Effects of Intermittent Generation on the Economics and Operation of Prospective Baseload Power Plants

by

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Submitted to the Institute for Data, Systems, & Society and
the Department of Nuclear Science & Engineering
in partial fulfillment of the requirements for the degrees of

Master of Science in Technology & Policy
and
Master of Science in Nuclear Science & Engineering
at the
MASSACHUSETTS INSTITUTE OF TECHNOLOGY

September 2017

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Abstract

The electricity system is transitioning from a system comprised primarily of dispatchable generators to a system increasingly reliant on wind and solar power—intermittent sources of electricity with output dependent on meteorological conditions, adding both variability and uncertainty to the system. Dispatchable generators with a high ratio of fixed to variable costs have historically relied on operating at maximum output as often as possible to spread these fixed costs over as much electricity generation as possible. Higher penetrations of intermittent capacity create market conditions that lead to lower capacity factors for these generators, presenting an economic challenge. Increasing penetrations of intermittent capacity, however, also leads to more volatile electricity prices, with highest prices in hours that renewable sources are unavailable. The ability of dispatchable generators to provide energy during these high priced hours may counteract the loss of revenue from reduced operating hours. Given the disparate revenues received in this volatile market, the relative competitiveness of generation technologies cannot be informed by their cost alone; the value of generators based on their production profiles must also be considered. Consequently, comparisons of generator competitiveness based on traditional metrics such as the levelized cost of electricity are misleading, and power system models able to convey the relative value of generators should instead be used to compare generator competitiveness.

The purpose of this thesis is to assess the relative competitiveness of generation technologies in an efficient market under various penetrations of intermittent power. This work is specifically concerned with the relative competitiveness of power plants equipped with carbon capture and storage (CCS) technology, nuclear power plants, and renewable generation capacity. In order to assess relative competitiveness, this work presents an extensive literature review of the costs and technical flexibility of generators, with particular attention to CCS-equipped and nuclear capacity. These costs and flexibility parameters are integrated into a unit commitment model. The unit commitment model for co-optimized reserves and energy (UCCORE), developed as part of this thesis, is a mixed integer linear programming model with a focus on representing hourly price volatility and the intertemporal operational constraints of thermal generators. The model is parameterized to represent the ERCOT power system and is used to solve for generator dispatch and marginal prices at hourly intervals over characteristic weeks. Data from modeled characteristic weeks is interpolated to estimate generator profits over a year to allow for a comparison of generator competitiveness informed by both costs and revenues.

Scenario analysis conducted using the UCCORE model shows that the difference in energy prices captured by generators becomes an important driver of relative competitiveness at modest penetrations of intermittent power. Increasing the ratio of intermittent to dispatchable capacity causes intermittent generators to depress market prices during the hours they are available due to their coordinated output. Prices, however, rise in hours when intermittent capacity is unavailable because of scarcity of available capacity. This work develops the weighted value factor to compare the revenues of intermittent and dispatchable generation capacity. The weighted value factor is the market value of a generators production profile relative to an ideal generator dispatched at full capacity for all hours. The results show that as the proportion of intermittent capacity increases, the relative value of dispatchable generators also increases and at an increasing rate. At high penetrations of intermittent capacity, the power system experiences increasing risk of generation shortages leading to exceptionally high prices. In these systems, dispatchable generators able to capture peak pricing become most profitable. At lower penetrations of intermittent capacity, peak pricing remains influential, but is less extreme and the relative importance of low capital and fixed costs increases. The sensitivity of generator profitability to assumed value of lost load, oil and gas price, and carbon price is also assessed.

The key implication of these results is that efficient price signals may lead to opportunities for investment in dispatchable generators as the proportion of intermittent capacity on a power system increases. Markets and models that do not capture the full hourly volatility of efficient energy prices, however, are missing critical signals. The importance of these signals on relative competitiveness increases with the penetration of intermittent power. Without accounting for price volatility, markets and models will undervalue dispatchable capacity and overvalue intermittent capacity.

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Acknowledgments

I would like to thank Howard Herzog for his advising and mentorship throughout this thesis as well as my career in TPP and at MIT as a whole. Without his continual contributions and patience, this thesis would not have been possible.

Similarly, I would like to thank Scott Kemp for serving as my advisor in the NSE department and for his thorough feedback and suggestions regarding this work.

I thank Sergey Paltsev for his involvement throughout this project, specifically for his help with the GAMS formulation of the model, the economic interpretation of results, and his feedback on the final draft.

A sincere thanks to my colleague, Alex Yee, for his repeated assistance improving and debugging the model.

Finally, I would like to thank ExxonMobil for funding this work through the CCS technology assessment project and for the input and support from the ExxonMobil team.

The time and contributions from these individuals has improved this document and is greatly appreciated.

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List of Acronyms

AP1000	Advanced Passive 1000 MWe Nuclear Power Plant
BWR	Boiling Water Reactor
CAISO	California Independent System Operator
CANDU	Canada Deuterium Uranium
CCGT	Combined Cycle Gas Turbine
CCS	Carbon Capture and Storage
CDF	Cumulative Distribution Function
CEMS	Continuous Emission Monitoring System
CO_2	Carbon Dioxide
EFORd	Equivalent Forced Outage Rate Demand
EIA	Energy Information Administration
EOR	Enhanced Oil Recovery
EPA	Environmental Protection Agency
EPR	European Pressurized Reactor
ERCOT	Electric Reliability Council of Texas
GADS	Generating Availability Data System
GAMS	General Algebraic Modeling System
GDP	Gross Domestic Product
HHV	Higher Heating Value
IEA	International Energy Administration
LCOE	Levelized Cost of Electricity
LMP	Locational Marginal Price
LOLP	Loss of Load Probability
MILP	Mixed Integer Linear Programming
MISO	Midcontinent Independent System Operator
NERC	North American Electric Reliability Corporation
NGST	Natural Gas Steam Turbine
O&M	Operation and Maintenance
OCGT	Open Cycle Gas Turbine
ORDC	Operating Reserve Demand Curve
PC	Pulverized Coal
PV	Photovoltaic
PWR	Pressurized Water Reactor

REC	Renewable Energy Certificate
RPS	Renewable Portfolio Standard
UCCORE	Unit Commitment Model for Co-Optimized Reserves and Energy
USC	Ultra-Supercritical
VOLL	Value of Lost Load

Chapter 1

Introduction

The electricity sector is undergoing rapid and marked change. Previously dependent on large, centralized, dispatchable generators, electricity generation is increasingly reliant on small, decentralized generators utilizing local, renewable resources. Wind turbines and solar photovoltaics are intermittent sources of electricity with variable and uncertain output dependent on meteorological conditions. Aside from curtailment, power output from these sources is outside of the electricity system operator's control. As these sources increase their share of generation, the power system may become more volatile, demanding dispatchable generators operate more flexibly.

The objective of this thesis is to assess the effects of increasing penetrations of intermittent generation capacity in a power system on the operation and economic competitiveness of new carbon capture and storage (CCS) equipped fossil-fuel and nuclear generation capacity.

CCS-equipped power plants and nuclear plants constitute a class of dispatchable, low-carbon generation that may be important compliments to renewable capacity in a future generation portfolio. In power systems of the 20$^{\text{th}}$ century with low penetrations of intermittent resources, these types of generators would have operated as baseload power plants maintaining a steady output to supply the system's minimum electricity demand. Higher penetrations of intermittent power present an existential challenge to the economic justification of these types of generators. Increased intermittent generation reduces the output of baseload generators increasing their per unit energy costs, thus worsening their economic prospects. On the other hand, these generators may accrue substantial revenues for balancing intermittent generation and providing energy reserves. Whether an economically efficient electricity system with high penetrations of intermittent power would demand these technologies is not obvious and cannot be informed by conventional cost-based measures of competitiveness such as levelized cost of electricity (LCOE).

This thesis adopts a value-based approach to evaluating economic competitiveness by comparing the profits earned by these generators in a system with efficient pricing of energy and reserves at various penetrations of intermittent generation. Prices are based on the marginal costs of production and the marginal benefit of consumption using an improved representation of reserve demand. Profits are estimated under different assumptions using an economic model developed as part of this thesis, the unit commitment model for co-optimized reserves and energy (UCCORE). The UCCORE model and various scenarios are parameterized using current literature on the costs and technical flexibility of CCS-equipped and nuclear power plants with historic data from the ERCOT power system.

The focus of the UCCORE model is to better portray hourly generator operations and market prices to account for the system effects of intermittent generation. This approach considers the technical limitations to flexible operation and calculates dispatch with an hourly temporal resolution, allowing for an appropriate comparison of different generation technologies in the context of a volatile market. Furthermore, by examining the price signals to which these generators respond, the drivers of the value of these generators can be determined. Understanding the relative economic merits of different types of generation capacity is crucial for informing energy policy and market design as well as directing the research and development of future generation technologies. By incorporating the insights of this thesis, energy policy objectives could be met at lower cost and research and demonstration efforts could be aimed at the generation technologies that will provide the most value to future power systems. The thesis is organized as follows:

Chapter 1 has presented a brief introduction to the thesis, its objective, approach, and motivation.

Chapter 2 provides background on the economic theory of electricity generation, detailing the economic problem intermittent generation poses to baseload generators and the limitations of cost-based methods for comparing the economic competitiveness of generators. The chapter concludes by advocating for the adoption of value-based methods from comparing generator economics and explaining how value-based methods can be used.

Chapter 3 examines current data of how increasing penetrations of intermittent power are changing the economic landscape for electricity generation, demonstrating the flaws of cost-based metrics and further proving the need for value-based methods. This chapter establishes connection between intermittent generation and increased volatility in net load and wholesale prices with important implications for existing plants.

Chapter 4 explains the economic theory behind electricity markets and efficient reserve pricing. This chapter describes a simplified power market that prices energy and reserves to appropriately incentivize short-term dispatch as well as long-term investment. This economic framework is used by the UCCORE model to simulate energy market dispatch. This chapter also estimates the loss of load probability and the operating reserve demand curve used as an input to the UCCORE model.

Chapter 5 reviews literature on the costs of new electricity generation infrastructure with particular attention to post-combustion capture CCS-equipped and advanced nuclear capacity. This literature review is used to establish the base assumptions for cost in the UCCORE model.

Chapter 6 reviews literature on the flexibility of power plants with particular attention to post-combustion capture CCS and advanced nuclear capacity. This literature review is used to parametrize the technical constraints of thermal generators applied in the UCCORE model.

Chapter 7 presents the UCCORE model. The model is based on the economic theory presented in Chapter 4 and generators are parameterized using the data collected in Chapters 5 & 6. The model is then used to assess the impact of increasing wind penetration on the value and profitability of various generation types on an ERCOT case system. To compare the relative value of generators the weighed value factor metric is developed.

Chapter 8 concludes the thesis.

The appendices describe the mathematical formulation of the UCCORE model and formally define the weighted value factor introduced in Chapter 7.

Chapter 2

Competitiveness and Economics of Electricity Generation

2.1 Capacity Factor

Coal, nuclear, and hydroelectric power plants are dispatchable generation technologies characterized by high capital costs and low variable costs.[1] Their economic viability is dependent on their ability to defray these capital costs over many hours of operation at maximum energy output; consequently, they are operated at full capacity as often as possible. The average output of a plant is measured by the capacity factor: the fraction of actual plant energy output to maximum nominal output (Equation 2.1).[2]

$$CF = \frac{\int_0^t G(t)dt}{C \cdot t} \tag{2.1}$$

Where

CF is capacity factor

t is time

G is generation

C is capacity

Typically capacity factor is evaluated over the course of a year to account for seasonal variations in operation and at hourly time intervals, h (Equation 2.2).

$$CF = \frac{\sum_{h} G(h)}{8760 \cdot C} \tag{2.2}$$

In 2015, the U.S. nuclear fleet operated at a capacity factor of about 92%,[3] and the coal fleet at 55%, down from over 67% in 2005.[4] The capacity factor of natural gas combined cycle plants is increasing in the United States due to low natural gas prices, with fleet capacity factors reaching 56%, surpassing that of the coal fleet.[4] The operation of hydroelectric plants is more complex owing to the environmental constraints on discharge rates and their coupling with water storage reservoirs.

Plants with the highest ratio of capital to variable costs are baseload power plants and are operated to meet the minimum energy demand—the baseload—of an electric power system. Economic forces limit the aggregate capacity of baseload plants to approximately the system's baseload. Investments in baseload capacity beyond this minimum demand will result in all baseload plants reducing their capacity factor as at some times the total capacity of baseload plants in a system will be greater than total energy demand. A lower capacity factor in turn increases the share of the capital costs that must be borne per unit of electricity generated. A sufficiently low capacity factor prevents capital costs from being recouped, making further investments in baseload capacity uneconomical. Thus, in competitive systems and well-designed centrally planned systems, the total capacity of these types of plants are limited by the baseload.

2.2 Renewable Energy and Baseload Generation

The output of intermittent renewable energy sources, such as wind turbines and solar photovoltaics, are dependent on meteorological conditions outside a power system operator's control, but, when available, the marginal cost of this energy is zero. Since this energy output (aside from curtailment) cannot be controlled and is free on the margin, it is often grouped with energy demand as net load—electricity demand minus the power contribution from variable renewable sources. In many ways, electric grid and power plant operators respond to net load, and as renewable generation capacity is added, the minimum net load experienced by the system decreases. Already many power systems have met their entire electricity demand with renewable sources for short periods of time, implying a minimum net load of zero.[1] Baseload generators operating in these systems will experience lower capacity factors, greatly increasing their costs per unit generation and potentially eliminating their economic rationale.

While increased renewables threaten baseload generation through lower capacity factors, the volatile availability of these sources creates a new opportunity for generation to supplement renewable sources. Intermittent renewable energy sources are both variable and uncertain. In power systems with high penetrations of intermittent renewable energy sources, the value of supplying electricity when these sources are unavailable may be quite high due to scarcity. The higher revenues available during these periods counteracts the loss of revenue imposed by lower capacity factors. Whether this increased revenue will fully compensate the reduced revenue caused by lower capacity factors is not obvious and may differ between systems. Conventionally, these high value periods would be characterized as peak conditions, and be met by peaker plants. In contrast to baseload plants, peaker plants have low capital costs and higher variable costs, making them economically better suited for operation at low capacity factors. These plants are typically oil or gas fired combustion turbines with lower efficiencies and with higher emissions than baseload plants.[1] Future policy may restrict or penalize plant emissions, restricting investments in dispatcable capacity to low-carbon power plants. Under such a scenario, dispatcable, low-carbon generators such as CCS-equipped power plants and nuclear power plants will compete with additional renewables, transmission expansion, electricity storage, and demand management to capture the revenue available when renewables are insufficient to meet

[1] Portugal and Denmark have both met the entirety of domestic load with renewable technologies over several hours, though these countries benefit from being part of a larger European system. Costa Rica has also famously met the entirety of its load for over a hundred days with renewable sources, though this system benefits bigly from hydroelectric storage capacity, which, while renewable, is a dispatchable resource not available in many systems.

load.

In power systems experiencing minimum net loads of zero, true baseload operation will cease. To manage lower capacity factors and capture the revenue from supplementing renewable energy sources, capacity traditionally providing baseload power must operate flexibly.

2.3 Levelized Cost of Electricity

One traditional method of evaluating the relative economic merit of various types of electricity generation capacity is to compare costs via the levelized cost of electricity (LCOE). LCOE is simply the real lifetime cost of a generator divided by the lifetime electricity output of the generator. Thus, LCOE is the constant dollar price the generator must receive for electricity to cover all incurred costs including an adequate return on investment; fundamentally, it represents the unit cost of electricity and is expressed in currency per unit energy (e.g. \$/kWh).[5]

$$LCOE = \frac{\sum Costs}{\sum Generation} \tag{2.3}$$

The total lifetime costs of a generator can be decomposed into various fixed costs and variable costs. Fixed costs are costs proportional to capacity, primarily capital costs and fixed operation and maintenance (O&M), while variable costs are proportional to generation: fuel and variable O&M. Other applicable costs, such as taxes, can be added to make LCOE more reflective of a specific project. Since costs are incurred at different times and electricity generation may not be constant over the life of the project, a complete analysis of LCOE also considers the effects of discounting. Equation 2.4 considers the costs and generation incurred in each period n to account for discounting.[6][2]

[2]For a generator with output that varies over time, it is necessary to consider the effects of discounting on costs as well as generation if LCOE is defined as the constant dollar price the generator must receive to cover costs. The need to discount future generation is more readily apparent if both sides of Equation 2.4 are multiplied by the denominator of the equation's right side such that total discounted costs are equal to discounted revenues.

$$LCOE = \frac{\sum_n [k_n + FOM_n + (FC_n \cdot HR_n + VOM_n)(C \cdot CF_n \cdot t)](1+r)^{-n}}{\sum_n (C \cdot CF_n \cdot t)(1+r)^{-n}} \tag{2.4}$$

Where

n is the time period

k is the capital cost

FOM is fixed O&M

VOM is variable O&M

FC is fuel cost

HR is heat rate

C is plant capacity

CF is capacity factor

t is the time duration of each period n

r is the interest rate

LCOE is often invoked to compare the costs of various types of generation. To facilitate comparison, costs such as taxes are neglected and parameters are assumed to be constant over the economic life of the project simplifying the effects of discounting. Parameters are assigned to their average value, typically evaluated over a single year to account for seasonal variations and annual maintenance cycles. Since variable costs are proportional to generation, their effects on the unit cost is constant with generation and they can be separated from generator output. This is the standard form of LCOE typically used in cost estimation studies.[7][3]

$$LCOE = \frac{k \cdot FCF + FOM}{C \cdot CF \cdot 8760} + HR \cdot FC + VOM \tag{2.5}$$

Where FCF is the fixed charge factor. The fixed charge factor is a function of the discount rate and the plant's economic life. It represents the portion of the total capital cost that must be recouped each year.[5] The appeal of LCOE as a

[3]Given the simplification of using average values for parameters, the simplified Equation 2.3 may not equal the more precise Equation 2.4

metric of relative competitiveness is its simplicity. It can be easily calculated using average data from existing generators and appears independent of the rest of the power system, making it a neutral metric for comparing different types of generation. This intuition, however, is flawed as the metric assumes a capacity factor independent of the makeup of the power system, neglects flexibility constraints, and implies a constant value of electricity. Furthermore, increasing penetrations of variable renewable energy weaken the implicit assumptions made when LCOE is used to compare the economic competitiveness of different generators.

A key term of the LCOE formula is the capacity factor, the proportion of plant energy output to maximum nominal output, previously defined in Equations 2.1 and 2.2. The capacity factor determines the fraction of the fixed costs borne by each unit of energy sold; higher capacity factors are able to spread these costs more thinly minimizing their impact on unit cost. It is important to distinguish between capacity factor and availability factor of a generator. Though in some cases, particularly for generators with the lowest marginal costs such as renewables and nuclear power plants, these may be equal, capacity factor reflects the actual dispatch of a power plant, while availability factor is the ability to dispatch.[8, 9] While availability factor is primarily dependent on the plant (as well as the associated fuel supply chain) capacity factor is a function of the economics of the power system and is particular to the system. Consequently, the capacity factor contains implicit assumptions about the makeup and operation of the power system in which the plant operates. In the developed power systems of the 20$^{\text{th}}$ century, which were dominated by dispatchable thermal and hydroelectric power plants, assuming a general capacity factor could yield satisfactory comparisons as systems tended to operate similarly. With the modern transition to utilize increasing amounts of non-dispatchable, local resources, the individual characteristics of power systems, such as weather patterns, demand profile, and penetration of renewable energy, are increasingly important, and applying a general parameter for capacity factor is commensurately less appropriate.

Changes to capacity factor have the greatest effect on LCOE for generators with a high proportion of fixed costs. Figure 2-1 shows the sensitivity of LCOE to capacity

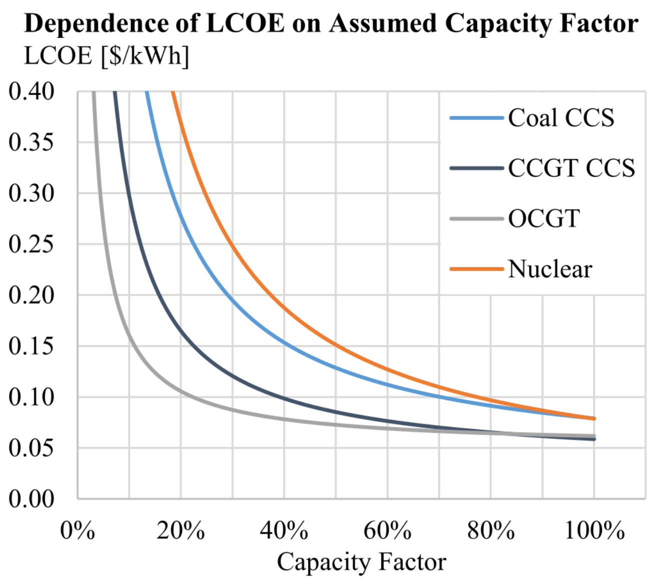


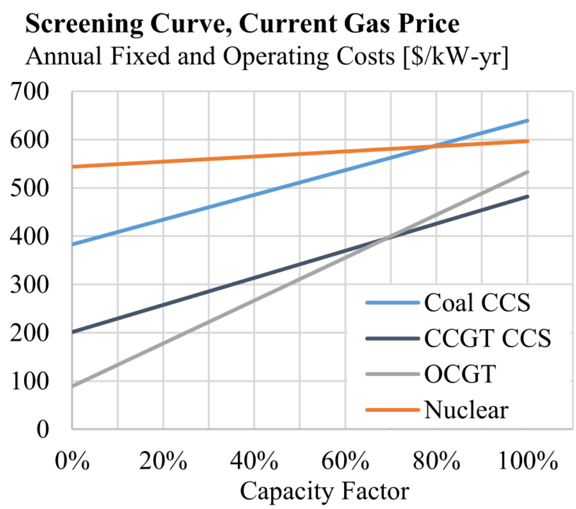
Figure 2-1: Dependence of LCOE on Assumed Capacity Factor

factor for several generator types. These curves assume a constant efficiency across loadings and no additional costs for start-up and shutdown. LCOE is calculated based on plant cost assumptions from the EIA and Rubin et al. and fuel cost data from the EIA.[10, 11, 12, 13] Plant costs are reviewed more rigorously in Chapter 6.

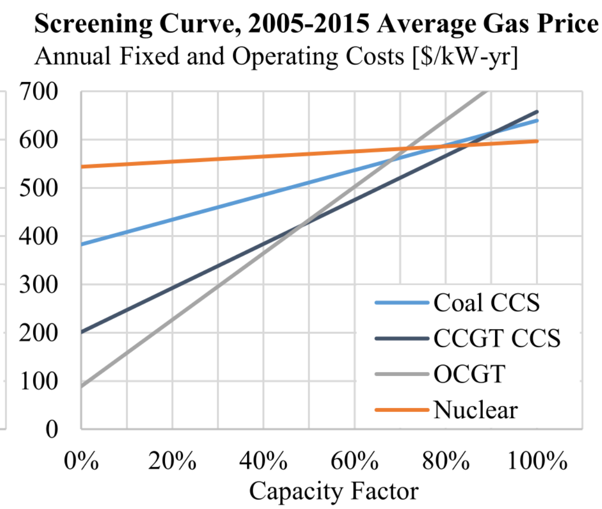
2.4 Screening Curves

Screening curves improve on the LCOE method by separating the dependence on capacity factor. A screening curve plot shows the annual cost of operation plus annualized capital expense as a function of capacity factor, and shows the least expensive technology to operate at a given capacity factor.[14] Figure 2-2a shows the screening curves of several dispatchable technologies based on the cost data used above. The method is generalizable to other generation technologies and a complete assessment would include all available technologies, but only four are shown here to demonstrate the method.

Given the current low price of natural gas and lower investment requirements compared to ultra-supercritical (USC) coal or nuclear plants, open cycle gas turbines (OCGT) and CCS-equipped combined cycle gas turbine (CCGT) are the lower cost



(a) Current Fuel Prices



(b) Historic Fuel Prices

Figure 2-2: Screening Curves for Select Thermal Generation Technologies

power plants across all capacity factors when compared to CCS-equipped coal or advanced nuclear plants. To give a longer term perspective and better demonstrate the screening curve method, Figure 2-2b shows an adjusted curve using the ten-year average gas price. The assumed historic gas price is $6.05/MWh compared to the 2015 price of $3.37/MWh used in the current gas price case. Under these technology options and set of assumptions, OCGTs bound the interior frontier for capacity factors between 0% and 48%, followed by CCGTs equipped with CCS between 48% and 85% and nuclear for capacity factors above 85%. Under these assumptions, pulverized coal equipped with post-combustion CCS is just beyond the frontier of least cost generation and would not be deployed.

Combining the screening curve with a load duration curve that characterizes a power system's demand, one can approximate the least cost generation mix for that particular system in the absence of demand response and storage. The load duration curve is a system's hourly load profile sorted by the magnitude of load as opposed to chronology. Matching the screening curve with the load duration curve approximates the optimal amount of capacity for each generation type in a system.[14]

The load duration curve can be modified to show the net load in systems with variable renewables by subtracting the contribution of renewable generation in each

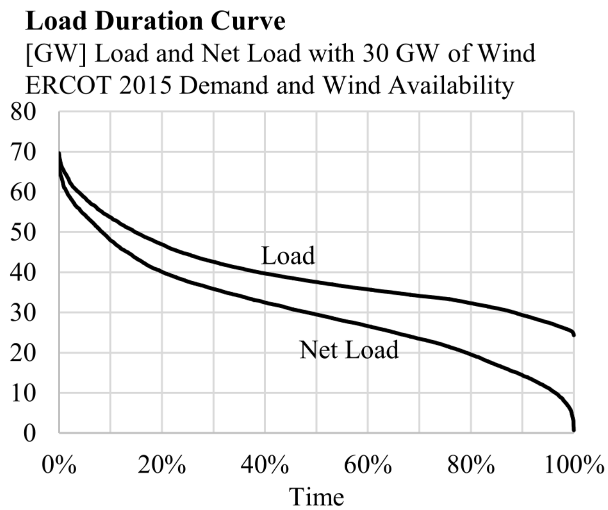
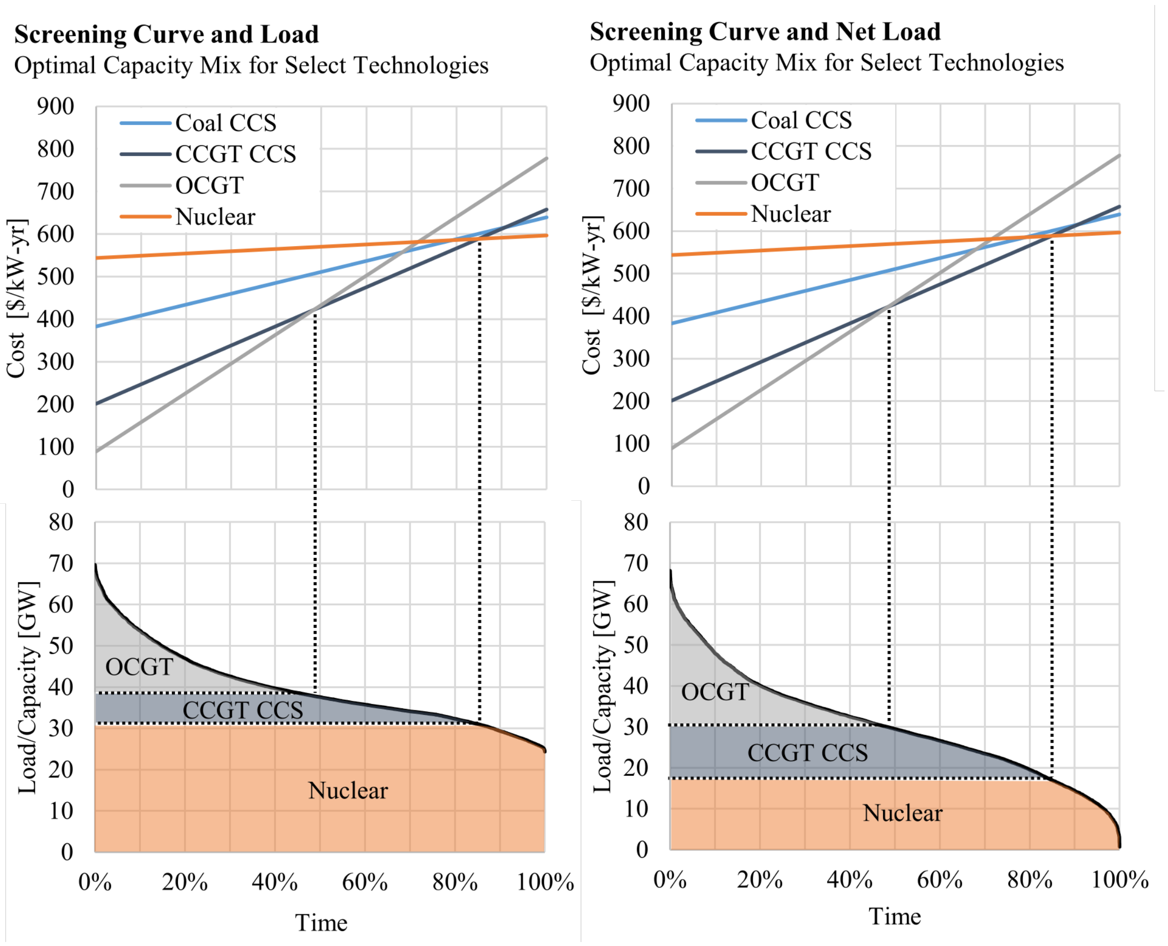


Figure 2-3: Load and Net Load Duration Curves, ERCOT 2015 With Added Wind Capacity

hour from that hour's load. As previously discussed, since wind and solar power have zero marginal cost and are not dispatchable, they are often characterized as negative load. Figure 2-3 shows load duration curve based on load and net load with added renewable capacity. Data is ERCOT load and wind availability in 2015 with 30 GW of wind capacity.[4] The load and Figures 2-4a and 2-4b use the screening curve method to determine the optimal capacity mix. The screening curve method demonstrates the traditional division of plants into baseload, intermediate, and peaker plants. The reduced minimum load caused by intermittent sources greatly decreases the optimal capacity of baseload generators in a least cost mix.

The screening curve method partially addresses the problem of the assumed capacity factor in the LCOE framework and reveals the importance of a mix of technologies to meet different sections of load. It does not, however, allow one to discern the capacity of renewables leading to a least-cost portfolio since they are an exogenous input. This method also neglects the chronology of the load. The load duration curve sorts load by magnitude, not chronology. While using the lowest cost generator for each segment of the load duration curve would be ideal, technical constraints may preclude

[4]30 GW is roughly twice the actual amount of wind capacity installed in ERCOT in 2015 to demonstrate the effect of increased wind penetration. 2015 load and availability data is used to accurately capture coincidence of wind availability and demand profiles.



(a) Screening Curve and Load

(b) Screening Curve and Net Load with 30 GW of Wind

Figure 2-4: Screening Curve and Optimal Capacity Mix for Select Technologies this possibility. Figure 2-5 is the load profile with chronology corresponding to the load duration curve in Figure 2-3. Figure 2-6 is the net load profile assuming 30 GW of wind capacity showing the increase in volatility caused by the intermittent generation.

Volatile changes in net load may require power plants to change output quickly, or to turn on for short periods if they are to enter the market. The lowest cost generator suggested by the screening curve method may not be able to provide output, may provide lesser output, or may face increased costs to provide power due to start-up costs and decreased efficiencies from excessive ramps or partial loads. As renewable power sources increase volatility in the net load, these constraints could become more binding, increasing deviation of the optimal capacity mix from the mix suggested by the screening curve method.

