A Framework to Assess the Economic and Uncertainty Implications for Technologies for Use in Decarbonization

By

Karen Dawson

B.S., Chemical Engineering, Environmental Engineering, Political Science (2014) Clarkson University

M.S., Nuclear Science and Engineering (2017) Massachusetts Institute of Technology

SUBMITTED TO THE
DEPARTMENT OF NUCLEAR SCIENCE AND ENGINEERING

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY IN NUCLEAR SCIENCE AND ENGINEERING

AT THE
MASSACHUSETTS INSTITUTE OF TECHNOLOGY
September 2019

Signature of Author: ____

Karen Dawson
Department of Nuclear Science and Engineering
August 28, 2019

Certified by: ____

Dr. Michael Golay
Professor of Nuclear Science and Engineering, MIT
Thesis Supervisor

Certified by: ____

Dr. Charles Forsberg
Principal Research Scientist, MIT
Thesis Reader

Accepted by: ____

Ju Li
Battelle Energy Alliance Professor of Nuclear Science and Engineering
and Professor of Materials Science and Engineering
Chair, Department Committee on Graduate Students

A Framework to Assess the Economic and Uncertainty Implications for Technologies for Use in Decarbonization

By

Karen Dawson

Submitted to the Department of Nuclear Science and Engineering on August 28, 2019 in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Nuclear Science and Engineering

Abstract

The accumulation of greenhouse gasses is causing climate change on a global scale. From simulations of warming scenarios, it appears that complete replacements of fossil fuels within the global energy economy must occur within about 60 years if warming is to be limited to 2°C (Prinn et al., 2011). This means that the discussion about which pathways to decarbonization to pursue will need to occur soon, and will likely be difficult to correct later. This thesis developed and demonstrated two frameworks that can be used to guide discussions on decarbonization pathway choices. The first framework determines the economic usefulness of a technology by finding the difference in total system cost with and without that technology (the opportunity cost of not utilizing the technology). The second framework quantifies uncertainties in proposed decarbonization pathways, propagates them through to target variables (such as carbon emissions), and calculates the probability of failing (or succeeding) to meet a target.

Each framework is demonstrated with an example case set in the year 2050. The first framework assessed the economic usefulness of nuclear technology in regions in the United States, China and the United Kingdom at carbon emission constraints from 500 g/kWh to 1 g/kWh. It was found that the economic usefulness of nuclear technology depends upon the capital cost of nuclear as well as the renewable resources of the region. The second framework is used to assess the probability of meeting carbon emission targets at different carbon prices. It is found that nuclear technology increases the probability of succeeding to meet a carbon emission target (as compared to a scenario where nuclear technology is unavailable). In addition, it is found that cases that benefit nuclear technology (such as electrification of space heating or a flexible, low-price electricity market) further increase the probability of succeeding to meet a carbon emission target. It is also found that the uncertainty in discount rate and nuclear capital cost have the biggest influence upon the distribution of possible carbon emissions in 2050.

The development and demonstration of these frameworks show how discussions on decarbonization pathway choices can be guided. As the timeline to decarbonize diminishes, the choice of which decarbonization pathway to choose will shift from optimizing based on cost to a balance of optimizing cost and risk.

Thesis Supervisor: Michael Golay

Title: Professor of Nuclear Science and Engineering

Acknowledgements

This thesis work would not have been possible without the thoughtful guidance and support of my advisor, Pr. Michael Golay. Over the past five years, he has constantly worked to make me a better student, a better researcher, and a better thinker. In addition, this thesis work would not have been possible without the direction and counsel of Dr. Piyush Sabharwall and Dr. Charles Forsberg. Both have provided great advice about the work in this thesis and my professional development goals. I am grateful to have my three committee members be such advocates for my career.

There are several other people that have played a crucial role in my Ph.D. process as well as my professional development. Pr. Michael Corradini supervised my work for the Future of Nuclear study and has always given good advice in my research and professional pursuits. Pr. Jacopo Buongiorno has also advocated for me and that has enabled me to achieve my true potential in the NSE Department. Dr. David Petti has also been a tremendous support through his words of wisdom and advice.

In addition, I must acknowledge all of those experts that have been so helpful in teaching me and providing me a sounding board for the various topic areas in my thesis. This work would not have been possible without these numerous experts.

I cannot express enough the inspiration and support I have received from the pursuits of my fellow classmates. The emotional rollercoaster that accompanies the Ph.D. process was lessened by the constant encouragement and friendship from my classmates. I wish success to all of my classmates in all of their endeavors.

It is hard to convey the influence that my family has had upon my choices that has led me to this point. I have never felt like there is a career path that I could not take because of the environment that I was raised in. My brother and sisters have shown me what is possible if I am courageous enough to pursue my passions.

Finally, I would like to thank my significant other, Adam Higgins. He has always been my biggest support crew throughout the Ph.D. program we well as any other career pursuit.

Table of Contents

List of Figures

List of Tables

Acronyms

CAGR	Compound Annual Growth Rate
CCGT	Closed Cycle Gas Turbine
CCS	Carbon Capture and Sequestration
EIA	Energy Information Agency
ERCOT	Electric Reliability Council of Texas
GDP	Gross Domestic Product
IDDRI	Institute for Sustainable Development and International Relations
IGCC	Integrated Gasification Combined Cycle
IPCC	Intergovernmental Panel on Climate Change
ISO	Independent System Operator
LWR	Light Water Reactor
MISO	Midwest ISO
NERC	North American Electric Reliability Corporation
NREL	National Renewable Energy Laboratory
NYISO	New York ISO
OCGT	Open Cycle Gas Turbine
PJM	Pennsylvania, New Jersey, Maryland Interconnection
PV	Photovoltaic
RTO	Regional Transmission Organization
T-B-T	Tianjin-Beijing-Tangshan
TxDOT	Texas Department of Transportation
U.K.	United Kingdom
U.S.	United States
USDOT	US Department of Transportation
WWS	Wind, Water, and Sunlight

