off quickly, after roughly 100,000 TCLs are present in the aggregation.

Figure 4.4 shows this leveling off even more starkly. After only 50,000 TCLs are present, the marginal benefit of adding an additional device in not identifiably different from zero. We compute the marginal benefit as the ratio of the change in operating cost resulting from each incremental addition of a 1000 TCL aggregation to the total capacity of TCL aggregations present.These results suggest that, like large storage devices, there is a carrying capacity for TCL aggregations, after which there is no more additional market benefit that is able to be captured [52].

We can see why this is happening more clearly in Table 4.1. At low penetrations of enabled TCLs, they are able to participate in all markets roughly equally, in roughly an eighth of the hours in a year. This is much better than the initial performance of added bulk energy storage, which reaches that level of penetration in the regulation market at 250 MWh, at 2 GWh in the load following market, and never in the energy market. As a result, TCL aggregations are much more valuable at low penetrations than are bulk energy storage additions, but, unlike bulk energy storage, TCL aggregations are unable to sustain their increase in value as their concentrations on the grid increase.

The point at which the marginal benefit for TCL aggregations levels out corresponds to roughly $300 million in savings discounted over a 20-year period, which can be achieved with a population of 200,000 TCLs in the aggregation. For the high renewables, low gas

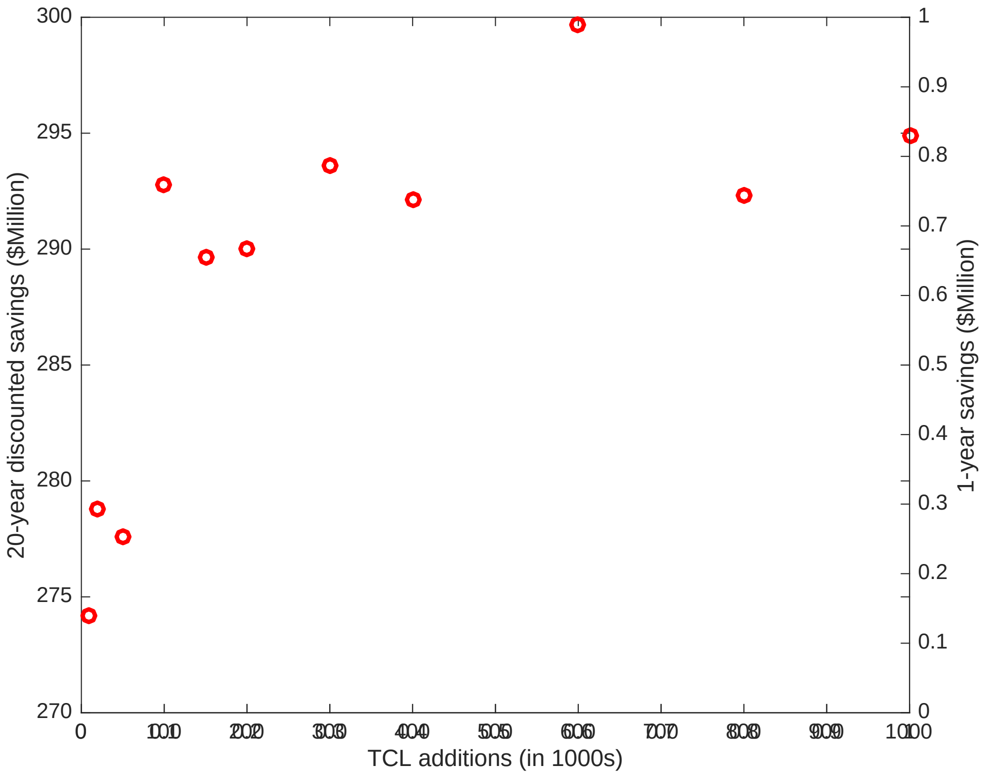

Figure 4.3: TCL System Cost Savings