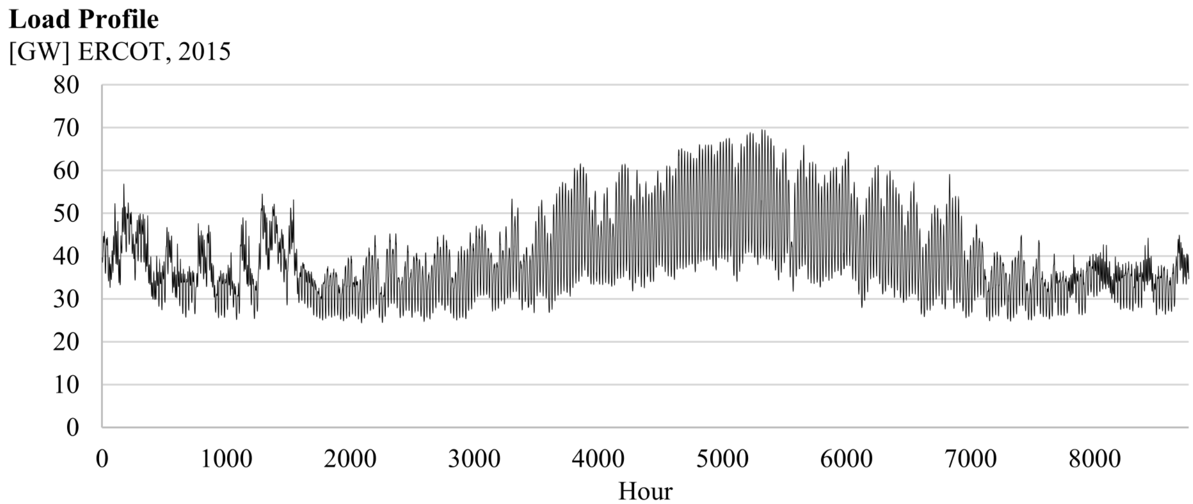


Figure 2-5: ERCOT Load Profile, 2015

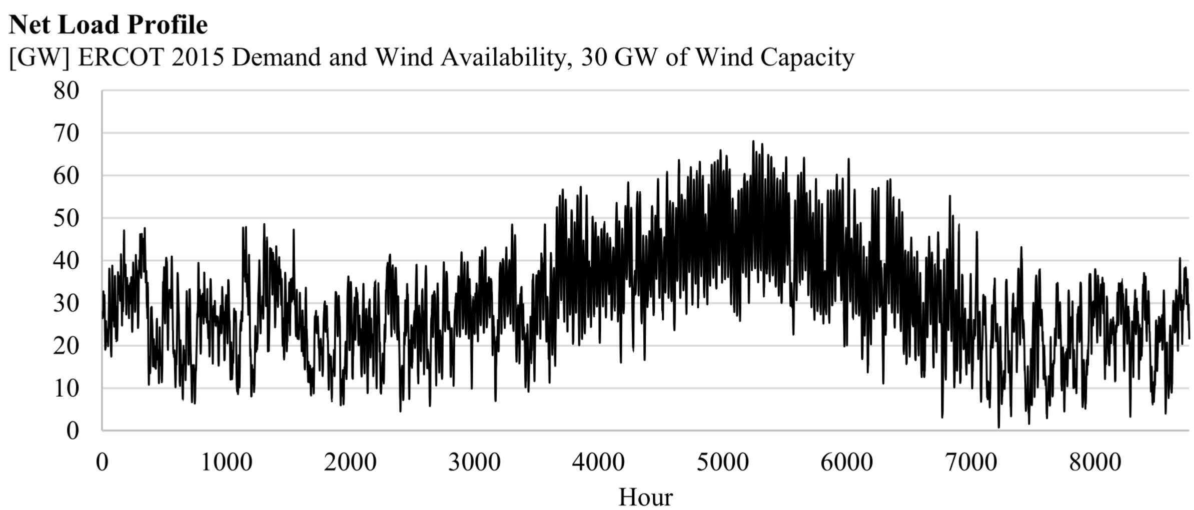


Figure 2-6: ERCOT Net Load Profile, 2015 with 30 GW of Wind Capacity

2.5 Electricity as a Commodity and Limitations of Cost-Based Approaches

Cost-based metrics would be appropriate if electricity were a homogenous commodity. Homogenous products are governed by the law of one price: any two units of the product are identical and their value is, by definition, equivalent.[15] When comparing the competitiveness of processes that produce homogenous products, it is appropriate to compare on the basis of cost, as the value of the products is equivalent. The value of electricity, however, has high locational and temporal dependencies.[1, 15]

The locational value of electricity arises from the cost of transporting electricity—grid losses, congestion constraints, and charges levied to pay for grid construction and maintenance.[16] Depending on network topology and existing injections and withdrawals of electrical energy, injections topologically close to points of withdraw will reduce losses in the network creating more value than an equivalent injection of energy at a more distant point. Similarly, when a line is congested energy additions past the congestion will have more value than an equal addition ahead of the congested line. These effects are important for distributed generators that may gain additional value by being topologically close to the consumption point, bypassing congestion and grid losses. Conversely, distributed renewable generators built in a meteorologically favorable area, but distant from load may produce less value per unit of energy due to higher losses. In the ideal case of a perfectly developed grid without losses or congestion, the locational value of electricity disappears.[16]

The temporal value of electricity arises from variations in generator availability and costs, changes in electricity demand, and the inability to store electricity inexpensively. This temporal value of electricity is the focus of this thesis. Since electrical storage capacity in most power systems is relatively small, electricity supply and demand must be matched continuously with excessive deviations resulting in system collapse. In an ideal case of limitless and costless energy storage able to respond instantaneously, there would be no temporal value for electricity.[17]

Alternating current electric grids, used for most power systems in the world, operate at a nominal frequency, for example 60 Hz in the United States and 50 Hz in Europe. If electricity demand begins to exceed generation, the energy deficit is drawn from the kinetic energy of spinning generator rotors and system frequency begins to drop. In the same way, excess generation adds to the kinetic energy of the rotors and system frequency increases.

These deviations from nominal frequency cannot remain indefinitely. Generators and electrical devices are designed to operate at nominal frequency and substantial or sustained deviations from the nominal frequency damages equipment. To protect against this damage, protective circuits will trip to shed load and restore balance. A sufficiently large imbalance, however, will also induce generators to trip offline to protect from damage to the generator. In the case of an energy deficit, this loss of large amounts of generation leads to greater system imbalance, in turn causing more assets to disconnect with the end result being a cascading failure leading to system collapse.

Balance between electricity supply and demand has traditionally been met on the supply side. While minor fluctuations in load are continuously occurring and are balanced by inertia, major changes in load occur on a time scale of tens of minutes or hours and are balanced by generators changing output and coming on and offline to follow load.[18] Markets dispatch generators according to merit order with generators with the lowest marginal price being dispatched first, subject to technical constraints.[19] During periods of peak demand the most expensive generators must be dispatched, increasing the price of electricity during these times. Increasing penetrations of renewable resources augment this effect by increasing the volatility in net load that dispatchable generators must follow. Not all generators can operate flexibly enough to respond to these changes in net load causing more flexible, but more expensive generators to be dispatched. Electricity provided at periods of high demand or low renewable output are consequently more valuable as providing electricity during those times is more expensive. The converse is also true. Chapter 3 explains these effects in more detail with quantitative examples.

That the value of electricity varies with time should be apparent. A residential electricity consumer would be very dissatisfied with their electricity provider if they received their desired monthly quantity of electrical energy but at random times. The energy provided at random times would have very little value to the consumer and they would demand to pay less for this service. This gets at the foundation of the problem of cost-based metrics: these metrics consider unit costs, but end users are more concerned with electricity as a service, with power provided reliably and on-demand. In short, electrical energy at one place and time is a different product from electricity provided elsewhere at another time; as distinct products they will have distinct values and likely command distinct prices. Comparing their costs as if they were the same product is inappropriate.

2.6 Real-Time Locational Marginal Price and Value-Based Approaches to Comparing Generation

Since electrical energy is not a homogenous product, two approaches to assessing competitiveness remain: consider the cost of providing the entire package of electrical service or disaggregate electricity into appropriately differentiated products. Vertically integrated power companies, ubiquitous during the beginnings of the electric power sector and still common in many countries today, should seek to minimize cost when properly informed and regulated.[20] In markets, economic coordination is achieved by the price mechanism and competitive forces. Schweppe's seminal work, further developed by Hogan, prepared the path for liberalization of the power sector by differentiating electricity by time and location though real-time locational marginal prices (LMP).[21, 22]

In markets with real-time LMPs, generators bid to sell electricity in hourly (or sub-hourly) time slots, and all clearing bids are paid the same market clearing price adjusting for transmission losses. Network models show the resulting electricity flows and the added network cost incurred by injecting at different network nodes.[21] Competitive forces incentivize generators to bid their true short-run cost for each hour. Markets adopt varying levels of spatial and temporal granularity. Some well-connected systems neglect location, or divide the system into zones based on network topology and common congestions.[5] Other markets operate on shorter increments of time.[6] The ideal market would perfectly distinguish the value of electricity by differ-

[5]For example, Germany operates on a uniform price throughout the country and Nordpool operates zonal prices throughout the Nordic and the Baltic region. U.S. ISOs operate on nodal prices.

[6]ERCOT, for example, operates a real-time market that settles prices at 15 minute intervals.

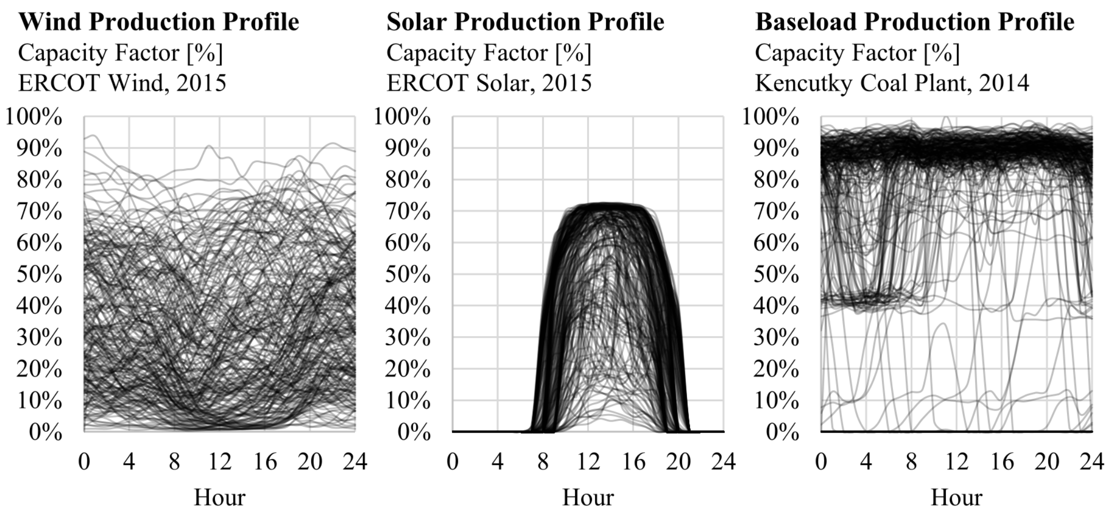
entiating between injection points down to the distribution level and at each instant of time, but the diminishing efficiency gains of higher fidelity must be balanced against the burden of data management, higher resolution network models, and increased market complexity.[17] Relevant aspects of electricity market design and theory are explained in more detail in Chapter 4.

By appropriately differentiating energy, LMPs communicate the relevant information of energy value to individual generators who then employ their private knowledge to make decisions in a decentralized fashion.[23] In a competitive electricity market, these generators act to maximize their profit, and by responding to appropriate price signals, individual profit is aligned with societal economic efficiency.[24]

In the ideal case, a perfectly informed and benevolent central planner seeking to minimize the cost of providing electricity and a perfectly competitive electricity market operating on LMPs should provide the same generation mix.[1] Most polities, however, adopt hybrid systems combining competitive markets with policy constraints and incentives in order to account for externalities, promote economic equity, and favor other organized interests. The United States, and many other countries, have adopted policies promoting intermittent renewable energy sources. This increase in intermittent generation capacity due to policy constraints and incentives will change the price signals, affecting the operation and competitiveness of other generators. For other generators not subsidized or mandated by a government, this price signal is what will determine actual investments, yet many popular, political, industry, and academic publications continue to use cost-based metrics to compare technologies.

Joskow convincingly argues that because of the temporal variations in electricity value reflected in the market price, expected profitability should be used over cost-based metrics to compare prospective generators.[15] This becomes particularly important as growing amounts of intermittent resources increase the temporal volatility of electricity value. Generators that produce electricity at different times are compensated with different revenues. This is not a market failure, but a reflection of the shifting costs and value of electricity generation. Power system models can be used to estimate the production profiles and hourly prices of electricity, which determine the generator's revenue. Wind, for example, in many inland locations tends to blow at night when electricity demand is lower and electrical energy is less valuable. Solar photovoltaics, however, produce during the day when the sun is visible and electricity demand is high. A baseload generator typically maintains steady output at maximum capacity. These production profiles are visualized in Figure 2-7. The figure shows the daily production profiles of wind and solar power based on 2015 ERCOT data along with the output of a coal plant representative of conventional baseload power from the EPA's CEMS database.[25] Even if the costs per unit energy of each of these technologies are equal, the value created and prices captured by their production profiles, shown in Figure 2-7, will be very different and dependent on the particular power system in which they are located.

This thesis follows Joskow's recommendation and develops a power system model to estimate generator profits and compares the economic competitiveness of alternative renewable and dispatchable, low-carbon generators under increasing penetrations of intermittent power, using the ERCOT system as a case study. As intermittent power increases the volatility of load and price, flexible operation becomes of paramount importance, even for generators previously operated as baseload. The unit commitment model for co-optimized reserves and energy (UCCORE) was developed as part of this thesis specifically to inform how increasing intermittent generation affects the economics and operation of dispatchable, low-carbon units in an efficient market. The subsequent chapters describe the economic theory and parameter inputs used to develop the model.



(a) Wind (b) Solar (c) Baseload

Figure 2-7: Sample Generator Daily Production Profiles

Chapter 3

Current Effects of Intermittent Generation on Electricity Markets

3.1 Growth of Intermittent Generation Capacity

The previous decade has witnessed remarkable growth in renewable electrical generation capacity, specifically wind turbines and solar photovoltaics, both globally and within the United States. From 2005 to 2015, wind capacity increased in the United States from 8.7 GW to 72.6 GW and solar capacity from tens of megawatts to 11.9 GW.[26] As a proportion of U.S. electricity generation, wind and solar resources increased from less than 1% to 4.7% and a negligible amount to 0.5% respectively.[27, 28] This growth has accelerated in recent years and the EIA predicts continued growth over the next decade.[29]

While still small on a national scale, within the United States several regions have seen particular growth in intermittent capacity. Of the states, Texas has realized the highest amount of installed wind capacity, topping 17.6 GW as of 2015.[30] As a proportion of electrical generation, Iowa has the highest amount of wind generation: 31.5% of electrical generation compared to 10.0% in Texas;[31] however, the intermittent capacity of Iowa is balanced by the Eastern Interconnect synchronous grid while Texas is mostly served by Electrical Reliability Council of Texas (ERCOT), which operates its own grid with only minor DC interconnections beyond Texas. Of the states, California has seen the greatest expansion of solar power, with solar providing 7.5% of the state's generation and wind accounting for another 6.2% in 2015.[31]

The federal production and investment tax credit, state renewable portfolio standards, and cost reductions have driven the growth of renewables. The federal production tax credit provides a credit for each kilowatt-hour of energy generated during the first ten years of operation from eligible generators including wind and solar. The subsidy essentially operates as a feed-in-premium for eligible technologies provided a tax liability exists. The credit is adjusted for inflation and in 2016 amounted to \$0.023/kWh. As of 2017, new capacity was no longer eligible for the production tax credit with the exception of wind facilities.[32] The investment tax credit provides a credit for a portion of eligible investment costs for certain generators including solar PV. As of 2016, credits were equal to 30% of eligible investments. This program is effectively an investment subsidy provided a sufficient tax liability exists.[33]

Twenty-nine states have established renewable portfolio standards (RPS) mandating utilities provide a certain amount of generation or capacity from eligible renewable sources.[34] In some of these state programs, utilities are able to meet their RPS requirements by purchasing renewable energy certificates (RECs) from other eligible entities. RECs represent the legal right to various environmental and other non-power attributes associated with the production of electricity.[35] Voluntary markets for RECs also exist outside of RPS compliance markets, but the value of RECs in these markets has been low and has not had a measurable impact on renewable investment.[36] All of these programs reduce the extent to which renewable generators must compete directly with lower cost generation.

Finally, this expansion has also been driven by reductions in cost. The capital cost of residential, commercial, and utility scale solar to end consumers fell by more than 50% between 2009 and 2016.[37] Capital costs for wind, have also fallen, but more slowly, as would be expected for a more mature technology. The capital cost of wind fell approximately 22% between 2010 and 2015.[38]

3.2 Intermittent Generation and Volatility

Wind turbines and solar photovoltaics produce coordinated output. The output of these generators, while dependent on pseudo-random weather conditions, cannot be considered independent. The meteorological conditions allowing generation from wind turbines or solar PV tend to persist over large areas leading to all generators of these types producing, or failing to produce, together. In other words, if the sun is shining on one PV cell or the wind is blowing for one turbine, all PV cells or turbines in a region will have similar output. Studies show high coordination in wind availability over the United States[39] and European continent,[40] particularly inland. A similar coordination obviously exists with solar availability. The wide geographic extent of this coordination, suggests limits to the ability to use renewable resources from other regions to balance local renewables.

The economics of generation for wind turbines and solar PV in the short-term are characterized by zero marginal costs. Once built and capital costs are sunk, the costs of energy from these generators are nil whenever they are available, neglecting maintenance. The result is that these generators are the first to clear the market as they will accept any positive price for electricity, or even a negative price if their production is subsidized. Additionally, it is important to note that the marginal costs are essentially identical for each of these generators, again, absent subsidy.[1] While fossil generators have variable efficiencies leading to a gradually increasing supply curve for electrical generation, the supply curve for renewable generation is nearly perfectly elastic as these generators all produce at the same price.

The sum result of coordinated output at zero marginal cost is that renewables sources can have a punctuated downward effect on system net load and price, increasing operational and market volatility. These effects began gaining substantial attention with the publication of the ”duck curve” by the California Independent

[1] The maintenance costs associated with wind turbines and solar PV are overwhelmingly fixed maintenance costs. Fixed maintenance costs are also sunk in the dispatch time horizon and consequently do not factor into dispatch decisions. Only maintenance costs directly proportional to generation contribute to generator marginal costs and are considered during dispatch. While wind turbines must incur some wear associated with spinning, this cost is negligible. Assessments such as EIA list variable O&M costs for wind and solar as zero.[41, 42]

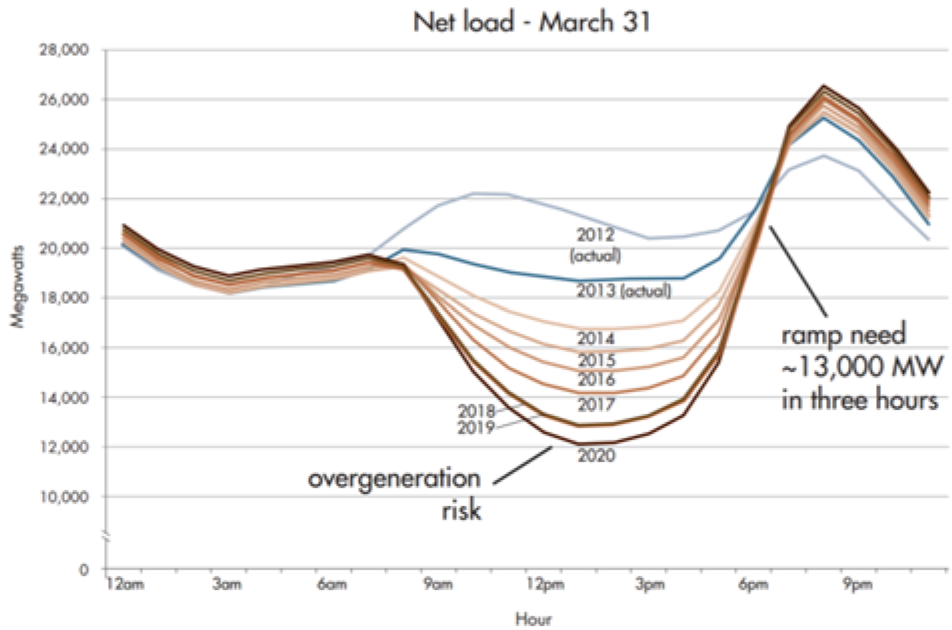


Figure 3-1: CAISO Duck Curve [43]

System Operator (CAISO). The duck curve (Figure 3-1) shows the effect of yearly increases in solar PV capacity on the net load of CAISO on a typical spring day.[43] While peak load grows slowly, the minimum net load decreases by a third, leading to risks of over generation at midday as net load dips below the generation output of must-run facilities (such as hydroelectric plants with environmental constraints, nuclear power plants, or plants needed to support local reliability) and power plants with long start times needed to meet the upcoming evening ramp.[44] This ramp occurs as the sun sets in the evening and output from all solar PV begins to decline. This evening ramp was expected to increase to roughly 13 GW in three hours from the previous ramp of 3 GW over the same period.

Many of the effects predicted by the CAISO duck curve are already occurring. By 2016, CAISO experienced spring days with net load below the 2020 minimum suggested by the duck curve originally published in 2013.[43] Over generation has also led to renewable curtailment and negative electricity spot market prices as generators compete to stay online during periods of over generation.[45] Further complicating the problem of over generation is the lack of information communication technology on residential rooftop solar PV necessary for these units to respond to these price signals or for system operators to curtail their output during negatively priced periods.[44] Price responsive generators will accept negative prices for their electricity if they are receiving production subsidies, or believe prices will soon rise and would like to remain online to capture anticipated higher prices. As low or negative prices force generators offline during the midday, fewer resources are available to respond to the evening ramp, leading to price spikes coinciding with the ramping period. The EIA has already observed this effect in CAISO,[45] and the MIT Future of Solar study also concludes increasing penetrations of solar PV will lead to increasing frequency of both very low priced hours and very high priced hours.[46]

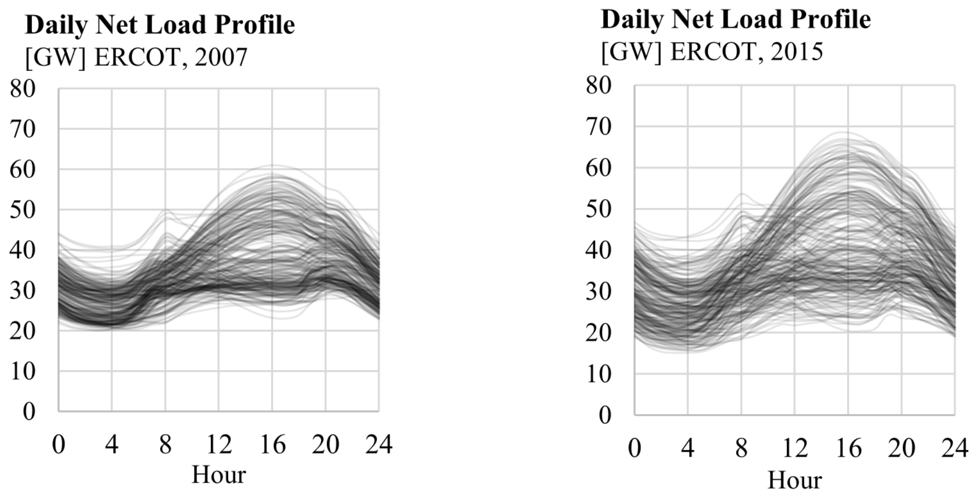
As markets become increasingly volatile, the importance of a generator's production profile on generator profits also increases. Due to their coordinated output, intermittent generators capture only the downside of the volatility they produce. The MIT Future of Solar study goes on to state that as a result of basic supply-and-demand dynamics, solar capacity systematically reduces electricity prices during the very hours when solar generators produce the most electricity.[46] The study reports that while at low penetrations solar is able to reap revenues above the average price of electricity since its production profile coincides with peak electricity pricing, as penetration of solar PV increases, the prices received by solar generators drop far below the average price of energy due to their coordinated output suppressing prices.[46] Hirth finds the same decline in revenue with increasing penetration in historic data of market prices and wind and solar production profiles in Germany.[47] Hirth also presents a stylized dispatch model of Europe with existing generation stock to model results beyond historic levels of penetration. The drop modeled by Hirth, is more drastic than that in the Future of Solar study, reporting a decrease to half of the average market price at 15% solar penetration. The value of wind in this model experiences a similar, but less precipitous, drop, reaching half the average value of electricity at 30% penetration.[47] Increased price volatility will lead to new opportunities for dispatchable generators as well as energy storage, demand response, and transmission expansion.

3.3 Historical Effect of Increasing Wind Penetration on Volatility in the ERCOT System

Given the theoretical link between increasing penetration of intermittent resources and volatility in both the net load and ultimately the electricity spot market price, as well as evidence for this link in empirical data in the Californian and German systems, it is expected that a similar relation would be apparent in Texas with the recent rise of wind generation in the state. This section presents a brief examination of recent empirical market data on increasing wind capacity and net load and price volatility of the ERCOT system.

For this exercise, the volatility of net load and spot market price are measured using two metrics over yearly intervals. The first is standard deviation, the typical measure of volatility. Standard deviation, however, does not fully describe system volatility. A system could experience volatility on different timescales with very different effects on plant operation even if the standard deviation as measured over a year were the same. For example, if most of the standard deviation results from seasonal variation, temporal constraints such as ramp rates are much less binding than standard deviation resulting from volatility on an intraday timescale. To capture this dimension of volatility, I also measure the average of the first derivative of these values: the average hourly change in net load and spot market price over a given year.

Figure 3-2 visualizes the impact of increasing wind penetration on net load volatility in ERCOT. Both graphs show daily fluctuations in net load for the ERCOT system and are drawn from historical load and wind production data.[48, 49] The left graph shows conditions in 2007, the earliest year for which data is available and when 3.6 GW of wind were installed on the system. The right graph shows conditions in 2015 when wind capacity had more than quadrupled to 14.7 GW.[49] The figures indicate an increase in peak net load, attributable to growth in demand,[50] alongside a reduction in minimum net load. The 2007 figure shows a dark base, indicating a relatively consistent minimum net load of approximately 20 GW occurring in the night. In the



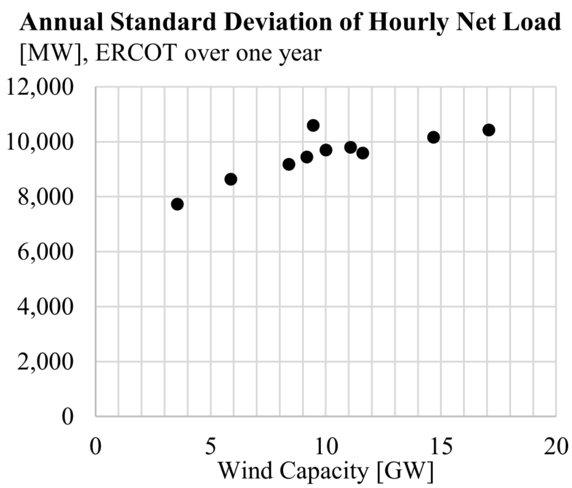
(a) 2007 (b) 2015

Figure 3-2: ERCOT Daily Net Load Profiles

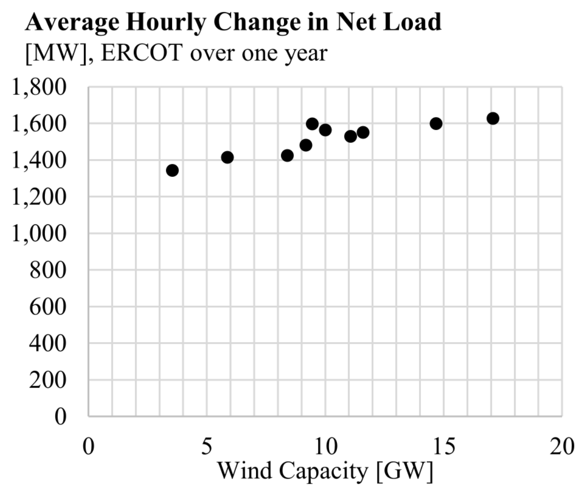
2015 figure, the minimum net load is more variable and drops to less than 15 GW. As in the CAISO duck curve, the ERCOT data indicates wind penetration has led to an increase in the daily ramping required by the system. The ERCOT ramp occurs in the morning over 8-12 hours as opposed to the CAISO evening ramp, which takes 3-4 hours to complete.

Figures 3-3a and 3-3b quantify the relation between increasing wind capacity and net load volatility. In both figures each point represents a calendar year of ERCOT data from 2007 to 2016, which are plotted on the x-axis by the average wind capacity that was available in the given year. The y-axis represents the standard deviation and average hourly change in net load for Figures 3-3a and 3-3b respectively. The figures indicate a strong positive correlation between wind capacity and both measures of volatility for net load.

A simple linear regression suggests wind capacity explains 69% of the variation in standard deviation of net load and an increase of 181 MW in standard deviation for each gigawatt of installed wind capacity. The residuals from the linear relation indicate the linear relationship is weaker at limits of the data, which may indicate a linear relation is inappropriate at higher penetrations and that a non-linear relation may better relate wind capacity to net load volatility over a wider range of capacities.



(a) Standard Deviation of Hourly Net Load



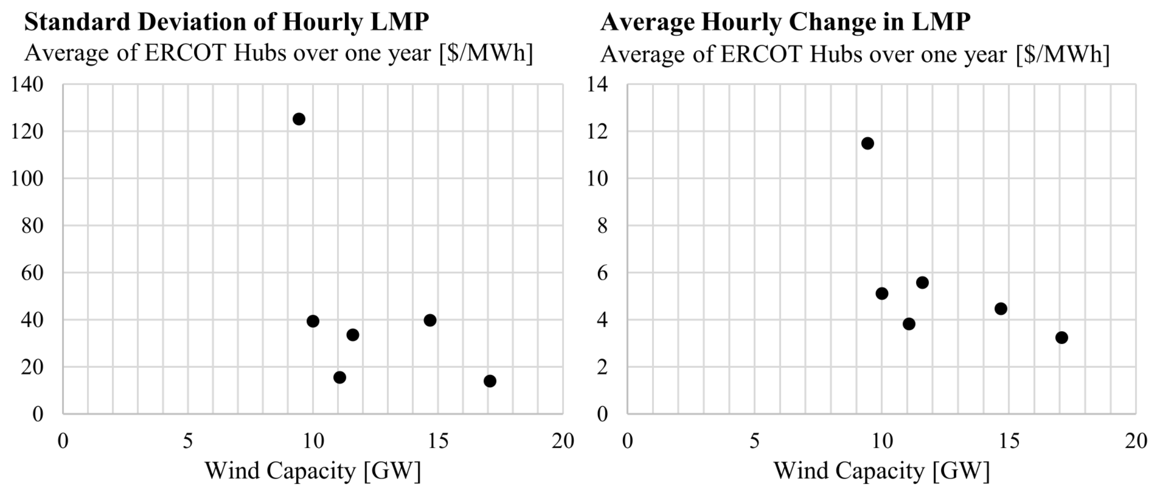
(b) Average Derivative of Hourly Net Load

Figure 3-3: Wind Capacity and Volatility in Hourly Net Load

A linear regression also explains 78% of the variation in average hourly change in net load via wind capacity and suggests an increase of 21 MW in average hourly change in net load per gigawatt of wind capacity. On average, this is a relatively small increase. More important for system operation would be the extreme cases for which the system must be prepared. A regression analysis of the 90$^{\text{th}}$ and 95$^{\text{th}}$ percentile hourly ramps shows similar correlations, but with a larger coefficient. The 90$^{\text{th}}$ percentile hourly ramp tends to increase 41 MW per gigawatt of wind capacity and the 95$^{\text{th}}$ percentile by 49 MW per gigawatt of wind, suggesting the increase in average hourly ramps is concentrated in the most extreme ramping events.

In a controlled environment, increased volatility in net load is expected to lead to an increase in the volatility of prices. This increase in price volatility, expected theoretically and measured in other systems, however, has not appeared in ERCOT. Figures 3-4a and 3-4b show a heavy downward correlation between installed wind capacity and price volatility.

This natural experiment lacks controls on other factors affecting price volatility. There are several reasons the expected increase in price volatility might not have occurred in ERCOT. Through the merit order effect there is a strong and direct connection between net load volatility and price, but price volatility is also influenced by other factors including fuel prices, market design, generation stock, and transmission infrastructure. Since wind capacity has monotonically increased with time, concurrent changes to these other variables will also influence the apparent relationship between wind capacity and price volatility. During the 2011 to 2016 period for which price data is available, several important changes to these other factors have occurred. In June of 2014, ERCOT adopted new market rules increasing the energy price cap and introducing scarcity pricing through a reserve market.[51] The adopted rules change was based on a proposal laid outlined by Hogan for an operating reserve demand curve (ORDC).[52] Critics argued the implementation of the ORDC would adversely affect markets by increasing price volatility.[53] Hogan also concedes the ORDC would increase price volatility, but asserts that this is an efficient outcome as it reflects true volatility in the cost of serving electric load.[52] Other factors put downward pressure on price volatility. ERCOT's 2016 state of the market report suggests expansions to the transmission network reduced price volatility in the western part of the state by better linking its growing wind capacity to Texas load centers.[54] The overall increase in generation capacity by approximately 10 GW also would have increased supply elasticity, reducing volatility.[30] Potentially the most important dampening effect on price volatility was the decline in natural gas prices in the state over this same period. From 2011 to 2016 the price paid by electric utilities for natural gas in Texas decreased from \$4.36/MMBTU to \$2.67/MMBTU.[55] Since generators fueled by natural gas operate over a wide range of efficienies, the decrease in gas prices has the effect of greatly flattening the supply curve.



