# The Potential of Wind Power and Energy Storage in California

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A great deal of new electricity generating capacity will be needed in California over the next few decades. Given California's Renewable Portfolio Standard and greenhouse gas reduction goals, a significant fraction of this capacity is likely to be renewable; and among renewables, wind energy is particularly promising. Other likely types of capacity additions are natural gas and coal. Unlike these conventional generators, wind farms produce power intermittently and cannot be dispatched when needed. For this reason, the incorporation of energy storage technologies into the electric power system may increase the economic attractiveness of large-scale wind power. In addition, energy storage may add value to the system due to its ability to displace expensive peaker plant generation. However, questions remain about the economic feasibility of energy storage, as well as its effects on the electric power system in terms of capacity additions and the generation mix. The purpose of this study is twofold: to evaluate the effects of energy storage on the future California electric power system, especially its effect on wind capacity and generation, and to assess the relative values of different energy storage technologies. To do this, I use a dispatch simulation/optimization model of the California generating sector in 2020. The optimization portion of the model chooses new capacities of wind (at four California sites), energy storage, natural gas (simple and combined cycle) and coal (pulverized and gasified) in order to meet the shortfall in generating capacity caused by retirements and increasing demand over the next decade and a half. Simultaneously, the dispatch portion of the model, which takes into account hourly wind speeds at each of the four sites, chooses new and existing generators in order of increasing marginal cost to meet hourly demand over one year. The storage unit takes in energy when the marginal cost of electricity is low, releasing it when the marginal cost is high. I find that if storage were free and perfectly efficient, it could decrease the total cost of the electric power system by about 5%. Though all storage technologies are currently too expensive for this purpose, the costs of compressed air storage and advanced batteries may fall far enough for these technologies to become competitive in the next few decades. Energy storage appears to have a relatively minor effect on system structure and generation mix, including wind penetration. If our goal is to reduce carbon emissions, other policies, such as carbon taxes, are likely to be more effective than the promotion of energy storage.

## Background

### *California's Electricity Generation*

California currently obtains more than 60% of its electricity from fossil fuels, mostly natural gas. The rest of the state's load is met largely by nuclear and hydro facilities. About 11% of load is met by renewables, especially geothermal, biomass, and wind (CEC 2004). Over the next few decades, many existing California generators are likely to retire. Based on simple assumptions about generator lifetimes (Table 1), about half of current (2004) generating capacity will have retired by 2020 (Figures 1 and 2). New generating capacity built between now and 2020 must replace this retiring capacity as well as accommodate an increasing demand for electricity; the California Energy Commission (CEC 2005a) projects that demand will grow by about 1.2% per year through 2016. Though actual retirement dates are sure to differ somewhat from the projections used in this analysis, it is clear that a great deal of new generating capacity will be needed in the next few decades.

| Plant Type | Lifetime (y) |
|---|---|
| Coal | 40 |
| Natural gas | 40 |
| Petroleum products | 35 |
| Nuclear | 60[1] |
| Hydro and pumped storage | 60 |
| Geothermal | 40 |
| Biomass, landfill gas, digester gas, MSW | 40 |
| Wind | 20 |
| Solar thermal | 20 |

Table 1. Generator lifetime assumptions. Data are from Bosi (2000), Shibaki (2003), Danish Wind Energy Association (2003), and US DOE (2005).

[1] Based on an initial 40-year license, plus a 20-year license renewal.

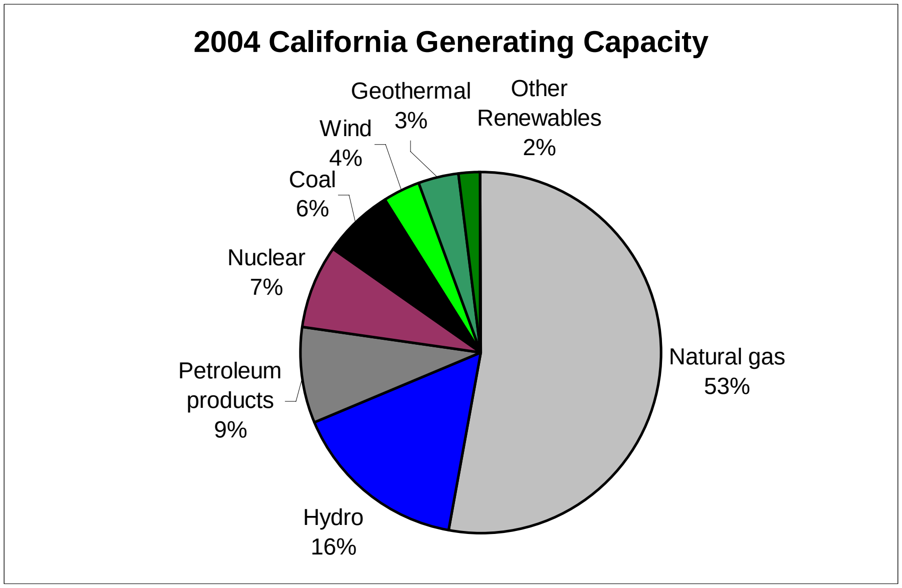


Figure 1. California in-state generating capacity mix in 2004. From CEC 2005b. 81% of California's electricity demand is met with in-state generation; the rest is met with imports from the Northwest (mostly hydro) and Southwest (mostly coal).

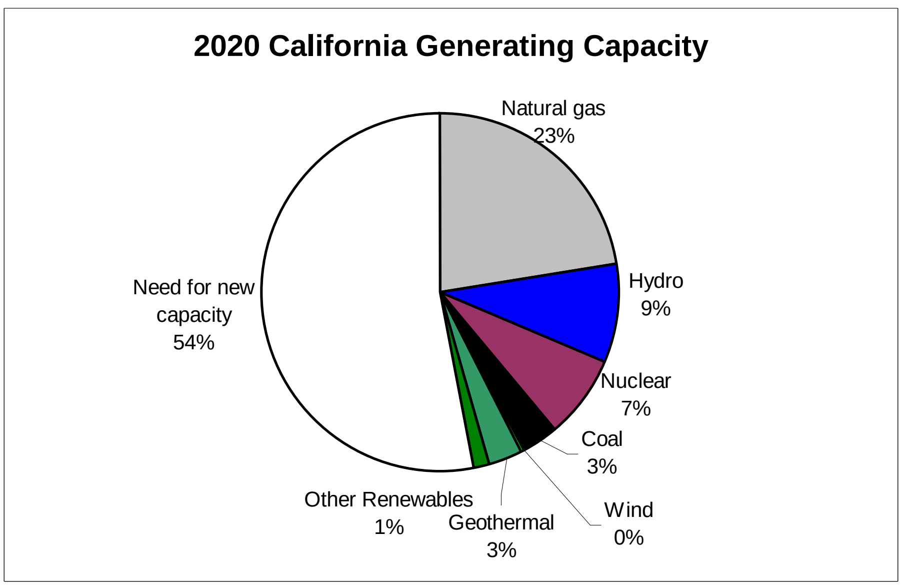


Figure 2. Projected in-state generating capacity mix in 2020. Based on 2004 capacity mix, and assuming retirements according to Table 1. This figure does not take into account demand growth between 2004 and 2020, which will increase the need for new capacity.

Most of the large hydro sites in California have been exploited, and state law prohibits the construction of new nuclear plants until a federal nuclear waste depository has been built (CEC 2005c). Therefore, most of the new generating capacity built in the state over the next few decades is likely to be natural gas, coal, and renewable.[2] The specific mix will depend on the relative capital costs and fuel (natural gas and coal) prices, as well as on state and federal policies that encourage or discourage specific types of generation. For example, if a tax were levied on carbon emissions, renewable generators would benefit at the expense of fossil fuels, particularly carbon-intensive coal. Though carbon taxes have yet to be enacted in the United States, two recent California policies aim to increase renewable penetration in other ways. These are described in the next section.

### *California Renewables and Climate Policy*

In 2002, California enacted a Renewable Portfolio Standard (RPS), which required electricity providers to meet 20% of their load with renewable energy (excluding large hydro facilities) by 2017. This deadline has since been pushed to 2010. In addition, Governor Schwarzenegger has endorsed an additional goal of 33% renewables by 2020 (Hamrin et al. 2005). New wind turbines are expected to contribute a large fraction of this renewable energy. A report by the Center for Resource Solutions (Hamrin et al. 2005) predicts that wind will provide half of the new renewable energy to meet the 33% RPS; the rest will met with geothermal (30% of the total), biomass (10%), and solar (10%).

California climate policy will also affect the electricity generation sector. Executive Order S-3-05, issued by Governor Schwarzenegger in March 2005, calls for state greenhouse gas (GHG) emissions to be reduced to 2000 levels by 2010; to 1990 levels by 2020; and to 80% below 1990 levels by 2050 (Schwarzenegger 2005). These long-term goals are quite ambitious[3]; but this

[2] The descriptor "in-state" is used here to include coal plants built in neighboring states that primarily supply California demand. Two existing plants fit this description: Intermountain (in Utah) and Mohave (in Nevada). California air quality regulations prevent coal plants from being built within the state's borders.

[3] To put Schwarzenegger's goals in context: if the US had ratified the Kyoto Protocol, the country would be required to reduce GHG emissions to 7% below 1990 levels by the period 2008-2012. Kyoto does not currently include

type of action, on a much broader scale, will likely be necessary if we are to avoid increasingly destructive climate change. The electric power sector is the second largest contributor to carbon dioxide emissions in California, after transportation (CEC 2002). Greenhouse gas emissions from electricity generation will therefore need to be reduced dramatically if California is to reach Governor Schwarzenegger's targets. A portion of this reduction is likely to be achieved through a transition from fossil to renewable generators;[4] and the most likely renewable resource to be exploited on a large scale is the wind.

***Wind Power in California***

About 2000 MW of installed wind capacity currently supplies about 1.5% of California's electrical energy (CEC 2004). Nearly 95% of this energy comes from wind farms in three locations: Tehachapi and San Gorgonio in Southern California, and Altamont in Northern California (Yen-Nakafuji 2005). Hamrin et al. (2005) identify 11,800 MW of high-speed (Wind Class 5 and above) sites, and 19,000 MW of low-speed (Class 3 and 4) sites in the state that have yet to be developed. Lipman, Ramos and Kammen (2005) claim that significant growth in wind capacity is likely at four California sites: Tehachapi, San Gorgonio, Altamont, and Solano County (Northern California). They predict that 90% of new development will occur at the Southern California sites, and 10% at the Northern California sites.

Wind is likely to play a significant role in the future California electricity sector as a result not only of the resource availability, but also of its relatively low costs. Based on the assumptions used in the 2004 Annual Energy Outlook (EIA 2004), the total generation cost of wind (taking

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subsequent targets. Executive Order S-3-05 allows more time to reduce emissions below 1990 levels, but goes beyond Kyoto in requiring sharp reductions by mid-century.

[4] Other possibilities include increased nuclear generation, carbon capture and storage technologies, efficiency improvements, and demand-side management. Though these alternate strategies would advance Schwarzenegger's goals, they would not count toward the renewable portfolio standard.

into account capital and O&M costs) is between three and four cents per kWh. This is far less costly than solar photovoltaic ($0.15/kWh, according to the same source), and slightly less costly than natural gas generation. However, though the bus-bar cost of wind is low, it imposes additional costs on the system due to its intermittency (DeCarolis and Keith, 2006).[5] Because wind generators cannot be dispatched when needed, a system with high wind penetration requires either (1) a significant amount of load-following capacity on the grid; (2) dispatchable backup generation; or (3) energy storage.[6] Load following generators adjust their output to changes in the supply/demand balance on a short timescale; backup generators are coupled to wind farms and respond to the wind's intermittency by increasing their own generation when the wind is low; and energy storage systems take in electricity when the electricity price is low (such as when the wind speed is high), and return it to the grid when the electricity price is high (such as when the wind speed is low).

Energy storage has some potential advantages over additional load-following or backup generation. For instance, a large-scale wind system with no storage could result in the waste of excess wind power that was generated when demand was low.[7] In addition, load-following and backup generators often burn fossil fuels (and thus emit GHGs), while most storage technologies do not.[8] In addition, aside from their role managing intermittency, energy storage systems may prove profitable through their ability to arbitrage (buy power when its price is low, and sell it when its price is high). However, energy storage has rarely been used on a large scale, and its costs are relatively high. The next section provides a brief overview of energy storage

[5] The same applies to solar power, of course.
[6] Another possibility,mentioned by DeCarolis and Keith (2006), is increasing the price elasticity of electricity demand. To be useful in this context, demand would need to be responsive to price on a very short timescale.
[7] This would only be a problem if wind capacity were large enough that wind was often the marginal generator.
[8] The exception is compressed air energy storage, which requires some natural gas. However, this technology still uses stored energy to replace fuel.

technologies. The following section discusses the potential economic effects of energy storage on an electric power system.

***Energy Storage Technologies***

Electricity can be stored *as electricity*, but it is generally converted into potential, kinetic, or chemical energy in order to be stored. Table 2 lists energy storage technologies of each of these types.

| Form of Energy | Storage Technologies |
|---|---|
| Potential | Compressed air energy storage (CAES) |
| | Pumped hydro |
| Kinetic | Flywheels |
| Chemical | Batteries (lead acid, advanced, flow) |
| | Fuel cells |
| Electrical | Supercapacitors |
| | Superconducting magnetic energy storage (SMES) |

Table 2. Categorization of energy storage technologies by form of energy stored.