Nomenclature

CC_A	Capital Cost of Technology *A*
CF	Capacity Factor
COV	Coefficient of Variation
CSU_A	Cost of a Start Up Event (normalized to unit capacity)
CP	Carbon Price
FC_A	Fixed Cost of Technology *A*
FE_F	Fuel Carbon Emissions from Fuel Type *F*
FP_F	Fuel Price of Technology *A*
FOM_A	Fixed Operating and Maintenance Cost of Technology *A*
HR_A	Heat Rate of Technology *A*
IC_A	Installed Capacity of Technology *A*
L_A	Lifetime of Technology *A*
$MFSP_A$	Minimum Stable Power of a Fleet of Generators of Technology *A*
MHR_A	Maximum Power that Technology *A* can Ramp in an Hour
$MHRP_A$	Maximum Percent of Power that Technology *A* can Ramp in an Hour
$MSPP_A$	Minimum Stable Percent of Power of Technology *A*
N	Number of Iterations in a Monte Carlo Simulation
NSU	Number of Start Ups
OC_A	Opportunity Cost of Technology *A*
POC_A	Opportunity Cost of Technology *A* as a Percent of Total System Cost
r	Discount Rate
SC	System Cost
SE	System Emissions
TC_A	Total Cost of Technology *A*
TSC_{LCOS}	Total System Cost of Optimal Solution
$TSC_{LCOS,-A}$	Total System Cost of Optimal Solution without Technology *A*
U	Sample Mean Estimate of a Monte Carlo Simulation
VC_A	Variable Cost of Technology *A*
VOM_A	Variable Operating and Maintenance Cost of Technology *A*
x_i	Data Point from a Monte Carlo Simulation

Executive Summary

Background

The accumulation of greenhouse gases is causing climate change on a global scale. Carbon dioxide, a greenhouse gas, is released through the burning of fossil fuels such as coal or natural gas. Global demand for energy is expected to increase. The International Energy Outlook 2016, released by the U.S. Energy Information Administration, shows a rising level of global energy consumption over the next 25 years (U.S. Energy Information Agency, 2016). The 2016 Food, Water, Energy, and Climate Outlook released by the MIT Joint Program on the Science and Policy of Global Change predicts that global emissions will rise to 64 gigatons of carbon dioxide-equivalent. Fossil fuel will account for 75% of global primary energy by 2050. The global mean surface temperature will increase 1.9 to 2.6°C by 2050 and will increase 3.1 to 5.2°C by 2100 (relative to pre-industrial levels, 1860-1880 mean) (Change, 2016).

From simulations of warming scenarios, it appears that complete replacements of fossil fuels within the global energy economy must occur within about 60 years if warming is to be limited to 2°C. This timescale to decarbonize includes all research and development, infrastructure replacement, and policy implementation. This means that the discussion about which pathways to decarbonization to pursue will need to occur soon, and will likely be difficult to correct later (Prinn et al., 2011).

If a move towards decarbonization of the energy market is desired, society will need to select a pathway to a decarbonized energy sector. In comparing alternative proposed pathways, there can be a lot of uncertainty. In modeling the different pathways, uncertainties in input variables propagate through to decision-making variables. However, most of the time proposed decarbonization pathways are presented as solutions without mention that success may not occur if the proposed pathway is pursued. Reflecting these uncertainties, a particular pathway may fail under some circumstances but succeed otherwise. The probability of success of proposed decarbonization pathways needs to be quantified.

The objective of this work is to develop and demonstrate two frameworks that can be used to guide discussions on decarbonization pathways choices. Specifically, the frameworks are able to provide an assessment of the usefulness of a technology.

The first framework determines the economic usefulness of a technology by finding the difference in total system cost with and without that technology (the opportunity cost of not utilizing the technology). The second framework quantifies uncertainties in proposed decarbonization pathways, propagates them through to target variables (such as carbon emissions), and calculates the probability of failing to meet a target. It will also be able to determine the important factors leading to the failure to meet the target.

Economic Opportunity Costs

The first framework developed shows a way to analyze the economic prospects for technologies in the future by calculating the opportunity cost of forgoing the technology. The opportunity cost is defined as the lowest possible system cost without the technology minus the lowest possible system cost with the technology.

The usefulness of the framework is shown through an example analyzing the economic prospects of nuclear technology in the year 2050. Emission limits from 500 g/kWh (business as usual case) down to 1 g/kWh are imposed upon five different regions: Texas (United States), New England (United States), Tianjin-Beijing-Tangshan (China), Zhejiang (China), and United Kingdom. The optimal installed capacity as well as the dispatch of that capacity are generated for the optimization of the lowest average system cost. Three optimization scenarios are calculated for each emission limit for each region:

1. No nuclear technology permitted in the optimal installed capacity mix,
2. Nuclear technology permitted in the optimal installed capacity mix at nominal capital cost, and
3. Nuclear technology permitted in the optimal installed capacity mix at capital cost 25% below nominal capital cost.

The optimal average generation cost for New England for each carbon emission limit and for each optimization scenario is depicted in Figure 10 below. The opportunity cost of forgoing nuclear technology is the difference between the scenario with no nuclear technology permitted and the scenario with nuclear technology permitted. The optimal cost is negligible for the emission limits from 500 g/kWh to 50 g/kWh for both the nominal and low-cost nuclear cases. However, there is a significant opportunity cost at emission levels of 10 g/kWh and 1 g/kWh. The opportunity cost increases with decreasing capital cost of nuclear.

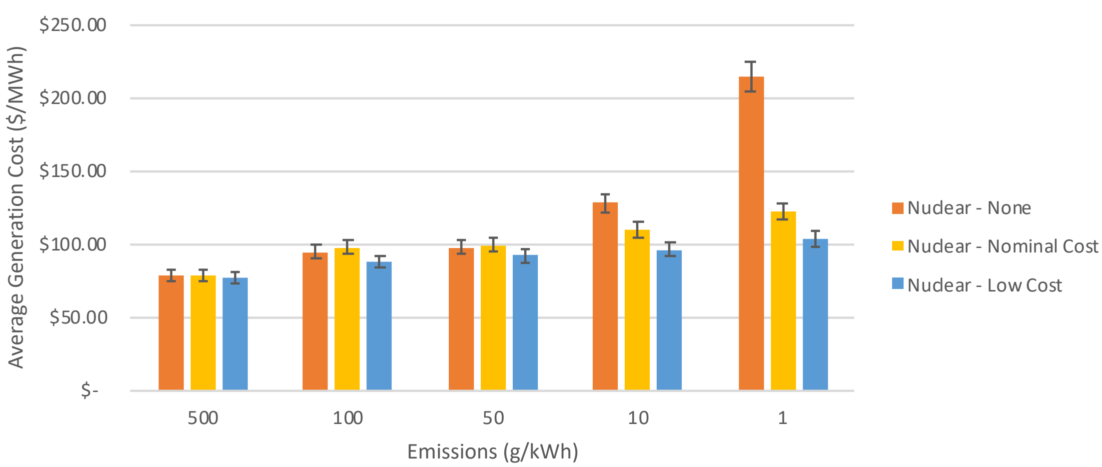


Figure 1: New England Cost of Electricity Generation

The reason for the opportunity cost at 10 g/kWh and 1 g/kWh is the need to build large amounts of wind and solar capacity those emission constraint levels. This is because there is not enough natural gas (due to the emission constraint) to provide the dispatchable generation that the system needs. Because wind and solar are not dispatchable, there is the requirement for massive amounts of installed capacity in order to guarantee demand. Figure 2 shows the installed capacity mix for each carbon emission limit and for each optimization scenario. In the no nuclear technology permitted scenario, there is an exponential increase in total installed capacity beginning after the 50 g/kWh emission constraint. In the nuclear technology permitted scenarios, there is not this increase in total installed capacity.