(a) Standard Deviation of Hourly LMP (b) Average Derivative of Hourly LMP

Figure 3-4: Wind Capacity and Volatility in Electricity Price

3.4 Conclusion

Buoyed by government incentives and falling costs, intermittent generation capacity has grown tremendously over the past decade, but from a low starting point. Though overall penetration remains low at the national level, some states have realized sizeable penetrations of intermittent generation. These wind turbines and solar PV panels provide coordinated output at zero marginal cost, resulting in dramatic reductions in minimum net load and increases to system ramp rates, but little reduction to peak load.

An examination of the empirical evidence in Texas shows volatility in net load has increased over time with increased wind capacity. A strong positive correlation exists between installed wind capacity and net load volatility as measured by standard deviation in net load and average hourly system ramp.

Increased volatility in net load is expected to increase volatility in the price signal, which sets operation decisions for generators. As prices become more volatile, the times at which a generator sells electricity (the production profile), become a more important influence on a generator's revenue. Empirical evidence from Germany and multiple electricity market models show that increasing renewable capacity tends to depress prices when renewables are available to a greater extent than the overall average electricity price.

The historical data in Texas, however, does not suggest a positive correlation between installed wind capacity and price volatility. The absence of increasing price volatility may be attributable to the lack of controls in the natural experiment. ERCOT also implemented changes in market rules that were expected to increase price volatility. The expected increase in price volatility from growth in wind capacity and these market reforms might have been counteracted by reductions in volatility arising from transmission network improvements, increased dispatchable generation capacity, and, most importantly, a dramatic decrease in natural gas prices flattening the electricity supply curve.

Chapter 4

Electricity Market Theory

This chapter establishes the economic theory on which the UCCORE model is built. The chapter explains the assumptions used to set the electricity supply and demand curves and explains their use in the calculation of dispatch and market prices. The chapter also explains the importance of the co-optimized reserve market and the operating reserve demand curve (ORDC). The ORDCs used in the UCCORE model are derived from the loss of load probability (LOLP) assessment developed at the end of this chapter.

4.1 Simplified Energy-Only Market

In an energy-only market, the only product traded is electrical energy differentiated by the location and time of delivery. Typically power markets are structured with a single market clearing price. Leaving aside the costs resulting from transmission losses and congestion, generators bid the lowest cost they will accept for their electricity, the market authority accepts these bids from lowest to highest until scheduled demand is met, and all generators are paid the price of the highest cleared bid—the market clearing price. These market clearing prices are calculated at hourly (or sub-hourly) intervals at various electrical nodes, resulting in the hourly locational marginal price

(LMP) discussed in Chapter 2.[1]

4.1.1 Electricity Supply Curve

A competitive market incentivizes generators to bid their true short-term cost of production—typically the generator's marginal cost. Costs such as capital and fixed O&M are sunk and do not factor into the short-term market. Under competitive conditions, the LMP also represents the marginal cost of the system at that time and location and results in the same generation dispatch that would be achieved under a centralized system with complete knowledge seeking to minimize the cost of electricity provision.[57] In a well-functioning market, efficient investments should recoup both their short-term operating costs as well as their long-term investment costs through the LMP.[58]

Again neglecting the network, the market clearing price can be calculated as the intersection of the microeconomic supply and demand curves for the power system. The electricity supply curve is composed of the individual generator bids, which are equivalent to their marginal cost in a competitive setting. At the bottom of the electricity supply curve are plants with near-zero marginal costs such as wind turbines, solar photovoltaics, and run-of-river hydroelectric facilities. Next are thermal units operating near baseload such as nuclear, coal, and, increasingly, combined cycle gas plants. The aggregate supply curve is highly elastic over these generators. The supply curve becomes increasingly inelastic as it moves to generators with higher variable costs such as older natural gas steam turbine generators and open cycle natural gas or petroleum fired turbines before all capacity is exhausted and supply becomes perfectly inelastic. Figure 4-1 shows a representative curve based on the ERCOT market and current fuel prices if all dispatchable capacity was online. Generator costs for the ERCOT fleet are discussed in more detail in Chapter 6.

The electricity supply curve, however, is not static. In the long-term, as in other markets, if producer profits rise, competition will attract new investment in genera-

[1] Alternatively, some markets differentiate prices by zones or do not differentiate by location at all. This may be done for reasons of logistics or equitability, but is less efficient.[56]

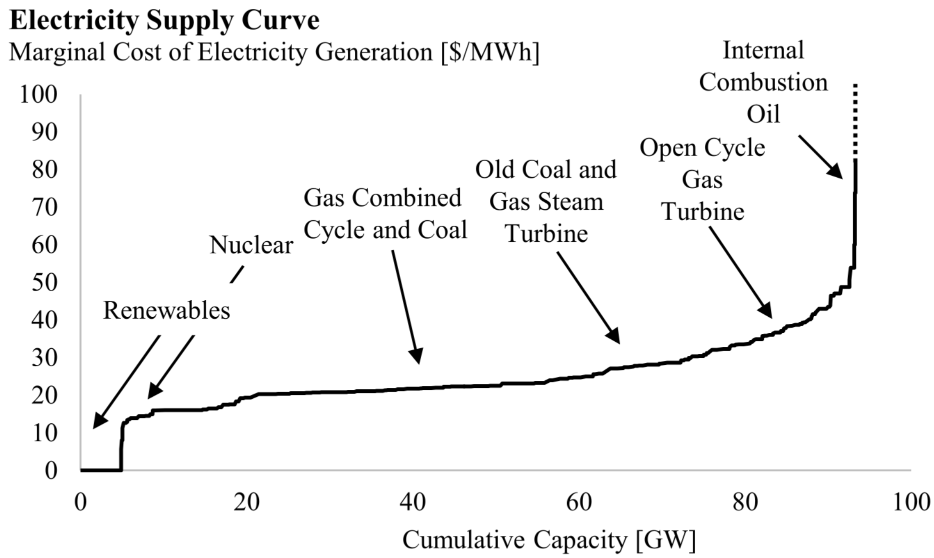


Figure 4-1: Representative Electricity Supply Curve for ERCOT

tion expanding the supply curve, and if profits fall generators will exit the market. Importantly, the electricity supply curve is also highly dynamic in the short-term. This is a relatively unique attribute of electricity markets resulting from the general dearth of grid-scale electrical storage capacity. Short-term changes to the electricity supply curve arise from the variable availability of wind, solar, and hydro generators and the time constants associated with thermal generators. A nuclear plant, for example, once shutdown will not be available to produce for the hours after shutdown. Thus decisions in one hour affect the supply options available in subsequent hours establishing intertemporal links between the hourly markets.

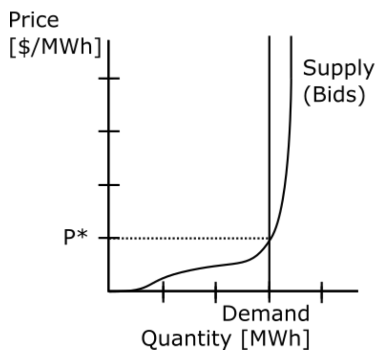
Broadly, markets have two systems to address these intertemporal links, though many actual markets use a hybrid system. In a complex bidding system, generators submit their technical constraints and operating costs to the market authority that then algorithmically optimizes dispatch to minimize the cost of electricity over a given period simultaneously, such as a day. Again, if the system is competitive, generators have the incentive of revealing their true costs and constraints to maximize the time that they are profitably dispatched. In a simple bid system, generators must anticipate the dispatch and adjust their bids accordingly.[57] For example, a peaking generator may anticipate being dispatched for only a single hour and incorporate their start-up costs to their "marginal" bid, or a nuclear plant may bid below their marginal cost to ensure they remain online to capture anticipated higher revenues in following hours. Ultimately, the goal of both systems is to reflect the forward looking behavior of generators and true costs over the dispatch time horizon into the electricity supply curve.

The UCCORE model developed in this thesis and described in Chapter 7 simulates a complex bidding process in a competitive environment, building a dynamic supply curve using generator flexibility and cost data developed in Chapters 5 & 6 respectively.

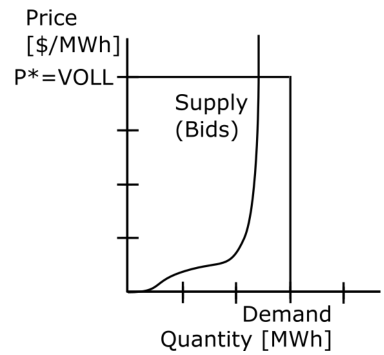
4.1.2 Electricity Demand Curve

An ideal electricity demand curve would reflect consumers' true valuation of energy and be downward sloping with price, following the law of demand. In the developed world, however, most electricity consumers are price insensitive in the short-term as they value electricity far above typical market clearing prices. Most consumers purchase electricity through a retailer that offers electricity at a flat rate that is somewhat above the average market clearing price. Furthermore, even if consumers were exposed to the real-time market price, the transaction costs of active participation in the electricity market have historically been much higher than the potential savings from participation for most consumers. For this reason, much of electricity demand is considered perfectly inelastic such that the quantity of electricity demanded in the short-term is exogenous to the market and is instead determined by daily and seasonal patterns.

When demand is perfectly inelastic, market prices must clear on the supply side. This is the normal state of the market and is shown in Figure 4-2a with market clearing price, $P*$. If, however, there is insufficient generation capacity to meet the inelastic demand the market cannot clear at the system marginal cost and is in a scarcity state. During scarcity periods, prices should rise very high—to the maximum price consumers would pay for electricity. The ability for prices to clear on the demand side and rise above system marginal cost plays an important role in allow-



(a) Normal Conditions



(b) Scarcity Conditions

Figure 4-2: Electricity Market Clearing

ing generation investments to recoup their fixed costs and earn an adequate rate of return. Quantifying consumers' willingness-to-pay for any product, though, is difficult because consumers' *stated* preferences when surveyed often differ from their *revealed* preferences when confronted with actual choices.[59] In electricity markets, willingness-to-pay is further complicated by the fact that the grid operator cannot discriminate provision of service between individual consumers during scarcity events. When demand must be curtailed, grid operators institute rolling blackouts that curtail load for entire portions of the network at once, not the consumers with the lowest willingness-to-pay. For this reason scarcity prices for electricity are set administratively based on estimates for the aggregate willingness-to-pay or social value of electricity. This scarcity price is the value of lost load (VOLL) shown in Figure 4-2b.

Estimates for VOLL vary by several orders of magnitude and are dependent on the consumer, time, and duration of the loss of load. Commercial and industrial customers with significant labor or capital that is only productive when electricity is available likely value electricity more than a residential consumer. Similarly a residential consumer likely values electricity more at midday during a heat wave than during a temperate afternoon. VOLL also changes with the duration of the outage. Over longer outages, VOLL could decline as consumers adapt and find substitutes for electricity or find other valuable uses of time that are not reliant on electricity. A very long outage, however, would begin to disrupt essential services, causing VOLL to rise. Given the complexity of mapping VOLL, markets regulators tend to select a single average VOLL for use in market design. Selection of VOLL is an important regulatory decision that will influence generation investment and the frequency of loss of load events due to insufficient generation capacity if investors rely primarily upon the energy market for returns.

Literature reviews of estimates for average VOLL (hereafter, simply VOLL), in the developed world range from the low thousands of dollars per megawatt-hour to hundreds of thousands of dollars per megawatt-hour.[60, 61, 62] A simple method for estimating VOLL is to associate GDP directly to electricity consumption and assume all economic activity stops during an outage. Using this method and taking Texas GDP as $1.6 trillion[63] and Texas electricity consumption as 400 TWh[64] yields a VOLL on the order of $4,000/MWh. Depending on the assumed type of outage, actual disrupted economic activity could be greater or lesser.

VOLL may be much higher than a strict economic productivity analysis would suggest to reflect the health, safety, and security benefits of electricity not captured by GDP. Electricity may have values above a GDP derived VOLL for uses such as water treatment and pumping, electricity provision to hospitals, and restoration of offsite power to nuclear power plants requiring active cooling. Since many of these health, safety, and security services relying on electricity are provided by governments and not markets, the selection of value of lost load becomes a political decision.

In ERCOT, the administratively set VOLL is $9,000/MWh,[65] approximately twice what would be expected from the simple GDP analysis. This price is used as the as the VOLL in the UCCORE base case, but sensitivity to this value is also tested by using a VOLL of $1,000/MWh and $100,000/MWh, extreme bounds for VOLL estimates.

Demand response is adding elasticity to the electricity demand curve beyond rolling blackouts. The goal of demand response is to make consumers responsive to real-time electricity pricing and voluntarily curtail consumption during high priced hours or shift that consumption to lower priced hours. Growing market volatility has widened the spread between electricity peak and off-peak prices, retail unbundling has led to business model innovation, and internet-of-things enabled appliances have lowered the transaction costs of demand side market participation, all contributing to growth of demand response. Since the focus of this thesis the effects of intermittent generation, demand response is not considered, and demand in UCCORE is modeled as perfectly inelastic up to VOLL. This is not to imply the effects of demand response on dispatcable plant operation and economics are unimportant, only that they are beyond the scope of this work and represents an important opportunity for future inquiry.

The quantity of energy demanded in the UCCORE model is set hourly based on historical ERCOT loads transformed to account for forecast growth.

4.2 Reserve Market

The simplified energy-only market presented above relies on some amount of scarcity periods (i.e. rolling blackouts) to allow generators to recover their fixed costs. Given the political unacceptability of rolling blackouts in the developed world, regulators often incentivize generation expansion through rule changes or out-of-market mechanisms. Depending on their construction, these new incentives may not properly remunerate prior existing capacity while removing the scarcity prices upon which these generators financially relied. This regulatory mutability stifles future investment in generation capacity, creating further need for interventions.[66, 67]

The traditional approach to ensuring long-term capacity adequacy while not allowing scarcity pricing has been separate forward markets for available generation capacity. Hogan makes several criticisms of capacity markets. Firstly, capacity markets require an administratively determined long-term forecast of capacity needs. Secondly, these markets require a definition of available capacity that is difficult to measure and validate since no energy is actually delivered in capacity markets. Thirdly, capacity markets have been more prone to market manipulation and non-competitive behavior than energy markets. Fourthly, capacity markets do not send short-term signals to the actors contributing to scarcity conditions and instead socialize the costs of peak capacity.[68]

Hogan advocates using the operating reserve market to send scarcity signals in the short-term that would promote long-term resource adequacy. Operating reserves are generation resources available to meet unpredicted variations in generation and load to maintain system balance.[18] Several types of operating reserves are used, with definitions varying between system operators.[69] Broadly, reserves can be differentiated by their intended use, such as balancing a large unexpected event (contingency reserve) or balancing continuous second-to-second noise from minor load or generation changes (regulating reserve).[18]

The UCCORE model considers only one type of following reserve as a simplifying assumption. Following reserves are the reserves used to balance the overall patterns of load profiles and renewable generation. These reserves are also used to meet the uncertainty in day-ahead or hour-ahead markets.[18] Since these reserves are used to balance the variability and uncertainty of intermittent generation, their pricing captures the most relevant effects of intermittent generation on the system's reserve needs. The reserve definition used in the UCCORE model is energy able to be provided within ten minutes, which is the time scale .

From first principles, the value of operating reserves is equal to the product of the expected reduction in lost load the reserves provide and VOLL. The loss of load probability (LOLP) curve used in this calculation must also be administratively determined, but benefits from being a more certain short-term forecast as opposed to the long-term forecast required for capacity markets. The LOLP curve scaled by VOLL is the operating reserve demand curve (ORDC).[68] The operating reserve market clears at the intersection of the ORDC and the operating reserve supply curve, which is simply aggregated generator bids for the supply of reserves. For a dispatchable unit, the marginal cost for supplying operating reserves is the marginal opportunity cost of not supplying energy.[70] Co-optimization of reserves and energy accounts for this opportunity cost and links the two markets. Thus, when prices rise in the reserve market, energy prices will also rise to reflect the opportunity cost of generators that could provide either energy or reserves. This system sends a range of scarcity price signals to the short-term market that reflects the range of scarcity conditions better than the discontinuous, binary signal of sufficient or insufficient capacity used in the energy-only market with inelastic demand.

Hogan's system is attractive as it unifies long-term investment incentives with short-term markets based on the economic first principles of marginal benefits. This system also has a very practical benefit for use in deterministic power system modeling in that loss of load events in a simplified energy-only market are important drivers of generator revenue, but are so infrequent they may not occur in the period examined by the model. By sending more continuous scarcity signals through the ORDC, this is avoided.

4.3 Estimating Loss of Load Probability Curves in ERCOT

The operating reserve demand curve (ORDC), is used to represent consumer valuation of reserves and is a key input to the UCCORE model. The ORDC is the loss of load probability (LOLP) curve scaled by VOLL. LOLP is a function of generator forced outages and deratings, load forecast errors, and intermittent generation forecast errors. Derived from these inputs, the LOLP curve shows the probability that a power system will have insufficient generation capacity to meet hourly load at a given level of reserves (Figure 4-3). The representative LOLP curve in Figure 4-3 can be read as a reserve margin of 10% of expected hourly demand corresponds to 20% probability of insufficient generation for that hour. To ensure instances of generation shortfall are rare, reserves are kept at a level such that LOLP for most hours is quite low. Assuming a constant load for each hour, the integral of the LOLP curve between the reserve level and an infinite level of reserves is the loss of energy expectation for that hour.

Equivalent forced outage rate of demand (EFORd) is used to model dispatch error due to generator forced outage and deratings. EFORd data is collected by NERC as part of the generator availability data system (GADS) and industry average values

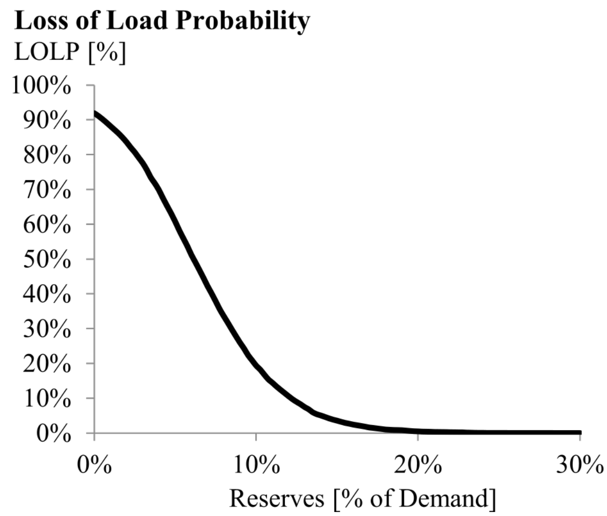


Figure 4-3: Representative Loss of Load Probability Curve

are published by generator type and capacity.[71] EFORd represents the probability a generator will not be available when dispatched and is weighted to account for both complete outages and partial deratings.[72] A Monte Carlo simulation of ten-thousand draws using the EFORd data from GADS applied to the ERCOT fleet at average dispatch conditions yields an approximation of hourly dispatch error for ERCOT due to forced outages (Figure 4-4).[2] This method assumes that generator outages are independent events, which is a fair assumption during normal operation, but neglects situations such as disruptions of natural gas supply or a coordinated attack against the power system.

ERCOT does not publish historical records of load forecast errors. To estimate the distribution of load forecast errors in ERCOT, published data from MISO's Southern Region are used as an analog (Figure 4-5).[73] This choice is based on the assumption that the weather and seasonal patterns that are a major source of load forecast errors will be comparable for these systems. Use of this analog is also justified as it will be shown that the contribution of demand forecast errors to LOLP is small. Unlike error from forced outages, demand forecast error can be positive or negative.

[2] An argument could also be made for basing assumed LOLP distribution on peak conditions. Since peaker units have a higher EFORd than baseload units, the expected dispatch error under peak conditions would be greater. Generalizing from a peak condition LOLP curve would better characterize reserve value in peak conditions, but overestimate the value of reserves in all other hours.

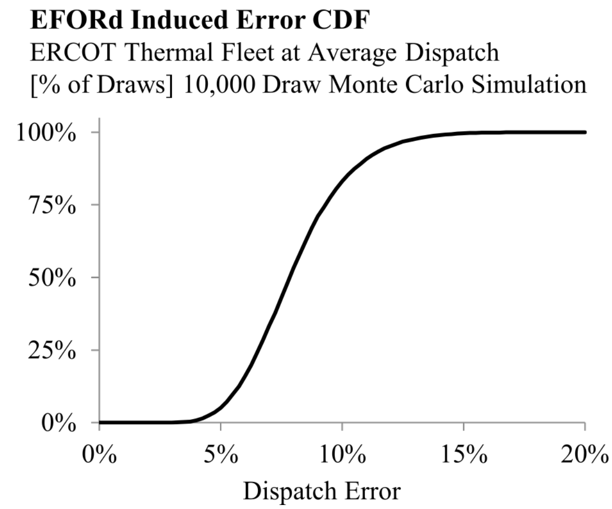


Figure 4-4: Simulated Cumulative Distribution of ERCOT Forced Outage Induced Dispatch Error

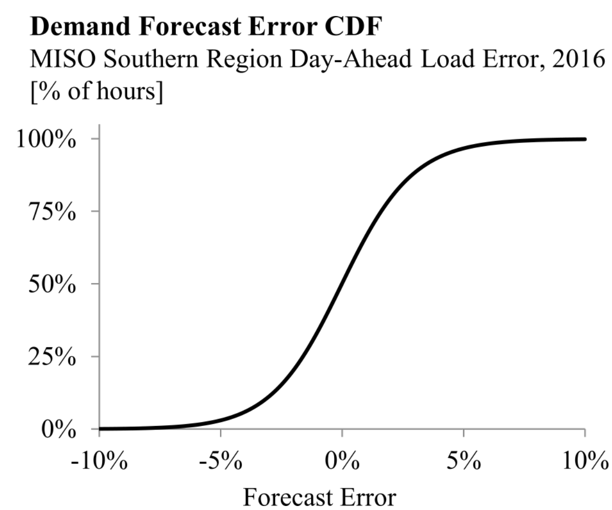


Figure 4-5: Cumulative Distribution of MISO Southern Region Day-Ahead Load Forecast Error, 2016 Outage Induced Dispatch Error

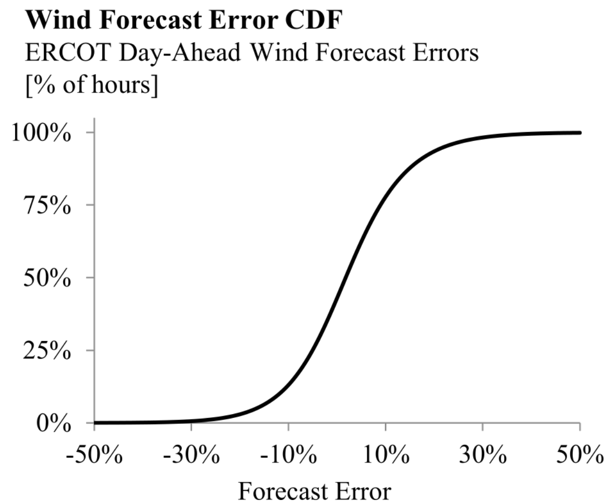


Figure 4-6: Cumulative Distribution of ERCOT Day-Ahead Wind Forecast Errors

The final component of LOLP is the forecast error of intermittent generation. Hodge et al. have characterized the distribution of wind forecast errors in several systems, including ERCOT, and find these errors are best characterized by a hyperbolic distribution.[74] The corresponding cumulative distribution function is shown in Figure 4-6. As would be expected, wind forecast errors are regularly of much greater magnitude than demand forecast errors or forced generator outages. At high penetrations of wind, wind forecast error dominates the overall LOLP distribution

Solar forecast errors are less well characterized in the literature. Given the current low penetration of solar in the ERCOT system, solar forecast errors are less important to system operation. The importance of solar forecast error will grow if solar penetration increases, making the characterization for forecast errors, and their integration into power system models, an important area for future work. In the UCCORE model, only wind forecast errors are considered and solar capacity is kept at current levels, where its effect on LOLP is presumably small.

These inputs are used to generate LOLP curves for ERCOT under various assumptions for wind penetration. LOLP is one minus the total error from dispatchable generators, demand forecast, and wind forecast. A Monte Carlo simulation with ten-thousand draws is used to simulate individual generator forced outages as well as the forecast error for system demand and aggregated wind generation. Wind forecast errors are then weighted by the assumed wind penetration of the system and the total dispatchable generator error is weighted by the remaining proportion of generation.[3] This assumes wind forecast errors will not improve with further buildout of wind generators in ERCOT, which is appropriate as wind generation is already dispersed throughout the state and it is likely that reductions in aggregate wind variability from geographic variation are already mostly exploited, with the exception of expansion into the offshore.[4] The treatment of thermal-generator forced outage is stylized and assumes the generation fleet continues to operate as it does in the current system at the penetration of wind increases. This is a weak assumption, but its use is justified by the fact that at higher penetrations of wind, wind forecast error dominates the overall LOLP distribution and the contribution from forced generator outages are relatively less important.

The UCCORE model makes use of a single representative LOLP curve to generate an ORDC that is applied at all hours of the test year for each assumed penetration of wind power. An actual implementation of an ORDC in a market would calculate the LOLP based on short-term forecasts and use a different a LOLP curve to reflect varying conditions across daily and seasonal conditions making it a better approximation of the true LOLP. The use of a single LOLP curve for each UCCORE scenario is an abstraction of the true conditions experienced by a power system, but it represents a step forward in the representation of the value of reserves in unit commitment models. A selection of the LOLP curves at different assumed penetrations of wind power and used as inputs for the UCCORE model are shown in Figure 4-7.

Figure 4-7 shows the general effect of increased wind penetration and the LOLP curve. For a pure dispatchable power system (0% wind penetration), the probability of insufficient capacity with no reserves is close to one. After day-ahead scheduling,

[3]Ideally, unit commitment models would endogenously calculate the unique LOLP for each hour and include the effects of hourly generator dispatch and wind penetration on LOLP in the optimization. While a more accurate representation, this would introduce non-linearities into the model that would increase its computational requirements reducing its usefulness for scenario analyses that rely on many model runs.

[4]Wind forecasting models could also be improved to reduce uncertainty. The potential for this effect, however, is not considered, though it could represent a valuable opportunity to reduce system costs and the needed amount of reserves and overall capacity.

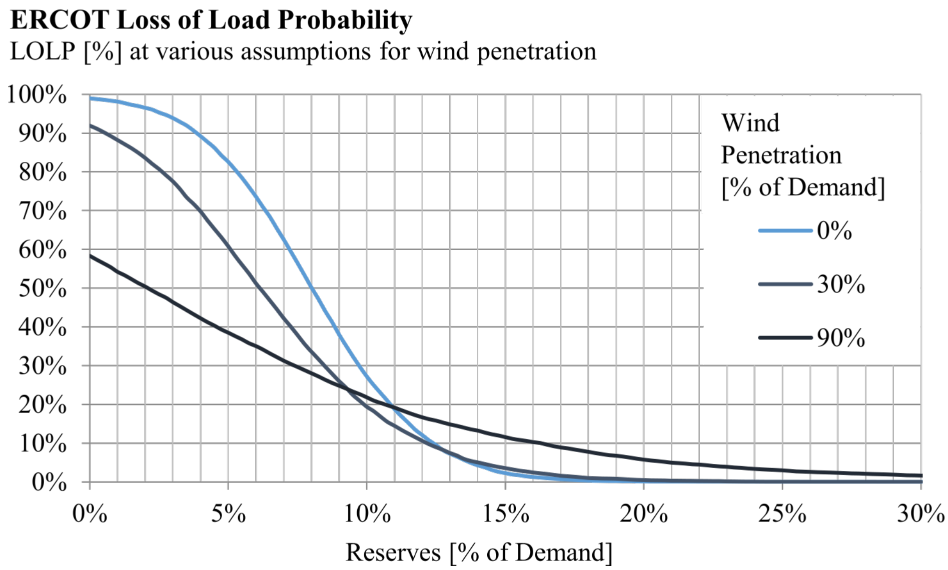


Figure 4-7: Evaluated ERCOT Loss of Load Probability Curves at Various Wind Penetrations

there is a high likelihood that at least one of the scheduled dispatchable units will have some amount of forced derating during real-time, or load could be somewhat higher than forecast. The first reserves are therefore valued almost as much as energy (LOLP $\sim$ 100%). The LOLP, and incremental value of reserves, decreases as reserves are added. By the law of large numbers, the likelihood that many generators will fail simultaneously is small, and the LOLP drops correspondingly. For a system almost entirely reliant on wind energy (90% wind penetration), more reserves are required to achieve the same reduction in LOLP due to the greater uncertainty of the wind generation. The value of the first reserve, however, is much less than in a dispatchable power system because the wind system also has a high probability of over generation. Since LOLP is scaled by the VOLL to create the ORDC, even small changes to LOLP are important; for example, at the ERCOT VOLL of $9000/MWh, a 1% increase in LOLP corresponds to an increase in reserve price of $90/MWh. In a well-developed power system, prices will most frequently clear far out on the tail of the distribution where LOLP is small.

Chapter 5

Power Plant Flexibility

5.1 Flexibility

Flexibility is the ability of a power plant to alter its electrical output with time. More flexible plants can vary output more quickly, over a larger range, at lower cost than less flexible power plants.[75] The importance of flexibility to profitable operation may increase with market volatility. The primary technical parameters used to describe flexible operation are ramp rates, minimum stable load, and start-up time as well as the associated costs of operating at partial load and cycling. Figure 5-1 is a qualitative illustration of these attributes.

Ramp rates describe the maximum rate that a plant can change its electrical output, expressed either in absolute (e.g. MW/min) or relative terms (e.g. % of rated capacity/min). Often this is summarized as a single value, though plant ramp rate may vary over plant output and may differ for upward or downward ramps. Plants may also allow ramps above nominal maximum rates during emergency procedures or if otherwise willing to accept an increase in operation and maintenance costs caused by a greater thermal stress. The ramp rate of nuclear plants is also dependent on reactor history due to the time delayed effects of fission products and their decay chains, and face additional constraints to ramping at the beginning and end of a refueling cycle. In Figure 5-1, ramp rate is the slope of the line during power transients.

Minimum stable load refers to the lowest output a plant can continuously maintain

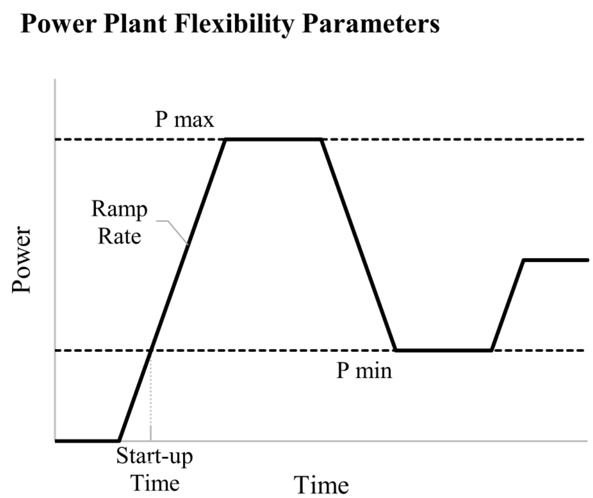


Figure 5-1: Power Plant Flexibility Parameters[75]

while also complying with relevant environmental regulations.[76] This may also be expressed in absolute (e.g. MW) or relative terms (e.g. % of rated capacity). In Figure 5-1, minimum stable load is the dotted line labeled Pmin, and Pmax denotes the rated capacity. Reducing load and cycling also incur costs. Costs associated with partial load are reduction in efficiency compared with running at rated capacity. Changes in partial load efficiency are typically non-linear.

The costs of cycling a power plant between on and off states are start-up costs. Start-up costs vary with the initial boiler temperature and are often disaggregated into hot, warm, and cold starts. More fuel is required to warm the boiler from colder starts before generation begins, leading to greater costs and longer start-up times.

