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Construction of Hybrid Nuclear Thermal Energy Storage Systems Under Electricity Market Uncertainty

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Construction of Hybrid Nuclear Thermal Energy Storage Systems Under Electricity Market Uncertainty

by

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Abstract

Construction of Hybrid Nuclear Thermal Energy Storage Systems Under Electricity Market Uncertainty

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The objective of this thesis is to simulate the construction of thermal energy storage systems for nuclear power plants in the ERCOT grid. Steam accumulators were selected as the thermal energy storage technology. A thermo-economic model was used to estimate the operating and cost parameters for sixteen different steam accumulator designs. A new capacity expansion model of the ERCOT grid was built on top of an existing production cost model for wholesale electricity market simulations. Sixteen permutations of four scenario pairs were simulated to illustrate the uncertainty of future market conditions. It was optimal to build steam accumulators in three of the permutations. Scenarios common to these permutations were high future natural gas prices (three permutations), aggressive capital cost declines for solar PV and wind generators (three), high load growth (two), and a carbon tax (two). This suggests that large-scale thermal energy storage systems may be most successful in future markets under these conditions.

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Introduction

Human demand for energy, especially in the electric power and transportation sectors, is releasing unsustainable quantities of greenhouse gases into the atmosphere. If greenhouse gas emissions are not sharply curtailed in the coming decades, there will likely be catastrophic environmental damage from coastal flooding, food shortages, and ocean acidification, among others [1]. We must develop compelling alternatives that minimize point-of-use and lifecycle greenhouse gas emissions while energy demand grows worldwide.

Nuclear power has a unique advantage amongst thermal generating technologies: it does not emit greenhouse gases during operation and has very low lifecycle emissions. However, nuclear power plants are very expensive to build and maintain. Bringing together nuclear power, solar, wind, hydroelectric, geothermal, and other forms of greenhouse-gas-free power could create much cleaner electric grids. The complexity arises when we consider where, when, and in what combination these technologies can be built in a particular region. For example, there may not be enough ramping capability from these generators to constantly match supply and demand with the reliability we have come to expect. Energy storage technologies could help fill these gaps by acting as controllable load and generation, depending on the situation.

Energy storage is simply stockpiling potential energy until it is needed in the future. Fossil hydrocarbons can be considered an extremely long-term store of ancient solar energy. But energy storage is most commonly thought of as storing an intermediate form of energy: energy available after harvesting or conversion from a fuel, but before final use. Potential energy can take many forms: heat, pressure, momentum, gravitational potential, electrochemical potential, and electromagnetic potential. The energy-to-power ratio between storage ranges over several orders of magnitude greater and less than one. Thus, some energy storage could act like a thermal power plant with stockpiles of fuel, while others could supply extremely large bursts of power for a fraction of a second.

Many governments around the world have moved to deregulate electricity markets. Their aim is to create incentives to build the lowest-cost facilities needed to sustain an electric grid. In the last ten years in the United States, low natural gas prices and federal tax incentives for solar and wind generators have driven down wholesale electricity market prices. Baseload power plants, primarily coal and nuclear, have been under increasing revenue pressure, and many have been prematurely closed. At the same time, nuclear power plants produced nearly 60% of the carbon-free electricity in the United States in 2016 [2].

While most nuclear and coal plants can change their power output with load, they seek to generate at maximum power as much as possible to maximize revenue. However, the stochastic nature of the weather means that the net load on many electric grids (gross demand minus intermittent generation) has become more erratic as solar photovoltaic (PV) and wind generators have been added to these systems. This creates opportunities for generators that can ramp up and down quickly. Energy storage systems—including electrochemical batteries, pumped hydroelectric, and compressed air—can capitalize on these ramping events, but so far they have been burdened by high capital costs and low electricity prices. One often-overlooked type of energy storage can be coupled with a nuclear reactor steam supply system: thermal energy storage (TES). TES systems for hybrid nuclear applications include steam accumulators, refractory bricks, molten salts, metal hydrides, and artificial geothermal. Steam accumulator and molten salt storage systems have been built at utility-scale solar thermal plants.

This work focuses on hybrid nuclear thermal energy storage (TES) systems that will work in tandem with other low- and zero-carbon technologies to mitigate climate change risk. Using a market-driven engineering design approach, the most robust TES systems will be found for the Texas electric grid (ERCOT) under market uncertainty. The market uncertainty will be explored through a series of scenarios expected to have the greatest effects on market conditions including natural gas prices, total demand and peak load forecasts, capital cost declines for solar PV and wind, and a carbon tax. Steam accumulator systems will be considered as retrofits to existing nuclear power plants. A set of steam accumulator candidates will be based on varying the power, energy capacity, and ramp rate. These will be accompanied by estimates for major costs including capital costs (power and energy capacity), fixed and variable operating and maintenance, and start costs. The robustness of a steam accumulator candidate will be based on one or more criteria within and across scenarios. Ultimately, this will result in design parameter ranges that could be used for preliminary hybrid nuclear TES designs.

Literature Review

Energy Storage

Energy storage systems can provide useful services to electric grids, although expected revenues may not be enough to cover long-term costs. The various energy storage technologies have different roles to play in electricity grids and markets, from a large pumped hydroelectric generator supplying bulk power to an uninterruptable power supply at a hospital. Energy storage systems can be classified by how quickly they can discharge their stored energy (energy-to-power ratio) and by the types of market roles they can serve (generation/capacity, transmission and distribution, or demand). Typically, very fast discharge energy storage systems, like batteries and flywheels, are limited in total energy capacity. They can provide services like frequency regulation and voltage support. Systems with intermediate discharge times (seconds to hours) could provide load following, reserves, and backup power roles. Hourly and longer discharge systems could provide black start, long-term capacity, peak shifting, and capital investment deferral, among others [3].

Some services are not compensated in electricity markets (e.g., governor and inertial response), but in some cases, private entities may find that energy storage systems can replace or augment existing services at lower cost (e.g., as an alternative to a new transmission line). Bulk energy storage systems (those that provide megawatts of power) are often thought of time-shifting devices: buy or store energy when prices are low, and then sell it when prices are high [3]. However, this generation time-shifting or peak shaving behavior requires a certain spread between low and high prices to be economically viable. Instead of relying on a single revenue stream, many energy storage projects now combine several revenue streams (or cost-saving streams) together, sometimes called benefit stacking [4].

Of the many types of energy storage systems proposed for the electric power sector, only four are in widespread use today: pumped hydroelectric [4], lead acid batteries [4, 5], chilled water [6], and underground thermal storage [6]. Among these, chilled water and underground thermal are primarily used in demand-side management, leaving pumped hydroelectric and lead acid batteries as the two widely available bulk energy storage options.

Today, lead acid batteries are primarily deployed for distribution support or for uninterruptible or backup power at the site level. Lithium ion and sodium sulfur batteries are becoming more commercially available, and flow batteries are under development [4, 5, 6], although the use cases for all of technologies are very similar. Flywheels [4, 5, 6] are sometimes used in lieu of batteries, and extremely fast response supercapacitors [4, 5, 6] and superconducting magnets [5, 6] are being developed as well. For demand-side management, in addition to chilled water and underground thermal storage, ice storage is becoming more widespread [6].

On the bulk transmission side, there are a few compressed air energy storage (CAES) projects globally [4, 6], and several others have been proposed, primarily using underground salt caverns or aquifers. Alternative CAES technologies in development include aboveground tank-based storage and adiabatic underground storage with a secondary thermal energy storage system to eliminate the need for natural gas combustion in the expansion train [4, 5]. Liquefied air is also being studied as a denser alternative to compressed air [4].

Energy storage and electricity storage are not synonymous. Although many energy storage systems for electrical grids do use grid electricity to store energy, there is another set of storage systems that store energy in an intermediate form between primary fuel (if any) and electricity. Such systems have been recently classified as generation-integrated thermal energy storage [7]. Natural hydroelectric systems fall into this category—with natural inflows "charging" the reservoir—as do direct mechanical storage of wind power into compressed air, thermal energy storage for heat-based power plants, and plant-level hydrogen production (if the hydrogen itself is stored and later used to generate power). Thermal energy storage systems can also be used for power plant cooling. Storing ice overnight has been proposed for cooling nuclear power plants [8] and gas turbines [9].

Thermal Energy Storage for Power Generation

The largest thermal energy storage systems for electric power installed to date have been for concentrating solar power (CSP) plants. In CSP using parabolic troughs or Fresnel reflectors, solar radiation is used to heat a working fluid in a pipe, typically mineral oil or water. In some designs, steam is generated directly in the pipe and used to drive a steam turbine. These systems are well-suited for heat storage via steam accumulators [10, 11]. Steam accumulators are primarily holding tanks for large quantities of hot water and steam that can release steam on demand. Sensible and latent heat materials can be added around a steam accumulator to decrease losses [12]. In the latter case of latent heat phase-change materials (PCM), a reheater may be necessary during discharge if the phase transition temperature is too far below the charging steam temperature [13, 11]. The 11 MW PS10 plant near Sevilla, Spain includes a 20 MWh steam accumulator system [14]. Other solar TES projects have utilized tank-based thermoclines, mineral oil, molten salts (typically kept liquid except as a PCM), solid media such as concrete, and chemical reactors [14, 15].

For large nuclear power plants with high capital costs, high fixed operating and maintenance (O&M) costs, and low variable operating costs, electricity markets must yield average prices above long-term costs to break even and be economically viable. In competitive markets, having low operating costs means that the plant can be dispatched most hours of the year, earning a rent via the higher marginal price of the market. Thus, over the last several decades, nuclear power plants in the United States have sought to maximum their capacity factors, in some cases exceeding 90%. Two factors have threatened this business model in the last ten years: the dramatic fall in natural gas prices due to shale gas and hydraulic fracturing, and the construction of significant amounts of wind and solar PV. Because wind and solar resources are driven by weather and the Earth's rotation, wind and solar generator output can be mismatched with demand. They also have near-zero variable costs, so they tend to drive down the average price of electricity.

Thermal energy storage (TES) coupled with nuclear power plants has been proposed to deal with greater uncertainty in net load due to wind and solar integration [16, 17, 18]. TES power plant system designs include steam accumulators, artificial geothermal [19], molten nitrate salts, silica or alumina firebricks, and metal hydrides (for high-temperature reactors). A generic thermal energy storage system design was found to be a feasible retrofit for a subcritical steam oil-fired power plant [20]. Because energy storage systems can act as dispatchable generation and controllable load (or negative generation), they may be helpful in managing net load swings and could enable additional wind and solar capacity to come online [21].

Electricity Market Models

A variety of energy and electricity market models are used in the electricity market modeling literature. They range in scope from electricity-only models to global equilibrium energy models. Some were developed by government researchers, others by private companies or individuals. Most use a higher-level modeling language to create linear or mixed integer-linear programs that are passed to an optimization solver.

The U.S. Environmental Protection Agency (EPA) uses ICF's Integrated Planning Model (IPM) to model the impacts of emissions policies on electricity markets [22, 23]. It covers both U.S. and Canadian power markets divided into 75 regions. The EPA uses significant detail for airborne emissions, including scrubber types, efficiencies, and permissible rates for each generator. Units are aggregated into larger plants by grouping similar parameters such as technology type, region, heat rate, and emissions rates. For energy storage, only pumped hydroelectric storage is included. Reserve margin constraints are included, but no operating reserves are modeled. Capacity expansion uses a load duration curve (LDC) algorithm. Unlike most other models, the EPA model includes several different retrofit options for thermal power plants including emissions controls and fuel switching.

The National Renewable Energy Laboratory (NREL) developed the Regional Energy Deployment System (ReEDS) model for electricity system planning in the 48 contiguous states of the U.S. [24]. It divides this area into various regions: major interconnections (3), grid balancing areas (134), and solar and wind resource areas (356). Load is balanced during 17 yearly time-slices, which is a relatively coarse temporal resolution (0.2% of an hourly chronology). Mercury, sulfur dioxide, and nitrogen oxide emissions are included. Individual generators are aggregated by technology at the balancing area level, and energy storage candidates include pumped hydroelectric, batteries, compressed air, and building-level thermal storage (chilled water or ice). Capacity and operating reserves are modeled, with the latter including frequency response, contingency reserves, and wind and solar forecast error. Retirements are based on assumed technical lifetimes rather than economics for non-renewables, while renewables are assumed to be immediately replaced at end-of-life.

The Balmorel model was originally developed by a consortium of research groups around the Baltic Sea to model markets in that region, but it has been expanded into an open source project and applied in studies of other parts of Europe and elsewhere [25]. It includes combined heat and power (CHP) and heat market functionality in addition to electricity market clearing. Individual generators can be specified, and several energy storage classes are available: hydroelectric, short-term electric, and short-term heat. However, storage cannot be used as an expansion candidate. Neither operating nor long-term capacity reserves are included. Demand is met by using a demand elasticity function during each time step. Retrofits and retirements are not modeled.

The SWITCH model was initially developed by Matthias Fripp at the University of California, Berkeley to assess the value of new solar and wind generation in California to minimize carbon dioxide emissions [26, 27]. It has since expanded into an open source project with analyses conducted on power grids in several countries [28]. Generators can be defined as individual units or aggregated; however, unit commitment is done in blocks by technology. Energy storage systems include batteries, compressed air, pumped hydroelectric, and solar thermal with heat storage. Operating reserves cover contingency and wind and solar forecast errors, but do not include frequency regulation; long-term reserves are specified with a reserve margin. Dispatch is calculated from user-defined demand curves that may vary between simulation steps. Retirements occur based on assumed technical lives only, and retrofits are not available.

PLEXOS is a commercial energy market modeling software package that has been used in grid operations and capacity planning studies worldwide [29]. In addition to the core electricity market module, it can also simultaneously model natural gas, water, and heat markets. Pre-built models of North American, South American, European, African, Asian, and Australian power markets are available. Units can be defined individually, grouped into power plants, or aggregated into larger groups. Two classes of energy storage are available: the Battery class, and the Storage class. Either can be used to define most energy storage devices, including losses and efficiencies. The Storage class also includes hydro-specific parameters like natural inflow rates. Operating reserves can include frequency response, spinning reserves, and non-spinning reserves, while reserve margins can be defined for long-term capacity. The Long-Term Plan algorithm can use load duration curves, reduced-resolution time series, or full-resolution samples to calculate dispatch. Both retirements and retrofit candidates can be included in the capacity expansion problem.

LONG-TERM CAPACITY EXPANSION

The market potential for energy storage systems can be evaluated based on technical characteristics (highest technical performance) as well as the market value (market estimates and detailed market simulations) [3]. Many capacity expansion models do not include energy storage candidates, and of those that do, many only consider one technology or a have a very limited treatment of storage.

The International Energy Agency (IEA) Technology Roadmap 2014 evaluated several non-thermal energy storage technologies and calculated their levelized costs in three scenarios. The report also included competition from demand response technologies, but no nuclear hybrid technologies were included. The NREL Renewable Electricity Futures Study evaluated capacity expansion scenarios for the continental U.S. with 30–90% of generation coming from renewable sources (biofuels, hydroelectric, wind, solar, *et c.*) [30]. The study used the ReEDS model, and thus it only included batteries, pumped hydroelectric, and compressed air energy storage candidates. Zakeri, Rinne, and Syri modeled several feasibility scenarios for combinations of nuclear, solar PV, and wind in Finland [18]. They also included some demand-side management technologies, batteries, and building thermal energy storage, but no options for nuclear thermal energy storage. Denholm *et al.* evaluated combinations of nuclear with thermal energy storage, wind, and solar to meet demand in a fully decarbonized ERCOT grid [21]. Their method varied the proportions of renewable and nuclear with TES generation over two historical years rather than modeling generator builds and retirements over time. Finally, Mann and Schneider ran a capacity expansion model without energy storage candidates first, and then they added individual candidates into separate production cost model runs for a single future year. By varying the energy storage candidate parameters (power, energy capacity, and ramp rate), they explored the design space and their effects on market outcomes [31].

Methodology

Overview

In order to find the most robust TES system, a set of candidates will be simulated in sixteen different scenario permutations to capture some of the major market and policy uncertainties. To accomplish this, three different models will be used together to overcome the limitations of each. First, a techno-economic model of large-scale steam accumulators is used to calculate the capital and operating costs of various steam accumulator systems given inputs for power and energy. Next, the desired steam accumulator candidates are used as inputs to a capacity expansion model of the ERCOT wholesale electricity market. This model minimizes the total system cost over a time horizon of 20 years (2011–2030). It incorporates scenario-based uncertainty to cover a range of future market conditions. Finally, the capacity expansion solutions are input into a production cost model of ERCOT to simulate generator revenues and other parameters at a finer resolution. The construction frequency of the built steam accumulator candidates will then be compared to determine the most robust candidate.

This approach attempts to capture uncertainties in steam accumulator designs and costs, while at the same time incorporating market uncertainties due to fuel prices and load, among other risks. This market-driven engineering approach can be used to down-select the most promising steam accumulator candidates at an early stage of research and development. This screening could reduce the risk of investing in technologies that may ultimately perform poorly in future markets.

FINANCIAL ASSUMPTIONS

General Assumptions

All costs and prices have been converted into 2011 U.S. dollars (USD) unless otherwise noted. The Consumer Price Index for All Urban Consumers (CPI-U) conversion factors were used in all cases (see Appendix A). For long-term capacity expansion, the discount rate was set to 8%. For depreciation benefits for new projects, the declining balance method was used with a 35% tax rate. Because the tax effects of depreciation are on a nominal basis, an inflation rate of 2.5% was assumed for those annuities.