All energy storage systems have three components: a charge component (which converts incoming electricity into the form in which it will be stored), a storage component, and a discharge component (which converts the stored energy back into electricity). Energy storage technologies are often characterized by their discharge capacities and the time they can discharge at maximum power, which is the ratio of the size of the storage tank (in MWh) to the discharge capacity (in MW). These characteristics determine whether a storage technology is appropriate for a particular application. For example, storage systems that are used for power quality purposes (to deal with short-term fluctuations in voltage, frequency, and harmonics) have large power/energy ratios, and are discharged for, at most, a few seconds at a time. On the other hand, storage systems that are used in conjunction with wind energy systems must have long enough discharge times to be able to fill in for hours at a time when the wind is low. Of the technologies listed in Table 2, supercapacitors and SMES have insufficiently long discharge times to be useful for managing wind's intermittency. According to Schoenung 2003, the most promising technologies for large-scale ("bulk") energy storage are batteries of various types, CAES, and pumped hydro.

***Energy Storage and Electric Power Systems***

There are two reasons that energy storage might be a valuable addition to an electric power system. First, as mentioned above, the existence of storage on the grid might improve the economics of wind power, since storage can mitigate wind's intermittency and reduce the need for additional load-following capacity. Second, and independent of its effects on wind generation, storage may reduce the total cost of the system by reducing the need for generation from expensive peaker plants. That is, when demand is low, the storage system can buy power that is generated by relatively inexpensive plants; and when demand is high, the storage system can sell that power back to the grid, replacing peaker generation. The storage unit can thus essentially serve to substitute generation from baseload or intermediate plants for generation from peaker plants. This benefit of energy storage may accrue either to the owner of the storage unit, if he/she profits through arbitrage, or to consumers, if the reduced system cost is passed through in the form of reduced electricity rates.

There are two possible configurations of an electric power system that includes wind power and energy storage: (1) standalone storage, in which the storage unit is attached to the grid and arbitrages between high and low prices; and (2) coupled wind/storage system, in which the storage unit is coupled to a wind farm and buys power only from that source. The second type of system may be useful in a market structure in which a wind generator faces penalties for not providing a contracted amount of power each hour (a "firm capacity" contract; see Lamont 2004). However, not all wind generators face such a contract. In particular, the California Independent System Operator has implemented a Participating Intermittent Resource Program

(PIRP), which eliminates such penalties for wind generators (CAISO 2005). Under these circumstances, a standalone storage system is likely to be more profitable than a storage system coupled to a wind farm, because the standalone system has greatly expanded opportunities to buy power. In this study, I model standalone storage in order to assess the maximum value that storage can provide to the electric power system.

To maximize its value, a standalone storage unit should buy power from the grid when the systemwide electricity price is low, and sell it back to the grid when the systemwide price is high. In practical terms, this involves setting price "thresholds": when the electricity price is below the lower threshold, the storage unit buys power; and when the price is above the upper threshold, the storage unit sells power.

## Purpose of this Study

A great deal of new electricity generating capacity will need to be built in California during the next few decades. California renewable and climate policies ensure that a significant fraction of this new capacity will be renewable. Wind looks particularly promising, due to its relatively low costs and the considerable wind resource in California. However, as a result of the intermittency of the wind, the feasibility of large-scale wind generation may be increased by the addition of energy storage to the system. Energy storage may also allow for a more economical configuration of the balance of the system, and it may decrease the total cost of the generation due to its arbitrage capability.

The general purpose of this study is to analyze the effects of energy storage on California's electricity sector. Specifically, I investigate the effects of a variety of storage capacities and characteristics on (1) the optimal capacities of new generators (natural gas, coal, and wind) added to the system; (2) generator dispatch, including wind penetration and carbon emissions; and (3) total system cost. The effect of storage on the total system cost is a measure of the value that storage provides to the system. Comparing this value with the costs of particular storage technologies allows me to assess whether storage technologies are economic at current prices, and which technologies are the most promising. In addition, determining the impacts of storage on wind penetration and carbon emissions allows me to assess whether storage could be an effective and economic means of reaching greenhouse gas reduction goals.

## Methods

To address the questions discussed above, I built a simulation/optimization model of the 2020 California electricity generating sector. This year was chosen because of its relevance to the California RPS and Executive Order S-3-05. I assume that current generators remain in the system until they retire, based on the simple assumptions about generator lifetimes presented above (see Table 1). See Figure 2 for an illustration of generating capacity that is projected to remain online in 2020. In order to ensure that projected 2020 electricity demand is met, additional generating capacity is added to the system based on the optimization process described below.

The optimization portion of the model minimizes annual system cost, which includes levelized capital costs and annual operating costs of new and existing generators and energy storage. In each run of the model, the energy storage capacity is fixed. The optimization involves ten decision variables: capacities of eight new generators types (two types of natural gas, two types of coal, and wind at four locations), and the two marginal cost thresholds that determine when the storage unit charges and discharges (see Table 3).

| Decision Variables in Optimization | |
|---|---|
| Generator capacities | Simple-cycle natural gas |
| | Combined-cycle natural gas |
| | Pulverized coal |
| | IGCC coal |
| | Wind at San Gorgonio site |
| | Wind at Altamont site |
| | Wind at Solano site |
| | Wind at Tehachapi site |
| Marginal cost thresholds for storage | Lower threshold (storage charges) |
| | Upper thresholds (storage discharges) |

Table 3. Optimization model decision variables. The capacity of the storage unit was not treated as a decision variable, but was varied between model runs.

A constraint is included to ensure that total generation (including storage output) meets or exceeds demand in nearly every hour of the year.[9] The energy storage component can be used to model different storage technologies by changing its charge/discharge ratio, discharge time, component costs, efficiencies, and GHG emissions. I model storage as perfectly efficient in order to be as favorable to storage as possible in the preliminary analysis.[10] To evaluate the economic efficiency of storage, I compare the value storage provided to the system with the costs of the various storage technologies.

Within this optimization, the model simulates generator dispatch for each hour of a year. Existing and new generators are chosen in order of increasing marginal cost in order to meet a varying hourly demand. Demand is assumed to be perfectly inelastic (unresponsive to electricity price), which is a reasonable assumption given today's retail electricity market.[11] Energy storage is modeled in three parts: a charge component, discharge component, and storage component. During hours when the marginal cost of electricity (the cost of the most expensive generator

[9] For computational tractability, I did not include a separate constraint for each hour, but rather a single constraint requiring that the difference between demand and generation (including output from energy storage) be positive for no more than 10 hours per year. I allow demand to exceed generation for up to 10 hours because it would be unrealistic to require the model to build capacity that is essentially never used.
[10] The storage technologies I consider actually have efficiencies of about 70-75% (see Table 6).
[11] Today, consumers are charged fixed or block rates that do not reflect short-term variations in the marginal cost of electricity production. In order for demand to be responsive to price on an hourly basis, not only would consumers need to be charged real-time prices, but they would need to be aware of what these prices were.

operating) is below the lower threshold, the storage device is charged; and when the marginal cost of electricity is above the upper threshold, the storage device is discharged. Of course, the ability of the storage unit to charge or discharge at any particular time depends on the quantity of energy in storage at that time. Storage output effectively displaces the most expensive generator that would otherwise be operating at the time. As discussed above, the storage unit is not coupled to the wind generators, but is available for use by the system as a whole. Further description and a mathematical representation of the model are presented in the Appendix.

## Comparison to Previous Studies

A recent study by Lipman, Ramos, and Kammen (2005) examines the costs of battery and hydrogen storage systems in conjunction with wind generation in California. They consider the same wind sites that I do (in fact, I borrow their wind speed data). However, their study differs from mine in that they model storage that is coupled to wind farms (takes in only wind-generated electricity), while I model standalone storage systems. They also assume that stored electricity is sold to the grid under a fixed-price contract, at \$0.065/kWh,[12] whereas I assume that the storage unit buys and sells power at the market price each hour. In addition, whereas my model optimizes the capacities of new wind generators, Lipman et al. analyze fixed wind capacities (scenarios in which wind meets 10% and 20% of California demand). Lipman et al. find that that storage is useful in conjunction with wind power only when wind penetration exceeds about 10%. At 20% wind penetration, hydrogen storage is more promising than advanced battery storage.

[12] This assumption is based on new rules that have been proposed for valuing renewable generators in California, which involve compensating these generators at the utilities' avoided cost of generation, with preference given to dispatchable renewables. Under this proposal, storage coupled to a wind farm would increase the value of wind generation by increasing its dispatchability and thus its "rank" relative to other intermittent renewables (including other wind generators). The \$0.065/kWh value includes an assumed production tax credit of \$0.015/kWh.

Another recent study (DeCarolis and Keith, 2006) considers the potential long-term role of wind and storage in the Midwest. DeCarolis and Keith optimize the capacities of new wind farms (at five Midwestern sites), transmission lines, compressed air energy storage, and natural gas generators (simple and combined cycle) to meet future demand at a simulated Chicago demand center. The basic structure of their model is thus very similar to mine; like mine, it includes an hourly dispatch component as well as an optimization component. They also model storage as a standalone system, rather than coupled to wind generation. The most significant difference between their study and mine is that they analyze the long-term rather than the medium-term, and so do not take into account existing generation capacity. DeCarolis and Keith find that using wind to supply about half of demand would increase the cost of electricity by about 1-2 cents per kWh. They also find that even under a carbon tax, compressed air energy storage is unable to compete effectively with natural gas generation because of its higher costs and residual carbon emissions.

Two studies have analyzed the value of technology-neutral storage in electric power systems, taking hourly electricity prices as given and optimizing the price thresholds at which a storage unit charges and discharges. In "Opportunities for Electricity Storage in Deregulated Markets," Graves et al. (1999) optimize these thresholds for each of 26 periods in a year, assuming 1 MW of storage charge and discharge capacities, 20 MWh of storage tank capacity, and 75% round-trip efficiency. Using price patterns for a number of US and international electricity markets, they find storage values ranging from less than \$5 to more than \$100 per kW-y, with most regions having values between \$20 and \$40/kW-y. In "Improving the Value of Wind Energy Generation Through Back-up Generation and Energy Storage," Lamont (2004) carries out a similar analysis to Graves et al. as a part of his study of the effects of storage and back-up generation on the value of wind power. With slightly different assumptions than Graves et al., Lamont's finds the maximum value of storage to be about $30/kW-y (which occurs with an optimal storage tank to discharge capacity ratio of 6:1).

The storage component of my model is similar to the models used by Graves et al. and Lamont. The major difference between my model and these two is that theirs evaluate storage capacities that are small relative to the size of the electricity market, whereas I consider much larger storage capacities. Therefore, whereas their models take hourly electricity prices as given, mine calculates electricity prices based on generator dispatch and storage behavior. In addition, Graves et al. and Lamont do not investigate the effects of storage on optimal generator capacities.

## Data

Hourly wind speed data from four California sites (Tehachapi, San Gorgonio, Altamont, and Solano) were obtained from the authors of Lipman et al. (2005), who had originally obtained them from Lawrence Berkeley National Laboratory and the California Wind Energy Collaborative (see their paper for details). I found data on the available wind resource in the state in Yen-Nakafuji (2005). Wind turbine power curve data were obtained from the brochure for the Vestas V80 1.8 MW turbine, which was designed for the North American market (Vestas Wind Systems 2003). For existing wind turbines, I used power curve data for the NEG Micon NM54/950, a 950 kW turbine (Nazaroff 2005).

I obtained 2004 California hourly load data from the California Independent System Operator (CAISO 2005b). According to this source, peak California load in 2004 was 45.6 GW, and total annual generation was 239 million MWh. I scaled these data to match the California Energy Commission's data on 2004 gross system in-state electricity production, which gives the total annual generation as 223 million MWh (CEC 2006, CEC 2004). There are three reasons for the discrepancy between the ISO data and the CEC data: (1) Some portion of the demand reported by the ISO is met by out-of-state generation; (2) the ISO service area does not include the whole state; and (3) there are energy losses in the transmission and distribution systems. I then scaled these data up based on California Energy Commission (CEC 2005a) projections of future state electricity demand increases (1.2% per year), for a total generation requirement of 270 million MWh in 2020.

The CEC also provides a database of existing California generators, their capacities, and the dates they began operating (CEC 2005b). For baseload generators, I approximated the annual availability factor as an hourly constraint (see the Appendix); availability factor data were obtained from the North American Electric Reliability Council (NERC 2005). I obtained power plant cost data from two sources: for existing plants, I used the Electric Power Research Institute's Technology Assessment Guide (EPRI 1989), and for new plants I used the Energy Information Administration's Assumptions for the Annual Energy Outlook (EIA 2004). Storage characteristics and cost data were obtained primarily from a Sandia National Laboratory report (Schoenung and Hassenzahl 2003). Fuel price projections (natural gas, coal, petroleum, and biomass) were obtained from the Energy Information Administration (EIA 2005, EIA 2006) and the California Biomass Collaborative (2005). All costs were converted to 2005 dollars.