Other parameters describing power plant flexibility include the minimum up-time once started and minimum down-time after shutdown and limits to the number of ramping or on-off cycles permissible over a given period.

Flexibility parameters are used characterize the intertemporal constraints of generator operation in the UCCORE model. Accurately representing the technical ability for generators to operate flexibly is necessary for assessing generator response to volatile market prices, which is the focus of this study. This section assess the flexibility of prospective CCS-equipped power plants and nuclear power plants.

5.2 Flexibility of CCS-Equipped Power Plants

5.2.1 Background

Little experience exists flexibly operating utility-scale power plants with CCS.[77] Since CCS-equipped plants incur a penalty to net energy output due to the energy requirements of the capture and compression systems, they will operate at lower efficiency and with higher variable costs than comparable plants without CCS.[78] In isolation, these higher variable costs would make CCS-equipped plants better economic candidates for flexible operation compared to their unabated counterparts. Since the capture and storage of CO_2 makes plants more expensive, CCS plants have only been built to comply with, or take advantage of, environmental regulation or the ability to sell the separated CO_2 as a byproduct for use in enhanced oil recovery (EOR).[79] These regulations and CO_2 offtake agreements typically also incentive the generator to operate continuously as a baseload plant. An increase in the penetration of intermittent generation capacity and CCS-equipped capacity, however, could lead to an incentive to operate CCS plants more flexibly to balance the variability and uncertainty in output from intermittent generators. There may be a particular need for CCS-equipped plants to operate flexibly if regulation requires unabated fossil fuel plants to be phased out of the power system.

Existing unabated combined cycle gas turbine (CCGT) and pulverized coal (PC) plants are already operated flexibly to balance electricity supply and demand at a range of timescales. Due to their large capacity, these plants are sensible candidates for the added capital required for CCS. Depending on the design, addition of a post-combustion capture system could reduce the ability of the power plant to operate flexibly due to the addition of potential bottlenecks at the CO_2 capture, compression, and offtake stages.

5.2.2 Technical Aspects of Flexible Operation of Post-Combustion CCS-Equipped Power Plants

Despite a paucity of historical plant data on flexible operation, there is a consensus that, if properly designed, the addition of post-combustion CO_2 capture need not reduce power plant flexibility and may be able to increase plant flexibility through selective bypass of the capture facility's parasitic load.[77, 78, 80, 81] Designing a CCS-equipped plant for flexible operation, however, may require additional capital investment relative to a plant designed for baseload operation to eliminate flexibility bottlenecks in the CCS chain.

Typical post-combustion capture schemes use an amine solvent to chemically absorb CO_2 from flue gas. The CO_2 is then stripped from the rich solvent, yielding a high purity stream of CO_2. Brasington simulated current amine technology and concluded that capture systems can match coal plant load following while maintaining steady capture rate.[77] Start-up, however, may be delayed due to the time required for the amine regeneration unit to heat to operational temperatures after steam is available. This start-up delay can be avoided by adding storage containers allowing use of stored lean solvent and storage of CO_2 rich solvent to be stripped later. Alternatively, this constraint can be avoided simply by venting CO_2 to atmosphere during start-up if permissible by regulation.[82]

Following chemical separation, CO_2 is compressed for pipeline transport and eventual subsurface injection. The compression stage poses a potential bottleneck to flexible operation common to all CCS plants. Most compressors can only turndown to 70-75% of rated load; for most natural gas combined cycle and coal plants, this would be a binding constraint to minimum stable load. Recycling CO_2 through the compressor, can allow the continued operation of the compressor with a reduced CO_2 stream, but since the power draw of the compressor then remains constant over decreasing plant output, the efficiency penalty of the CCS system increases and overall partial load efficiency is reduced. Using multiple smaller compressors can allow lower partial loads without CO_2 recycling and the associated reduction in efficiency by turning off individual compressors at low loads. Use of multiple compressors may be necessary anyways as available compressors may not be of sufficient size for large CCS projects, but, when a sufficiently large compressor is available, the choice of multiple smaller compressors is expected to increase capital costs due to forgone economies of scale.[78]

Changes to the throughput of CO_2 at the power plant propagate through to transport and injection; consequently, these stages must be able to accept variable throughput if the plant is to operate flexibly. Near the critical point, small changes in pressure lead to large changes in CO_2 volume, allowing the pipeline system to provide storage and accommodate some variability in CO_2 throughput. Excessive reductions in throughput would lead to a reduction in pipeline pressure possibly leading to a phase change, but this can be avoided by designing pipelines with proper valves and insulation to maintain pressurization.[78] In either case, flexible operation would still lead to variable injection rates at the wellhead, which have not been well studied for storage and may be undesirable for EOR projects. Constant injection rates can be maintained by adding interim storage facilities for either compressed CO_2 or CO_2 rich solvent. Sizing the interim storage requires predictive modeling to estimate future power plant cycling needs, but the expected increase in capital cost is relatively small.[82]

The effect of the addition of a capture unit to power plant start-up costs has not been evaluated, but Brouwer assess that these costs are not likely to significantly affect operation or profits,[76] though their importance could grow as electricity market volatility increases.

Post-combustion CCS also affords the opportunity for enhanced flexibility vis-á-vis its unabated counterparts by selectively reducing parasitic load through solvent storage or selectively venting CO_2 to atmosphere. During peak electricity price periods, compression and solvent regeneration could be paused, increasing the net generation of the plant by removing these parasitic loads. Continuous capture could be maintained using stored lean solvent and storing CO_2 rich solvent for later regeneration and compression during periods of low priced power. The added capital cost of the solvent storage system is dependent on the expected operation. Similarly, the energy penalty from regeneration and compression can be avoided by bypassing the capture unit altogether and venting CO_2 directly to atmosphere if economical and permissible by regulation under peak or emergency conditions. Under either of these arrangements, the turbine must also be sized to accept the greater steam load, which would also increase capital costs in new build plants.[82]

5.3 Flexibility of Nuclear Power Plants

5.3.1 Background

Historically, nuclear power plants have epitomized baseload power. In the levelized cost framework, costs per unit energy are more sensitive to capacity factor for nuclear power than any other widespread generation source. This is due to nuclear power's exceptionally high ratio of fixed costs to variable costs. Nuclear power plants minimize electricity costs by running at maximum capacity as frequently as possible in order to spread the high fixed costs over the most amount of energy. In response to this economic signal, nuclear power plants have operated inflexibly, maintaining steady-state operation at maximum rated capacity and have improved their ability to do so, with capacity factors for the U.S. nuclear fleet improving steadily with time, reaching 92% in 2015.[3]

This operation strategy of cost minimization through high capacity factors has historically produced the highest profits for nuclear power plants, but this may not be the case in future power systems. In historic power systems, the price of electricity is nearly always higher than the low marginal cost of nuclear power, and electrical energy is the most valuable commodity the nuclear plant can provide. In such a market, cost minimization through high capacity factors is sensible. Increasing amounts of renewable sources, however, may upend this strategy through increased price volatility. First, renewable intermittency may lead to periods in which the price of electricity is below even the marginal cost of nuclear power, or negative if such generators receive production subsidies.[1] Since operation during these periods entails a loss,

[1]Some models assume a marginal cost of zero for nuclear power plants.[83] This is true for the

plants face an incentive to reduce output as much as possible during these times. Second, renewable uncertainty may increase the value of reserves in some hours to an extent that the profit from providing reserves is higher than the profit received for energy production. This condition would be atypical, occurring only over limited hours when renewable and other must-run facilities have completely met anticipated energy demand. Overall revenues and profitability would still be dominated by sales of energy, but during these hours plants would have an incentive to continue running, but below their maximum output, keeping some amount of capacity in reserve. The scale of this effect is dependent on the variability and uncertainty of the renewable resource over a given time-frame and the costs associated with demand side curtailment of power consumption in the event of a generation shortfall (VOLL). Avoiding low-priced hours or maintaining capacity in reserve both lead to lower overall capacity factors and, consequently, higher costs per unit energy, but higher profitability in some circumstances.

5.3.2 Technical Aspects of Flexible Operation of Nuclear Power Plants

Significant experience exists operating nuclear power plants flexibly. The common perception that nuclear power plants are inflexible is rooted in the traditional economic incentive to run as baseload power, not a technical inability. Several methods of changing electrical power output from nuclear power plants exist, falling into two camps: reducing the thermal power output of the reactor, and reducing the flow of steam to turbines without directly altering conditions in the reactor.[85]

The typical approach to reducing electrical output of thermal power plants is

current refueling cycle in which reductions in load are unplanned. Since the refueling schedule is preplanned and unspent fuel will be wasted, the fuel costs for nuclear power are sunk and the marginal cost of nuclear power is zero. If load reductions are anticipated and included in the refueling schedule, fuel costs can be saved through power reduction and the marginal cost of nuclear power becomes the cost of fuel and variable O&M. In practice, however, actual power reductions will differ from anticipated reductions and some amount of fuel will be wasted making savings from reducing power somewhat less than the cost of fuel.[84] This inefficiency is not included in the UCCORE model and it is instead assumed the marginal cost of nuclear power is the fuel cost plus variable O&M.

to reduce the consumption of fuel. In a nuclear power plant this is accomplished by reducing the rate of fission in the reactor, thereby directly reducing the thermal power output. Operators have several means of controlling reactor power, and multiple techniques are often used together.

Control rods are the most direct and familiar means of changing reaction rate in a nuclear reactor, but have several challenges for use in flexible operation. First, the maneuverability offered by control rods decreases with fuel burnup. Towards the end of a refueling cycle, control rods are mostly withdrawn to compensate for the reduced number density of unspent fuel, reducing maneuverability.[86] Second, control rod movements lead to changes in the axial distribution of neutron flux, causing asymmetric conditions in the reactor, which must be monitored and controlled. This includes the immediate effect of the control rods on power distribution within the core as well as time-delayed effects through the uneven buildup of the neutron poison xenon-135. If improperly managed, asymmetric heating of the reactor could lead to localized overheating and fuel cladding failures.[85] The primary added cost of flexible operation using control rods is added maintenance and wear to the control rod drive mechanism.[84]

Standard control rods can be supplemented with gray or partial length rods for additional control over the neutron flux distribution in a reactor. Gray rods absorb fewer neutrons than a standard rod and are currently used to facilitate load following on nuclear power plants in France, where nuclear power constitutes 75% of electricity generation and must operate flexibly.[86] Partial length control rods could also be used to assist with flux shaping during load-following.

The difficulties of using control rods for flexible operation have been successfully managed; the French and German nuclear programs have significant experience using control rod maneuvers for routine load-following, and neither country has reported an increase of fuel cladding failure with flexible operation via control rods.[86]

For pressurized water reactors (PWRs), boric acid, a neutron absorber, can be added to the water in the primary loop to reduce reactor power. In contrast to control rod movements, boron has the benefit of reducing power uniformly throughout the reactor. Boron, however, has its own drawbacks for use in flexible operation. The introduction of boron to the primary loop is limited by the chemical control system, which is much slower than a control rod maneuver, and in older PWRs, this control system may need to be upgraded before flexible operation is possible.[86] Increased use of boron also increases the effluents that must be chemically and radiologically treated by the plant's effluent processing systems. These systems may also require upgrades to routinely use boron for flexible operation.[85] Use of boron may also be restricted at the beginning and end of a reactor's fueling cycle.[85]

For boiling water reactors (BWRs), reactor power is typically controlled via recirculation pumps. At sufficiently high power levels, increasing the flow rate of the water coolant/moderator decreases the steam void fraction in the reactor, thereby increasing neutron moderation and reactor power.[87] Controlling power via the recirculation pumps has the advantages of relatively uniform changes to reactor power and the ability to perform rapid power ramps.[86] For reductions in power below 60-80% of rated capacity, control rods must be used in conjunction with recirculation control.[86] Above this level, the main drawback to using recirculation pumps for flexible operation is increased wear on the recirculation system.[85] The Columbia Generating Station in Washington uses recirculation pump control to accommodate seasonal hydroelectric power in the Pacific Northwest, which must run at times due to environmental regulatory constraints. For deeper reductions in load, control rods maneuvers are performed in conjunction with adjustments to the recirculation pumps.[88]

In addition to restrictions on reactor flexibility at the end of the refueling cycle due to fuel burnup, nuclear power plants also face limitations at the very beginning of the fuel cycle. Pelletized nuclear fuel heats and expands during operation adding pressure to the fuel cladding. To avoid a failure of the fuel cladding, the fuel pellet must be brought slowly to, and held at, full reactor power in a process known as conditioning before flexible operation can commence. If the reactor operates at reduced output for several days, fuel will need to be reconditioned before rapid ramps can again be performed.[85] Elforsk's analysis concludes that while flexible operation will likely exacerbate prior damage to fuel, experience in Sweden, Finland, Germany, and France suggests no impact of flexible operation on fuel reliability.[84]

The simplest means of reducing power output is to maintain reactor conditions, but divert the produced steam away from the generating turbines. Steam bypass results in rapid ramp rates, and since reactor power is not directly changed, minimal changes occur to the fuel life, though overall fuel efficiency decreases. Bypassing the turbine and dumping steam to the condensers can increase wear on the condenser system and forces more heat to be rejected to the environmental heat sink, which may be limited for environmental protection. PWRs and Canada deuterium uranium (CANDU) reactors can also vent steam directly to atmosphere since these designs include a secondary loop; for BWRs, since the water is directly heated by the reactor and contaminated, steam rejection to atmosphere is not permissible. While rejection of steam to atmosphere avoids added wear on the condenser system, water in the secondary loop of PWRs and CANDU reactors will still contain higher levels of tritium, which may be regulated and the demineralized water used in these loops must be replaced at a cost.[85] Bypassing the turbine and dumping steam to the condenser is frequently used in CANDU reactors in Ontario to accommodate wind energy and reduce plant electrical output to 60% of capacity.[88] Since nuclear fuel continues to be spent during the bypass, this method of flexibility is most useful for avoiding negative electricity prices or accommodating power plants that must run for technical or regulatory reasons.

European Utilities' Requirements (EUR) state that modern reactors must be able to operate flexibly, specifying several minimum requirements. The EUR specifies reactors to be able to operate continuously between 50% and 100% of rated capacity and able to follow scheduled and unscheduled ramps over 90% of the fuel cycle. Plants should be able to cycle twice daily and up to 200 times per year at a rate of 5% of rated power per minute. PWRs are required to meet criteria primarily with control rods without adjusting the concentration of boron, and BWRs are instructed to minimize control rod movements in favor of control via recirculation pumps. The Electric Power Research Institute has published similar design recommendations for advanced light water reactors in the United States.[86]

Increased flexible operation is not expected to accelerate aging of large plant components.[89] Elforsk's analysis of the costs of load-following with nuclear power plants in Sweden, Finland, Germany, and France concludes that well prepared load following entails very few additional costs for reactors.[84]

5.4 Flexibility of Current U.S. Generation Fleet

Key parameters describing the flexibility of the current U.S. generation fleet were assessed to represent the dispatch of the existing generation fleet in the UCCORE model. The flexibility of the current U.S. generation fleet can be assessed with publicly available generator level data supplemented with industry averages. The EIA collects annual data on all U.S. generators greater than 1 MW in capacity.[90] Schedule 3 of the EIA-860 reports the name, location, type, age, and capacity of each generator on the system. Generators also report the minimum stable load and approximate time from cold start to full capacity, which can be used to crudely estimate start-up time. Figure 5-2 shows the distribution of minimum loads for individual coal generators, natural gas open cycle generators, and natural gas combined cycle plants.

Data on ramp rates and accurate start-up time is not available on an individual generator or plant basis and was estimated using industry averages. Black and Veatch report typical performance data including ramp rates for many types of electric generators.[81] Agora Energiewende reports similar performance data for natural gas and coal plants,[75] Lindsay and Dragoon also report similar data for coal plants,[91] and the Nuclear Energy Agency reports similar data for nuclear plant flexibility.[86] Kumar et al. and Lindsay and Dragoon estimate start-up costs and start-up times for various coal and natural gas plants.[91, 92] The range of typical values for flexibility parameters from U.S. fleet data and industry literature is summarized in Table 5.1 for a variety of thermal plants. Ranges represent the range of published "typical" values as variously defined in the preceding sources.

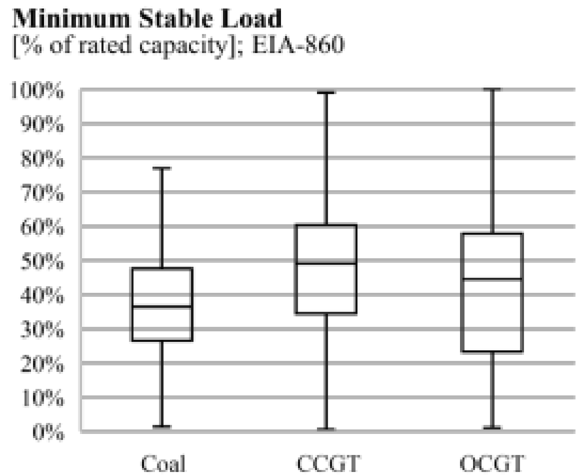


Figure 5-2: Minimum Stable Load of Operating U.S. Coal and Natural Gas Generation Units [90]

Table 5.1: Flexibility Parameters in Literature for Typical U.S. Thermal Plants

Technology	Ramp Rate [%/min]	Minimum Stable Load [%]	Start-up Time [h]			Start-up Cost [$/MW]		
			Hot	Warm	Cold	Hot	Warm	Cold
OCGT	8-15	25-60	0.17 - 0.5			22-47	26-145	31-118
CCGT	2-5	35-60	0.75	2	3	28-56	32-93	46-101
Coal	1-4	25-50	1-2	3-5	6-12	37-60	54-89	63-124
Nuclear	5	50	-	-	-	-	-	-

5.5 Flexibility Assumptions for the UCCORE Model

Based on the above review, Table 5.2 presents the flexibility assumptions used in the base case of the UCCORE model. Existing generators in the model use their individually reported minimum stable load reported in the EIA-860.[90]

Table 5.2: Flexibility Parameters Assumed in UCCORE Model

Technology[a]	Ramp Rate [%/min][b]	Minimum Stable Load [%][c]	Minimum Up Time [h][d]	Minimum Down Time [h][e]
OCGT	8.3	45	-	-
CCGT	5	50	4	-
NGST	5	20	4	-
Coal	2	35	6	-
Nuclear	5	50	36	36

[a] Coal and CCGT include both unabated and CCS-equipped generators. Internal combustion generators are assumed to have the same parameters of OCGTs. Nuclear values represent new nuclear with load following capabilities.

[b] Assumed ramp rates from[81].

[c] Minimum stable load values are median values for current ERCOT fleet as reported in[90] except for nuclear which is assumed to be 50%. Existing generators use reported minimum stable load when available.

[d] Minimum up times from[93].

[e] Since UCCORE does not differentiate between hot, warm, and cold starts, start-up time is not considered a binding constraint, except for the case of nuclear power plants. This characteristic is accounted for via minimum down time.

Chapter 6

Power Plant Cost

6.1 Components of Generation Cost

Levelized Cost of Electricity simplifies generator costs into a single term, but, as discussed in Chapter 2, LCOE makes implicit assumptions about the plant's dispatch, which is dependent on the rest of the power system. In order to present costs independent of operational assumptions, total cost must be disaggregated into fixed and variable cost components.

Fixed costs scale with plant capacity and include the capital cost of the plant and fixed operation and maintenance costs. Fixed-costs factor into the long-run economics of a power plant. When making an investment decision, plants forecast and compare their operation and expected revenues to their total cost, which includes all fixed costs, and invest if the anticipated discounted revenues sufficiently exceeds the discounted costs. Once these investment costs are paid, however, they are sunk and no longer factor into short-term operational decisions.

Variable costs are directly proportional to generation and are primarily fuel costs and variable operation and maintenance costs. These costs are the marginal costs of production on which short-term operational decisions are made and the price a plant would typically bid in a competitive market with a single market clearing price.[1]

[1] Neglecting forward looking behavior caused by intertemporal constraints, as discussed in Chapter 4.

Start-up costs, discussed in Chapter 5, are semi-fixed costs. If a plant is already online, it will treat the start-up cost as sunk and bid the variable cost of operation, but if the plant is offline it may try to include start-up costs in its bid in a simple bid system. The decision to start-up becomes a new investment decision, and the plant must anticipate recouping this investment cost over the time the plant is online. Since power markets typically operate on daily bidding schedules and a plant may start-up for less than a day, how a plant treats start-up costs is dependent on market bidding rules.[2] Over a longer time horizon, fixed O&M can also be considered a semi-fixed cost as a plant that does not anticipate recouping its yearly fixed O&M will exit the market.

This chapter divides costs into operational costs and fixed costs. Operational costs include start-up costs, variable O&M, and fuel costs since they are short-term costs that influence operation decisions in a weekly unit commitment model.[3] Fixed costs include fixed O&M and capital costs as the decision to be available to operate over the year is exogenous to a unit commitment model on this time horizon and these costs are sunk. The UCCORE model uses operational costs to determine generator dispatch and market prices. The effect of fixed costs on profitability is evaluated externally from the model, since these costs are sunk and do not factor into dispatch or market prices. This chapter only evaluates fixed costs for prospective generators evaluated by the model: CCS-equipped combined-cycle gas, CCS-equipped ultra-supercritical pulverized (advanced) coal, generation III nuclear power plants, and wind and solar capacity. This chapter also establishes the assumed operational costs applied to new capacity evaluated using the model. For the existing generation fleet, operational costs are based individual plant data where available. Unless otherwise stated, costs

[2]In a simple bid system, the start-up decision becomes a new investment decision with a time horizon of the anticipated dispatch. The plant must expect to meet the average cost of production over this time horizon, which is the marginal cost plus the start-up cost divided over the anticipated amount of energy produced before shut-off. In this system, a generator may bid its expected average cost of energy and not its marginal cost. In a complex bid system, dispatch is optimized according to least cost based on reported generator constraints and generators are paid the marginal prices as computed through the optimization algorithm. In these systems additional mechanisms may or may not exist to make generators whole for start-up costs.

[3]Only variable O&M and fuel costs are variable costs. Start-up costs effect dispatch, as previously explained, but are not marginal.

presented are adjusted to 2013 dollars using the consumer price index.

6.2 Cost of CCS-Equipped Power Plants

New fossil fuel power plants equipped with CCS technology will face added fixed and variable costs compared to unabated plants due to the investment, maintenance, and energy consumption of the capture, compression, transportation, and storage systems.

6.2.1 Capital Cost of CCS-Equipped Power Plants

Rubin et al. present a survey of engineering studies on the capital cost of post-combustion CCS-equipped power plants and estimate an increase in total capital requirement on a $/kW basis between 58% and 91% for an advanced coal plant and between 76% and 121% for natural gas combined cycle plants.[11] The EIA's 2013 estimates for overnight capital cost are similar, estimating a 61% increase in capital costs for adding CCS to advanced coal plants and a 105% increase for equipping natural gas combined cycle plants with CCS.[41, 94] The IEA's overnight estimates are based on the expected cost of CCS in 2030 and are much lower, presumably due to learning effects, estimating an increase in capital cost of 40% for equipping advanced coal plants in the United States with CCS and an increase of 57% for U.S. natural gas combined cycle plants.[6] The representative estimates for plant capital cost and percent increase in capital cost relative to an unabated plant are presented in Figures 6-1 and 6-2.

6.2.2 Operation and Maintenance Costs of CCS-Equipped Power Plants

The addition of CCS to a power plant will increase fixed O&M, expressed as $/kW-yr, due to the additional equipment in the CCS chain and the overall derating of the plant's net electrical capacity. The EIA assumes an increase of 66% for advanced (ultra-supercritical) coal units and a 107% increase for natural gas combined cycle

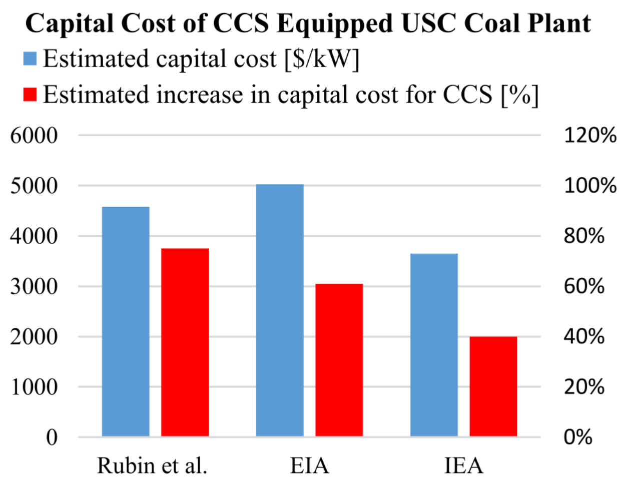


Figure 6-1: Overnight Capital Cost of U.S. CCS-Equipped Ultra-Supercritical Coal Plant

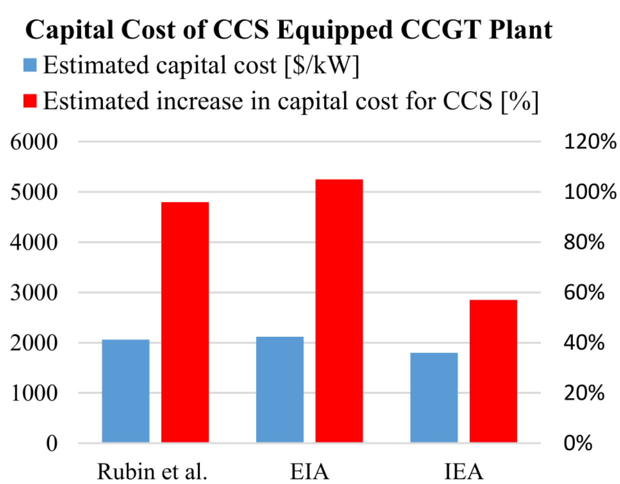


Figure 6-2: Overnight Capital Cost of U.S. CCS-Equipped Combined Cycle Gas Turbine Plant

plants. The EIA attributes this additional cost to maintenance of compression and storage equipment as well as additional labor associated with the CCS equipment.[41]

CCS will also increase variable O&M compared to an unabated plant due to maintenance costs proportional to usage for the CCS equipment and the variable costs of transport and storage of captured CO_2. The variable costs associated with capture and compression will be manifest in the lower net efficiency of the plant. The review of CCS costs conducted by Rubin et al. presents onshore transport costs ranging from \$1.7 to \$10.9 per ton of CO_2 moved 250 km and storage costs ranging from \$1 to \$13 per ton of CO_2.[11] Using the capture assumptions in the study, these transport and storage costs can be converted into a per megawatt-hour charge; since this neglects the maintenance of equipment, this charge reflects the minimum increase in variable O&M compared to an unabated plant. The variable O&M assumed by EIA is intended to cover costs up to injection in a pipeline at the plant fence, but neglects transport and storage costs. The EIA bases its variable O&M estimate for CCS-equipped facilities on those of an unabated plant plus an additional 113% for advanced coal plants and 107% for natural gas combined cycle units.[41] The variable cost used in the UCCORE model is the sum of the CO_2 transport and storage costs reported by Rubin et al. and the variable O&M cost neglecting transport and storage reported by EIA.

6.2.3 Fuel Costs of CCS-Equipped Power Plants

Total fuel cost per unit of electricity is the product of the price of fuel and the power plant's heat rate. Heat rate is the inverse of efficiency and represents the energy input required to generate an amount of electrical energy. Heat rate is a dimensionless quantity, but given different standard units for reporting energy content of fuel and electrical energy, it is commonly reported in units of MMBTU/MWh or similar. Given that fossil-fuel prices are independent of the generator and volatile, this section focuses on the heat rate component of fuel cost. The addition of CCS will increase the variable cost of a plant through the impact of parasitic load on net plant efficiency (Figures 6-3 and 6-4). Since the CCS system requires significant energy

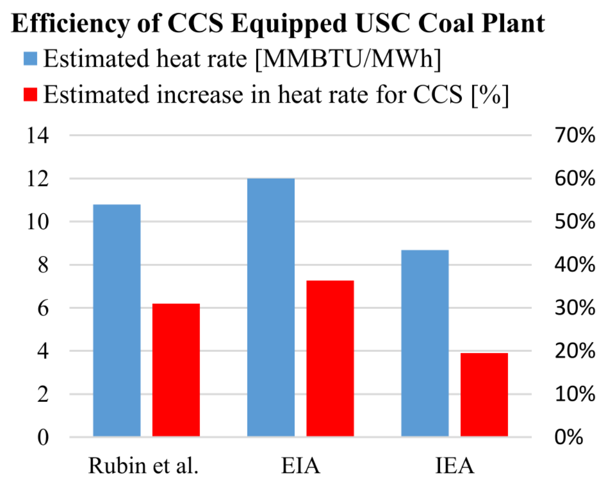


Figure 6-3: Efficiency of CCS-Equipped Ultra-Supercritical Coal Plant; HHV Basis

inputs to regenerate the capture solvent and compress the captured CO_2, the net electrical output of the plant decreases relative to a plant without capture. Rubin et al. report an increase in heat rate of 31% and 16% for adding CCS to advanced coal and combined cycle natural gas plants, respectively.[11] The EIA's estimated increase in heat rate is greater, 36% for coal and 17% for combined cycle national gas.[41] The estimates for both Rubin et al. and the EIA consider plants with roughly 90% capture rates. The IEA's estimates for heat rate gain due to CCS are much lower: 20% for advanced coal and 7% for natural gas combined cycle.[6] The IEA's estimate is for CCS technologies in 2030, and may assume further technological development to improve efficiency such as adoption of more efficient solvents,[11] but the assumed capture rate is also not stated, making the cause of their higher efficiency assumptions unclear.

6.2.4 Summary of Costs for CCS-Equipped Power Plants

Costs and efficiency data from the literature are summarized in Table 6.1 for CCS-equipped ultra-supercritical coal plants and in Table 6.2 for CCS-equipped CCGT plants.

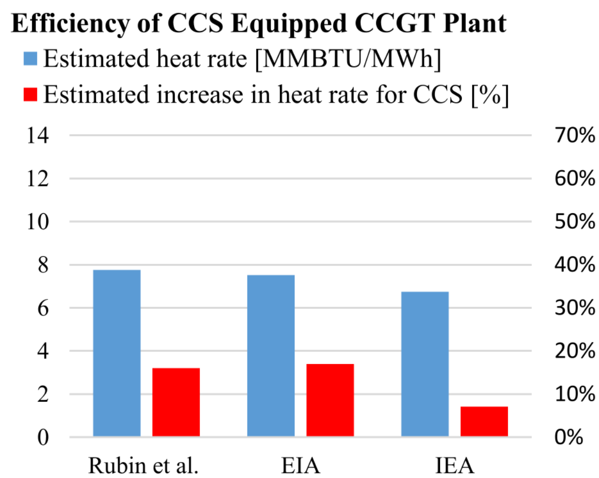


Figure 6-4: Efficiency of CCS-Equipped Combined Cycle Gas Turbine Plant; HHV Basis

Table 6.1: Estimated Cost and Efficiency of CCS-Equipped Ultra-Supercritical Coal Power Plants

Source	Overnight Capital Cost [$/kW]	Heat Rate [MMBTU/MWh][a]	Fixed O&M [$/kW-yr]	Variable O&M/ T&S [$/MWh][b]
Rubin et al.	4091 - 5252	9.31 - 12.54	-	5.70 - 10.76
EIA	4771 - 5279	12	67.09 - 81.34	9.61
IEA	3650	8.68	-	-

[a] HHV Basis.
[b] Rubin et al. value covers cost of transportation and storage only.
EIA value excludes cost of transportation and storage.

Table 6.2: Estimated Cost and Efficiency of CCS-Equipped CCGT Power Plants

Source	Overnight Capital Cost [$/kW]	Heat Rate [MMBTU/MWh][a]	Fixed O&M [$/kW-yr]	Variable O&M/ T&S [$/MWh][b]
Rubin et al.	1422 - 2626	7.26 - 8.04	-	2.30 - 4.35
EIA	2116	7.525	32.11	6.85
IEA	1800	6.747	-	-

[a] HHV Basis.
[b] Rubin et al. value covers cost of transportation and storage only.
EIA value excludes cost of transportation and storage.