Production Tax Credit

The Production Tax Credit (PTC) is a federal tax credit available to developers of certain types of power plants. It was first established with the Energy Policy Act of 1992 for wind, solar PV, solar thermal, biomass, hydroelectric, geothermal, landfill gas, municipal solid waste, and ocean power (thermal, tidal, and wave) [32] [33]. Starting in 2017, only new wind projects are eligible to claim the PTC. The wind power industry has greatly expanded under PTC support, but new construction has relied heavily on extensions of the original law.

The PTC was set up as a post-tax credit of 1.5¢/kWh produced ($15/MWh in 1993 USD) for the first 10 years of operation, adjusted for inflation each year. It was modeled on a pre-tax basis as a credit to the variable O&M cost [34]. The credit is gradually reduced to zero by 2020 consistent with current legislation (see Appendix B for the full schedule). Because the eligible credit amount changes each year starting in 2017, separate wind candidates were created for each tax year[1].

[1] See New Resource Candidates below for more details.

Investment Tax Credit

The Business Energy Investment Tax Credit (ITC) is similar in scope and intent to the PTC, but the details differ somewhat. Unlike the PTC, the ITC is a tax credit on the construction cost of certain power plants, so the total value is the same regardless of electricity production. Before 2017, many different transmission-scale power plants were eligible to claim the ITC, including solar PV, solarthermal, wind, CHP, fuel cells, and geothermal. Since the beginning of 2017, CHP and fuel cells have been removed, and credits for wind are being phased out (by 2020) and curtailed for solar (by 2022). The ITC was set up as a credit to fixed O&M costs over the lifetime of the plant. The ITC for 2011–2019 was set to 30%, and then it was modeled to decline to 10% by 2022 (see Appendix C for the full schedule).

Although wind plants can elect to take the ITC in lieu of the PTC, the large majority have chosen the PTC, while the ITC has been heavily used by solar developers due to the differences in generation profiles. Both the PTC and ITC were modeled as amended through fiscal year 2016 (ended Sept. 30, 2016) [35].

STEAM ACCUMULATOR MODEL

There are a variety of thermal energy storage technologies that could be considered for coupling with nuclear power plants[2]. For this study, steam accumulator systems were selected that could be retrofit to existing PWR plants. There are several ways to integrate steam accumulators into nuclear power plants. The general design chosen here adds a diversion valve to the secondary steam loop (Figure 1). This allows the steam to flow to the

[2] For example, steam could be stored and then used to heat feedwater in a regenerative cycle [72], although this would probably be better suited to a new plant design.

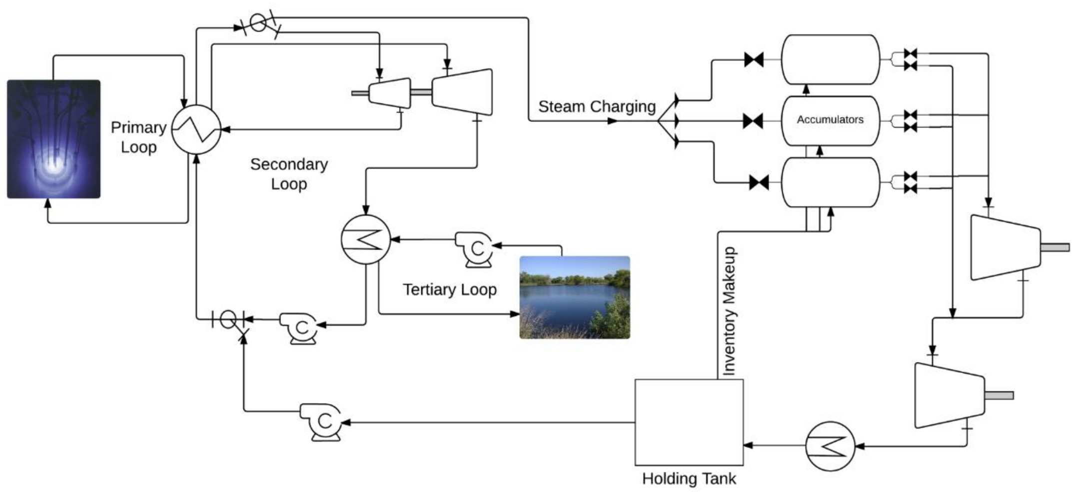

Figure 1. Schematic of a PWR nuclear power plant with a steam accumulator system utilizing separate steam turbines (reprinted from [36]).

existing turbine generator, to the steam accumulator, or possibly both. The steam accumulator is modeled as a bank of pipes held in an insulated building. Stored steam can then be released to a separate steam turbine generator to sell into the market.

This steam accumulator design with a separate turbine generator has been modeled using MATLAB [36, 37]. The MATLAB model includes both thermodynamic and economic components. The thermodynamic sub-model simulates charging, storage, and discharging of steam using a discrete, non-equilibrium approach [38]. The economic sub-model calculates the net revenue using a fixed sinusoidal price model[3] as well as capital and O&M costs. Capital costs include both power-related costs (steam turbine, generator) and energy-related costs (steam storage pipe, building, insulation, pumps). Annual fixed O&M costs are calculated as a percentage of capital costs. This model was used to estimate capital and fixed operating costs for sixteen different steam accumulator systems. These were used as inputs to the capacity expansion model (see Retrofit Candidates below).

[3] The revenue calculations from the MATLAB model will be ignored in lieu of the more detailed market clearing model in PLEXOS.

ERCOT Market Model

ERCOT is the independent grid operator for the electric grid operated entirely within the state of Texas. It serves about 75% of the state's land area and 90% of its electricity demand [39]. It operates day-ahead markets for energy and ancillary services (primarily operating reserves) and a real-time market for energy. It also conducts longer-term auctions for congestion revenue rights. Day-ahead markets are settled at one-hour intervals, while the real-time energy markets are settled every fifteen minutes at settlement points and every five minutes for locational marginal price points. There are over 8,000 nodes where locational marginal prices are calculated, and each is assigned to a hub. These are then averaged together into hub prices. Unlike most other competitive wholesale markets, ERCOT does not operate a forward market for generation capacity. The North American Electric Reliability Corporation (NERC) recommends a reserve margin of 13.75% for the ERCOT region [40], and there have not been any major capacity shortfalls since the competitive market was introduced.

Beyond the operations of the wholesale markets, there are other issues that should be considered when modeling generator dispatch and behavior, especially when performing optimizations over small time steps (minutes to hours). Although interrelated, unit commitment and economic dispatch may occur over different timescales. For instance, the minimum down time constraint of a nuclear power plant may span longer than the optimization step interval of the day-ahead or real time markets. In this case, a model needs to optimize over a longer time horizon to fully incorporate the longer-term constraint. In some cases, uneconomic generators may need to stay online for reliability reasons. Constraints over weeks or months may govern hydroelectric generator availability as well as maintenance outages. Generally, power plants avoid outages during months of peak demand to take advantage of higher prices and to ensure grid stability. Finally, the addition and retirement of generation capacity may consider revenues and costs over months to years. Thus, a variety of timescales from minutes to years must be considered depending on the modeling objectives.

PLEXOS [29], a commercial energy market modeling software package, was used to model both long-term capacity expansion and the day-ahead energy and reserves markets. All simulations used PLEXOS version 7.400 R01 x64 with the solver Xpress-MP 28.01.13 [41].

ERCOT Capacity Expansion Model

Capacity Expansion Modeling Goals

The goal of this work is to simulate the construction and retirement of generation assets across several scenarios while including steam accumulator retrofits for existing nuclear power plants. This can be accomplished with a capacity expansion model that simulates the turnover of assets over a future period. Ideally, this would involve simulating market clearing for all settlement intervals over a 20-year horizon or longer, finding the least-cost mix of generation and storage that would meet load, incorporating all operating reserve requirements and generator constraints, and including policy incentives and constraints. Simulating all of these together at the finest resolution is too computationally expensive, so the tradeoffs of several simplifying assumptions were examined.

Time Horizon

The capacity expansion plans will cover the period from 2011–2030. This period was selected because it incorporates several years of historical fuel price data (2011–2016); there are reputable forecasts for fuel prices, load, and capital costs for wind and solar PV through 2030; it incorporates the current rules for the PTC (through 2019) and ITC; and, it covers the period for development of TES projects for nuclear power plants by the U.S.

Department of Energy (DOE) [42]. While running simulations over a longer horizon is feasible, there are benefits to stopping in 2030. For ERCOT, the buildout of wind generation began in earnest around 2005, and typical design lifetimes of wind turbines are 20 years [43]. Therefore, wind generators built in the early years would need to be considered for retirement or retrofitting beyond 2030. Other long-term effects beyond 2030 could include capacity loss for wind and solar PV.

Long-Term Plan Settings

The Long-Term Plan module (LT Plan) in PLEXOS seeks to find the combination of retirements and new construction that will minimize the net present value of total system costs. The most accurate capacity expansion simulation would include hourly (or sub-hourly) market clearing, but this is typically too computationally burdensome for an optimization problem of this size. Hourly market clearing over 20 years would result in approximately 175,320 hours, but the primary problem concerns long-term constraints. An optimization problem needs to cover all short- and long-term constraints to give an accurate answer. In this case, build limits each year and project lead times mean that the optimization should span several years at once to enforce these constraints. Thus, rather than optimizing a single 24-hour period, it is likely than an optimization step of 43,830 hours (5 years) or longer is required. Thus, without separate logic to enforce long-term constraints, the resolution of the simulation must be reduced to be computationally tractable.

There are three primary options for simulating chronological market clearing in PLEXOS: load duration curve (LDC), curve fitting/reduced resolution, and sampling. The LDC method is very common in capacity expansion models of electricity markets. It reorders the load for a specific block of time from highest to lowest, destroying the inter-temporal nature of the load in the process. This means that constraints can only be enforced between LDC time blocks, not within them. The LDC method implemented in PLEXOS also does not model generator startup or shutdown, so minimum up and down time constraints cannot be enforced. The fitted/reduced resolution method preserves the chronology of the load, and it uses a weighted least-squares function to fit a lower-resolution curve to it. However, it typically needs more time blocks than the LDC to achieve a similar result. The sampling method runs a full-resolution dispatch for some number of days, weeks, or months of the year and then extrapolates the results for the remaining parts of the year. The LDC method was chosen because of its speed and the relative insensitivity to lower resolutions (see Complexity Reduction below).

Because unit commitment, build, and retirement decisions are made for individual generators (since units come in integer increments), a mixed integer program (MIP) is preferred over a linear program (LP), even though it incurs a higher computational cost. However, in certain circumstances, a MIP was found to be infeasible, but its corresponding LP was feasible. In these cases, the LP fallback solution was used. These integer infeasibilities were common when attempting to find the optimal energy storage candidate in the last five years of the time horizon.

The step size is the time horizon of each optimization sub-problem. It can span the entire planning horizon from 2011–2030 (ideal), or it can be shorter depending on the length of constraints. Larger step sizes yield more optimal results, but the tradeoffs include the problem of perfect foresight as well as computational complexity. For capacity expansion, the years from 2011–2025 were relatively quick to solve because storage was not available, but the final 5 years took substantially longer. Because no single constraint covered more than three years, a five-year step size was chosen. Thus, the optimization sub-problems covered the 4 periods 2011–2015, 2016–2020, 2021–2025, and 2026–2030.

Generator market bids can be set to include no-load costs (average) or ignore them (marginal). However, in this model, only constant average heat rates are used, so the no-load costs are zero. Average pricing was chosen, but they were equivalent in this case. Although generator startup and shutdown is not modeled with the LDC method, there is an option to amortize start costs over a certain number of hours to approximate these costs. A 24-hour amortization period was used to prevent high-start-cost generators from being over-penalized. Longer-term costs were modeled using a discount rate and declining balance depreciation (see Financial Assumptions above).

Fuel Prices

Historical and forecast prices were used for the various fuels in the model. Historical prices were typically quoted in nominal USD, while different forecasts used either nominal or constant USD for a certain year. Because of these disparities, all fuel prices were converted to 2011 USD[4]. Historical fuel prices were used for biomass [44], lignite coal [45], subbituminous coal [45], landfill gas (LFG) [46], natural gas [44], and uranium [47]. Forecasts for future prices for all fuels except LFG and natural gas were created with linear regressions of historical data. Future LFG prices were assumed to be constant. Natural gas price forecasts for two scenarios were taken from the U.S. Energy Information Administration's (EIA) Annual Energy Outlook 2015 [48]. For full details and data on fuel prices, see Appendix D.

Load Profile

The hourly load profile shape was taken from the 2011 ERCOT hourly average. This yearly base profile was scaled by peak and total energy for future years in two load growth scenarios (see Market and Policy Scenarios below). As part of the nodal market

[4] See Financial Assumptions for more details.

implementation, ERCOT introduced a system-wide offer cap (SWOC) in 2011. The SWOC is designed to provide scarcity price signals in the absence of a forward capacity market, and it prevents scarcity prices from rising to excessive levels. The SWOC was set to $3,000/MWh in 2011 and was incrementally increased to $9,000/MWh in 2015. The SWOC is modeled in PLEXOS as the Value of Lost Load (VoLL). Setting the VoLL creates a soft constraint for unserved energy, helps prevent infeasibilities, and emulates a basic scarcity price signal for long-term capacity.

Wind and Solar Profiles

The hourly wind profile was based on ERCOT wind production for 2011, while the solar PV profile was based on ERCOT solar production for 2014. The solar PV profile year was different because only three units were operating in 2011 (41.6 MW). By 2014, there were 13 units (190.7 MW). For capacity expansion, using a single profile for a class of geographically-dispersed generators fixes the geographic distribution of that class for future years. For example, if five generators were spread amongst two counties in the base year, then all future construction would assume that more generation was built in the same counties with the same proportions. It would be more accurate to allow several different candidates to be constructed in different areas to allow the aggregate output to change over time. Wind and solar PV generators are pre-committed in the model, so they are always dispatched. In reality, curtailment sometimes occurs for reliability reasons, but this effect is minor for long-term expansion and is ignored. Finally, the generation from wind and solar PV resources was subtracted from load during LDC slicing in PLEXOS to create a more accurate net LDC.

Reserve Margin

The capacity reserve margin is the percentage of capacity available above the seasonal peak load. This is an important reliability metric that includes the probabilities of unexpected generation loss and excess load. All generators except wind and solar were assumed to be available at 100% capacity. Following ERCOT's current guidelines, firm solar PV capacity was rated at 80%, and firm wind capacity was rated at 12% [40]. Some regions have mandatory reserve margins, but ERCOT's energy-only market does not require a reserve margin. The North American Electric Reliability Corporation (NERC) recommends reserve margins between 10–15% depending on the percentage of hydroelectric capacity. Their recommended reserve margin for ERCOT is 13.75% [40]. This 13.75% reserve margin was enforced as a constraint in PLEXOS to prevent undersupply problems and to keep reliability at expected levels. To investigate the impact of this assumption, the reserve margin constraint was removed in a separate sensitivity study (see Sensitivit below).

New Resource Candidates

Ten different capacity expansion candidates were modeled based primarily on parameters for candidates in the EIA's Annual Energy Outlook 2015 [49]. These included biomass (steam turbine), coal (IGCC, steam turbine), natural gas (combined cycle, combustion turbine), nuclear, solar PV (single-axis tracking), and wind (inland). Capital costs for wind and solar PV were modeled in more detail. Historical values for wind and solar PV (2011–2016) were taken from Lazard [50], while cost declines used in the Aggressive Capital Cost Declines scenario were taken from International Renewable Energy Agency (IRENA) estimates [51].

Modeled short-term technical parameters included heat rate, net capacity, minimum stable level, maximum ramp rate, minimum down time, minimum up time, planned outage rate, and forced outage rate. Operating reserves participation was inferred from existing generators of the same type of prime mover[5]. Long-term technical parameters included firm capacity (for solar PV and wind reserve margin), lead time, maximum units built per year, and project start date (for solar PV and wind with declining tax credit values). Short-term operating costs included fuel cost, variable O&M cost, and emissions cost (in the Carbon Tax scenario). Long-term costs included build cost (overnight capital cost), economic life, fixed O&M cost, and start cost. All build costs were assumed constant over the planning horizon except for wind and solar PV. A complete list of parameters can be found in Appendix G.

Other resource candidates were modeled in the Annual Energy Outlook 2015 but were excluded here. These included any carbon capture technology (CCS), fuel cells, municipal solid waste (MSW) combustion, natural gas internal combustion engines, greenfield hydroelectric, geothermal, nuclear small modular reactors, storage (batteries, CAES, pumped hydroelectric), solar thermal, and offshore wind. Most of these were excluded because they had direct competitors that were less expensive (e.g., land-based wind vs. offshore wind). In some cases, the uncertainties around siting and resource availability (CCS, MSW, hydroelectric, geothermal) were beyond the scope of this work. Although simulating multiple storage technologies was desirable, integer infeasibilities only allowed one storage type to be simulated at a time.

Units Built and Under Construction 2011–2017

Although historical data on units built and retired from 2011–2016 is available, it was excluded from the model so that the simulations could be compared to the actual

[5] Prime movers are mechanical devices that convert initial forms of energy into rotational energy to spin generators. Prime movers include combustion turbines, steam turbines, internal combustion engines, hydroelectric turbines, and wind turbines, among others.

changes. These are compared in Historical vs. Simulated Capacity Expansion, 2011–2016 (below). Additionally, units under construction and in the ERCOT interconnection queue were ignored.

