The Value of Power Grid Flexibility: Applied Optimization Methods for Bulk Electricity Storage and Technology RD&D

by

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Abstract

As power systems adapt to include aging infrastructure, new socio-political priorities, and renewable electricity resources, grid operators look to a more flexible grid. Electricity storage flexibility is one strategy gaining interest. Clean energy advocates see benefits in terms of greater renewables integration and lower emissions; grid operators see storage as an improved security system in the face of supply and demand variability and uncertainty. However, as power systems are designed for reliable and efficient operations using available technologies, newer, better-performing technologies such as energy storage devices may not always win the market.

Several market barriers to storage remain, including high storage capital costs and a lack of trusted tools for modeling and estimating the lifetime value of new capacity investments [1]. Most storage modeling strategies omit constraints that describe the technical operating boundaries of different power generating technologies, which can lead an overestimation of total operating costs for the power system [2]. I describe a mixed integer linear optimization framework for estimating the optimal control and value of energy storage in a virtual power generation system with economic, regulatory, and technical performance characteristics.

The model consists of power plant commitment, dispatch, and selective capacity expansion constraints that simulate optimal investments and operations of the power generation system. A new formulation for modeling energy storage is also developed in order to improve the accuracy of round-trip efficiencies and allow for the inclusion of minimum storage output constraints. Using this model, I solve for break-even target prices for storage capital costs under a range of scenarios (storage futures scenarios).

A second challenge slowing the adoption of storage is a lack of spending on performance improvements and cost-reductions. A two-factor learning curve and optimization approach is developed to solve for the optimal portfolio of research, development, demonstration, and diffusion investments (RDD&D) over multiple investment periods. Using the target capital costs from unit commitment model output as the investment model input value, innovating firms and policy planners may better identify cost targets and investment strategies for reaching target levels of storage deployment.

Electricity storage becomes more valuable as net load variability increases. The impact of net load variability is tested by changing the level of renewable generation resources in the system. The current capital cost of storage—here, compressed air energy storage (CAES)—generally exceeds the target cost needed to make CAES economical when it is used to provide load following, load shifting, and operating reserve services in high-voltage power generation systems. Scenario analysis shows that when renewables generation reaches 35%, CAES becomes economical in limited quantities due to the added value from providing renewables integration and greater operating reserves. Using this framework, I identify different levels of cost reductions needed to drive improved adoption and make several RDD&D recommendations.
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1 Introduction

In 2010, Beacon Power, a flywheel energy storage company, received a $43 Million Loan Guarantee from the U.S. Department of Energy by way of American Recovery and Reinvestment Act of 2009 appropriations [3]. Flywheel electricity storage provides 2-5X faster response times for frequency regulation services compared to traditional natural gas generators. But when Beacon Power’s product hit the competitive market for power generation, the company received the same rate payments as its competing, gas-fired counterparts. The added value provided to the grid through faster response times was not captured in the payments it received [4]. Beacon Power filed for bankruptcy in 2011; shortly following, the U.S. Federal Regulatory Commission (FERC) passed Order 755 to “ensure(s) that providers of frequency regulation receive just and reasonable... rates” [5]. The new rule made storage-based frequency regulation a more profitable venture, and Beacon Power returned to business under its reorganized structure. The case of Beacon Power shows that non-technical factors such as market design and policy can impact the success of promising new energy technologies.

Storing power has gained much recent interest as a way to increase the ability of the power grid to handle the growing base of intermittent renewable electricity supplies. In the absence of storage, grid operators must continually adjust available power generators to perfectly match changing levels of power consumption. Due to this real-time balancing of supply and demand, the grid is not always well equipped to use intermittent and uncertain electricity sources such as wind and solar power. As the installed base of renewables increases, grid operators seek a more ‘flexible’ grid. Storage flexibility can offer faster power supply response times and the ability to store excess electricity for later use, benefiting grid operators through renewables integration efforts and a suite of other services.

Today’s dominant electricity storage technology is pumped hydroelectric power, a mature technology that gained popularity in the 1970s and 1980s for storing power during low-price hours and selling power when demand and prices are higher. While pumped hydroelectric is attractive for its ability to store large amounts of energy with roughly 80% round-trip efficiency,
the citing of new pumped hydroelectric is limited by geological constraints. New technologies like advanced batteries, flywheels, and compressed air electricity storage (CAES) offer increasingly mobile and flexible forms of electricity storage. In addition, the recent deregulation of U.S. power generation markets has brought about a broader set of grid services that may be met by electricity storage [1]. These services range from the provision of bulk generation capacity, operating reserves, frequency response, renewables integration, and other ancillary services.

While the range of services that may be met by electricity storage has increased, new installations have declined since the 1980s in the United States and have been limited to small projects such as the 110-megawatt compressed air energy storage (CAES) project in McIntosh, Alabama, and other demonstration-scale projects.

One major challenge slowing electricity storage innovation and deployment is low spending on technical innovations. Despite widespread call for increased funding on the order of 2-10 times current spending [6], scarce energy funding from the private and public sectors has limited public and private research, development, deployment, and diffusion activities (RDD&D). In the last 5 years, recent government initiatives show promise of increased funding for grid modernization efforts. These include the development of new research facilities and the temporary prioritization of grid modernization that came with funding from the 2009 American Recovery and Reinvestment Act of 2009.

Low R&D funding is thought to be partially a result of a lack of tools for estimating the value of future storage operations [1]. Traditional methods for estimating the future value of storage have two major shortcomings: First, a class of “price-taker” models rely on the assumption that market prices are fixed and perfectly known in advance [7]. Second, these models and other simple cost-based models known as “economic dispatch” do not include key technical performance characteristics of generators such as ramping rates and minimum operating times due to a lack of proper time-series resolution and power-plant scheduling. Palmintier and Webster (2011) find that ignoring the technical characteristics of power generators can lead to
unrealistic estimations of the power generation mix and an overestimation of total generation system operating costs.

This thesis addresses these challenges through the lens of integrated technical, economic, and regulatory systems. The framework developed here helps us answer three main questions:

1. What are the dynamics of operating electricity storage in the presence of various levels of renewable electricity capacity?
2. What is the estimated target capital cost at which different levels of storage capacity become economical?
3. What is the optimal (lowest cost) portfolio of RDD&D needed to bring current capital costs down to target levels?

To begin answering these questions, a full simulation of an example power generation system is developed. Power plant scheduling and dispatch decisions are simulated for each consecutive hour of grid operations. The annualized value of storage is then quantified by calculating the difference in total operating costs of the grid between scenarios with and without storage. We further derive a lifetime future cost savings from adding storage to the grid which represents the target cost for storage. Lastly, an optimal investment framework is developed to estimate the least-cost portfolio of investments needed to reach identified target costs.

By testing a variety of energy storage futures scenarios developed for this analysis, it is shown that the value of storage is proportional to the level of renewables integration services provided by electricity storage. Similar to prior studies, we find that renewable energy integration is not a significant value-added service until the combined generation of wind and solar power exceeds 35% of total power generation. Similar to the findings of [8], we show that total system CO₂ emissions are increased when storage is used by “dirtier” base-load generators to displace cleaner burning units serving marginal, peaking capacity. However, we also find that these earlier studies do not capture a set of scenarios where emissions can decrease from added
storage; such is the case when renewable electricity generation is high (> 35% of total generation) or when base-load generators are cleaner-burning than peaking generators.

By testing two versions of an optimal investment model constructed from the existing literature on two-factor learning curves, we find innovation spending should be staged over several time-periods so that later-period investments can take advantage of reduced technology costs that are brought about by early-period investments.

Chapter 2 provides a background for the analysis of energy storage by describing several key dynamics of the power system as well as the various services that may be met by energy storage.

Chapter 3 explores the current state of energy research, development, deployment and diffusion investments (RDD&D) and looks at how innovation policies can drive technological change.

Chapter 4 provides an overview of the two-stage unit commitment model with generation capacity expansion that is built for this study. A new formulation for electricity storage is proposed that can more accurately capture the effect of electricity storage round-trip efficiencies.

Chapter 5 applies the power system model to several energy storage futures scenarios to observe the impact of different levels of installed storage, wind, and solar capacities on the value of storage. I also describe a strategy for identifying the target cost of storage to achieve a desired level of deployment where the benefits of storage outweigh total costs.

Chapter 6 describes single- and multiple-period investment decision making models that can be used to identify the optimal portfolio of RDD&D spending needed to achieve target costs of storage. The models combine cost optimization methods and two-factor learning curves formulations that describe technological change as a function of RDD&D investment.

Chapter 7 concludes and presents several recommendations for energy innovation firms and policy makers based on key findings of this research.
2 Power grid supply, demand, and the roles of electricity storage

2.1 The electricity value chain and flexible electricity storage
To understand the role of electricity storage in today’s power system, it is helpful to define the underlying system. The primary need being served by the grid—delivery of electric power—requires the input of several connected subsystems, from fuel extraction and refinement, power generation, transmission, distribution, and consumption. These subsystems are often referred to as the electricity value chain.

Figure 1 represents the interface of storage and the traditional electricity value chain.

![Electricity Value Chain and its interface with storage](image)

Today’s storage technologies can be described as playing a supportive role to the value chain. When storage capacity is present, the system may benefit from certain operational efficiencies provided by both storage charging and discharging cycles. However, if electricity storage is removed, the system will continue to operate. This test does not hold true for any of the other 5 subsystems in the electricity value chain; their removal leads to immediate systematic failure.

The role of storage in the value chain also has modeling implications. Electricity storage is not a fundamental sub-system of the value-chain per se and therefore must compete with other technologies to support the needs of the system. Thus, the emergent behavior of storage is
dependent on the interaction between storage, renewables, and thermal power plants in a complex market environment. This logic suggests that estimating the future value of energy storage requires the simultaneous evaluation of all generation-side technologies as well as the governing policies and underlying market mechanisms.

Storage can be an attractive technical solution to several power grid needs in part due to its ability to provide operational flexibility. Operational flexibility is broadly defined here as the rate at which power generation assets can adjust operations to meet changing needs of the grid. The most common changing need is the current level of demand for power. An open cycle gas turbine (OCGT) is more flexible to demand than a nuclear power plant, and a battery is more flexible to demand than OCGT. Storage also provides flexibility by storing power, which creates value though providing grid operators the ‘option’ to store power for later use.

2.1.1 Performance qualities of the grid: the “ilities”

Electricity markets are designed to deliver power resources to meet demand at lowest cost, but the economics of power delivery is only one important metric describing the performance of the power system. Today’s grid also requires power to be delivered reliably, efficiently, sustainably, and with (voltage) quality. In the field of system architecture, these attributes are often referred to as the “ilities”. They are attribute of the grid’s primary value-related function—electricity delivery—that are served by the coordinated subsystems of the grid—the value chain (Figure 2).

Various changes in today’s power grid have led to a renewed focus in the “ilities”. These changes are highly coupled. For example, the recent deregulation of the U.S. generation supply has brought with it variety of operating reserve requirements that ensure power is delivered reliably even when the wind cuts short or grid assets fail [9]. These operating reserves require thermal generators to reserve ‘spinning’ output capacity to adjust to changing demand and renewable electricity generation [10]. An increase in spinning reserve requirements can lead to concerns over the operational efficiency of thermal generators that are operated at sub-optimal levels of output [11]. Further, operating reserves are proportional to the level of variable
renewable electricity generation [9], which has grown in part out of environmental sustainability concerns and the adoption of Renewable Portfolio Standards in most states. When REG is generated and delivered at the level of medium- to low voltage distribution networks, power quality becomes a concern as renewables can impact the frequency and voltage of the grid. In all, the power grid is a highly coupled system that faces the challenge of maintaining high performance standards under changing technology and socio-political landscapes.

The provision of electricity storage services discussed later in this chapter describes several methods being implemented by grid operators to maintain expected levels of performance. We later address how simulations of the power grid can take these performance attributes into account when estimating the value of storage.

2.1.2 Variable Power Demand

The variable nature of demand is defined using historical hourly power demand data. The demand curve is then used to explain various functions (services) that are increasingly served by electricity storage in today’s grid.

The demand curves in Figure 2 show 2012 demand data from the PJM operating region [12]. PJM is a Regional Transmission Organization that oversees the operation of the electricity transmission system for most of Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia and the District of Columbia. The boxes represent 25% and 75% quartiles with “whiskers” spanning the remaining tails of data; outlier levels of demand are shown in red. The daily moving median load is also plotted.
Four major characteristics of daily electricity demand are visualized here:

- Aggregate demand is intertemporally variable across days (depicted by bars) and hours (depicted by daily moving average of demand).
- Daily Aggregate demand is bimodal, with a first peak in demand occurring between 9:00 a.m. and 5:00 p.m. when businesses are most active. A second peak between 7:00 p.m. and 9:00 p.m. represents higher levels of household activity in the evening hours.
- Higher demand periods exhibit higher demand variability compared to hours of lower demand.
- Summer months, July – to September, exhibit higher median peak demand due to the use of air-conditioning units. The highest demand spikes visible as outliers in the full-year demand data (Figure 2, left) are attributed to periods of high demand in summer months (Figure 2, right). The greatest demand peaks typically result from warmer days and the consequent high use of air-conditioning. Air conditioning alone accounts for about 5% of total electricity consumption in the U.S. each year [13].
2.1.3 Economic dispatch and unit commitment

The National Renewable Energy Laboratory (NREL), a U.S. Department of Energy funded R&D lab, defines economic dispatch as the “commitment and operation of electric generating units or load control activities so as to meet demand with minimum total system operating costs” [14]. To minimize total system cost, generators are dispatched in accordance to their economic “merit order”. Lowest-cost generators deliver bulk power near the base of the demand curve, and higher-cost generators are added to as demand increases. The marginal operating cost \((\Delta$/\Delta power)\) of the plant serving the last unit of power (the “marginal generator”) sets the marginal price of power for that time step, which is generally equivalent to the price of power that is remunerated to all generators producing power at that instant [15].

In wholesale markets such as PJM and MISO, economic dispatch is performed in 5-minute increments, while regions in the Western Interconnection perform generation dispatch decisions on an hourly schedule [16]. The process of scheduling for later dispatch is known as “unit commitment”.

Using merit order to define the order of generator dispatch is economically convenient for power generators due to a fixed cost – variable cost tradeoff. Generators with lower operating costs such as coal, nuclear, and large-scale hydroelectric power are deployed at near full-capacity at the base of the demand curve. These generators typically face large fixed costs.

\[
fixed\ cost = (annualized\ capital\ cost) + (fixed\ operations\ &\ maintenance\ cost)
\]

High fixed costs can be recovered by base-load generators over many hours of bulk power service at low marginal cost of delivery. Generators with higher marginal costs and lower fixed costs—typically combustion turbines, natural gas combined cycle, and steam turbines—are dispatched later in the merit order to serve power to meet variations in demand.
Merit order is also technically convenient for grid operators. Generators that serve power at higher marginal costs generally have better time-response characteristics that aid in responding to higher variations in demand at the levels of demand being served.

2.2 Energy Storage Services

Energy storage can be used to meet several services required to operate a reliable, more efficient, power grid. This section uses a daily summer demand curve to help visualize properties of operating storage service within a simplified electricity generation mix.

2.2.1 Storage services: Load-shifting (price arbitrage)

Figure 3. Daily Demand Curve and Generation Mix With and Without Load Shifting

Figure 3 is a simplified illustration of one day of variable electricity demand and the supplying generation mix based on the 2012 PJM summer load curve. While many power plants make up the true generation mix, generators are grouped into three categories for the purpose of these diagrams: base-load generation, intermediate-load generation, and peak-load generation. In the base case, demand is met in the early hours by both base-load generators as well as generators serving intermediate load. In the middle of the day, additional peak-load serving plants are
dispatched to meet peak hours of demand. Peak-load serving plants are typically natural-gas fired turbines that have the ability to ramp up and down quickly on the order of minutes, versus base-load generators such as coal or nuclear that can take hours or even a full day to change output. The energy price set for all generators is called the marginal price, and is roughly equal to the additional cost required by the marginal plant to serve the last unit of power demand.

An increase in power in this early hour would require the intermediate-load serving plant to increase its output; therefore, the market clearing price for power is roughly equal to the marginal operating cost of the intermediate load-serving plant. When storage is added for load-shifting services, energy is stored during these low-price hours, later discharged to displace more expensive peak-load serving generation in more expensive, peak hours of demand. This practice, alternatively referred to as price arbitrage, was the only use of energy storage up until the mid-1980s [17].

In addition to price arbitrage, load-shifting has been recently used to store power from renewable energy generators in the case where renewable energy cannot be consumed immediately. In this way, the level of curtailed renewable energy can be reduced, making REGs more profitable and saving the grid operator (and potentially consumers) money, since REGs have a zero marginal operating cost and can displace high-cost peak generation through load-shifting. With predictable supply of storage for load-shifting, the grid operator can potentially reduce cost further by increasing output from base-load generators (e.g. nuclear power) to displace more costly generation serving intermediate load (e.g., natural gas).