6.3 Cost of Nuclear Power Plants

Capital cost dominate the economics of nuclear power plants. These costs have grown over time and recent plants have experienced significant cost overruns and delays. Though fuel and O&M costs represent much smaller portions of the long-term cost of nuclear power, some nuclear power plants in the United States are struggling to recoup even these short-term costs, indicating their continuing importance.[83] Eleven early plant closures occurred during the 1990s,[95] and four plant closures since 2013.[96] An additional plant is expected to close in 2019,[97] and several other plants have been deemed at risk of early closure.[98] As many as two-thirds of U.S. nuclear plants may be unprofitable in the short-term.[83] Rising O&M costs contribute to the failure to run a short-term profit, but likely more important are falling revenues caused by lower natural gas prices, stagnant power demand, and subsidized renewable production.[83, 96, 99]

6.3.1 Capital Cost of Nuclear Power Plants

The capital cost of nuclear power plants in the United States and European Union have escalated over time. Overnight capital costs fell in the early years of the U.S. nuclear industry as reactors grew larger and benefitted from economies of scale, but overnight capital costs began to rise in the late 1960s.[100] This rise accelerated with the Three Mile Island incident, and, in addition to a rise in overnight capital cost, overall construction time also increased.[100, 101] The last generation of nuclear reactors completed in the United States began construction between 1968 and 1978 with overnight capital costs ranging from $1,900/kW and $11,800/kW and the majority of reactors between $3,200/kW and $6,400/kW. A similar, but less severe, escalation also occurred in France for reactors built between 1971 and 1991.[100]

Recent nuclear power plants have also experienced cost overruns and delays. Investigations into construction issues for several recently completed or currently under construction plants have revealed many of the problems are in part attributable to a lack of experience among engineering, procurement, and construction firms and contractors working in the design and safety requirements of nuclear power plants.[4]

Watts Bar 2 came online in October 2016, becoming the first nuclear power reactor completed in the United States for twenty years.[102] Construction began on Watts Bar 2 in 1976, but stopped in 1985 as problems emerged. Construction resumed in 2007 with plans to complete construction by 2012,[102] but the project immediately began to fall behind schedule. A corrective action plan identified problems with project management and initial estimates caused in part by the lack of experience in large nuclear power projects.[103] Construction was completed in 2015 with a final capital cost of \$4.7 billion, up from an initial estimate of \$2.5 billion.[102] This corresponds to \$4,087/kW in nominal dollars, but neglects the investments made prior to 1985 and includes financing and cost escalation, making it difficult to compare to overnight costs typically reported in cost estimation studies.

The Finnish Olkiluoto 3 is the next European plant expected to come online with commencement of operation planned for 2018.[104] The plant is a 1,600 MW reactor of the generation III+ EPR design. Construction began on Olkiluoto 3 in July of 2005—a thirteen year lead time if the current timetable is met.[105] Capital expenditure is currently reported at €8.5 billion (\$9.9 billion); the project was originally scheduled for a four year lead time at a cost of €3.2 billion (\$3.7 billion).[104] Current costs imply a total capital expenditure of \$6,206/kW in nominal dollars. An investigation conducted by STUK, the Finnish nuclear regulatory agency, examined three case studies of construction problems arising during the construction of Olkiluoto 3 and found a lack of knowledge of nuclear safety standards in hired contractors as a contributing factor for each problem. The investigation also reports in the case study on the concrete base slab that continuous concreting of structures of this size is extremely rare in Finland, and that the concrete composition used in the base slab is not used in conventional construction work, indicating further issues from lack of nuclear construction experience.[106]

[4] Throughout this thesis, an effort is made to report prices in inflation-adjusted 2013 dollars. Since detailed data on the cost schedules for these recent nuclear power projects are not available and available cost data are preliminary, costs in the following section on recent nuclear power plants are given as reported and no attempt is made to adjust to 2013 dollars.

Construction began in late 2016 on Hinkley Point C, a dual reactor nuclear power plant in the United Kingdom.[107] The Hinkley Point C reactors are also of the EPR design and 1,630 MW each.[108] Expected construction costs have already escalated to £19.6 billion ($25.6 billion) with expected operation between 2025 and 2027.[109] With no further increases to construction costs or delays, Hinkley Point C would have a total capital expenditure of $8,013/kW in nominal dollars and a construction period of eight to ten years.

Directly comparing the capital requirements from these recent projects to each other or prospective plants is difficult as total capital requirement includes interest costs. This cost of capital will be dependent on the economic climate and perceived credit worthiness of the borrower, and final financing costs will also depend on the specific cash flows during the construction period. Several studies estimate overnight capital costs for new nuclear projects, which is more generalizable. The MIT Future of Nuclear Study estimated overnight capital costs at $4,500/kW for an unspecified reactor and estimated a five year lead time.[110, 111] This study, however, was conducted before the Fukushima Daiichi nuclear accident, which may have influenced costs and construction time due to heightened regulatory standards. The study was also based on Japanese data, which may limit its ability to be generalized. The EIA evaluated a dual unit AP1000 design, a generation III+ reactor, built as an expansion to an existing nuclear site. The EIA estimates this project would have an overnight capital cost of $5,767/kW and a six year construction period.[42, 112] The IEA estimated overnight capital costs for an unspecified advanced light water reactor at $4,100/kW and a seven year construction period.[6] These results are summarized in Figure 6-5. Overnight capital costs and build times reported in these estimates are lower than recent experience suggests. In the UCCORE model, nuclear overnight capital cost and build time are based on these reports, and assumes recent issues from a lack of human capital experienced with nuclear power projects are overcome. Using recent build data would result in nuclear plants much less competitive than other forms of generation.

Given the capital intensity of nuclear power plants, total capital requirement is

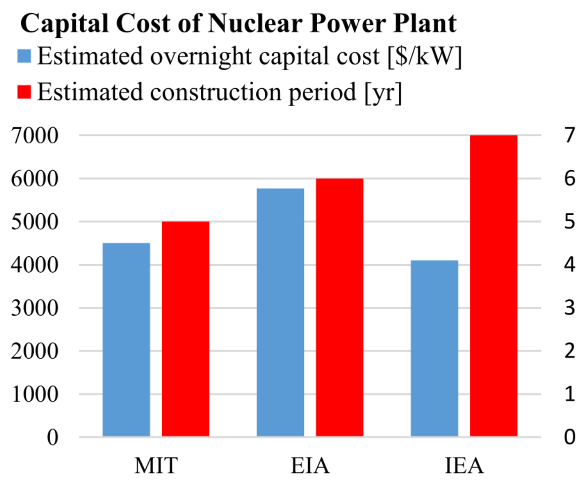


Figure 6-5: Overnight Capital Cost and Construction Time for U.S. Nuclear Power Plant

highly sensitive to the cost of capital, construction period, and cash flows during construction. Given the recent difficulties of constructing nuclear power plants on time and on budget in the United States and Europe, the MIT study, for example, assumes higher costs of capital for nuclear power plants as a risk premium (10% compared to 7.8% for other generators),[110] and IEA presents capital requirement under different cost of capital assumptions.[6] Plants built by state-owned enterprises or by companies in traditionally regulated electricity markets may have access to a lower cost of capital than a plant built by a merchant generator without a revenue guarantee, which can have a dramatic effect on total capital requirement. A 3% cost of capital, potentially available to a government, would make nuclear the lowest cost dispatchable technology on a levelized cost basis, when operating at a high capacity factor. At 10% cost of capital, however, the relative cost is much higher and more sensitive to the assumed overnight cost and construction parameters.[99]

It may be possible to reduce capital costs for U.S. reactors. Data from India and Japan show a halt to overnight capital cost escalation for reactors beginning construction after 1980, and South Korea has maintained a continual decrease in real overnight capital costs.[100] This experience suggests capital cost escalation is not inevitable. Serial production of reactors in a given region could produce human capital experienced in managing and constructing nuclear projects, improving cost estimates and reducing costly construction mistakes.[99] Better budgeting and construction could also help eliminate the risk premium for nuclear financing, which alone could reduce the life-cycle costs of nuclear power by as much as 20%.[110] Factory production of small modular reactors has also been proposed as a strategy to reduce capital costs. Such reactors would be small enough to be constructed at a factory and shipped to an assembly site by truck or rail. The goal is to reduce costs through shorter construction times, utilization of a specialized labor pool, learning through serial production of reactors of the same design, and access to lower cost of capital by virtue of a more manageable absolute capital cost. Proponents assert these benefits of small modular reactors would outweigh the loss of traditional economies of scale gained by making reactors as large as possible.

6.3.2 Operation and Maintenance Costs of Nuclear Power Plants

Total O&M for nuclear power plants has also escalated over time. Escalation of total nuclear power O&M in the United States has been estimated between 7% and 20% between 2002 and 2014 in real terms.[96, 99, 113] These costs have substantial regulatory dependence.[99] Most studies group both fixed and variable O&M into a total O&M figure and estimate total O&M between $11/MWh and $20/MWh, though it must be stressed that these figures are not truly proportional to production and actually are primarily composed of fixed O&M costs divided across generation.[6, 42, 96, 99, 113] Tendency to report total O&M is likely because of the difficulty in disentangling the two types, particularly in the absence of significant experience operating nuclear power plants flexibly in the United States.

Most of the increases in cost from flexible operation discussed in Chapter 5 were found to be from increased wear on components and increased chemical effluents that are typically associated with variable O&M, but these were not precisely quantified. The EIA is the only reviewed source that disaggregates total O&M into fixed and variable components, making it the most useful source from a modeling perspective, but it is not clear that the variable component will continue to be strictly proportional to generation if flexible operation increases since the EIA does not fully explain the source of their estimate. If a 90% capacity factor is assumed, the fixed and variable O&M costs estimated by the EIA are equivalent to $14.57/MWh, which is in agreement with other published estimates for total O&M.[42]

6.3.3 Fuel Costs of Nuclear Power Plants

The literature often presents the costs of nuclear fuel as a proportion of levelized cost, which ranges from 8% to 20% in the reviewed studies.[95, 113, 114] The width of this range, however, is mostly a reflection of the uncertainty of the capital costs of a nuclear plant and the aforementioned importance of assumptions on construction time and financing costs. Prices for uranium oxide are volatile, varying by a factor of five over the last twenty years on the spot market,[99] but this volatility has little effect on the overall economics of a nuclear power plant since the cost of uranium is small relative to other costs. Furthermore, at current uranium prices, the cost of the uranium itself is less than half the total cost of fuel, with processing, enrichment, fabrication, and disposal fees comprising a larger share.[99] In the reviewed literature, absolute nuclear fuel prices ranged from $6.77/MWh to $11.33/MWh, with most falling close to $8/MWh.[6, 96, 99, 110, 113]

6.3.4 Summary of Costs for Nuclear Power Plants

Cost data of nuclear plants from reviewed literature is summarized in Table 6.3.

Table 6.3: Estimated Cost of U.S. Nuclear Power Plants

Source	Overnight Capital Cost [$/kW]	Fuel Cost [$/MWh]	Fixed O&M [$/kW-yr]	Variable O&M [$/MWh]	Total O&M [$/MWh][a]
MIT	4500	8.72	-	-	9.81
EIA	5767	-	97.27	2.23	14.57
IEA	4100	11.33	-	-	11
World Nuclear Assoc.	-	7.5	-	-	17.06
Nuclear Energy Inst.	-	6.77	-	-	20.21
Davis and Hausman	-	8.2	-	-	15.8

[a] EIA value is implied by fixed and variable O&M at assumed 90% capacity factor.

6.4 Cost Assumptions for UCCORE Model

Table 6.4 presents fixed costs for the five new generation technologies examined in the base case of the UCCORE model. These costs are sunk and are not considered within the model, but are useful for evaluating the annual profitability of these generators in conjunction with modeled revenues and operating costs.

Table 6.5 presents the variable and operating costs for the new generation technologies examined in the UCCORE model, and Table 6.6 presents the ranges of variable and operating costs for the existing generation fleet in Texas.

Table 6.4: Capital and Other Fixed Costs for New Generators Assumed in UCCORE Model

Technology	Fixed O&M [$/kW-yr][a]	Overnight Capital Cost [$/kW][b]	Lead Time [yr][c]	Annuitized Capital cost [$/kW-yr][d]
USC Coal CCS	74.21	4580	4	472.43
CCGT CCS	32.11	2061	3	200.97
CCGT	15.52	1071	3	104.42
Nuclear	94.21	4800	6	549.28
Solar	26.48	2591	2	238.02
Wind	39.95	1821	3	177.53

[a] CCS data from [41].
All others from [42].
Coal is average of single and dual unit values, and solar is average of small and large facilities.
[b] CCS estimates representative values from [11].
Nuclear estimate average from [6, 110, 42]
All others from [42].
[c] Lead time assumptions from [112].
[d] Based on overnight capital cost, lead time, a cost of capital of 7%, and a book life of 30 years for all plants except wind and solar which assume 25 year book lives.

Table 6.5: Variable and Operating Costs for New Generators Assumed in UCCORE Model

Technology	Start-up Cost [$/MW][a]	Variable O&M [$/MWh][b]	T&S [$/MWh][c]	Heat Rate [MMBTU/MWh][d]	Fuel Cost [$/MMBTU][e]	Total Variable Cost [$/MWh]
USC Coal CCS	67	9.70	8.23	10.6625	2.11	32.15
CCGT CCS	58	6.92	3.33	7.755	2.83	28.85
CCGT	58	3.40	-	6.3	2.83	21.22
Nuclear	100	2.23	-	10.449	0.77	10.28
Solar	0	0	-	-	-	0
Wind	0	0	-	-	-	0

[a] Assumes warm starts from [81].
CCS plants use values from comparable unabated plant based on prior findings that added start-up costs for CCS had negligible effects on plant profits[115].
Nuclear start-up costs are not well studied.[76]
[115] suggests start-up costs on the order of a large coal plant or $64,000 for a gigawatt plant.[116] assumes $1M. Selected value is between these and is based on[93, 117].

[b] CCS data from [41].
All others from [42].

[c] CO_2 transport and storage values from [11].

[d] CCS plant values from [11].
Unabated CCGT from advanced combined cycle values in[42].
Nuclear values from [42].

[e] Coal and gas values based on Texas average values from [118].
Nuclear based on $8/MWh at listed heat rate.

Table 6.6: Variable and Operating Costs for Existing Generators Assumed in UCCORE Model

Technology	Start-up Cost [$/MW][a]	Variable O&M [$/MWh][b]	Heat Rate [MMBTU/MWh][c]	Fuel Cost [$/MMBTU][d]	Total Variable Cost [$/MWh]
Pulverized Coal					
Subcritical <300MW	165	4.56	10.13 - 12.69	1.91 - 2.46	26.07 - 35.89
Subcritical >300MW	68	4.56	10.13 - 12.69	1.91 - 2.46	26.07 - 35.89
Supercritical	67	4.56	9.43 - 12.61	1.91 - 2.46	24.42 - 32.65
CCGT	58	3.40	4.36 - 11.09	2.48 - 5.24	15.75 - 34.77
OCGT					
<50MW	25	3.40	4.43 - 18.67	2.48 - 5.24	15.94 - 56.23
>50MW	132	3.40	4.43 - 18.67	2.48 - 5.24	15.94 - 56.23
NGST	61	3.40	10.51 - 15.23	2.48 - 5.24	16.54 - 46.30
Internal Combustion Gas	25	5.67	9.23 - 10.19	2.48 - 5.24	31.80 - 35.09
Internal Combustion Oil	25	5.67	8.229	12.98 - 15.66	115.90
Nuclear	100	2.23	10.458	0.77	10.28
Hydro	0	0	-	-	0
Wind	0	0	-	-	0
Solar	0	0	-	-	0

[a] Assumes warm starts from [81].
Limit for small OCGT assumed to be aero-derivative from [119].
Internal combustion costs assumed similar to small, aero-derivative OCGT.
Nuclear start-up costs are not well studied.[76]
[115] suggests start-up costs on the order of a large coal plant or $64,000 for a gigawatt plant.[116] assumes $1M. Selected value is between these and is based on[93, 117].

[b] Coal data from [41].
All others from [42].

[c] Individual generator or plant data from [90].

[d] Individual generator or plant data from [118] when available.
Others use average of reported values.
Nuclear based on $8/MWh at listed heat rate.

Chapter 7

Unit Commitment Model for Co-Optimized Reserves and Energy

7.1 Unit Commitment Modeling

The unit commitment problem is the optimization of electric generators' operation schedules. Unit commitment schedules the start-up and shut-down as well as the hourly output of all generating units on the power system with the goal of minimizing system costs, subject to relevant technical and regulatory constraints. When the cost of unserved demand is included in the optimization through the value of lost load (VOLL), minimizing system cost is equivalent to the traditional economic formulation of maximizing total welfare.[1]

As discussed in Chapter 4, system cost cannot be minimized by considering each hour independent of other hours due to generators' intertemporal constraints. Instead, the unit commitment problem is solved over a longer time scale, from a day up to a week in duration. Unit commitment models differ in their treatment of generator's intertemporal constraints and technical attributes. Adding detail requires more knowledge and computational power as actual operation of generators involves non-linear and discontinuous characteristics. Ultimately, all unit commitment models require simplifications, which are selected based on question the model is used to inform, but overly simplified models may not capture relevant constraints.

7.2 UCCORE Overview

The unit commitment model for co-optimized reserves and energy (UCCORE) was developed specifically to inform how increasing intermittent generation affects the economics and operation of dispatchable, low-carbon units in an efficient market. UCCORE is a mixed integer linear programming (MILP) formulation written in GAMS and solved using the commercially available solver, CPLEX. It follows conventional MILP formulations of the unit commitment problem with the exception of the co-optimized reserve market that includes a linearized version of the operating reserve demand curve (ORDC) described and developed in Chapter 4. The model itself is deterministic, but through the ORDC includes the results of the stochastic loss of load probability (LOLP) assessment. The addition of the co-optimized reserve market based on the ORDC provides efficient scarcity signals to the short-term market.[68] These signals become increasingly important for an efficient system as the market grows more volatile with higher proportions of intermittent capacity. UCCORE is not an equilibrium model and does not consider investment feed-back. In a real market, investment would occur once generation becomes profitable. Scenarios beyond the point of first plant profitability can describe a system far from equilibrium and present unrealistic prices. These results are, however, informative for describing the profits a generator would receive from efficient short-term price signals if poor policy or market design led to a system far from economic equilibrium without these signals. A qualitative description of the model is provided here. Appendix A provides the complete algebraic formulation of the model.

UCCORE considers the operation of individual generating units over hourly time slices within characteristic weeks. Generators are characterized as thermal, hydroelectric, wind, or solar capacity. The objective function is minimization of system cost over the week, where system cost is the sum of generator variable costs and start-up costs, as well as the cost of unserved demand. Assumptions for generator variable and start-up costs are described in Chapter 6. The cost of unserved demand is the amount of demand explicitly not-served plus the loss of energy expectation due to insufficient reserves, all multiplied by the VOLL. The loss of energy expectaton is the integral of the LOLP curve estimated in Chapter 4. Demand is assumed to be inelastic and is based on historic hourly load profiles from ERCOT, scaled by the historic growth in average and peak load.[48, 50]. An average transmission loss factor is also applied.[120]

UCCORE restricts generator operation according to several constraints. The model handles start-up and shut-down through binary logic and provides constraints to thermal generators' minimum-up and minimum-down times. Thermal and hydroelectric generators are also constrained by their minimum stable load and their maximum ramp rate. The assumed parameters describing these constraints are established in Chapter 5. Hydroelectric generators with storage reservoirs are given an allotment of water to be used over the examined week.[1] The ERCOT system does not include pumped storage, so provisions for storage are not made in the model.[2] The output of wind and solar generators is constrained by the availability of these resources. These availability profiles are also sourced from historic ERCOT data from the same sample year from which demand profiles are sourced.[49][3]

The result of a single UCCORE model run is the scheduled output of each unit on the system and the hourly prices for energy and reserves, which are the system marginal costs of energy and reserves during each hour computed by the model. The resulting hourly generator output and hourly prices can provide the revenues for generators. Subtracting generators' variable costs and start-up costs yields the net revenues for the week.

Characteristic weeks are used to capture the daily and weekly periodicity of elec-

[1]This may overestimate the flexibility hydroelectric power as it does not subject water discharge to any non-power constraints. The overall effect on the model is expected to be small as hydroelectric capacity is a small component of ERCOT generation.

[2]Adding storage is expected to increase the prices of energy when intermittent sources are available and decrease peak pricing. This would improve the competitiveness of intermittent energy sources compared to dispatchable sources. The extent of this increase would be dependent on the amount of storage capacity on the system, the system discharge rate, and associated costs and efficiencies.

[3]The data used here is actually the historic capacity factor of these resources. Since current penetration of these resources are low, it is assumed that curtailment is minimal and these capacity factors are equivalent to the availability factor.

tricity demand and the daily cycles of wind and solar availability. One week was randomly selected from each season to capture seasonal variation in demand profiles as well as wind and solar availability.[4] The results from each season's characteristic week are interpolated to estimate that year's net revenues. Finally, annuitized capital costs and other fixed costs are subtracted from annual net revenue to estimate generator profits for the test year. These capital costs and other fixed costs are sunk, and do not factor into the short-term decisions made in UCCORE, but still must be recouped if a generator is to operate profitably. Assumptions for capital and fixed costs are described in Chapter 6.

The flow of information through the model is shown in Figure 7-1.

[4] The same characteristic weeks are used for consistency across all scenarios.

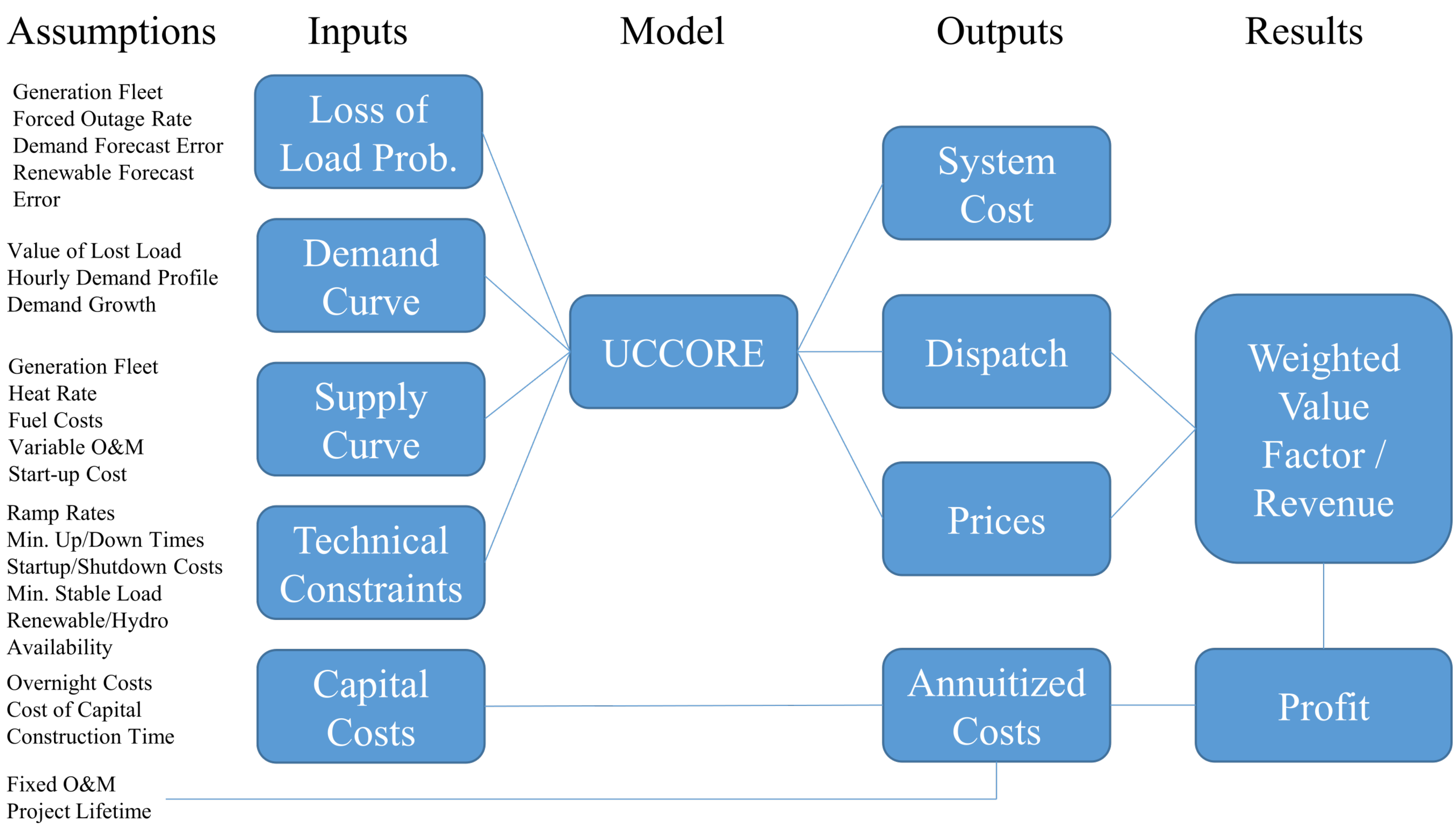


Figure 7-1: Flow Chart of Information in the UCCORE Model

The UCCORE model makes several simplifying assumptions to make the unit commitment problem tractable. First the UCCORE model uses a single node approximation, neglecting network topology and constraints.[121] This a common approach in unit commitment modeling and is appropriate here since the focus of this study is temporal differences in energy value and not locational differences. Second, the UCCORE model does not differentiate between start-ups of various initial boiler temperatures leading to a more approximate treatment of cycling costs. Since some scenarios suggest frequent plant cycling, adding detail to the characterization of start-ups could be an area for model improvement. Third, plants are assumed to operate at constant efficiency regardless of output and variable O&M is independent of ramping. A linearized curve reflecting partial load efficiency could be added, but this would require additional binary variables and increase computational requirements. Fourth, the loss of load probability is exogenously determined for a given annual penetration of wind energy and assumed to remain constant. The model is run iteratively adjusting wind capacity until the model converges on the assumed penetration of wind energy. Making the loss of load probability curve endogenous to the model would require non-linear programming greatly increasing the complexity and computational requirements of the model. A more accurate treatment of LOLP is expected to lead to a higher price for reserves during hours in which intermittent power is abundant and a lower reserve price and energy price when demand is met primarily by thermal generation.

By changing the inputs to the model, the effects of various assumptions can be tested on several test power plants via scenario analysis. The key independent variable is penetration of wind energy on the system, which is used as a proxy for intermittent capacity in general. The dependent variables are indicators of generator's operation and economic competitiveness, the most important of which relate to revenue and profits. Since the test generators are marginal units, their revenues are equal to the system value.[122] Subtracting all private costs yields generator profit, which is the net system value including generator costs. Assumptions regarding value of lost load, fuel price, and carbon pricing are also assessed as a sensitivity analysis.

An important decision is how to adjust the capacity of the rest of the generation fleet as wind capacity is added to the system. Broadly there are three ways of considering the rest of the generation fleet.

1. Long-term equilibrium: Investment in dispatchable generation capacity is endogenous to the model and capacity can be added or retired until equilibrium is achieved. This method typically assumes investments occur based entirely on modeled market forces in an environment without regulatory risk, allowing capacity to reach efficient equilibrium. In equilibrium, the profitability of all units on the margin would be zero. This method is inappropriate for a unit commitment model, as investments in capacity are not based on the demands of individual weeks, and thus should not be endogenous to a weekly model. In capacity investment models, a longer time horizon is used, but at the expense of technical exactness as generator attributes and constraints are further aggregated and relaxed to make the optimization problem computationally tractable. Since the goal of this study is to examine the effects of intermittency that occur on the order of hours, a short-term model without endogenous investment is required.

2. Constant dispatchable generation fleet: The rest of the generation fleet remains constant as intermittent capacity is added to the system. This method seems neutral on the surface, but introduces a confounding effect in the experiment. By adding intermittent capacity while keeping the rest of the fleet capacity constant, both the penetration of intermittent capacity and the overall amount of generation capacity increase. The overall increase in generation capacity depresses prices and reduces capacity factors for all generators. The effect is particularly apparent at the capacities required for intermittent generators to achieve high penetrations of delivered energy. Due to confounding, the effects of an overall capacity increase cannot be distinguished from the effects of increased intermittent capacity. Since the goal of this study is to examine the effects of intermittent capacity, it is necessary to control for total fleet capacity.

Table 7.1: Assumed Retirement Age of Generating Units Based on [6, 123]

Technology	Retirement Age [yr]
Nuclear	60
Coal	50
Oil	50
NGST	50
CCGT	40
OCGT	40
Wind	25
Solar	25

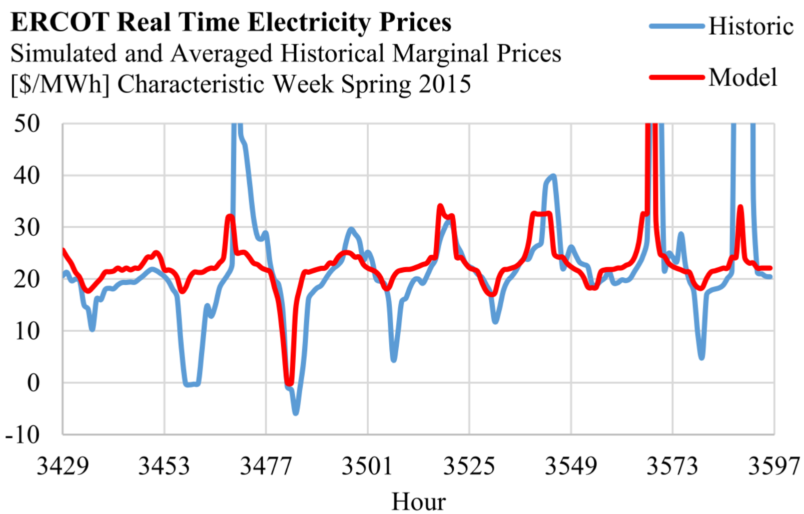
3. Constant generation capacity: Dispatchable generators are removed as intermittent capacity is added to the system to keep the total amount of generation potential equal while changing the ratio of intermittent to dispatchable generators. This ensures the total amount of energy the system can produce remains constant across scenarios, eliminating the confounding effects caused by increasing energy generation supply.

This scenario analysis adopts the latter approach, keeping the generation potential constant across scenarios. The purpose for using generation potential instead of nameplate capacity is to account for the lower availability factor of intermittent generators compared to dispatchable generators. Generation potential is approximated as the product of nameplate capacity and availability factor. In this approximation. One unit of wind capacity is weighted as three-tenths of the capacity of a dispatchable unit, roughly the availability factor of wind in the ERCOT system. The choice of how dispatchable units are removed from the system is, however, arbitrary and can have important effects of the modeled results. The convention used in these scenarios is as wind capacity is added, the dispatchable generators closest to their assumed retirement age are removed until reaching the initial weighted capacity of the system. Assumed retirement age of generating units by technology is shown in Table 7.1.

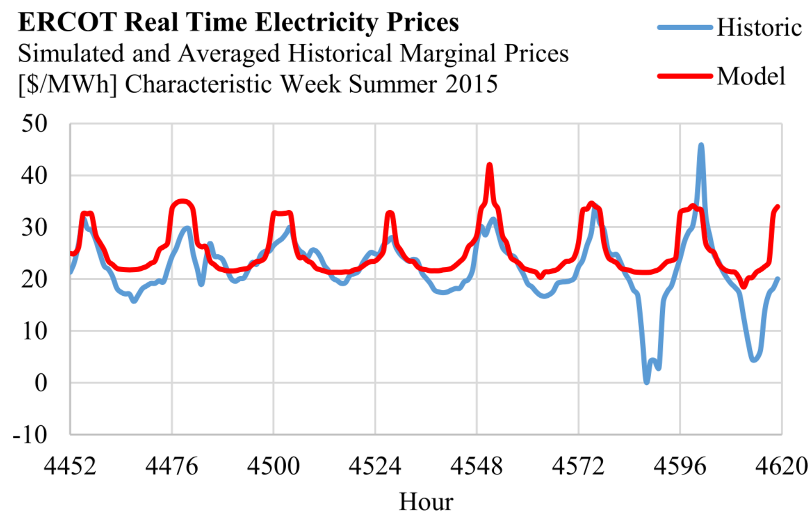
The treatment of the generation fleet determines how the results should be interpreted. The UCCORE model is not an investment model as it does not model the time horizon covering the generator's economic life. The scenario analysis also does not imply the progression of a single system through time, nor does the removal of the existing generation fleet imply that the addition of intermittent capacity will directly replace existing capacity in the system, though depressed prices from increased capacity supply may cause other generators to exit in the long-term. Instead, the UCCORE model is used to assess the economic performance of test generators in a snap-shot year of a system. The scenarios present snap-shot years of comparable systems with the same weighted generation capacity, but with various ratios of intermittent to dispatchable capacity. By comparing profits and operation during these snap-shot years, the model and scenario analysis intends to determine the effect of increasing intermittent capacity on dispatchable, low-carbon generators in an efficient market.