price scenario described in [52], a savings of $300 million corresponds to roughly 2 GWh of energy storage capacity. An additional MWh of energy storage capacity from dedicated storage devices therefore has an equivalent order of magnitude to adding an aggregation of 1000 TCLs with the properties identified in 4.3. Stated differently, 1 TCL is equivalent to 1 kWh of traditional energy storage when neither provide substantial additional value to the system. In terms of the additional marginal benefits that TCLs can provide, each TCL brings $2700 in marginal benefit for the first 10,000 TCLs, but the total benefits do not increase substantially for additional TCLs, and these are worth much less to the system. When compared to energy storage, this means that the first 10,000 added TCLs are worth even more than the first 100 MWh of energy storage capacity provided by traditional storage, which is valued at up to $1800/additional kWh in [52]. The next additions of TCLs after the first 10,000 are no longer worth more than the equivalent energy storage, which continues to be worth more than $0/additional kWh until at least 4 GWh of capacity are on the system [52]. While the benefits to using TCL aggregations drop off much more quickly than bulk energy storage, the costs to use TCL aggregations may be smaller, and they will require less maintenance than larger storage devices.

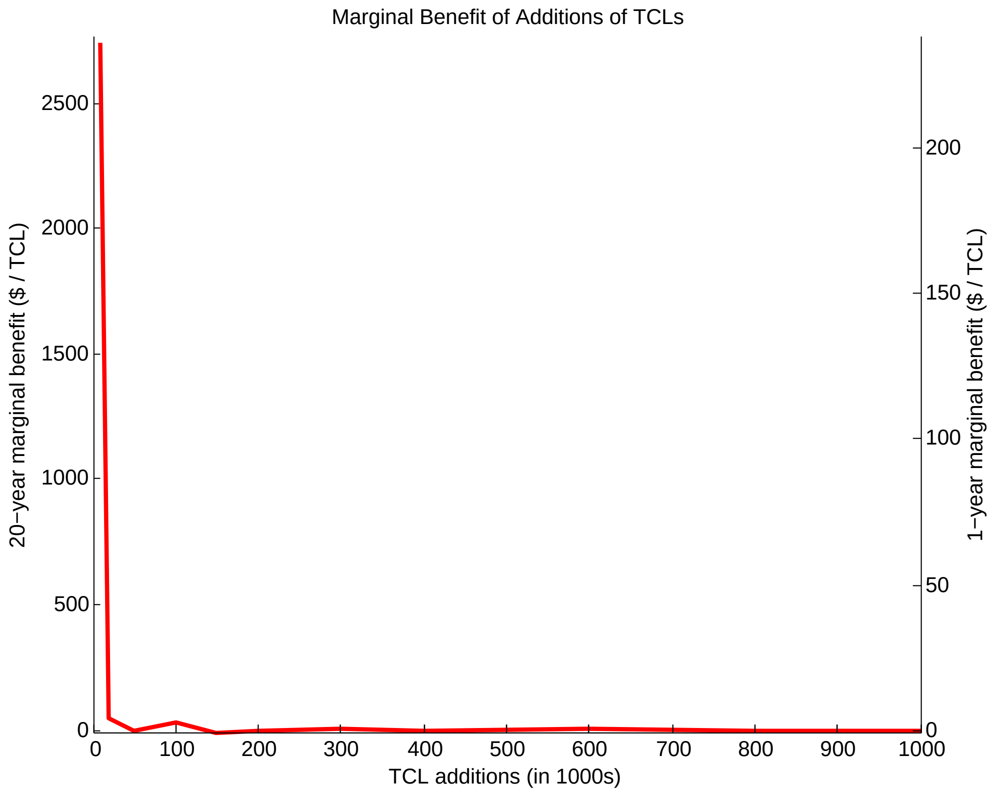

Figure 4.4: Marginal Benefit for TCLs

4.5 Discussion

In this paper we show that the marginal benefit of additional air conditioning TCLs used to provide storage services drops off such that there is no additional marginal benefit for the Western Interconnection after roughly 1 million of these devices are in place. As in [52], we expect that the marginal benefit for storage devices will eventually become zero. This is because storage will eventually be unable to arbitrage prices in any market–all the price differences will have been arbitraged away, so there will be no more additional value that storage can capture. Before this marginal benefit levels out at zero, however, there are some benefits that such devices can provide.