Predicting the effect of load-shifting on system emissions has to do with the total round-trip efficiency of the energy storage unit, emissions that may arise from operation of the storage facility—in the case of compressed air energy storage, simple cycle natural gas turbines may be used, creating non-zero emissions—and the relative marginal carbon intensities of time period when energy is stored (charged) and delivered (discharged) [18]. A deeper evaluation of this effect is described in Chapter 5. One generalization can be made such that emissions will be reduced when peak-load generators are ‘dirtier’ (more carbon intensive) than base generator;
however, this is not always the case, as in ERCOT, the Texas power interconnection, where base-load is mostly met by coal generation, and ‘peaking’ plants are typically newer, less- carbon intensive natural gas plants. Further, it can be shown that market power and other operational dynamics of the grid can play a large role in the net effect on emissions [8].

2.2.2 Storage services: Generation capacity upgrade deferral

The addition of electricity storage reduces the system’s reliance on expensive thermal generators to meet peak hours of demand. Therefore, as grid operators consider strategies for upgrading their infrastructure in response to greater reserve requirements, increased renewables and supply variability, or increases in demand, they may prefer to install storage capacity instead of new thermal generators.

Replacing thermal generators requires storage facilities with high energy storage capacity that can deliver at least 2-6 hours of power at full output [17]. This limits the types of storage facilities and locations that may be suitable for generation capacity upgrade deferral. Pumped hydroelectric and compressed air energy storage using underground salt caverns may be suitable for this service as they can store over 10-times their hourly output capacity; however, the current state of these technologies constrains their installation to areas that are geologically suitable to storing large amounts of compressed air or water.

2.2.3 Storage services: Supplying reserve capacity

Reserve capacity provides the backbone for power security. Reserves commit a portion of their generation to respond in different ways to deviations away from the stable load point of the grid. The amount of reserve capacity required to ensure the regulated level of power security is known as the reserve requirement. Each Balancing Authority Area carries its own reserve requirements based on its historical and forecasted performance [19]. While total reserve requirements vary over time and geographic regions, reserve capacity must be large enough to cover the failure of the largest power resource. The reserve margin is a measurement of the size of the current
reserve requirements compared to current power supply, and is generally set between 15% to 20% [17]. The North American Electric Reliability Corporation is the primary body responsible for developing these Reliability Standards, overseeing reserve margins, and ensuring compliance in each of its regulated Balancing Authority Areas in the U.S., Canada, and increasingly, Mexico [19].

Table 1 provides an overview of the three major types of operating reserves and their functional characteristics as described by [9], [20], [21], [17], and [19].

Table 1. Classification of Operating Reserves

<table>
<thead>
<tr>
<th>REGULATION SERVICE INTERVAL</th>
<th>Primary Control (Primary Frequency Regulation)</th>
<th>Secondary Control (Secondary Frequency Regulation)</th>
<th>Tertiary Control (Supplemental Reserves, Tertiary Frequency Regulation)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NERC Operating Reserves type</td>
<td>Spinning Reserves</td>
<td>Spinning Reserves</td>
<td>Non-Spinning and Spinning Reserves</td>
</tr>
<tr>
<td>Maximum Response Requirement</td>
<td>5-10 seconds</td>
<td>up to a few minutes</td>
<td>Several minutes to 10+ minutes</td>
</tr>
<tr>
<td>Control mechanism</td>
<td>Automatic Generation Control (AGC) for up and down reserves</td>
<td>AGC + manual generation control for up and down reserves</td>
<td>Manual control of generation and/or load (demand-side management) for up and down reserves</td>
</tr>
<tr>
<td>Value Delivery</td>
<td>Early response to grid contingency to ensure power reliability</td>
<td>Support Primary Regulators by targeting small variations in Area Control Error</td>
<td>Respond to major contingencies to reduce larger deviations in Area Control Error where secondary reserves are too little; Provide backup support for serving fast-response primary and secondary generators</td>
</tr>
</tbody>
</table>
2.2.4 Storage services: Primary and Secondary Frequency Regulation

While grid operators continually match bulk power supply with the dynamic demand curve, there are smaller fluctuations in the frequency of the grid that require fast-responding regulation from subscribed generators that can change their output on the order of seconds and minutes.

Departures from the stable frequency of the grid (60Hz in the U.S.) are often produced at power exchanges between interconnected grid areas where neighboring grid frequencies are not identically matched [17]. Additionally, adding renewable energy capacity to the system adds fluctuations from changes in resource inputs from the wind and sun; however, increasing the geographic separation between renewable generators can help reduce power variability. When output is not perfectly matched across unique generation sources, there exists a balancing effect at the aggregate level. Conversely, co-located REGs can lead to greater variability [22].

The total effect of this variation, termed Area Control Error (ACE), is a measurement of the difference between current and stable grid frequencies.

Maintaining power supply quality and reliability through secondary frequency response (supply-demand adjustment in a few minutes or less) is carried out using a combination of automated and manual responses. Committed thermal generators—typically combined cycle natural gas turbines, gas turbines, and steam turbines—and energy storage facilities rely on Automated Generation Control (AGC) to continuously govern small amounts of output to meet secondary frequency regulation targets. To supplement AGC, the grid operator can make phone calls to generators, order power purchases, or call on demand-side management to adjust for larger deviations in ACE.

Energy Storage technologies such as batteries and flywheel energy storage can respond to primary and secondary regulation more quickly than thermal plants—often at greater than 2X the rate of thermal AGC—leading to an increase in power quality and reliability [23].
The variable frequency of the grid can also be managed by temporarily controlling demand through voluntary or involuntary load shedding. With the advent of demand-side management strategies, grid operators can call on demand response (DR) to curb power demand at major sources of demand—typically, at larger commercial and industrial load centers. Demand management is more widely used in providing tertiary frequency control, due to both timing constraints on DR and uncertainties around the impact of changing loads on the frequency of the grid [9].

Figure 4 illustrates the basic concept of using regulation services to balance variable frequencies on the grid.

**Figure 4.** Generation Frequency With and Without Power Regulation

As energy storage increasingly delivers regulation services, thermal generator that traditionally supplied this service can dedicate more of their total capacity to providing stable, bulk services, resulting in lower O&M costs and improved operating efficiencies [23], [24]. Further, as renewable energy resources increase, more stringent reserve requirements are expected to create market opportunities for storage technologies that can providing a range of regulation services [25].
2.2.5 Storage services: Load following (including renewables integration)

While the various forms of frequency regulation described earlier deal with fast changes in the balance of supply and demand—changes in load that are responded to on the order of seconds or several minutes—energy storage technologies can also help manage slower cycles of demand that may occur from predicted changes or unpredicted changes in demand. Load following services, also referred to as economic dispatch, is the response of generators to meet changes in load that occur over a timeframe of 10-minutes to several hours [16].

Thermal generators provide load following by reserving a portion of their maximum capacity to respond to slow load cycles. For following upward trends in demand, load-following generators operate below their rated output capacity to reserve room to gradually increase output to meet increased demand. When demand trends downward, thermal generators can follow load by gradually reducing output to their minimum safe level of output (their ‘minimum capacity’). While various thermal generator technologies meet the technical requirement of load following, they bear the operational burden of generating at sub-optimal levels of output, where heat rates, emissions, and variable operational costs are greater [17].

Adding variable supply from renewable energy generators changes the operational dynamics of how generators meet demand through load following. Unlike thermal generators and hydroelectric power, renewable energy output depends on the variable inputs of solar radiation and wind availability. To evaluate the ability of economic dispatch to accommodate variable supply and demand, changes in demand and changes in wind and solar output are often considered assessed as “net load”. Net load is calculated as total power demand minus the current supply of non-dispatchable generation sources—wind and solar [26]. Figure 5 shows the generalized effect of renewables and the corresponding change in net load.
The hypothetical case of variable wind generation in Figure 5 illustrates how renewable energy supplies can increase the variability of net load—an effective increase in the adjustments required by dispatchable generators.

In this case, base load generators slightly decrease their output in order to accommodate the net load swings that are not met by intermediate-load generators due to physical limitations of the technology (ramping constraints or minimum generation constraints). However, in cases of high renewables generation, the remaining generation supply may not fully absorb the entire output of renewables due to technical limitations of the generation fleet, leading to the consequent curtailment of a portion of renewable energy supply [27]. A more flexible power supply from the addition of electricity storage can help the grid adjust to planned or unplanned variability from renewable electricity generation [28] and can lead to reduced curtailment of renewables [29].

While renewable energy is generally discussed as a non-dispatchable resource due to the inability to control output, the ability to curtail output means renewables are partially-
dispatchable—their output can be reduced (curtailed) or increased from a prior state of curtailment [17], [30].

2.2.6 Storage services: Transmission relief and upgrade deferral

In addition to displacing generation capacity, storage capacity can also reduce over-congestion of transmission lines and delay expensive line upgrades. Transmission line over-congestion occurs when the amount of electricity demanded is greater than the power bandwidth of the transmission line providing electricity. To reduce congestion, storage is sited on the demand side of a transmission line to supplement generation during hours of extraordinarily high demand. This reduces the supply burden on generators upstream of the transmission lines, alleviating transmission congestion.

Transmission relief and upgrade deferral provides benefit to system operators by reducing capital- and time-intensive transmission projects. Significant transmission line congestion at a given point (node) generally takes place within a window of two hours or less during only a few days of the year [31], though some nodes may experience more than 3,500 hours of annual congestion [32]. The deferral of large transmission upgrades may be provided by small amount of storage capacity that are otherwise used for price arbitrage and ancillary services throughout the remainder of the year [31].

Consumers may also benefit from transmission relief. An over-congested transmission line forces grid operators to make up for the power shortage by increasing output from additional transmission routes. These supplemental transmission routes are generally fed by more expensive generators due the cost prioritization (merit order) of generators, leading to higher locational marginal prices (LMPs). By reducing transmission line congestion, energy storage can stabilize LMPs and ultimately lower the price of power paid by consumers [32].
2.3 Conclusion: storage services

A new age of the power grid is being defined by increases in the levels renewable electricity generation, changing fuel prices, aging grid infrastructure. This has ushered in much interest on grid modernization technologies and regulations that will ensure the reliable delivery of power, as well as its sustainability, efficiency, and power quality. Electricity storage can provide a range of solutions to support the evolved needs and requirements of grid operators and regulators. Some of these services are discussed in this chapter, including load following, load shifting, generation and transmission asset relief and deferral, frequency regulation, operating reserves provision, and renewables integration. The range of service being met by electricity storage is also evolving as the technology and market conditions allow. For example, storage can also provide voltage control and black starting services in distribution networks, important value-added services that are outside of the scope of this study.

The benefits of storage have implications for various stakeholders, including policy makers, grid operators, innovating firms, and consumers. This study unpacks several dynamics of operating electricity storage under the assumption that storage can serve various services, including load following, load-shifting, renewables integration, and operating reserves fulfillment. Other emergent benefits are also discussed, including reduced thermal generator starts and various impacts on total emissions. The value of storage will depend on the services being met under different operating conditions, and the ability of markets to remunerate electricity storage for its full range of benefits [7].

The next chapter reviews the state of technology innovation strategies and explores how technology progress—specifically, development cost reductions—may result from more optimal innovation investment strategies.
3 Technology Research, Development, Deployment, and Diffusion

3.1 Optimal Technology RDD&D: Overview

Technology research, development, deployment, and diffusion (RDD&D) is terminology adopted by the U.S. Department of Energy to describe a key objective of advancing the Nation’s leadership and sustainability in energy technology. Research and development (R&D) describes the selection, development, and demonstration of new or improved technologies. Deployment and diffusion (D&D) represents the end-goal in the development process for new energy technologies, where emerging technologies cross over from demonstration projects to fully functional products and services to be adopted by industry.

RDD&D is carried out by the public sector and funded through the U.S. government science and technology initiatives, as well as private industry. Private firms are often deemed better-suited for investing in deployment and diffusion (D&D) stages of the technology development continuum, due to their ability to take on investment risk. However, energy companies are proven reluctant spenders of R&D capital; firms typically spend between 0.23% and 1.1% of annual revenues on R&D activities [6], which is low in comparison to other industries. Several studies show that private spending on innovation in the energy sector is driven by federal interventions such as RDD&D investment programs.

The U.S. government’s role in technology RDD&D can be thought of as the identification, advancement, and stimulus of beneficial new technologies to the point where technologies can be handed off to private industry for further development and diffusion. Luiten and Blok (2003) extend on this notion of public-supported private development by suggesting government efforts should be “additional” to efforts that would otherwise be carried out successfully by private industry. They recommend governments focus on fostering “momentum of a [private] technology network” by partnering with leading private enterprises in technology development. Holaschutz (2012) reports one successful example of this in the U.S. solar industry, where
innovation networks, or “tribes”, develop in close proximity to one or more innovation champions, catalyzing further technology RDD&D through knowledge sharing networks.

Econometric studies have measured the impact of public RDD&D on private innovation and development as the difference between actual industry production and a production function that includes inputs of capital, labor, etc. [35]. In one example, González and Pazó (2008) looked at the impact of government subsidies on Spanish manufacturing firms and conclude that some firms likely engaged in RD&D primarily as an effect of government funding.

While evidence has been developed that points to historical cases of accelerated innovation as a response to public RDD&D, Luiten and Blok (2003) argue that identifying the impact of government RDD&D on industry ex ante can be more difficult, and should be a primary focus of policy makers. However, forecasting the benefits of RDD&D spending is wrought with challenges of imperfect information on the current state of private enterprise activities and the potential for technical improvements that can be brought about by the various roles of government RDD&D.

While this chapter examines historical RDD&D practices in government, universities, and private industry, this main focus is to develop an understanding of the dynamics of RDD&D investments and impacts. The chapter concludes by describing an adaptation of the two-factor learning curve methodology that has been used in various studies to describe the evolution of technological outputs in response to changes in various inputs. We also add a cost optimization method that can be used to identify the optimal RDD&D portfolio for achieving technology cost reductions.

3.2 **An improving landscape for Energy R&D?**

By the numbers, the energy R&D funding landscape has been arid in the last few decades. Energy companies are estimated to have spent less than 50% of revenues on R&D activities between 1991 and 2003 [37]; Meanwhile, U.S. government energy budgets fell by 68% (IEA
Data Services). Lubell (2013) estimated that U.S. Department of Energy R&D budgets declined 25% to 35% between 1988 and 2008. Under the Obama Administration, there has been limited evidence of increased spending. We find that an increasing trajectory in spending remains unclear as the vast majority of recent RDD&D spending came from 2009 American Recovery and Reinvestment Act funding – not from the traditional budgeting process administered by Congress (See Figure 7).

Private R&D in the energy industry is also very low compared against other industries, as discussed earlier. Kammen & Nement (2007) report that average R&D from energy companies peaked at 1.4% of revenues in 1978, though spending was only 0.23% between 1988 and 2003. By way of comparison, leading aerospace R&D firms spent between 3% and 20% of revenue on R&D in 2004—18% to 31% of revenue in biotechnology firms, 6% to 17% in semiconductors, and 5% to 50% in pharmaceuticals [39]. Similarly, public R&D has declined relative to other sectors. Figure 6 from Nemet and Kammen (2007) shows that R&D was nearly 10% of total U.S. public R&D in 1978, but declined to less than 2% by the late-'90s. Their study indicates a reduction in annual public energy R&D budgets of about $1 billion during this time period, which is particularly surprising given the total growth in U.S. government R&D budgets.

Figure 6. Total U.S. R&D and percentage for energy
Federal energy R&D budgets have declined since the 1980s despite several studies that suggest an increase in federal energy funding on the order of 2-10X current spending will be necessary to set us on a path to reach our energy technology and environmental goals [6]. These studies often focus beyond the borders of the U.S.; they are a global call-to-action. The International Energy Agency has recently asked for a tripling of RD&D investments in response to low levels of energy investment as a share of total research spending in IEA countries (3-4%), which includes the U.S. [40].

Despite the receding state of federal and private RDD&D funding of the 1980s- to mid-2000s, there has been limited recent evidence of a turnaround in this trend. The U.S. Department of Energy, under leadership of Energy Secretary Steven Chu, created energy innovation research laboratories such as ARPA-E, DOE Innovation Hubs, and Energy Frontier Research Centers. The general mission of these programs is to advance research, development, and deployment and diffusion (RDD&D) of breakthrough clean energy technologies through partnerships between government, academia, and industry. While the Energy Department’s allocation of half of its budgets to these contractor-led innovation centers has been criticized by many [38], energy hubs and ARPA-E received bipartisan praise during the 2012 Presidential elections [41]. A second wave of support came in the form of the 2009 American Recovery and Reinvestment Act (ARRA) funding, where Congress appropriated $21 billion to federal energy budgets. Within the 2009 ARRA funding, R&D for grid modernization efforts was prioritized as one of two priority targets. In a report entitled ‘Blueprint for a Secure Energy Future’ the U.S. Administration reported $4.5 billion of these funds would be allocated to grid modernization efforts, including the creation of a U.S. Energy Hub laboratory dedicated to the advancement of smart grid technologies [42].