7.3 UCCORE Validation

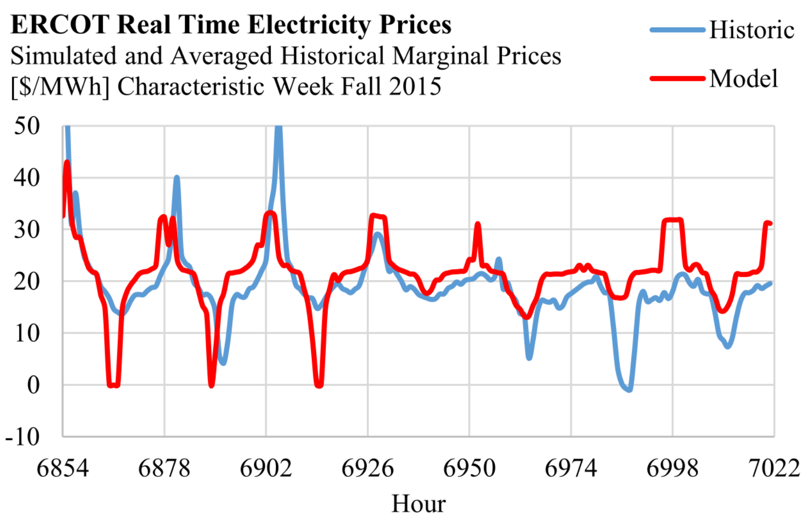
To validate the UCCORE model, a scenario was constructed parameterized to represent the ERCOT system in 2015. In this scenario, demand is based on the historic average demand for each hour and renewable availability is based on historical data. No test generators were added and existing generators are based on data reported in EIA-860[90], yearly average fuel prices in EIA-923[118], and Table 5.2, and Table 6.6 Modeled prices for four characteristic weeks are compared to the historic ERCOT prices in Figure 7-2. The ERCOT price is taken as the hourly average of the four ERCOT hub LMPs. The validation run shows that the relatively simple UCCORE model captures the major features of the electricity spot market. The largest consistent discrepancy was in the winter test. This may be attributable to the use of the 2015 average natural gas price while monthly data shows the price of gas was at its lowest during December of that year,[55] the month from which the example is drawn.



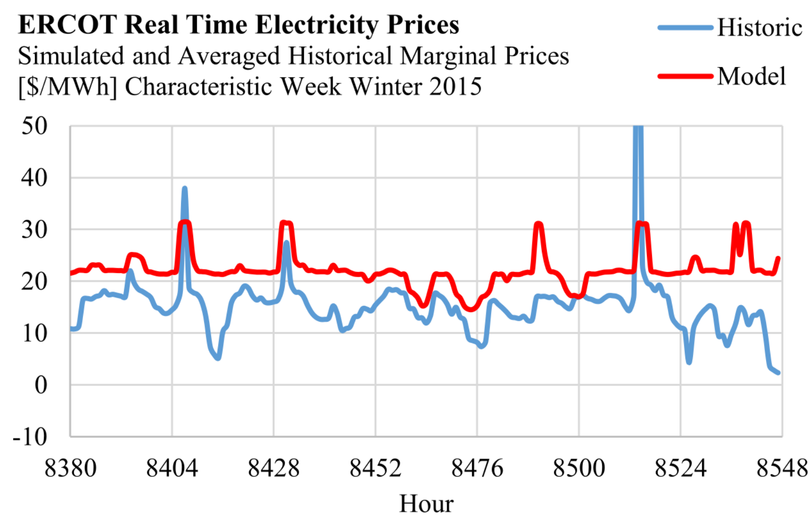
(a) Spring



(b) Summer



(c) Fall



(d) Winter

Figure 7-2: Modeled and Historic Prices for Select Weeks, ERCOT 2015

7.4 Base Case Results

The base case considers a more constrained system by projecting the ERCOT fleet and demand profile to 2018. Generators past the retirement age specified in Table 7.1 are removed from the system and demand has grown slightly from the 2015 data at a rate of 1.5% per year for both peak and average load based on the historic ERCOT growth.[50] This start year was selected because at this time, current generation capacity is sufficient to meet demand in all hours, but the system is becoming constrained and has little excess capacity. Without retiring older generators or considering demand growth, the system is flush with generation capacity and prices are so low that nearly all generators are unprofitable.

Parameters characterizing generator flexibility are as reported in EIA-860 for minimum stable load of existing generators[90] and as described in Table 5.2. Generator variable costs are based on current fuel prices in Texas and are reported in Table 6.5 for the added test generators and Table 6.6 for existing generators. The assumed capital costs for the added test generators are shown in 6.4

The VOLL is assumed to be \$9000/MWh—the current ERCOT value—and the demand for reserves is characterized by the LOLP curves described in Chapter 4.

Scenarios were run with wind energy penetrations of 10%, 30%, 50%, and 70%, keeping overall generation potential constant.[5] The actual wind penetration in ERCOT system was 11% in 2015.[124]

Overall, the goal of the base case is to describe the existing ERCOT system after capacity closures and demand have slightly tightened the power market and various amounts of intermittent capacity have been added through policy.

Figure 7-3 shows the development of energy prices in the system as wind penetration is increased. The figure shows the mean energy price as well as the 10^{th} and 90^{th} percentile prices (the values such that hourly prices are less than the given value 10% and 90% of the time, denoted P10 and P90 respectively). Between 10% and 30% wind penetration, mean prices rise slightly from \$28/MWh to \$32/MWh and

[5] Generation potential is the product of nameplate capacity and availability factor.

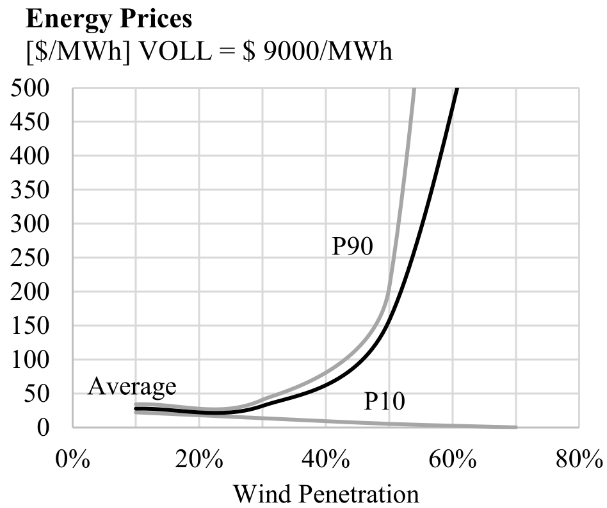


Figure 7-3: Effect of Wind Penetration on Energy Prices, Base Case

are close to current wholesale prices. Also, 80% of prices exist within a relatively narrow ±$10/MWh range at 10% penetration. As wind penetration increases, prices change in several ways. First, the mean price of energy increases—slowly at first, but at an accelerating rate. By 50% penetration prices average over $150/MWh and at 70% penetration the average price is beyond the scale of the chart at more than $850/MWh. Second, the average energy price closely tracks the P90 value of energy prices as prices in some hours clear far above even the P90 value, giving the distribution of prices a strong positive skew, pulling up the average energy price. Third, though some prices increase dramatically, prices do not increase for all hours. As average price and the P90 price increase, the P10 energy price *decreases* eventually reaching $0/MWh.

Figure 7-3 confirms the intuition laid out in Chapter 3 that increasing penetrations of intermittent capacity should increase the volatility of energy prices. This is also shown in Figure 7-4, which plots the standard deviation of energy prices at various penetrations of wind energy.

As the gaps between peak, average, and off-peak prices grow, the production profiles of generators is expected to become an increasingly important determinant of the revenues the generator receives for its energy. While assuming generators receive similar prices and comparing them only on the basis of cost may have been

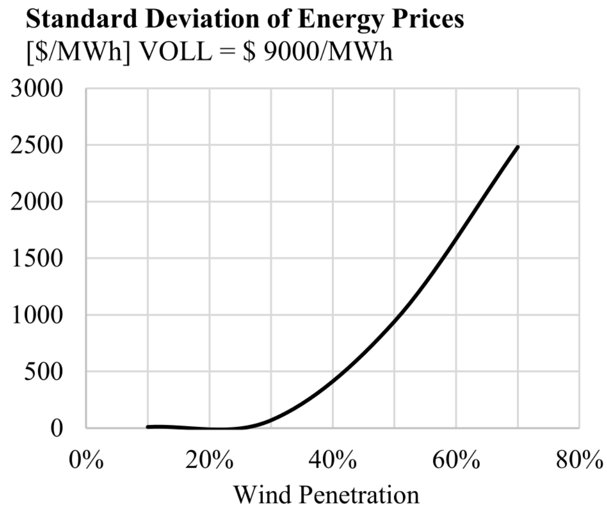
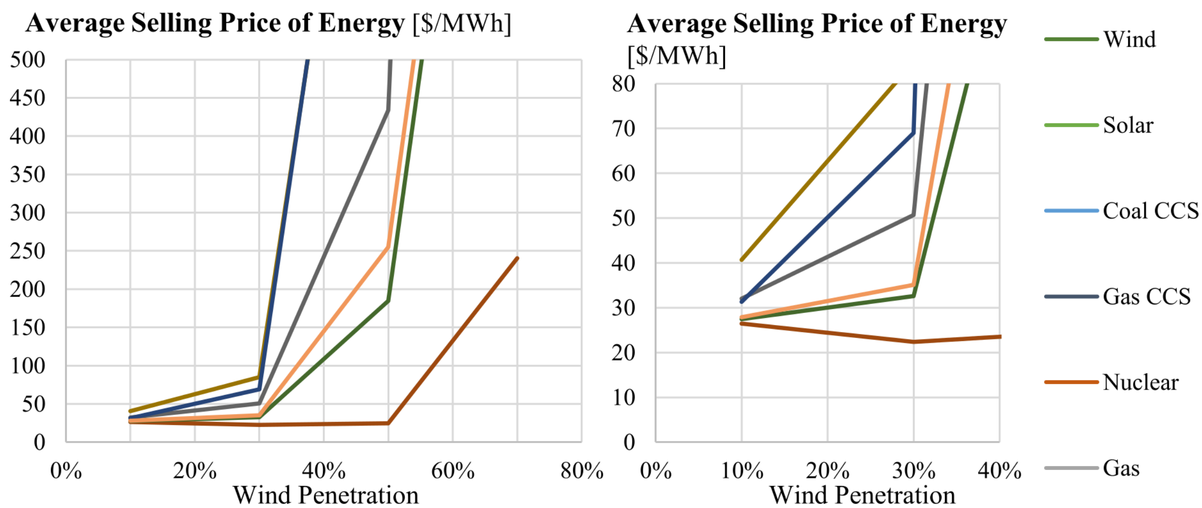


Figure 7-4: Effect of Wind Penetration on Energy Price Volatility, Base Case

an acceptable approximation at low penetration of intermittent capacity, it is clearly a poor assumption in volatile markets. Figure 7-5 shows the average revenue per megawatt-hour received by each generator as wind penetration increases. Due to their high variable costs, coal and gas power plants equipped with CCS only operate around peak hours and capture the highest average energy prices. Solar remains at low penetrations and does not affect market prices significantly, but is correlated with ERCOT's peak prices that occur around midday and in the summer. Unabated natural gas and nuclear power operate at low variable costs and operate for many hours, roughly capturing the average price of energy. Wind, however, only captures the off-peak energy prices due to its coordinated output. As wind capacity is added, prices crash when wind is available due to excess supply.

The total revenue received by a generator is the product of the average revenue per unit energy sold and the amount of energy sold, which is represented by the capacity factor. Figure 7-6 shows how capacity factors change for power plants as wind penetration increases. At low penetrations, natural gas and nuclear power plants operate as baseload plants with capacity factors close to one. As wind penetration increases, however, the number of hours in which the price of energy is below the variable costs of combined cycle natural gas or even nuclear power increases and these generators reduce their output accordingly. At low penetrations, coal and natural gas



(a) Full View

(b) Detail

Figure 7-5: Effect of Wind Penetration on Generators' Annual Average Selling Price of Energy, Base Case

plants equipped with CCS operate as peaker plants with very low capacity factors as prices are rarely above their variable costs. The capacity factors of these generators increase with wind penetration as prices increase when wind is unavailable leading to more hours of operation. Wind begins to be curtailed at penetrations between 30% to 50%. Excess generation from wind also leads to curtailment of solar during some hours. An important result is that at higher penetrations of wind, no generators operate as baseload because the minimum net load of the system is zero. All generators operate flexibly to reduce output during low-price/high-wind hours and ramp up during high-price/low-wind hours.

The product of average revenue per unit energy and capacity factor is average revenue per unit of capacity.[6] This is shown in Figure 7-7. As would be expected from the prior graphs, natural gas and nuclear reap similar revenues due to their similar dispatch. The revenues of CCS-equipped units start out low due to a low capacity factor, but increase as higher prices lead to both a higher revenue per unit energy and more hours of operation. The revenues of wind capacity are subject to two competing effects. The first is that due to its coordinated output, wind depresses

[6] Average revenue also includes revenue from the sale of reserves but the contribution directly from reserves is small as is shown later in Figure 7-10

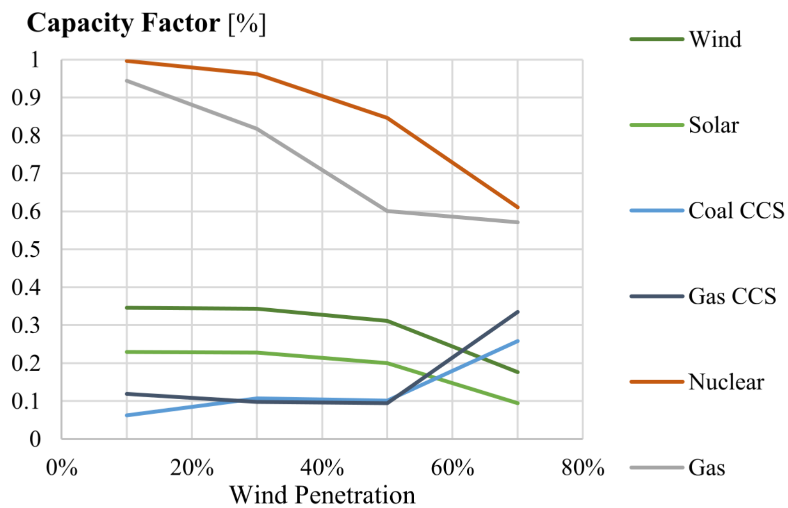
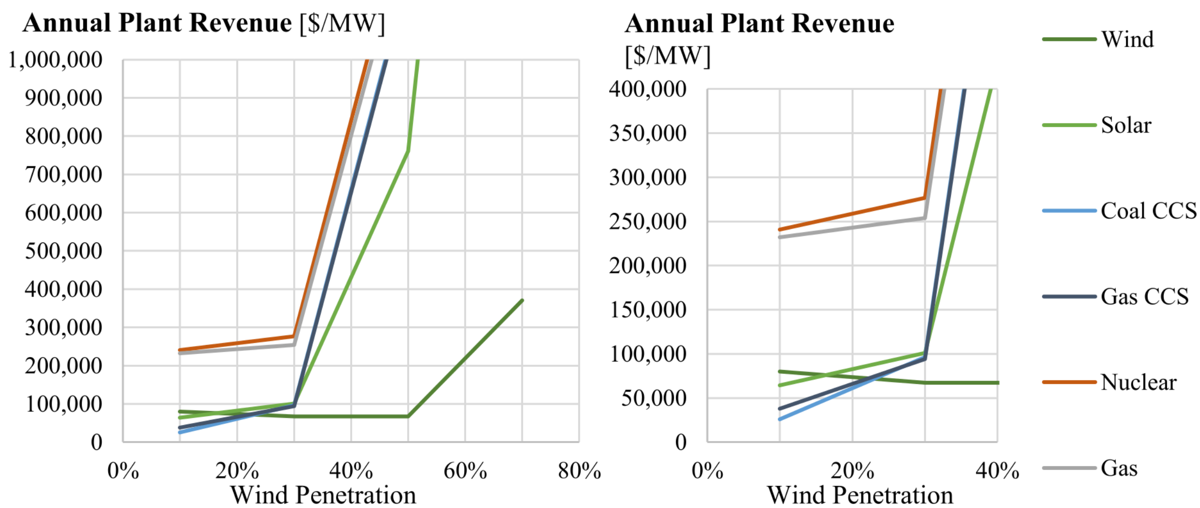


Figure 7-6: Effect of Wind Penetration on Generator Capacity Factors, Base Case

its own prices at high penetrations. The second is at very high penetrations, there are many hours where the price of energy is quite high, close to the VOLL. Though wind captures less of these high price hours than dispatchable or solar generators, some wind generation still exists in these low-wind/high-price hours and prices are so high that these revenues dominate the wind generators' total revenues.

To fully capture the relative competitiveness of the test generators, costs must be subtracted from revenues, yielding generator profit shown in Figure 7-8. At low penetrations of wind, only unabated natural gas is profitable. Low prices resulting from the low gas price and the highly dispatchable system make capital intensive projects such as CCS or nuclear unattractive. Wind and solar generators lose less money, being less capital intensive. Nuclear and CCS-equipped coal generators are least profitable owing to a combination of low energy prices and highest captial costs. As wind penetration increases the profitability of all dispatchable generators increase. At high penetrations, revenues are so high that differences in capital and variable costs are unimportant to overall profitability and the profits of all dispatchable generators converge. Profits are dictated by the ability to provide energy during the highest priced hours when wind output is lowest. Solar profitability also increases due to its correlation with peak demand and anti-correlation with wind, which tends to blow most at night. Wind profits remain low at all penetrations. Wind profits decline



(a) Full View (b) Detail

Figure 7-7: Effect of Wind Penetration on Average Annual Revenue per Megawatt of Capacity, Base Case

well before substantial curtailment of wind occurs and in systems with high prices, dispatchable generators and solar are far more competitive. Of low-carbon generators, CCS-equipped natural gas combined cycle becomes profitable at the lowest penetration of wind, followed by solar, nuclear, and CCS-equipped coal.

As intermittent capacity increases, demand for reserves increases also and dispatchable generators are relied upon to provide more reserves (Figure 7-9). While dispatchable generators provide more reserves, reserves continue to be a small component of generator revenue (Figure 7-10). The importance of the reserve market is in sending scarcity signals through co-optimization with the energy market and less the revenues directly resulting from reserves. This is further explained in the following section.

Hirth defines the value factor for generators, which normalizes the average revenue generators receive per unit electricity sold. The value factor is defined as the average price of energy over a generator's production profile divided by the average electricity price of the system.[47] Hirth only applies the value factor to intermittent renewable resources, but as market volatility increases the difference between revenues for all generators, applying the value factor to both dispatchable and renewable resources

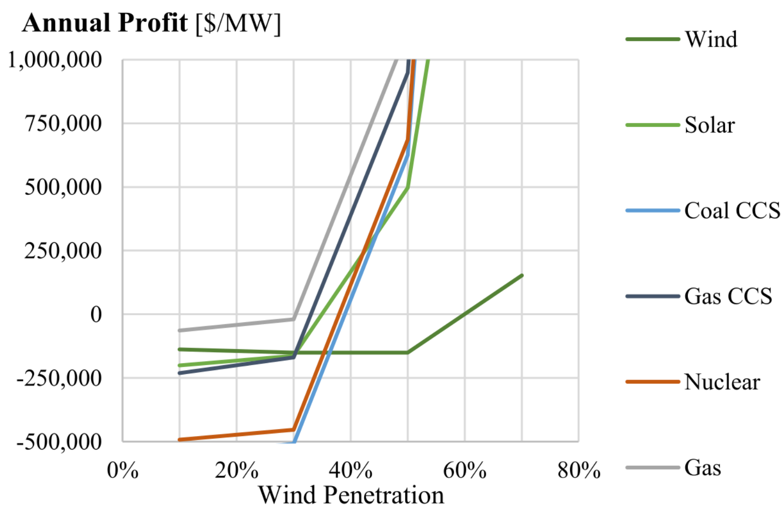


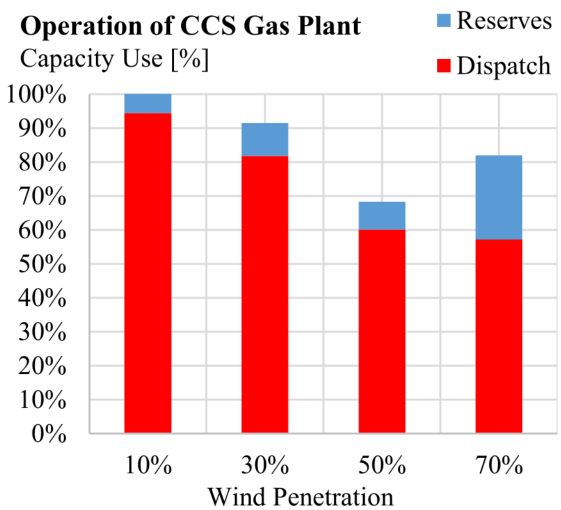
Figure 7-8: Effect of Wind Penetration on Generator Annual Profit, Base Case

Table 7.2: Generator Value Factors, Base Case

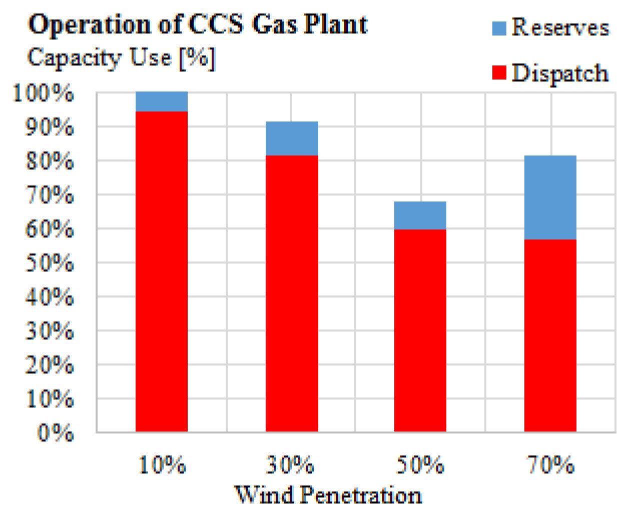
	Wind Penetration			
Technology	10%	30%	50%	70%
Wind	1.0	0.7	0.2	0.3
Solar	1.2	1.6	2.8	5.1
Coal CCS	1.5	2.7	7.6	3.7
Gas CCS	1.1	2.2	7.8	2.8
Nuclear	1.0	1.0	1.2	1.6
Gas	1.0	1.1	1.6	1.7

can facilitate comparisons of the relative value these generators contribute to the system. Value factor is only the market value of the service and does not reflect the private costs incurred to provide it. Table 7.2 shows the value factors of the test generators at various penetrations of wind energy. The value factor for wind of 1.0 and solar of 1.2 at 10% wind penetration are in line with the literature review provided by Hirth.[47] The value factors behave unintuitively at high wind penetrations because the denominator—the average energy price—becomes quite high due to loss of load events.

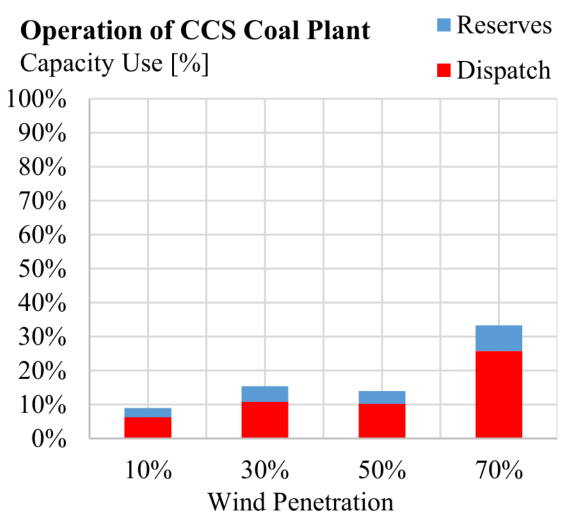
Hirth's value factor describes the difference in value contributed per unit energy of a generator. To compare the relative value of the generators themselves, the value factor should be weighted according to the amount of energy produced—the capacity



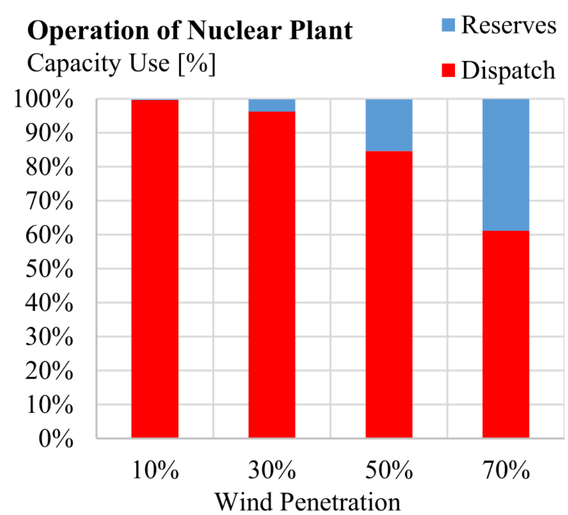
(a) Unabated Natural Gas combined cycle



(b) CCS-Equipped Natural Gas combined cycle

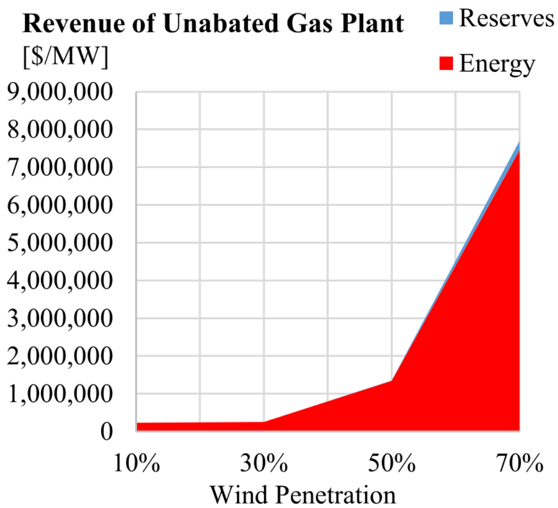


(c) CCS-Equipped Ultra-Supercritical Pulverized Coal

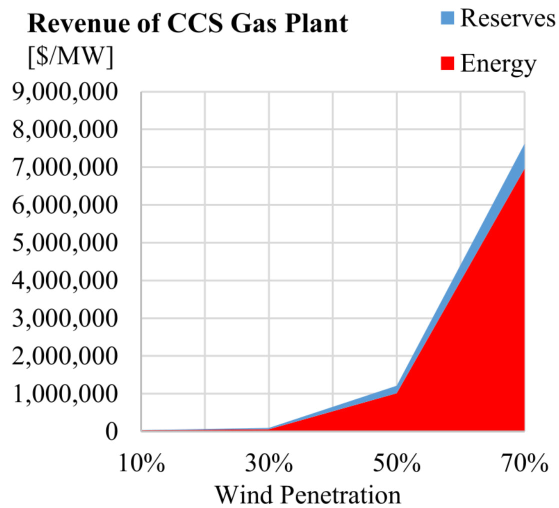


(d) Nuclear

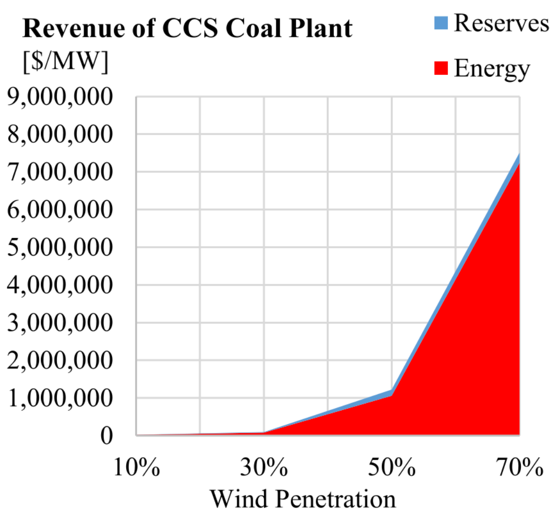
Figure 7-9: Operation of Dispatchable Generation Units, Base Case



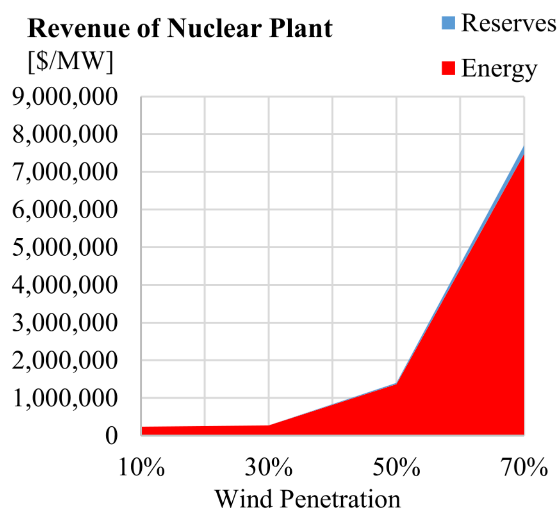
(a) Unabated Natural Gas combined cycle



(b) CCS-Equipped Natural Gas combined cycle



(c) CCS-Equipped Ultra-Supercritical Pulverized Coal



(d) Nuclear

Figure 7-10: Revenue from Energy and Reserves, Dispatchable Generation Units, Base Case factor. A capacity factor weighted value factor (hereafter, weighted value factor) of one indicates a generator operates as a perfect baseload generator with continuous output at full capacity. If prices are always positive, this generator captures all revenue from the system. If negative prices occur, weighted value factors greater than one are possible by avoiding negatively priced hours. Alternatively, weighted value factor could be defined in relation to all positive revenues from the system, keeping one as the maximum. This would represent a perfectly flexible generator able to shutdown for negatively priced hours and restart at full output once positive prices resume. Given the formulation of the UCCORE model, negative prices are not possible so the two definitions of weighted value factor are equivalent here. The weighted value factor is defined formally in Appendix B.

Applied to the test units, weighted value factor allows the direct comparison of the marginal revenues accrued by dispatchable and intermittent generation sources. In a perfect market, these marginal revenues are equal to the marginal economic value of the technologies to the system. Table 7.3 shows the weighted value factors of the test technologies at various penetrations of wind power. Wind's weighted value factor begins at its capacity factor since the energy it produces is of average value, but the weighted value factor declines as higher penetrations lead to both lower value per unit energy and a reduced capacity factor. The value factor of CCS-equipped plants increases due to a rise in both capacity factor and the average value of energy sold as balancing intermittent wind energy becomes more important to the grid. Nuclear operates closest to baseload operation for all penetrations of wind, reducing output only when the price of energy is close to zero and thus always captures nearly the maximum possible revenue. Unabated gas operates similarly due to its low variable cost.

Table 7.3: Generator Weighted Value Factors, Base Case

	Wind Penetration			
Technology	10%	30%	50%	70%
Wind	0.33	0.24	0.05	0.05
Solar	0.27	0.36	0.55	0.48
Coal CCS	0.09	0.29	0.77	0.96
Gas CCS	0.14	0.21	0.73	0.93
Nuclear	0.99	0.99	0.99	1.00
Gas	0.96	0.91	0.97	0.99

7.5 Sensitivity to Co-Optimized Reserve Market

The base case scenario was repeated, but without the co-optimized reserve market. The results show the importance of a market design that reflects the range of scarcity conditions in the price signal.

Without the ORDC, scarcity pricing is binary: the price either clears at the system marginal cost of production or at the VOLL. The effect on energy prices is an abrupt change from low prices insufficient to attract investment to extremely high prices after rolling blackouts are instituted. Figure 7-11 shows the development of prices as the penetration of intermittent energy increases. Prices are flat up until roughly 50% wind penetration, at which point the average price is pulled above the P90 price as infrequent rolling blackouts occur. Beyond 50% wind penetration, involuntary demand curtailments are frequent and prices rise to reflect scarcity. This is shown in Figure 7-12, which shows the price duration curve for the system. Figure 7-13a shows the same figure but with the axes scaled to show the maximum price and the binary nature of the pricing structure. Figure 7-13b shows the price duration curve corresponding to the base case on the same scale, demonstrating the ORDC's ability to allow prices to rise gradually with the risk of generation shortfalls.