For this model, TCLs are allowed to provide both regulation and load following services in addition to energy arbitrage. While this provides some additional benefit opportunities for TCLs, in practice load following services of longer duration are unlikely to be reasonably provided by TCLs, since these services require durations of 2 hours. As in [41], we assume no change in end-use performance of the load, i.e. that temperatures never leave their original temperature deadband. To achieve this requires loads to be operated within constraints that in some cases may disallow actions that would otherwise be beneficial to the system as a whole. In addition to only being available for a few hours a day, TCL aggregations are less likely to be able to consistently provide service as the duration of required control signal

Table 4.1: TCL Aggregation Market Participation: Number of hours that aggregations of TCLs participated in energy, regulation, and load following markets per year of simulation

TCL count (000s)	Hours/year participating in energy markets	Hours/year participating in regulation markets	Hours/year participating in load following markets
10	1189	1215	1169
20	1199	1217	1172
50	1202	1220	1197
100	1201	1223	1200
150	1201	1231	1205
200	1201	1234	1222
300	1196	1235	1234
400	1200	1234	1235
600	1198	1235	1235
800	1199	1235	1235
1000	1198	1235	1235
1200	1195	1235	1235
1600	1196	1235	1235
2000	1197	1235	1235
2400	1197	1235	1235
2800	1196	1235	1235

increases. The power to energy ratios of the modeled TCLs are also very high, which allows them to contribute to regulation and load following markets quickly and maximally. We also observe that TCLs are providing all of the required regulation capacity at the outset, and are contributing to the load following capacity up to their physical limits. On most days, there are insufficient energy arbitrage opportunities for TCLs due to the short duration over which the outdoor air temperature allows the TCLs to operate within their deadbands.

There are several other areas for further research. We have explored a single set of fuel prices and renewables penetrations; more tests of these could show improvements in the value of TCL aggregations to system operations. Also, using temperature data and hourly load data that are collocated spatially and temporally may indicate synergies between TCL availabilities and load requirements that we do not model here. We investigate only air conditioners here, but other devices could be modeled similarly, and may, when combined with the benefits from air conditioners, provide additional benefits that air conditioners alone cannot, particularly when seasonal variations are taken into account. Finally, using other locations for aggregations may produce additional benefits, especially in places like San Diego or Arizona, where the temperature is more frequently in a range where air conditioners comprise a larger portion of the load. In addition to broad locational benefits driven by climactic variation, locational value may also be observed due to decreased transmission congestion. We do not look at this in depth in this paper, but transmission congestion amelioration could be an important consideration for the valuation of TCL aggregations as well.

4.6 Conclusions and Policy Implications

We find that the overall operational value of added air conditioning TCLs is limited in size, even when these devices are allowed to provide ancillary services. This is likely due to the fact that the devices are only available for a few hours every day because only a few hours of the day have the right average temperatures to allow the devices to be controlled within their deadband. Therefore, if TCLs are to be aggregated to provide these types of services, it will likely be necessary that both air conditioning and heat pumps be included, such that the energy storage they can provide is available over a larger temperature range. This is particularly important for the overnight case, when wind capacity may be large and charging in preparation for the morning ramp will be desirable. We also find that TCL aggregations are very beneficial when they are first installed, because their high power capacity allows them to provide substantial reserve services, which are more valuable than energy arbitrage services. It is also possible that capacity markets could play a role in facilitating the buildout of the technology required for TCL aggregations.