The recent boom in energy storage RDD&D budgets can be attributed to the trickling down of ARRA funding and does not necessarily indicate a shift in funding priorities toward energy storage RDD&D in the medium-term. One indication of this is that specific targets for grid-scale
energy storage remain absent from the U.S. Department of Energy Strategic Plan (2011) or the Strategic Plan Update (2012).

Figure 7 shows U.S. Department of Energy budgets for energy storage between 1974 and 2011 as recorded by the International Energy Agency. U.S. Department of Energy budgets do not represent actual spending on these technologies, but can be used as a best-available proxy for the level of RDD&D spending allocated to various technologies. Additional sources of capital not included in these figures may be contributed through other public sources that receive DOE funding, such as national laboratories, universities, and DOE investment mechanisms such as the Loan Programs Office which is not part of a particular technology office at the Department of Energy.

**Figure 7. U.S. Government RD&D Budget for Energy Storage**

Figure 7 shows that in the two decades ending in 2008 (before 2009 ARRA funds), the average annual energy storage budget was only $17.7 million (2012 dollars) according IEA records, representing about 0.5% of annual R&D budgets during this period (ann. standard deviation of 0.78%).
Variations in energy budgets can be primarily explained by changing research and development priorities both at the U.S. government level, and within the Energy Department. Higher energy storage spending in the late-1970s and 1980s coincide with a period of higher spending on pumped hydroelectric storage. Energy storage R&D budgets increased again between 2002 and 2003, peaking at around $100M in R&D funds available and comprising about 3% of the federal energy and science R&D budget (DOE) in 2003. Congressional records from a 2002 hearing before the U.S Senate Committee on Appropriations explains the cost and performance goals and proposed strategy for the requested appropriations:

“Energy Storage and Transmission Reliability program goals are to develop energy storage facilities with an energy density greater than 5kWh per square foot at a cost below $700/kWh”...

Energy Storage Systems funds the design of integrated systems, research on advanced storage components, and development of economic and performance models.” [45]

In 2009, energy storage budgets were again increased to meet renewed grid modernization priorities under spending plans for American Recovery and Reinvestment Act funds, as described earlier.

Changes in actual federal budgets for annual energy storage follow closely with changes in energy storage budgets as a percentage of total energy RD&D budgets as shown in Figure 7. This indicates that variations in energy storage budgets are largely decoupled from changes in total energy RD&D budgets (including all technology areas). Further, a National Science Foundation special report on R&D shows that variations in the total RD&D budget for the U.S. Department of Energy are mostly independent of changes in U.S. Gross Domestic Product [46]. Therefore, variations in federal energy spending are more likely an effect of changing priorities than of changes in total availability of capital.

While several approaches are being taken to moving political priorities, from acts of civil disobedience to effort to weight the balances Congressional office seats toward clean-energy leadership, this study takes a more analytical approach. We assume that a shift in political
priorities can be supported by developing a clearer picture of the future value of energy investments from federal energy RDD&D. We do not look at the specific connection between federal spending and private industry investment; rather, strategies discussed may be adapted for the evaluation of federal, energy sector, or firm-level RDD&D spending.

The remainder of this chapter reviews several studies that explore how RDD&D and power-sector regulations can lead to accelerated technology development. This topic is also explored through the lens of state-of-the-art statistical techniques that describe how various spending policies can lead to increased technology ‘knowledge stocks’, a source of improved technological performance and cost reductions. The chapter concludes with several key strategy considerations for federal policy planners.

3.3 Public Policy modeling considerations: “Bottom-up” RDD&D versus “top-down” regulation

Policies for innovation in the electricity sector are generally separated into two classes: RDD&D-based policies such as government university R&D grants, SBIR grants, commercial technology demonstration projects, subsidies, and tax credits that promote “bottom-up” innovation, and regulation-based policies like carbon trading schemes and emissions limits that seek “top-down” innovation.

To evaluate the effectiveness of policies, studies often tie their analyses to metrics such as President Obama’s 80% goal for clean energy sources by 2035. One common finding is that a combination of both RDD&D and regulation policies leads to an acceleration in private investment in abatement technologies such as solar photovoltaic, coal with carbon capture and sequestration (coal CCS), and nuclear. Combining RDD&D policies with emissions regulations may also lead to a multiplier effect, where the total performance benefits realized through RDD&D and emissions regulation policies are greater than the sum of their independent contributions [47].
Conversely, Bosetti, et. al (2010) find that RDD&D interventions alone are likely insufficient to meet aggressive climate change mitigation targets, even when public R&D funding is readily available. Blanford (2009) provides a review of recent literature and finds corroborating evidence that emissions regulations alone are not sufficient for reaching long-term energy and environmental targets. Blanford’s work attributes this finding to his observation that firms facing emissions regulation are driven to make short-term adaptations in their technologies and operations as opposed to investing in long-term technology breakthroughs that are necessary for meeting long-term climate objectives.

From a review of the literature, it appears that many studies seek lofty clean-energy scenarios, but do not consider the underlying infrastructure scenarios that will enable these targets. This study is motivated by the idea that these processes should happen in concert; environmental and energy goals that describe what we want to achieve should be supported by frameworks that describe how we get there from here.

3.4 Private Industry Viewpoint

Due to the often proprietary nature of private R&D, clear measures for private R&D spending on particular technologies remain elusive. Several studies have attempted to use patent database analysis as a proxy for private R&D; however, these approaches have their shortcomings. First, patents are not developed for all private R&D efforts; further, the proportion of technological knowledge accounted for in patent databases is unknown.

As a result of limited reliable data, studies of industry spending on R&D are typically classified across high-level parameters such as industry and geographic region. Battelle’s Global R&D Funding Forecast looks at macro trends in international R&D spending and finds that growth in energy R&D spending and patenting in China will outpace the U.S. in the coming years [49]. These studies help develop intuition around trends in industry spending, but offer limited insight into spending for specific classes of technologies.
This chapter looks primarily at federal R&D spending, the principal focus surrounding research on the stimulation of private energy and climate-change innovation, but venture capital has proven itself a considerable alternative source of funding. One study attributes 15% of the total share of innovation across industries to venture capital investments [50]. But VC spending in the energy sector has also declined in recent years. U.S. venture capital spending on energy was roughly $1 billion in 2000, a figure that declined by roughly half by mid-decade [6] and has not garnered much increased interest since.

Private industry R&D in energy is considerably lower than in other industries. One explanation could be the high level of “knowledge spillovers” in the energy sector, where private firms do not capture the full value of internal R&D programs, and prefer to benefit from knowledge obtained from other firms and industries [25]. Therefore, as a technology is more widely developed, a “free-rider” problem can emerge leading to the underinvestment in new R&D by individual companies [48]. Further, energy infrastructure investments are characterized by high capital costs, long capital investment-periods, and high degrees of uncertainty around market adoption and technological change. These factors contribute to high discount rates, making it harder for innovating firms to secure capital [50] or justify R&D spending. Low R&D spending can also be propagated by the idea that energy R&D investments take decades to reach market [51].

3.5 Understanding Technology Learning Rates to Inform RDD&D

Economic evidence has shown that long-run economic productivity is best explained by improvement of technology—or more specifically, the growth in technology knowledge [52]. This basic concept underpins the importance of investing in processes that lead to technological improvement, and is used in this study to build up to a framework that describes a reduction in the capital costs of energy storage as an effect of technology investments over time.

T.P. Wright (1936) is credited as credited as the first study to explain technology cost reductions through the lens of learning curves. He discovered that airplane manufacturing costs were
reduced when a firm became more experienced in the manufacturing process (learning-by-doing). More recent studies have extended this work while focusing on specific energy technologies, including Pan and Köhler (2007) for the case of wind turbines, and [55] for solar photovoltaic costs. Both studies also include a second learning factor for research-based learning. The literature refers to this type of learning as R&D, learning-by-researching, or learning-by-searching—a source of knowledge generation that leads to technological improvement and cost reductions through the study of new- and emerging technologies in a lab environment.

Further efforts have been made to improve on the two-factor learning curve model. Kahouli-Brahmi (2008) identify several other mechanisms that have been attributed to growth in technological knowledge, including learning-by-using, where customer feedback helps enhance future designs, and learning-by-interacting, where corporations and research labs share knowledge across their networks, leading to increased knowledge development.

The combination of learning-by-doing and learning-by-searching inputs has been popularized as the two-factor learning curve, and is later discussed in Chapter 6 under the context of optimal investment strategies for investors and policy planners.

3.6 Predicting the effect of RDD&D and regulation policies on storage growth

Growth in technologies that help integrate low-carbon energy generators such as energy storage or improved electricity transmission infrastructure, are often omitted from system-level energy models for several reasons. First, new technologies can experience discontinuous technological change, where the pace of technological improvement is hard to predict with learning-curves [48]. Further, accurately modeling storage requires additional technical complexities that make these models more difficult to combine into one integrated model.

The U.S. Department of Energy NEMS model is one example of a current state-of-the-art model that omits storage dynamics when estimating the future of the U.S. electricity generation
landscape. Figure 8 shows recent U.S. Department of Energy storage capacity forecasts from their Annual Energy Outlook reports, plotted against actual levels of hydroelectric energy storage capacity. During a brief conversation with a member of Department of Energy team responsible for delivering the Annual Energy Outlook, it was confirmed that future storage capacity levels are flat-lined for all future energy and policy scenarios due to modeling difficulties.

Figure 8. U.S. Storage Capacity: pumped hydroelectric

While there is interest in including storage forecasts in future versions of NEMS, adapting the model to accurately capture the dynamics of various storage services could require significant modifications due to the lack of daily and hourly levels of demand and reserve requirements.
3.7 Conclusion and Key Strategic Policy Recommendations

As discussed in this chapter, there is some hope for increased spending on grid modernization, including RDD&D for energy storage technologies; yet the contrast between actual- and recommended innovation spending suggests new approaches are needed to increase funding priorities.

Federal RD&D Funding and energy storage budgets are driven largely by political priorities. Improved methods for estimating the future value of advanced energy technologies, services and energy policies is one challenge preventing the alignment of political priorities and increased RDD&D [1]. The remainder of this thesis describes a new modeling framework for energy storage and optimal RDD&D activities to address this information gap.

Four RDD&D investment recommendations are presented as common themes from the literature:

1. **Identify technology momentum and learning rates**: Gauging the need for public RDD&D (*ex ante*) should be carried out by studying the RDD&D characteristics of existing innovation firms, including their ability and willingness to carry out technology development using existing production networks [33]. By simultaneously considering the state of technologies and their production networks, technologies should then be classified into their respective stages of development or technology readiness [52]. Understanding these development states can inform estimates of technology learning rates and appropriate levels of RDD&D intervention [52], [54], [55], [57], [58].

2. **Catalyze global-scale interaction for global-scale problem solving**: Collaboration between innovating firms and laboratories can lead to more productive knowledge networks [59], where the ultimate goal should aim to extend networks and RDD&D planning processes across national boundaries [47].
3. **Coordinate RDD&D investments with regulations that drive innovation:** Public RDD&D intervention can accelerate private sector technology development and should be coordinated with top-down regulations that send a price signal to innovating firms [47], driving both short-term and long-term technology development [48].

4. **Improve frameworks for estimating the potential value of energy technologies:** Modeling the technical, operational, and learning characteristics of technologies can help decision-makers understand the socio-economic benefits of technologies and policies and inform appropriate levels of RDD&D interventions (this topic is discussed here, and also in [60]–[64]).
4 Methods

4.1 Overview: Modeling Energy Storage

The behaviors of a system depend on the interactions between its component parts. As described in the previous section, the components of the electric power generation system can be categorized into several coordinated subsystems responsible for generating, delivering, and consuming electric power. Given the real-time nature of power supply and demand, proper coordination of these subsystems is critical to successfully meeting customer needs—the service of reliable electric power.

Decoupling the coordination of the generators would lead to a shortage in power generation or overburdened transmission lines, affecting downstream consumers and the profitability of upstream fuel extractors. Failure in the electric power system is typically met by power outages that also affect neighboring systems. For example, the transportation system relies on electric power to operate traffic lights.

Due to the complexities underlying the electric power system, grid operators and regulatory authorities often rely on computational methods such as the unit commitment model developed in this chapter to predict day-ahead and weekly demand levels. Power plant scheduling and dispatch decisions are made according to a set of governing rules (constraints) and best practices (heuristics). These may be technical limitations such as maximum generator output, market mechanisms such as pricing schemes, or technical constraints such as operating reserve requirements.

While the electric power system can be decomposed into much more detail, the model described in this chapter considers a system boundary that includes the generation system and the underlying market for electric power, where power plants are developed, scheduled, and dispatched to meet demand.
4.2 Key progress in modeling energy storage

Several studies have been developed to estimate the value of various types of energy storage technology for one or more services. The majority of this work use cost-based strategies termed in the literature as the ‘price taker’ approach. These models use historical prices to estimate the value of a particular technology under the assumption of perfect energy price foresight. Denholm et al. (2013) provide a review of these models, and explain that the price-taker strategy generally leaves out important information regarding the technical characteristics of generators. Further, price taker models do not allow the dispatch of generators to influence market prices and the underlying operations of the generation mix. Drury, Denholm, and Sioshansi (2011) use a price-taker model to estimate the value of compressed air energy storage, and show that lower-cost CAES storage technologies are able to recover their costs from reserve and arbitrage revenues.

A handful of existing studies simulate the operation of electricity storage using simulations of the full generation mix in order to address some of the shortcomings of the ‘price-taker’ approach. Denholm et al. (2013) uses a commercial security constrained unit commitment model, PLEXOS, to estimate the value of battery storage for providing operating reserves and price arbitrage services. They find that price arbitrage revenues alone are not likely to make up for the high costs of battery-based storage, and suggest that markets will need to remunerate a broader range of energy storage services to increase the profitability of batteries. Tuohy and O’Malley (2011) use a modified unit-commitment model based on a model called the Wilmar Planning tool to show that pumped hydro-electric plants become economically attractive when wind levels are high (30%-50% of total generation) and uncertain. Harris, Meyers, and Webber (2012) evaluated the value of various storage technologies on a small system in Texas, but do not develop the operational and capital costs that impact the long-run economic viability of these technologies.

4.3 Model Formulation: Unit Commitment with Selective Generation Capacity Expansion

The optimization model developed for this study is a security constrained, multi-period, cost optimization model. While some of the formulations are unique to this model—in particular,
there is a new proposed treatment of energy storage—the majority of the model is adapted from best-practices in power systems modeling.

The model treats storage and power generators (‘units’) as independent entities. Each unit may be scheduled (committed) to turn on, generate power, or shut down. Storage units may also be scheduled to charge, which is required for later generation (discharging). Units scheduled to operate are then “dispatched”, generating power or charge storage units at an optimal level of power to collectively meet demand and reserve requirements in each 1-hour operating period. Scheduling and dispatch decisions are made each hour to represent the process in most U.S. power markets.

The model is also defined as ‘security constrained’, which refers to backup power reserves that are required by regulatory authorities to ensure the reliable operations of the grid. Reserve requirements change each hour and derived from the amount of variable renewable energy present as well as the level of forecasted demand.

Due to the binary formulation of commitment states, the problem is classified as a mixed integer linear optimization problem. The GAMS (General Algebraic Modeling System) environment is used for the development of the model code base and optimization. MATLAB is used for post-processing of output data for analysis. MATLAB and Adobe Illustrator are used in parallel for data visualization.

This chapter provides an overview of key formulations in the model, and features a new formulation for energy storage that can be applied to future unit commitment models where bulk electricity storage is present.
4.3.1 Objective function and indices

The model described in this chapter is used to calculate the optimal operation of over 350 individual power generators on sequential hourly basis in order to capture a reasonable load.

Thermal and renewable electricity generators are represented by index, \( i \). Electricity storage units are defined by index \( j \). \( dl \) is the hourly demand period for the given hour of operations in current time period, \( t \). The time period index is included here for future multi-year capacity expansion studies where investment decisions are made over the course of two or more multi-year time periods.

The objective function minimizes total fixed costs—this is the sum of annualized capital costs \( C_i^{CAP} \) and fixed operating and maintenance costs \( C_i^{FIXOM} \)—thermal startup costs, \( C_i^{START} \), fuel costs, \( C_i^{FUEL} \), emissions costs, \( C_i^{EMISS} \), and a penalty cost for non-served power, \( C_{t,dl}^{PNS} \), which is the cost of coming up short on meeting demand. \( x \) is the level of power generation for thermal units, renewables, and storage. An accumulated return rate factor \( \rho \) is included to recursively calculate the present value of future costs in multi-year simulations.