Figure 7-14 shows plant profitability. No generator is profitable until involuntary demand curtailments begin to occur at 50% wind penetration when prices in a few hours of generation scarcity rise to VOLL making unabated and CCS-equipped combined cycle gas plants profitable as well as solar. At higher penetrations of wind,

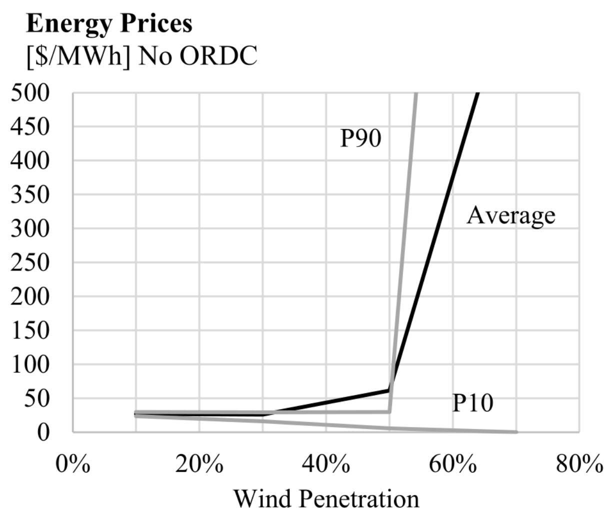


Figure 7-11: Effect of Wind Penetration on Energy Prices, No ORDC

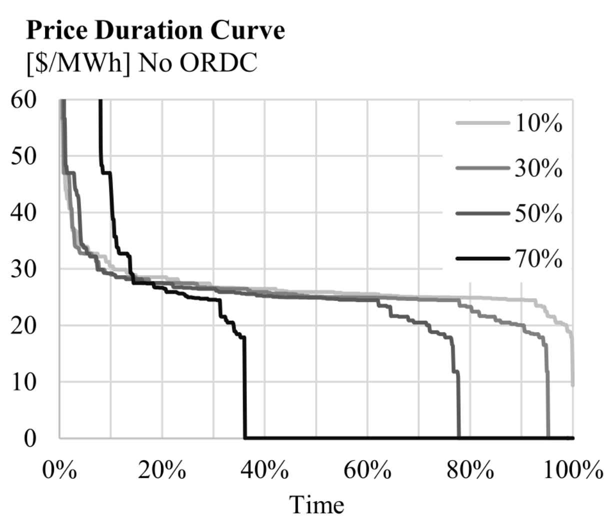
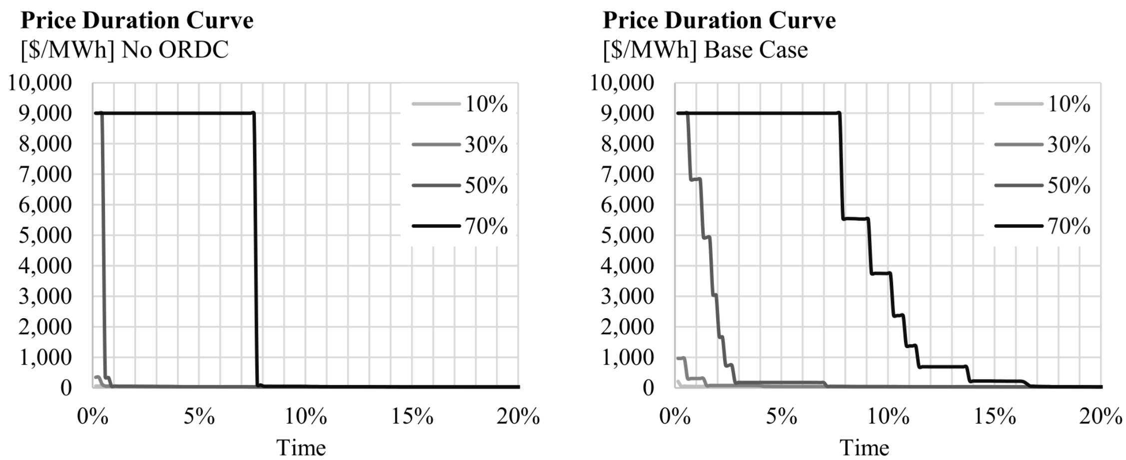


Figure 7-12: Price Duration Curves, No ORDC



(a) Without ORDC

(b) With ORDC

Figure 7-13: Effect of ORDC on Price Duration Curve

rolling blackouts become more frequent causing all generators to become very profitable, excepting wind.

Compared to the base case, prices rise more abruptly and only after involuntary demand curtailments are a certainty. The inclusion of the ORDC allows prices to rise more continuously as the *risk* of involuntary demand curtailments increases but before these events have a high probability of occurring. This change in pricing will have important implications for when new investments become profitable and the expected frequency of involuntary demand curtailments at a given VOLL.

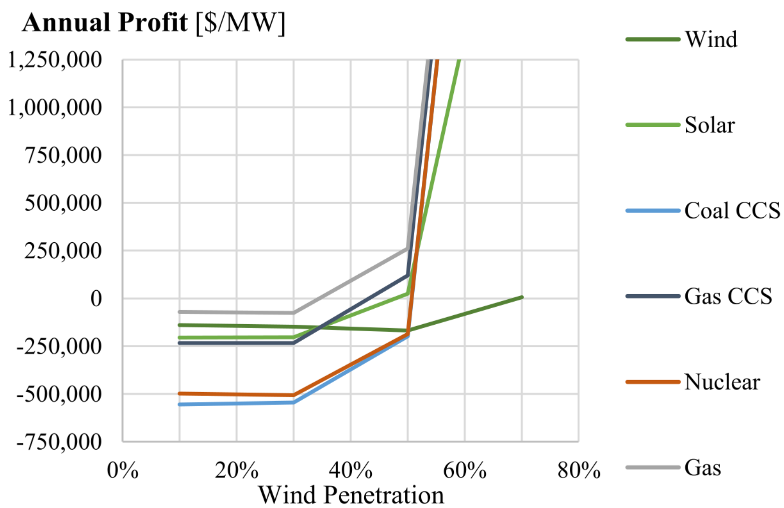


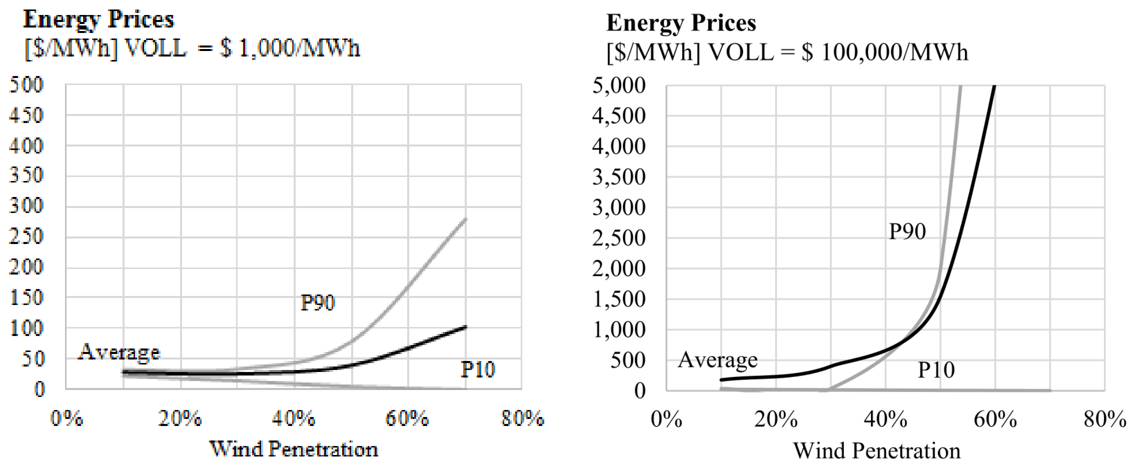
Figure 7-14: Effect of Wind Penetration on Generator Annual Profit, No ORDC

7.6 Sensitivity to VOLL

In developed power markets, consumers expect that rolling blackouts will almost never occur and planning on these events occurring regularly to remunerate generators would be politically unacceptable. While consumers might feel they would like a system that is perfectly reliable, there is some limit to the amount of resources they would be willing to spend for added reliability and some small amount of risk of insufficient generation capacity must be accepted. This willingness-to-pay for a reliable system is expressed through the VOLL explained in Chapter 4. The VOLL and the costs of available generation technologies will determine the expected frequency of loss of load events.

To assess the sensitivity of profitability to the VOLL, scenarios were run with VOLL set at $100,000/MWh and $1,000/MWh. All other parameters are as in the base case.

Figure 7-15 shows the progression of prices in the low and high VOLL scenarios. Prices increase less with wind penetration in the low VOLL case as the cost of involuntary demand curtailments is less, leading to a higher acceptable risk of generation shortfalls. Prices rise rapidly in the high VOLL case due to the low tolerance for risk of insufficient generation implied by the VOLL.

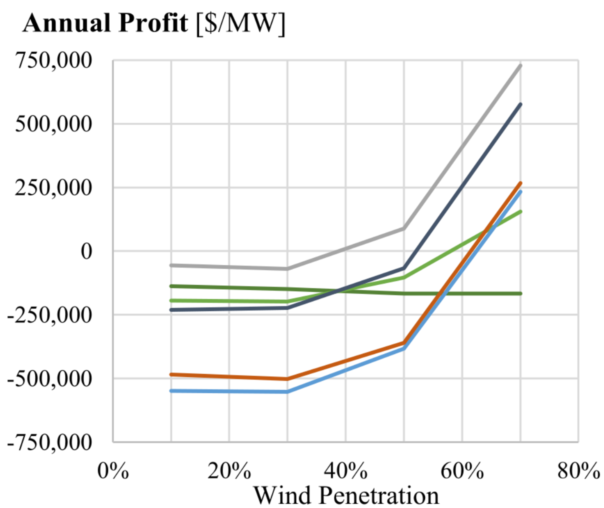


(a) VOLL = $1,000/MWh (b) VOLL = $100,000/MWh

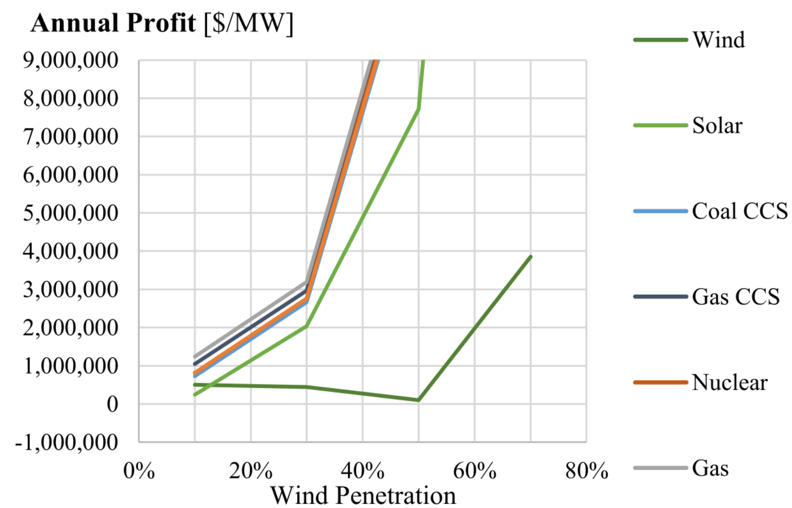
Figure 7-15: Effect of VOLL and Wind Penetration on Energy Prices

Generator profits are shown for both cases in Figure 7-16. In the low VOLL case, no generator is profitable until rolling blackouts begin to occur at 50% wind penetration. Of the dispatchable plants, unabated and CCS-equipped combined cycle gas turbines are the first to become profitable owing to their lower capital costs. In the high VOLL case, capital costs are dwarfed by revenue and the difference in profit between dispatchable generators are small, particularly at higher penetrations of wind power. In this case, profits converge into three cases, dispatchable power plants able to capture all of the highest revenue hours, solar, which happens to coincide with many high price hours, and wind. In the high VOLL case, generators are profitable before loss of load events occur, indicating in equilibrium investments in new capacity would be made to keep the risk of generation shortfalls much less than in the low VOLL case.

Table 7.4 shows the effect of assumed VOLL on generator weighted value factor. Changing VOLL does not affect the weighted value factor in systems with very low or high penetrations of intermittent capacity, but it does appreciably affect weighted value factor at intermediate penetrations. A higher VOLL leads to significant declines of the value of wind capacity at lower penetrations of wind energy. Simultaneously, a higher VOLL leads to an increase in the value of dispatchable capacity at lower wind penetrations.



(a) VOLL = $1,000/MWh



(b) VOLL = $100,000/MWh

Figure 7-16: Effect of VOLL and Wind Penetration on Generator Annual Profit

Table 7.4: Effect of VOLL on Generator Weighted Value Factors

(a) VOLL =$1,000/MWh

	Wind Penetration			
Technology	10%	30%	50%	70%
Wind	0.33	0.30	0.15	0.06
Solar	0.26	0.29	0.46	0.47
Coal CCS	0.04	0.13	0.47	0.93
Gas CCS	0.12	0.14	0.44	0.89
Nuclear	1.00	0.98	0.95	0.99
Gas	0.97	0.88	0.88	0.98

(b) VOLL =$100,000/MWh

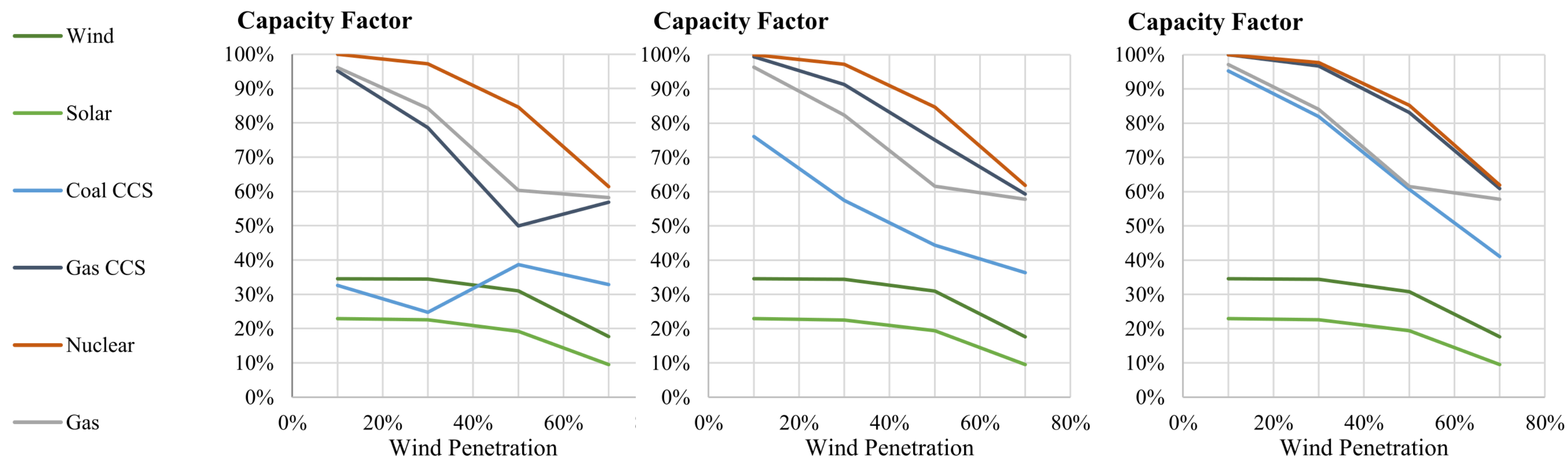
	Wind Penetration			
Technology	10%	30%	50%	70%
Wind	0.32	0.09	0.02	0.05
Solar	0.27	0.57	0.59	0.48
Coal CCS	0.12	0.64	0.84	0.97
Gas CCS	0.17	0.42	0.81	0.93
Nuclear	1.00	1.00	1.00	1.00
Gas	0.96	0.97	0.99	0.99

7.7 Sensitivity to Carbon Pricing

In the base case, low-carbon generators compete directly with unabated generators. Given their higher variable costs, CCS-equipped plants operate at low capacity factors to cover peak load. To examine the sensitivity of profitability to carbon pricing, scenarios were run with carbon prices of \$30, \$60, and \$90 per tonne of CO_2. The additional cost of CO_2 emissions was calculated using the carbon dioxide emissions coefficients published by the EIA and an assumed 90% capture rate for CCS units.[125]

Adding a price on CO_2 emissions increases the capacity factor and profits of CCS-equipped generators. In the base case, CCS-equipped gas and coal plants operated as peaking plants due to their higher variable costs compared to the unabated plants on the system. Figure 7-17 shows how generators' capacity factors change with carbon price. Assuming the fuel prices and efficiencies used in the base case, CCS-equipped natural gas combined cycle plants have a lower variable cost than their unabated counterparts at a carbon price greater than or equal to \$37/tCO_2. Above this price, CCS-equipped gas plants will be dispatched more often than unabated gas plants as seen in Figure 7-17b. At a carbon price of \$90/tCO_2, the CCS-equipped gas plant was operated nearly as frequently as the nuclear plant. The variable cost of the nuclear plant is lower than any fossil-fuel plant regardless of carbon price, thus its dispatch is relatively unaffected by carbon price. In all cases, the nuclear plant operates at full capacity except for hours when wind and solar alone can meet demand, in which case it reduces output to minimum stable load.

Figure 7-18 shows generator profits at various carbon prices. As would be expected, implementing a carbon price in a system comprised primarily of fossil-fuel generators increases the profits of all prospective low-carbon generators by increasing the variable costs of existing generators and thereby elevating market prices. Despite the carbon price, unabated natural gas combined cycle generators remain the most profitable plants even at a carbon price of \$90/tCO_2 due to their lower capital and fixed costs. Table 7.5 shows the impact of carbon pricing on generator value factor. As previously discussed, the value of CCS-equipped generators increases due to an improved standing in the economic merit order.



(a) Carbon Price = $30/tCO_2$ (b) Carbon Price = $60/tCO_2$ (c) Carbon Price = $90/tCO_2$

Figure 7-17: Effect of Carbon Price and Wind Penetration on Capacity Factors

Table 7.5: Effect of Carbon Pricing on Generator Weighted Value Factors

(a) Carbon Price = $30/tCO_2$

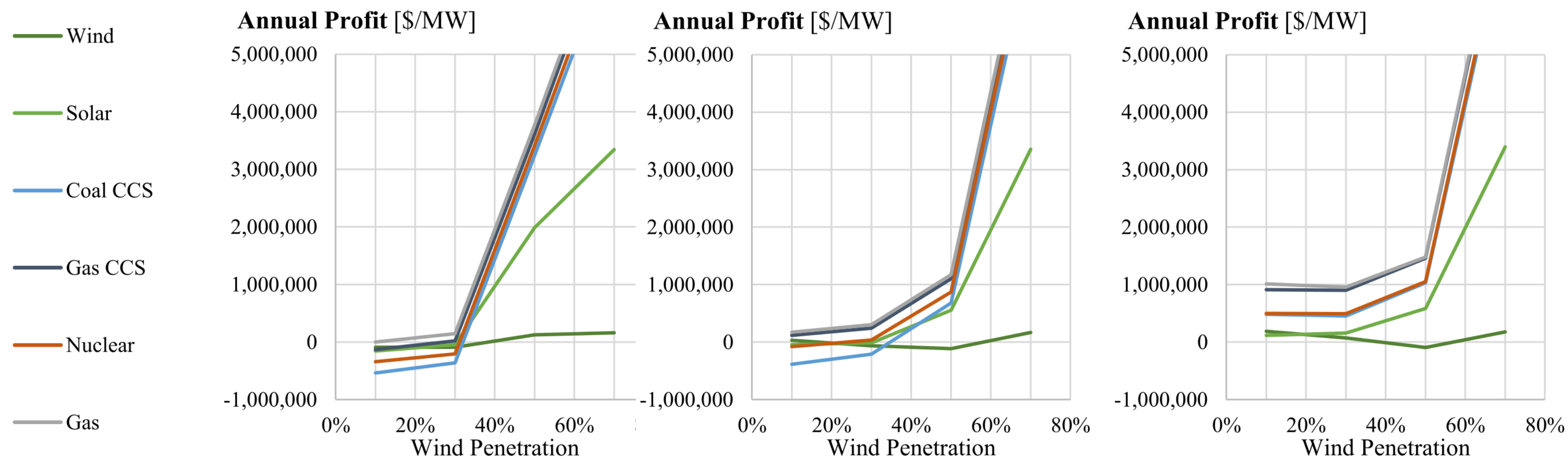
	Wind Penetration			
Technology	10%	30%	50%	70%
Wind	0.33	0.24	0.08	0.05
Solar	0.27	0.42	0.55	0.48
Coal CCS	0.41	0.48	0.96	0.98
Gas CCS	0.96	0.92	0.91	0.99
Nuclear	1.00	1.00	1.00	1.00
Gas	0.97	0.94	0.98	0.99

(b) Carbon Price = $60/tCO_2$

	Wind Penetration			
Technology	10%	30%	50%	70%
Wind	0.38	0.20	0.07	0.05
Solar	0.34	0.32	0.53	0.48
Coal CCS	0.85	0.81	0.93	0.99
Gas CCS	0.99	0.98	0.98	0.99
Nuclear	1.00	1.00	1.00	1.00
Gas	0.98	0.94	0.97	0.99

(c) Carbon Price = $90/tCO_2$

	Wind Penetration			
Technology	10%	30%	50%	70%
Wind	0.34	0.23	0.08	0.05
Solar	0.37	0.40	0.51	0.48
Coal CCS	0.97	0.94	0.97	0.99
Gas CCS	1.00	0.99	0.99	0.99
Nuclear	1.00	1.00	1.00	1.00
Gas	0.98	0.94	0.96	0.99



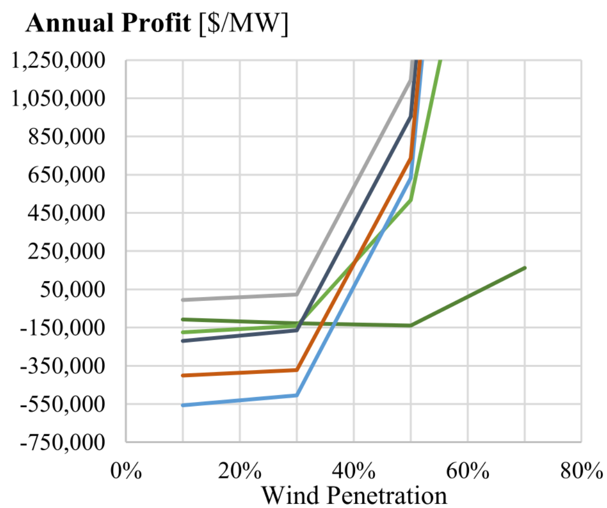
(a) Carbon Price = $30/tCO_2$ (b) Carbon Price = $60/tCO_2$ (c) Carbon Price = $90/tCO_2$

Figure 7-18: Effect of Carbon Price and Wind Penetration on Generator Annual Profit

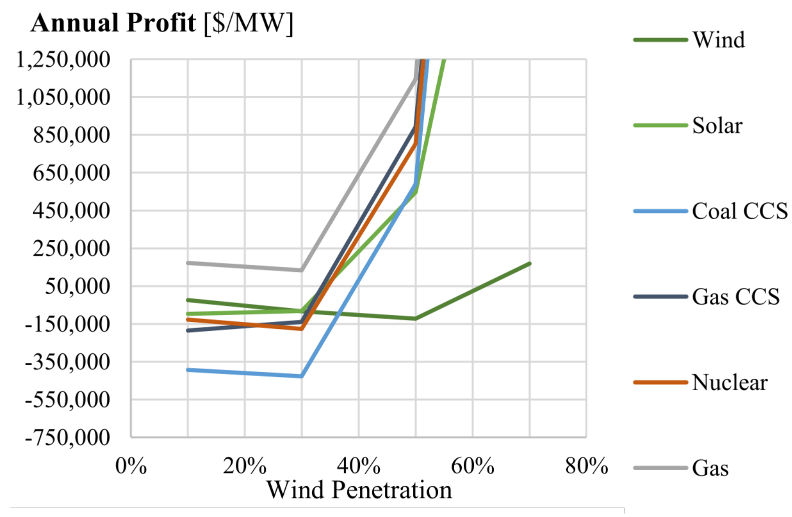
7.8 Sensitivity to Fuel Price

The base case applies 2015 fuel prices for generators in Texas. The EIA Annual Energy Outlook provides perspectives based on various assumptions of oil and gas price. The EIA's assumptions for high oil and gas prices and the reference case are above the current Texas prices. Assumptions based on the Annual Energy Outlook long-term price ranges are adopted to test the sensitivity of results to fuel price. Base assumptions for fuel prices are based on generator reporting and average $2.8/MMBTU for natural gas and $35/bbl for oil. In the moderate fuel price scenario prices are $5/MMBTU for natural gas and $109/bbl for oil. The high cost scenario assumes $10/MMBTU for natural gas and and $226/bbl for oil.[112] EIA assumes the price of coal is decoupled from the price of gas, so it is not altered in these scenarios.

Figure 7-19 shows the effect of higher oil and gas prices on generator profits. Natural gas with CCS becomes less competitive and nuclear becomes relatively more competitive. Coal plants with CCS are operated more frequently in high oil and gas price scenarios, approaching the capacity factor of nuclear, however, profits increase more slowly than for nuclear power owing to higher variable costs. Table 7.6 shows the effect of fuel price on weighted value factor. Fuel price has the greatest effect on weighted value factors at low penetrations of wind. Coal becomes relatively more valuable, owing to the aforementioned higher capacity factor, while the weighted value factors for gas fired plants decrease.



(a) Moderate Fuel Price



(b) High Fuel Price

Figure 7-19: Effect of Fuel Price and Wind Penetration on Generator Profits

Table 7.6: Effect of Fuel Price on Generator Weighted Value Factors

(a) Moderate Fuel Price

	Wind Penetration			
Technology	10%	30%	50%	70%
Wind	0.33	0.25	0.05	0.05
Solar	0.27	0.35	0.55	0.48
Coal CCS	0.32	0.43	0.89	0.99
Gas CCS	0.08	0.14	0.75	0.94
Nuclear	1.00	0.99	0.99	1.00
Gas	0.69	0.64	0.93	0.99

(b) High Fuel Price

	Wind Penetration			
Technology	10%	30%	50%	70%
Wind	0.32	0.24	0.07	0.05
Solar	0.28	0.33	0.56	0.48
Coal CCS	1.00	0.98	0.99	1.00
Gas CCS	0.10	0.14	0.72	0.95
Nuclear	1.00	0.97	0.99	1.00
Gas	0.65	0.58	0.90	0.99

7.9 Discussion

The UCCORE model demonstrates the mechanism through which new dispatchable generators, traditionally envisioned as baseload facilities, could operate profitably in a volatile market with significant intermittent generation despite lower capacity factors. The model demonstrates that differences in the revenue received by different production profiles could be quite large, particularly if policies continue to push investment only in intermittent capacity.

It is important to note that the exceptionally high energy prices and revenues shown in scenarios with high penetrations of wind represent systems far from equilibrium. In the scenarios, wind capacity is increased exogenously, representing, for example, a policy of subsidizing investment in wind capacity. Eventually, these scenarios present systems ill suited to meeting electricity demand. In reality there would be feedback mechanisms to illicit a market or political response before these scenarios and high prices manifest. These scenarios, however, are important for demonstrating the limitations of models that do not properly account for the difference in generator value arising from hourly volatility. This work proposes the use of the weighted value factor to distinguish between the relative value of generation technologies in power markets and profit to compare the net of market value and private costs.

When generators receive efficient price signals based on the current VOLL, revenues reach an inflection point between 30% and 50% wind energy penetration. In the base case, CCS-equipped natural gas combined cycle achieves profitability at the lowest penetration of wind capacity, just beyond 30%. CCS gas is followed by solar, then nuclear and coal CCS. Figure 7-20 shows a snapshot of their relative profitability at 50% wind penetration, just beyond the point at which the first low-carbon generator is profitable. Forcing higher proportions of wind capacity beyond 30-50% result in wildly volatile prices and dispatchable generators capture enormous prices while prices when wind is abundant remain low. Between these penetrations the weighted value factor of wind drops precipitously from 0.24 to 0.05 in the base case presented here. In the absence of storage, this result indicates that, beyond this penetration,

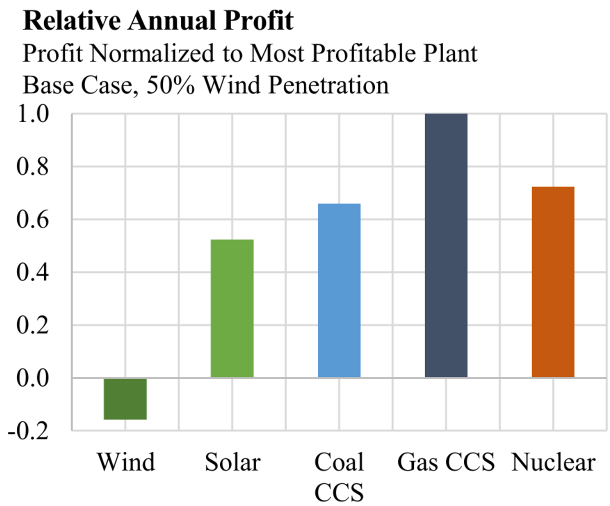


Figure 7-20: Normalized Annual Profit of Low-Carbon Generators, Base Case - 50% Wind Penetration

additional wind capacity will not contribute much value to the power system, regardless of its cost. This drop in value occurs before large drops in the capacity factor of wind. Though the system is able to accommodate additional wind energy in this domain, it is primarily displacing economically efficient generation such as combined cycle gas and nuclear and not contributing during peak conditions, making the added energy of little value. This implies using curtailment alone to discount the value of wind capacity in a high wind penetration system will overvalue the wind capacity. In general, this result is not dependent on the assumed VOLL. The weighted value factor for generators tend toward the same values at each VOLL in the cases of either low or very high wind penetrations. Assumed VOLL does affect the weighted value factor in intermediate cases; increasing the VOLL accelerates the decline in weighted value factor for wind as a higher VOLL increases the relative value of contributing to scarcity reduction. This implies that in equilibrium, systems with a higher VOLL would build less intermittent capacity.

The weighted value factor of dispatchable technologies increase with wind penetration, approaching one at high penetrations. CCS-equipped coal and gas plants begin with lower value factors due to reduced capacity factors, but at the same inflection point when the weighted value factor of wind declines rapidly, these units increase in value owing to both a higher capacity factor and the higher relative value of contributing during peak hours. Nuclear units operate at nearly all hours in which the price of energy is above zero, capturing all available revenues and thus maintaining a weighted value factor of approximately one at all wind penetrations. The value factors of fossil-fuel units are dependent on the relative cost of fuels, though the trend towards a value factor of one at high wind penetrations remains regardless. In the case of high gas prices, the coal CCS unit operates similarly to the nuclear plant, entering the market early in the merit order given a variable cost lower than that of unabated gas. Similarly, including a carbon price increases the value of factor of CCS-equipped units by improving their rank in the merit order.

This analysis has also shown the importance of market design for the relative competitiveness of generators and investment in generation capacity. If markets do not implement more continuous scarcity signals, such as though the ORDC, investment in dispatchable capacity may not occur until involuntary demand curtailments are regular occurrences. Without the ORDC, scarcity pricing occurs only when there is a generation shortfall, thus the weighted value factor of CCS-equipped generators remains quite low until shortfalls occur. For the same reason, the value factor of wind remains higher in systems with intermediate wind penetrations. Without proper scarcity signals generators are not rewarded for their contribution to avoidance of loss of load. Naturally, increasing the VOLL is shown to be an effective market mechanism for reducing the risk of generation shortfalls by elevating prices to induce more investment.

Finally, the UCCORE model confirms that an efficient price signal would be more volatile in markets with high penetrations of wind capacity. It is expected that similar effects would be observed in systems with high penetrations of solar capacity. This has important implications for power system economic models as at higher penetrations of intermittent capacity the assumption of a uniform value for electricity becomes increasingly weak. Particularly at high penetrations of intermittent capacity, it becomes important that these models have the temporal resolution to incorporate the effects of volatility. Future work could implement the ORDC into investment equilibrium models, though this would require sophisticated models able to capture both the long time horizon of generation investments and the hourly market volatility that this work has shown to become a crucial determinant of revenues and overall profitability. This limitation could potentially be overcome using bottom-up models to construct approximate curves of generators' weighted value factors under various market conditions for use as inputs into larger economic models.

Chapter 8

Conclusions

This thesis set out to assess the effects of increasing penetrations of intermittent generation capacity on the operation and economic competitiveness of new CCS-equipped fossil-fuel and nuclear generation capacity. Popular thinking suggests these generators will become less competitive as the costs of wind and solar generation fall and increasing intermittent capacity decreases the capacity factors of these power plants, conventionally envisioned as baseload power. This neglects the relative value of generators owing to their distinct production profiles and the temporal variation of electricity value. This thesis makes several contributions to the understanding of the relationship between intermittent capacity and the competitiveness of CCS-equipped fossil-fuel and nuclear generation capacity and can inform future inquiries on the subject.