Retirements and Age-Based Degradation

All existing thermal generators were allowed to retire except for large industrial combined heat and power (CHP) units. These CHP units are installed primarily for industrial process heat applications, so it is unlikely that electricity market conditions alone would force their retirement. Only economic retirements were considered. Some models implement technical life constraints that force retirements after a certain number of years. However, this excludes the possibility of overhauls and retrofits to keep a plant running. As plants age, their heat rates (for thermal plants) and O&M costs typically increase, while net capacity may decrease. These effects would become more pronounced over a longer time horizon.

Wind turbines and solar PV panels have design lifetimes of 20–25 years, but at least for wind turbines, they may be candidates for repowering projects at the end of the warranty period. Both wind and solar PV projects are subject to net capacity degradation over time, some due to individual unit failure [52, 53].

Retrofit Candidates

Retrofit candidates for this work were limited to steam accumulators for nuclear power plants[6]. Sixteen different candidates were created from three sets of parameters: net capacity from the secondary turbine generator (500 or 1,000 MW), energy storage capacity (5, 10, 20, 40 hours at max output), and turbine ramp rate (0.54%/min., 1.67%/min.). Any

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[6] Additional retrofits appropriate for longer time horizons or more detailed models are discussed in Future Work.

of the sixteen candidates could be built at any of the four reactors in ERCOT: Comanche Peak 1&2, or South Texas 1&2. Only one candidate was allowed per reactor, so ultimately up to four steam accumulators could be built. Due to expected research and development time estimated by DOE [42], candidates were not eligible for construction until 2026. A complete list of parameters for the steam accumulator candidates can be found in Appendix H.

ERCOT Production Cost Model

Production cost models are designed to simulate the hourly or sub-hourly market clearing of a market in fine-enough detail to closely match historical market prices. In this work, the output from the capacity expansion model is input into the production cost model to simulate more accurate market clearing and calculate annual net revenues. This production cost model was originally developed for compressed-air energy storage integration studies in ERCOT [54], and it has been extended for hybrid nuclear TES system [55, 56].

Time Horizon Settings and Resolution

Typically, the day-ahead energy and ancillary services markets are simulated with an hourly resolution. However, due to the long time horizon involved, the interval length was increased to reduce computational complexity with minimal impact to results. More details are given in Complexity Reduction below. Unlike the capacity expansion module, the full chronology of the load is retained, and full unit commitment and economic dispatch is performed. The optimization step size was set to 2 days so that multi-day market opportunities for the 40-hour steam accumulator candidates could be seen if they were built.

Day-Ahead Markets

ERCOT coordinates day-ahead markets for energy and ancillary services (primarily reserves) as well as a real-time market for energy. Day-ahead markets can help reduce the risk of unexpected outages by having generators bid in advance. It also gives the grid operator a chance to run predictive reliability unit commitment analyses to ensure grid stability. Bids into the energy market are not binding, and the unexpected loss of a generator or transmission line will lead to corrections in the real-time market. The day-ahead market was modeled because of the potential revenue from ancillary services that is not captured by running a purely real-time market. Although it is possible to run day-ahead and real-time market simulations sequentially for each day, it is assumed that the price spread is minor compared to the additional computational complexity.

Like the capacity expansion model, the production cost model uses a combination of linear programming and mixed integer programming to solve the unit commitment and economic dispatch problems. It co-optimizes energy and ancillary services procurement. Four types of ancillary services are included as defined by ERCOT: frequency regulation up (RegUp), frequency regulation down (RegDn), responsive reserve service (RRS, known as spinning reserves in other grids), and non-spinning reserve service (NSRS)

Generator Modeling

Most of the parameters used by Garrison in the base model [54] were taken from a database developed by an ERCOT Long-Term Study Task Force [57]. Technical parameters included the number of units, fuel used[7], prime mover, heat rate, net capacity, firm capacity (for reserve margin), minimum stable level, max ramp rate, minimum down time, minimum up time, planned outage (maintenance) rate, forced outage rate, emissions rates (CO_2, NO_x, SO_2), repair times (coal, nuclear), and operating reserves participation. Short-

[7] Although some generators can use multiple types of fuels for primary operation, it was assumed that only one fuel was used per generator. Secondary fuels used for auxiliary start-up were also ignored.

term operating costs included fuel costs and variable O&M costs, while long-term costs included fixed O&M costs and start costs.

Settings Common to Both Models

In general, it is desirable to find unit commitment solutions where supply exactly matches demand, at least cost, over an entire period. However, sometimes problem infeasibilities cause a significant increase in computation time. Therefore, unserved energy and dump energy (overgeneration) were disallowed from simulations unless infeasibilities prevented solutions from being found.

Complexity Reduction

Given a finite amount of computational time and resources, it is important to consider how the parameters and structure of a model will affect the results. Some parameters will strongly affect the results and come at a high computational cost, while others may have only a modest effect on results and have a disproportionate computational cost. Thus, careful complexity reduction should result in improved accuracy for a given computational time or similar accuracy with a shorter computational time. There are several areas of the model where complexity reduction is justified.

Optimization Tradeoffs

In the modeling of physical systems and markets, there are often tradeoffs between accuracy and computational complexity. For instance, decreasing the dispatch interval from 1 hour to 15 minutes may yield a slightly lower-cost solution, but the number of dispatch decisions for a given period goes up by a factor of 4. Or, grouping several similar generators into a single, larger generator may have a minimal impact on dispatch and prices, but it reduces the computation time. This has important implication for how the model is physically and temporally divided.

One of the main tradeoffs is between temporal resolution and the number of divisions of the time horizon (time step). For the capacity expansion problem, a finer temporal resolution means more accurate dispatch and pricing, and the most optimal solution covers the entire time horizon in a single problem. However, the amount of memory available to run the simulation limits the values of these parameters. Thus, a simulation could be run with a coarser temporal resolution but cover the entire time horizon (e.g., 20 years), or it could be run with a finer temporal resolution and smaller time steps of only a few years. These tradeoffs will be explored in the Results section.

ERCOT Grid

The transmission system of the ERCOT grid is complex, with over 8,000 nodes and 46,000 miles of transmission lines [39]. The nodal market structure was introduced to reveal more precisely where transmission constraints were binding, and this in turn should spur generation or transmission construction in those areas. However, especially after the CREZ transmission line projects were built, the difference in price amongst all nodes throughout a year is small. Therefore, the current practice of socializing transmission construction was assumed to continue, and thus transmission constraints were ignored. This will significantly reduce the computational complexity, especially compared to a DC optimal power flow solution for the full-resolution grid. With only a single node to connect to, all load is lumped together rather than being assigned into different load zones. For similar reasons, one wind profile and one solar profile are used for the ERCOT region. However, as noted before, this fixes the geographic dispersion of assets for capacity expansion. While the geographic diversity of wind is not expected to increase significantly, the same cannot be said for solar. Thus, solar construction may respond more to transmission access and costs than to resource availability. The limited deployment of solar up to this point may not reflect the future geographic diversity.

Capacity Expansion Algorithm

The load duration curve (LDC) method is used to calculate capacity expansion. One disadvantage of this approach for energy storage is that storage constraints are only balanced between LDC time blocks, not within them. Thus, if the LDC step size is significantly larger than the storage energy capacity (e.g., one LDC per month), then the opportunities for storage to participate in the markets will be significantly reduced or eliminated. The same is true of reducing the resolution of chronological algorithms as well. This could be an advantage of a higher-resolution sampling algorithm that runs hourly dispatch over multiple daily or weekly samples.

Unit Commitment and Dispatch

Generators are dispatched into the market based on their offer price. In some cases, offer prices are consistently low enough that they are nearly always dispatched except during contingencies. These generators can be pre-committed and thus removed from the unit commitment formulation, reducing computation time. Four classes of generators were chosen for pre-commitment: biomass, nuclear, solar PV, and wind. In the case of solar PV and wind, production is sometimes curtailed for grid reliability reasons, but they generally bid near zero into the markets. In certain circumstances, they may bid negative costs due to their tax credits. Coal and hydroelectric generators were also considered for pre-commitment. Coal-fired power plants may compete with some cheaper combined-cycle natural gas plants in the merit order stack, especially if natural gas prices are low relative to coal prices. Thus, pre-committing them could distort the dispatch in favor of coal in some cases.

There are certain seasons (summer) and times of day (10 A.M.–10 P.M.) where pre-commitment could be used, but this is problematic for capacity expansion models where the assumptions at the beginning of the time horizon might not apply by the end. For hydroelectric, although their operating costs are near zero, they are constrained by water management issues, and they usually do not behave like baseload generators in ERCOT.

Another method of reducing dispatch is to aggregate multiple generators into larger individual units. This acts to reduce the total number of units for the unit commitment problem. Five different plant types were aggregated into larger units: biomass (11 into 2), natural gas combined cycle (75 into 56), natural gas combustion turbines (77 into 30), natural gas internal combustion engines (27 into 2), and natural gas steam turbines (50 into 23). Thus, the number of units for commitment was reduced by 127 units. The units were aggregated by power plant (e.g., the six turbines at Greens Bayou were aggregated into one), and parameters that are relative to capacity were scaled accordingly (e.g., net capacity, minimum stable level, maximum ramp rate, start cost). Hydroelectric, solar PV, and wind generators were already aggregated in the base model. Nuclear plants were not aggregated so that steam accumulator candidates could be built in appropriate sizes, and coal plants were also excluded to prevent dispatch distortions. Additional details are presented in the Results section below.

An additional optimization-based method of complexity reduction comes in the formulation of the unit commitment problem itself. Unit commitment can be solved as an integer program (most accurate) or a linear program, with tradeoffs in computational cost and accuracy. For the production cost model, the gains from using an LP were modest, while dispatch accuracy suffered noticeably. Thus, integer unit commitment was used throughout.

Market and Policy Scenarios

Future market conditions are subject to a wide range of forces that lead to uncertainty. However, some parameters are expected to have large impacts on market dynamics based on market history and technical fundamentals. For instance, the offer price of the last unit of load establishes the marginal price, so examining the marginal unit history can give some clues to the most influential technologies. If fuel costs are a large proportion of the operating costs of the most common marginal units, then one fuel cost may be highly correlated with electricity prices. In fact, this is the case with natural gas and electricity prices in ERCOT (Figure 2). Note that low supply in electricity (low reserve margin) as is found in July and August does not translate into low supply in natural gas, but the converse is likely true.

To address future market uncertainty, four trends were identified that each have a significant impact on market outcomes: natural gas prices, peak load and total demand,

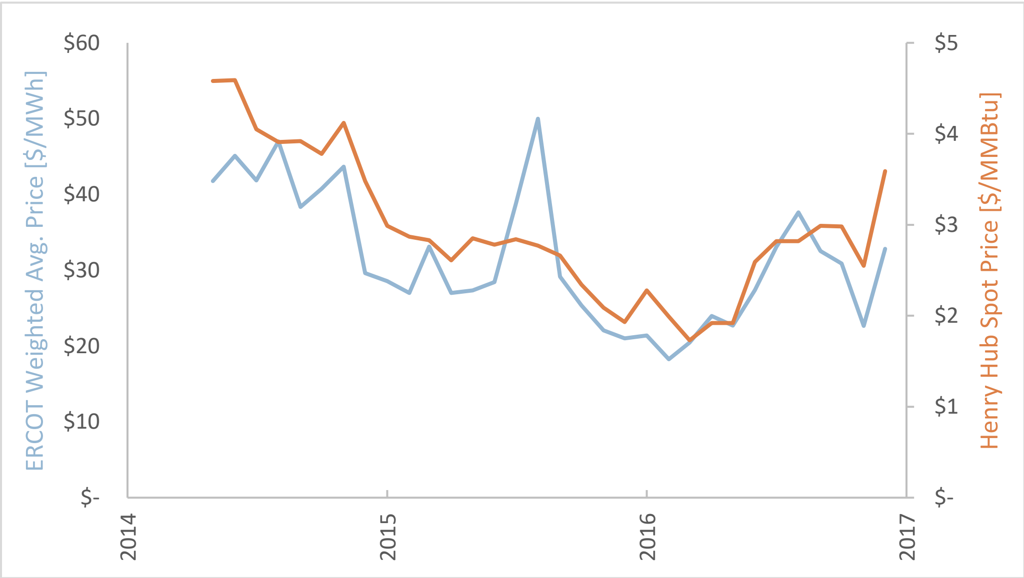

Figure 2. ERCOT Weighted-Average Price vs. Henry Hub Spot Price, 2014–2016. Data from [73, 74]

capital cost declines for wind and solar PV, and the application of a carbon tax. All four of these are important both for capacity expansion planning and production cost modeling.

Two different natural gas price forecast scenarios were chosen from the Annual Energy Outlook 2015: High Oil Price, and High Oil and Gas Resource [48]. These cover the years 2012–2040, but only years 2017–2030 were used. Prices were for natural gas delivered to the electric power sector rather than Henry Hub spot prices. These are more appropriate and were typically 5–20% higher than Henry Hub. See Appendix D for more details.

Peak load and total energy demand for future years was modeled in two load growth scenarios: one from AEO 2015 (Low Economic Growth scenario) [48], and one forecast based on ERCOT historical data [58]. The Low Economic Growth scenario assumes annual growth for summer peak and total energy to be 0.6%/year. An exponential regression was used to estimate the average annual growth rates from ERCOT historical data from 2007–2016: 1.4%/year for summer peak and 1.54%/year for total energy. Additional details are given in Appendix F.

In the base scenario, costs for new wind and solar PV projects are constant starting in 2016. In the alternative Aggressive Capital Cost Declines scenario, capital costs for wind and solar PV drop from 2017–2025. Average annual growth rates were taken from an IRENA study [51]. For solar PV, the average annual growth rate is -8.8%/year, and for wind it is -1.3%/year. To accommodate additional construction demand, the maximum allowed capacity built per year was doubled for both technologies starting in 2017. A table comparing the capital cost declines can be found in Appendix G.

Carbon taxes have been proposed as one method of including the environmental and economic costs of carbon dioxide emissions into energy markets. The social cost of carbon (SCC) is a metric that attempts to capture many of these external costs. In economic terms, it represents the marginal change in discounted economic welfare from each additional unit of carbon dioxide emitted into the atmosphere. To model an aggressive climate change mitigation scenario, carbon prices were chosen from the latest version of the DICE model [59] that kept global atmospheric temperatures below 2.5 °C above pre-industrial levels, on average, over 100 years. This corresponds to a global SCC of $106.70/tonne CO_2 (2010 USD) for 2015 with an annual escalation of 4.77%. For the United States, a regional SCC equal to 15% of the global SCC was assumed starting in 2015. Additional details are provided in Appendix E.

STEAM ACCUMULATOR CANDIDATES

Several different steam accumulator candidates were created to outline the design space. Generator power was either 500 MW or 1,000 MW; energy capacity was either 5, 10, 20, or 40 hours at full power; and generator ramp rate was either 0.54%/min. or 1.67%/min. These combinations created sixteen different candidates. Only one of the sixteen candidates could be built at a given reactor, but different candidates could be built at different reactor sites. Up to four steam accumulator systems could be built in total.

Modeling steam accumulators connected to nuclear power plants presents some unique challenges. Unlike most bulk energy storage technologies, grid electricity is not used to run pumps (pumped hydro, compressed air) or charge batteries. Instead, heat from the reactor is stored directly as steam, and a separate steam turbine generator is used for power conversion. Thus, the whole system is like a combined heat and power plant with heat storage and a second generator.

PLEXOS has two different classes of energy storage: Battery and Storage. The two classes function similarly and have nearly identical parameters. The Storage class can be used to represent pumped hydro and CAES systems, so it is also an appropriate choice for steam accumulators with some careful considerations. It would be ideal to model the system as CHP with heat storage since this most closely approximates the actual energy flows and conversions of the system. CHP in PLEXOS is set up to capture waste heat from the prime mover, but a steam accumulator captures heat before conversion, so this method is inappropriate. It is, however, a good way to model waste heat for a heat recovery steam generator in a combined cycle plant. If heat from the reactor could be diverted directly, heat storage works correctly in PLEXOS, but there is no way to use that waste heat as an input to a steam turbine. Instead, heat storage is designed for an external heat market like residential district heating.

Instead of storing heat directly, the Storage class was used to model a steam accumulator system as a pumped storage device. Normally, a pumped storage system uses grid electricity to pump water up into an upper head reservoir (charging). Later, water can flow down into a lower tail reservoir via a hydroelectric turbine to generate electricity (discharging). In the modeled steam accumulator systems, reactor heat is always used to run the main turbine and generate electricity when operational. An electric pump acts as a proxy for a steam diversion valve, and the efficiency of the pump is calculated from the MATLAB model's expected heat loss during charging and discharging (3–16% loss). Thus, part of the optimization is deciding how much energy to store, via the electric pump, and how much to sell to the grid. The proxy pump's load[8] was set to the difference between the primary turbine's maximum power and its minimum stable level. This mimics the steam portion that would have been diverted from the primary turbine. The proxy pump also acts as generator during discharging, and its discharging power is set separately (500 MW or 1,000 MW).

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[8] Pump load is the load during the pumping or charging phase.