Generator investment decisions ('build decisions') are represented for each generator and storage unit by the binary index, \( y \). This decision variable is used throughout the model to constrain the operations and cost functions to include only built generators \( (y = 1) \). Setting \( y \) equal to zero in the initial list of generators enables the selective capacity expansion feature of the model; the model can then choose to invest in (build) additional power plants or storage units to accompany the existing (pre-built) generation fleet as necessary.

\[
\text{(1) } \quad \text{MIN } \sum_{i,j,t} (C_i^{CAP} + C_i^{FIXOM}) y_{i,j,t} x_{i,j,t} + \sum_{i,j,dl,t} (C_i^{START} + C_i^{FUEL} + C_i^{EMISS} + C_{t,dl}^{PNS}) p_t + C_{t,dl}^{PNS} PNS
\]

Traditionally, solving the unit commitment model together with the generation capacity expansion problem has been difficult due to the high dimensionality across equations and variables—hundreds of operating periods and hundreds of generators. To keep model runs under ten hours, two strategies are applied to address the curse of dimensionality [68]: First, only four
weeks of hourly operations are used to approximate a year of hourly operations. This strategy along with the input data for demand and variable renewable resources are borrowed from recent work by de Sisternes and Webster (2013). Four weeks of power demand, wind and solar resources (capacity factors) are selected from annual historical data to best approximate the full range of annual input data. To convert the four-week simulation to an annual approximation of operating costs, the model’s variable costs are multiplied by an adjustment factor, \( \omega \), where \( (\omega = 8760/672) \). To further reduce the problem size, I limit the selection of technologies that the model can build, as described in Chapter 4.3.4.

### 4.3.2 Unit Commitment Constraints

At the core of the unit commitment (UC) model are a set of decisions that simulate the scheduling of units for power generation. UC constraints also enforce a number of technical characteristics of the generating units, such as maximum ramping rates and minimum up and down-times. Nuclear power plants, for example, can take as much as a day to turn on (ramp up), and may be required to remain operational for several days at a minimum to maintain the reliability of the plant; conventional nuclear power is generally only suitable for base-load power. Various electricity storage technologies, on the other hand, can ramp to their full output capacity in a matter of seconds or minutes, and may be turned on and off over the course of hours to meet variations in the last unit of demand; this makes storage well-suited for serving marginal and peak-hour demand.

Scheduling decisions are represented in equation (2) as a set of binary decisions to turn a plan ‘on’, ‘off’, or to keep an ‘on’ generator operational in a given hour; these are \( S_{UP} \), \( S_{DOWN} \) and \( S_{ON} \), respectively.

\[
S_{i>1,t,dl}^{ON} = S_{i,t,dl-1}^{ON} + S_{i,t,dl}^{UP} - S_{i,t,dl}^{DOWN} \quad \forall i \in \text{therm}, \forall t, dl
\]

Once a plant is scheduled to become operational or change its power output, it is constrained by the speed at which it can change its output – the ramping rate. Each generating technology has a
different ramping ability. Technologies with fast ramping rates such as energy storage and peaking thermal generators (e.g., OCGT, steam turbines) are considered to be more flexible due to their ability to respond more quickly to changes in demand. Equations (3) and (4) define the amount of power that is available to be changed, $w$, where $x$ is the current generation level for the power plant, $\overline{x}_i$ is the maximum technical output of the unit, and $x_i$ is the minimum output.

\begin{equation}
(3) \quad w_{i,t,dl} = x_{i,t,dl} - S_{i,t,dl}^{ON} \overline{x}_i \quad \forall i, t, dl
\end{equation}

\begin{equation}
(4) \quad w_{i,t,dl} \leq S_{i,t,dl}^{ON} \overline{x}_i - x_i \quad \forall i, t, dl
\end{equation}

Equations (5) and (6) enforce up- and down ramping limits, respectively. The constraints compare the ancillary variable $w$ in current and preceding hours of operation, $dl$ and $dl - 1$.

\begin{equation}
(5) \quad w_{i,t,dl} - w_{i,t,dl-1} \leq ramp_{i}^{UP} \quad \forall i, t, dl
\end{equation}

\begin{equation}
(6) \quad w_{i,t,dl-1} - w_{i,t,dl} \leq ramp_{i}^{DOWN} \quad \forall i, t, dl
\end{equation}

Minimum up-time and down-time constraints are described using the formulation in [70]. Here, $\overline{m}_i^{UP}$ and $\overline{m}_i^{DOWN}$ represent the minimum time a unit must remain operational before it is shut down, and the minimum time an idle unit must remain ‘off’ before generating power again.

\begin{equation}
(7) \quad S_{i,t,dl}^{ON} \geq \sum_{i,t,dl > dl - \overline{m}_i^{UP}} S_{i,t,dl}^{UP} \quad \forall i, t, dl
\end{equation}

\begin{equation}
(8) \quad 1 - S_{i,t,dl}^{ON} \geq \sum_{i,t,dl > dl - \overline{m}_i^{DOWN}} S_{i,t,dl}^{DOWN} \quad \forall i, t, dl
\end{equation}
4.3.3 Generation Dispatch Constraints

Each hour of power supply and demand are balanced in (9). The left-hand side of the equation includes thermal and renewable generation, $x_i$, and storage generation, $outflow_j$. The right-hand side includes hourly demand which is adjusted by an annual demand growth factor, $\delta_t$. Storage unit charging, $inflow_j$, and a slack variable for power non-served, $PNS$, are also included.

\[
(9) \quad \sum_i x_{i,t,dl} + \sum_j outflow_{j,t,dl} = DEM_{dl} \delta_t + \sum_j inflow_{j,t,dl} + PNS_{t,dl} \quad \forall i, j, t, dl
\]

Equation (10) is a coupling constraint that links capacity and dispatch decisions. Thermal generators that are built must operate below their maximum output capacity, $x_i$; otherwise, the build decision variable $y_i$ is equal to zero and no power generation is permitted.

\[
(10) \quad x_{i,t,dl} \leq y_{i,t} \overline{x}_i \quad \forall i \in THERM, t, dl
\]

Similar to thermal generators, wind and solar generators are constrained by their maximum output capacities in (11) and (12), respectively. The formulation differs from that of thermal generators by the inclusion of capacity factors, $f^{WIND}$ and $f^{SOLAR}$, which are proportional to wind and solar resources available in a given hour.

\[
(11) \quad x_{i,t,dl} \leq y_{i,t,dl} \overline{x}_i f^{WIND} \quad \forall i \in WIND, t, dl
\]

\[
(12) \quad x_{i,t,dl} \leq y_{i,t,dl} \overline{x}_i f^{SOLAR} \quad \forall i \in SOLAR, t, dl
\]

Reserve Requirements are modeled as provided by Milligan et al., 2010. This formulation is also used in the IMRES model (de Sisternes, 2013). Equation (13) defines the up- and down spinning reserves; (14) enforces the minimum reserves requirement, which is a function of hourly demand wind and solar power given their maximum forecasted output. $K$, $\alpha$, $\gamma$, $\delta$, $\beta$, $\epsilon$, and $\theta$ are
calibration parameters for the magnitude of total reserves required as a proportion of demand, wind, and solar capacity.

\[
\sum_{i} (s_{i,t,dl}^{ON} \bar{x}_i - x_{i,t,dl}) + \sum_{j} (\text{level}_{j,t,dl} - \text{outflow}_{j,t,dl} + \text{inflow}_{j,t,dl}) \leq \text{RES}^{UP}_{t,dl} \quad \forall i, j, t, dl
\]

\[
\sum_{i} (x_{i,t,dl} - s_{i,t,dl}^{ON} x_i) + \sum_{j} (y_{j,t,level} - \text{level}_{j,t,dl} + \text{outflow}_{j,t,dl} - \text{inflow}_{j,t,dl}) \leq \text{RES}^{DOWN}_{t,dl}
\]

\[
\text{RES}^{UP}_{t,dl} \geq K^{UP} \left[ \alpha \text{DEM}^{2}_{dl} + \gamma \left( \sum_{i \in \text{WIND}} y_i \bar{x}_i \right)^2 + \delta \left( \sum_{i \in \text{SOLAR}} y_i \bar{x}_i \right) \right]^{1/2}
\]

\[
\text{RES}^{DOWN}_{t,dl} \geq K^{DOWN} \left[ \beta \text{DEM}^{2}_{dl} + \epsilon \left( \sum_{i \in \text{WIND}} y_i \bar{x}_i \right)^2 + \theta \left( \sum_{i \in \text{SOLAR}} y_i \bar{x}_i \right) \right]^{1/2}
\]

4.3.4 Generation capacity expansion constraints

An existing fleet of generators is pre-built before the model runs to represent the existing power generation system. Generation capacity expansion constraints enable the investment in and construction of additional units. An initial list of both pre-built and available units to build are presented as inputs to the model. This approach is similar to [71] and enables the selective capacity expansion strategy used in this study where the additional built capacity is limited to storage units. As shown in Chapter 5, the optimal level of new storage capacity is dependent on the other generation technologies in the power system as well as the existing installed capacity of storage. Selective capacity expansion can be used to solve for the optimal level of installed storage given different power systems and technology costs.
Three equations govern the build decision for new storage plants in the selective generation capacity portion of the model. The model operator can pre-build an existing generation fleet by forcing a binary ‘build’ decision variable, $Y$, equal to 1 in the pre-model period, when $t = 0$. $\text{rate}_{j}^{\text{OUT}}$ is the maximum power output rating [MW] of the unit. All ‘built’ generators bear annualized capital costs and fixed operations & management costs defined in equation (15). Equation (16) requires built generators to remain into future time periods, requiring built storage facilities bear an annualized fixed annuity payment into future periods. Thus, generator retirements are not allowed in this study.

\begin{equation}
C_{t}^{\text{FIXOM}} = \sum_{j \in J} Y_{j,t} \text{rate}_{j}^{\text{OUT}}
\end{equation}

\begin{equation}
Y_{j,t} \geq Y_{j,t-1}
\end{equation}

For the sensitivity analysis described later in this study, no generation capacity expansion is allowed in order to provide greater control in comparing results between scenarios. In this case, all units, including storage, are pre-built as part of the existing grid infrastructure.

### 4.3.5 Three-state electricity storage formulation

Prior formulations for electricity storage place an efficiency parameter in front of the amount of stored energy, simplifying efficiency losses to the charging state of the storage unit. In an example scenario where a storage unit exhibits 80% efficiency, 1 MWh of charging (or pumping air or water to a reservoir) results in 0.8 MWh of stored energy that can be converted back to electricity (discharge state) at 100% efficiency. This traditional formulation faces the problem of not accounting for energy losses during the conversion from stored energy back to electric power and can lead to the overestimation of storage capacity in the storage reservoir (battery, water reservoir, or compressed air cavern). Likewise, capacity can be underestimated with this formulation when the effective round-trip efficiency of the storage unit is greater than 100%, which is the case with many new concepts of compressed air storage (CAES), where a natural
gas turbine is used to pre-heat compressed air before its final conversion from stored energy to electric power.

A second oversimplification also exists in the classical two-state electricity storage model, where the operational states of the storage unit are ‘charging’ and ‘discharging’. In the two-state formulation, an idle unit is simulated as charging (or discharging) at the rate of zero kW. However, introducing a non-zero minimum charge rate in this case would force the unit to charge at a non-zero rate during all time periods when the unit is not generating power. Therefore, two-state storage models cannot include minimum charge rates, which is an important performance factor that differentiates various new storage technologies and affects performance in the electric power system.

4.3.6 Proposed Storage Formulation

A revised formulation for calculating the effect of round-trip energy on the level of stored energy is developed. Instead of calculating efficiency on either the charging or discharging phase as shown in equations (17) and (18), round-trip efficiency is divided equally between storage charging and discharging phases, simulating energy losses on both ends of the storage cycle. While this study does not delve into proving the ‘best’ formulation for various storage technologies, possible benefits and pitfalls are discussed for each of three variations.

\[
levell_{j,t,dt} = levell_{j,t,dt-1} + \varepsilon_j inflow_{j,t,dt} - outflow_{j,t,dt} \quad \forall j, t, dl
\]

Equation (17) factors round-trip efficiency into the charging stage (inflows)

\[
levell_{j,t,dt} = levell_{j,t,dt-1} + inflow_{j,t,dt} - \frac{outflow_{j,t,dt}}{\varepsilon_j} \quad \forall j, t, dl
\]

Equation (18) factors efficiency into the discharging stage (outflows)
Equation (19) is the new proposed storage formulation that splits the round-trip efficiency penalty between charging and discharging stages.

[29], [72] and [71] use a similar formulation to equation (17) for pumped hydro-electric energy storage, where the efficiency penalty is calculated during the pumping (storage charging) state. [67] calculates the impact of round-trip storage efficiency on energy outflow only, similar to equation (18), though their calculation is included in the demand constraint. Equation (19) is a new formulation for energy storage where efficiency losses are represented at both ends of the charging/discharging process.

While storage inflows and outflows are constrained to upper and lower limits (see (20), (21)) during each time period and are not directly affected by the above formulations, the estimated level of stored energy is directly impacted. In the theoretical scenario of a storage unit with 80% round-trip efficiency, where one [1] MWh of energy is already stored, one [1] MWh of electricity is committed to charging the unit, and one [1] MWh of energy is committed to leaving the unit, the resulting level of stored energy using each formula is 0.8 MWh, 0.75 MWh, and 0.776 MWh for (17), (18), and (19), respectively. (19) achieves a ‘middle-ground’ estimate of energy storage levels as compared to the other two. In order to prevent overestimation or underestimation of technical storage capacity limits, (19) is developed as a preferred modeling method for problems where the specific division of round-trip efficiencies between charging and discharging phases are not known.

While (19) seems most broadly-applicable to modeling different energy storage technologies that incur losses on both ends of the charging-discharging cycle, it may be more appropriate to use (18) when modeling isothermal compressed air energy storage (CAES). The effective round-trip energy efficiency of CAES is rated at 125% as a result of the pre-heating of compressed air using a standard combustion turbine before stored energy is converted back to electric power. While it
is unknown to this study how much loss/gain is owing to each phase of the charging-discharging cycle, it is assumed that CAES round-trip efficiency is primarily influenced by the pre-heating and discharge phase (outflows).

Three operating states replace the two-state model: charging, \((s_{j,t,dl}^{IN})\), discharging, \((s_{j,t,dl}^{OUT})\), and idling, \((s_{j,t,dl}^{IDLE})\). This allows for the inclusion of minimum charging and minimum discharging constraints described in (20) and (21).

(20) constraints the hourly charging rate of each storage unit, \(inflow_{j,t,dl}\), to its upper and lower technical bounds, \(\text{rate}_{j}^{IN}\) and \(\text{rate}_{j}^{IN}\), respectively. Equation (21) is the comparable constraint for storage unit discharging, \(outflow_{j,t,dl}\).

\[
\begin{align*}
(20) & \quad s_{j,t,dl}^{IN} \text{rate}_{j}^{IN} \leq inflow_{j,t,dl} \leq s_{j,t,dl}^{IN} Y_{j,t} \text{rate}_{j}^{IN} & \forall j, t, dl \\
(21) & \quad s_{j,t,dl}^{OUT} \text{rate}_{j}^{OUT} \leq outflow_{j,t,dl} \leq s_{j,t,dl}^{OUT} \text{rate}_{j}^{OUT} & \forall j, t, dl
\end{align*}
\]

The three operational states of electricity storage units are governed by (22). For a given hour of operations, \(dl\), each storage unit is either charging, discharging, or idling. Equipping the storage model with three states enables the addition of minimum charging limits presented in (20), which are otherwise left out from existing two-state formulations. Startup decisions are not explicitly modeled as with thermal generators because the startup costs of storage units are assumed to be zero.

\[
(22) \quad s_{j,t,dl}^{IN} + s_{j,t,dl}^{OUT} + s_{j,t,dl}^{IDLE} = 1 \quad s_{j}^{IN}, s_{j}^{OUT}, s_{j}^{IDLE} \in \{0, 1\}
\]

Total level of stored energy (GWh) must remain below its technical limit as described in (23).

\[
(23) \quad level_{j,t,dl} \leq level_{j} \quad \forall j, t, dl
\]
A visual representation of bulk energy storage as described in equation (19) is provided below, where three segments portray the change in reservoir level over a three-hour period.

**Figure 9. Representation of Energy Storage Formulation**

The full unit commitment model with embedded economic dispatch and generation capacity expansion is reviewed in Figure 10. Table 2 and Table 3 present the performance and cost characteristic of thermal generators and storage units used in the model.