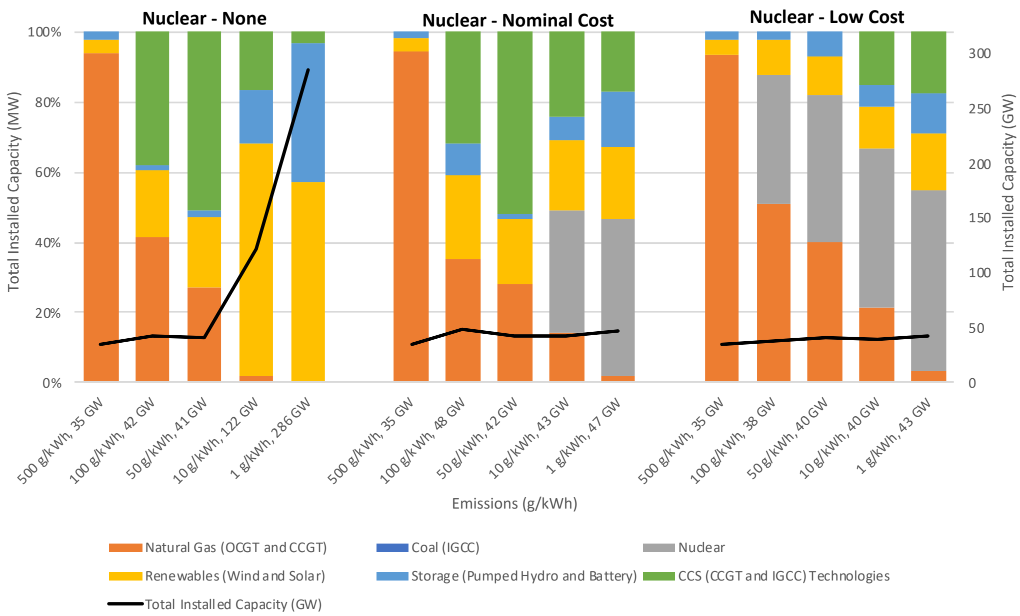


Figure 2: New England Installed Capacity

The increase in installed capacity (Figure 2) in the no nuclear technology permitted scenario corresponds to the increase in total average system cost of electricity generation (Figure 1). This show that without dispatchable, zero carbon-emitting technology, the requirement to increase installed capacity of renewables and storage leads to a large increase in system cost as carbon emission limits become stricter. With nuclear technology playing the role of dispatchable, zero carbon-emitting technology, the increase in installed capacity of renewables and storage is not necessary and therefore the system cost does not increase so drastically. This is the basis for the opportunity cost of forgoing nuclear technology at low carbon emission levels. The opportunity cost increases as the capital cost of nuclear decreases.

Framework to Assess the Usefulness of Technologies through Uncertainty Assessment

This work generated a six-step process to analyze the uncertainties associated with decarbonization. This framework is summarized in Figure 3, and each step is summarized below.

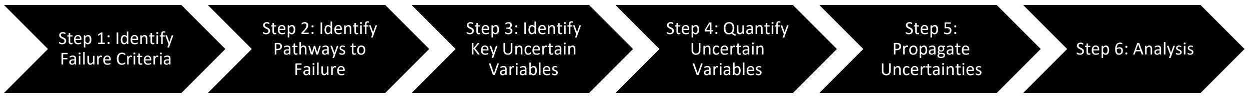


Figure 3: Summary of Six-Step Framework

Step 1: Identify Failure Criteria

In this step, you should think about what would be considered a failure in implementing your solution to decarbonize. Failure can be economic (i.e. implementing a solution being too costly), social (i.e. a solution changes too many social norms), or political (i.e. a solution failing to meet stated goals). It is possible that there are multiple ways of failing or possibly only one criterion satisfied for failure. Each criterion of failure will have both a quantifiable variable as well as a threshold for what is considered a failure and what is considered a success.

Step 2: Identify Pathways to Failure

The next step is to identify all of the ways that the failure criteria can be satisfied. For economic failures, it is important to consider all of the costs associated with the solution. For social failure, it is important to consider all of the social norms which are not allowed to be violated. An example of this in decarbonization of the electricity sector is the expectation of reliability on the grid. In the U.S. for example, brownouts are not acceptable. In other global regions, however, it may be acceptable for there to be brownouts due to lack of adequate installed capacity. For political or goal failures, it is important to consider how to quantify the goal (for example, a goal could be reduction in carbon emissions) and what ways that efforts to meet that goal could be unsuccessful. This can be analyzed through use of an event tree analysis in which critical junctures determining the success of the pathway are identified.

Step 3: Identify Key Uncertain Variables

The next step is to recognize the variables that affect the pathway to failure. This is done by recognizing which variables are present in the identified pathways to failure. A list of variables should be created. Best practices for brainstorming this list include: 1) Work individually first, 2) Engage a diverse group of people, and 3) Don't think of feasibility until the end. From this list, the next step is to select the variables that have two characteristics: 1) plays a large role in the pathway to failure and 2) has a large uncertainty.

Step 4: Quantify Uncertain Variables

Once the key uncertain variables have been identified, their probability distributions need to be quantified so that the uncertainties can be propagated through to the failure criteria variables. This can be done in several different ways. If it is random process (i.e. weather), it is possible that the uncertainty has already been quantified. If not, a good resource to use is historical data. If it is an uncertainty associated with lack of knowledge (i.e. future costs), then expert elicitations can be used.