Table 4 presents cost data used for the new capacity considered by the optimization model, and Table 5 presents fuel cost assumptions. Storage costs are presented in Table 6. In the analysis below, I consider five storage technologies: compressed air, pumped hydro, lead-acid batteries, sodium sulfur batteries, and polysulfide bromide flow batteries. These technologies were chosen because Schoenung (2003) identifies them as being appropriate for large-scale energy storage. Schoenung also includes nickel cadmium batteries on this list, but I neglected these because they have much higher costs than the other technologies.

| New Generator Costs and Efficiencies (2005 $) | | | | |
|---|---|---|---|---|
| **Generator Type** | **Capital ($/kW)** | **Fixed O&M ($/kW-y)** | **Variable O&M ($/kWh)** | **Efficiency (%)** |
| Wind | $1117 | $29 | $0 | N/A[13] |
| Natural gas (simple cycle) | $513 | $9 | $0.0034 | 40% |
| Natural gas (combined cycle) | $677 | $11 | $0.0023 | 54% |
| Pulverized coal | $1285 | $27 | $0.0034 | 40% |
| IGCC with C seq. | $2297 | $45 | $0.0028 | 43% |

Table 4. New generator costs and efficiencies, based on assumptions used in the 2004 Annual Energy Outlook (EIA 2004). Variable O&M figures do not include fuel costs.

| 2020 Fuel Cost Assumptions (2005 $/million Btu) | |
|---|---|
| Coal | $1.32 |
| Natural gas | $5.52 |
| Petroleum products | $9.98 |
| Nuclear | $0.62 |
| Biomass | $1.45 |

Table 5. Fuel cost assumptions. Data sources: EIA 2005, EIA 2006, and CA Biomass Collaborative 2005.

| Storage Technology | Capital storage cost ($/kWh) | Capital Power cost ($/kW) | Balance of Plant cost ($/kWh) | O&M ($/kW-y) | Efficiency | Lifetime (y) | Natural gas input (Btu/kWh) |
|---|---|---|---|---|---|---|---|
| **Compressed Air** | $3 | $463 | $55 | $2.70 | 0.73 | 20 | 4000 |
| **Pumped Hydro** | $11 | $1090 | $4 | $2.70 | 0.75 | 20 | - |
| **Lead-Acid Battery** | $164 | $136 | $164 | $16 | 0.75 | 6 | - |
| **Sodium Sulfur Battery** | $273 | $164 | $55 | $22 | 0.7 | 10 | - |
| **Flow Battery** | $109 | $300 | $55 | $16 | 0.65 | 10 | - |

Table 6. Energy storage technology costs. Data are from Schoenung 2003. Variable O&M costs are small for these technologies, and are included in the fixed O&M values where appropriate. All costs are given in 2005$, based on the assumption that costs provided in Schoenung 2003 were in 2002$.

[13] Efficiency is used to calculate fuel costs, and so is not relevant for wind turbines. Wind turbine efficiency is implicit in the power curve data (which relate turbine output to wind speed).

## Results: No Storage Case

The optimal capacities of new natural gas, coal, and wind generators to meet California electricity demand in 2020, in the absence of energy storage, are presented in Table 7. The resulting generation mix is presented in Figure 3.

| Generator Fuel | Generator Type/Location | New Capacity (MW) |
|---|---|---|
| **Natural gas** | Simple Cycle | 0 |
| | Combined Cycle | 576 |
| **Coal** | Pulverized | 19,995 |
| | Gasified with C sequestration | 0 |
| **Wind** | San Gorgonio | 5,131 |
| | Altamont | 0 |
| | Solano | 540 |
| | Tehachapi | 1,772 |
| | **Total Wind** | **7,443** |

Table 7. Optimal capacities of new California generators in 2020 in no-storage scenario.

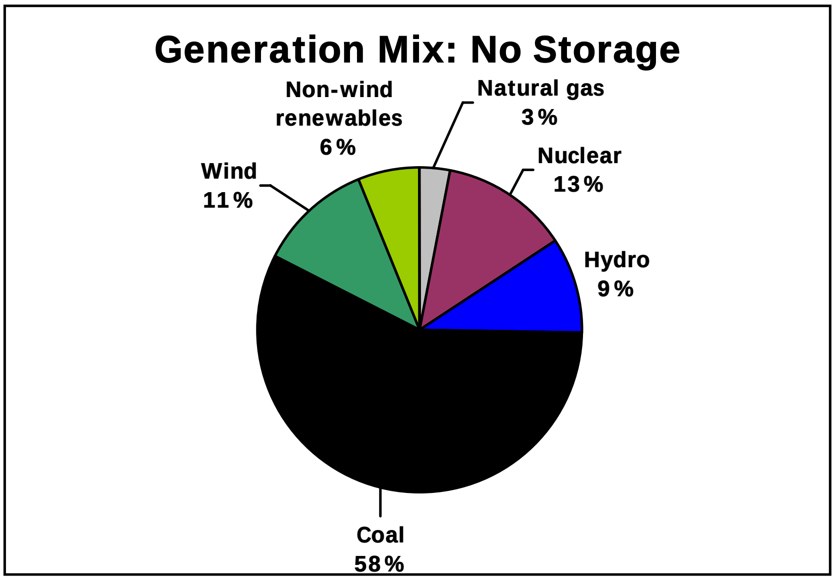


Figure 3. California generation mix in 2020, based on optimal capacities of new generators (see Table 7) and existing generators that have not retired by 2020.

The most noteworthy aspects of these results are the prevalence of pulverized coal, especially in comparison to natural gas, and the increased wind penetration compared to 2004. Coal penetration is so high because the low price of coal fuel and relatively high natural gas price (see Table 5). In fact, in this scenario, even existing natural gas capacity that has not retired by 2020 goes largely unused due to its high fuel cost: capacity factors are just 2% for existing simple-cycle natural gas and 13% for existing combined-cycle gas. Finally, it is interesting to note that wind penetration increases from 1.5% in 2004 to 11% in 2020, in the absence of storage or any policy to promote renewables. At the Solano wind site, the maximum wind resource is exploited in this scenario, indicating that but for this constraint the optimal wind penetration would be even higher.[14] No new wind capacity is installed at the Altamont site, probably because Altamont has the lowest average wind speed of the four sites.

***No Storage with Carbon Tax***

Carbon taxes of $20, $50, $100, and $200 per metric ton were imposed on the system to evaluate their effects on the optimal capacity mix, generation mix, and system cost. Resulting capacity and generation mixes are shown in Table 8 and Figure 4. At a carbon tax of $20/t, the generation mix includes slightly less coal and more wind than in the baseline (no tax) case. The changes are much more significant when the tax reaches $50. While pulverized coal is the major energy source in the baseline and $20 tax scenarios, in the $50, $100, and $200 tax cases, the major energy source is IGCC with carbon sequestration. IGCC plants with carbon sequestration are significantly more expensive than pulverized coal plants (see Table 4), which is why they do not appear in the $0 or $20 carbon tax scenarios. However, this technology becomes attractive in scenarios with high carbon taxes, as its additional capital cost is outweighed by the tax on emissions from pulverized coal plants. For this reason, IGCC replaces pulverized coal to an increasing extent as the carbon tax increases, until at a $200 carbon tax the IGCC penetration is more than 50% and the pulverized coal penetration less than 1%.

[14] Running the model with no storage and unconstrained wind capacities increases wind penetration from 11% to 13%, while the wind capacity at the Solano site more than quadruples (from 540 to 2213 MW).

The other major change that occurs as the carbon tax increases is an increase in wind penetration.[15] With carbon taxes of $50/t and above, new wind capacities are essentially at the maximum allowed in the model.[16] This constraint was set at nearly 12 GW, the estimated available high-speed wind resource in the state (Hamrin et al. 2005), for the four wind sites combined. To investigate the effect of this constraint on wind capacity, I ran the model with a $50 carbon tax and unconstrained wind capacity. The result is nearly a tripling of new wind capacity from the constrained case, from 11.9 GW to 31.4 GW.[17] Wind penetration increases by roughly the same factor, from 18% to 45% of total annual generation. This increase in wind generation is matched by a decrease in IGCC generation. A comparison of the generation mix with and without the constraint on wind capacity is shown in Figure 5.

| | | New Capacity (MW) | | | | |
|---|---|---|---|---|---|---|
| **Generator Fuel** | **Generator Type/Location** | **$0 C tax** | **$20 C tax** | **$50 C tax** | **$100 C tax** | **$200 C tax** |
| **Natural gas** | Simple Cycle | 0 | 0 | 0 | 0 | 0 |
| | Combined Cycle | 576 | 1,785 | 3,252 | 2,426 | 1,979 |
| **Coal** | Pulverized | 19995 | 17505 | 1488 | 0 | 0 |
| | Gasified with C capture | 0 | 0 | 14,463 | 17,294 | 19,358 |
| **Wind** | San Gorgonio | 5,131 | 5,400 | 5,400 | 5,400 | 5,400 |
| | Altamont | 0 | 0 | 540 | 490 | 540 |
| | Solano | 540 | 540 | 540 | 540 | 540 |
| | Tehachapi | 1,772 | 5,400 | 5,400 | 5,400 | 5,400 |
| | **Total Wind** | **7,443** | **11,340** | **11,880** | **11,830** | **11,880** |

Table 8. Optimal capacities of new California generators in 2020 in no-storage scenario with various carbon taxes. New wind capacity is constrained to be no more than 5400 MW at the San Gorgonio and Tehachapi sites, and 540 MW at the Altamont and Solano sites.

[15] My model does not allow the addition of new nuclear capacity, since new nuclear plants are unlikely to be built in California in the short- to medium-term due to negative public opinion and the problem of nuclear waste. However, since nuclear generation does not involve carbon emissions, it would be interesting to examine how nuclear would compete with wind under a carbon tax.

[16] The exception is Altamont at the $100 carbon tax. I am not sure why the optimal wind capacity drops slightly below the 540 MW constraint in this case.

[17] Wind capacity at two sites (San Gorgonio and Altamont) actually decreases when wind capacity is unconstrained, but this is more than compensated for by increased capacity at the other two sites. It is interesting to note that the optimal unconstrained wind capacity, with a $50/t carbon tax, is very close to the total available wind resource in the state, including both high- and low-speed sites (estimated by Hamrin et al. to be about 31 MW). This correspondence is purely coincidental.

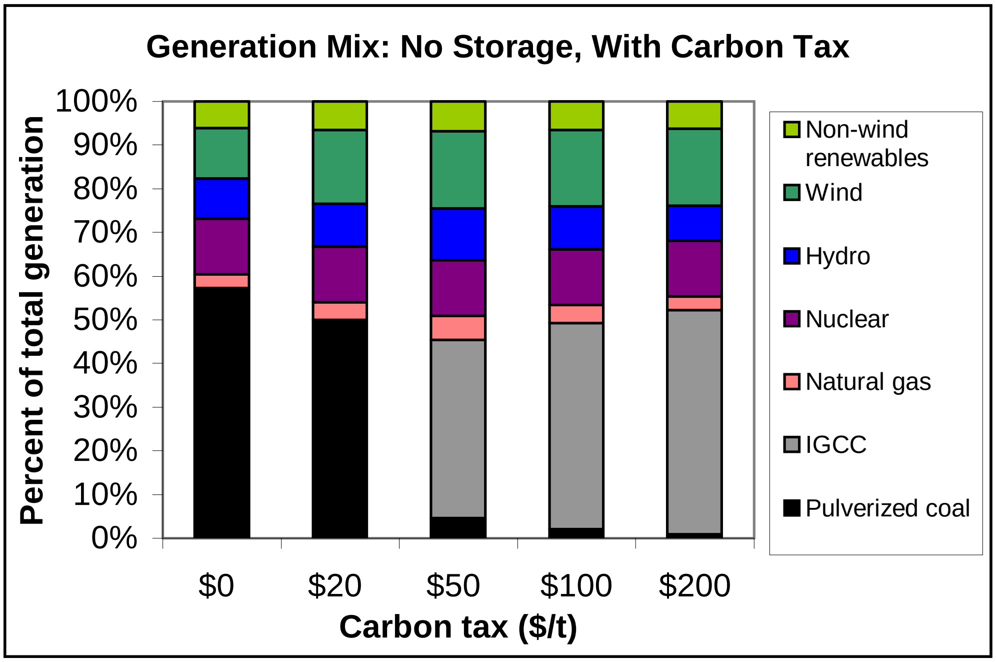


Figure 4. 2020 generation mix with no storage and various carbon taxes.

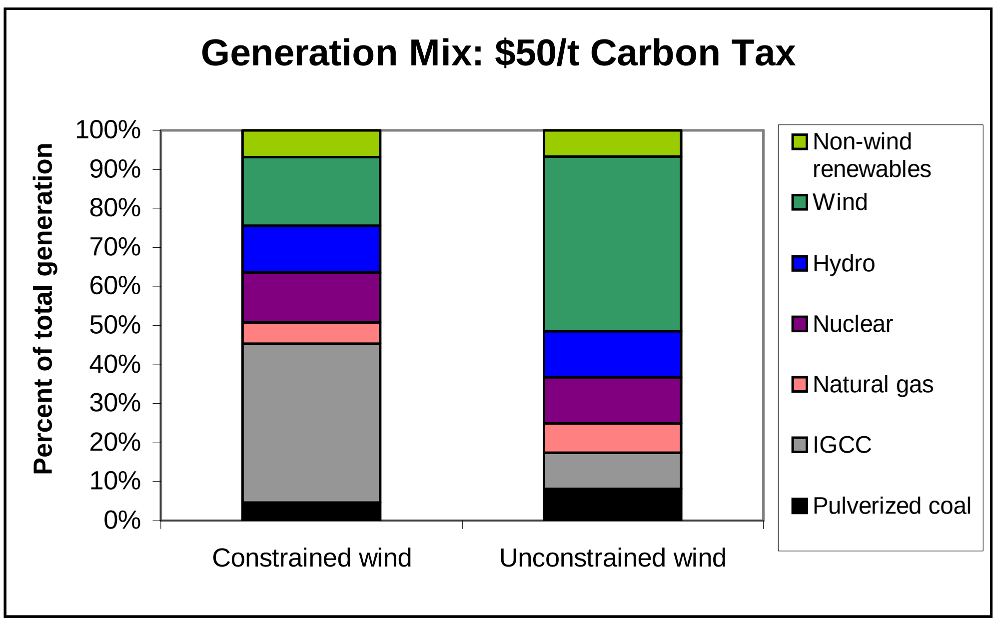


Figure 5. 2020 generation mix with no storage and $50/t carbon tax. In all model runs but the one presented on the right of this figure, new wind capacity was constrained by high-speed wind resource availability in the state, much of which exists at the four wind sites considered in the model. This constraint limits new wind capacity to about 12 GW, and limits wind penetration to 18%. When the constraint was ignored, new wind capacity increased to 31 GW and wind penetration increased to 45%.