The model described in this section was developed by the author under the guidance of Mort Webster, and is used in the following section to evaluate the cost and performance impacts of energy storage in different future scenarios. We find that the technical model provides a good framework for estimating the future value of adding energy storage capacity to an existing generation fleet of thermal generators, wind, and solar. The validity of the model results were calibrated against the IMRES output data—a model developed by Fernando de Sisternes, PhD researcher in Mort Webster’s research group at MIT [73].
**Figure 10.** Model diagram: unit commitment with selective capacity expansion

![Model Diagram]

**Table 2. Performance Parameters for Thermal and Renewable Energy Generators**

<table>
<thead>
<tr>
<th>Generator Type</th>
<th>Annualized Fixed Cost</th>
<th>Variable O&amp;M Cost</th>
<th>Startup Cost</th>
<th>Maximum Output</th>
<th>Minimum Output</th>
<th>Ramping rate</th>
<th>Minimum up/down time</th>
<th>Emissions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nuclear</td>
<td>502.55</td>
<td>0.007</td>
<td>1.00</td>
<td>1.20</td>
<td>0.90</td>
<td>0.19</td>
<td>36</td>
<td>0</td>
</tr>
<tr>
<td>Solar</td>
<td>313.18</td>
<td>0.000</td>
<td>0.00</td>
<td>1.00</td>
<td>0.00</td>
<td>1.00</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Wind</td>
<td>228.00</td>
<td>0.000</td>
<td>0.00</td>
<td>1.00</td>
<td>0.00</td>
<td>1.00</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Coal</td>
<td>181.00</td>
<td>0.028</td>
<td>0.05</td>
<td>0.50</td>
<td>0.35</td>
<td>0.21</td>
<td>6</td>
<td>800</td>
</tr>
<tr>
<td>CCGT</td>
<td>108.00</td>
<td>0.053</td>
<td>0.02</td>
<td>0.40</td>
<td>0.15</td>
<td>0.20</td>
<td>3</td>
<td>350</td>
</tr>
<tr>
<td>CCGT</td>
<td>108.69</td>
<td>0.053</td>
<td>0.02</td>
<td>0.40</td>
<td>0.15</td>
<td>0.20</td>
<td>3</td>
<td>350</td>
</tr>
<tr>
<td>OCGT</td>
<td>106.58</td>
<td>0.091</td>
<td>0.00</td>
<td>0.20</td>
<td>0.02</td>
<td>0.20</td>
<td>0</td>
<td>570</td>
</tr>
</tbody>
</table>

**Table 3. Performance Parameters for Electricity Storage (CAES)**

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>CAES</td>
<td>1100</td>
<td>11.60</td>
<td>0.00155</td>
<td>15</td>
<td>0.75</td>
<td>0.3</td>
<td>1</td>
<td>0.25</td>
<td>1.25</td>
<td>200</td>
</tr>
</tbody>
</table>

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4.3.7 Summary of Unit Commitment Model for Simulating Optimal Electric Power Generation

The most prominent effect of changing the generation fleet to include higher levels of renewable electricity generation and storage capacity is a shift in the merit order of generators – the order in which generation capacity is dispatched to meet demand, where generators with lowest variable are dispatched for base-load capacity. While generalized modeling approaches such as economic dispatch and screening curve heuristic methods consider the merit order effect when estimating the optimal generation mix, they ignore many technical dynamics of operating the systems and can lead to an overestimation of total operating costs and other issues discussed in Palmintier & Webster (2011). One major benefit of the unit commitment model developed in this study over simpler economic dispatch models is the inclusion of hourly power plant scheduling, where changes in power output of generating units (up and down) are limited by the unit’s technical ramping characteristics. Wind and solar power have zero- variable costs, but the next lowest-cost generator (often nuclear) is not always able to adjust its output to “match” the variability of solar and wind. Simpler models do not impose this constraint; however, the unit commitment model developed in this study can effectively simulate how sufficient provisions of energy storage or other fast-ramping thermal generators can help “smooth” variability in net load, making REG more manageable for providing reliable capacity. At higher levels of renewables, this can lead to less wasted (curtailed) wind and solar power. In addition to analyzing reduction in renewables curtailment under different future infrastructure scenarios, the following section considers changes to the total generation mix, total operating costs, fixed costs (operations and maintenance costs), variable costs (fuel costs, thermal unit starting costs, emissions costs), and CO₂ emissions rates.
5 Results

The increased deployment of renewable electricity generation has helped bolster the market proposition for energy storage services. In the U.S., wind power generation grew to 2.3% of the U.S. generation mix by the end of 2010 after enjoying 1884 percent total growth between 2001 and 2011 [74]. Further, the U.S. Department of Energy expects 2.6 percent annual growth in solar between 2011 and 2040. Wind power is expected to continue to lead growth in the renewables category, followed by solar power which is expected to increase of 9.8 percent over the same time period [75]. As renewable electricity generation increases as a percentage of the overall generation mix, the need for storage services to stabilize increasing variability in generation also increases [76]. Though while the technical performance of the current state of energy storage technologies can benefit the stability and efficiency of the power grid, particularly as renewable energy generation increases [29], market adoption is stifled by high capital costs [77] and a lack of reliable valuation tools to help investors and planners estimate future costs and benefits [78].

This section uses the electric power generation system model described in chapter 4 to evaluate the electric generation supply at varying levels of electricity storage and renewable electricity generation (REG). We find that the value of storage is proportional to the amount of REG and storage capacity present. The chapter concludes by presenting a new methodology for estimating a ‘Target Cost’ of storage, the capital cost at which adding energy storage becomes a profitable venture.

5.1 Analysis of Model Inputs: Net Load (Demand) and Renewables

While renewable energy is a source of power generation, its output is highly variable due to its dependence on sun or wind resources. This added variability presents a new challenge for grid operators. Conventional generators and storage are required to meet residual demand that is not already being served by solar and wind generators. Renewable energy generation can be thought of as a reduction in residual demand—net load.
\[ \text{net load}_{time} = \text{load}_{time} - \sum_{i \in I} \text{renewables}_{time,i} \]

To illustrate how renewables impact net load, Figure 11 shows one-week of hourly demand and total renewable energy resources from a high renewable energy scenario (45\% of total generation comes from wind and solar).

**Figure 11. Impact of Renewables on Net Load**

![Graph showing the effect of renewables on net load](image)

The addition of renewables reduces the overall demand that must be met by conventional generators; however, the hourly variation in net load increases substantially due to the presence of wind and solar generation.

The full four weeks of demand and available renewable energy resources are visualized in Figure 12 in descending order of demand. Ordering net load data in this way is known in the power sector as the load-duration curve (LDC). The LDC is used as a screening method to understand the total variability of net load, and the type of power generation that is needed to balance supply and demand. A flatter LDC typically requires less flexibility from generators, as generators do...
not need to change their output as frequently to meet variations in demand. Conversely, high variability in net load puts pressure on grid operators to provide more flexible generators.

Figure 12 shows that the variability of net load nearly doubles with the addition of 100 GW of wind capacity and 75 GW of solar capacity.

**Figure 12. Impact of Renewables on Load Duration Curve variability**

Denholm et al. (2010) describe four important effects on the load duration curve that arise from the addition of renewable electricity generation (REG). These are: increased need for frequency regulation that requires second or sub-second level response from generators; increased need for fast ramping generators to meet greater load variability on the minute-to-hours timeframe; increased total range of net load, which can push generators to operate at low levels of output or increase starting costs by forcing generators to cycle on and off more regularly; and increased uncertainty in net load forecasting that arises from imperfect knowledge of future wind and solar resources [79]. Additionally, REG puts upward pressure on the amount of operating reserves.
required by the system to maintain reliability in the presence of a more variable power supply [11], [21]. Each of these effects can be captured by the unit commitment model developed for this study. The exception is frequency regulation, which requires models that can simulate the response to changes in net load on the order of milliseconds-to-seconds.

The remainder of this chapter uses the unit commitment model described in chapter 4 to evaluate the various costs and operational dynamics of the power generation system given different levels of installed storage capacity and renewable energy generation (REG).

Each model run simulates optimal generation levels for each of 350+ generators for the four weeks of operations. Total generation is then aggregated into seven technology classes—nuclear, solar, wind, coal, combined-cycle gas turbines (CCGT), open-cycle gas turbines (OCGT), and storage. Figure 13 presents results for two scenarios, high-renewables generation (~45%) with no storage, and high-renewables with 5 GW of bulk electricity storage capacity.
No Storage: Hourly Unit Commitment of Generation Capacity

$30 / ton CO2 price, 45% renewables penetration

With Storage: Hourly Unit Commitment of Generation and Storage Capacity

$30 / ton CO2 price, 45% renewables penetration, 5GW CAES storage output capacity
With the high penetration of renewables represented in Figure 13, storage charging (shown as negative generation below the x-axis) occurs primarily during two distinct time intervals: First, units are charged in low-demand hours to move low-cost generation to displace higher-cost generators such as CCGT during higher periods of demand. Charging of storage units also occurs during peak-demand periods, which correspond to periods of high levels of renewable energy generation (REG). In these peak hours of REG, wind and solar is difficult to fully integrate as it requires thermal units to quickly reduce their output or shut down entirely. Storage units respond to the over-supply of REG by storing unused wind and solar power for later use.

Storage generation is traditionally explained as shifting cheap generation during low-demand periods to displace expensive generation during demand peaks. But in the presence of high-renewables generation as in Figure 13, storage does not meet peak demand. Instead, storage capacity is discharged on the edges of the demand peaks (the “shoulder”) for two reasons: First, since periods of high REG are positively correlated with peak hours of demand, REG meet much of the load, requiring less generation from storage and thermal units. Second, individual storage units are scheduled to charge during peak REG output to reduce wasted (curtailed) wind and solar power. Accordingly, storage units free up storage capacity in off-peak hours to make room for storing REG during the peaks.

This early analysis of bulk grid-scale electricity storage shows that the operation of storage is a complex scheduling problem for grid operators. Storage can provide valuable services during both charging and discharging phases. Their optimal operation is highly dependent on characteristics of the demand curve, renewables resources, and existing fleet of thermal generators, discussed in more detail below.

5.2 Unpacking the impact of storage on the operation of existing generators

Bulk storage services interact with different generation technologies to improve the efficiency of the total generation supply. One strategy for understanding the interaction of energy storage with
each of the six remaining technology classes requires simulating the same model with different levels of storage capacity. Table 4 evaluates the impact of 5 increasing levels of storage on the total hourly generation provided by the remaining technologies. The standard deviation of hourly output is also calculated to show how storage reduces (increases) the amount of ramping required by thermal and renewable generators.

Table 4: Hourly generation by technology type for different levels of storage
(45% renewables penetration, $30 / ton CO₂ price)

<table>
<thead>
<tr>
<th>Installed Storage Capacity (max output)</th>
<th>% Δ in mean and std. dev as storage increases from 1 GW to 5 GW</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 GW</td>
<td>2 GW</td>
</tr>
<tr>
<td>Nuclear</td>
<td>hourly mean</td>
</tr>
<tr>
<td></td>
<td>std. dev.</td>
</tr>
<tr>
<td>Solar</td>
<td>hourly mean</td>
</tr>
<tr>
<td></td>
<td>std. dev.</td>
</tr>
<tr>
<td>Wind</td>
<td>hourly mean</td>
</tr>
<tr>
<td></td>
<td>std. dev.</td>
</tr>
<tr>
<td>Coal</td>
<td>hourly mean</td>
</tr>
<tr>
<td></td>
<td>std. dev.</td>
</tr>
<tr>
<td>CCGT</td>
<td>hourly mean</td>
</tr>
<tr>
<td></td>
<td>std. dev.</td>
</tr>
<tr>
<td>OCGT</td>
<td>hourly mean</td>
</tr>
<tr>
<td></td>
<td>std. dev.</td>
</tr>
<tr>
<td>Storage</td>
<td>hourly mean</td>
</tr>
<tr>
<td></td>
<td>std. dev.</td>
</tr>
</tbody>
</table>

Storage can provide load following by changing power output near peak hours of demand. This results in less load following required by thermal technologies that would otherwise provide this service. Table 4 shows that coal and CCGT reduce total output and variability at higher levels of storage. This downward pressure can be explained by less reliance on these technologies for load following services in the presence of storage. This effect is a similar to the findings of Harris et. al. (2012), though their study describes the aggregate effect of added storage as a “leveling”, or reduced total variability, of net load.
Inspection of the variability of output from different technologies shows that coal has a standard deviation similar in size to wind and solar, which are highly variable. This suggests that coal is the primary technology providing generation flexibility for load-following services; however, this is not to say that coal is the most flexible technology per se. In fact, CCGT, OCGT, and storage all have more responsive ramping rates than coal. Rather, coal is able to provide the majority of load following due to the sheer number of coal plants in the system. These units can coordinate changes in their individual generation levels to emulate a more flexible technology—following load more responsively as a coordinated group. This shows that ramping rates are not the only source of generation-side flexibility. Due to the number of coal units available, coal is able to provide the bulk of load following services that is usually considered the task of more responsive, but also more expensive units. As is the case with complex systems like the power system, the behavior of the system is dependent on the interaction between its components (generators)—behavior cannot be described by the components themselves.

The second clear dynamic in Table 4 is the upward trend in solar and wind power variability (standard deviation) as storage capacity increases from 1 GW to 5 GW of total output potential. This effect is explained the role of storage in reducing renewables curtailment during peak hours of renewable energy generation.

Nuclear provides base-load power at low cost, though is not technically capable of quick changes to its output. Adding storage allows nuclear to slightly increase average output (1.1% increase) by reducing the amount it must turn down its output to make room for hours of high REG.

Due to the flexibility of OCGT supply, it can quickly ramp its output up and down to meet peak hours of demand. However, OCGT is also the most expensive technology to operate. OCGT generators contribute the smallest share of total generation in this model (<1%) because more affordable generators are used to provide flexible capacity. However, while OCGT is both expensive to operate and can be outcompeted by storage in terms of ramping flexibility, OCGT and storage are found to be complementary technologies in this scenario. As storage increases from 1 GW to 5 GW of capacity, OCGT increases its average output by 5%, coordinating its
output with storage units to more efficiently meet peak demand. This dynamic shows how
 generation technologies can work together to provide improved services to the grid.

The results in this section show how bulk electricity storage can put both downward \textit{and} upward
 pressure on the variability of power supply when renewable energy generation is high in
 penetration and variability. While the contribution from each of these balancing effects is not
 analyzed in detail, we find that in a system where storage is used to integrate high levels of
 renewables, variability of net load may actually \textit{increase}. This makes the case for technical
 models that can simulate behavior that arises from interactions between the generators within the
 system and is not picked up by traditional cost-based analysis, such as in economic dispatch
 models and screening heuristics.

\section*{5.3 Bulk energy storage futures scenarios: A description of scenarios}

55 bulk electricity storage futures scenarios are developed for this study to compare the
 performance of 11 different levels of electricity storage against five different levels of wind and
 solar generation. The various scenarios are shown in matrix form in Figure 14.

For consistency across the analysis, all storage units are modeled as compressed air energy
 storage (CAES). In addition to testing several levels of energy storage in the scenarios, various
 levels of renewable energy generation are tested in order to assess the performance of storage at
 increasing levels of net load variability that results from the addition of wind and solar
 generation (see Chapter 5.1). We find that storage becomes increasingly valuable at higher levels
 of renewable energy generation.
Energy storage futures scenarios are defined by changes in storage, wind, and solar capacity, keeping the fleet of thermal generators fixed. In practice, the generation mix will change depending on the capacity of renewable generation that is mandated. While the unit commitment and capacity expansion model described in Chapter 4 can solve for the optimal level of thermal technologies under different REG levels, such generation capacity expansion analysis is beyond the scope of this study.

A combined capacity of 12 GW of nuclear (10 plants), 33 GW of standard coal (66 plants), ~30 GW of combined-cycle natural gas turbines (77 CCGT plants), and ~5 GW of single-cycle natural gas turbines (23 OCGT plants) comprises the underlying thermal generator fleet of ~80 GW total output capacity from thermal generators (this does not include wind, solar, or storage capacities). This generation fleet is roughly comparable in size and generation type to the current generation in ERCOT; however, no effort has been made to calibrate demand, capacity, or infrastructure performance characteristics with the ERCOT power system. Additional work could use this model to estimate the future operations of specific power systems under different political, economic, and technical environments.
Five renewable electricity generation scenarios—45%, 35%, 25%, and 15% REG—are compared together with 11 levels of available electricity storage capacity, ranging between 0 GW and 10 GW of output capacity, in 1 GW increments. The level of REG is defined as the percentage of total annual renewables generation in the zero-storage runs of the model, minus curtailed REG. In all scenarios, renewable resources are comprised of about 40% solar and 60% wind power. Storage scenarios represent the maximum output capacity of installed storage units. Compressed air energy storage is the representative storage technology in this study.

For each sensitivity test in this section, I approximate a full-year of operations and the resulting costs using the unit commitment model described in the previous section. The impacts of various scenarios on renewable electricity curtailment, CO₂ emissions, and total system costs are examined in detail.

5.4 Operational dynamics of power supply in the storage futures scenarios
Before delving into full sensitivity analysis, I consider four scenarios to explore several of the operational dynamics that exist in different energy storage futures scenarios.

Figure 15 illustrates generator operations for four unique energy storage futures scenarios. The scenarios selected for this analysis are diagrammed in Figure 15. They are: low REG penetration (5%) with zero storage capacity, low REG with moderate storage (5 GW), high REG (45%) with zero storage, and high REG with moderate storage.
Figure 15. Selection of energy storage futures scenarios used in Figure 19

Figure 16 shows the same two days of operations under for each of the four selected energy storage futures scenarios marked in Figure 15. The short time-series view is used to estimate the operational tradeoffs made by the power dispatcher to meet variable demand at lowest cost while satisfying operating reserves and technical constraints.