Step 5: Propagate Uncertainties

With the quantified key uncertain variables and the pathways to failure, it is then possible to propagate the uncertainties. There are many methods of doing this. With simple pathways, analytically propagating the uncertainty may be possible. With more complex pathways, a tool such as a Monte Carlo analysis may be used. The results from this step will be a probability distribution function for each failure criteria variable.

Step 6: Analysis

The last step is to calculate the probability of failure from the probability distribution function(s). If there is more than one, it is necessary to determine the union of failure probabilities. In this stage, it is also possible to see the order of influence of each key uncertain variable upon the overall uncertainty.

Assessing the Uncertainty of Carbon Emissions and Cost of Generation

A model was developed using an improved screening curve method to determine the optimal capacity mix and dispatch of that capacity mix. It is used in a Monte Carlo simulation with uncertainty inputs in the capital costs of nuclear, solar, wind, storage, and natural gas with CCS, discount rate, natural gas fuel price, and weather. The model is used to evaluate the effect upon the risk of not meeting a carbon emission target in various scenarios:

- Base Case
- Nuclear technology is not available
- 30% electrification of passenger vehicles
- 30% electrification of space heating
- Addition of a low-price, flexible heat market

This analysis shows a role for nuclear technology in decreasing carbon emissions for all carbon price values (even at no carbon price). This would not have been seen in a deterministic scenario. This shows the advantage of considering uncertainties in decarbonization analyses.

In addition, the uncertainty treatment of this analysis shows that nuclear has a role in increasing the probability of meeting carbon emission targets. In the cases where nuclear is not available, the probability of meeting these carbon emission targets decreases. This is especially true for more aggressive carbon emission targets such as 10 g/kWh.

The uncertainty treatment also shows that the discount rate is the most important uncertainty in the future in determining both carbon emissions and the total system cost. This is because the discount rate affects the investment cost of technologies, which has more of an influence upon non-carbon emitting technologies due to high capital costs (solar, wind, and nuclear).

In the case of electrification of the transportation sector, the demand profile changes to be more peaked. The added demand is met with either renewables (if it is at time when renewable potential is high) or with natural gas (CCS if the carbon price is high enough). This can increase the annual emissions.

In the case of electrification of the space heat sector, the demand profile changes to have a higher annual baseload demand. This is beneficial for nuclear technology and if nuclear technology is not too expensive then the additional demand will be supplied with nuclear generation. This decreases carbon emissions. However, if producing electricity with nuclear technology is more expensive than producing electricity to meet the same demand with renewables or natural gas, then that demand will be met with the renewable or natural gas technology. If it is met with natural gas technology, then this has the potential of increasing emissions. In this case, the uncertainty around the capital cost of nuclear becomes more important.

The presence of a flexible market for low price electricity increases the probability of meeting carbon emission targets, especially as the carbon emission target becomes more ambitious. This is because it allows nuclear technology to be more flexible and therefore replace some of the generation from natural gas. This demonstrates that the establishment of the flexible market will be beneficial to the goal of decarbonization because it enhances the role of less flexible non-carbon emitting technologies.

The addition of the flexible market decreases the importance of the uncertainty in natural gas fuel price and the uncertainty in the natural gas CCS capital cost in determining the carbon emission distribution. This means that because nuclear technology will be enabled to supply demand during more demand periods that are traditionally supplied by flexible generators (natural gas), there is less reliance of the electricity sector upon these flexible generators.

Conclusions

The framework examples show a key role that nuclear power can play in a low carbon electricity sector. Nuclear power decreases the total system cost and improves the economics of solar and wind. This is largely the result of installed capacity mixes with nuclear power require less building out of solar and wind in order to guarantee that electricity demand is met. The building out of solar and wind causes two things:

1. The capital costs of solar and wind contributing to the large growth in energy costs at low carbon emission levels (without nuclear) and
2. A lowering the of capacity factor of solar and wind because much of the capacity of the building out is only utilized for a few hours of the year.

The uncertainty framework also shows that nuclear technology has a role in lowering the expected carbon emissions. Nuclear technology increases the probability of succeeding at meeting a given carbon emission target. It was also demonstrated in an example where there was a flexible, low-price electricity market further enhanced the role of nuclear technology and also increased the probability of succeeding at meeting a given carbon emission target.

The framework examples support the idea that while nuclear may not be economic now, it can be crucial in the future. Support to keep nuclear industry knowledge available (such as how to construct nuclear power plants and how to operate nuclear power plants) is critical so that if the electricity sector is decarbonized, nuclear choices will be available.

These frameworks can be very useful for many of the stakeholders in the decarbonization discussion. Governments can use the frameworks to show what is the cost of neglecting timely research and development funding of a particular technology. Investors can use the framework to see what technologies can be valuable in the future (even if they are not valuable today). In addition, the frameworks can show what factors contribute most to either the success likelihood of a strategy or the economic value of a technology. For example, capital cost of nuclear play a large role in determining at which carbon emission limits nuclear is in the optimal installed capacity mix. Average clearing price and capacity factor play a large role in the profit of solar, wind, and nuclear.

Chapter 1: Introduction and Motivation

Carbon and Climate Change

The accumulation of greenhouse gases is causing climate change on a global scale. Carbon dioxide, a greenhouse gas, is released through the burning of fossil fuels such as coal or natural gas. Global demand for energy is expected to increase. The International Energy Outlook 2016, released by the U.S. Energy Information Administration, shows a rising level of global energy consumption over the next 25 years (U.S. Energy Information Agency, 2016). Figure 4 shows the historical and predicted energy consumption, separated by energy source, from the International Energy Outlook 2016. While the increase in coal consumption is seen to slow, there is still an overall increase in energy consumption from fossil fuel sources (coal, natural gas, and liquid fuels/petroleum).