As expected, systemwide carbon emissions decrease as the carbon tax increases. Table 9 shows annual carbon emissions and total annual system cost. The $50, $100, and $200 taxes result in much sharper emission reductions than the $20 tax, due to the switch from pulverized coal to IGCC. Of the taxes investigated, the $50 tax results in the lowest cost of avoided emissions: about $34/tC.

| Carbon Tax ($/t) | Carbon Emissions[18] (MT/y) | Total Annual Cost (billions of dollars, including tax) |
|---|---|---|
| **$0** | 36.4 | $8.9 |
| **$20** | 32.2 | $9.5 |
| **$50** | 4.8 | $9.9 |
| **$100** | 2.8 | $10.2 |
| **$200** | 1.7 | $10.5 |

Table 9. Carbon emissions and total system cost under various carbon taxes.

## Results With Energy Storage

As discussed above, there are two reasons that we might value the addition of storage to an electric power system. First, storage might decrease the total cost of the system, thus benefiting either the storage owner or electricity consumers. Second, storage might increase the penetration of renewables and/or decrease carbon emissions. These two potential effects are considered separately below.

### *The Effect of Storage on Total System Cost*

Figure 6 displays the total annual cost of the system (operating costs and annualized capital costs of new and existing generators and storage) with no carbon tax and varying energy storage capacities. Storage is modeled to be free and perfectly efficient[19], and the ratio of storage tank capacity (in MWh) to storage charge/discharge capacity (in MW) is varied among 10, 30, and 50 hours. The leftmost point is the no-storage case, discussed above. As the storage capacity increases to about 6000 or 7000 MW, the system cost decreases by about 5%. This is because the storage system is reducing the need for generation from expensive peaker plants by

[18] 2004 California electric power sector carbon emissions were about 26 MT.
[19] Storage as modeled as free in order to determine the maximum value that storage can provide to the system. This value is then compared to the costs of different storage technologies (see below). The question of efficiency is discussed in the Methods section.

discharging during high-demand periods.[20] However, beyond about 7000 MW, additional storage capacity has very little effect on the total system cost. The greater the storage tank capacity (the larger the number of hours at which the storage unit can discharge at maximum capacity), the greater its effect on total system cost, since it is able to displace expensive generators during a greater number of hours.

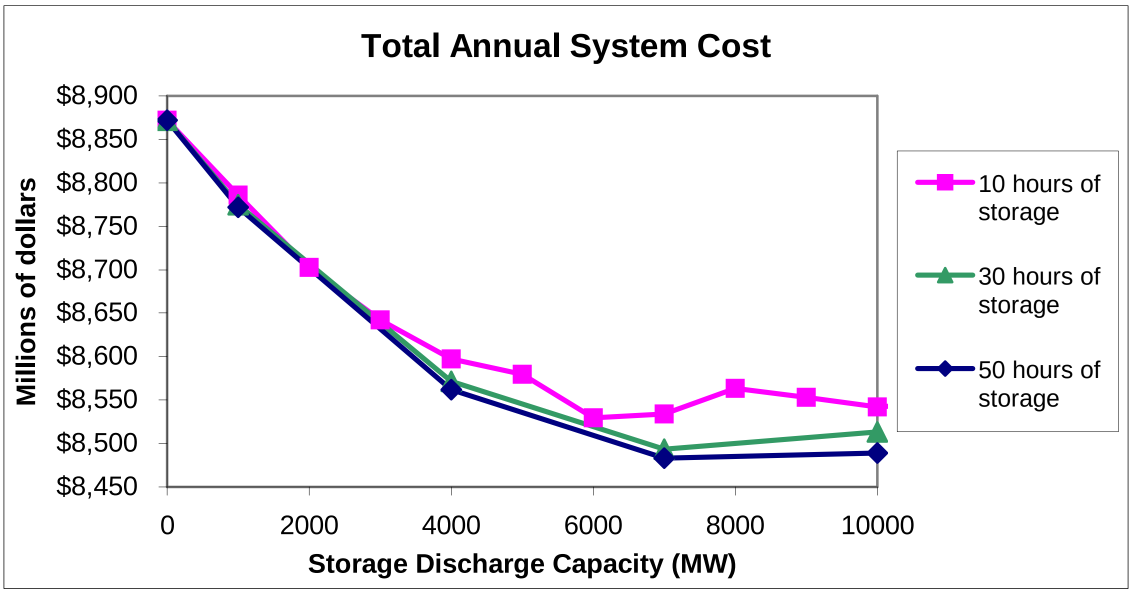


Figure 6. Total annual system cost, including levelized capital costs and annual operating costs of all generators and storage. Storage is modeled as free and perfectly efficient.

The annual value of storage is the decrease in total system cost associated with a particular storage capacity (Figure 7).

[20] Storage can also change the total system cost by changing the optimal capacities of new generators. However, as will be seen below, this is not a major factor in the cost decrease observed here.

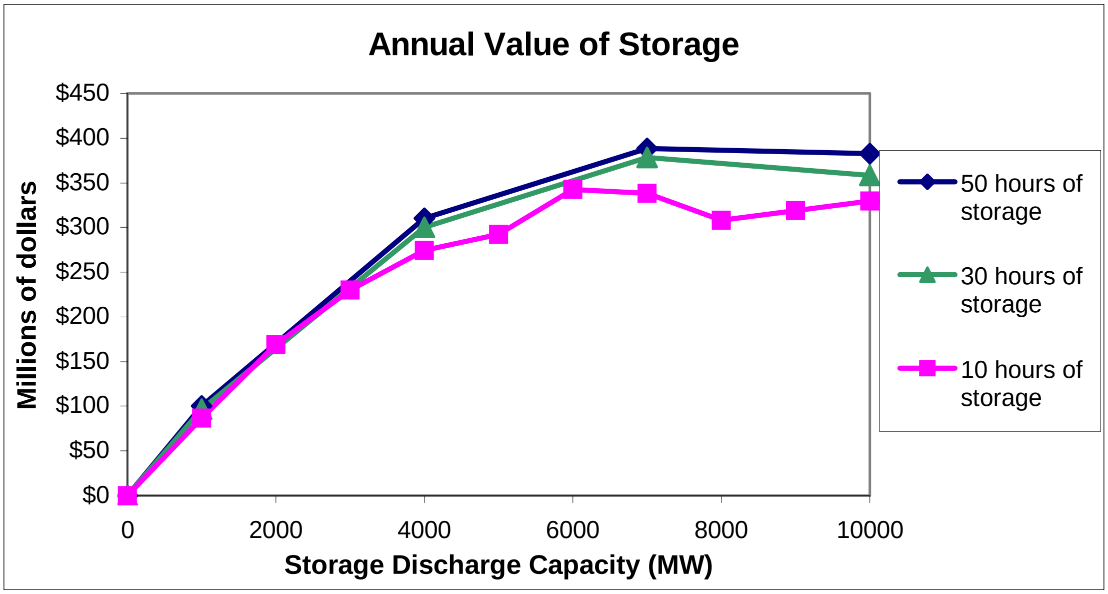


Figure 7. Value of storage. The value of particular storage capacity is the difference between the total system cost with no storage and the total system cost with that storage capacity.

The value of storage presented here can be compared to the storage values calculated by Lamont (2004) and Graves et al. (1999). Since those studies considered small storage capacities, it is most reasonable to compare their values of storage with the value I determined for 1000 MW of storage (the smallest storage capacity I consider). From Figure 7, the value of 1000 MW of storage is about $100 million per year, which is equivalent to $100/kW-y. This is higher than the storage value presented by Lamont, but is within the range of values presented by Graves et al.

As Figures 6 and 7 indicate, storage would be a valuable addition to the system if it were free and perfectly efficient. In order to determine whether actual storage technologies are economical, we must compare the value that storage provides to the system (Figure 7) with the costs of actual storage technologies. These data are presented in Figures 8, 9, and 10 for the three storage tank capacities (10, 30, and 50 hours) and five storage technologies: compressed air energy storage (CAES), pumped hydro storage, lead-acid batteries, sodium sulfur batteries, and flow batteries. The "Value of Storage" curves at the bottom of Figures 8-10 are the same curves that are depicted in Figure 7.

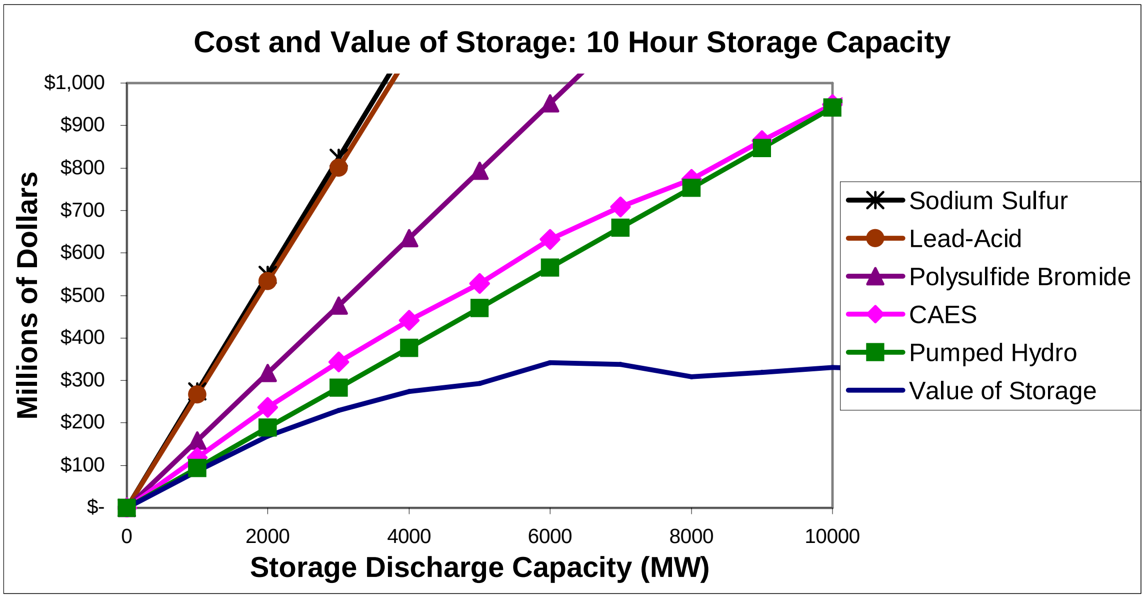


Figure 8. Annual value of technology-neutral storage, with 10 hours of discharge capacity, compared to current costs of actual storage technologies. The CAES cost curve is not straight because it has a significant per-kWh operating cost (it requires natural gas fuel). While the other technologies' costs are almost completely dependent on installed capacity, the CAES cost depends on both installed capacity and the amount of energy that passes through storage. This energy pass-through is determined endogenously by the model.

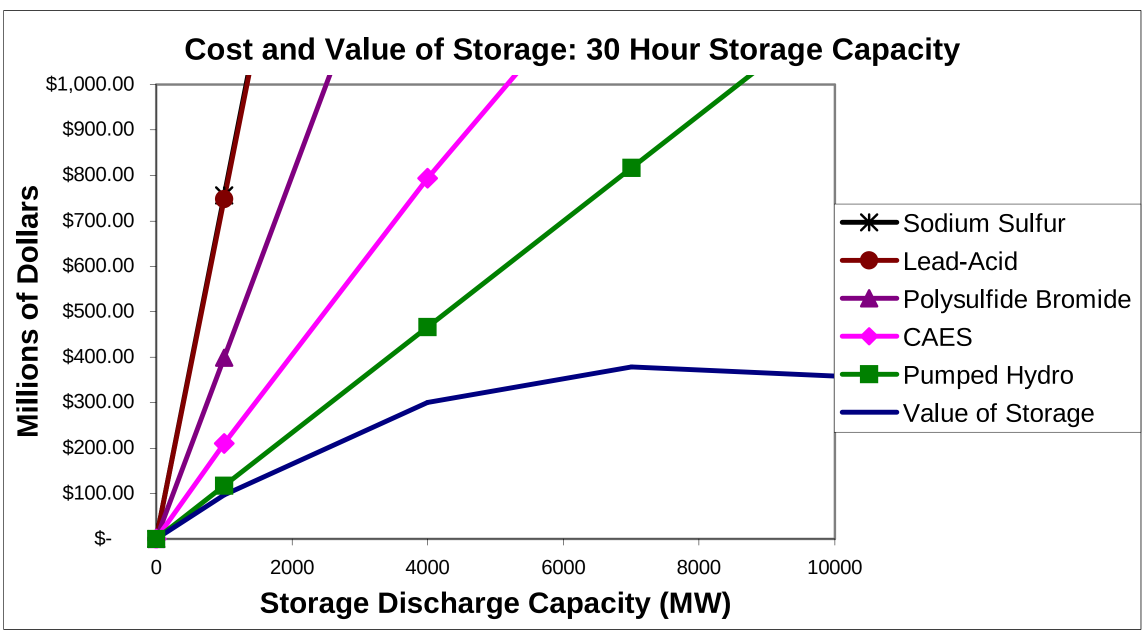


Figure 9. Annual value of technology-neutral storage, with 30 hours of discharge capacity, compared to current costs of actual storage technologies.