The proxy pump moves energy from a tail reservoir into a head reservoir with a defined maximum capacity. All head storages have a loss rate of 0.258%/hour based on simulations from the MATLAB model. Although the loss rate is modest here, it is important to include the loss during storage to avoid overstating the available capacity. Finally, the optimization decides when it is appropriate to sell the stored energy via a secondary generator, which is just the proxy pump run in reverse. The reduction in steam quality during storage may be an important loss to consider in future work. The secondary steam turbine generator is allowed to have a lower minimum stable level than the primary turbine so that it can behave more like a non-nuclear boiler's steam turbine (e.g., biomass or natural gas-fired boiler).

To mimic the behavior of an actual steam accumulator coupled to the secondary loop of a PWR, storage is only allowed when the main steam turbine is at or above its minimum stable level. This was set with a constraint on the pump load and generation from the main turbine (Equation 1). This constraint means that the proxy pump can operate at maximum only when the main generator is operating at maximum, and it must decrease linearly to zero when main generation reaches the minimum stable level.

$$MainGeneration - PumpLoad \geq MinStableLevel \tag{1}$$

It is also important to prevent grid electricity from powering the proxy pump. In this model, it should only charge with electricity from the main turbine (analogous to storing steam). This is accomplished by creating a separate transmission node for the primary (reactor) generator and the secondary (steam accumulator) generator. The two generators are allowed to send electricity outward to the grid, but electricity cannot flow from the grid back to the proxy pump.

Robustness Criteria

Several different metrics could be used to assess the robustness of a steam accumulator candidate to uncertainty. From an operations perspective, the total hours of generation and total generation (MWh) showcase a plant's effectiveness, while the net income shows a plant's financial health. The construction of a candidate amongst the scenario permutations will be used to evaluate robustness to emphasize the long-term results. If a steam accumulator candidate is not built in any scenario, there are several possible causes: another candidate had a lower discounted cost; no candidate was viable for new construction under those market conditions; or, the structure of the model itself prevented all the potential revenues from being captured. This last point implies that a low temporal resolution will disadvantage large-scale technologies that can take advantage of sub-weekly or sub-daily imbalances.

Results

Complexity Reduction

Long-Term Capacity Expansion

Although increasing the temporal resolution should improve the accuracy of unit dispatch, the effect on the long-term capacity expansion results is insignificant beyond a certain point (Figure 3). The baseline resolution of 1 load block per month (0.14%) was increased to 1 per week (0.6%), 1 per day (4%), 2 per day (8%), and 3 per day (13%). The difference in the number of units built per category beyond 0.6% resolution was typically less than 3 units. In the 4% resolution case, the step size was also decreased from 2 years to 1 year. The effect of this was much greater wind and solar PV construction and more natural gas steam turbine retirements. Thus, using a larger optimization step size should lead to lower overall construction costs with the caveat of longer foresight.

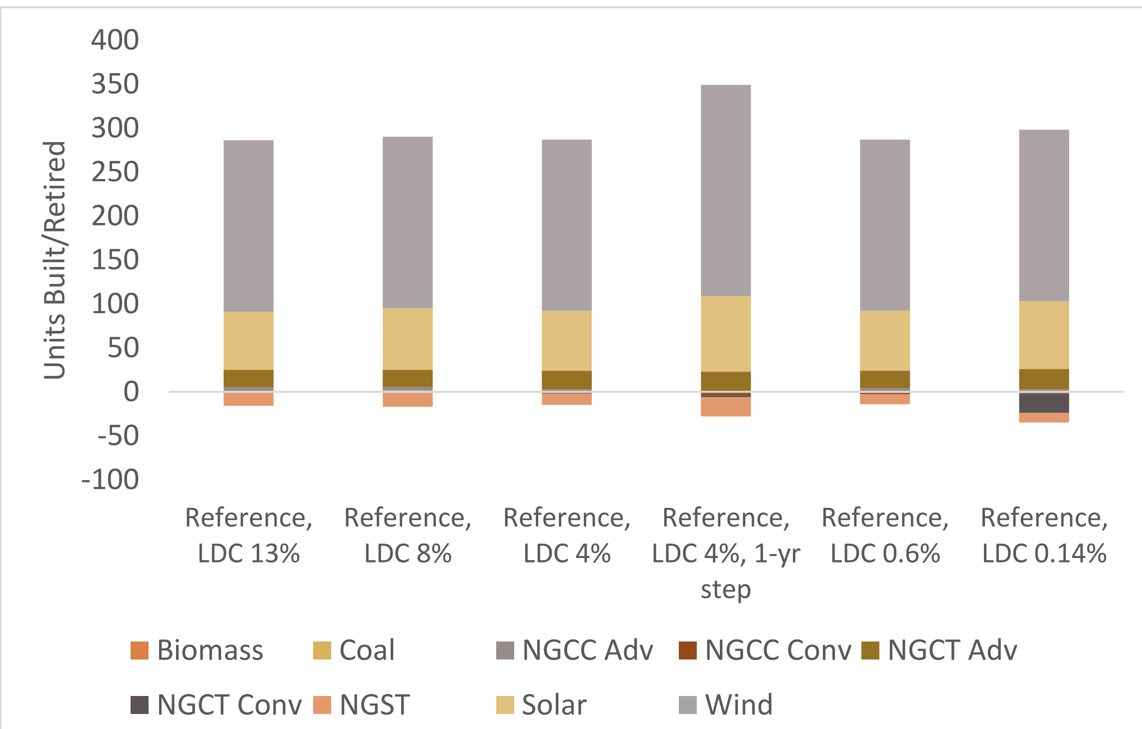

Figure 3. The effects of varying the LDC resolution on the capacity expansion results.

Short-Term Production Cost—Resolution

The goal of production cost modeling is to accurately simulate the hourly or sub-hourly dispatch and prices, so the choice of temporal resolution has a greater effect on the results than in the capacity expansion model (Figures 4–12). As the resolution is decreased from 6 intervals per day (25%) to 1 interval per day (4%), the dispatch and generation changes somewhat. For biomass, the effects are largest in the later years of the horizon, where higher resolutions tended to increase dispatch, but lower resolutions had little impact. Coal generation tended to increase with lower resolutions but followed the same trend over time. Hydroelectric and natural gas steam turbine generation tended to decrease with lower resolutions. The trends were mixed for natural gas combined cycle, combustion turbine, and internal combustion engine, but all tended to follow the same shape over time. Nuclear and wind generation were essentially unchanged with decreasing resolution.

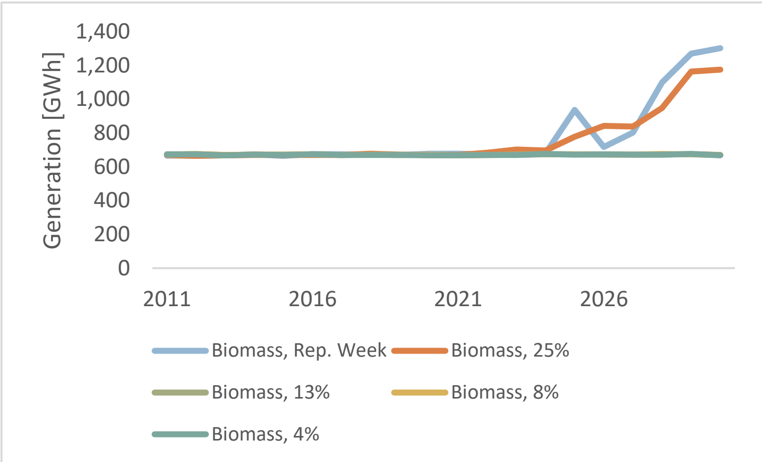

Figure 4. Effects of decreasing short-term simulation resolution—biomass.

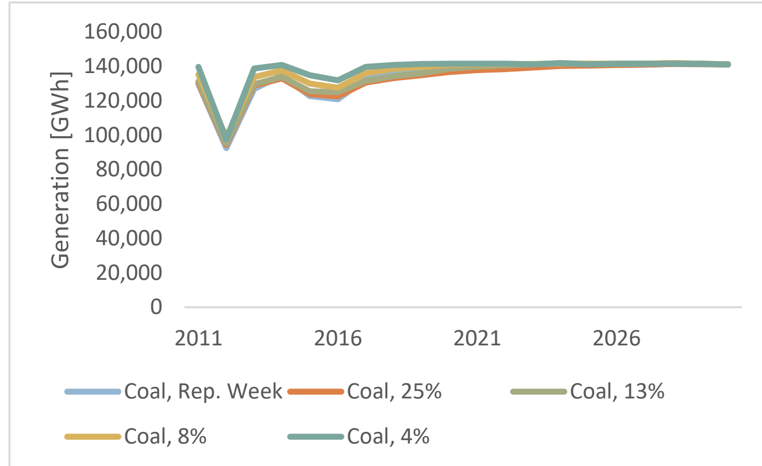

Figure 5. Effects of decreasing short-term simulation resolution—coal.

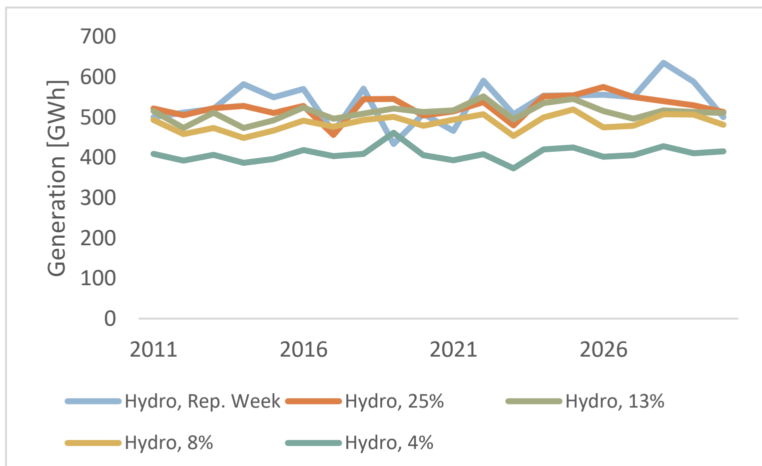

Figure 6. Effects of decreasing short-term simulation resolution—hydroelectric.

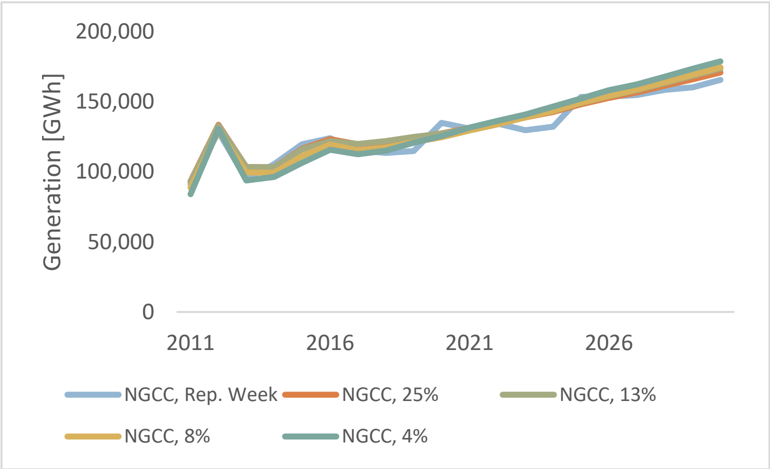

Figure 7. Effects of decreasing short-term simulation resolution—natural gas combined cycle.

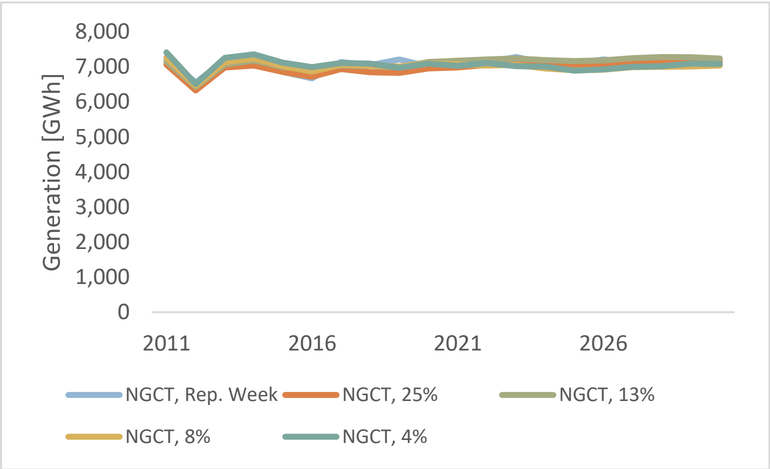

Figure 8. Effects of decreasing short-term simulation resolution—natural gas combustion turbine.

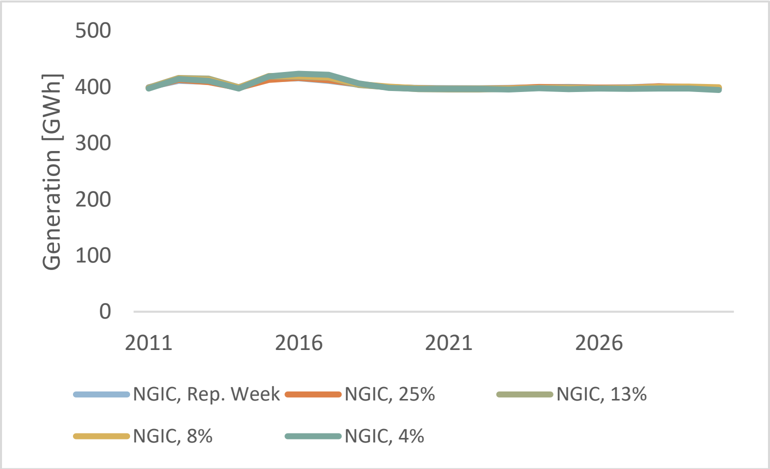

Figure 9. Effects of decreasing short-term simulation resolution—natural gas internal combustion engine.

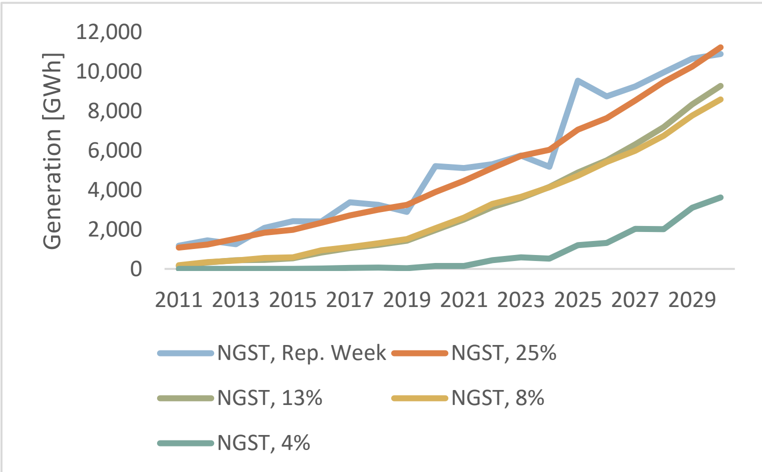

Figure 10. Effects of decreasing short-term simulation resolution—natural gas steam turbine.

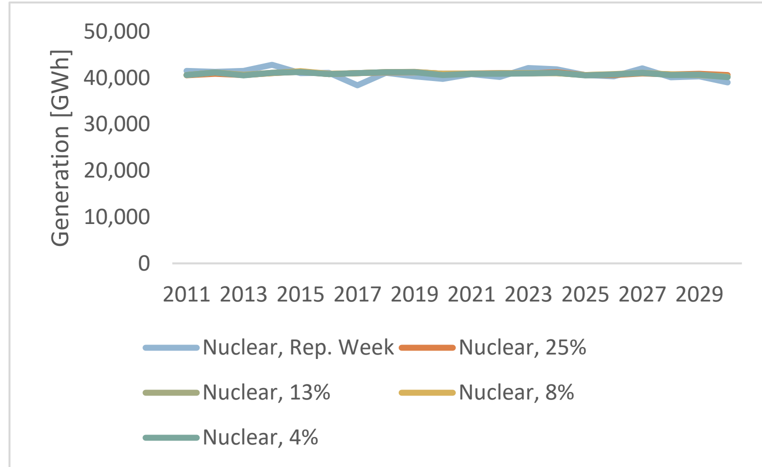

Figure 11. Effects of decreasing short-term simulation resolution—nuclear.

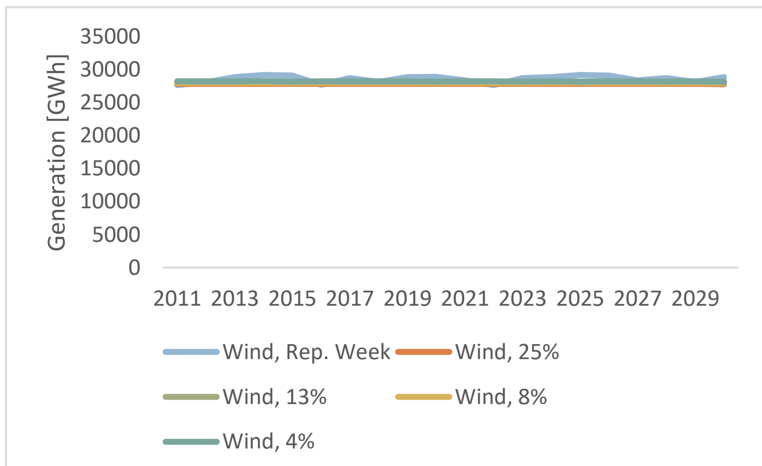

Figure 12. Effects of decreasing short-term simulation resolution—wind.

