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**A Techno-economic Plant- and Grid-Level Assessment of
Flexible CO₂ Capture**

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**A Techno-economic Plant- and Grid-Level Assessment of
Flexible CO₂ Capture**

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Dedicated to my parents, Harvey and Katherine Cohen, and my sister, Jessica Cross.

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A Techno-economic Plant- and Grid-Level Assessment of Flexible CO₂ Capture

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Carbon dioxide (CO₂) capture and sequestration (CCS) at fossil-fueled power plants is a critical technology for CO₂ emissions mitigation during the transition to a sustainable energy system. Post-combustion amine scrubbing is a relatively mature CO₂ capture technology, but barriers to implementation include high capital costs and energy requirements that reduce net power output by 20–30%. Capture energy requirements are typically assumed constant, but work investigates whether flexibly operating amine scrubbing systems in response to electricity market conditions can add value to CO₂ capture facilities while maintaining environmental benefits.

Two versatile optimization models have been created to study the electricity system implications of flexible CO₂ capture. One model assesses the value of flexible capture at a single facility in response to volatile electricity prices, while the other represents a full electricity system to study the ability of flexible capture to meet electricity demand and reliability (ancillary) service requirements. Price-responsive flexible CO₂ capture has limited value at market conditions that justify CO₂ capture investments. Solvent storage can add value for price arbitrage by allowing flexible operation without additional CO₂ emissions, but only with favorable capital costs.

The primary advantage of flexible CO₂ capture is an increased ability to provide grid reliability services and improve grid resiliency at minimum and maximum electricity demand. Flexibility mitigates capacity shortages because capture energy requirements need not be replaced, and variable capture at low demand helps respond to intermittent renewable generation.

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Units and Acronyms

AS = ancillary services

CAES = compressed air energy storage

CCS = carbon capture and sequestration

CE = certain equivalent

CHP = combined heat and power

CO = carbon monoxide

CO₂ = carbon dioxide

DOE = Department of Energy

EOR = enhanced oil recovery

EPA = Environmental Protection Agency

EPRI = Electric Power Research Institute

ERCOT = Electric Reliability Council of Texas

EU-ETS = European Union Emissions Trading System

FMSE = forecast mean square error

FOM = fixed operation and maintenance

GAMS = General Algebraic Modeling System

GB = gigabytes

GHG = greenhouse gas

GHz = gigahertz

Gt = gigaton (metric)

GW = gigawatt

H₂ = hydrogen

HP/IP/LP = high pressure/intermediate pressure/low pressure

HPC = high performance computing

IPCC = Intergovernmental Panel on Climate Change

kg = kilogram

kmol = kilomoles

kW = kilowatt

7m = 7 molal

m³ = cubic meter

MACRS = modified accelerated cost recovery system

MAPE = mean average percent error

MCS = McNamee and Celona shortcut

MEA = monoethanolamine

MIP = mixed-integer (linear) program

MISO = Midwest Independent System Operator

MMBTU = million British thermal units

mol = moles

MW = megawatt

MWh = megawatt-hour

Mt = megaton (metric)

NaOH = sodium hydroxide (caustic)

NETL = National Energy Technology Lab

NGCC = natural gas combined-cycle

NPV = net present value

NSRS = non-spinning reserve service

O₂ = oxygen

O&M = operation and maintenance

PJM = Pennsylvania-Jersey-Maryland

PUCT = Public Utilities Commission of Texas

RD = regulation down

RRS = responsive reserve service

RU = regulation up

SERC = Southeast Reliability Corporation

SO₂ = sulfur dioxide

SPP = Southwest Power Pool

SRMC = short-run marginal cost

t = metric ton

TWh = terawatt-hour

UT = The University of Texas at Austin

WECC = Western Electricity Coordinating Council

VOM = variable operation and maintenance

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Chapter 1

Introduction

1.1 Carbon Dioxide Capture and Sequestration for Climate Change Mitigation

Growing concerns with global climate change induced by anthropogenic carbon dioxide (CO₂) emissions have motivated the scientific and policy-making communities to explore several short- and long-term options for reducing CO₂ emissions from fossil-fuel burning. Without action, climate change could contribute to sea-level rise, strained fresh water availability, changes in agriculture-dependent precipitation patterns, and increased frequency of extreme weather events [IPCC, 2008]. Though the degree and impact of these environmental changes are uncertain, the potentially severe economic consequences justify exploring a wide range of climate change mitigation and adaptation approaches. Each response to climate change has technical, environmental, and economic implications that must be weighed against its expected benefits, but CO₂ emission reductions of the magnitude recommended by the International Panel on Climate Change (IPCC) will require an all-of-the-above approach [IPCC, 2008]. One representation of this comprehensive approach was popularized by Pacala and Socolow 2004 when they identified fifteen climate “stabilization wedges” required to stabilize annual global CO₂ emissions [Pacala & Socolow, 2004].

Of the more than 30 metric gigatons (Gt) of global annual CO₂ emissions, roughly 40% can be attributed to the electricity sector, primarily from coal and natural gas burning [IEA, 2011]. While eliminating coal and other fossil fuels in the

electricity sector is a worthwhile long-term goal, coal and natural gas account for approximately 40% and 20% of worldwide electricity use, respectively, and 45% and 25% in the United States [USEIA, 2011, USEIA, 2012]. Coal burning for electricity alone produces 30% of total U.S. CO₂ emissions [USDOE, 2012]. The quantity of CO₂ emissions and relatively small number of emitters makes the electricity sector a primary target for CO₂ emissions mitigation.

An Electric Power Research Institute (EPRI) report applies the “wedge” approach to the U.S. electricity sector, and one critical component to a full portfolio approach to CO₂ emissions reductions is carbon dioxide capture and sequestration (CCS) [James, 2009]. CCS typically involves capturing a near-pure CO₂ stream before or after fossil fuel burning, then the CO₂ is transported by pipeline to a suitable geologic sequestration site for deep underground injection. CCS allows continued use of fossil fuels for electricity with greatly reduced CO₂ emissions. Though fossil-fuel use, and thus CCS, is not sustainable indefinitely, CCS is a critical technology while society transitions to a sustainable energy system.

A primary application for CCS is coal-based power generation, though natural gas-fired power plants can also utilize the technology. Coal is typically the focus of CCS because it contributes more worldwide CO₂ emissions, and though the analysis herein focuses exclusively on CO₂ capture at coal-based facilities, natural gas can be considered under the same framework. Historically, coal has been widely used for electricity generation because it is a relatively abundant, politically secure, and inexpensive fuel. Though increasingly stringent environmental regulations and low natural gas prices in the United States will facilitate reduced coal use, plants typically operate for several decades, and other countries such as China are expected to continue substantial coal use for the foreseeable future [Paltsev et al., 2011, Liang et al., 2008].

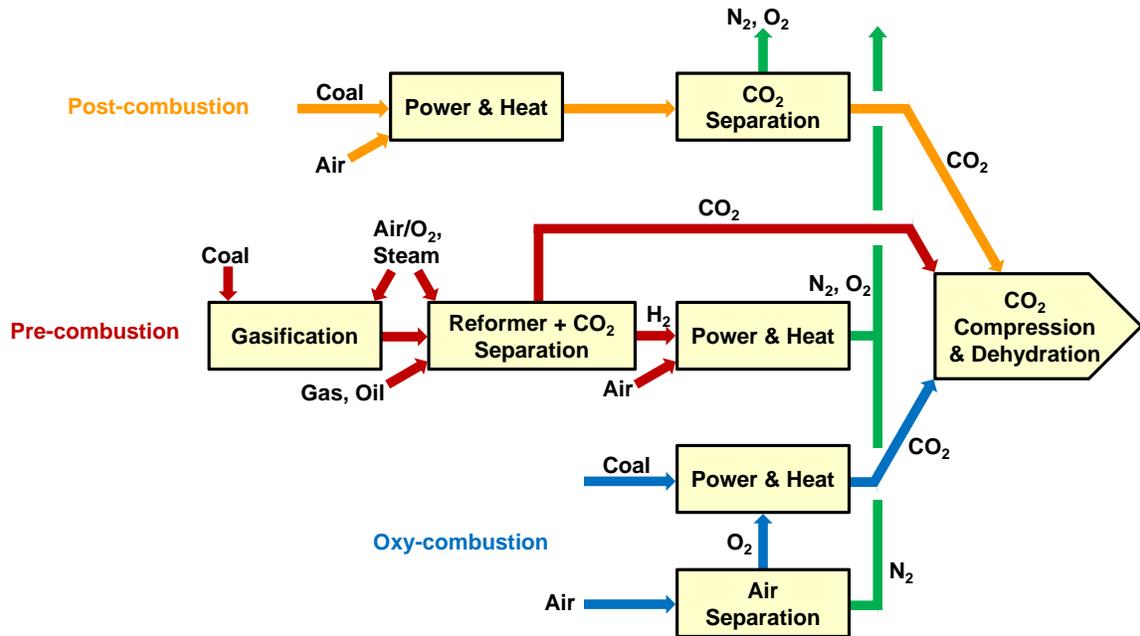


Figure 1.1: There are three general approaches to CO₂ capture.

CCS for coal-based generators can play a major role in a long-term climate change mitigation strategy.

There are three general approaches to capturing CO₂ at coal-fired power plants: pre-combustion, oxycombustion, and post-combustion (Fig. 1.1, adapted from [Metz, 2005]). Pre-combustion capture involves first gasifying coal into a synthesis gas (syngas) mixture of hydrogen (H₂) and carbon monoxide (CO), then using a water-gas shift reaction to convert CO to CO₂ and additional hydrogen. The hydrogen is burned as fuel and the CO₂ is transported and sequestered. With oxycombustion, pure oxygen (O₂) is separated from air and burned with the coal to produce an exhaust gas stream with high CO₂ concentration that is further purified before transport and sequestration. Post-combustion capture removes CO₂ from flue gas after burning in a conventional boiler. The IPCC Special Report on CCS compares these technologies in detail [Metz, 2005].

Regardless of the CO₂ capture technology, the primary disadvantages of CCS are the capital and energy costs of CO₂ capture systems. CO₂ capture systems are typically designed to achieve about 90% CO₂ removal from power plant flue gas, but energy requirements for CO₂ capture and compression typically reduce net power output by 20–30% [Rochelle et al., 2011]. Long-distance CO₂ pipeline transport and underground CO₂ injection is well-understood from enhanced oil recovery (EOR) operations ongoing in West Texas since the 1970s [Ambrose et al., 2006, Metz, 2005]. Commercial CO₂ removal has also been performed for several decades in the natural gas purification and ammonia production industries, but these applications are smaller-scale and more economically viable than CO₂ removal from power plant flue gas [Metz, 2005]. Nevertheless, CO₂ capture demonstrations on a tens of megawatts (MW) scale exist today, and CCS technology is ready for commercial installation (hundreds of MW) given sufficient economic and policy incentives [Javedan, 2012].

1.2 Post-Combustion Amine Scrubbing for CO₂ Capture

CO₂ capture technology comparisons consistently establish post-combustion amine scrubbing as a leading technology for CO₂ capture useful both for retrofits and new facilities [Davidson, 2007, Figueroa et al., 2008, Rochelle, 2009, Freeman & Bhowan, 2011]. Relative to pre-combustion and oxycombustion technologies, post-combustion amine scrubbing is relatively less integrated into power systems, making it more suitable in retrofit applications. For the same reason, amine scrubbing is particularly well-suited to flexible operation independent of power systems, which is the main focus of this dissertation. Amine scrubbing is also more mature than other technologies due to its long-standing commercial use in natural gas purification and ammonia production.

A well-designed amine scrubbing system at a coal-fired power plant reduces net output by $\sim 20\%$. Though substantial, this energy performance is only about double the minimum theoretical energy requirement for CO_2 removal and compression to 150 bar, a typical pipeline pressure [Rochelle et al., 2011]. An actual-to-minimum energy requirement ratio of 2:1 is much better than other separation processes in commercial operation (distillation, cryogenic air separation, reverse osmosis desalination), which have actual-to-minimum energy ratios on the order of 3–5:1 [Rochelle et al., 2011]. Technology comparisons with amine scrubbing should include CO_2 compression energy to a consistent outlet pressure, as exiting CO_2 partial pressures can vary across different separation processes. Maturity, energy performance, and flexibility are reasons why amine scrubbing is considered exclusively in the present analysis, though the modeling frameworks discussed herein could be adapted for other capture technologies.

Figure 1.2 shows a simplified diagram of an amine scrubbing process integrated into a coal-fired power plant. Coal is burned in the furnace in the normal fashion to produce steam in the boiler that expands through high-, intermediate-, and low-pressure turbines (HP, IP, LP) that drive a generator. Flue gas passes through pollution control equipment to remove particulates, sulfur dioxide (SO_2), and nitrogen oxides (NO_x) before entering the CO_2 absorption column. Amine solvent flows countercurrently with flue gas in the absorber, where it typically removes 90% CO_2 at 40–75°C and exits as rich solvent (high in CO_2). The solvent then passes through a cross heat exchanger before entering the stripping column, where solvent is heated to 100–150°C to reverse the solvent- CO_2 reaction and desorb the CO_2 [Davidson, 2007, Rochelle et al., 2011]. After condensing any steam exiting the stripper, the nearly-pure CO_2 stream is compressed to a pressure suitable for pipeline transport and underground CO_2 injection (typically 90–150 bar) [McCoy & Rubin, 2008]. The

“lean” (low in CO₂) solvent exiting the stripper then flows back through the cross heat exchanger and back to the absorber, and the cycle repeats.

Stripping heat is provided is provided by saturated steam slightly above the required stripper temperature, which typically requires extracting 30–40% of the steam from between the IP and LP turbines, depending on steam cycle design [Gibbins & Crane, 2004, USNETL, 2007]. With a high enough pressure, the extracted steam could be expanded through a let-down turbine to drive the CO₂ compressor before being used to heat the solvent, but Fig. 1.2 shows the compressor driven by an electric motor. A motor-driven compressor can operate more flexibly, so this analysis assumes compressor work is supplied with electricity [Lucquiaud & Gibbins, 2011]. Steam extraction and CO₂ compression work account for the bulk of CO₂ capture energy requirements, with the remainder of the energy requirement coming from rich/lean solvent pumps and a flue gas blower (not shown in Fig. 1.2).

1.3 Concepts for Flexibly Operating Amine Scrubbing Systems

Before discussing the motivation for flexible CO₂ capture (the “why”), this section will define and discuss how flexible capture systems can be designed and operated in the context of amine scrubbing (the “how”).

In the context of this work, flexible CO₂ capture refers to operating CO₂ capture systems independently of most base power systems, particularly the boiler unit. Base power systems refer to equipment installed in a generating unit without CO₂ capture. If the base plant must ever operate variably due to market forces or operating requirements, some degree of CO₂ capture flexibility is required to ensure stable capture operation across the base plant power output range [Davison, 2010].

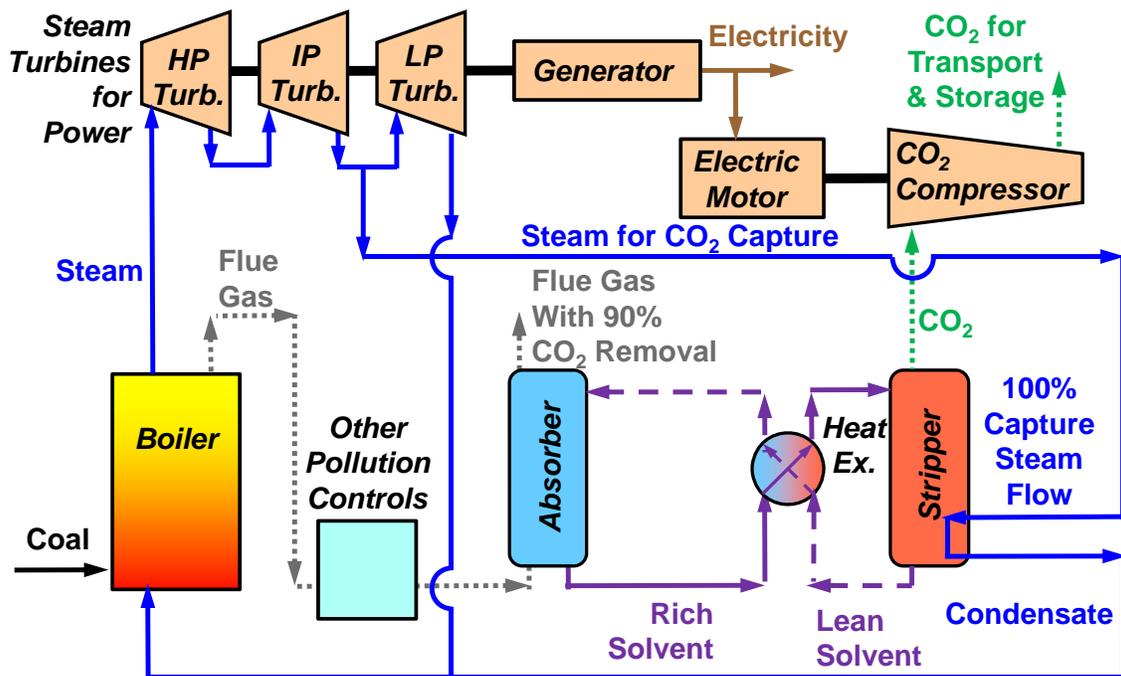


Figure 1.2: Post-combustion amine scrubbing at coal-fired power plants can achieve 90% CO₂ removal but reduces net electrical output by 20–30%.

However, this work defines flexible CO₂ capture as operating energy-intensive CO₂ capture systems at a different, typically lower, fractional load than the base power plant. With sufficient turbine-generator capacity and a capture system conducive to flexible operation, reducing load on energy intensive CO₂ capture systems during full-load base plant operation could allow net power output to approach non-capture levels.

1.3.1 Venting-Only Flexible Capture

This work considers two basic concepts for flexible CO₂ capture using amine scrubbing. A “venting-only” flexible capture configuration reduces the energy requirements of solvent stripping and CO₂ compression while allowing the CO₂ removal rate to fall. Figure 1.3 displays one way to implement this concept, where steam and rich solvent flow rates to the stripper are reduced equally and simultaneously during partial- or zero-load operation [Ziaii et al., 2008]. At partial load, stripping steam is redirected back to the low pressure (LP) turbine for increased electricity production, and rich solvent diverted from the stripper is recycled to the absorber. Recycling rich solvent to the absorber will increase the lean loading of solvent entering the absorber, so CO₂ removal rates will decrease as solvent becomes saturated with CO₂. Less CO₂ exits out the top of the stripper, so compression work falls as well. Stripping and compression work account for roughly 90% of the total energy requirement of CO₂ capture, so operating these systems at partial or zero load could allow a significant increase in net electrical output [Chalmers et al., 2010].

This method of controlling the ratio of steam to lean solvent has been shown to maintain good process performance and shorten capture system response time to 30 minutes or less for load changes of up to 30% [Ziaii et al., 2009, Lawal et al., 2009, Brasington & Herzog, 2012]. Modeling by Lawal demonstrates capture sys-

tem response time of 30–60 minutes when stripping heat is reduced by 10% over 10 seconds, which implies that redirecting steam to the low pressure turbine could be accomplished much faster than it takes the capture process to fully stabilize as long as the LP turbine is maintained above its minimum flow rate and at its normal operating temperature [Lawal et al., 2010]. Ratio control facilitates process stability by keeping liquid-to-gas flow ratios constant, which maintains stable hydraulic conditions [Lin et al., 2011].

Additional modeling results suggest that when accounting for CO₂ and electricity prices, the optimal steam to solvent flow ratio might be slightly less than one, but this work is based on assumed constant CO₂ and electricity prices [Ziaii et al., 2011]. Since electricity prices vary diurnally, and effective CO₂ prices exhibit temporal variations for many carbon policies, the analysis within this dissertation assumes that ratio controlled operation changes steam and rich solvent flow to the stripper by equal amounts (ratio = 1).

This work also assumes throughout that stripper and compressor load are equal, so any reference to stripper load also refers to compressor load. The connection between stripping and compression systems is especially important in establishing a minimum load on stripping and compression systems. Low flow rates in the stripper could prevent solvent from being distributed equally across the column cross sectional area, which would hurt stripper performance. However, minimum CO₂ compressor load is likely a more critical constraint because below a minimum flow rate, compressor surge can cause significant damage to compressor blades. Ziaii has dynamically modeled an amine scrubbing system integrated with the CO₂ compressor and steam turbine train and has found that minimum load of 20% is achievable with anti-surge control, where CO₂ is recycled through the compressor to maintain its minimum flow

rate at lower CO₂ capture system load [Ziaii, 2012]. Furthermore, the energy required per unit of CO₂ captured actually decreases during CO₂ recycling because optimal operation at low-load stripping produces CO₂ at a higher initial partial pressure [Ziaii, 2012].

Zero-load CO₂ capture could involve recirculating all solvent through the absorber and shutting down stripping and compression systems, or the CO₂ capture system could be bypassed completely. Complete shutdown of any components, however, could increase the time necessary to return to operation due to process control requirements and startup time of turbomachinery.

The primary tradeoff when operating a venting-only flexible capture systems is between the value of increased electrical output and any cost of additional CO₂ emissions. One advantage is low capital cost. In a CO₂ capture retrofit application where the low pressure turbine and generator have been sized to operate without CO₂ capture, this design should have negligible capital cost because maintenance requirements will likely necessitate the ability to vent CO₂ or bypass capture systems. Additional piping, valves, and control equipment are the only additional components that might be required. For a new facility, the capital cost of flexibility could include the incremental cost of a larger LP turbine and generator relative to an inflexible capture design where the turbine-generator is sized for reduced LP steam flow.

1.3.2 Flexible Capture with Solvent Storage

Another flexible CO₂ capture concept uses auxiliary solvent storage tanks to maintain high CO₂ removal when stripping and compression systems operate at partial or zero load (Fig. 1.4) [Chalmers & Gibbins, 2007]. When additional electrical output is desired, the plant can reduce stripper and compressor load while maintaining full-load CO₂ absorption by feeding the absorber from a lean solvent storage

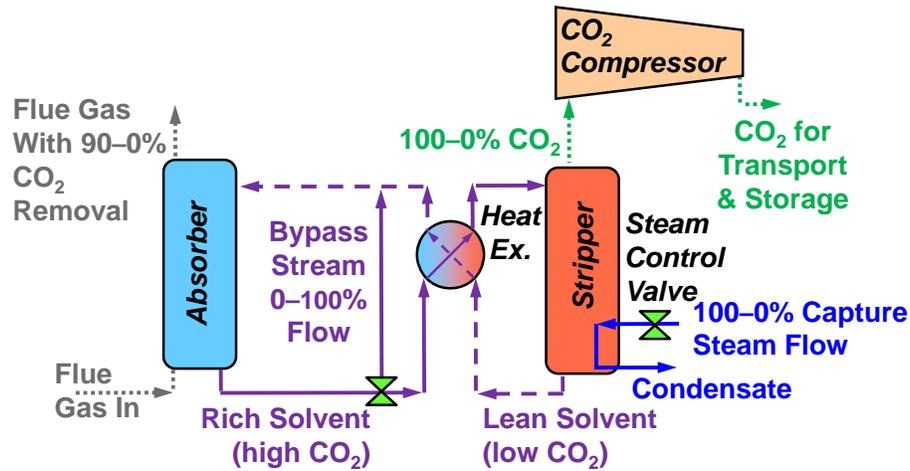


Figure 1.3: A venting-only flexible configuration allows increased power output but requires additional CO₂ emissions.

tank and depositing rich solvent into another tank. When additional power is no longer needed, stripping and compression systems return to a higher load to treat the current process stream and the stored rich solvent. To treat both streams, either absorber load must be reduced, or stripping and compression systems must be over-sized. Absorber load can be reduced without additional CO₂ emissions if base plant load is reduced at the same time. Though solvent storage decouples absorption and stripping/compression equipment, process dynamics are not expected to differ significantly from those of a venting-only configuration. Maintaining high CO₂ removal keeps operating costs down while storing rich solvent, but any operating profit improvement must be weighed against the capital cost of solvent inventory, storage tanks, and larger stripping and compression equipment. Though solvent storage avoids the need to emit additional CO₂ during reduced-load stripping and compression, a facility with solvent storage would likely maintain the ability to vent CO₂ when economically desirable or necessary for maintenance.

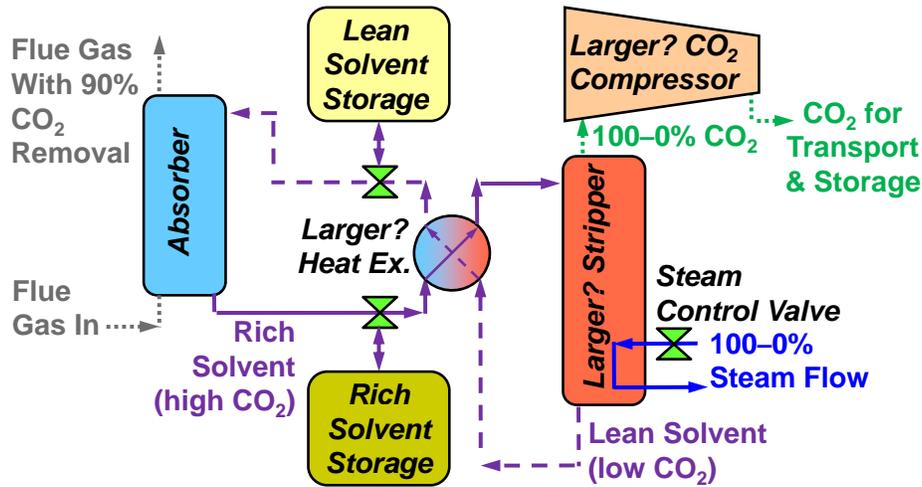


Figure 1.4: Solvent storage allows increased power output without increasing CO₂ emissions but requires additional capital expense. Stripping and compression equipment could be oversized to treat stored rich solvent during full-load absorption.

1.4 The Importance of Flexible CO₂ Capture

Most studies assume that CO₂ capture and compression systems operate continuously whenever the base plant operates, so any energy required for CO₂ capture and compression is constant [Davison, 2007, E. S. Rubin & Rao, 2007, Zhang et al., 2009]. In a retrofit application, this energy requirement would entail a permanent reduction in electrical output and increase in electricity production costs. However, there is a growing attention to the value of operating some or all CO₂ capture systems at partial or zero load and utilizing this flexibility to operate CO₂ capture in response to variable electricity market conditions. In addition to the development of dynamic CO₂ capture process models discussed above, the interest in capture flexibility has motivated an International Energy Agency workshop, and several authors have examined the feasibility and value of flexible capture [Chalmers, 2010, Chalmers et al., 2009, Husebye et al., 2010, Ludig et al., 2010, Patiño Echeverri & Hoppock, 2012]. The objective of this research area is testing the hypothesis that flexibility can improve

CO₂ capture economics while maintaining its environmental benefits. If so, flexibility can hasten widespread CCS deployment.

Using flexible CO₂ capture to temporarily increase power output is valuable during periods of peak electricity demand. In a retrofit application, doing so eliminates the need to invest in new generating capacity to replace the output lost to CO₂ capture energy requirements, and peak demand infrequency prevents any significant CO₂ emissions increase [Cohen et al., 2010b, Wiley et al., 2010]. Figure 1.5 demonstrates this concept for the Electric Reliability Council of Texas (ERCOT) electricity system. The figure plots electrical output by plant type on the peak demand day in 2009 assuming hypothetical use of flexible CO₂ capture on the entire ERCOT coal fleet. When demand is below peak, CO₂ capture operates at full load and reduces output at coal-fired facilities. At peak demand, flexible capture systems reduce capture load to increase electrical output. An inflexible CO₂ capture system would require continuous capture operation, so new capacity would be required to meet peak demand. This benefit of flexibility would be important in any electricity system where reserve capacity is limited.

In electricity systems with deregulated markets, partial- or zero-load CO₂ capture also allows increased electricity sales when electricity prices are high, which improves profits if the increased electricity sales offset any cost of flexibility. Figure 1.6 demonstrates this concept for the venting-only flexible capture configuration using output from the model presented in Chapter 2. Electricity prices from two sample days in 2008 have been adjusted for a \$50 per metric ton of CO₂ (tCO₂) emissions penalty; capture load and net power output fraction are plotted on a percent basis. Net power output fraction is the ratio of net electrical output to gross electrical output without CO₂ capture. Electricity prices below \$52 per megawatt-hour (MWh)

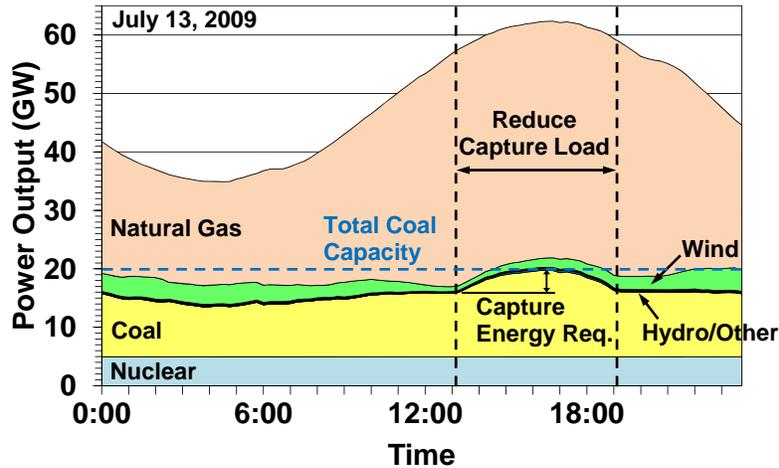


Figure 1.5: Flexible CO₂ capture allows increased power output to meet annual peak electricity demand.

are below operating costs at full capture load, so the facility shuts down or operates at minimum load if operating losses are below power plant startup costs. Between \$52/MWh and \$136/MWh, full-load capture operation is optimal, so capture systems operate at 100% load, reducing net power output to $\sim 75\%$, which reflects the 25% energy penalty for full-load CO₂ capture. Above \$136/MWh, capture systems shut down, and net power output returns to 100% because additional electricity sales offset the costs of venting CO₂.

Figure 1.7 shows operating behavior under the same conditions but with a solvent storage system that allows up to 30 minutes of zero-load stripping/compression with the absorber at full load. Though this solvent storage system is small, its impact on operation is substantial. When prices are low, the facility regenerates stored rich solvent and reduces operating losses by raising stripper load above absorber load. At high prices, CO₂ is vented despite the presence of a solvent storage system. Solvent storage is instead utilized for increasing output at intermediate electricity prices. Op-

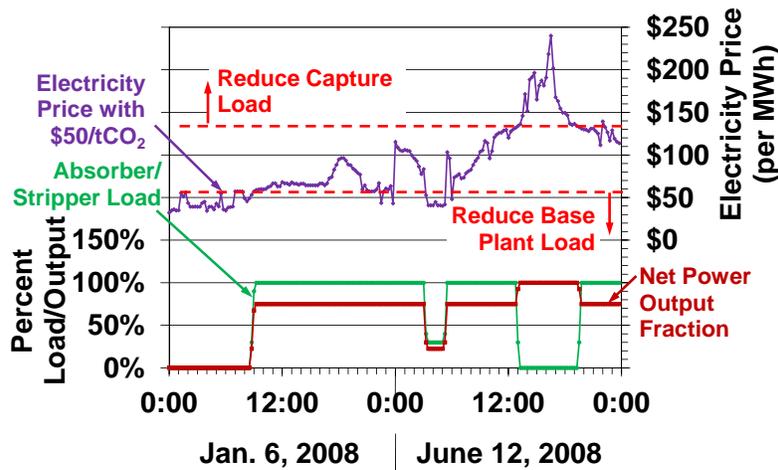


Figure 1.6: Venting CO₂ can be profitable at high electricity prices if additional electricity sales offset emissions costs.

timal operation with solvent storage is not necessarily straightforward, so detailed investigation is necessary to assess its value.

Earlier work by this author has examined price-responsive flexible capture using a first-order electricity dispatch model developed to study the value of venting CO₂ at peak electricity prices. This model was used to study a wide range of electricity market conditions and three different electricity systems [Cohen et al., 2011, Fyffe et al., 2011, Cohen et al., 2009, Cohen, 2009]. Results suggest venting CO₂ is valuable at intermediate CO₂ prices, but the first-order model does not represent constraints on dynamically operating power and capture systems, and it does not reproduce realistic electricity price spikes that could be particularly valuable for flexible capture. Chalmers has performed marginal cost calculations to identify electricity and CO₂ price conditions suitable for bypassing capture systems or using solvent storage [Chalmers et al., 2010]. These findings inform operating decisions but do not account for power, capture, or electricity system dynamics. Husebye used a dynamic

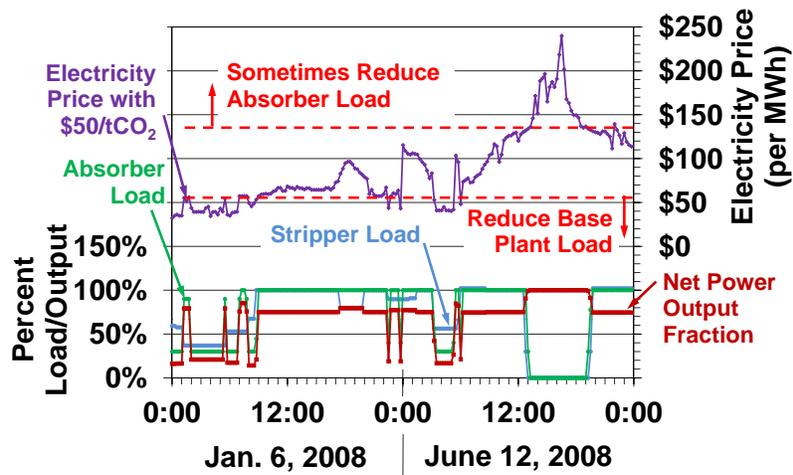


Figure 1.7: Solvent storage allows increased operating flexibility at intermediate electricity prices.

optimization model with discrete operating modes to examine the value of price-responsive flexible capture as a function of electricity price volatility [Husebye et al., 2010]. This model allows a detailed characterization of flexible CO₂ capture systems, but it assumes constant full-load operation of power systems and instantaneous transitions between designated CO₂ capture operating modes. Patiño-Echeverri and Hoppock have studied the value of price-responsive solvent storage in several U.S. electricity systems. Their results show limited potential for solvent storage but note the importance of capital cost assumptions in drawing such conclusions. This approach also considers only two or three discrete operating modes with solvent storage, so it has limited ability to represent the dynamic interplay between power and CO₂ capture systems. The amount of research in price-responsive flexible capture indicates its potential value; however, all of these works are limited either in their representation of electricity price volatility or the dynamics of power and CO₂ capture operation. One objective of this dissertation is to demonstrate a modeling framework with a more comprehensive representation of power, capture, and electricity systems.

Electricity price response is valuable only in competitive electricity markets, but capture flexibility could benefit any electricity system by providing grid reliability services [Gibbins et al., 2005]. CO₂ capture load could be reduced to increase electrical output in response to a sharp demand increase or a transmission or generation outage. Conversely, a flexible capture system operating below maximum load could respond to a rapid drop in demand or increase in supply by increasing capture load and reducing net power output. With increased penetration of intermittent wind and solar resources in electricity systems, greater flexibility at controllable generators will likely be necessary to maintain reliable electricity systems [Chalmers et al., 2006]. If an electricity system employs a competitive market for grid reliability services, often called ancillary services (AS), AS payments from flexible capture operation could be quite lucrative [Chalmers et al., 2009]. Ludig uses a long-term capacity planning model to explore the relationship between wind and CO₂ capture installation with and without flexibility and finds that capture flexibility reduces overall costs of providing electricity [Ludig et al., 2010]. Zhang analyzes a facility that integrates both CO₂ capture and wind, and integration improves plant profitability by using wind to help supply capture energy and increase total electrical output [Zhang, 2011]. These analyses highlight the potential for flexible CO₂ capture to improve grid reliability and complement renewable energy, but fully understanding these phenomena requires an approach that accounts for the dynamic nature of power plant and electricity system operation. Demonstrating such an approach is another primary goal of this dissertation.

1.5 Flexibly Operating Other CO₂ Capture Technologies

Other authors have examined the potential for flexibly operating pre-combustion and oxycombustion CO₂ capture systems. If chemical absorption and stripping is used

for pre-combustion CO₂ capture in an integrated gasification combined-cycle (IGCC) facility, CO₂ removal and compression systems could be flexibly operated in the same manner as with post-combustion capture [Chalmers et al., 2008]. However, doing so could negatively affect performance by changing the gas composition entering the gas turbine. In addition, the energy intensive water-gas shift reaction that converts syngas to H₂ and CO₂ cannot be avoided without again altering the gas turbine inlet composition. Process integration makes flexible pre-combustion capture difficult, but Davison along with Newcomer and Apt suggest continuous syngas or hydrogen production and storage could allow plant flexibility typical of natural gas combined-cycle (NGCC) units given sufficiently low capital costs for gas storage [Davison, 2010, Newcomer & Apt, 2007].

CO₂ removal and compression systems could be operated flexibly at an oxy-combustion facility as well, but doing so has no effect on the energy intensive air separation unit (ASU) used to produce O₂ for combustion [Chalmers et al., 2008]. Flexible ASU operation is possible but requires a boiler unit designed for combustion with O₂ or air and the ability to transition between the two.

More research is required before disregarding the possibility for flexibly operating pre-combustion or oxycombustion capture systems. Though outside the scope of current work, potential future work includes adapting the modeling frameworks discussed herein for CO₂ capture systems other than amine scrubbing.

1.6 Scope and Objectives

This work addresses several knowledge gaps and limitations on earlier flexible CO₂ capture research. Chapters 2 and 3 discuss an optimization model created to maximize operating profits at a flexible capture facility in response to volatile

electricity prices. This model considers both the venting-only and solvent storage configurations under a wide range of plant specifications and electricity market conditions while representing realistic electricity price volatility. The modeling approach builds upon the current literature on price-responsive flexible capture by representing intertemporal plant constraints, a continuous range of power and capture operating conditions, and realistic electricity price volatility. Its versatility and robustness make it useful for assessing the economic and environmental impacts of power, capture, and electricity system specifications. While the profit maximization model assesses the value of flexible capture for price arbitrage, Chapter 4 presents a full electricity system model created to study the value of flexible capture for providing both energy and ancillary services and examine how flexible CO₂ capture interacts with other advanced energy technologies such as wind and energy storage. The electricity system model minimizes the cost of meeting time-varying electricity demand and ancillary service requirements across a fleet of generating units, making its results applicable to both competitive and regulated electricity systems. It represents the first example of a unit commitment modeling approach employed specifically to assess the implications of flexible CO₂ capture. Economic results from both optimization models then inform the investment analysis presented in Chapter 5, which discusses the effect flexible CO₂ capture has on CO₂ capture installation decisions.

The objectives of this work are as follows:

1. Develop and use optimization models to simulate electricity market operation with flexible CO₂ capture in response to dynamic electricity market behaviors.
2. Determine the electricity market conditions where flexibility adds value to CO₂ capture and electricity systems through price arbitrage and supply of energy and ancillary services.

3. Establish relationships between power and capture operating and design parameters and the value of flexible capture, particularly in the context of solvent storage.
4. Describe interactions between flexible CO₂ capture, wind, energy storage, and traditional generating technologies using a unit commitment model.
5. Analyze flexible and inflexible CO₂ capture investment decisions under uncertain technological and economic parameters.

1.7 The ERCOT Market as a Case Study

Though the modeling frameworks presented here are developed with the versatility to consider any electricity system, the ERCOT electric grid is used exclusively as a case study in this body of work. ERCOT has approximately 84 gigawatts (GW) of total generating capacity across 550 generating units and serves 85% of Texas electricity demand (portions of the state lie within the Southwest Power Pool-SPP, SERC Reliability Corporation-SERC (formerly Southeast Reliability Corp.), and the Western Electricity Coordinating Council-WECC) [ERCOT, 2011c]. Its capacity by plant type in 2010 is shown in Fig. 1.8, taken from the 2011 version of *ERCOT Quick Facts*, which demonstrates the large share of gas-fired capacity, followed by coal, wind, nuclear, and other facilities [ERCOT, 2011c]. At the end of 2011, ERCOT had over 10 GW of rated wind capacity, which is more than any U.S. state and all but 4 nations [ERCOT, 2011e, ERCOT, 2011c].

Figure 1.9, also taken from *ERCOT Quick Facts*, shows electricity generation by plant type in 2010. The fraction of generation from natural gas is below its capacity fraction, while the fraction of coal- and nuclear-based generation are higher than their capacity fractions. Coal and nuclear fuel prices per unit of energy content

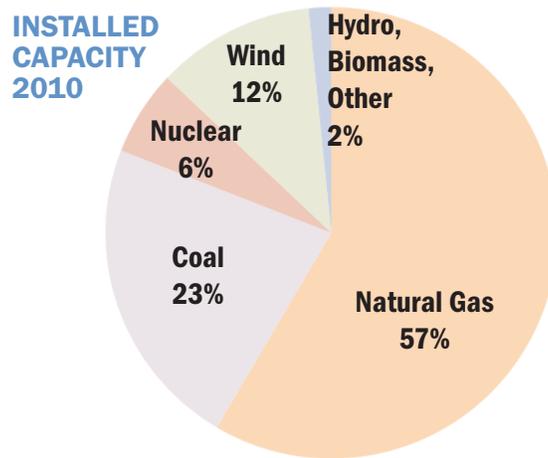


Figure 1.8: Natural gas fuels the majority of ERCOT generating capacity.

are typically below that of natural gas, so these facilities provide most base load generation, meaning they operate nearly continuously at maximum output. However, greater wind capacity and lower natural gas prices have reduced the amount of base load electricity provided by some coal-fired units.

The size and diversity of the ERCOT grid make it an excellent case study to yield useful conclusions relevant to other electricity systems. Its substantial wind capacity and suitable conditions for both CCS and energy storage make it a realistic system for studying interactions of different advanced energy technologies [Ambrose et al., 2006, Ridge, 2005, Fertig & Apt, 2011]. While ERCOT is expected to have sufficient capacity to meet reserve capacity requirements through 2013, reserve capacity will be insufficient by 2014 if load growth and capacity changes occur as expected [ERCOT, 2012]. Thus, using flexible capture to meet peak demand is a relevant issue in ERCOT. Additionally, ERCOT operates a competitive electricity market, making it an appropriate arena to examine the value of flexible CO₂ capture for price arbitrage and meeting market-based AS requirements. Relevant aspects of the ERCOT market are discussed in greater detail in subsequent sections to clearly present the

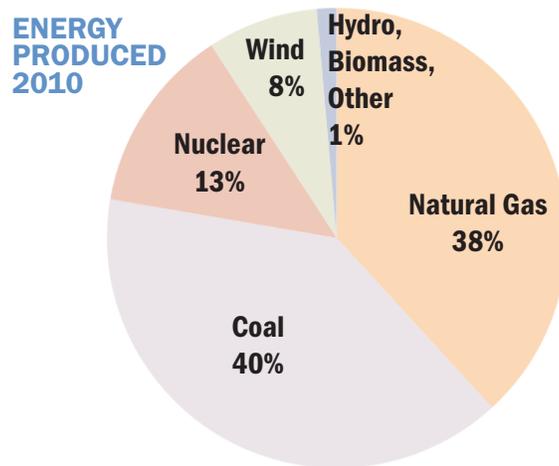


Figure 1.9: Nuclear- and coal-based facilities generate more than their capacity share due to lower fuel prices than natural gas.

relationship between ERCOT market operations and modeling activities. Another major advantage of ERCOT is data availability from the ERCOT website, online federal databases, and relationships between The University of Texas at Austin (UT) and ERCOT staff. Though some model characteristics are currently tailored to the ERCOT market, models could be readily modified to study other electricity systems with sufficient market information and input data.

Chapter 2

Optimizing CO₂ Capture in Response to Electricity Prices: Forecasting and CO₂ Price Sensitivity

This chapter is the first of two addressing flexible CO₂ capture in response to volatile electricity prices. Here, volatility is defined as price variations on the order of one hour or less. A modeling framework is first presented that assesses the performance, economic, and environmental impacts of price-responsive flexible CO₂ capture by optimizing the operation of a facility with CO₂ capture for an input electricity price series. The framework is a tool for evaluating CO₂ capture investments while accounting for operating characteristics in greater detail than traditional investment analysis.

Figure 2.1 demonstrates the motivation for considering electricity price volatility when analyzing price arbitrage opportunities for flexible capture. Previous work used a first-order electricity dispatch and pricing model to characterize flexible operation in response to electricity prices, but that model does not reproduce price spikes that occur periodically and could add value to flexible operation [Cohen et al., 2011, Ziaii et al., 2008]. Figure 2.1 illustrates the difference between the first-order model and the one presented below. In this figure, historical prices in the ERCOT grid are shifted uniformly to account for a \$50/tCO₂ price by adding the average CO₂ emissions cost of an ERCOT natural gas-fired facility. This approximation is reasonable for ERCOT because as a gas-dominated electricity system, electricity prices are

typically set by gas-based generators [PE-Ltd., 2010]. The first-order model calculates electricity prices that trend with electricity demand; they do not reproduce irregular, short-term price spikes seen in shifted historical prices. While the first-order model might not find it profitable to reduce CO₂ capture load in the afternoon of August 22, the historical price spike could justify reducing capture energy to increase power output. Analyses that order historical electricity prices from highest to lowest and use these price-duration curves to define price regimes suitable for different operating modes can account for the full range of observed electricity prices. However, this type of analysis does not include intertemporal plant operating constraints such as system response time, and these constraints are expected to impact the value of flexible operation. Though a rigorous grid-level least-cost dispatch model could reproduce some price spike behavior, a detailed stochastic model of outage events is necessary to reproduce electricity price volatility that often arises from uncertain events such as outages and transmission congestion [PE-Ltd., 2011]. Chapter 4 describes an electricity system optimization model that demonstrates some price volatility, but using electricity prices directly as input is assumed to be the most direct way to assess the potential benefit from price arbitrage.

This chapter presents a versatile model formulation that assesses the value of CO₂ capture in response to price variations while including a detailed representation of plant operation. The model integrates concepts from power, CO₂ capture, and electricity system engineering with economics and carbon mitigation policy in electricity markets. Though initially applied to a coal-fired power plant with amine scrubbing for CO₂ capture, the model could be used to analyze other post-combustion CO₂ capture technologies and fossil-fueled power plant types with appropriate changes to input parameters. Continued development could adapt the formulation to include a more detailed representation of the plant or to assess flexible operation of pre-

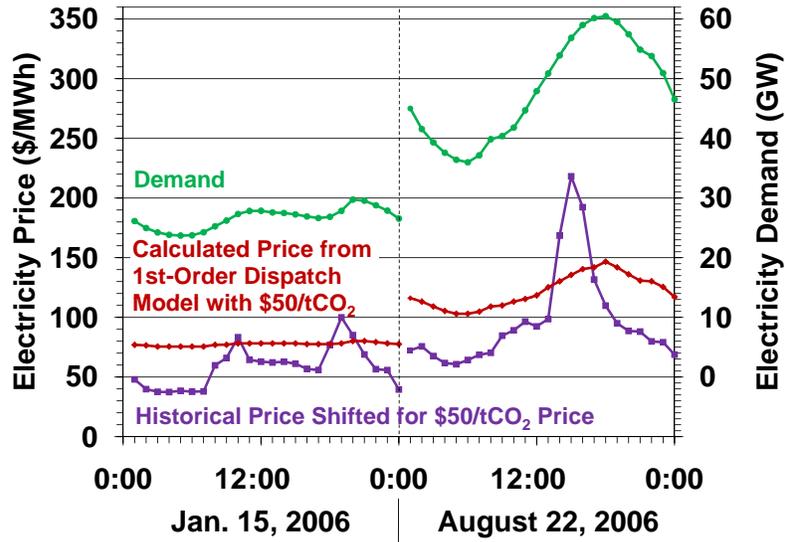


Figure 2.1: The first-order model calculates prices that closely follow trends in demand, which do not reproduce historical ERCOT electricity price spikes.

combustion or oxycombustion technologies with CO₂ capture.

After a detailed description of the optimization model, results are presented that demonstrate the importance of modeling price volatility and describe the impact of price-forecasting ability, CO₂ price, and power/capture system specifications. Also discussed is a first-order method to approximate the effect of CO₂ price on electricity prices in a gas-dominated market such as ERCOT.

2.1 Nomenclature

Table 2.1 lists common subscripts and superscripts used in defining the model, Table 2.2 lists decision variables, and Tables 2.3–2.7 list the parameters used by the model. These tables are a reference for the sections that follow.

Table 2.1: The following subscripts and superscripts are commonly used in variable and parameter definitions.

<i>Subscript</i>	<i>Description</i>	<i>Units</i>
t	Time index	Unitless
<i>Common Superscripts</i>	<i>Designation</i>	<i>Relevant Variables and Parameters</i>
a	Absorption systems	$y, u, on, off, E, \underline{y}$
s	Stripping/compression systems	$y, u, on, off, E, \underline{y}$
c	Capture systems	S^u, S^d
b	Base plant systems	$u, on, off, S^u, S^d, \delta, \Theta$
u	Up	$\Delta, \hat{\eta}, \delta, \Theta$
d	Down	$\Delta, \hat{\eta}, \delta, \Theta$

Table 2.2: The following variables are optimized or calculated by the model.

<i>Variable</i>	<i>Description</i>	<i>Units</i>
x	Gross power output	MW
x^{net}	Net power output	MW
y	Capture system load	Fractional
Δ	Load change	Fractional
u	Commitment status	Binary: 1 = on, 0 = off
on	Startup indicator	Binary: 1 = yes, 0 = no
off	Shutdown indicator	Binary: 1 = yes, 0 = no
l	Quantity of CO ₂ in rich solvent storage tank	tCO ₂
Π	Total operating profits	\$

Table 2.3: The following parameters help define power and CO₂ capture systems in the single plant optimization model.

<i>Parameter</i>	<i>Description</i>	<i>Units</i>
T	Final time index	Unitless
τ	Length of time in each interval t	Hours
$P^{e,h}$	Historical electricity price	\$/MWh
$P^{e,f}$	Pseudo-forecasted electricity price	\$/MWh
σ	Standard deviation of historical electricity prices	\$/MWh
N	Number of historical electricity prices in a moving average	Unitless
n	Polynomial order in Savizky-Golay smoothing filter	Unitless
f	Frame size in Savizky-Golay smoothing filter	Unitless
E	Capture system equivalent work	MWh/tCO ₂
R^b	Base plant CO ₂ emissions rate	tCO ₂ /MWh
F	Design CO ₂ removal	Fractional
\bar{x}	Maximum gross power output	MW
\underline{x}	Minimum gross power output	MW
\underline{y}	Minimum capture system load	Fractional

Table 2.4: The following cost parameters make up the total cost function.

<i>Parameter</i>	<i>Description</i>	<i>Units</i>
C^{Sup}	Startup cost	\$
C^{SDown}	Shutdown cost	\$
C^{Fuel}	Fuel cost	\$
C^{CO_2}	Carbon dioxide emissions cost	\$
$C^{b,O\&M}$	Operation and maintenance cost	\$
C^{Solv}	Solvent makeup cost	\$
$C^{Caustic}$	Caustic sodium hydroxide (NaOH) makeup cost	\$
C^{Waste}	Reclaimer waste disposal cost	\$
C^{CapWat}	Cost for additional water used for CO ₂ capture	\$
$C^{T/S}$	CO ₂ transport and storage cost	\$
$C^{CapRamp}$	Cost for ramping CO ₂ capture components	\$

2.2 Methodology

2.2.1 General Model Formulation

The model is a mixed-integer linear program (MIP) created in the General Algebraic Modeling System (GAMS) modeling language and solved using the IBM ILOG CPLEX Optimizer. The formulation contributes to literature on solving the unit commitment problem of least-cost electricity dispatch by providing a framework for modeling several CO₂ capture system configurations integrated with a fossil-fueled power plant [Baldick, 1995, Frangioni & Gentile, 2006, Zendejdel et al., 2008]. Many model constructs are derived from this literature. However, while least-cost dispatch models use input electricity demand to minimize operating costs across all facilities in an electricity system, the model described in this chapter solves the inverse problem by using input electricity prices to maximize profit at a single plant.

Table 2.5: The following parameters are utilized to calculate costs and performance of the facility being modeled (MMBTU=million British thermal units, m³=cubic meters, kg=kilogram).

<i>Parameter</i>	<i>Description</i>	<i>Units</i>
S^u	Cost per startup	\$/startup
S^d	Cost per shutdown	\$/shutdown
H^b	Base plant heat rate	MMBTU/MWh
OM^b	Base plant operation and maintenance cost	\$/MWh
D	Total solvent degradation rate	kg solvent per tCO ₂ stripped
D^{th}	Solvent degradation rate from thermal effects	kg solvent per tCO ₂ stripped
$D^{Caustic}$	Caustic consumption rate	kg caustic per tCO ₂ stripped
P^{Fuel}	Fuel price	\$/MMBTU
P^{CO_2}	CO ₂ price	\$/tCO ₂
P^{Solv}	Solvent price	\$/kg solvent
$P^{Caustic}$	Caustic price	\$/kg caustic
P^{Waste}	Waste disposal price	\$/kg waste
P^{Water}	Water price	\$/m ³
$P^{T/S}$	CO ₂ transport and storage cost	\$/tCO ₂ stripped
$P^{e,avg}$	Annual average electricity price	\$/MWh

Table 2.6: The following parameters are also utilized to calculate costs and performance of the facility being modeled (MMBTU=million British thermal units, m³=cubic meters, kg=kilogram).

<i>Parameter</i>	<i>Description</i>	<i>Units</i>
w	Water used for CO ₂ capture and compression per MW gross plant size	m ³ /MW
w^R	Water fraction in the reclaimer	Fractional
η^b	Base plant efficiency	Fractional
$\hat{\eta}$	Efficiency point penalty for a 100% ramp of capture systems	Fractional
δ^b	Base plant ramp rate	MW/min
δ^a	Absorption system ramp rate	Fractional load/min
δ^s	Stripping system ramp rate	Fractional load/min
Θ	Minimum number of intervals on after startup or off after shutdown	Unitless
Θ^0	Minimum number of intervals on or off after initial time period	Unitless

Table 2.7: The following parameters constrain flexible capture operation and help define solvent storage systems.

<i>Parameter</i>	<i>Description</i>	<i>Units</i>
f^{Steam}	Fraction of maximum LP steam flow to treat all solvent exiting the absorber at full load	Fractional
Z_{min}^{Turb}	Minimum LP turbine load	Fractional
f^{Equip}	Stripping/compression equipment oversizing fraction	fractional
α	Maximum time capture system with solvent storage could operate with 100% absorption and 0% stripping and compression (storage hours)	Hours
ψ	Solvent storage tank size	m ³
ρ	Solution density	kg solution/m ³
ω	Solvent weight fraction	kg solvent/kg solution
Ω	Design CO ₂ carrying capacity	mol solvent/mol CO ₂
M^{CO_2}	CO ₂ molecular weight	kg/kmol CO ₂
M^{Solv}	Solvent molecular weight	kg/kmol solvent
\bar{l}	Capacity for CO ₂ storage in rich storage tank	tCO ₂

Least-cost dispatch modeling has demonstrated CO₂ capture as a base and intermediate load technology in a carbon constrained electricity system [Johnson & Keith, 2004, Luckow et al., 2010, Ludig et al., 2010, Wise & Dooley, 2009]. These models enable detailed technology comparisons over long-term market conditions, but they do not represent short-term price volatility and intertemporal plant operating constraints needed to study flexible CO₂ capture. Single plant profit maximization is thus a complementary technique that approximates behavior of other facilities through input electricity prices while allowing detailed representation of short-term price volatility and flexible CO₂ capture operation. The operating model for flexible capture developed for this formulation is then used in least-cost electricity dispatch modeling described in Chapter 5.

Price-based profit maximization has previously been used to study generator operation in competitive electricity markets and can consider multiple units in a generation portfolio [Dicorato et al., 2009, Solanki et al., 2006]. The model presented here, however, analyzes a single facility. Profit maximization at a single facility is directly applicable to firms that operate one plant; firms with several generation assets seek to maximize profits across their full portfolio. In 2007, there were 46 plant operators in the United States (2 in ERCOT) that only operate one coal-fired facility larger than 50 MW and 83 plant operators (11 in ERCOT) that only operate one gas-fired facility larger than 50 MW [USEPA, 2010]. Portfolio profit maximization finds the optimal electricity offer strategy based on expected demand, expected offers by competitors, and plant constraints. Modeling competitor offer strategies is outside the scope of this work, but single plant profit maximization provides a conservative profit estimate when assessing CO₂ capture investment options.

A linear formulation is chosen to facilitate robust model solution with com-

putation times of minutes to hours. By definition, all model equations are defined as linear functions of decision variables. Thus, the model cannot represent nonlinear behaviors such as the change in power generation efficiency over its output range or the change in CO₂ capture energy performance over its load range. All input performance parameters thus represent average values across the relevant operating range. A nonlinear or piece-wise linear representation of performance parameters would improve solution accuracy, but the simple linear formulation is assumed sufficient to draw general conclusions based on aggregate results. Future work could explore a more detailed representation of plant operating characteristics.

2.2.1.1 Required Input Information

Input electricity prices, P_t , are required for each time interval, t in the study period, and these prices relate the optimized plant to the rest of the electricity system. All other facilities implicitly participate in the market to produce the electricity prices used for single plant profit maximization. As long as prices exceed costs long enough to recoup startup costs and satisfy plant constraints, the optimized plant will run. Competition with other facilities is not represented explicitly, but those plants are also assumed to run if prices exceed their costs. All analysis with this model uses a one year study period, and the time step is set to 15 minutes, corresponding to ERCOT price settlement intervals. However, the time step can be adjusted within the GAMS code, and the length of the study period is specified by the number of prices imported into the model.

The facility is assumed to be a price-taker in a competitive electricity market; that is, changes in its net output have a negligible effect on electricity prices. This assumption is more accurate if the facility primarily provides base load because marginal facilities set electricity prices. Output at a large base load facility can affect

which plant is marginal, but this effect is assumed small.

Several parameters are required to specify the cost and performance of power and CO₂ capture systems along with the market conditions faced by the facility. These parameters are listed in Tables 2.3–2.7 and described in detail below in the context of the objective and constraint equations.

2.2.1.2 Decision Variables

The model seeks to maximize profit by choosing the value of continuous base plant, absorber, and stripper load variables in each interval while also determining binary characteristics such as commitment status (on or off) and whether or not a startup or shutdown occurred.

Base plant load is defined as the ratio of gross power output, x_t , to maximum power output, \bar{x} . Gross power output is used as a decision variable rather than net power output to simplify calculation of fuel and CO₂ emissions costs. Net power output after accounting for CO₂ capture energy requirements, x_t^{net} , is only needed to determine revenue from electricity sales; this calculation is discussed in 2.2.1.3.

Absorber load, y_t^a , is the ratio of the quantity of CO₂ removed to the maximum possible quantity of CO₂ removed when treating all flue gas with the base plant at full load. Stripper load, y_t^s , which is assumed equal to compressor load, is the ratio of stripping steam mass flow to the mass flow required to strip all CO₂ from an absorber at 100% load. Absorber and stripper load are defined using maximum flue gas and steam flow rates rather than current available flows in order to preserve model linearity. Absorber and stripper load also represent the load on any associated components such as pumps, fans, and heat exchange devices. When a solvent storage system is available, the model uses another continuous variable, l_t , to track the

available CO₂ storage capacity by monitoring the quantity of CO₂ currently stored in the rich solvent tank. This variable must also be positive.

To allow the model to assess a cost for ramping the CO₂ capture system, continuous variables are defined to represent the fractional load change by absorption and stripping/compression equipment in either direction (up or down): $\Delta_t^{a,u}$, $\Delta_t^{a,d}$, $\Delta_t^{s,u}$, $\Delta_t^{s,d}$. These load change variables are defined as $\Delta_t^u \geq y_t - y_{t-1}$ and $\Delta_t^d \geq y_{t-1} - y_t$ for each type of CO₂ capture system. They must also be positive ($\Delta_t^u, \Delta_t^d \geq 0$) to prevent the model from assigning negative values to produce an artificial cost saving in intervals when a load change did not occur.

Binary variables describe the commitment status (on or off) of the base plant, absorption, and stripping systems (u_t^b, u_t^a, u_t^s). Additional binary variables are also used to indicate the presence of a startup (on_t^b, on_t^a, on_t^s) or shutdown ($off_t^b, off_t^a, off_t^s$) for each of the three equipment categories.

2.2.1.3 Objective Function

The objective in this model is to maximize total operating profits, Π , across the time duration of interest. Total operating profits are defined in 2.1 as the sum of electricity sales revenue minus all costs. Revenue is the product of the electricity price, P_t , the length of time in an interval, τ , and the x_t^{net} after subtracting any energy requirement for CO₂ capture. Costs, denoted as C with superscripts and subscripts, are assessed for the following: equipment startup and shutdown, fuel, CO₂ emissions, base plant operation and maintenance (O&M), solvent makeup to offset losses, caustic sodium hydroxide (NaOH) for thermal solvent reclaiming, reclaimer waste disposal, additional water use for CO₂ capture, CO₂ transport and storage, and ramping the capture system components up and down. CO₂ capture ramping costs are a proxy for efficiency losses during transient CO₂ capture operation.

$$\Pi = \sum_{\forall t} \left(\begin{array}{l} P_t x_t^{net} \tau - C_t^{SUP} - C_t^{SDown} - C_t^{Fuel} - C_t^{CO_2} - C_t^{b,O\&M} \\ - C_t^{Solv} - C_t^{Caustic} - C_t^{Waste} - C_t^{CapWat} - C_t^{T/S} - C_t^{CapRamp} \end{array} \right) \quad (2.1)$$

In Eqn. 2.1, x_t^{net} is the difference between gross output and the energy requirements of absorption and stripping/compression systems (Eqn. 2.2). The energy requirement for stripping and compression is the product of stripping load, stripping equivalent work, E^s , base plant CO₂ emissions rate, R^b , design CO₂ removal fraction, F , and base plant gross capacity, \bar{x} . An analogous term for absorption energy requirement is produced by substituting absorber load for stripper load and absorption equivalent work, E^a , for stripping/compression equivalent work.

$$x_t^{net} = x_t - E^s R^b F \bar{x} y_t^s - E^a R^b F \bar{x} y_t^a \quad (2.2)$$

Startup and shutdown costs, C_t^{SUP} and C_t^{SDown} , are the product of the cost per startup or shutdown, S^u or S^d , and startup/shutdown indicator variables for the base plant, absorption, and stripping systems (Eqns. 2.3 and 2.4). As formulated below, absorption and stripping systems are assumed to have the same startup and shutdown cost, $S^{u,c}$ and $S^{d,c}$, but differentiating between the two is a straightforward modification.

$$C_t^{SUP} = S^{u,b} on_t^b + S^{u,c} (on_t^a + on_t^s) \quad (2.3)$$

$$C_t^{SDown} = S^{d,b} off_t^b + S^{d,c} (off_t^a + off_t^s) \quad (2.4)$$

Fuel costs, C_t^{Fuel} , are the product of gross power output, base plant heat rate, H^b , the price of fuel, P^{Fuel} , and the time interval length (Eqn. 2.5). CO₂

emissions costs, $C_t^{CO_2}$, are the product of the assumed CO₂ price, P^{CO_2} , and the difference between the quantity of CO₂ produced by the base plant, $R^b x_t \tau$, and that removed by absorption systems, $R^b \bar{x} F y_t^a \tau$ (Eqn. 2.6). Non-fuel or CO₂ operation and maintenance costs for the base plant, $C_t^{b,O\&M}$, are also calculated as the product of marginal O&M costs, OM_b , gross power output, and time interval length (Eqn. 2.7).

$$C_t^{Fuel} = P^{Fuel} H^b x_t \tau \quad (2.5)$$

$$C_t^{CO_2} = P^{CO_2} (R^b x_t - R^b \bar{x} F y_t^a) \tau \quad (2.6)$$

$$C_t^{b,O\&M} = OM_b x_t \tau \quad (2.7)$$

Solvent makeup costs, C_t^{Solv} , are incurred by the need to add new solvent to compensate for volatile losses out the absorber, thermal degradation in the stripping section, and oxidative degradation in the absorption section (Eqn. 2.8). Thermal degradation is assumed constant because solvent remains in the bottom of the stripper for the same amount of time regardless of load, so solvent makeup costs include a term that is not dependent on stripper load. This term incurs a fixed cost equal to the product of the solvent price, P^{Solv} , the quantity of CO₂ produced by a base plant at full load, $R^b \bar{x} F \tau$, and the quantity of solvent thermally degraded per ton of CO₂ produced, D^{th} . The other term in Eqn. 2.8 accounts for all other losses, $D - D^{th}$, and is scaled by the stripper load.

$$C_t^{Solv} = P^{Solv} R^b F \bar{x} ((D - D^{th}) y_t^s + D^{th}) \tau \quad (2.8)$$

Caustic NaOH is assumed to be used in thermal solvent reclaiming to mitigate solvent losses (Eqn. 2.9). Cost for caustic, $C_t^{Caustic}$, is the product of the caustic price, $P^{Caustic}$, quantity of CO₂ stripped, $R^b \bar{x} F y_t^s \tau$, and quantity of caustic consumed per amount of CO₂ stripped, $D^{Caustic}$.

$$C_t^{Caustic} = P^{Caustic} R^b \bar{x} F D^{Caustic} y_t^s \tau \quad (2.9)$$

The reclaimer waste disposal cost, C_t^{Waste} , is the product of the waste disposal price, P^{Waste} , and the total mass of waste produced (Eqn. 2.10). The total waste mass is equal to the sum of the caustic and solvent makeup, because makeup flows into the capture system must equal the flow of exiting waste products at equilibrium. From the waste product mass flow, the total mass flow exiting the reclaimer is found by scaling the waste product mass by the fraction of water in the reclaimer, w^R .

$$C_t^{Waste} = \frac{P^{Waste} R^b \bar{x} F [D^{th} + (D^{Caustic} + D - D^{th}) y_t^s] \tau}{1 - w^R} \quad (2.10)$$

Incremental water costs from CO₂ capture and compression, C_t^{CapWat} , are the product of the water price, P^{Water} , the incremental amount of water used for CO₂ capture and compression per MW of gross plant size, w , and gross power output, which is then scaled by the time interval length and absorber and stripper load (Eqn. 2.11). The 1/2 factor in Eqn. 2.11 equation implies that incremental water use is attributed equally to absorption systems (direct contact cooling for flue gas, water wash to remove volatile products exiting the absorber, lean amine cooling) and stripping systems (compressor intercooling). This assumption could be inaccurate, but any inaccuracy has a negligible effect on model behavior with the low water price used in this work.

$$C_t^{CapWat} = P^{Water} w \bar{x} \frac{1}{2} (y_t^s + y_t^a) \tau \quad (2.11)$$

CO₂ transport and storage costs, $C_t^{T/S}$, are equal to the quantity of CO₂ stripped multiplied by the transport and storage price, $P^{T/S}$ (Eqn. 2.12).

$$C_t^{T/S} = P^{T/S} R^b F \bar{x} y_t^s \tau \quad (2.12)$$

CO₂ capture ramping costs assess a penalty proportional to the magnitude of absorber and stripper load changes (Eqn. 2.13). The constant of proportionality is the product of the expected average annual electricity price, time interval length, maximum gross power output, and ratio of the efficiency point penalty associated with a 100% ramp, $\hat{\eta}$, to the base plant efficiency, η^b [Husebye et al., 2010]. The average annual electricity price, $P^{e,avg}$, approximates the value of lost electrical output during transient operation and should be estimated from the assumed electricity market conditions. A more rigorous formulation would use electricity prices in each interval and incorporate efficiency losses into the net power output calculation. However, these effects are assumed small and are ignored to preserve model linearity.

$$C_t^{CapRamp} = P^{e,avg} \tau \bar{x} \frac{1}{\eta^b} \left(\Delta_t^{a,u} \hat{\eta}^{a,u} + \Delta_t^{a,d} \hat{\eta}^{a,d} + \Delta_t^{s,u} \hat{\eta}^{s,u} + \Delta_t^{s,d} \hat{\eta}^{s,d} \right) \quad (2.13)$$

2.2.1.4 Base Plant Constraints

The model formulation includes several typical power plant operating constraints. Gross power output is constrained between minimum and maximum values, and output is not permitted between 0 MW and minimum load. Ramp rate constraints specify how fast the plant can increase or decrease gross power output over

time, and minimum up and down time constraints define the minimum amount of time a plant must remain on after startup or off after shutdown. Additional constraints are also defined to ensure startup and shutdown costs are assessed properly.

Limits on minimum and maximum gross power output are enforced by Eqn. 2.14, which utilizes commitment variables to prevent output between zero and minimum load. Equations 2.15 and 2.16 ensure correct assignment of startup and shutdown indicator variables as long as S^u and S^d are positive. Ramp rate constraints (Eqns. 2.17 and 2.18) use ramp rate specifications, $\delta^{b,u}$ and $\delta^{b,d}$, to limit how fast the base plant can increase or decrease gross power output. The constant, 60τ , converts $\delta^{b,u}$ and $\delta^{b,d}$ from MW/min to MW/interval. The terms containing \underline{x} in Eqns. 2.17 and 2.18 ensure a proper transition between 0 MW and minimum load during startup and shutdown.

$$\forall t, \underline{x}u_t^b \leq x_t \leq \bar{x}u_t^b \quad (2.14)$$

$$\forall t|t > 1, on_t^b \geq u_t^b - u_{t-1}^b \quad (2.15)$$

$$\forall t|t > 1, off_t^b \geq u_{t-1}^b - u_t^b \quad (2.16)$$

$$\forall t|t > 1, x_t - x_{t-1} \leq 60\tau\delta^{b,u}u_{t-1}^b + (1 - u_{t-1}^b)\underline{x} \quad (2.17)$$

$$\forall t|t > 1, x_{t-1} - x_t \leq 60\tau\delta^{b,d}u_t^b + (1 - u_t^b)\underline{x} \quad (2.18)$$

Minimum up and down time constraints specify the minimum number of time intervals the base plant must remain on after startup, $\Theta^{b,u}$, or off after shutdown,

$\Theta^{b,d}$. Minimum up time constraints are separated into three parts (Eqns. 2.19, 2.20, and 2.21). Equation 2.19 is only active during initial time intervals, $1 \leq t \leq \Theta^{b,u,0}$, and forces the plant to remain on from the first time interval until the $\Theta^{b,u,0}$ interval. Setting the $\Theta^{b,u,0}$ parameter to a value greater than one implies that a startup occurred sometime before the time period being studied, so the plant must remain online for the remaining duration of its minimum up time. Equation 2.20 is active when $\Theta^{b,u,0} \leq t \leq T - \Theta^{b,u} + 2$ and enforces the minimum up time constraint throughout most time intervals. Equation 2.21 is active only in the final time intervals $T - \Theta^{b,u} + 2 \leq t \leq T$. If a startup occurs, and the remaining number of time intervals is less than the minimum up time, Equation 2.21 assures the plant remains online for the remainder of the study period. Minimum down time constraints (Eqns. 2.22, 2.23, and 2.24) are defined analogously to minimum up time constraints.

$$\forall t | 1 \leq t \leq \Theta^{b,u,0}, u_t^b = 1 \quad (2.19)$$

$$\forall t | \Theta^{b,u,0} \leq t \leq T - \Theta^{b,u} + 2, \sum_{t'=t}^{t+\Theta^{b,u}-1} u_{t'}^b \geq \Theta^{b,u}(u_t^b - u_{t-1}^b) \quad (2.20)$$

$$\forall t | T - \Theta^{b,u} + 2 \leq t \leq T, \sum_{t'=t}^T u_{t'}^b \geq (T - t + 1)(u_t^b - u_{t-1}^b) \quad (2.21)$$

$$\forall t | 1 \leq t \leq \Theta^{b,d,0}, u_t^b = 0 \quad (2.22)$$

$$\forall t | \Theta^{b,d,0} \leq t \leq T - \Theta^{b,d} + 2, \sum_{t'=t}^{t+\Theta^{b,d}-1} (1 - u_{t'}^b) \geq \Theta^{b,d}(u_{t-1}^b - u_t^b) \quad (2.23)$$

$$\forall t | T - \Theta^{b,d} + 2 \leq t \leq T, \sum_{t'=t}^T (1 - u_{t'}^b) \geq (T - t + 1)(u_{t-1}^b - u_t^b) \quad (2.24)$$

2.2.1.5 CO₂ Capture System Constraints

The model also contains minimum/maximum load, startup/shutdown indication, ramp rate, and minimum up/down time constraints for absorption and stripping systems. Minimum absorber and stripper load constraints (Eqns. 2.25 and 2.26) are analogous to the left hand side of Eqn. 2.14 and prevent operation between zero load and a minimum fractional load \underline{y} . Startup/shutdown indication, ramp rate, and minimum up/down time constraints are formulated analogously to the corresponding base plant constraints (Eqns. 2.15–2.24) with variable and parameter substitutions as indicated in Table 2.8. Maximum load constraints depend on the CO₂ capture configuration and are described below.

$$\forall t, \underline{y}^a u_t^a \leq y_t^a \quad (2.25)$$

$$\forall t, \underline{y}^s u_t^s \leq y_t^s \quad (2.26)$$

When modeling an inflexible CO₂ capture system, absorber and stripper load must equal fractional base plant load, implying that all flue gas being produced must be treated by the CO₂ capture system (Eqn. 2.27). Thus, minimum and maximum capture load must equal minimum and maximum fractional base plant load. If minimum absorption and stripping load does not equal minimum fractional base plant load, Eqns. 2.14, 2.25, and 2.26 will not allow power or capture systems to turn off once they are turned on.

Table 2.8: Analogous CO₂ capture system constraints are produced by making the following substitutions in Eqs. 2.15–2.24.

Variable or parameter in Eqs. 2.15–2.24	Substitution for absorption systems	Substitution for stripping systems
u_t^b	u_t^a	u_t^s
on_t^b	on_t^a	on_t^s
off_t^b	off_t^a	off_t^s
x_t	y_t^a	y_t^s
\underline{x}	\underline{y}^a	\underline{y}^s
$\delta^{b,u}$	$\delta^{a,u}$	$\delta^{s,u}$
$\delta^{b,d}$	$\delta^{a,d}$	$\delta^{s,d}$
$\Theta^{b,u,0}$	$\Theta^{a,u,0}$	$\Theta^{s,u,0}$
$\Theta^{b,u}$	$\Theta^{a,u}$	$\Theta^{s,u}$
$\Theta^{b,d,0}$	$\Theta^{a,d,0}$	$\Theta^{s,d,0}$
$\Theta^{b,d}$	$\Theta^{a,d}$	$\Theta^{s,d}$

$$\forall t, y_t^a = y_t^s = \frac{x_t}{\bar{x}} \quad (2.27)$$

A flexible CO₂ capture system with venting capability but no solvent storage (Fig. 1.3) is modeled by requiring absorber and stripper load to be equal but allowing capture load below the fractional base plant load (Eqns. 2.28 and 2.29). In this configuration, maximum capture load is limited by the quantity of flue gas being produced, but the facility can choose not to treat the entire flue gas stream.

$$\forall t, y_t^a = y_t^s \quad (2.28)$$

$$\forall t, y_t^a \leq \min \left(u_t^a, \frac{x_t}{\bar{x}} \right) \quad (2.29)$$

Absorber and stripper load are decoupled at a flexible CO₂ capture facility with solvent storage. In this configuration, maximum absorber load is still limited by flue gas availability (Eqn. 2.29), but stripper load is instead constrained by low pressure steam availability or stripping equipment size. Low pressure steam availability depends on the current base plant load, the minimum mass flow rate through the LP turbine, Z_{min}^{Turb} , and the fraction of LP steam flow required to treat all solvent exiting the absorber at full load, f^{Steam} (Eqn. 2.30). Steam availability could be limiting if stripping systems are oversized or the base plant is operating at reduced load.

$$\forall t, y_t^s \leq \frac{1 - Z_{min}^{Turb}}{f^{Steam}} \frac{x_t}{\bar{x}} \quad (2.30)$$

Stripping and compression equipment must be oversized to enable full-load absorption while regenerating stored rich solvent. However, the degree to which systems are oversized will depend on whether improved operating economics from oversizing offsets additional capital costs. Generally, stripping load is constrained by equipment size using Eqn. 2.31, where f^{Equip} is the equipment oversizing fraction. Sensitivity of economic results to equipment oversizing is explored in Chapter 3. One heuristic for oversizing stripping and compression equipment is assuming the facility cycles its solvent storage system daily, so stripping/compression equipment are oversized by the average load required in the remaining hours of one day to regenerate all stored rich solvent produced if the facility operates for α hours with zero-load stripping and full-load absorption. Hence, the equipment oversizing fraction is set to $24/(24 - \alpha)$, which represents the equipment size-limited maximum load. The α parameter can be called the number of daily “storage hours,” though this terminology is somewhat misleading because this model does not require solvent storage to occur for any particular amount of time each day. This approach to oversizing is based on

the initial hypothesis that solvent storage would be cycled daily in response to diurnal electricity price variations instead of shorter- or longer-term variations. Equation 2.32 relates α to the solvent storage tank size, ψ , and the capacity for CO₂ storage in the tank, which is a function of solution density, ρ , solvent weight fraction, ω , design CO₂ carrying capacity, Ω , the molecular weights of CO₂ and solvent, M^{CO_2} and M^{Solv} , and the maximum CO₂ capture rate, $R^b \bar{x} F$.

$$\forall t, y_t^s \leq f^{Equip} u_t^s \quad (2.31)$$

$$\alpha = \frac{\psi \omega \rho}{R^b \bar{x} F \Omega} \frac{M^{CO_2}}{M^{Solv}} \quad (2.32)$$

A solvent storage configuration also requires specifying the CO₂ storage capacity and a CO₂ flow balance constraint to monitor the quantity of CO₂ stored in rich solvent over time. Equation 2.33 specifies the maximum capacity for CO₂ storage in the rich solvent tank, \bar{l} . Equation 2.34 defines \bar{l} using the tank size and solvent properties and displays its relation to α after substituting Eqn. 2.32. The definition of CO₂ storage capacity using tank size and solvent properties always holds, but the relationship with α would not exist without the equipment oversizing approach that implies daily cycling of the solvent storage system. The CO₂ flow balance is a function of CO₂ absorbed and stripped in each time interval, and its formulation is analogous to representations of other energy storage systems, such as the water balance at a pumped hydroelectric facility (Eqn. 2.35). In a flexible CO₂ capture system with solvent storage, stored lean solvent is a form of indirect energy storage, where energy storage capacity is related to the energy requirement for capture and quantity of solvent inventory. To reflect the inability to plan further than one day

in advance, the model also allows the user to specify a fixed quantity of stored CO₂ that must be stored in rich solvent at the beginning of each day.

$$\forall t, l_t \leq \bar{l} \quad (2.33)$$

$$\bar{l} = \frac{\psi\omega\rho M^{CO_2}}{\Omega M^{Solv}} = \alpha R^b \bar{x} F \quad (2.34)$$

$$\forall t | t > 1, l_t = l_{t-1} + \tau R^b \bar{x} F (y_t^a - y_t^s) \quad (2.35)$$

2.2.2 Adjusting Electricity Prices for Forecasting Ability and CO₂ Price

The electricity prices used to optimize plant operation should reflect its forecasting ability and the current electricity market conditions. Using historical prices, $P_t^{e,h}$, directly to optimize plant operation implies perfect foreknowledge of electricity prices over all time periods, which is one year in the analyses presented here. Perfect foreknowledge over a year is unrealistic, particularly for large irregular price spikes, but profits calculated assuming perfect price foreknowledge represent an upper-bound on economic performance.

A more realistic approach has been developed that uses historical electricity prices to produce a pseudo-forecasted price series meant to approximate expected prices from day-ahead forecasts. Longer or shorter planning periods might be preferred by some operators, but optimizing in response to a day-ahead forecast should yield a reasonable approximation of actual performance. When assuming day-ahead forecasting, plant operation is optimized in response to pseudo-forecasted prices, then profits are calculated using historical prices.

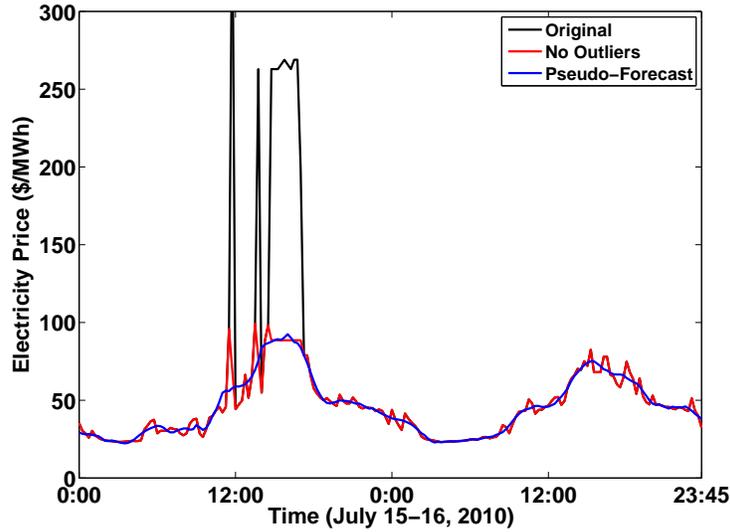


Figure 2.2: Outlier removal and smoothing of electricity price data produce a pseudo-forecasted electricity price series.

Pseudo-forecasted prices are calculated in two steps. First, outliers are identified as those prices that exceed a specified multiple of σ standard deviations from a moving average of N prices centered on the current price under consideration. Any outliers are removed, and prices in outlier intervals are linearly interpolated between the nearest non-outlier prices. After removing outliers, price data are then smoothed using a Savitzky-Golay polynomial smoothing filter, which requires specifying an order of the polynomial fit n and the frame size f within which to produce the fit. Figure 2.2 is a graphical example of this procedure using electricity prices from July 15–16, 2010. Price spikes are removed by outlier removal, then irregularities in price variations are smoothed by the Savitzky-Golay filter to produce the pseudo-forecast curve.

Pseudo day-ahead forecasted prices used in the model, $P_t^{e,f}$, are generated by iterating the outlier removal and smoothing procedures while adjusting σ , N , n , and

f until the mean average percent error (MAPE, Eqn. 2.36) and forecast mean square error (FMSE, Eqn. 2.37) are consistent with current day-ahead forecasting models [Li et al., 2005, Li et al., 2007]. The parameter T is the total number of time intervals, and the factor of 100 in the MAPE equation converts from fraction to percent.

$$MAPE = \frac{100}{T} \sum_{t=1}^T \frac{|P_t^{e,h} - P_t^{e,f}|}{P_t^{e,h}} \quad (2.36)$$

$$FMSE = \sqrt{\frac{1}{T} \sum_{t=1}^T (P_t^{e,h} - P_t^{e,f})^2} \quad (2.37)$$

Another unrealistic but conservative case would assume no price foreknowledge, where a facility simply operates in response to the most recent price signal. Some price prediction is necessary with solvent storage to plan when to store and regenerate rich solvent, but a venting-only flexible CO₂ capture system could potentially operate in a purely reactive fashion. Venting-only flexible capture without price foreknowledge is analyzed using a rule-based MATLAB model that includes constraints on the CO₂ capture system ramp rate and the maximum load of the base plant and CO₂ capture system. This simplified model does not include minimum up/down time constraints, startup costs, minimum load, CO₂ capture ramping costs, or base plant ramp limits, so the GAMS model must be run with limited constraints to enable direct comparison. Assuming CO₂ prices are high enough for short-run marginal costs (SRMC) of electricity production to be lowest with full-load CO₂ capture, the model chooses to turn the base plant off in the following interval if the electricity price in the current interval falls below the SRMC at full-load CO₂ capture. If the electricity price in the current interval is high enough for additional electricity sales at partial-load CO₂ capture to offset increased CO₂ emissions costs, capture load will decrease

in the following interval. Between these two price thresholds, the facility will move towards full-load base plant and CO₂ capture operation.

In addition to using pseudo-forecasted price series to approximate forecasting error, electricity prices should also be adjusted for electricity market conditions to ensure that the effect of changing market conditions is applied consistently to the plant being optimized and the rest of the electric grid. In this chapter, CO₂ emissions penalty is the primary market condition varied in sensitivity analysis. The CO₂ emissions penalty on the plant is a function of its operating point and performance characteristics. The CO₂ emissions penalty on the grid can be represented by adjusting electricity prices by the emissions costs of marginal generating facilities. About 60% of ERCOT generating capacity utilizes natural gas, so even with relatively low natural gas prices, coal-based generation typically provides base load, with gas-fired facilities providing intermediate and peaking generation [ERCOT, 2011c]. Thus, electricity prices most often correspond to the operating cost of natural gas-based plants [PE-Ltd., 2010]. Prior modeling indicates that this phenomenon is likely to persist under a wide range of fuel and CO₂ price conditions [Cohen et al., 2009]. Newcomer and co-authors demonstrate that ERCOT dispatch order is largely unaffected by CO₂ prices up to \$50/tCO₂ [Newcomer et al., 2008]. Additionally, ERCOT reports that around \$100/tCO₂ is needed for combined cycle gas-fired units to replace coal-based units for base load, but less efficient gas-based units will remain marginal above that CO₂ price [ERCOT, 2009a]. Therefore, the increase in electricity prices with CO₂ price is reasonably approximated by uniformly shifting electricity prices by the average emissions cost of natural gas-fired facilities in ERCOT.

To demonstrate the assumed effect of CO₂ price on input electricity prices, Figure 2.3 shows the 2008 ERCOT price-duration curve along with adjusted curves

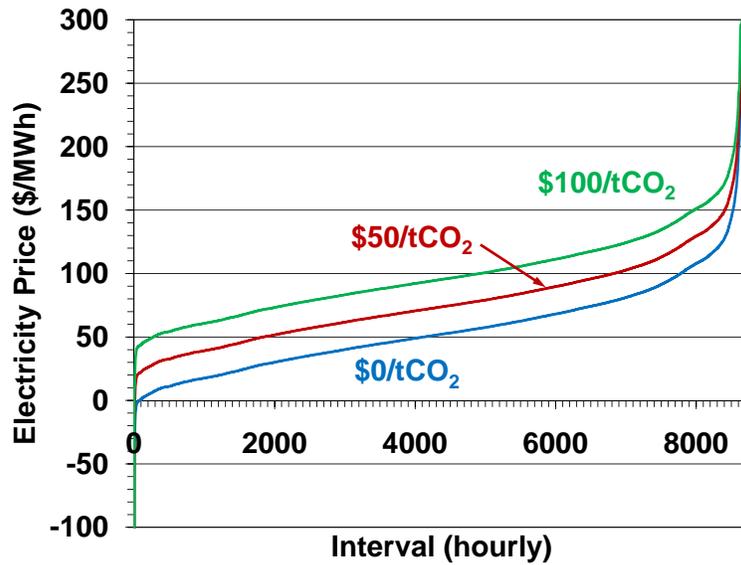


Figure 2.3: The 2008 ERCOT electricity price-duration curve is shown with two adjusted curves for $\$50/\text{tCO}_2$ and $\$100/\text{tCO}_2$.

for $\$50/\text{tCO}_2$ and $\$100/\text{tCO}_2$. Even at CO_2 prices of $\$100/\text{tCO}_2$ or greater, where marginal generating costs without CO_2 capture exceed $\$125/\text{MWh}$, electricity prices can still be high enough to justify operation without CO_2 capture. Carbon-intensive capacity will likely have been replaced under these market conditions, but an existing, available facility could continue to operate with a low capacity factor [Luckow et al., 2010]. Changes to electricity demand, fuel prices, and available capacity will also contribute to variations in electricity prices over time, but these effects are outside the current scope of this work.

This method of adjusting electricity prices for CO_2 price is less accurate for more diverse electricity markets such as the PJM and Midwest Independent System Operator (MISO) systems, and it does not allow electricity price adjustment for any other market conditions (i.e. coal price, natural gas price) [Newcomer et al., 2008]. Section 3.1.2 provides a framework for adjusting electricity prices for fuel and CO_2

price changes while accounting for the capacity mix and changes to plant dispatch order as market conditions vary. This procedure allows study of electricity systems other than ERCOT with sufficient input data. However, the first-order adjustment for CO₂ price is used in all analysis throughout this chapter, where CO₂ emissions penalty is the only electricity market independent variable.

2.3 Analysis and Results

2.3.1 Limited Model Formulation for Efficient Analysis

The general model formulation permits accurate representation of many power and CO₂ capture system behaviors over long and short time scales. However, initial testing on the UT Mechanical Engineering Department high performance computers (HPCs) found that computation time for each model run was often on the order of several hours when all constraints and objective function terms were included. The ME department HPC linux cluster consists of 12 rack-mounted Dell Poweredge 2950 workstations with 2 dualcore, hyperthreading 3.73 gigahertz (GHz) Xeon processors and 24 gigabytes (GB) shared memory as well as 9 rack-mounted Dell Poweredge T610 machines with 2 sixcore, hyperthreading 3.33 GHz Xeon processors and 24 GB shared memory. Though UT has more powerful computational resources available, the present analytical objective is approximating aggregate results over an annual time scale for tens to hundreds of different plant and market conditions, so a multi-hour computation time for each model run is undesirable. Therefore, several costs and constraints were examined to assess whether eliminating them from the model reduces computational expense without significant deviation from full model results. This evaluation is performed by varying the key parameters associated with each cost and constraint and observing the impact on 1) computation time and 2) annual operating profits. Removing constraints does sometimes cause unrealistic short-term

plant behavior (e.g. rapid startup/shutdown cycling of coal-fired facilities when minimum up/down time constraints are removed). While this behavior is unacceptable if using the model for short-term operational planning, it is tolerable when seeking only to analyze annual aggregate results.

The following costs and constraints were examined for possible elimination to produce a limited, more efficient formulation without significantly affecting results:

1. base plant minimum up/down time
2. absorber/stripper minimum up/down time
3. absorber/stripper startup costs
4. absorber/stripper ramping costs.

All other constraints and costs were deemed essential from the outset for satisfactory accuracy, but they could be subjected to a similar analysis if desired.

2.3.1.1 Costs and Constraint Parameter Ranges

Table 2.9 summarizes the parameter ranges used to study the solution deviation-computation time tradeoff for the four costs and constraints chosen for possible exclusion from the limited formulation. Parameters are assumed the same for the absorber and stripper and in either direction (on and off, up and down) for minimum up/down time and ramp rates. Minimum up and down time for a large coal-fired unit is typically on the order of several hours to one day or more [Johnson et al., 1997, Lee, 1989]. There is limited understanding of CO₂ capture operating limits at the scale of commercial power plants; thus, operating ranges are chosen assuming that a CO₂ capture system designed for flexible operation should ramp or turn on and off faster

than the base plant and at lower cost. Though Eqn. 2.13 is preferred for calculating ramping costs, ramping costs are assigned directly here to enable a straightforward sensitivity analysis. Realistic ramping costs are difficult to estimate, but Husebye assumes an efficiency point penalty of 3% during transient stripping and compression operation, which implies an average ramping cost of about \$10 per 1 percent load change in the 2008 ERCOT market with a \$50/tCO₂ price [Husebye et al., 2010]. Absorber and stripper startup costs are examined up to the nominal startup cost of the base plant, but realistic startup costs are expected to be much lower because unlike the base plant, CO₂ capture startup does not require substantial consumption of petroleum-based fuel.

A cost or constraint is deemed unnecessary for the limited formulation if realistic parameter values change annual operating profits by less than 1% relative to results when the cost or constraint is excluded. If changes to annual profits are greater than 1%, a substantial increase to computation time could still warrant exclusion if the resulting solution deviation is justified within the context of the particular analysis.

Table 2.9: Parameters for several constraints and costs were varied to examine their effect on computation time and deviation from the general formulation solution.

Constraint/cost parameter (units)	Min	Max
Base plant minimum up/down time (hours)	0	96
Absorber/stripper minimum up/down time (hours)	0	12
Absorber/stripper startup cost (\$/startup for each component)	0	10,000
Absorber/stripper ramping cost (\$/startup for each component)	0	50

2.3.1.2 Input Parameters

Table 2.10 lists key input parameters for this analysis. A 500 MW plant size is chosen as a representative size for a large coal-fired unit. Base plant heat rate and

CO₂ emissions rate are averages across ERCOT coal-fired facilities, and startup cost and ramp limits are estimated from literature [Mortensen et al., 1998, Pang & Chen, 1976, USEPA, 2008].

A baseline CO₂ capture system using 7 molal (7m) monoethanolamine (MEA) is assumed. A typical 90% CO₂ removal value is used along with a design CO₂ carrying capacity and CO₂ capture equivalent work from previous modeling results [Oyenekan & Rochelle, 2006, Ziaii et al., 2008]. CO₂ is assumed compressed to 150 bar for a conservative energy requirement estimate. Though the equivalent work for CO₂ capture is split between absorption and stripping/compression in subsequent analysis, attributing the full CO₂ capture energy requirement to stripping and compression is considered appropriate for the cost and constraint evaluation. Capture system minimum load is nominally 20%, but 30% is used for the inflexible capture configuration to satisfy equality between base plant and capture system fractional load. Default capture system ramp limits are set slightly faster than those of the base plant on a percent per minute basis on the premise that a flexible CO₂ capture system should be able to respond faster than the base plant. Stripping and compression equipment is assumed oversized by $24/(24 - \alpha)$, so systems are approximately 2.1% larger than with the inflexible or venting-only configurations. The default solvent storage system size is chosen as relatively small so that some benefit from solvent storage is achieved without exorbitant capital costs. Chapter 3 discusses solvent storage system size in detail. A day-ahead planning period for solvent storage is enforced by requiring the rich storage tank to be 71% full at the beginning of each day, the annual average daily starting level without this constraint.