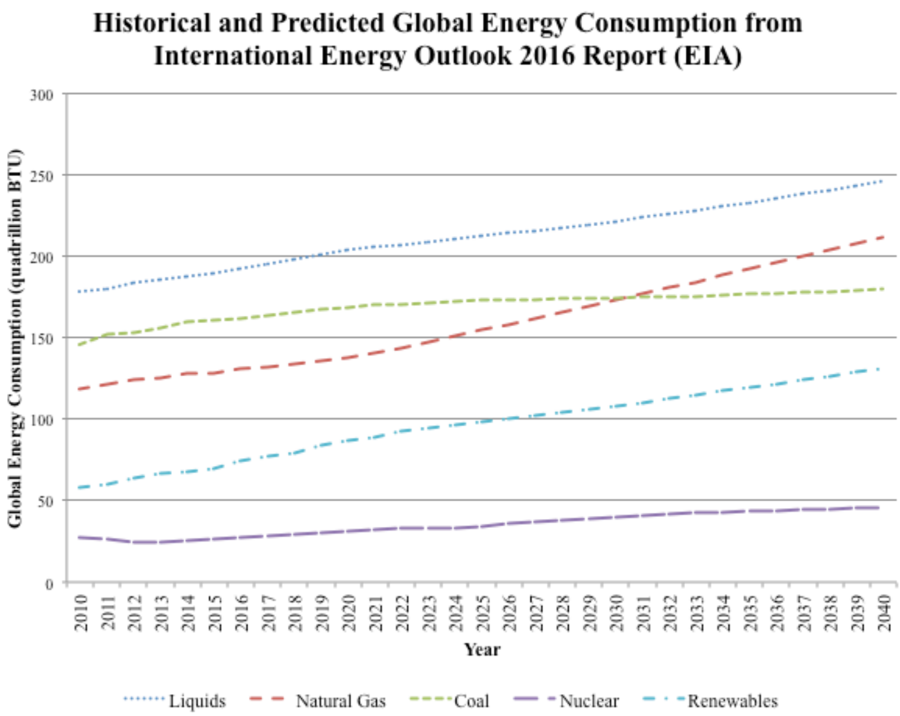


Figure 4. Historical and Predicted Global Energy Consumption from the International Energy Outlook 2016 Report (EIA) (U.S. Energy Information Agency, 2016)

The 2016 Food, Water, Energy, and Climate Outlook released by the MIT Joint Program on the Science and Policy of Global Change predicts that global emissions will rise to 64 gigatons of carbon dioxide-equivalent. Fossil fuel will account for 75% of global primary energy by 2050. The global mean surface temperature will increase 1.9 to 2.6°C by 2050 and will increase 3.1 to 5.2°C by 2100 (relative to pre-industrial levels, 1860-1880 mean) (Change, 2016). There are several identified problems with burning fossil fuels and the release of carbon dioxide including climate change, air pollution, and water pollution.

Focusing on the effect of carbon emissions on global warming, the effect of carbon dioxide and other greenhouse gas concentration in the atmosphere is "extremely likely" to be the cause of observed global warming seen in the last half-century (IPCC, 2014). In order to stay below a given temperature rise, there is a value of cumulative carbon emissions which must not be exceeded. This is known as the carbon budget. For example, to keep average global temperature rise to within 1.5°C, the carbon budget remaining is between 570 and 770 gigatons of carbon dioxide (IPCC, 2018).

This indicates a need to reduce carbon emissions before the carbon budget is exceeded. There are many proposed pathways towards the decarbonization of the energy market, ranging from high use of renewable energy, high use of nuclear energy, high use of carbon capture and sequestration technology, as well as hybrids of these (Williams, et al., 2014). From simulations of warming scenarios, it appears that effectively complete replacements of fossil fuels within the global energy economy must occur within about 60 years if warming is to be limited to 2°C. This timescale to decarbonize includes all research and development, infrastructure replacement, and policy implementation. This means that the discussion about which pathways to decarbonization to pursue will need to occur soon, and will likely be difficult to correct later (Prinn et al., 2011).

If a move towards decarbonization of the energy market is desired[1], society will need to select a pathway. In order to decide, there are several causal factors that can be chosen from in order to determine which pathway is the best. These include:

- Cost/Energy Prices
- Technological Feasibility
- Total Carbon Dioxide Emissions

In the determination of these causal factors for comparing alternative proposed pathways, there can be a lot of uncertainty. For example, the cost of energy storage in the future remains unknown. Pathways having large amounts of wind and solar energy generation often rely on energy storage technologies to account for the intermittent nature of this type of energy generation. To calculate the total system cost, the cost of storage is estimated (The Solutions Project, 2017). This creates uncertainty in the total system cost. This shows the first problem in analyzing decarbonization pathways: *Uncertainties in input variables, such as cost of storage, propagate through to decision-making factors, such as total system cost.*

Proposed decarbonization pathways are presented as solutions. They are assumed to be able to succeed. However, because of uncertainties in costs, technological readiness, and other technology characteristics, success may not occur if the proposed pathway is pursued. Reflecting these uncertainties, a particular pathway may fail under some circumstances but

[1] There are other pathways to decarbonization, such as geo-engineering solutions. While the proposed framework can be used for comparing these pathways, this work focuses on decarbonization of energy generation.

succeed otherwise. This shows the second problem in analyzing decarbonization pathways: *The probability of success of proposed decarbonization pathways needs to be quantified.*

Factors in Decarbonization

A challenge associated with the mitigation of climate change effects is the large time frame associated with the effects as well as with the solutions. Actions (or inactions) taken in the short term can have long-lasting implications for both the climate as well as the availability of technologies in the future decades. Because of this, decision makers should consider a broad range of possible futures and the implications of the choices that they make (Keppo & van der Zwaan, 2012). An example of this is with the retirement of the U.S. nuclear power plant fleet. If no action is taken to preserve the nuclear industry's knowledge expertise and supply chain in the U.S., then it could take a long time to regain this expertise needed to begin designing and building nuclear power plants in the U.S. if that were desired.

Compounding the implications of short-term actions upon climate and technology availability in the future are the effects of uncertainties. Given the large time frame involved, it is no surprise that there exist many uncertainties in the potential economics, technological states, and climates (just to name a few) of the future. These uncertainties grow as one looks further into the future. In the modeling of climate, uncertainties take on an additional role as there are many non-linearities in the dynamics of modeling of climate and energy systems that can cause the effects of the combined uncertainties to be compounded. In particular, there are many thresholds which, once reached, can be irreversible. These thresholds are also known as tipping elements or tipping points. Examples include large ocean ice sheet melting or large-scale ocean circulation changes (Gillingham et al., 2015). If the uncertainty range of one input variable used in a model gives response variables on either side of this threshold, it is crucial not to assume only one possible value for this input as this can lead to conclusions on one side of the threshold without ever acknowledging the possibility of landing on the opposite side of the threshold. Instead, a more prudent approach is to predict not just one value for each desired output variable: but a range of values. This range will show whether the results are entirely on one side of a threshold, or possibly straddling the threshold. Even more useful than a range for each desired output variable is a probability distribution function for each output variable. This will not only show if the variable straddles a threshold, but also what the estimated probability is for being on either side of the threshold.