Each of the results in Figure 16 follow the same two-day demand curve; however, total generation exceed demand in the two scenarios with storage (Figure 16B, D) because additional generation is dispatched for the purpose of charging storage units.
5.4.1 Figure 16-A. discussion: 5% Renewables, No Storage

Providing only 5% of total power generation, all solar power and wind power can be integrated into the generation mix by changing the output of CCGT. Further, periods of high solar output occur mid-day when demand is higher, which means that thermal generators are required to do less ramping to compensate for renewables generation variability (see Figure 16-A1). Wind resources behave differently than solar resources. Higher periods of wind are generally negatively correlated with demand; however, this is not an issue in this scenario given the low-levels of wind capacity. In addition to providing renewable integration services, CCGT also provides load-following (see A2). Coal generators serve intermediate loads and also support CCGT plants during low-demand periods, when CCGT units would otherwise be forced to shut down, incurring startup costs (see A3). No ramping support is required by nuclear, so units maintain stable base-load generation levels.
5.4.2 Figure 16-B. discussion: 5% Renewables, 5GW Storage

As shown in Figure 16-A, CCGT and coal provide sufficient flexibility to integrate renewables while also following load. Therefore, the introduction of bulk storage capacity is mainly used for price arbitrage by coal generators. Storage units charge with coal during off-peak hours (see B1), shifting the capacity to displace more-expensive CCGT generation during hours of higher variability and peak demand (see B2). Some storage charging also occurs during peak hours of solar output, shifting capacity to meet secondary demand peaks in the late afternoon (see B3).

Figure 16-A and B show us that storage is primarily used as a tool for price arbitrage when renewable electricity generation is low. Existing thermal generators provide sufficient flexibility to meet variable net loads. Any investments in additional storage capacity at this point would likely be in response to higher anticipated future levels of REG, where the provisioning of storage services becomes more critical to the ability to meet demand during periods of high variability in net load. As shown later in this chapter, the operational roles of storage in different energy storage futures scenarios directly impact the economic value of storage services.

5.4.3 Figure 16-C. discussion: 45% Renewables, No Storage

As renewables reach 45% of total generation, the optimal dispatch of thermal units changes considerably from the 5% REG scenarios for different economic and technical reasons. Most notably, CCGT is pushed out of the mix during the mid-day peak due to the diurnal cycle of solar power; however, CCGT plants continue to serve the late-afternoon secondary demand peak when REG output is lower (see C1). OCGT increases slightly from the 5% REG case, but is still minimally deployed to provide peaking capacity (see C2). Coal and CCGT are sufficiently flexible to meet most of the load-following needs though they are now forced to more actively ramp their output to meet greater variability in net load. For example, coal units must now reduce output to the lower end of their physical limits while meeting the last unit of demand during mid-day peak hours. Reducing thermal output or shutting off entirely to provide ‘up’ load following services—that is, load following while demand is increasing—is unique to the high-renewables case, and puts burdens thermal generators with increased wear-and-tear, greater startup costs,
and ultimately, less product (power) that can be sold to the market (see C3). Coal and CCGT also may also be forced to operate at suboptimal levels due to the higher reserve requirements under the presence of high levels of wind and solar. While the number of units dispatch is not shown, greater reserves could force more units to share total output in order to satisfy spinning reserve requirements.

Wind power generation is negatively correlated with demand. This effect is common in power systems with wind penetration, and can act as a natural reduction in the variability of net load in the presence of solar power (see C4).

Nuclear base-load generation is reduced to support the REG integration effort during peak hours. Nuclear is also reduced slightly in off-peak hours of demand to help coal meet down-load following services and spinning reserve requirements, though the relative contribution of these effects is not clear from this view (see C5).

### 5.4.4 Figure 16-D. discussion: 45% Renewables, 5GW Storage

Whereas storage was used primarily for price arbitrage at low levels of REG, at 45% REG, storage units are also used to help reduce wasted solar and wind power (renewables integration). In doing so, storage units charge up to their maximum charging rates during peak hours of REG (see D1). Stored REG is then dispatched during high hours of demand where REG generation is lower (see D2), displacing CCGT generation during late afternoon demand peaks (see D3).

OCGT generation increases output from the zero-storage scenario in order to complement storage in meeting increased variability in net load during secondary peak hours (see D4).

### 5.5 Impact of Storage and Renewable Electricity Generation (REG) on the Generation Mix

In electric power systems, a subset of available power generators is dispatched to meet current demand. The share of total power delivered by various technology types (coal, natural gas
combined cycle, nuclear, etc.) is known in the power sector as the generation mix. Here, the power system is evaluated under various energy storage futures scenarios to understand how the proportion of supply being met by different generation technologies (the generation mix) changes under different levels of energy storage and renewable energy generation.

Four unique storage futures scenarios are evaluated in Table 5: low REG (5%) with no storage, low REG with high-storage (10 GW), high REG (45%) with no storage, and high REG with high storage. Storage capacity is not shown below because energy storage is not a true generation technology—it uses generation from thermal and REG units to store and deliver power. Table 5 illustrates how the dispatched generation mix is proportional to the amount of solar, wind, and storage capacity available to the existing thermal generation fleet.

Table 5. Generation mix for high- and low penetration of renewables and storage

<table>
<thead>
<tr>
<th>Annual Generation Mix (GWh)</th>
<th>Low Renewables (5%)</th>
<th>High Renewables (45%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No Storage</td>
<td>10 GW Storage</td>
</tr>
<tr>
<td>OCGT</td>
<td>1.5</td>
<td>1.8</td>
</tr>
<tr>
<td>CCGT</td>
<td>6730.0</td>
<td>5572.2</td>
</tr>
<tr>
<td>Coal</td>
<td>21296.0</td>
<td>21832.2</td>
</tr>
<tr>
<td>Wind</td>
<td>1240.4</td>
<td>1240.4</td>
</tr>
<tr>
<td>Solar</td>
<td>735.3</td>
<td>735.3</td>
</tr>
<tr>
<td>Nuclear</td>
<td>8061.6</td>
<td>8064.0</td>
</tr>
<tr>
<td>Storage</td>
<td>0</td>
<td>3094.7</td>
</tr>
</tbody>
</table>

Table 5 shows the annual impact of generation from adding storage and renewables capacity to the existing generation fleet. In the high-renewables scenarios, output from generators with high variable costs are displaced by zero- variable cost renewables. Increasing renewables generation from 5% to 45% leads to a reduction in CCGT and coal output by 87% and 40%, respectively.
Adding storage to low and high renewables scenarios leads to less reliance on combined cycle natural gas turbines (CCGT). In this study, natural gas generators (CCGT and OCGT) are the most expensive power plants to operate. As a result, grid operators use storage capacity for price arbitrage to store the less expensive power to displace more expensive generation from CCGT. In the low-renewables, high-storage case, coal generation displaces CCGT. Although coal generation has historically had lower variable cost than natural gas generation, these roles have recently changed in some U.S. markets. In these markets, storage would more likely be used to store natural gas power to displace more expensive coal generation.

Nuclear has lower variable costs than coal and natural gas units, and a cost-minimization without constraints would lead to a strategy of storage coupled with nuclear for price arbitrage. However, technical constraints prevent this pairing. In fact, nuclear does not substantially increase output in response to storage when renewables are low (Table 5B). As shown in the previous section, storage is used for faster charging and discharging cycles than nuclear can support.

While nuclear does not directly benefit from storage in the low-renewables scenario, nuclear plants do substantially increase output in the high-renewables cases (Table 5B). But because nuclear and storage are not directly paired for price arbitrage, there must be an indirect effect that explains why nuclear increases as storage is added in the high-renewables case. When storage is absent, nuclear is called on to suppress output to make room for renewables during hours of high renewables generation. Adding storage increases the flexibility of the generation supply and allows nuclear generators to fill the traditional role of baseload generation at nearly constant levels.

5.6 Sensitivity analysis of curtailed (wasted) renewable electricity generation

Renewables curtailment is defined as the “wasted” energy that cannot be used either due to hours where energy demand is less than total REG supply and storage is not available, or when generators are unable to match the variability in net load that is created by fast changes in REG
output. Energy storage and flexible thermal generators with fast ramping times can reduce REG curtailment [28]. Figure 17 shows the effect on curtailment with added storage capacity in all 55 scenarios where the generation mix is predicted for one year of operations.

**Figure 17. Impact of added storage on renewables curtailment**

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Percent Renewables</th>
<th>Electricity Generation</th>
</tr>
</thead>
<tbody>
<tr>
<td>45% Renewables</td>
<td>8%</td>
<td></td>
</tr>
<tr>
<td>35% Renewables</td>
<td>7%</td>
<td></td>
</tr>
<tr>
<td>25% Renewables</td>
<td>6%</td>
<td></td>
</tr>
<tr>
<td>15% Renewables</td>
<td>5%</td>
<td></td>
</tr>
<tr>
<td>5% Renewables</td>
<td>4%</td>
<td></td>
</tr>
</tbody>
</table>

![Graph showing impact of added storage on renewables curtailment](image)

Inspection of Figure 17 shows that there is no curtailed renewable electricity generation (REG) at 5% and 15% REG, and very little curtailment at 25% REG, even in the low energy storage scenarios (less than 4 GW storage). At these low levels of REG, the total variability in net load can be balanced by conventional power generators. All other scenarios show a decrease in curtailed REG as additional capacity of storage is introduced. The rate of reduced curtailment in response to added storage is shown by the slope of the plots, and is greater at higher levels of REG.

Even at 25% renewables, there is very little REG curtailment (<1%) in the zero-storage case. For the given system, the value of bulk energy storage for in terms of renewables integration grows
substantially as REG exceeds 35% renewables generation. This is similar to findings of other studies, though it should be noted that the level at which storage contributes significantly to renewables integration services is proportional the existing flexibility of the generation fleet. Tuohy & O’Malley (2009) examine the power grid in Ireland and find that wind curtailment remains insignificant (<2%) below 40% wind penetration. A study commissioned by NREL estimated that for the U.S. Eastern Interconnection power grid, lack of storage or generator flexibility would account for less than 1% of curtailment when REG penetration was below 30% [80].

This study does not consider voltage issues, weather forecasting errors, or transmission constraints—all of which could lead to different curtailment outcomes.

5.7 Impact on CO₂ Emissions

Storage can reduce system emissions by reducing curtailment of wind and solar as described above. High levels of REG sources lead to reduced market prices as zero-variable cost REG displaces expensive, higher-emissions peaking capacity from gas and coal [81]. However, while it is popular among clean energy advocates to advocate for electricity storage for the benefit of lowering greenhouse gas emissions, I show that storage can also lead to increased emissions for three reasons: First, when conventional generators use storage capacity for price arbitrage, the effect can be the displacement of cleaner-burning peaking capacity with more emissions-intensive generation. This result is also found by Sioshansi (2011). Second, adding storage may not contribute to renewables integration at low levels of REG as shown in Figure 17. The third reason is that the conversion of electricity to storage energy and back to electrical energy leads to energy losses, further contributing to increased emissions. However, while emissions may increase in low REG scenarios, in the next section (Chapter 5.8), I show that the added costs are very small (<.001% increase in total costs) when CO₂ emissions are priced at $30 per ton.

This section use scenario analysis to understand the effect of storage on system-level CO₂ emissions—the primary greenhouse gas that is produced during power generation.
Figure 18. Impact of storage on system emissions relative to zero-storage case

Figure 18 shows an inflection point near 35% REG where storage leads to lower CO₂ emissions at higher levels of REG, but higher CO₂ emissions when REG is less than 35% of total electricity supply. This effect is a result of the impact of storage on REG curtailment discussed earlier. At higher levels of REG (>35%), storage is used by the system to integrate variable supply from solar and wind, displacing carbon-intensive coal electricity generation—coal produces 800 tons CO₂ per GWh—with zero-carbon REG. At low levels of REG (<35%), storage capacity is primarily used for price arbitrage to increase combined coal utilization, displacing CCGT generation, a less CO₂ technology than coal. CCGT produces 350 tons of CO₂ per GWh.

The findings here appear new to the literature due the wider range of assumptions tested. The upward influence of storage on emissions in a market with pure competition between generators has been shown by [8], though their work does not consider higher REG scenarios storage capacity can lead to emission reductions.
[8] is similar to this study in that they consider systems where storage is used primarily for price arbitrage for coal in lower-REG scenarios (<35%), displacing cleaner-burning gas turbines during peak hours of demand. But other grid regions, peak- and intermediate generators may emit less CO₂ per MWh than base-load generators. In these regions, storage may lead to reduced emissions even in low-REG scenarios, due to the use of more efficient generators for storing energy—displacing power from more carbon-intensive peaking units.

To illustrate this point, Figure 19 shows the relative CO₂ intensity of baseload generators compared against the CO₂ intensity of non-baseload generators. The data presented is from the U.S. Environmental Protection Agency’s eGRID database (2012).

**Figure 19.** Relative CO₂ emissions of baseload and non-baseload generators adapted from Whitcomb and Nath (2012); data source: U.S. eGRID 2012
The negative CO$_2$e differentials (orange colored regions) represent eGRID regions where baseload generators are more CO$_2$-intensive on average than non-baseload generators. But in most eGRID regions, baseload generators emit less CO$_2$ than non-baseload generators. Given the emissions impact from adding storage is dependent on the relative CO$_2$ emissions of the generators charging energy storage units and the generators displaced by the delivered electricity, we can expect storage units to result in different CO$_2$ outcomes based on their location.

While the high-level analysis of generator emissions intensities presented in Figure 19 shows how location is an important factor when estimating emission outcomes from added storage, it does not tell the whole story. Storage units do not always use baseload electricity to displace non-baseload electricity. Further, emissions outcomes depend on the round-trip efficiencies of storage units as well as their impact on increasing renewable generation. Regional studies of the impact of storage on emissions should therefore include the technical constraints of power generators as presented in this study.

5.8 Sensitivity analysis of fixed and variable operating costs in energy storage futures scenarios

This section evaluates the economic value of energy storage by comparing the system operating costs between model runs with and without storage capacity.

Figure 20 describes the impact on total system costs for each level of renewables and storage capacity in the storage futures scenarios. Total operating and capital costs in Figure 20A are decomposed into fixed costs and variable costs. Total fixed costs represent operating and maintenance (O&M) and annualized capital costs (Figure 20B). Variable costs include fuel costs, thermal startup costs, and emissions costs (Figure 20C, D, and E).

Total O&M costs include all costs associated with operating and maintaining a power plant for a given year as well as annualized capital cost payments for thermal units and renewable electricity
generators (wind and solar). Fixed capital costs include the annualized cost of capital amortized using a 7% weighted average cost of capital over the estimated lifetime of the project.

As for the above sensitivity analyses, the generation fleet is pre-defined for each storage futures scenario. This strategy forces the model to ‘build’ storage capacity even when storage leads to an increase in total system costs. This strategy is used in order to identify scenarios where the total benefits of storage outweigh the added costs.
Figure 20. Annual operating and capital costs relative to the zero-storage scenarios

A. Relative Total Costs
(ann. operating & capital costs)

B. Relative Fixed Costs
(ann. O&M + capital costs)

C. Relative Variable Costs
(ann. fuel costs)

D. Relative Startup Costs

E. Relative Emissions Costs
5.8.1 Total system cost savings

Total operating costs generally increase (Figure 20A) as storage is added due to increasing fixed operations and maintenance (O&M) and annualized capital costs that are incurred (Figure 20B) as storage capacity is added. However,

For the 15% and 5% REG cases, storage capacity leads to an increase in total system costs regardless of the level of installed capacity. This shows that at low REG levels, the value of storage flexibility does not recover its costs by providing price arbitrage and operating reserve capacity alone. Additional benefit or cost reductions are needed to make these storage investments worthwhile to investors.

As REG increases, storage becomes increasingly valuable as tool for helping integrate a larger proportion of renewables generation (see also Chapter 5.6). The engineering-economic analysis presented here shows a number of scenarios where storage becomes economical. This occurs when storage services lead to a reduction in total operating costs that outweigh the costs associated with building and operating the units.

These scenarios are indicated by negative-costs in Figure 20A. In storage futures scenarios with 45% REG, all tested storage scenarios (up to 10 GW) lead to a reduction in total system costs. In energy futures scenarios with 25% and 35% REG, low-to moderate capacities of storage (6 GW and less) may be economical. However, at these levels of REG, storage capacity above 6 GW becomes uneconomical. This finding is represented by the convex shape of the cost function and indicates that there are declining benefits from the incremental addition of storage capacity. Declining returns are explained primarily by startup costs describe below and shown in Figure 20D.