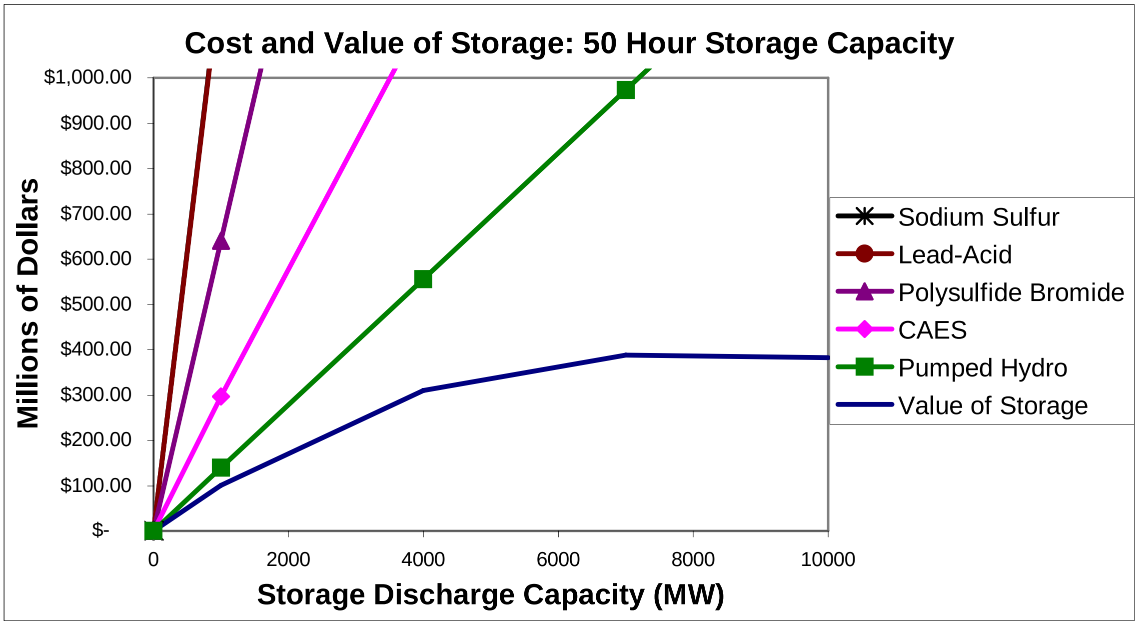


Figure 10. Annual value of technology-neutral storage, with 50 hours of discharge capacity, compared to current costs of actual storage technologies.

Comparing Figures 8, 9, and 10 reveals that as the storage tank capacity increases from 10 to 30 to 50 hours, the costs of storage technologies increase more rapidly than does the value of storage. For all technologies considered, storage cost is closest to storage value when the storage capacity is smallest (10 hours of tank capacity, and 1000 MW of discharge capacity, as shown on the left of Figure 8). Even in this case, all the batteries considered cost more than the value they provide to the system. Unless their costs decrease substantially (discussed further below), batteries are therefore not an effective means of decreasing the total cost of the system. Pumped hydro and compressed air storage, meanwhile, are already very close to being competitive at this smallest storage capacity. However, one important aspect of the storage technologies is not captured by this comparison: their imperfect efficiencies. Pumped hydro and compressed air storage both have round-trip efficiencies of about 0.75 (see Table 6), and therefore would not provide as much value to the system as Figures 6-10 indicate. Further model runs are necessary to determine the value of imperfectly efficient storage. However, since pumped air and compressed hydro storage are just on the edge of being competitive when perfect efficiency is assumed, these technologies will almost certainly be uncompetitive, at current costs, when their actual efficiencies are taken into account.

***Storage Cost Decreases: Learning Curve Analysis***

As discussed above, energy storage technologies are too expensive, at today's prices, to be competitive in the 2020 California electric power system (that is, to reduce the total cost of the system). However, as experience is gained with these storage technologies, their costs are likely to decrease. For many technologies in the electric power sector, costs have been observed to decline about 20% for each doubling of installed capacity (Kammen 2003). For the energy storage technologies considered here, insufficient data exist to predict future cost declines based on past experience. However, if we assume that these technologies will follow a 20% learning curve, we can project their costs in 2020 under the various storage capacity assumptions discussed above. The cost decreases projected by a 20% learning curve depend, essentially, on the quantity of previously installed capacity of each technology. For instance, pumped hydro is the most prevalent storage technology, with 90 GW of capacity currently installed worldwide. An addition of 1-10 GW of additional pumped hydro capacity will be a small change, percentage-wise, so the cost projected cost decreases from adding this capacity will be relatively small. On the other hand, only about 25 MW of large sodium sulfur storage facilities exist worldwide. An addition of 1-10 GW of capacity will amount to many doublings of current capacity, so cost will be expected to decrease sharply.

Estimates of the existing worldwide capacity of each storage technology are presented in Table 10. Figures 11-13 show the same cost-benefit comparison as Figures 8-10, but with the assumption of storage cost decreases according to a 20% learning curve. Only storage installed in California according to model assumptions is taken into account in calculating learning curve-related cost decreases; storage that may be installed elsewhere is ignored. Cost curves in these figures are not linear because the greater the new storage capacity, the greater the learning curve effect and so the greater the change between current storage costs and projected storage costs. The pumped hydro curves are nearly linear because the large amount of existing pumped hydro capacity makes the learning curve effect negligible.

| Technology | Approximate Installed Capacity (MW) |
|---|---|
| Compressed Air | 400 |
| Pumped Hydro | 90,000 |
| Lead-Acid Batteries | 55 |
| Sodium Sulfur Batteries | 25 |
| Polysulfide Bromide Flow Batteries | 30 |

Table 10. Installed capacities of energy storage technologies. Data from Electricity Storage Association (2003). Note that the capacity given for lead-acid batteries includes only large battery installations for energy storage, not small batteries. Inclusion of all lead-acid batteries would increase this capacity dramatically, and result in much slower cost decreases according to the learning curve analysis.

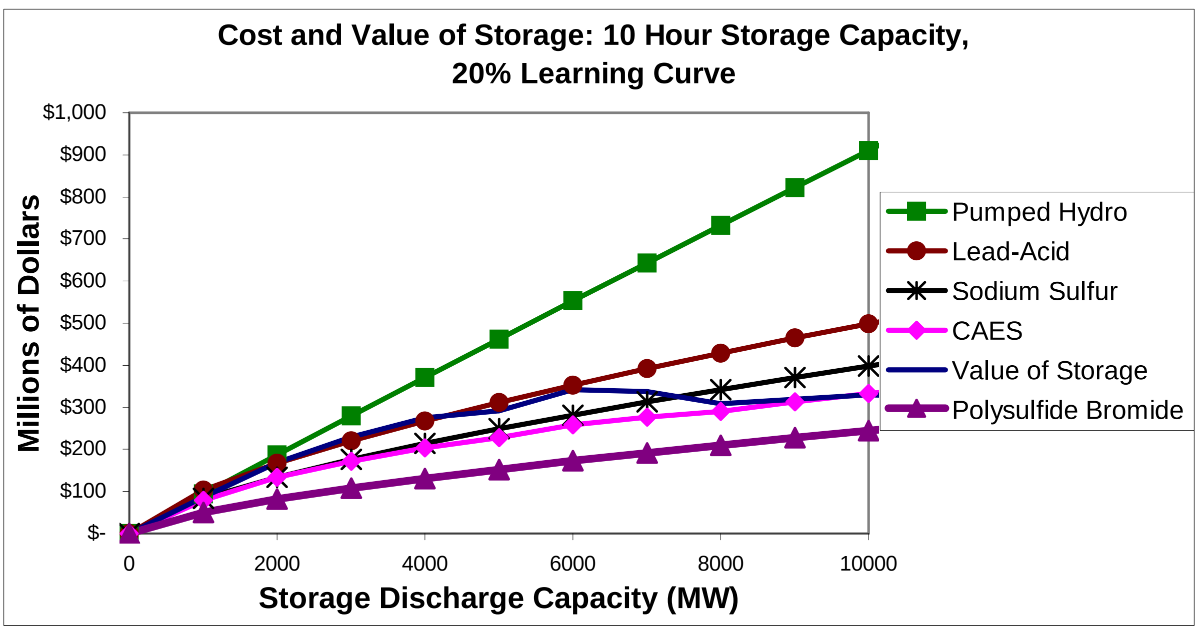


Figure 11. Annual value of technology-neutral storage, with 10 hours of discharge capacity, compared to future costs of actual storage technologies assuming cost decreases according to a 20% learning curve.

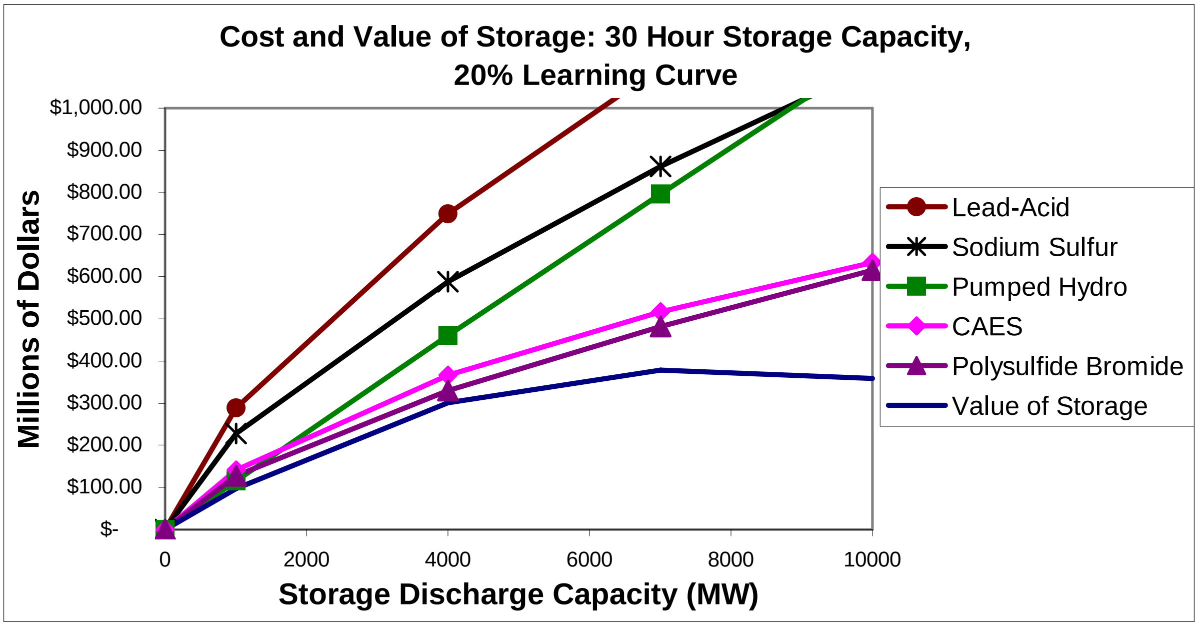


Figure 12. Annual value of technology-neutral storage, with 30 hours of discharge capacity, compared to future costs of actual storage technologies assuming cost decreases according to a 20% learning curve.

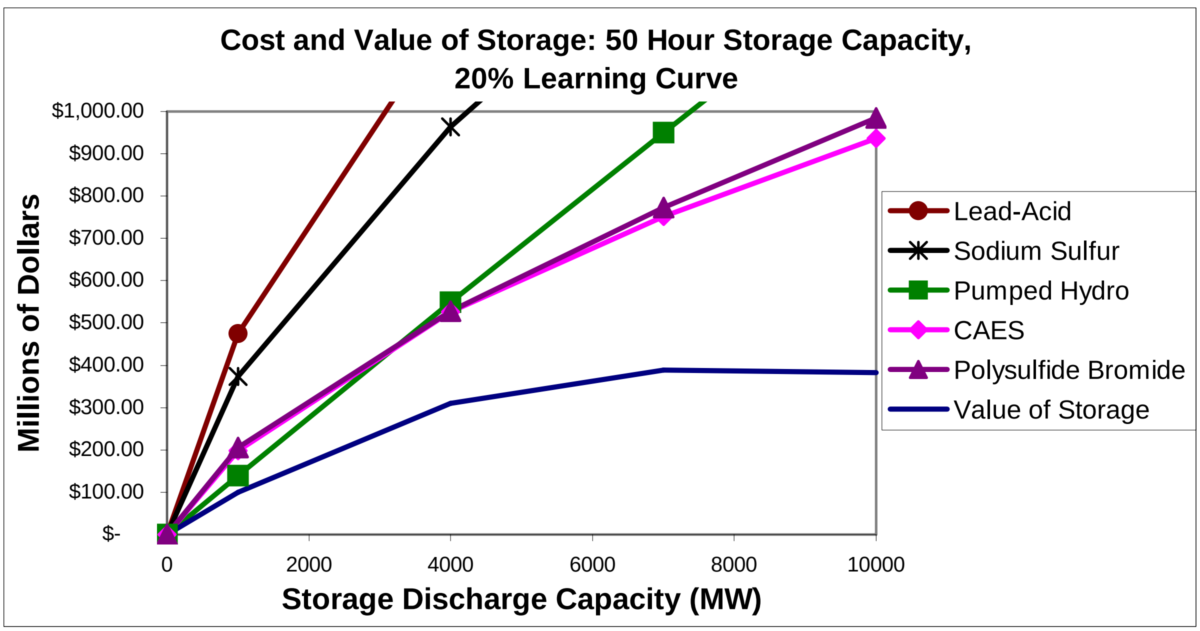


Figure 13. Annual value of technology-neutral storage, with 50 hours of discharge capacity, compared to future costs of actual storage technologies assuming cost decreases according to a 20% learning curve.