Quantifying the probability distribution function for each desired output variable is useful, but another great value in the use of uncertainty in decarbonization models is the potential to find which uncertain variables will give the biggest payoff in reducing the uncertainty. Doing this can show short-term actions that can be done in order to better predict long term results.

Objective of This Work

The objective of this work is to develop and demonstrate two frameworks that can be used to guide discussions on decarbonization pathways choices. Specifically, the frameworks are able to provide an assessment of the usefulness of a technology.

The first framework determines the economic usefulness of a technology by finding the difference in total system cost with and without that technology (the opportunity cost of not utilizing the technology).

The second framework quantifies uncertainties in proposed decarbonization pathways, propagates them through to target variables (such as carbon emissions), and calculate the probability of failing to meet a target. It will also be able to determine the important factors leading to the failure to meet the target.

Organization of This Work

The first chapter of this work introduces the motivation for the this work as well as some of the challenges and goals.

The second chapter of this work provides a background discussion of the current state of the electricity market as well as potential future market states and/or market policies. It provides a literature review of uncertainty modeling techniques used in decarbonization analyses. Finally, it highlights the gaps in previous decarbonization studies.

The third chapter outlines the framework to assess the economic usefulness of a technology. It then provides an example of the framework by finding the economic usefulness of nuclear power in a decarbonized electricity sector. This work was used in the first chapter of the Future of Nuclear Energy in a Carbon-Constrained World study (Petti, Buongiorno, Corradini, & Parsons, 2018).

The fourth chapter outlines the framework to assess the probability of failing to meet decarbonization goals. The fifth chapter describes the model used to propagate uncertainties for use in the framework.

The sixth through eight chapter are case examples using the framework outlined in the fourth chapter and the model outlined in the fifth chapter. The sixth chapter presents the comparison between a case with nuclear technology available and without nuclear technology available. The seventh chapter examined the effect of the electrification of the space heating and transportation sector. The eighth chapter presents the influence of a low price, flexible electricity market upon the chance of succeeding at meeting carbon emission targets.

The ninth chapter provides a discussion of the usefulness of these two frameworks and how the use of them can benefit and transform discussions on decarbonization methods.

Chapter 2: Background

United States Electricity Market Mechanisms

This section describes the current state of electricity markets in the United States and summarizes various proposed future states of electricity markets in the United States. It is important to note that decarbonization must occur globally, not just in the United States. Therefore, the energy market of all countries is important. However, space restrictions permit me to only discuss the 2019 U.S. market here. The important points concern how the costs of the various technologies play a role in the market as well as the revenue streams for the owners of the facilities using various technologies.

The major players in the electricity market are (mostly) private companies that can own and operate power plants, the state and federal governments who are in charge of ensuring safety and reliability of power operations and transmission, and the consumers of the electricity who determine the demand at any given time.

Current State

There are two main alternative mechanisms for the sale and delivery of electricity: regulated and competitive.

In the regulated model, utilities are vertically integrated. That is to say, utilities are in charge of producing the electricity and the transmission and distribution of that electricity to customers in a specified region. The utility either owns the power plants that are producing the electricity or have purchase agreements with electricity generators. The customer sees a price of electricity that is based on the utility's cost of producing and distributing the electricity over a longer period of time (i.e. averaged out). In other words, customers typically don't see widely varying electricity prices. The utilities in the regulated model are regulated by a state regulatory commission. The state regulatory commission approves the electricity rates that the customers see. Therefore, utilities in regulated market face less risk in investing in new capital projects because they know the rate of electricity. Because of this, there is less uncertainty in the rate of electricity, and therefore the utilities can only invest in capital expenditures that they are certain will give them a positive rate of return.

In the competitive model, electricity is bought and sold in a wholesale market. Electricity producers bid the amount of generating capacity that they can provide for the market at the lowest price at which they are willing to sell that generated electricity. A dispatch curve (also known as a supply stack) is created by arranging all of these bids in increasing order of value. See Figure 5 for an example of a dispatch curve.

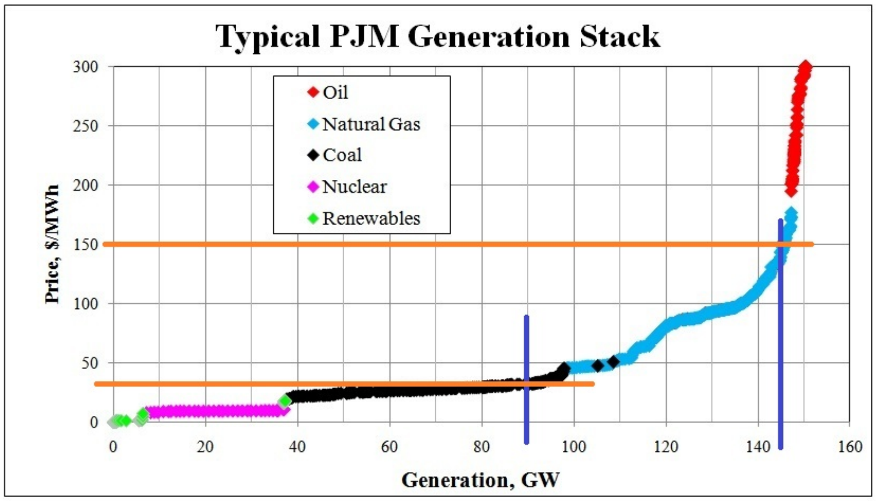


Figure 5: Typical Dispatch Curve (Penn State, 2019)

The bid at which the demand is the same as the generation on the dispatch curve is set as the clearing price. All generators below this price produce electricity and get paid this price (see orange horizontal lines in Figure 5). This process is administered by either an independent system operator (ISO) or regional transmission organization (RTO). These bids typically are offered the day before that of actual production (in the "day ahead market") using demand projections as well as real time (in the "real time market") using actual demand. In addition, there is a market for transmission services and ancillary services (such as maintaining generating capacity reserves and correct voltage).

We focus more on the competitive model because it more directly shows the economics of electricity generation and consumption. Traditionally, clearing prices were set by high marginal cost electric generators, such as natural gas, coal, and oil. These have a high cost because their cost of generation is dominated by fuel costs. However, recently, the U.S. clearing prices have been lowering because of two factors: 1) the decline in natural gas prices and 2) the increased installed capacities of low marginal cost electric generators such as wind and solar.

These effects of the decline in clearing price are shown in Figure 6. Here, the clearing price for each hour of the day are shown for the second Sunday in April for 2012 (when there was low penetration of solar) and 2017 (when there is high penetration of solar).