Short-Term Production Cost—Aggregating Generators

Two different methods of aggregating generators were compared against the baseline (all individual units): aggregating biomass, natural gas combined cycle, natural gas combustion turbines, natural gas internal combustion engines, and natural gas steam turbines; and aggregating all of those technologies plus coal (Figures 13–21). The first set of aggregations without coal had a very minor effect on the generation breakdown overall. The largest relative changes in generation were +34% for natural gas internal combustion engines, +20% for natural gas combustion turbines, +14% for biomass, and -4% for natural gas steam turbines. The small relative decrease in coal generation was almost entirely replaced by natural gas combined cycle and natural gas combustion turbine generation. Overall, the effects of these aggregations were small compared to the computational boost.

Aggregating coal plants with the others caused significant distortions in generation. Biomass generation increased by 14%, hydroelectric by 3%, natural gas combined cycle by 46%, natural gas combustion turbines by 28%, natural gas internal combustion engines by 58%, and natural gas steam turbines by 262% (3.6×). These increases came at the expense of coal generation, which dropped 53% (Figure 14). Nuclear and wind generation stayed the same. These effects are likely due to the larger size of the coal plants relative to the other generator types. Another consequence of this aggregation is that retirements for these types would happen in larger chunks than otherwise. However, this may be more appropriate since it is likely that an entire power plant would retire rather than an individual unit at a plant.

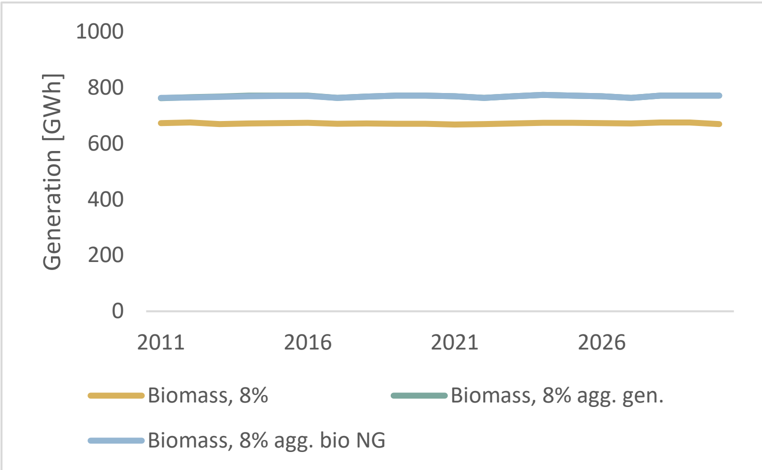

Figure 13. Effects of aggregating generators on short-term dispatch—biomass.

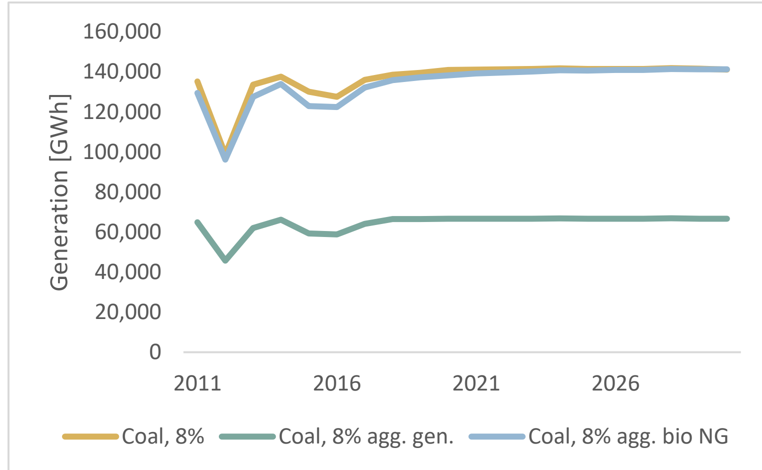

Figure 14. Effects of aggregating generators on short-term dispatch—coal.

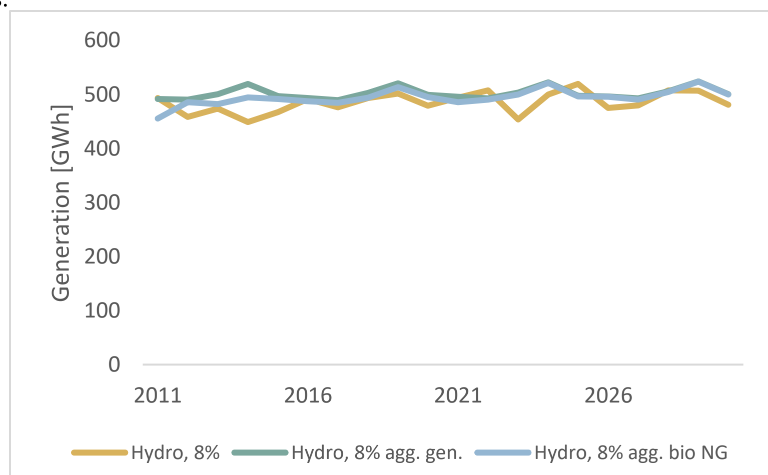

Figure 15. Effects of aggregating generators on short-term dispatch—hydro.

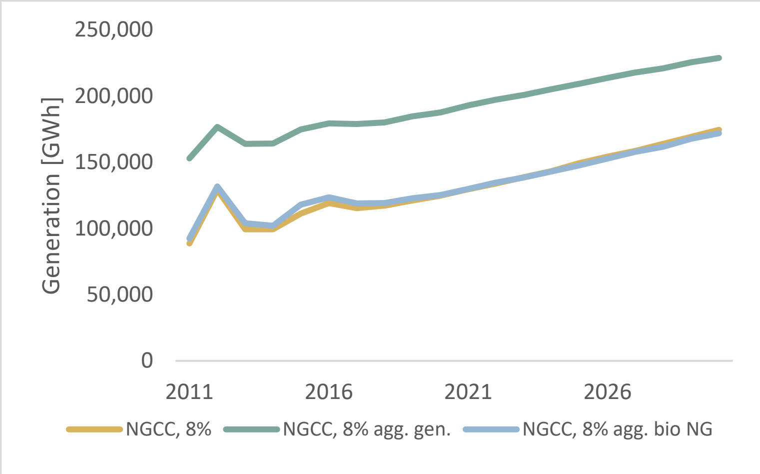

Figure 16. Effects of aggregating generators on short-term dispatch—natural gas combined cycle.

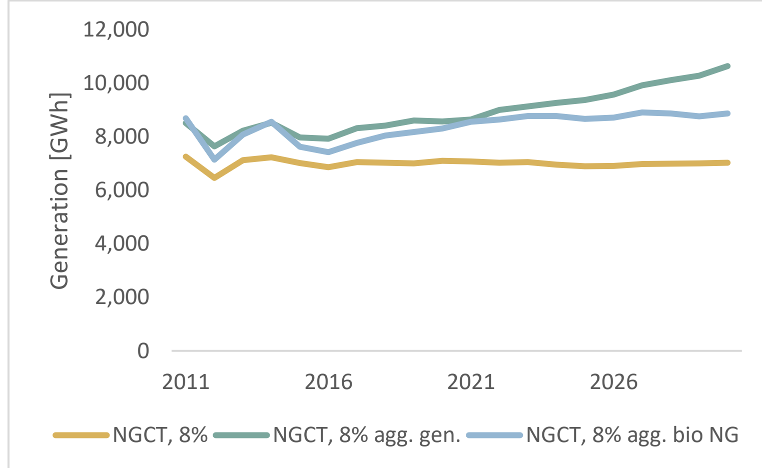

Figure 17. Effects of aggregating generators on short-term dispatch—natural gas combustion turbine.

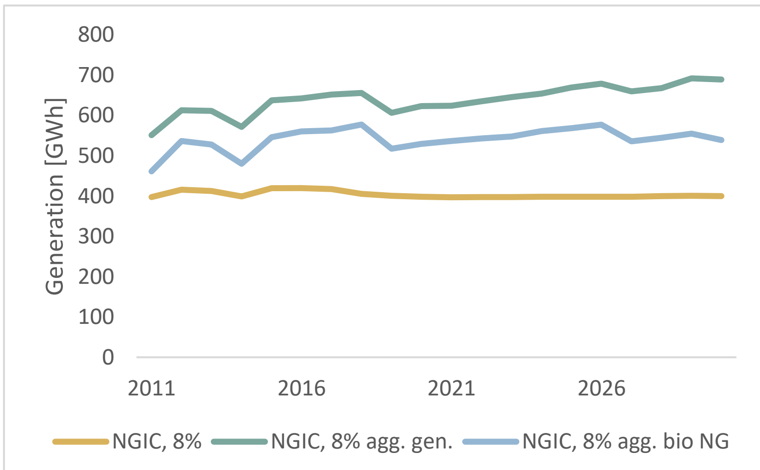

Figure 18. Effects of aggregating generators on short-term dispatch—natural gas internal combustion engine.

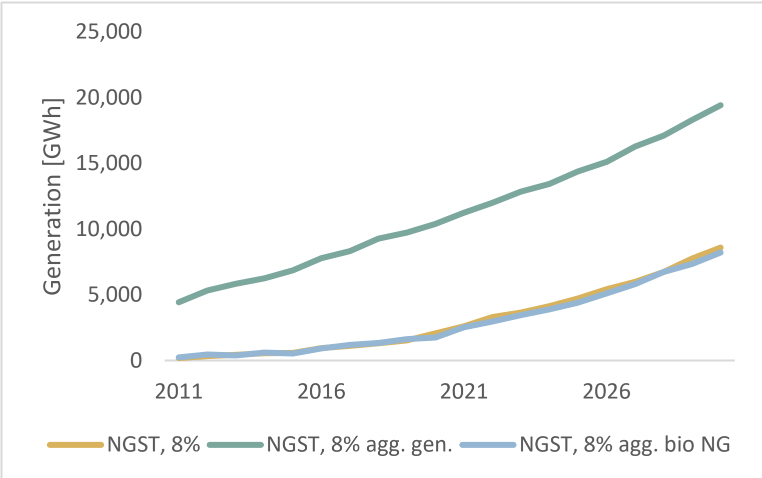

Figure 19. Effects of aggregating generators on short-term dispatch—natural gas steam turbine.

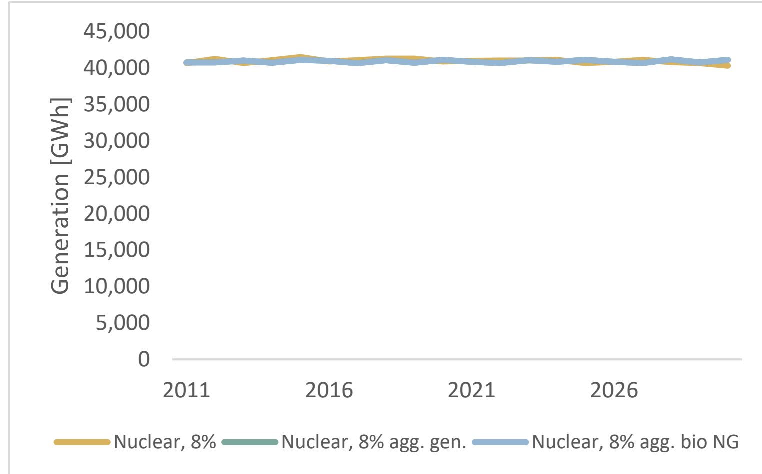

Figure 20. Effects of aggregating generators on short-term dispatch—nuclear.

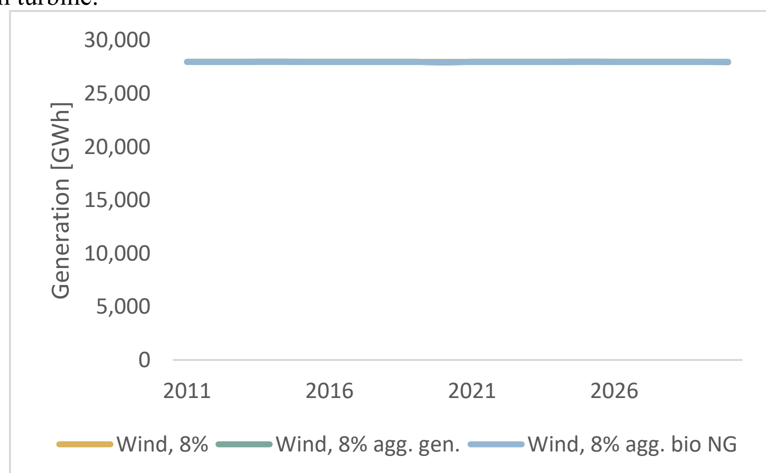

Figure 21. Effects of aggregating generators on short-term dispatch—wind.

Model Runtimes

The model runtimes for a select number of simulations are shown in Figures 22 and 23. In both cases, the total runtime tended to increase at least linearly as the number of non-zero integers increased. This illustrates the value of minimizing the optimization step size.

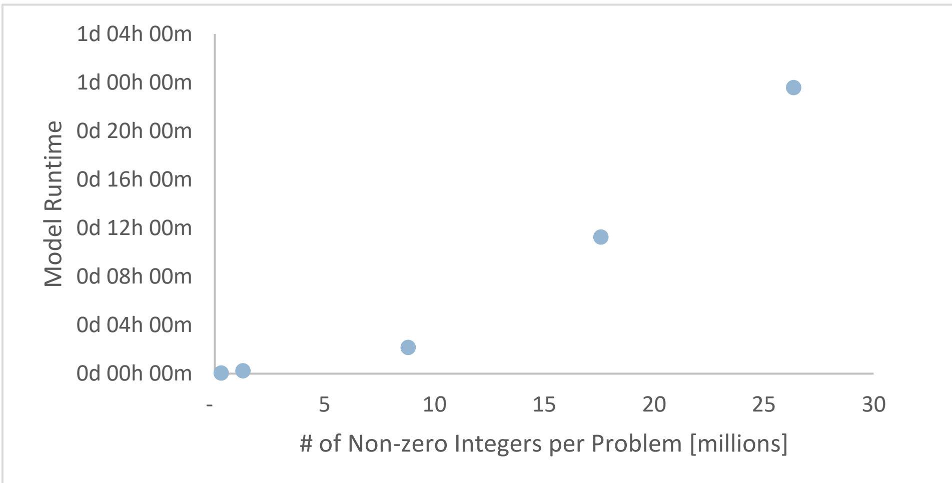

Figure 22. Capacity expansion model runtimes.

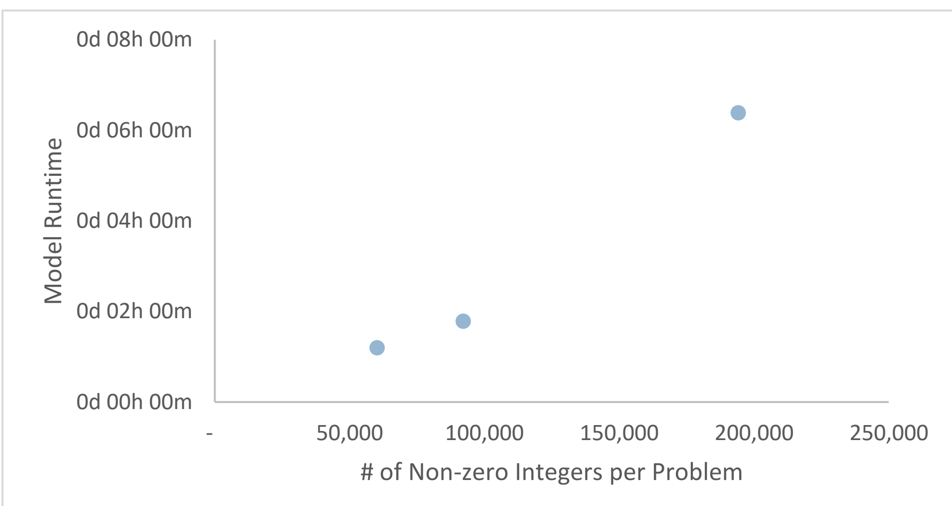

Figure 23. Production cost model runtimes.

HISTORICAL VS. SIMULATED CAPACITY EXPANSION, 2011–2016

The long-term capacity expansion model simulated new construction and retirement for the period from 2011–2030 across sixteen scenarios. The scenarios were set up as permutations of four different parameters, each with two possible values. For brevity, these were assigned a position in a sequence of four characters, with values of either A or B (Table 1). For example, permutation AAAA corresponds to the High Oil Price natural gas price forecast, the Low Economic Growth load growth forecast, the baseline capital cost declines for wind and solar PV, and no carbon tax.

Table 1. Scenario permutation nomenclature.