First, this work connects increased penetrations of intermittent capacity with energy price volatility. Coordinated output of renewable generators at the same marginal cost adds a fluctuating amount of elasticity to the energy supply curve. Higher penetrations of wind cause this supply curve fluctuation to lead to larger price swings. Since energy prices are the primary economic signal to which dispatchable generators respond, increased price volatility leads to more volatile operation for all dispatchable generators. Joskow first introduced the problem of comparing intermittent to dispatchable generators noting that generators appropriately earn distinct revenues based on the distinct value of their production profiles.[15] Market data simulated using the UCCORE model shows that the difference in value captured by a generator's production profile is substantial and increases with market volatility. This results builds on Joskow's introduction showing the underlying assumption that electricity is of homogenous value becomes weaker as intermittent capacity is added to the system and price volatility increases. Many power system models and comparisons of competitiveness from cost-based metrics such as LCOE implicitly rely on this assumption.

Second, this work presents a review of the latest literature on generator flexibility and costs. This information is condensed into parameters that can be readily adopted by unit commitment or other power system models, making it a useful resource.

Third, UCCORE scenarios with and without the ORDC introduced by Hogan[68] show the importance of continuous scarcity price signals for attracting new investment. By sending an appropriate short-term price signal, the ORDC allows new capacity to become profitable as the generation shortfalls become more likely, but before they are a certainty. Without the ORDC, or another mechanism of sending more continuous scarcity signals, profitability for new capacity investments is shown to occur only after the system is experiencing generation shortfalls with some regularity. Given the political unacceptability of rolling blackouts in developed systems, the likely result is to resort to out-of-market mechanisms to support capacity, creating a further disconnect between market signals and investment.

Fourth, building on Hirth, this work introduces the concept of the weighted value factor, the product of a generator's capacity factor and value factor as defined by Hirth.[47] The weighted value factor is the ratio of the revenue a generator receives to the revenues the generator would receive for operating at full capacity at all hours or at all hours for which electricity has a positive value. For a marginal generator in an efficient market, the revenues received are equivalent to the generator's value to the system. The weighted value factor could be used in conjunction with cost to compare the economic competitiveness of generators in a manner that accounts for the distinct value the generators provide.

Finally, this thesis begins to quantify the relative competitiveness of generation technologies in a competitive market with efficient short-term pricing signals using the UCCORE model. The scenario analysis conducted using the UCCORE model suggests that natural gas combined cycle generation equipped with CCS tends to be the most profitable generation technology with a low-carbon intensity and the first to reach positive profitability with increasing wind penetration. This result is robust to tested assumptions for carbon price and fuel price. CCS-equipped natural gas combined cycle benefits from its ability to capture prices during peak hours, common to all dispatchable generators and increasingly important in volatile systems, coupled with annuitized capital and fixed O&M cost half that of either CCS-equipped coal or nuclear power plants. Relative competitiveness will depend on a combination of fuel price, capital and fixed O&M costs, and flexibility, but these results suggest reducing capital and fixed O&M costs are particularly important for CCS-equipped coal and nuclear power plants to become competitive with CCS-equipped natural gas combined cycle as a source of dispatchable, low-carbon power. The results also show the reduced value of intermittent power sources. At the low penetrations explored here, the value of solar remains high due to a positive correlation with peak demand and a slight negative correlation with wind availability. The relative value of wind is much lower than dispatchable generators or low penetration solar and decreases with wind penetration faster than capacity factor alone. The implication of these results is that assessments that assume a constant value of electricity or do not adequately capture the volatility of efficient real-time pricing may undervalue dispatchable capacity and overvalue intermittent capacity, particularly in systems with large amounts of intermittent resources.

Future work could focus on incorporating these results into long-term investment models in which capacity investments reach an equilibrium. Investment models that do not account for the distinct value of the electricity produced by different generators, as demonstrated in this work, will undervalue dispatchable resources and overvalue intermittent sources. Expanding investment models to include the detailed hourly data necessary to directly capture the effects of volatility may lead to models too computationally intensive to be of use. A possible solution could be constructing weighted value factor curves from historical data and additional unit commitment case studies for use as an input for long-term investment models. This would allow long-term models to approximate the differences in value arising from hourly price volatility while considering an investment time horizon. Finally, future work should explore the effect of increased intermittency on the value of other solutions beyond dispatchable capacity and their relative competitiveness. The framework developed in this thesis could be applied to assess the value of energy storage or demand response options.

Appendix A

UCCORE Formulation

The UCCORE formulation is based on formulations presented in [121, 126]

A.1 Notation

A.1.1 Indicies and Sets

$h \in H$	where h denotes an hour in H the set of hours
$h' \in H$	where h' denotes an hour in H the set of hours
$g \in G$	where g denotes a generator in G the set of generators
$T \subset G$	where T denotes the subset of thermal generators
$S \subset G$	where S denotes the subset of solar generators
$W \subset G$	where W denotes the subset of wind generators
$HY \subset G$	where HY denotes the subset of hydro generators
$i \in I$	where i denotes a segment of the linearized loss of energy expectation curve in I the set of segment

A.1.2 Scalars

VOLL	Value of Lost Load [$/MWh]
Hydro	Hydro reserve allotment [MWh]
Loss	Average losses [%]

A.1.3 Parameters

System Parameters	
D_h	Demand in hour h [GW]
SA_h	Solar availability factor in hour h [%]
WA_h	Wind availability factor in hour h [%]
Generator Parameters	
IC_g	Initial condition of generator g [0,1]
VC_g	Variable cost of generator g [$/MWh]
SUC_g	Start-up cost of generator g [$k]
$Qmax_g$	Maximum output (net capacity) of generator g [GW]
$Qmin_g$	Minimum stable load of generator g [GW]
MU_g	Minimum up-time of generator g [h]
MD_g	Minimum down-time of generator g [h]
R_g	Maximum ramp rate of generator g relative to $Qmax_g$ [%/h]
Linearized Loss of Energy Expectation Parameters	
xi_i	Initial x-value for LOEE segment i
xf_i	Final x-value for LOEE segment i
m_i	Slope of LOEE segment i
$f(xi_i)$	LOEE value for initial x-value of LOEE segment i

A.1.4 Variables

System Variables	
$C \in \mathbb{R}$	System cost [$k]
$NSE_h \in \mathbb{R}_+$	Non-served energy in hour h due to dispatch [GWh]
$LOEE_h \in \mathbb{R}_+$	Loss of energy expectation in hour h due to reserves [GWh]
$R_h \in \mathbb{R}_+$	Reserves supplied in hour h [GWh]
Generator Variables	
$Qg_{h,g} \in \mathbb{R}_+$	Generation in hour h of generator g [GWh]
$Qg'_{h,g} \in \mathbb{R}_+$	Generation above $Qmin_g$ in hour h of generator g [GWh]
$Qr_{h,g} \in \mathbb{R}_+$	Reserves supplied in hour h by generator g [GWh]
$UC_{h,g} \in \{0,1\}$	Unit commitment decision in hour h for generator g
$SUD_{h,g} \in \{0,1\}$	Start-up decision in hour h for generator g
$SDD_{h,g} \in \{0,1\}$	Shut down decision in hour h for generator g
Linearized Loss of Energy Expectation Variables	
$Ri_h, i \in \mathbb{R}_+$	Reserves supplied in hour h in LOEE segment i [GWh]
$Z_h, i \in \{0,1\}$	Selection in hour h of LOEE segment i

A.2 Formulation

Objective Function

$$\min \sum_{h \in H} \sum_{g \in G} (VC_g \cdot Qg_{h,g} + SUC_g \cdot SUD_{h,g}) + VOLL \cdot (NSE_h + LOEE_h) \tag{A.1}$$

s.t.

Linearized Loss of Energy Expectation

$$LOEE_h = \sum_{i \in I} \left[f(xi_i) \cdot Z_{h,i} + \left(\frac{Ri_{h,i}}{Dh} - xi_i \cdot Z_{h,i} \right) \cdot m_i \right] D_h \qquad \forall h \in H \tag{A.2}$$

Demand Balance

$$\sum_{g \in G} Qg_{h,g} \cdot (1 - Loss) = D_h - NSE_h \qquad \forall h \in H \tag{A.3}$$

Reserve Balance

$$\sum_{g \in G} Qr_{h,g} = R_h \qquad \forall h \in H \tag{A.4}$$

Reserve Segmentation

$$\sum_{i \in I} Ri_{h,i} = R_h \qquad \forall h \in H \tag{A.5}$$

Unit Initial Conditions

$$IC_t - UC_{h,g} + SUD_{h,g} - SDD_{h,g} = 0 \qquad \forall g \in T, h = 1 \tag{A.6}$$

Unit Operation Logic

$$UC_{h-1,g} - UC_{h,g} + SUD_{h,g} - SDD_{h,g} = 0 \qquad \forall g \in T, h > 1 \tag{A.7}$$

Unit Total Generation

$$Qg_{h,g} = Qmin_g \cdot UC_{h,g} + Qg'_{h,g} \qquad \forall h \in H, g \in T \tag{A.8}$$

Unit Capacity

$$Qg_{h,g} + Qr_{h,g} \leq Qmax_g \cdot UC_{h,g} \qquad \forall h \in H, g \in G \tag{A.9}$$

Unit Generation Limit

$$Qg_{h,g} \geq Qmin_g \cdot UC_{h,g} \qquad \forall h \in H, g \in T \tag{A.10}$$

Unit Reserve Limit

$$Qr_{h,g} \leq \left(R_g - \frac{(Qg_{h+1,g} - Qg_{h.g})}{Qmax_g} \right) \frac{Qmax_g}{6} \qquad \forall h \in H, g \in G \quad \text{(A.11)}$$

Unit Reserve Limit

$$Qr_{h,g} \leq Qmax_g \cdot UC_{h,g} \qquad \forall h \in H, g \in G \quad \text{(A.12)}$$

Solar Reserve Limit

$$Qr_{h,g} = 0 \qquad \forall h \in H, g \in S \quad \text{(A.13)}$$

Wind Reserve Limit

$$Qr_{h,g} = 0 \qquad \forall h \in H, g \in W \quad \text{(A.14)}$$

Unit Ramp Up Limit

$$Qg'_{h,g} \leq Qg'_{h-1,g} + (R_g \cdot Qmax_g) \qquad \forall h \in H, g \in T \quad \text{(A.15)}$$

Unit Ramp Down Limit

$$Qg'_{h,g} \geq Qg'_{h-1,g} - (R_g \cdot Qmax_g) \qquad \forall h \in H, g \in T \quad \text{(A.16)}$$

Minimum Up-Time

$$\sum_{h' \in \{h,\ldots,h+MU_g\}} (UC_{h',g} - SUD_{h,g}) \geq 0 \qquad \forall h \in H, g \in T \quad \text{(A.17)}$$

Minimum Down-Time

$$\sum_{h' \in \{h,\ldots,h+MD_g\}} (1 - UC_{h',g} - SDD_{h,g}) \geq 0 \qquad \forall h \in H, g \in T \quad \text{(A.18)}$$

Solar Availability Limit

$$Qg_{h,g} \leq Qmax_g \cdot UC_{h,g} \cdot SA_h \qquad \forall g \in S \quad \text{(A.19)}$$

Wind Availability Limit

$$Qg_{h,g} \leq Qmax_g \cdot UC_{h,g} \cdot WA_h \qquad \forall g \in W \quad \text{(A.20)}$$

Hydro Allotment

$$\sum_{h \in H} Qg_{h,g} \leq Hydro \qquad \forall g \in HY \quad \text{(A.21)}$$

Linearized LOEE Segment Selection

$$\sum_{i \in I} Z_{h,i} = 1 \qquad \forall h \in H \quad \text{(A.22)}$$

Segment Initial Point Selection

$$\frac{Ri_{h,i}}{D_h} \geq xi_i \cdot Z_{h,i} \qquad \forall h \in H, i \in I \quad \text{(A.23)}$$

Segment Final Point Selection

$$\frac{Ri_{h,i}}{D_h} \leq xf_i \cdot Z_{h,i} \qquad \forall h \in H, i \in I \quad \text{(A.24)}$$

Appendix B

Weighted Value Factor

The capacity factor weighted value factor (weighted value factor) is the product of a generator's capacity factor and value factor, as defined by Hirth [47].

$$\text{Weighted Value Factor} = \text{Capacity Factor} \cdot \text{Value Factor} \tag{B.1}$$

Decomposing capacity factor (Equations 2.1 and 2.2) and value factor:

$$\text{Weighted Value Factor} = \frac{\sum\limits_{h \in H} G(h)}{|H| \cdot C} \cdot \frac{\sum\limits_{h \in H} G(h) \cdot Pe(h)}{\sum\limits_{h \in H} G(h)} \cdot \left(\frac{\sum\limits_{h \in H} Pe(h)}{|H|} \right)^{-1} \tag{B.2}$$

Where

h is hour

H is the set of hours in the period

$|H|$ is the number of hours in the set H

C is capacity

$G(h)$ is generation in hour h

$Pe(h)$ is the price of energy in hour h

Simplifying Equation B.2:

$$\text{Weighted Value Factor} = \frac{\sum_{h \in H} G(h) \cdot Pe(h)}{C \cdot \sum_{h \in H} Pe(h)} \tag{B.3}$$

Intuitively, Equation B.3 is the ratio of revenue captured by a generator to the revenue of an equally sized generator capturing all revenue, that is producing at full capacity constantly. In a system with only positive prices, the maximum weighted value factor is one.

If the system includes negative prices, Equation B.3 creates an opportunity for weighted value factors above one for generators reducing dispatch during negatively priced hours. Equation B.3 can be redefined as the ratio of generator revenue to the *maximum* revenue captured by an equally sized generator. This is more intuitive and maintains a theoretical maximum of one.

$$\text{Weighted Value Factor} = \frac{\sum_{h \in H} G(h) \cdot Pe(h)}{C \cdot \sum_{h \in H | Pe(h) > 0} Pe(h)} \tag{B.4}$$

Where $h \in H|Pe(h) > 0$ is all hours in the set H for which $Pe(h)$, the price of energy, is greater than zero.

Bibliography

[1] Mariano Ventosa, Pedro Linares, and Ignacio J. Pérez-Arriaga. Power System Economics. In Ignacio J. Pérez-Arriaga (Ed.), *Regulation of the Power Sector*. Springer, 2013.

[2] NRC. Capacity Factor, 2017. URL https://www.nrc.gov/reading-rm/basic-ref/glossary/capacity-factor.html.

[3] Nuclear Energy Institute. U.S. Nuclear Fleet Capacity, 2017.

[4] Tyler Hodge. Average Utilization for Natural Gas Combined-Cycle Plants Exceeded Coal Plants in 2015, EIA, 2016. URL https://www.eia.gov/todayinenergy/detail.php?id=25652.

[5] EIA. Levelized Cost of Electricity and Levelized Avoided Cost of Electricity Methodology Supplement, 2013.

[6] IEA. Projected Costs of Generating Electricity, 2015.

[7] Edward S. Rubin. Understanding the Pitfalls of CCS Cost Estimates. *International Journal of Greenhouse Gas Control*, 10, 2012.

[8] NREL. Cost and Performance Assumptions for Modeling Electricity Generation, 2010.

[9] NREL. Simple Levelized Cost of Energy (LCOE) Calculator Documentation, 2013. URL http://www.nrel.gov/analysis/tech_lcoe_documentation.html.

[10] EIA. Assumptions to the Annual Energy Outlook 2015, 2015.

[11] Edward S. Rubin, John E. Davison, and Howard J. Herzog. The cost of CO_2 Capture and Storage. *International Journal of Greenhouse Gas Control*, 40, 2015.

[12] EIA. Natural Gas Prices, 2017. URL https://www.eia.gov/dnav/ng/ng_pri_sum_dcu_nus_a.htm.

[13] EIA. Table 34. Average Price of Coal Delivered to End Use Sector by Census Division and State, 2015 and 2014. URL https://www.eia.gov/coal/annual/pdf/table34.pdf.

[14] Steven Stoft. *Power System Economics*. IEEE Press, 2002.

[15] Paul L. Joskow. Comparing the Costs of Intermittent and Dispatchable Electricity Generating Technologies. *The American Economic Review*, 100(3), 2011.

[16] Michael Rivier, Ignacio J. Pérez-Arriaga, and Luis Olmos. Regulation of the Electric Power Sector. In Ignacio J. Pérez-Arriaga (Ed.), *Regulation of the Power Sector*. Springer, 2013.

[17] MIT. Utility of the Future, 2016.

[18] Erik Ela, Michael Milligan, and Brendan Kirby. Operating Reserves and Variable Generation, NREL, 2011.

[19] DOE. Economic Dispatch of Electric Generation Capacity, 2007.

[20] Carlos Batlle and Carlos Ocaña. Regulation of the Electric Power Sector. In Ignacio J. Pérez-Arriaga (Ed.), *Regulation of the Power Sector*. Springer, 2013.

[21] Fred C. Schweppe, Michael C. Caramanis, Richard D. Tabors, and Roger E. Bohn. *Spot Pricing Electricity*. Kluwer Academic Publishers, 1988.

[22] William Hogan. A Competitive Electricity Market Model, 1993.

[23] Friedrich Hayek. The Use of Knowledge in Society. *The American Economic Review*, 35(4), 1945.

[24] Adam Smith. *An Inquiry into the Nature and Causes of the Wealth of Nations*. Methuen & Co., Ltd., 1904.

[25] EPA. State-Level Hourly Sulfur Dioxide Data, 2015. URL `https://www.epa.gov/air-emissions-modeling/state-level-hourly-sulfur-dioxide-so2-data`.

[26] EIA. Table 4.2B. Existing Net Summer Capacity of Other Renewable Sources by Producer Type, 2005 through 2015, 2016. URL `https://www.eia.gov/electricity/annual/html/epa_04_02_b.html`.

[27] EIA. Table 1.1A. Net Generation from Renewable Sources: Total, 2017. URL `https://www.eia.gov/electricity/monthly/epm_table_grapher.php?t=epmt_1_01_a`.

[28] EIA. Table 1.1. Net Generation by Energy Source: Total, 2017. URL `https://www.eia.gov/electricity/monthly/epm_table_grapher.php?t=epmt_1_01`.

[29] EIA. Annual Energy Outlook with Projection to 2050, 2017.

[30] EIA. Existing Nameplate and Net Summer Capacity by Energy Source, Producer Type and State, 2016. URL https://www.eia.gov/electricity/data/state/.

[31] EIA. Net Generation by State by Type of Producer by Energy Source, 2016. URL https://www.eia.gov/electricity/data/state/.

[32] DOE. Renewable Electricity Production Tax Credit. URL https://energy.gov/savings/renewable-electricity-production-tax-credit-ptc.

[33] DOE. Business Investment Tex Credit. URL https://energy.gov/savings/business-energy-investment-tax-credit-itc.

[34] Jocelyn Durkav. State Renewable Portfolio Standards and Goals, NCSL, 2017. URL http://www.ncsl.org/research/energy/renewable-portfolio-standards.aspx.

[35] EPA. Renewable Energy Certificates. URL https://www.epa.gov/greenpower/renewable-energy-certificates-recs.

[36] Michael Gillenwater, Xi Lu, and Miriam Fischlein. Additionality of Wind Energy Investments in the U.S. Voluntary Green Power Market. *Renewable Energy*, 63, 2014.

[37] Ran Fu, Donald Chung, Travis Lowder, David Feldman, Kristen Ardani, and Robert Margolis. U.S. Solar Photovoltaic System Cost Benchmark: Q1 2016, NREL, 2016.

[38] Christopher Mone, Maureen Hand, Mark Bolinger, Joseph Rand, Donna Heimiller, and Jonathan Ho. 2015 Cost of Wind Energy Review, NREL, 2017.

[39] Bhaskar Gunturu and C. Adam Schlosser. Characterization of the Wind Power Resource in the United States and its Intermittency, MIT Joint Program, 2011.

[40] Alexandra Cosseron, C. Adam Schlosser, and U. Bhaskar Gunturu. Characterization of the Wind Power Resource in Europe and its Intermittency, MIT Joint Program, 2014.

[41] EIA. Updated Capital Cost Estimates for Utility Scale Electricity Generating Plants, 2013.

[42] EIA. Updated Capital Cost Estimates for Utility Scale Electricity Generating Plants, 2016.

[43] CAISO. What the Duck Curve Tells us About Managing a Green Grid, 2016.

[44] Paul Denholm, Matthew O'Connell, Gregory Brinkman, and Jennie Jorgenson. Overgeneration from Solar Energy in California: A Field Guide to the Duck Chart, NREL, 2015.

[45] Christ Namovicz. Rising Solar Generation in California Coincides with Negative Wholesale Electricity Prices, EIA, 2017. URL `https://www.eia.gov/todayinenergy/detail.php?id=30692`.

[46] MIT. The Future of Solar Energy, 2015.

[47] Lion Hirth. The Market Value of Variable Renewables: The Effect of Solar Wind Power Variability on Their Relative Price. *Energy Economics*, 38, 2013.

[48] ERCOT. 2015 ERCOT Hourly Load Data, 2016. URL `http://www.ercot.com/gridinfo/load/load_hist/`.

[49] ERCOT. Hourly Aggregated Wind Output 2007-2016. URL `http://www.ercot.com/gridinfo/generation`.

[50] ERCOT. 2017 Long Term Hourly Peak Demand Energy Forecast, 2017.

[51] ERCOT. ORDC Workshop. URL `http://www.ercot.com/content/wcm/training_courses/109606/ordc_workshop.pdf`.

[52] William Hogan. Electricity Scarcity Pricing Through Operating Reserves: An ERCOT Window of Opportunity, 2012.

[53] NRG. NRG Energy Comments on Reserve Margin Requirements and ERCOT Resource Adequacy, 2013. URL `http://interchange.puc.state.tx.us/WebApp/Interchange/Documents/40000_470_768565.pdf`.

[54] Potomac Economics. 2016 State of the Market Report for the ERCOT Electricity Markets, 2017.

[55] EIA. Texas Natural Gas Price Sold to Electric Power Consumers, 2017. URL `https://www.eia.gov/dnav/ng/hist/n3045tx3A.htm`.

[56] William Hogan. Competitive Electricity Market Design: A Wholesale Primer, 1998.

[57] Carlos Batlle. Electricity Generation and Wholesale Markets. In Ignacio J. Pérez-Arriaga (Ed.), *Regulation of the Power Sector*. Springer, 2013.

[58] Ignacio J. Pérez-Arriaga and Claudia Meseguer. Wholesale Marginal Prices in Competitive Generation Markets. *IEEE Transactions on Power Systems*, 12(2), 1997.

[59] Christoph Breidert, Michael Hahsler, and Thomas Reutterer. A Review of Methods for Measuring Willingness-to-Pay. *Innovative Marketing*, 2006.

[60] London Economics International. Estimating Value of Lost Load, 2013.

[61] Schröder Thomas and Kuckshinrichs Wilhelm. Value of Lost Load: An Efficient Economic Indicator for Power Supply Security? A Literature Review. *Frontiers in Energy Research*, 3, 2015.

[62] Clara F. Heuberger. Quantifying the Value of CCS for the Future Electricity System. *Energy & Environmental Science*, 9, 2016.

[63] Bureau of Economic Analysis. Regional Data, 2017. URL https://www.bea.gov/regional/.

[64] EIA. Table 2.8. Sales of Electricity to Ultimate Customers by End-Use Sector, 2016. URL https://www.eia.gov/electricity/annual/html/epa_02_08.html/.

[65] ERCOT. ORDC Workshop. URL http://www.ercot.com/content/wcm/training_courses/109606/ordc_workshop.pdf.

[66] William Hogan. On an 'Energy Only' Electricity Market Design for Resource Adequacy, 2005.

[67] Paul Joskow. Capacity Payments in Imperfect Electricity Markets: Need and Design, 2007.

[68] William Hogan. Electricity Scarcity Pricing Through Operating Reserves, 2013.

[69] NERC. Ancillary Services Matrix, 2014. URL http://www.nerc.com/docs/pc/ivgtf/NERC_ancillary_services%20ERCOT%20IESO%20NYISO%20MISO%20PJM%20SPP%20WECC%2012%2014.pdf.

[70] Paul Joskow. Competitive Electricity Markets and Investment in New Generating Capacity, 2006.

[71] NERC. 2015 Generating Unit Statistical Brochure – Five Years, 2011 - 2015, Units Reporting Events, 2016. URL http://www.nerc.com/pa/RAPA/gads/Pages/Reports.aspx.

[72] NERC. Data Reporting Instruction, 2017. URL http://www.nerc.com/pa/RAPA/gads/DataReportingInstructions/2017%20GADS%20Data%20Reporting%20Instructions.pdf.

[73] MISO. Historical and Regional Forecast and Actual Load 2016, 2016. URL https://www.misoenergy.org/Library/MarketReports/Pages/MarketReports.aspx.

[74] Bri-Mathias Hodge, Erik Ela, and Michael Milligan. The Distribution of Wind Power Forecast Errors from Operational Systems.

[75] Agora Energiewende. Flexibility in Thermal Power Plants - With a Focus on Existing Coal-Fired Power Plants, 2017.

[76] Anne Sjoerd Brouwer, Machteld van den Broek, Ad Seebregts, and Andr Faaij. Operational Flexibility and Economics of Power Plants in Future Low-Carbon Power Systems. *Applied Energy*, 156, 2015.

[77] Robert Brasington. *Integration and Operation of Post-Combustion Capture System on Coal-Fired power Generation: Load Following and Peak Power*. Master's thesis, MIT, 2012.

[78] IEAGHG. Operating Flexibility of Power Plants with CCS, 2012.

[79] Howard Herzog. Lessons Learned from CCS Demonstration and Large Pilot Projects, MIT Energy Initiative, 2016.

[80] Colin Henderson. Increasing the Flexibility of Coal-Fired Power Plants, IEA Clean Coal Centre, 2014.

[81] Black & Veatch. Cost and Performance Data for Power Generation Technologies, NREL, 2012.

[82] Rosa Domenichini, Luca Mancuso, Noemi Ferrari, and John Davison. Operating Flexibility of Power Plants with Carbon Capture and Storage (CCS). *Energy Procedia*, 37, 2013.

[83] Geoffrey Haratyk. Early Nuclear Retirements in Deregulated U.S. Markets: Causes, Implications and Policy Options, MIT Center for Energy and Environmental Policy Research, 2017.

[84] Elforsk. Additional Costs for Load-Following Nuclear Power Plants, Experience from the Swedish, Finnish, German, and French Nuclear Power Plants, 2012.

[85] EPRI. Program on Technology Innovation: Approach to Transition Nuclear Power Plants to Flexible Power Operations, 2014.

[86] Nuclear Energy Agency. Technical and Economic Aspects of Load Following With Nuclear Power Plants, OECD, 2011.

[87] DOE. *Nuclear Physics and Reactor Handbook*, 1993.

[88] Nuclear Energy Consulting Group. Nuclear Flexibility, 2015. URL `http://nuclear-economics.com/12-nuclear-flexibility/`.

[89] A. Lokhov. Load-Following with Nuclear Power Plants, OECD, 2011.

[90] EIA. Form EIA-860 Detailed Data, 2016. URL `https://www.eia.gov/electricity/data/eia860/`.

[91] Jimmy Lindsay and Ken Dragoon. Summary Report on Coal Plant Dynamic Performance Capacity, 2010.

[92] N. Kumar, P. Besuner, S. Lefton, D. Agan, and D. Hilleman. Power Plant Cycling Costs, NREL, 2012.

[93] Andreas Schröder, Friedrich Kunz, Jan Meiss, Roman Mendelevitch, and Christian von Hirschhausen. Current and Prospective Costs of Electricity Generation until 2050, Deutsches Institut für Wirtschaftsforschung, 2013.

[94] EIA. Assumptions to the Annual Energy Outlook 2013, 2013.

[95] Paul Joskow and John Parsons. The Economic Future of Nuclear Power, 2009.

[96] Lucas Davis and Catherine Hausman. Market Impacts of Nuclear Power Plant Closure. *American Economic Journal: Applied Economics*, 8(2), 2016.

[97] Entergy. Operational Update, 2016. URL `http://www.pilgrimpower.com/operational-update`.

[98] NEI. DOE Summit Raises Urgency of Preserving Existing Nuclear Plants, 2016. URL `https://www.nei.org/News-Media/News/News-Archives/DOE-Summit-Raises-Urgency-of-Preserving-Existing-N`.

[99] World Nuclear Association. Nuclear Power Economics and Project Structuring, 2017.

[100] Jessica R. Lovering, Arthur Yip, and Ted Nordhaus. Historical Construction Costs of Gloabl Nuclear Power Reactors. *Energy Policy*, 91, 2016.

[101] Lucas W. Davis. Prospects for Nuclear Power. *Journal of Economic Perspectives*, 26(1), 2012.

[102] Sara Hoff and Marta Gospodarczyk. First New U.S. Nuclear Reactor in Almost Two Decades Set To Begin Operating, EIA, 2016. URL `https://www.eia.gov/todayinenergy/detail.php?id=26652`.

[103] Tennessee Valley Authority. Watts Bar Nuclear Plant Unit 2 Completion Project: Estimate to Complete, 2012.

[104] Andrew Ward. Nuclear Plant Nears Completion After Huge Delays, 2017. URL `https://www.ft.com/content/36bee56a-3a01-11e7-821a-6027b8a20f23`.

[105] Areva. Olkiluoto 3 Finland. URL `http://www.new.areva.com/EN/operations-2389/finland-olkiluoto-3.html`.

[106] Stuk. Management of Safety Requirements in Subcontracting During the Olkiluoto 3 Nuclear Power Plant Construction Phase, 2006.

[107] EDF Energy. Hinkley Point C FAQ. URL https://www.edfenergy.com/energy/nuclear-new-build-projects/hinkley-point-c/faq.

[108] World Nuclear Association. Nuclear Power in the United Kingdom, 2017. URL http://www.world-nuclear.org/information-library/country-profiles/countries-t-z/united-kingdom.aspx.

[109] BBC. Hinkley Point: EDF Adds 1.5bn to Nuclear Plant Cost, 2017. URL http://www.bbc.com/news/business-40479053.

[110] MIT. Update of the MIT 2003 Future of Nuclear Power, 2009.

[111] Yangbo Du and John Parsons. Update on the Cost of Nuclear Power, MIT Center for Energy and Environmental Policy Research, 2009.

[112] EIA. Assumptions to the Annual Energy Outlook 2017, 2017.

[113] Nuclear Energy Institute. Nuclear Costs in Context, 2016.

[114] MIT. The Future of the Nuclear Fuel Cycle, 2011.

[115] Stuart Cohen. *A Techno-economic Plant- and Grid-level Assessment of Flexible CO_2 Capture*. Ph.D. thesis, University of Texas at Austin, 2012.

[116] Nestor Sepulveda. *Decarbonization of Power Systems: Analyzing Different Technological Pathways*. Master's thesis, MIT, 2016.

[117] Wolf-Peter Schill, Michael Pahle, and Christian Gambardella. On Start-Up Costs of Thermal Power Plants in Markets with Increasing Shares of Fluctuating Renewables, Deutsches Institut für Wirtschaftsforschung, 2016.

[118] EIA. Form EIA-923 Detailed Data, 2016. URL https://www.eia.gov/electricity/data/eia923/.

[119] IEA. Gas-Fired Power, Energy Technology Systems Analysis Programme, 2010.

[120] EIA. State Electricity Profiles: Texas 2015, Table 10, 2017. URL https://www.eia.gov/electricity/state/texas/.

[121] Javier García González. Decision Support Models in Electric Power Systems, Pontifical University of Comillas, 2014.

[122] Falko Ueckerdt, Lion Hirth, Gunnar Luderer, and Ottmar Edenhofer. System LCOE: What are the Costs fo Variable Renewables? *Energy*, 63, 2013.

[123] Neil Powell. America's Aging Generation Fleet, 2013. URL http://www.powermag.com/americas-aging-generation-fleet/.

[124] EIA. Electric Power Annual, 2016. URL https://www.eia.gov/electricity/data.php.

[125] EIA. Carbon Dioxide Emissions Coefficients, 2016. URL https://www.eia.gov/environment/emissions/co2_vol_mass.php.

[126] Kory W. Hedman, Richard P. O'Neill, and Shmuel S. Oren. Analyzing Valid Inequalities of the Generation Unit Commitment Problem, 2008.