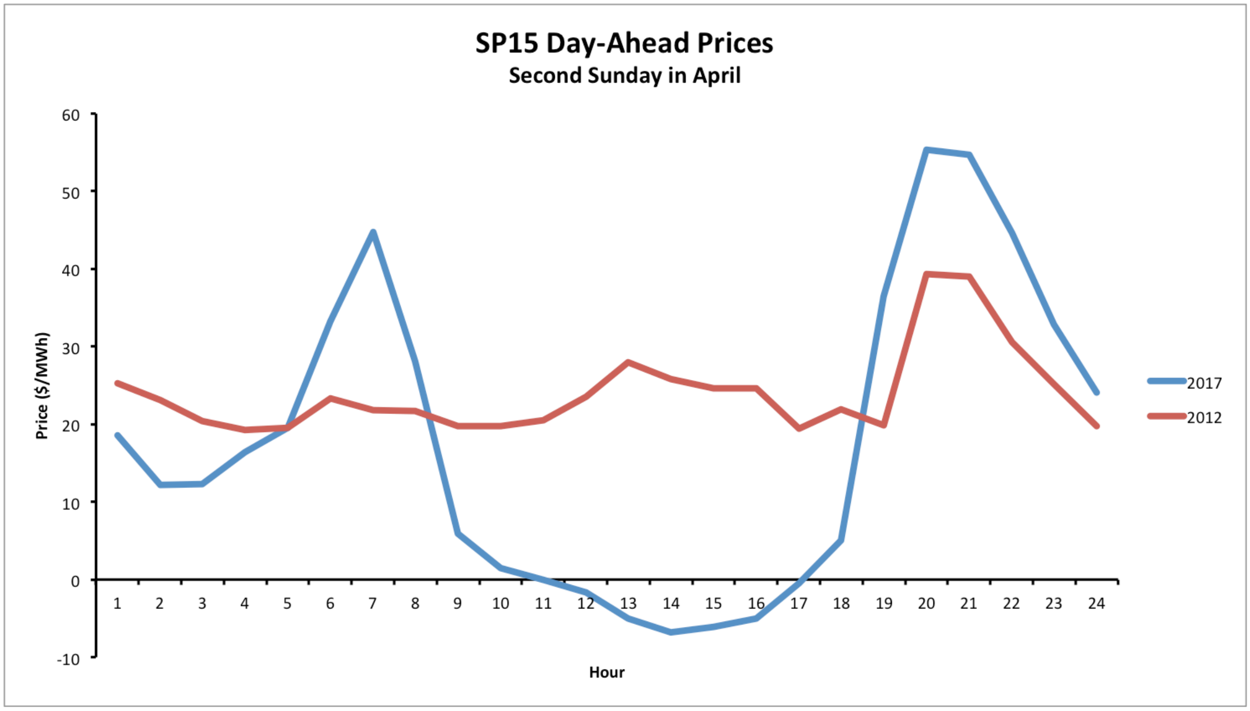


Figure 6: Day-Ahead Prices in CAISO[2]

It is seen in Figure 6 that at times of typical high solar generation (mid-day), the clearing price collapses from the 2012 value to a negative value in 2017. The negative value is the result of subsidies making the marginal cost of solar negative (marginal cost = operating cost – subsidy) and the clearing price being set by solar. This happens because there is so much solar generation available that it meets demand without the need for other generators (i.e. solar sets the clearing price). However, at times of low solar output combined with high demand (early morning and early evening), the clearing price on the 2017 curve increases to above the 2012 values. This is because there is no longer enough solar generation to meet demand and so all of the fossil fuel plants need to ramp up quickly (which can be expensive).

There are many implications seen from Figure 6. Perhaps the most important implication is that the average clearing price that a solar generator will see decreases with increasing installed solar capacity. This indicates a decrease in revenue received from a wholesale market and overall a decrease in the attractiveness of solar to investors. There is a similar problem for wind and nuclear: In a competitive market, too much penetration of low marginal cost electric generators (solar, wind, and nuclear) leads to a decrease in investment attractiveness for these technologies.

From an economic perspective, a decrease in investment of solar, wind, and nuclear is not a bad thing. It is simply the market sorting out the economic optimum of what technologies should be installed. However, there is a problem from a carbon reduction standpoint. The

[2] https://energyathaas.wordpress.com/2017/04/24/is-the-duck-sinking/

market currently does not account for the negative externality of carbon emissions. The technologies that provide electricity without carbon emissions are mostly low marginal cost technologies. By discouraging investment in these technologies, the competitive market is discouraging a reduction in carbon emissions.

Potential Future Challenges

The two main problems with the current electric market state are that the market does not account for the externalities in cost associated with carbon emissions and that high penetrations of low marginal cost electric generators leads to a decrease in investment for these technologies. This section discusses other challenges that are foreseen in the likely future.

The first challenge is associated with the increased penetration of variable renewable energy generation. This can lead to increased cycling of traditionally baseload units (such as coal and nuclear). This can result in increased damage to the unit due to the thermal cycling causing material stresses leading to increased failure rates (Carney, Abdurrahman, Robertson, & Evans-mongeon, 2016). The cycling is a result of the installed renewable energy being able to provide all of the electricity at times of high renewable potential and low demand (Figure 6). However, if there is suddenly low renewable potential (the wind stops blowing or a cloud covers the solar PV array), a dispatchable generator will be needed to ramp up. Traditionally, this would be natural gas because natural gas plants are designed to be operated only at peak loads. However, as renewable penetration increases, nuclear and coal may need to perform in this manner as well.

Another challenge is with the timescales needed for infrastructure change. Infrastructure takes time to be built. It takes several years for the permit process and the construction of new generating assets. According to NERC (2016), estimated build time for gas pipelines is 3 years, for utility-scale wind and solar 3 years, for combined-cycle gas turbine plants 5 years, and for bulk-electric transmission 8-15 years. There is uncertainty in these estimates as project-specific circumstances (such as availability of construction crew) can delay the estimated times (Carney et al., 2016). Methods of carbon emission reduction will involve infrastructure change and therefore there needs to be significant planning in advance.

Potential Future Solutions and States

This section highlights some proposed solutions to these challenges in the previous section. It also discusses other potential changes to the current electric market state.

Grid operators are responsible for ensuring that there is always electricity supply in order to meet demand. In order to make sure that the proper investments are made in installing the necessary new capacity, ISO/RTOs can offer capacity payments. These typically work through an auction where prices for electric installed capacity are bid upon anywhere from a few months to a few years out. It essentially guarantees a revenue stream for the owner of a power plant. Prices in the auction typically depend upon location and the time of the capacity commitments.