Results are compared under 2008 conditions in ERCOT, so all monetary quantities are taken as 2008 U.S. dollars. The single plant profit maximization model uses

a pseudo-forecast of the zonal-average electricity prices from 2008 as input, and the assumed coal price is the Texas average for 2008 [ERCOT, 2008b, USEPA, 2010]. For reference, the average natural gas price in ERCOT in 2008 was \$7.8/MMBTU [USEIA, 2009]. A range of natural gas prices is analyzed in Chapter 3. The generation weighted-average emissions rate from ERCOT gas-fired facilities is calculated from the U.S. Environmental Protection Agency (EPA) eGRID database [USEPA, 2008]. A \$50/tCO₂ price is chosen because it is high enough for marginal operating costs to be lower with full-load CO₂ capture but low enough for CO₂ venting to be economical at high electricity prices.

Pseudo day-ahead forecast electricity prices adjusted for \$50/tCO₂ are used for optimizing plant operation, and historical prices shifted for \$50/tCO₂ are used to calculate operating profits. Pseudo-forecasted prices are generated by removing outliers from historical data and smoothing the result until prices achieve a FMSE of \$13.0/MWh and MAPE of 9.0%, values which are reasonably close to the \$5–7/MWh FMSE and 10–12% MAPE achieved with accurate day-ahead price forecasting models [Li et al., 2005, Li et al., 2007]. These results are achieved by designating outliers as falling 2 standard deviations outside a moving average of 672 pricing intervals (1 week), and using a 4th degree polynomial and 21 interval frame size in the smoothing algorithm. These outlier removal and smoothing parameters are used throughout all reported analysis with the single plant profit maximization model.

Additional input parameters are listed in Table 2.11. Typical variable operation and maintenance (VOM) costs for coal-fired power plants after excluding fuel and CO₂ emissions costs are taken from a Nuclear Energy Institute report [NEI, 2007]. The minimum load on the LP steam turbine is from an article on CO₂ capture-ready steam turbines and flexible CO₂ capture [Lucquiaud et al., 2008]. MEA and

Table 2.10: The following are the key input parameters used when examining the necessity of several costs and constraints. (*Minimum absorber/stripper load is 0.3 with inflexible capture to be consistent with Eqn. 2.27.)

Parameter (units)	Value
<i>Base Plant: Coal-Fired</i>	
Maximum output (MW)	500
Minimum output (MW)	150
CO ₂ emissions rate (without CO ₂ capture) (tCO ₂ /MWh)	1.03
Heat rate (without CO ₂ capture) (MMBTU/MWh)	10.8
Ramp limit (MW/min)	20
Startup cost (\$/startup)	10,000
<i>CO₂ Capture System: 7m MEA solvent</i>	
CO ₂ removal (fractional)	0.9
Energy requirement (equivalent work) (MWh/tCO ₂)	0.269
Minimum absorber/stripper load (fractional)	0.2*
Absorber/stripper ramp limit (%/min)	5
Design capacity (rich minus lean loading) (molCO ₂ /molMEA)	0.12
Solvent storage system size (if applicable) (max hours with full absorption and no stripping)	0.5
<i>Electricity Market</i>	
Coal price (\$/MMBTU)	1.54
Average CO ₂ emissions rate from ERCOT gas-fired facilities (tCO ₂ /MWh)	0.43
CO ₂ emissions penalty (\$/tCO ₂)	50

NaOH price and consumption rates, additional water use for CO₂ capture, water price, waste disposal cost, water composition in reclaimer waste, and CO₂ transport and storage costs are all taken from previous CO₂ capture plant design analyses [USNETL, 2007, Rao & Rubin, 2002, Rao et al., 2004, E. S. Rubin & Rao, 2007]. Solvent density is slightly greater than that of water and is the average of 7m MEA density at rich and lean loading conditions based on absorber modeling performed at The University of Texas at Austin. With these parameters, the cost of NaOH, water, and waste disposal are relatively small. However, solvent makeup and CO₂ transport and storage costs make up a significant portion of the VOM costs of CO₂ capture.

Table 2.11: The following are the additional input parameters used when examining the necessity of several costs and constraints.

Parameter (units)	Value
Non-fuel or CO ₂ base plant VOM cost (\$/MWh)	5.77
Minimum mass flow in LP turbine	10%
LP steam fraction extracted for capture	40%
MEA price (\$/kg)	2.52
MEA consumption rate (kg/tCO ₂ stripped)	1.5
Subset of MEA consumption from thermal degradation (kg/tCO ₂ stripped)	0.1
Caustic NaOH price (\$/kg)	0.5
Water fraction in reclaimer waste stream	40%
Waste disposal cost (\$/kg waste)	0.22
Water price (\$/m ³)	0.29
Additional water use for capture (m ³ /MW gross capacity)	1.63
CO ₂ transport and storage cost (\$/tCO ₂)	9.69
Solvent density (kg/m ³ solution)	1,060
MEA molecular weight (kg/kmol)	61.08

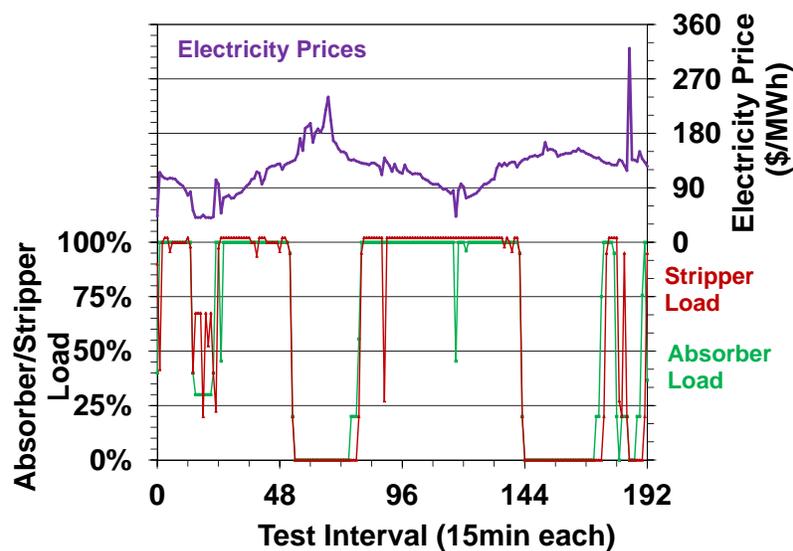


Figure 2.4: Absorber and stripper load can be erratic with no ramping cost. ($\$50/\text{tCO}_2$)

2.3.1.3 Effects on Computation Time and Annual Profits

As a qualitative example of improved representation of plant behavior, Figs. 2.4 and 2.5 display operating characteristics for the solvent storage configuration with and without a ramping cost of $\$10$ per 1% load change of the absorber and stripper. Each figure plots a test set of two days of electricity prices along with the resulting optimal absorber and stripper percent load for a facility with solvent storage. Absent any ramping penalty (Fig. 2.4), absorber and stripper load ramp up and down several times within a very short amount of time. The 5 %/min ramp limit allows this behavior, but realistic operational difficulties and expected maintenance costs could prohibit such operation. However, adding a cost of $\$10/\%$ ramp damps erratic load changes and produces a more realistic operating curve (Fig. 2.5).

Figures 2.6 and 2.7 demonstrate how CO_2 capture ramping costs affect computation time and the deviation from general formulation results. Figure 2.6 displays

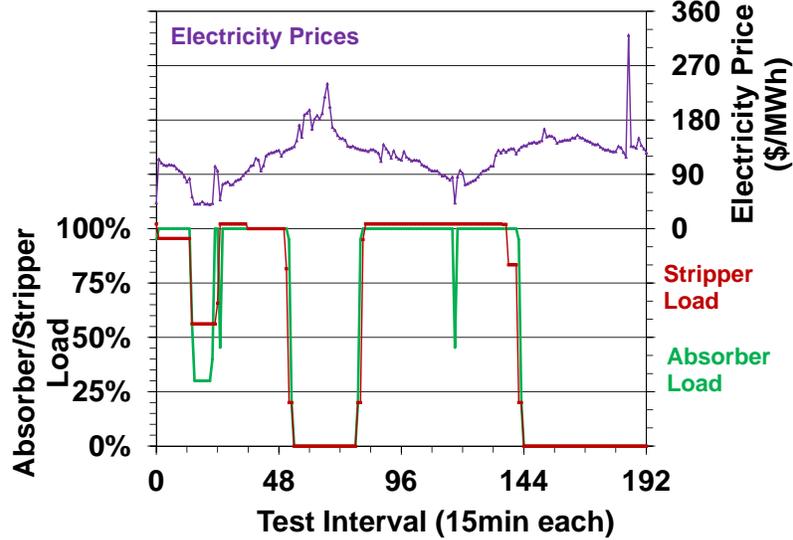


Figure 2.5: Including a ramping cost of \$10 for each 1% change in absorption and stripping load damp most rapid load changes. (\$50/tCO₂)

the annual operating profits for each CO₂ capture configuration versus CO₂ capture ramping cost, and Figure 2.7 shows the corresponding computation time. Flexible CO₂ capture is utilized often at \$50/tCO₂, so ramping the CO₂ capture system is often desirable. Profits are reduced by 1% or more above a ramping cost of \$5/% with solvent storage, \$7.5/% with venting-only flexible capture, and \$10/% for inflexible capture. Computation time remains low (1–2 min.) for the inflexible and venting-only configurations. Ramping costs only substantially increase computation time for the solvent storage scenario, for which achieving sufficient convergence required raising the model computation time limit from 10,000 seconds to 30,000 seconds at low ramp costs and 20,000 seconds at high ramp costs. However, ramp costs do not increase computation time for the solvent storage configuration at the \$10/% implied by Husebye [Husebye et al., 2010]. The effect of ramping costs on annual operating profits exceeds the 1% threshold discussed above, and increased computation time is only an issue for certain cases with solvent storage, so ramping costs are included in

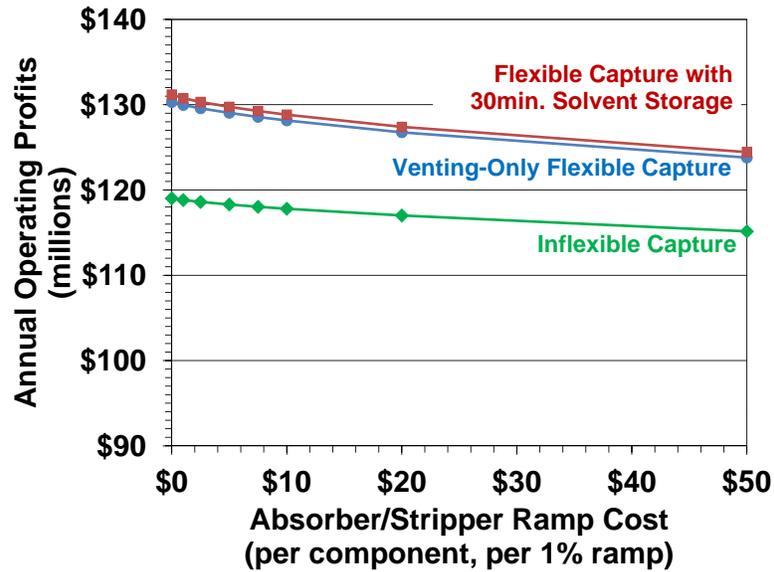


Figure 2.6: At $\$50/\text{tCO}_2$, higher ramping costs lead to a modest decrease in annual operating profits.

the limited formulation.

Figures 2.8 and 2.9 are analogous to Figs. 2.6 and 2.7 for base plant minimum up and down time constraints. Error bars in Fig. 2.8 express difficulty converging on an optimal solution. Achieving true optimality could require inordinate computation time, so the model is set to exit computations when either an optimality tolerance or a computation time limit is reached. The optimality tolerance is defined as the gap between the best feasible solution that satisfies all integer constraints and the best possible solution when some integer constraints are relaxed, and the MIP algorithm iterates between the integer and relaxed problems while attempting to close this gap. In this work, the optimality tolerance is set to $\$50,000$, but solutions converging within $\$100,000$ are often accepted. Points on the curves in Figure 2.8 are best feasible solutions at run completion, and error bars indicate the remaining optimality gap for model runs that reached maximum computation time (20,000 seconds without

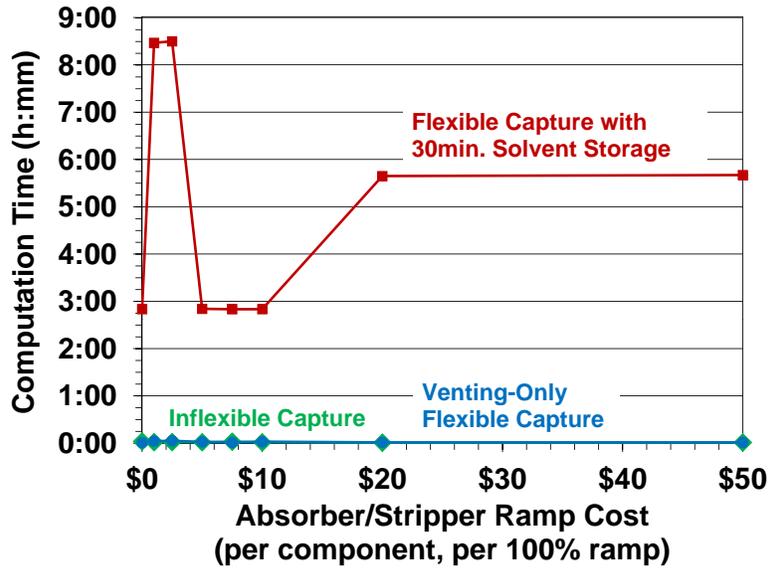


Figure 2.7: Reasonable CO₂ capture ramping costs do not excessively increase computation time. (\$50/tCO₂)

capture and 10,000 seconds for all other configurations).

All CO₂ capture configurations have high capacity factors at \$50/tCO₂, so startup and shutdown cycles are infrequent, and minimum up and down time constraints are rarely binding. For both flexible capture configurations, annual profits fall by less than 1% for all minimum up/down times studied. Profits fall by less than 1% for inflexible capture at a minimum up and down time 48 hours or lower. Without CO₂ capture, profits fall by greater than 1% for a 12-hour or greater minimum up/down time because a plant without CO₂ capture is far less economical at \$50/tCO₂, so startup and shutdown cycles are more frequent. Computation time remained near 3 hours for the solvent storage configuration regardless of minimum up and down time. However, increasing minimum up and down time increased computation time for all other configurations from under 3 minutes to 3–6 hours. A multi-hour runtime for all configurations is undesirable. Though the profit change threshold is exceeded for

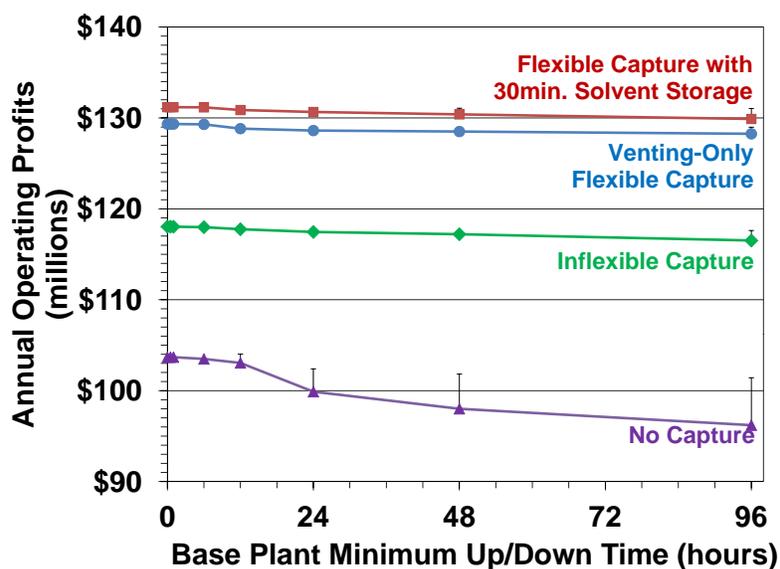


Figure 2.8: Base plant minimum up and down time has little effect on operating profits when facilities with CO₂ capture primarily provide base load. (\$50/tCO₂)

the configuration without capture in a realistic parameter range, minimum up and down time constraints are excluded from the limited formulation. This compromise is acceptable because doing so will produce a more conservative estimate of the value of CO₂ capture, which is preferable to an overestimation.

Minimum up/down time constraints on absorption and stripping systems demonstrate similar behavior to base plant minimum up/down time constraints (Figs. 2.10 and 2.11). Exceeding the 1% profit change threshold required absorber/stripper minimum up/down times on the order of 8 hours, which would be uncharacteristic of a system designed for flexible operation. Increasing absorber and stripper minimum up/down times caused computation time to grow from a few minutes to several hours for the inflexible and venting-only flexible capture configurations. For the solvent storage configuration, the model could not find a feasible solution within 6 hours of computation time when absorber/stripper minimum up/down time exceeded 2 hours.

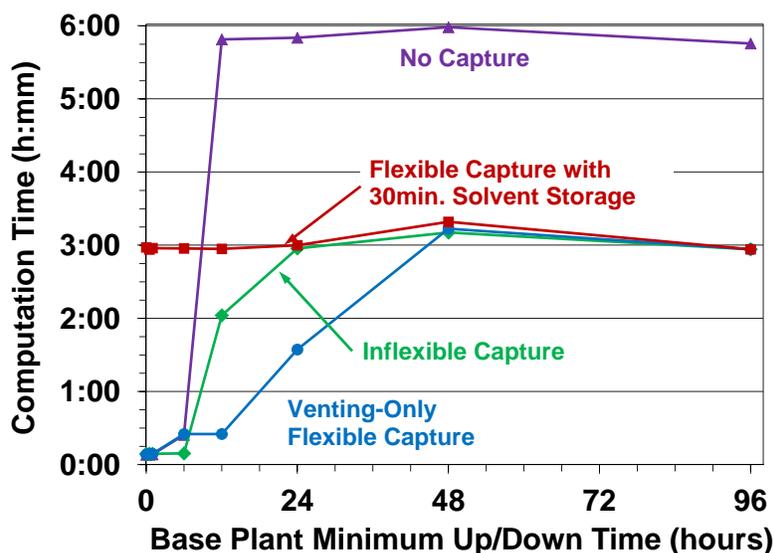


Figure 2.9: Including base plant minimum up and down time constraints in the model adds significant computation time. (\$50/tCO₂)

These constraints are excluded from the limited formulation for their minimal impact on annual operating profits and substantial increase in computational difficulty.

Absorber and stripper startup costs are only analyzed for flexible capture configurations, because CO₂ capture startup costs with inflexible capture would simply augment base plant startup costs (Figs. 2.12 and 2.13). Though absorber/stripper startup costs have minimal effect on computation time under most conditions, a 1% decrease in annual profits requires greater than \$1,000/startup/component with venting-only flexible capture and \$5,000/startup/component with solvent storage. CO₂ capture startup costs should not be on the same order as base plant startup costs, so these costs are excluded from the limited formulation for their negligible impact on annual operating profits.

In summary, absorber and stripper ramping costs are included in the limited formulation because they had a substantial impact on the optimal solution while

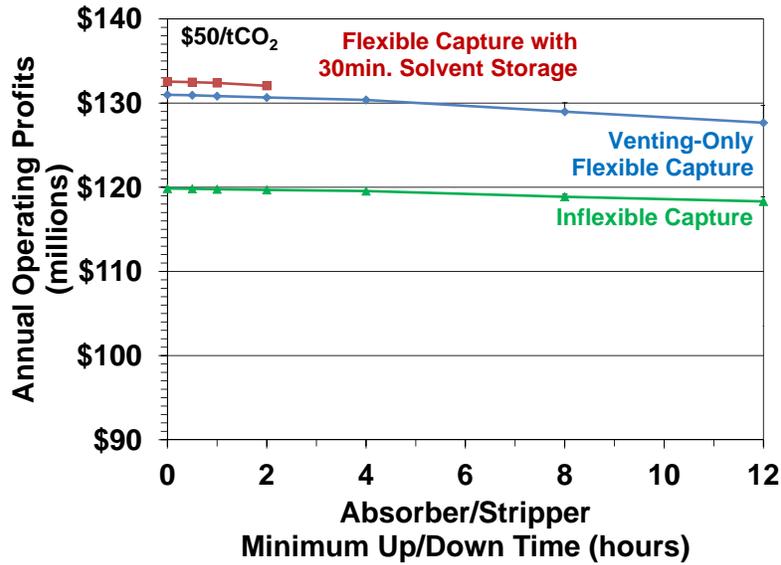


Figure 2.10: Minimum up and down time on capture systems do not significantly affect operating profits with reasonable system specifications. ($\$50/\text{tCO}_2$)

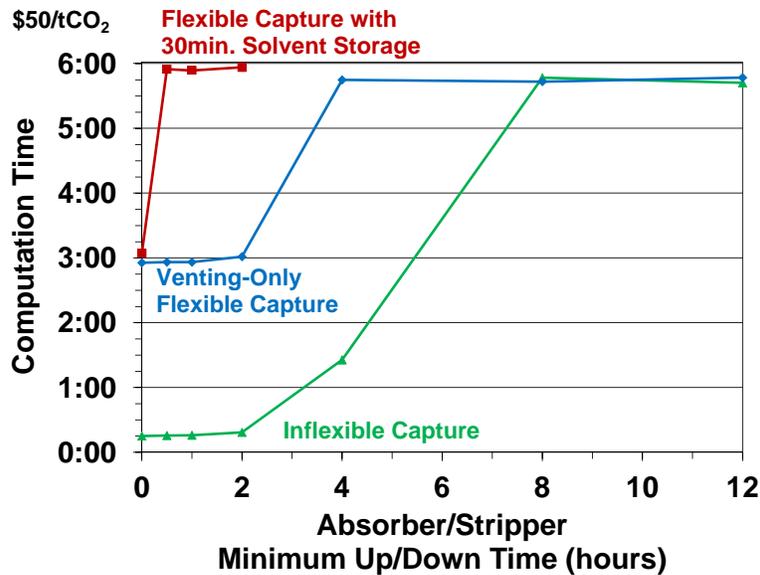


Figure 2.11: Capture system minimum up and down time constraints greatly increase computational expense and prevent feasible solutions with solvent storage within tested computation time limits. ($\$50/\text{tCO}_2$)

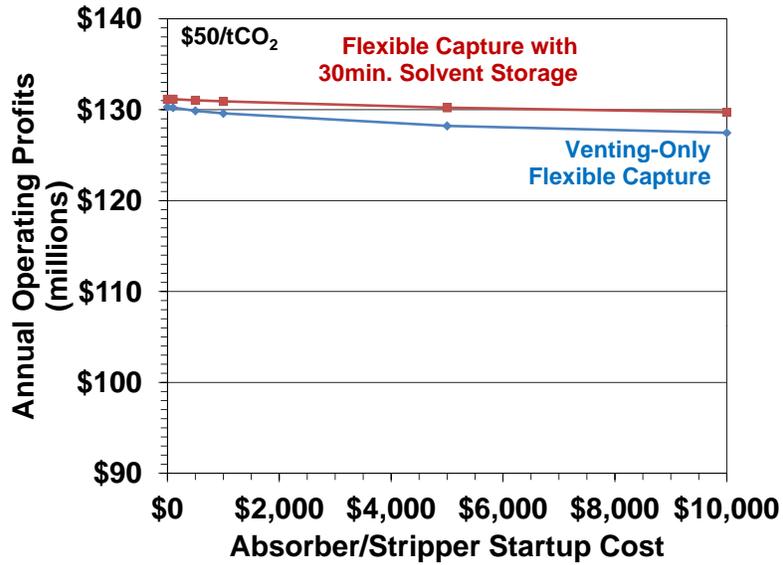


Figure 2.12: Startup costs on the order of base plant startup costs are required to substantially reduce annual operating profits. (\$50/tCO₂)

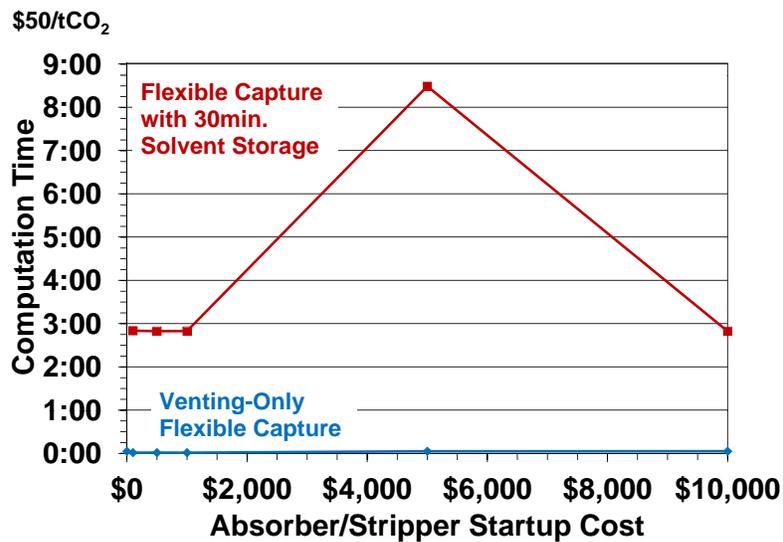


Figure 2.13: Capture system startup costs have little effect on computation time except for when \$5,000/startup is assessed with solvent storage. (\$50/tCO₂)

having little effect on computation time with ramping costs on the order of \$10/% load change. Absorber and stripper startup costs were eliminated from the limited formulation because they had minimal effect on results, and all minimum up/down time constraints were eliminated because they drastically increased computation time without significant deviation from full model results.

An undesirably long computation time can also be addressed by modifying CPLEX solver options that influence the solution procedure. With some trial and error, some reduction in computation time was achieved using the options `nodefileind=3`, `workmem=2056`, `nodesel=0`, and `varsel=3`. CPLEX uses a branch and cut algorithm for MIP optimization, which seeks the optimal solution by progressively cutting groups of nodes from a branched tree that represents all possible integer variable combinations [CPL, 2007]. Setting `nodefileind=3` and `workmem=2056` transfers MIP node files from memory to disk and compresses them when they reach 2,056 Megabytes (MB) to mitigate optimization termination due to memory limitations. Setting `nodesel=0` selects a depth-first search during the MIP optimization, which can reduce computation time if the most recently created nodes contain improved feasible solutions. Setting `varsel=3` selects a “strong branching” procedure that can help improve solution convergence when solving large, difficult problems [CPL, 2007].

The limited formulation is most applicable for a facility that primarily provides base load electricity, where power and CO₂ capture systems rarely undergo full startup and shutdown cycles. Under market conditions where base load operation is unlikely, the general formulation is more appropriate. Subsequent analysis in this dissertation assumes predominantly base load operation, so the limited formulation is utilized. When high capacity factors are not achieved, the limited formulation is expected to give a conservative estimate of the value of flexible CO₂ capture because

the relaxed constraints will provide greater benefit to facilities without capture at market conditions of interest to CO₂ capture analysis.

2.3.2 Operating Modes with Flexible CO₂ Capture

To provide greater insight into short-term flexible capture operation, Fig. 2.14 demonstrates different operating modes by plotting optimal CO₂ capture load and net power output fraction (net output divided by maximum gross output) across two sample days, January 6 and June 12, 2008 with electricity prices adjusted for a \$50/tCO₂ emissions penalty. These figures repeat Figs. 1.6 and 1.7, but this section includes additional context and description. The limited formulation and input parameters from Tables 2.10 and 2.11 are used to produce these results. With venting-only flexible CO₂ capture, the base plant ramps down when electricity prices fall below \$52/MWh, its SRMC at full-load CO₂ capture. On Jan. 6, low prices persist long enough to justify a full shutdown and incur startup costs at 7:00. Between 12:45 and 19:30 on June 12, capture load falls to zero when electricity prices exceed the \$136/MWh necessary for revenue from selling an extra 125 MW to offset costs of venting additional CO₂. At \$52–136/MWh, the base plant and CO₂ capture systems tend to operate at full load with 375 MW net output.

Figure 2.15 demonstrates operation with a solvent storage system. When prices are relatively low, stripper load is greater than absorber load to regenerate stored rich solvent and compress the resulting CO₂. Absorber load exceeds stripper load when electricity prices are relatively high and increased power output is desirable. The base plant still ramps down below prices of \$52/MWh, but increased stripping capacity reduces net minimum power output and allows the plant to avoid startup costs and remain online before 7:00 on Jan. 6. During the June 12 high price period 12:45–19:30, both absorber and stripper load fall to 0%, meaning CO₂ is being vented

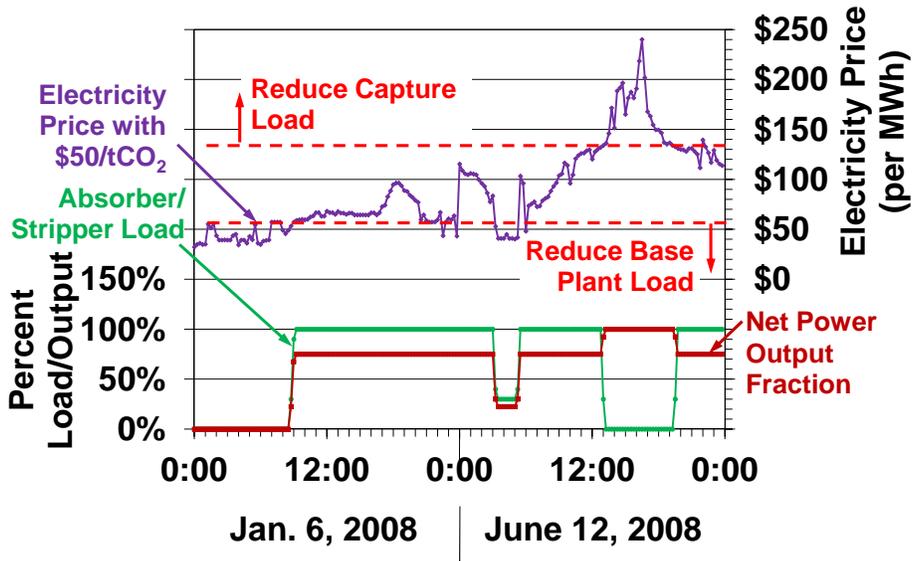


Figure 2.14: Venting CO₂ can be profitable at high electricity prices.

despite the existence of a solvent storage system. Though solvent storage eliminates the need to emit additional CO₂ during flexible capture operation, CO₂ venting might sometimes be economically justified to withhold storage capacity for later or return to a specified CO₂ level at a particular time.

2.3.3 The Importance of Representing Electricity Price Volatility

To demonstrate the importance of modeling electricity price volatility when assessing the value of flexible CO₂ capture, results from the profit maximization model are compared to results from a MATLAB first-order dispatch model created by this author in previous research [Cohen, 2009]. This model does not represent intertemporal plant constraints such as ramp rates. It uses input hourly electricity demand along with cost and performance data for each facility in an electricity system to determine which facilities should supply electricity in each hour to achieve the lowest dispatch costs. Electricity prices in each hour are then set equal to the marginal generating

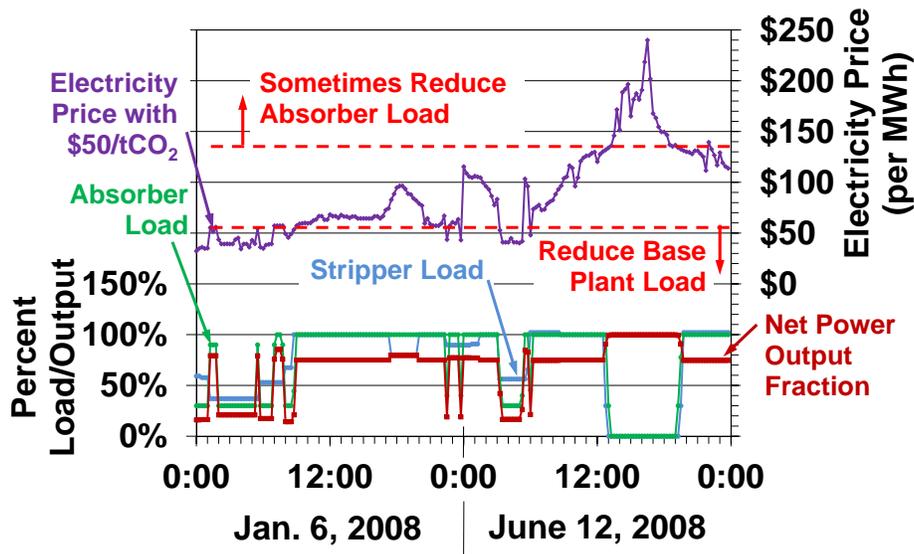


Figure 2.15: Solvent storage allows operating flexibility at intermediate electricity prices, but CO₂ might still be vented at high prices.

cost of the most expensive facility required to meet demand in that hour, and plant output and electricity prices are used to calculate operating profits. A graphical representation of this process is depicted in Fig. 2.16, which plots a typical electricity supply curve, or bid stack, for the ERCOT system. To create this figure, facilities are put in cost order and plotted as a function of their cumulative output capacity. In the figure, wind capacity is credited only for the average available wind turbine capacity, which is around 30% of rated capacity. The red dashed lines show that given an electricity demand of 40 GW, a first-order dispatch model would calculate a \$75/MWh electricity price. As demonstrated by Fig. 2.1, this procedure produces electricity prices that trend with electricity demand, and potentially valuable price spikes are not reproduced.

The first-order dispatch model compares facilities without CO₂ capture to those with inflexible and flexible CO₂ capture. However, this model can only choose

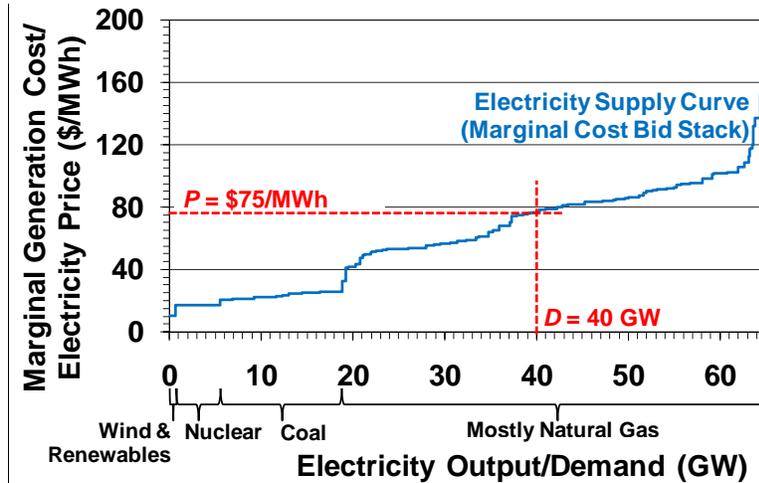


Figure 2.16: The first-order dispatch model sets electricity prices equal to the marginal cost of the most expensive facility needed to meet demand.

between two CO₂ capture operating modes (0% and 100% load), and it cannot represent solvent storage systems. Thus, its capabilities are limited relative to the optimization model described above, but comparing results between the two models demonstrates the effect of incorporating price volatility in an analysis of price-responsive flexible capture.

2.3.3.1 Input Parameters

The models are compared under 2008 conditions in ERCOT. Input parameters are the same as described in Section 2.3.1.2 and Tables 2.10 & 2.11 with a few exceptions: (1) CO₂ capture ramping costs are calculated using Eqn. 2.13 instead of direct specification, (2) 89% of CO₂ capture energy is allocated to stripping/compression systems and 11% to absorption systems, and (3) capture system minimum load is always set to 30%. Allocating capture energy in a 89%/11% split is based on analysis by Chalmers, Leach, and Gibbins and assumed representative of a typical system [Chalmers et al., 2010]. Actual energy allocation will be design-specific.

The energy allocation between absorption and stripping/compression systems is also reflected in the 3.3% fractional efficiency penalty due to transient CO₂ capture operation, so 3% is attributed to stripping/compression and 0.3% to absorption. This parameter is in units of reduced MW electrical output per MW thermal heat input per 100% ramp ($MW_e/MW_{th}/100\%$ ramp). A constant 30% minimum capture load is used for consistency across all plant configurations since the inflexible capture configuration requires minimum load equal to the 30% minimum fractional base plant load.

The first-order dispatch model uses 2008 ERCOT hourly load as input [ERCOT, 2008a]. Power plant cost and performance parameters are taken primarily from the U.S. EPA eGRID 2010v1.1 database, which includes average annual heat rates and emissions rates from 2007 [USEPA, 2010]. The Public Utilities Commission of Texas (PUCT) provides a list of rated capacities for facilities installed through year-end 2008, and these facilities are assigned plant type-specific performance parameters provided by ERCOT [PUCT, 2010, ERCOT, 2011d]. The model accounts for the impact of planned and unplanned outages and intermittent renewable generation by limiting dispatch capacity to the average available capacity in a year. In addition to the \$1.45/MMBTU Texas average coal price in 2008, the model uses the \$7.78/MMBTU Texas average natural gas price [USEIA, 2009].

To maintain consistency with the profit maximization model, the first-order dispatch model is configured so that CO₂ capture is installed on just one coal-fired facility with approximately 500 MW of average available capacity. The same CO₂ capture cost and performance parameters are assumed except that there are no ramping costs in the first-order dispatch model because it does not contain ramp rate constraints.

2.3.3.2 Results Comparison

Annual operating profits for the facility are calculated with each model for CO₂ prices ranging from \$0–200/tCO₂ with the plant having no CO₂ capture, inflexible CO₂ capture, and flexible CO₂ capture. As has been demonstrated in previous work with both models, annual profits without CO₂ capture are high at low CO₂ prices but fall with CO₂ price as plant emissions costs rise more quickly than electricity prices that are changing by the emissions costs of gas-fired facilities. Operating profits are low with inflexible CO₂ capture at low CO₂ prices because operation is less expensive without CO₂ capture, but profits rise with CO₂ price because emissions costs with CO₂ capture are lower than those at gas-fired facilities.

To observe the economic benefit from flexibility with and without a model that incorporates electricity price volatility, Fig. 2.17 plots the annual operating profit benefit provided by flexible operation at each CO₂ price, and the profit benefit is normalized by the gross electrical output capacity before CO₂ capture energy requirements (500 MW in the profit maximization model, 492 MW in the first-order dispatch model) to display results in dollars per kilowatt (kW). The normalized profit benefit is plotted with both flexible configurations for the optimization model and the venting-only configuration for the first-order dispatch model. Flexible capture facilities will operate CO₂ capture nearly continuously at 0% load at low CO₂ prices and 100% load at high CO₂ prices, and the primary opportunity to obtain value from flexible operation occurs at moderate CO₂ prices. At low CO₂ prices in the profit maximization model, profits with flexible capture are lower than those without CO₂ capture because Eqn. 2.8 includes a fixed cost for solvent degradation that is assessed even though capture is rarely utilized if at all. If capture utilization was expected to be near 0%, systems would likely be shut down completely, and this cost would not

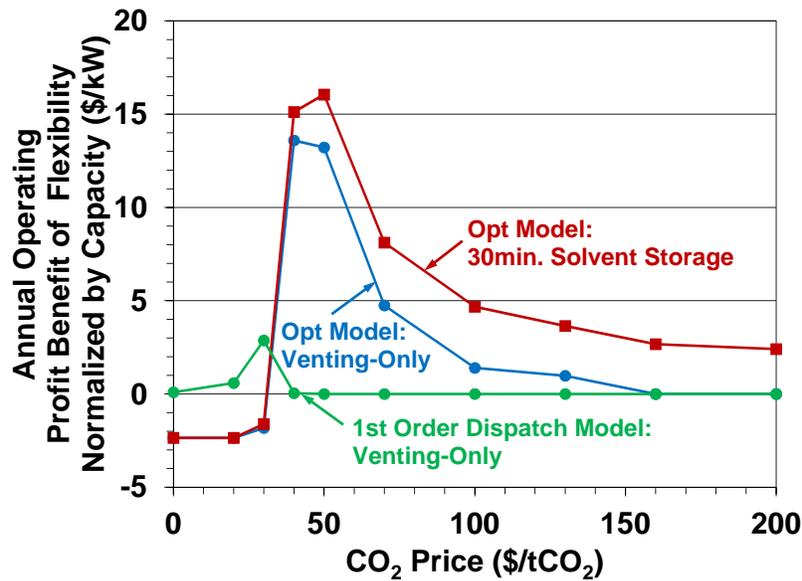


Figure 2.17: By incorporating electricity price volatility, the optimization model calculates a much greater benefit of CO₂ capture flexibility.

be incurred.

By using realistic electricity price volatility, the profit maximization model finds a much greater economic benefit for flexibility at moderate CO₂ prices than the first-order dispatch model while accounting for system operating constraints in much greater detail. The first-order model finds a small range of CO₂ prices where venting CO₂ at high electricity prices provides some operating profit benefit, but the profit maximization model finds a much larger range of CO₂ prices where flexible operation is beneficial and to a much greater extent. Figure 2.17 also demonstrates that while the venting CO₂ to increase power output is uneconomical at high CO₂ prices, solvent storage allows the economic benefit from flexibility to continue into high CO₂ prices. While the first-order model successfully demonstrates price-responsive flexible CO₂ capture, operation should be optimized in response to realistic electricity price ranges and volatility to effectively quantify the benefit of flexible CO₂ capture.

2.3.4 The Influence of Forecasting Accuracy

This section discusses the effect of assuming different degrees of price foreknowledge when optimizing plant operation. Day-ahead pseudo forecast curves are expected to be the most realistic representation of the information available to plant operational planners, but this analysis examines how operating economics might change with better or worse forecasting accuracy. Table 2.12 compares annual aggregate model results for the venting-only configuration under 2008 conditions and \$50/tCO₂ with no price foreknowledge using the rule-based MATLAB model (Sec. 2.2.2) and with day-ahead forecasting or perfect knowledge using the profit maximization model. To enable direct comparison between the MATLAB and GAMS models, the limited formulation described in Sec. 2.3.1 is further reduced by eliminating base plant startup costs, base plant minimum load constraints, base plant ramp limits, and capture system ramp costs. In addition, all capture energy is attributed to stripping and compression systems in this analysis. All other inputs are the same as in Tables 2.10 and 2.11. Though annual output is nearly the same for all cases, profits are over 4% greater with perfect or no knowledge than with day-ahead forecasting. Reactive operation is nearly as profitable as having perfect price foreknowledge because CO₂ capture can ramp quickly in response to irregular high price spikes that are ignored during day-ahead forecasting. With venting-only flexible capture, a combination of day-ahead and reactive planning (i.e. response to real-time price spikes) would likely produce greater profits than those earned when adhering to a strict day-ahead schedule.

Results for all plant configurations (no capture, inflexible capture, venting-only flexible capture, and flexible capture with solvent storage) are compared under the same market conditions for perfect foreknowledge and day-ahead forecasting in

Table 2.12: Pseudo-forecasting ignores price spikes, so reactive operation without foreknowledge earns greater profits by quickly responding to price spikes (TWh=terawatt-hours, Mt=million metric tons).

Quantity	Units	Venting-only flexible capture		
		none	day-ahead	perfect
Degree of price foreknowledge		none	day-ahead	perfect
Total output to the grid	TWh	2.549	2.549	2.550
Total CO ₂ emitted	MtCO ₂	0.646	0.610	0.659
Total CO ₂ captured	MtCO ₂	2.742	2.792	2.727
Total operating cost	millions	\$144.9	\$144.4	\$145.6
Total operating profits	millions	\$131.1	\$125.7	\$131.6
Forecast error reduction in operating profits	percent	-0.31%	-4.45%	
Capture capacity factor when base plant is on	percent	89.9%	91.2%	89.5%
Capture capacity factor - overall	percent	67.3%	68.5%	66.9%
Base plant capacity factor	percent	79.7%	75.1%	74.8%
Average CO ₂ emissions rate	tCO ₂ /MWh	0.254	0.239	0.258

Table 2.13. All of these results are generated using the GAMS profit maximization model with base plant startup costs, base plant minimum load constraints, and ramp limits on power and capture systems activated. CO₂ capture ramping costs are not included as they had not been added to the formulation at the time of this analysis. All CO₂ capture energy requirements are again attributed to stripping and compression for this analysis.

For all configurations, aggregate operating statistics do not change significantly with forecasting ability. The reduction in operating profits due to forecast error is less than 1% with inflexible capture and never much more than 4% for all other configurations. Though these results are specific to the input electricity market parameters, an annual profit reduction due to forecast error on the order of 1–5% could probably be expected under many conditions. As shown in the sections that follow, \$50/tCO₂ is an emissions penalty where flexible CO₂ capture is particularly valuable, so the operating profit reduction from forecast error might even be smaller at CO₂ prices or other market conditions where near-continuous 0% or 100% load capture is optimal.

2.3.5 Initial Study of CO₂ Price Sensitivity

A CO₂ emissions mitigation policy is necessary for there to be widespread deployment of CCS systems, and any policy will manifest in the form of an emissions penalty in \$/tCO₂. A carbon tax represents this emissions penalty directly, a CO₂ allowance cap-and-trade market will have CO₂ price settlements, and an emissions standard levies an implicit CO₂ price dependent on the cost of CO₂ emissions mitigation at the facility. Each CO₂ mitigation technology will be economically viable above a certain CO₂ price. This section uses the ERCOT case study to understand how flexible CO₂ capture affects the CO₂ price at which CCS could become econom-

Table 2.13: Forecast error with pseudo-forecast price series reduces annual operating profits by 1–5%.

Quantity	Units	Venting-only flexible capture		Flexible capture with solvent storage	
		day-ahead	perfect	day-ahead	perfect
Degree of price foreknowledge					
Total output to the grid	TWh	2.615	2.616	2.646	2.635
Total CO ₂ emitted	MtCO ₂	0.619	0.667	0.482	0.471
Total CO ₂ captured	MtCO ₂	2.875	2.810	3.108	3.108
Total operating cost	millions	\$148.9	\$150.1	\$146.8	\$146.1
Total operating profits	millions	\$124.0	\$129.5	\$132.7	\$137.2
Forecast error reduction in operating profits	percent	-4.30%		-3.29%	
Capture capacity factor when base plant is on	percent	91.4%	89.8%	96.2%	96.5%
Capture capacity factor - overall	percent	70.5%	69.0%	76.3%	76.3%
Base plant capacity factor	percent	77.2%	76.8%	79.3%	79.0%
Average CO ₂ emissions rate	tCO ₂ /MWh	0.237	0.255	0.182	0.179
		Inflexible capture		No capture	
		day-ahead	perfect	day-ahead	perfect
Degree of price foreknowledge					
Total output to the grid	TWh	2.545	2.535	2.202	2.249
Total CO ₂ emitted	MtCO ₂	0.350	0.348	2.271	2.319
Total CO ₂ captured	MtCO ₂	3.147	3.135	0.000	0.000
Total operating cost	millions	\$139.4	\$138.9	\$164.0	\$167.6
Total operating profits	millions	\$116.9	\$118.0	\$99.8	\$103.7
Forecast error reduction in operating profits	percent	-0.95%		-3.77%	
Capture capacity factor when base plant is on	percent	100.0%	100.0%	n/a	n/a
Capture capacity factor - overall	percent	77.2%	77.2%	n/a	n/a
Base plant capacity factor	percent	77.2%	77.2%	50.1%	51.2%
Average CO ₂ emissions rate	tCO ₂ /MWh	0.137	0.137	1.031	1.031

ically viable. It addresses the effects of both the venting-only and solvent storage configurations on the CO₂ emissions and operating economics of the nominal 500 MW coal-fired facility.

For results reported in this section, the limited model formulation and input parameters from Tables 2.10 and 2.11 are utilized with the following exceptions: (1) there are no CO₂ capture ramping costs, (2) all capture energy is attributed to stripping and compression systems, and (3) a larger solvent storage system is modeled that can operate stripping/compression systems at 0% load for up to four hours with absorption systems at 100% load. CO₂ capture ramping costs are excluded because that portion of the model formulation had not been developed at the time of this analysis. Profits with CO₂ capture would be slightly lower if ramping costs were included, but qualitative results would not differ significantly. A larger solvent storage system is modeled because chronologically, this analysis took place before any detailed study of the tradeoff between operating profits and capital costs with solvent storage. It is now known that a 4-hour system is capital cost prohibitive under most market conditions, but its operating economics clearly demonstrate the potential value of solvent storage. Heuristic oversizing based on daily cycling is used, so stripping and compression equipment are 120% their standard size, and a 4-hour solvent storage system requires 21 million kg of MEA for 66,400 m³ of solvent inventory. Personal communication with representatives in the chemical manufacturing industry indicates that this quantity of MEA is a significant portion of annual manufacturing capacity at a typical facility, and the quantities of other products of MEA synthesis would not be trivial.

2.3.5.1 Configuration Comparison

CO₂ price was varied from \$0–100/tCO₂, and pseudo-day ahead forecasting was used with a CO₂ price adjustment to represent the most realistic case of price foreknowledge. Each plant configuration: no capture, inflexible capture, venting-only flexible capture, and flexible capture with solvent storage, was modeled across this CO₂ price range.

Figure 2.18 provides initial insight into how flexible CO₂ capture is utilized across the CO₂ price range by plotting the capacity factor of capture systems when the base plant is on, which is the sum of the number of time periods when capture is online divided by the sum of the number of time periods when the base plant is online. Below \$20/tCO₂, operating costs are greater with capture online, so capture is never utilized. Above \$25/tCO₂, marginal operating costs are lower with 100% load capture, and by \$70/tCO₂, capture systems operate whenever the base plant is online. In the \$25–70/tCO₂ range, marginal costs are similar across the range of CO₂ capture load, so there is opportunity to vent CO₂ and sell more electricity when prices are high. The facility still vents CO₂ in this range when solvent storage is available, but solvent storage does allow greater utilization of CO₂ capture at these intermediate CO₂ prices by expanding the electricity price range when operating capture is economical.

Figure 2.19 shows annual CO₂ emissions at each CO₂ price for each capture configuration to demonstrate the environmental impact of changes in CO₂ capture and base plant utilization. Since flexible systems do not utilize CO₂ capture below \$20/tCO₂, CO₂ emissions with flexible capture equal those without CO₂ capture. From \$25–70/tCO₂, increased capture utilization causes emissions to fall towards those with inflexible capture. As mentioned above, any emissions above those with

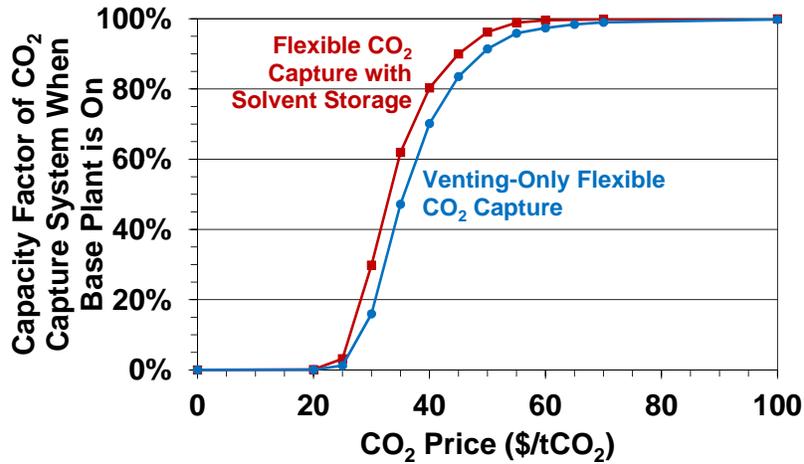


Figure 2.18: Solvent storage allows greater utilization of CO₂ capture systems at intermediate CO₂ prices.

inflexible capture reflect CO₂ venting, so solvent storage reduces, but does not eliminate, CO₂ venting at intermediate CO₂ prices. Emissions trends with inflexible and no CO₂ capture correspond to changes in the base plant capacity factor. A facility without CO₂ capture becomes less economical to operate as the CO₂ emissions penalty increases, so emissions fall due to lower base plant utilization. A facility with inflexible capture is utilized more often as CO₂ price increases, so CO₂ emissions, while remaining low, increase slightly with CO₂ price.

Figure 2.20 shows annual operating profits with each capture configuration at each CO₂ price, normalized by the 500 MW gross power output capacity. Because electricity prices increase with CO₂ price at the emissions cost of an average ERCOT gas-fired facility, changes in operating profits with CO₂ price reflect the CO₂ emissions rate of the plant relative to 0.43 tCO₂/MWh. As CO₂ price increases, profits fall monotonically without CO₂ capture and rise monotonically with inflexible CO₂ capture. Profits with venting-only flexible capture are greater than those with inflexible and no-capture by as much as 10% during the \$20–70/tCO₂ transition period,

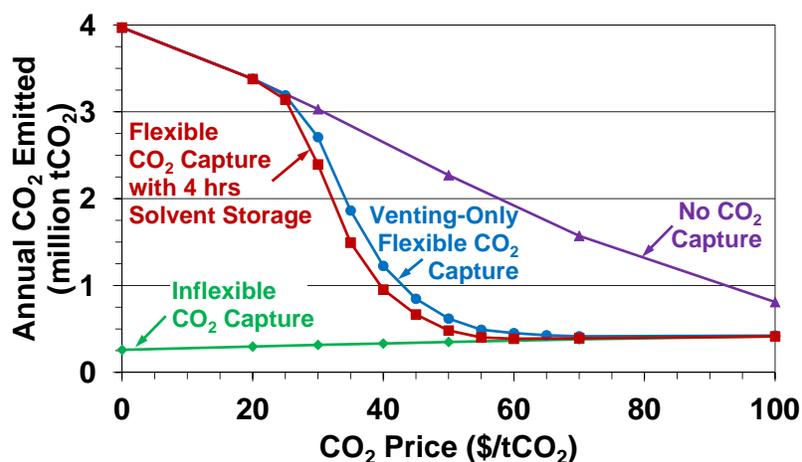


Figure 2.19: CO₂ emissions with flexible capture drop rapidly towards those with inflexible capture at CO₂ emissions penalties above \$25/tCO₂.

but a facility with solvent storage maintains an economic advantage at any CO₂ price above the minimum required for CO₂ capture operation. The profit improvement with solvent storage over inflexible CO₂ capture decreases slightly with CO₂ price, but remains over 9% at \$100/tCO₂. The operating profit benefit of solvent storage, however, must be weighted against its increased capital cost, and this tradeoff is explored in detail in Section 3.2.2.

Figure 2.21 yields additional insight into the operation of solvent storage systems across the CO₂ price range. The annual average quantity of CO₂ stored in the rich solvent at each 15 minute time interval is plotted to demonstrate the typical cycling of a 4-hour solvent storage system that must return to 71% of its maximum capacity at the end of each day. The maximum quantity of stored CO₂ for this system is 1,860 tCO₂. Solvent storage systems sit mostly idle at low CO₂ prices and are utilized only rarely up to \$25/tCO₂. However, a daily cycle becomes apparent by \$35/tCO₂ and eventually equilibrates to the profile seen at \$50–100/tCO₂. Once it is economical to use solvent storage, CO₂ level typically increases in the late-afternoon

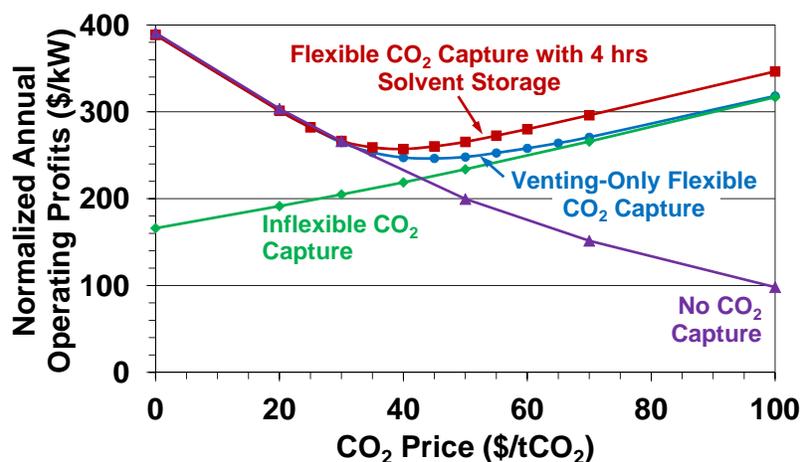


Figure 2.20: Normalized annual operating profits depend on plant emissions costs relative to those of price-setting gas-fired plants, but profits are always best with solvent storage.

and early evening when electricity demand and price are greatest. Then, CO₂ levels fall at night so that stored rich solvent can be regenerated when electricity prices are lower. Though average storage levels do not demonstrate full cycling of the system, there are days when stored CO₂ reaches either 0 tCO₂ or the 1,860 tCO₂ maximum.

2.3.5.2 Profit Comparison with a Small Solvent Storage System

Since analysis subsequent to that in the above section found that a 4-hour solvent storage system is likely prohibitively expensive, the CO₂ price sensitivity was repeated for a solvent storage system sized for a maximum of 30 minutes with stripping and compression systems off while absorption continues at 100% load. With the same design parameters as above, this system can store up to 232 tCO₂ in the rich solvent tank using 2.6 million kg MEA in 8,300 m³ of aqueous solvent. Using the heuristic that assumes daily-cycling of the solvent storage system, stripping and compression equipment need only be 2% larger than the standard design.

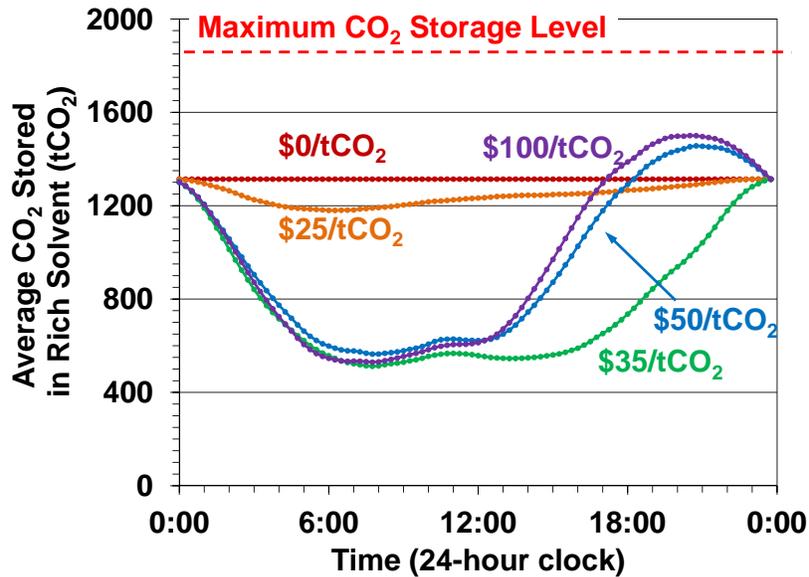


Figure 2.21: When a 4-hour solvent storage system is utilized on a daily cycle, CO₂ is stored and electrical output increased during early-evening peak price hours, and CO₂ is regenerated at night when prices are relatively low.

Normalized annual operating profits for this case are plotted in Fig. 2.22, where all curves are repeated except for the solvent storage profits. With such a small storage system, the benefit of solvent storage is significantly reduced. However, trends remain the same in that solvent storage continues to improve operating profits at high CO₂ prices when venting CO₂ is not profitable.

2.3.6 Sensitivity to Power and CO₂ Capture System Specifications

The configuration comparison in Sections 2.3.5.1 and 2.3.5.2 provides valuable conclusions for a set of default power and CO₂ capture performance parameters, but a more complete understanding of flexible CO₂ capture in response to volatile electricity prices requires investigating results sensitivity to plant-level performance parameters.

For instance, ramp rate sensitivity at various CO₂ prices must be studied to find the minimum ramp rate required for flexible CO₂ capture to be valuable across a

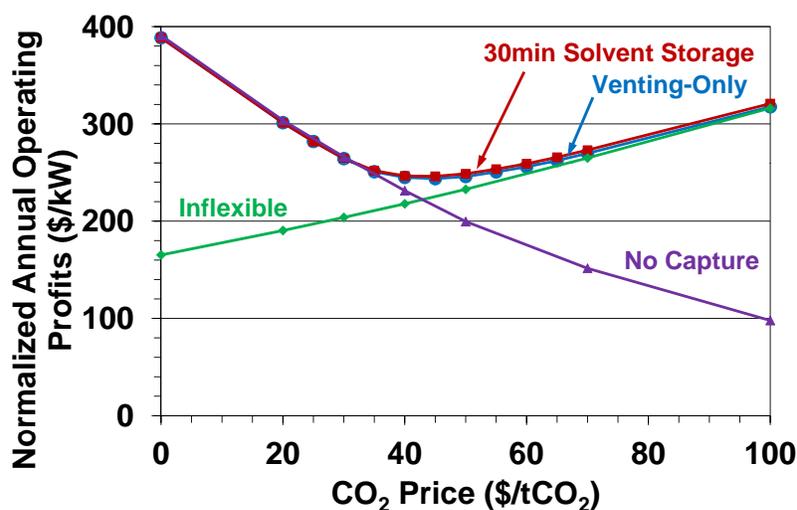


Figure 2.22: The incremental operating profit benefit from solvent storage decreases with storage system size but still persists at high CO₂ prices.

range of electricity market conditions. In addition, base plant ramp limits could also influence flexible CO₂ capture operation.

The normalized economic benefit of flexible CO₂ capture is not expected to change with base plant size, but verifying this hypothesis is a useful exercise. Larger base plant capacity entails a larger quantity of CO₂ capture energy that can be utilized for price arbitrage, so the effect of base plant size on the value of capture flexibility might not be obvious.

Decreasing the energy requirement for CO₂ capture is extremely important for successful CO₂ capture commercialization, but doing so could mitigate the benefits of flexible operation. With less CO₂ capture energy available for price arbitrage, more energy-efficient CO₂ capture systems might be poorer candidates for flexible operation.

Thus, the following four parameters are the focus of plant-level sensitivity analysis: (1) CO₂ capture system ramp limit, (2) base plant ramp limit, (3) base plant

capacity, and (4) CO₂ capture energy performance. These parameters are studied across the ranges identified in Table 2.14 for CO₂ prices listed in the table. The maximum ramp rates of 8%/min would allow systems to transition from minimum to maximum load in one 15-minute interval. When base plant capacity is varied, base plant ramp rate and minimum output are scaled accordingly. The 50% maximum reduction in CO₂ capture energy from the baseline is only illustrative because this value nears or exceeds what is thermodynamically possible; a 10–25% reduction is more practical [Rochelle et al., 2011]. CO₂ prices are generally chosen to surround the range of CO₂ prices where flexibility has proven valuable in previous results.

Table 2.14: These parameter ranges and CO₂ prices are used to analyze the sensitivity of results to capture and power system performance.

Parameter (units)	Min	Max	CO ₂ Prices Considered (\$/tCO ₂)
CO ₂ capture system ramp rate (%/min)	0.25	8	20, 35, 50, 70
Base plant ramp rate (%/min)	0.25	8	50
Base plant capacity (MW)	250	1,000	35, 50, 70
CO ₂ capture energy performance (% reduction from baseline)	0	50	20, 35, 50, 70, 100

2.3.6.1 Model Formulation and Default Input Parameters

This analysis again uses the limited model formulation described in Section 2.3.1 and input parameters from Tables 2.10 and 2.11 with the exceptions described in Section 2.3.3.1. For clarity, these exceptions include: (1) CO₂ capture ramping costs are calculated using Eqn. 2.13 instead of direct specification, (2) 89% of CO₂ capture energy is allocated to stripping/compression systems and 11% to absorption systems, and (3) capture system minimum load is always set to 30%. Though base plant minimum load and ramp rate are scaled with base plant size, changes to startup cost with

base plant size are ignored because the influence of startup costs on annual profits has been relatively small in previous work where the facility remains online for most of the year. The size of the solvent storage system is also kept constant for all base plant sizes. A larger base plant might warrant building a larger solvent storage system, but a detailed assessment of solvent storage options is explored later.

2.3.6.2 Results: Capture System Ramp Rate

Figure 2.23 presents the sensitivity of normalized annual operating profits to CO₂ capture ramp rate for each CO₂ capture configuration at \$50/tCO₂. For a given configuration, profits do not decrease significantly with ramp rate until below 1%/min. The maximum decrease in profits is 1.88% for the venting-only configuration at 0.25%/min (optimization convergence was not achieved with 0.25%/min ramp rate, solvent storage, and \$50/tCO₂). Across all CO₂ prices, the maximum decrease in profits with capture ramp rate is 2.7% for the solvent storage case at 0.25%/min and \$70/tCO₂. The profit improvement with flexibility also decreases with ramp rate for \$50/tCO₂, and this effect is measured by calculating the relative change in profit improvement between a system with a given ramp rate and a system that can ramp from minimum to maximum load in one 15-minute time interval (8%/min).

Profits are not highly sensitive to CO₂ capture ramp rate at \$50/tCO₂, and Fig. 2.24 demonstrates that this sensitivity is greater at \$70/tCO₂ but falls with CO₂ price. Figure 2.24 plots the percent change in profit improvement with ramp rate for all flexible configurations and CO₂ prices. A value of 0% means that all the possible benefit of flexibility is achieved. Below 0%, flexibility is less valuable, and above 0%, flexibility is more valuable. At ramp rates of 1%/min or higher, the profit improvement from flexibility falls by less than 5% for all combinations of CO₂ price and flexible configuration. The improvement with flexibility is actually greatest

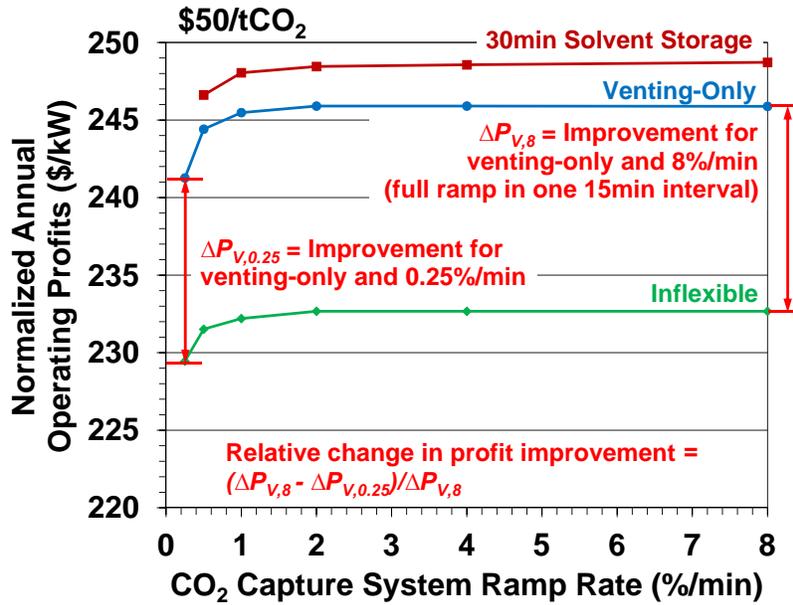


Figure 2.23: At \$50/tCO₂, operating profits and the improvement with flexibility do not change substantially at 1%/min or above.

at low ramp rates for \$20/tCO₂ and \$35/tCO₂ because low capture ramp rate is more detrimental to an inflexible capture system than a flexible capture system at these CO₂ prices. CO₂ capture operation is generally less profitable at these low CO₂ prices. Under these circumstances, the capture system ramp rate at an inflexible facility restricts the ability of the base plant to reduce load or go offline when low electricity prices justify doing so.

2.3.6.3 Results: Base Plant Ramp Rate

Annual operating profits are also insensitive to base plant ramp rate at \$50/tCO₂ (Figure 2.25). For CO₂ capture configurations, profits decrease by less than 0.6% when ramp rate changes from 8%/min to 0.5%/min, and the decrease never exceeds 1.5% at the 0.25%/min minimum tested ramp rate. Profits are slightly more sensitive to base plant ramp rate when the facility does not have CO₂ capture installed

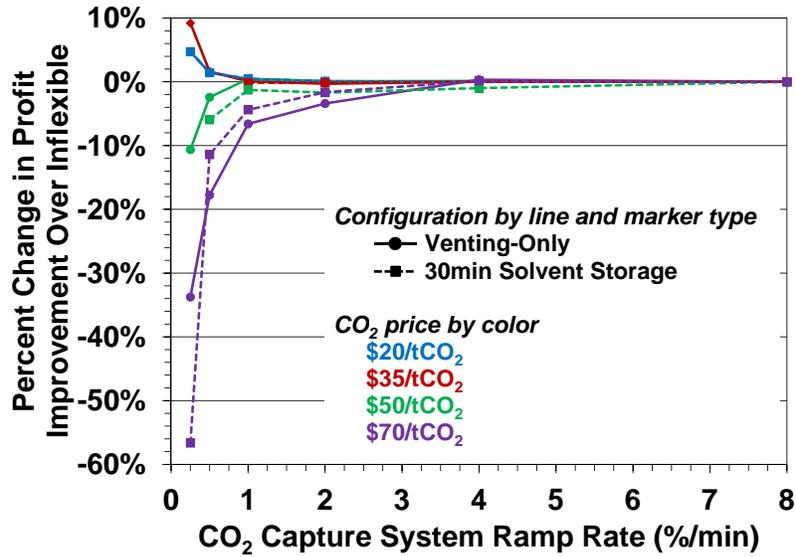


Figure 2.24: Any profit improvement with flexibility is largely maintained at or above 1%/min capture system ramp rate.

because a facility without CO₂ capture is less competitive than one with capture at \$50/tCO₂, so ramp and startup/shutdown cycles are more often justified.

Generally, the more often marginal operating costs are close to market electricity prices, the more often ramping will be used to decrease output when prices are below costs and increase output when prices exceed costs. Similarly, ramping CO₂ capture is more desirable when there is more incentive for flexible operation. Under these circumstances, operating profits are more sensitive to ramp rate, but sensitivity is still low across a wide range of CO₂ prices.

2.3.6.4 Results: Base Plant Size

Figure 2.26 plots annual operating profits normalized by base plant capacity as a function of gross base plant capacity for \$50/tCO₂. Normalized profits are insensitive to base plant size. There is a slight increase in normalized profit with base plant size for all combinations of CO₂ price and plant configuration except for the

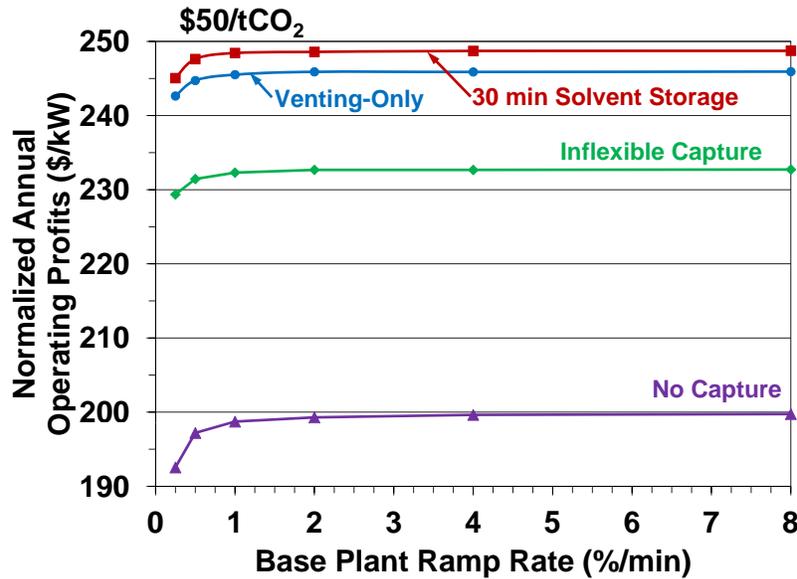


Figure 2.25: Profits fall substantially with base plant ramp rate only below 1%/min without CO₂ capture.

solvent storage configuration. Changes in normalized profits with plant size likely stem from the assumption that startup costs and solvent storage system size are not scaled with base plant size. The largest variation exists without CO₂ capture, which has more frequent startup/shutdown cycles than CO₂ capture configurations, so scaling startup costs with base plant size should mitigate this effect. Likewise, the relative benefit of solvent storage decreases as its size decreases in relation to the base plant, so slightly lower normalized profits are expected. The only break from these trends at other tested CO₂ prices is an increase in normalized profits with base plant size for the solvent storage configuration at \$35/tCO₂. Venting CO₂ at high electricity prices accounts for most of the incremental benefit of flexibility at this CO₂ price, so the influence of the storage-to-base plant size ratio is less significant.

Figure 2.27 highlights the economic differences between CO₂ capture scenarios by plotting, for each CO₂ price, the percent improvement in annual operating profits

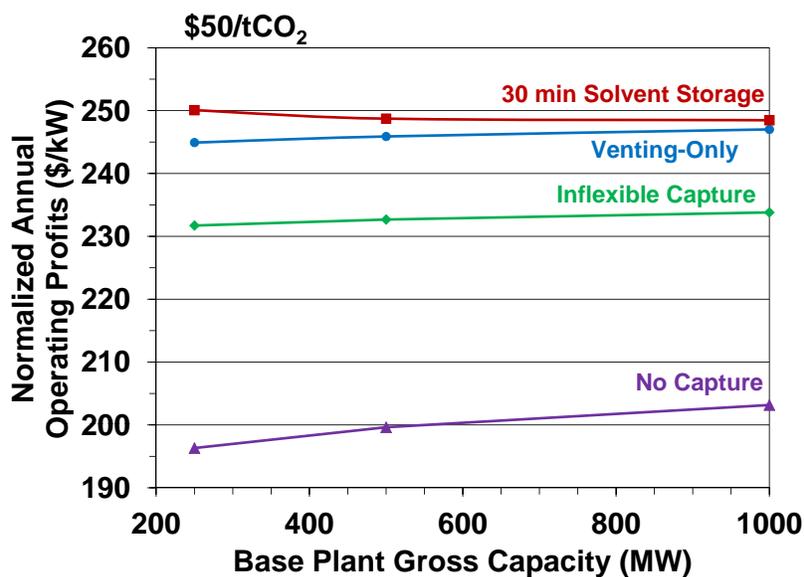


Figure 2.26: Operating profits do not vary significantly with base plant size at \$50/tCO₂.

for flexible configurations over profits at an inflexible facility. As has been shown previously, the improvement from flexibility decreases with an increase in CO₂ price, but the solvent storage configuration sustains a greater benefit than a venting-only facility because it allows partial-load stripping and compression without an increase in CO₂ emissions. The benefit of solvent storage might seem minor, but a 2% annual profit improvement is substantial considering the supplementary storage system is roughly the size of the surge tank already necessary for process stability. Profit improvement decreases with base plant size for the solvent storage configuration because it is not scaled with the base plant. There is a slight decrease in profit improvement with base plant size for the venting-only configuration as well, but the overall change is negligible.

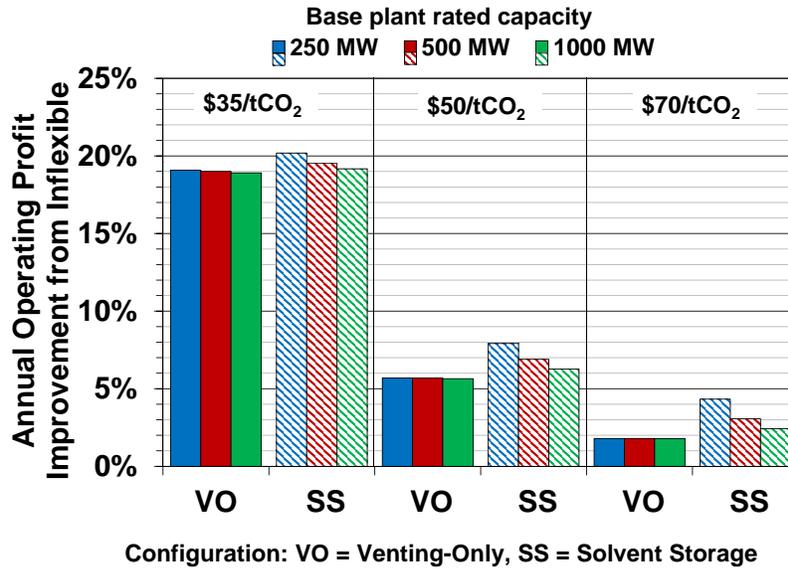


Figure 2.27: The incremental profit improvement from flexibility is insensitive to base plant size. Solvent storage is relatively less beneficial at large base plant size because the storage system is not scaled with the base plant.

2.3.6.5 Results: Capture Energy Performance

Figure 2.28 plots normalized annual operating profits as a function of CO₂ price with no CO₂ capture, inflexible capture, and 30 minutes of solvent storage at the three tested energy performance values. A subset of the full data set is plotted to highlight the areas where flexible capture improves profits over the facility without capture or with inflexible capture. Profits with venting-only flexible capture are not shown because they are very near those with solvent storage, similar to results shown in Fig. 2.22. Profits increase with improved CO₂ capture energy performance because lower costs with capture lead to greater plant utilization and higher profit margins. However, improved energy performance decreases the profit improvement of flexibility and thins the range of CO₂ prices where flexibility adds significant value. As energy performance improves, there is less CO₂ capture energy available for price arbitrage, and lower emissions reductions costs create less incentive to offset CO₂ capture costs

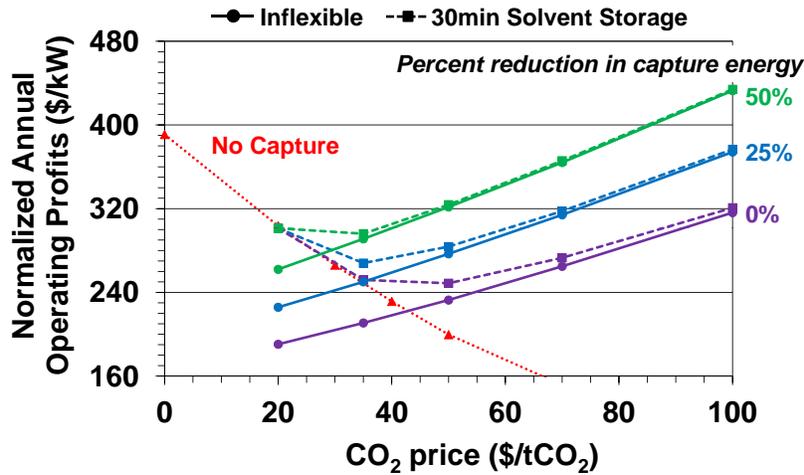


Figure 2.28: The CO₂ price range where flexibility is valuable shrinks and the benefit decreases as capture energy performance improves.

with price-responsive flexible operation.

Decreased benefit from flexibility with reduced capture energy is particularly apparent in Fig. 2.29, which plots the percent improvement of flexible facilities over an inflexible system at \$35/tCO₂, \$50/tCO₂, and \$70/tCO₂. Though a 50% reduction in capture energy is unreasonable and a 25% reduction would be very difficult to achieve, these results demonstrate that any reduction in capture energy significantly diminishes the value of flexible capture in response to electricity prices. Better energy performance is necessary for widespread CO₂ capture deployment, but a highly efficient capture system is a poorer candidate for price-responsive flexible operation, especially in the context of venting CO₂ to increase output when electricity prices are high.

More energy efficient CO₂ capture also reduces the net emissions rate at full-load CO₂ capture (Fig. 2.30), so total annual CO₂ emissions would decrease if annual electrical output remained the same. However, annual electrical output also increases with lower CO₂ capture energy because improved operating economics allows greater

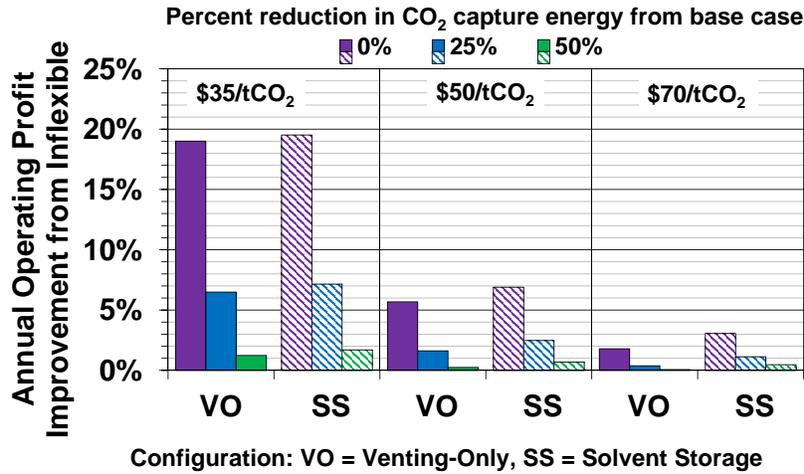


Figure 2.29: Improved energy performance drastically reduces the benefit of price-responsive flexible capture, even at intermediate CO₂ prices.

utilization of the facility. Figure 2.31 demonstrates the net effect of energy performance on CO₂ emissions by plotting emissions across the CO₂ price range for the no capture configuration and select points with solvent storage and inflexible capture. Emissions with the venting-only configuration are equal or slightly greater than those with solvent storage for a given energy performance value. Emissions with inflexible capture increase slightly with improved energy performance due to greater facility utilization, but the maximum increase never exceeds 0.04 MtCO₂, which occurs at \$20/tCO₂ and a 50% energy reduction. Predominantly, lower capture energy reduces the CO₂ price required to justify CO₂ capture operation, so emissions with flexible capture approach those with inflexible capture at lower CO₂ prices, and they do so more rapidly as CO₂ price increases.

Generally, reduced capture energy requirement improves operating economics and lowers the CO₂ price necessary for economical capture operation. However, reduced capture energy diminishes the value of price-responsive flexible capture by decreasing the quantity of energy available for price arbitrage.

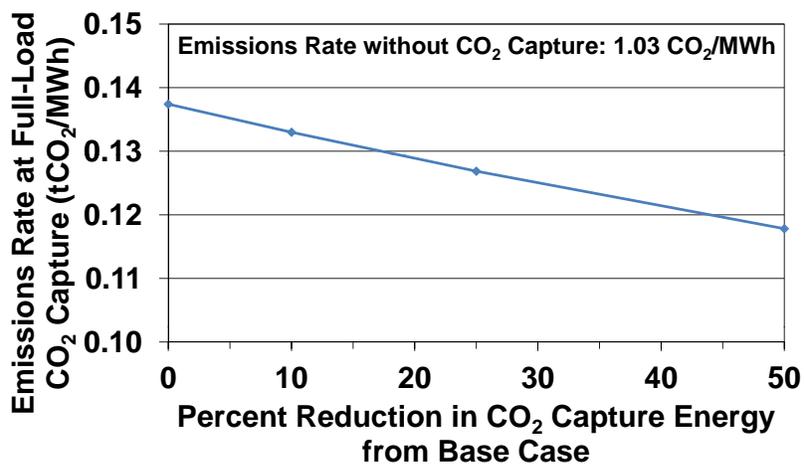


Figure 2.30: CO₂ emissions rate at 100% load absorption falls as capture energy performance improves.

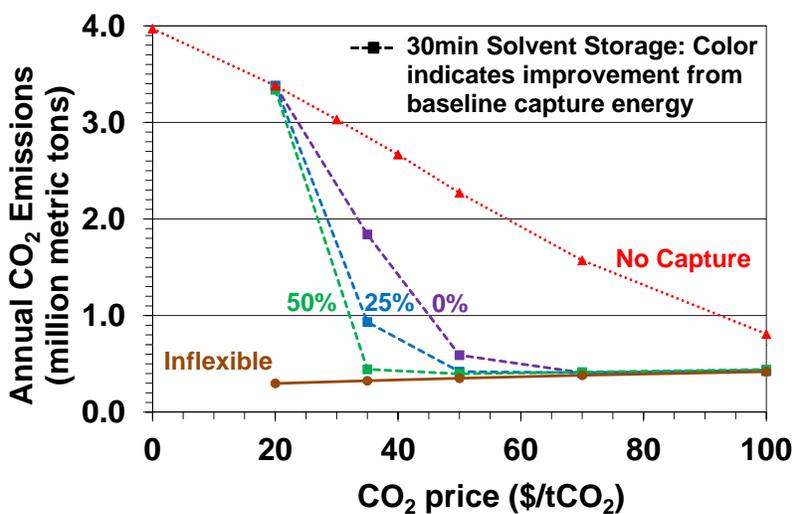


Figure 2.31: Improved energy performance reduces the CO₂ price necessary to justify CO₂ capture operation.

2.4 Conclusions

2.4.1 Model Development

A versatile modeling framework has been created that integrates concepts from thermal power generation, CO₂ capture, and electricity markets to study flexible CO₂ capture operation in response to volatile electricity prices. The model, implemented in GAMS, is a mixed-integer linear program that maximizes operating profits at a power generation facility with post-combustion CO₂ capture, choosing the optimal operation consistent with constraints on plant integration, load limits, and system response time. The model is initially tailored to study a fossil-based unit using an amine scrubbing CO₂ capture system. A 500 MW coal-fired facility using a 7m MEA solvent for CO₂ capture is used as a case study. The model can compare a facility without CO₂ capture to one with inflexible CO₂ capture, flexible CO₂ capture that vents CO₂ at partial load, and flexible CO₂ capture that uses solvent storage to enable partial-load stripping and compression without additional CO₂ emissions.

When studying a facility meant primarily to provide base load electricity, minimum up and down time constraints and CO₂ capture startup costs can be ignored. Removing these features has minimal change on results and can substantially increase computation time.

Modeling electricity price spikes and volatility is necessary to effectively value flexible CO₂ capture in response to electricity prices. When compared to a model that does not incorporate electricity price volatility, the profit maximization model finds a much greater operating profit benefit from flexible capture operation over a wider range of CO₂ price conditions.

Electricity price forecasting ability is important to consider when

modeling price-responsive flexible capture. A procedure has been developed to generate a pseudo day-ahead price forecast from historical electricity prices and adjust for CO₂ price. Electricity prices can be reasonably adjusted for CO₂ price in a natural gas-dominated market such as ERCOT by adding the average CO₂ emissions cost of gas-fired facilities. Annual profit comparisons between perfect and pseudo day-ahead forecasting found that perfect price forecasts would improve annual operating profits by 1–5%. The difference is relatively small because responding to pseudo-forecast prices is sufficient to benefit from most of the unpredictable price spikes.

2.4.2 Analysis

Annual performance and economics of the nominal facility is compared across the CO₂ capture configuration options for CO₂ emissions penalties from \$0–100/tCO₂. ERCOT electricity prices in 2008 are adjusted for CO₂ price for this analysis. A sensitivity analysis also explored the effects of varying CO₂ capture and base plant ramp rate, base plant size, and CO₂ capture energy requirements.

Operating CO₂ capture systems is economical above \$25/tCO₂, and flexible capture systems will operate CO₂ capture nearly continuously above \$50/tCO₂. Occasionally venting CO₂ is profitable during the transition to near-continuous CO₂ capture, but emissions remain far below those without CO₂ capture at CO₂ prices that justify capture operation. *At intermediate CO₂ prices, venting CO₂ when electricity sales offset emissions costs can improve profits by up to 10%.* The value of venting CO₂ disappears at high CO₂ prices, but a flexible CO₂ capture system with solvent storage maintains an operating profit advantage at high CO₂ prices.

Solvent storage allows higher profits and lower CO₂ emissions with flexible capture by increasing the range of electricity prices where capture

operation is profitable. However, solvent storage operation does not necessarily follow a predictable daily cycle, and optimal operation might still entail CO₂ venting at high electricity prices to reserve solvent storage systems for arbitrage at intermediate CO₂ prices. The benefits from solvent storage will ultimately depend on capital costs, which are addressed in the next chapter.

Nearly the full operating profit benefit from flexible capture is achieved for base plant and capture system ramp rates above 1%/min. The implications of flexible CO₂ capture are insensitive to base plant size. *Improved CO₂ capture energy performance increases operating profits but diminishes the value of flexibility by reducing the quantity of energy available for price arbitrage.*

These results suggest that *flexibility offers a modest economic benefit for CO₂ capture; however, this advantage is greatest with CO₂ prices that still might be too low to justify CO₂ capture investment.* However, these results do not consider additional electricity system variables such as natural gas price, which can significantly affect electricity prices. Different electricity systems could also yield disparate results, and similarly, changes to the ERCOT fleet could affect the value of flexible CO₂ capture. There are also many design and operating variables for a solvent storage system that impact its value to the facility. The strength of the modeling approach presented within this chapter is its relative simplicity and ease of adaptation for a particular site. The following chapter further demonstrates its utility for studying a wider range of electricity market conditions and performing a detailed solvent storage design analysis.

Chapter 3

Optimizing CO₂ Capture in Response to Electricity Prices: Market Sensitivity and Solvent Storage Design

The previous chapter introduced a mixed-integer linear programming (MIP) model that maximizes operating profits in response to electricity prices at a single facility with CO₂ capture. Chapter 2 compares different plant configurations for a range of power and capture performance specifications, but CO₂ emissions penalty is the only independent variable representing electricity market conditions. All other market conditions are implicitly assumed constant. The impact of CO₂ price on electricity prices was approximated by uniformly increasing all electricity prices by the average CO₂ emissions cost of gas-fired facilities in ERCOT, which is reasonable under moderate CO₂ prices and moderate-to-high natural gas prices when gas-based capacity will typically be the marginal generator, that is, that with highest operating cost amongst dispatched capacity. However, this approximation does not account for variability in the emissions costs of natural gas-based generators, and it breaks down further under market conditions where gas begins to replace coal as base load fuel and coal-fired facilities are more frequently marginal. In 2012, natural gas prices have typically been below \$3/MMBTU, so gas is already poised to largely displace coal as a base load fuel [Bloomberg, 2012].

To confidently use the model to assess flexible CO₂ capture under a wider range of electricity market conditions or in other electricity systems, a more accurate

method is required to approximate the effect of fuel and CO₂ prices on electricity prices. This chapter describes such a method then employs this electricity price adjustment procedure to assess the value of flexible CO₂ capture under a range of CO₂ and natural gas prices. Coal price is also very important to the economics of a coal-fired facility with CO₂ capture, but coal-prices are historically stable compared to natural gas prices [USDOE, 2012]. Natural gas price plays a major role in establishing the economic viability of CO₂ capture because gas prices strongly influence electricity prices over a wide range of market conditions. Even in electricity markets with proportionally less gas-fired capacity than ERCOT, gas-based facilities are often the marginal generators [USDOE, 2012].

This chapter also presents a detailed design sensitivity analysis of solvent storage systems before establishing characteristics of good solvent storage design and operation over a range of CO₂ and natural gas price conditions. While other authors have used specific solvent storage design assumptions for their analyses, this dissertation investigates solvent storage operating economics for various stored solvent quantities, CO₂ capture operating points, and the degree to which stripping and compression equipment is oversized for regenerating stored rich solvent [Husebye et al., 2010, Patiño Echeverri & Hoppock, 2012].

3.1 Methodology

3.1.1 Model Formulation

All analysis in this chapter utilizes the limited formulation of the single plant profit maximization model as described in Section 2.3.1. Major model characteristics are summarized here for convenience.

The model optimizes power and CO₂ capture system operation in response to

input electricity prices in 15-minute intervals. At any set of market conditions, pseudo day-ahead forecast prices (Section 2.2.2) are used to optimize plant operation for one year, and the price series with historical volatility is used to calculate profits. The objective function includes base plant startup costs, fuel and CO₂ emissions costs, and base plant VOM costs. When modeling a CO₂ capture configuration, additional costs are included for solvent makeup to replace degraded solvent, caustic for use in degraded solvent reclaiming, degraded solvent waste disposal, additional water use for CO₂ capture, and CO₂ transport and storage. In addition, a cost is assessed for ramping the CO₂ capture system.

The model includes constraints on the minimum and maximum load of power, absorption, and stripping/compression systems as well as limitations on the ramp rate, or system response time, of each system. An inflexible capture system must treat all flue gas that is produced, so CO₂ capture load must equal fractional power systems load. A facility with venting-only flexible capture can reduce capture load below that of the base plant, but absorption, stripping, and compression load must be equal. With solvent storage, absorption and stripping/compression load are decoupled. Maximum absorption load is limited by available flue gas, while maximum stripping/compression load is limited by steam availability and stripping/compression equipment size. A solvent storage system also requires specifying a maximum capacity for stored solvent and a constraint to monitor the quantity of CO₂ stored in rich solvent. To be consistent with presumed day-ahead forecasting ability, the quantity of solvent stored in each of the rich and lean tanks must also return to a specified set point at the end of each day. Thus, solvent storage can only balance load over a 24-hour period.

3.1.2 First-Order Dispatch to Approximate Price Adjustment for Fuel and CO₂ Prices

This section presents a more accurate method to approximate the effect of fuel and CO₂ prices on electricity prices, which enables use of the single plant profit maximization model for a wider range of electricity market conditions or in other electricity systems. The price-adjustment procedure accounts for changes in relative dispatch order of generating facilities when estimating the impact of changing market conditions on electricity prices. However, it also preserves historical price volatility so both the optimization model and subsequent profit calculations use a realistic price series. To account for the effect of fuel and CO₂ price changes on dispatch order while preserving historical electricity price volatility, the following procedure has been implemented using the MATLAB environment.

1. Use a first-order electricity dispatch model to calculate electricity prices under historical and adjusted fuel and CO₂ price conditions from historical electricity demand and power plant characteristics.
2. Calculate the change in first-order electricity prices from historical to adjusted conditions.
3. Add the calculated change in first-order prices to historical electricity prices to produce an adjusted electricity price series that preserves historical volatility.