As expected, storage costs are much closer to storage benefits when these cost decreases are taken into account. However, even under the 20% learning curve assumption, none of the storage technologies considered appear to be competitive at 30 or 50 hours of storage tank capacity. At 10 hours of storage tank capacity, polysulfide bromide batteries, compressed air, and sodium sulfur batteries all appear likely to be economically feasible (Figure 11).[21]

***The Effect of Storage on Wind Penetration and Carbon Emissions***

Even if energy storage does not decrease the total cost of the system, we may be willing to pay for it if we value its systemwide effects. In particular, storage may be an effective means of increasing renewable penetration and/or decreasing carbon emissions.

In this analysis, storage can change the generation mix in two ways. First, because the capacities of new generators are re-optimized with each storage capacity, storage can affect the generator capacities available to be dispatched. Second, storage changes the generation mix by displacing generators that are marginal when the storage unit discharges, and increasing the generation of generators that are marginal when the storage unit charges. The first effect turns out to be relatively minor. As storage is added to the system, the capacity of new pulverized coal changes by up to 7% from the baseline no-storage case (from 20.0 to 18.7 GW), and the largest change in new wind capacity is an increase of 8% (from 7.4 to 8.0 GW). These maximum changes occur at capacities of 6000-8000 MW of storage, and seem relatively insensitive to the storage tank capacity. It is perhaps surprising that storage does not have a greater effect on new wind capacity, since one of the supposed benefits of storage is its ability to mitigate the intermittency of the wind and thus increase wind's competitiveness relative to other types of generators. As it turns out, wind capacity seems to be limited more by its capital costs than by its intermittency. Though the cost of building a new wind generator is less, per MW of capacity, than the cost of building a new coal generator, wind has a much lower capacity factor than coal. Storage can, in

[21] Again, this analysis assumes perfect efficiency. However, the projected relative costs of these technologies would not change much if their imperfect efficiencies were taken into account, since all have fairly similar efficiencies.

effect, shift the *timing* of wind generation (smoothing its intermittency), but it cannot cause the wind to blow more hours of the day (increasing its capacity factor).

Figures 14-16 present the change in generation mix associated with various storage capacities. In each of these figures, the bar on the far left represents the no-storage case, which was also depicted in Figure 3. The other bars show how the generation mix changes as increasing storage capacities are added to the system.

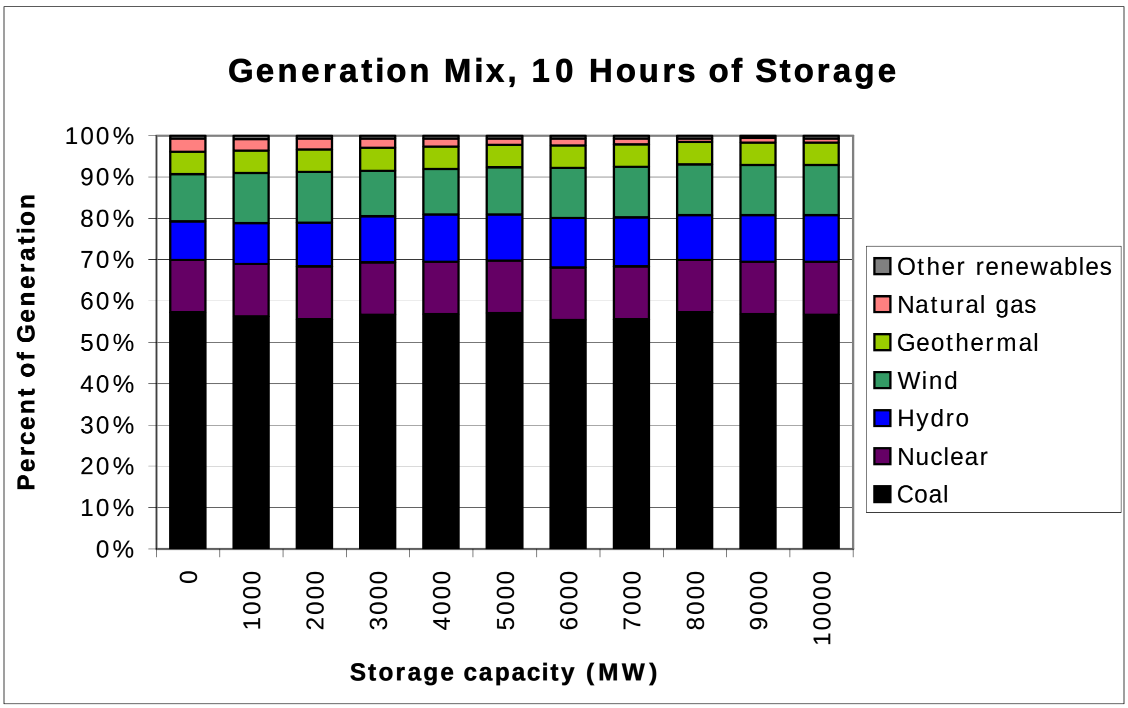


Figure 14. Generation mix with 10 hours of storage and varying storage discharge capacities.

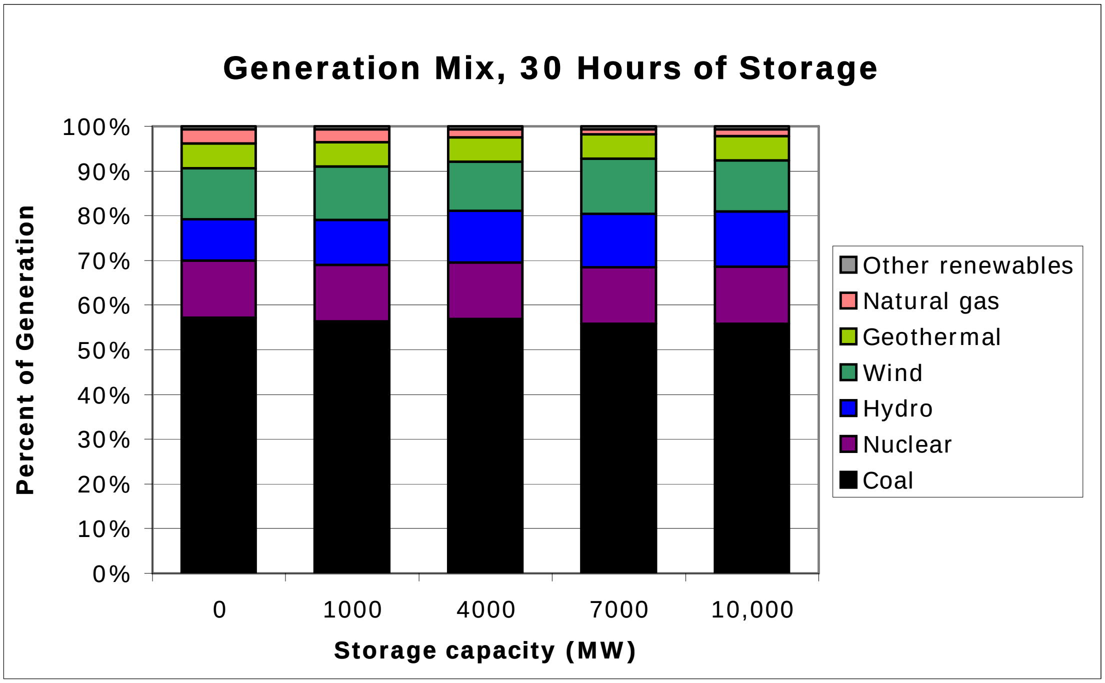


Figure 15. Generation mix with 30 hours of storage and varying storage discharge capacities.

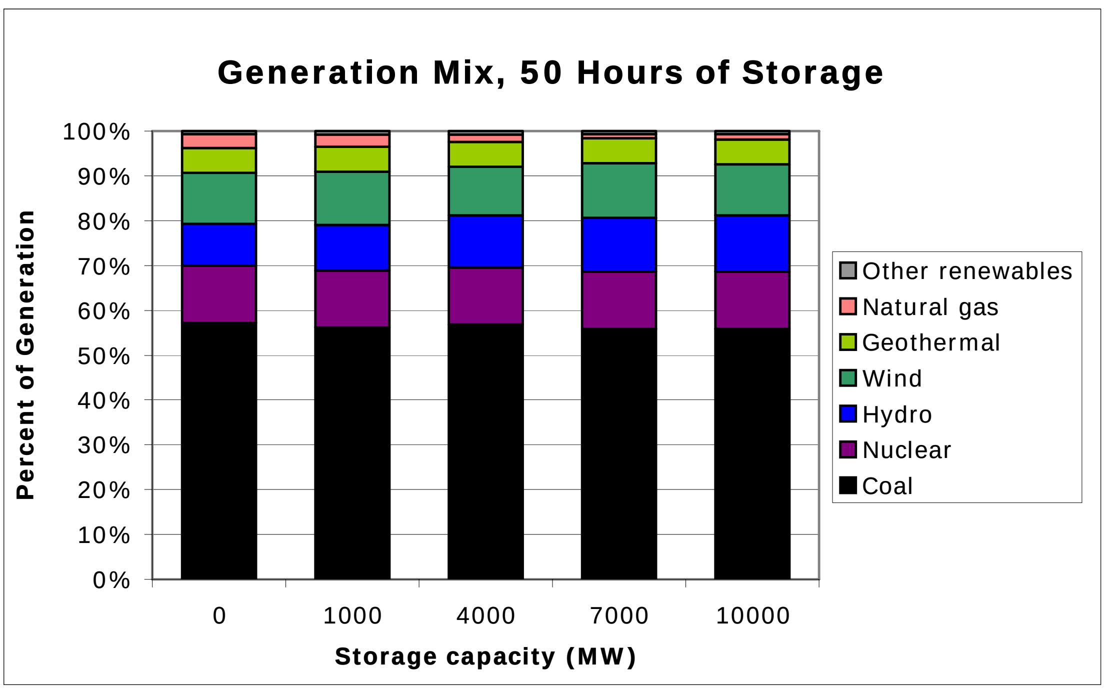


Figure 16. Generation mix with 50 hours of storage and varying storage discharge capacities.

The most noticeable result from Figures 14-16 is that the generation mix changes very little as storage is added to the system. This indicates that the impact of storage on generator dispatch, like its effect on optimal generator capacities, is fairly minor. As it turns out, hydro is often the marginal generator when the storage unit charges. Therefore, as expected, Figures 14-16 show hydro penetration increasing slightly, from about 9% to 12% of total generation.[22] Likewise, natural gas is usually marginal when the storage unit discharges, and natural gas penetration decreases from 3% to 1% of total generation as storage is added to the system. Since wind has essentially no marginal cost of generation, it is never the marginal generator; whether storage is present or not, wind is always dispatched when it is available.

Figure 17 shows the change in systemwide carbon emissions with changing storage capacities. Carbon emissions decrease slightly (less than 5%) as storage is added to the system. The variability evident in the 10-hour curve is masked in the other curves because fewer different capacities were modeled. This decrease in carbon emissions is not a result of an increasing renewable penetration, but of the slight decrease in natural gas generation described above.

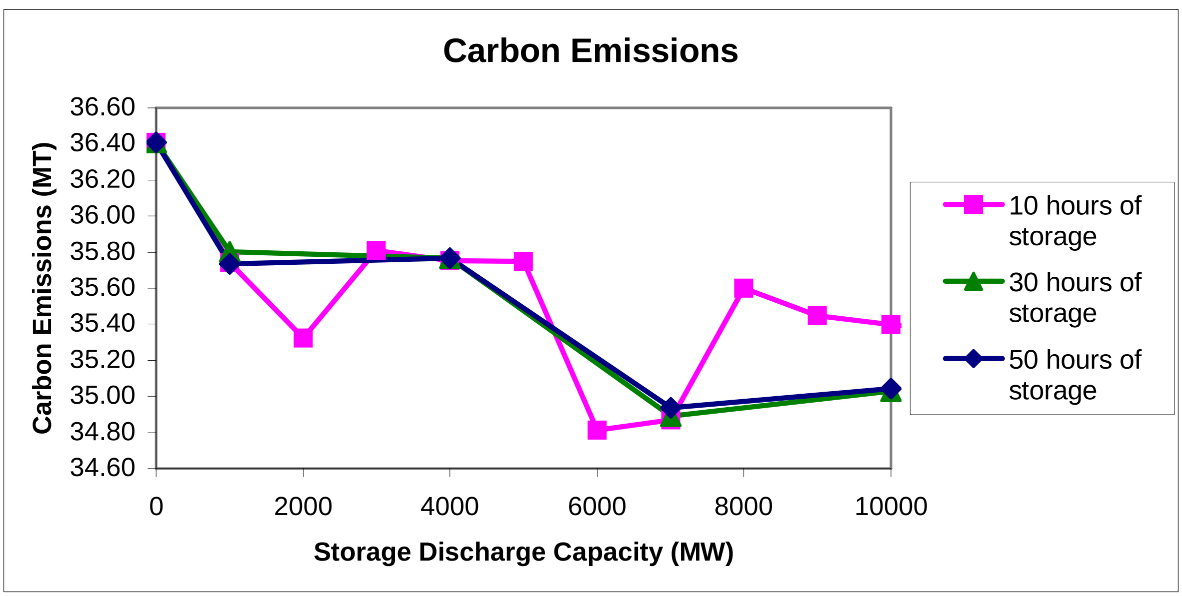


Figure 17. System carbon emissions with various storage capacities.