	Natural Gas Price	**Load Growth**	**Capital Cost Declines**	**Carbon Tax**
A	High Oil Price	Low Economic Growth	Base	None
B	High Oil and Gas Resource	ERCOT Historical	Aggressive	Social Cost of Carbon

The permutation BBAA is most similar to the historical trends, so it can be compared against the builds and retirements in ERCOT from 2011–2016 (Figures 24–26). For this analysis, retirements include permanent shutdowns, mothballed plants, and plants that otherwise disconnected from the ERCOT grid. Over this period, there was one new biomass plant built in ERCOT and one retirement; the simulation did not build any new biomass, but it did retire a similar amount. Two new coal plants came online, while two retired; the simulation did not build or retire any coal. The construction lead time for new coal plants means that new build decisions were made several years before 2011. Likewise, actual coal retirements may have been partially due to expected emissions compliance costs rather than simple economics. There was a significant amount of new natural gas generation built, including over 3,200 MW of combined cycle, 1,100 MW of combustion turbine, and 600 MW of internal combustion engines; retirements were primarily steam turbines (almost 1,700 MW), with one combined cycle plant retired and another switching to a different grid (750 MW). The simulation did not build any new combined cycle or internal combustion engines, but it did build some new combustion turbines (nearly 1,500 MW); retirements included some combined cycle and combustion turbines, but were primarily steam turbines (3,800 MW). Historical solar additions were over 500 MW, while the simulation did not build any. For wind, historical new construction was over 8,500 MW, while the simulation built 4,500 MW.

The largest discrepancies between historical and simulated new construction were for wind, natural gas combined cycle, and wind. If historical coal retirements are included, the net change in coal is nearly zero, which essentially matches the simulation. It is likely that combined cycle generation was overbuilt based on optimistic projections of wholesale prices. Indeed, one nearly-new combined cycle plant in ERCOT recently filed for Chapter 11 bankruptcy protection [60]. Both wind and solar had lead time constraints built in, so new generators already planned or under construction before 2011 were not included. If the yearly wind construction in the simulation was extrapolated to 2011, new construction would have been nearly 7,500 MW for the period. The difference in retirements is significant for natural gas steam turbines, with more than twice the capacity retired in the simulation as in reality. It is possible that operating costs or heat rates for these plants are overestimated. Finally, the objective function of the capacity expansion model is to minimize total system costs, while power producers in ERCOT are free to build new plants if financing can be secured, so there may be excess capacity at times.

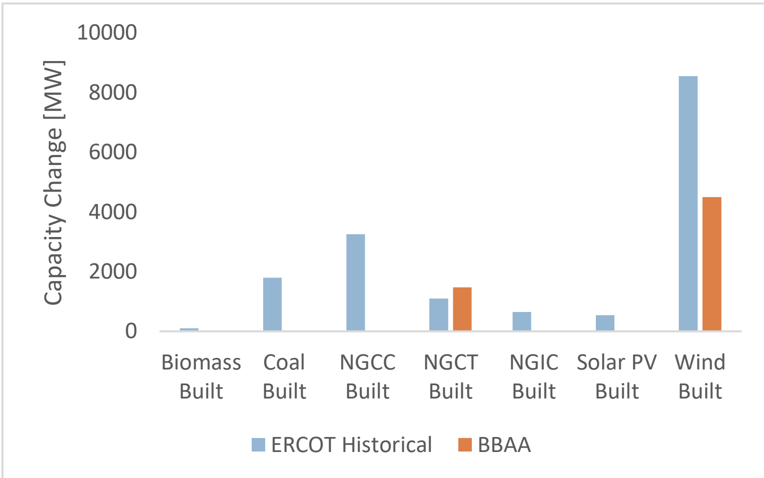

Figure 24. New construction 2011–2016, ERCOT historical vs. permutation BBAA.

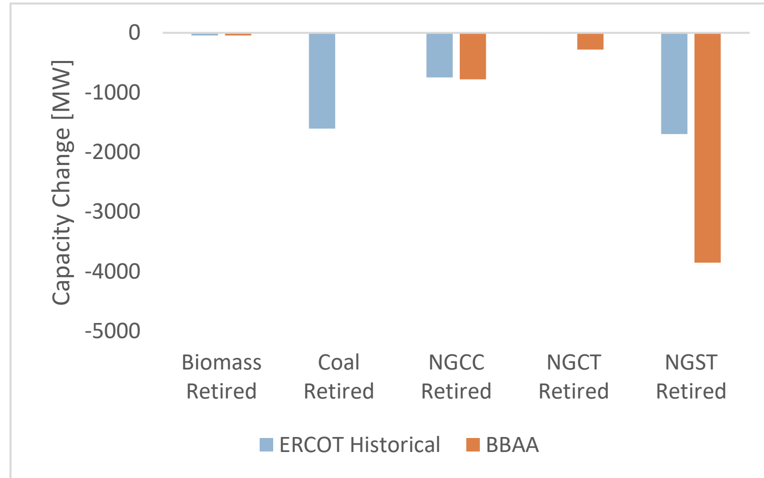

Figure 25. Retirements 2011–2016, ERCOT historical vs. permutation BBAA.

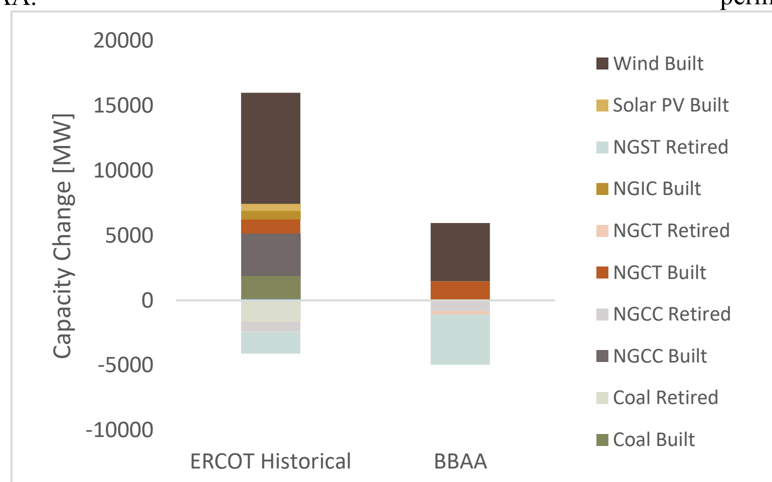

Figure 26.Total construction and retirements 2011–2016, ERCOT historical vs. permutation BBAA.

Capacity Expansion

Construction and retirement results from the capacity expansion runs are presented in Figure 27. In general, the higher natural gas prices in the High Oil Price scenario (permutations beginning with Axxx) tended to support the construction of more wind and solar PV than the High Oil and Gas Resource scenario. These permutations also tended to build less new natural gas plants and retire more existing natural gas plants. Only one or two coal

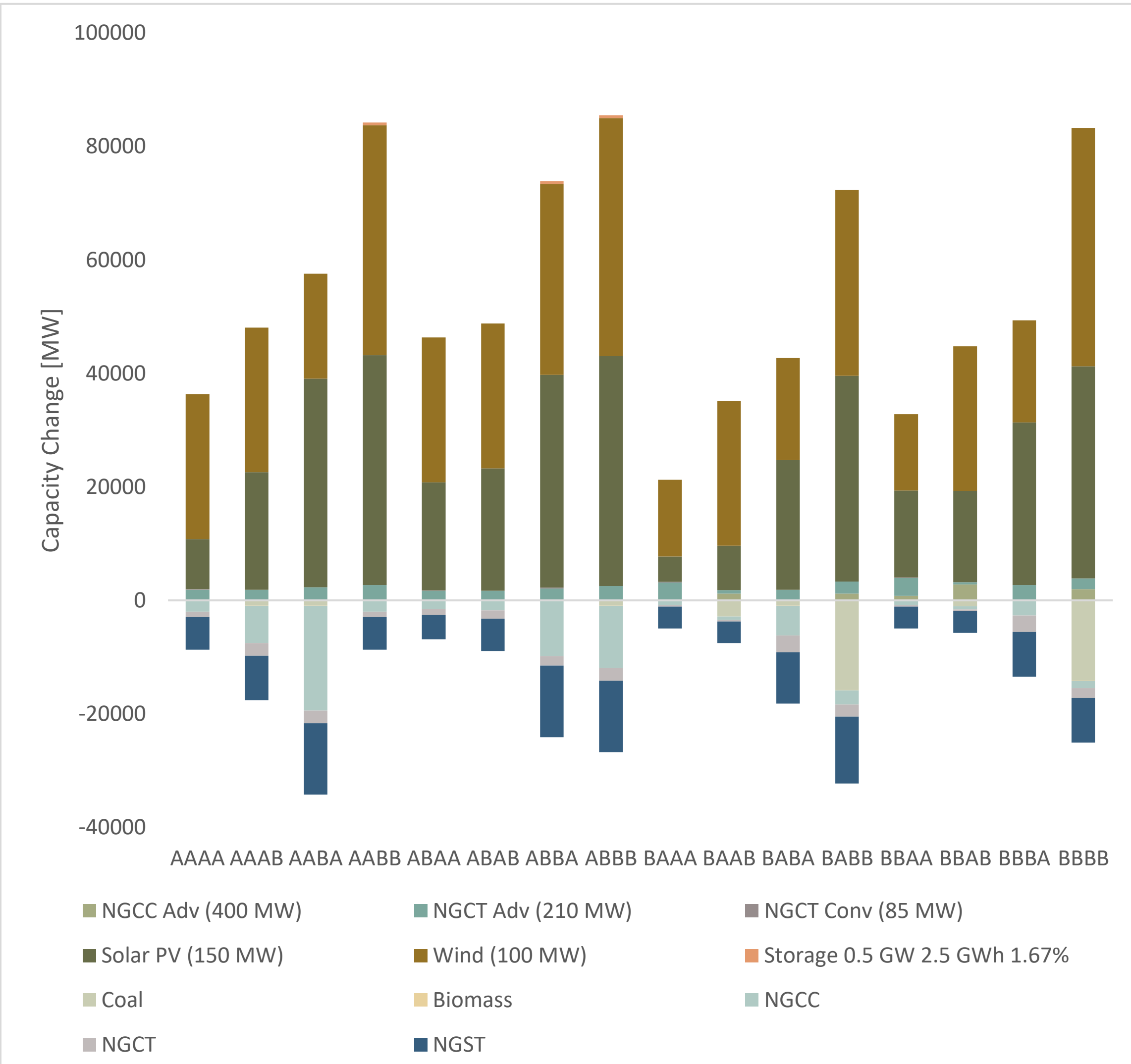

Figure 27. Long-term capacity expansion results for sixteen permutations.

plants were retired in any of the eight High Oil Price permutations. The lower peak and total demand growth of the Low Economic Growth scenario tended to support less new construction but more existing retirements than the ERCOT Historical scenario of higher growth. The Aggressive Capital Cost Declines scenario tended to enhance the construction of solar PV and wind compared to the baseline capital cost scenario, and in most cases this led to the retirement of more existing resources. The same trend was generally true for the carbon tax, but acting together, these two scenarios produced the largest amount of coal retirements in two permutations (BABB and BBBB). Coal retirements were very limited otherwise.

Steam accumulator candidates were built in three permutations: AABB, ABBA, and ABBB. These were permutations where the natural gas prices were relatively high and the largest amounts of wind and solar PV were built. The same type of steam accumulator was chosen in all three: a 500 MW generator, 2.5 GWh of energy capacity, and a faster ramp rate of 1.67%/min. This system did not have the lowest capital or fixed O&M costs; the comparable 1,000 MW system had lower fixed costs. However, the annuitized cost for the smaller system was less due to lower capital requirements. These results for steam accumulators are likely sensitive to financing assumptions, especially the cost of capital and tax rates.

SENSITIVITY STUDIES

Increasing the temporal resolution of the simulation may improve the accuracy of dispatch, among other things, but it comes at a computational cost. To see the effects of increasing resolution on the long-term capacity expansion problem, the LDC step size was changed from 1 block per week (0.6%) to 1 block per day (4%). Because the LDC algorithm only balances storage reservoirs between LDCs, the simulation was expected to build storage. However, the significant increase in problem size manifested as an integer infeasibility, so a linear optimization was used instead. The difference in total additions was about +5%, with retirements increasing +15% (Figure 28). The composition of the additions was slightly different, with less solar being built and much more natural gas combined cycle and combustion turbine capacity in the higher resolution case. Wind additions were identical. The additional retirements in the 4% resolution case were natural gas combustion turbines and steam turbine units. Although the higher-resolution scenario resulted in steam accumulator additions at all four reactors, the total additions were only 53 MW, which is much smaller than one single project. Thus, it can be difficult to interpret linear-optimal expansion results in terms of sub-unit capacities. This will be an area of further exploration to determine if the integer infeasibilities can be addressed.

In defining the steam accumulator candidates, the fixed O&M costs were assumed to be 5% of the overnight capital costs per year. For a sensitivity study, the fixed O&M

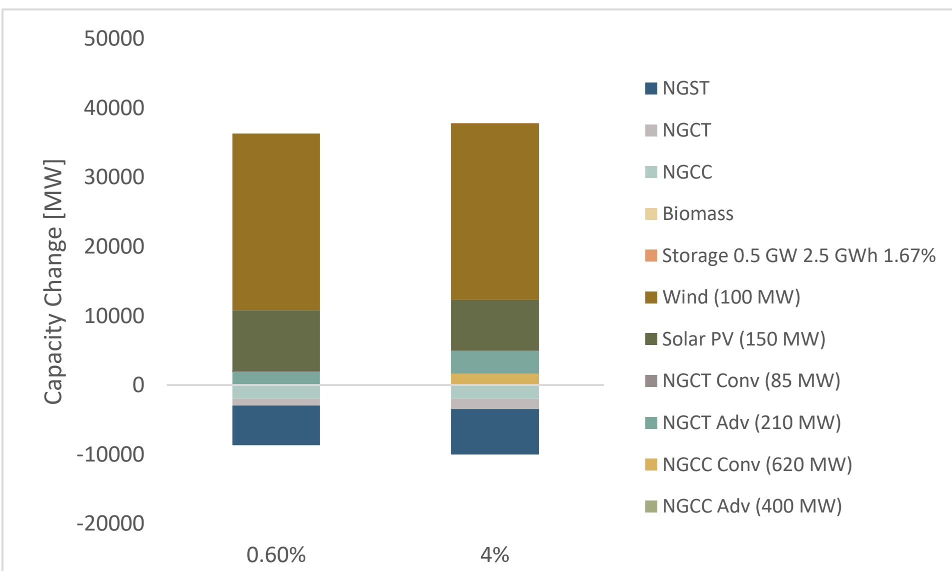

Figure 28. Build and retirement comparison, 0.6% vs. 4% resolution.

costs were reduced to 2% to investigate the number and variety of steam accumulator candidates that would be built. The results were almost identical to the original 5% fixed O&M cost scenario except that a steam accumulator was built in the AAAA permutation where none was built before. This came at the expense of some solar PV capacity.

In ERCOT's market design, market participants must secure financing to build new generation based on economics alone. This energy-only market model is contrasted with other competitive wholesale markets that have forward capacity auctions (e.g., PJM) and traditional wholesale and capacity markets that are wholly regulated. One of the potential downsides of an energy-only market is that price signals may not support enough generation to ensure a certain level of reliability. In the primary simulations, a reserve margin of 13.75% was set as recommended by NERC. This constraint was removed to see the effect on capacity reserves and average wholesale price. In the case with no reserve margin, the available capacity drops to near-zero by 2016 (Figure 29). However, the effect on average

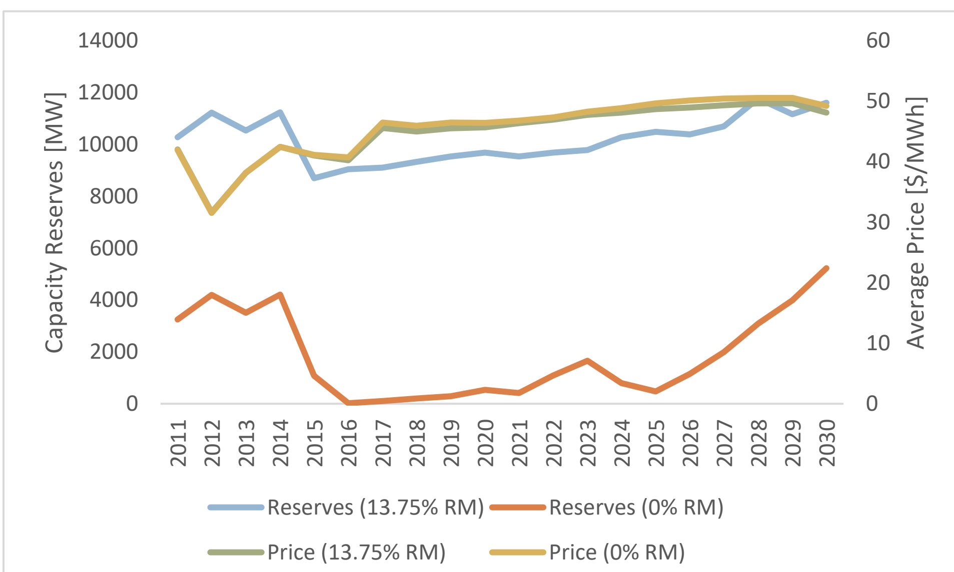

Figure 29. Reserve margin and price comparison, permutation BBBB

price is negligible. The same permutations that supported building steam accumulator candidates in the main study (AABB, ABBA, AABB) also built storage in the no reserve margin cases.

Conclusions

In this work, the construction of steam accumulator retrofits was successfully simulated for nuclear power plants in the ERCOT grid. Sixteen different permutations of four scenarios pairs were used to outline the uncertainty of future market conditions. Steam accumulator retrofits were added in three of the permutations that had high future natural gas prices and aggressive capital cost declines, which led to significant construction of solar PV and wind generators. Two of the permutations saw higher total demand and peak load growth, and two had a carbon tax. This suggests that large-scale thermal energy storage systems may be most successful in future markets with these three conditions.