3.1.2.1 First-Order Electricity Price Calculation

The MATLAB program imports a time series of net electricity load (demand minus wind production), generating unit characteristics, and a daily time series of historical and adjusted fuel and CO₂ prices. Electricity demand and wind data are provided by ERCOT. To synchronize with electricity prices in 15 minute intervals,

demand data are up-sampled using a linear interpolation between each hourly demand datum point. The first-order dispatch procedure is identical to the one described in Section 2.3.3, so it does not account for detailed generating unit constraints such as minimum load, ramp rates, and minimum up/down time. Thus, only the following power plant characteristics are imported: unit name, unit type, maximum electrical output, heat rate, CO₂ emissions rate, base plant VOM costs, and whether or not the facility is designated as a combined heat and power (CHP) facility.

After importing requisite data, the program iterates through each 15-minute time interval and calculates first-order electricity prices at each interval under historical and adjusted fuel and CO₂ prices. It calculates marginal generating costs for each generating unit, placing units in cost order, choosing the least-expensive available plants to meet current electricity demand, and setting the electricity price equal to the most expensive facility required to meet current demand. Costs at fossil-fueled and biomass-based facilities are the sum of fuel costs, base plant VOM costs, and CO₂ emissions costs, if applicable. Nuclear and hydroelectric facilities are assigned VOM costs, and wind turbines are not represented in the plant database because wind production is subtracted from the imported demand data. Since CHP facilities typically follow relatively constant heat and process loads, CHP facility operation is approximated by assuming all CHP facilities produce their maximum output at all times.

3.1.2.2 Adjusted Prices with Volatility

After determining first-order electricity price series under historical and adjusted fuel and CO₂ price conditions, the model calculates the difference in first-order price between historical and adjusted conditions at each time interval. This difference is then added to historical electricity prices in each interval to produce an adjusted

electricity price series that approximates the effect of fuel and CO₂ price changes while preserving historical volatility. Adjusted volatile electricity prices can then be used to produce a pseudo-forecast price series for each fuel and CO₂ price condition using the outlier removal and smoothing procedure discussed in Section 2.2.2.

3.1.2.3 Sample

This section demonstrates the electricity price adjustment procedure for a sample set of data from December 1, 2009–November 30, 2010. A full year of 2010 data are not available because ERCOT changed its market structure on December 1, 2010 and has not subsequently made price data available in the same format. Historical electricity demand, prices, and wind production are retrieved from ERCOT [ERCOT, ,ERCOT, 2010a,ERCOT, 2011a]. Generating unit data are taken from the a generating unit-specific database created using the EPA eGRID database along with information provided by ERCOT [USEPA, 2010,ERCOT, 2011d]. Creation of this database is discussed in detail in Section 5.3.2 because it was originally created for unit commitment modeling of the full electricity system.

While the price-adjustment procedure can accommodate daily-varying commodity prices, constant values for fuel and CO₂ prices are used in sample calculations. Table 3.1 lists historical 2010 average fuel and CO₂ prices along with three sample adjusted-price cases [USDOE, 2012]. Adjustment 1 adds a \$50/tCO₂ emissions penalty, Adjustment 2 uses a \$25/tCO₂ price and reduces natural gas prices to \$3/MMBTU, and Adjustment 3 uses the historical natural gas price and \$100/tCO₂.

Figure 3.1 plots electricity demand along with first-order electricity prices under historical and adjusted fuel and CO₂ price conditions for February 4 and 5, 2010, a moderate net load day. For the same dates, Figure 3.2 plots electricity demand with historical electricity prices and adjusted volatile electricity prices for

Table 3.1: The following historical and adjusted fuel and CO₂ prices are used in sample price-adjustment calculations.

Price set	Coal price (\$/MMBTU)	Natural gas price (\$/MMBTU)	Oil price (\$/MMBTU)	CO ₂ price (\$/tCO ₂)
Historical (2010)	2.25	5.14	12.34	0
Adjustment 1	2.25	5.14	12.34	50
Adjustment 2	2.25	3	12.34	25
Adjustment 3	2.25	5.14	12.34	100

each fuel and CO₂ price combination. The ordinate axis range is larger for volatile price data so that all comparable figures (3.2, 3.4, and 3.6) can be plotted on the same scale. In Fig. 3.1, a \$50/tCO₂ price increases electricity prices nearly uniformly by approximately \$30/MWh, which is greater than the \$21.5/MWh increase used in previous analysis. This discrepancy arises because marginal gas-based facilities have higher CO₂ emissions rates than the previously used average emissions rate from all gas-fired facilities. Therefore, electricity prices, operating profits, and the value of flexible CO₂ capture calculated above is likely to be conservative. At \$100/tCO₂, prices increase by roughly \$60/MWh, which implies that gas-fired facilities are still marginal under these market conditions. With \$25/tCO₂ and \$3/MMBTU natural gas, reduced fuel prices dampen the increase in electricity prices caused by CO₂ prices.

These first-order prices are used to adjust volatile historical electricity prices as shown in Fig. 3.2. Actual prices are greater than the first-order prices shown in Fig. 3.1 but follow a similar pattern of relative uniformity over the two-day duration. Prices calculated by the first-order approach will match poorly with historical data without highly accurate cost information, but adjusting historical prices by the change in first-order prices allows realistic absolute price levels that account for the effects of changing electricity market conditions.

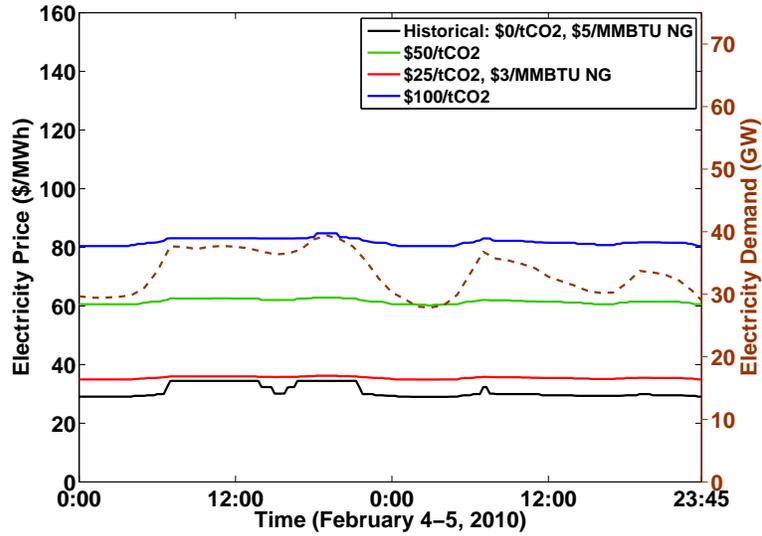


Figure 3.1: At moderate net load, changes to first-order electricity prices reflect CO₂ and fuel costs of marginal gas-fired facilities.

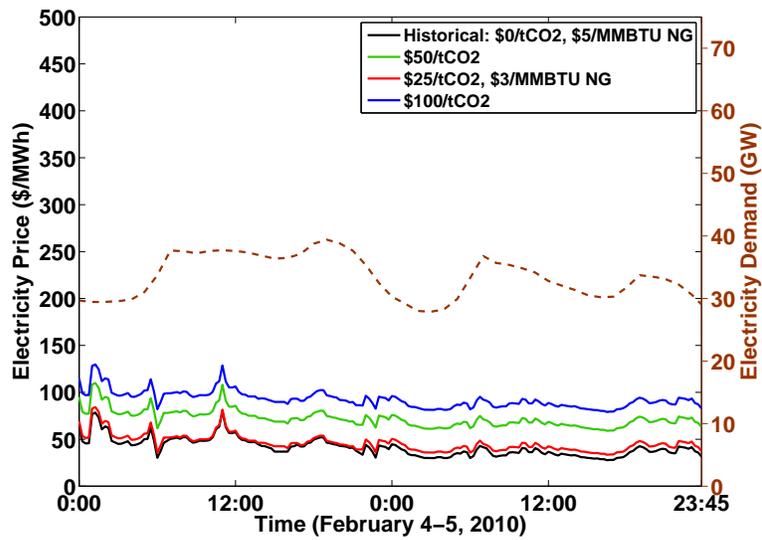


Figure 3.2: Historical and volatile adjusted prices are relatively steady but are higher than first-order prices.

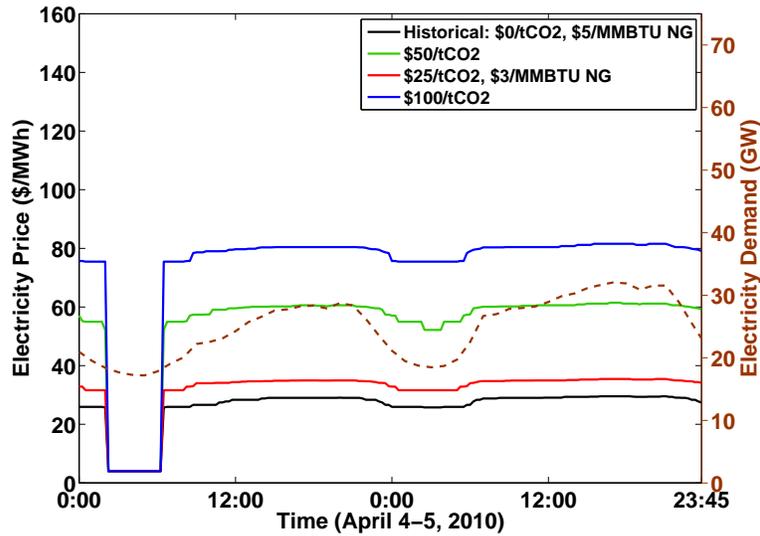


Figure 3.3: At low net load, first-order calculations find that CHP facilities supply enough electricity for nuclear capacity to be marginal at some times.

Figures 3.3 and 3.4 display the same results for April 4 and 5, 2010, where net electricity demand is particularly low. First-order electricity price calculations typically find gas-fired facilities to be marginal generators; however, there is a short period of low demand where first-order prices fall to \$4/MWh, which is the operating cost for nuclear power plants in the database. At these demand levels, net electricity demand is met almost entirely by CHP capacity, so nuclear capacity is found to be marginal. While not necessarily realistic, it is likely that low-carbon capacity would be marginal under these circumstances, so the resulting adjustment of \$0/MWh is reasonable.

Figures 3.5 and 3.6 display the same results for July 15 and 16, 2010, when demand was relatively high. Below ~40 GW of net load, gas-based capacity is usually marginal, so the typical electricity price shift reflects the change in fuel and CO₂ emissions costs at gas-based facilities. However, coal-fired capacity is marginal at

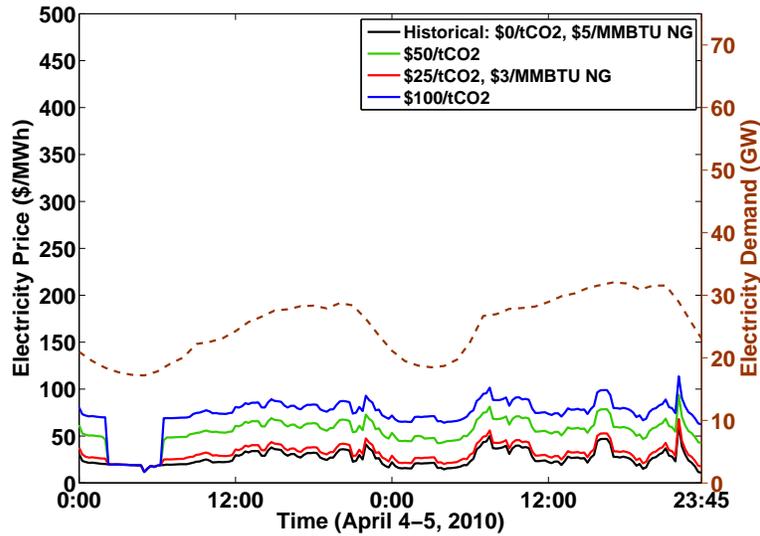


Figure 3.4: At low net load, historical and adjusted volatile prices are relatively stable.

higher demand, so the electricity price shift more closely reflects the emissions cost of coal-based generation. Fig. 3.6 also illustrates the utility of preserving historical price volatility, as the electricity price spikes and period of high prices on July 15 would not be reproduced using a first-order approach.

3.2 Analysis and Results

Three sets of analysis comprise this section. The first examines the implications of the venting-only flexible capture configuration over a range of CO₂ and natural gas prices. Next, solvent storage design is discussed in detail, and a set of favorable solvent storage design parameters is identified. Last, the favorable solvent storage configuration is studied for a range of CO₂ and gas prices.

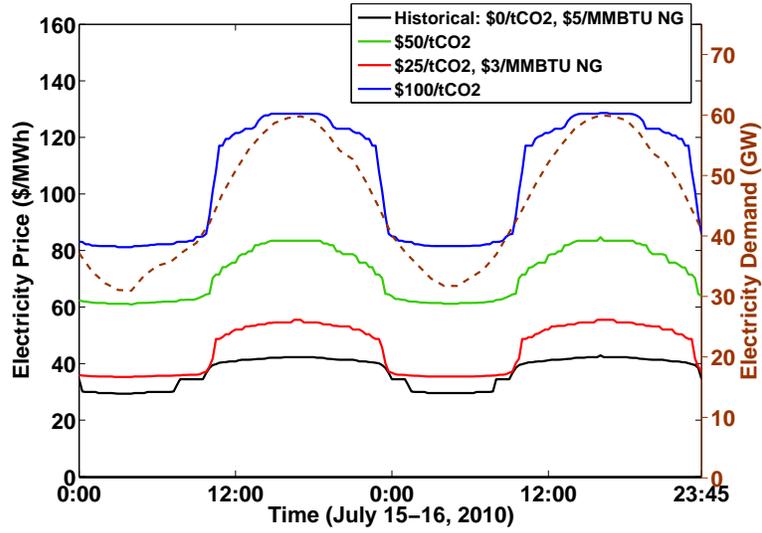


Figure 3.5: First-order dispatch calculations find coal-fired facilities to often be marginal above ~ 40 GW net load.

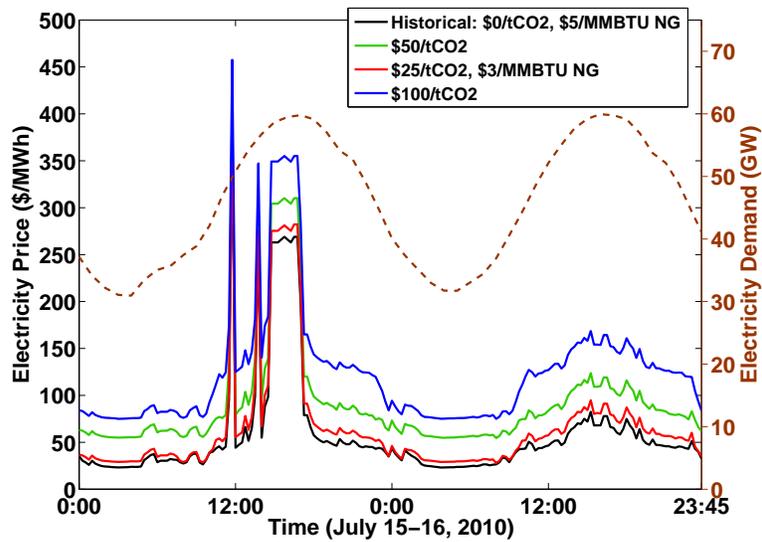


Figure 3.6: Periods of high prices occurring on this high demand day are not reproduced by first-order modeling.

3.2.1 The Value of Venting CO₂ Across Electricity Market Conditions

3.2.1.1 Power and Capture System Parameters

Key power and CO₂ capture system specifications are listed in Table 3.2. These parameters are identical to those in Table 2.10 with the exception of CO₂ capture energy requirement. The lower CO₂ capture energy requirement is taken from more recent results from an AspenPlus CO₂ capture system model developed at The University of Texas at Austin; this model uses a better optimized 7m MEA CO₂ capture process [Wagener & Rochelle, 2011]. The energy requirement and design capacity listed in the table correspond to the operating point where equivalent work is minimized. The design capacity, however, is unused in the profit maximization model for the venting-only configuration because 90% CO₂ removal is assumed for any reasonable operating point. All other performance parameters are identical to those listed in Table 2.11. As explained in the next section, this study assumes 2010 ERCOT conditions, so all prices in Table 2.11 are increased by 1.3% to reflect average inflation between 2008 and 2010 [USDOL, 2012].

3.2.1.2 Electricity System Parameters

All analysis in this chapter assumes 2010 ERCOT conditions. As mentioned in the discussion of price adjustment procedures, electricity prices, demand, and wind production from December 1, 2009–November 30, 2010 are used because electricity price data are not available after November 30, 2010. The power plant characteristics used for the price-adjustment procedure are again taken from a 2010 generating unit-specific database described fully in Section 5.3.2.

Table 3.3 provides the range of fuel and CO₂ prices considered in this analysis. All prices are kept constant throughout each one-year optimization. Historically, natural gas prices have been quite volatile throughout the year, and the European Union

Table 3.2: The following are key power and CO₂ capture system parameters used to study the venting-only configuration across CO₂ and natural gas prices.

Parameter (units)	Value
<i>Base Plant: Coal-Fired</i>	
Maximum output (MW)	500
Minimum output (MW)	150
CO ₂ emissions rate (without CO ₂ capture) (tCO ₂ /MWh)	1.03
Heat rate (without CO ₂ capture) (MMBTU/MWh)	10.8
Ramp limit (%/min)	4
Startup cost (\$/startup)	10,000
<i>CO₂ Capture System: 7m MEA solvent</i>	
CO ₂ removal (fractional)	0.9
Energy requirement (equivalent work) (MWh/tCO ₂) 11% absorption, 89% stripping/compression	0.247
Minimum load (%)	30
Ramp rate (%/min)	5
Design capacity (rich minus lean loading) (molCO ₂ /molMEA)	0.12

Emissions Trading System (EU-ETS) suggests CO₂ prices could also be volatile in a cap-and-trade setting [PE-Ltd., 2011, EU-ECX, 2008]. While the modeling framework is capable of handling daily-varying fuel and CO₂ prices, constant annual averages are used to establish a baseline of market conditions where capture flexibility is valuable. Future work could investigate the impact of stochastically varying prices.

Since coal price is historically stable, it is kept constant at \$2.25/MMBTU, the 2010 U.S. average for steam coal used in the electric power sector [USDOE, 2012]. This price is significantly higher than \$1.54/MMBTU used in Chapter 2 for 2008 conditions, so higher fuel costs can be expected to substantially reduce operating profits. The ranges of natural gas and CO₂ prices are chosen to bracket the price conditions that might be expected over the next 0–20 years. Oil-fired generators make up a very small portion of ERCOT generating capacity, but first-order dispatch model employed in electricity price adjustment also uses the 2010 average oil price in the electric power of \$12.34/MMBTU [USDOE, 2012]. Each combination of CO₂ and natural gas price is utilized to produce an adjusted volatile electricity price series based on historical 2010 electricity prices, and each of these volatile series produce a pseudo-forecasted price series for optimizing plant operation. The annual average pseudo-forecast electricity price at each CO₂-gas price pair is used in Eqn. 2.13 to calculate CO₂ capture ramping cost. Average pseudo-forecast price is used in ramping cost calculations rather than average adjusted volatile price because operational planning reflects expected, not actual, market conditions.

3.2.1.3 Results

The annual base plant capacity factor provides a general indication of how power and CO₂ capture systems are utilized over the range of electricity market conditions. Figure 3.7 plots the power system capacity factor with no capture and

Table 3.3: System performance is studied for the following fuel and CO₂ prices.

Commodity (units)	Price
Coal (\$/MMBTU)	2.25
Natural Gas (\$/MMBTU)	2–11
CO ₂ (\$/tCO ₂)	0–200

inflexible capture over the full range of CO₂ prices and three natural gas prices: \$2/MMBTU (minimum), \$11/MMBTU (maximum), and \$5.14/MMBTU (actual 2010 average) [USDOE, 2012]. Since the model holds coal price constant, higher natural gas prices will increase electricity prices relative to coal-based operating costs, providing more opportunity for profitable operation. However, a facility without CO₂ capture never exceeds a 52% capacity factor at any natural gas price because the assumed coal price and heat rate are relatively high. Changes in capacity factor with CO₂ price reflect the facility CO₂ emissions rate relative to that of marginal generators. When capture is unavailable, capacity factor falls with CO₂ price because emissions costs at the facility increase faster than those of marginal facilities, which are often gas-fired facilities but switch to efficient coal-fired facilities at high CO₂ and low natural gas prices. The emissions rate with inflexible CO₂ capture is about 0.13 tCO₂/MWh, much less than typical values of ~ 0.5 tCO₂/MWh for natural gas and ~ 1 tCO₂/MWh for coal without capture, so capacity factor increases with CO₂ price. A plant without CO₂ capture is more profitable under these conditions, so capacity factors are lower with inflexible capture than without capture at CO₂ prices below about \$30/tCO₂.

Figure 3.8 shows an analogous plot for the venting-only flexible capture configuration. Flexible capture facilities forgo capture at low CO₂ prices when capture is uneconomical, and they utilize capture when CO₂ prices are high. Thus, capacity

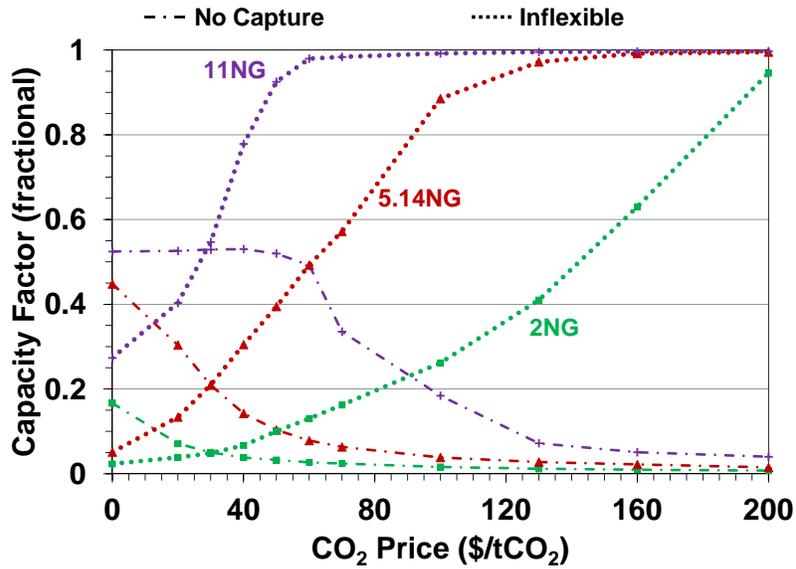


Figure 3.7: Power system capacity factors reflect emissions costs relative to emissions costs of marginal generators (NG prices are \$/MMBTU).

factors with flexible capture roughly follow the upper envelope of the curves with inflexible or no capture. For all natural gas prices except \$11/MMBTU, capacity factor first drops with CO₂ price before recovering at higher CO₂ prices where CO₂ capture operation is economical.

Capacity factor trends are reflected in CO₂ emissions results, which are expressed as the fraction of maximum possible annual emissions in Fig. 3.9 for the inflexible and no capture configurations and Fig. 3.10 for the venting-only flexible configuration. The fraction of maximum possible emissions is the ratio of annual CO₂ emitted to the quantity of CO₂ emitted by the 500 MW facility without capture if operated 100% of the year. Thus, emissions fractions without capture are nearly identical to capacity factors, and any discrepancy results from partial-load operation while ramping between offline, minimum output, and maximum output. With inflexible capture, the fraction of maximum possible emissions is very low when CO₂

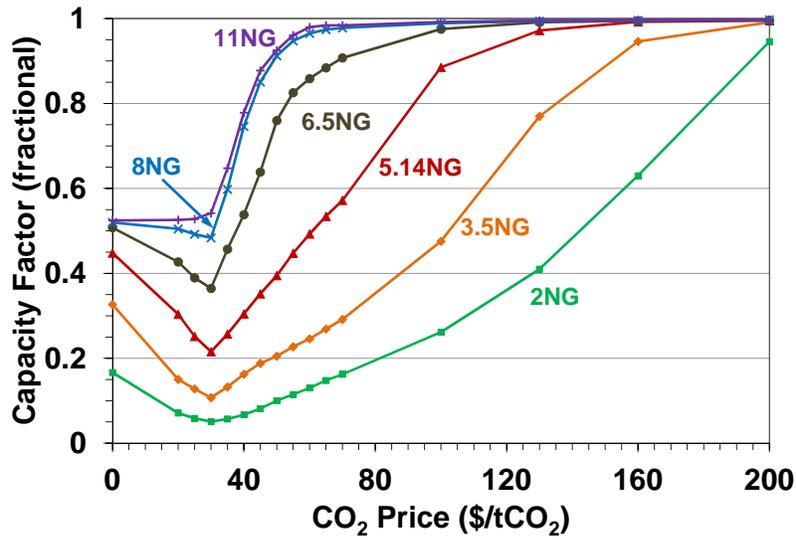


Figure 3.8: Venting-only flexible CO₂ capture allows greater capacity factors over the full CO₂ price range (NG prices are \$/MMBTU).

prices are low because facilities operate infrequently, then the fraction approaches 0.1 at high CO₂ prices because CO₂ capture systems are designed for 90% CO₂ removal.

While CO₂ emissions with flexible capture are the same as those without capture at CO₂ prices below \$20/tCO₂, they transition quickly to levels achieved by inflexible capture by \$40–50/tCO₂. Higher gas prices slow this transition somewhat by increasing the frequency of high electricity prices where venting CO₂ is profitable. Regardless, given CO₂ prices that justify capture operation, approximately \$30/tCO₂, flexible capture systems significantly reduce CO₂ emissions.

The CO₂ price regime where flexible capture systems transition from primarily being offline to online is highlighted in Fig. 3.11, which plots the average CO₂ emissions rate for the flexible capture configurations from \$20–50/tCO₂ at several natural gas prices. Though the transition region behavior varies little with gas price, there are subtle differences. The transition occurs more quickly at intermediate natural gas

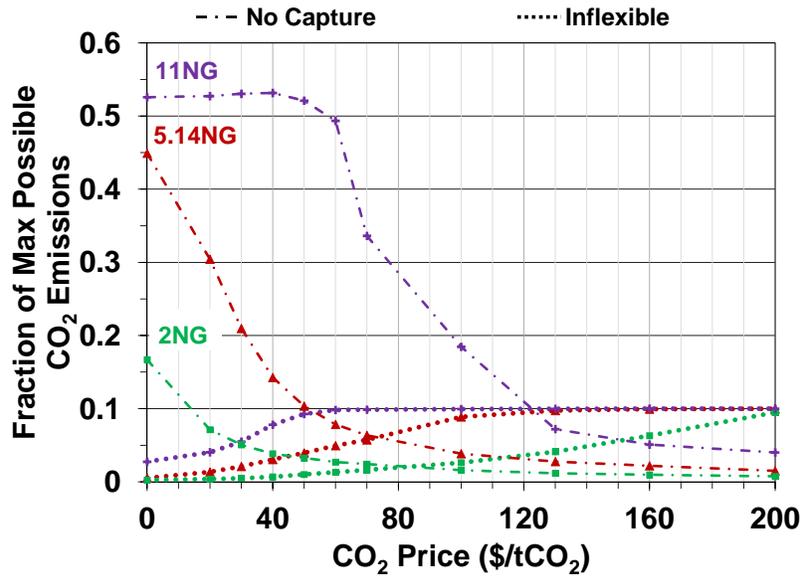


Figure 3.9: CO₂ emissions fall without capture due to lower capacity factor, while inflexible capture ensures low emissions at all market conditions (NG prices are \$/MMBTU).

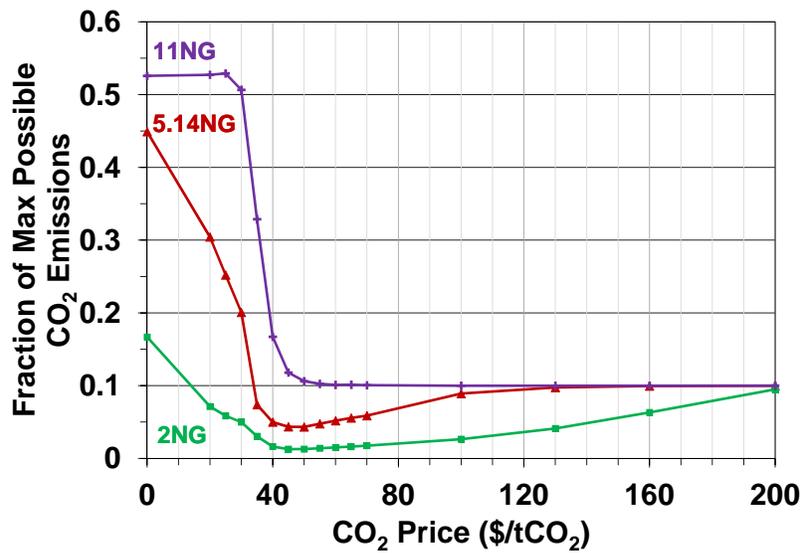


Figure 3.10: Venting-only flexible capture allows substantial reductions in CO₂ emissions above \$30/tCO₂. (NG prices are \$/MMBTU.)

prices such as \$5.14/MMBTU than at low and high natural gas prices. This phenomenon is explained using Figs. 3.12 and 3.13. Generally, the facility is online when electricity prices exceed marginal electricity production costs, both of which vary with electricity market conditions. Figure 3.12 plots facility marginal costs at \$0–50/tCO₂ when CO₂ capture systems are off (0% load) and on at 100% load. At any CO₂ price where costs are lower with 100% capture, there is a breakeven electricity price where additional electricity sales with capture offset the additional CO₂ emissions costs.

Figure 3.13 plots price-duration curves at \$35/tCO₂ for the maximum, minimum, and actual 2010 natural gas prices. Price-duration curves are generated by ordering electricity prices throughout the year from highest to lowest, and the horizontal axis indicates the fraction of electricity prices below a given price level. Also shown is the breakeven electricity price for venting CO₂ at \$35/tCO₂. The solid vertical lines mark capacity factors for the venting-only flexible capture facility at each market condition, and the dashed vertical lines mark the fraction of prices when venting is economical at each market condition. At low natural gas prices, electricity prices are low, so the facility operates very infrequently, but venting is often profitable when the facility is online. At high natural gas prices, capacity factor is much higher, but higher prices provide more opportunities to economically vent CO₂. These two behaviors produce higher average CO₂ emissions rates at low and high natural gas prices relative to those at intermediate natural gas prices, when venting is profitable during a relatively small portion of online hours.

To begin discussing the economic implications of flexible CO₂ capture, Fig. 3.14 shows annual operating profits normalized by gross power capacity with \$5.14/MMBTU natural gas and \$0–80/tCO₂ for the facility with no capture, inflexible capture, and venting-only flexible capture. This figure exhibits the same trends as Figs. 2.20 and

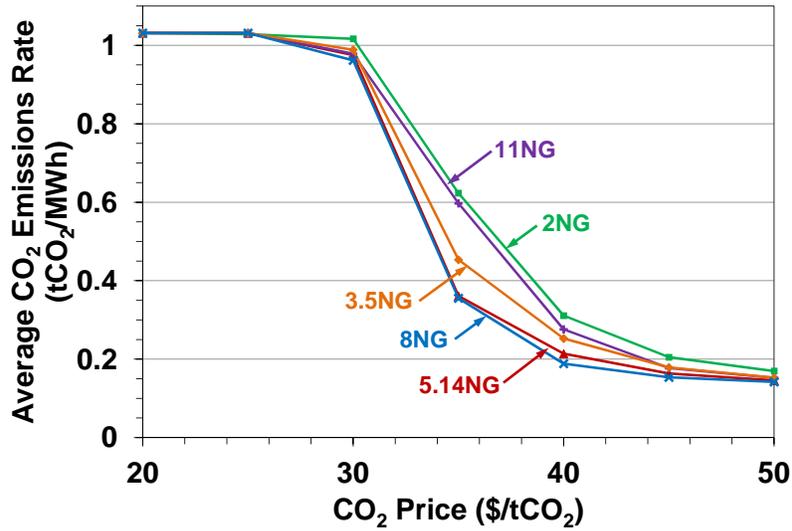


Figure 3.11: The transition to primarily full-load CO₂ capture for venting-only flexible capture systems is slower at high and low natural gas prices (NG prices are \$/MMBTU).

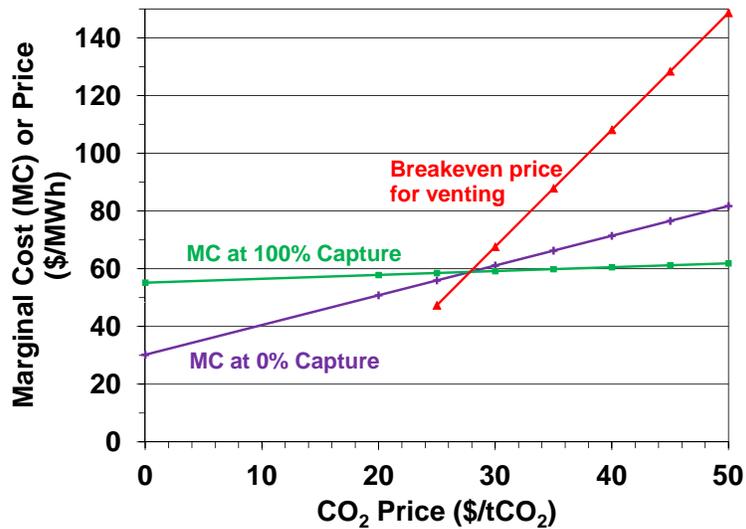


Figure 3.12: Venting CO₂ is more often profitable when marginal costs are only slightly higher with capture systems turned off.

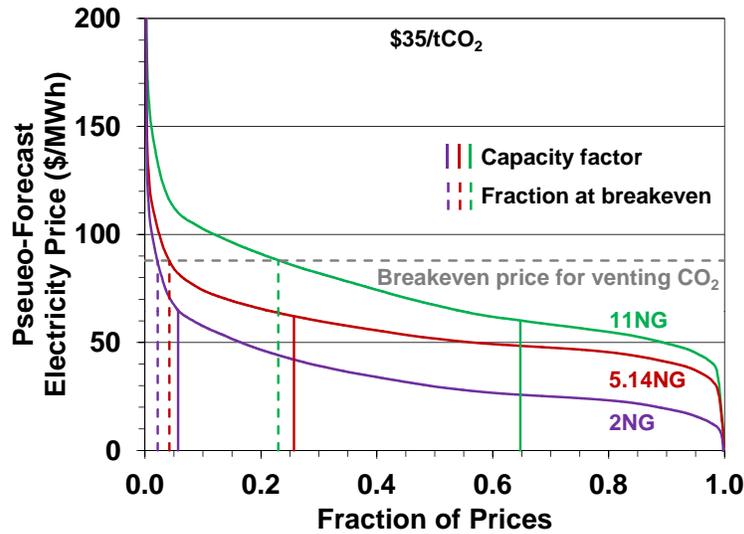


Figure 3.13: Average emissions rate at transition CO₂ prices depends on the fraction of online time when venting CO₂ is profitable (NG prices are \$/MMBTU).

2.22. As CO₂ price increases, profits fall without capture and rise with inflexible capture, while the flexible capture facility generally follows the upper envelope and provides some additional benefit at intermediate CO₂ prices when venting CO₂ is valuable. The absolute scale on this figure, however, is substantially different from Figs. 2.20 and 2.22 because lower electricity prices and higher coal prices in 2010 relative to 2008 combine to greatly reduce profits at the coal-fired facility. Lower electricity prices largely result from lower natural gas prices: \$5.14/MMBTU in 2010 versus \$7.8/MMBTU in 2008. Fuel costs increase significantly with coal at \$2.25/MMBTU instead of \$1.54/MMBTU in 2008. While coal price to an individual facility can vary and might be much lower than \$2.25/MMBTU, these results demonstrate the sensitivity of operating profits to coal price.

The smaller overall scale in Fig. 3.14 relative to Figs. 2.20 and 2.22 highlights the reduction in profits with flexible capture relative to inflexible capture for CO₂ prices below \$35/tCO₂. This difference reflects the fixed operating and maintenance

(FOM) cost of thermal solvent degradation when assuming capture systems are always kept at operating temperature. Realistically, this cost would only be incurred given a reasonable expectation to use the CO₂ capture system, which is not likely the case at the lowest CO₂ prices.

A primary economic metric for flexible capture is the difference between operating profits with flexible capture and the maximum of those with inflexible or no CO₂ capture. This incremental operating profit benefit can then be weighed against any incremental capital costs of flexibility. A contour plot of the incremental operating profit benefit with the venting-only flexible capture system, normalized by gross power output capacity, is plotted for the full natural gas price range and \$0–130/tCO₂ in Fig. 3.15. This figure demonstrates that the emissions penalty from venting CO₂ is worth the benefit of additional electricity sales only in a CO₂ price range of approximately \$30–60/tCO₂, with the range and benefit being greater at high natural gas prices. Higher electricity prices that accompany high natural gas prices increase the frequency of instances when venting CO₂ is profitable, and this benefit is largely absent below natural gas prices of about \$4/MMBTU. Natural gas prices have been below \$3/MMBTU in the United States in 2012, so venting-only flexible capture in response to high electricity prices is unlikely to provide significant benefit if these market conditions persist [Bloomberg, 2012].

3.2.2 Solvent Storage Design Study

A design sensitivity study yields insight into the appropriate solvent storage design and operating parameters to use in the market sensitivity analysis of the previous section. Results in Chapter 2 demonstrate the potential for solvent storage to provide economic benefit at the high CO₂ prices; however, the true value of solvent storage depends on the tradeoff between operating profit benefit and incremental

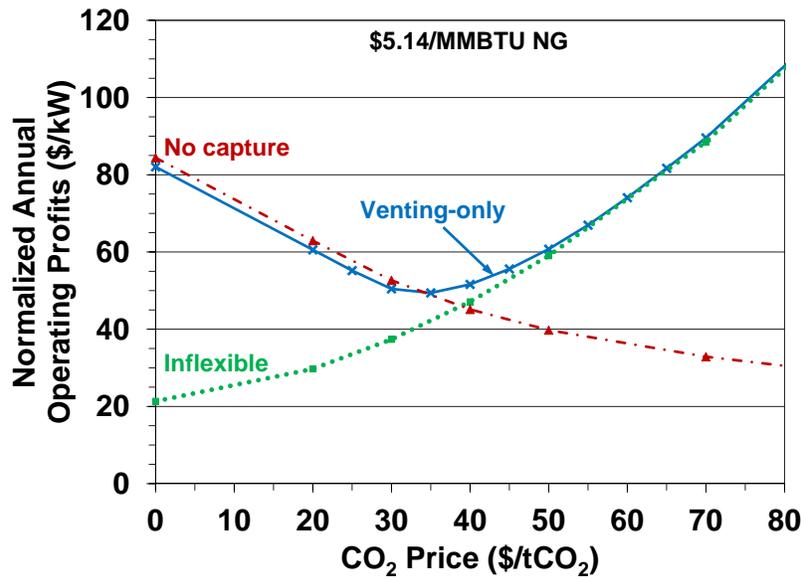


Figure 3.14: Profits for each configuration depend on capacity factor and the availability of flexible CO₂ capture systems.

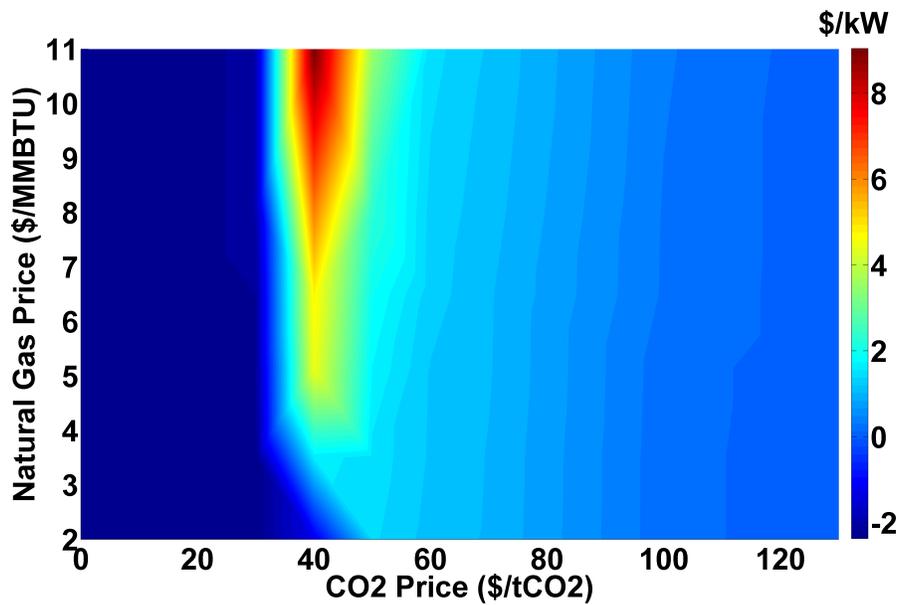


Figure 3.15: Venting CO₂ at high prices is valuable only with \$30–60/tCO₂ and high natural gas prices.

capital costs. Solvent storage systems require additional capital for solvent inventory, storage tanks, and potentially larger stripping and compression equipment to regenerate stored rich solvent. The incremental capital cost of solvent storage is a strong function of the solvent storage design and operating parameters as well as accounting procedures that determine which costs are attributed to the solvent storage system and to what extent.

For example, Fig. 3.16 plots an estimate of the incremental capital cost of solvent storage, normalized by gross plant capacity, as a function of the maximum amount of time stripping/compression systems could be offline during full-load absorption before filling the rich solvent tank. Referred to as “storage time,” this quantity is a proxy for the quantity of solvent inventory and the storage tank size. Additional parameters assumed in this cost model are listed in Table 3.4.

Solvent inventory volume and mass is determined from Eqn. 2.34, with $\Omega = 8.33 \text{ molMEA/molCO}_2$ ($0.12 \text{ molCO}_2/\text{molMEA}$), the CO_2 carrying capacity chosen to have minimum equivalent work for CO_2 capture and compression. Then, the assumed MEA price in 2010 dollars, $\$2.55/\text{kgMEA}$ is used to find solvent inventory costs, CC^{Solv} , for a given storage system size.

With the solvent inventory volume known, storage tank cost, $CC^{StorTank}$, is calculated using Eqn. 3.1, which is regressed from the cost-volume relationship for large field-erected tanks in the Peters, Timmerhaus, and West plant design text and scaled by the appropriate Chemical Engineering Plant Cost Index ratio from 2002 to 2010 ($CEPCI_{R,2010/2002}$) [Peters et al., 2002, CES, 2009, Che, 2012]. There is a factor of 2 because both lean and rich solvent storage tanks are necessary. The quantity 0.874 is an economy of scale factor, and $10^{2.195}$ is a regressed parameter.

$$CC^{StrTank} = 2 (CEPCI_{R,2010/2002}) 10^{2.195} \psi^{0.874} \quad (3.1)$$

Incremental capital cost for stripping and compression equipment are calculated using the baseline equipment cost from a U.S. National Energy Technology Lab (NETL) plant design study for all stripping/compression equipment, $CC^{StrComp,0}$, multiplied by the equipment oversizing factor raised to a conservative economy of scale factor of 0.85 (Eqn. 3.2) [USNETL, 2007, Fisher, 2007]. The incremental cost of larger stripping/compression equipment is $CC^{StrComp} - CC^{StrComp,0}$. In Fig. 3.16, the oversizing factor, f^{Equip} , is assumed equal to $24/(24 - \alpha)$, the heuristic scaling factor that assumes daily cycling of the solvent storage system. Though there are economies of scale with equipment size, the α on the denominator of the oversizing term causes the upwards curvature of equipment costs as storage time increases.

$$CC^{StrComp} = CC^{StrComp,0} (f^{Equip})^{0.85} \quad (3.2)$$

Table 3.4: The following additional parameters are used to calculate the incremental capital costs of solvent storage.

Parameter (units)	Value
2002 to 2010 chemical engineering plant cost index ratio, $CEPCI_{R,2010/2002}$ (fractional)	1.39
Base stripping/compression equipment cost, $CC^{StrComp,0}$ (\$/kW)	388
MEA price, P^{MEA} (\$/kg)	2.55

These capital cost calculations ignore many site- and design-specific contributors to capital cost, but many parameters used could still vary widely. For instance, oversizing stripping and compression equipment is only justifiable if increased equipment costs are offset by the operating profit benefit of being able to regenerate stored

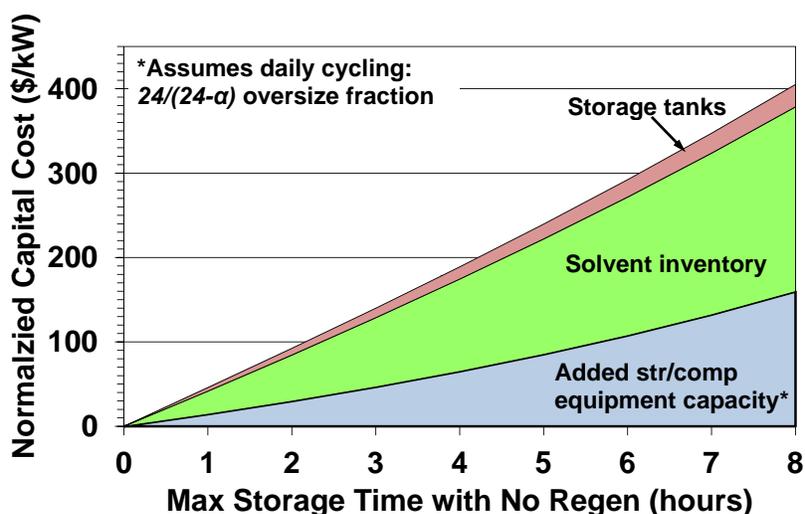


Figure 3.16: Solvent storage capital costs rise quickly with system size, predominantly due to solvent inventory and oversized stripping and compression equipment. (assumes 0.12 molCO₂/molMEA capacity)

rich solvent during full-load absorption. With sufficiently high capital costs, overall value might instead be greater with standard equipment size using reduced-load absorption to regenerate stored rich solvent [Chalmers et al., 2010]. Doing so would not require additional CO₂ venting if base plant load is reduced simultaneously. In addition, some additional stripping and compression capacity might already be built into a conservative design, so increased capacity might not be attributed to the cost of solvent storage. Process improvements could also increase stripping and/or compression capacity without any additional equipment costs for solvent storage. Any of these scenarios could entirely remove equipment costs from the incremental capital cost of solvent storage.

Solvent inventory and storage tank costs are highly dependent on the chosen carrying capacity of the CO₂ capture system. The amine scrubbing process for CO₂ capture is commonly designed by finding the minimum energy requirement as a function of chosen CO₂ carrying capacity. Figure 3.17 plots this relationship for 7m MEA,

and the vertical red dotted line highlights the operating point of minimum energy requirement used in all analysis within Section 3.2.1 [Wagener & Rochelle, 2011]. This analysis assumes a constant temperature reboiler where heat is exchanged between extracted steam and MEA, so energy requirement increases at high design capacity because lower CO₂ partial pressures exiting the stripper column result in greater compression work requirements. Energy requirement increases at low design capacity because a higher solvent circulation rate is necessary to achieve 90% CO₂ removal, so pump work increases, and more sensible heat is necessary to heat solvent in the stripper. In a capture system without solvent storage, minimum energy requirement is always desirable. However, operating with a higher design capacity would reduce the solvent inventory necessary to store a given CO₂ quantity in rich solvent, which would decrease both solvent inventory and storage tank costs. Figure 3.17 also shows the normalized capital costs of solvent inventory and storage tanks per hour of solvent storage capacity as a function of chosen CO₂ carrying capacity. Given assumed parameters, these capital costs could be reduced by 45% if doubling the design capacity is worth a 6% increase in CO₂ capture energy requirements.

Regardless of the chosen operating point, extra solvent inventory might be kept on site to maintain or quickly resume desired CO₂ capture operation in the event of a process upset or equipment failure such as a leak or a sudden influx of products from the upstream SO₂ removal process. If this inventory will be purchased regardless of whether the stored solvent will be used for price-responsive flexible operation, the capital costs of solvent inventory and storage tanks might not be attributed to the solvent storage system.

Lastly, CO₂ capture capital cost estimates are highly uncertain. The cost of storage tanks and stripping/compression equipment are highly dependent on cur-

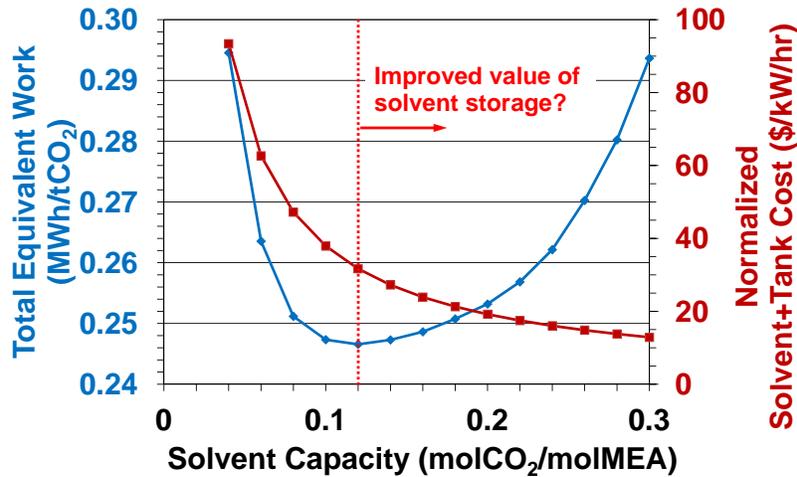


Figure 3.17: Operating CO₂ capture with high capacity increases capture energy requirement but reduces solvent inventory and storage tank costs.

rent market prices of steel and cement, and solvent price could vary considerably if widespread CO₂ capture deployment significantly changes the market dynamics for amine solvents. For all of these reasons, the incremental capital cost of solvent storage is highly uncertain and dependent on a range of design and market assumptions. Characteristics of a good solvent storage design can only be identified by studying the capital and operating economics of solvent storage over a range of parameter values.

3.2.2.1 Studied Parameter Ranges

Table 3.5 lists the parameter ranges chosen for this design sensitivity study. A storage capacity up to 8 hours is expected to be capital cost prohibitive under most market conditions and system specifications, but a large storage capacity could be economical with high design capacity and low capital costs for storage tanks and any other necessary equipment. The maximum equipment oversizing of 20% is the heuristic value for a 4-hour storage system. Minimum CO₂ carrying capacity occurs at the minimum equivalent work operating point, and the maximum capacity provides

a doubling in capacity at the expense of 6% greater energy requirement. These ranges are generally chosen so that they will contain a global optimum economic value. Had analysis found otherwise, ranges would have been expanded.

Table 3.5: The following parameter ranges are used to study the sensitivity of solvent storage economics to design and operating choices.

Parameter (Units)	Minimum	Maximum
Storage capacity (hours)	0	8
Stripping/compression equipment over-sizing fraction (fractional)	1	1.2
Solvent design capacity/energy requirement (molCO ₂ /molMEA, MWh/tCO ₂)	0.12/0.247	0.24/0.262

The value of the solvent storage system is assessed by calculating a net present value (NPV) of the solvent storage system from its incremental capital cost and the annual operating profit benefit over a facility with no capture or inflexible capture. Annual operating profits depend on the system design and market conditions. While a comprehensive analysis would explore a range of market conditions and possibly incorporate stochasticity, a single market condition is used throughout this analysis to yield initial insights into solvent storage design. Computation time with the solvent storage configuration is typically on the order of a few hours, so the need to reduce the number of independent variables in this analysis led to focusing on the parameters in Table 3.5 rather than electricity market conditions. The primary market conditions of interest are CO₂ and natural gas price, so this analysis will identify an optimal design for a single CO₂ and natural gas price combination, then investigate how it performs at other conditions discussed in Section 3.2.3. In addition, the NPV calculation uses a constant annual operating profit value over the economic life of the facility, which implies constant market conditions over the plant life. This assumption is unrealistic,

but studying the effects uncertain CO₂ and natural gas price paths over time is outside the scope of this particular analysis.

Table 3.6 lists the economic assumptions used in NPV calculations. The actual 2010 average natural gas price is used. While significantly higher than 2012 natural gas prices, \$5.14/MMBTU is viewed as a reasonable future natural gas price [USDOE, 2012]. A \$40/tCO₂ emissions penalty is chosen for solvent storage design optimization because the analysis in Section 3.2.1 demonstrates that flexibility is valuable at this price, and all capture configurations (none, inflexible, venting-only, and solvent storage) are relatively competitive with each other. The assumed economic lifetime is 20 years. Capital costs are depreciated on a 20-year modified accelerated cost recovery system (MACRS) half-year convention schedule, profits are taxed at 38%, and future cash flows are discounted by a 10.3% inflation-adjusted discount rate [NETL, 2005]. This discount rate, however, is implemented in real terms while annual cash flows are valued in constant dollars, so calculations provide conservative estimates of solvent storage NPV. Future work could examine the effect of discount rate on optimal solvent storage design.

Table 3.6: The following economic assumptions are used in calculating the NPV of solvent storage systems.

Parameter (Units)	Value
Natural gas price (\$/MMBTU)	5.14
CO ₂ price (\$/tCO ₂)	40
Discount rate (%)	10.3
Profit tax rate (%)	38
Depreciation schedule	20 year MACRS

3.2.2.2 Results With Reference Capital Cost Assumptions

Figure 3.18 presents the NPV, normalized by gross plant capacity, as a function of storage system size for all design sensitivity cases given the capital cost assumptions listed in the previous section, which make up the reference case. Each panel provides results for a particular capture operating point, and each curve within a panel represents an equipment oversizing fraction. Results with negative NPV (a loss) are not shown, and simulations were not run above a storage system size that is suboptimal for the capital cost assumptions in both the reference case and the favorable case discussed in Section 3.2.2.3. As discussed in Section 2.3.1.3, positive vertical error bars terminate at the best possible relaxed solution found by the MIP solver at the end of user-specified computation time limits, so truly optimal profits could be as high as these values. Also shown on each panel is the normalized NPV of the venting-only configuration, which is calculated assuming no capital cost and a constant normalized operating profit benefit of \$4.5/kW per year relative to normalized profits with the inflexible and no capture configurations. The annual benefit of the venting-only configuration with \$40/tCO₂ and \$5.14/MMBTU natural gas is calculated previously from the analysis in Section 3.2.1.

For all capture operating points, oversizing the stripping and compression equipment reduces investment value under the reference case assumptions. Though larger equipment provides greater ability to regenerate stored rich solvent without reducing output or incurring CO₂ emissions costs, any such benefits are offset by increased capital costs. The optimal storage size for each operating point is also a weak function of equipment oversizing, and changes in optimal storage size for different amounts of equipment oversizing might disappear given greater data resolution and longer computation time to close the remaining optimality gap. Also apparent from

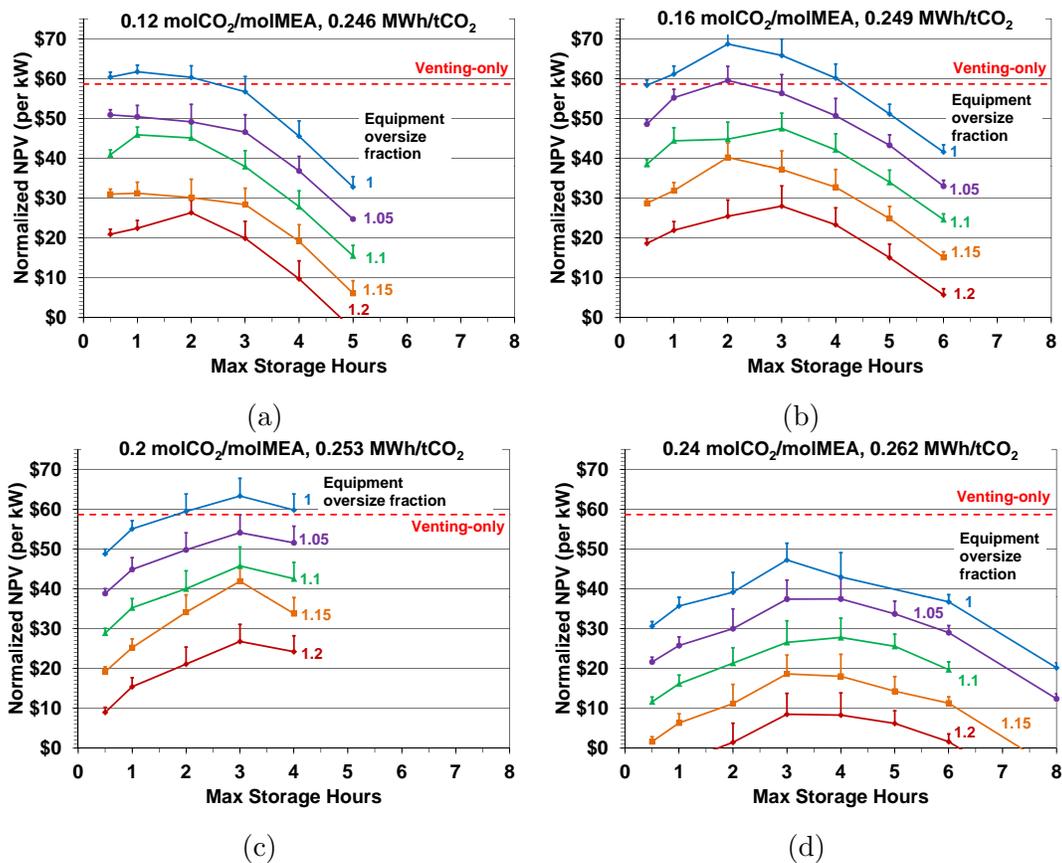


Figure 3.18: Oversizing stripping/compression equipment has no value, and optimal storage size increases with design capacity. The highest observed NPV occurs with no oversizing, 0.16 molCO₂/molMEA capacity, and 2 hours of maximum storage time.

this figure is the relatively few combinations of design and operating parameters that perform better than the venting-only configuration. A 33% increase in design capacity at the expense of a 0.84% increase in energy requirement improves the 20-year investment value of flexible capture by \$10/kW with a 2-hour storage system, which is considered a modest improvement given the increased complexity of operating a solvent storage system. Nevertheless, these results demonstrate that reducing solvent inventory costs by increasing design capacity can offset a slight increase in capture energy requirements.

Figure 3.19 is a contour plot of the optimal NPV from each curve in Fig. 3.18

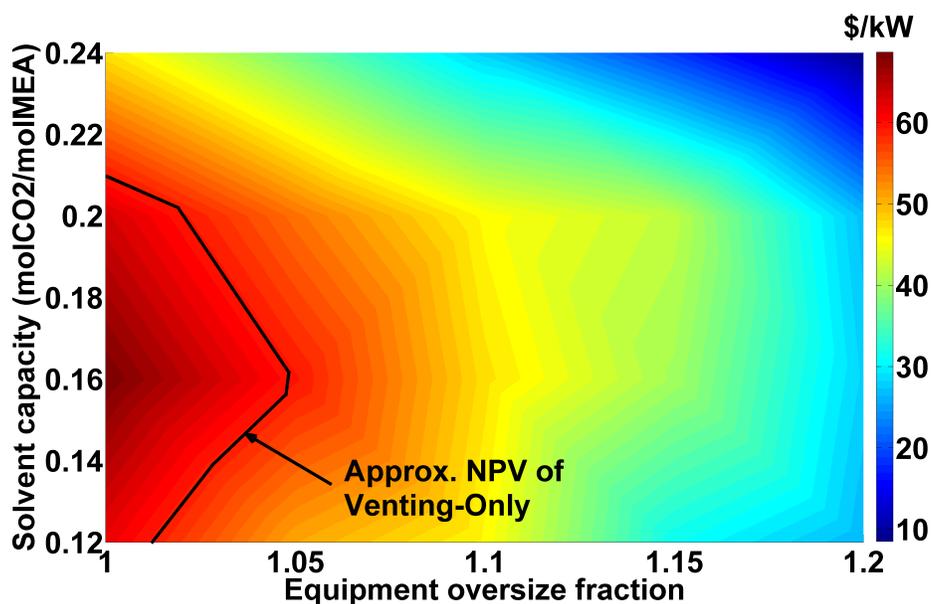


Figure 3.19: Normalized NPV increases with a modest increase in CO₂ carrying capacity but falls if stripping and compression equipment are oversized to regenerate stored rich solvent. Solvent storage improves upon venting-only capture for only a small range of configurations.

as a function of solvent capacity and equipment oversizing fraction. The manually-created black line roughly follows the contour of the venting-only NPV of \$58.6/kW. Trends in optima are clearly demonstrated in this figure. Oversizing stripping and compression equipment is never worth the additional capital expense, and slightly increased solvent capacity is worth the added energy costs. The global optimum with reference case capital cost assumptions is clearly shown at 0.16 molCO₂/molMEA design capacity and no equipment oversizing.

Figure 3.20 plots contours of the optimal storage system size for each optimal NPV in Fig. 3.19. Patterns are less evident in this figure because data resolution is limited, and NPV often has little variation within ± 1 hour of the optimal storage time. Given these data limitations, Fig. 3.20 shows relatively small changes in optimal storage system size with equipment oversizing fraction for a given operating

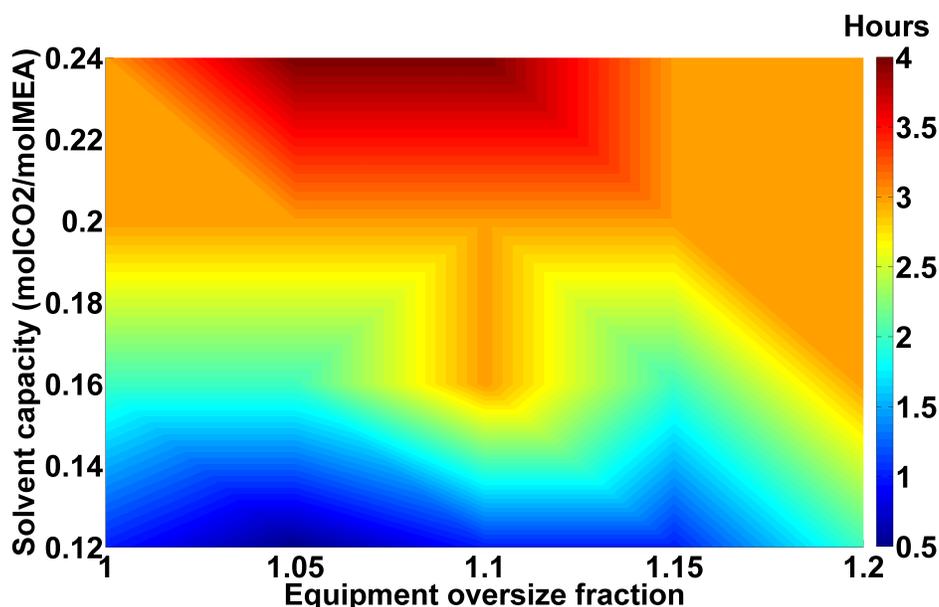


Figure 3.20: Optimal solvent storage system size (maximum storage hours) increases with CO₂ carrying capacity but is a weak function of equipment oversizing.

point (solvent capacity). Larger stripping and compression capacity does not beget a larger solvent storage system when their relationship is not directly coupled by a heuristic such as the $24/(24 - \alpha)$ oversizing fraction assumed previously. Conversely, optimal storage system size increases monotonically with design capacity. Lower solvent inventory and storage tank costs allows for a larger solvent storage system to provide operating profit benefit. However, the optimal storage size is 2 hours for the global optimum NPV under reference capital cost assumptions.

3.2.2.3 Results with Favorable Capital Cost Assumptions

As discussed above, solvent storage system capital cost estimates can vary widely with steel, cement, and chemical markets as well as the degree to which incremental costs of stripping/compression equipment and solvent inventory/tanks are attributed to the solvent storage system. To demonstrate the impact of these as-

sumptions, calculations are repeated for a set of “favorable” capital cost assumptions that reflect a possible best-case scenario. These assumptions include the following.

1. Stripping/compression equipment oversizing has no cost. Additional stripping/compression capacity is part of a conservative design, or extra capacity is achieved by process improvements.
2. Solvent inventory cost is 50% of the reference case. Solvent price has fallen and/or extra solvent inventory is part of a risk management strategy.
3. Storage tank cost is 50% of the reference case. Steel and cement prices have fallen and/or tanks are included for the extra solvent inventory purchased to mitigate risk.

Figure 3.21 plots normalized solvent storage capital costs on the same scale as Fig. 3.16 under the favorable capital cost assumptions and a 0.16 molCO₂/molMEA design capacity. The impact is readily apparent, as capital costs at 8 hours of storage time are below the \$100/kW exceeded at just over 2 hours of storage with a 0.12 molCO₂/molMEA design capacity and reference assumptions.

Figure 3.22 plots the normalized NPV with favorable capital cost assumptions in the same manner as Fig. 3.18. The y-axis scale is shifted by up \$30/kW to display results under favorable conditions because NPV is generally much higher with the substantial reduction in capital costs. With no cost for oversizing stripping and compression equipment, NPV is nearly the same regardless of equipment size for a given operating point and storage system size. In most cases, larger stripping/compression equipment adds some value by increasing the amount of time when stored rich solvent can be regenerated without reducing plant output or increasing emissions costs.

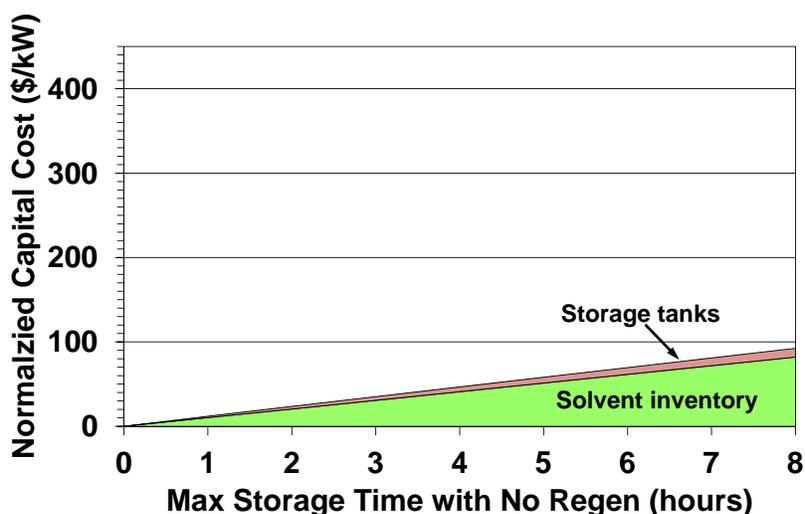


Figure 3.21: The incremental capital cost of solvent storage is much lower under favorable cost assumptions (costs assume 0.16 molCO₂/molMEA design capacity).

There is a much larger range of conditions where NPV is greater than the NPV of a venting-only flexible system, and all optima fall above the venting-only NPV. Lower solvent inventory and storage tank costs also allow larger optimal storage system sizes because relative to the reference case, a greater operating profit benefit can be achieved with the same investment in solvent inventory. However, the operating point with greatest NPV, 0.16 molCO₂/molMEA capacity and 0.249 MWh/tCO₂, is the same as optimal operating point under reference capital cost assumptions. At the global optimum under favorable conditions, storage systems are sized for a maximum of 4 hours with stripping/compression off and full-load absorption, stripping and compression equipment are oversized by 20%, and NPV is \$34.0/kW greater than the venting-only NPV of \$58.6/kW.

Figure 3.23 plots contours for optimal NPV under favorable capital cost assumptions. The contour scale demonstrates that all optima have NPV exceeding the venting-only NPV. Though oversizing stripping/compression equipment is typ-

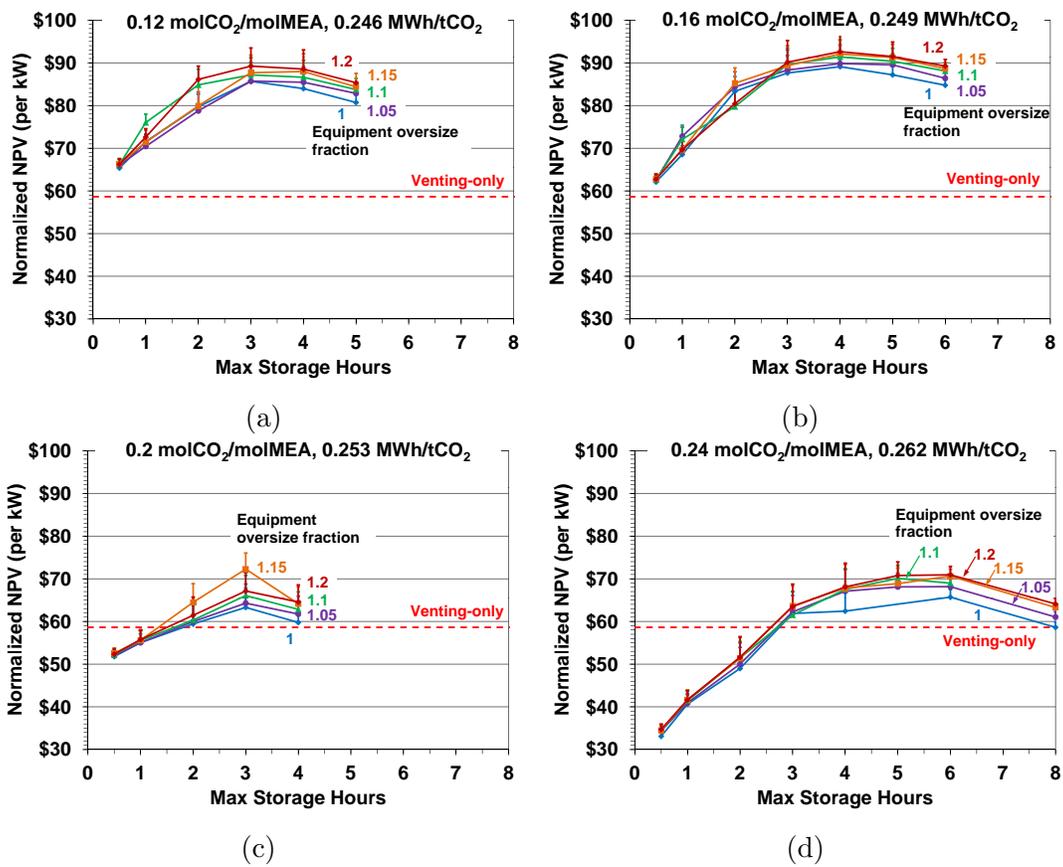


Figure 3.22: Favorable capital cost assumptions allow solvent storage systems to have much greater value, and optimal storage systems are larger.

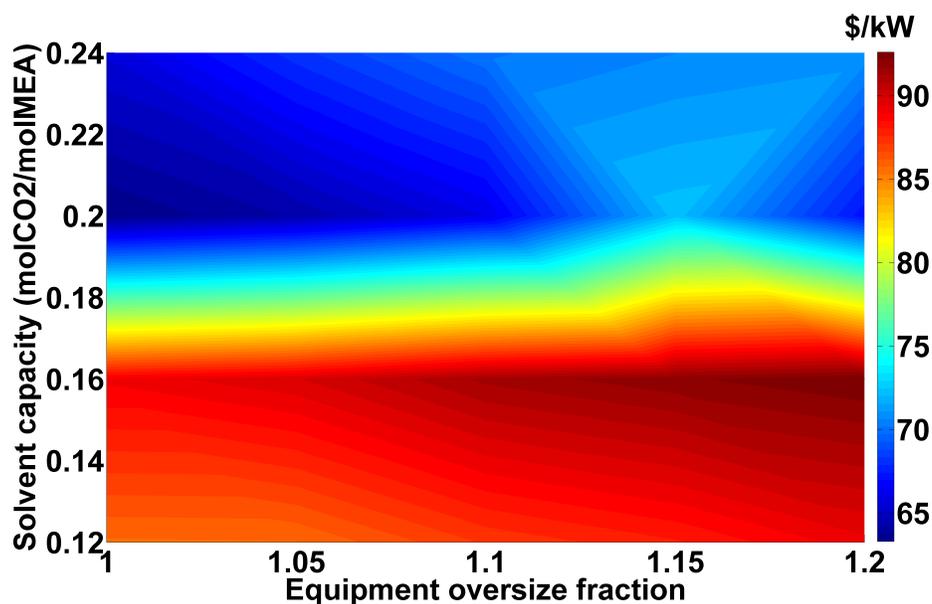


Figure 3.23: With favorable capital cost assumptions, normalized NPV increases drastically, and oversizing is valuable. However, the optimum operating point is constant.

ically favorable absent any cost for doing so, this figure demonstrates that NPV is a relatively weak function of equipment oversizing, which suggests that any added capital cost for oversized equipment is likely to offset the improvement in operating economics. For a given stripping/compression equipment size, NPV always peaks at 0.16 molCO₂/molMEA carrying capacity. Under these capital cost assumptions, a conservative designer could obtain nearly all the added value of solvent storage by operating at minimum equivalent work, but NPV drops substantially at design capacities above 0.16 molCO₂/molMEA.

Figure 3.24 shows the optimal storage size corresponding to each point in Figure 3.23. Similar to results under reference capital cost assumptions, optimal storage system size does not vary significantly with stripping/compression equipment oversizing, and optimal size generally increases with design solvent capacity. Though

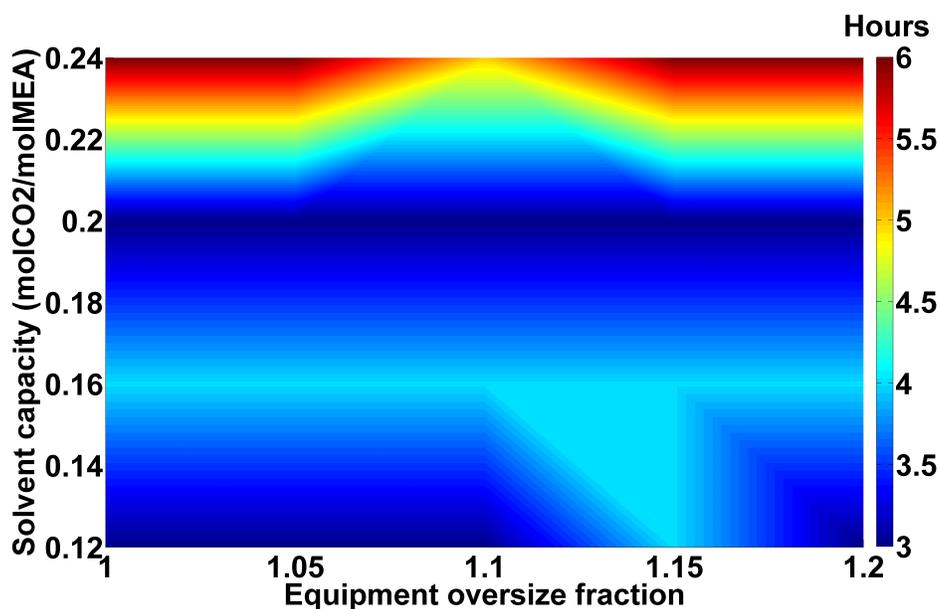


Figure 3.24: Optimal solvent storage system size again increases with CO₂ carrying capacity and is significantly larger with favorable capital cost assumptions.

optimal size decreases from 4 to 3 hours from 0.16 to 0.2 molCO₂/molMEA, NPV again varies little ± 1 hour of the optimum, and greater data resolution and longer allowable computation time would likely reduce this effect. Relative to results with reference capital costs, optimal storage sizes are significantly larger, with up to a 6-hour system achieving the greatest NPV at 0.24 molCO₂/molMEA. However, energy costs are not justified at this operating point; 4 hours is the optimum storage size at the global optimal NPV with favorable capital costs.

Table 3.7 compares the optimal configuration and its economic performance for reference and favorable capital cost assumptions. As discussed above, lower capital costs of solvent inventory, storage tanks, and stripping/compression equipment allow for a larger solvent storage system, but the optimal operating point remains constant. The larger system under favorable conditions earns an additional \$1.8/kW annually over the optimal system under reference assumptions, and capital costs are slightly

lower. Since solvent inventory and storage tank costs are halved, storage system size doubled, and oversizing costs removed under favorable conditions, the \$0.2/kW capital cost reduction reflects only the economy of scale factors. Normalized NPV is 35% greater under favorable capital cost assumptions. Though this section compares only two sets of capital cost assumptions, the optimal solvent storage system size and its economic performance are clearly sensitive to these assumptions. The primary determinant of optimal storage system size is solvent inventory cost, and the analysis here suggests that optimal storage system size is closely related to solvent price. Any solvent storage plant design should carefully consider its economic assumptions and perform sensitivity analysis to determine how solvent storage design decisions might change with market conditions and other CO₂ capture design variables.

Table 3.7: Favorable capital cost assumptions promote a larger solvent storage system, but the optimum operating point does not change.

Parameter (Units)	Reference	Favorable
Storage system size (hours)	2	4
Stripping/compression equipment oversizing fraction (fractional)	1	1.2
Solvent operating capacity/ energy requirement (molCO ₂ /molMEA, MWh/tCO ₂)	0.16/0.249	0.16/0.249
Normalized annual operating profit benefit from no/inflexible capture (\$/kW)	7.5	9.3
Normalized capital cost (\$/kW)	23.6	23.4
Normalized NPV (\$/kW)	68.7	92.6

3.2.3 The Value of Solvent Storage Across Electricity Market Conditions

The optimal solvent storage configuration under reference capital cost assumptions (2-hour storage time, 0.16 molCO₂/molMEA design capacity, no stripping/compression oversizing) is then optimized for the full range of CO₂ and nat-

atural gas prices explored in Section 3.2.1, \$0–200/tCO₂ and \$2–11/MMBTU natural gas. The optimal solvent storage configuration is determined for \$40/tCO₂ and \$5.14/MMBTU natural gas, so this section examines its performance over a wide range of electricity market conditions. Several figures from Section 3.2.1 are repeated with solvent storage results superimposed, then economic performance is discussed in greater detail.

Figure 3.25 adds data for the solvent storage configuration to the Fig. 3.8 plot of base plant capacity factor as a function of CO₂ emissions penalty for each natural gas price. Relative to the venting-only configuration, capacity factors are slightly greater with solvent storage at some intermediate CO₂ prices because solvent storage expands the profitable range of electricity prices. However, capacity factors are often higher for the venting-only configuration at high CO₂ prices because CO₂ capture typically operates at full load at these conditions, and the slightly higher capture energy with solvent storage raises marginal generating costs and reduces plant utilization under these conditions.

Figure 3.26 follows from Fig. 3.11, plotting the average CO₂ emissions rate for flexible capture facilities in the CO₂ price range where systems are transitioning from near-continuous 0% load absorption to near-continuous 100% load absorption. Data are shown for fewer natural gas prices to highlight the difference between the venting-only and solvent storage configurations. Slightly higher average emissions rates at high and low natural gas price exist for solvent storage for the same reason as discussed in Section 3.2.1.3. For all natural gas prices, emissions rates are slightly lower with solvent storage in the transition CO₂ price regime. Though any operation above the minimum emissions rate signifies CO₂ venting, CO₂ capture utilization is greater with solvent storage in the transition regime because the facility does sometimes operate

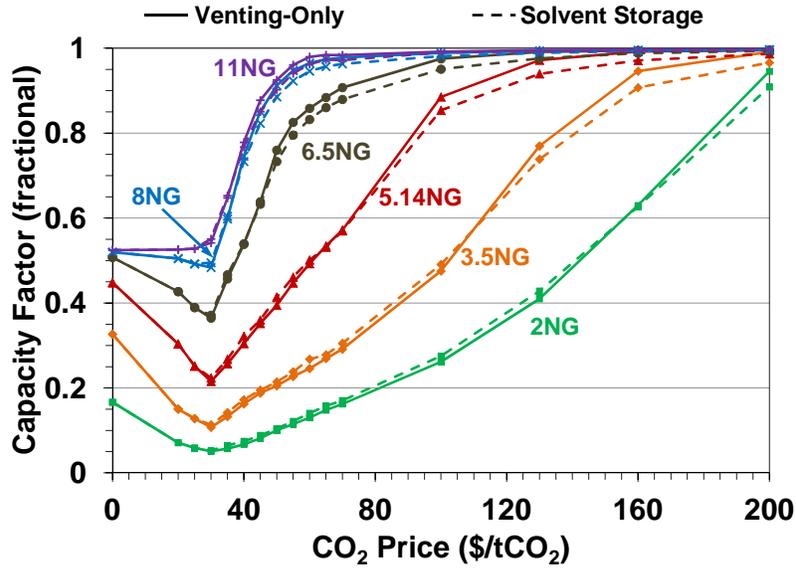


Figure 3.25: Solvent storage allows greater plant utilization at intermediate CO₂ prices, but the higher capture energy requirement reduces capacity factor at high CO₂ prices when capture operation is nearly continuous. (NG prices are \$/MMBTU)

flexibly without additional CO₂ emissions.

Figure 3.27 adds a curve for solvent storage for the Fig. 3.14 plot of normalized operating profits for \$0–80/tCO₂ at \$5.14/MMBTU natural gas. Though the incremental benefit of venting CO₂ disappears at higher CO₂ prices, benefits persist with solvent storage because the facility can perform price arbitrage without incurring additional emissions costs. With the chosen solvent storage design, the incremental benefit of flexibility remains approximately \$7/kW at \$80/tCO₂.

To examine the benefits of solvent storage across both CO₂ and natural gas prices, Figure 3.28 plots contours for the normalized incremental operating profit benefit with solvent storage over the facility with no or inflexible capture. This figure can be compared to Fig. 3.15, which plots the corresponding data for the venting-only configuration. Figure 3.28 demonstrates that solvent storage extends the benefit

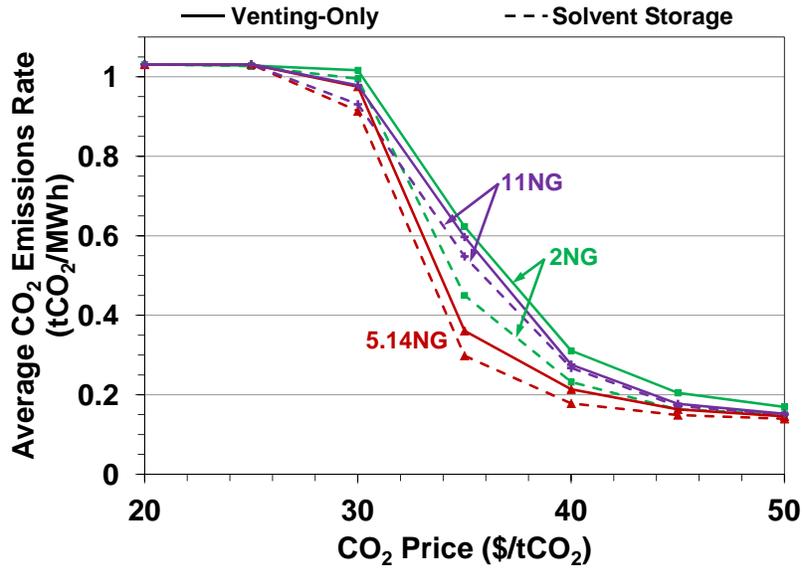


Figure 3.26: CO₂ capture utilization is slightly greater with solvent storage when systems are transitioning between primarily 0% and 100% load operation. (NG prices are \$/MMBTU)

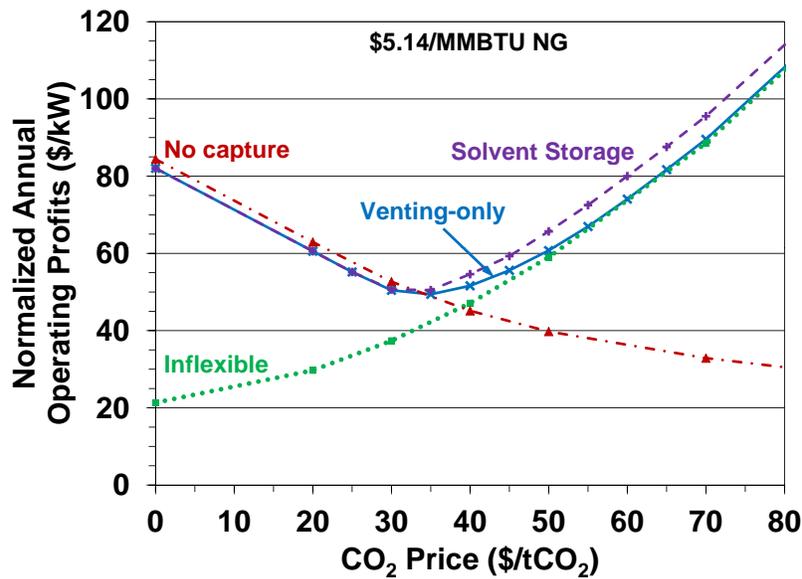


Figure 3.27: Solvent storage maintains operating profit benefits at high CO₂ prices.

of flexibility to higher CO₂ prices and increases its magnitude in the region where venting is valuable. However, benefits at high CO₂ prices are greatest at low to moderate natural gas prices. The benefit of solvent storage is reduced when both CO₂ and natural gas prices are high because these market conditions provide little opportunity when increased energy cost while regenerating stored solvent is worth the increased electricity sales revenue when solvent is stored at low stripping/compression load. Operational results suggest that the preferred time to regenerate stored solvent is when electricity prices are near or slightly above marginal costs at full-load CO₂ capture, when increased energy costs while regenerating stored solvent result in the facility taking a small loss. These conditions occur frequently at high CO₂ prices and low to moderate natural gas prices, but high natural gas prices produce high electricity prices where lost profit while regenerating stored solvent is seldom worth the increased profits while storing solvent. Under these circumstances, solvent storage is used less often, and its operating profit benefit decreases.

The benefit of solvent storage is closely related to the base plant capacity factor. Figure 3.29 plots the same data from Fig. 3.25 for the solvent storage configuration as a contour plot. Comparing this figure to Fig. 3.28, solvent storage is most valuable when capacity factors are 40–80% given CO₂ prices above \$30/tCO₂. The high CO₂-high natural gas price region where benefits decrease corresponds to the high capacity factor region, suggesting that expected capacity factor might be a good metric to decide whether or not to build a solvent storage system. Figure 3.30 explores this relationship by plotting capacity factor and operating profit benefits from solvent storage for \$0–200/tCO₂ at the minimum, maximum, and actual 2010 natural gas prices. For instance, if \$4/kW is the minimum acceptable annual operating profit benefit, a capacity factor can be identified for each natural gas price above which that benefit is no longer achieved. For \$5.14/MMBTU and \$11/MMBTU natural gas, this

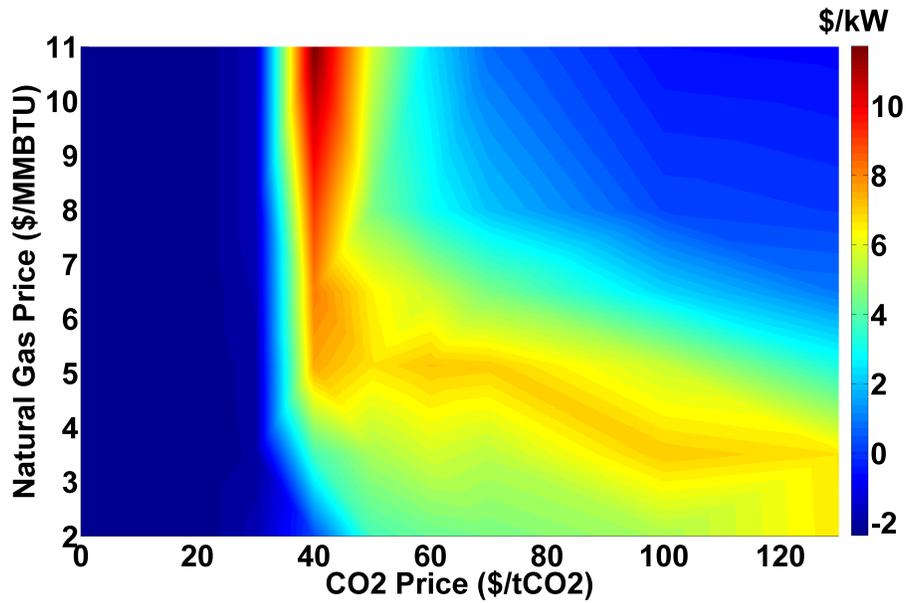


Figure 3.28: Solvent storage economic benefits are greatest at low-to-moderate natural gas prices and CO₂ prices \$40/tCO₂ and above.

capacity factor is approximately 90%, indicating that in general, a capacity factor above 90% would not achieve a \$4/kW annual benefit from solvent storage. This capacity factor is achieved with \$2/MMBTU natural gas at \$200/tCO₂, and trends suggest that the benefit from solvent storage at \$2/MMBTU will fall below \$4/kW at higher CO₂ prices.

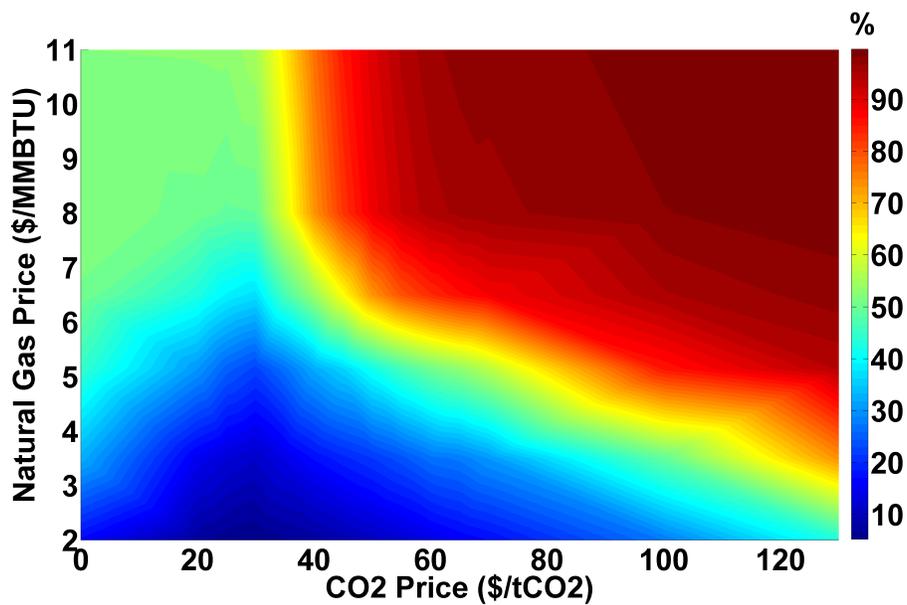


Figure 3.29: The value of solvent storage is negatively correlated to base power plant capacity factor at high CO₂ and natural gas prices.

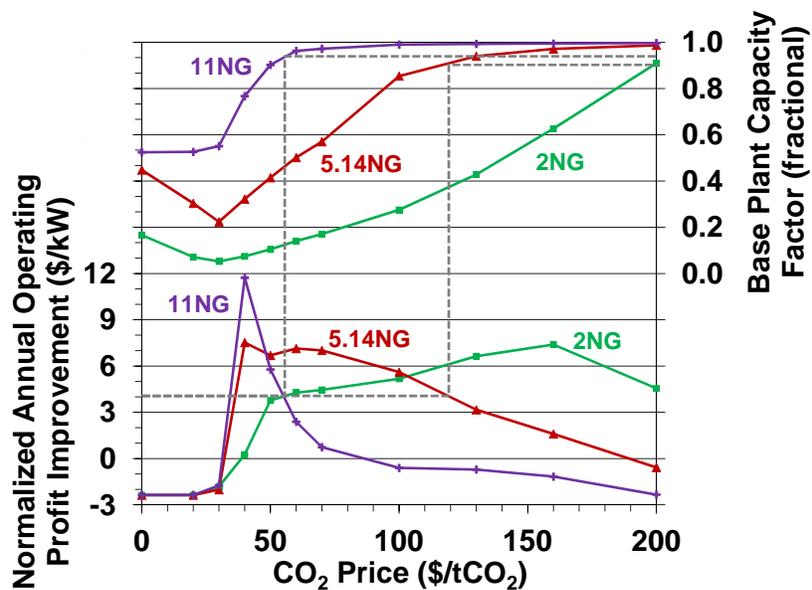


Figure 3.30: The minimum acceptable benefit of solvent storage can be related to a maximum capacity factor where that benefit will be achieved (NG prices are \$/MMBTU).

3.3 Conclusions

The single plant profit maximization model presented in Chapter 2 has been utilized to determine the environmental and economic implications of electricity price-responsive flexible CO₂ capture for a wide range of market conditions: \$2–11/MMBTU natural gas price and \$0–200/tCO₂ CO₂ price. This analysis is made possible through a procedure that uses historical electricity demand, prices, and power plant information to adjust historical electricity prices for varying fuel and CO₂ price conditions in a manner that accounts for changes in plant dispatch order while preserving realistic price volatility.

3.3.1 Venting-Only Flexibility

Flexible CO₂ capture systems transition from rarely using capture to near-100% utilization at \$30–40/tCO₂, largely independent of natural gas price. As long as operating costs are lower with capture at full load, a facility with flexible capture achieves significant CO₂ emissions reductions despite the ability to vent CO₂ at high electricity prices. Average annual CO₂ emissions rates are slightly higher at transition CO₂ prices for low and high natural gas prices because venting CO₂ is profitable for a larger fraction of online time under these conditions.