[22] In the actual electric power system, hydro generation depends primarily on the available hydro resource, and would probably not be affected by changes in energy storage capacity. However, this does not invalidate the conclusion that the generation mix is likely to change only slightly with the addition of energy storage to the system.

## Conclusions

My simulation/optimization model of the California electric power system indicates that even in the absence of energy storage or any policy to promote renewables, wind penetration is likely to increase from 1.5% in 2004 to more than 10% by 2020. At the same time, pulverized coal penetration is likely to increase to more than 50%, unless it is limited by a carbon tax or other policy. If a tax of $50 per ton of carbon is imposed on the system, much of this pulverized coal capacity will likely be replaced by IGCC coal with carbon capture and storage. In addition, with this carbon tax, wind penetration will increase up to the wind resource constraint: 18% if only high wind speed sites are considered, and significantly more if low-speed sites are included as well. This $50 carbon tax is projected to decrease carbon emissions by nearly 90%, at an average cost of $34/tC.

There are two reasons that we might value the addition of energy storage to the electric power system: (1) it might decrease the total cost of the system, and (2) it might increase wind penetration and/or reduce carbon emissions. According to my model, if storage were free and perfectly efficient, it could decrease the total system cost by about 5%. Actual storage technologies are too costly, at today's prices, to reduce the system cost. However, as experience is gained with these technologies, their costs are likely to decrease. Compressed air storage and advanced batteries (polysulfide bromide and sodium sulfur) are the most likely to become competitive if storage costs decrease in proportion to the percent change in installed capacity.

Surprisingly, it appears that energy storage has only a minor impact on the electricity generation mix, including wind penetration. The presence of storage does not result in an increase in wind capacity, because wind capacity appears to be limited more by its capital costs than by its intermittency. Since storage has a negligible impact of the generation mix, its effect on carbon emissions is small as well. If our goal is to reduce carbon emissions from the electric power sector, a policy such as a carbon tax is likely to be more effective than the promotion of energy storage.

## References


Baker, Alexandra, and David Jollie. 2004. Fuel Cell Market Survey: Large Stationary Applications. *Fuel Cell Today*, 6 October 2004.

Bosi, Martina. 2000. An Initial View on Methodologies for Emission Baselines: Electricity Generation Case Study. International Energy Agency Information Paper.

California Biomass Collaborative. 2005. Biomass Resource Assessment in California. Draft Consultant Report Prepared for the California Energy Commission. CEC-500-2005-006-D.

California Energy Commission. 2006. California Gross System Power for 2004 (Updated January 10, 2006). http://www.energy.ca.gov/electricity/gross_system_power.html.

California Energy Commission. 2005a. California Energy Demand 2006-2016: Staff Energy Demand Forecast. CEC-400-2005-034-SF-ED2.

California Energy Commission. 2005b. California Power Plants Database. http://www.energy.ca.gov/database/index.html#powerplants.

California Energy Commission. 2005c. Integrated Energy Policy Report. CEC-100-2005-007-CMF.

California Energy Commission. 2004. California Electrical Energy Generation, 1995-2004. http://www.energy.ca.gov/electricity/electricity_generation.html.

California Energy Commission. 2002. Inventory of California Greenhouse Gas Emissions and Sinks: 1990-1999. 600-002-001F.

California Independent System Operator. 2005a. Participating Intermittent Resource Program. http://www.caiso.com/docs/2003/01/29/2003012914230517586.html.

California Independent System Operator. 2005b. System Load Reports. http://oasis.caiso.com/.

California Independent System Operator. 2003. Zonal Average Energy Prices. http://oasis.caiso.com/.

Cavallo, Alfred. 1995. High-Capacity Factor Wind Energy Systems. *Journal of Solar Energy Engineering* 117, pp. 137-143.

Cavallo, Alfred. 2001. Energy Storage Technologies for Utility Scale Renewable Energy Systems. *Journal of Solar Energy Engineering* 123:4, p. 387.

Danish Wind Energy Association. 2003. Operation and Maintenance Costs for Wind Turbines. http://www.windpower.org/en/tour/econ/oandm.htm.

DeCarolis, Joseph F. and David W. Keith. 2006. The Economics of Large-Scale Wind Power in a Carbon-Constrained World. *Energy Policy* 34, pp. 395-410.

Denholm, Paul. 2006. Improving the Technical, Environmental, and Social Performance of Wind Energy Systems Using Biomass-Based Energy Storage. *Renewable Energy* 31, pp. 1355-1370.

Electric Power Research Institute. 1989. Technology Assessment Guide: Electricity Supply – 1989. EPRI P-6587-L, Volume 1: Rev. 6.

Electricity Storage Association. 2003. Storage Technologies and Applications. http://www.electricitystorage.org/tech/technologies_technologies.htm.

Energy Information Administration, United States Department of Energy. 2006. Annual Energy Outlook 2006 with Projections to 2030 (Early Release). http://www.eia.doe.gov/oiaf/aeo/index.html.

Energy Information Administration, United States Department of Energy. 2005. Annual Energy Outlook 2005: Market Trends – Electricity Supply and Demand. http://www.eia.doe.gov/oiaf/archive/aeo05/electricity.html.
Energy Information Administration, United States Department of Energy. 2004. Assumptions for the Annual Energy Outlook 2004. DOE/EIA-0554(2004).
Gonzales, Adolfo, et al. 2004. Study of Electricity Storage Technologies and Their Potential to Address Wind Energy Intermittency in Ireland. University College Cork Sustainable Energy Research Group, Project RE/HC/03/001.
Gordon, S.P, and P.K. Falcone, eds. 1995. The Emerging Roles of Energy Storage in a Competitive Power Market: Summary of a DOE Workshop. Sandia Report SAND95-8247.
Graves, Frank, Thomas Jenkin, and Dean Murphy. 1999. Opportunities for Electricity Storage in Deregulating Markets. *The Electricity Journal* 12:8, pp. 46-56.
Hamrin, Jan, et al. 2005. Achieving a 33% Renewable Energy Target. Report for California Public Utilities Commission by the Center for Resource Solutions Team.
Kammen, Daniel. 2003. Committee on Science, United States House of Representatives. Hearing on the Future of University Nuclear Science and Engineering Programs. June 10, 2003.
Lamont, Alan. 2004. Improving the Value of Wind Energy Generation Through Back-up Generation and Energy Storage. Lawrence Livermore National Laboratory, UCRL-TR-202208.
Lipman, Timothy, Ryan Ramos, and Daniel Kammen. 2005. An Assessment of Battery and Hydrogen Energy Storage Systems Integrated with Wind Energy Resources in California. California Energy Commission, PIER Energy-Related Environmental Research. CEC 500-2005-136.
Nazaroff, William. 2005. Lecture Notes for Civil and Environmental Engineering 107, University of California, Berkeley, Spring 2005.
North American Electric Reliability Council. 2005. 2000-2004 Generating Availability Report. Available from http://www.nerc.com/~filez/gar.html.
Schoenung, Susan and William Hassenzahl. 2003. Long- vs. Short-Term Energy Storage Technologies Analysis: A Life-Cycle Cost Study. Sandia Report SAND2003-2783.
Schoenung, Susan. 2001. Characteristics and Technologies for Long- vs. Short-Term Energy Storage. Sandia Report SAND2001-0765.
Schwarzenegger, Arnold. 2005. Executive Order S-3-05. Executive Department, State of California.
Shibaki, Masashi. 2003. Geothermal Energy for Electric Power: A REPP Issue Brief. Renewable Energy Policy Project.
United States Department of Energy, Office of Energy Efficiency and Renewable Energy. 2005. State Energy Alternatives: Solar Thermal-at-a-Glance. http://www.eere.energy.gov/state_energy/technology_factsheet.cfm?techid=6.
Vestas Wind Systems. 2003. Brochure: V80 – 1.8 MW. Available from http://www.vestas.com/uk/Products/download/download_UK.htm.
Yen-Nakafuji, Dora. 2005. Strategic Value Analysis – Economics of Wind Energy in California. California Energy Commission, Draft Staff Paper. CEC 500-2005-107-SD.

## Appendix: Model Description and Mathematical Representation

**List of abbreviations:**

$CapCost_i$ = Capital cost of generator $i$ ($/MW)
$CapCost_{SI}$ = Capital cost of storage input device ($/MW)
$CapCost_{SO}$ = Capital cost of storage output device ($/MW)
$\mathrm{CapCost}_{\mathrm{ST}}$ = Capital cost of storage tank device ($/MWh)
$Cap_i$ = Capacity of generator $i$ (MW)
$Cap_{SI}$ = Input capacity of storage unit (MW)
$Cap_{SO}$ = Output capacity of storage unit (MW)
$Cap_{ST}$ = Storage tank capacity (MWh)
$Dem_t$ = Electricity demand to be met in hour $t$ (MW)
$FAF_i$ = Fixed availability factor of generator $i$ (set at 1 for non-baseload plants)
$FuelCost_i$ = Fuel cost for generator $i$ ($/MWh)
$FuelCost_{SO}$ = Fuel cost for storage output device ($/MWh) (only applies to CAES)
$Gen_{i,t}$ = Electric power generated by generator $i$ in hour $t$ (MW)
$LF(y_i)$ = Levelization factor (to convert capital costs to an annual payment), which is a function of generator lifetime
$y_i$ = Lifetime of generator $i$ (years)
$y_{SI}$ = Lifetime of storage input device (years)
$y_{SO}$ = Lifetime of storage output device (years)
$y_{ST}$ = Lifetime of storage tank device (years)
$LMC$ = Lower marginal cost threshold for storage
$MC_t$ = System marginal cost in hour $t$
$MC_{iter,t}$ = System marginal cost in hour $t$ as calculated in the current iteration of the model
$MC_{iter-1,t}$ = System marginal cost in hour $t$ as calculated in the previous iteration of the model
$N_i$ = Number of wind turbines at wind site $i$
$OMf_i$ = Fixed O&M cost of generator $i$ ($/MW-y)
$OMf_{SI}$ = Fixed O&M cost of storage input device ($/MW-y)
$OMf_{SO}$ = Fixed O&M cost of storage output device ($/MW-y)
$OMv_i$ = Variable O&M cost of generator i ($/MWh)
$OMv_{SO}$ = Variable O&M cost of storage output device ($/MWh)
$r$ = Interest rate
$SIeff$ = Efficiency of storage input device
$SI_t$ = Storage input in hour $t$ (MW)
$SI_{iter,t}$ = Storage input in hour $t$ as calculated in the current iteration of the model (MW)
$SIU_{iter,t}$ = Storage input in hour $t$ that is actually *used* in the current iteration of the model (distinct from the storage input *calculated* in the current iteration) (MW)
$SIU_{iter-1,t}$ = Storage input in hour $t$ that was *used* in the previous iteration of the model (MW)
$SOeff$ = Efficiency of storage output device
$SO_t$ = Storage output in hour $t$ (MW)
$SO_{iter,t}$ = Storage output in hour $t$ as calculated in the current iteration of the model (MW)
$SOU_{iter,t}$ = Storage output in hour $t$ that is actually *used* in the current iteration of the model (distinct from the storage input *calculated* in the current iteration) (MW)
$SOU_{iter-1,t}$ = Storage output in hour $t$ that was *used* in the previous iteration of the model (MW)
$ST_t$ = Quantity in storage in hour $t$ (MWh)

$UMC$ = Upper marginal cost threshold for storage
$WF_{i,t}$ = Fraction of installed wind capacity at site $i$ that is available to generate in hour $t$ (MW)
$WR_i$ = Wind resource available at wind site $i$ (MW)

**Objective Function:**
Minimize total annual cost, which includes (1) levelized capital costs, fixed O&M, variable O&M, and fuel costs of new and existing generators, and (2) storage costs, including capital costs for storage input, output, and tank devices, fixed O&M for input and output devices, and variable O&M and fuel costs[23] for the output device. In the formula below, $i$ = 1,2,…20 refers to the 20 types of new and previously existing generators in the model, which are listed in the table below. The capacities of existing generators are taken from 2004 California power plant data, reduced to reflect retirements through 2020. The capacities of new generators are decision variables in the model (see below). Mathematically, the objective function is:

MIN Total annual cost

$$= \sum_{i=1}^{20}\left(\left(CapCost_i \times LF(y_i) \times Cap_i\right) + \left(OMf_i \times Cap_i\right) + \left(\left(OMv_i + FuelCost_i\right) \times \sum_{t=1}^{8760} Gen_{i,t}\right)\right)$$

$$+\left(CapCost_{SI} \times LF(y_{SI}) \times Cap_{SI} + OMf_{SI} \times Cap_{SI}\right) + \left(CapCost_{ST} \times LF(y_{ST}) \times Cap_{ST}\right)$$

$$+\left(CapCost_{SO} \times LF(y_{SO}) \times Cap_{SO}\right) + \left(OMf_{SO} \times Cap_{SO}\right) + \left(\left(OMv_{SO} + FuelCost_{SO}\right) \times \sum_{t=1}^{8760}(SO_t)\right)$$

In the formula above, the top line refers to new and existing generator costs (including wind), the middle line refers to the storage input and storage tank costs, and the bottom line refers to the storage output costs.