Future Work

Although the models used in these studies contain many parameters and constraints, there are many other details that were omitted. Some of these are especially important in the context of energy storage and decarbonized electricity objectives. The tradeoffs between more accurate models and increased computation time are ever present, but the areas discussed below could add significant value in future studies.

The design of the optimization problem can have a large effect on the runtime and results. For example, multi-year constraints like mutually-exclusive projects generally require that the step size cover the entire constraint horizon. In this case, if one type of steam accumulator is built, no other types should be built later. The increase in step size significantly increases the solution time without much change in results. It would be beneficial to pre-solve very long-term constraints outside of the main model so that step sizes could be minimized. There are also some sub-yearly, medium-term constraints that could be more accurately modeled, including hydroelectric generator releases, planned maintenance outages (especially related to reserve margins), and large thermal generator unit commitment (e.g., minimum down times for coal and nuclear plants).

For the capacity expansion model, increasing the resolution between LDCs had a small effect on construction and retirement results, but it is unclear if there was an impact on storage because a linear solution had to be used. Thus, finding a way around the integer infeasibilities would allow long-term expansion to be run at finer resolutions. This would show if the increased complexity is warranted. This may only be useful if the capacity expansion formulation includes estimated revenues in the build decisions. In addition to this, the performance of the LDC algorithm could be compared to a fitted chronology or high-resolution sampling algorithm.

There are several improvements that could be made to the existing generator database. CHP generators were modeled with deratings based on their average historical electrical output, but an industrial CHP operator might want to self-dispatch when the value of electricity is higher than the value of the industrial heat. If heat values could be obtained, this would improve the dispatch accuracy. Currently, combined cycle natural gas plants are set up as single units with lower heat rates than combustion turbines in the ERCOT market models. PLEXOS allows waste heat from combustion turbines to be ported to a heat recovery steam generator to model combined cycles more realistically. For longer-term analyses, the effects of age on plant components should be modeled. For instance, the heat rates of thermal power plants typically decline with age [61], as does wind farm capacity [52]. At some point, the plant would need to make major investments in maintenance or retrofits to continue operating. In ERCOT, this will be important for wind farm operation beyond 2030. Besides component wear, other types of retrofits could be considered including carbon capture for combustion-based generators and emissions scrubbers for older coal plants to comply with air quality standards. Nuclear plant license extensions could also be factored into long-term fixed costs [62].

For long-term capacity expansion, at least three major areas of the model could be enhanced: new generator candidates, transmission, and distribution-level resources. The generator candidates used in this work were a subset of those available in the Annual Energy Outlook. Additional candidates could be added, including coal and natural gas generators with CCS, fuel cells, smaller nuclear reactors, concentrating solar thermal, and offshore wind. However, without financial incentives or subsidies, many of these technologies will be less profitable than their counterparts (e.g., CSP vs. PV). Other technologies, like new hydroelectric, municipal solid waste, and geothermal, are constrained by site resource requirements, which would require separate research. Additional thermal energy storage options for nuclear power plants could be modeled, including molten salt and silica/alumina materials. It would be advantageous to include other types of energy storage as competitors in the model, especially various types of batteries, compressed air, and pumped hydroelectric (assuming site availability).

Large amounts of wind and solar PV generation were built in many permutations of this study. If a certain degree of reliability is desired, the types and amounts of operating reserves may need to be adjusted to accommodate large swings in net load. It is also clear that more transmission capacity would need to be built to accompany increased wind and solar production without curtailment. Including a reduced-order transmission network would help pinpoint congestion, and including transmission expansion in the problem formulation would show the additional infrastructure costs of wind and solar buildout. However, this would increase the computational complexity of the model, especially if a detailed network was used. Although distribution networks are usually beyond the scope of region-wide long-term planning, the falling costs of residential solar PV and introduction of large residential battery systems mean that distribution-level resources could become non-trivial players in future electricity markets [63]. In addition to solar PV and batteries, building management technologies that reduce or shift peak loads are becoming more prevalent, especially for heating and cooling loads. Incorporating demand response technologies as an alternative to peak capacity could produce interesting results.

The scenario-based implementation of uncertainty could be improved in several ways. Generally, adding one or more intermediate cases (e.g., low, medium, high natural gas prices) would cover more of the option space, but it is unclear if the intermediate results would give additional insight into the underlying uncertainty. Fuel price forecasts could be improved with finer temporal resolution (e.g., monthly prices), coupling delivered subbituminous coal prices to oil prices (due to diesel costs driving rail delivery prices), and including demand curves. The load forecasts only covered growing demand and peak load, so including flat and declining forecasts could be helpful, at least as sensitivity studies. The Aggressive Capital Cost Declines scenario only covered wind and solar PV, but cost declines are also happening for many battery technologies. The social cost of carbon metric employed was one amongst many, and it only included the U.S. contribution to the global social cost. Various other carbon taxes could be explored, including more and less aggressive mitigation cases. Finally, other types of market and policy uncertainty could be explored. For instance, the financing assumptions could bias the model towards building more capital-intensive projects than if the cost of capital were higher. Different policies that cover generator subsidies, environmental standards, market design, and grid reliability could be simulated as well.

Appendices

APPENDIX A—U.S. CONSUMER PRICE INDEX: HISTORICAL VALUES AND FORECAST

The U.S. Department of Labor, Bureau of Labor Statistics publishes several indices for inflation in the United States. The Consumer Price Index for All Urban Consumers (CPI-U) was used with the baseline value of 100 for 1982–1984 (CUUR0000SA0) [64]. This series covers 2007–2016. A simple linear regression was calculated to forecast the CPI-U from 2017–2030. For the forecast years, the annual inflation rate ranges from 2.4%/yr in 2017 (first forecast year), 1.5%/yr in 2018, and 1.3%/yr by 2030.

Table 2. U.S. Consumer Price Index—historical (2007–2016) [64] and forecast.

Year	CPI-U Annual	Relative to 2011
2007	207.342	0.922
2008	215.303	0.957
2009	214.537	0.954
2010	218.056	0.969
2011	224.939	1.000
2012	229.594	1.021
2013	232.957	1.036
2014	236.736	1.052
2015	237.017	1.054
2016	240.007	1.067
2017	245.860	1.093
2018	249.535	1.109
2019	253.210	1.126
2020	256.884	1.142
2021	260.559	1.158
2022	264.234	1.175
2023	267.907	1.191
2024	271.583	1.207
2025	275.258	1.224
2026	278.933	1.240
2027	282.608	1.256
2028	286.282	1.273
2029	289.957	1.289
2030	293.632	1.305

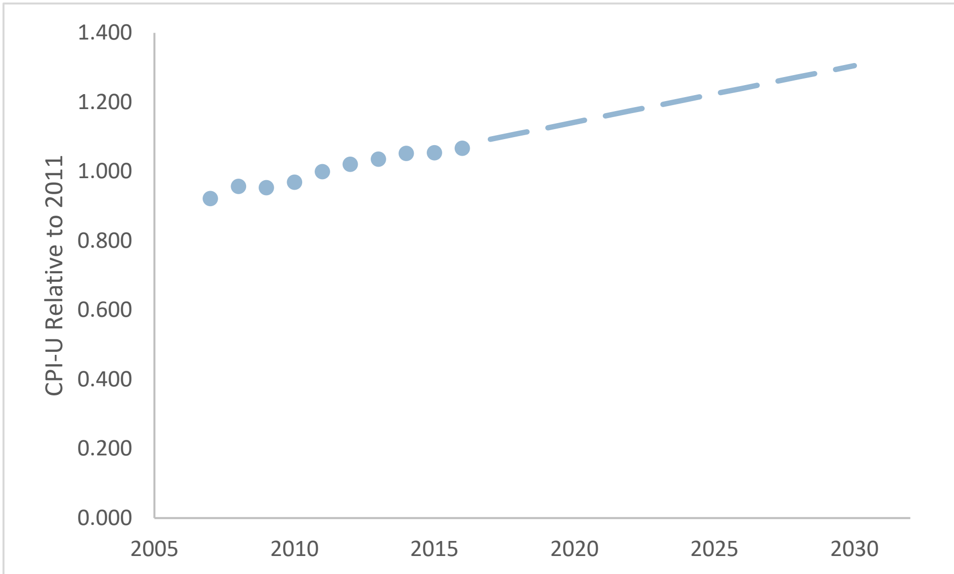

Figure 30. Inflation relative to 2011, historical and forecast.

APPENDIX B—PRODUCTION TAX CREDIT FOR WIND PROJECTS

The baseline year for the PTC is 1993 when the PTC was set at 1.5¢/kWh ($15/MWh). The IRS publishes a new inflation adjustment factor each year to hold the credit value steady in real terms. To calculate the pre-tax value of the PTC, the post-tax value is divided by one minus the corporate tax rate (assumed to be 35%).

$$PTC_{pre} = \frac{PTC_{post}}{1 - TaxRate} \tag{2}$$

Thus, the post-tax PTC in 2011 was $21.69/MWh, while the pre-tax PTC was $33.37/MWh.

Table 3. PTC Schedule and PTC-Adjusted VO&M.

Year	**IRS Inflation Adjustment Factor**	**PTC [$/MWh]**	**PTC-Adjusted VO&M [2011 $/MWh]**
2011	1.4459	(33.37)	(33.37)
2012	1.4799	(34.15)	(33.37)
2013	1.5063	(34.76)	(33.37)
2014	1.5088	(34.82)	(33.37)
2015	1.5336	(35.39)	(33.37)
2016	1.5556	(35.90)	(33.37)
2017	1.5762	(29.10)	(26.69)
2018	1.5966	(22.11)	(20.02)
2019	1.6169	(14.93)	(13.35)
2020	-	0.00	0.00

APPENDIX C—INVESTMENT TAX CREDIT FOR SOLAR PROJECTS

Because the overnight capital cost for solar PV projects declines over time in the Baseline and Aggressive Capital Cost Declines scenarios, the value of the ITC in absolute terms also changes over time. Thus, there is a different ITC schedule for each scenario. The fixed O&M cost for solar PV in both scenarios was $24.69/kW-yr (2011 USD).

Table 4. ITC for the Baseline Scenario.

Year	PV Capital Cost [2011 $/kW]	ITC [%]	ITC [2011 $/kW]	FO&M Subtractor [2011 $/kW-yr, 20 yr]	ITC-Adjusted FO&M [2011 $/kW-yr]
2011	2,500.00	30%	750.00	(37.50)	(12.81)
2012	1,959.45	30%	587.84	(29.39)	(4.70)
2013	1,689.77	30%	506.93	(25.35)	(0.66)
2014	1,425.25	30%	427.58	(21.38)	3.31
2015	1,376.11	30%	412.83	(20.64)	4.05
2016	1,218.38	30%	365.52	(18.28)	6.41
2017	1,218.38	30%	365.52	(18.28)	6.41
2018	1,218.38	30%	365.52	(18.28)	6.41
2019	1,218.38	30%	365.52	(18.28)	6.41
2020	1,218.38	26%	316.78	(15.84)	8.85
2021	1,218.38	22%	268.04	(13.40)	11.29
2022	1,218.38	10%	121.84	(6.09)	18.60

Table 5. ITC for the Aggressive Capital Cost Declines Scenario.

Year	**PV Capital Cost [2011 $/kW]**	**ITC [%]**	**ITC [2011 $/kW]**	**FO&M Subtractor [2011 $/kW-yr, 20 yr]**	**ITC-Adjusted FO&M [2011 $/kW-yr]**
2011	2,500.00	30%	750.00	(37.50)	(12.81)
2012	1,959.45	30%	587.84	(29.39)	(4.70)
2013	1,689.77	30%	506.93	(25.35)	(0.66)
2014	1,425.25	30%	427.58	(21.38)	3.31
2015	1,376.11	30%	412.83	(20.64)	4.05
2016	1,218.38	30%	365.52	(18.28)	6.41
2017	1,111.17	30%	333.35	(16.67)	8.02
2018	1,013.38	30%	304.02	(15.20)	9.49
2019	924.21	30%	277.26	(13.86)	10.83
2020	842.88	26%	219.15	(10.96)	13.73
2021	768.70	22%	169.11	(8.46)	16.23
2022	701.06	10%	70.11	(3.51)	21.18

Appendix D—Fuel Prices: Historical Values and Forecasts

Biomass

Historical biomass prices for Texas were taken from the U.S. EIA State Energy Data System, "Table ET7. Electric Power Sector Price and Expenditure Estimates, 1970–2014, Texas" [44]. This excludes landfill gas generators (see Landfill Gas below).

Table 6. Biomass prices—historical (2008–2014) [44] and forecast (2015–2030).

Year	Biomass [$/MMBtu]	Biomass [2011$/MMBtu]
2008	2.66	2.78
2009	2.20	2.31
2010	2.40	2.48
2011	2.43	2.43
2012	2.22	2.17
2013	2.25	2.17
2014	2.70	2.57
2015		2.24
2016		2.20
2017		2.16
2018		2.11
2019		2.07
2020		2.03
2021		1.98
2022		1.94
2023		1.90
2024		1.85
2025		1.81
2026		1.77
2027		1.72
2028		1.68
2029		1.64
2030		1.59

Coal, Lignite

Historical lignite prices for Texas were taken from the U.S. EIA Coal Data Browser [45], with the primary source from EIA Form 923.

Table 7. Lignite coal prices—historical (2008–2015) [45] and forecast (2016–2030).

Year	Lignite [$/short ton]	Lignite [2011$/short ton]	Heat Content [Btu/lb.]	Lignite [2011$/MMBtu]
2008	20.11	21.01	6514	1.61
2009	23.52	24.66	6434	1.92
2010	22.84	23.56	6521	1.81
2011	22.02	22.02	6566	1.68
2012	23.80	23.32	6541	1.78
2013	23.09	22.30	6584	1.69
2014	23.42	22.25	6598	1.69
2015	25.07	23.79	6536	1.82
2016				1.75
2017				1.75
2018				1.75
2019				1.76
2020				1.76
2021				1.76
2022				1.76
2023				1.76
2024				1.76
2025				1.76
2026				1.76
2027				1.76
2028				1.76
2029				1.76
2030				1.76

Coal, Subbituminous

Historical subbituminous prices for Texas were taken from the U.S. EIA Coal Data Browser [45], with the primary source from EIA Form 923.

Table 8. Subbituminous coal prices—historical (2008–2015) [45] and forecast (2016–2030).

Year	Subbit. [$/short ton]	Subbit. [2011$/short ton]	Heat Content [Btu/lb.]	Subbit. [2011$/MMBtu]
2008	28.12	29.38	8485	1.73
2009	27.68	29.02	8516	1.70
2010	32.10	33.11	8486	1.95
2011	33.64	33.64	8472	1.99
2012	32.77	32.11	8531	1.88
2013	35.95	34.71	8552	2.03
2014	36.14	34.34	8514	2.02
2015	34.11	32.37	8524	1.90
2016				2.05
2017				2.09
2018				2.12
2019				2.16
2020				2.19
2021				2.22
2022				2.26
2023				2.29
2024				2.33
2025				2.36
2026				2.39
2027				2.43
2028				2.46
2029				2.50
2030				2.53

Landfill Gas

EIA estimates for biomass fuel costs currently exclude landfill gas. Although the gas itself flows freely from a landfill, it is only 50–60% methane, with the remainder as carbon dioxide and some trace gases [65]. Thus, it must be processed to a higher quality for use in a heat engine, typically a gas turbine or reciprocating internal combustion engine. Waste Management estimated in 2013 that LFG processing costs for power production were between $4–6/MMBtu [46]. Therefore, a fixed price of $5/MMBtu was used across the entire planning horizon (2011–2030).

Natural Gas

Historical natural gas prices (2011–2016) were found in [44], Table ET7 for the United States. These are quoted in nominal USD and were converted to 2011 USD. All prices in the AEO 2015 scenarios were in 2013 USD and were also converted to 2011 USD. The assumed conversion factor was 1.027 million Btu per thousand cubic feet of gas ($1.027\ MMBtu/Mcf$).

Table 9. Natural gas prices—historical (2011–2016) [44] and AEO 2015 forecast scenarios (2017–2030) [48].

	High Oil and Gas Resource		High Oil Price	
Year	**\$/Mcf**	**2011\$/MMBtu**	**\$/Mcf**	**2011\$/MMBtu**
2011	4.89	4.76	4.89	4.76
2012	3.54	3.38	3.54	3.38
2013	4.49	4.24	4.49	4.24
2014	5.19	4.80	5.19	4.80
2015	3.37	3.12	3.37	3.12
2016	2.99	2.74	2.99	2.74
2017	4.13	3.90	4.37	4.13
2018	3.84	3.63	4.47	4.22
2019	3.81	3.60	4.83	4.56
2020	3.77	3.56	5.25	4.96
2021	3.84	3.63	5.76	5.44
2022	3.88	3.67	6.22	5.88
2023	4.00	3.78	6.94	6.55
2024	4.03	3.80	7.40	6.99
2025	4.10	3.87	7.69	7.27
2026	4.15	3.92	7.84	7.41
2027	4.19	3.96	7.87	7.44
2028	4.25	4.01	7.79	7.36
2029	4.24	4.01	7.91	7.47
2030	4.25	4.01	8.10	7.65

Uranium

Unlike other fuels which have fixed heating values, the energy content of uranium-based fuel is a function of reactor *burnup*, defined as the amount of thermal energy extracted from fuel per unit mass of initial heavy metal, usually in units of megawatt-days per tonne of initial heavy metal (MWd/MTIHM) or gigajoules per kilogram of initial heavy metal (GJ/kgIHM). The burnup in a reactor is a function of fuel enrichment, core geometry, fuel shuffling patterns, and operational history, among other factors. In this analysis, a burnup of 3,888 GJ/kgIHM (45,000 MWd/MTIHM) was assumed, a typical value for U.S. reactors in the 2000s [66].