Chapter 5

Conclusions and Future Developments

5.1 Conclusions

In this thesis I assess the implications of a variety of options for incorporating additional energy storage resources onto the grid at a large scale. I show that the value of storage to the overall grid drops off as penetrations of storage increase. Similarly, as the amount of storage on the grid increases, the gross profit available to new storage operators entering the market quickly drops off on a $/kWh basis. Because of this sharp drop in value, it is important for policy makers to target the rollout and development of additional storage capacity such that the storage that is added can provide optimal value. Storage can provide a variety of grid functions, but their corresponding system benefits are not equivalent. In this research I show that reserve functions are the most optimal functions for storage to serve. Policies that encourage increases in storage penetrations should focus on this source of value before other sources, such as arbitrage.

Buildouts of storage also have the potential to increase carbon emissions in the absence of policies to prevent such an event. Additional storage capacity is currently being considered as a way to enable renewables and reduce the overall carbon intensity of the current grid. If, however, storage increases carbon emissions overall, some of the expected benefits from such policies may be mitigated. One of the most obvious policy approaches to decreasing carbon emissions is adding a tax on carbon, which disincentivizes plants that produce more carbon in favor of those that are cleaner and have a lower carbon intensity. In this research I show that storage does not follow these kinds of dynamics. Implementing a carbon tax in conjunction with storage does not necessarily decrease emissions relative to baseline if the carbon tax is not high enough, and the gaps between the marginal costs of natural gas and coal plants are simultaneously too large. Further still, I show that the benefits of storage to the system decrease if carbon prices are too low, and the benefits to storage operators do as well.

Other mechanisms for introducing energy storage resources onto the grid may be easier and more efficient. By aggregating TCLs into single storage resources, their thermal energy storage capabilities can be harnessed and used for providing grid-level resources. In this research, I explore the extent to which TCL aggregations might be comparable to other forms of more traditional energy storage. Because storage from TCLs is dependent on temperature and its energy and power capabilities are time varying, I am able to show that the savings and benefits that result from adding TCLs are smaller than they are for energy storage without time-varying constraints. I also show that the value of TCL aggregations drops off more quickly than does the value of more consistent energy storage. While TCLs do have high power capacity in some hours, their lack of full-time capacity severely limits their value to ISOs, particularly for energy arbitrage functions over large time scales. Nevertheless, the high power capacity of TCL aggregations makes them attractive and feasible at at least a moderate scale, if they focus primarily on services like regulation and load following that require high power capacity, but are less dependent on that power for long durations.

5.2 Future developments and uses of this work

Policy applications and improvements

Storage has already been identified in specific policies as a key piece of the puzzle in moving toward a high renewables, low carbon electricity system. While there are certainly some benefits to using storage in this manner, there are also several possible courses of deployment that storage could take that would be unideal. In order for storage to contribute optimally to the end goal of decarbonizing the electricity system, it needs to be deployed primarily for the provision of reserves, and reserves markets need to be adjusted so that storage resources can participate. Future work in this area should explore the changes that will be necessary for allowing and encouraging storage devices to participate in reserves markets. Additionally, investment should be focused on storage devices that can contribute power over energy, since reserves markets require fast-responding power capabilities, but do not necessarily require these powers over longer durations.

New markets for reserves

More exploration should be done regarding the effects of storage the new and much discussed flexiramp market for CAISO. In this work, I have established that reserves provision is the most valuable use of storage, and many other papers also confirm this. I show that both reserves and load following are more valuable than arbitrage. Given that flexiramp is intended to be a ramp capability that covers both time scales, storage should be ideally suited for this application. More research will need to be done to determine the extent to which energy storage investment is justified for this particular purpose.

TCL aggregations

Additional climactic zones should be explored to determine whether or not TCL aggregation-based storage is viable in some regions over others, particularly when other types of TCLs are considered that have opposite temperature operation profiles. Also, I do not consider the effects of climate change here, and it is very likely that, as climate change progresses, the value of thermal storage will increase due to higher variability in the climate overall. It is also likely that using existing devices to provide storage capabilities may be better from a life cycle perspective than building new devices. This is an area for further research.

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