Generator types included:

| **Existing Generators** | **New Generators** |
|---|---|
| Natural gas (simple cycle) | Natural gas (simple cycle) |
| Natural gas (combined cycle) | Natural gas (combined cycle) |
| Coal | Pulverized coal |
| Nuclear | IGCC with C sequestration |
| Hydro | Wind: Tehachapi |
| Geothermal | Wind: Altamont |
| Other renewables (mostly biomass) | Wind: San Gorgonio |
| Petroleum products | Wind: Solano |
| Wind: Tehachapi | |
| Wind: Altamont | |
| Wind: San Gorgonio | |
| Wind: Solano | |

[23] The fuel cost of the storage output device does not refer to the cost of fuel that was used to generate the electricity that is being stored; rather, it refers to the cost of fuel actually used to remove energy from storage. The only storage technology with an associated fuel cost is compressed air storage, since the storage output device in this case involves mixing the compressed air with natural gas.

Calculations underlying various terms in the objective function are discussed below.

**Decision Variables:**
Capacities of new generators:

$Cap_i$ = Capacity of new generator i

Where *i* is one of the 8 new generators listed in the table above.

Marginal cost thresholds for storage:

*LMC*

*UMC*

**Constraints:**
*Wind resource:*
The wind capacity included at each site (number of turbines, multiplied by turbine capacity) cannot exceed the wind resource available at that site. "Wind resource" at each site ($WR_i$) is an estimate of the MW of wind capacity that could be installed at that site. Wind capacity is assumed to consist of Vestas V80 1.8 MW turbines. This constraint is equivalent to a limit on the number of wind turbines that can be installed at each site.

$$N_i \times 1.8 \leq WR_i$$

*Generation shortfall:*
Demand is not allowed to exceed generation (plus storage output, minus storage input) for more than 10 hours during the year.

(Number of hours in which (demand-generation)>0) ≤ 10

*Storage thresholds:*
The lower marginal cost threshold must be smaller than the upper marginal cost threshold, to minimize the number of hours during which the storage unit buys and sells at the same time. In addition, both thresholds should be within the range of observed system marginal costs.

$$LMC \leq UMC$$
$$0.01 \leq LMC \leq 0.12$$
$$0.01 \leq UMC \leq 0.12$$

**Optimization Procedure:**
For each optimization, I fixed storage output capacity ($Cap_{SO}$), storage input capacity (in all cases, I set $Cap_{SI}$ equal to $Cap_{SO}$), and the ratio of the storage tank capacity to storage discharge capacity ($Cap_{ST}$/ $Cap_{SO}$). I then used Solver to optimize the 10 decision variables. This generally required a number of Solver runs.

During these Solver runs, the storage behavior (input and output) in each hour was a function of the system marginal cost for the *previous* hour. This is less than ideal, because system marginal cost can change significantly from hour to hour. For instance, if the system marginal cost is low in hour 1, the storage unit will buy power in hour 2, even if the system marginal cost is high in hour 2. This strategy, therefore, does not maximize the value of the storage system. Ideally, storage behavior in each hour would instead be based upon the system marginal cost in that hour itself. Unfortunately, this would involve circularity in the model: the marginal cost in any hour depends on generator dispatch *and storage behavior* in that hour; so the storage behavior cannot also depend on that marginal cost.

However, a series of iterations can be used to solve this problem. The general strategy is to include two sets of hourly system marginal costs in the model. One set of marginal costs is determined endogenously by the model according to generator dispatch and behavior. For the reason described above, this set of marginal costs cannot also be used to determine same-hour storage input and output. Instead, an exogenous set of marginal costs, derived from marginal costs calculated in previous iterations, is used for this purpose. The goal of the iterations is to converge upon a solution in which the two sets of marginal costs are equal; that is, the marginal costs used to determine hourly storage input and output are the same as the marginal costs resulting from hourly generation and storage behavior. When such a solution is reached, it is essentially the case that storage input and output are based on the system marginal cost in the same hour.

The process is as follows: with storage decisions based on system marginal cost from the previous hour, I first use Solver to optimize the 10 decision variables. Holding the resulting values of the decision variables fixed for the moment, I then run a series of iterations (described in detail below) in order to base storage input and output decisions on the same-hour system marginal cost, rather than the previous-hour system marginal cost. The result of this process is a new system marginal cost pattern, hourly generator dispatch, and total system cost. At this point, I re-optimize the decision variables with Solver, but this time storage input and output are dependent upon the marginal cost pattern resulting from the iterations, rather than the previous-hour marginal cost. I then repeat the iterations. In some cases, I repeated the entire process (optimization and then iterations) additional times. The reason for repeating the process is to more closely approach the globally optimal solution.

**Calculations Underlying Objective Function:**
*Levelization factor for capital costs:*

$$LF(y_i) = \frac{r}{1-(1+r)^{y_i}}$$

For storage input, output, and tank devices, the $y_i$ in the above expression is replaced with $y_{SI}$, $y_{SO}$, and $y_{ST}$, respectively.

*Hourly generation (non-wind):*
Hourly generation of each non-wind generator is equal to the smaller of (1) the sum of demand and input to storage in that hour, minus the output of all generators (including storage output) that are before the generator of interest in the dispatch order; and (2) the capacity of the generator of interest. For baseload plants, the generator capacity is multiplied by a fixed availability factor, to prevent the plant from generating at full capacity all 8760 hours. Thus, for these plants, the annual availability factor is approximated as an hourly constraint. In the formula below, $n$ = 1,2…($i$-1) refers to the generators listed above, plus storage output, in

dispatch order. The summation ends with generator ($i$-1) since this is the generator immediately preceding the generator of interest in the dispatch order. The dispatch order is determined based on generator marginal costs (variable O&M plus fuel cost), except for hydro, which is included in the dispatch order in a position so as to ensure that the available annual hydro resource is not exceeded.[24]

$$Gen_{i,t} = Max\left( Min\left( \left( Dem_t + SI_t - \sum_{n=1}^{i-1} \left( Gen_{n,t} \right) \right), Cap_i \times FAF_i \right), 0 \right)$$

*Hourly generation (wind):*
The hourly generation calculation for wind is the same as for non-wind generators except that the generation at each wind site cannot exceed the fraction of installed wind capacity that is available to generate at that site in that hour, which is a function of the hourly wind speed and the wind turbine power curve. Hourly wind speed data were used for each of the four sites considered. New turbines were assumed to be Vestas V80 1.8 MW turbines, whereas for old turbines I used the power curve for the NEG Micon 950 kW.

$$\text{For wind, } Gen_{i,t} = Max\left( Min\left( \left( Dem_t + SI_t - \sum_{n=1}^{i-1} \left( Gen_{n,t} \right) \right), Cap_i \times WF_{i,t} \right), 0 \right)$$

*Storage input:*
If the marginal cost in the previous hour is below a specified threshold (*LMC*), the storage unit will charge. In order to prevent sharp discontinuities in storage behavior with changing marginal cost, this behavior is smoothed in the following way. If the MC is exactly equal to the threshold, the storage unit charges at half of its input capacity. As the MC falls slightly below the threshold, the unit approaches full charge capacity; and as the MC rises slightly above the threshold, the unit approaches zero input. The storage input is also limited by the room available in the storage "tank" (the capacity of the storage tank minus the amount in the tank in the previous hour, taking into account the efficiency of the storage input device).

$$SI_t = Max\left( Min\left( \left( \frac{Cap_{ST} - ST_{t-1}}{SIeff} \right), \left( Cap_{SI} \times \left( \frac{MC_{t-1}^{-50}}{MC_{t-1}^{-50} + LMC^{-50}} \right) \right) \right), 0 \right)$$

*Quantity in storage:*
In any particular hour, the quantity in storage is determined by the quantity that was in storage the previous hour, plus the storage input, minus the storage output. Charge and discharge efficiencies are also taken into account.

$$ST_t = ST_{t-1} + SI_t \times SIeff - \frac{SO_t}{SOeff}$$

[24] Biomass generation is also energy-limited; however, the installed biomass capacity is small enough that the resource constraint is not limiting.

*Storage output:*
The storage unit only discharges if (1) there is energy available in storage, and (2) the generators before storage in the dispatch order are not sufficient to meet demand that hour. If these two conditions apply, the amount of energy that is released depends on how far from the storage output threshold (*UMC*) the MC is. If the MC is equal to the threshold, the storage unit will discharge at 50% of its output capacity; as the MC rises above the threshold, the storage unit will approach its full discharge capacity; and as the MC falls below the threshold, the storage unit approaches zero discharge.

$$SO_t = Max\left( Min\left( \left( Dem_t + SI_t - \sum_{n=1}^{SO-1} \left( Gen_{n,t} \right) \right), Cap_{SO} \times \left( \frac{MC_{t-1}{}^{50}}{MC_{t-1}{}^{50} + UMC^{50}} \right), ST_{t-1} \times SOeff \right), 0 \right)$$

*Basing storage behavior on same-hour marginal cost: iterative process*
I will now describe in more detail the iteration process mentioned above. For each iteration, it is important to distinguish two sets of hourly system marginal costs: the marginal costs calculated in the current iteration ($MC_t$) and the marginal costs calculated in the previous iteration ($MC_{iter-1,t}$). It is also important to distinguish *three* sets of storage input and output behavior: storage inputs/outputs calculated in the current iteration ($SI_{iter,t}$ and $SO_{iter,t}$), storage inputs/outputs that are actually *used* in the current iteration ($SIU_{iter,t}$ and $SOU_{iter,t}$), and storage intputs and outputs that were used in the previous iteration ($SIU_{iter-1,t}$ and $SOU_{iter-1,t}$).

The storage input and output to be used in the current iteration are defined as a weighted sum of the input (output) from the previous iteration and the input (output) that is calculated in the current iteration, plus constraints to ensure that the storage tank is not overfilled and that it cannot discharge when it is empty. The reason for using a weighted sum is to achieve a gradual convergence. The $\alpha$ in the formulas below can be set to be 0.1 or 0.01, depending on how gradual a convergence is required.

$$SIU_{iter,t} = Max\left( Min\left( \left( (\alpha - 1) \times SIU_{iter-1,t} + \alpha \times SI_{iter,t} \right), \left( \frac{CapST - ST_{iter,t-1}}{SIeff} \right) \right), 0 \right)$$

$$SOU_{iter,t} = Max\left( Min\left( \left( (\alpha - 1) \times SOU_{iter-1,t} + \alpha \times SO_{iter,t} \right), \left( ST_{iter,t-1} \times SOeff \right) \right), 0 \right)$$

Formulas for storage input/output calculated in the current iteration ($SI_{iter,t}$ and $SO_{iter,t}$) are identical to the formulas for $SI_t$ and $SO_t$ given above, except that they depend on the current-hour marginal cost from the previous iteration ($MC_{iter-1,t}$), rather than the previous-hour marginal cost from the current iteration ($MC_{t-1}$).

$$SI_{iter,t} = Max\left( Min\left( \left( \frac{Cap_{ST} - ST_{t-1}}{SIeff} \right), Cap_{SI} \times \left( \frac{MC_{iter-1,t}{}^{-50}}{MC_{iter-1,t}{}^{-50} + LMC^{-50}} \right) \right), 0 \right)$$

$$SO_{iter,t} = Max\left( Min\left( \left( Dem_t + SI_t - \sum_{n=1}^{SO-1}\left(Gen_{n,t}\right)\right), Cap_{SO} \times \left( \frac{MC_{iter-1,t}{}^{50}}{MC_{iter-1,t}{}^{50} + UMC^{50}} \right), ST_{t-1} \times SOeff \right), 0 \right)$$

Each iteration simply involves re-defining $SIU_{iter,t}$ as $SIU_{iter-1,t}$,and $SOU_{iter,t}$ as $SOU_{iter-1,t}$, and $MC_t$ as $MC_{iter-1,t}$. By this process, the storage behavior and marginal costs change gradually until the marginal cost from the previous iteration no longer differs significantly from the marginal cost from the current iteration. At this point, we have converged upon a consistent solution in which the storage behavior essentially depends on the current-hour marginal cost.

*System marginal cost:*
The marginal cost of electricity in hour t ($MC_t$) is the marginal cost of the most expensive generator (including wind and the storage output device) operating that hour.

*Generator marginal costs:*
For baseload plants, MC does not depend on generator output; it is simply the sum of the variable O&M and fuel costs per MWh for that generator: $MC_{i,t} = MC_i$

In order to make system marginal cost a relatively smooth function of total power output, the marginal cost of variable load and peaking plants depends on generator output. The smoothness of this function is useful for convergence of the model, and is also more realistic than a simple stepping-stone function (in which each type of generator has a single marginal cost regardless of its output). For simplicity, I made $MC_{i,t}$ a linear function. The marginal cost of each generator is equal to the sum of its variable O&M and fuel costs when the generator is operating at half of its capacity. When it is generating less than half capacity, the MC is lower than this. At its lowest, the MC for this generator is the average of the sum of variable O&M and fuel costs for this generator, and the sum of variable O&M and fuel costs for the next-cheapest generator. When the generator is operating at more than half its capacity, its MC is higher. At full capacity, the MC is the average of the sum of variable O&M and fuel costs for this generator, and the sum of variable O&M and fuel costs for the next most expensive generator. That is, When $Gen_{i,t} = 0$, $MC_{i,t}$ is the average of $MC_i$ and $MC_{i-1}$, and when $Gen_{i,t}$ is at its maximum ($Gen_{i,t} = Cap_i \times FCF_i$), $MC_{i,t}$ is the average of $MC_i$ and $MC_{i+1}$.