Venting CO₂ while selling additional electricity at high prices is valuable only at \$30–60/tCO₂ and above \$4/MMBTU natural gas under the conditions studied. These market conditions are necessary for electricity prices consistently high enough to make venting valuable. The benefit from venting exceeds \$8/kW per year with \$11/MMBTU natural gas, but current and expected future prices are not expected to reach that level. Nevertheless, the ability to vent CO₂ at peak electricity prices is still valuable if it requires negligible capital cost, which is

likely true for a retrofit application.

3.3.2 Solvent Storage

Oversizing stripping and compression equipment for regenerating stored rich solvent is not worth any increased capital cost. Increased stripping/compression capacity adds little operating profit benefit to a solvent storage system.

Regardless of capital costs, the reduction in stored solvent inventory cost achieved by choosing a higher CO₂ carrying capacity offsets a ~1% increase in capture energy requirement. Larger design capacity allows greater opportunity for profit-seeking flexible operation for a given quantity of solvent inventory. The case study found that increasing chosen CO₂ carrying capacity by 33% adds significant value to a solvent storage system despite an 0.84% increase in capture energy requirement.

With a reference MEA price of \$2.55/kg, the optimal solvent quantity allows for a maximum of 2 hours with stripping/compression systems offline and the absorber at full load. However, the optimal solvent storage system size, and thus the optimal quantity of solvent inventory, is directly related to solvent price. When this price is halved, optimal solvent storage system size doubles to 4 hours, suggesting that optimal storage system size could be estimated from solvent price for a given electricity system if the optimal storage size is known for one solvent price. The total value of solvent storage is highly sensitive to capital cost assumptions. While solvent storage adds up to \$10/kW of investment value relative to a venting-only configuration under reference capital cost assumptions, \$34/kW of added value is achieved with favorable capital cost assumptions.

The optimal solvent storage design under reference capital costs (2-hour storage time, no equipment oversizing, 0.16 molCO₂/molMEA design capacity) is optimized across \$2–11/MMBTU and \$0–200/tCO₂. *Solvent storage improves incremental profits of flexible capture and broadens the region where flexibility is valuable to higher CO₂ prices at low-to-moderate natural gas prices: above \$40/tCO₂ and below ~\$5/MMBTU gas in the case study.* Solvent storage has greatest value when expected power system capacity factors are 40–80% given CO₂ prices high enough to justify CO₂ capture operation. Above 90% capacity factor, typically when both CO₂ and natural gas prices are high, electricity prices are too high for the profit loss while regenerating stored rich solvent to be offset by increased electricity sales when storing rich solvent. However, this effect could be damped if increased wind production depresses off-peak electricity prices and makes rich solvent regeneration more attractive when net electricity demand is low, even when gas and CO₂ prices are high. The transition to near-continuous full-load capture is also slightly faster with solvent storage than with venting-only capture because solvent storage allows price arbitrage without increasing CO₂ emissions.

Chapter 4

Investment Decisions with Flexible CO₂ Capture

The profit maximization model demonstrates operating economics for flexible CO₂ capture systems over many electricity market conditions, but investment decisions should account for capital costs and expected market behavior over the plant lifetime. The solvent storage design analysis used net present value calculations to analyze different solvent storage configurations, but these calculations used a single set of market conditions (fuel and CO₂ prices). Investment decisions are better made when incorporating variation and uncertainty in both technological and market specifications. This analysis can be done deterministically for many conditions, or a stochastic representation could be utilized.

This chapter provides illustrative examples of investment decision analysis for the nominal 500 MW coal-fired facility using results from the optimization model described in the previous chapter. Deterministic NPV calculations are first used to compare the value of different CO₂ capture configurations under different future CO₂ price paths resulting from a greenhouse gas mitigation policy. Then a stochastic representation of future natural gas prices is used to demonstrate CO₂ capture decision making under uncertainty. Market variability is the focus of this chapter, but similar analysis could examine uncertainty in future technological characteristics given the knowledge of operating economics with these characteristics. The results within this chapter do not constitute a comprehensive study of CO₂ capture investment decisions, but they demonstrate how rigorous optimization modeling results can be used

to make such decisions.

4.1 Deterministic CO₂ Price Path Scenario Analysis

This section examines the economic and environmental performance of the facility with each capture configuration under three projected 20-year CO₂ price paths. The analysis presented in Section 2.3.5.2 provides performance and economics of each configuration for each CO₂ price. This, plant performance is defined by Tables 2.10 and 2.11 except that minimum capture load is 30%, and capture energy is split 89% to stripping/compression and 11% to absorption. Results at intermediate CO₂ prices are linearly interpolated between the nearest analyzed prices. Operational modeling used the limited formulation described in Section 2.3.1, and the solvent storage configuration uses a small storage system sized for 30 minutes of operation with stripping/compression offline and full-load absorption. This analysis, published before developing the more rigorous electricity price adjustment procedure described in Section 3.1.2, assumes a first-order price adjustment where electricity prices are uniformly increased with CO₂ price by the average emissions cost of gas-fired facilities [Cohen et al., 2012]. This estimation likely produces conservative operating profit estimates because marginal units typically have higher CO₂ emissions rates than average. The analysis in this section is deterministic in that it does not account for the probability of future CO₂ price paths. However, results can be viewed as outcomes for which probabilities could be assigned.

4.1.1 Input Parameters and CO₂ Price Paths

The three CO₂ price paths are chosen from the EIA analysis of the proposed American Power Act of 2010 (APA2010), which included a cap-and-trade program for CO₂ and six other greenhouse gases (GHGs) [USEIA, 2010]. Though this act did

not pass, estimated price paths from the EIA National Energy Modeling System are illustrative of possible CO₂ price trajectories. Future CO₂ prices in the United States are highly uncertain, and a CO₂ emissions reduction policy could take many other forms than cap-and-trade. Nevertheless, any policy will produce an effective CO₂ price, so facility behavior under low, intermediate, and high CO₂ price conditions is examined in this work using the last 20 years of CO₂-equivalent allowance price paths for the “Basic,” “No International,” and “Limited Tech., No International” scenarios (Fig. 4.1). “Basic” is the nominal scenario, “No International” implies more expensive GHG mitigation because international offsets cannot be used to meet GHG limitations, and “Limited Tech.” assumes key GHG abatement technologies do not develop more quickly in response to GHG limitations [USEIA, 2010]. The assumptions of the “Limited Tech.” scenario are not entirely consistent with the use of CO₂ capture in this work, but the scenario still provides a representative high CO₂ price curve.

In this analysis, CO₂ prices are kept constant over each year. Doing so ignores daily price volatility that could exist in a cap-and-trade system, and indeed the European Union Emissions Trading System has experienced significant CO₂ price volatility on the daily spot market [EU-ECX, 2008]. However, CO₂ emissions allowances are expected to be purchased on a longer-term basis such as monthly, quarterly, or annually, which would reduce effective CO₂ price volatility to power generation facilities.

While electricity price patterns over a 20-year period will also be affected by variations in coal price, natural gas price, the power plant fleet, and other market conditions, these effects are not included in this case study. Section 4.2 demonstrates inclusion of future natural gas price variability into CO₂ capture investment analysis.

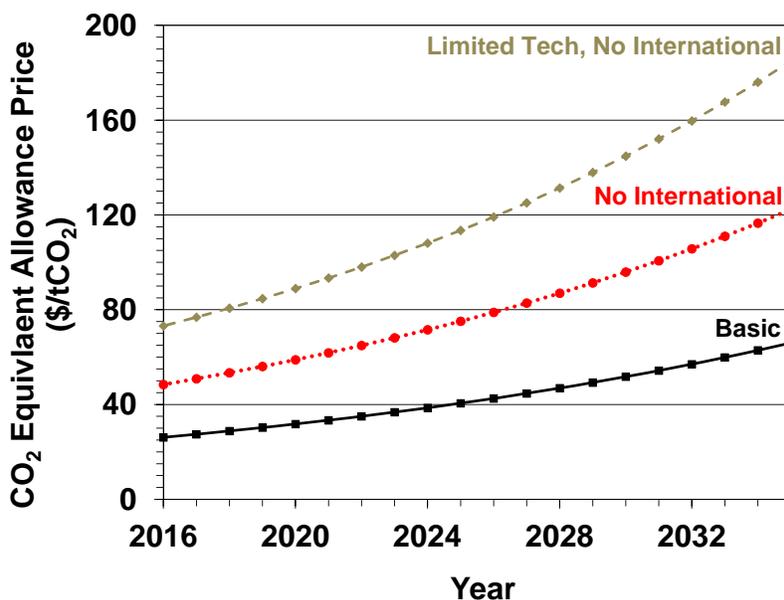


Figure 4.1: Three CO₂ price paths from the EIA analysis of the APA2010 provide scenarios to compare each CO₂ capture configuration.

4.1.2 Results

Figure 4.2 displays CO₂ emissions in each year for a facility with no capture, inflexible capture, and flexible capture with solvent storage under the Basic and No International CO₂ price paths. Emissions with the venting-only configuration are nearly identical but slightly greater than those with solvent storage because solvent storage allows greater utilization of CO₂ absorption during partial-load stripping and compression. Electricity prices increase with the CO₂ emissions costs of a gas-fired facility, so increased costs at a coal-fired facility without capture reduce its utilization as time goes on (and CO₂ price rises), so its CO₂ emissions fall. Conversely, increased utilization of inflexible capture facilities over time causes CO₂ emissions to increase slightly.

CO₂ price path has the biggest effect on the solvent storage configuration. The Basic scenario has relatively low initial CO₂ prices, so CO₂ emissions with flexible

capture are high because capture systems are typically operating at zero load. Any emissions above the inflexible configuration indicate CO₂ venting. Zero-load CO₂ capture becomes less desirable as time progresses until annual emissions approach those with inflexible capture. The flexible capture system enables a high base plant capacity factor across the full range of CO₂ prices. With higher CO₂ prices in the No International case, CO₂ venting is rarely economical even in 2016, and emissions quickly approach levels with inflexible capture. Solvent storage systems are still utilized by operating stripping and compression systems flexibly, but partial-load absorption is rarely economical once CO₂ prices exceed \$70/tCO₂. CO₂ emissions trends in the Limited Tech., No International scenario have similar behavior as the No International scenario, but emissions without CO₂ capture actually fall below those with CO₂ capture after 2028 when the plant capacity factor has fallen below 10%.

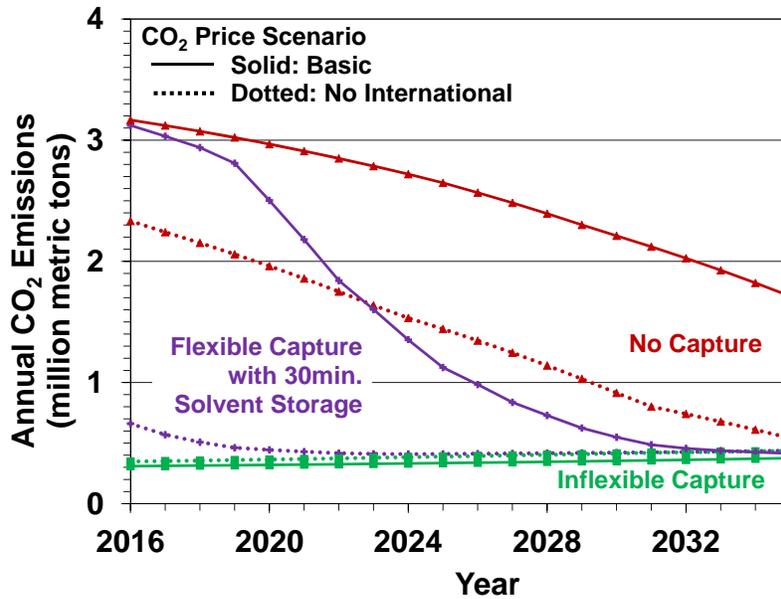


Figure 4.2: CO₂ emissions at the facility decrease over time due to increased CO₂ capture utilization and decreased operation without CO₂ capture.

Average emissions rate is also informative for understanding environmental

implications, especially if a CO₂ emissions rate regulation is being considered. Figure 4.3 plots the average CO₂ emissions rate over time (annual CO₂ emissions divided by annual net electrical output) for the facility with no capture, inflexible capture, and solvent storage. Regardless of the CO₂ price path, when the facility has no CO₂ capture systems, it always emits CO₂ at the base rate of 1.03 tCO₂/MWh. Likewise, an inflexible system always emits at 0.14 tCO₂/MWh. The average emissions rate with flexible capture can vary between these bounds and transitions between them along on a similar trajectory as shown with CO₂ emissions in Fig. 4.2. CO₂ emissions rate with the Limited Tech, No International CO₂ price path is at or near 0.14 tCO₂/MWh for the entire time period. In the Basic scenario, it takes until 2024 and a CO₂ price of \$38/tCO₂ before the average emissions rate falls to 0.5 tCO₂/MWh, a typical CO₂ emissions rate for a natural gas-fired power plant.

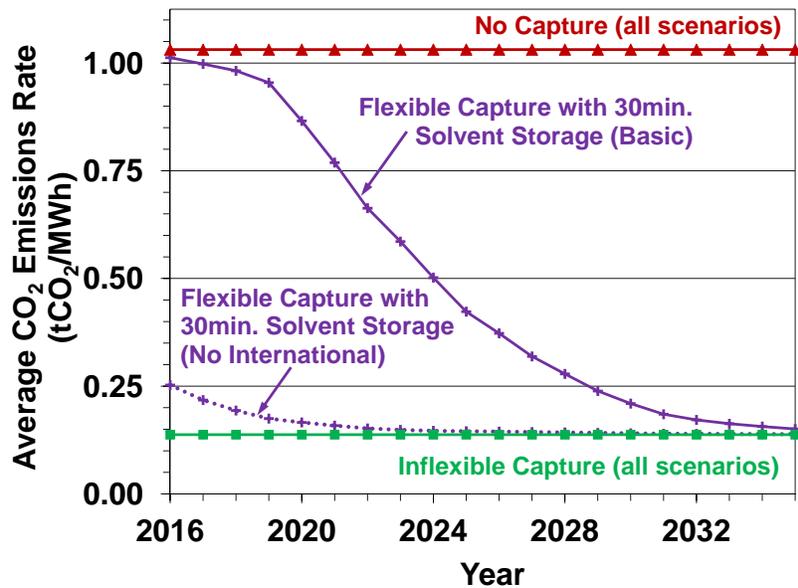


Figure 4.3: Facility average CO₂ emissions rate demonstrates the transition of flexible capture systems from near-continuous 0% load operation to continuous 100% load operation.

Economic results are displayed in Fig. 4.4, which shows annual before-tax

operating profits. Despite increasing electricity prices, operating profits fall over time without CO₂ capture due to decreased utilization and increased emissions costs, but profits without capture are higher than those with inflexible capture at low CO₂ prices early in the Basic scenario. In the Basic scenario, profits with inflexible CO₂ capture are below those without CO₂ capture until 2027, when the CO₂ price is about \$45/tCO₂. However, profits with flexible CO₂ capture and solvent storage follow the upper envelope of the No Capture and Inflexible Capture curves, exceeding both after 2021. The benefits of flexibility decrease as CO₂ prices increase, but cumulative advantages would be significant if CO₂ prices instead hovered around \$40–50/tCO₂. Operating profits for the venting-only flexible capture configuration are generally slightly below those with solvent storage, with solvent storage allowing some additional revenue without increasing CO₂ emissions costs.

The No International scenario has much higher CO₂ prices than the Basic scenario, so profits without CO₂ capture are much lower, and there is less benefit to CO₂ capture flexibility. CO₂ capture is critical to maintaining operating profits with these CO₂ price conditions, and while the benefit from flexibility is small, it is maintained throughout the time horizon. The temporal trends in the No International scenario are exaggerated in the Limited Tech., No International scenario, where there is an even larger discrepancy between profits with and without CO₂ capture.

The NPV of the facility with each capture configuration under each CO₂ price path is calculated by adjusting before-tax operating profits with a tax rate of 38%, discounting at 10.3% per year, and adding any CO₂ capture capital costs depreciated on a Modified Accelerated Cost Recovery Schedule (MACRS) 20-year half-year convention. Tax and discount rates are recommended values from the U.S. NETL CCS systems analysis guidelines [NETL, 2005]. As with solvent storage design analysis,

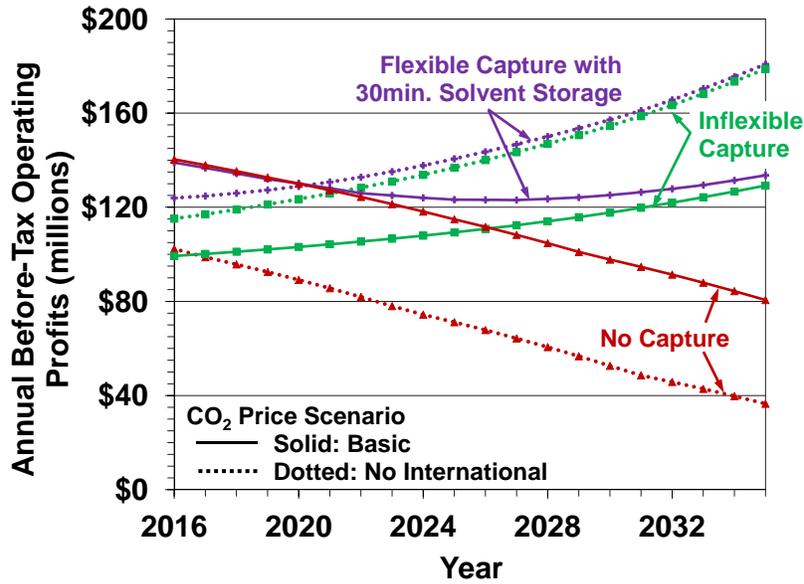


Figure 4.4: CO₂ capture flexibility allows greatest operating profits for the facility, especially at the intermediate CO₂ prices experienced in 2025–2029 under the Basic CO₂ price path.

the chosen discount rate provides a conservative estimate of system value. All CO₂ capture configurations are assumed to be retrofits, so a facility without CO₂ capture has no incremental capital costs. CO₂ capture systems are assumed to be \$908/kW of rated power plant capacity, and the solvent storage system costs \$23/kW when sized for up to 30 minutes with stripping/compression off [Cohen et al., 2010a, E. S. Rubin & Rao, 2007]. For comparison, a new coal-fired plant without carbon capture is expected to cost ~\$1500/kW or more [E. S. Rubin & Rao, 2007]. Unlike other pollution control equipment, CO₂ capture systems comprise a significant fraction of total plant capital costs.

The resulting NPVs are displayed in Fig. 4.5. The difference in NPV with and without CO₂ capture is highly dependent on the assumed capital cost for CO₂ capture systems. With \$908/kW, NPV is greater with CO₂ capture only for the Limited Tech., No International scenario, which has very high CO₂ prices. However,

differences in NPV among CO₂ capture scenarios are independent of base CO₂ capture system capital costs, assuming there is negligible capital expense for venting-only flexible capture. Discount rate also plays a role, as the high discount rate used in this analysis diminishes the future value of CO₂ capture when CO₂ prices are high.

Flexible configurations have greater NPV than inflexible for all scenarios studied, especially under the Basic scenario where CO₂ prices are often in the region where flexibility is most valuable. CO₂ capture flexibility allows the operator to better cope with changes in CO₂ prices, which should reduce uncertainty in operating profits and improve investment decisions. Future carbon policies and any implied CO₂ prices are very uncertain, and the ability of flexible capture to maintain profitability under this policy uncertainty is valuable. However, if the analysis were modified to assume additional capital or operating costs for capture flexibility, operating economic benefits could diminish, negating some or all of the added investment value of flexible CO₂ capture.

Though solvent storage provides an operating profit benefit in this analysis, NPV with solvent storage is slightly less than with venting-only flexible capture for all studied CO₂ price paths. Solvent storage sized for 30 minutes with stripping/compression offline add value when CO₂ price is a constant \$50/tCO₂ for 20 years, but benefits do not offset the capital cost of solvent storage for the CO₂ price paths studied. However, these results assume a suboptimal solvent storage system design. Section 3.2.2 identified improved design characteristics for solvent storage, and these are implemented in the analysis in the following section.

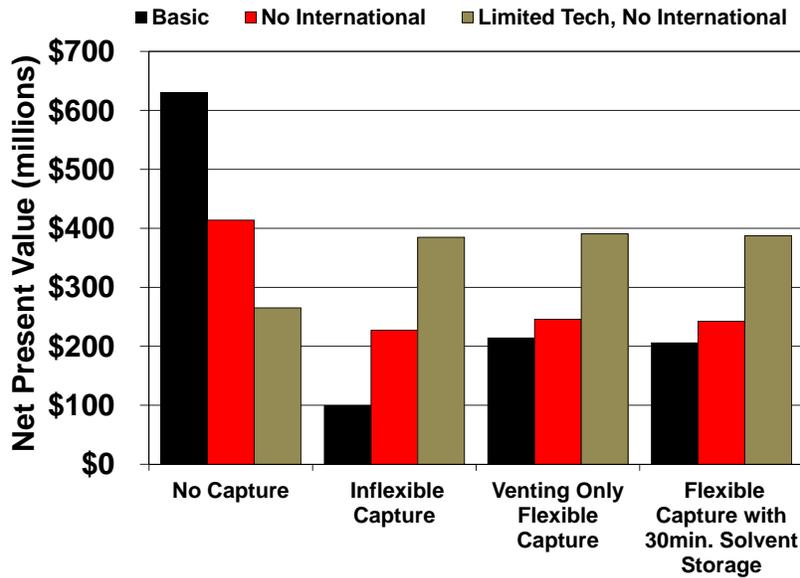


Figure 4.5: High CO₂ prices are required for NPV to be greatest with CO₂ capture, but flexibility provides at least some benefit relative to an inflexible CO₂ capture configuration for all three scenarios that were considered.

4.2 Decision Analysis Under Uncertainty

The decision analysis approach provides a logical framework for making good decisions under uncertainty based on the relative value and probability of possible outcomes, where each outcome follows from a combination of choices and chance events. A primary decision in the current context is whether or not to install CO₂ capture at an existing coal-fired power plant and which capture configuration to install. This decision is based on several uncertain parameters, such as the performance of the CO₂ capture system and the future electricity market conditions. Technical performance might be well-known for a given CO₂ capture design, but future market conditions are very difficult to predict. This section presents a simple decision analysis framework to analyze the CO₂ capture configuration decision with uncertain future natural gas prices. As shown in Chapter 3, natural gas prices have a major impact on operating profitability of different CO₂ capture configurations, so investment decisions should

be sensitive to future gas prices.

4.2.1 Methodology

Future natural gas prices are estimated from historical data using a mean reversion model, which is known to be a good representation of commodity prices. In a mean reversion model of gas price, values vary stochastically based on historical volatility but tend to revert to a long-term mean value. Necessary model parameters are estimated from historical EIA data using the Technique 2 procedure described in Oftedal 2008 [USDOE, 2012, Oftedal, 2008]. These parameters then allow calculation of a 10th, 50th, and 90th percentile (P10, P50, P90) natural gas price path. Annual operating profits are calculated for each year given an assumed CO₂ price and interpolating from optimization results for each gas-CO₂ price combination. Economic assumptions then allow a P10, P50, and P90 NPV to be calculated for each configuration, and a certain equivalent (CE) NPV for the configuration is determined by assigning probabilities to each NPV percentile. The present analysis uses the McNamee and Celona shortcut (MCS) for assigning probabilities. The MCS shortcut approximates weightings for a normal distribution by assigning a 25% probability to each of the P10 and P90 values and a 50% probability to the P50 value [Bickel et al., 2011]. Other probability values could be examined if desired. The certain equivalent NPVs for each configuration are then compared to determine which configuration should be built.

The percentile price path estimation procedure does not fully characterize natural gas price uncertainty and volatility. Doing so requires a more sophisticated approach that generates numerous price paths using a Monte Carlo estimation procedure. Thus, results within this chapter could undervalue flexible capture, but they provide a basis for future work that uses a more rigorous uncertainty representation.

In this analysis, CO₂ prices are not treated stochastically in the same manner as natural gas prices. Some historical CO₂ price data exist from the EU-ETS market, but insufficient data are available to confidently produce mean reversion parameters and percentile price paths. Instead, certain equivalent NPVs are compared for \$0–200/tCO₂ with CO₂ price held constant for the economic lifetime of the facility. The optimal configuration decision is then compared across this CO₂ price range. Future work could incorporate a stochastic representation of CO₂ prices.

Figure 4.6 plots the P10, P50, and P90 natural gas price paths calculated using 1997–2011 U.S. average natural gas prices for electric power producers. Flattening of these curves reflects reversion to the percentile long-term mean. For consistency with the deterministic analysis in Section 4.1, the study period is again 2016–2035, so natural gas prices are held nearly steady at approximately \$3/MMBTU, \$5/MMBTU, and \$8/MMBTU for the P10, P50, and P90 levels.

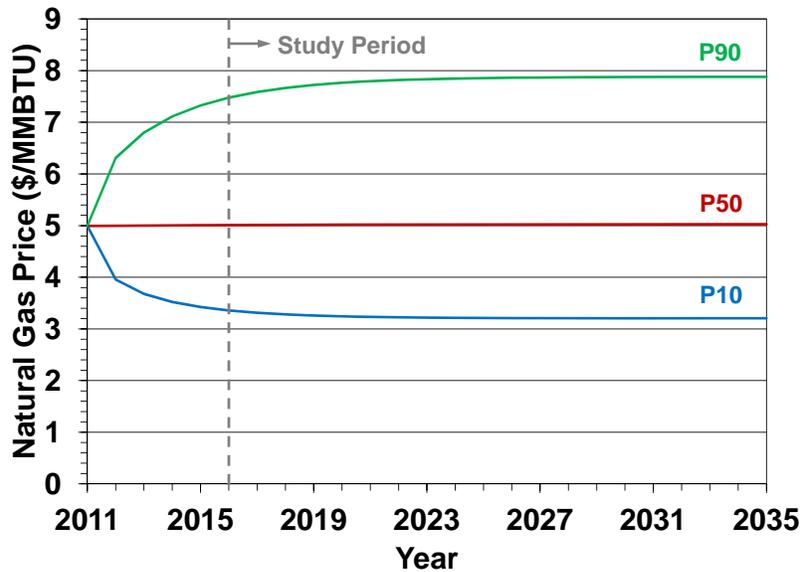


Figure 4.6: The 10th, 50th, and 90th percentile natural gas price paths revert to \$3/MMBTU, \$5/MMBTU, and \$8/MMBTU, respectively.

Capital depreciation, discount rate, and tax rate are the same as in Section 4.1,

and this analysis again assumes a 20 year economic lifetime. Base capture system capital cost remains \$908/kW. For this analysis, the solvent storage design is assumed to be the best found under reference assumptions in Section 3.2.2, so added capital costs for solvent storage are \$23.6/kW. Again, assuming a retrofit application, the configuration without capture has no capital costs, and the venting-only flexible capture configuration has no additional capital costs over those of the base capture system.

Figure 4.7 shows the decision analysis tree used to determine the best configuration for each CO₂ price given uncertain natural gas prices. The four configurations (no capture, inflexible capture, venting-only, solvent storage) are the decision alternatives, each with three possible outcomes corresponding to the P10, P50, and P90 natural gas price paths. The probabilities of each path (0.25, 0.50, 0.25) allow calculating a certain equivalent NPV for each configuration, and the maximum CE corresponds to the preferred configuration.

4.2.2 Results

Figure 4.8 plots normalized annual operating profits over time for the venting-only configuration with a constant \$100/tCO₂ price before adjusting for tax, depreciation, and discount rate. Nearly constant profit trajectories reflect nearly constant natural gas prices for each percentile path. Nevertheless, this figure demonstrates the large discrepancy between the potential operating profits and the property of the mean reversion model where the difference between P90 and P50 profits exceeds that between the P50 and P10 profits.

Figure 4.9 displays the discounted cash flows for the same configuration and CO₂ price after accounting for capital depreciation, profit tax, and discount rate in each year. Differences between percentile curves reflect those in Fig. 4.8, and it is

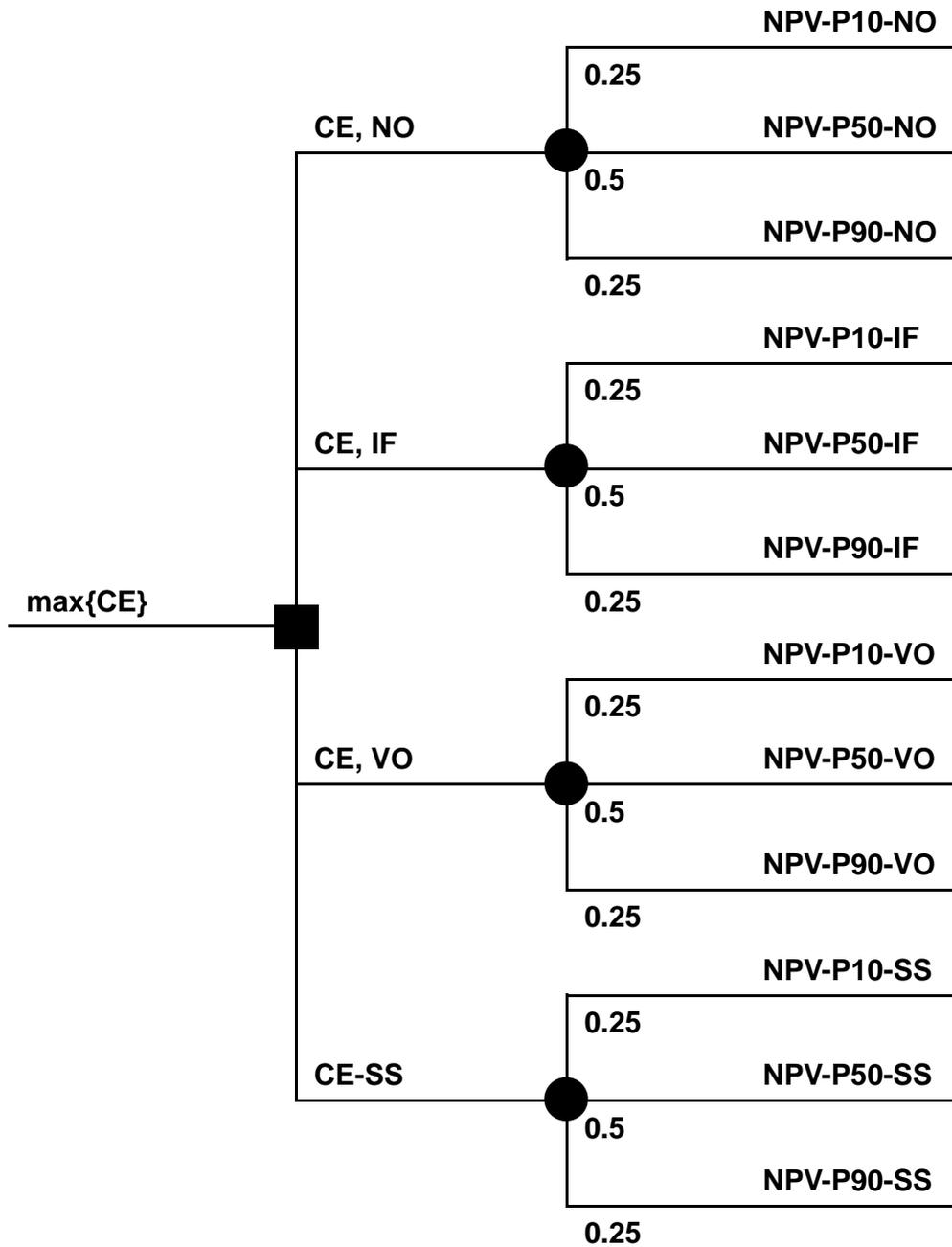


Figure 4.7: This decision tree represents the capture configuration decision under natural gas price uncertainty.

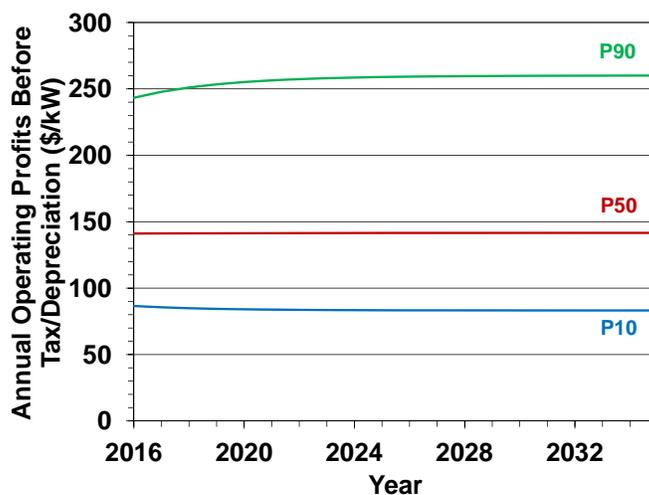


Figure 4.8: For each percentile path, steady annual operating profits for the venting-only configuration at \$100/tCO₂ reflect little variation in natural gas price for each path past 2016. (P10/P50/P90 = 10th/50th/90th percentiles)

clear that most value is attained in the first half of the plant economic lifetime. This figure demonstrates how a 10.3% real discount rate greatly diminishes the future value of CO₂ capture, and future work could explore the effect of less conservative discount rates.

Summing these discounted cash flows produces the percentile NPVs shown in Fig. 4.10 for the venting-only configuration at \$100/tCO₂. Both the P10 and P50 NPV are negative, but the large positive P90 NPV allows a positive CE NPV of \$47.6/kW.

Figure 4.11 plots the CE NPV for all four configurations at \$0–150/tCO₂. Given the large capital cost of CO₂ capture, CE NPV with any capture configuration is negative below \$95/tCO₂ and does not exceed that without CO₂ capture until \$110/tCO₂ or above. Though flexible capture configurations have much greater NPV than inflexible capture below \$35/tCO₂ when capture systems are primarily offline, capital costs are not offset. Solvent storage adds value to an inflexible capture system,

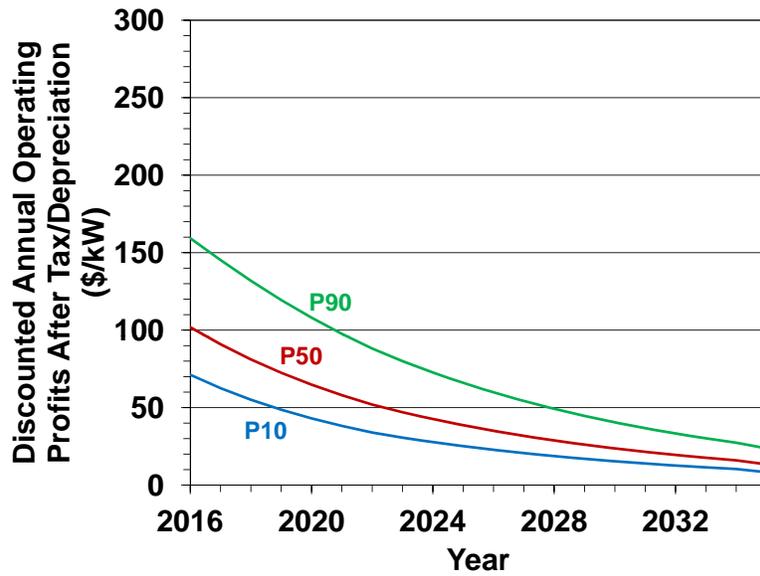


Figure 4.9: Most of the investment value is attained in the first half of the 20-year economic life (venting-only, \$100/tCO₂, P10/P50/P90 = 10th/50th/90th percentiles)

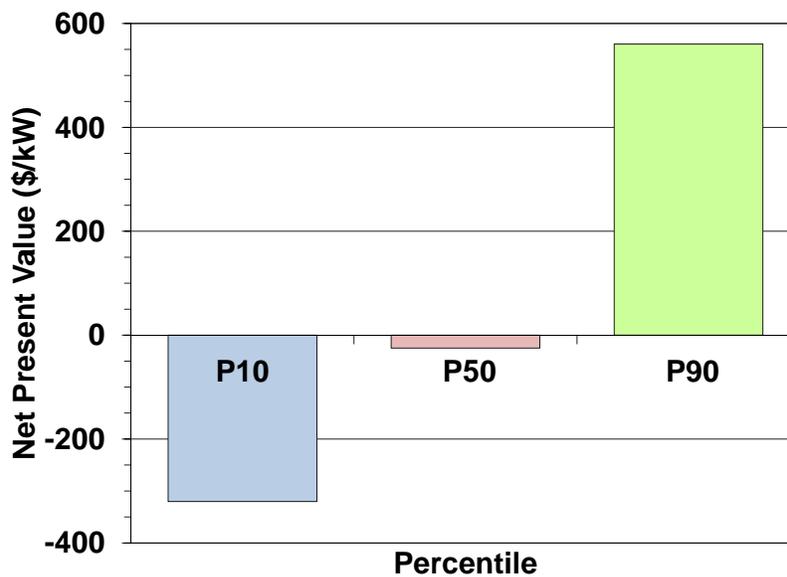


Figure 4.10: P10 and P50 NPV for the venting-only configuration at \$100/tCO₂ are negative, but the P90 NPV is high enough for a positive certain equivalent NPV.

but the benefit decreases with CO₂ price when the operating profit benefit becomes smaller relative to solvent storage capital costs. This figure demonstrates the difficulty justifying CO₂ capture installation without very strong policy signals.

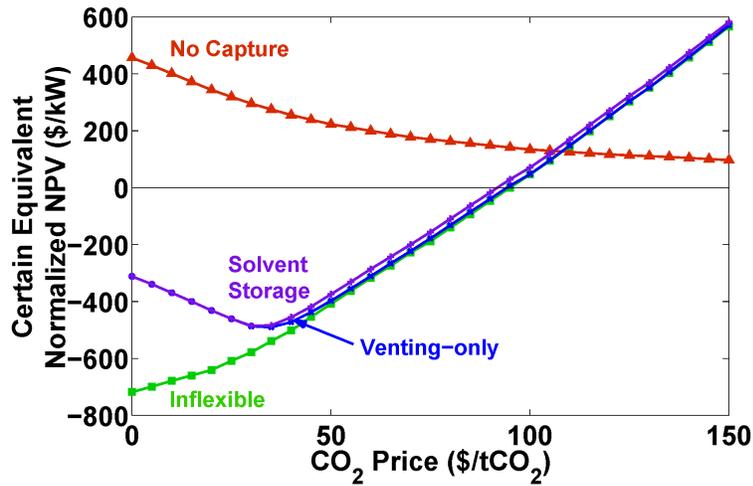


Figure 4.11: High capital costs prevent CO₂ capture from adding value until CO₂ prices are relatively high. (P10/P50/P90 = 10th/50th/90th percentiles)

Figure 4.12 is the decision diagram that plots the configuration with maximum CE NPV for \$0–200/tCO₂. When CO₂ capture becomes valuable at \$110/tCO₂, flexible capture with solvent storage is preferred because its operating profit benefits outweigh the additional capital costs. However, at \$200/tCO₂ (and presumably above), the operating profit benefit of solvent storage does not offset its additional costs, and an inflexible capture configuration is preferred. CO₂ venting for price arbitrage is never performed at this CO₂ price, so an inflexible capture system is sufficient to maximize investment value.

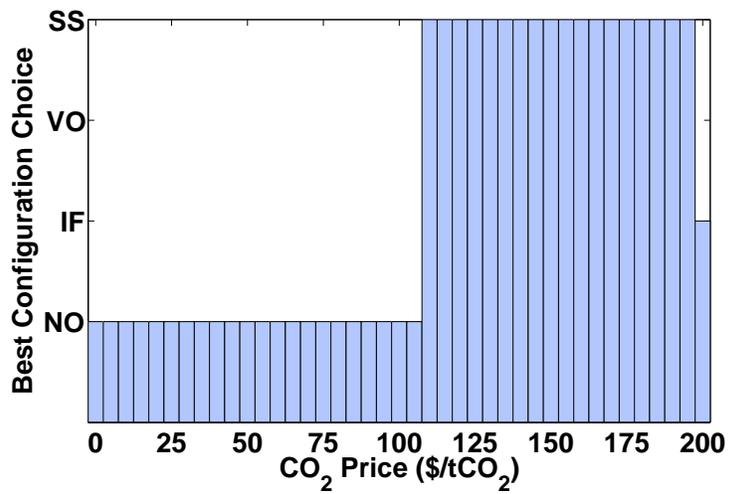


Figure 4.12: Solvent storage is the most valuable capture configuration at \$110–195/tCO₂, but operating profit benefits do not offset additional capital costs at \$200/tCO₂. (NO=no capture, IF=inflexible, VO=venting-only, SS=solvent storage)

4.3 Conclusions

Operating economics from the profit maximization model have been used illustrate two forms of CO₂ capture investment analysis. First, the NPV of different capture configurations was calculated deterministically for low, intermediate, and high 20-year CO₂ price paths. Then, a stochastic representation of future natural gas prices is used to determine a certain equivalent NPV for each configuration with CO₂ fixed at \$0–200/tCO₂ to demonstrate decision analysis and examine how configuration decisions vary with CO₂ price.

Capture equipment capital costs prevent investment viability with or without flexible capture unless CO₂ prices are \$100/tCO₂ or more under the assumptions used. Venting CO₂ is not valuable at these prices, and while benefits from solvent storage persist at high CO₂ prices, improvement in investment value is modest relative to inflexible capture. These results demonstrate that CCS is not cost-competitive with other low carbon technologies such as wind without additional economic incentives. However, assuming capture is installed, lifetime CO₂ emissions with flexible CO₂ capture will be much lower than those without capture even if low CO₂ prices early in the plant lifetime allow CO₂ venting when electricity prices are high.

There appears to be minimal value of price-responsive flexible CO₂ capture at market conditions where capture installation is justified, but these results are case-specific. Lower capital cost or discount rate are expected to significantly affect the conditions where CO₂ capture installation is economical. The investment analysis framework within this chapter can be modified to include a wider range of conditions and uncertain parameters. More important, the value of each capture configuration for a given set of market conditions could be reassessed

after accounting for other sources of value, such as ancillary service markets. The following chapter assesses the impact of flexible capture on AS quantities provided by coal-fired facilities, so future work could use these results and an AS value assessment to reanalyze the investment value of different CO₂ capture configurations.

Chapter 5

Electricity System Optimization with Flexible CO₂ Capture

The profit maximization model for a single price-taking facility demonstrates the utility of flexible CO₂ capture in response to prices in a competitive electricity market. To explore the value of flexible capture in a non-competitive or regulated market, a least-cost electricity dispatch model is created that minimizes the costs of meeting electricity demand and ancillary services across the full ERCOT electricity system. Doing so over a range of electricity system and market conditions can quantify the value of flexible CO₂ capture for AS provision and investigate its role in an advanced electricity system with technologies such as energy storage or substantial wind integration. The model can also examine the utility of using flexible capture to meet peak electricity demand. Since shadow prices for electricity and AS are a product of the optimization procedure, the model can also offer additional insights into flexible capture in a competitive electricity market.

After introducing the unit commitment modeling approach for electricity system dispatch optimization, the model formulation is presented prior to a section describing the generating unit databases employed in subsequent analysis. Results are first presented for an aggregated power plant data set to demonstrate the use of flexible capture for peak demand and ancillary service provision. After this proof-of-concept, the impacts of capture flexibility on grid and plant performance are explored by comparing ERCOT dispatch across a range of natural gas and CO₂ prices when

roughly half the coal fleet has: (1) no CO₂ capture, (2) inflexible capture, (3) venting-only flexible capture, and (4) flexible capture with solvent storage. To examine the interactions between flexible capture and wind generation, simulations are performed for one week in each season under projected 2020 ERCOT conditions assuming 20% of annual electricity demand is supplied by wind. Finally, electricity dispatch is simulated with both flexible capture and compressed air energy storage (CAES) to explore how these technologies compete with or complement each other.

5.1 Unit Commitment Modeling

5.1.1 A Brief Review of Unit Commitment Modeling

The model formulation described in this chapter is classified as a unit commitment model, so named because it includes binary decisions about commitment status (on or off) of individual generating units. By definition, these binary decisions produce a MIP model. Unit commitment modeling of electricity systems has been extensively studied within electrical engineering and operations research, and the literature provides several approaches that can be applied to an analysis considering CO₂ capture flexibility. Solving the unit commitment problem determines which power generation units are online and the quantity of electricity they should produce in order to meet time-varying electricity demand and other system requirements. Common objectives are minimizing the total cost of electricity dispatch or maximizing profits across all power plants over a given time frame.

Power plant cost models generally depend on the power plant type; LINDO Systems publishes a guide to formulating plant behavior that includes startup costs, fixed operating costs, variable operating costs, capacity limits, and special considerations for hydroelectric generation [LINDO, 2003]. The model formulation described in Chapter 2 uses many of these costs and constraints. Muckstadt and Koenig pre-

sented a classic formulation of unit commitment problem, much of which applies in contemporary models [Muckstadt & Koenig, 1977]. Baldick later published a generalized formulation that includes constraints on unit output, ramp rate, power line flow and voltage limits, reserve capacity, generator minimum up/down time, and total fuel and energy limitations [Baldick, 1995]. Zendejdel provides a linear formulation of minimum up and down time constraints [Zendejdel et al., 2008]. Many of the plant-level constraints in these models were utilized and adapted for flexible CO₂ capture to create the model described in Section 2.2.1.

5.1.2 Unit Commitment Modeling with CO₂ Capture

Relatively little previous work has employed the unit commitment approach to study CO₂ capture systems. Alie presented a detailed formulation of the unit commitment problem that includes CO₂ capture facilities and suggests using the CO₂ removal percentage as a decision variable [Alie, 2005]. The change in power plant output and CO₂ emissions rate with CO₂ capture load are included along with a grid-wide CO₂ emissions limit [Alie, 2005]. However, published results from this model are limited to a case study using the Institute of Electrical and Electronics Engineers (IEEE) reliability test electric system, and the formulation does not discuss how the model represents power plant and CO₂ capture system performance [Alie, 2005, Alie et al., 2006]. Shu discusses a unit commitment model of the Western Electricity Coordinating Council (WECC) system used to investigate dispatch of facilities using CO₂ capture, but this analysis focuses primarily on variations in dispatch with plant location and does not include flexible CO₂ capture operation [Shu et al., 2008].

This dissertation contributes to literature on both unit commitment modeling and CO₂ capture by presenting a detailed formulation that integrates the plant-level constraints developed in Section 2.2.1 into a full electricity system model. Though

initially tailored for ERCOT, the formulation can be adapted for other electricity systems by modifying, adding, or removing constraints as necessary to reflect electricity market protocols in an alternative system.

5.2 Model Formulation

5.2.1 ERCOT Market Protocols

ERCOT market protocols are discussed first to provide context for ERCOT-specific model characteristics. ERCOT operates markets for electricity to meet consumer demand as well as ancillary services to ensure grid reliability. Market participants submit electricity and ancillary service offers to ERCOT, and ERCOT finds the combination of generation resources that minimizes the cost of supplying electricity and ancillary services. Consumer electricity demand can be accurately forecast a day ahead based on weather and economic conditions, so ERCOT plans hourly electricity supply in a day-ahead market then reconciles any discrepancy between planned and actual demand every 5 minutes in a real-time market. The day-ahead market determines which units will be online in each hour, and prices paid to generators are 15-minute averages of real-time market settlements.

Ancillary service requirements are specified by ERCOT and can change with market conditions at ERCOT discretion. For instance, increased wind capacity in ERCOT has altered the method for calculating some ancillary service requirements [ERCOT, 2011b]. There are four ancillary service markets in ERCOT. Regulation Up (RU) and Regulation Down (RD) services are procured to respond within 5 minutes to discrepancies between expected and actual demand [ERCOT, 2011b]. The quantity of RU and RD required varies throughout the day and year and depends on current demand uncertainty, historical regulation deployments, and installed wind capacity [ERCOT, 2011b]. Responsive Reserve Service (RRS), commonly called spin-

ning reserves, must be provided by online units or load (demand) resources capable of responding within 10 minutes [ERCOT, 2011b]. Total RRS procurements must exceed the greatest possible single-facility outage within ERCOT, currently 2,300 MW, the capacity of the South Texas Project nuclear facility [ERCOT, 2011b]. Non-Spinning Reserve Service (NSRS) can be provided by online or offline units and must be able to respond within 30 minutes. The quantity of NSRS required in each hour depends on the RU procurement and demand uncertainty [ERCOT, 2011b]. All AS procurements are co-optimized with electricity in the day-ahead market.

5.2.2 Model Structure

The structure of the grid-level model reflects ERCOT operating procedures (Fig. 5.1). Input parameters describe the cost and performance specifications of generating units as well as the market conditions and electricity system requirements. After defining plant operating variables, objective and constraint equations describe the operating characteristics that govern power, CO₂ capture, and electricity systems.

The model uses a two-stage optimization in each day to mimic the ERCOT market. A day-ahead forward market optimization uses an hourly time step, τ^{FW} , and the resulting unit commitments and ancillary service procurements are fixed before determining generator output in the real-time market optimization. If the grid contains energy storage systems, the input to energy storage systems is also determined in the real-time optimization. The real-time market optimization uses a 15-minute time step, τ^{RT} . Though ERCOT currently optimizes its real-time market in 5 minute intervals, settlement prices for electricity load and generation are averages over 15 minutes, so a 15 minute time interval is assumed sufficient to characterize electricity market behavior. After performing the real-time optimization for the current day, the solution informs initial conditions for the following day, and the process repeats

for the desired number of days.

The model represents the day-ahead and real-time markets generally so that their time intervals can be set to any length as long as $\tau^{RT} \leq \tau^{FW}$. The day-ahead market is also implemented as a generalized forward market so that the overall time length could be shorter or longer than one day. The length of the forward planning period, L^{FW} , is set to 96 real-time intervals to represent a day-ahead market with 15-minute real-time market intervals, but a longer length could be specified given sufficient computational resources to solve the unit commitment problem over longer time scales. Unfortunately, the nature of mixed-integer problems and solving algorithms makes computation time difficult to estimate strictly from problem size. In addition to better representing ERCOT procedures, the two-stage approach reduces computation time by optimizing many integer variables on a coarser time step before solving for remaining integer and continuous variables on a shorter time step. If desired, the two-stage process could be bypassed and all variables optimized on a single time scale by setting τ^{FW} to the desired time interval and bypassing the real-time market optimization.

The model optimizes AS procurements but does not perform AS deployments, which are executed in ERCOT in response to discrepancies in planned and actual electricity demand, wind generation, and unplanned transmission and generation outages. Modeling the manner in which AS are deployed is outside of the scope of this work. Instead, the model assesses a large cost penalty to any imbalances between electricity supply and demand, and the existence of these penalties indicates when AS deployments would likely be required. The frequency of these cost penalties indicates the need for AS deployments under a given set of input conditions.

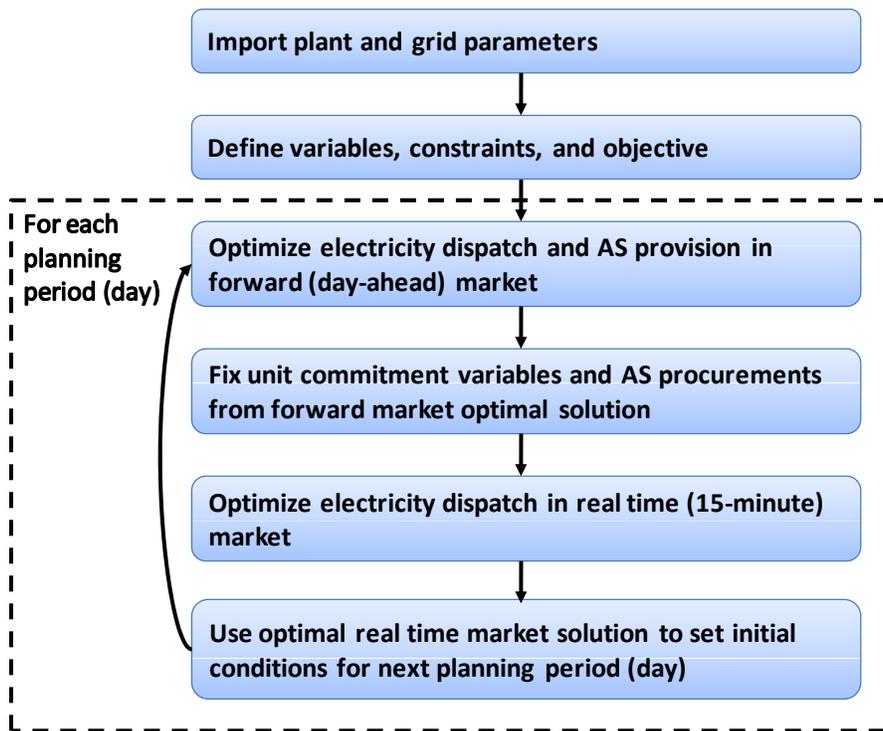


Figure 5.1: The model structure mimics the two-stage operating procedure used by ERCOT.

5.2.3 Required Input Information

5.2.3.1 Generating Units

Extensive input data are required to fully characterize the generating unit fleet. The model is built to consider several types of electricity generating facilities, including coal-fired plants with and without CO₂ capture, nuclear power plants, natural gas-based plants (combined-cycle NGCC, open-cycle OCGT, steam boiler NGBLR, and internal combustion NGIC), oil-fired plants, biomass-based facilities, and hydroelectric turbines. Hydroelectric turbines are not given pumped storage capabilities, but pumped hydroelectric units could be included using the energy storage system specifications discussed later in this section. Instead of representing wind turbines as generating units, wind production is subtracted from input electricity demand, and all other facilities are optimized in response to the resulting net electricity demand. Thermal generation facilities can also be designated as CHP units. CHP facilities are typically designed to meet near-constant heat and process loads, so these systems are assumed to operate continuously at their maximum electrical output regardless of operating costs. Interruptible load systems can also be included but are only permitted to provide RRS and NSRS per ERCOT restrictions. The model also includes a generic framework for energy storage systems so that a variety of storage system types could be examined.

Table 5.1 lists the input parameters required for all generating units. Plant names must be unique for each plant and are used as elements p within set \mathbb{P} . Plant type is used to appropriately assign costs and constraints for p within a set of each plant type. The boolean CHP flag is also used to identify facilities in the set of CHP facilities \mathbb{M} , which must operate continuously at maximum output, \bar{x}_p . If a particular parameter is not applicable for a unit, such as CO₂ emissions rate for carbon-free electricity sources, the quantity is set to zero in the generating unit database.

Table 5.1: The following input parameters are required for each generating unit.

Parameter (Units)	Symbol
Plant name	p
Plant type	n/a
Non fuel or CO ₂ base plant VOM cost (\$/MWh)	OM_p^b
Heat rate (MMBTU/MWh)	H_p^b
CO ₂ emissions rate (tCO ₂ /MWh)	R_p^b
Base plant startup cost (\$/startup)	$S_p^{b,u}$
Base plant shutdown cost (\$/shutdown)	$S_p^{b,d}$
Minimum output (MW)	\underline{x}_p
Maximum output (MW)	\bar{x}_p
Base plant ramp limit up (MW/min)	$\delta_p^{b,u}$
Base plant ramp limit down (MW/min)	$\delta_p^{b,d}$
Base plant minimum up time (hr)	$\Theta_p^{b,u}$
Base plant minimum down time (hr)	$\Theta_p^{b,d}$
Base plant initial up time (hr)	$\Theta_p^{b,u,0}$
Base plant initial down time (hr)	$\Theta_p^{b,d,0}$
CHP flag (1=yes, 0=no)	n/a

Explicit limits on the minimum and maximum of each type AS provision are not needed. Minimum AS provision is zero because a facility could use all available capacity to meet electricity demand, leaving none for AS. Maximum AS provision is constrained by ramp rates and the combination of energy and AS provided in the current time period.

For each facility with a CO₂ capture system, several additional parameters are required to determine the energy requirement for CO₂ capture, CO₂ removal rate, and solvent storage capabilities if applicable. Minimum and maximum load, ramp rate limits, startup/shutdown costs, and minimum up/down time for the absorber and stripper are also specified. Parameters required of all CO₂ capture systems are listed in Table 5.2, and parameters specific to solvent storage systems are found in Table 5.3. Similar to plant type and the CHP flag, the CO₂ capture indicator is used to appropriately assign costs and constraints to p within the set of capture facilities \mathbb{C} .

Additional parameters are required to define CO₂ capture costs and constraints within the framework developed in Chapter 2. These parameters, listed in Table 5.4, are assumed constant across all capture facilities, but making them plant-specific is possible by adding them to the generating unit database and modifying the parameter import code.

No additional input parameters are required to model interruptible load; facilities are represented using constraints discussed in Section 5.2.7. However, energy storage systems require constraints on power input systems that are analogous to those on power output. Thus, minimum and maximum capacity, ramp rate, and minimum up and down time must be specified for input power systems. For some storage systems, like batteries, these parameters are likely the same for input and

Table 5.2: The following input parameters are required for each unit with CO₂ capture.

Parameter (Units)	Symbol
CO ₂ capture indicator (1=yes, 0=no)	n/a
Absorber minimum load (fractional)	\underline{y}_p^a
Stripper minimum load (fractional)	\underline{y}_p^s
Design CO ₂ removal (fractional)	F_p
Stripping/compression energy requirement (MWh/tCO ₂)	E_p^s
Absorption energy requirement (MWh/tCO ₂)	E_p^a
Absorber ramp rate up (load fraction/min)	$\delta_p^{a,u}$
Absorber ramp rate down (load fraction/min)	$\delta_p^{a,d}$
Stripping/compression ramp rate up (load fraction/min)	$\delta_p^{s,u}$
Stripping/compression ramp rate down (load fraction/min)	$\delta_p^{s,d}$
LP steam fraction for stripping (fractional)	f_p^{Steam}
Absorber startup cost (\$/startup)	$S_p^{a,u}$
Absorber shutdown cost (\$/startup)	$S_p^{a,d}$
Stripper startup cost (\$/startup)	$S_p^{s,u}$
Stripper shutdown cost (\$/startup)	$S_p^{s,d}$
Absorber minimum up time (hr)	$\Theta_p^{a,u}$
Absorber minimum down time (hr)	$\Theta_p^{a,d}$
Absorber initial up time (hr)	$\Theta_p^{a,u,0}$
Absorber initial down time (hr)	$\Theta_p^{a,d,0}$
Stripping/compression minimum up time (hr)	$\Theta_p^{s,u}$
Stripping/compression minimum down time (hr)	$\Theta_p^{s,d}$
Stripping/compression initial up time (hr)	$\Theta_p^{s,u,0}$
Stripping/compression initial down time (hr)	$\Theta_p^{s,d,0}$
CO ₂ transport and storage cost (\$/tCO ₂)	$C_p^{T/S}$

Table 5.3: The following input parameters are required for each unit with CO₂ capture that has a solvent storage system.

Parameter (Units)	Symbol
Solvent storage tank size (m^3)	ψ_p
Design CO ₂ carrying capacity (mol solvent/mol CO ₂)	Ω_p
Day-starting CO ₂ quantity in rich storage tank (tCO ₂)	l_p^0

Table 5.4: The following input parameters are held constant for all units with CO₂ capture.

Parameter (units)	Symbol
Minimum mass flow in LP turbine	Z_{min}^{Turb}
Fractional efficiency point penalty of ramping stripping/compression systems 0–100% (MW_e for ramp/ MW_{th} heat input)	$\hat{\eta}^s$
Fractional efficiency point penalty of ramping absorption systems 0–100% (MW_e for ramp/ MW_{th} heat input)	$\hat{\eta}^a$
Solvent price (\$/kg)	P^{Solv}
Total solvent degradation rate (kg/tCO ₂ stripped)	D
Solvent degradation rate from thermal effects (kg/tCO ₂ stripped)	D^{th}
Caustic NaOH price (\$/kg)	$P^{Caustic}$
Water fraction in the reclaimer	w^R
Waste disposal price (\$/kg waste)	P^{Waste}
Water price (\$/m ³)	P^{Water}
Additional water use for capture (m ³ /MW gross capacity)	w
Solution density (kg/m ³ solution)	ρ
Solvent molecular weight (kg/kmol)	M^{Solv}
Stripping/compression equipment oversizing fraction	f^{Equip}

output because power flows both ways in the same equipment. However, for systems such as pumped hydroelectric storage or CAES, power input devices (pumps, compressors) and power output devices (turbines) could have different capacities and operating characteristics. For all types of storage, a round-trip efficiency of energy output from storage per energy input to storage, η^{es} , must also be specified along with the storage capacity limit, \bar{v}_p . A daily set point for the storage system, v_p^0 , is also required when using one day for the forward market planning period. Energy storage parameters are listed in Table 5.5.

Table 5.5: The following input parameters are required for all energy storage units.

Parameter (Units)	Symbol
Minimum input capacity (MW)	\underline{x}_p^{IN}
Maximum input capacity (MW)	\bar{x}_p^{IN}
Output/input efficiency	η^{es}
Energy storage capacity (MWh)	\bar{v}_p
Day-starting stored energy level (MWh)	v_p^0
Input ramp limit up (MW/min)	$\delta_p^{IN,u}$
Input ramp limit down (MW/min)	$\delta_p^{IN,d}$

5.2.3.2 Electricity System

The model imports total ERCOT electricity demand, L_t , as well as data for electricity production from wind, W_t , in each time period. The difference $L_t - W_t$ is the net electricity demand, L_t^{net} , that all other facilities must satisfy.

To determine ancillary service requirements in each time period, RU and RD requirements (RU_t, RD_t) are imported for each hour. ERCOT calculates RU_t and RD_t as a function of total wind-based generating capacity in the grid, \bar{W} , so this adjustment is performed to ensure regulation requirements are appropriate for the

assumed wind capacity. Tables 5.6 and 5.7 show these adjustment factors, which vary by month and hour. The RRS requirement, RRS , is always 2,300 MW as stated above. An hourly net load uncertainty, σ_t^L , is required to determine the necessary quantity of NSRS in each time interval, and the parameter f^{NLU} is used in NSRS constraints as discussed in Section 5.2.11. ERCOT requires that offers in each AS market be no greater than the amount of capacity that could be supplied to (or removed from) the electricity market in a specified period of time, κ . For RU and RD, $\kappa^{RU} = \kappa^{RD} = 5$ minutes; for RRS, $\kappa^{RRS} = 10$ minutes; and for NSRS, $\kappa^{NSRS} = 30$ minutes. RRS offers by generating units (but not load) are also restricted to $f^{RRS,Gen} = 20\%$ of maximum output capacity, and interruptible load systems cannot provide more than $f^{RRS,Load} = 50\%$ of the 2,300 MW RRS requirement.

Fuel prices for coal, natural gas, oil, and biomass (P^{Coal} , P^{NG} , P^{Oil} , and P^{Bio}) are necessary for fuel cost calculations. The CO₂ price, P^{CO_2} , is nonzero when examining a policy to reduce CO₂ emissions. Fuel and CO₂ prices are kept constant throughout the simulation time period in this analysis. Variable fuel prices would be straightforward to implement, but constant values are assumed sufficient for the days-to-weeks time scales simulated. Furthermore, assuming constant annual prices would still yield important insights into the operation of electricity systems with flexible CO₂ capture. An estimated average annual electricity price is also required to calculate CO₂ capture ramping costs; Section 5.5.2.1 describes how this parameter is specified. Table 5.8 summarizes the input parameters necessary to define electricity system constraints and market conditions.

Rather than require strict equality between electricity supply and demand, the model allows supply/demand imbalances in both the day-ahead and real-time optimizations but penalizes any imbalances using the same procedure as ERCOT.

Table 5.6: The following factors adjust regulation up requirements by the stated quantity per 1,000 MW additional wind capacity.

	Month											
	1	2	3	4	5	6	7	8	9	10	11	12
0	7.8	6.1	0.3	7.2	3.5	3.0	1.3	9.4	2.0	7.9	9.2	5.7
1	6.5	6.7	6.1	1.1	8.9	5.8	7.4	9.5	7.2	5.7	3.4	7.3
2	7.0	6.9	2.4	8.8	2.3	8.6	6.2	4.4	6.3	9.9	1.1	2.6
3	3.3	9.4	3.4	3.9	3.0	7.6	2.8	5.4	2.4	5.4	7.2	4.0
4	6.0	6.0	6.0	4.5	3.6	5.4	6.5	9.0	5.5	9.9	3.9	3.9
5	8.3	5.2	7.2	3.8	2.9	6.0	1.7	1.7	6.6	9.9	6.6	1.7
6	5.6	6.9	3.9	3.5	6.1	8.6	8.9	8.4	5.0	2.6	3.8	8.0
7	9.3	6.3	5.8	6.5	3.0	9.5	3.3	9.6	3.9	3.4	0.1	2.0
8	9.2	2.4	6.0	7.4	0.0	5.5	1.7	7.9	4.0	7.9	1.9	8.3
9	9.3	2.7	7.6	5.3	6.7	0.2	5.6	6.7	0.6	6.6	5.6	7.9
10	8.3	3.0	7.2	7.0	9.1	8.1	9.6	7.2	4.2	0.7	7.6	2.5
11	1.4	4.5	5.9	0.2	7.9	3.5	4.8	0.3	4.2	9.7	4.3	3.6
12	9.9	1.8	0.6	7.1	1.9	8.0	0.3	5.8	8.2	8.6	9.1	3.6
13	4.1	4.3	9.3	6.1	2.5	5.4	1.0	7.6	7.7	2.4	3.8	3.4
14	0.9	1.6	1.6	5.8	1.7	5.1	9.8	1.4	2.9	3.3	1.4	2.8
15	8.2	9.6	1.5	9.2	8.8	9.4	8.8	5.4	8.8	2.8	3.4	1.1
16	5.1	0.5	5.6	5.5	1.8	7.6	7.5	7.2	5.4	9.4	5.0	3.5
17	5.1	1.0	0.0	8.2	0.1	5.4	4.4	9.1	7.4	0.7	9.7	7.4
18	4.0	4.0	8.2	5.8	8.9	6.0	3.2	6.5	7.2	7.2	2.0	5.1
19	7.4	3.1	0.6	2.9	6.6	7.1	3.6	9.4	1.6	6.4	5.7	3.0
20	9.9	6.2	5.8	5.3	4.0	2.6	8.3	2.1	6.4	2.3	8.2	1.5
21	3.3	9.0	8.8	0.7	5.4	9.1	5.7	1.6	1.5	6.3	8.5	4.3
22	5.8	1.2	7.2	8.2	2.8	7.2	9.9	4.7	5.8	1.4	8.8	2.4
23	0.5	5.8	4.3	4.1	1.2	7.6	9.7	9.3	1.4	7.7	0.6	5.7

Table 5.7: The following factors adjust regulation down requirements by the stated quantity per 1,000 MW additional wind capacity.

	Month											
	1	2	3	4	5	6	7	8	9	10	11	12
0	8.7	6.6	0.6	0.9	5.6	2.6	9.0	8.1	2.9	2.9	3.5	5.7
1	9.9	0.6	4.1	4.4	2.1	7.3	1.1	7.3	4.5	1.2	4.5	1.6
2	2.4	5.8	5.3	5.7	9.9	7.5	4.0	6.9	8.3	4.4	8.5	5.9
3	5.7	6.9	1.0	5.7	8.6	9.9	1.1	4.1	1.5	0.6	3.7	6.2
4	8.2	9.8	8.8	3.4	2.8	7.4	5.3	9.4	9.2	4.0	1.7	8.8
5	9.2	1.9	5.7	7.9	0.6	1.9	7.4	9.9	1.3	5.9	5.7	1.6
6	7.0	1.6	8.9	2.0	3.8	5.5	2.3	7.6	5.0	0.7	8.7	2.3
7	6.3	1.1	1.9	4.7	2.1	3.9	2.1	4.3	3.5	1.4	7.5	5.1
8	0.4	7.3	0.3	5.8	5.0	9.4	3.0	8.6	7.5	6.0	4.4	9.6
9	1.6	3.8	1.3	7.4	4.9	9.3	7.3	4.9	3.2	7.2	6.2	2.4
10	2.6	1.3	2.3	4.5	6.8	8.3	0.9	8.0	7.9	5.4	9.2	4.9
11	4.1	2.5	7.4	9.9	1.4	8.1	3.3	6.6	5.6	9.0	5.0	4.0
12	4.3	2.3	3.5	7.5	1.5	0.3	6.8	9.3	2.8	7.4	8.2	3.6
13	1.7	9.3	7.5	6.7	1.5	8.8	6.9	8.3	5.7	3.8	3.8	3.0
14	2.3	9.7	4.2	0.8	5.4	1.4	4.8	3.0	6.5	6.4	6.7	0.4
15	3.4	2.8	2.1	8.8	9.0	9.0	4.4	7.0	4.1	1.2	8.7	8.0
16	2.0	4.3	5.0	4.2	1.7	3.2	3.1	5.3	3.6	9.2	3.4	6.9
17	4.4	4.0	8.9	2.6	9.3	2.0	7.5	2.3	2.3	3.7	2.1	1.5
18	5.9	7.7	5.9	5.3	3.9	5.6	3.0	5.3	8.3	7.6	3.5	6.4
19	9.9	1.4	6.1	3.2	7.7	1.5	8.5	4.9	7.8	7.8	1.3	7.4
20	5.1	9.5	1.4	4.5	3.8	5.1	1.7	0.6	7.8	9.0	7.9	0.1
21	1.6	6.8	1.0	8.6	7.6	9.4	5.2	4.6	0.7	0.6	5.3	5.3
22	7.6	3.7	1.5	3.6	8.9	9.1	5.2	9.1	4.6	6.4	4.3	4.1
23	0.7	7.5	6.1	2.3	1.3	5.5	3.8	6.5	3.9	1.6	3.4	7.9

Table 5.8: The following input parameters are required to specify electricity system constraints and market conditions.

Parameter (Units)	Symbol
Electricity demand (MW)	L_t
Wind production (MW)	W_t
Net electricity load (MW)	L_t^{net}
Regulation down requirement (MW)	RU_t
Regulation up requirement (MW)	RU_t
Responsive reserves requirement (MW)	RRS
Net demand uncertainty (MW)	σ_t^L
Fraction of net demand uncertainty (fractional)	f^{NLU}
Required response time for regulation up (min)	κ^{RU}
Required response time for regulation down (min)	κ^{RD}
Required response time for responsive reserves (min)	κ^{RRS}
Required response time for non-spinning reserves (min)	κ^{NSRS}
Maximum capacity fraction allowed for RRS (fractional)	$f^{RRS,Gen}$
Maximum fraction of RRS that can be met by interruptible load (fractional)	$f^{RRS,Load}$
Coal price (\$/MMBTU)	P^{Coal}
Natural gas price (\$/MMBTU)	P^{NG}
Oil price (\$/MMBTU)	P^{Oil}
Biomass price (\$/MMBTU)	P^{Bio}
CO ₂ price (\$/tCO ₂)	P^{CO_2}
Estimated average electricity price (\$/MWh)	$P^{e,avg}$

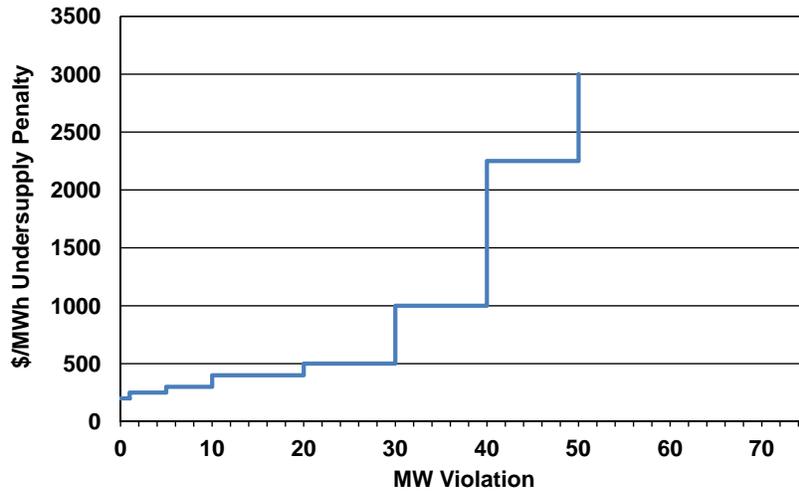


Figure 5.2: ERCOT assesses a penalty for electricity undersupply that increases with supply deficiency towards the market maximum electricity price.

Any oversupply or undersupply of electricity in the day-ahead market is penalized by $\Gamma^{FW} = \$5,000,000/\text{MWh}$ [ERCOT, 2010b]. This hefty penalty does not influence real-time electricity prices; it primarily serves to ensure economical unit commitment. An oversupply penalty in the day-ahead market indicates that net demand is exceeded due primarily to uncontrollable supply such as wind and fixed output from CHP facilities. Undersupply in the day-ahead market means the grid has insufficient capacity available to meet demand. The real-time market penalty for oversupply is $\Gamma^{O,RT} = \$250/\text{MWh}$, and the penalty for undersupply, $\Gamma_g^{U,RT}$, increases with the supply deficiency until reaching the market maximum electricity price of $\$3,000/\text{MWh}$ ¹ above 50 MW undersupply (Fig. 5.2) [ERCOT, 2010b]. The subscript index g represents the segment on Fig. 5.2.

¹As of August 1, 2012, the market maximum electricity price is $\$4,500/\text{MWh}$. This market change could be incorporated into future analysis by modifying undersupply penalties appropriately.

5.2.4 Decision Variables

For each time period in the day-ahead and real-time markets, the model must find optimal electrical output, $x_{p,t}$, and procured AS quantities; $ru_{p,t}$, $rd_{p,t}$, $rrs_{p,t}$, and $nsrs_{p,t}$; for each power generation facility. To allow NSRS procurements by offline facilities, $nsrs_{p,t}$ has two components, NSRS procured when online, $nsrs_{p,t}^{on}$, and NSRS procured when offline, $nsrs_{p,t}^{off}$. The model must also determine the optimal commitment status, $u_{p,t}^b$, (on or off) in the day-ahead optimization, and commitment variables are used to specify binary startup and shutdown variables, $on_{p,t}^b$ and $off_{p,t}^b$. Energy storage facilities must also optimize storage level, $v_{p,t}$, and electrical input, $x_{p,t}^{IN}$, along with commitment, startup, and shutdown status for power input systems, $u_{p,t}^{IN}$, $on_{p,t}^{IN}$, and $off_{p,t}^{IN}$. Facilities with CO₂ capture must also determine absorption and stripping load, $y_{p,t}^a$ and $y_{p,t}^s$, along with the on/off status of CO₂ capture systems, $u_{p,t}^a$ and $u_{p,t}^s$, and when they undergo startup or shutdown, $on_{p,t}^a$, $on_{p,t}^s$, $off_{p,t}^a$ and $off_{p,t}^s$. Load change variables for absorption and stripping systems in either direction (up or down), $\Delta_{p,t}^{a,u}$, $\Delta_{p,t}^{a,d}$, $\Delta_{p,t}^{s,u}$, and $\Delta_{p,t}^{s,d}$, are also required to define CO₂ capture ramping costs. If the CO₂ capture system utilizes solvent storage, a variable for the amount of CO₂ stored in rich solvent, $l_{p,t}$, is used to govern solvent storage operation. Lastly, to allow penalized imbalances in electricity supply and demand, slack variables for oversupply quantity, z_t^O , and undersupply quantity, $z_{t,g}^U$, are defined.

All commitment, startup, and shutdown variables are binary. All output, input, AS procurement, capture load, storage level, load change, and supply/demand imbalance variables are defined as positive. Table 5.9 reviews the subscripts used as index sets, and all decision variables are summarized in Tables 5.10 and 5.11.

Structurally, the model is defined with one time set with elements in each of the real-time market time intervals. In the forward market optimization, variables

are fixed across each day-ahead time interval using constraints. This implementation eliminates the need to compose two sets of each constraint type within the model. If desired, a reformulation could utilize unique time indices for each market.

Table 5.9: The following subscripts are used to index decision variables within their sets.

Subscript	Description
t	Time index
p	Plant index
g	Index of segments on electricity undersupply penalty curve

5.2.5 Objective Function

The model seeks to minimize the total cost of electricity dispatch, TC , across all units and time periods within the day being optimized. Variables are defined across many days, so the objective function for each daily optimization is restricted between the first and last time interval of the day, m and k , to prevent erroneous assignment of variables in future days. The general form of the objective function is defined for the day-ahead market in Eqn. 5.1 and the real-time market in Eqn. 5.2. Separate objective functions are required because supply/demand imbalance penalties represented by the second and third terms differ between markets. Power plant cost functions, $C_{p,t}$, are the same for both markets.

$$TC = \sum_{p,m \leq t \leq k} C_{p,t} + \sum_{m \leq t \leq k} \Gamma^{FW} z_t^O + \sum_{g,m \leq t \leq k} \Gamma^{FW} z_{t,g}^U \quad (5.1)$$

$$TC = \sum_{p,m \leq t \leq k} C_{p,t} + \sum_{m \leq t \leq k} \Gamma^{O,RT} z_t^O + \sum_{g,m \leq t \leq k} \Gamma_g^{U,RT} z_{t,g}^U \quad (5.2)$$

Table 5.10: The following variables describe power systems, energy storage systems, and electricity supply/demand imbalances.

Variable (Units)	Symbol
Gross power output (MW)	$x_{p,t}$
Regulation up procurement (MW)	$ru_{p,t}$
Regulation down procurement (MW)	$rd_{p,t}$
Responsive reserves procurement (MW)	$rrs_{p,t}$
Non-spinning reserves procurement (MW)	$nsrs_{p,t}$
Non-spinning reserves procurement when online (MW)	$nsrs_{p,t}^{on}$
Non-spinning reserves procurement when offline(MW)	$nsrs_{p,t}^{off}$
Base plant commitment status (1=on, 0=off)	$u_{p,t}^b$
Base plant startup indicator for base plant (1=yes, 0=no)	$on_{p,t}^b$
Base plant shutdown indicator for base plant (1=yes, 0=no)	$off_{p,t}^b$
Power input to storage (MW)	$x_{p,t}^{IN}$
Stored energy level (MWh)	$v_{p,t}$
Input system commitment status (1=on, 0=off)	$u_{p,t}^{IN}$
Input system startup indicator for base plant (1=yes, 0=no)	$on_{p,t}^{IN}$
Input system shutdown indicator for base plant (1=yes, 0=no)	$off_{p,t}^{IN}$
Quantity oversupply (MW)	z_t^O
Quantity undersupply (MW)	$z_{t,g}^U$

Table 5.11: The following variables describe CO₂ capture system operation.

Variable (Units)	Symbol
Absorption system load (fractional)	$y_{p,t}^a$
Stripping/compression system load (fractional)	$y_{p,t}^s$
Absorption system commitment status (1=on, 0=off)	$u_{p,t}^a$
Stripping/compression system commitment status (1=on, 0=off)	$u_{p,t}^s$
Absorption system startup indicator for base plant (1=yes, 0=no)	$on_{p,t}^a$
Stripping/compression system startup indicator for base plant (1=yes, 0=no)	$on_{p,t}^s$
Absorption system shutdown indicator for base plant (1=yes, 0=no)	$off_{p,t}^a$
Stripping/compression system shutdown indicator for base plant (1=yes, 0=no)	$off_{p,t}^s$
Absorption load change up (fractional)	$\Delta_{p,t}^{a,u}$
Absorption load change down (fractional)	$\Delta_{p,t}^{a,d}$
Stripping/compression load change up (fractional)	$\Delta_{p,t}^{s,u}$
Stripping/compression load change down (fractional)	$\Delta_{p,t}^{s,d}$
Quantity of CO ₂ in rich solvent storage tank (tCO ₂)	$l_{p,t}$

Startup and shutdown costs can be assessed for all units, and the framework also includes the ability to assess startup costs for CO₂ capture and energy storage input systems. Startup and shutdown costs, $C_{p,t}^{SUP}$ and $C_{p,t}^{SDown}$, for all possible components are calculated using Eqns. 5.3 and 5.4.

$$C_{p,t}^{SUP} = S_p^{b,u} on_{p,t}^b + S_p^{a,u} on_{p,t}^a + S_p^{s,u} on_{p,t}^s \quad (5.3)$$

$$C_{p,t}^{SDown} = S_p^{b,d} off_{p,t}^b + S_p^{a,d} off_{p,t}^a + S_p^{s,d} off_{p,t}^s \quad (5.4)$$

For thermal generating units without CO₂ capture fueled by coal, natural gas, oil, and biomass, $C_{p,t}$ is composed of fuel costs, $C_{p,t}^{Fuel}$, CO₂ emissions costs, $C_{p,t}^{CO_2}$, and additional VOM costs, $C_{p,t}^{b,O\&M}$ (Eqns. 5.5–5.7). Fuel costs are assessed with the fuel price appropriate for each unit type. If biomass is assumed carbon neutral, CO₂ emissions costs can be neglected by setting the emissions rate, R_p^b , to zero in input parameters. Nuclear and hydroelectric facilities are assigned a total VOM cost, so operating costs are calculated using Eqn. 5.7 only.

$$C_{p,t}^{Fuel} = P^{Fuel} H_p^b x_{p,t} \tau^{RT} \quad (5.5)$$

$$C_{p,t}^{CO_2} = P^{CO_2} R_p^b x_{p,t} \tau^{RT} \quad (5.6)$$

$$C_{p,t}^{b,O\&M} = OM_p^b x_{p,t} \tau^{RT} \quad (5.7)$$

Operating costs at energy storage facilities are defined generally to include any fuel and CO₂ emissions costs when there is net electrical output (Eqns. 5.5 and 5.6).

Though some energy storage systems such as batteries and pumped hydroelectric facilities have no fuel or CO₂ emissions costs, CAES facilities typically burn natural gas to heat the compressed air when generating electricity, so these costs are included for generality. VOM costs for energy storage facilities, $C_{p,t}^{Stor,O\&M}$, also include a modification to Eqn. 5.7 that assesses VOM costs when electricity is input to storage (Eqn. 5.8).

$$C_{p,t}^{Stor,O\&M} = OM_p^b (x_{p,t} + x_{p,t}^{IN}) \tau^{RT} \quad (5.8)$$

For coal-fired facilities with CO₂ capture, fuel and base plant VOM costs are assessed using Eqns. 5.5 and 5.7. No changes are required because these equations use gross output before subtracting CO₂ capture energy requirements rather than net electrical output available to meet electricity demand. CO₂ emissions costs, $C_{p,t}^{Capt.CO_2}$, account for the quantity of CO₂ removed by absorption systems (Eqn. 5.9). Additional costs are again assessed for the following: solvent makeup to offset degradation and volatility losses, $C_{p,t}^{Solv}$; caustic sodium hydroxide (NaOH) for thermal solvent reclaiming, $C_{p,t}^{Caustic}$; reclaimer waste disposal, $C_{p,t}^{Waste}$; additional water use for CO₂ capture, $C_{p,t}^{CapWat}$; CO₂ transport and storage, $C_{p,t}^{T/S}$; and ramping the capture load, $C_{p,t}^{CapRamp}$. These costs are calculated in the same manner as described in Section 2.2.1.3 and are repeated below for clarity with appropriate index changes (Eqns. 5.10–5.15).

$$C_{p,t}^{Capt.CO_2} = P^{CO_2} (R_p^b x_{p,t} - R_p^b \bar{x}_p F_p y_{p,t}^a) \tau^{RT} \quad (5.9)$$

$$C_{p,t}^{Solv} = P^{Solv} R_p^b F_p \bar{x}_p ((D - D^{th}) y_{p,t}^s + D^{th}) \tau^{RT} \quad (5.10)$$

$$C_{p,t}^{Caustic} = P^{Caustic} R_p^b F_p \bar{x}_p D^{Caustic} y_{p,t}^s \tau^{RT} \quad (5.11)$$

$$C_{p,t}^{Waste} = \frac{P^{Waste} R_p^b F_p \bar{x}_p [D^{th} + (D^{Caustic} + D - D^{th}) y_{p,t}^s] \tau^{RT}}{1 - w^R} \quad (5.12)$$

$$C_{p,t}^{CapWat} = P^{Water} w \bar{x}_p \frac{1}{2} (y_{p,t}^s + y_{p,t}^a) \tau^{RT} \quad (5.13)$$

$$C_{p,t}^{T/S} = P_p^{T/S} R_p^b F_p \bar{x}_p y_{p,t}^s \tau^{RT} \quad (5.14)$$

$$C_{p,t}^{CapRamp} = P^{e,avg} \tau^{RT} \bar{x}_p \frac{1}{\eta_p^b} \left(\Delta_{p,t}^{a,u} \hat{\eta}^{a,u} + \Delta_{p,t}^{a,d} \hat{\eta}^{a,d} + \Delta_{p,t}^{s,u} \hat{\eta}^{s,u} + \Delta_{p,t}^{s,d} \hat{\eta}^{s,d} \right) \quad (5.15)$$

There are typically no direct costs for AS procurements, though there are opportunity costs if the AS procurement prevents the use of low-cost supply and requires more expensive units to meet electricity demand. The facility is contracted to have capacity available without necessarily needing to deploy that capacity. However, to prevent the model from grossly over-procuring AS, costs on the order of 10^{-5} \$/MW are assessed for each. To ensure the model properly prioritizes the each service entailing an output increase (RU, RRS, NSRS), AS costs are placed in the order NSRS < RRS < RU. Since interruptible load facilities can only provide RRS and NSRS, these facilities are essentially costless in the model. Additional operating costs could be specified for interruptible load to represent lost revenue from reducing electricity demand, but estimating these costs is outside the scope of this work. Market prices for AS in ERCOT are determined by settlement of AS offers provided by generating

units. Future work could use bid data to ascertain the opportunity costs of AS provision to ERCOT generating units, but this procedure was not performed for the present analysis.

5.2.6 Power System Constraints

Within each optimization, all constraints are defined only between the first interval, m , and the last interval, k , in a given optimization period. All simulations optimize one day at a time, so $m - k = 96$ fifteen-minute intervals.

Several power system constraints have the same form as those listed in Section 2.2.1.4, including those that bound gross power output capacity, define startup and shutdown indication variables, and enforce minimum runtime and downtime. These constraints are repeated in Eqns. 5.16–5.24 with updated indices and time restrictions for clarity.

$$\forall \{t | m \leq t \leq k\}, \underline{x}_p u_{p,t}^b \leq x_{p,t} \leq \bar{x}_p u_{p,t}^b \quad (5.16)$$

$$\forall \{t | t > 1, m \leq t \leq k\}, on_{p,t}^b \geq u_{p,t}^b - u_{p,t-1}^b \quad (5.17)$$

$$\forall \{t | t > 1, m \leq t \leq k\}, off_{p,t}^b \geq u_{p,t-1}^b - u_{p,t}^b \quad (5.18)$$

$$\forall \{t | 1 \leq t \leq \Theta_p^{b,u,0}, m \leq t \leq k\}, u_{p,t}^b = 1 \quad (5.19)$$

$$\forall \{t | \Theta_p^{b,u,0} \leq t \leq T - \Theta_p^{b,u} + 2, m \leq t \leq k\}, \sum_{t'=t}^{t+\Theta_p^{b,u}-1} u_{p,t'}^b \geq \Theta_p^{b,u} (u_{p,t}^b - u_{p,t-1}^b) \quad (5.20)$$

$$\forall \{t|T - \Theta_p^{b,u} + 2 \leq t \leq T, m \leq t \leq k\}, \sum_{t'=t}^T u_{p,t'}^b \geq (T - t + 1)(u_{p,t}^b - u_{p,t-1}^b) \quad (5.21)$$

$$\forall \{t|1 \leq t \leq \Theta_p^{b,d,0}, m \leq t \leq k\}, u_{p,t}^b = 0 \quad (5.22)$$

$$\forall \{t|\Theta_p^{b,d,0} \leq t \leq T - \Theta_p^{b,d} + 2, m \leq t \leq k\}, \sum_{t'=t}^{t+\Theta_p^{b,d}-1} (1 - u_{p,t'}^b) \geq \Theta_p^{b,d}(u_{p,t-1}^b - u_{p,t}^b) \quad (5.23)$$

$$\forall \{t|T - \Theta_p^{b,d} + 2 \leq t \leq T, m \leq t \leq k\}, \sum_{t'=t}^T (1 - u_{p,t'}^b) \geq (T - t + 1)(u_{p,t-1}^b - u_{p,t}^b) \quad (5.24)$$

Ramp rate constraints also have the same form as those in Section 2.2.1.4. However, separate ramp rate constraints are required for the real-time market (Eqns. 5.25 and 5.26) and forward (day-ahead) market (Eqns. 5.27 and 5.28) due to model construction, and a special modification is required for the first interval in the forward market (Eqns. 5.29 and 5.30). The model uses the 15-minute real-time market interval in both optimizations while fixing variables across each hour in the day-ahead market optimization, so allowable output changes each hour in the day-ahead market must be four times that allowed in each 15 minutes in the real-time market. Equations 5.29 and 5.30 are the exception, where the real-time market allowable ramp is used for the first hour in each day-ahead market optimization. Initially, several simulations using a generating unit-specific data set had difficulty finding feasible solutions because first-hour ramps from the forward market optimization could not be achieved in the real-time optimization. The additional term applying only in the first interval of each

forward market optimization eliminates these infeasibilities with minimal impact on operational realism.

$$\forall\{t|t > 1, m \leq t \leq k\}, x_{p,t} - x_{p,t-1} \leq 60\tau^{RT} \delta_p^{b,u} u_{p,t-1}^b + (1 - u_{p,t-1}^b) \underline{x}_p \quad (5.25)$$

$$\forall\{t|t > 1, m \leq t \leq k\}, x_{p,t-1} - x_{p,t} \leq 60\tau^{RT} \delta_p^{b,d} u_{p,t}^b + (1 - u_{p,t}^b) \underline{x}_p \quad (5.26)$$

$$\forall\{t|t > 1, m + 1 \leq t \leq k\}, x_{p,t} - x_{p,t-1} \leq 60\tau^{FW} \delta_p^{b,u} u_{p,t-1}^b + (1 - u_{p,t-1}^b) \underline{x}_p \quad (5.27)$$

$$\forall\{t|t > 1, m + 1 \leq t \leq k\}, x_{p,t-1} - x_{p,t} \leq 60\tau^{FW} \delta_p^{b,d} u_{p,t}^b + (1 - u_{p,t}^b) \underline{x}_p \quad (5.28)$$

$$\forall\{t|t > 1, t = m\}, x_{p,t} - x_{p,t-1} \leq 60\tau^{RT} \delta_p^{b,u} u_{p,t-1}^b + (1 - u_{p,t-1}^b) \underline{x}_p \quad (5.29)$$

$$\forall\{t|t > 1, t = m\}, x_{p,t-1} - x_{p,t} \leq 60\tau^{RT} \delta_p^{b,d} u_{p,t}^b + (1 - u_{p,t}^b) \underline{x}_p \quad (5.30)$$

AS offers are limited by plant ramping capability as specified by ERCOT [ERCOT, 2009b]. RU and RD offers must not exceed the $\kappa^{RU} = \kappa^{RD} = 5$ -minute ramping capability of a facility (Eqns. 5.31 and 5.32). RRS cannot exceed the $\kappa^{RRS} = 10$ -minute up ramping capability of a facility less any RU procurements (Eqn. 5.33). ERCOT also limits RRS procurement to $f^{RRS,Gen} = 20\%$ of maximum output capacity for generation resources (not interruptible load) (Eqn. 5.34). Committed NSRS

cannot exceed the $\kappa^{NSRS} = 30$ -minute up ramping capability less any RU and RRS procurements (Eqn. 5.35). NSRS procured by an uncommitted (off) facility cannot exceed its maximum output capacity (Eqn. 5.36). If an uncommitted unit were deployed for NSRS, it would need to supply at least its minimum output capacity. However, ERCOT does not explicitly constrain the minimum NSRS offer by offline units, so no such constraint is included.

$$\forall \{t|m \leq t \leq k\}, ru_{p,t} \leq \kappa^{RU} \delta_p^{b,u} u_{p,t}^b \quad (5.31)$$

$$\forall \{t|m \leq t \leq k\}, rd_{p,t} \leq \kappa^{RD} \delta_p^{b,d} u_{p,t}^b \quad (5.32)$$

$$\forall \{t|m \leq t \leq k\}, rrs_{p,t} \leq \kappa^{RRS} \delta_p^{b,u} u_{p,t}^b - ru_{p,t} \quad (5.33)$$

$$\forall \{t|m \leq t \leq k\}, rrs_{p,t} \leq f^{RRS,Gen} \bar{x}_p \quad (5.34)$$

$$\forall \{t|m \leq t \leq k\}, nsrs_{p,t}^{on} \leq \kappa^{NSRS} \delta_p^{b,u} u_{p,t}^b - rrs_{p,t} - ru_{p,t} \quad (5.35)$$

$$\forall \{t|m \leq t \leq k\}, nsrs_{p,t}^{off} \leq \bar{x}_p (1 - u_{p,t}^b) \quad (5.36)$$

The sum of electricity output and all AS requiring an output increase (RU, RRS, NSRS when committed) must not exceed the maximum power output capacity (Eqn. 5.37), and output minus procured RD must exceed the minimum output capacity (Eqn. 5.38). These constraints ensure generation facilities do not offer any energy or ancillary services they cannot provide within capacity limitations. If all capacity

is utilized for electricity output, no AS can be procured. Generally, AS procurements reduce the range of available electrical output.

$$\forall \{t|m \leq t \leq k\}, ru_{p,t} + rrs_{p,t} + nsrs_{p,t}^{on} \leq \bar{x}_p u_{p,t}^b - x_{p,t} \quad (5.37)$$

$$\forall \{t|m \leq t \leq k\}, rd_{p,t} \leq x_{p,t} - \underline{x}_p u_{p,t}^b \quad (5.38)$$

5.2.7 CHP and Interruptible Load Constraints

For all CHP facilities, $p \in \mathbb{M}$, gross electrical output is fixed to maximum capacity, $x_{p,t} = \bar{x}_p$. Doing so prevents also the facility from providing any RU, RRS, and NSRS by Eqn. 5.37, and RD variables are fixed to 0 for CHP facilities assumed to be firm supply and unavailable to provide any grid reliability services.