There are several steps in the uranium fuel fabrication process, from mining to final assembly, and each step has an associated cost that may be only slightly correlated with other steps. Historical prices for milled U_3O_8 were taken from the 2015 Uranium Marketing Annual Report, Table S1b [47]. For the final fuel assembly, a typical value of 8.9 kg of U_3O_8 per kg of assembly was used; most of the mined and milled uranium ends up as depleted uranium tails during enrichment. Enrichment costs were taken from Table S2 [47] in \$/kg SWU[9]. Fuel fabrication costs were assumed to be a constant \$300/kg. Total fuel assembly costs were calculated as follows:

$$Price_{FuelAssy} = \left(Price_{U_3O_8} \times \frac{8.9\ kg\ U_3O_8}{kg\ fuel\ assy}\right) + \left(Price_{SWU} \times \frac{7.3\ kg\ SWU}{kg\ fuel\ assy}\right) + \frac{\$300\ fuel\ fab}{kg\ fuel\ assy} \tag{3}$$

[9] SWU stands for separative work unit, the amount of effort and energy to enrich a feedstock to a specified enrichment of ^{235}U.

Given a burnup of 3,888 GJ/kgIHM, the heat price of uranium is

$$Price_{UraniumHeat} = \frac{Price_{FuelAssy}}{3{,}888\,\frac{GJ}{kgIHM}} \times \frac{1.055\ GJ}{MMBtu} \qquad (4)$$

Although there have been major price spikes in the U_3O_8 markets since 2004, the long-term trend over the last ten years has been relatively flat.

Table 10. Uranium prices—historical (2008–2015) [47] and forecast (2016–2030).

Year	U3O8 [$/kg]	kg U3O8/ kg Fuel Assy	SWU [$/kg SWU]	kg SWU/ kg Fuel Assy	Fuel Fab. [$/kg]	Fuel Assy [$/kg]	Burnup [GJ/kg]	Uranium [$/MMBtu]	Uranium [2011$/MMBtu]
2008	101.17	8.9	121.33	7.3	287.15	2,073.23	3,888	0.56	0.59
2009	101.12	8.9	130.78	7.3	286.13	2,140.80	3,888	0.58	0.61
2010	108.68	8.9	136.14	7.3	290.82	2,251.93	3,888	0.61	0.63
2011	122.69	8.9	136.12	7.3	300.00	2,385.58	3,888	0.65	0.65
2012	121.25	8.9	141.36	7.3	306.21	2,417.29	3,888	0.66	0.64
2013	114.64	8.9	142.22	7.3	310.69	2,369.18	3,888	0.64	0.62
2014	101.78	8.9	140.75	7.3	315.73	2,249.08	3,888	0.61	0.58
2015	97.31	8.9	136.88	7.3	316.11	2,181.36	3,888	0.59	0.56
2016	108.19	8.9	145.46	7.3	320.10	2,344.82	3,888	0.64	0.60
2017	108.10	8.9	147.63	7.3	327.90	2,367.69	3,888	0.64	0.59
2018	108.02	8.9	149.79	7.3	332.80	2,387.65	3,888	0.65	0.58
2019	107.93	8.9	151.96	7.3	337.70	2,407.62	3,888	0.65	0.58
2020	107.84	8.9	154.13	7.3	342.61	2,427.58	3,888	0.66	0.58
2021	107.76	8.9	156.30	7.3	347.51	2,447.54	3,888	0.66	0.57
2022	107.67	8.9	158.47	7.3	352.41	2,467.50	3,888	0.67	0.57
2023	107.58	8.9	160.64	7.3	357.31	2,487.46	3,888	0.67	0.57
2024	107.50	8.9	162.81	7.3	362.21	2,507.43	3,888	0.68	0.56
2025	107.41	8.9	164.98	7.3	367.11	2,527.39	3,888	0.69	0.56
2026	107.32	8.9	167.15	7.3	372.01	2,547.35	3,888	0.69	0.56
2027	107.24	8.9	169.31	7.3	376.91	2,567.31	3,888	0.70	0.55
2028	107.15	8.9	171.48	7.3	381.81	2,587.28	3,888	0.70	0.55
2029	107.06	8.9	173.65	7.3	386.71	2,607.24	3,888	0.71	0.55
2030	106.98	8.9	175.82	7.3	391.62	2,627.20	3,888	0.71	0.55

APPENDIX E—CARBON TAX

The carbon tax was set up in PLEXOS as a shadow price on emissions rather than a direct price. This allows carbon emissions to be included in the objective function during the optimization. Only coal and natural gas fuels were counted in the carbon accounting. Production rates used were published by EIA [67], although the rates do vary somewhat depending on the source. Biomass and landfill gas were excluded because they are usually considered carbon neutral. Hydroelectric and nuclear units were excluded as well.

Table 11. Carbon tax rates based on a social cost of carbon metric [59].

Year	2011$/tonne CO_2	2011$/tonne C	2011$/lb. CO_2
2011	-	-	-
2012	-	-	-
2013	-	-	-
2014	-	-	-
2015	16.49	60.46	0.0075
2016	17.27	63.34	0.0078
2017	18.10	66.36	0.0082
2018	18.96	69.53	0.0086
2019	19.86	72.85	0.0090
2020	20.81	76.32	0.0094
2021	21.80	79.96	0.0099
2022	22.84	83.78	0.0104
2023	23.93	87.77	0.0109
2024	25.07	91.96	0.0114
2025	26.27	96.35	0.0119
2026	27.52	100.94	0.0125
2027	28.84	105.76	0.0131
2028	30.21	110.80	0.0137
2029	31.65	116.09	0.0144
2030	33.16	121.62	0.0150

Table 12. Carbon emissions rates for select fuels [67].

Fuel	**Production Rate [g C/MJ$_{th}$]**	**Production Rate [lbs. CO_2/MMBtu]**
Coal, lignite	25.25	215.4
Coal, sub.	25.12	214.3
Natural gas	13.72	117.0

APPENDIX F—LOAD GROWTH FORECASTS AND VALUE OF LOST LOAD

Table 13. Load growth forecasts.

	AEO 2015, Low Economic Growth [48]		ERCOT Historical [58]	
Year	**Peak [MW]**	**Energy [GWh]**	**Peak [MW]**	**Energy [GWh]**
2007	62,115	307,000	62,115	307,000
2008	62,103	311,000	62,103	311,000
2009	63,407	307,000	63,407	307,000
2010	65,713	318,000	65,713	318,000
2011	67,557	331,960	67,557	331,960
2012	66,558	325,000	66,558	325,000
2013	67,253	332,000	67,253	332,000
2014	66,464	340,000	66,464	340,000
2015	69,620	347,000	69,620	347,000
2016	71,093	349,000	71,093	349,000
2017	71,520	351,094	72,088	354,375
2018	71,949	353,201	73,098	359,832
2019	72,380	355,320	74,121	365,373
2020	72,815	357,452	75,159	371,000
2021	73,252	359,596	76,211	376,714
2022	73,691	361,754	77,278	382,515
2023	74,133	363,924	78,360	388,406
2024	74,578	366,108	79,457	394,387
2025	75,025	368,305	80,569	400,461
2026	75,476	370,515	81,697	406,628
2027	75,928	372,738	82,841	412,890
2028	76,384	374,974	84,001	419,248
2029	76,842	377,224	85,177	425,705
2030	77,303	379,487	86,369	432,261

The system-wide offer cap (SWOC) is used as a proxy for the value of lost load (VoLL) in the PLEXOS model. Historical values for the SWOC were found in [68, 69]. The SWOC was assumed to be in 2011 USD for all years rather than adjusting for inflation.

Table 14. ERCOT system-wide offer cap 2001–2015 [68, 69].

SWOC (VoLL) [$/MWh]	**Start Date**	**End Date**
$1,000	2001-07-31	2007-02-28
$2,000	2007-03-01	2008-02-29
$2,500	2008-03-01	2009-02-28
$3,000	2009-03-01	2012-07-31
$4,500	2012-08-01	2013-05-31
$5,000	2013-06-01	2014-05-31
$7,000	2014-06-01	2015-05-31
$9,000	2015-06-01	

APPENDIX G—CAPACITY EXPANSION CANDIDATES

Table 15. New generation candidates—construction and cost parameters.

Technology	Overnight Capital Cost [2011 $/kW]	Project Start Date	Lead Time [yrs]	Max Units Built in Year	Economic Life [yrs]	WACC [%]	FO&M [2011 $/kW-yr]	VO&M [2011 $/MWh]	Start Cost [$/MW-start]
Scrubbed Coal	2,925	2011	4	2	20	8%	31.18	4.47	42
IGCC	3,771	2011	4	2	20	8%	51.39	7.22	42
NGCC Conv	915	2011	3	6	20	8%	13.17	3.6	35
NGCC Adv	1,021	2011	3	6	20	8%	15.37	3.27	35
NGCT Conv	971	2011	2	12	20	8%	7.34	15.45	25
NGCT Adv	673	2011	2	6	20	8%	7.04	10.37	25
Nuclear Adv	5,501	2011	6	1	20	8%	93.28	2.14	100
Biomass	3,919	2011	4	2	20	8%	105.64	5.26	20
Wind, On-shore	2,205	Staggered	3	15	20	8%	39.55	0	0
Solar PV	3,564	Staggered	2	10	20	8%	24.69	0	0
Data Source	[49, 50]		[49]			[49]	[49]	[49]	[54]

Table 16. New generation candidates—technical parameters.

Technology	**Fuel**	**Prime Mover**	**Capac-ity [MW]**	**Firm Capacity [%]**	**Heat Rate [Btu/kWh]**	**Min Stable Level [%]**	**Max Ramp Rate [%/min]**	**Min Down Time [hrs]**	**Min Up Time [hrs]**
Scrubbed Coal	Coal-Sub.	ST	1300	100%	8,740	50%	0.25%	12	24
IGCC	Coal-Sub.	CCGT	1200	100%	7,450	50%	0.40%	12	24
NGCC Conv	NG	CCGT	620	100%	6,800	25%	0.40%	6	14
NGCC Adv	NG	CCGT	400	100%	6,333	25%	0.40%	6	14
NGCT Conv	NG	OCGT	85	100%	10,450	25%	20%	1	1
NGCT Adv	NG	OCGT	210	100%	8,550	25%	20%	1	1
Nuclear Adv	Uranium	ST	2234	100%	10,464	50%	0.25%	24	168
Biomass	Biomass	ST	50	100%	13,500	50%	0.25%	6	8
Wind, On-shore	Wind	WT	100	12%	-	0%	-	0	0
Solar PV	Solar	PV	150	80%	-	0%	-	0	0
Data Source			[49]	[70]	[49]	[54]	[54]	[54]	[54]

Table 17. New generation candidates—outage rates and reserves.

Technology	**Planned Outage Rate [%]**	**Forced Outage Rate [%]**	**Reserves**
Scrubbed Coal	10	6	RegDn, RRS, NSRS
IGCC	12	8	RegDn, RRS, NSRS
NGCC Conv	6	4	RegDn, RegUp, RRS, NSRS
NGCC Adv	6	4	RegDn, RegUp, RRS, NSRS
NGCT Conv	5	3	RegDn, RegUp, RRS, NSRS
NGCT Adv	5	3	RegDn, RegUp, RRS, NSRS
Nuclear Adv	6	4	None
Biomass	7.6	9	RegDn, RegUp, RRS, NSRS
Wind, Onshore	0.6	5	None
Solar PV	2	0	None
Data Source	[71]	[71]	[54]

Table 18. Capital cost scenarios for new solar PV and wind projects, 2011–2030.

	Utility Solar PV [$/kW]		Onshore Wind [$/kW]	
Year	**Base**	**-8.8%/yr (2017–2025)**	**Base**	**-1.3%/yr (2017–2025)**
2011	2500.00	2500.00	1300.00	1300.00
2012	1959.45	1959.45	1469.59	1469.59
2013	1689.77	1689.77	1448.37	1448.37
2014	1425.25	1425.25	1330.24	1330.24
2015	1376.11	1376.11	1186.30	1186.30
2016	1218.38	1218.38	1171.52	1171.52
2017	1218.38	1111.17	1171.52	1156.29
2018	1218.38	1013.38	1171.52	1141.26
2019	1218.38	924.21	1171.52	1126.43
2020	1218.38	842.88	1171.52	1111.78
2021	1218.38	768.70	1171.52	1097.33
2022	1218.38	701.06	1171.52	1083.06
2023	1218.38	639.36	1171.52	1068.98
2024	1218.38	583.10	1171.52	1055.09
2025	1218.38	531.79	1171.52	1041.37
2026	1218.38	531.79	1171.52	1041.37
2027	1218.38	531.79	1171.52	1041.37
2028	1218.38	531.79	1171.52	1041.37
2029	1218.38	531.79	1171.52	1041.37
2030	1218.38	531.79	1171.52	1041.37

APPENDIX H—STEAM ACCUMULATOR CANDIDATES

Table 19. Steam accumulator parameter assumptions.

Power [MW]	Energy [hrs @ max power]	Turbine Ramp Rate [%/min.]	Min. Stable Level [% of max. power]	Scheduled Outage Rate [%]	Forced Outage Rate [%]	Var. O&M Cost [$/MWh]	Start Cost [$/MW-start]
500	5	0.54%	25%	6%	3%	8.00	11.00
500	10	0.54%	25%	6%	3%	8.00	11.00
500	20	0.54%	25%	6%	3%	8.00	11.00
500	40	0.54%	25%	6%	3%	8.00	11.00
1000	5	0.54%	25%	6%	3%	8.00	11.00
1000	10	0.54%	25%	6%	3%	8.00	11.00
1000	20	0.54%	25%	6%	3%	8.00	11.00
1000	40	0.54%	25%	6%	3%	8.00	11.00
500	5	1.67%	25%	6%	3%	8.00	11.00
500	10	1.67%	25%	6%	3%	8.00	11.00
500	20	1.67%	25%	6%	3%	8.00	11.00
500	40	1.67%	25%	6%	3%	8.00	11.00
1000	5	1.67%	25%	6%	3%	8.00	11.00
1000	10	1.67%	25%	6%	3%	8.00	11.00
1000	20	1.67%	25%	6%	3%	8.00	11.00
1000	40	1.67%	25%	6%	3%	8.00	11.00

Table 20. Steam accumulator parameters calculated from the MATLAB thermodynamic model.

Power [MW]	**Energy [hrs @ max power]**	**Turbine Ramp Rate [%/min.]**	**Heat Loss Rate during Storage [%/min.]**	**Pump Efficiency [%]**	**Fixed O&M Cost [$/kW-yr]**	**Overnight Capital Cost [$/kW]**
500	5	0.54%	0.258%	96.5%	64.31	1286.00
500	10	0.54%	0.258%	94.7%	68.40	1368.00
500	20	0.54%	0.258%	90.9%	77.90	1558.40
500	40	0.54%	0.258%	83.2%	98.30	1966.80
1000	5	0.54%	0.258%	96.7%	56.87	1137.50
1000	10	0.54%	0.258%	94.8%	61.30	1226.00
1000	20	0.54%	0.258%	90.9%	71.16	1423.00
1000	40	0.54%	0.258%	83.8%	88.86	1777.00
500	5	1.67%	0.258%	97.5%	62.95	1259.00
500	10	1.67%	0.258%	95.7%	67.03	1354.66
500	20	1.67%	0.258%	92.1%	75.88	1517.60
500	40	1.67%	0.258%	84.5%	95.60	1912.34
1000	5	1.67%	0.258%	97.6%	55.85	1117.00
1000	10	1.67%	0.258%	95.7%	60.28	1206.00
1000	20	1.67%	0.258%	91.9%	69.80	1396.00
1000	40	1.67%	0.258%	84.8%	87.50	1750.00

Glossary

Acronym	Description
Btu	British thermal unit
CAES	Compressed air energy storage
CCGT	Combined-cycle gas turbine
CCS	Carbon capture and sequestration
CHP	Combined heat and power plant
CSP	Concentrating solar power
DOE	U.S. Department of Energy
EIA	U.S. Energy Information Administration
EPA	U.S. Environmental Protection Agency
ERCOT	Electric Reliability Council of Texas
IEA	International Energy Agency
IRENA	International Renewable Energy Agency
ITC	Business Energy Investment Tax Credit
LDC	Load duration curve
LFG	Landfill gas
LP	Linear programming
MIP	Mixed integer programming
MSW	Municipal solid waste
NSRS	Non-Spinning Reserve Service
NERC	North American Electric Reliability Corporation
NREL	National Renewable Energy Laboratory
O&M	Operations and maintenance
OCGT	Open-cycle gas turbine
PCM	Phase-change materials

Acronym	Description
PTC	Production Tax Credit
PV	Solar photovoltaic
PWR	Pressurized water reactor
RM	Reserve margin
RRS	Responsive Reserve Service
SCC	Social cost of carbon
ST	Steam turbine
SWOC	System-wide offer cap
SWU	Separative work unit
TES	Thermal energy storage
USD	United States dollars
VoLL	Value of lost load
WT	Wind turbine

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