5.8.2 Fixed costs from storage

The primary costs from adding storage are fixed operating and maintenance (O&M) costs and annualized overnight capital costs (Figure 20B). Fixed O&M costs come from staffing and
keeping the facilities in working condition and amount to around $11.6 million per GW-year of installed storage capacity (see compressed air energy storage parameters, Table 3). Total capital costs are assumed to be $1 billion per GW of CAES storage capacity, which falls roughly in the middle of the range of current estimates (see Chapter 5.9). The annual capital expense is $85.8 million after amortizing over the expected 25-years lifetime of the project. This represents the annual annuity calculated using the capital recover factor equation (24), where \( WACC \) is the weighted average cost of capital (7%), and \( LIFE \) is the expected lifetime of the project (25 years), and represents the number of years over which the annuity is paid.

\[
CRF = \frac{WACC(1 + WACC)^{LIFE}}{(1 + WACC)^{LIFE} - 1}
\]

**5.8.3 Fuel cost savings from storage**

Thermal fuel cost savings resulting from added storage capacity represent the largest cost-saving area. Fuel costs represent between 9% and 39% of total operating costs, where higher costs are present at lower levels of renewable electricity generating capacity due to higher utilization of thermal units. Total fuel savings from storage do not vary substantially across renewable generation scenarios (Figure 20C), and represent between $520 million and $630 million in annual cost savings (percentage) between zero-storage scenarios and 10 GW storage scenarios.

This fuel savings estimate in this model may be an underestimate due the omission of certain non-linear constraints that describe the efficiency of power generators at different levels of output. In practice, as renewable generation and operating reserve requirements increases, thermal units providing spinning operating reserves are forced to run at sub-optimal levels of generation. When electricity storage capacity is used to provide operating reserves, thermal units can generate power at more fuel-efficient levels [23], [24].
5.8.4 Startup cost savings from storage

Thermal units benefit from storage flexibility through reduced startups. This effect is exacerbated by higher levels of renewable generation, where thermal generators are forced to turn on and off more regularly to meet greater variability in net load. Adding 10 GW of storage to the system with low renewables (5% or 15% REG) reduces thermal startup costs from around 0.4% of total system costs to less than 0.05%, representing around $110 million in annual savings (Figure 20C). In the high REG scenario a similar level of storage (10 GW) reduces startup costs from nearly 9% of total costs to 3%, or nearly $400 million in annual savings. As discussed in Chapter 5.1, renewables increase the variability of net load and force thermal units to respond by changing their output or cycling units on and off more frequently. While startup costs are relatively low to begin with, they are likely to be higher in practice. Demand, wind, and solar forecasting errors in regions with high REG may lead to an increase in startups as high as 220% or more [82].

5.8.5 CO₂ emissions cost savings from storage

CO₂ emissions contribute to climate change [83]. This study applies a conservative emissions (CO₂) ‘tax’, which is born by generators that release CO₂ emissions through the combustion of burn fossil fuels. (Refer to Table 2 and Table 3 for the emissions rates of the various power generation technologies). While CO₂ emissions are not currently priced or capped in the United States, a $30 per ton price on carbon is set in the model to emulate one possible future emissions policy. In a 2012 MIT Energy Conference Keynote, Russ Ford, Shell Oil Company Executive Vice President of On-shore Gas, remarked that Shell’s new capital investments are evaluated under an assumed $40 per ton price on CO₂. Based on this evidence, a $30 / ton CO₂ tax is applied as conservative estimate.

The model incurs less than a 0.012% increase in total costs from the added emissions policy. As discussed earlier in this chapter, added storage capacity leads to higher emissions when REG is less than 35%. While the cost impact from emissions from the addition of storage capacity is small as a percentage of total operating costs, storage can also lead to lower renewable
generation curtailment and improved revenues for investors and operators. While beyond the scope of this study, the effect of storage on REG profits may drive increased investments and further emissions reductions.

5.9 Estimating Target Costs for electricity storage capacity

In the previous section, I explored scenarios where CAES is economical given an assumed capital cost. This section tries to answer the opposite question: “what are the capital costs at which storage becomes economical for each scenario?”

Figure 21 shows the incremental lifetime cost savings of storage, also referred to as ‘target cost’ in this study. The target cost is defined as the upper limit for storage capital cost, below which the marginal benefits of an additional unit of storage outweigh marginal capital costs. If the actual capital cost of the next unit of storage is less than the incremental target cost, the system will find it profitable to invest in (build) the next GW of storage capacity.

The process of using a modified unit commitment model to estimate the target capital cost of the next unit of storage capacity is the primary novel contribution of this study.

The transformation of total annual operating costs (Figure 20A) to target costs (Figure 21) requires two main steps. First, I compare the zero-storage base-case against different storage scenarios to find the total annualized savings of the next unit of storage capacity. Next, I calculate the discounted lifetime savings assuming annual savings are consistent.

Equation (25) defines the first step: finding total annualized savings $TAS$ for a given level of storage capacity. The number of storage units is defined by $J$. $TOC$ is the total annualized operating cost from Figure 20A minus the annualized capital costs of storage, $ACC^{STORAGE}$. The total annualized savings are the difference in calculated system costs between a model run with positive storage capacity ($J>0$), and the scenario with no storage ($J = 0$). Annualized capital
costs are reduced to zero in order to compare the value of storage operations irrespective of overnight capital costs.

\[
TAS_{j,t}^{STORAGE} = (TOC_t | ACC_j^{STORAGE} = 0) - (TOC_t | J = 0)
\]

Equation (26) finds the total lifetime average savings, \( TargCost \), by using a standard formulation for the present value of future annuities, where annuities are the total annual savings from (25). \( LIFE \) is the lifetime of the capital investment (25 years) and \( dr \) is and the discount rate (8%). Due to the long lifetime of the project, the estimation of the long-run value of storage is sensitive to the chosen discount rate.

\[
TargCost_{j,t}^{STORAGE} = TAS_{j,t}^{STORAGE} \left( \frac{1 - (1 + dr)^{-LIFE-1}}{dr} \right) + TAS_{j,t}^{STORAGE}
\]

Figure 21 compares the discounted lifetime savings of storage (including operating costs) against current capital costs for all energy storage futures scenarios.
Adding storage capacity to the generation mix reduces operating costs in all renewable electricity generation (REG) scenarios, indicated by positive savings in Figure 21. Scenarios above the breakeven line indicate storage installments that are expected to break even over the lifetime of their operations.

Storage added to lower REG scenarios experience faster declining returns. Therefore, storage is not only more likely to break-even in high-renewables cases, but the value of the next GW of capacity is more stable. Still, the system receives the most benefit (cost savings) from the first units of storage and less benefit from each additional unit. This point shows that the benefit gained from additional storage capacity is not only dependent on the existing thermal and
renewable generators—incremental storage benefits also depend on the level of existing storage capacity.

Current high capital costs of storage technologies have led to low rates of deployment, and continue to be the greatest challenge to their profitability [77]. A storage technology cost survey by EPRI (2008) estimates total capital costs for CAES storage with attached combustion turbine and 10-hours of underground storage capacity (CAES Air Injection, CAES-AI) at $506 per kW of output capacity [85]. This early report appears to be a low-end, or perhaps simply an underestimate, of current capital costs. A more recent EPRI (2010) study places the cost per kW at $960 for an 8-hour storage CAES-CT storage unit. A third study conducted for U.S. National Renewable Energy Laboratory that informs their well-known model of the U.S. power system, REEDs, estimates the capital costs for a CAES-CT storage unit with 15-hours of storage capacity at $900 per kW, with upper- and lower bounds of $630 and $1575 per kW that appear to represent both the confidence bounds of their estimate (very few actual cost figures were available for CAES) and the fact that costs will vary across suppliers and contractors, particularly when lack of competition and economies of scale exist. Table 6 shows three CAES concepts and their capital costs, adapted from EPRI (2008) estimates.
Table 6. Capital Cost Estimates of Compressed Air Energy Storage

<table>
<thead>
<tr>
<th></th>
<th>CAES Conventional $/kW</th>
<th>CAES Al with Expanders $/kW</th>
<th>CAES Adiabatic $/kW</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equipment Cost</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Combustion Turbine</td>
<td>88</td>
<td>53</td>
<td>125</td>
</tr>
<tr>
<td>Air Compressor</td>
<td>82 11%</td>
<td>53 11%</td>
<td>125 12%</td>
</tr>
<tr>
<td>Heat Exchangers</td>
<td>32 4%</td>
<td>32 6%</td>
<td>146 15%</td>
</tr>
<tr>
<td>HP Expander</td>
<td>58 8%</td>
<td>37 7%</td>
<td>111 11%</td>
</tr>
<tr>
<td>LP Expander</td>
<td>135 19%</td>
<td>55 11%</td>
<td>97 10%</td>
</tr>
<tr>
<td>Electrical &amp; Controls</td>
<td>43 6%</td>
<td>17 3%</td>
<td>58 6%</td>
</tr>
<tr>
<td>Total Major Equipment</td>
<td>350 48%</td>
<td>283 56%</td>
<td>538 54%</td>
</tr>
<tr>
<td>Construction Cost</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Materials</td>
<td>64 9%</td>
<td>21 4%</td>
<td>43 4%</td>
</tr>
<tr>
<td>Labor</td>
<td>145 20%</td>
<td>91 18%</td>
<td>204 20%</td>
</tr>
<tr>
<td>CAES Storage</td>
<td>73 10%</td>
<td>44 9%</td>
<td>83 8%</td>
</tr>
<tr>
<td>Indirect Costs</td>
<td>95 13%</td>
<td>67 13%</td>
<td>133 13%</td>
</tr>
<tr>
<td>Total Construction Cost</td>
<td>377 52%</td>
<td>223 44%</td>
<td>464 46%</td>
</tr>
<tr>
<td>Total Capital Cost ($/kW)</td>
<td>727</td>
<td>506</td>
<td>1001</td>
</tr>
</tbody>
</table>


Cost-screening methods such as the one presented in this chapter and in Figure 21 can be used to identify economical levels of storage capacity where the discounted lifetime benefits of storage outweigh current capital costs. This result may be useful for summarizing similar complex engineering-economic analyses for investment decision makers. Further, lifetime savings can also be used to estimate target capital cost needed for the economical deployment of storage. This insight can help inform the market readiness of emerging technologies, or help policy planners or innovating firms identify appropriate technology research, development, demonstration, and diffusion (RDD&D) strategies as described in the next chapter.
6 Optimal investment decision-making

Existing research often identifies the high capital cost of emerging electricity storage options as the most critical factor for advancing the profitability of these technologies today [1], [77]. While first generations of compressed air energy storage are considered a mature technology, only two units have been commercially developed to date [17]. Technological improvements or economies of scale can help suppress the development costs associate with the construction of emerging electricity storage technologies. Recent political strategies have steered focus toward technology cost reductions as a key strategy for integrating new energy technologies to improve the performance of the electric power system, and to reduce its ecological footprint.

Two primary strategies for cost reduction emerge from the literature: investing in R&D investments and investing in demonstration and deployment projects. For many technologies, it has been proven that technological improvement can be described by intertemporal changes in technological learning, or experience. This method was formally introduced by Arrow (1962) in the form of a single input experience variable, learning-by-doing; however, a similar concept in economic theory can be traced back to the Cobb-Douglas production function, which describes technological production as a function of labor and capital inputs [87]. Several studies have used learning curves to study declining technology costs within the energy sector by considering learning-by-doing and/or learning-by-searching through research and development activities. Such studies include natural gas turbines [52], wind farms and wind prices [57], solar photovoltaic [88], fuel cells [89], and others.

Other studies extend the inputs for technology improvement beyond the two-factor learning curve model described by learning-by-doing and learning-by-searching methods. These inputs include technology considerations such as renewable energy capacity factors, economies of scale, materials and fuel prices, learning-by-using, and learning-by-interacting [56], [58].

Several challenges exist in choosing the appropriate scope and scale for learning curves. In particular, local energy policies can affect technology learning rates differently across large
timeframes and disperse geographic regions [57]. Further, the effect of experience on technology development can vary drastically across industries, organizations, or even within organizations [90].

R&D, and demonstration and deployment are carried out by both private industry and public service entities such as the U.S. Department of Energy, NGO research labs, and universities. An ongoing challenge for these entities is in identifying the optimal portfolio of investments to improve the performance or lower the development costs associated with new energy technologies.

This section of the study on bulk electricity energy storage combines a modified two factor learning curve methodology based on the literature describe above, and cost minimization approach to estimate the optimal investment portfolio required to reduce capital costs to target levels identified in the previous section. The investment portfolio strategy in this study can include any combination of two investment choices: investing in research and development (R&D), where research groups “search” for improved technology concepts in a lab environment; and investing in deployment and demonstration (D&D), where private and public entities invest in technology development for field deployment and operations. In solving for the least-cost investment portfolio, the two-factor learning curve model is used as a modeling constraint, where the selected investment portfolio must be included in the set of investment combinations that can achieve a pre-define reduction in technology costs.

While combining the two-factor learning curve methodology with least-cost optimization methods, two approaches are developed: a single-period model and a multi-period model. For the purpose of this study, the combined approach to learning and cost optimization is termed ‘two-factor cost targeting’.
6.1 Single-period Cost Targeting with R&D, Demonstration and Development (D&D)

A single-period cost targeting model is described where investment decisions in one period lead to cost reductions in the same period. This model is useful for showing the cost tradeoff between all estimated investment combinations in R&D and D&D that can lead to the desired level of capital costs through technology “learning”. However, it is unrealistic to assume the simultaneous occurrence of investments and cost savings—both R&D and D&D projects require development time to pass before benefits (here, technology cost savings) are realized.

Learning curves require the exogenous calibration learning percentages. In equation (27), learning-by-doing (LBD) represents the percentage of cost reductions resulting from a doubling of investment in demonstration and deployment projects for the given technology, \( j \). LBS represents the analogous cost savings from research and development efforts (investments). For the examples in this section, a learning-by-doing factor of 0.08 and a learning-by-searching factor of 0.20 are used, representing greater learning potential from R&D efforts compared to D&D.

\[
\text{LBD}^j = 1 - 2^B
\]

\[
\text{LBS}^j = 1 - 2^A
\]

Equation (27) describes the set of R&D and D&D investments \((R^j, D^j)\) required to improve from current technology costs, \( \text{Cost}_0^j \), to target costs \( \text{Cost}_1^j \), given the learning coefficients \( \beta \) and \( \alpha \) found in (28).

\[
\text{COST}_1^j = \text{COST}_0^j \left( \frac{D^j}{D_0^j} \right)^B \left( \frac{R^j}{R_0^j} \right)^A
\]
1.1.1 Solving for the least-cost investment portfolio

Given the full set of possible investment combinations that can achieve the desired cost reductions, a cost-minimization formulation is used to choose the ‘best’ portfolio, minimizing total investment costs, $Z$.

\[
\text{MIN}_j \quad Z = D^j + R^j
\]

Equation (29) follows a non-linear curve due to the learning coefficient exponents, $\beta$ and $\alpha$. The set of investment combinations can be fit to a power-law curve using the MATLAB computing environment’s ‘fit’ function or other comparable curve-fitting process. Given the unimodal shape of the fit, a gradient search algorithm is implemented to find the least-cost investment portfolio.

The set of possible investment combinations to achieve the desired target cost given predetermined learning rates is illustrated in Figure 22. The cost-dimension is the combination of R&D and D&D investments, and is added using a color gradient scaled where red denotes higher cost and green denotes lower cost. Initial investments in R&D and D&D are set to ‘1’, to show the % change in cumulative investments needed. The optimal investment portfolio is at the point where the R&D investment ratio is 2.82, and D&D ratio is 1.45; that is, if historical R&D investments in the given technology are equal to $100$ million, the prescribe level of total investment after new investments are made and including historical investments should be $282$ million ($100M$ old investments plus $182M$ in new investments).
Setting the initial investment equal to 1 and describing the optimal portfolio as a function of historical investments is done for two reasons: First, starting R&D and D&D figures are not always known as a result of proprietary information in the case of private industry, or incomplete record keeping in public databases, and the optimal R&D and D&D levels are dependent on cumulative historical investments. Further, the ratio makes clear the relative impact of assets investment (D&D versus R&D) on cost reductions. Policy makers can use these ratios to evaluate past and current investment strategies, and appropriately scale investment strategies depending on available budgets. One use of this metric could be applied by industry financial or R&D executives to make the case for greater RDD&D allocations.

In a scenario where investment budgets are fixed, equation (28) can also be used to solve for the expected cost reduction associated with optimal portfolio allocation; however, this study assumes RDD&D budgets are not bound.
6.2 Multi-period Cost Targeting with R&D and D&D and endogenous technological learning:

To address the missing time-dimension of the single-period model, a multi-period cost targeting model is developed where investment decisions in R&D and D&D are made in each period, leading to an accumulated “knowledge stock” and the associated cost reductions. In this model, investments are made over a 5-year period. A number of additional dynamics are amended to the single-period model to show the optimal timing of investment. These amendments are: the time value of money (discount factor), a knowledge depreciation rate, and an investment-to-knowledge time delay.