Interruptible load facilities must have a nonzero output capacity to allow RRS or NSRS provision. However, these facilities must not provide any output in the model because load is interrupted only when necessary for AS deployments, which are not modeled. To represent interruptible load facilities, all output variables are fixed to 0 ($x_{p,t} = 0$), all commitment variables are fixed to 1 ($u_{p,t}^b = 1$), and \underline{x}_p must be 0. These constraints ensure capacity limits (Eqn. 5.16) are satisfied while RRS can be procured from interruptible load by Eqns. 5.33 and 5.37. ERCOT does not allow interruptible load to provide regulation service, so $ru_{p,t}$ and $rd_{p,t}$ are also fixed to 0 for interruptible load facilities.

5.2.8 Energy Storage System Constraints

Energy storage systems can provide any AS and either supply electricity from storage or increase demand with input to storage. Input systems have mini-

mum/maximum load, startup/shutdown indication, ramp rate, and minimum up/down time constraints that are analogous to the corresponding base plant constraints (Eqns. 5.16–5.30) with variable and parameter substitutions as indicated in Table 5.12.

Table 5.12: Analogous energy storage system constraints are produced by making the following substitutions in Eqs. 5.16–5.30.

Variable or parameter in Eqs. 5.16–5.30	Substitution for energy storage systems
$u_{p,t}^b$	$u_{p,t}^{IN}$
$on_{p,t}^b$	$on_{p,t}^{IN}$
$off_{p,t}^b$	$off_{p,t}^{IN}$
$x_{p,t}$	$x_{p,t}^{IN}$
\underline{x}_p	\underline{x}_p^{IN}
\bar{x}_p	\bar{x}_p^{IN}
$\delta_p^{b,u}$	$\delta_p^{IN,u}$
$\delta_p^{b,d}$	$\delta_p^{IN,d}$
$\Theta_p^{b,u,0}$	$\Theta_p^{IN,u,0}$
$\Theta_p^{b,u}$	$\Theta_p^{IN,u}$
$\Theta_p^{b,d,0}$	$\Theta_p^{IN,d,0}$
$\Theta_p^{b,d}$	$\Theta_p^{IN,d}$

Equation 5.39 is the flow balance for stored energy, which calculates stored energy in each time interval, $v_{p,t}$, as the sum of the previous stored energy level, $v_{p,t-1}$, energy output, and energy input. Energy input is multiplied by the output-to-input efficiency to account for energy losses in the storage-retrieval cycle. The efficiency parameter, η^{es} , depends on the energy storage system type. Though this round-trip efficiency should eliminate any cost incentive to operate both input and output systems simultaneously, Eqn. 5.40 is included in the model to ensure independent operation. Equation 5.41 specifies the maximum energy storage capacity. In addition, energy storage level must be specified at the beginning of each forward

market planning period, which is one day in the present work. Without doing so, an energy storage facility would have no incentive to reserve stored energy for future days because the model prevents facilities from planning ahead of the current optimization period. Utilities with large-scale storage systems might seek optimal operation over longer time periods. The model formulation can consider longer forward market planning periods, but day-ahead planning is used exclusively to ensure reasonable computation time. Results are expected to be nearly optimal for storage systems sized primarily to leverage diurnal variations in energy and ancillary service demand and prices.

$$\forall \{t | t > 1, m \leq t \leq k\}, v_{p,t} = v_{p,t-1} - x_{p,t} \tau^{RT} + \eta^{es} x_{p,t}^{IN} \tau^{RT} \quad (5.39)$$

$$\forall \{t | m \leq t \leq k\}, u_{p,t} + u_{p,t}^{IN} \leq 1 \quad (5.40)$$

$$\forall t, v_{p,t} \leq \bar{v}_p \quad (5.41)$$

AS offer limitations with energy storage account for the fact that ramping input systems down is akin to ramping output systems up, and vice versa. Equations 5.42–5.45 redefine the AS offer limitations for energy storage systems to account for input system ramp rates when the facility is storing energy. Constraints also ensure that combined energy output and AS procurements fall within the input capacity range when a facility is storing energy. Equations 5.46 and 5.47 thus redefine Eqns. 5.37 and 5.38 for energy storage systems so that combined energy input and RD procurement does not exceed maximum input capacity, and energy input less combined RU, RRS, and NSRS exceeds minimum input capacity. Additional

constraints (Eqns. 5.48 and 5.49) also account for the duration-limited nature of energy storage, ensuring that RU, RRS, and NSRS cannot be procured when there is insufficient stored energy, and RD cannot be procured if there is insufficient available storage capacity. At the writing of this dissertation, ERCOT had not incorporated such constraints for energy storage systems into its market protocols, so the duration-limited nature of energy storage is not explicitly represented in ERCOT operations. These constraints are included for operational realism even though they do not match ERCOT procedures.

$$\forall \{t|m \leq t \leq k\}, ru_{p,t} \leq \kappa^{RU} (\delta_p^{b,u} u_{p,t}^b + \delta_p^{IN,d} u_{p,t}^{IN}) \quad (5.42)$$

$$\forall \{t|m \leq t \leq k\}, rd_{p,t} \leq \kappa^{RD} (\delta_p^{b,d} u_{p,t}^b + \delta_p^{IN,u} u_{p,t}^{IN}) \quad (5.43)$$

$$\forall \{t|m \leq t \leq k\}, rrs_{p,t} \leq \kappa^{RRS} (\delta_p^{b,u} u_{p,t}^b + \delta_p^{IN,d} u_{p,t}^{IN}) - ru_{p,t} \quad (5.44)$$

$$\forall \{t|m \leq t \leq k\}, nsrs_{p,t}^{on} \leq \kappa^{NSRS} (\delta_p^{b,u} u_{p,t}^b + \delta_p^{IN,d} u_{p,t}^{IN}) - rrs_{p,t} - ru_{p,t} \quad (5.45)$$

$$\forall \{t|m \leq t \leq k\}, ru_{p,t} + rrs_{p,t} + nsrs_{p,t}^{on} \leq (\bar{x}_p u_{p,t}^b - x_{p,t}) + (x_{p,t}^{IN} - \underline{x}_p^{IN} u_{p,t}^{IN}) \quad (5.46)$$

$$\forall \{t|m \leq t \leq k\}, rd_{p,t} \leq (x_{p,t} - \underline{x}_p u_{p,t}^b) + (\bar{x}_p^{IN} u_{p,t}^{IN} - x_{p,t}^{IN}) \quad (5.47)$$

$$\forall \{t|t > 1, m \leq t \leq k\}, (x_{p,t} + ru_{p,t} + rrs_{p,t} + nsrs_{p,t}^{on}) \tau^{RT} \leq v_{p,t} \quad (5.48)$$

$$\forall \{t|t > 1, m \leq t \leq k\}, (x_{p,t}^{IN} + rd_{p,t})\tau^{RT} \leq \bar{v}_p - v_{p,t} \quad (5.49)$$

5.2.9 CO₂ Capture System Constraints

Additional constraints on CO₂ capture systems are unchanged from those included in the single plant profit maximization model and described in Section 2.2.1.5. Minimum load, startup/shutdown indication, ramp rate, and minimum up/down time constraints are again analogous to corresponding base plant constraints (Eqs. 5.16–5.30) with variable and parameter substitutions as indicated in Table 5.13. Equations 5.50 and 5.51 redefine CO₂ capture load change variables for indices used in the unit commitment model.

Table 5.13: Analogous CO₂ capture system constraints are produced by making the following substitutions in the left hand side of Eqn. 5.16 and Eqs. 5.17–5.30.

Variable or parameter in Eqs. 2.15–2.24	Substitution for absorption systems	Substitution for stripping systems
$u_{p,t}^b$	$u_{p,t}^a$	$u_{p,t}^s$
$on_{p,t}^b$	$on_{p,t}^a$	$on_{p,t}^s$
$off_{p,t}^b$	$off_{p,t}^a$	$off_{p,t}^s$
$x_{p,t}$	$y_{p,t}^a$	$y_{p,t}^s$
\underline{x}_p	\underline{y}_p^a	\underline{y}_p^s
$\delta_p^{b,u}$	$\delta_p^{a,u}$	$\delta_p^{s,u}$
$\delta_p^{b,d}$	$\delta_p^{a,d}$	$\delta_p^{s,d}$
$\Theta_p^{b,u,0}$	$\Theta_p^{a,u,0}$	$\Theta_p^{s,u,0}$
$\Theta_p^{b,u}$	$\Theta_p^{a,u}$	$\Theta_p^{s,u}$
$\Theta_p^{b,d,0}$	$\Theta_p^{a,d,0}$	$\Theta_p^{s,d,0}$
$\Theta_p^{b,d}$	$\Theta_p^{a,d}$	$\Theta_p^{s,d}$

$$\forall \{t|t > 1, m \leq t \leq k\}, \Delta_{p,t}^u \geq y_{p,t} - y_{p,t-1} \quad (5.50)$$

$$\forall \{t | t > 1, m \leq t \leq k\}, \Delta_{p,t}^d \geq y_{p,t-1} - y_{p,t} \quad (5.51)$$

When modeling an inflexible CO₂ capture system, absorber and stripper load must equal fractional base plant load (Eqn. 5.52), and specified minimum capture load must equal minimum fractional base plant load.

$$\forall \{t | m \leq t \leq k\}, y_{p,t}^a = y_{p,t}^s = \frac{x_{p,t}}{\bar{x}_p} \quad (5.52)$$

Absorber and stripper load must be equal for a venting-only flexible CO₂ capture system, but capture load can be below fractional base plant load (Eqns. 5.53 and 5.54).

$$\forall \{t | m \leq t \leq k\}, y_{p,t}^a = y_{p,t}^s \quad (5.53)$$

$$\forall \{t | m \leq t \leq k\}, y_{p,t}^a \leq \min \left(u_{p,t}^a, \frac{x_{p,t}}{\bar{x}_p} \right) \quad (5.54)$$

With solvent storage, absorber and stripper load are decoupled. Absorber load is limited by available flue gas (Eqn. 5.54), and maximum stripper load is constrained by steam availability (Eqn. 5.55) and equipment size (Eqn. 5.56). Equations 5.57 and 5.58 redefine the stored CO₂ flow balance and CO₂ storage capacity limits for the unit commitment model. Similar to energy storage systems, the model requires a set point for the quantity of CO₂ stored in rich solvent at the beginning of each day.

$$\forall \{t | m \leq t \leq k\}, y_{p,t}^s \leq \frac{1 - Z_{min}^{Turb}}{f_p^{Steam}} \frac{x_{p,t}}{\bar{x}_p} \quad (5.55)$$

$$\forall \{t|m \leq t \leq k\}, y_{p,t}^s \leq f^{Equip} u_{p,t}^s \quad (5.56)$$

$$\forall \{t|t > 1, m \leq t \leq k\}, l_{p,t} = l_{p,t-1} + \tau^{RT} R_p^b \bar{x}_p F_p (y_{p,t}^a - y_{p,t}^s) \quad (5.57)$$

$$\forall \{t|m \leq t \leq k\}, l_{p,t} \leq \bar{l}_p \quad (5.58)$$

The presence of CO₂ capture systems impacts AS offer limitations at a facility. If CO₂ capture systems are inflexible, both minimum and maximum net electrical output is reduced, so the net ramp rate at a facility should reflect CO₂ capture energy requirements. Equations 5.59–5.62 redefine AS offer limitations for an inflexible capture facility, where the factor within parentheses uses CO₂ capture energy requirements, E_p^a and E_p^s , base plant emissions rate, R_p^b , and design CO₂ removal, F_p , to calculate the ratio of net to gross power output. Equations 5.63 and 5.64 similarly redefine the constraints restricting total energy and AS procurements for inflexible CO₂ capture facilities.

$$\forall \{t|m \leq t \leq k\}, ru_{p,t} \leq \kappa^{RU} \delta_p^{b,u} u_{p,t}^b (1 - (E_p^a + E_p^s) R_p^b F_p) \quad (5.59)$$

$$\forall \{t|m \leq t \leq k\}, rd_{p,t} \leq \kappa^{RD} \delta_p^{b,d} u_{p,t}^b (1 - (E_p^a + E_p^s) R_p^b F_p) \quad (5.60)$$

$$\forall \{t|m \leq t \leq k\}, rrs_{p,t} \leq \kappa^{RRS} \delta_p^{b,u} u_{p,t}^b (1 - (E_p^a + E_p^s) R_p^b F_p) - ru_{p,t} \quad (5.61)$$

$$\forall \{t|m \leq t \leq k\}, nsrs_{p,t}^{on} \leq \kappa^{NSRS} \delta_p^{b,u} u_{p,t}^b (1 - (E_p^a + E_p^s) R_p^b F_p) - rrs_{p,t} - ru_{p,t} \quad (5.62)$$

$$\forall \{t|m \leq t \leq k\}, ru_{p,t} + rrs_{p,t} + nsrs_{p,t}^{on} \leq (\bar{x}_p u_{p,t}^b - x_{p,t}) (1 - (E_p^a + E_p^s) R_p^b F_p) \quad (5.63)$$

$$\forall \{t|m \leq t \leq k\}, rd_{p,t} \leq (x_{p,t} - \underline{x}_p u_{p,t}^b) (1 - (E_p^a + E_p^s) R_p^b F_p) \quad (5.64)$$

Conversely, flexible CO₂ capture systems enhance ramping capabilities. Capture system load could decrease while base plant load increases, producing a larger net up ramp rate and greater ability to offer RU, RRS, and NSRS. Even at maximum power system plant load, RU, RRS, and NSRS could be offered given the ability to ramp down CO₂ capture systems. RD offer limits also increase because the facility could ramp capture systems up while decreasing base plant load or decrease minimum base plant load using the energy requirement for capture. Thus, capture system load and ramp rate play a role in AS offer limits and the total quantity of energy and AS the facility can provide. Equations 5.65–5.70 again recast Eqns. 5.31–5.33, 5.35, 5.37, and 5.38 for flexible CO₂ capture facilities. The two additional terms in each AS offer limit represent the supplemental ramping capability provided by flexible capture systems. The quantities $E_p^s R_p^b F_p$ and $E_p^a R_p^b F_p$ again represent the fractional energy requirement for capture, and \bar{x}_p scales the CO₂ capture ramp rates in fractional load per minute to the appropriate MW/min net ramp rate. Additional terms in Eqn. 5.69 account for the RU, RRS, and NSRS offer capacity provided by the capacity to ramp down or turn off capture systems. The additional terms in Eqn. 5.70 similarly represent the available capacity to ramp capture systems up and reduce net electrical output.

$$\begin{aligned} \forall \{t|m \leq t \leq k\}, ru_{p,t} \leq \kappa^{RU} & \left(\delta_p^{b,u} u_{p,t}^b + E_p^s R_p^b F_p \bar{x}_p \delta_p^{s,d} u_{p,t}^s \right. \\ & \left. + E_p^a R_p^b F_p \bar{x}_p \delta_p^{a,d} u_{p,t}^a \right) \end{aligned} \quad (5.65)$$

$$\begin{aligned} \forall \{t|m \leq t \leq k\}, rd_{p,t} \leq \kappa^{RD} & \left(\delta_p^{b,d} u_{p,t}^b + E_p^s R_p^b F_p \bar{x}_p \delta_p^{s,u} u_{p,t}^s \right. \\ & \left. + E_p^a R_p^b F_p \bar{x}_p \delta_p^{a,u} u_{p,t}^a \right) \end{aligned} \quad (5.66)$$

$$\begin{aligned} \forall \{t|m \leq t \leq k\}, rrs_{p,t} \leq \kappa^{RRS} & \left(\delta_p^{b,u} u_{p,t}^b + E_p^s R_p^b F_p \bar{x}_p \delta_p^{s,d} u_{p,t}^s \right. \\ & \left. + E_p^a R_p^b F_p \bar{x}_p \delta_p^{a,d} u_{p,t}^a \right) - ru_{p,t} \end{aligned} \quad (5.67)$$

$$\begin{aligned} \forall \{t|m \leq t \leq k\}, nsrs_{p,t}^{on} \leq \kappa^{NSRS} & \left(\delta_p^{b,u} u_{p,t}^b + E_p^s R_p^b F_p \bar{x}_p \delta_p^{s,d} u_{p,t}^s \right. \\ & \left. + E_p^a R_p^b F_p \bar{x}_p \delta_p^{a,d} u_{p,t}^a \right) \\ & - rrs_{p,t} - ru_{p,t} \end{aligned} \quad (5.68)$$

$$\begin{aligned} \forall \{t|m \leq t \leq k\}, ru_{p,t} + rrs_{p,t} + nsrs_{p,t}^{on} & \leq (\bar{x}_p u_{p,t}^b - x_{p,t}) + E_p^s R_p^b F_p \bar{x}_p (y_{p,t}^s - \underline{y}_p u_{p,t}^s) \\ & + E_p^a R_p^b F_p \bar{x}_p (y_{p,t}^a - \underline{y}_p u_{p,t}^a) \end{aligned} \quad (5.69)$$

$$\begin{aligned} \forall \{t|m \leq t \leq k\}, rd_{p,t} & \leq (x_{p,t} - \underline{x}_p u_{p,t}^b) + E_p^s R_p^b F_p \bar{x}_p (f^{Equip} u_{p,t}^s - y_{p,t}^s) \\ & + E_p^a R_p^b F_p \bar{x}_p (u_{p,t}^a - y_{p,t}^a) \end{aligned} \quad (5.70)$$

5.2.10 Fixing Variables Across Forward Market Intervals

As discussed in Section 5.2.4, using a common time index for both the day-ahead and real-time optimization requires constraints in the forward market to fix variables across each forward market time interval (1 hour). This constraint for $x_{p,t}$ is shown in Eqn. 5.71. Analogous constraints are defined in the forward market model for the following variables: $x_{p,t}^{IN}$, $ru_{p,t}$, $rd_{p,t}$, $rrs_{p,t}$, $nsrs_{p,t}^{on}$, $nsrs_{p,t}^{off}$, $y_{p,t}^a$, $y_{p,t}^s$, $u_{p,t}^b$, $u_{p,t}^{IN}$, $u_{p,t}^a$, and $u_{p,t}^s$. The startup/shutdown indicator variables (*on*, *off*) and CO₂ capture load change variables (Δ) are fixed by commitment variables (u) and capture load (y). Stored energy levels cannot be fixed within a forward market interval with constant input or output in that interval. Likewise, CO₂ levels in a solvent storage system will vary across the forward market interval for any unequal absorber and stripper load.

$$\forall \left\{ t \mid t \geq 1, m \leq t \leq k, \left((t-1) \bmod \frac{\tau^{FW}}{\tau^{RT}} \right) < \left(\frac{\tau^{FW}}{\tau^{RT}} - 1 \right) \right\}, x_{p,t} = x_{p,t+1} \quad (5.71)$$

5.2.11 Electricity System Constraints

Real-time dispatch is optimized in response to 15-minute net demand data, and day-ahead dispatch is optimized in response to the average electricity load in each 1-hour forward market time interval, so different net demand quantities are used in each optimization to enforce the balance between electricity supply and net demand. Using hourly averages in the day-ahead optimization is expected to most closely approximate actual ERCOT practices. The model was tested using hourly maximum net demand in the forward market to help ensure enough units are committed to respond to hourly demand variations; however, hourly averages are used exclusively in the present analysis. Future activity could study the effect of net demand forecasting accuracy by using discrepant net demand data for the forward and real-time

optimizations. Electricity supply/demand balance is satisfied by Eqns. 5.72 and 5.73. Energy requirements for CO₂ capture are subtracted from the gross output of units with CO₂ capture, and input to energy storage increases net demand. Undersupply and oversupply variables allow slack in the supply/demand balance to ensure model feasibility, but these imbalances are penalized in the objective function (Eqns. 5.1 and 5.2).

$$\begin{aligned}
\forall \{t|m \leq t \leq k\}, L_t^{net,FW} &= \sum_p x_{p,t} - \sum_p x_{p,t}^{IN} \\
&+ \sum_{p \in \mathbb{C}} (x_{p,t} - E_p^s R_p^b F_p \bar{x}_p y_{p,t}^s - E_p^a R_p^b F_p \bar{x}_p y_{p,t}^a) \\
&+ \sum_g z_{t,g}^U - z_t^O
\end{aligned} \tag{5.72}$$

$$\begin{aligned}
\forall \{t|m \leq t \leq k\}, L_t^{net,RT} &= \sum_p x_{p,t} - \sum_p x_{p,t}^{IN} \\
&+ \sum_{p \in \mathbb{C}} (x_{p,t} - E_p^s R_p^b F_p \bar{x}_p y_{p,t}^s - E_p^a R_p^b F_p \bar{x}_p y_{p,t}^a) \\
&+ \sum_g z_{t,g}^U - z_t^O
\end{aligned} \tag{5.73}$$

As the highest-priority AS, regulation up and down procurements must meet or exceed requirements in all hours (Eqns. 5.74 and 5.75). ERCOT requires $RRS = 2,300$ MW at all times, but the model is implemented to establish priority of $RU > RRS > NSRS$, so higher-priority RU can be used for lower-priority RRS if economical (Eqn. 5.76). In practice, AS offers for each service establish appropriate priorities, but this model does not include an offer-bid settlement process. ERCOT constrains NSRS by requiring the sum of RU and NSRS to cover $f^{NLU} = 95\%$ of the total uncertainty in forecasted net demand, σ_t^L (Eqn. 5.77). Additional terms along with objective

penalties establish AS priorities, so $ru_{p,t}$ actually appears twice in this representation of the NSRS constraint. Finally, Eqn. 5.78 invokes the ERCOT protocol limiting the quantity of RRS that can be provided by interruptible load to $f^{RRS,Load} = 50\%$ of the RRS requirement.

$$\forall \{t|m \leq t \leq k\}, \sum_p ru_{p,t} \geq RU_t \quad (5.74)$$

$$\forall \{t|m \leq t \leq k\}, \sum_p rd_{p,t} \geq RD_t \quad (5.75)$$

$$\forall \{t|m \leq t \leq k\}, \sum_p rrs_{p,t} + ru_{p,t} \geq RRS + RU_t \quad (5.76)$$

$$\forall \{t|m \leq t \leq k\}, \sum_p ru_{p,t} + nsrs_{p,t}^{on} + nsrs_{p,t}^{off} + ru_{p,t} + rrs_{p,t} \geq f^{NLU} \sigma_t^L + RRS + RU_t \quad (5.77)$$

$$\forall \{t|m \leq t \leq k\}, \sum_{p \in Load} rrs_{p,t} \leq f^{RRS,Load} RRS \quad (5.78)$$

5.2.12 Details of the Two-Stage Optimization

Time series of electricity demand, wind production, and AS requirements are imported over a span of several days, with the total number of days defined as T/L^{FW} . The day-ahead and real-time market optimizations are then solved within a loop from intervals m to k in that day, and m to k are updated to the appropriate indices at each iteration. After optimizing the day-ahead market, the following variables are fixed for $m \leq t \leq k$ before real-time market optimization: $u_{p,t}^b, u_{p,t}^{IN}, on_{p,t}^b, off_{p,t}^b, on_{p,t}^{IN}$,

$off_{p,t}^{IN}$, $ru_{p,t}$, $rd_{p,t}$, $rrs_{p,t}$, $nsrs_{p,t}^{on}$, and $nsrs_{p,t}^{off}$. Commitment of CO₂ capture system components is allowed to change between the forward and real-time markets. After optimizing the real-time market, the following variables are fixed for $m \leq t \leq k$ before solving the forward market optimization for the next day: $x_{p,t}$, $x_{p,t}^{IN}$, $v_{p,t}$, $y_{p,t}^a$, $y_{p,t}^s$, $u_{p,t}^a$, $u_{p,t}^s$, $on_{p,t}^a$, $on_{p,t}^s$, $off_{p,t}^a$, $off_{p,t}^s$, $l_{p,t}$, z_t^O , and $z_{t,g}^U$.

5.2.13 Model Limitations

Though many detailed power and electricity system operating behaviors are represented in this model formulation, there are some limitations that deserve notice. The model does not represent transmission constraints, so it implicitly functions as if no transmission constraints in ERCOT are binding. Transmission constraints can have a significant effect on electricity prices when there are locational supply/demand mismatches, so while the model can be used to demonstrate trends in shadow electricity prices, absolute price values might not be accurate. The addition of transmission constraints could allow future research to determine the value of flexible capture in a transmission-constrained system, but results produced without transmission provide a basis for discussing the value of flexible capture in a grid-level context. An intermediate extension could represent the electricity system as a small number of aggregate nodes, or zones, prior to implementing a full nodal transmission system.

As mentioned in the discussion of the single plant profit maximization model, all power and capture system specifications are kept constant across their operating ranges to preserve model linearity. A nonlinear or piecewise-linear representation of performance curves would improve the detailed short-term representation of operating behavior, but constant-average performance parameters are assumed sufficient to make conclusions about long-term aggregate performance.

Another common set of constraints in unit commitment modeling accounts for

the difference between “hot” and “cold” startups by varying minimum up/down time and the transition between zero and minimum load based on time spent on or offline. These effects are assumed negligible to the aggregate performance of the electricity system, so they are not included in this formulation.

5.3 Power Plant Database Creation

Accurate input data are essential for meaningful modeling results. Generating unit data are often difficult to find because specifications are proprietary. High-resolution generating unit information improves realism; however, model output for a large unit database is more difficult to interpret when verifying proper model functionality. This section describes two power system databases used to produce the results in Section 5.5. An aggregated representation of the ERCOT system is used for model testing and demonstration. Then, a generating unit-specific database for ERCOT allows greater accuracy when studying the implications of flexible capture in a least-cost dispatch framework.

5.3.1 Aggregated Ten-Facility Test System

Model testing and demonstration uses an aggregated 10-facility system that roughly approximates the capacity of each plant type in ERCOT, including interruptible load. ERCOT does not currently contain any energy storage systems with hundreds of MW input/output capacity, but a large energy storage system is included in this database for functionality testing. Though parameter specifics were often varied to test different conditions, Table 5.14 contains the parameter set used in simulations discussed in Section 5.5.1. Marginal costs for electrical output are also shown with \$1.54/MMBTU coal, \$4/MMBTU natural gas, and \$0/tCO₂ to illustrate the typical dispatch order in ERCOT, where nuclear- and coal-based facilities primarily

supply base load and natural gas combined-cycle (NGCC) and open-cycle gas turbines (OCGT) provide intermediate and peak supply. Startup costs are also intended primarily to preserve relative order of startup costs among plant types. Maximum output of thermal, nuclear, and hydroelectric facilities reflects approximate total ERCOT capacity of those plant types. The capacity for interruptible load purposefully exceeds the quantity allowed for RRS provision. Minimum output is set to 30% of the maximum for nuclear- and coal-based facilities and a smaller percentage for gas-based facilities. Ramp rates are also defined to reflect relative ramping capabilities of each plant type, and hydroelectric, load, and storage facilities are effectively given infinite ramp rates (the ability to ramp from minimum to maximum output within one 15-minute time interval). Minimum up and down times echo the greater difficulty of startup and shutdown for nuclear- and coal-based plants relative to gas-based, hydroelectric, and most storage facilities. Ramp rate and minimum up and down times are assumed the same in both directions.

Table 5.15 lists additional parameters used when simulating the energy storage system. Storage input and output capacity are 1,000 MW, and the storage system is given 10 hours of storage, or 10,000 MWh. The energy output-to-input efficiency is set to 90%. The stored energy level must be 5,000 MWh at the start of each day, an arbitrary but sufficient value for initial testing and demonstration. The parameters in Tables 5.14 and 5.15 for the energy storage facility combine best-case specifications across many types of energy storage to ensure the storage system is utilized. Pumped hydroelectric systems can have up to 87% round trip efficiency and large storage capacity, but lack of suitable geography and environmental impacts are barriers to new large hydroelectric facilities [APS, 2007]. Efficiencies >90% are achievable with flywheels and supercapacitors, but energy storage types and batteries are currently impractical at a hundreds of MW scale [APS, 2007]. Since CAES often heats

Table 5.14: An aggregated 10-facility data set is used for model testing and proof-of-concept analysis. (*at \$1.54/MMBTU coal, \$4/MMBTU natural gas, \$0/tCO₂)

Plant	Startup cost (\$/startup)	Base Plant VOM Cost (\$/MWh)	Minimum output (MW)	Maximum output (MW)	Ramp rate up/down (MW/min)	Base plant minimum up/down time (hr)	Marginal generating costs* (\$/MWh)
Nuclear	15,000	17.15	1,380	4,600	50	168	17.15
Hydro	100	24.3	0	200	1000	0.5	24.3
Coal 1	12,000	5	2,100	7,000	140	24	20.4
Coal 2 - capture	12,002	0	1,050	3,500	70	24	20.7
Coal 3 - capture	12,003	5	1,050	3,500	70	24	21.2
NGCC 1	8,000	5	3,125	12,500	375	6	39
NGCC 2	8,001	5	3,125	12,500	375	6	41
OCGT 1	500	5	1,300	26,000	2,600	0.5	45
Load	0	5	0	2,000	200	n/a	0
Storage	0	3	0	1,000	500	0.5	0

air by natural gas burning before expanding it through a gas turbine, output/input efficiencies are above 100%, but electrical output incurs fuel and possibly CO₂ emissions costs. The unit-specific database described in the next section provides a more realistic representation of energy storage systems.

Table 5.15: The following parameters describe the generic energy storage system used for testing purposes.

Parameter (Units)	Value
Minimum input capacity (MW)	0
Maximum input capacity (MW)	1,000
Output/input efficiency (fractional)	0.9
Energy storage capacity (MWh)	10,000
Day-starting stored energy level (MWh)	5,000
Input system ramp rate up/down (MW/min)	500
Input system minimum up/down time (hr)	0.5

Table 5.16 contains key specifications for the Coal 2 and Coal 3 generation blocks when being tested in a CO₂ capture configuration. Again, a baseline 7m MEA capture system is assumed. These values are identical to those used in the limited formulation of the single plant profit maximization model (Tables 2.10 and 2.11) except that minimum capture load is 30% and capture energy requirements are split between absorption and stripping/compression systems. Only a small solvent storage system is tested with the aggregated unit dataset. All other input parameters required to specify CO₂ capture system costs are identical to those in Table 2.11.

5.3.2 Unit-Specific Database

5.3.2.1 Power System Specifications

Before creating a database for each ERCOT generating unit, successful simulations were completed with the 10-facility data and semi-aggregated databases with

Table 5.16: The following CO₂ capture parameters are used when simulating the 10-unit data set with CO₂ capture systems.

Parameter (Units)	Value
Absorber/stripper min load (fractional)	0.3
Design CO ₂ removal (fractional)	0.9
Stripping/compression energy requirement (MWh/tCO ₂)	0.239
Absorption energy requirement (MWh/tCO ₂)	0.030
Absorber/stripper ramp rate up/down (load fraction/min)	0.05
LP steam fraction to stripping (fractional)	0.4
CO ₂ transport and storage cost (\$/tCO ₂)	9.69
Solvent storage tank size (m ³)	8,300
Design CO ₂ carrying capacity (molCO ₂ /molMEA)	0.12
Day-starting CO ₂ quantity in rich storage tank (tCO ₂)	164

~40 and ~140 facilities to ensure model solvability within reasonable computation time for larger databases. After favorable results with the ~140-unit database, a unit-specific database for ERCOT was created to produce the most realistic dispatch achievable within model limitations. This section provides key parameters and describes how the database is created. Appendix D lists all database parameters.

The unit-specific database is built from a 2010 list of ERCOT generating units containing unit-specific maximum capacity as well as generic plant-type specific values for minimum capacity fraction, ramp rate, minimum up/down time, startup cost, heat rate, CO₂ emissions rate, and non-fuel/CO₂ VOM cost [ERCOT, 2011d]. These data are publicly available as part of a contract between ERCOT and the U.S. Department of Energy (DOE).

The ERCOT database provides both summer and winter maximum capacities; the average is assumed sufficient for this analysis. ERCOT-provided values for minimum capacity fraction, ramp rate, minimum up/down time, startup cost, and

non-fuel/CO₂ VOM cost are used for all units of each plant type; these quantities are shown in Table 5.17. Also listed is the corresponding classification for each plant type within the unit commitment model, which is used for appropriately calculating operating costs and displaying results. Oil-based units make up a negligible portion of ERCOT capacity, so these facilities are not included in the database. Parameters in Table 5.17 were not varied among individual units of each type unless the ERCOT database contained an alternate value for that facility.

All quantities in Table 5.17 are zero for hydroelectric units because hydroelectric dams in ERCOT have negligible costs and operating restrictions. OCGT and internal combustion units have the lowest minimum output, minimum up/down time, and startup costs among fossil-fueled units, followed by NGBLR and NGCC units. Coal- and nuclear-based units have the highest minimum up/down time, but more advanced NGCC units such as F/G/H-Class NGCC units are assigned higher startup costs. In practice, startup costs depend on power plant size. For example, startup costs for coal-based units are proportional to the amount of diesel fuel used to pre-heat the boiler, which rises with plant size. However, absent unit-specific startup cost information, generic startup costs by plant type are considered sufficient to establish priority among unit types and produce realistic dispatch patterns. Shutdown costs are set to 0 for all facilities. Every plant startup will eventually require a shutdown, so the startup cost can be thought to include any shutdown costs. Required initial up and down times are also set to 0 for all units.

Ramp rates on the order of 0.2–0.7% in either direction are assumed for all unit types except OCGT, NGIC, and hydroelectric facilities. ERCOT uses these data for an hourly dispatch model, so these ramp rates appear conservative. Short-term ramp rates could be faster than average hourly ramp rates listed in Table 5.17, but

ERCOT-provided values are used as conservative input specifications in the absence of better data. OCGT, NGIC, and hydroelectric facilities are assumed able to ramp from 0–100% of maximum output capacity within one hour, so ERCOT simply ignores ramp rate limits for these unit types. These unit types could also be expected to ramp from 0–100% within the 15-minute time interval used in the present model, so ramp rates for these unit types are set to 6.7%/min.

ERCOT does not provide a minimum capacity fraction for nuclear facilities because its studies assume constant full-load operation, but the present work will relax this assumption so that nuclear facilities have the option to reduce output or provide regulation down service. Minimum capacity for nuclear facilities is assumed to be 30% of the maximum. Though possibly unrealistic, nuclear VOM costs are only \$4/MWh, so these facilities will only ramp down if the difference between net electricity demand and firm supply from CHP units is less than nuclear-based output capacity. ERCOT also does not specify a startup cost for nuclear facilities since it assumes continuous operation at maximum output. Since the present analysis relaxes this assumption, nuclear units are assigned a \$7,200/startup cost to be reasonably close to startup costs of other large base load facilities.

Generic values for each plant type are sufficient for the parameters discussed above. However, if generic heat rates and CO₂ emissions rates are used, facilities of each plant type with nonzero heat and CO₂ emissions rates will have identical operating costs, which could lead to inaccurate dispatch. This situation also creates “ties” in the optimization procedure, which can increase solution difficulty and complicate results interpretation because dispatch decisions are often arbitrary artifacts of the solver algorithm. The EPA eGRID database provides plant-specific heat rates and CO₂ emissions rates for many facilities in ERCOT; however, it lacks sufficient data to

Table 5.17: The following parameters from an ERCOT database are kept constant for all units of a given type.

ERCOT plant type	Plant type in UC model	Minimum output (fractional)	Minimum down time (hr)	Minimum up time (hr)	Non-fuel/CO ₂ VOM cost (\$/MWh)	Startup cost (\$/startup)	Ramp rate (load fraction/min)
Biomass	Biomass	0.25	6	8	9.5	2,500	0.0054
Coal	Coal	0.48	12	24	5	5,000	0.0026
Hydro	Hydro	0.00	0	0	0	0	non-binding
GSSUP	NGBLR	0.28	8	8	6.5	2,500	0.0054
Non-reheat	NGBLR	0.43	8	8	5	2,500	0.0054
Reheat	NGBLR	0.38	8	8	8	2,500	0.0054
CC-E Class	NGCC	0.24	4	4	3	3,000	0.0066
CC-F Class	NGCC	0.32	4	6	3	10,000	0.0066
CC-LM6000	NGCC	0.36	8	4	5	5,000	0.0066
G&H Class	NGCC	0.63	8	6	2.9	15,000	0.0066
Internal combustion	NGIC	0.20	1	1	3	0	non-binding
Nuclear	Nuclear	-	24	168	4	-	0.0026
CT-E Class	OCGT	0.25	1	1	4	1,000	non-binding
CT-LM6000	OCGT	0.36	1	1	8	2,000	non-binding
LMS100	OCGT	0.70	1	1	3	0	non-binding
Older	OCGT	0.25	1	1	3	0	non-binding

calculate unit-specific performance parameters [USEPA, 2010]. Furthermore, eGRID values are averaged over a calendar year, so heat rates and CO₂ emissions rates for plants with multiple units depend on the relative utilization of each unit, which is not reported. When all units are the same type, equivalent performance across units is often a reasonable assumption, but there is greater uncertainty in unit performance for plants with multiple unit types. To maximize the utilization of the plant-specific information in eGRID while creating the unit-specific database used in the unit commitment model, the following procedures are utilized to specify unit heat rates and CO₂ emissions rates.

Case 1: Performance specifications for the plant appear in both the eGRID and ERCOT databases.

- If all units are the same type, use the eGRID heat rate and CO₂ emissions rate for all units.
- If the plant has units of multiple types, use the following procedures.
 - If generic ERCOT values are within 10% of the eGRID values for one of the unit types, use the eGRID value for that unit type and the generic ERCOT value for all other unit types.
 - If the ERCOT specifications are not within 10% of the eGRID specifications, use ERCOT generic values for all unit types.
 - Heat rate only: If the ERCOT specifications are not within 10% of the eGRID specifications for any unit type and some units are NG internal combustion engines, use eGRID values for non-NGIC units and use ERCOT generic values for NGIC units (eGRID does not list any NGIC units in its ERCOT plant database).

Case 2: Performance specifications for the plant appear do not appear in eGRID (plant might not be listed in eGRID): Use the generic ERCOT values for heat rate and CO₂ emissions rate.

The above procedure ensures all applicable units are assigned a heat rate and CO₂ emissions rate and helps minimize the number of facilities with the same performance characteristics, but several units will still have identical performance and cost. To ensure no units have exactly the same cost and performance, heat rates and CO₂ emissions rates were multiplied by a random number from 0.995–1.005 to differentiate performance with minimal change to parameters. For each unit, the same random number is used for both the heat rate and CO₂ emissions rate to make adjustments in a consistent manner. Rather than isolating units with identical performance, all units with nonzero heat rate and CO₂ emissions rate are adjusted in this manner for consistency.

The ERCOT database does not contain information on which units are CHP unless unit names indicate CHP status. The eGRID database provides CHP status by plant, so all units at plants designated as CHP in eGRID are marked as CHP units in the database used for optimization. There is a large portion of CHP capacity in eGRID not listed in the ERCOT database, but there are also several unnamed Private Use Network (PUN) units in the ERCOT database whose names are withheld in the public version of the ERCOT database. It is assumed that PUN units are on-site units at industrial facilities such as oil refineries and chemical manufacturers, and since units at these facilities are typically CHP units, all PUN units in the ERCOT database are marked as CHP units. The resulting total CHP capacity is similar to that reported in eGRID.

Interruptible load is not included in the unit-specific database for the analysis

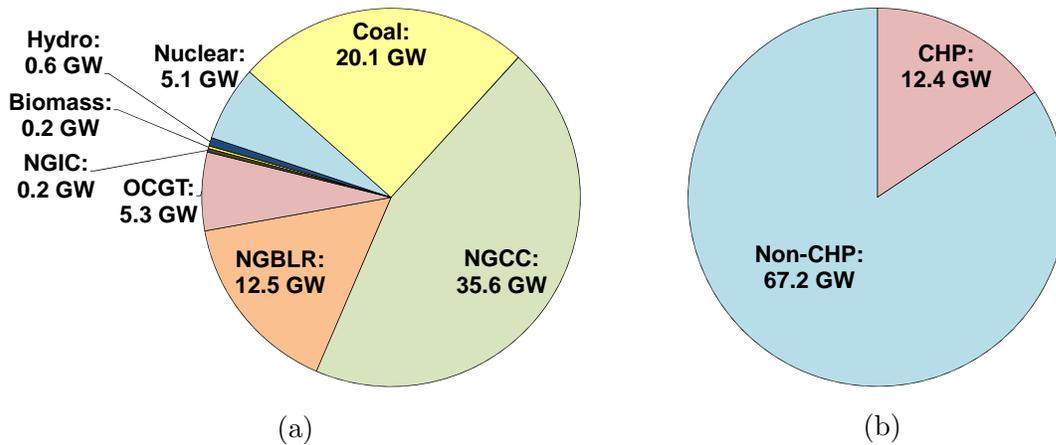


Figure 5.3: The completed unit-specific database demonstrates the dominance of natural gas in the 2010 ERCOT fleet, and over 12 GW of capacity is combined heat and power (CHP).

presented within this dissertation. Its inclusion would yield more accurate RRS and NSRS procurements. However, initial testing found that load resources were almost always used for the maximum allowable RRS requirement, significantly limiting the amount of AS provided by other unit types. A primary goal of the present work is to understand the potential role of flexible capture for AS provision, so interruptible load is omitted to provide greater opportunity for flexible capture to provide AS and allow a clearer picture of how different electricity system conditions affect AS provision by flexible capture facilities.

Panel (a) in Fig. 5.3 displays the capacity by plant type in the unit-specific database under 2010 conditions, and Panel (b) shows the portion of capacity designated as CHP. Total capacity is 79.6 GW (omitting wind capacity). CHP facilities are primarily NGCC and OCGT units, but there is also 705 MW of coal-based capacity designated as CHP based on information in the eGRID database.

5.3.2.2 Capture System Specifications

To study the impact of widespread CCS deployment in ERCOT, approximately half the coal-fired capacity is chosen to compare with four different CO₂ capture configurations: none, inflexible, venting-only, and solvent storage. The viability of CO₂ capture retrofit depends on available space for capture equipment, power system specifications, accessibility to requisite power systems such as the IP/LP crossover pipe, and proximity to a suitable CO₂ sequestration site. While more efficient facilities have lower absolute costs with CO₂ capture, the impact of CO₂ capture on plant performance is independent of base plant efficiency [Lucquiaud & Gibbins, 2011]. High-performance SO₂ and NO_x removal systems are also necessary when using amine scrubbing for CO₂ capture, because these compounds accelerate solvent degradation. Expected future economic conditions and opportunities to sell CO₂ for EOR also impact CO₂ capture investment decisions. Analyzing the interplay between these constraints and suggesting ERCOT facilities for CO₂ capture retrofit is outside the scope of this work, which seeks primarily to study the general impacts of flexible CO₂ capture. As a result, units are chosen for CO₂ capture consideration to span a range of base plant performance and include some but not all units that currently have SO₂ removal systems.

As before, CO₂ capture systems use a baseline 7m MEA solvent. Key CO₂ capture input parameters are summarized in Table 5.18, and these parameters are the same for all capture facilities. When capture systems are assumed inflexible or have venting-only flexibility, capture performance parameters use the minimum equivalent work operating point from recent AspenPlus modeling results produced at UT-Austin [Wagener & Rochelle, 2011]. If systems have solvent storage, an operating point with slightly higher CO₂ carrying capacity and energy requirement is used per

the conclusions from Section 3.2.2. Minimum up and down time for absorption and stripping/compression equipment at all facilities is set to 1 hour. Startup costs were found to have negligible effect on system economics in Section 2.3.1, so startup and shutdown costs are assigned positive values on the order of 10^{-5} solely to ensure capture system startup/shutdown indicator variables are assigned properly. All other parameters used to calculate capture system VOM costs are the same as those in Table 2.11 with appropriate price adjustments for inflation.

Table 5.18: CO₂ capture systems in the unit-specific database use the following performance parameters.

Parameter (Units)	Value if inflexible or venting-only	Value if solvent storage
Absorber/stripper min load (fractional)	0.3	0.3
Design CO ₂ removal (fractional)	0.9	0.9
Stripping/compression energy requirement (MWh/tCO ₂)	0.219	0.221
Absorption energy requirement (MWh/tCO ₂)	0.027	0.028
Absorber/stripper ramp rate up/down (load fraction/min)	0.05	0.05
LP steam fraction to stripping (fractional)	0.4	0.4
Solvent storage system size (max hrs of absorption with no stripping/compression)	-	2
Design CO ₂ carrying capacity (molCO ₂ /molMEA)	0.12	0.16
Day-starting CO ₂ quantity in rich storage tank (%)	-	71

5.3.2.3 Energy Storage System Specifications

While the aggregated 10-facility databases used overly favorable energy storage performance parameters to verify model functionality, more realistic parameters are necessary to effectively study the interactions between flexible capture and energy storage. This work is interested in large-scale energy storage, and inadequate water

resources and geography prevent large pumped hydro facilities within ERCOT, so energy storage systems are given realistic parameters for CAES systems.

Table 5.19 provides parameters used to specify CAES systems when included in the unit-specific database. There are two existing large-scale CAES facilities that provide a basis for parameter specifications. A facility in Huntorf, Germany can output 290 MW for up to 2 hours while a facility in McIntosh, Alabama can generate 110 MW over 26 hours [Ridge, 2005]. To fall within the range of these output capacities and capacity-to-energy ratios, CAES scenarios are modeled with 200 MW output capacity for up to 8 hours (1,600 MWh energy storage capacity). Ten such CAES units are included for enough total CAES capacity to make a substantial impact on ERCOT dispatch. The ratio of input-to-output capacity is 25% at Huntorf and 62.5% at McIntosh, so 50% is chosen for the present analysis (100 MW input capacity) [Ridge, 2005]. McIntosh and Huntorf heat rates are 4.51 and 6.05 MMBTU/MWh, respectively, so a slightly lower 4.1 MMBTU/MWh is used as a basis and randomized to prevent identical performance [Ridge, 2005]. CO₂ emissions rate and heat rate have a direct relationship, so the linear relationship between these quantities across ERCOT facilities is used to determine a CO₂ emissions rate of 0.237 tCO₂/MWh for a facility having a 4.1 MMBTU/MWh heat rate [USEPA, 2010]. Minimum capacities are 50% of maximum to reflect relatively inefficient operation of CAES turbomachinery at low load. Since combusted natural gas adds energy to the system in addition to that stored during air compression, the output-to-input efficiency is 1.25 in this analysis. Recent work by Fertig and Apt uses a larger output/input efficiency, but those authors also assume a lower 3.8 MMBTU/MWh heat rate [Fertig & Apt, 2011]. CAES systems are expected to have rapid ramping capabilities, so ramp rates reflect the ability to ramp from 0% to 100% load within one 15-minute time interval. The required storage level at the start of each day is 30% of capacity, which corresponds to

the similar requirement that solvent storage systems must start each day with stored CO₂ in rich solvent at 71% the maximum. Non-fuel/CO₂ VOM costs of \$3/MWh are assessed for operation of turbomachinery, pollution controls, and operation of the air storage cavern. Startup costs and minimum up/down time are assumed equal to those of OCGT units.

Table 5.19: Energy storage system parameters reflect typical values of current and future CAES designs.

Parameter (Units)	Value
Maximum output capacity (MW)	200
Minimum output capacity (MW)	100
Heat rate (MMBTU/MWh)	4.10
CO ₂ emissions rate (tCO ₂ /MWh)	0.236
Output ramp limit up/down (MW/min)	13.3
Maximum input capacity (MW)	100
Minimum input capacity (MW)	50
Input ramp limit up/down (MW/min)	6.67
Output/input efficiency	1.25
Energy storage capacity (MWh)	1,600
Day-starting stored energy level (MWh)	480
Minimum up/down time for input and output (hr)	1
Non-fuel/CO ₂ VOM cost for input and output (\$/MWh)	3
Startup cost for input and output (\$/startup)	1,000

5.3.2.4 Additional Facilities for 2020

To study flexible CO₂ capture in ERCOT with a substantial increase in wind-based electricity, analysis uses a projected 2020 ERCOT electricity system. The unit-specific database is thus modified to reflect changes to non-wind capacity between 2010 and 2020. No facilities are assumed retired during the 10-year period. Though

some older systems such as gas-fired boilers could be shut down, keeping them in the database should have negligible effect on results because these facilities typically operate very infrequently. Projected 2020 capacity data provided by ERCOT includes 10 new NGCC units with 400 MW output each (4,000 MW total) and 17 new OCGT units with 100 MW or 200 MW output each (2,100 MW total), so these units are added to the database. Projected capacity information does not include any other performance specifications, so these units are assigned generic characteristics of state-of-the-art G/H-class NGCC units and LM6000 OCGT units.

After projecting 2020 ERCOT electricity demand and wind production by the methods discussed in Section 5.5.2.1, the total output capacity was found to be insufficient for meeting annual peak demand and AS requirements, even with significantly increased wind production and the additional gas-fired units expected by ERCOT. The capacity shortage is greater when accounting for the fixed energy requirement of inflexible CO₂ capture systems. Any capacity shortage would be reflected in the model by an undersupply penalty, but an expected shortage on the order of several GW is assumed unrealistic. To ensure peak demand and AS could be met for any scenario, 5,600 MW NGCC and 2,800 MW OCGT capacity is added to the database with the same generic performance specifications of other new gas-based facilities. Heat rates and CO₂ emissions rates of all new gas-fired facilities are subjected to the same randomization procedure used for existing facilities.

5.4 Output Post-Processing

The unit commitment model produces a large amount of output information that is impractical to manipulate using spreadsheet software. A typical output file when optimizing the unit-specific database over one week is ~350 MB. To increase

the efficiency and versatility of unit commitment data analysis, a MATLAB post-processing tool was created to automatically read text-based output from the GAMS unit-commitment model, perform desired calculations, plot results, and export aggregate performance metrics. The script automatically detects the number of facilities modeled and the total time being optimized. It then reformats raw output data into a form that can be easily observed in the MATLAB command window. Quantities such as output and AS procurements are totaled by plant type for each time period, and aggregated statistics over the full time span are calculated for individual units and by plant type. Several plots are created and exported as graphics files to facilitate rapid solution visualization, which is critical for troubleshooting and fully understanding model behavior. Output plots include time series of electrical output and AS procured from each facility and facility type, shadow prices for energy and AS, absorption load, stripping/compression load, and stored CO₂ level. If energy storage systems are included in input database, energy storage levels over time are plotted. Aggregate statistics for each unit type and the electricity system are then exported to a comma-separated-value (CSV) file that can be easily manipulated using spreadsheet software.

5.5 Analysis and Results

5.5.1 Proof-of-Concept: Flexible Capture for Ancillary Services and Peak Demand

The aggregated 10-facility database is used in this section to demonstrate the potential for flexible capture to provide AS and meet peak electricity demand. Results are presented for a single set of electricity market conditions, but additional tests were performed with various CO₂ prices, natural gas prices, coal prices, and demand levels to ensure realistic solutions across a range of conditions. These tests built confidence

in model robustness prior to implementation with the unit-specific plant database and longer-term, more realistic electricity demand and ancillary service requirements.

5.5.1.1 Electricity System Input Parameters

Proof-of-concept analysis is performed using a near-sinusoidal net electricity demand varying from 41.8 GW to 60.3 GW. The same demand curve is repeated for a two-day period. Variable wind production is not represented in these input data. To include some temporal AS variability, regulation up and down requirements are adjusted from a typical value of 500 MW for 10,000 MW wind capacity using the factors in Tables 5.6 and 5.7. For testing purposes, hourly net demand uncertainty, which is used to determine NSRS requirements, is randomized between 1,000 MW and 1,500 MW. Responsive reserve requirements are always 2,300 MW as specified by ERCOT.

All studies reported here assume \$1.54/MMBTU coal and \$4/MMBTU natural gas. A CO₂ price of \$35/tCO₂ is also used for demonstration because previous work has found flexible CO₂ capture to be valuable near this CO₂ price level. Under these conditions, marginal costs of generation are similar across NGCC capacity and coal-fired capacity with and without CO₂ capture. Dispatch is compared with the coal+capture capacity having inflexible capture, venting-only flexible capture, and flexible capture with solvent storage.

5.5.1.2 Results

Figure 5.4 compares electricity dispatch over the two days when CO₂ capture systems on half the coal-based capacity are inflexible (5.4a) and flexible without solvent storage (5.4b). In both cases, hydroelectric and nuclear facilities are dispatched continuously at maximum output. In practice, hydroelectric turbine output depends

on water resource availability and market signals, but these effects are not included because hydroelectric capacity comprises a very small portion of the ERCOT system. At \$35/tCO₂ and the input electricity demand, coal-based capacity without CO₂ capture also remains base load along with the lower-cost NGCC 1 facility. OCGT capacity is marginal most of the time, but NGCC 2 is marginal when demand is lowest.

When CO₂ capture is inflexible, facilities operate continuously at maximum net output, providing base load supply. Energy storage provides some grid flexibility and cost reduction under these conditions. Input to storage increases electricity demand when the NGCC 2 capacity is marginal, and stored energy is output when demand is greater and OCGT capacity is marginal. The marginal cost of OCGT generation does not change with output, so the timing of output from energy storage systems is arbitrary as long as OCGT is marginal. OCGT capacity is given a minimum load of just 1,300 MW, so the storage system also prevents the need for a shutdown/startup cycle at this facility. This result is partly an artifact of input conditions but demonstrates the potential for energy storage to reduce dispatch costs.

With venting-only flexible capture, flexible capture systems operate at 100% load during demand troughs but turn off at higher electricity demand to reduce the required output from OCGT capacity. Though marginal costs at coal+capture facilities are lowest with full-load capture, the difference is relatively small at \$35/tCO₂ (see Fig. 3.12), and costs of coal-based electricity at zero load are lower than the cost of OCGT generation. Thus, overall dispatch costs are reduced using flexible CO₂ capture systems. Results demonstrate that generation costs follow the following order: Coal+100% Capture < Coal+0% Capture < NGCC 2 < OCGT. Under these conditions, energy storage is rarely utilized. This result motivates further analysis

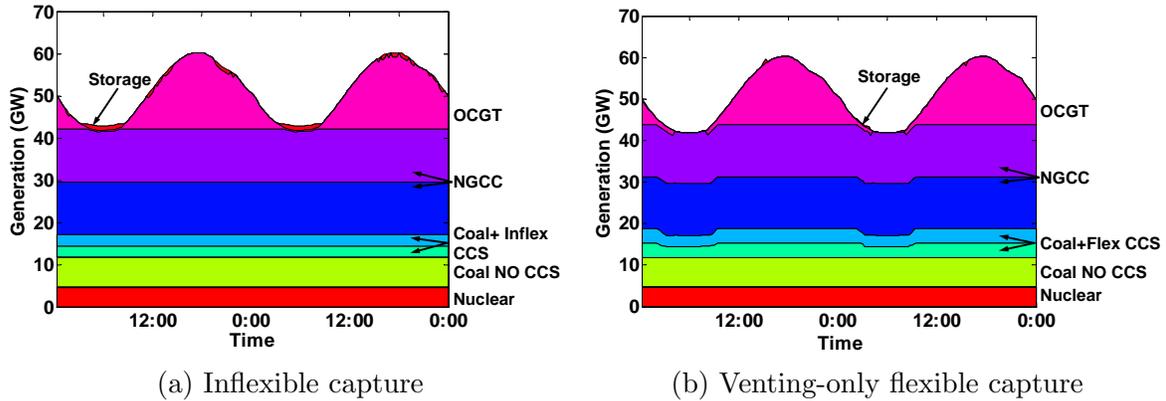


Figure 5.4: When available, flexible capture systems are used instead of energy storage to reduce dispatch costs at peak electricity demand. (\$1.54/MMBTU coal, \$4/MMBTU natural gas, \$35/tCO₂)

of the interactions between energy storage and flexible capture under more realistic electricity system conditions.

Figure 5.5 displays regulation up procurements from each unit, with RU requirements varying by the adjustments for 10,000 MW of wind capacity. With inflexible capture, RU is provided exclusively by the OCGT capacity, which is marginal over the entire time period. With flexible capture, OCGT often provides RU when marginal, but energy storage also provides RU, and flexible capture facilities provide most RU during the lowest demand periods. While energy storage is used sparsely for electrical input/output, storage systems are utilized for RU when output systems are online. Flexible capture operates at 100% load during electricity demand troughs, so RU can be provided by the ability to reduce capture load. The seemingly arbitrary choice between OCGT and storage in many time periods exists because neither facility has direct costs for AS provision, so total electricity system costs are the same regardless of which facility is used for RU. This behavior would likely disappear if even small direct costs were used to differentiate between units.

Analogous plots for regulation down appear in Fig 5.6, which also demon-

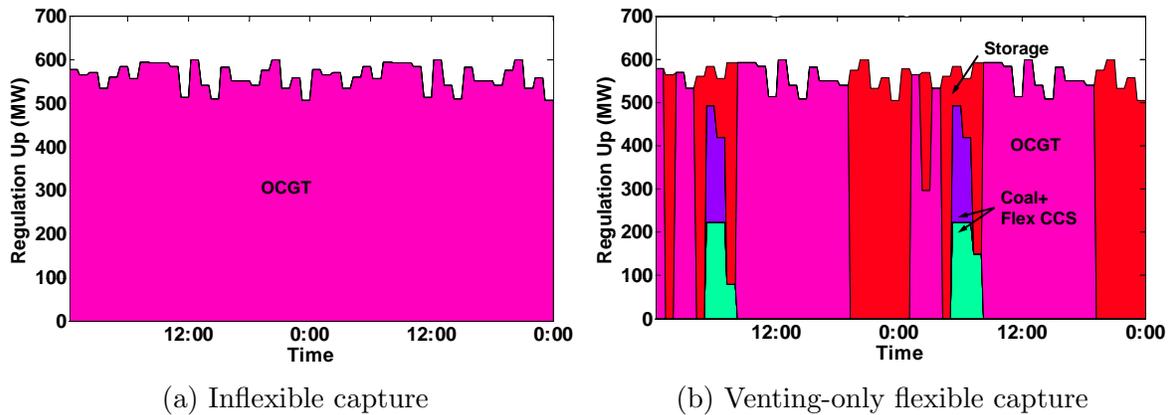


Figure 5.5: Capture facilities provide some regulation up service when flexible. (\$1.54/MMBTU coal, \$4/MMBTU natural gas, \$35/tCO₂)

strates variability due to wind capacity adjustments. With inflexible capture, energy storage is briefly used for RD, but RD is primarily provided by the base load NGCC 1 unit. RD is procured from variety of facilities when flexible capture is available. Since RD has no direct cost to any online facility with the ability to reduce output (or increase input for energy storage), the solution algorithm can choose arbitrarily between facilities for RD. The discrepancy with RD procurements when capture is inflexible is thought to derive more from differences in solver behavior than the existence of flexible capture. Worth noting, however, is that flexible capture facilities are among those chosen for RD procurements during time periods surrounding capture ramps between 0% and 100% load. In these hours, flexible capture systems could begin ramping up sooner or ramp down later if a decrease in net output were desirable for grid stability.

Figure 5.7 plots responsive reserve service procurements when capture systems are inflexible or have venting-only flexibility. The RRS requirement is a constant 2,300 MW. In both scenarios, most RRS is provided by interruptible load (limited to 50% of the total RRS requirement) and the open-cycle turbine when it is online.

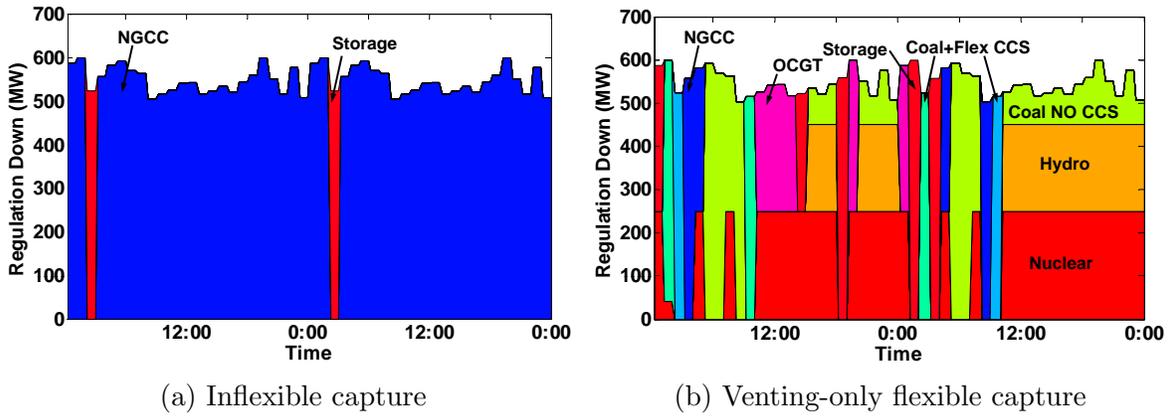


Figure 5.6: Regulation down procurements are arbitrarily distributed among online generators because no direct cost is assessed for RD procurements. (\$1.54/MMBTU coal, \$4/MMBTU natural gas, \$35/tCO₂)

Energy storage systems also provide some RRS with their ability to increase output or decrease input. When available, flexible capture facilities provide RRS during demand troughs. When these facilities operate CO₂ capture at full load, they may reduce CO₂ capture load if additional electricity supply is needed. Without flexible CO₂ capture, these facilities could not supply RRS without reducing available power output capacity.

Figure 5.8 plots NSRS procurements along with the total RU procurement to reflect the NSRS constraint that requires the sum of RU and NSRS to equal or exceed 95% of the hourly net demand uncertainty. Both RU and net demand uncertainty vary by hour. The portion of NSRS+RU not met by RU is supplied by interruptible load, energy storage, and marginal OCGT capacity regardless of the existence of capture flexibility. Differences in procurements between these facilities are likely arbitrary for the same reason as similar behavior for other AS procurements.

Figure 5.9 demonstrates the full impact of flexible CO₂ capture on AS offer capability. This figure plots gross and net power output along with average CO₂ capture load and total AS procurements from the coal+capture capacity in the first

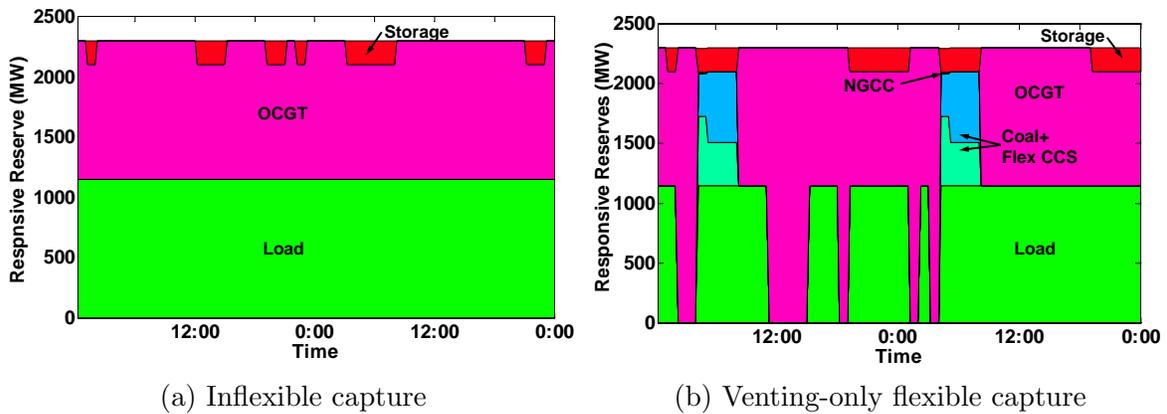


Figure 5.7: Flexibility allows facilities with CO₂ capture to provide responsive reserve service when capture systems are online but could turn down or off if necessary. (\$1.54/MMBTU coal, \$4/MMBTU natural gas, \$35/tCO₂)

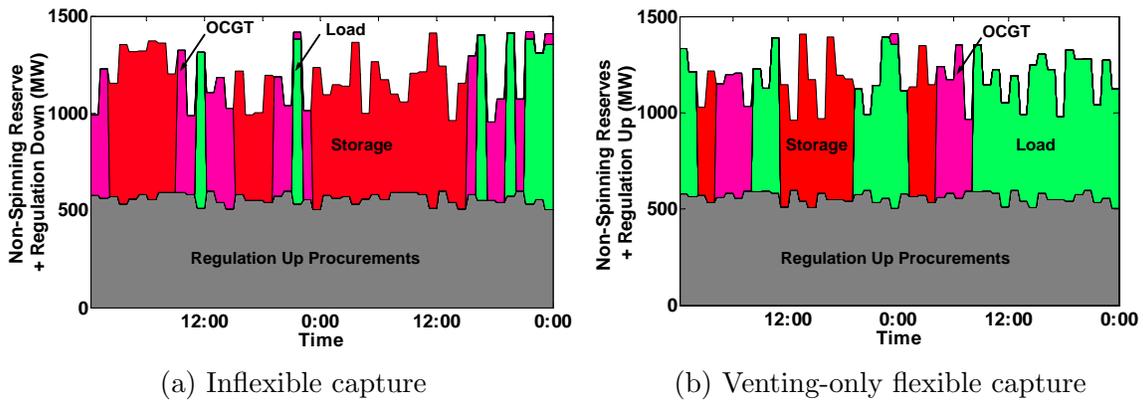


Figure 5.8: Non-spinning reserve service is provided by interruptible load, energy storage, and marginal OCGT capacity regardless of capture flexibility. (\$1.54/MMBTU coal, \$4/MMBTU natural gas, \$35/tCO₂)

12 hours (48 intervals) of demand data. This time period encompasses one of the electricity demand troughs where flexible CO₂ capture systems operate at 100% load. When capture facilities are inflexible, fractional load on power and CO₂ capture systems must be equal, so the only opportunity for AS provision is a regulation down offer if the facility is willing to reduce load on power systems to keep capacity available for RD. The least-cost dispatch solution does not procure RD from inflexible capture capacity, so fractional net load is constant at approximately 75%. However, flexible CO₂ capture allows the facility to offer RU, RD, and RRS while maintaining constant load on power systems. When CO₂ capture load is low, the facility can offer RD with its ability to increase CO₂ capture load and reduce net output. When CO₂ capture load is high, the facility provides RU and RRS because capture load could be reduced if desirable to increase net power output. Though also possible to offer NSRS when flexible capture systems are online, no NSRS is procured from these units under the conditions examined. These results are a proof-of-concept that there are market conditions when flexible CO₂ capture improves the ability to offer into AS markets. The analysis in Sections 5.5.2 and 5.5.3 examines the range of market conditions where this result is true.

In addition to optimal decision variables, the optimization output includes marginal values on all constraints. In the case of energy supply/demand constraints, these quantities represent the marginal cost of increasing net demand by an infinitesimal amount, often called the shadow price. If dispatch optimization is performed in an electricity market context, these shadow prices represent the price of electricity that gives incentive for optimal dispatch in each time period (assuming convergence to the optimal solution).

Figure 5.10 presents these calculated electricity prices with inflexible and

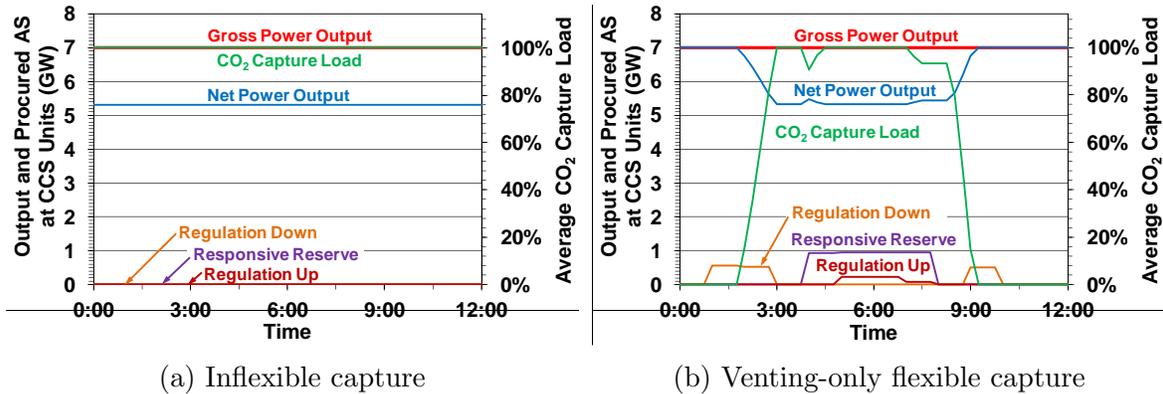


Figure 5.9: Capture flexibility allows facilities with CO₂ capture to provide several ancillary services during the low demand periods. (\$1.54/MMBTU coal, \$4/MMBTU natural gas, \$35/tCO₂)

venting-only flexible capture systems available. With inflexible capture, electricity price equals the marginal cost of the NGCC 2 unit (\$58/MWh) when demand is lowest and the OCGT unit (\$84/MWh) at higher electricity demand. Though OCGT capacity is online during periods of lowest demand, a marginal increase in electricity demand will be met by increasing output at the NGCC 2 facility, so its costs set the electricity price. There are also intermediate electricity prices calculated at the transitions between when NGCC 2 and OCGT set electricity prices. Prices with flexible capture are much more volatile when electricity demand is low and briefly exceed \$100/MWh in a few time periods. Flexible capture shortens the time when prices are steady at \$84/MWh, but volatility exists because prices at low demand often account for CO₂ capture ramping costs or the need to startup or shutdown the OCGT capacity, which incurs \$500/startup. Even though flexible capture reduces overall dispatch costs, in this scenario it actually increases price volatility.

Similar results can be presented for AS prices; however, without assigning direct costs to facilities for AS procurements, AS prices are nonzero only if their procurement influences electricity dispatch costs. This phenomenon does not occur

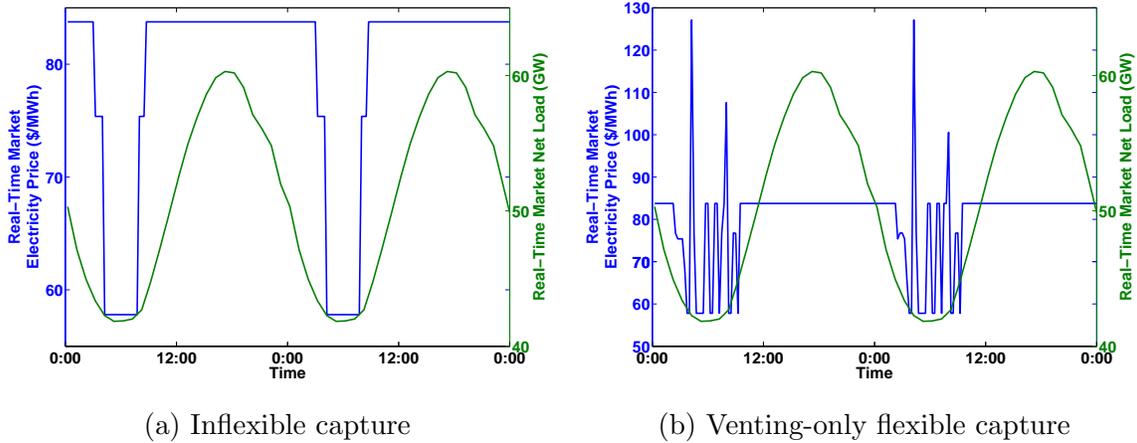


Figure 5.10: Electricity prices are often equal to costs of marginal generation but are also influenced by startup and CO₂ capture ramping costs. (\$1.54/MMBTU coal, \$4/MMBTU natural gas, \$35/tCO₂)

for the conditions and assumptions examined in this section, so all results produce no AS prices across the two-day period regardless of the CO₂ capture configuration.

Under the market conditions examined, results with solvent storage are identical to those with venting-only flexible capture. Additional testing over a wide range of coal, natural gas, and CO₂ prices produced the same result. No conditions were found when the solvent storage systems themselves were utilized, while flexible capture facilities provided energy and AS in a similar manner as venting-only systems. It appears that while solvent storage can be valuable for arbitrage between volatile electricity prices (Chapter 3), solvent storage does not improve the ability to reduce peak demand dispatch costs or procure additional AS. AS procurement ability is a function of CO₂ capture energy requirements, which only change between venting-only and solvent storage systems if stripping/compression systems are oversized or a different capture operating point is used with solvent storage. However, should AS deployment be necessary, the cost of deploying AS would differ between venting-only and solvent storage systems. Such cost differences should influence AS offers in an

actual electricity market. This model does not include AS deployments or offer/bid settlements, so it could underestimate the AS value of solvent storage over venting-only flexible capture.

5.5.2 Flexible Capture for AS and Peak Demand: 2020 ERCOT with 20% Wind

After successfully demonstrating the concept that flexible CO₂ capture can be useful for reducing electricity dispatch costs and providing ancillary services, this section examines which electricity market conditions are conducive to flexible CO₂ capture operation in a least-cost dispatch context. Contrary to profit maximization results, this analysis applies to both regulated and competitive electricity systems. To understand how flexible capture integrates into future electricity systems with several advanced energy technologies, a projected 2020 ERCOT electricity system is modeled with a considerable increase in wind generating capacity. Large penetration of wind-based electricity could introduce greater variability in net electricity load and increase the frequency of time when net demand is nearly or entirely met by firm supply from CHP facilities. Studying flexible capture in this context yields insights into the potential for flexible capture to complement increased renewable electricity.

Electricity dispatch using the 2020 unit-specific database is optimized over four 1-week time periods, one week for each season, to provide a wide range of net electricity load. Results from each week are compared with approximately half of coal-based facilities having (1) no CO₂ capture, (2) inflexible CO₂ capture, (3) venting-only flexible capture, and (4) flexible capture with solvent storage. CAES systems are not included in this section but are considered in Section 5.5.3. Each week with each capture configuration is optimized for five CO₂ prices; \$0/tCO₂, \$30/tCO₂, \$40/tCO₂, \$50/tCO₂, and \$80/tCO₂; and three natural gas prices; \$3/MMBTU, \$4.91/MMBTU,

and \$8/MMBTU. This CO₂ price range spans conditions where capture operation is most economical at both zero load (\$0/tCO₂) and full load (\$80/tCO₂). Natural gas prices include 2020 EIA projection of \$4.91/MMBTU along with low and high prices chosen to span a wide range of conditions. Coal price is again kept constant to reflect its historical stability, and analysis uses the EIA-projected \$2.46/MMBTU coal price for 2020 [USDOE, 2012]. In summary, the analysis requires 240 one-week simulations across the following independent variables: season, capture configuration, CO₂ price, and natural gas price. This large sensitivity analysis identifies fuel price, CO₂ price, and net demand conditions where flexible capture is useful for meeting electricity demand and AS requirements.

5.5.2.1 Electricity System Input Parameters

In addition to the projected 2020 ERCOT generating units described in Section 5.3.2, projections are necessary for 2020 electricity demand, wind production, and AS requirements. These projections are made by adjusting historical 2010 data for projected electricity demand growth and increased wind production to supply roughly 20% of annual generation. There is substantial interest in studying the implications of 20% wind in ERCOT without CO₂ capture, so this analysis complements that research thrust by exploring the effects of flexible capture. All monetary quantities use a 2010 dollar basis to correspond to the source historical data.

Electricity demand from a typical week in each season is chosen for simulation to preserve historical variability without representing extreme situations that are not applicable to normal grid operation. Specific weeks are chosen instead of seasonal averages because averages smooth variability that could be important for studying the impact of fast-responding flexible systems. Extreme cases are avoided because the present goal is understanding the value of flexible capture under com-

monly encountered situations. Future work could explore flexible capture operation during extremes such as annual peak demand or extremely rapid demand changes. The weeks chosen for analysis are listed in Table 5.20. Projections for monthly 2020 demand were provided by ERCOT, and these data are used to determine monthly 2020:2010 demand scale factors. Scale factors are generally higher for summer months than in other times of the year, reflecting the expectation that annual peak demand will grow faster than annual total demand. These scale factors, listed in Table 5.20 for the relevant weeks, are then applied to 2010 15-minute demand data to produce projected 2020 15-minute demand.

Table 5.20: Typical weeks from each season in 2010 are chosen for simulation, and demand is scaled using ERCOT 2020 projections.

Season	Week simulated	2020:2010 demand scaling factor
Winter	February 15–21	1.26
Spring	April 12–18	1.32
Summer	August 9–15	1.38
Fall	October 18–24	1.30

A time series of 2010 ERCOT wind production is scaled to estimate 15-minute wind production in an electricity system where wind supplies 20% of annual electricity demand [ERCOT, 2011a]. To do so, 2010 ERCOT monthly demand is scaled by the 2020:2010 demand factors discussed previously, then historical 2010 monthly wind production is scaled uniformly until total annual wind production supplies 20% of projected 2020 demand. Due to wind turbine capacity factors on the order of 35%, wind production must be scaled by a factor of 3.41 from historical 2010 production [Papalexopoulos et al., 2011]. Average rated wind capacity in 2010 was 9,180 MW, so the modeled wind capacity in 2020 is 31,300 MW [PUCT, 2010]. Though this

quantity is quite high, the rapid ERCOT wind buildout since 2000 suggests it is possible given sufficient incentives. New transmission capacity being built in 2012 specifically for wind interconnection is one major incentive for another substantial increase in ERCOT wind production, as is the growing interest in wind production along the Gulf Coast [ERCOT, 2011c, Papalexopoulos et al., 2011].

Figure 5.11 plots net electricity load and wind production for each of the four chosen weeks. The sum of the two areas is the total electricity demand. There is usually a morning and evening peak demand in the winter, and all other demand curves have an evening peak. The evening peak is particularly high relative to base load in the summer, which experiences the largest ramps of any season. Wind production has a major impact on the net load curve seen by controllable generation. Wind production in the week of February 15–21 varies from nearly zero to roughly half the total electricity demand. Wind production is more stable in the spring week, and net demand falls as low as 12.8 GW on this week. The current mismatch between wind and demand is apparent in the summer week, where wind provides little supply at peak demand and strains grid ramping capabilities by supplying more electricity during periods of low demand. Wind production is also highly variable in the fall, significantly changing the net demand shape from a relatively consistent daily demand curve.

RU and RD requirements for 2020 are determined by adjusting historical 2010 RU/RD requirements provided by the PUCT for the 22,120 MW increase in wind capacity using the Table 5.6 and 5.7 adjustment factors. Lacking any substantial reason for change, the RRS requirement is kept at 2,300 MW. Greater wind penetration could increase net demand uncertainty and hence the need for NSRS (Eqn. 5.77). However, establishing a rigorous method to adjust net demand uncertainty for in-

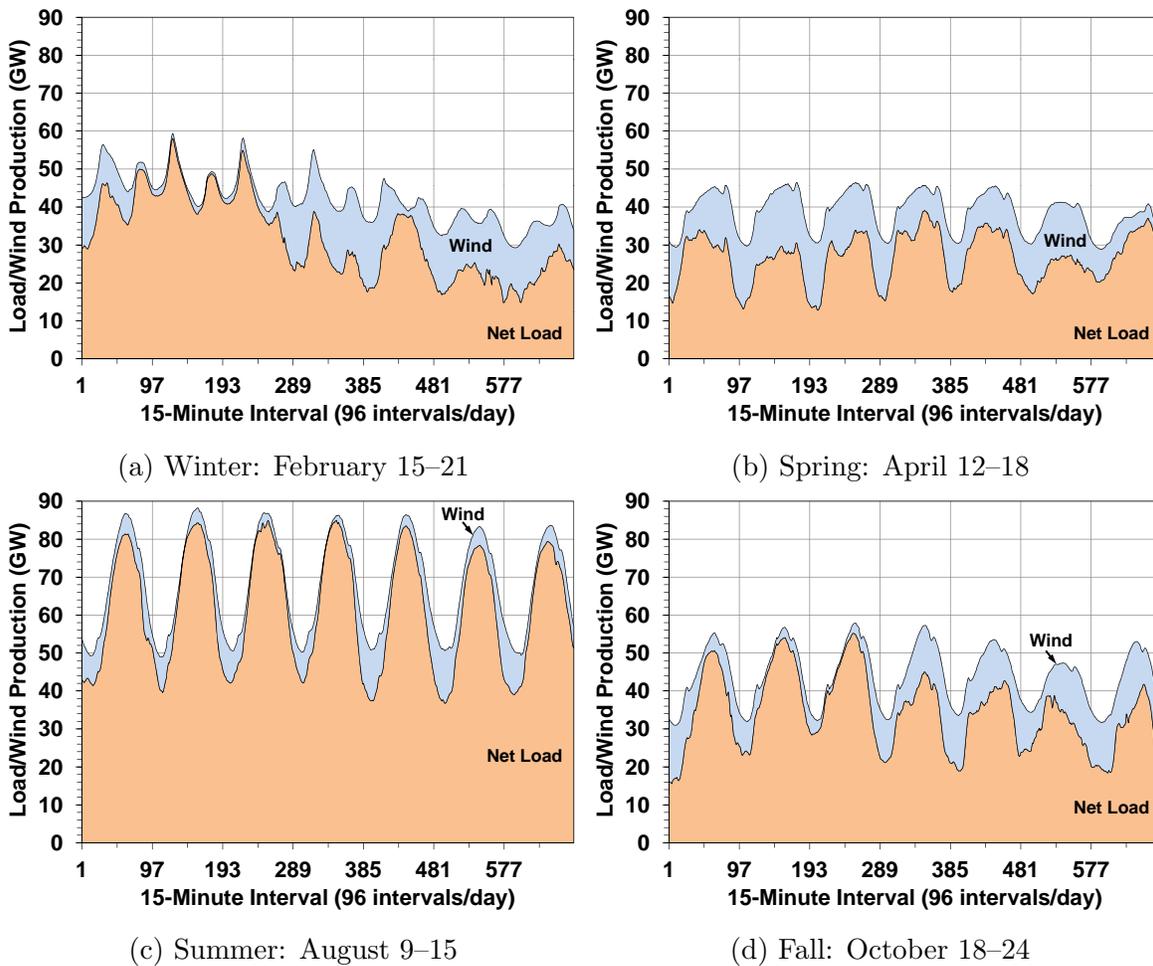


Figure 5.11: Wind variability has a significant effect on projected 2020 net electricity load and can vary considerably by season.

creased wind capacity is outside the scope of this work, so historical 2010 hourly net demand uncertainty is used in the analysis. Net demand uncertainty in 2010 is not reported directly by ERCOT, but Eqn. 5.77 allows back-calculation from historical RU and NSRS procurements provided by the PUCT.

Figure 5.12 displays the resulting AS requirements for each week. AS requirements are highly variable but generally fall between 500 MW and 1500 MW with a few exceptions. NSRS requirements up to 2,000 MW on August 13–15 could have resulted from strained grid conditions on those days in 2010 that are not represented in this model.

The cost model for CO₂ capture systems requires an estimate of average electricity price to calculate CO₂ capture ramping costs. For the profit maximization model with input electricity prices, calculating this quantity is straightforward. However, electricity prices are an output from the unit commitment model. A reasonable estimate for this parameter is thus calculated using results from the electricity price adjustment procedure described in Section 3.1.2. The average pseudo-forecast electricity price under the appropriate CO₂ and gas price combination is assumed a reasonable estimate of the value of electricity in 2020 under those conditions. While not a complete representation of changes in the electricity system between 2010 and 2020, this procedure at least captures the effect of changing fuel and CO₂ prices, which are expected to play a major role in shaping future electricity prices.

5.5.2.2 Optimization Solver Parameters

Experience running weekly simulations with the unit-specific database found that several CPLEX solver parameters are useful to ensure feasible solution convergence. The GAMS relative optimality tolerance is set to 0.001% (`optcr=0.00001`) between the best possible and best feasible solutions, and satisfying this tolerance

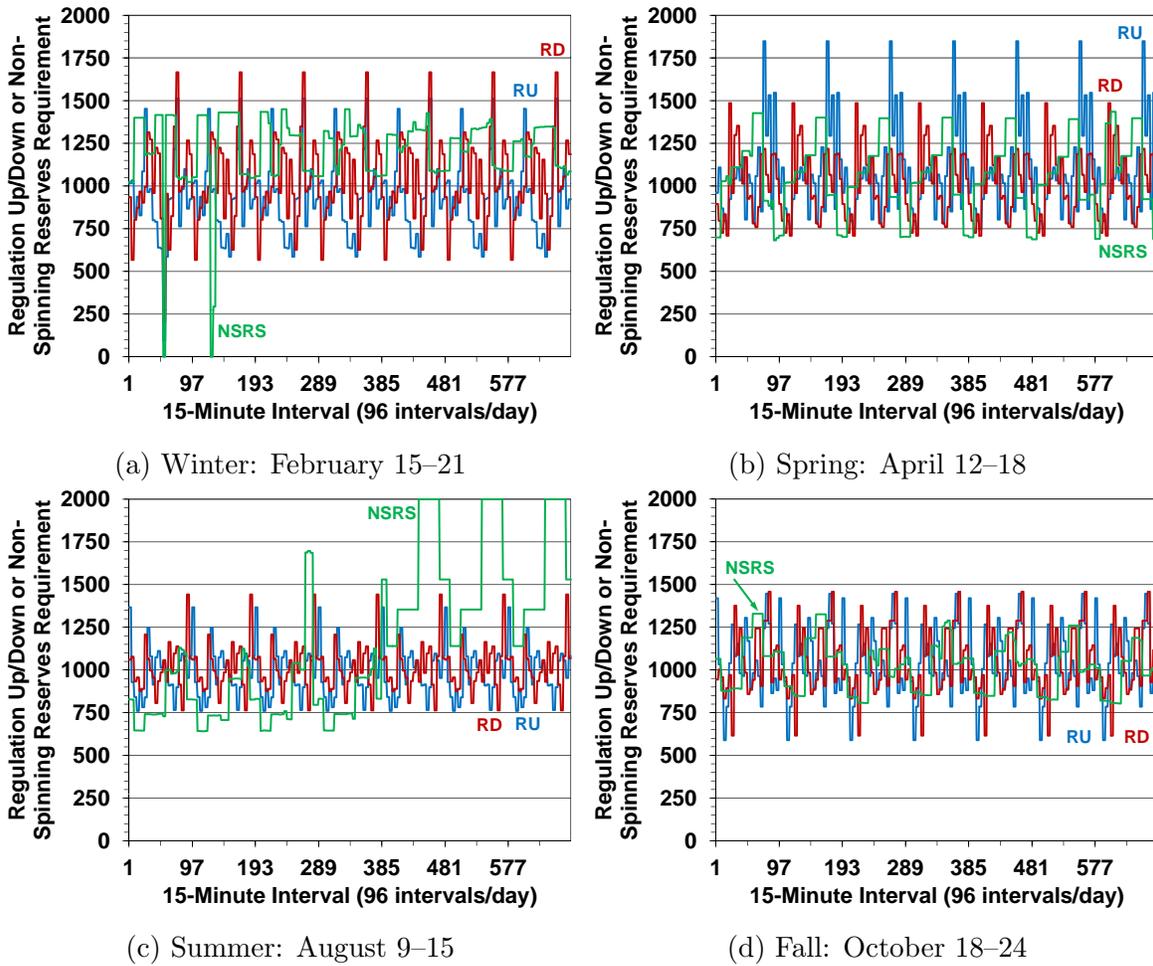


Figure 5.12: Projected 2020 RU, RD, and NSRS requirements in each week typically fall between 500 MW and 1,500 MW for each service.

typically requires 6–11 hours of computation time on the HPCs as described in Section 2.3.1. This tolerance was not always achieved in the forward market optimization on all days, but solutions were accepted as long as electricity demand is not grossly over or undersupplied. Initially, difficulty finding feasible solutions sometimes resulted in binary variables set to nonbinary values on the order of 10^{-7} . Doing so satisfies the default CPLEX integrality tolerance but would typically cause an infeasible constraint in the real-time market. Therefore, the CPLEX parameter `epint` is set to 0 to ensure strict integrality. Doing so risks longer computation time but prevents real-time market infeasibilities due to nonintegrality in the forward market solution. Finally, `relaxfixedinfeas=1` is used to ensure a full solution is reported including marginal values (such as shadow electricity prices) even if there are small infeasibilities in the solution. Consistent success was achieved with these parameters given sufficient computation time for the forward market optimization.

5.5.2.3 Dynamic Behavior with \$40/tCO₂ and \$4.91/MMBTU Natural Gas

This section presents dynamic operation of the electricity system for a single CO₂-natural gas price combination. Before discussing the aggregate impact of flexible capture over the range of conditions studied, dynamic behavior for one scenario demonstrates model functionality with the unit-specific database and introduces several phenomena that influence higher-level aggregate results. Electricity system operation is compared when CO₂ capture systems (1) are inflexible and (2) have venting-only flexibility for summer and winter demand/AS requirements. Operation with solvent storage is both qualitatively and quantitatively similar to that with venting-only flexible capture. There are quantitative differences when no facilities have CO₂ capture systems, but since results are qualitatively similar, figures for this

configuration are omitted. All major observable phenomena take place in the summer and winter with \$40/tCO₂ and \$4.91/MMBTU natural gas, so data are not shown for spring and fall.

Results for the summer are discussed first. For demonstration purposes, Fig. 5.13 displays net output by individual unit for the first two days in the summer week (August 9–15) with venting-only flexible capture. Each color represents a generating unit. Net demand is met by supply, and abrupt shifts indicate unit startups and shutdowns, which can only occur at the beginning of each hour. Given the data density, there is no discernible difference between Fig. 5.13 and the corresponding figure with inflexible capture.

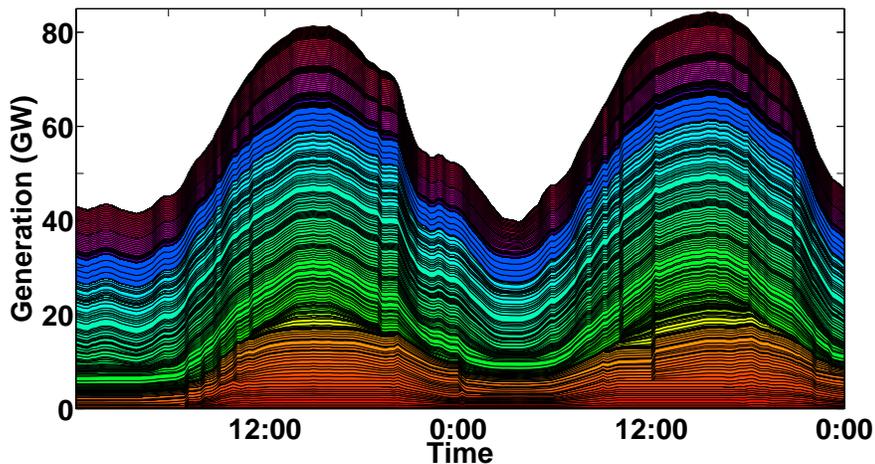


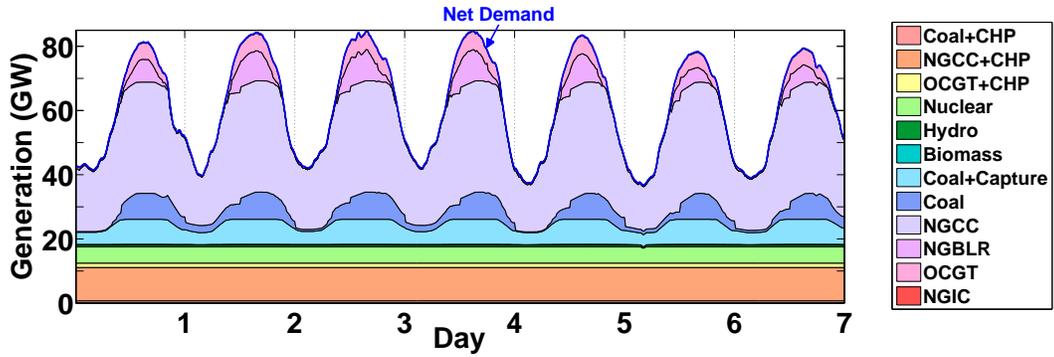
Figure 5.13: Electricity dispatch by individual unit for the first two summer days demonstrates the capabilities of the unit commitment model. Each color represents a generating unit.

Figure 5.14 displays generation data aggregated by plant type for the entire summer week with inflexible and venting-only flexible capture installed on half the coal-fired capacity. Midnight on each day is indicated on the x-axis. The qualitative

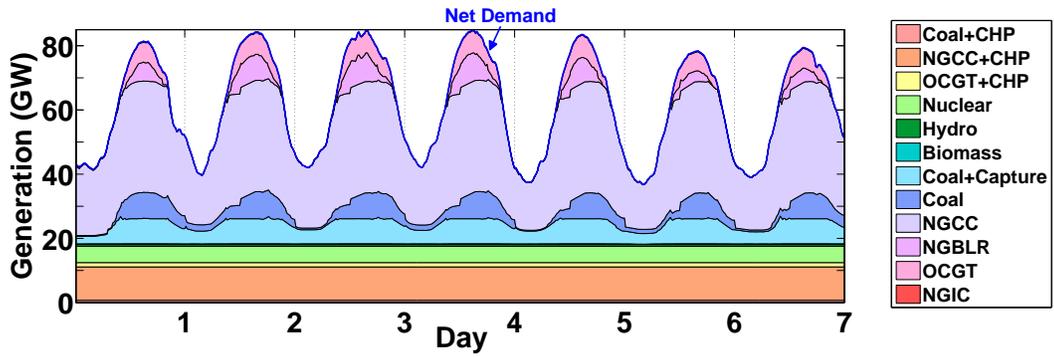
differences between output are small. CHP capacity must operate at full load, so its output is constant. Nuclear and hydroelectric facilities also continuously operate at maximum output. At \$40/tCO₂, operating costs are lower for coal-fired facilities with CO₂ capture than without, so coal+capture units provide intermediate load in both cases, while coal without capture typically shuts down or operates at minimum output when demand is low and operates consistently at high output only when demand is above ~70 GW. NGCC units supply the bulk of intermediate electricity load. Peak demand is also satisfied by gas-fired boiler units (NGBLR) and additional OCGT capacity along with some NGIC output during the highest peaks each day.

When coal+capture facilities have venting-only flexible capture, there are several irregular increases and decreases in output throughout the week; these instances correspond to times when capture systems are ramping up or down to decrease total dispatch costs. This result indicates that even in a realistic electricity system, flexible capture could be useful for responding to changes in demand in the absence of a profit motive.

Figure 5.15 demonstrates operation at facilities with CO₂ capture by plotting the percent load on CO₂ capture systems over time for each CO₂ capture facility. Each colored line represents a different facility. Also plotted are the shadow electricity prices from the real-time market optimization. Electricity prices generally trend with electricity demand, with volatility representing the contribution of startup costs and penalties on electricity undersupply. Units are committed in response to hourly average net demand, which does not always commit enough online units to respond to rapid changes in electricity demand. When online units cannot ramp fast enough to meet a change in demand, there is electricity undersupply, and the shadow electricity price is set using the penalty curve shown in Fig. 5.2. Price spikes indicate times when



(a) Inflexible capture



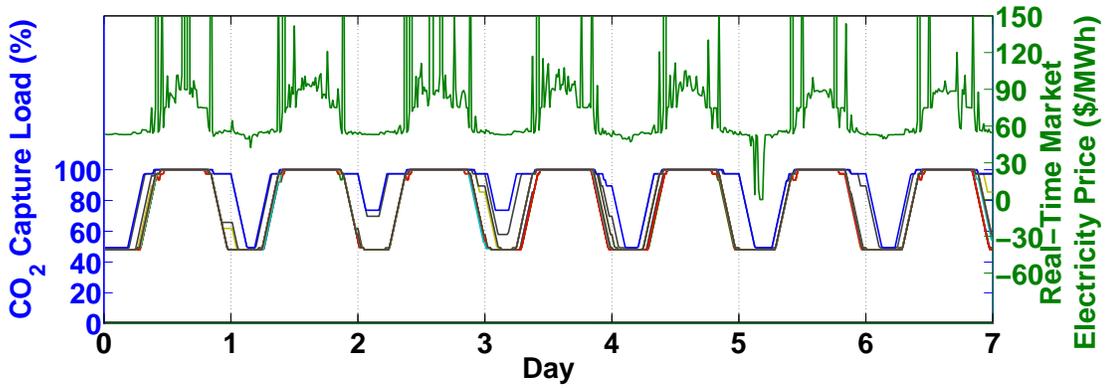
(b) Venting-only flexible capture

Figure 5.14: With venting-only flexible capture, irregularities in output indicate when capture system ramping is used to decrease system dispatch costs. (Summer: \$2.54/MMBTU coal, \$4.91/MMBTU natural gas, \$40/tCO₂)

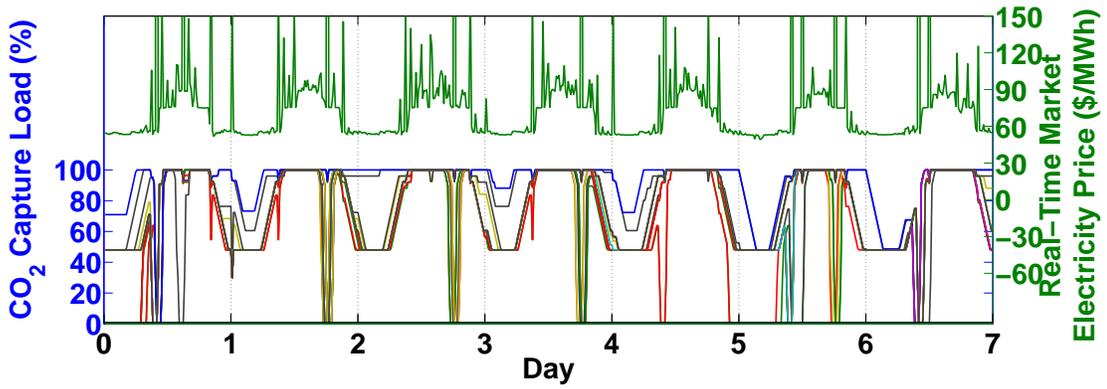
AS deployments might be necessary. The model includes only AS procurements, not deployments, so price spikes occur more frequently than typically observed in historical data. There is also one instance on day 6 with inflexible capture when prices drop to \$0/MWh because facilities cannot ramp down fast enough to respond to an abrupt drop in demand. In this situation, oversupply is imminent, so the shadow price of electricity drops to zero.

Online units with CO₂ capture typically operate at minimum load when electricity demand is low; 48% CO₂ capture load indicates that the base plant is at its minimum output, with capture load equaling fractional base plant load. With inflexible capture, capture ramps to 100% load during peak electricity demand when the base plant ramps up to produce additional electricity. Flexible CO₂ capture systems also ramp with the base plant, but there are several instances where capture systems ramp down or briefly turn off. These events coincide with high electricity prices. When the marginal cost of electricity production increases drastically, electricity dispatch costs are lower with capture at 0% load than at 100% load. In a competitive market, this behavior corresponds to turning capture systems off when electricity prices are high, but these results indicate similar behavior being valuable in a least-cost dispatch framework.

Figure 5.16 plots regulation up by plant type in the summer week with inflexible and venting-only flexible capture. The blue line provides the RU requirement over time. Regulation up service is usually provided by marginal generating units, which are typically NGCC and OCGT facilities with some contribution from NGIC units. With inflexible capture, RU is over-procured and used towards the RRS requirement when electricity demand is high, which is allowed by Eqn. 5.76. Though costs on the order of 10^{-5} are assessed for AS procurements in order of $RU, RD >$



(a) Inflexible capture



(b) Venting-only flexible capture

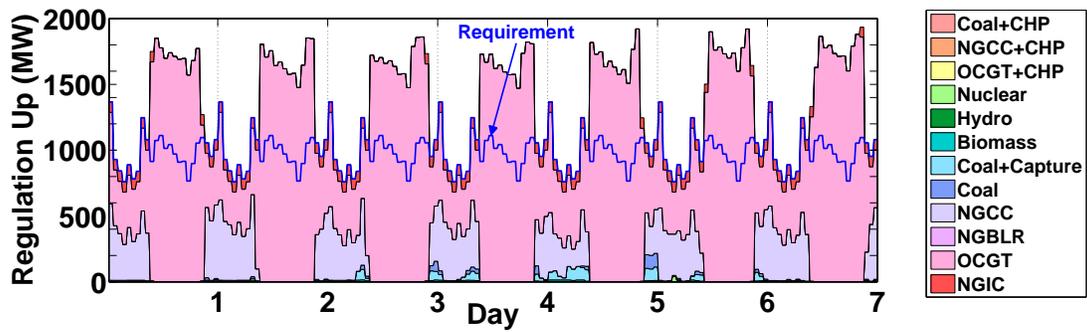
Figure 5.15: Flexible capture responds to high marginal dispatch costs (electricity prices) by reducing CO₂ capture load. Each capture load line represents a different unit with CO₂ capture. (Summer: \$2.54/MMBTU coal, \$4.91/MMBTU natural gas, \$40/tCO₂)

RRS > NSRS, over-procuring RU has lower costs than meeting all AS requirements independently in some cases. In an actual market with offers and bids, these costs would be more clearly differentiated, and less over-procurement should occur. Lack of substantial cost differentiation between RU, RRS, and NSRS in the current model motivates their consideration together as “up” ancillary services. With venting-only flexible capture, units with capture systems also provide some RU service at both low and high electricity demand. When demand is low, capture units are marginal. However, RU is provided during 100% load capture because a facility with capture can offer the ability to increase its output by turning capture systems to partial or zero load.

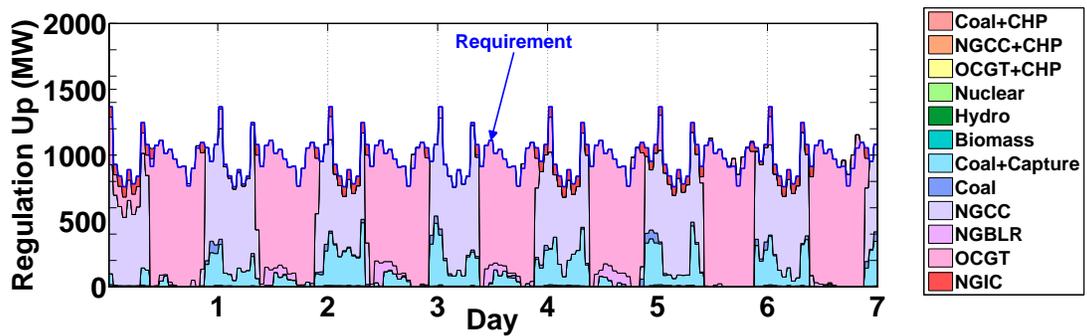
RRS procurements follow similar patterns as RU (Fig. 5.17). RRS appears under-procured when electricity demand is high, but total RRS requirements are satisfied by over-procuring RU. Coal-fired facilities with and without CO₂ capture provide some RRS when capture systems are inflexible because these units are often marginal. However, a great deal more RRS is provided by capture-equipped units when capture systems are flexible. Under these conditions, the ability to reduce capture load allows much greater opportunity to offer into the RRS market.

NSRS procurements are primarily met by marginal NGCC, NGBLR, Coal, and NGIC units. The blue line in Figure 5.18 is the required sum of RU and NSRS by Eqn. 5.77, so the figure also plots the RU contribution to this total. Coal-based units without capture provide some NSRS because they can do so while offline. Unlike RU and RRS, coal-based units with capture are not significantly utilized for NSRS with any capture configuration.

Figure 5.19 plots regulation down procurements over time with inflexible and venting-only flexible capture. RD is typically provided by base load units with the

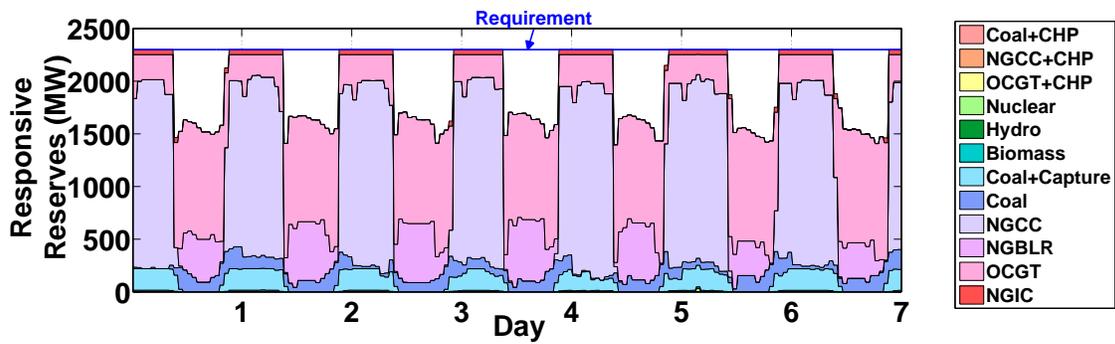


(a) Inflexible capture

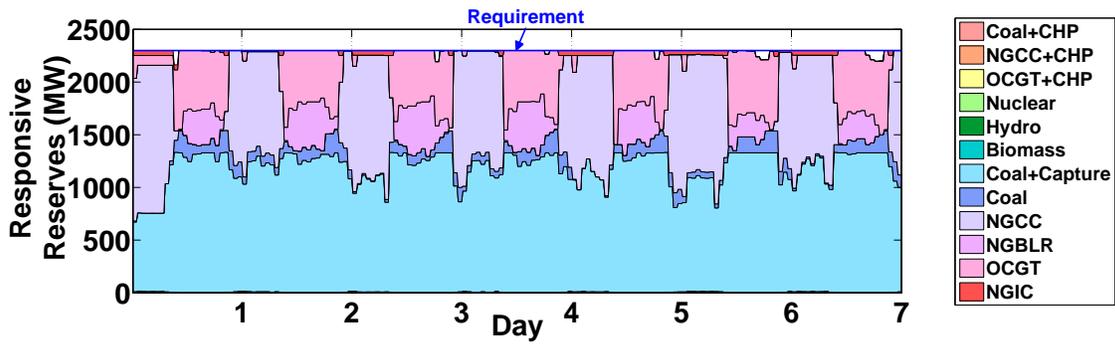


(b) Venting-only flexible capture

Figure 5.16: Regulation up is over-procured with inflexible capture to contribute towards RRS requirements, and flexibility allows coal+capture units to provide more RU service. (Summer: \$2.54/MMBTU coal, \$4.91/MMBTU natural gas, \$40/tCO₂)

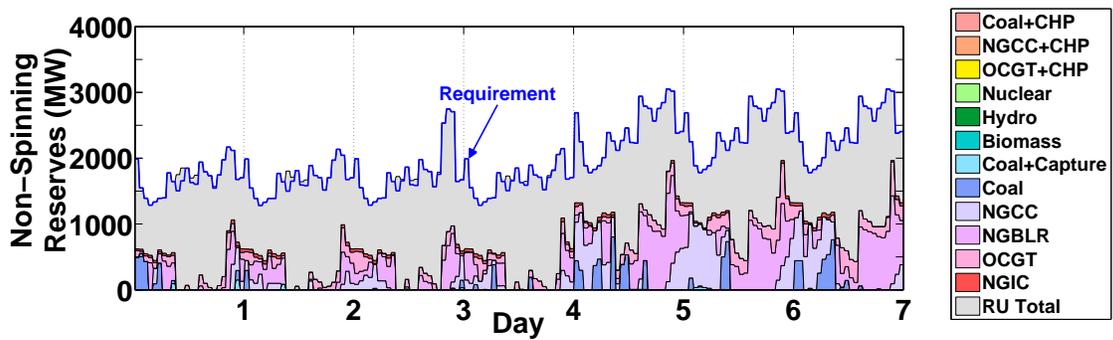


(a) Inflexible capture

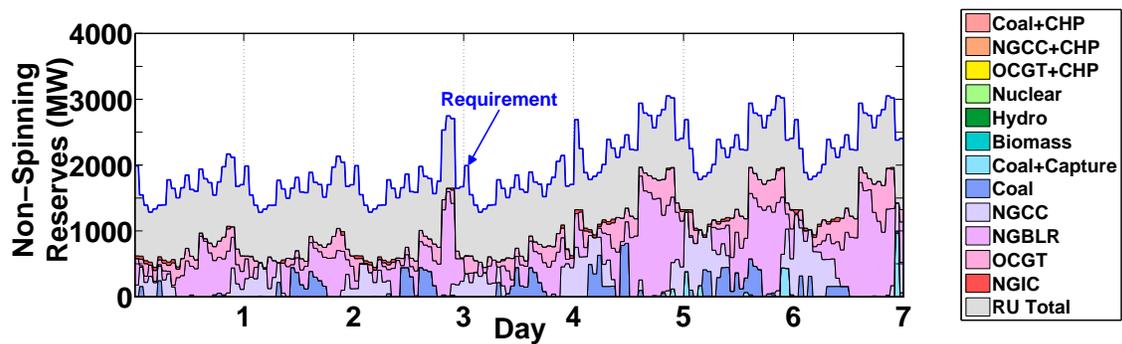


(b) Venting-only flexible capture

Figure 5.17: Coal+capture units provide a substantial share of RRS when flexible units can offer the energy requirement for capture as available capacity. (Summer: \$2.54/MMBTU coal, \$4.91/MMBTU natural gas, \$40/tCO₂)



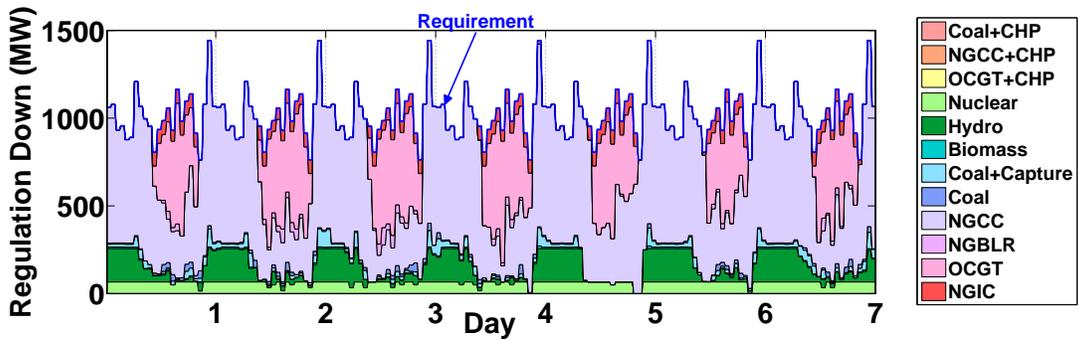
(a) Inflexible capture



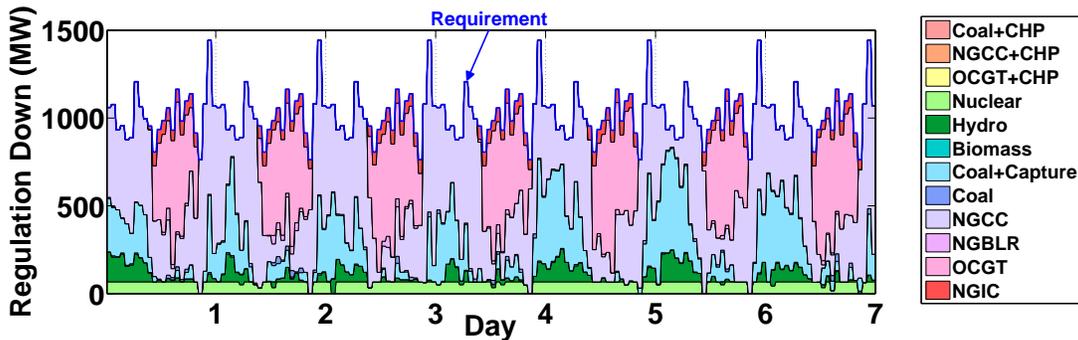
(b) Venting-only flexible capture

Figure 5.18: Non-spinning reserve service is primarily supplied by marginal coal- and gas-fired facilities, not coal+capture units. (Summer: \$2.54/MMBTU coal, \$4.91/MMBTU natural gas, \$40/tCO₂)

ability to reduce net electrical output. CHP units may not provide RD because they are assumed to run continuously at maximum output without the ability to reduce output. Thus, RD is primarily provided by base load nuclear, hydro, and NGCC capacity but also comes from OCGT or NGIC capacity when units are online above their minimum load. Coal-based units with flexible capture provide more RD than with inflexible capture because capture systems allow reduced net output by increasing CO₂ capture load.



(a) Inflexible capture



(b) Venting-only flexible capture

Figure 5.19: Flexible capture systems increase RD offer capability if capture load can be increased to reduce net electrical output. (Summer: \$2.54/MMBTU coal, \$4.91/MMBTU natural gas, \$40/tCO₂)

The next set of figures repeats the same set of results for the winter week of February 15–21. Generation by individual unit is plotted for February 15–16 in

Fig. 5.20 when CO₂ capture facilities have venting-only flexibility. The analogous figure with inflexible capture is qualitatively similar. Again, this figure is primarily for demonstration purposes, and seemingly abrupt shifts represent plant startups and shutdowns.

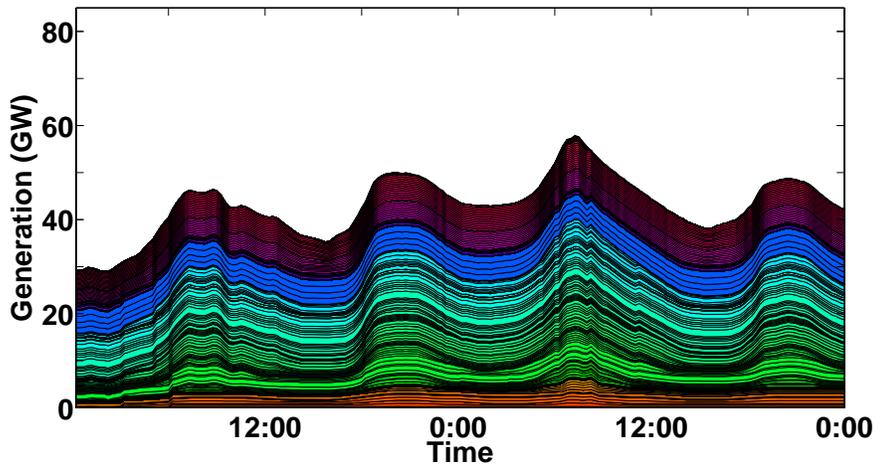


Figure 5.20: Unit-specific generation for the first two winter days displays electricity demand and two demand peaks each day. Each color represents a generating unit.

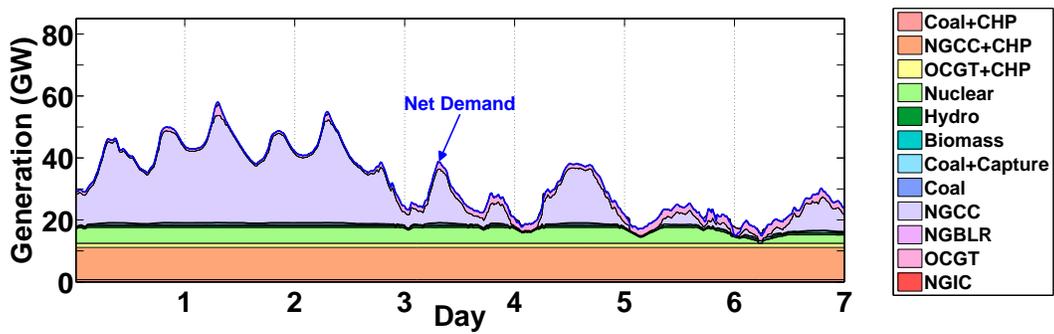
Generation in the winter week with inflexible and venting-only flexible capture after aggregating by plant type is shown in Fig. 5.21 on the same scale as the corresponding figure for the summer (Fig. 5.14). While total demand follows a repeatable pattern, high wind production on February 18–21 causes a significant drop in net electricity demand on these days. At the lowest net demand levels, electricity demand is met almost entirely by fixed CHP supply, and even nuclear-powered units must ramp down to avoid electricity oversupply. In practice, wind electricity production would likely be curtailed under these circumstances. Wind production is a fixed input parameter in the model, but future work could incorporate wind curtailment for times with low net demand. When net electrical load is higher, most intermediate and

peaking load is met by NGCC units, with lower-cost OCGT capacity being online to provide some electricity and satisfy AS requirements. Coal-based units without CO₂ capture are almost entirely displaced by gas-fired capacity at these demand levels and market conditions (\$40/tCO₂, \$4.91/MMBTU natural gas, \$2.46/MMBTU coal).

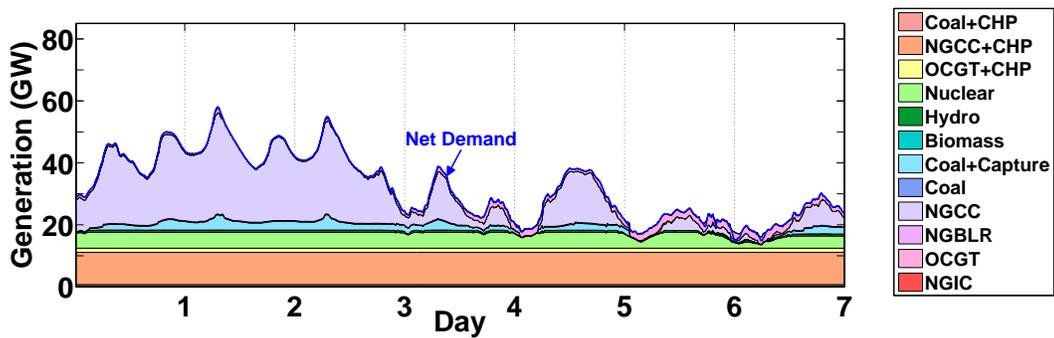
Though coal-based operating cost are lower with CO₂ capture, very little electricity demand is met with coal+capture facilities when capture systems are inflexible. However, these units supply a noticeable share of electricity when flexible, particularly at higher winter net demand levels. Reasons for this behavior are made clear in the following figures, but these results demonstrate that capture flexibility can increase the overall utilization of power systems.

Figure 5.22 plots real-time shadow prices of electricity along with percent CO₂ capture load at each capture facility. Electricity prices are relatively consistent around \$50–60/MWh at higher net electricity load, but prices are very volatile at low net load. When net demand is low, very few gas-fired units with fast ramp rates are available to respond to changes in electricity demand, so electricity prices are strongly influenced by startup costs and supply/demand imbalance penalties. The challenge of satisfying low net demand is also observed in the form of computational difficulty for winter simulations. This phenomenon demonstrates the potential electricity price impacts with large quantities of wind generation and low electricity demand. Wind curtailment could mitigate price volatility, or AS deployments might be necessary. There are also several time periods where electricity price is negative. These instances represent oversupply of electricity. Ramp limits, minimum load constraints, and minimum runtime constraints prevent further reduction in electricity supply, so the \$250/MWh oversupply penalty is applied.

Only one facility with CO₂ capture operates when capture systems are inflexi-



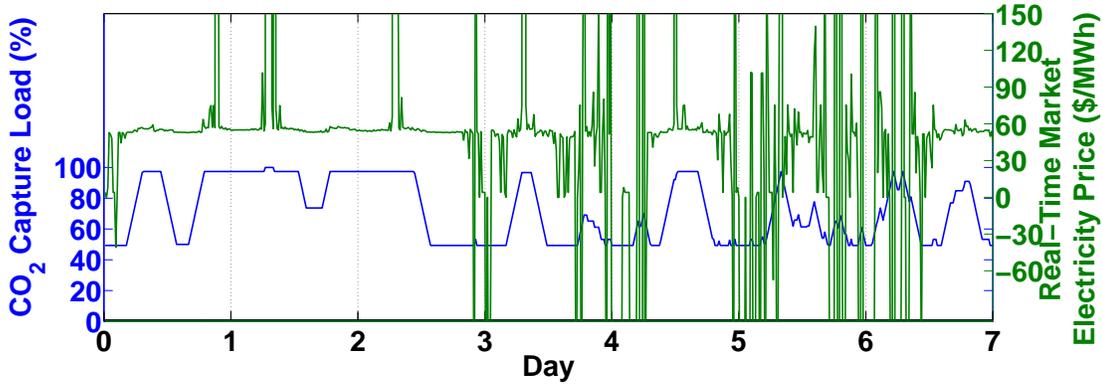
(a) Inflexible capture



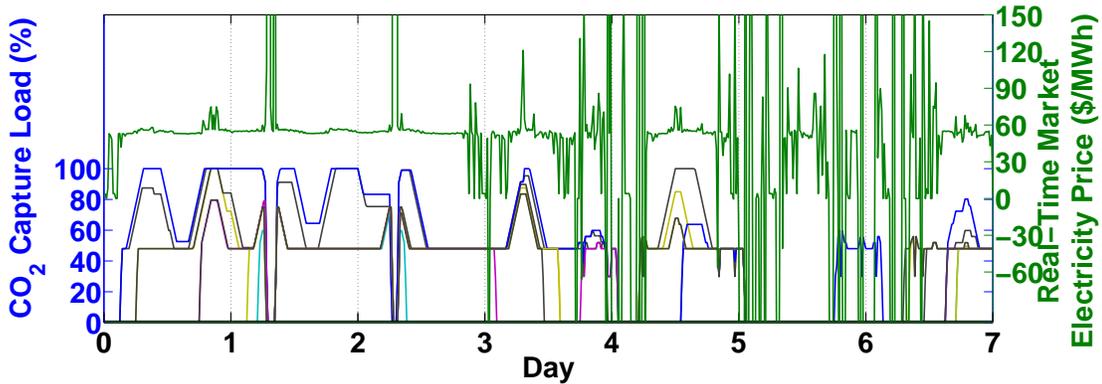
(b) Venting-only flexible capture

Figure 5.21: Coal+capture units are utilized more often at low and intermediate electricity demand when capture systems are flexible. (Winter: \$2.54/MMBTU coal, \$4.91/MMBTU natural gas, \$40/tCO₂)

ble, and its load follows base plant fractional load. With venting-only capture, many more capture facilities are online. With venting-only flexible capture, load generally equals fractional base plant load, but there are high-price times when partial-capture load is utilized to reduce overall dispatch costs.



(a) Inflexible capture

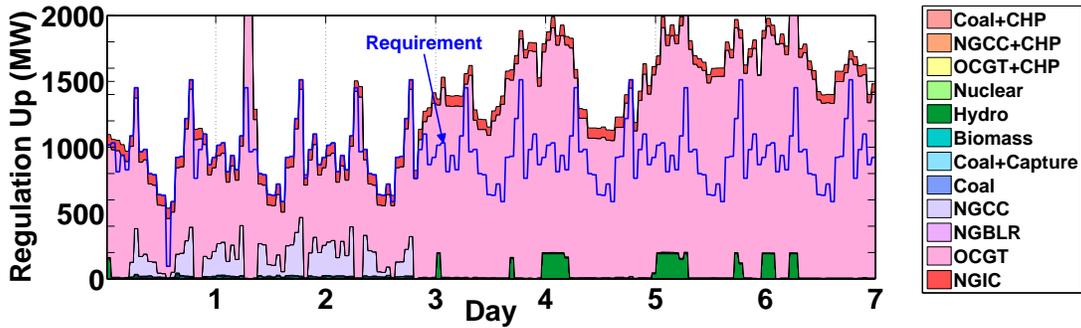


(b) Venting-only flexible capture

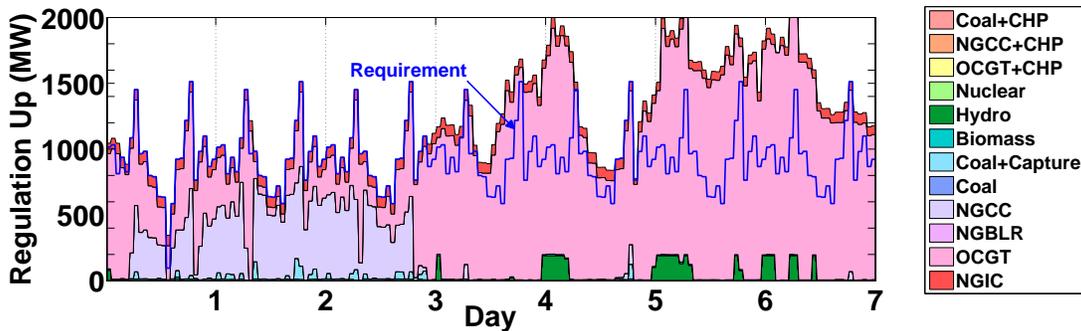
Figure 5.22: Electricity prices are very volatile when net electricity demand is low. Flexible capture sometimes reduces load during high marginal dispatch costs even in the winter. Each capture load line represents a different unit. (Winter: \$2.54/MMBTU coal, \$4.91/MMBTU natural gas, \$40/tCO₂)

Regulation up is again provided by marginal generating units, which is primarily OCGT capacity (Fig. 5.23). NGIC provides some RU throughout the week as well. In contrast with the summer, nuclear capacity also provides a portion of RU

when high wind production significantly reduces net electricity demand and forces nuclear facilities to decrease output. NGCC facilities also provide RU when marginal at higher winter demand, and coal+capture facilities provide a small amount of RU in these time periods. Similar to the summer, RU is often over-procured to meet overall RU, RRS, and NSRS requirements.



(a) Inflexible capture

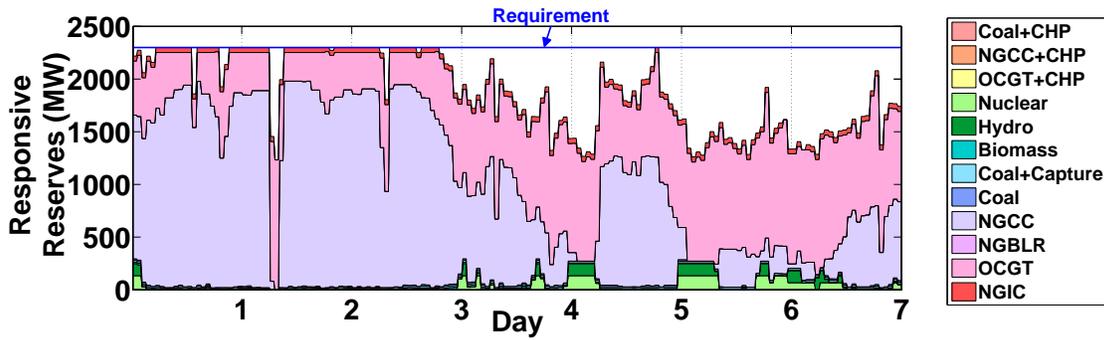


(b) Venting-only flexible capture

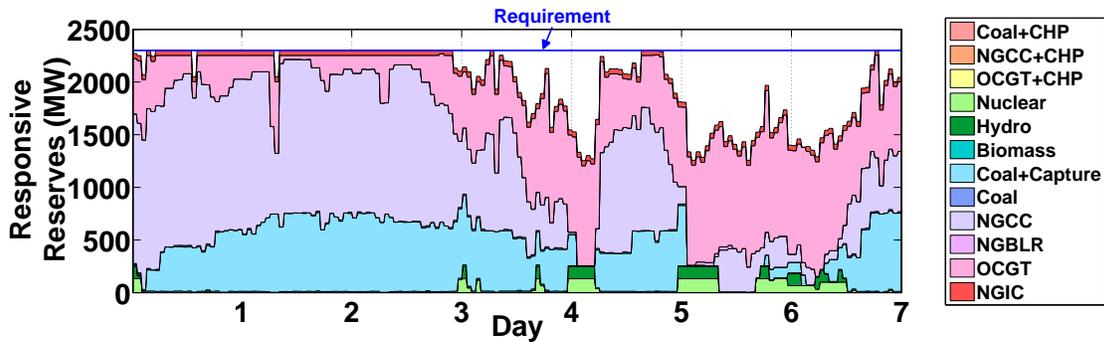
Figure 5.23: Regulation up is over-procured at low net demand to contribute to responsive reserve supply, and coal+capture units provide little RU service in either configuration. (Winter: \$2.54/MMBTU coal, \$4.91/MMBTU natural gas, \$40/tCO₂)

RRS procurements reveal the primary difference between the inflexible and venting-only capture scenarios (Fig. 5.24). A large share of RRS is supplied by OCGT and NGCC units as well as nuclear units at periods of low net demand. Coal+capture units provide a negligible quantity of RRS when inflexible, but a signifi-

cant portion of RRS is supplied by these units when capture is flexible. Though most coal+capture units are offline with inflexible capture, they are online with flexible capture primarily to provide ancillary services. Even when facilities are uneconomical to operate without CO₂ capture or with inflexible CO₂ capture, capture flexibility increases the overall plant utilization with its ability to provide greater quantities of ancillary services.



(a) Inflexible capture

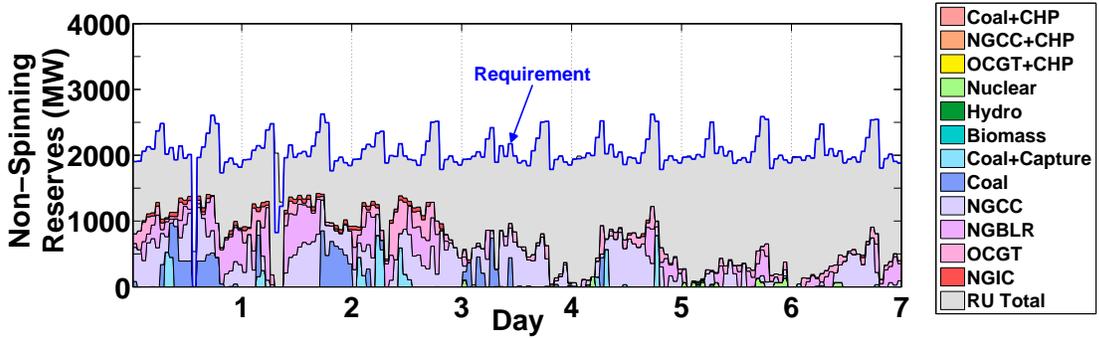


(b) Venting-only flexible capture

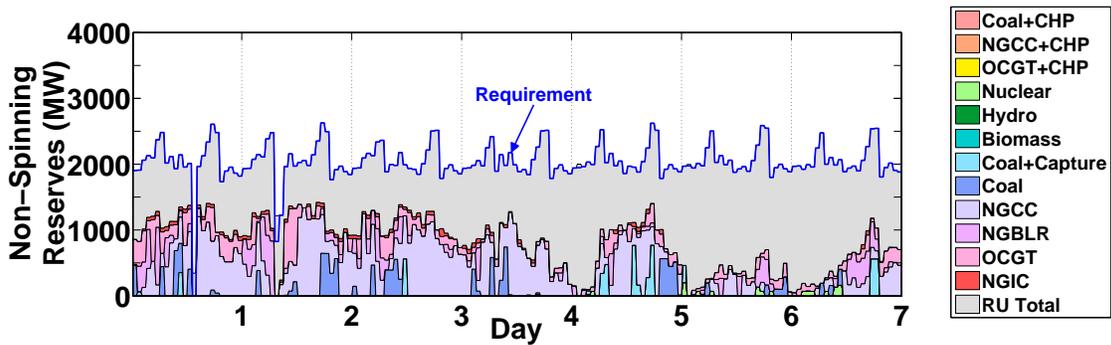
Figure 5.24: Flexible coal+capture units are online primarily to provide RRS, which is why plant utilization is higher than with inflexible capture. (Winter: \$2.54/MMBTU coal, \$4.91/MMBTU natural gas, \$40/tCO₂)

Much of the NSRS+RU requirement is met with RU procurements, and the remainder is supplied mostly by a combination of NGCC, OCGT, NGBLR, and coal-based units with and without CO₂ capture (Fig. 5.25). There is little change in NSRS

procurements with capture configuration.



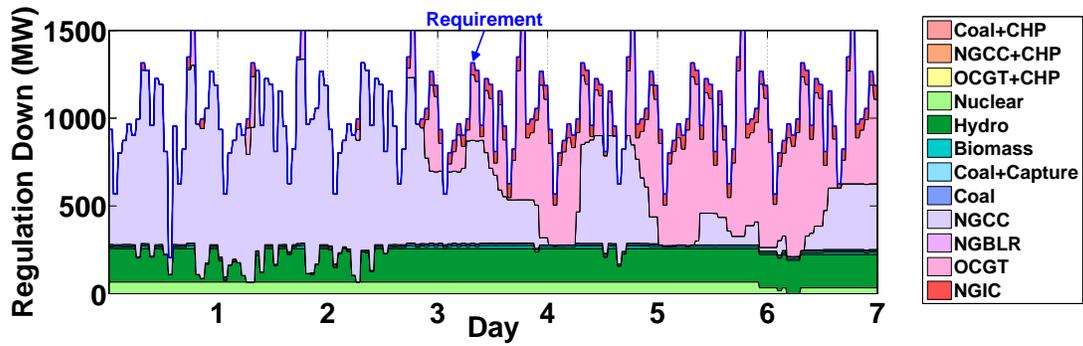
(a) Inflexible capture



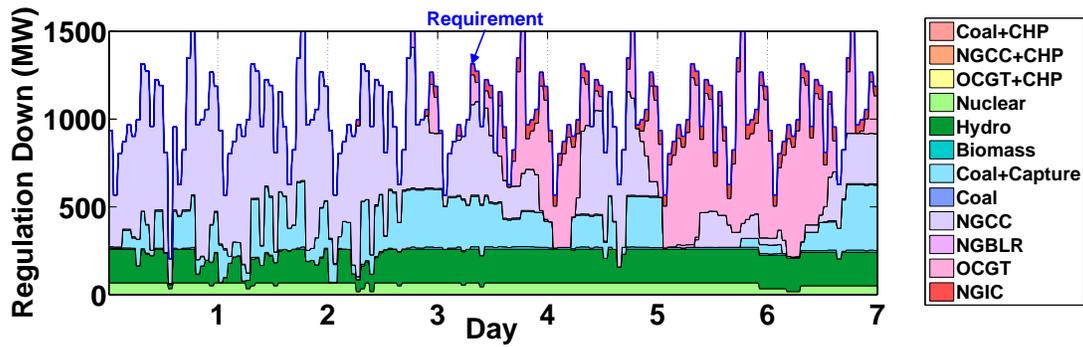
(b) Venting-only flexible capture

Figure 5.25: NSRS procurements do not change substantially with capture configuration. (Winter: \$2.54/MMBTU coal, \$4.91/MMBTU natural gas, \$40/tCO₂)

Figure 5.26 plots RD procurements, which are again supplied in large part by base load units with the ability to reduce output towards their minimum generation. Coal+capture units provide significantly more RD when flexible. Flexible capture allows RD offers even at minimum base plant load because net output could fall further if capture energy requirement is increased. This model does not represent the process implications of overstripping CO₂ to reduce net power output, but the ability to do so is reflected in RD offer limits.



(a) Inflexible capture



(b) Venting-only flexible capture

Figure 5.26: Coal+capture units provide much more RD in the winter when flexible capture systems allow the ability to increase capture energy requirements to reduce net power output. (Winter: \$2.54/MMBTU coal, \$4.91/MMBTU natural gas, \$40/tCO₂)

5.5.2.4 CO₂ Price Sensitivity in Winter with \$4.91/MMBTU Natural Gas

This section plots energy and AS totals by plant type across CO₂ prices with \$4.91/MMBTU natural gas. These results represent an intermediate step in data aggregation before displaying performance statistics for all market conditions. Results are compared with each capture configuration for the winter week of February 15–21. Winter is displayed exclusively because large variations in wind production produce a wide range of net demand, so all major phenomena are demonstrated.

Figure 5.27 plots total generation by plant type for each CO₂ price and capture configuration. In all cases, a large portion of electricity demand is supplied by CHP and nuclear generation, and OCGT capacity provides peaking power. Key differences exist between output from NGCC facilities and coal-fired units with and without capture. Without CO₂ capture, coal-based units supply a substantial share of electricity demand at \$0/CO₂, but these facilities are almost entirely displaced by NGCC units at \$30/tCO₂ and above. Coal-based units without capture are necessary to meet peak summer demand, but emissions costs prevent their utilization with winter demand. With inflexible capture, output from coal+capture facilities increases with CO₂ price, but output share is substantial only at \$80/tCO₂. Though operating costs are lower with capture than without at \$30/tCO₂ and above, capture facilities are still more expensive to operate than many gas-fired facilities at intermediate CO₂ prices.

For both flexible capture configurations, coal+capture facilities operate most frequently at low and high CO₂ prices. Capture systems remain offline at \$0/tCO₂, so output matches the no capture configuration. Capture systems generally run at the maximum possible load for all other CO₂ prices, though gas-fired units are typically less expensive except at \$80/tCO₂. However, output from these units is greatest with flexible capture at intermediate CO₂ prices. Under these conditions, flexibility

increases overall utilization of facilities with capture by increasing their ability to procure ancillary services and respond to demand variations. Enhanced grid flexibility is observed by comparing results for inflexible and flexible capture at \$80/tCO₂. Nuclear output is lower and OCGT output greater with inflexible capture because difficulty satisfying plant constraints at low net demand requires shutting down nuclear units in the inflexible case, which invokes a 24 hour minimum downtime constraint. Flexible capture can respond to demand variations at low net demand, but OCGT units are necessary with inflexible capture.

Differences are indistinguishable between the venting-only and solvent storage configurations. Though results are not identical due to the greater capture energy requirement with solvent storage, solvent storage does not change aggregate results because the solvent storage systems themselves are never utilized. Though solvent storage is valuable in responding to electricity prices, it appears unable to reduce electricity dispatch costs in this model. The cost penalty for stored solvent regeneration appears too great to justify using stored lean solvent to temporarily reduce stripping and compression load and increase net output. Solvent storage also has no effect on AS procurement ability. AS offers are based on available capacity to increase or decrease output, and this ability does not change substantially with solvent storage unless oversized equipment increases the capacity to reduce output and offer more RD. This effect is not observed, as equipment is not oversized in this analysis. Solvent storage might be practically useful if AS deployments are needed because additional output would not necessarily increase CO₂ emissions costs. This model does not include AS deployments, so further study is required to confirm this hypothesis.

Figure 5.28 demonstrates the impact of capture flexibility on AS provision by plotting the share of total RU, RRS, and NSRS procured from each plant type. The

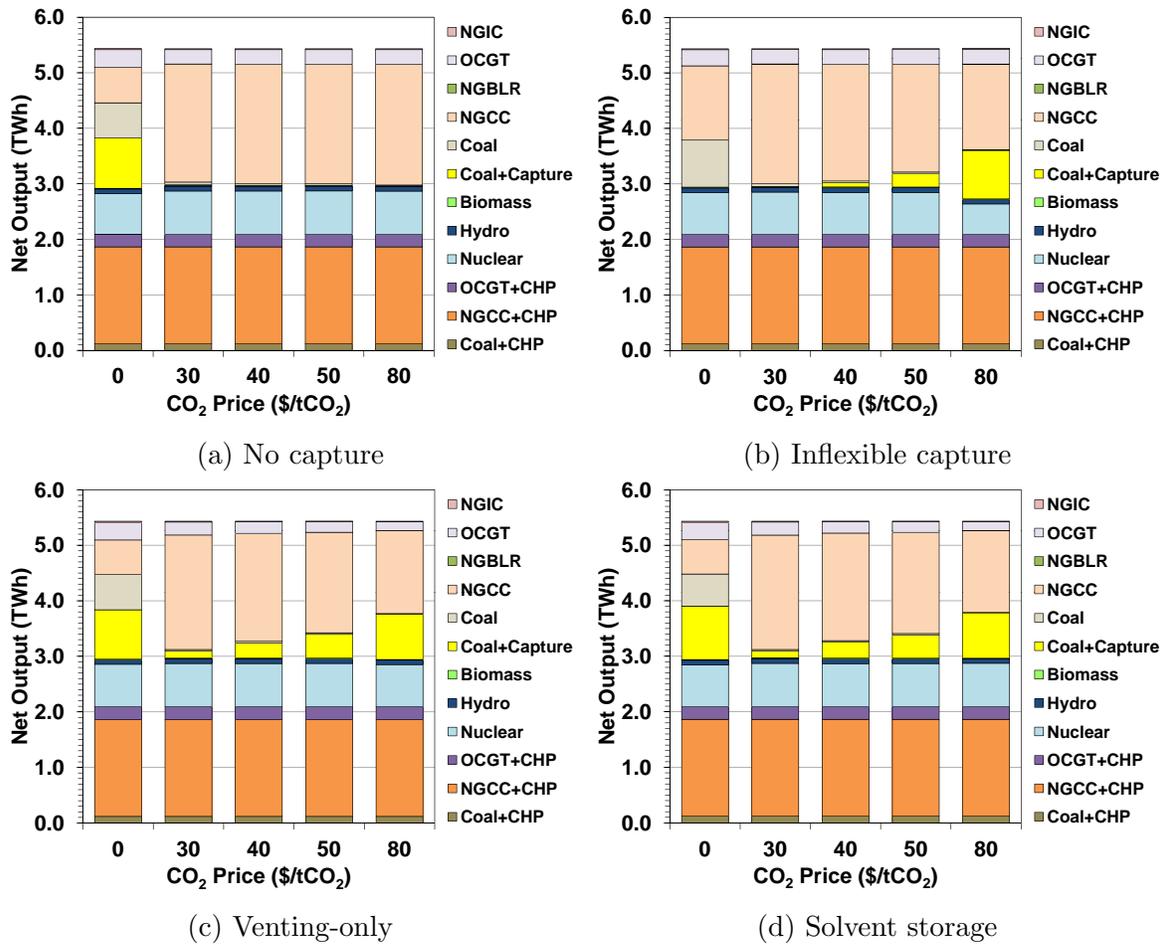


Figure 5.27: CO₂ prices dictate utilization of coal+capture units, and capture flexibility increases plant utilization at intermediate CO₂ prices. (Winter: \$2.54/MMBTU coal, \$4.91/MMBTU natural gas)

total of these AS is useful to consider because other than a slight difference in cost penalty, these AS are indistinguishable in the model. RU, RRS, and NSRS procured primarily from marginal generating units, so OCGT and NGCC are the primary contributors. Gas boilers and NGIC units also consistently provide a small quantity of these services. Some procurements also come from hydroelectric and nuclear units when net demand is lowest. Hydroelectric units are more often used for low-cost peak supply and water resource maintenance, but these effects are not included because hydroelectricity plays a relatively small role in the ERCOT system. Coal-fired units without capture are marginal or offline in all cases but can provide AS at high CO₂ prices if NSRS is procured while offline.

When CO₂ prices are high, AS procurements from coal+capture units are greater with inflexible than no capture because units are online more often and marginal. These facilities provide substantially more AS when capture systems are flexible, with the share of RU+RRS+NSRS increasing with CO₂ price as the facilities are utilized more often. The increased AS offer capability derived from flexible CO₂ capture increases base plant utilization across a wide range of CO₂ prices.

Figure 5.29 compares RD procurements by plant type across CO₂ prices and capture configurations. Regulation down is primarily supplied by lowest-cost generation, which includes nuclear, hydroelectric, NGCC, and OCGT capacity in all cases. Coal-fired units without CO₂ capture rarely provide RD because they operate infrequently at \$30/tCO₂ and above. Coal-fired units with inflexible capture provide no significant quantities of RD except at \$80/tCO₂ when plant utilization is greater. However, flexible coal+capture units provide substantial RD service across all CO₂ prices. The ability to reduce net electrical output by increasing capture energy allows these facilities to provide up to 38% of the total RD requirement at \$80/tCO₂.

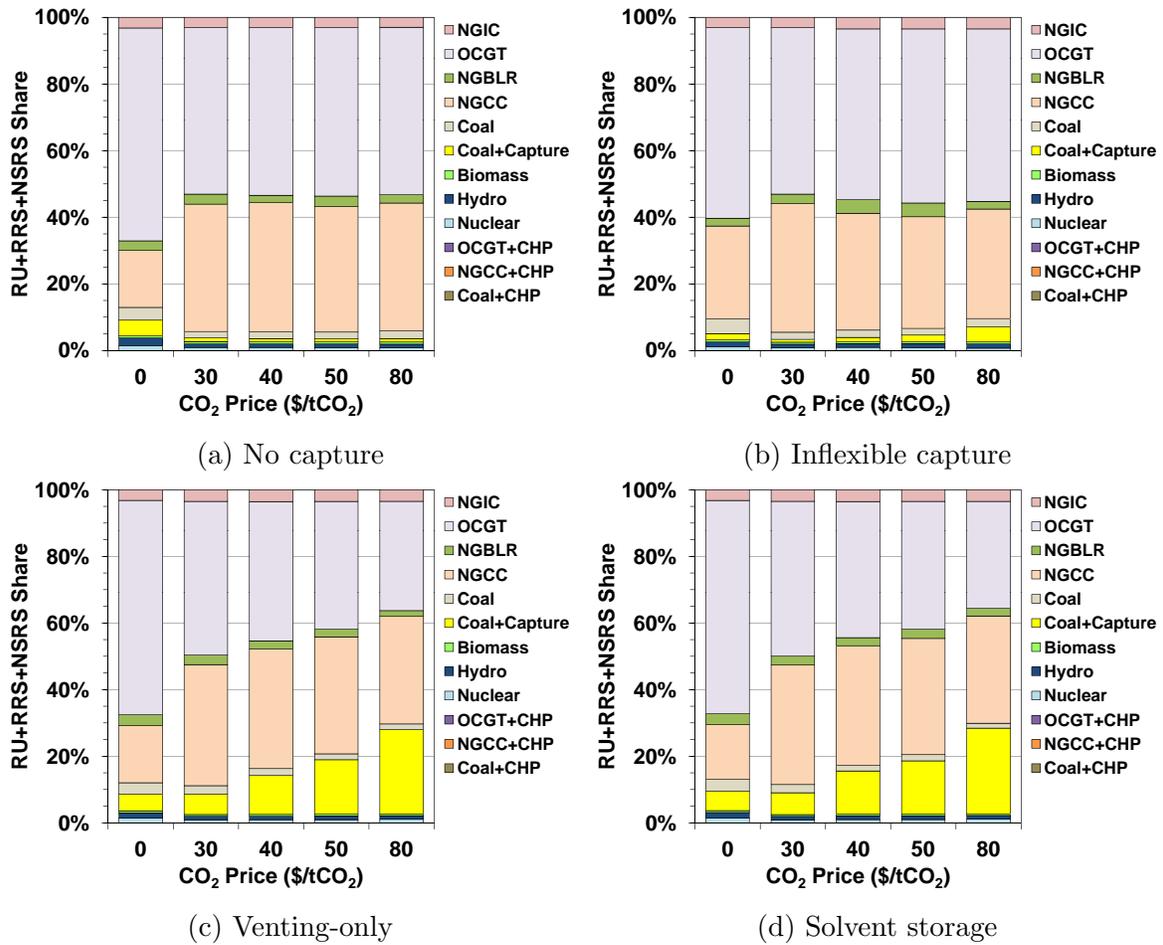


Figure 5.28: Flexible capture allows much greater provision of ancillary services that require an output increase (RU, RRS, and NSRS). (Winter: \$2.54/MMBTU coal, \$4.91/MMBTU natural gas)

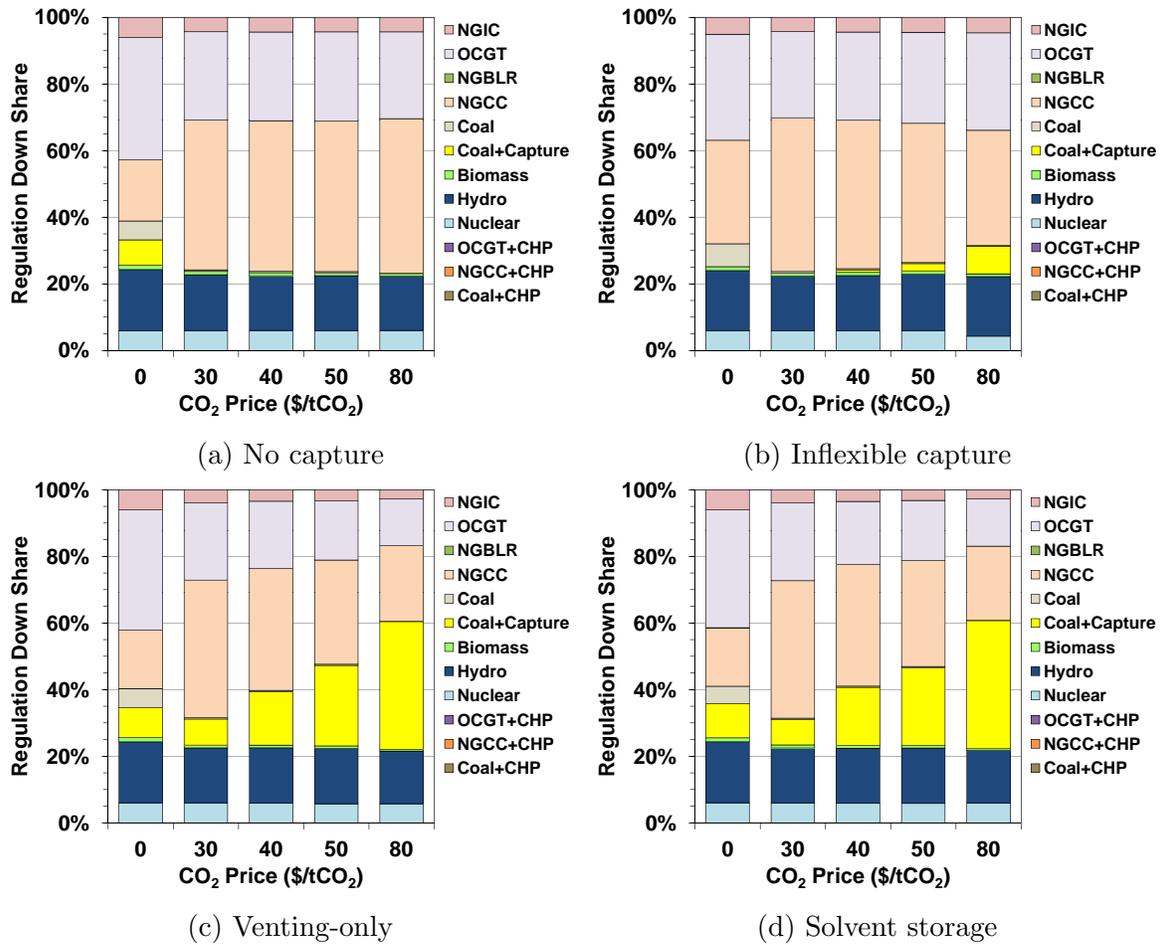


Figure 5.29: Regulation down procurements increase with capture flexibility due to increased plant utilization and the ability to increase total capture energy requirements. (Winter: \$2.54/MMBTU coal, \$4.91/MMBTU natural gas)

5.5.2.5 Flexible Capture Operation Across CO₂ and Natural Gas Prices

Flexibility significantly increases AS procurements from coal-fired facilities with CO₂ capture for winter conditions and \$4.91/MMBTU natural gas, and this section examines the consistency of these and other results across seasons and natural gas prices. This section focuses exclusively on coal-fired units considered with and without flexible and inflexible CO₂ capture. Aggregate performance statistics for each capture configuration are compared in each season across the range of studied CO₂ and natural gas prices. Smooth trends are not expected in these results due to the complexity of the optimization problem and the potential for multiple dispatch solutions with similar total operating costs. Thus, the emphasis is on general trends rather than absolute measures. In all figures, 3NG, 5NG, and 8NG refer to natural gas prices in \$/MMBTU, where 5NG is rounded from \$4.91/MMBTU. The codes NO, IF, VO, and SS refer to the capture configuration: none, inflexible, venting-only, and solvent storage.

Figure 5.30 plots the base plant capacity factor for each CO₂ and natural gas price combination when facilities have no capture, inflexible capture, or venting-only flexible capture. Capacity factors with solvent storage are nearly the same as those with venting-only flexible capture for each set of conditions. In the winter, spring, and fall, facilities are rarely used when natural gas is \$3/MMBTU unless CO₂ price is \$80/tCO₂ and flexible capture is available. At this price, coal-based capacity is displaced by most gas-fired units regardless of capture configuration, so plants do not operate at low and intermediate electricity demand. Thus, many subsequent figures omit data for \$3/MMBTU.

For all configurations, capacity factors are lowest in spring, highest in the summer, and intermediate in winter and fall due to seasonal variations in net electricity

demand. Utilization is high in the summer under most circumstances because high electricity demand requires nearly all grid capacity to be online. Capacity factors generally reflect marginal costs at coal+capture units relative to ERCOT gas-based capacity, so plant utilization increases with natural gas price for all configurations.

In all seasons, facilities without capture are utilized less often as CO₂ price increases. Capacity factors without capture are much higher with \$8/MMBTU natural gas but still fall to zero at \$80/tCO₂ for all seasons except summer, when the output is required to meet high net demand. When capture systems are inflexible, units operate less frequently at low CO₂ prices because operating costs are greater than those of most gas-fired units. High capacity factors are achieved with inflexible capture at low CO₂ prices only with high natural gas prices or high net demand in the summer. Absent these conditions, inflexible capture units operate infrequently at \$40/tCO₂ and below, and inflexible units never operate in the spring under any conditions.

Venting-only flexibility generally allows facilities to maintain the highest possible capacity factor, though capacity factors are higher in the winter with inflexible capture at \$8/MMBTU gas and \$30/tCO₂ or above. Dynamic data reveal that under these market conditions, nuclear units shut down when net demand is lowest and capture is inflexible, and coal+capture units fill the gap in supply. However, inflexible capture units cannot respond to rapid changes in net demand, so electricity oversupply is much greater (see Fig. 5.38). Increased operating flexibility with venting-only capture allows most nuclear units to remain online and limits oversupply under these conditions, but the coal+capture capacity factor suffers. In practice, wind curtailment and AS deployment would likely prevent such a scenario.

Under many circumstances, capacity factors with flexible capture are much

higher than those with inflexible or no capture at a given market condition. Flexible capture systems are used extensively for ancillary services, especially at higher CO₂ and natural gas prices, so capacity factors are much higher than those of inflexible systems unable to participate similarly in AS markets. Summer capacity factors are similar between inflexible and venting-only capture because high demand requires similar utilization of the facilities regardless of AS procurements.

Generally, it appears that flexibility can increase base plant utilization over a wide range of market conditions. Flexible systems can choose an operating point with costs appropriate for the current market state, and the increased ability to offer AS broadens the range of conditions where operation is economical.

Figure 5.31 shows utilization of CO₂ capture systems by plotting the average CO₂ emissions rate across coal+capture facilities. Emissions rates without CO₂ capture are approximately 1 tCO₂/MWh, and emissions rates with 100% load capture are ~0.12 tCO₂/MWh, so deviation from these values with flexible capture reflects how often capture systems operate when the base plant is online.

Operation without capture is uneconomical at intermediate or high CO₂ prices unless gas prices or electricity demand is high. Average emissions rate decreases without capture when higher emitting facilities go offline, and a quantity of zero indicates these facilities are no longer dispatched. Inflexible capture systems always emit roughly 0.12 tCO₂/MWh when online. At \$0/tCO₂, emissions rates with flexible capture demonstrate that capture operation is uneconomical, but emissions rates fall quickly towards 0.12 tCO₂/MWh above \$30/tCO₂. This transition is slower at high electricity demand and high gas prices because there are times when dispatch costs are lower when using high-emitting coal-fired units over expensive gas-fired units. Emissions rates with flexible capture typically remain slightly above those

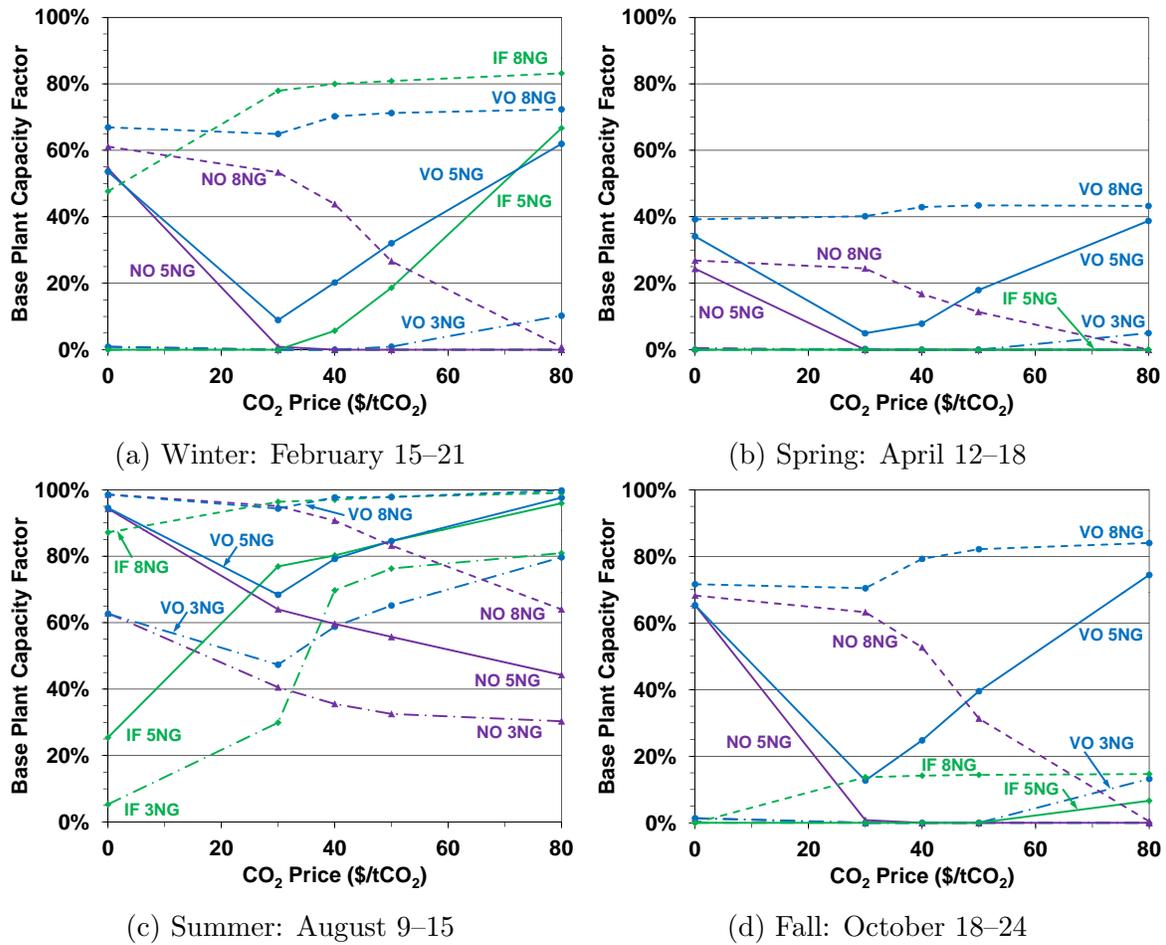


Figure 5.30: Power system utilization is as good or better with flexible capture at most market conditions. (NO=no capture, IF=inflexible, VO=venting-only; \$2.54/MMBTU coal)

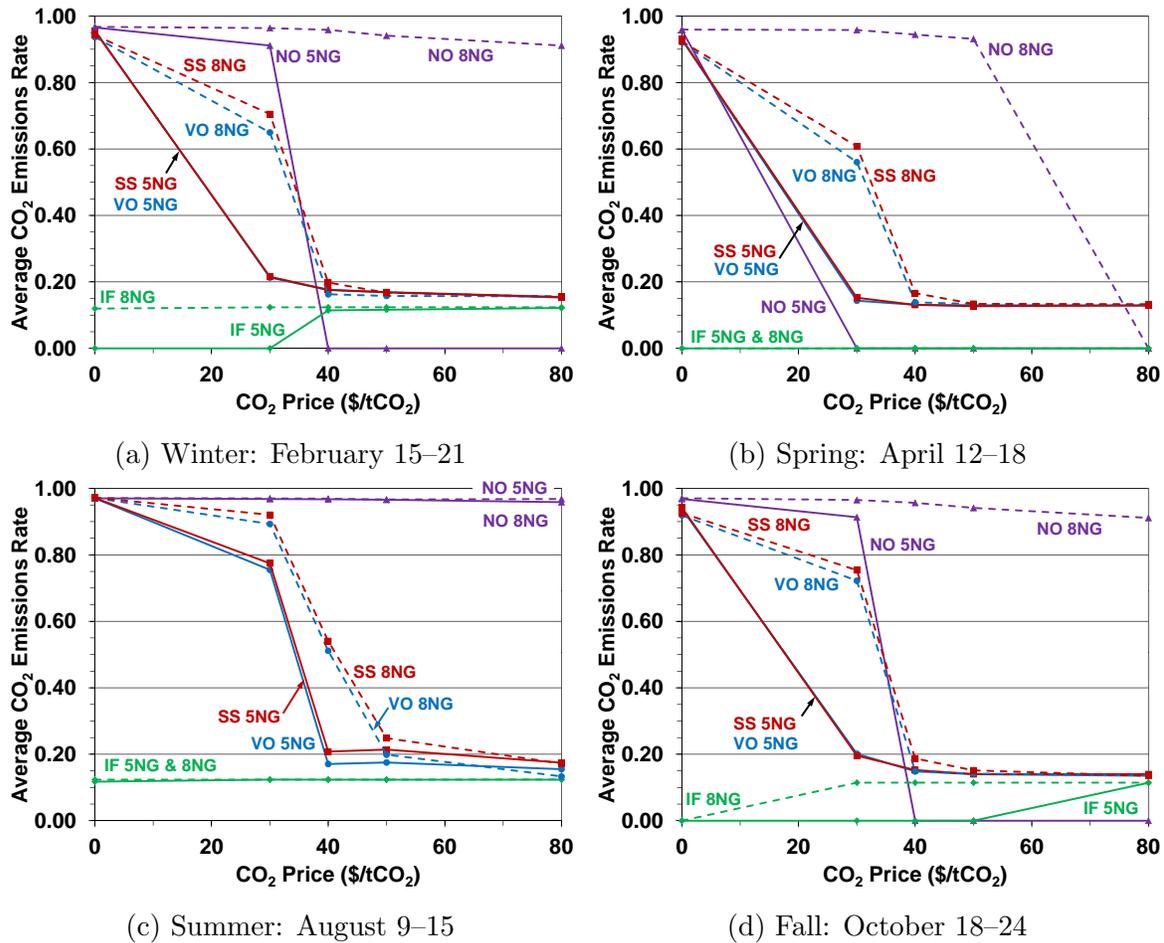


Figure 5.31: CO₂ capture systems typically operate at full load >\$30/tCO₂ but sometimes utilize partial-load capture even at high CO₂ prices. (NO=no capture, IF=inflexible, VO=venting-only, SS=solvent storage; \$2.54/MMBTU coal)

with inflexible capture even at \$80/tCO₂. Despite high emissions penalties, there are still times when difficulty responding to demand variation justifies varying capture load to reduce total dispatch costs. These instances are indicated by price spikes such as those observed in Section 5.5.2.3. Results do not vary significantly between the venting-only and solvent storage configurations because solvent storage systems are not utilized, so electricity dispatch is nearly identical.

Primary metrics for evaluating flexible CO₂ capture compare performance with

flexibility to that with inflexible or no capture systems. Figure 5.32 does so by plotting the percent increase in market share of electricity output with flexible capture relative to the maximum market share between the inflexible and no capture configurations. A positive quantity indicates an increase in output share with flexibility, while a negative quantity indicates that capture flexibility actually reduces the share of demand supplied by coal+capture facilities. Trends in this metric are closely follow those with base plant capacity factor.

Changes in output share are small in the summer and winter but rise with CO₂ price to up to 10–15% in the spring and fall. In the summer, output share never changes more than $\pm 1.3\%$. High summer demand makes operation necessary regardless of capture configuration. Output shares are nearly constant with \$3/MMBTU gas because output is nearly zero, but some increase is observed at \$80/tCO₂. For the relatively consistent low and intermediate net demand in the spring and fall, flexibility allows increased output as CO₂ price increases, and share is often greater with high gas prices. These market conditions make capture operation more economical and provide more opportunities for flexible systems to supply AS and respond to potential supply/demand imbalances. Output share falls in the winter at high CO₂ and gas prices because capacity factors with flexibility are lower than with inflexible capture. As discussed above, these conditions result in using inflexible coal+capture systems instead of nuclear capacity, which is likely unrealistic but constitutes the best solution found within computation time limits. There are no significant differences between results with the venting-only and solvent storage configurations; storage systems provide no benefit in the context of this optimization problem.

The biggest change with flexible CO₂ capture is a significant increase in ancillary service procurements from coal+capture facilities. Figure 5.33 plots the share

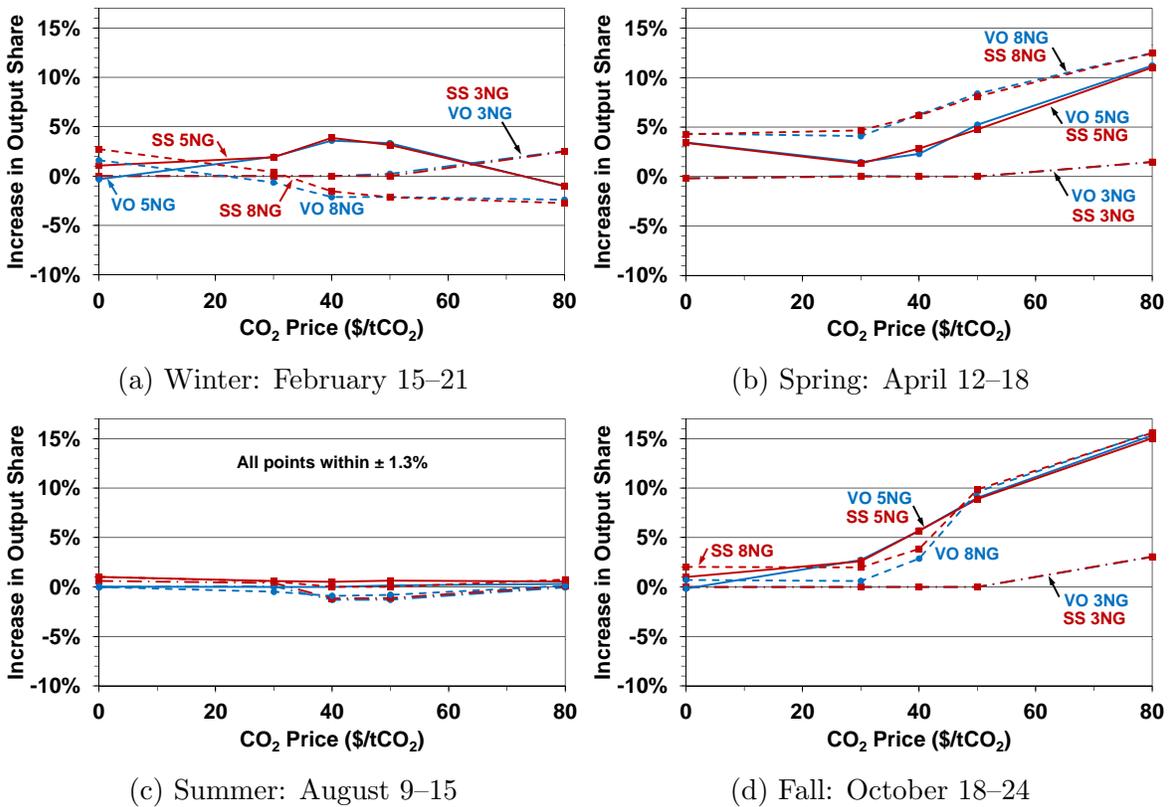


Figure 5.32: Flexibility allows coal+capture facilities to meet increased shares of electricity demand with intermediate load, high CO₂ price, and intermediate-to-high natural gas prices. (VO=venting-only, SS=solvent storage; \$2.54/MMBTU coal)

of total RU+RRS+NSRS services procured from these facilities in the winter for the venting-only, inflexible, and no capture configurations. With \$3/MMBTU natural gas, procurements are small for all configurations but are greatest at \$80/tCO₂ with flexible capture. At higher gas prices, procurements with flexible capture are substantially greater than those with inflexible or no capture, sometimes exceeding 25% of the system requirement. With inflexible or no CO₂ capture, facilities only provide “up” ancillary services when marginal. Capture flexibility allows RU, RRS, and NSRS offers when both the base plant and capture systems operate at full load and capture systems have the ability to reduce load if greater net output is desired. Procuring RU, RRS, and NSRS from flexible capture is less expensive than doing so from many gas-fired facilities because facilities are already operating at their lowest marginal cost, so low-cost capacity is not withheld while offering AS.

Figure 5.34 plots the increase in share of RU+RRS+NSRS with flexibility for all seasons. Whenever CO₂ capture operation is economical (above \$30/tCO₂) and electricity demand is high enough for frequent dispatch (summer or above \$3/MMBTU natural gas in other seasons), flexibility significantly increases the share of “up” AS from coal+capture facilities. Benefits grow with CO₂ price and natural gas price at low and intermediate electricity demand because opportunities to provide AS increase with overall plant utilization.

In the summer, natural gas prices have a smaller impact on the dispatch order of capture+capture facilities because nearly all available capacity must be online to meet electricity demand. Flexible capture facilities have relatively high summer capacity factors for all gas prices, so changes in RU+RRS+NSRS procurements are influenced primarily by the relative costs of flexible capture facilities at 0% capture and those of marginal gas-fired generation. At intermediate CO₂ prices, capture load

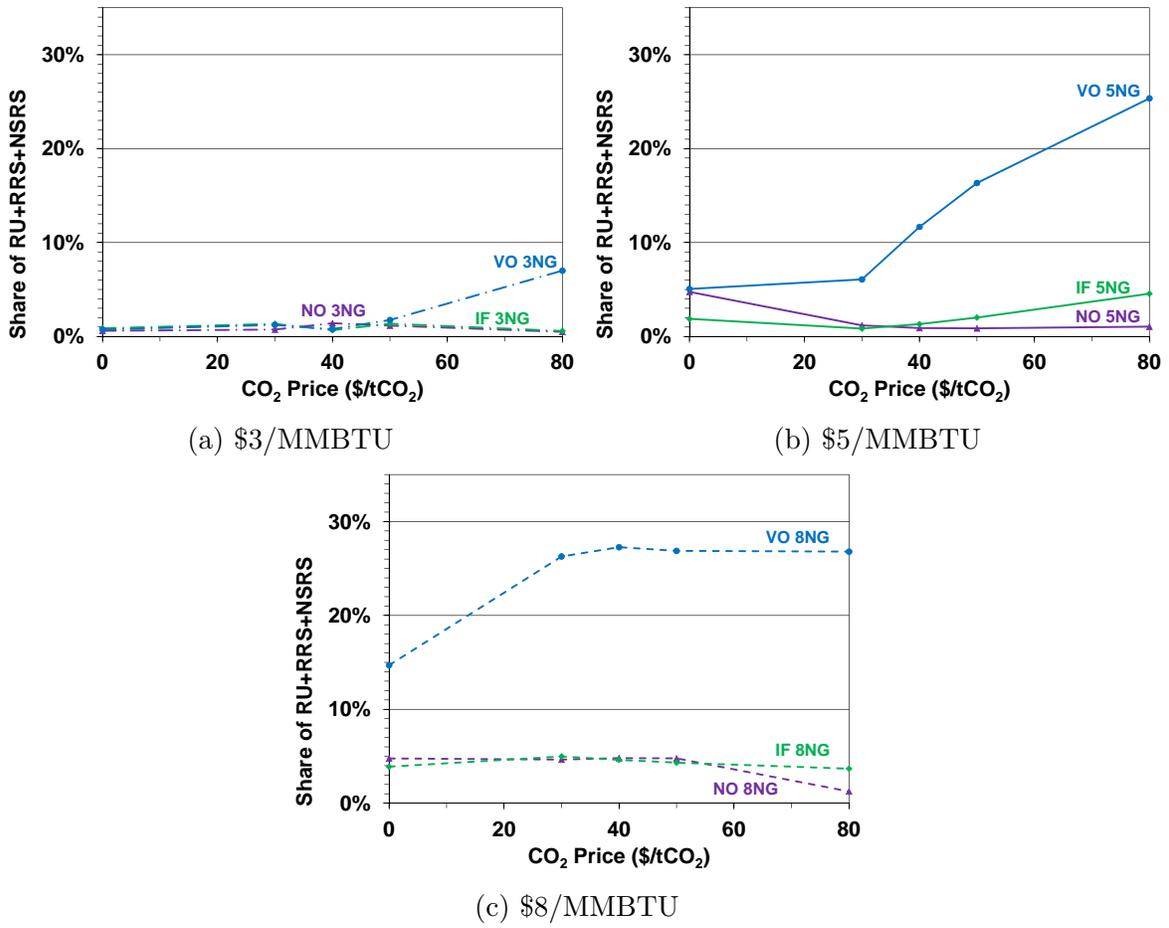


Figure 5.33: Total RU, RRS, and NSRS procurements in the winter increase substantially with flexible capture at high CO₂ and gas prices. (NO=no capture, IF=inflexible, VO=venting-only; \$2.54/MMBTU coal)

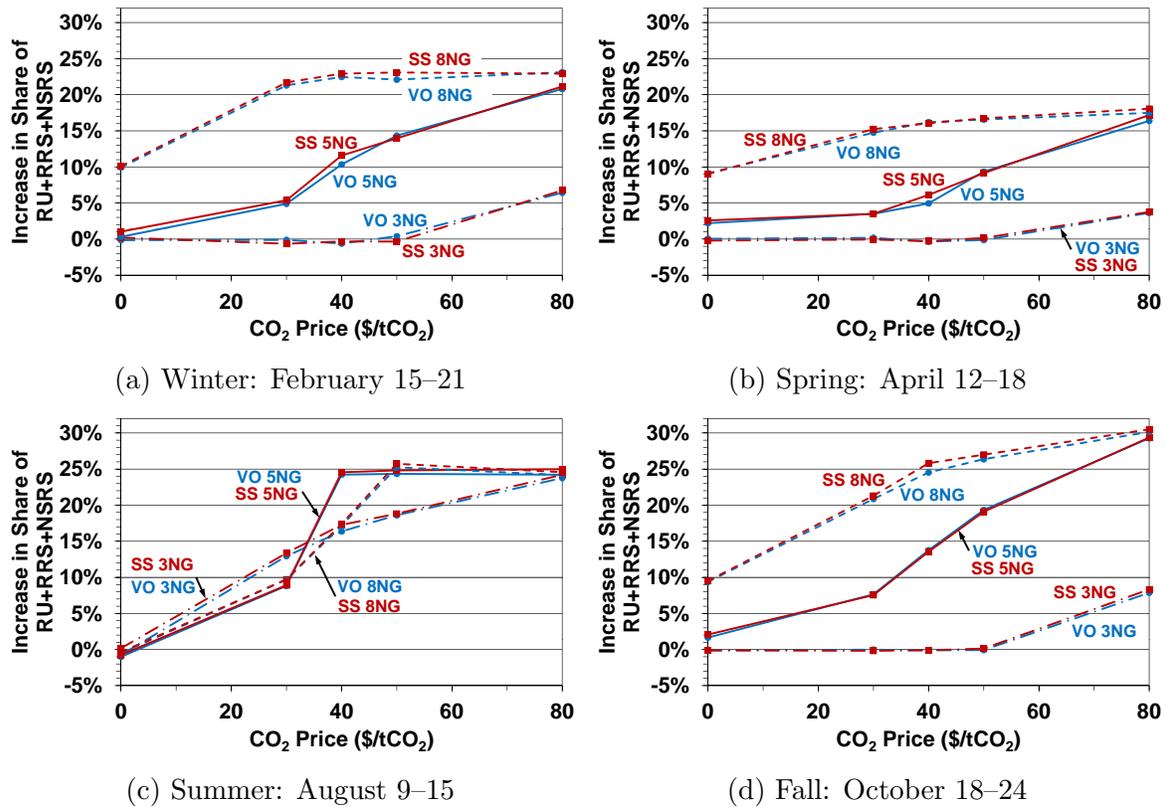


Figure 5.34: Flexibility allows much greater shares of RU, RRS, and NSRS across many electricity market conditions. (VO=venting-only, SS=solvent storage; \$2.54/MMBTU coal)

often decreases during peak demand to reduce total dispatch costs, but doing so hinders RU, RRS, and NSRS offer capability. At high CO₂ prices, facilities operate nearly continuously with 100% capture load, so RU, RRS, and NSRS offer capability is high but equivalent for all gas prices. Again, there are no significant differences between results with the venting-only and solvent storage configurations.

Figure 5.35 plots the regulation down share by coal+capture facilities in the winter week with no capture, inflexible capture, and venting-only flexible capture. RD is typically provided by base load facilities, so coal+capture units with inflexible or no capture rarely provide RD because they do not operate or are marginal. RD

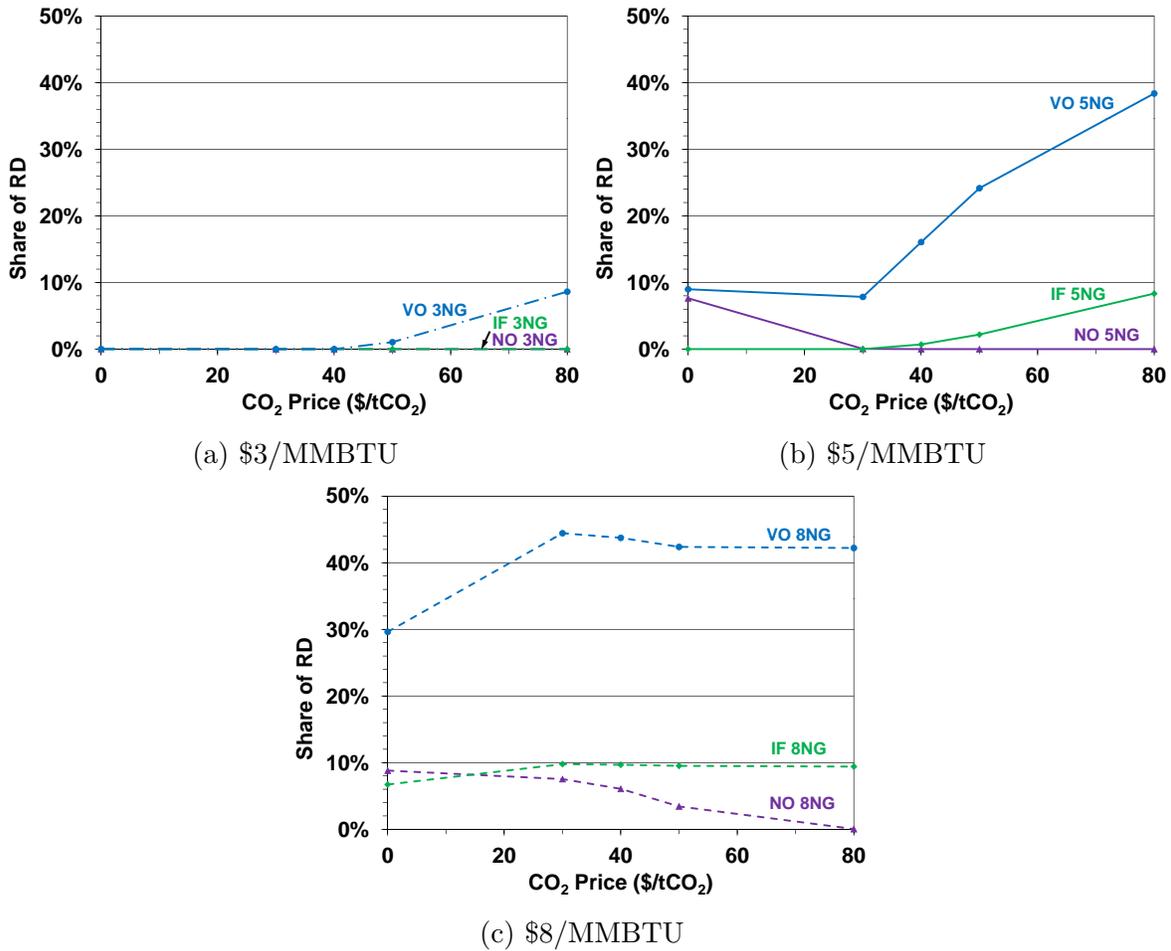


Figure 5.35: Winter regulation down procurements are significantly greater with flexible capture at intermediate and high CO₂ and natural gas prices. (NO=no capture, IF=inflexible, VO=venting-only; \$2.54/MMBTU coal)

is only procured from units without capture at low CO₂ prices and high natural gas prices, and inflexible capture units provide some RD at high CO₂/gas prices when these units provide base load electricity. However, flexible capture facilities can supply RD by offering the ability to increase capture energy requirements, so RD procurements increase with overall plant utilization in a similar manner as RU+RRS+NSRS procurements. With flexible capture, RD procurements increase both with CO₂ and natural gas price to over 40% of the total RD requirement under some conditions.

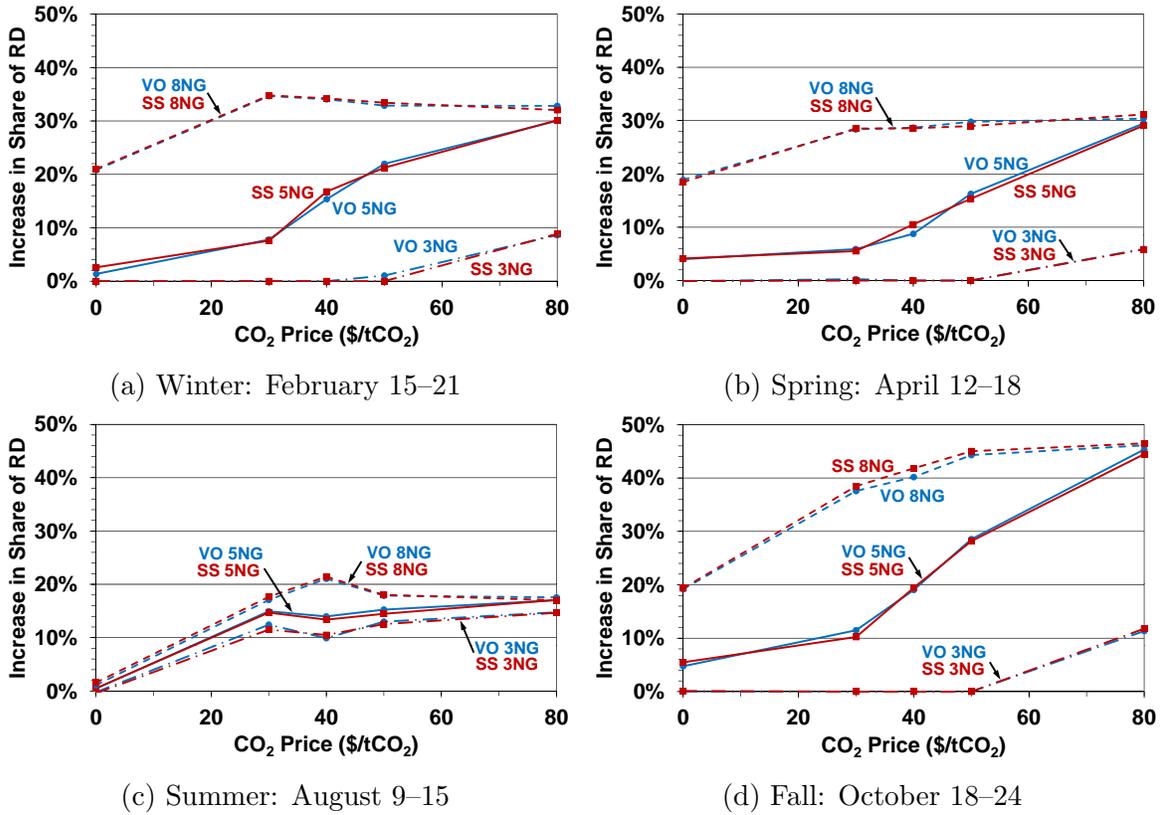


Figure 5.36: Shares of RD are much greater with flexible capture over many market conditions where capture operation is economical. (VO=venting-only, SS=solvent storage; \$2.54/MMBTU coal)

Results from Fig. 5.35 are reflected in Fig. 5.36, which plots the increase in RD share with capture flexibility for all seasons. Trends in RD shares mirror those seen in “up” ancillary services (Fig. 5.34). As plant utilization increases with CO₂ and natural gas price, there is greater opportunity to offer RD with the ability to increase capture energy requirement if desired.

The remaining figures in this section demonstrate the impact of market conditions and CO₂ capture configuration on aggregate electricity system metrics.

Shadow electricity prices in the real-time market reflect overall grid economics and are particularly interesting in a competitive electricity market context. However,

weekly average prices are difficult to compare across scenarios because averages are highly skewed by price spikes encountered when inadequate ramping capability incurs an oversupply or undersupply penalty. The magnitude and stepped nature of the undersupply penalty curve generates prices that cloud the underlying impacts of market conditions and CO₂ capture (Fig. 5.2). To mitigate the influence of price spikes, Fig. 5.37 plots average electricity prices after filtering out any prices exceeding 2 standard deviations from the weekly mean and replacing them with values linearly interpolated between the nearest non-outliers. Average prices without outliers are plotted with no capture, inflexible capture, and venting-only capture for \$5/MMBTU and \$8/MMBTU natural gas and all seasons and CO₂ prices.

Corresponding to differences in net electricity demand, prices are highest in the summer, lowest in the spring, and intermediate in the winter and fall. At low CO₂ prices, average price is sometimes negative when electricity oversupply is frequent enough for persistent negative electricity prices. Electricity prices rise with CO₂ price as the emissions costs of marginal generators increase, and prices are typically higher with \$8/MMBTU gas because marginal generators are often gas-fired. Prices are lower with \$3/MMBTU natural gas, but results are not shown because units with capture rarely operate at \$3/MMBTU in most seasons. In the summer, prices rise faster with CO₂ price when high electricity demand requires more carbon-intensive marginal generating units.

There are no clear trends indicating that electricity prices increase with the use of CO₂ capture systems for a given CO₂ and natural gas price. Variations are very small in the summer, and there is not a consistent price order between capture configurations across many market conditions. Though some price outliers have been removed, trends remain clouded by price volatility. However, absent evidence other-

wise, it appears that under most conditions in ERCOT, CO₂ capture will not have major impact on electricity prices, even when installed on half the coal-based capacity in the grid.