6.2.1 Modeling the two-factor, multi-period cost-targeting curves

The derivation of learning coefficients is the same as in the single-period model described in (27). The multi-period model described in (30) adds an updating cost formulation, such that current-period technology costs $\text{Cost}_t^i$ are a function technology costs in the prior investment period $(t - 1)$, the new knowledge stock for R&D and D&D $(RK_t^i, DK_t^i)$, and their prior-period knowledge stocks $(RK_{t-1}^i$ and $DK_{t-1}^i)$. Learning coefficients $\beta$ and $\alpha$ are unchanged throughout the investment period.

This cost updating step adds endogenous technological learning to the investment model, which means the model, whether an investor or government planner, can take advantage of lower technology costs brought about by earlier-period investments when making later-period investment decisions.

\[\text{COST}_t^i = \text{COST}_{t-1}^i \left( \frac{DK_t^i}{DK_{t-1}^i} \right)^B \left( \frac{RK_t^i}{RK_{t-1}^i} \right)^A\]

Equation (30) also differs from the single-period model in its use of accumulating “knowledge stocks” defined in (31). The current knowledge stock is represented in this study as the cumulative investment dollars spent. Two modifications describe critical dynamics of knowledge generation: First, new investments face a knowledge stock time delay, which describes the time
that is required for new investments to propagate to the knowledge stock where they have an impact on technology cost reductions. This study chooses a delay of 2 years for demonstration and deployment investments, \( D^j_t \), and 4 years for R&D investments, \( R^j_t \). The knowledge stock penalty, \( \rho \), represents knowledge depreciation over time, where the existing knowledge stock plays less of a role in driving new technology improvements (cost reductions) as it ages. Conversely, new knowledge plays a greater role.

\[
\begin{align*}
A. & \quad DK^j_t = DK^j_{t-1}(1 - P) + D^j_{t - \text{delay}DK} \\
B. & \quad RK^j_t = RK^j_{t-1}(1 - P) + R^j_{t - \text{delay}RK}
\end{align*}
\]

Two more constraints are added in (32) to set the initial capital cost and target capital cost for the investment. For the examples in this study, $1 billion per GW of storage output capacity is used for the initial capital cost of compressed air energy storage, and $750 million per GW is used for the target cost to be achieved by the end of the 5-year investment period.

\[
\begin{align*}
A. & \quad Cost^j_{t=0} = (\text{Initial Capital Cost})^j \\
B. & \quad Cost^j_{t=t} = (\text{Target Capital Cost})^j
\end{align*}
\]

### 6.2.2 Solving the least-cost investment portfolio for multiple investment periods

Finally, the multi-period cost targeting formulas described above are solved under a least-cost optimization framework described by (33), where the objective function \( Z \) represents total costs for all periods (years):

\[
\begin{align*}
\text{MIN}_{j} \quad f(Z) = \sum_{t=1}^{\bar{t}} D^j_t + R^j_t
\end{align*}
\]
Similar to the single-period investment model, technology learning coefficients $\beta$ and $\alpha$ make this problem non-linear (NLP). Also, the multi-period model is also non-convex due to the added endogenous technological learning and multi-period time dimension. To make the problem even harder to solve, this study finds that the timing of investments has a very small impact on the level of cumulative investments. Therefore, it can be inferred that the timing of investments has a very small effect on total costs, making the optimal choice less ‘obvious’ to the solver. This class of problems requires a global non-linear solver, as opposed to ‘local’ solvers that often settle on the nearest minimum solution that is not the global minimum.

The GAMS optimization environment is chosen for developing and solving the optimization problem. Due to solution space non-linearities and non-convexity, a global minimum solution cannot be guaranteed. The study implements three commercial NLP solvers—CONOPT, Baron, and LINDOGlobal to improve the chance of finding the global optimum. A set of initial starting points are tuned by trial-and-error for each algorithm. Finally, the best (lowest cost) solution of the three outputs is selected for each of the 16 sensitivity runs shown in Figure 23. Each of the three solvers contributed at least one best solution. While LINDOGlobal proved to be the most effective, finding 7 of the 16 best runs, it required a computation time of the order of 100X the next-best solver (CONOPT). Further work in terms of scaling of the model, algorithm selection and tuning could improve the performance of the optimization.

Given the short duration of the total investment period (five years), the knowledge stock penalty is set to zero, assuming all past knowledge contributes equally to current capital costs. Further, it can be debated as to whether a knowledge penalty should be used in R&D models at all. The knowledge stock leads to a diminishing stock of prior knowledge, which can increase capital costs calculated by the model. While this study does not look into this topic in detail, it seems unlikely that future technology capital costs will become more expensive in the case where R&D or D&D investments are minimal or not present.
Figure 23. Multi-period, Two-factor Cost Targeting Curves: Sensitivity of the knowledge stock delay on the optimal timing of investments

(Initial Tech Cost: $1000M, Target: $750M, LBD: 8%, LBS: 15%)

D&D Knowledge Lag (years)

- R&D Investment Factor [$M \times \text{cumulative investment to date}$]
- D&D Investment Factor [$M \times \text{cumulative investment to date}$]
- New Technology Capital Cost [$M / \text{GW}$]
The accumulated investment portfolio for the time period is very similar to the single-period model, where learning rates, starting costs, and target costs are equivalent. The single-period model estimate the optimal investment factors are 2.82 for R&D, and 1.45 for D&D; the multi-period investment factors are between 2.842 and 2.844 for R&D, and 1.483 and 1.484 for D&D for the sensitivity runs. This tells us two things: the single-period model is a ‘good’ approximation of the more detailed multi-period investment model; and total cumulative investment levels do not change significantly for the different knowledge stock delay scenarios.

Timing of investments is impacted mostly by the knowledge stock delay, the time it takes a new investment to become ‘knowledge’ and lower capital costs. For example, when R&D delay is set to 4-years, R&D investments must occur in the first year in order to be added to the knowledge stock by year-5, when the investment finally pays off in terms of reduced capital costs.

Staging investments over several time periods can take advantage of lower capital costs that result from earlier investments. In the 5-year investment model, knowledge stock delays of one or two years leads to separated investments as opposed to a single period of high investment.

For scenarios where the total combined knowledge stock delay (including the delay on both R&D and D&D) is less than the total investment period (5 years in this model), a greater initial investment is often made, followed by a small investment and increasingly large investments. This two-peak investment strategy emerges for two reasons: First, the early investment peak takes advantage of exponentially declining returns to learning, a feature of equation (30) where learning happens more quickly as a result of early investments, and more slowly for later-period investments. Further, the later investments are made to take advantage of lower capital costs brought about RDD&D investments in earlier periods.

For scenarios where both knowledge stock delays are greater than or equal to half the total investment period—this includes delays of three- and four years for the five-period investment model—it is not feasible to space out investments such that later investments take advantage of reduced costs produced from earlier investments. For example, a delay of three years means the
earliest cost reductions can be achieved in year four, when it’s too late to make new investments that will pay off by year six. The four scenarios in the bottom-right quadrant of Figure 23 illustrate this finding, where all R&D and D&D investments are committed in the preliminary investment period.

Knowledge stock penalties are not included in this analysis due to a lack of evidence supporting their use. After testing several scenarios with a knowledge stock penalty, one generalized finding is that the penalty results in greater investments in the investment option with greater learning rates, and very little change in investments in the investment option with the lower learning rate.

6.3 Key improvements for optimal cost-targeting analysis

Currently, the capital cost target is met by the final investment period; however, it could be seen as socially advantageous to achieve cost reductions as early as possible, to expedite the commercial deployment of the technology. A reward function for achieving capital cost reductions earlier in the investment period could be formulated as a constraint by adding multiple cost reduction targets. Alternatively, a modification of the objective function could reward cost reductions each period.

This study does not include a budget or yearly spending cap in order to develop theoretical insights around optimal spending given minimally-bounded resources. A budget should be included in cases where the optimal investment strategy is estimated for a specific investor or policy planner in a resource constrained environment.
7 Conclusion

Introducing a new generation of technologies to today’s power grid is more complex than bringing costs down to ‘parity’ with thermal generators. While wind and solar are hailed as low-carbon, low variable cost alternatives to fossil-fuel based generators, the intermittent and uncertain nature of their power supply can present several challenges and costs to grid operators. To maintain supply reliability, efficiency, and sustainability in the face of increasing renewable electricity generation and a changing regulatory landscape, operators look to a more ‘flexible’ grid.

Electricity storage is one option for increasing the flexibility of the grid. While over 99% of bulk energy storage in the U.S. is in the form of pumped hydroelectric power, the expansion of hydroelectric power is constrained to geographies where water can be pumped into elevated reservoirs. Thermal peaking generators can also provide added flexibility, though these technologies are expensive and inefficient to operate due to high levels of fuel consumption. New electricity storage technologies such as advanced batteries and compressed air energy storage (CAES) are alternative solutions for storing and delivering large amounts of energy to improve system reliability, reduce thermal power plant operating costs, and reduce carbon emissions. However, accurate analysis tools for predicting the future benefits of these storage investments remain scarce [1], [91], and limited market deployment makes drawing reliable conclusions from case studies difficult.

This research examines the value of grid scale electricity storage through the lens of integrated technical, economic, and regulatory systems. To capture the technical complexity of various generation sources, a unit commitment model is developed with a higher-resolution formulation for electricity storage. I find that the value of storage is highly dependent on the existing generation fleet, since storage must compete with existing sources of flexible generation. The techniques developed in this study can be used in future studies to evaluate the performance and value of various electricity storage technologies in different power systems.
Similar to [7], I show that some of the value of electricity storage may not be captured by current market payment mechanisms. In particular, increasing storage capacity can lead to significant reduction in thermal generator starts by providing load-following services. While thermal starts costs represent a small fraction of total operating costs—less than 1% even in the high-renewables scenario—the resulting efficiency gains and reduced wear-and-tear on thermal generators may become an important selling point for storage as the thermal generation fleet ages. Policy makers aiming to increase the deployment of grid flexibility should consider new policy and market mechanisms that more fully internalize the benefits of electricity storage services.

Storage can also benefit the grid by enabling the dispatch of a larger share of installed renewable electricity capacity. However, this study shows that storage does not always lead to a reduction in emissions per se; rather, the direction and size of the impact in total emissions depends largely on the types and capacities of existing power generators. Lacking sufficient grid flexibility, wind and solar power will be curtailed when their output exceeds demand, or when the rate of changes in net load surpasses the response-time of available generators. In this study, renewables integration from storage becomes a significant value-added service when renewables generation exceeds 35% of the total generation mix. At these high levels of renewables, storage is used to manage high variability of net load, increasing renewables usage (reducing REG curtailment) and driving emissions reductions. However, when renewables are below 35% penetration, storage does not significantly contribute to renewables integration, which leads to lower estimated values for storage. At these lower levels of REG, the resulting effect on emissions depends on the carbon intensities of thermal generators being used to charge storage units compared to the carbon intensities of generators being displaced by discharged storage units. For example, with the recent decline in natural gas prices, storage may decrease system emissions when storage is used by CCGT units to displace more carbon-intensive coal or OCGT supply.

While thermal generators and storage compete for providing supply, they can also be complementary when providing flexibility services such as load following services. I show that
several less-flexible generators such as coal plants may coordinate ramping schedules to emulate the performance of more flexible units. Coordinated flexibility can lead to less intuitive results that are not captured by price-taker or other cost-based models. For example, generation from open cycle gas turbines (OCGT) may increase as storage is added to the grid. This effect is strengthened as the level of intermittent renewable electricity generation is increased, suggesting that storage and OCGT may be complementary in providing load-following for peak hours of demand, particularly when variability of net load is high and operating reserve requirements are increase.

Despite the various grid benefits of new storage technologies, high capital costs remain a critical barrier to commercial deployment [77]. Federal and private spending on energy RDD&D remains low relative to other industries and recommended levels. Increased federal spending and regulation is thought to catalyze innovation from private firms, but the appropriate level and timing of innovation funding is difficult to forecast. This study addresses two questions to inform more optimal RDD&D funding for storage. These are: “what is the estimated target capital cost at which storage capacity will be deployed?”, and, “what is the lowest-cost portfolio of RDD&D needed to bring current capital costs down to target levels?”

The average lifetime value of storage capacity exhibits diminishing benefits as additional storage capacity is added. This suggests that grid control areas with limited flexibility can extract more value from adding storage capacity than control areas with higher levels of supply flexibility. Further, as flexibility can be improved as a greater number of generators can be deployed to meet demand, it can be inferred that storage capacity may have greater value in smaller control areas or micro-grids with fewer generators. In order to derive the most benefit from storage, developers and grid planners should target regions with limited existing.

The estimated value of storage is also proportional to the level of renewable electricity generation. For the baseline grid studied here with no pre-installed storage capacity, there is sufficient thermal generator flexibility to allow up to 25% of the generation mix from intermittent renewable electricity generators with very little curtailment (<.05%) of combined
wind and solar generation. Due to the existing flexibility of the grid, a compressed air energy storage unit with $1 billion in total capital costs and a 25-year lifetime is only economical to build in the 45% REG scenario. Therefore, storage developers should target regions where net load variability is high or expected to increase with the addition of significant wind or solar resources.

Optimal investment models can be used to represent endogenous technology learning in socio-technical models [64]. In this study, I present a framework for estimating optimal RDD&D spending by using the output of a valuation model (see Chapter 4) as the input to an optimal RDD&D model (see Chapter 6).

Technological progress can be described as a function of accumulated knowledge inputs. This study uses a two-factor learning curve methodology, where knowledge is generated from learning-by-searching, defined as spending on research and development (R&D), and learning-by-doing, defined as spending on development and diffusion (D&D). I assign hypothetical learning coefficients for learning-by-doing (D&D) investments and learning-by-searching investments (R&D) of 8% and 15%, respectively. In other words, a doubling of R&D spending will lead to an estimated decrease in storage capital costs by 15%. While electricity storage learning coefficient estimates are not yet available in the literature, these coefficients are within the range of learning estimates drawn from historical analysis of wind farm costs, and are assumed to be “good enough” for this exploratory analysis of electricity storage. It is shown that a single-period optimal investment model provides a close approximation of the more detailed multi-investment period model. Both the single-period and multi-period model find that additional R&D investments should be roughly three-times the historical cumulative level of R&D spending, and that additional D&D spending should be roughly 1.5-time historical spending in order to achieve the target cost reductions—a reduction of capital costs from an initial cost of $1 billion per GW installed capacity to a target cost of $750 million per GW. Innovating firms and policy planners should use methods such as expert elicitations and historical price analysis to improve estimates of storage learning coefficients. This process can
lead to improved spending targets and also act as a strategy for including multiple leaders in the decision-making process.

My analysis of optimal RDD&D investments shows that the timing of investments depends largely on the knowledge stock delay, where the delay is the time it takes for innovation spending in R&D or D&D activities to impact technology cost reductions. By staging innovation investments over several time periods, total investment costs can be reduced. In scenarios where the total combined knowledge-stock delay is less than the total investment period, a larger investment is often made in the initial investment period, followed by smaller investments of increasing size. This two-peaked investment strategy emerges for two reasons: First, the early investment peak takes advantage of exponentially declining returns to learning. Further, the later investments are made to take advantage of lower capital costs brought about by RDD&D investments in early periods. Longer knowledge stock delays tend to move investments toward the early investment periods in order to ensure cost savings are realized by the completion of the investment period.

The example generation system, technology capital costs, and learning parameters chosen for this study are rough estimates and provide limited insight into actual optimal levels of RDD&D spending. However, the tools developed here offer a more complete framework for estimating optimal innovation portfolio spending based on best-available figures for the technical, regulatory, and market-based characteristics of the grid. These power system simulations are also used in Chapter 5 to understand the operational dynamics of purely competitive, coordinated power plants that are scheduled and dispatched to meet demand and reserve requirements under several energy storage futures scenarios.

Further research is needed to explore the value of storage in providing services at time intervals shorter than one hour. Smaller time intervals may provide greater insight into the use of storage in providing primary regulating reserves which are responsive within a window of seconds- to minutes. As generation resources such as wind and solar power are increasingly deployed in low-voltage distribution networks, additional studies may explore the value of smaller-scale
installations of distributed storage for the purpose of voltage support, load leveling, frequency response, and renewables integration in the distribution system. Further work is also needed to evaluate demand-side management strategies such reducing the demand of consumers during peak hours of demand (i.e., demand response) as a source of power system flexibility. Modeling many of the benefits in terms of price stabilization or transmission line upgrade deferrals requires the inclusion of transmission networks which can be computationally restricting; therefore, integrated models have not yet successfully combined transmission planning with full-system unit commitment and generation capacity expansion formulations such as in this study.

Private firms and policy makers worldwide are continually adapting their electricity infrastructure to reliably meet power demand. In the U.S., critical energy related issues such as global climate change, distributed generation, energy security, and an aging grid infrastructure are shaping the new requirements for the power grids of the future. As power system planners look to adapt existing systems to meet these needs, they face complex technical and market dependencies that may require the implementation of state-of-the-art modeling techniques in the design and decision-making process. As capital costs fall with increased experience and economies of scale, electricity storage may emerge as a leading option for providing the flexibility needed to ensure the sustainable, reliable, and efficient operation of the electric power system.
Bibliography