Shadow electricity prices can be used to estimate electricity sales revenues and operating profits. However, these results are not reported due to the inconsistent and volatile nature of shadow electricity prices. While prices are illustrative of dispatch behavior, there is lower confidence in profitability comparisons due to model limitations. Without including transmission, AS deployments, and wind curtailment, strong conclusions are difficult to draw from profit calculations based on shadow prices produced by the unit commitment model. More robust conclusions can be deduced from operating behavior. The profit maximization model discussed in Chapters 2-4 is thought to better assess flexible capture for price arbitrage because this model implicitly incorporates all ERCOT market characteristics by using electricity prices as input. Similarly, shadow prices for AS are not reported because the model does not fully represent AS costs in the form of opportunity costs or an offer/bid settlement process.

Electricity oversupply and undersupply provide another grid performance metric. A more robust electricity system should have less supply/demand imbalance throughout the week, so changes in these imbalances with capture configuration can indicate whether or not flexible capture improves grid resiliency.

Figure 5.38 plots total weekly oversupply for all scenarios except \$3/MMBTU natural gas and the solvent storage configuration. Solvent storage results are nearly identical to those with venting-only flexible capture, and results with \$3/MMBTU natural gas offer no additional insights and are inconsequential for evaluating capture systems. Oversupply commonly occurs when CHP capacity is nearly sufficient to meet

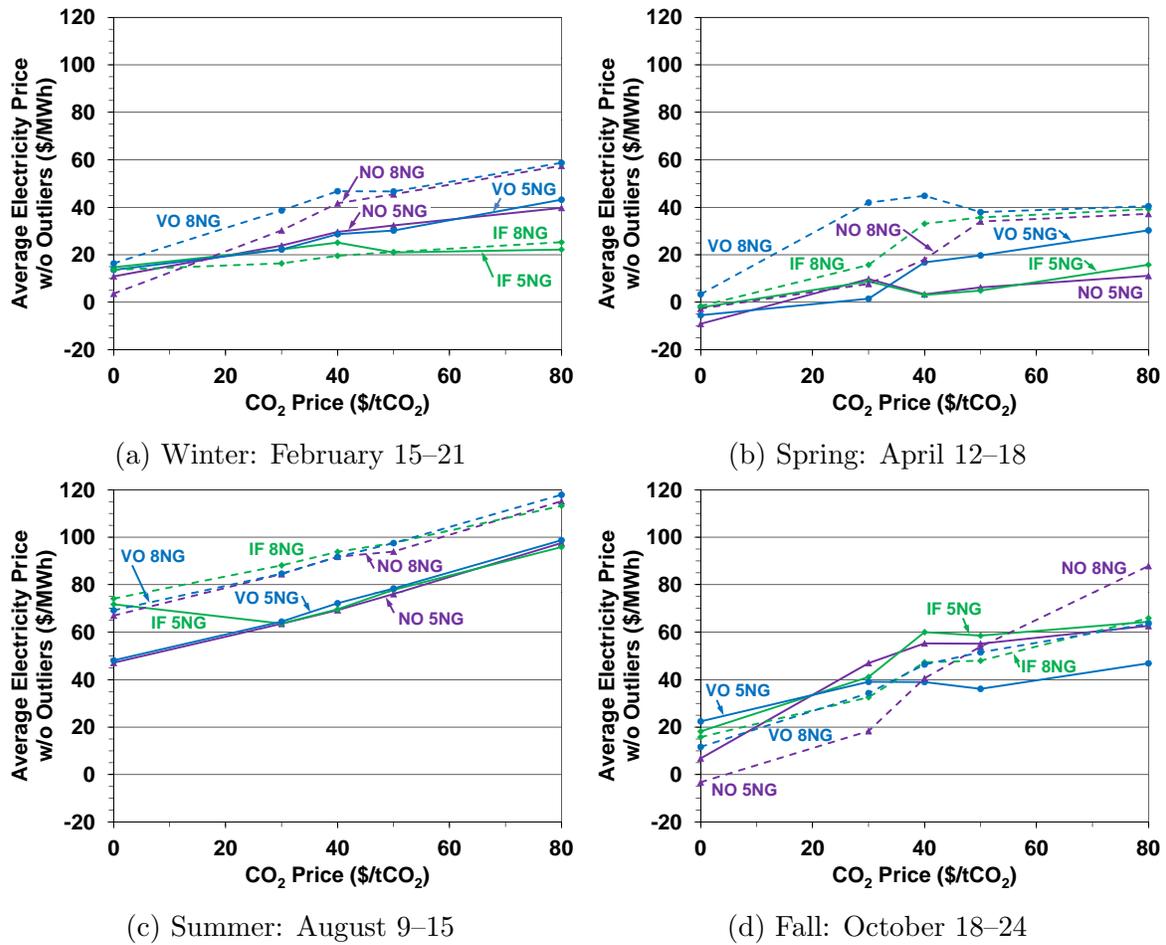


Figure 5.37: Electricity prices rise with CO₂ and natural gas price, but there is no clear relationship with CO₂ capture configuration. (NO=no capture, IF=inflexible, VO=venting-only; \$2.54/MMBTU coal)

net electricity demand, so minimum load constraints and the inability of units to ramp output down or go offline requires total electricity supply to exceed demand. These circumstances would motivate wind curtailments or regulation down deployments. Seasonal differences reflect the frequency of low net demand conditions. There is rarely oversupply in the summer week, and oversupply is consistently greater in the spring when net demand is consistently low. However, even the greatest quantities of oversupply are on the order of 2% total weekly net demand.

Oversupply is greatest under market conditions where low-cost units are relatively inflexible. In the winter, oversupply is highest with inflexible capture at high CO₂ prices because inflexible capture units are online but cannot respond to rapid net demand variations when wind production is high. At low CO₂ prices in the fall, oversupply is highest without CO₂ capture because the substantial online coal-fired capacity cannot respond to net demand variations. Oversupply is lower with inflexible capture at low CO₂ prices in the fall because coal-fired units with capture are not dispatched. When CO₂ and natural gas prices are high enough to justify CO₂ capture operation, oversupply is often lower with flexible capture systems that ramp CO₂ capture load to respond to net load variations.

Figure 5.39 similarly plots electricity undersupply. Undersupply penalties typically occur when online units have insufficient ramping capability to respond to rapid changes in electricity demand. Undersupply is lowest in the spring, though ramping limitations still require some undersupply even at low net demand. Under most conditions in winter, summer, and fall, undersupply is on the order of 0–15 GWh, less than 0.3% of total net demand. Penalties of up to \$3000/MWh help limit undersupply quantities relative to oversupply, which incurs a \$250/MWh penalty. Undersupply is often lower with \$8/MMBTU natural gas in the winter and fall, likely because flex-

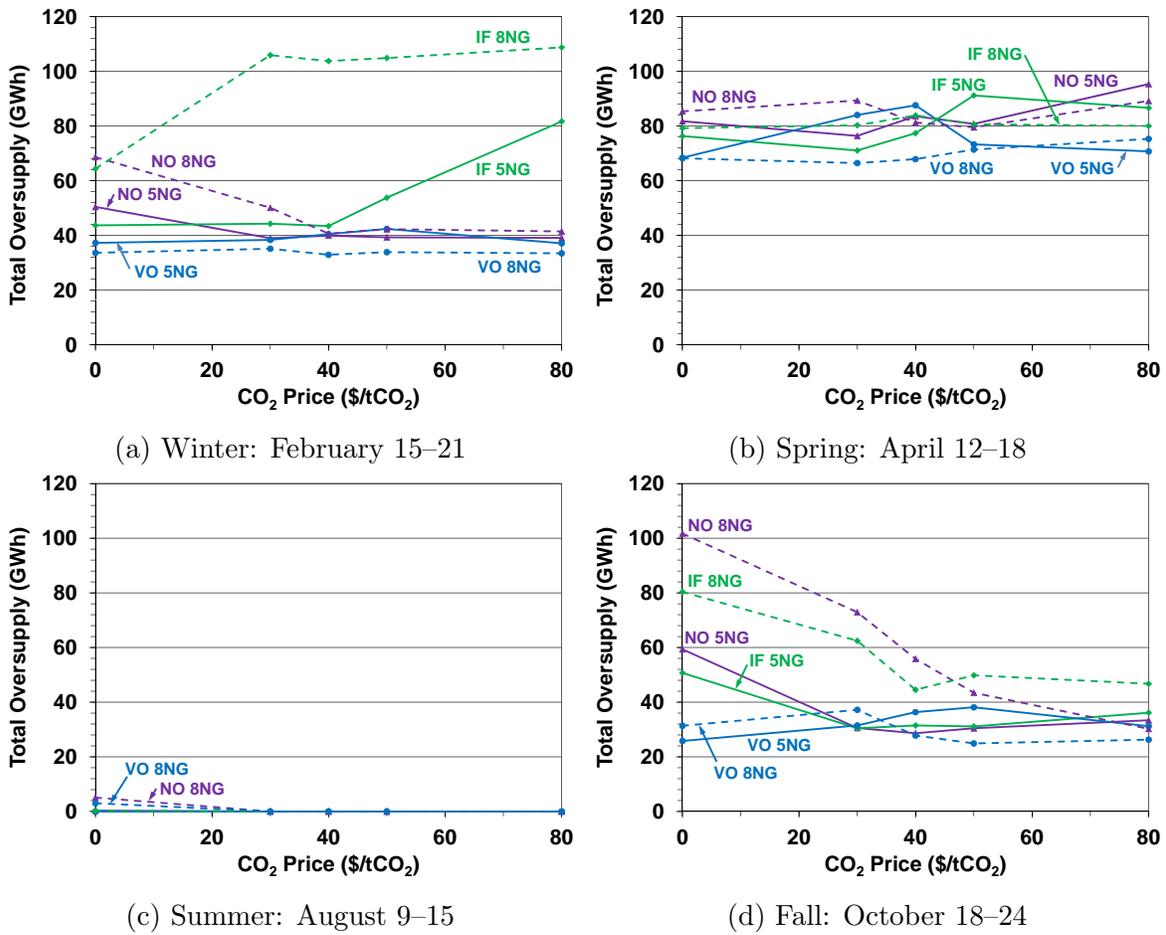


Figure 5.38: Oversupply quantities are greatest when low-cost units are inflexible, so flexible capture can reduce oversupply when CO₂ capture operation is economical. (NO=no capture, IF=inflexible, VO=venting-only; \$2.54/MMBTU coal)

ible gas turbines are more often marginal under these conditions. Like oversupply, undersupply is often lowest with flexible capture when coal+capture facilities operate frequently. Capture ramping ability improves the grid response to variable net demand.

In the summer, undersupply is very high inflexible capture at \$0/tCO₂ because total dispatch costs are actually lower when paying an oversupply penalty at peak demand rather than bringing online uneconomical units with inflexible capture. This effect is even greater with \$3/MMBTU natural gas. In these situations, undersupply is lower without CO₂ capture operating because low-cost coal-fired units without capture are online to meet electricity demand.

The model objective seeks to minimize total dispatch costs, so any impact of flexible capture on grid economics should be revealed by comparing total costs. Costs increase with both CO₂ and natural gas prices, but the impact of flexible capture is better represented by the percent decrease in total dispatch cost with flexible capture. Figure 5.40 displays these results; a positive quantity indicates a cost reduction, while a negative quantity indicates higher dispatch costs with flexible capture. At high electricity demand (summer) and low spring demand and \$5/MMBTU gas, minimal change in dispatch cost is observed. However, flexible capture does appear to reduce dispatch costs in the spring at \$8/MMBTU gas and in the winter and fall, and benefits increase with both CO₂ and natural gas price in these seasons. Under conditions where capture units are used frequently, the ability to respond to rapid changes in supply and demand helps reduce dispatch costs. The ability to offer large quantities of ancillary services also helps limit the need to reduce output at other units for AS provision. Though benefits are often modest, it appears that flexible capture should not increase total dispatch costs.

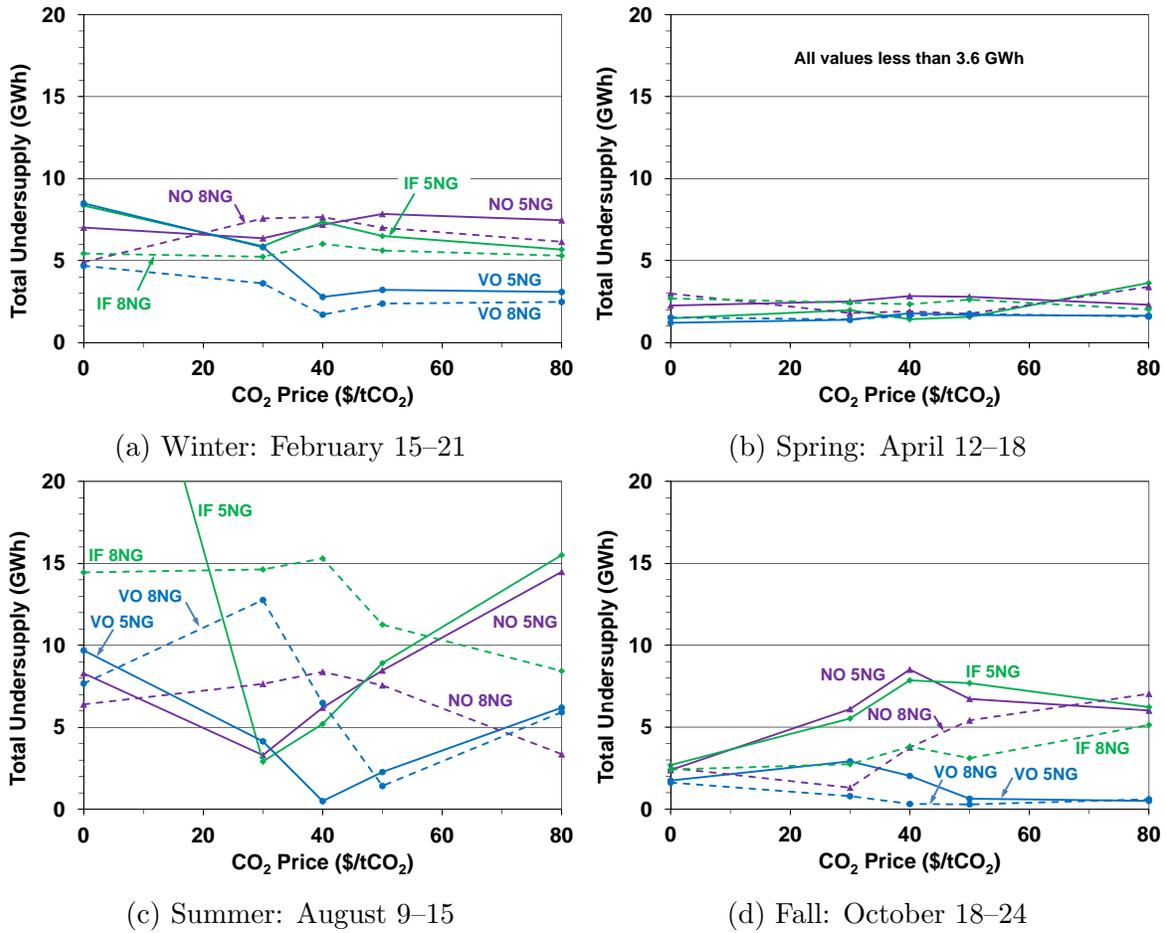


Figure 5.39: Flexible capture helps reduce undersupply when capture operation is economical, but undersupply never exceeds 0.3% total net demand except with inflexible capture in the summer when both CO₂ and gas prices are low. (NO=no capture, IF=inflexible, VO=venting-only; \$2.54/MMBTU coal)

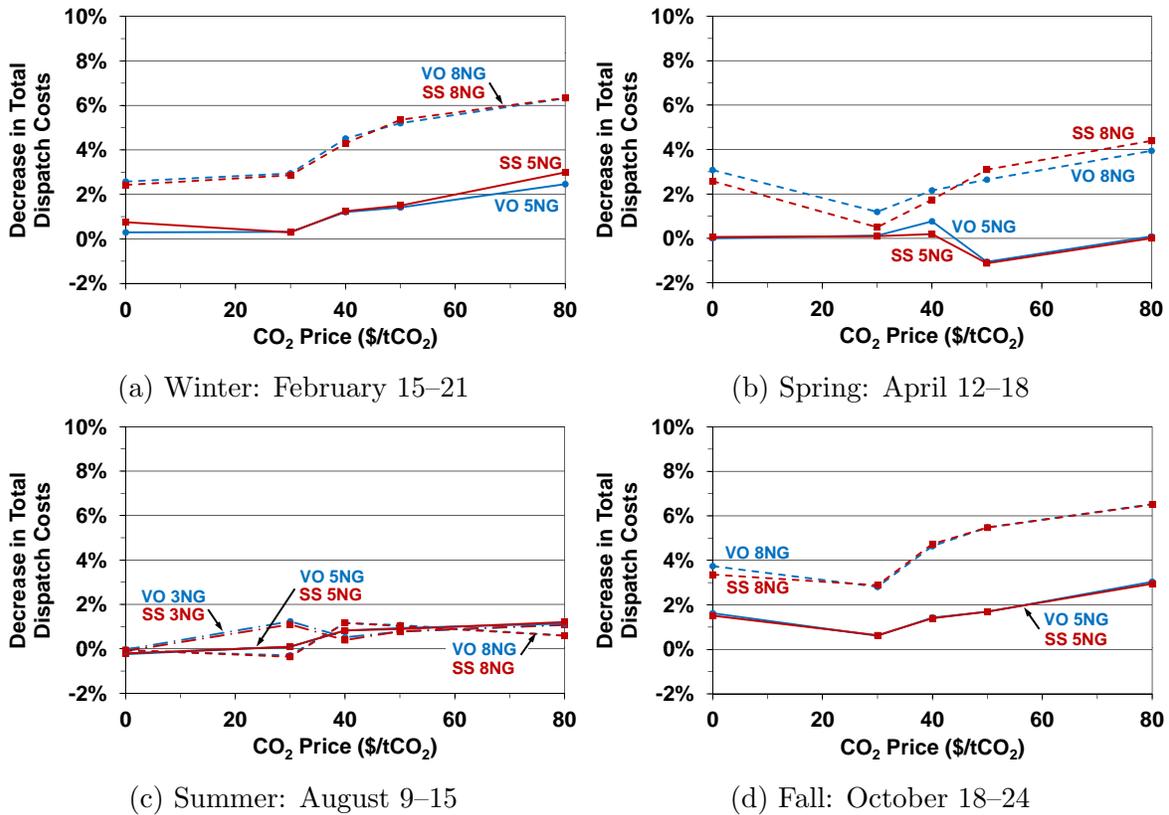


Figure 5.40: Capture flexibility allows a slight decrease in total electricity dispatch costs at intermediate demand when CO₂ and natural gas prices are high. (VO=venting-only, SS=solvent storage; \$2.54/MMBTU coal)

The average grid CO₂ emissions rate demonstrates the environmental implications of changes in season, market conditions, and CO₂ capture configuration (Fig. 5.41). Higher electricity demand requires less efficient, more carbon-intensive generating units, so emissions rate is greatest in the summer and lowest in the spring. Absent a CO₂ price, emissions are high in all seasons. Emissions rate decreases with CO₂ price even without CO₂ capture because coal-based units are displaced by gas-fired units having lower emissions rates. High natural gas price also increases emissions rates by widening the CO₂ price range where carbon-intensive coal-fired units without capture are less expensive than gas-fired units. CO₂ reductions are greatest with inflexible capture at lower CO₂ prices but higher with flexible capture above \$40/tCO₂ for all seasons except summer. Flexibility allows increased utilization of coal+capture systems under these market conditions, so grid CO₂ emissions are lower.

5.5.3 Flexible Capture for AS and Peak Demand: Effects of Energy Storage

This section examines the impact of grid-scale energy storage on flexible CO₂ capture operation. Similar to flexible capture, energy storage systems are touted for their ability to provide ancillary services and meet peak electricity demand. Coal+capture facility operation is compared with and without the ten CAES units described in Section 5.3.2.3 for the summer and winter weeks and two gas-CO₂ price combinations: (1) \$4.91/MMBTU gas and \$40/tCO₂, and (2) \$8/MMBTU gas and \$30/tCO₂. These conditions are chosen to cover a range of grid operating conditions. For instance, partial-load CO₂ capture to meet peak demand is cost-effective in the summer at \$30/tCO₂ and \$8/MMBTU gas, but capture load is only reduced at \$40/tCO₂ and \$4.91/MMBTU gas when supply/demand imbalances are imminent.

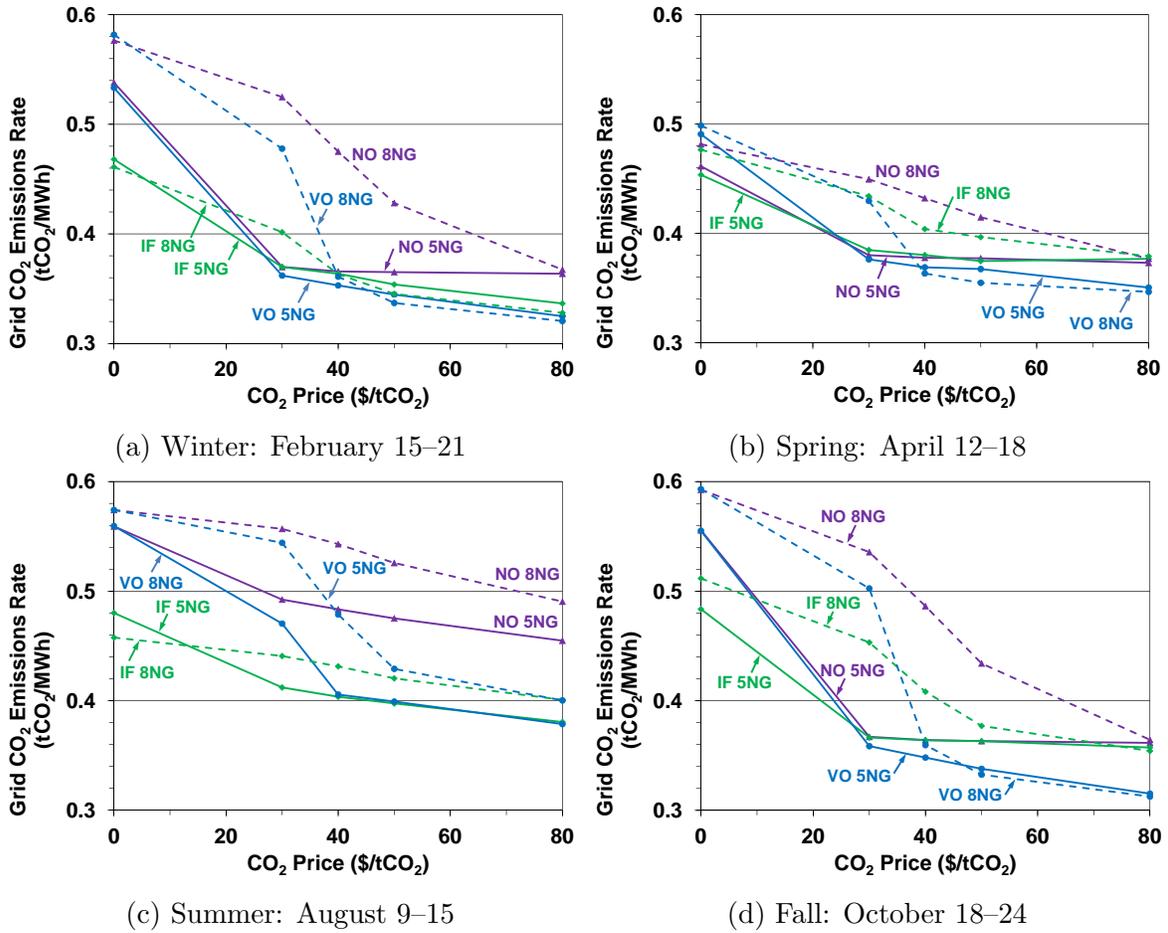


Figure 5.41: Flexible capture allows lower grid CO₂ emissions rates at \$40/tCO₂ and above by increasing the utilization of CO₂ capture facilities. (NO=no capture, IF=inflexible, VO=venting-only; \$2.54/MMBTU coal)

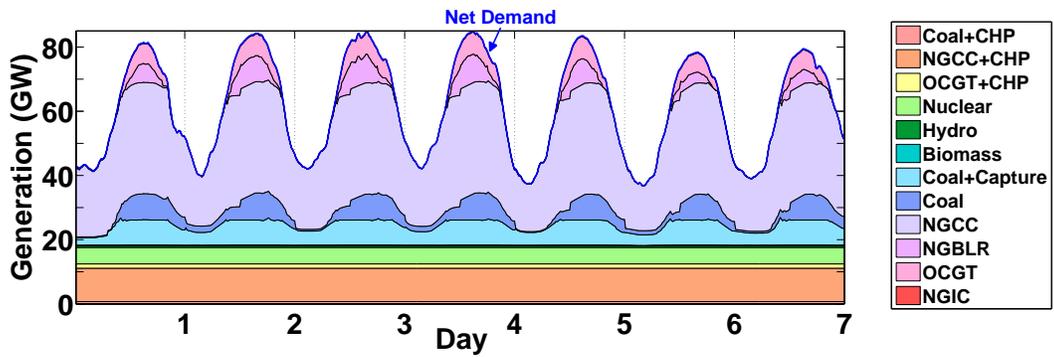
Capture systems provide substantial RRS in the summer for both price combinations, but coal+capture units operate relatively infrequently in the winter with \$40/tCO₂ and \$4.91/MMBTU gas. Given low natural gas prices expected in the future, the \$8/MMBTU case is primarily illustrative, with \$4.91/MMBTU viewed as more representative to expected future conditions.

5.5.3.1 Results

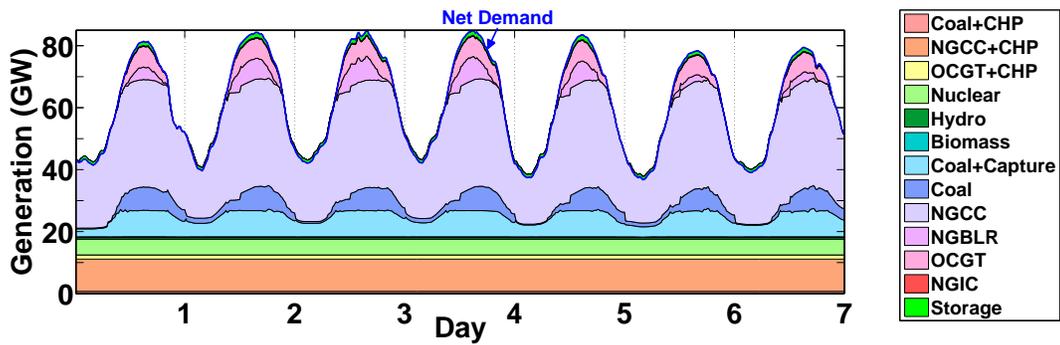
Figure 5.42 plots generation by plant type in the summer with \$4.91/MMBTU natural gas and \$40/tCO₂ when capture systems have venting-only flexibility. Panel (a) is repeated from Fig. 5.14b. Generation from most plant types, including coal+capture, is qualitatively similar with and without CAES units. Panel (b) demonstrates that CAES units output electricity during peak demand, and the red area atop the generation stack during demand troughs is the corresponding electrical input to storage that increases net electricity demand. Storage systems primarily reduce peak output from OCGT units while increasing NGCC generation when demand is low. Storage is used similarly in cases studied, even during winter when average demand is much lower.

Figure 5.43 compares RRS procurements for the same market conditions. With and without energy storage, a substantial portion of the RRS requirement is met by flexible capture units. CAES facilities do supply RRS when available, but they do so at the expense of marginal OCGT and NGCC units, not flexible capture systems. Any perceived RRS under-procurements represent portions of RRS supplied by over-procured RU service.

Figure 5.44 compares regulation down procurements with and without CAES units. Energy storage systems are sometimes used for RD when units have capacity to increase electrical input or reduce output. However, doing so primarily displaces RD

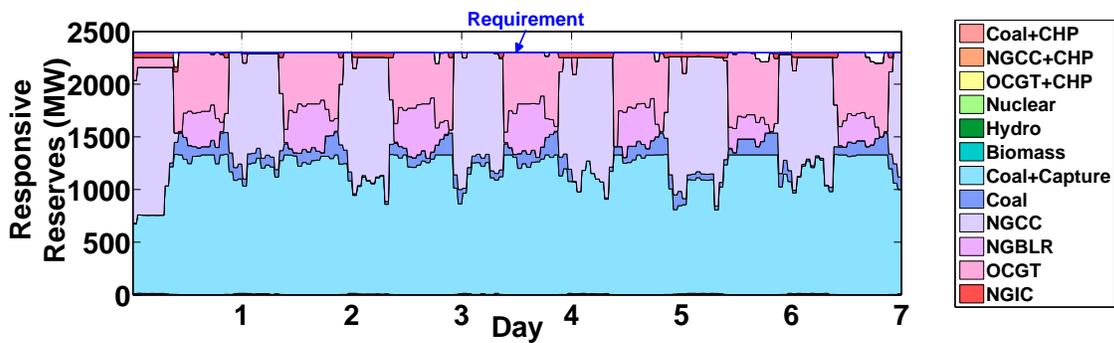


(a) Venting-only flexible capture: No CAES

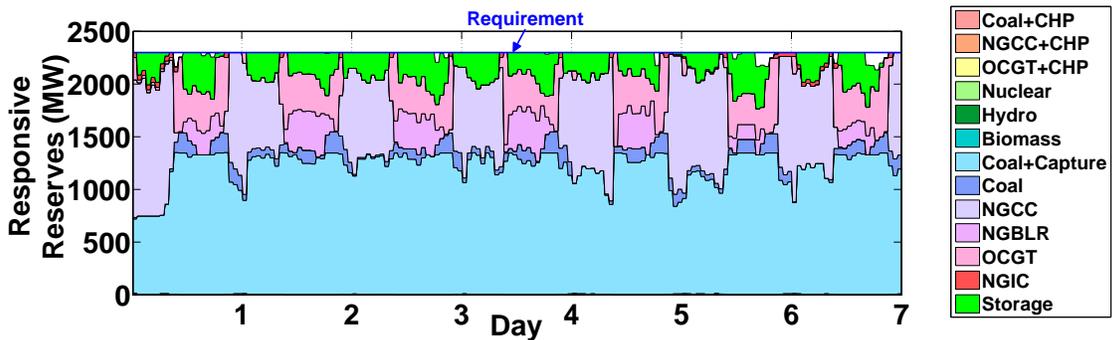


(b) Venting-only flexible capture: With CAES

Figure 5.42: Compressed air energy storage (CAES) units are used to reduce OCGT generation at peak, but coal+capture output is largely unchanged. (Summer: \$2.54/MMBTU coal, \$4.91/MMBTU natural gas, \$40/tCO₂)



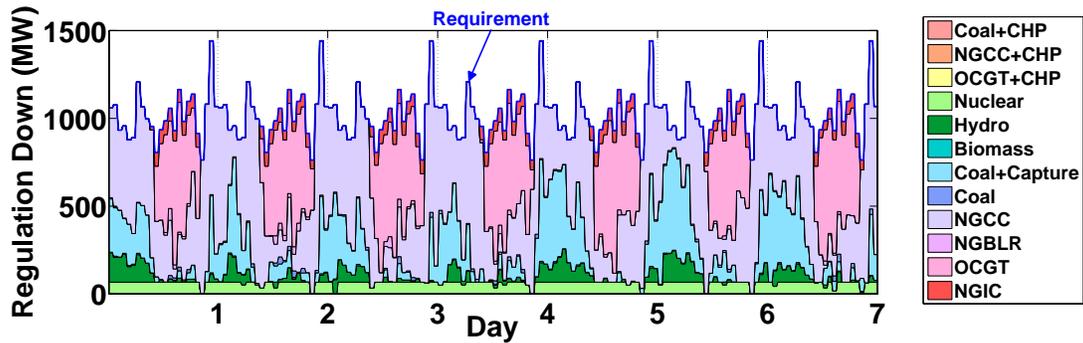
(a) Venting-only flexible capture: No CAES



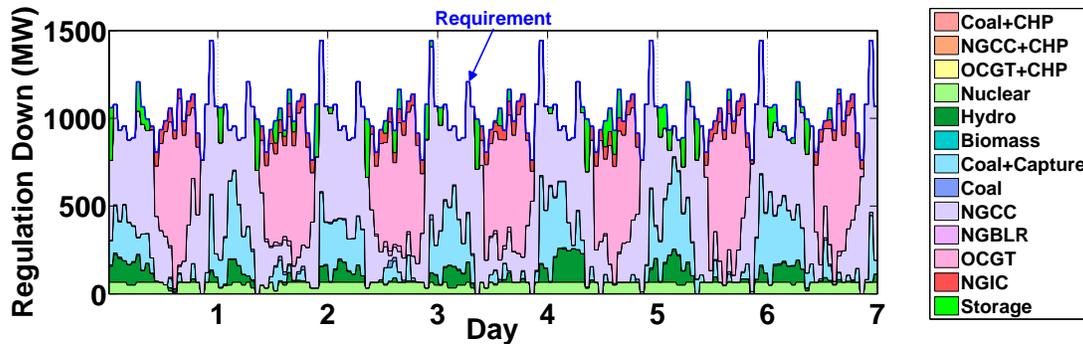
(b) Venting-only flexible capture: With CAES

Figure 5.43: CAES systems displace OCGT and NGGC units for RRS provision, but coal+capture provides substantial RRS even with energy storage systems. (Summer: \$2.54/MMBTU coal, \$4.91/MMBTU natural gas, \$40/tCO₂)

provided by NGIC and NGCC units, not coal-based facilities with flexible capture. Coal+capture units provide a substantial amount of RD regardless of CAES at these market conditions.



(a) Venting-only flexible capture: No CAES



(b) Venting-only flexible capture: With CAES

Figure 5.44: RD procurements from coal+capture units are largely unchanged when CAES facilities are available. (Summer: \$2.54/MMBTU coal, \$4.91/MMBTU natural gas, \$40/tCO₂)

Figure 5.45 quantifies the impact of CAES on energy supply and AS procurements from capture units for the four studied market conditions. Panels (a)–(d) plot differences in power system capacity factor, output share, “up” AS, and RD for coal+capture units with and without CAES units. A positive quantity indicates an increase when CAES systems are available, while a negative quantity could signal that CAES detracts from the value of the flexible capture.

Capacity factors and commodity shares rarely differ by more than 2%, which is likely insignificant within the tolerance of the optimization procedure. Changes in capacity factor and output share are shown for inflexible and no capture as well to demonstrate small differences regardless of capture configuration. The only exception is without CO₂ capture in the winter with \$8/MMBTU gas and \$30/tCO₂. In this scenario, capacity factor increases by more than 4% because marginal coal-fired units without capture are utilized more often to provide energy input to storage when net demand is low. Though these results are taken over a limited set of market conditions, CAES does not appear to significantly affect the value of flexible capture. RD procurements decrease by more than 2% in the summer, but dynamic data show qualitatively similar solutions with and without CAES units. More CAES capacity could produce greater effects, but significant impact on the value of flexibility is observed with 2 GW/1 GW total output/input and 16 GWh of storage capacity.

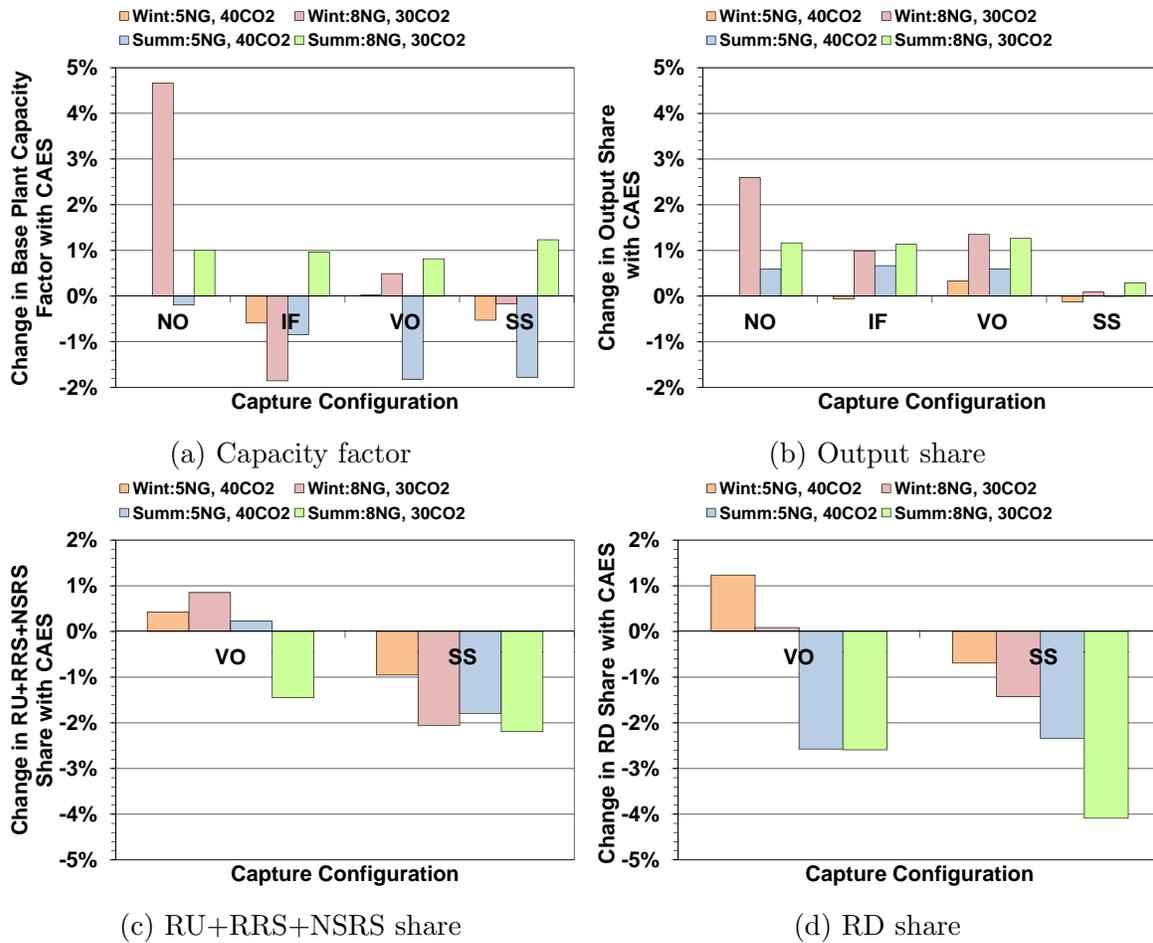


Figure 5.45: CAES units typically have a negligible impact on the utilization of flexible capture systems for energy and ancillary services.

5.6 Conclusions

An electricity system unit commitment model has been developed to study the energy and ancillary service implications of flexible CO₂ capture. The model is initially tailored for the ERCOT electric grid, but other competitive or regulated systems could be modeled with appropriate changes to input parameters and electricity system constraints.

An aggregated ERCOT generation fleet is modeled to demonstrate the existence of market conditions where flexible capture systems are used to reduce dispatch costs and provide AS. Partial-load CO₂ capture can supply additional electricity at peak demand if generation without capture is less expensive than electricity from marginal units. The ability to turn capture systems off while maintaining maximum gross power output allows flexible capture facilities to offer additional regulation up, responsive (spinning) reserve, and non-spinning reserve service. Offers for regulation down service can also increase if capture systems have capacity to increase energy requirements and reduce net electrical output.

High-resolution electricity system behavior with CO₂ capture is studied using a generating unit-specific database for ERCOT. Unit dispatch is optimized over a typical week in each season for several CO₂ and natural gas prices (\$0, \$30, \$40, \$50, and \$80/tCO₂; \$3, \$4.91, and \$8/MMBTU natural gas). Interactions with renewable electricity are studied using projected 2020 conditions with 20% electricity supplied by wind. Least-cost dispatch of energy and ancillary services is compared for each electricity market condition with half the coal-based capacity having (1) no CO₂ capture, (2) inflexible capture, (3) venting-only flexible capture, and (4) flexible capture with solvent storage.

Power system utilization and electricity market share are as good

or better with flexible CO₂ capture for most market conditions studied.

Capture flexibility allows increased capacity factors at intermediate electricity demand because units are online primarily to provide ancillary services. Increased plant utilization with flexible CO₂ capture reduces overall CO₂ emissions in the electricity system.

AS procurements are significantly greater when capture systems are flexible, and benefits increase with CO₂ and natural gas price as facilities are utilized more often. Regulation up and reserve services are preferentially procured from flexible capture facilities over marginal gas-fired units because flexible capture units can provide reserve capacity without being marginal. Regulation down service is also economical to procure from flexible capture units not operating at 100% load capture. The AS benefits of flexible capture are not mitigated by the introduction of substantial CAES capacity. CAES units primarily displace marginal generating units for peak electricity supply and ancillary services but do not significantly impact energy and AS supply from flexible capture units.

Flexible capture units can decrease total dispatch costs by varying capture load in response to electricity demand variations or turning capture off when operating costs without capture are less than those of other marginal generators. Capture flexibility is especially useful at low net demand induced by high wind production, where electricity oversupply can be reduced through flexible capture operation. Flexible capture also avoids electricity undersupply at high demand that is difficult to meet with inflexible capture that reduces available coal-based generation. Observed dispatch cost reductions are typically modest but increase at high CO₂ and natural gas prices and intermediate electricity demand. Under market conditions where low-cost capacity is inflexible, flexible capture systems can

improve grid flexibility by responding to rapid changes in electricity demand. However, CO₂ capture flexibility does not have a consistent positive or negative impact on electricity prices.

Solvent storage is never utilized in the electricity system model under the conditions studied. While profit maximization modeling finds value in solvent storage for price arbitrage, solvent storage is not used for energy arbitrage in the least-cost dispatch model because lower operating costs during partial-load stripping/compression are offset by higher costs when regenerating stored rich solvent. A solvent storage system does not impact AS offer capability unless greater design CO₂ carrying capacity or oversized stripping and compression equipment increase total capture energy requirements. A larger design capacity was assumed with solvent storage for this analysis, but the <1% increase in capture energy has a negligible impact on results. However, the value of solvent storage for AS would be better assessed by a model that includes AS deployments. The differences in AS value between the venting-only and solvent storage configurations can only be assessed when cost differences of AS deployments are taken into account.

Chapter 6

Summary of Conclusions

Two versatile optimization models have been created to study the electricity system implications of flexible CO₂ capture. One model assesses the value of flexible capture at a single facility in response to volatile electricity prices, while the other represents a full electricity system to study the ability of flexible capture to meet electricity demand and reliability (ancillary) service requirements. All analyses use the ERCOT grid as a case study and exclusively considers coal-fired generation using a 7m MEA solvent for post-combustion CO₂ capture. Facilities are compared with no capture, inflexible capture, flexible capture that vents CO₂ at partial load, and flexible CO₂ capture that uses solvent storage to enable partial-load stripping and compression without additional CO₂ emissions.

When studying price-responsive flexible capture, including price volatility and forecasting ability is important to accurately assess the value of flexible capture. Flexible capture in response to electricity prices was studied for a wide range of market conditions: \$2–11/MMBTU natural gas price and \$0–200/tCO₂ CO₂ price. Flexible CO₂ capture systems transition from rarely using capture to near-100% utilization at \$30–40/tCO₂, largely independent of natural gas price. As long as operating costs are lower with capture at full load, a facility with flexible capture achieves significant CO₂ emissions reductions despite the ability to vent CO₂ at high electricity prices. Under the conditions studied, venting CO₂ while selling additional electricity at high prices is valuable only at \$30–60/tCO₂ and natural gas prices exceeding \$4/MMBTU.

Nevertheless, the ability to vent CO₂ at peak electricity prices is still valuable if it requires negligible capital cost, which is likely true for a retrofit application.

A sensitivity analysis explored the effects of varying CO₂ capture and base plant ramp rate, base plant size, and CO₂ capture energy requirements. Nearly the full operating profit benefit from flexible capture is achieved for base plant and capture system ramp rates above 1%/min, and benefits are insensitive to base plant size. Improved CO₂ capture energy performance increases total operating profits but reduces the quantity of energy a flexible capture system can utilize for price arbitrage, diminishing the incremental value of flexibility.

A flexible CO₂ capture system with a well-designed solvent storage system improves the incremental benefits of flexible capture and broadens the region where flexible CO₂ capture is valuable into higher CO₂ prices at low-to-moderate natural gas prices. The conditions where solvent storage has significant value correspond to power plant capacity factors below 90%, and the economic benefit of solvent storage is greatest when expected capacity factors are 40–80% given CO₂ prices high enough to justify CO₂ capture operation. Under the present case study, this situation occurs with CO₂ prices above \$40/tCO₂ and natural gas prices below ~\$5/MMBTU. The optimal time for regenerating stored rich solvent is when the additional energy cost produces a small profit loss, and these conditions rarely occur at high CO₂ and natural gas prices because electricity prices are too high for the loss to be offset by increased electricity sales when storing rich solvent. Optimal solvent storage operation does not necessarily follow a predictable daily cycle, and CO₂ venting might still be reasonable at high electricity prices to reserve solvent storage for other times. The transition to near-continuous full-load capture is slightly faster with solvent storage than with venting-only capture because solvent storage allows price arbitrage without increasing

CO₂ emissions.

A detailed design study identified favorable characteristics of solvent storage systems. Oversizing stripping and compression equipment is not worth any increased capital cost. Choosing to operate with 33% greater CO₂ carrying capacity is worth a <1% increase in capture energy requirements because solvent inventory costs are significantly reduced. The optimal storage system size depends strongly on the solvent price. With an MEA price of \$2.55/kg, the optimal design for an intermediate CO₂ and natural gas price combination allows a maximum of 2 hours with stripping/compression systems offline with full-load absorption. Lower solvent price allows larger optimal storage system designs. The incremental profit benefit of solvent storage is highly sensitive to capital cost assumptions, varying by over 300% between reference and favorable capital cost assumptions.

Operating profit estimates were utilized to illustrate both deterministic and stochastic CO₂ capture investment analysis. There appears to be minimal value of price-responsive flexible CO₂ capture at market conditions where capture installation is justified, but it is important to emphasize these results are case-specific. The investment analysis frameworks consider only a limited range of conditions and uncertain parameters, and analysis could be improved by incorporating the ancillary service value of flexible capture.

The full electricity system model is used to simulate electricity dispatch and AS provision for several CO₂ and natural gas prices in projected 2020 ERCOT conditions where 20% of annual electricity demand is supplied by wind. Partial-load CO₂ capture supplies additional electricity at peak demand if generation without capture is less expensive than electricity from marginal units. The ability to turn capture systems off while maintaining maximum gross power output allows flexible capture facilities to

offer additional regulation up, responsive (spinning) reserve, and non-spinning reserve service. Offers for regulation down service can also increase if capture systems have capacity to increase energy requirements and reduce net electrical output.

Power system utilization and electricity market share are as good or better with flexible CO₂ capture for most market conditions studied. Capture flexibility allows increased capacity factors at intermediate electricity demand because units are online primarily to provide ancillary services. Increased plant utilization with flexible CO₂ capture reduces overall CO₂ emissions in the electricity system. AS procurements are significantly greater when capture systems are flexible, and benefits increase with CO₂ and natural gas price when facilities are utilized more often. Regulation up and reserve services are preferentially procured from flexible capture facilities over marginal gas-fired units because flexible capture units can provide reserve capacity without being marginal. The AS benefits of flexible capture are not mitigated by the introduction of substantial CAES capacity. CAES units primarily displace marginal generating units for peak electricity supply and ancillary services but do not significantly impact energy and AS supply from flexible capture units.

Flexible capture can decrease total dispatch costs and reduce the frequency of supply/demand imbalances by varying capture load in response to electricity demand or turning capture off when operating costs without capture are less than those of other marginal generators. Capture flexibility is especially useful at low net demand induced by high wind production, particularly under market conditions where low-cost capacity is inflexible. CO₂ capture flexibility is not observed to have a consistent positive or negative impact on electricity prices.

Solvent storage is never utilized in the least-cost electricity dispatch framework because the solvent storage design included in analysis does not significantly

impact AS offer capability. While profit maximization modeling finds value in solvent storage for price arbitrage, solvent storage is not used for energy arbitrage in the least-cost dispatch model because reduced operating costs during partial-load stripping/compression are offset by increased costs when regenerating stored rich solvent. However, the value of solvent storage for AS would be better assessed by accounting for cost differences in AS deployments from different flexible capture configurations.

To summarize, price-responsive flexible CO₂ capture has limited value at market conditions that justify CO₂ capture investments. Solvent storage can add value for price arbitrage, but only with favorable capital costs. The primary advantage of flexible CO₂ capture is an increased ability to provide grid reliability services and improve grid resiliency at minimum and maximum electricity demand.

The strength of the models developed in this body of work is their transparency and adaptability for market- and site-specific considerations. The results presented herein aim to comprehensively value flexible CO₂ capture, but the true utility of this work lies in the modeling tools that are useful for much broader range of electricity systems analysis.

Chapter 7

Future Work

There are several opportunities for future work to extend the modeling activities presented in this dissertation. The only CO₂ capture process considered herein is amine scrubbing for post-combustion CO₂ capture, and 7m MEA is the only solvent examined. Future work could examine how the value of flexible capture varies with other amine solvents such as piperazine (PZ), methyl diethanolamine (MDEA), and various solvent blends. Solvent properties such as energy performance, CO₂ carrying capacity, and cost can vary widely and have a significant effect on the value flexible capture. The optimization models developed for this work are tailored for post-combustion amine scrubbing, but future work could examine other CO₂ capture technologies by adjusting the constraints that govern relationships between power and CO₂ capture systems. Persistent low natural gas prices could significantly reduce the contribution of coal to the U.S. electricity system, so future study might also examine the implications of flexible CO₂ capture on natural gas-based generators, which are already more flexible than coal-based units.

This work provides insights that apply for other electric grids, but case studies for contrasting electricity systems would improve the understanding of flexible CO₂ capture within different regulated and competitive electricity systems. The existing modeling framework could be tailored for alternative electricity systems with appropriate input information and adjustment for electricity system-specific characteristics such as ancillary service protocols.

Several additional features would improve the accuracy of the single plant profit maximization model and the least-cost dispatch unit commitment model. Non-linear or piece-wise linear performance curves would better represent the relationships between efficiency of power and capture systems across their operating range, and doing so would yield more accurate estimates of emissions. Minimum up/down times and startup/shutdown times that vary with online or offline duration would also improve operating realism.

Solvent storage design was optimized by the profit maximization model for only one market condition, so a similar study at different market conditions would reveal any changes in optimal design parameters. If optimal design differs significantly, a stochastic representation of market conditions might be necessary to determine optimal solvent storage characteristics within computational and analytic capabilities. Completed analysis also focused primarily on daily planning of solvent storage and energy storage systems, so future work could examine longer planning periods to determine optimal planning length as a function of storage system size.

Including the transmission system in the unit commitment would substantially increase input data requirements, but doing so would better represent the locational implications of flexible CO₂ capture, particularly if flexible capture systems are geographically distant from variable wind supply to which they are responding. A zonal representation of the transmission system could be implemented as an intermediate step between unconstrained and fully nodal transmission modeling. A better representation of the competitive electricity market would reformulate the objective as an offer/bid model with both energy and AS. Given necessary offer/bid data, this change could produce a more accurate representation of shadow prices for electricity and AS, which would make the unit commitment model more relevant for calculating revenues

and profits. A framework for modeling AS deployments would also be useful to fully understand the value of solvent storage for meeting ancillary service requirements.

Additional unit commitment simulations could be performed for extreme grid conditions such as annual peak demand or maximum net demand changes in speed or magnitude. Simulating a capacity-constrained electricity system could assess the utility of flexible capture when peak demand and ancillary service provision are most valuable. Electricity undersupply in these conditions could be compared with inflexible and flexible capture to value flexible capture for eliminating the need to replace output lost to CO₂ capture energy requirements. In addition, transmission or generation outage events could be simulated to study grid response with different flexible capture configurations. Grid flexibility and thus flexible capture should be especially valuable under these circumstances. The impact of forecasting accuracy could be examined in greater detail by using different net demand to optimize the forward and real-time markets.

The unit commitment model is capable of analyzing electricity system behavior outside the realm of CO₂ capture. It already includes energy storage systems, and future development could incorporate a more detailed representation of wind turbines that includes curtailment ability. Interruptible load is included and permitted to meet some AS requirements, but continued development could add a more sophisticated demand-response framework to represent industrial load, retail demand, or electric vehicles. Commercial software exists that includes many of the capabilities described in this section, but a custom model offers the benefits of transparency and adaptability that commercial models might not provide. These benefits allow research to remain on the forefront of electricity systems thought and analysis.

Future work using the decision analysis approach could include more complex

multi-stage decisions with options to retrofit, rebuild, or build new facilities of various types. Decisions could take place at various time periods and include a greater number of uncertain parameters. Uncertainty could be characterized in a more sophisticated manner using Monte Carlo simulation. Ancillary service value could also be estimated and included in investment decision analysis for a more complete assessment of flexible capture value. A broader range of economic assumptions could be studied to better assess the impact of capital cost and discount rate on the comparative value of CO₂ capture configurations.

Appendices

Appendix A

Model Limitations and Qualitative Uncertainty Analysis

This appendix summarizes the assumptions and limitations of the modeling approach and qualitatively discusses their impact on uncertainty of results. Uncertainty is difficult to quantify in electricity systems modeling, because performing controlled experiments on an electric grid is impractical, and obtaining comparable results from individual facilities is also extremely difficult. Though some pilot- and demo-scale amine scrubbing facilities are operational, there are no commercial-scale systems on power generating units that could test the value of flexible capture in a functioning electricity system. Lack of data or its unavailability also make uncertainty analysis challenging. ERCOT makes a substantial amount of market data publicly available, but generating unit data are often proprietary. This work used generic generating unit information provided by ERCOT along with plant-specific information from the EPA eGRID database, so discrepancies with actual unit performance would introduce errors in absolute results. It might be possible to determine unit-specific performance information from publicly available offers into energy and AS markets, but doing so is outside the scope of this work.

A key limitation within all modeling activities is imposed by model linearity, which requires constant power and capture system performance parameters across an operating range. Linear model formulations facilitate optimal solution convergence within minutes to hours of computation time. Piece-wise linear representations of

load-performance curves could be incorporated in the future. However, these are not implemented because they would significantly increase problem size, and by extension, solution difficulty. A nonlinear formulation is similarly avoided, though no testing was performed on either of these alternatives.

Daily and seasonal variations in plant availability, fuel prices, and CO₂ prices are not included in this analysis. In practice, maintenance requirements periodically bring systems systems offline, which might affect value of flexible capture if power and capture systems are not offline equal amounts of time. Reduced operating time would scale annualized results accordingly, but trends should be unaffected with downtimes on the order of days to weeks. Fuel and CO₂ price variability could have a significant impact on results. Natural gas price in particular have been historically volatile. As an initial valuation of flexible capture, constant fuel and CO₂ prices are assumed sufficient to understand aggregate plant and grid behaviors. However, the models could be adapted to use variable fuel and CO₂ prices if desired.

The single plant profit maximization model assumes the facility is a price-taker, meaning its operations do not affect electricity prices. This assumption is not accurate for most facilities in an electricity system; either they strongly influence prices as marginal generators, or they indirectly influence prices by affecting which facilities provide marginal generation. Depending on market conditions, the facility optimized in this work has capacity factors typical or base, intermediate, or peak load, so the price-taking assumption will not affect accuracy in the same way in all cases. Nevertheless, the effect of a single facility on prices is typically small, so price-taking is sufficient to understand price-responsive flexible capture using a consistent methodology for all analysis.

The profit maximization model uses electricity prices that are adjusted for fuel

and CO₂ prices, but this adjustment procedure does not account for price elasticity of electricity demand. The effect of demand elasticity is likely small but could be incorporated into future versions of the electricity price adjustment procedure described in Section 3.1.2.

The electricity system unit commitment model also has several limitations, many of which are discussed in Section 5.2.13. The model does not include the transmission system, so it effectively represents an electricity system with no transmission congestion. Thus, results could overstate the value of flexible capture if constrained transmission lines prevent capture systems from responding to net demand variations. Conversely, results could understate the benefits from flexible capture if variable supply and demand are in close proximity to flexible capture units and more able to benefit from them. Coal-fired units are typically far from demand centers and not necessarily near wind turbines, but the net effect of transmission congestion on flexible capture is unclear. Locational considerations are outside the scope of this work but would be a good candidate for future study.

The unit commitment model also ignores demand elasticity to changes in market conditions. In the short term, electricity demand is highly inelastic, but long-term elasticity could reduce electricity demand if fuel prices increase or CO₂ prices are introduced. These effects would temper any increase in electricity price, which would reduce the value of flexible capture for responding to high marginal dispatch costs. However, since impacts of flexible capture are observed over a wide range of market conditions, demand elasticity is expected to have a small effect on the overall benefits of flexible capture.

RRS and NSRS requirements were not adjusted when projecting a 2020 ERCOT electricity system. Though NSRS requirements could increase if additional

wind-based power production increases net load uncertainty, ignoring this effect does not prevent the present analysis from evaluating flexible capture for providing AS. In the future, adjusted requirements for NSRS or other AS could help assess the impact of different AS policies and how flexible capture can play a role.

While calculated shadow electricity and AS prices can reveal dispatch economics, a more complete representation of the market is required for direct price comparison. ERCOT prices are settled using offers from generation and bids from wholesale electricity consumers, so a representation of this bidding behavior is necessary to produce more accurate prices. These bids must also represent the opportunity costs of providing AS, which are not included in the current framework that assesses only direct costs for producing electricity. Including responses to potential supply/demand imbalances, such as wind curtailment or ancillary service deployment, are also useful for reproducing realistic price dynamics.

Certain unit types have simplified representations in the unit commitment model. The restriction of CHP units to continuously produce their maximum electrical output is thought to be a reasonable assumption, but some variable output is expected, particularly when the electricity system is strained. Hydroelectric units are not modeled with water resource limitations and peak shaving incentives taken into account. These effects are assumed negligible for ERCOT but could be significant in electricity systems with large quantities of hydroelectric generation.

Additional plant-level constraints in either model would provide more realistic short-term operation but are unexpected to substantially affect the overall conclusions of this work. These include variable minimum up/down time and variable startup/shutdown time that depend how long a unit was previously on or off. Startup costs could be similarly varied for offline time before each startup.

These modeling limitations reduce absolute accuracy of modeling results. However, modeling activities are intended primarily for making high-level conclusions, so the model development goal was to include enough rigor to assess aggregate plant- and grid-level behaviors on time scales of weeks to decades. In this respect, there is high confidence in the trends demonstrated by the models and the conclusions drawn from them. Results have been produced with the appropriate rigor to assess whether or not flexible capture is worth detailed consideration and under what market conditions. Using ERCOT-specific results as a guide, the modeling frameworks can be adapted for site-specific considerations and decision-making for particular facilities and electricity systems. If benefits are marginal in ERCOT, inaccuracies introduced by model limitations could play a role in determining the ultimate utility of a flexible capture system. However, when benefits are substantial, the value of flexibility is expected to exist in a realistic system.

Appendix B

Manual: Single Plant Profit Maximization Model

This appendix is a users manual for performing simulations with the single plant profit maximization model, which is available upon request to the author at `stuart.cohen@utexas.edu`. The first section discusses importing input data from a Microsoft Excel workbook. The next section describes setting up the GAMS code for a simulation. The last section guides the user on analyzing output data in Microsoft Excel. Several examples of GAMS code are included to explain model features, but GAMS syntax is not discussed in detail. Individuals unfamiliar with GAMS programming are encouraged to reference the GAMS Users Guide or the Expanded GAMS Guide by McCarl [Rosenthal, 2008, McCarl et al., 2009].

B.1 Setting Up and Importing Input Data

The model optimizes operation of a single facility, so all power and capture system cost and performance parameters are defined within the GAMS code. Electricity prices, however, are imported from an Excel workbook so market conditions or time duration can be easily changed.

GAMS uses the GDX file format for storing tabular data, so the built-in GDXXRW utility converts Excel data to the GDX format. The current model version imports data from `input_data_single_plant_ccs_gams.xls` using the line of code `$call GDXXRW input_data_single_plant_ccs_gams.xls`
`@input_data_single_plant_ccs_gams.txt`. The file

`input_data_single_plant_ccs_gams.txt` is a text file that tells the GDXRW utility which Excel worksheets and cell ranges to import. After this line of code reads Excel data into the GDX format, the data are stored as a GDX file with the line of code `$gdxin input_data_single_plant_ccs_gams.gdx`. Filenames can be adjusted if desired.

The `input_data_single_plant_ccs_gams.txt` file includes code in GAMS syntax to import data from the `input_data_single_plant_ccs_gams.xls` workbook. Since the elements in the time set ($t \in [1, T]$) depend on input data, values for t are imported using statements of the form `dset=t rng=pricesheet!I7 rdim=1`. The set index name is specified by `dset`, `rng=` is followed by the sheet name and cell containing the upper-leftmost element, and `rdim=1` indicates one-dimensional (vector) data. The list of set elements must be in column format. Before using these the t set in the model, it must be declared within a `sets` list and retrieved from the GDX file using `$load t`.

Electricity prices with the parameter name `price_raw` are then imported as a one-dimensional parameter with code in the form `par=price_raw rng=pricesheet!I7 rdim=1`. The code `par=` indicates a parameter will be imported, and `rng=` and `rdim=1` have the same meaning as discussed above. The `_raw` subscript is a legacy of earlier analysis where electricity prices were adjusted for CO₂ price within the GAMS code by adding the average emissions cost of gas-fired facilities in ERCOT. GAMS requires one-dimensional parameters to be imported as a column of data to the right of its controlling set elements, so the upper-leftmost cell I7 is actually the first element in the time set, not the first electricity price (which would be contained in cell J7). Table B.1 provides an example.

Cell references and sheet names can be modified as desired. It is possible to

Table B.1: The column of input price data must be preceded by a column containing the elements of t .

Price interval (element in t)	Electricity price (\$/MWh)
1	46.8
2	46.7
3	46.6

specify the exact cell range in the format I7:J199 if I7 is the upper-leftmost cell and J199 is the lower-rightmost cell. However, this practice is avoided to eliminate the need to edit the *.TXT file whenever the number of elements in t is modified.

Many different electricity price series were analyzed, so the ability to rapidly change input data is desirable. Typically, several price series are included within the same sheet in `input_data_single_plant_ccs_gams.xls` so the price series for the current simulation can be quickly copied and pasted into the cell range referenced in `input_data_single_plant_ccs_gams.txt`. The Excel file must be saved before GAMS will use the correct data.

The GDXXRW utility requires a local installation of Microsoft Excel. However, it might be preferable to run simulations on computers with greater memory and processing resources that do not have an Excel installation. Most simulations completed for this dissertation were run on high-performance Linux-based computers without Excel. To do so, GDX files are created on a machine with Excel by running the model after commenting all GAMS `solve` statements. Then, the model is solved on the high-performance machine with `solve` statements uncommented and the `$call GDXXRW` statement commented.

B.2 Setting Up and Running the Model

The GAMS model runs without intervention either by clicking the Run button in the GAMS window or using the appropriate command line entry. This section discusses several options and adjustments that are available when setting up a simulation.

B.2.1 Parameter Adjustments

Several `scalar` values, or single-element parameters, are used to adjust power and CO₂ capture system cost and performance. Coal and CO₂ price, which influence input electricity prices, must also be specified in the model. Therefore, users should ensure coal and CO₂ prices in the GAMS code are consistent with those used to produce input electricity prices. Average electricity price, which is used for assessing CO₂ capture ramping costs, is calculated within GAMS from input electricity prices. The system-average CO₂ emissions rate for gas-fired facilities is used only if approximating the impact of CO₂ price on electricity prices by adding the average emissions cost of gas-fired facilities. This approximation is most applicable to gas-dominated electricity systems such as ERCOT.

The length of the time interval, `Tstep`, can also be adjusted as long as it remains consistent with input electricity prices. The `scenario` value specifies which CO₂ capture configuration is active for a particular simulation. Respectively, values of 1–4 activate the no capture, inflexible capture, venting-only, and solvent storage configurations using if-else trees that trigger the appropriate constraints and `solve` statements.

B.2.2 Code Options

There are several sections and lines of code that can be commented or uncommented to modify model definitions and study different power, CO₂ capture, and electricity system conditions.

B.2.2.1 Calculation and Constraint Options

If electricity prices are adjusted for fuel and CO₂ price conditions before being imported into the model, the imported price vector, `price_raw`, should be set equal to the adjusted price vector, `price_adj`, used to optimize the facility. Before the price adjustment procedure discussed in Section 3.1.2 was developed, electricity prices were adjusted for CO₂ price using the first-order method of adding average emissions costs at natural gas-fired facilities (Section 2.2.2). Though this procedure is considered obsolete, it can be reactivated by uncommenting the line of code below and commenting the line `price_adj(t)=price_raw(t);`.

```
price_adj(t)=price_raw(t)+avg_ercot_ng_co2_rate*price_co2;
```

The model includes two ways to define CO₂ capture ramping costs. Ramping costs are typically calculated using Eqn. 2.13. Alternatively, costs can be specified directly, which was done for the Section 2.3.1 sensitivity analysis.

When modeling flexible capture with solvent storage, maximum stripping and compression load is partially constrained by equipment size. The model includes options to specify stripping/compression equipment size directly or to calculate equipment size from solvent storage tank capacity, ψ , using Eqn. 2.32 and the heuristic that equipment should be oversized by the quantity $24/(24 - \alpha)$. This heuristic is based on assumed daily cycling of the solvent storage system, where a storage tank

sized for up to α hours with stripping/compression offline and full-load absorption has $24 - \alpha$ hours each day to regenerate stored solvent.

B.2.2.2 Model Definition and Solution Options

There are four `model` statements used to define each of the four CO₂ capture configurations. Model definitions are formatted so different constraints can be easily activated or deactivated by commenting or uncommenting the line of code listing constraint names. The objective function is required in the model definition, but different constraint sets can be used to vary model complexity or study different system specifications. For instance, minimum up and down time constraints are listed in model definitions but commented for the present work.

Three model-specific parameter values are assigned below each model definition. The relative and absolute optimality tolerances, `optcr` and `optca`, are defined, and the maximum CPU time (resource limit) is set by statements of the form `modelname.reslim=num`, where `num` is the maximum CPU time in seconds. For all analysis contained within this dissertation, `optcr=0.0001` and `optca=50000`. Absolute optimality tolerance is typically more restrictive, and \$50,000 is chosen because annual profits for a 500 MW facility are on the order of hundreds of millions of dollars, so closing the optimality gap to within \$50,000 ensures confidence to the precision of hundreds of thousands of dollars. The resource limit was typically set to 10,000 seconds. This time limit is observed to be sufficient for the majority of simulations without CO₂ capture, with inflexible capture, and with venting-only flexible capture, but the desired optimality tolerance was not always achieved within 10,000 seconds with solvent storage. Up to 30,000 seconds was allotted when modeling solvent storage, and even then the remaining optimality gap was sometimes on the order of hundreds of thousands of dollars.

B.2.2.3 Exporting Results

Before exporting results, marginal cost, total cost, and profit in each time interval are calculated to enable rapid data analysis. Several operating cost components are calculated separately to facilitate troubleshooting and detailed cost analysis.

Results are exported to a text-based CSV format, which can be easily manipulated in Excel or imported into MATLAB. CSV export is accomplished using the `gams2csv.gms` routine, which is not included with GAMS but can be downloaded from the website of University of Colorado Economics Professor Dr. Thomas F. Rutherford (<http://www.mpsge.org/gams2csv/gams2csv.htm>). Data export requires a `file` statement that defines a file handle and name, a `put` statement with the file handle, an `include` statement to call `gams2csv` and specify sets and variables or parameters for export, and a `putclose` statement to complete the export process. The example below would export the gross output variable, `x.l`, and the base plant unit commitment variable, `u_p.l`. The `$batinclude` statement requires `gams2csv.gms` to be located in the same directory as the `*.GMS` model file. Alternatively, `$libinclude` could be used if `gams2csv.gms` is in the appropriate GAMS home directory. The `include` statements must not end in a semi-colon, and there are no commas between variables exported within a single statement.

```
file single_plant_ccs_output /single_plant_ccs_output.csv/;
put single_plant_ccs_output;
$batinclude gams2csv t x.l u_p.l
putclose;
```

Several `include` statements can be contained between a given set of `put` and `putclose` statements, but only one `include` statement is used in the current model

version because all variables have the same set index. If certain variables or parameters are not needed for a particular simulation, they can be removed from the `include` statement or moved to another `include` and commented. Doing so might be desirable to reduce output file size. For instance, if the “no capture” configuration is analyzed exclusively, output file size is reduced by choosing not to export CO₂ capture variables and parameters.

B.3 Analyzing Output Data

The `gams2csv` utility exports elements of each variable in column format with data for each variable or parameter placed in rows below the previously exported variable. The variable or parameter name and text description from GAMS are also exported. Table B.2 provides an abbreviated example of exported data. This format is not conducive to efficient data analysis; for example, a one-year simulation with 15-minute time intervals produces a CSV file with several hundred thousand rows (and only 3 columns). However, output format consistency lends itself to standardized reformatting and analysis.

Table B.2: Variables and parameters are exported in the following format.

u.p.l	unit commitment (1=on, 0=off)	
		1 0
		2 1
	
x.l	gross output (MW)	
		1 500
		2 480
	

Output files for a typical one-year simulation are ~ 20 MB, which is considered manageable for Excel. Thus, the single plant profit maximization model has no automated MATLAB post-processing tool comparable to the one used to analyze unit commitment model results. Instead, an Excel spreadsheet template is created where data reformatting and post-processing calculations are performed by copying and pasting formulas from the template into the raw output file.

The Excel template is primarily cell references that recopy quantities from each variable into columns in the top of the spreadsheet. Dynamic data are reformatted for easily viewing by pasting the first few rows from the template into the raw output file then using Excel auto-fill to populate rows for all time periods. Row numbers in cell references depend on the total number of time intervals in the simulation, so the template must be edited for any changes to the total simulated time. Column headings are also included in the spreadsheet template.

In addition to data reformatting, the spreadsheet template includes formulas that calculate total output, total CO₂ emitted and captured, total costs and profits, capacity factors for power and capture systems, and average CO₂ emissions rate. To ensure these quantities are calculated correctly, startup/shutdown and CO₂ capture ramping costs must be manually entered into the raw output file after the formulas are copied from the spreadsheet template. If CO₂ capture ramping costs are dependent on average electricity price, the correct ramping cost must manually entered as well. These aggregate statistics can then be compiled for several simulations to analyze behavior across different input conditions.

For operating profits to be calculated correctly, the appropriate electricity price series must be pasted into the Excel output file. If the forecast price series used for optimization is the same as the “actual” price series used for calculating

profits, then profits exported by GAMS can be used directly. However, analyses within this dissertation typically optimize operation in response to pseudo-forecast electricity prices then calculate profits using prices with historical volatility. Thus, the necessary volatile price series must be pasted into the Excel output file for use in profit calculations.

Figure B.1 is a screen shot of an Excel output file after formulas have been copied from the spreadsheet template. Columns A–C are GAMS output, and the highlighted area (cell range D1:AJ12) is copied from the Excel template. Rows 13 and higher are populated using the auto fill feature. Cells highlighted yellow contain manually entered startup costs (cells K2:O2) and CO₂ capture ramping costs (cells AE2:AF2). Electricity prices used in profit calculations are pasted into column AC, rows 5 and higher (cells shaded blue). Other values in rows 1–3 are used to calculate aggregate statistics, which are included with labels and units in the cell range AM4:AJ12.

Appendix C

Manual: Unit Commitment Model

This appendix serves as users manual on how to perform simulations with the unit commitment model, which is available upon request to the author at `stuart.cohen@utexas.edu`. The first section discusses importing input data from a Microsoft Excel workbook. The next section describes setting up the GAMS code for a simulation. The last section guides the user on analyzing output data with the MATLAB post-processing tool. Several examples of GAMS code are included to explain model features, but GAMS syntax is not discussed in detail. Individuals unfamiliar with GAMS programming are encouraged to reference the GAMS Users Guide or the Expanded GAMS Guide by McCarl [Rosenthal, 2008, McCarl et al., 2009].

C.1 Setting Up and Importing Input Data

Input data that vary over time (i.e. electricity demand, ancillary service requirements) and generating unit information (i.e. heat rate, maximum output capacity) are imported from an Excel workbook. These data include any parameter with a p or t subscript in Tables 5.1–5.8. All other parameters are specified within the GAMS model code.

GAMS uses the GDX file format for storing tabular data, so the built-in GDXXRW utility converts Excel data to the GDX format. The current model version imports data from `input_data_unit_comm_ccs_v3.xls` using the line of code `$call GDXXRW input_data_unit_comm_ccs_v3.xls`

`@input_data_unit_comm_ccs_v3.txt`. The file `input_data_unit_comm_ccs_v3.txt` is a text file that tells the GDXXRW utility which Excel worksheets and cell ranges to import. After this line of code reads Excel data into the GDX format, the data are stored as a GDX file with the line of code

`$gdxin input_data_unit_comm_ccs_v3.gdx`. Filenames can be adjusted if desired.

The `input_data_unit_comm_ccs_v3.txt` file includes code in GAMS syntax to import data from the `input_data_unit_comm_ccs_v3.xls` workbook. The statement `SQ=N` ensures zeros are not skipped over when creating the GDX file. Data are retrieved from three Excel worksheets: (1) `plants` contains the generating unit database, (2) `load_RT` contains electricity demand and wind production, and (3) `AS_req` contains regulation requirements and net demand uncertainty.

Since the elements in the time and plant sets ($t \in [1, T]$ and \mathbb{P}) depend on input data, values for t and p are imported using `dset=p rng=plants!A3 rdim=1` and `dset=t rng=load_RT!C2 rdim=1`. The appropriate set index is specified by `dset`, `rng=` is followed by the sheet name and cell containing the upper-leftmost element, and `rdim=1` indicates 1-dimensional (vector) data. The list of set elements must be in column format. Before using these sets in the model, they must be declared within a `sets` list and retrieved from the GDX file using `$load t p`.

All power, capture, and energy storage parameters indexed by p are imported in the same manner and must similarly be declared and loaded within the model before use. For instance, power plant heat rates with the parameter name `hr_base` are imported from the `plants` worksheet with the line `par=hr_base rng=plants!F3 rdim=1`. The code `par=` indicates a parameter will be imported, and `rng=` and `rdim=1` have the same meaning as discussed above. GAMS requires one-dimensional parameters to be imported as a column of data to the right of its controlling set elements,

so the upper-leftmost cell **F3** is actually the first element in the controlling set, not the heat rate of the first unit (which would be contained in cell **G3**). As a result, the Excel spreadsheet must contain alternating columns of elements in \mathbb{P} with unit data in between. Table C.1 provides an example with three parameters and generating units.

Table C.1: Columns of input data indexed by p must be preceded by a column containing the associated set elements.

Plant Name (element in p)	Base Plant VOM Cost (\$/MWh)	Plant Name (element in p)	Heat Rate (MMBTU per MWh)	Plant Name (element in p)	CO ₂ Emissions Rate (tCO ₂ /MWh)
Unit 1	9.5	Unit 1	11.397	Unit 1	0.461
Unit 2	9.5	Unit 2	11.980	Unit 2	0.457
Unit 3	9.5	Unit 3	11.211	Unit 3	0.701

Parameters indexed by t are imported in the same manner as those indexed by p with the appropriate parameter name, worksheet name, and upper-leftmost cell reference. Again, the cell reference must point to the first element in the controlling set, not the first data element, so columns containing elements $[1, T]$ must be placed to the left of columns containing demand, wind, or AS data.

Cell references and sheet names can be modified as desired. It is possible to specify the exact cell range in the format **F3:G88** if **F3** is the upper-leftmost cell and **G88** is the lower-rightmost cell. However, this practice is avoided to eliminate the need to edit the *.TXT file whenever the number of elements in p or t are modified.

Many different sets of generating units and electricity market requirements were analyzed, so the ability to rapidly change input data is desirable. Thus, input data for several unit databases and electricity system requirements were maintained in the same Excel workbook in different worksheets to eliminate the need to edit the

GAMS model or the `input_data_unit_comm_ccs_v3.txt` import code when switching between input data sets. Instead, desired data are retrieved by renaming Excel worksheets to `plants`, `load_RT`, and `AS_req` as necessary. The Excel file must be saved before GAMS will use the correct worksheets.

The GDXRRW utility requires a local installation of Microsoft Excel. However, it might be preferable to run simulations on computers with greater memory and processing resources that do not have an Excel installation. Most simulations completed for this dissertation were run on high-performance Linux-based computers without Excel. To do so, GDX files are created on a machine with Excel by running the model after commenting all GAMS `solve` statements. Then, the model is solved on the high-performance machine with `solve` statements uncommented and the `$call GDXRW` statement commented.

Several parameters are imported but not typically used in the model. These are included for testing or informational purposes or to enable easy comparison between different scenarios. If desired, strict limits on AS offers can be imported as an alternative to the formulation based on ramp rates and available capacity. Though the model uses integers from $[1, T]$ as elements of t , the month, day, and hour of each t are also imported. The model also imports two sets of RU and RD requirements. Regulation requirements adjusted for wind capacity using Tables 5.6 and 5.7 are used in model calculations; however, unadjusted regulation requirements are also imported to facilitate rapid results comparison.

Regulation requirements are adjusted for wind capacity within the `input_data_unit_comm_ccs_v3.xls` workbook using user-defined Visual Basic functions. These functions, named `reg_up_wind_adj` and `reg_dn_wind_adj` are defined using the Visual Basic code below. The `reg_adj_matrices` worksheet contains the

adjustment factors in Tables 5.6 and 5.7, and the functions retrieve the adjustment factor for a given month and hour used for calculating the adjusted regulation requirement. The numbers 4, 2, and 32 are row and column offsets related to data placement within the `reg_adj_matrices` worksheet.

```
Function reg_up_wind_adj(month, hour) As Double
reg_up_wind_adj=Sheets("reg_adj_matrices").Cells(4+hour,2+month).Value
End Function
```

```
Function reg_dn_wind_adj(month, hour) As Double
reg_dn_wind_adj=Sheets("reg_adj_matrices").Cells(32+hour,2+month).Value
End Function
```

To ensure the model uses costs and constraints appropriate to each generating unit type, each unit p must be assigned a unit type code in the `plants` worksheet. GAMS cannot import string data directly, so a numeric code is imported then associated with a more intuitive string using the `acronyms` feature. An example is shown below. Unit type codes in the current model version are listed in the `plantcodes` worksheet within `input_data_unit_comm_ccs_v3.xls`. If a unit type code is entered incorrectly, no errors will be produced when the model is solved. However, the model will not recognize the unit type code, so it will assign no costs for operating the facility, and no constraints meant specifically for that unit type will be applied. Constraints on all unit types will still be active, but the unit will be modeled as “free” generation.

```
acronyms coal
plant_type(p)$(plant_type_code(p) eq 111122)=coal;
```

C.2 Setting Up and Running the Model

The GAMS model runs without intervention either by clicking the Run button in the GAMS window or using the appropriate command line entry. This section discusses several options and adjustments that are available when setting up a simulation.

C.2.1 Parameter Adjustments

In addition to generating unit information, electricity demand, wind production, and AS requirement information, several additional parameters can be adjusted within the GAMS code `unit_comm_ccs_vX.X.gms`.

Several `scalar` values, or single-element parameters, can be adjusted to examine changes in the electricity market or CO₂ capture performance. The most frequently adjusted parameters for this dissertation are natural gas and CO₂ price. The estimated average electricity price is also adjusted for a given combination of fuel and CO₂ prices to estimate CO₂ capture ramping costs, but this parameter is unused if modeling an electricity system without CO₂ capture. The `scenario` value specifies which CO₂ capture configuration is active for a particular simulation. Respectively, values of 1–4 activate the no capture, inflexible capture, venting-only, and solvent storage configurations using if-else trees that trigger the appropriate constraints and `solve` statements. Similarly, `chp_mustrun` allows the user to toggle whether or not CHP facilities must operate continuously at maximum electrical output; setting `chp_mustrun=1` invokes statements that fix output to its maximum and RD procurements to 0.

The values for `Tstep_FW` and `Tstep_RT` specify the length of time intervals in the forward and real-time markets and must match electricity system input data.

The `FW_period_length` parameter defines the length of the forward market planning period, which is 96 15-minute intervals for analyses within this dissertation. Adjusting time parameters enables the user to change the temporal resolution of the dispatch optimization or examine different planning horizons. Care is advised when increasing temporal resolution or lengthening the forward-market planning period. Problem size is directly proportional to the number of t elements, but computational difficulty is likely to increase faster than problem size for MIP formulations.

The `look_ahead` parameter was added to enable model solution over a longer time frame than the chosen planning horizon. A nonzero value lengthens the time frame of each optimization, but variables are fixed only within each planning period. This feature was added when troubleshooting infeasible solutions that sometimes occurred at junctions between planning periods during multi-day simulations. Allowing the model to “look-ahead” a few periods past the planning period was thought to ease the transition between planning periods, but this solution was ineffective. The feature remains in the model to allow its possible future use, but it is deactivated in all simulations within this dissertation by setting `look_ahead` to 0. Mathematically, this feature is implemented by converting all conditional statements on t within equation definitions from $m \leq t \leq k$ to $m \leq t \leq k + \lambda/\tau^{RT}$, where m and k are the first and last time intervals in the planning period, and λ is the number of hours to look ahead when performing the optimization.

C.2.2 Code Options

There are several sections and lines of code that can be commented or uncommented to modify model definitions and study different power, CO₂ capture, and electricity system configurations.

C.2.2.1 Calculation Procedures

Three options are available for calculating net electricity demand used for forward market optimization from higher-resolution demand data employed in real-time optimization. The analysis within this dissertation exclusively uses average electricity demand across a forward-market time interval (Option 2 in the model). If desired, Option 1 uses net demand in the first real-time interval of each forward-market period. This option was implemented for its ease during model testing. Activating Option 3 allows the forward-market optimization to use maximum net demand in each forward-market period. This option will reduce the occurrence of supply-demand imbalances, but the present analysis uses Option 2 to remain closer to assumed ERCOT operating procedures. Future development could modify the model to use entirely different net demand data in the forward and real-time optimizations. After modifying input data and model code as necessary, this feature would allow net demand forecast accuracy to be studied.

When modeling solvent storage with flexible CO₂ capture, maximum stripping/compression load is partially constrained by equipment size. The model includes options to specify stripping/compression equipment size directly or to calculate equipment size from solvent storage tank capacity, ψ_p , using Eqn. 2.32 and the heuristic that equipment should be oversized by the quantity $24/(24 - \alpha)$. This heuristic is based on assumed daily cycling of the solvent storage system, where a storage tank sized for up to α hours with stripping/compression offline and full-load absorption has $24 - \alpha$ hours each day to regenerate stored solvent. Stripping/compression equipment size influences RD offer limitations by Eqn. 5.70, so two versions of this constraint are included so the user may choose which formulation to use.

C.2.2.2 Constraint Options

The model includes two ways to define CO₂ capture ramping costs. Ramping costs are typically calculated using Eqn. 5.15. Alternatively, costs can be specified directly, which was done for the Section 2.3.1 sensitivity analysis with the single plant profit maximization model.

Alternative versions of the AS offer limit constraints are also included if the user wishes to set AS offer limits to a constant value for each unit using imported data. This formulation is inconsistent with ERCOT operation but might be applicable in other electricity systems.

The model currently declares variables for AS deployments and includes constraints that deployments must not exceed procurements. These constraints and variables are unused in the present model version because there is no framework to define when deployments are needed. However, they remain in the code as a starting point for future model development.

C.2.2.3 Error Checking

A “dummy” model is included to check for errors in equation definitions. This model includes an objective variable `dummy_obj` constrained to equal 0 and any equations to be tested. Setting the objective variable to 0 then minimizing the objective subject to additional constraints ensures model feasibility, so successful model solution indicates the tested equations are error-free. This model is particularly useful when defining new, complex equations where syntax errors could occur.

C.2.2.4 Model Definition and Solution Options

There are eight `model` statements used to define the forward and real-time market models for each of the four CO₂ capture configurations. Model definitions are formatted so different constraints can be easily activated or deactivated by commenting or uncommenting the line of code listing constraint names. The objective function is required in the model definition, but different constraint sets can be used to vary model complexity or study different system specifications. For instance, constraints that limit AS deployments, define minimum procurements of offline NSRS, and add offline and online NSRS are listed in model definitions but commented for the present work.

Two model-specific parameter values are assigned below each model definition. The relative optimality tolerance, `optcr`, is defined, and the maximum CPU time (resource limit) is set by statements of the form `modelname.reslim=num`, where `num` is the maximum CPU time in seconds. For all analysis contained within this dissertation, `optcr=0.00001`, which was found in early testing to give good solutions given sufficient computation time. Typically, the forward-market optimization is more difficult to solve than the real-time market optimization because it has more integer variables, so most simulations allotted 5000 seconds for forward-market solution and 3000 seconds for real-time solution. The desired optimality tolerance was not achieved in all forward-market simulations, but 5000 seconds was typically sufficient to produce a feasible dispatch solution that exhibits expected optimal behavior. Occasionally, some forward-market optimizations did not converge upon a reasonable solution within 5000 seconds. In these instances, 7000 seconds were allotted and found sufficient for solution convergence. Section C.3.3 continues the discussion of forward-market solution convergence.

In the portion of model code implementing the daily-cycling 2-stage optimization procedure, AS deployment variables are fixed to zero prior to real-time market optimization. Though AS deployments are not modeled, and these variables are unused, variables remain in the model for possible future versions including AS deployments. If AS deployments were modeled, these variables should not be fixed to zero, and the commented lines after real-time market `solve` statements should be uncommented so AS deployments are fixed each day like all other variables.

C.2.2.5 Exporting Results

Additional calculations are performed within GAMS after model solution, then results are exported to several CSV files for MATLAB post-processing. These calculations are conveniently made within GAMS but could be moved to the post-processor if all necessary parameters are exported. Electricity undersupply in each time interval is summed across segments of the undersupply penalty function, and online and offline NSRS procurements are added to find total NSRS procurements at each p and t . Net electrical output is calculated for both the forward and real-time markets. Marginal electricity production costs are calculated, and this quantity is set to \$99,999/MWh for offline units because calculated marginal costs will be infinite for these facilities. Online marginal production costs are calculated for all facilities with and without full-load CO₂ capture (if applicable) so that exported data can be used to examine the full dispatch order in any time period. Total operating costs including startup, shutdown, AS, and capture ramping costs are also calculated for each p and t to enable export of unit-specific cost information. Oversupply and undersupply costs are determined so total dispatch costs can be determined. CO₂ produced, captured, and emitted is calculated within the model to enable rapid assessment of environmental implications.

Results are exported to a text-based CSV format to facilitate import into MATLAB. CSV export is accomplished using the `gams2csv.gms` routine, which is not included with GAMS but can be downloaded from the website of University of Colorado Economics Professor Dr. Thomas F. Rutherford (<http://www.mpsge.org/gams2csv/gams2csv.htm>). Data export requires a `file` statement that defines a file handle and name, a `put` statement with the file handle, an `include` statement to call `gams2csv` and specify sets and variables or parameters for export, and a `putclose` statement to complete the export process. The example below would export the gross output variable, `x.l`, and the base plant unit commitment variable, `u.p.l`, which are indexed by `p` and `t`. The `$batinclude` statement requires `gams2csv.gms` to be located in the same directory as the *.GMS model file. Alternatively, `$libinclude` could be used if `gams2csv.gms` is in the appropriate GAMS home directory. The `include` statements must not end in a semi-colon, and there are no commas between variables exported within a single statement.

```
file output_uc_ccs_p_t /output_uc_ccs_p_t.csv/;
put output_uc_ccs_p_t;
$batinclude gams2csv p,t x.l u.p.l
putclose;
```

Several `include` statements can be contained between a given set of `put` and `putclose` statements. Variables or parameters in each `include` statement must have identical set indices, but the `gams2csv` utility allows exporting variables and parameters with different indices to the same CSV file. However, post-processing is more straightforward when there are separate files for each combination of indices (none, `t` only, `p` only, `p` and `t`), so each set of `put` and `putclose` statements contain only `include` statements with the same index sets. The `gams2csv` utility does not allow

an `include` statement with no set designation, so a single-element set `single` is used to copy and export non-indexed variables and parameters.

If certain variables or parameters are not needed for a particular simulation, the relevant `include` statements can be commented. Doing so might be desirable to reduce output file size. For instance, AS deployment variables would not need export when AS deployments are not modeled. If the model is being used exclusively in the “no CO₂ capture” configuration, output file size is reduced significantly by choosing not to export CO₂ capture variables and parameters.

C.3 Output Data Post-Processing

The `gams2csv` utility exports elements of each variable in column format with data for each variable or parameter placed in rows below the previously exported variable. For variables and parameters with multiple indices, all numerical values are in one column, and data for each variable or parameter are subdivided by elements from each set. The variable or parameter name and text description from GAMS are also exported. Tables C.2 and C.3 provide abbreviated examples of exported data with one and two indices. This format is not conducive to efficient data analysis; for example, simulations with several hundred generating units optimized over one week produce a CSV file with several million rows (and only 5 columns) for data indexed by both p and t . However, output format consistency lends itself to automated post-processing, which is performed by a custom MATLAB script `unit_comm_ccs_output_reformat_vX.X.m`.

After placing `gams2csv` output files in the MATLAB current folder, data import and post-processing are performed without intervention by clicking the Run button from the editor window containing

Table C.2: Variables and parameters with a single index are exported in the following format.

net_load	total demand less		
	wind production (MW)		
		1	50308
		2	49511
	
net_load_FW	net load for		
	forward market (MW)		
		1	49112
		2	49112
	

`unit_comm_ccs_output_reformat_vX.X.m`. The CSV file names defined in the `gams2csv` export statements must match those imported with MATLAB `fopen` statements. After importing CSV data, the post-processor uses the characteristics of GAMS output to automatically detect the number of generating units and time intervals in the simulation.

C.3.1 Data Reformatting and Aggregation

The post-processor reformats data into MATLAB struct arrays so numerical results can be easily viewed in the MATLAB command window. The variables beginning with `formatted_data` contain output data stored as easily navigable struct arrays, with the relevant indices included in the variable name. These formatted data variables allow detailed investigation of dynamic model behavior should the need arise. The variable `formatted_data_p_t` is a two-level nested struct array, with the exported GAMS variable or parameter in the upper level and unit name in the lower

Table C.3: Variables and parameters with two indices are exported in the following format.

x.l			
	nuclear	1	4600
	nuclear	2	4600

	'natural hydro'	1	200
	'natural hydro'	2	200

u_p.l			
	nuclear	1	1
	nuclear	2	1

	'natural hydro'	1	1
	'natural hydro'	2	1

level. Struct array field names cannot begin with a number, so the post-processor eliminates this possibility by placing the letter “n” in front of any number in a unit name. The variable `formatted_data_p` includes aggregate statistics for each generating unit, such as total electrical output or capacity factor across the entire simulated time period.

The variable `formatted_data_p_t_type` contains totaled quantities for each unit type in *each* time interval. All fields in the outer level of `formatted_data_p_t` are totaled. If some units of a particular type are CHP facilities, CHP and non-CHP data are separated. These data can be used to plot dynamic results by unit type when there are too many generating units to visualize output by individual unit. Totals for unit commitment variables and capture load allow capacity factors for different systems to be determined. Some totals, such as totaled marginal costs, have no clear meaning and are not used in subsequent calculations or plots.

Totals by unit type require the post-processor to search for units of a particular type using statements like the one below. Therefore, unit type names defined within GAMS must match those the post-processor detects. If additional unit types are added to the model formulation, the post-processing tool must be modified so new unit types will be detected. In addition to new statements to search for the new unit type with and without CHP, if-else trees used to initialize and calculate unit type totals must be expanded to accommodate the new unit types.

```
nucl_indices=find(strcmp(formatted_data_p.plant_type,'nucl'));
```

The variable `formatted_data_p_type` contains aggregate information for each unit type across *all* time intervals. CHP and non-CHP data are again stored separately. These statistics include totals (electrical output, AS procurements, CO₂

emitted, etc.); capacity factors for output, input, and capture systems; and average electricity prices when power input or output systems are online. The script calculates simple and input/output-weighted average electricity prices during power input/output to reveal the market conditions when different unit types operate. Daily statistics for each unit type are also calculated.

Aggregate electricity system statistics are also computed. These include average forward and real-time electricity prices as well as AS prices. Total costs and quantities of electricity oversupply/undersupply are also determined. Average electricity prices are strongly influenced by price spikes produced by oversupply and undersupply penalties, so another set of averages are also calculated after removing outliers. Outliers are defined as outside a certain number of standard deviations from the simple average. Care is required to produce electricity prices in the desired units. For instance, given 15-minute intervals in the real-time market, shadow prices output from GAMS will be in units of \$ per MW-quarter-hour, so these must be multiplied by 4 to convert to \$/MWh.

After performing the requisite calculations, aggregate statistics by unit type are exported to an Excel worksheet so they can be compared across simulations. These include the various totals (electrical output, AS procurements, CO₂ emitted, etc.), capacity factors, and average electricity prices while operating. Total output and input capacity by unit type are also exported. Aggregate electricity system statistics such as price averages are exported to the same Excel worksheet. Quantities are exported along with row titles to facilitate rapid copy/paste into a summary file used to compare results across simulations. A modified version of the built-in `xlswrite` function is used for Excel export. This function, `xlswrite1`, reduces computation time by opening and closing Excel one time outside of `xlswrite1` func-

tion calls rather than within each `xlswrite` call. The `xlswrite1` function can be downloaded from the MATLAB file exchange here: <http://www.mathworks.com/matlabcentral/fileexchange/10465-xlswrite1>.

C.3.2 Plotting

The post-processing tool creates and exports several figures that allow rapid assessment of model solutions. Dynamic results for each generating unit are plotted as area plots of electrical output in the real-time and forward markets, AS procurements, and stored energy (if available). Requirements for the commodity is overlaid on these plots to show whether or not facilities meet electricity and AS requirements. Stored energy levels are plotted with the net demand curve to demonstrate the relationship between the two. These plots are also produced by unit type because dispatch behavior by individual unit is difficult to visualize for simulations with large numbers of generating units. The aggregated plot for energy storage shows total energy stored over time.

Another set of figures plots electricity and AS prices over time along with their requirements. By exploring pricing trends and volatility, insight into solution difficulty and dispatch behavior can be gained.

The last set of figures is used to understand CO₂ capture system operation. Individual and average absorption and stripping/compression load are plotted over time, and total and individual stored quantities of CO₂ in rich solvent are displayed. Conclusions about flexible CO₂ capture are drawn from viewing these figures.

Plotting options can be modified as necessary. Typically, figures are automatically exported with a MATLAB `print` statement and not shown in a MATLAB figure window using the option `set(figname, 'visible', 'off');`. Figure display in

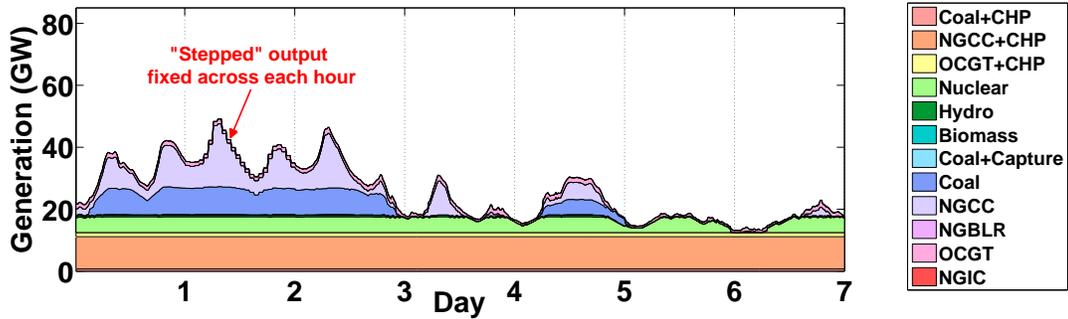
MATLAB can be resource-intensive, so automatically exporting figures to a manageable file format such as a PNG expedites post-processing. Additional plotting code is included to produce publication-quality figures, and these sections of code provide additional formatting options to improve figure aesthetics.

C.3.3 Troubleshooting with Plots

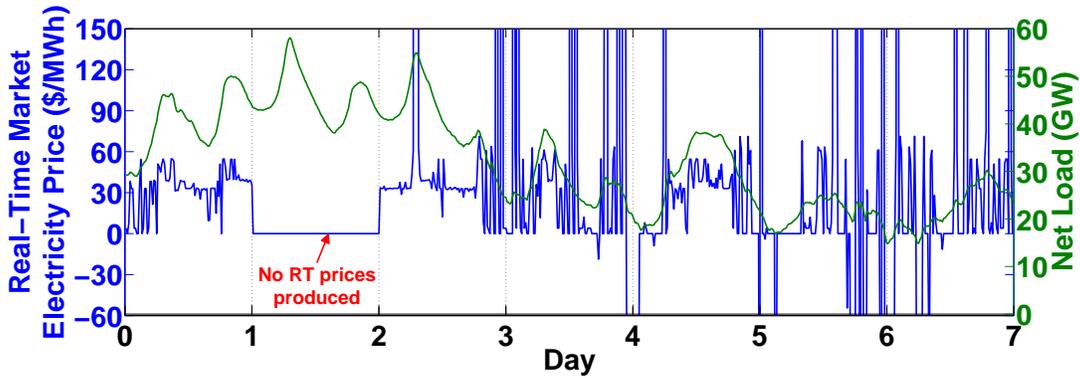
Figure output is extremely helpful for rapidly assessing GAMS solution quality. Inspecting electricity dispatch and shadow prices of electricity can reveal infeasible solutions or difficulties with solution convergence. These issues can also be investigated using GAMS *.LOG files, but figure inspection is often a faster way to assess solution quality. The following paragraphs describe several error types and provide sample figures.

If for a particular day, the forward market optimization converges, but the CPLEX pre-solve finds the real-time optimization to be infeasible, electricity generation for that day will look “stepped.” With this error, the forward market solution is exported for that day, so output at all facilities is constant over each forward market interval. Since the real-time market optimization did not occur, no real-time electricity prices are produced, so a day with no prices can also indicate an infeasible real-time optimization. Figure C.1 demonstrates this behavior for an unused simulation. This error sometimes occurred before modifying forward market ramp limits so the allowed ramp in the first interval of each day cannot exceed the allowable ramp in one real-time interval. Real-time market infeasibilities can also occur when the forward market optimization converges on a solution when integer variables are assigned a non-integer value on the order of 10^{-7} . This value is within the default CPLEX integrality tolerance but could produce infeasibilities in real-time market constraints. This error was avoided in subsequent simulations by setting the CPLEX integrality

tolerance to 0 with the option `epint=0`.



(a) Generation by plant type



(b) Real-time electricity prices

Figure C.1: An infeasible real-time optimization on day 2 causes stepped generation and no electricity prices. (Unused data for Winter, Inflexible capture, \$2.54/MMBTU coal, \$4.91/MMBTU natural gas, \$0/tCO₂)

GAMS *.LOG files can be examined to check solution convergence by viewing the remaining optimality gap for optimizations that terminate due to computation time limits. However, plots of electrical output over time can quickly show if a reasonable solution is found within computation time limits. The initial feasible solution found during optimization is typically one where enough facilities operate continuously at output levels that ensure peak demand is met or exceeded. If this solution is not significantly improved upon when the time limit is reached, the generation plot for that day will appear nearly rectangular. Electricity is oversupplied for the entire

day, so electricity prices will equal the oversupply penalty, $-\$250/\text{MWh}$ in this work. Figure C.2 provides an example. Occasionally, a better but still unreasonable solution is exported that exhibits substantial electricity undersupply for an entire day. Generally, any large discrepancy between electricity supply and demand signifies insufficient solution time for the forward market optimization. The greater number of integer variables makes the forward market solution more difficult, and convergence was not observed to be an issue in the real-time optimization. Increasing computation time limits or running the simulation on a more powerful computer can address issues with convergence difficulty.

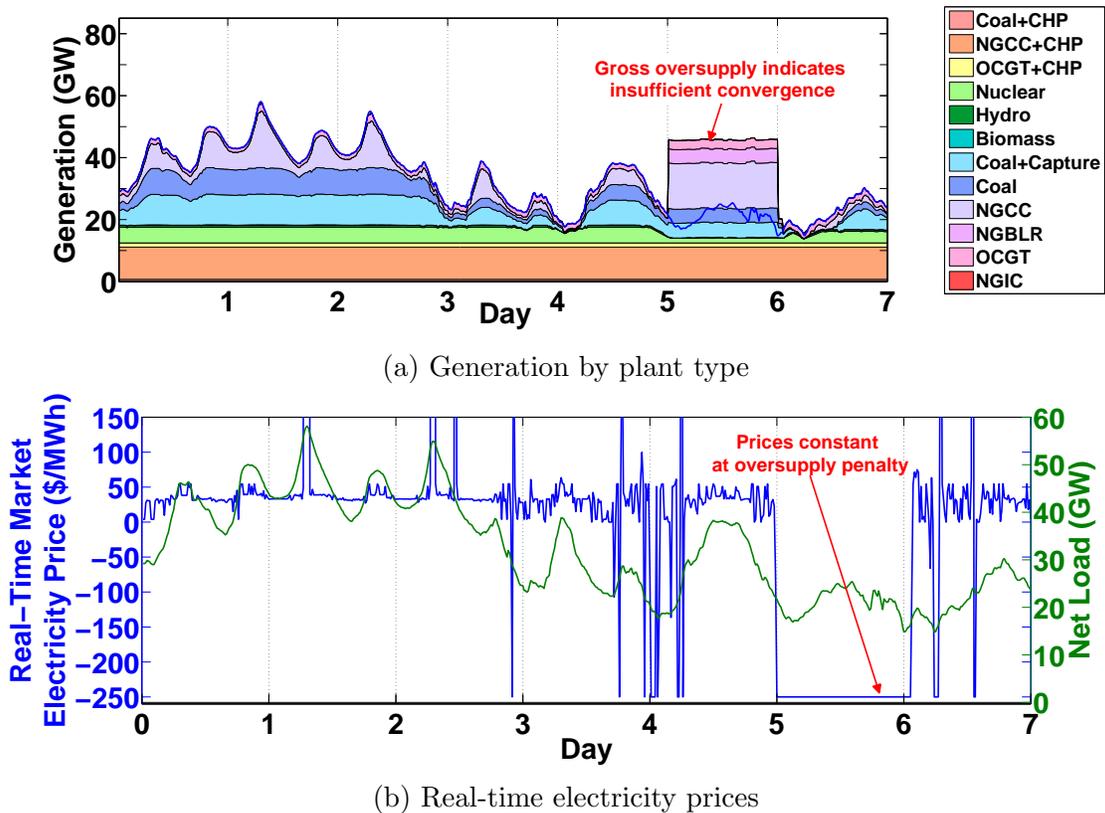


Figure C.2: In day 6, insufficient computation time to achieve convergence causes gross oversupply for the entire day. (Unused data for Winter, No capture, $\$2.54/\text{MMBTU}$ coal, $\$4.91/\text{MMBTU}$ natural gas, $\$0/\text{tCO}_2$)

Some simulations successfully converged on primal solutions, but CPLEX was unable to find a feasible dual solution during the final solve procedure. If true, operating variable output would appear normal, but shadow prices would not be produced. By default, inability to find a feasible dual solution will prevent assignment of dual variables for each constraint, which correspond to shadow prices for electricity and AS for the electricity supply/demand and AS requirement constraints. Setting `relaxfixedinfeas=1` ensures that electricity and AS prices are output despite small infeasibilities in the dual solution.

Appendix D

Unit-Specific Database

This appendix lists all the parameters within the generating unit-specific database described in Section 5.3.2. The first set of tables contains power system parameters for existing units in 2010.

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
Atascocita 1	biomass	11.40	0.46	2500	0	2.5	10.0
Bluebonnet 1	biomass	11.98	0.46	2500	0	1.0	3.9
Coastal Plains	biomass	11.21	0.70	2500	0	1.7	6.7
DFW Gas Recovery	biomass	18.11	0.70	2500	0	1.6	6.4
Lufkin Biomass	biomass	12.51	0.46	2500	0	11.7	46.8
Nacogdoches Project	biomass	12.51	0.46	2500	0	24.9	99.5
Tessman Road 1	biomass	16.34	0.46	2500	0	2.5	10.0
AES Deepwater	coal	12.00	1.16	5000	0	66.9	139.3
Big Brown 1	coal+capture	10.74	1.06	5000	0	284.2	592.0
Big Brown 2	coal+capture	10.68	1.06	5000	0	293.7	611.9
Coleto Creek	coal	10.16	0.95	5000	0	302.8	630.8
Fayette Power Project 1	coal+capture	10.69	0.99	5000	0	296.1	616.9
Fayette Power Project 2	coal+capture	10.71	1.00	5000	0	293.7	611.9
Fayette Power Project 3	coal+capture	10.67	0.99	5000	0	214.9	447.8
Gibbons Creek 1	coal	9.99	0.93	5000	0	224.5	467.7
J K Spruce 1	coal+capture	10.82	1.01	5000	0	269.8	562.2
J K Spruce 2	coal+capture	10.80	1.01	5000	0	368.7	768.1
J T Deely 1	coal	14.06	1.31	5000	0	212.5	442.8
J T Deely 2	coal	14.09	1.31	5000	0	212.5	442.8
Limestone 1	coal+capture	9.64	0.95	5000	0	396.9	826.8
Limestone 2	coal+capture	9.58	0.95	5000	0	409.8	853.7

Plant Name	Non-fuel/CO ₂ VOM cost (\$/MWh)	Base plant ramp rate up (MW/min)	Base plant ramp rate down (MW/min)	Base plant minimum up time (hr)	Base plant minimum down time (hr)	Base plant initial up time (hr)	Base plant initial down time (hr)	CHP indicator (1=yes, 0=no)
Atascocita 1	9.5	0.67	0.67	8	6	0	0	0
Bluebonnet 1	9.5	0.26	0.26	8	6	0	0	0
Coastal Plains	9.5	0.44	0.44	8	6	0	0	0
DFW Gas Recovery	9.5	0.42	0.42	8	6	0	0	0
Lufkin Biomass	9.5	0.25	0.25	8	6	0	0	0
Nacogdoches Project	9.5	0.54	0.54	8	6	0	0	0
Tessman Road 1	9.5	0.66	0.66	8	6	0	0	0
AES Deepwater	5.0	0.75	0.75	24	12	0	0	1
Big Brown 1	5.0	1.56	1.56	24	12	0	0	0
Big Brown 2	5.0	1.61	1.61	24	12	0	0	0
Coleto Creek	5.0	1.66	1.66	24	12	0	0	0
Fayette Power Project 1	5.0	1.62	1.62	24	12	0	0	0
Fayette Power Project 2	5.0	1.61	1.61	24	12	0	0	0
Fayette Power Project 3	5.0	1.18	1.18	24	12	0	0	0
Gibbons Creek 1	5.0	1.23	1.23	24	12	0	0	0
J K Spruce 1	5.0	1.48	1.48	24	12	0	0	0
J K Spruce 2	5.0	2.02	2.02	24	12	0	0	0
J T Deely 1	5.0	1.17	1.17	24	12	0	0	0
J T Deely 2	5.0	1.17	1.17	24	12	0	0	0
Limestone 1	5.0	2.18	2.18	24	12	0	0	0
Limestone 2	5.0	2.25	2.25	24	12	0	0	0

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
Martin Lake 1	coal	11.13	1.10	5000	0	389.2	810.9
Martin Lake 2	coal	11.06	1.09	5000	0	385.4	803.0
Martin Lake 3	coal	11.08	1.09	5000	0	374.9	781.1
Monticello 1	coal	10.93	1.08	5000	0	283.2	590.0
Monticello 2	coal	10.95	1.08	5000	0	283.2	590.0
Monticello 3	coal	10.94	1.08	5000	0	379.7	791.0
Oak Grove SES Unit 1	coal+capture	9.34	0.91	5000	0	374.9	781.1
Oak Grove SES Unit 2	coal+capture	9.31	0.91	5000	0	380.2	792.0
Oklunion 1	coal+capture	10.63	0.99	5000	0	310.4	646.8
Port Lavaca CFB1	coal	9.21	0.53	5000	0	62.1	129.4
Port Lavaca FB2	coal	9.21	0.53	5000	0	62.1	129.4
PUN25	coal	9.32	0.93	5000	0	271.3	565.2
San Miguel 1	coal	12.18	1.20	5000	0	188.7	393.0
Sandow 5	coal	11.12	1.10	5000	0	267.5	557.2
Sandy Creek 1	coal	9.33	0.91	5000	0	441.8	920.4
Twin Oaks 1	coal	10.89	1.08	5000	0	75.5	157.2
Twin Oaks 2	coal	10.84	1.07	5000	0	75.5	157.2
W A Parish 5	coal+capture	10.41	0.95	5000	0	308.1	641.8
W A Parish 6	coal+capture	10.35	0.94	5000	0	310.4	646.8
W A Parish 7	coal+capture	10.35	0.94	5000	0	269.8	562.2
W A Parish 8	coal+capture	10.35	0.94	5000	0	286.6	597.0

Plant Name	Non-fuel/ CO ₂ VOM cost (\$/MWh)	Base plant ramp		Base plant ramp down		Base plant minimum up time		Base plant minimum down time		Base plant up time		Base plant initial down time		CHP indicator (1=yes, 0=no)
		(MW/min)	(MW/min)	(MW/min)	(hr)	(hr)	(hr)	(hr)	(hr)	(hr)	(hr)	(hr)	(hr)	
Martin Lake 1	5.0	2.13	2.13	2.13	24	24	12	12	0	0	0	0	0	0
Martin Lake 2	5.0	2.11	2.11	2.11	24	24	12	12	0	0	0	0	0	0
Martin Lake 3	5.0	2.06	2.06	2.06	24	24	12	12	0	0	0	0	0	0
Monticello 1	5.0	1.55	1.55	1.55	24	24	12	12	0	0	0	0	0	0
Monticello 2	5.0	1.55	1.55	1.55	24	24	12	12	0	0	0	0	0	0
Monticello 3	5.0	2.08	2.08	2.08	24	24	12	12	0	0	0	0	0	0
Oak Grove SES Unit 1	5.0	2.06	2.06	2.06	24	24	12	12	0	0	0	0	0	0
Oak Grove SES Unit 2	5.0	2.09	2.09	2.09	24	24	12	12	0	0	0	0	0	0
Oklaunion 1	5.0	1.70	1.70	1.70	24	24	12	12	0	0	0	0	0	0
Port Lavaca CFB1	5.0	0.70	0.70	0.70	24	24	12	12	0	0	0	0	0	0
Port Lavaca FB2	5.0	0.70	0.70	0.70	24	24	12	12	0	0	0	0	0	0
PUN25	5.0	1.49	1.49	1.49	24	24	12	12	0	0	0	0	1	1
San Miguel 1	5.0	1.04	1.04	1.04	24	24	12	12	0	0	0	0	0	0
Sandow 5	5.0	1.47	1.47	1.47	24	24	12	12	0	0	0	0	0	0
Sandy Creek 1	5.0	2.42	2.42	2.42	24	24	12	12	0	0	0	0	0	0
Twin Oaks 1	5.0	0.41	0.41	0.41	24	24	12	12	0	0	0	0	0	0
Twin Oaks 2	5.0	0.41	0.41	0.41	24	24	12	12	0	0	0	0	0	0
W A Parish 5	5.0	1.69	1.69	1.69	24	24	12	12	0	0	0	0	0	0
W A Parish 6	5.0	1.70	1.70	1.70	24	24	12	12	0	0	0	0	0	0
W A Parish 7	5.0	1.48	1.48	1.48	24	24	12	12	0	0	0	0	0	0
W A Parish 8	5.0	1.57	1.57	1.57	24	24	12	12	0	0	0	0	0	0

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
Amistad Hydro 1	hydro_nat	0.00	0.00	0	0	0.0	38.0
Amistad Hydro 2	hydro_nat	0.00	0.00	0	0	0.0	38.0
Austin 1	hydro_nat	0.00	0.00	0	0	0.0	8.0
Austin 2	hydro_nat	0.00	0.00	0	0	0.0	9.0
Buchanan 1	hydro_nat	0.00	0.00	0	0	0.0	18.0
Buchanan 2	hydro_nat	0.00	0.00	0	0	0.0	18.0
Buchanan 3	hydro_nat	0.00	0.00	0	0	0.0	18.0
Canyon 1	hydro_nat	0.00	0.00	0	0	0.0	3.0
Canyon 2	hydro_nat	0.00	0.00	0	0	0.0	3.0
Denison Dam 1	hydro_nat	0.00	0.00	0	0	0.0	40.0
Denison Dam 2	hydro_nat	0.00	0.00	0	0	0.0	40.0
Dunlop							
Schumansville 1	hydro_nat	0.00	0.00	0	0	0.0	3.6
Eagle Pass 1	hydro_nat	0.00	0.00	0	0	0.0	7.0
Falcon Hydro 1	hydro_nat	0.00	0.00	0	0	0.0	12.0
Falcon Hydro 2	hydro_nat	0.00	0.00	0	0	0.0	12.0
Falcon Hydro 3	hydro_nat	0.00	0.00	0	0	0.0	12.0
GBRA 4 and 5	hydro_nat	0.00	0.00	0	0	0.0	4.8
Granite Shoals 1	hydro_nat	0.00	0.00	0	0	0.0	30.0
Granite Shoals 2	hydro_nat	0.00	0.00	0	0	0.0	30.0
Inks 1	hydro_nat	0.00	0.00	0	0	0.0	14.0
Lewisville 1	hydro_nat	0.00	0.00	0	0	0.0	2.8
Marble Falls 1	hydro_nat	0.00	0.00	0	0	0.0	21.0
Marble Falls 2	hydro_nat	0.00	0.00	0	0	0.0	21.0

Plant Name	Non-fuel/CO ₂ VOM cost (\$/MWh)	Base plant ramp		Base plant ramp		Base plant minimum		Base plant initial		CHP indicator (1=yes, 0=no)
		rate up (MW/min)	rate down (MW/min)	rate down (MW/min)	rate down (MW/min)	minimum up time (hr)	minimum down time (hr)	initial up time (hr)	initial down time (hr)	
Amistad Hydro 1	0.0	2.53	2.53	0	0	0	0	0	0	0
Amistad Hydro 2	0.0	2.53	2.53	0	0	0	0	0	0	0
Austin 1	0.0	0.53	0.53	0	0	0	0	0	0	0
Austin 2	0.0	0.60	0.60	0	0	0	0	0	0	0
Buchanan 1	0.0	1.20	1.20	0	0	0	0	0	0	0
Buchanan 2	0.0	1.20	1.20	0	0	0	0	0	0	0
Buchanan 3	0.0	1.20	1.20	0	0	0	0	0	0	0
Canyon 1	0.0	0.20	0.20	0	0	0	0	0	0	0
Canyon 2	0.0	0.20	0.20	0	0	0	0	0	0	0
Denison Dam 1	0.0	2.67	2.67	0	0	0	0	0	0	0
Denison Dam 2	0.0	2.67	2.67	0	0	0	0	0	0	0
Dunlop										
Schumannsville 1	0.0	0.24	0.24	0	0	0	0	0	0	0
Eagle Pass 1	0.0	0.47	0.47	0	0	0	0	0	0	0
Falcon Hydro 1	0.0	0.80	0.80	0	0	0	0	0	0	0
Falcon Hydro 2	0.0	0.80	0.80	0	0	0	0	0	0	0
Falcon Hydro 3	0.0	0.80	0.80	0	0	0	0	0	0	0
GBRA 4 and 5	0.0	0.32	0.32	0	0	0	0	0	0	0
Granite Shoals 1	0.0	2.00	2.00	0	0	0	0	0	0	0
Granite Shoals 2	0.0	2.00	2.00	0	0	0	0	0	0	0
Inks 1	0.0	0.93	0.93	0	0	0	0	0	0	0
Lewisville 1	0.0	0.19	0.19	0	0	0	0	0	0	0
Marble Falls 1	0.0	1.40	1.40	0	0	0	0	0	0	0
Marble Falls 2	0.0	1.40	1.40	0	0	0	0	0	0	0

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
Marshall Ford 1	hydro_nat	0.00	0.00	0	0	0.0	36.0
Marshall Ford 2	hydro_nat	0.00	0.00	0	0	0.0	35.0
Marshall Ford 3	hydro_nat	0.00	0.00	0	0	0.0	36.0
McQueeney							
Abbott	hydro_nat	0.00	0.00	0	0	0.0	8.0
Morris							
Sheppard 1	hydro_nat	0.00	0.00	0	0	0.0	24.0
Whitney 1	hydro_nat	0.00	0.00	0	0	0.0	15.0
Whitney 2	hydro_nat	0.00	0.00	0	0	0.0	15.0
B M Davis 1	ngblr	11.46	0.62	2500	0	126.0	331.7
Cedar Bayou 1	ngblr	10.78	0.58	2500	0	206.5	737.6
Cedar Bayou 2	ngblr	10.77	0.58	2500	0	207.6	741.5
Dansby 1	ngblr	11.31	0.61	2500	0	41.4	108.9
Decker Creek 1	ngblr	10.95	0.64	2500	0	120.4	316.8
Decker Creek 2	ngblr	11.01	0.65	2500	0	161.0	423.7
Graham 1	ngblr	11.94	0.64	2500	0	84.6	222.8
Graham 2	ngblr	11.94	0.64	2500	0	146.7	386.1
Handley 3	ngblr	13.84	0.75	2500	0	148.6	391.1
Handley 4	ngblr	13.79	0.74	2500	0	163.6	430.7
Handley 5	ngblr	13.88	0.75	2500	0	164.0	431.6
Lake Hubbard 1	ngblr	12.16	0.66	2500	0	147.5	388.1
Lake Hubbard 2	ngblr	12.10	0.66	2500	0	197.1	518.8
Leon Creek 3	ngblr	11.86	0.64	2500	0	25.5	59.4
Leon Creek 4	ngblr	11.84	0.64	2500	0	35.7	94.1

Plant Name	Non-fuel/CO ₂ VOM cost (\$/MWh)	Base plant ramp			Base plant minimum up time			Base plant minimum down time			Base plant initial up time		Base plant initial down time		CHP indicator (1=yes, 0=no)
		rate up (MW/min)	rate down (MW/min)	plant ramp (hr)	minimum up time (hr)	minimum down time (hr)	plant minimum down time (hr)	plant minimum up time (hr)	plant initial up time (hr)	plant initial down time (hr)	plant initial up time (hr)	plant initial down time (hr)			
Marshall Ford 1	0.0	2.40	2.40	2.40	0	0	0	0	0	0	0	0	0	0	
Marshall Ford 2	0.0	2.33	2.33	2.33	0	0	0	0	0	0	0	0	0	0	
Marshall Ford 3	0.0	2.40	2.40	2.40	0	0	0	0	0	0	0	0	0	0	
McQueeney															
Abbott	0.0	0.53	0.53	0.53	0	0	0	0	0	0	0	0	0	0	
Morris															
Sheppard 1	0.0	1.60	1.60	1.60	0	0	0	0	0	0	0	0	0	0	
Whitney 1	0.0	1.00	1.00	1.00	0	0	0	0	0	0	0	0	0	0	
Whitney 2	0.0	1.00	1.00	1.00	0	0	0	0	0	0	0	0	0	0	
B M Davis 1	8.0	1.80	1.80	1.80	8	8	8	8	8	8	8	8	8	0	
Cedar Bayou 1	6.5	4.00	4.00	4.00	8	8	8	8	8	8	8	8	8	0	
Cedar Bayou 2	6.5	4.02	4.02	4.02	8	8	8	8	8	8	8	8	8	0	
Dansby 1	8.0	0.59	0.59	0.59	8	8	8	8	8	8	8	8	8	0	
Decker Creek 1	8.0	1.72	1.72	1.72	8	8	8	8	8	8	8	8	8	0	
Decker Creek 2	8.0	2.30	2.30	2.30	8	8	8	8	8	8	8	8	8	0	
Graham 1	8.0	1.21	1.21	1.21	8	8	8	8	8	8	8	8	8	0	
Graham 2	8.0	2.09	2.09	2.09	8	8	8	8	8	8	8	8	8	0	
Handley 3	8.0	2.12	2.12	2.12	8	8	8	8	8	8	8	8	8	0	
Handley 4	8.0	2.33	2.33	2.33	8	8	8	8	8	8	8	8	8	0	
Handley 5	8.0	2.34	2.34	2.34	8	8	8	8	8	8	8	8	8	0	
Lake Hubbard 1	8.0	2.10	2.10	2.10	8	8	8	8	8	8	8	8	8	0	
Lake Hubbard 2	8.0	2.81	2.81	2.81	8	8	8	8	8	8	8	8	8	0	
Leon Creek 3	5.0	0.32	0.32	0.32	8	8	8	8	8	8	8	8	8	0	
Leon Creek 4	8.0	0.51	0.51	0.51	8	8	8	8	8	8	8	8	8	0	

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
Mountain Creek 6	ngblr	12.48	0.67	2500	0	51.9	120.8
Mountain Creek 7	ngblr	12.54	0.68	2500	0	50.2	116.8
Mountain Creek 8	ngblr	10.71	0.60	2500	0	157.4	562.3
O W Sommers 1	ngblr	12.06	0.65	2500	0	154.2	405.9
O W Sommers 2	ngblr	12.08	0.65	2500	0	150.5	396.0
Pearsall 1	ngblr	17.45	0.70	2500	0	10.6	24.8
Pearsall 2	ngblr	17.54	0.70	2500	0	10.6	24.8
Pearsall 3	ngblr	17.58	0.70	2500	0	10.2	23.8
Powerlane Plant 1	ngblr	23.42	0.70	2500	0	8.5	19.8
Powerlane Plant 2	ngblr	23.35	0.70	2500	0	11.3	26.2
Powerlane Plant 3	ngblr	23.37	0.70	2500	0	17.8	41.5
R W Miller 1	ngblr	12.64	0.70	2500	0	31.9	74.3
R W Miller 2	ngblr	11.28	0.64	2500	0	45.1	118.8
R W Miller 3	ngblr	11.38	0.65	2500	0	78.2	205.9
Ray Olinger 1	ngblr	12.29	0.70	2500	0	33.2	77.2
Ray Olinger 2	ngblr	11.35	0.65	2500	0	40.3	105.9
Ray Olinger 3	ngblr	11.35	0.65	2500	0	54.9	144.5
Sam Bertron 3	ngblr	11.57	0.62	2500	0	86.5	227.7
Sam Bertron 4	ngblr	11.56	0.62	2500	0	86.5	227.7
Sam Rayburn 3	ngblr	12.30	0.70	2500	0	11.1	25.7
Silas Ray 5	ngblr	11.04	0.59	2500	0	2.8	9.9
Sam Gideon 1	ngblr	11.46	0.62	2500	0	52.7	138.6
Sam Gideon 2	ngblr	11.42	0.62	2500	0	52.7	138.6
Sam Gideon 3	ngblr	11.51	0.62	2500	0	127.9	336.6

Plant Name	Non-fuel/ CO ₂ VOM cost (\$/MWh)	Base plant ramp rate up (MW/min)	Base plant ramp rate down (MW/min)	Base plant minimum up time (hr)	Base plant minimum down time (hr)	Base plant initial up time (hr)	Base plant initial down time (hr)	CHP indicator (1=yes, 0=no)
Mountain Creek 6	5.0	0.66	0.66	8	8	0	0	0
Mountain Creek 7	5.0	0.63	0.63	8	8	0	0	0
Mountain Creek 8	6.5	3.05	3.05	8	8	0	0	0
O W Sommers 1	8.0	2.20	2.20	8	8	0	0	0
O W Sommers 2	8.0	2.15	2.15	8	8	0	0	0
Pearsall 1	5.0	0.13	0.13	8	8	0	0	0
Pearsall 2	5.0	0.13	0.13	8	8	0	0	0
Pearsall 3	5.0	0.13	0.13	8	8	0	0	0
Powerlane Plant 1	5.0	0.11	0.11	8	8	0	0	0
Powerlane Plant 2	5.0	0.14	0.14	8	8	0	0	0
Powerlane Plant 3	5.0	0.23	0.23	8	8	0	0	0
R W Miller 1	5.0	0.40	0.40	8	8	0	0	0
R W Miller 2	8.0	0.64	0.64	8	8	0	0	0
R W Miller 3	8.0	1.12	1.12	8	8	0	0	0
Ray Olinger 1	5.0	0.42	0.42	8	8	0	0	0
Ray Olinger 2	8.0	0.57	0.57	8	8	0	0	0
Ray Olinger 3	8.0	0.78	0.78	8	8	0	0	0
Sam Bertron 3	8.0	1.23	1.23	8	8	0	0	0
Sam Bertron 4	8.0	1.23	1.23	8	8	0	0	0
Sam Rayburn 3	5.0	0.14	0.14	8	8	0	0	0
Silas Ray 5	6.5	0.09	0.09	8	8	0	0	0
Sam Gideon 1	8.0	0.75	0.75	8	8	0	0	0
Sam Gideon 2	8.0	0.75	0.75	8	8	0	0	0
Sam Gideon 3	8.0	1.82	1.82	8	8	0	0	0

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
Stryker Creek 1	ngblr	11.42	0.62	2500	0	64.3	169.3
Stryker Creek 2	ngblr	11.40	0.61	2500	0	188.9	497.0
Thomas C							
Ferguson 1	ngblr	11.04	0.59	2500	0	159.9	420.8
Trinidad 6	ngblr	13.51	0.73	2500	0	85.0	223.7
V H Braunig 1	ngblr	11.17	0.65	2500	0	82.8	217.8
V H Braunig 2	ngblr	11.19	0.65	2500	0	86.5	227.7
V H Braunig 3	ngblr	11.14	0.65	2500	0	155.0	407.9
W A Parish 1	ngblr	11.37	0.65	2500	0	65.5	172.3
W A Parish 2	ngblr	11.36	0.65	2500	0	65.5	172.3
W A Parish 3	ngblr	11.29	0.65	2500	0	104.6	275.2
W A Parish 4	ngblr	10.67	0.59	2500	0	153.0	546.5
Arthur Von							
Rosenberg 1	ngcc	7.48	0.40	10000	0	168.5	526.5
B M Davis 3	ngcc	6.13	0.62	2500	0	272.4	716.8
Bastrop Energy							
Center 1	ngcc	7.87	0.42	10000	0	184.7	577.2
Bosque							
County CC 1	ngcc	7.66	0.41	10000	0	159.4	498.2
Bosque							
County CC 2	ngcc	7.65	0.41	10000	0	102.3	319.8
Brazos Valley 1	ngcc	7.50	0.40	10000	0	189.4	591.8

Plant Name	Non- fuel/CO ₂ VOM cost (\$/MWh)	Base plant ramp rate up (MW/min)	Base plant ramp rate down (MW/min)	Base plant minimum up time (hr)	Base plant minimum down time (hr)	Base plant initial up time (hr)	Base plant initial down time (hr)	CHP indicator (1=yes, 0=no)
Stryker Creek 1	8.0	0.92	0.92	8	8	0	0	0
Stryker Creek 2	8.0	2.69	2.69	8	8	0	0	0
Thomas C								
Ferguson 1	8.0	2.28	2.28	8	8	0	0	0
Trinidad 6	8.0	1.21	1.21	8	8	0	0	0
V H Braunig 1	8.0	1.18	1.18	8	8	0	0	0
V H Braunig 2	8.0	1.23	1.23	8	8	0	0	0
V H Braunig 3	8.0	2.21	2.21	8	8	0	0	0
W A Parish 1	8.0	0.93	0.93	8	8	0	0	0
W A Parish 2	8.0	0.93	0.93	8	8	0	0	0
W A Parish 3	8.0	1.49	1.49	8	8	0	0	0
W A Parish 4	6.5	2.96	2.96	8	8	0	0	0
Arthur Von								
Rosenberg 1	3.0	3.45	3.45	6	4	0	0	0
B M Davis 3	8.0	4.63	4.63	8	8	0	0	0
Bastrop Energy								
Center 1	3.0	3.79	3.79	6	4	0	0	0
Bosque								
County CC 1	3.0	3.27	3.27	6	4	0	0	0
Bosque								
County CC 2	3.0	2.10	2.10	6	4	0	0	0
Brazos Valley 1	3.0	3.88	3.88	6	4	0	0	0

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
Calenergy Falcon							
seaboard 1	ngcc	6.10	0.46	3000	0	51.5	214.5
Cedar Bayou 4	ngcc	6.12	0.58	10000	0	194.1	606.5
Colorado Bend							
Energy Center 1	ngcc	7.42	0.40	3000	0	60.6	252.5
Colorado Bend							
Energy Center 2	ngcc	7.35	0.40	3000	0	60.6	252.5
CVC							
Channelview 1	ngcc	6.15	0.41	10000	0	201.9	630.8
Deer Park							
Energy Center 1	ngcc	5.55	0.30	10000	0	317.6	992.6
Ennis Power							
Station 1	ngcc	7.35	0.40	15000	0	218.2	349.1
Forney Energy							
Center 1	ngcc	7.37	0.40	10000	0	294.8	921.4
Forney Energy							
Center 2	ngcc	7.36	0.40	10000	0	294.8	921.4
Freestone Energy							
Center 1	ngcc	7.52	0.41	10000	0	162.2	507.0
Freestone Energy							
Center 2	ngcc	7.54	0.41	10000	0	162.2	507.0
Frontera 1							
	ngcc	7.56	0.41	10000	0	150.7	470.9

Plant Name	Non- fuel/CO ₂ VOM cost (\$/MWh)	Base plant ramp		Base plant minimum		Base plant up time		Base plant down time		CHP indicator (1=yes, 0=no)
		rate up (MW/min)	rate down (MW/min)	minimum up time (hr)	minimum down time (hr)	up time (hr)	down time (hr)	initial time (hr)	initial time (hr)	
Calenergy Falcon seaboard 1	3.0	1.41	1.41	4	4	4	4	0	0	0
Cedar Bayou 4	3.0	3.98	3.98	6	4	4	0	0	0	0
Colorado Bend Energy Center 1	3.0	1.66	1.66	4	4	4	0	0	0	0
Colorado Bend Energy Center 2	3.0	1.66	1.66	4	4	4	0	0	0	0
CVC Channelview 1	3.0	4.14	4.14	6	4	4	0	0	0	0
Deer Park Energy Center 1	3.0	6.51	6.51	6	4	4	0	0	0	1
Ennis Power Station 1	2.9	2.29	2.29	6	8	8	0	0	0	0
Forney Energy Center 1	3.0	6.04	6.04	6	4	4	0	0	0	0
Forney Energy Center 2	3.0	6.04	6.04	6	4	4	0	0	0	0
Freestone Energy Center 1	3.0	3.33	3.33	6	4	4	0	0	0	0
Freestone Energy Center 2	3.0	3.33	3.33	6	4	4	0	0	0	0
Frontera 1	3.0	3.09	3.09	6	4	4	0	0	0	0

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
Guadalupe Gen.							
Station 1	ngcc	7.43	0.40	10000	0	161.0	503.1
Guadalupe Gen.							
Station 2	ngcc	7.46	0.40	10000	0	158.5	495.3
Hays Energy							
Facility 1	ngcc	7.13	0.38	10000	0	73.9	231.1
Hays Energy							
Facility 2	ngcc	7.18	0.39	10000	0	73.9	231.1
Hays Energy							
Facility 3	ngcc	7.18	0.39	10000	0	77.1	240.8
Hays Energy							
Facility 4	ngcc	7.18	0.39	10000	0	77.1	240.8
Hidalgo 1							
	ngcc	7.19	0.39	10000	0	159.7	499.2
Jack County							
Gen. Facility 1	ngcc	7.26	0.39	10000	0	199.7	624.0
Jack County							
Gen. Facility 2	ngcc	7.31	0.39	10000	0	176.3	550.9
Johnson County							
Gen. Facility 1	ngcc	8.37	0.45	10000	0	88.3	275.9
Kiamichi Energy							
Facility 1	ngcc	6.15	0.41	10000	0	207.5	648.4
Kiamichi Energy							
Facility 2	ngcc	6.09	0.41	10000	0	207.5	648.4

Plant Name	Non-fuel/ CO ₂ VOM cost (\$/MWh)	Base plant ramp rate up (MW/min)	Base plant ramp down (MW/min)	Base plant minimum up time (hr)	Base plant minimum down time (hr)	Base plant initial up time (hr)	Base plant initial down time (hr)	CHP indicator (1=yes, 0=no)
Guadalupe Gen. Station 1	3.0	3.30	3.30	6	4	0	0	0
Guadalupe Gen. Station 2	3.0	3.25	3.25	6	4	0	0	0
Hays Energy Facility 1	3.0	1.52	1.52	6	4	0	0	0
Hays Energy Facility 2	3.0	1.52	1.52	6	4	0	0	0
Hays Energy Facility 3	3.0	1.58	1.58	6	4	0	0	0
Hays Energy Facility 4	3.0	1.58	1.58	6	4	0	0	0
Hidalgo 1	3.0	3.28	3.28	6	4	0	0	0
Jack County Gen. Facility 1	3.0	4.09	4.09	6	4	0	0	0
Jack County Gen. Facility 2	3.0	3.61	3.61	6	4	0	0	0
Johnson County Gen. Facility 1	3.0	1.81	1.81	6	4	0	0	1
Kiamichi Energy Facility 1	3.0	4.25	4.25	6	4	0	0	0
Kiamichi Energy Facility 2	3.0	4.25	4.25	6	4	0	0	0

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
Lamar Power							
Project 1	ngcc	7.76	0.42	10000	0	169.1	528.5
Lamar Power							
Project 2	ngcc	7.76	0.42	10000	0	169.1	528.5
Lost Pines 1	ngcc	7.19	0.39	10000	0	172.8	540.2
Magic Valley 1	ngcc	7.25	0.39	15000	0	457.0	731.3
Midlothian 1	ngcc	7.47	0.40	10000	0	73.9	231.1
Midlothian 2	ngcc	7.43	0.40	10000	0	73.9	231.1
Midlothian 3	ngcc	7.44	0.40	10000	0	73.9	231.1
Midlothian 4	ngcc	7.43	0.40	10000	0	73.9	231.1
Midlothian 5	ngcc	7.44	0.40	10000	0	77.1	240.8
Midlothian 6	ngcc	7.50	0.40	10000	0	77.1	240.8
Nueces Bay 8	ngcc	6.15	0.46	3000	0	169.4	705.9
Odessa Ector							
Gen. Station 1	ngcc	7.62	0.41	10000	0	165.7	517.7
Odessa Ector							
Gen. station 2	ngcc	7.60	0.41	10000	0	166.9	521.6
Paris Energy							
Center 1	ngcc	7.40	0.39	3000	0	65.8	274.0
PasGen	ngcc	6.00	0.32	10000	0	170.7	533.3
PUN11	ngcc	6.11	0.41	10000	0	177.8	555.8
PUN12	ngcc	8.47	0.46	3000	0	77.7	323.7
PUN12dup	ngcc	7.64	0.41	10000	0	103.6	323.7
PUN13	ngcc	7.57	0.41	10000	0	90.2	281.8

Plant Name	Non-fuel/CO ₂ VOM cost (\$/MWh)	Base plant ramp rate up (MW/min)	Base plant ramp rate down (MW/min)	Base plant minimum up time (hr)	Base plant minimum down time (hr)	Base plant minimum up time (hr)	Base plant initial up time (hr)	Base plant initial down time (hr)	CHP indicator (1=yes, 0=no)
Lamar Power									
Project 1	3.0	3.47	3.47	6	4	0	0	0	0
Lamar Power									
Project 2	3.0	3.47	3.47	6	4	0	0	0	0
Lost Pines 1	3.0	3.54	3.54	6	4	0	0	0	0
Magic Valley 1	2.9	4.80	4.80	6	8	0	0	0	0
Midlothian 1	3.0	1.52	1.52	6	4	0	0	0	0
Midlothian 2	3.0	1.52	1.52	6	4	0	0	0	0
Midlothian 3	3.0	1.52	1.52	6	4	0	0	0	0
Midlothian 4	3.0	1.52	1.52	6	4	0	0	0	0
Midlothian 5	3.0	1.58	1.58	6	4	0	0	0	0
Midlothian 6	3.0	1.58	1.58	6	4	0	0	0	0
Nueces Bay 8	3.0	4.63	4.63	4	4	0	0	0	0
Odesa Ector									
Gen. Station 1	3.0	3.40	3.40	6	4	0	0	0	0
Odesa Ector									
Gen. station 2	3.0	3.42	3.42	6	4	0	0	0	0
Paris Energy									
Center 1	3.0	1.80	1.80	4	4	0	0	0	1
PasGen	3.0	3.50	3.50	6	4	0	0	0	1
PUN11	3.0	3.65	3.65	6	4	0	0	0	1
PUN12	3.0	2.12	2.12	4	4	0	0	0	1
PUN12dup	3.0	2.12	2.12	6	4	0	0	0	1
PUN13	3.0	1.85	1.85	6	4	0	0	0	1

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
PUN14	ngcc	6.14	0.41	10000	0	458.0	1431.3
PUN17	ngcc	6.10	0.41	10000	0	197.8	618.2
PUN18	ngcc	6.12	0.41	10000	0	143.5	448.5
PUN19	ngcc	6.11	0.41	10000	0	114.2	356.9
PUN23	ngcc	7.62	0.41	10000	0	151.3	472.9
PUN24	ngcc	6.10	0.41	10000	0	149.8	468.0
PUN3	ngcc	6.12	0.46	3000	0	229.8	957.5
PUN5	ngcc	6.10	0.41	10000	0	216.8	677.6
PUN7	ngcc	7.61	0.41	10000	0	68.6	214.5
PUN9	ngcc	6.10	0.41	10000	0	144.1	450.5
Quail Run							
Energy 1	ngcc	8.56	0.46	3000	0	56.6	236.0
Quail Run							
Energy 2	ngcc	8.52	0.46	3000	0	56.6	236.0
Rayburn 10	ngcc	9.16	0.53	5000	0	67.0	186.2
Rio Nogales 1	ngcc	7.31	0.39	10000	0	264.6	826.8
San Jacinto							
SES 1	ngcc	13.49	0.73	3000	0	19.0	79.0
San Jacinto							
SES 2	ngcc	13.57	0.73	3000	0	19.0	79.0
Sand Hill							
Energy Center 5a	ngcc	7.35	0.40	10000	0	101.4	316.9
T H Wharton 3	ngcc	6.13	0.51	3000	0	77.7	323.7
T H Wharton 4	ngcc	6.10	0.50	3000	0	77.7	323.7

Plant Name	Non-fuel/ CO ₂ VOM cost (\$/MWh)	Base plant ramp rate up (MW/min)	Base plant ramp rate down (MW/min)	Base plant minimum up time (hr)	Base plant minimum down time (hr)	Base plant initial up time (hr)	Base plant initial down time (hr)	CHP indicator (1=yes, 0=no)
PUN14	3.0	9.39	9.39	6	4	0	0	1
PUN17	3.0	4.06	4.06	6	4	0	0	1
PUN18	3.0	2.94	2.94	6	4	0	0	1
PUN19	3.0	2.34	2.34	6	4	0	0	1
PUN23	3.0	3.10	3.10	6	4	0	0	1
PUN24	3.0	3.07	3.07	6	4	0	0	1
PUN3	3.0	6.28	6.28	4	4	0	0	1
PUN5	3.0	4.45	4.45	6	4	0	0	1
PUN7	3.0	1.41	1.41	6	4	0	0	1
PUN9	3.0	2.96	2.96	6	4	0	0	1
Quail Run								
Energy 1	3.0	1.55	1.55	4	4	0	0	0
Quail Run								
Energy 2	3.0	1.55	1.55	4	4	0	0	0
Rayburn 10	5.0	1.22	1.22	4	8	0	0	0
Rio Nogales 1	3.0	5.42	5.42	6	4	0	0	0
San Jacinto								
SES 1	3.0	0.52	0.52	4	4	0	0	0
San Jacinto								
SES 2	3.0	0.52	0.52	4	4	0	0	0
Sand Hill								
Energy Center 5a	3.0	2.08	2.08	6	4	0	0	0
T H Wharton 3	3.0	2.12	2.12	4	4	0	0	0
T H Wharton 4	3.0	2.12	2.12	4	4	0	0	0

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
Texas City 1	ngcc	5.99	0.32	3000	0	105.8	440.7
Tenaska							
Frontier 1	ngcc	6.90	0.37	10000	0	290.2	906.8
Tenaska							
Gateway 1	ngcc	7.47	0.40	10000	0	283.3	885.3
Victoria Power							
Station CC7	ngcc	7.76	0.41	10000	0	94.8	296.4
Wise Tractebel							
Power Proj 1	ngcc	7.60	0.41	15000	0	493.6	789.8
Wolf Hollow							
Power Proj 1	ngcc	7.91	0.43	15000	0	482.0	771.2
Covel Gardens							
LG Power Station	ngic	9.02	0.53	487	0	2.0	10.0
Landfill							
Austin ALL	ngic	17.43	0.94	487	0	1.5	6.0
Pearsall							
Power C10	ngic	9.80	0.53	487	0	1.7	8.4
Pearsall							
Power C11	ngic	9.75	0.53	487	0	1.7	8.4
Pearsall							
Power C12	ngic	9.76	0.53	487	0	1.7	8.4
Pearsall							
Power C13	ngic	9.77	0.53	487	0	1.7	8.4

Plant Name	Non-fuel/ CO ₂ VOM cost (\$/MWh)	Base plant ramp rate up (MW/min)	Base plant ramp rate down (MW/min)	Base plant minimum up time (hr)	Base plant minimum down time (hr)	Base plant initial up time (hr)	Base plant initial down time (hr)	CHP indicator (1=yes, 0=no)
Texas City 1	3.0	2.89	2.89	4	4	0	0	1
Tenaska								
Frontier 1	3.0	5.95	5.95	6	4	0	0	0
Tenaska								
Gateway 1	3.0	5.81	5.81	6	4	0	0	0
Victoria Power								
Station CC7	3.0	1.94	1.94	6	4	0	0	1
Wise Tractebel								
Power Proj 1	2.9	5.18	5.18	6	8	0	0	0
Wolf Hollow								
Power Proj 1	2.9	5.06	5.06	6	8	0	0	0
Covel Gardens								
LG Power Station	2.0	0.67	0.67	8	6	0	0	0
Landfill								
Austin ALL	2.0	0.40	0.40	8	6	0	0	0
Pearsall								
Power C10	3.0	0.56	0.56	1	1	0	0	0
Pearsall								
Power C11	3.0	0.56	0.56	1	1	0	0	0
Pearsall								
Power C12	3.0	0.56	0.56	1	1	0	0	0
Pearsall								
Power C13	3.0	0.56	0.56	1	1	0	0	0

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
Pearsall							
Power C14	ngic	9.77	0.53	487	0	1.7	8.4
Pearsall							
Power C15	ngic	9.79	0.53	487	0	1.7	8.4
Pearsall							
Power C16	ngic	9.82	0.53	487	0	1.7	8.4
Pearsall							
Power C17	ngic	9.79	0.53	487	0	1.7	8.4
Pearsall							
Power C18	ngic	9.83	0.53	487	0	1.7	8.4
Pearsall							
Power C19	ngic	9.75	0.53	487	0	1.7	8.4
Pearsall							
Power C20	ngic	9.78	0.53	487	0	1.7	8.4
Pearsall							
Power C21	ngic	9.76	0.53	487	0	1.7	8.4
Pearsall							
Power C22	ngic	9.77	0.53	487	0	1.7	8.4
Pearsall							
Power C23	ngic	9.82	0.53	487	0	1.7	8.4
Pearsall							
Power C24	ngic	9.84	0.53	487	0	1.7	8.4

Plant Name	Non-fuel/CO ₂ VOM cost (\$/MWh)	Base plant ramp rate up (MW/min)	Base plant ramp rate down (MW/min)	Base plant minimum up time (hr)	Base plant minimum down time (hr)	Base plant initial up time (hr)	Base plant initial down time (hr)	CHP indicator (1=yes, 0=no)
Pearsall								
Power C14	3.0	0.56	0.56	1	1	0	0	0
Pearsall								
Power C15	3.0	0.56	0.56	1	1	0	0	0
Pearsall								
Power C16	3.0	0.56	0.56	1	1	0	0	0
Pearsall								
Power C17	3.0	0.56	0.56	1	1	0	0	0
Pearsall								
Power C18	3.0	0.56	0.56	1	1	0	0	0
Pearsall								
Power C19	3.0	0.56	0.56	1	1	0	0	0
Pearsall								
Power C20	3.0	0.56	0.56	1	1	0	0	0
Pearsall								
Power C21	3.0	0.56	0.56	1	1	0	0	0
Pearsall								
Power C22	3.0	0.56	0.56	1	1	0	0	0
Pearsall								
Power C23	3.0	0.56	0.56	1	1	0	0	0
Pearsall								
Power C24	3.0	0.56	0.56	1	1	0	0	0

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
Pearsall							
Power IC1	ngic	9.76	0.53	487	0	1.7	8.4
Pearsall							
Power IC2	ngic	9.82	0.53	487	0	1.7	8.4
Pearsall							
Power IC3	ngic	9.76	0.53	487	0	1.7	8.4
Pearsall							
Power IC4	ngic	9.85	0.53	487	0	1.7	8.4
Pearsall							
Power IC5	ngic	9.75	0.53	487	0	1.7	8.4
Pearsall							
Power IC6	ngic	9.77	0.53	487	0	1.7	8.4
Pearsall							
Power IC7	ngic	9.80	0.53	487	0	1.7	8.4
Pearsall							
Power IC8	ngic	9.82	0.53	487	0	1.7	8.4
Pearsall							
Power IC9	ngic	9.80	0.53	487	0	1.7	8.4
Powerlane							
GRNV IC1	ngic	9.83	0.53	487	0	1.7	8.3
Powerlane							
GRNV IC2	ngic	9.76	0.53	487	0	1.7	8.3
Powerlane							
GRNV IC3	ngic	9.83	0.53	487	0	1.7	8.3

Plant Name	Non- fuel/CO ₂ VOM cost (\$/MWh)	Base plant ramp rate up (MW/min)	Base plant ramp rate down (MW/min)	Base plant minimum up time (hr)	Base plant minimum down time (hr)	Base plant initial up time (hr)	Base plant initial down time (hr)	CHP indicator (1=yes, 0=no)
Pearsall								
Power IC1	3.0	0.56	0.56	1	1	0	0	0
Pearsall								
Power IC2	3.0	0.56	0.56	1	1	0	0	0
Pearsall								
Power IC3	3.0	0.56	0.56	1	1	0	0	0
Pearsall								
Power IC4	3.0	0.56	0.56	1	1	0	0	0
Pearsall								
Power IC5	3.0	0.56	0.56	1	1	0	0	0
Pearsall								
Power IC6	3.0	0.56	0.56	1	1	0	0	0
Pearsall								
Power IC7	3.0	0.56	0.56	1	1	0	0	0
Pearsall								
Power IC8	3.0	0.56	0.56	1	1	0	0	0
Pearsall								
Power IC9	3.0	0.56	0.56	1	1	0	0	0
Powerlane								
GRNV IC1	3.0	0.55	0.55	1	1	0	0	0
Powerlane								
GRNV IC2	3.0	0.55	0.55	1	1	0	0	0
Powerlane								
GRNV IC3	3.0	0.55	0.55	1	1	0	0	0

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
Comanche Peak 1	nucl	0.00	0.00	7200	0	369.0	1230.0
Comanche Peak 2	nucl	0.00	0.00	7200	0	353.7	1179.0
South Texas 1	nucl	0.00	0.00	7200	0	408.9	1363.0
South Texas 2	nucl	0.00	0.00	7200	0	408.0	1360.0
Atkins 7	ocgt	14.45	0.78	0	0	5.0	19.8
Dansby 2	ocgt	9.47	0.51	2000	0	16.9	47.0
Dansby 3	ocgt	9.47	0.51	2000	0	16.9	47.0
Decker Creek G1	ocgt	9.46	0.51	2000	0	19.1	52.9
Decker Creek G2	ocgt	9.50	0.51	2000	0	19.1	52.9
Decker Creek G3	ocgt	9.50	0.51	2000	0	19.1	52.9
Decker Creek G4	ocgt	9.53	0.51	2000	0	19.1	52.9
DeCordova A	ocgt	12.19	0.66	1000	0	20.6	82.3
DeCordova B	ocgt	12.12	0.65	1000	0	20.6	82.3
DeCordova C	ocgt	12.12	0.65	1000	0	20.6	82.3
DeCordova D	ocgt	12.19	0.66	1000	0	20.6	82.3
ExTex La Porte Power Station							
AirPro 1	ocgt	12.63	0.68	2000	0	14.5	40.2
ExTex La Porte Power Station							
AirPro 2	ocgt	12.72	0.68	2000	0	14.5	40.2
ExTex La Porte Power Station							
AirPro 3	ocgt	12.69	0.68	2000	0	14.5	40.2

Plant Name	Non-fuel/CO ₂ VOM cost (\$/MWh)	Base plant ramp rate up (MW/min)	Base plant ramp rate down (MW/min)	Base plant minimum up time (hr)	Base plant minimum down time (hr)	Base plant initial up time (hr)	Base plant initial down time (hr)	CHP indicator (1=yes, 0=no)
Comanche Peak 1	4.0	3.33	3.33	168	24	0	0	0
Comanche Peak 2	4.0	3.33	3.33	168	24	0	0	0
South Texas 1	4.0	3.33	3.33	168	24	0	0	0
South Texas 2	4.0	3.33	3.33	168	24	0	0	0
Atkins 7	3.0	1.32	1.32	1	1	0	0	0
Dansby 2	8.0	3.14	3.14	1	1	0	0	0
Dansby 3	8.0	3.14	3.14	1	1	0	0	0
Decker Creek G1	8.0	3.53	3.53	1	1	0	0	0
Decker Creek G2	8.0	3.53	3.53	1	1	0	0	0
Decker Creek G3	8.0	3.53	3.53	1	1	0	0	0
Decker Creek G4	8.0	3.53	3.53	1	1	0	0	0
DeCordova A	4.0	5.49	5.49	1	1	0	0	0
DeCordova B	4.0	5.49	5.49	1	1	0	0	0
DeCordova C	4.0	5.49	5.49	1	1	0	0	0
DeCordova D	4.0	5.49	5.49	1	1	0	0	0
ExTex La Porte Power Station								
AirPro 1	8.0	2.68	2.68	1	1	0	0	0
ExTex La Porte Power Station								
AirPro 2	8.0	2.68	2.68	1	1	0	0	0
ExTex La Porte Power Station								
AirPro 3	8.0	2.68	2.68	1	1	0	0	0

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
ExTex La Porte							
Power Station							
AirPro 4	ocgt	12.63	0.68	2000	0	14.5	40.2
Greens Bayou 73	ocgt	14.67	0.79	2000	0	13.4	53.5
Greens Bayou 74	ocgt	14.73	0.79	2000	0	13.4	53.5
Greens Bayou 81	ocgt	14.63	0.79	2000	0	13.4	53.5
Greens Bayou 82	ocgt	14.73	0.79	2000	0	15.8	63.4
Greens Bayou 83	ocgt	14.71	0.79	2000	0	15.8	63.4
Greens Bayou 84	ocgt	14.66	0.79	2000	0	15.8	63.4
Laredo Peaking 4	ocgt	11.56	0.62	10000	0	65.5	93.6
Laredo Peaking 5	ocgt	11.62	0.63	10000	0	65.5	93.6
Leon Creek							
Peaking 1	ocgt	9.50	0.51	2000	0	16.9	47.0
Leon Creek							
Peaking 2	ocgt	9.48	0.51	2000	0	16.9	47.0
Leon Creek							
Peaking 3	ocgt	9.45	0.51	2000	0	16.9	47.0
Leon Creek							
Peaking 4	ocgt	9.50	0.51	2000	0	16.9	47.0
Morgan Creek							
Morgan Creek A	ocgt	13.86	0.74	1000	0	19.8	79.4
Morgan Creek B	ocgt	13.84	0.74	1000	0	19.8	79.4
Morgan Creek C	ocgt	13.85	0.74	1000	0	19.8	79.4
Morgan Creek D	ocgt	13.91	0.74	1000	0	19.8	79.4
Morgan Creek E	ocgt	13.78	0.74	1000	0	19.8	79.4

Plant Name	Non-fuel/ CO ₂ VOM cost (\$/MWh)	Base plant ramp rate up (MW/min)	Base plant ramp rate down (MW/min)	Base plant minimum up time (hr)	Base plant minimum down time (hr)	Base plant initial up time (hr)	Base plant initial down time (hr)	CHP indicator (1=yes, 0=no)
ExTex La Porte								
Power Station								
AirPro 4	8.0	2.68	2.68	1	1	0	0	0
Greens Bayou 73	3.0	3.56	3.56	1	1	0	0	0
Greens Bayou 74	3.0	3.56	3.56	1	1	0	0	0
Greens Bayou 81	3.0	3.56	3.56	1	1	0	0	0
Greens Bayou 82	3.0	4.22	4.22	1	1	0	0	0
Greens Bayou 83	3.0	4.22	4.22	1	1	0	0	0
Greens Bayou 84	3.0	4.22	4.22	1	1	0	0	0
Laredo Peaking 4	13.0	6.24	6.24	2	3	0	0	0
Laredo Peaking 5	13.0	6.24	6.24	2	3	0	0	0
Leon Creek								
Peaking 1	8.0	3.14	3.14	1	1	0	0	0
Leon Creek								
Peaking 2	8.0	3.14	3.14	1	1	0	0	0
Leon Creek								
Peaking 3	8.0	3.14	3.14	1	1	0	0	0
Leon Creek								
Peaking 4	8.0	3.14	3.14	1	1	0	0	0
Morgan Creek A	4.0	5.29	5.29	1	1	0	0	0
Morgan Creek B	4.0	5.29	5.29	1	1	0	0	0
Morgan Creek C	4.0	5.29	5.29	1	1	0	0	0
Morgan Creek D	4.0	5.29	5.29	1	1	0	0	0
Morgan Creek E	4.0	5.29	5.29	1	1	0	0	0

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
Morgan Creek F	ocgt	13.81	0.74	1000	0	19.8	79.4
Permian Basin A	ocgt	13.72	0.74	1000	0	16.9	67.6
Permian Basin B	ocgt	13.74	0.74	1000	0	17.4	69.6
Permian Basin C	ocgt	13.68	0.74	1000	0	18.1	72.5
Permian Basin D	ocgt	13.71	0.74	1000	0	18.1	72.5
Permian Basin E	ocgt	13.79	0.74	1000	0	18.4	73.5
PUN1	ocgt	14.50	0.62	1000	0	8.1	32.3
PUN10	ocgt	14.43	0.62	1000	0	7.1	28.4
PUN15	ocgt	11.66	0.62	1000	0	17.2	68.6
PUN16	ocgt	11.59	0.62	1000	0	109.3	437.1
PUN2	ocgt	11.68	0.62	1000	0	46.6	186.2
PUN20	ocgt	11.63	0.62	1000	0	29.9	119.6
PUN21	ocgt	14.52	0.62	1000	0	11.0	44.1
PUN27	ocgt	14.43	0.62	1000	0	3.7	14.7
PUN28	ocgt	14.45	0.62	1000	0	7.1	28.4
PUN4	ocgt	11.63	0.62	1000	0	19.8	79.4
PUN6	ocgt	11.65	0.62	1000	0	73.5	294.0
PUN8	ocgt	14.44	0.78	2000	0	4.5	18.0
R W Miller 4	ocgt	11.59	0.62	1000	0	28.2	112.7
R W Miller 5	ocgt	11.61	0.62	1000	0	28.2	112.7
Ray Olinger 4	ocgt	11.59	0.62	1000	0	20.6	82.3
Sam Bertron T2	ocgt	14.53	0.78	2000	0	3.2	12.9

Plant Name	Non- fuel/CO ₂ VOM cost (\$/MWh)	Base plant ramp		Base plant minimum		Base plant up time		Base plant down time		Base plant initial down time (hr)	CHP indicator (1=yes, 0=no)
		rate up (MW/min)	rate down (MW/min)	up time (hr)	down time (hr)	up time (hr)	down time (hr)				
Morgan Creek F	4.0	5.29	5.29	1	1	1	1	0	0	0	0
Permian Basin A	4.0	4.51	4.51	1	1	1	1	0	0	0	0
Permian Basin B	4.0	4.64	4.64	1	1	1	1	0	0	0	0
Permian Basin C	4.0	4.83	4.83	1	1	1	1	0	0	0	0
Permian Basin D	4.0	4.83	4.83	1	1	1	1	0	0	0	0
Permian Basin E	4.0	4.90	4.90	1	1	1	1	0	0	0	0
PUN1	4.0	2.16	2.16	1	1	1	1	0	0	0	1
PUN10	4.0	1.89	1.89	1	1	1	1	0	0	0	1
PUN15	4.0	4.57	4.57	1	1	1	1	0	0	0	1
PUN16	4.0	29.14	29.14	1	1	1	1	0	0	0	1
PUN2	4.0	12.41	12.41	1	1	1	1	0	0	0	1
PUN20	4.0	7.97	7.97	1	1	1	1	0	0	0	1
PUN21	4.0	2.94	2.94	1	1	1	1	0	0	0	1
PUN27	4.0	0.98	0.98	1	1	1	1	0	0	0	1
PUN28	4.0	1.89	1.89	1	1	1	1	0	0	0	1
PUN4	4.0	5.29	5.29	1	1	1	1	0	0	0	1
PUN6	4.0	19.60	19.60	1	1	1	1	0	0	0	1
PUN8	2.0	1.20	1.20	8	8	6	6	0	0	0	1
R W Miller 4	4.0	7.51	7.51	1	1	1	1	0	0	0	0
R W Miller 5	4.0	7.51	7.51	1	1	1	1	0	0	0	0
Ray Olinger 4	4.0	5.49	5.49	1	1	1	1	0	0	0	0
Sam Bertron T2	3.0	0.86	0.86	1	1	1	1	0	0	0	0

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
Sam Rayburn							
GT 1	ocgt	14.57	0.79	2000	0	3.2	12.9
Sam Rayburn							
GT 2	ocgt	14.50	0.78	2000	0	3.2	12.9
Sand Hill GT 1	ocgt	9.46	0.51	2000	0	16.2	45.1
Sand Hill GT 2	ocgt	9.51	0.51	2000	0	15.9	44.1
Sand Hill GT 3	ocgt	9.46	0.51	2000	0	16.6	46.1
Sand Hill GT 4	ocgt	9.54	0.51	2000	0	17.3	48.0
Sand Hill GT 5	ocgt	9.53	0.51	2000	0	16.2	45.1
Sand Hill GT 6	ocgt	9.46	0.51	2000	0	16.2	45.1
Silas Ray 10	ocgt	9.45	0.51	2000	0	16.9	47.0
Silas Ray 69	ocgt	14.45	0.78	2000	0	14.4	57.4
T H Wharton							
GT 1	ocgt	14.47	0.78	2000	0	14.4	57.4
T H Wharton							
GT 51	ocgt	11.65	0.62	1000	0	3.2	12.7
T H Wharton							
GT 52	ocgt	11.66	0.62	1000	0	14.2	56.8
T H Wharton							
GT 53	ocgt	11.62	0.62	1000	0	14.2	56.8
T H Wharton							
GT 54	ocgt	11.66	0.62	1000	0	14.2	56.8
T H Wharton							
GT 55	ocgt	11.57	0.62	1000	0	14.2	56.8

Plant Name	Non-fuel/ CO ₂ VOM cost (\$/MWh)	Base plant ramp rate up (MW/min)	Base plant ramp rate down (MW/min)	Base plant minimum up time (hr)	Base plant minimum down time (hr)	Base plant initial up time (hr)	Base plant initial down time (hr)	CHP indicator (1=yes, 0=no)
Sam Rayburn								
GT 1	3.0	0.86	0.86	1	1	0	0	0
Sam Rayburn								
GT 2	3.0	0.86	0.86	1	1	0	0	0
Sand Hill GT 1	8.0	3.01	3.01	1	1	0	0	0
Sand Hill GT 2	8.0	2.94	2.94	1	1	0	0	0
Sand Hill GT 3	8.0	3.07	3.07	1	1	0	0	0
Sand Hill GT 4	8.0	3.20	3.20	1	1	0	0	0
Sand Hill GT 5	8.0	3.01	3.01	1	1	0	0	0
Sand Hill GT 6	8.0	3.01	3.01	1	1	0	0	0
Silas Ray 10	8.0	3.14	3.14	1	1	0	0	0
Silas Ray 69	3.0	0.37	0.37	1	1	0	0	0
T H Wharton								
GT 1	3.0	3.83	3.83	1	1	0	0	0
T H Wharton								
GT 51	4.0	0.85	0.85	1	1	0	0	0
T H Wharton								
GT 52	4.0	3.79	3.79	1	1	0	0	0
T H Wharton								
GT 53	4.0	3.79	3.79	1	1	0	0	0
T H Wharton								
GT 54	4.0	3.79	3.79	1	1	0	0	0
T H Wharton								
GT 55	4.0	3.79	3.79	1	1	0	0	0

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
T H Wharton							
GT 56	ocgt	11.65	0.62	1000	0	14.2	56.8
Texas Gulf							
Sulphur	ocgt	14.55	0.79	2000	0	20.3	81.2
V H Braunig 5	ocgt	9.47	0.51	2000	0	16.8	46.6
V H Braunig 6	ocgt	9.46	0.51	2000	0	16.8	46.6
V H Braunig 7	ocgt	9.53	0.51	2000	0	16.8	46.6
V H Braunig 8	ocgt	9.52	0.51	2000	0	16.8	46.6
W A Parish T1	ocgt	14.47	0.78	2000	0	3.2	12.9
Wichita Falls 1	ocgt	14.48	0.78	2000	0	19.6	78.2
Winchester							
Power Park 1	ocgt	9.47	0.51	2000	0	15.9	44.1
Winchester							
Power Park 2	ocgt	9.45	0.51	2000	0	15.9	44.1
Winchester							
Power Park 3	ocgt	9.47	0.51	2000	0	15.9	44.1
Winchester							
Power Park 4	ocgt	9.51	0.51	2000	0	15.9	44.1

Plant Name	Non-fuel/ CO ₂ VOM cost (\$/MWh)	Base plant ramp rate up (MW/min)	Base plant ramp rate down (MW/min)	Base plant minimum up time (hr)	Base plant minimum down time (hr)	Base plant initial up time (hr)	Base plant initial down time (hr)	CHP indicator (1=yes, 0=no)
T H Wharton								
GT 56	4.0	3.79	3.79	1	1	0	0	0
Texas Gulf								
Sulphur	3.0	5.41	5.41	1	1	0	0	0
V H Braunig 5	8.0	3.10	3.10	1	1	0	0	0
V H Braunig 6	8.0	3.10	3.10	1	1	0	0	0
V H Braunig 7	8.0	3.10	3.10	1	1	0	0	0
V H Braunig 8	8.0	3.10	3.10	1	1	0	0	0
W A Parish T1	3.0	0.86	0.86	1	1	0	0	0
Wichita Falls 1	3.0	0.51	0.51	1	1	0	0	0
Winchester								
Power Park 1	8.0	2.94	2.94	1	1	0	0	0
Winchester								
Power Park 2	8.0	2.94	2.94	1	1	0	0	0
Winchester								
Power Park 3	8.0	2.94	2.94	1	1	0	0	0
Winchester								
Power Park 4	8.0	2.94	2.94	1	1	0	0	0

The next set of tables contains power system parameters for gas-fired units ERCOT projects to be operating by 2020.

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
WLFHOLW 5	ngcc	7.06	0.38	15000	0	250.0	400.0
RICHLND1 5	ngcc	7.13	0.38	15000	0	250.0	400.0
LAKE CRK1 5	ngcc	7.10	0.38	15000	0	250.0	400.0
SALADOSS 5	ngcc	7.11	0.38	15000	0	250.0	400.0
ELMCREEK	ngcc	7.10	0.38	15000	0	250.0	400.0
SAMSWITC	ngcc	7.11	0.38	15000	0	250.0	400.0
L GARFIE5 1Y	ngcc	7.07	0.38	15000	0	250.0	400.0
L FAYETT5 1Y	ngcc	7.10	0.38	15000	0	250.0	400.0
EDNBRG 6	ngcc	7.08	0.38	15000	0	250.0	400.0
LYTTON 34	ngcc	7.07	0.38	15000	0	250.0	400.0
WILLOWCK 5	ocgt	9.49	0.51	2000	0	36.0	100.0
FISHRDSS1 5	ocgt	9.55	0.52	2000	0	36.0	100.0
New 2020 CT1	ocgt	9.54	0.52	2000	0	36.0	100.0
New 2020 CT2	ocgt	9.47	0.51	2000	0	36.0	100.0
New 2020 CT3	ocgt	9.45	0.51	2000	0	36.0	100.0
New 2020 CT4	ocgt	9.54	0.51	2000	0	72.0	200.0
MIGUEL5	ocgt	9.46	0.51	2000	0	36.0	100.0
New 2020 CT5	ocgt	9.49	0.51	2000	0	36.0	100.0
KIRCHHOF7A	ocgt	9.48	0.51	2000	0	36.0	100.0
D3 SC BUS	ocgt	9.52	0.51	2000	0	36.0	100.0
NAVARRO	ocgt	9.54	0.51	2000	0	36.0	100.0
New 2017 CT1	ocgt	9.48	0.51	2000	0	36.0	100.0
New 2020 CT7	ocgt	9.54	0.51	2000	0	72.0	200.0

Plant Name	Non-fuel/CO ₂ VOM cost (\$/MWh)	Base plant ramp			Base plant minimum up time			Base plant minimum down time			Base plant initial down time (hr)	CHP indicator (1=yes, 0=no)
		rate up (MW/min)	rate down (MW/min)	ramp down (hr)	minimum up time (hr)	minimum down time (hr)	initial up time (hr)	initial down time (hr)				
WLFHOLW 5	2.9	2.62	2.62	6	8	0	0	0	0	0	0	
RICHLND1 5	2.9	2.62	2.62	6	8	0	0	0	0	0	0	
LAKE CRK1 5	2.9	2.62	2.62	6	8	0	0	0	0	0	0	
SALADOSS 5	2.9	2.62	2.62	6	8	0	0	0	0	0	0	
ELMCREEK	2.9	2.62	2.62	6	8	0	0	0	0	0	0	
SAMSWITC	2.9	2.62	2.62	6	8	0	0	0	0	0	0	
L GARFIE5 1Y	2.9	2.62	2.62	6	8	0	0	0	0	0	0	
L FAYETT5 1Y	2.9	2.62	2.62	6	8	0	0	0	0	0	0	
EDNBRG 6	2.9	2.62	2.62	6	8	0	0	0	0	0	0	
LYTTON 34	2.9	2.62	2.62	6	8	0	0	0	0	0	0	
WILLOWCK 5	8.0	6.67	6.67	1	1	0	0	0	0	0	0	
FISHRDSS1 5	8.0	6.67	6.67	1	1	0	0	0	0	0	0	
New 2020 CT1	8.0	6.67	6.67	1	1	0	0	0	0	0	0	
New 2020 CT2	8.0	6.67	6.67	1	1	0	0	0	0	0	0	
New 2020 CT3	8.0	6.67	6.67	1	1	0	0	0	0	0	0	
New 2020 CT4	8.0	13.33	13.33	1	1	0	0	0	0	0	0	
MIGUEL5	8.0	6.67	6.67	1	1	0	0	0	0	0	0	
New 2020 CT5	8.0	6.67	6.67	1	1	0	0	0	0	0	0	
KIRCHHOF7A	8.0	6.67	6.67	1	1	0	0	0	0	0	0	
D3 SC BUS	8.0	6.67	6.67	1	1	0	0	0	0	0	0	
NAVARRO	8.0	6.67	6.67	1	1	0	0	0	0	0	0	
New 2017 CT1	8.0	6.67	6.67	1	1	0	0	0	0	0	0	
New 2020 CT7	8.0	13.33	13.33	1	1	0	0	0	0	0	0	

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
GRAY	ocgt	9.52	0.51	2000	0	36.0	100.0
RIOBRAV	ocgt	9.46	0.51	2000	0	36.0	100.0
New 2017 CT2	ocgt	9.46	0.51	2000	0	36.0	100.0
New 2020 CT8	ocgt	9.54	0.51	2000	0	36.0	100.0

Plant Name	Non-fuel/ CO ₂ VOM cost (\$/MWh)	Base plant ramp			Base plant minimum			Base plant up time			Base plant down time			CHP indicator (1=yes, 0=no)
		rate up (MW/min)	rate down (MW/min)	rate up time (hr)	rate down time (hr)	minimum down time (hr)	minimum up time (hr)	initial up time (hr)	initial down time (hr)	initial up time (hr)	initial down time (hr)	CHP indicator		
GRAY	8.0	6.67	6.67	1	1	1	1	0	0	0	0	0	0	
RIOBRAV	8.0	6.67	6.67	1	1	1	1	0	0	0	0	0	0	
New 2017 CT2	8.0	6.67	6.67	1	1	1	1	0	0	0	0	0	0	
New 2020 CT8	8.0	6.67	6.67	1	1	1	1	0	0	0	0	0	0	

The next set of tables contains power system parameters for additional gas-fired units manually added to the 2020 database so there is sufficient capacity to meet peak 2020 electricity demand and ancillary service requirements.

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
Extra CC for 2020 peak 1	ngcc	7.08	0.38	15000	0	250.0	400.0
Extra CC for 2020 peak 2	ngcc	7.13	0.38	15000	0	250.0	400.0
Extra CC for 2020 peak 3	ngcc	7.09	0.38	15000	0	250.0	400.0
Extra CC for 2020 peak 4	ngcc	7.09	0.38	15000	0	250.0	400.0
Extra CC for 2020 peak 5	ngcc	7.07	0.38	15000	0	250.0	400.0
Extra CC for 2020 peak 6	ngcc	7.11	0.38	15000	0	250.0	400.0
Extra CC for 2020 peak 7	ngcc	7.13	0.38	15000	0	250.0	400.0
Extra CC for 2020 peak 8	ngcc	7.07	0.38	15000	0	250.0	400.0
Extra CC for 2020 peak 9	ngcc	7.12	0.38	15000	0	250.0	400.0
Extra CC for 2020 peak 10	ngcc	7.11	0.38	15000	0	250.0	400.0
Extra CC for 2020 peak 11	ngcc	7.13	0.39	15000	0	250.0	400.0

Plant Name	Non-fuel/ CO ₂ VOM cost (\$/MWh)	Base plant ramp rate up (MW/min)	Base plant ramp rate down (MW/min)	Base plant minimum up time (hr)	Base plant minimum down time (hr)	Base plant initial up time (hr)	Base plant initial down time (hr)	CHP indicator (1=yes, 0=no)
Extra CC for 2020 peak 1	2.9	2.62	2.62	6	8	0	0	0
Extra CC for 2020 peak 2	2.9	2.62	2.62	6	8	0	0	0
Extra CC for 2020 peak 3	2.9	2.62	2.62	6	8	0	0	0
Extra CC for 2020 peak 4	2.9	2.62	2.62	6	8	0	0	0
Extra CC for 2020 peak 5	2.9	2.62	2.62	6	8	0	0	0
Extra CC for 2020 peak 6	2.9	2.62	2.62	6	8	0	0	0
Extra CC for 2020 peak 7	2.9	2.62	2.62	6	8	0	0	0
Extra CC for 2020 peak 8	2.9	2.62	2.62	6	8	0	0	0
Extra CC for 2020 peak 9	2.9	2.62	2.62	6	8	0	0	0
Extra CC for 2020 peak 10	2.9	2.62	2.62	6	8	0	0	0
Extra CC for 2020 peak 11	2.9	2.62	2.62	6	8	0	0	0

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
Extra CC for 2020 peak 12	ngcc	7.08	0.38	15000	0	250.0	400.0
Extra CC for 2020 peak 13	ngcc	7.07	0.38	15000	0	250.0	400.0
Extra CC for 2020 peak 14	ngcc	7.10	0.38	15000	0	250.0	400.0
Extra CT for 2020 peak 1	ocgt	9.46	0.51	2000	0	72.0	200.0
Extra CT for 2020 peak 2	ocgt	9.52	0.51	2000	0	72.0	200.0
Extra CT for 2020 peak 3	ocgt	9.51	0.51	2000	0	72.0	200.0
Extra CT for 2020 peak 4	ocgt	9.47	0.51	2000	0	72.0	200.0
Extra CT for 2020 peak 5	ocgt	9.50	0.51	2000	0	72.0	200.0
Extra CT for 2020 peak 6	ocgt	9.53	0.51	2000	0	72.0	200.0
Extra CT for 2020 peak 7	ocgt	9.54	0.51	2000	0	72.0	200.0
Extra CT for 2020 peak 8	ocgt	9.46	0.51	2000	0	72.0	200.0

Plant Name	Non-fuel/ CO ₂ VOM cost (\$/MWh)	Base plant ramp rate up (MW/min)	Base plant ramp rate down (MW/min)	Base plant minimum up time (hr)	Base plant minimum down time (hr)	Base plant initial up time (hr)	Base plant initial down time (hr)	CHP indicator (1=yes, 0=no)
Extra CC for 2020 peak 12	2.9	2.62	2.62	6	8	0	0	0
Extra CC for 2020 peak 13	2.9	2.62	2.62	6	8	0	0	0
Extra CC for 2020 peak 14	2.9	2.62	2.62	6	8	0	0	0
Extra CT for 2020 peak 1	8.0	13.33	13.33	1	1	0	0	0
Extra CT for 2020 peak 2	8.0	13.33	13.33	1	1	0	0	0
Extra CT for 2020 peak 3	8.0	13.33	13.33	1	1	0	0	0
Extra CT for 2020 peak 4	8.0	13.33	13.33	1	1	0	0	0
Extra CT for 2020 peak 5	8.0	13.33	13.33	1	1	0	0	0
Extra CT for 2020 peak 6	8.0	13.33	13.33	1	1	0	0	0
Extra CT for 2020 peak 7	8.0	13.33	13.33	1	1	0	0	0
Extra CT for 2020 peak 8	8.0	13.33	13.33	1	1	0	0	0

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
Extra CT for 2020 peak 9	ocgt	9.53	0.51	2000	0	72.0	200.0
Extra CT for 2020 peak 10	ocgt	9.53	0.51	2000	0	72.0	200.0
Extra CT for 2020 peak 11	ocgt	9.48	0.51	2000	0	72.0	200.0
Extra CT for 2020 peak 12	ocgt	9.55	0.52	2000	0	72.0	200.0
Extra CT for 2020 peak 13	ocgt	9.48	0.51	2000	0	72.0	200.0
Extra CT for 2020 peak 14	ocgt	9.53	0.51	2000	0	72.0	200.0

Plant Name	Non-fuel/ CO ₂ VOM cost (\$/MWh)	Base plant ramp rate up (MW/min)	Base plant ramp rate down (MW/min)	Base plant minimum up time (hr)	Base plant minimum down time (hr)	Base plant initial up time (hr)	Base plant initial down time (hr)	CHP indicator (1=yes, 0=no)
Extra CT for 2020 peak 9	8.0	13.33	13.33	1	1	0	0	0
Extra CT for 2020 peak 10	8.0	13.33	13.33	1	1	0	0	0
Extra CT for 2020 peak 11	8.0	13.33	13.33	1	1	0	0	0
Extra CT for 2020 peak 12	8.0	13.33	13.33	1	1	0	0	0
Extra CT for 2020 peak 13	8.0	13.33	13.33	1	1	0	0	0
Extra CT for 2020 peak 14	8.0	13.33	13.33	1	1	0	0	0

The next set of tables lists CO₂ capture system parameters for all units modeled with CO₂ capture when capture systems are flexible with solvent storage. When inflexible or venting-only flexible capture are modeled, solvent storage capacity is eliminated, and equivalent work and CO₂ carrying capacity are set to values corresponding to the operating point with minimum equivalent work. Minimum equivalent work is 0.219 MWh/tCO₂ for stripping and compression and 0.0274 MWh/tCO₂ for absorption, and this operating point has a 8.33 molMEA/molCO₂ carrying capacity (0.12 molCO₂/molMEA). The 6.25 molMEA/molCO₂ capacity used with solvent storage corresponds to 0.16 molCO₂/molMEA.

With solvent storage, the model requires the stored CO₂ at the final time period, T , to be specified in addition to the day-starting stored CO₂ level. These values are equal for all simulations performed for this dissertation.

Plant Name	Absorber minimum load (fractional)	Stripper minimum load (fractional)	CO ₂ removal in absorber (fractional)	Equivalent work for stripping & compression (MWh/tCO ₂)	Equivalent work for absorption (MWh/tCO ₂)	Absorber ramp up (load fraction per min)	Absorber ramp down (load fraction per min)
Big Brown 1	0.3	0.3	0.9	0.221	0.0276	0.05	0.05
Big Brown 2	0.3	0.3	0.9	0.221	0.0276	0.05	0.05
Fayette Power Project 1	0.3	0.3	0.9	0.221	0.0276	0.05	0.05
Fayette Power Project 2	0.3	0.3	0.9	0.221	0.0276	0.05	0.05
Fayette Power Project 3	0.3	0.3	0.9	0.221	0.0276	0.05	0.05
J K Spruce 1	0.3	0.3	0.9	0.221	0.0276	0.05	0.05
J K Spruce 2	0.3	0.3	0.9	0.221	0.0276	0.05	0.05
Limestone 1	0.3	0.3	0.9	0.221	0.0276	0.05	0.05
Limestone 2	0.3	0.3	0.9	0.221	0.0276	0.05	0.05
Oak Grove SES Unit 1	0.3	0.3	0.9	0.221	0.0276	0.05	0.05
Oak Grove SES Unit 2	0.3	0.3	0.9	0.221	0.0276	0.05	0.05
W A Parish 5	0.3	0.3	0.9	0.221	0.0276	0.05	0.05
W A Parish 6	0.3	0.3	0.9	0.221	0.0276	0.05	0.05
W A Parish 7	0.3	0.3	0.9	0.221	0.0276	0.05	0.05
W A Parish 8	0.3	0.3	0.9	0.221	0.0276	0.05	0.05

Plant Name	Stripper ramp up (load fraction per min)	Stripper ramp down (load fraction per min)	LP steam fraction stripping (fractional)	Absorber startup cost (\$ per startup)	Absorber shutdown cost (\$ per startup)	Stripper startup cost (\$ per startup)	Stripper shutdown cost (\$ per startup)
Big Brown 1	0.05	0.05	0.4	0	0	0	0
Big Brown 2	0.05	0.05	0.4	0	0	0	0
Fayette Power Project 1	0.05	0.05	0.4	0	0	0	0
Fayette Power Project 2	0.05	0.05	0.4	0	0	0	0
Fayette Power Project 3	0.05	0.05	0.4	0	0	0	0
J K Spruce 1	0.05	0.05	0.4	0	0	0	0
J K Spruce 2	0.05	0.05	0.4	0	0	0	0
Limestone 1	0.05	0.05	0.4	0	0	0	0
Limestone 2	0.05	0.05	0.4	0	0	0	0
Oak Grove SES Unit 1	0.05	0.05	0.4	0	0	0	0
Oak Grove SES Unit 2	0.05	0.05	0.4	0	0	0	0
W A Parish 5	0.05	0.05	0.4	0	0	0	0
W A Parish 6	0.05	0.05	0.4	0	0	0	0
W A Parish 7	0.05	0.05	0.4	0	0	0	0
W A Parish 8	0.05	0.05	0.4	0	0	0	0

Plant Name	Absorber minimum up time (hr)		Absorber minimum down time (hr)		Absorber initial up time (hr)		Absorber initial down time (hr)		Stripper minimum up time (hr)		Stripper minimum down time (hr)		Stripper initial up time (hr)		Stripper initial down time (hr)	
	1	1	1	1	0	0	1	1	1	1	1	1	0	0	0	0
Big Brown 1	1	1	1	1	0	0	1	1	1	1	1	1	0	0	0	0
Big Brown 2	1	1	1	1	0	0	1	1	1	1	1	1	0	0	0	0
Fayette Power Project 1	1	1	1	1	0	0	1	1	1	1	1	1	0	0	0	0
Fayette Power Project 2	1	1	1	1	0	0	1	1	1	1	1	1	0	0	0	0
Fayette Power Project 3	1	1	1	1	0	0	1	1	1	1	1	1	0	0	0	0
J K Spruce 1	1	1	1	1	0	0	1	1	1	1	1	1	0	0	0	0
J K Spruce 2	1	1	1	1	0	0	1	1	1	1	1	1	0	0	0	0
Limestone 1	1	1	1	1	0	0	1	1	1	1	1	1	0	0	0	0
Limestone 2	1	1	1	1	0	0	1	1	1	1	1	1	0	0	0	0
Oak Grove SES Unit 1	1	1	1	1	0	0	1	1	1	1	1	1	0	0	0	0
Oak Grove SES Unit 2	1	1	1	1	0	0	1	1	1	1	1	1	0	0	0	0
W A Parish 5	1	1	1	1	0	0	1	1	1	1	1	1	0	0	0	0
W A Parish 6	1	1	1	1	0	0	1	1	1	1	1	1	0	0	0	0
W A Parish 7	1	1	1	1	0	0	1	1	1	1	1	1	0	0	0	0
W A Parish 8	1	1	1	1	0	0	1	1	1	1	1	1	0	0	0	0

Plant Name	CO ₂ transport and storage cost (\$/tCO ₂)	Solvent storage tank size (m ³)	CO ₂ carrying capacity (molMEA per molCO ₂)	Day-starting CO ₂ in rich storage tank (tCO ₂)	Final CO ₂ in rich storage tank (tCO ₂)
Big Brown 1	9.82	29975	6.25	778	778
Big Brown 2	9.82	30983	6.25	804	804
Fayette Power Project 1	9.82	31234	6.25	810	810
Fayette Power Project 2	9.82	30983	6.25	804	804
Fayette Power Project 3	9.82	22670	6.25	588	588
J K Spruce 1	9.82	28464	6.25	739	739
J K Spruce 2	9.82	38892	6.25	1009	1009
Limestone 1	9.82	41864	6.25	1086	1086
Limestone 2	9.82	43224	6.25	1122	1122
Oak Grove SES Unit 1	9.82	39547	6.25	1026	1026
Oak Grove SES Unit 2	9.82	40101	6.25	1041	1041
W A Parish 5	9.82	32494	6.25	843	843
W A Parish 6	9.82	32746	6.25	850	850
W A Parish 7	9.82	28464	6.25	739	739
W A Parish 8	9.82	30227	6.25	784	784

The final set of tables lists power output and input system parameters for the compressed air energy storage units included in select simulations.

energy storage system parameters

Plant Name	Plant Type	Heat rate (MMBTU per MWh)	CO ₂ emissions rate (tCO ₂ per MWh)	Base plant startup cost (\$ per startup)	Base plant shutdown cost (\$ per shutdown)	Minimum output (MW)	Maximum output (MW)
CAES 1	stor	4.10	0.24	1000	0	100.0	200.0
CAES 2	stor	4.10	0.24	1000	0	100.0	200.0
CAES 3	stor	4.10	0.24	1000	0	100.0	200.0
CAES 4	stor	4.10	0.24	1000	0	100.0	200.0
CAES 5	stor	4.10	0.24	1000	0	100.0	200.0
CAES 6	stor	4.10	0.24	1000	0	100.0	200.0
CAES 7	stor	4.10	0.24	1000	0	100.0	200.0
CAES 8	stor	4.10	0.24	1000	0	100.0	200.0
CAES 9	stor	4.10	0.24	1000	0	100.0	200.0
CAES 10	stor	4.10	0.24	1000	0	100.0	200.0

Plant Name	Non-fuel/ CO_2 VOM cost (\$/MWh)	Base plant ramp rate up (MW/min)	Base plant ramp rate down (MW/min)	Base plant minimum up time (hr)	Base plant minimum down time (hr)	Base plant initial up time (hr)	Base plant initial down time (hr)	CHP indicator (1=yes, 0=no)
CAES 1	3.0	13.33	13.33	1	1	0	0	0
CAES 2	3.0	13.33	13.33	1	1	0	0	0
CAES 3	3.0	13.33	13.33	1	1	0	0	0
CAES 4	3.0	13.33	13.33	1	1	0	0	0
CAES 5	3.0	13.33	13.33	1	1	0	0	0
CAES 6	3.0	13.33	13.33	1	1	0	0	0
CAES 7	3.0	13.33	13.33	1	1	0	0	0
CAES 8	3.0	13.33	13.33	1	1	0	0	0
CAES 9	3.0	13.33	13.33	1	1	0	0	0
CAES 10	3.0	13.33	13.33	1	1	0	0	0

Plant Name	Minimum input to storage (MW)	Maximum input to storage (MW)	Output to input efficiency (fractional)	Energy storage capacity (MWh)	Day-starting stored energy level (MWh)	Final stored energy level (MWh)	Input ramp rate up (MW/min)	Input ramp rate down (MW/min)
CAES 1	50	100	1.25	1600	480	480	6.67	6.67
CAES 2	50	100	1.25	1600	480	480	6.67	6.67
CAES 3	50	100	1.25	1600	480	480	6.67	6.67
CAES 4	50	100	1.25	1600	480	480	6.67	6.67
CAES 5	50	100	1.25	1600	480	480	6.67	6.67
CAES 6	50	100	1.25	1600	480	480	6.67	6.67
CAES 7	50	100	1.25	1600	480	480	6.67	6.67
CAES 8	50	100	1.25	1600	480	480	6.67	6.67
CAES 9	50	100	1.25	1600	480	480	6.67	6.67
CAES 10	50	100	1.25	1600	480	480	6.67	6.67

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Vita

Stuart M. Cohen was born in Silver Spring, Maryland. He graduated as valedictorian of Old Mill Senior High in May of 2002, after which he enrolled at Case Western Reserve University (CWRU) in Cleveland, Ohio for undergraduate study. As an undergraduate, Stuart completed a summer internship at the National Aeronautics and Space Administration Glenn Research Center in the Undergraduate Student Research Program and participated in CWRU's cooperative education program, working a total of 18 months for Codonics, Incorporated. Mr. Cohen graduated summa cum laude from Case Western Reserve University in May of 2007 with a Bachelor of Science in Engineering degree in mechanical engineering and a minor in psychology. He then received his Master of Science in mechanical engineering from The University of Texas at Austin in May 2007 for his thesis *The Implications of Flexible CO₂ Capture on the ERCOT Electric Grid*. Mr. Cohen continued his graduate study in the doctorate program in mechanical engineering at The University of Texas at Austin, and after completing his Doctor of Philosophy degree, he will begin a position as an Electric System Analyst Postdoctoral Researcher for the United States National Renewable Energy Laboratory.

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