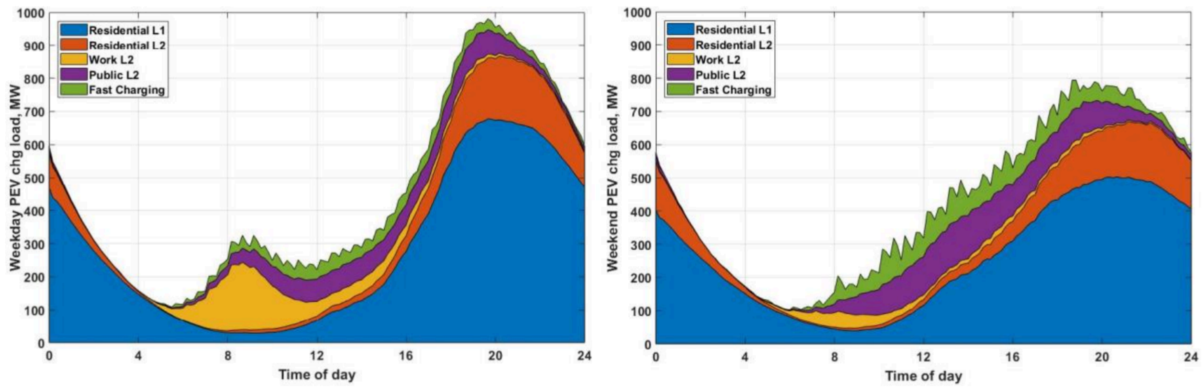
Some capacity markets exist in the U.S. (ISO New England, NYISO, MISO, and PJM) but future policies are likely to change them further. Capacity markets have been identified as a method to ensure there are sufficient capacity resources to serve the load plus required reserves (US Department of Energy, 2015).

Carbon taxes have been proposed as a method to quantify the social cost of carbon emissions. There would be a tax imposed upon every ton of carbon emitted from a fossil fuel plant. This would, in effect, increase that plant's marginal cost (marginal cost = fuel cost + operating cost + carbon tax). The idea behind carbon taxes is that it would raise the cost of fossil fuel plants enough to "drive them out of the market." In addition, the increase in the clearing prices from the times when the fossil fuel plants set the clearing price would increase the revenue generated by non-carbon-emitting electric generators. Advantages of the carbon tax are that the carbon tax directly addresses the source of the market externality, it generates revenue for the government, and it allows the market to find the most efficient solution. Disadvantages of the carbon tax is that it will increase the price of electricity for the consumer and it needs to be set at the value of the externality. Unfortunately, there is little agreement on what the externality value (or the social cost of carbon) is (Ricke, Drouet, Caldeira, & Tavoni, 2018) and so it would be difficult to justify the numerical value of the carbon tax.

On the flip side of carbon taxes, a carbon-free generation subsidy would directly give non-carbon-emitting electric generators an additional source of revenue. This currently exists with the wind and solar production tax credits. The idea here would be to expand that policy to include all non-carbon-emitting technologies (including nuclear). The advantages of carbon-free generation subsidies are that the subsidy directly rewards favorable behavior (not emitting carbon) and it will reduce the price of electricity to consumers because the marginal costs of non-carbon-emitting electric generators will decline. The disadvantages of carbon-free generation subsidies are that the subsidy requires a funding source and can make electricity prices negative. The negative electricity prices indicate that there is a surplus of supply, which is uneconomical.

Besides direct policies, there are other ways the electric market may change in the future. One such way is with the electrification of transportation. This adds an additional demand to the electric market. However, the demand is not uniform across the day. There will be typical times that people will plug in and charge their electric vehicles. The California Energy Commission produced a report in which they estimated the electric demand from charging cars for an entire weekday and weekend, as seen in Figure 7 (from the report) (Bedir, Crisostomo, Allen, Wood, & Rames, 2019).

Figure ES.2: PEV Charging Load Profiles in 2025



Source: California Energy Commission and NREL

Figure 7: Electric car charging load anticipated in 2025 in California

Figure 7 shows that the times of peak charging demand line up with the times of peak electric demand (and also low solar output). This means that not only will there need to be the capacity to ramp up due to the traditional peak electric demand, but the capacity will need to be increased to ramp up for the traditional electric demand plus the charging demand.

Microgrids are smaller isolated “islands” of electric generation, transmission, and distribution. Because they are completely self-supporting, they can disconnect from the main grid and operate on their own. One benefit of this is that the microgrid will not be subject to potential poor reliability in the overall grid (i.e. voltage frequency fluctuations). This is particularly important for electric consumers that have minimal tolerance for poor quality of electricity, such as computer chip manufacturers or server farms (Hirsch, Parag, & Guerrero, 2018). Another benefit of the microgrid is that at times of overall grid power outages due to storms or potential terrorist actions, the consumers on the microgrid will still have power.

Studying Decarbonization

Previous Studies of Decarbonization

There are too many studies to describe here that analyze the economics surrounding and potential of carbon emission reduction. Instead, I highlight some key studies.

Perhaps the most famous report on the economics of decarbonization is the report put out by The Solutions Project (Jacobson et al., 2017). This report shows pathways for the electricity, transportation, heating/cooling, industry and agriculture sectors of 139 countries to be powered by wind, water, and sunlight (WWS). The pathways mainly consist of electrifying all energy sectors and providing the electric demand with renewable resources, including solar, wind, hydropower, geothermal, tidal, and wave power. The report does not consider the use of nuclear power as part of the carbon-free solution. There have been many responses to this report, both in support of it as well as discounting its findings. The most important outcome of the report is the influence that is has had in society and politics. This experience shows that studies on decarbonization can have both a scientific as well as a political influence.

The Deep Decarbonization Pathways Project is a collaboration of energy researchers. They have published reports on the decarbonization pathways for several countries, including the United States, the United Kingdom, China, and Germany (among many others) (IDDRI, 2019).

There have been many studies by various government departments highlighting the necessity of reducing carbon emissions. One example is the Energy Information Administration in the United States that published a report every year entitles the Annual Energy Outlook in which shows modeled projection of energy trends (US EIA, 2019).

Uncertainties in Decarbonization

Now let us examine in more depth the studies that incorporate uncertainty into decarbonization analysis. Here, I highlight several methods used in uncertainty modeling of the decarbonization sector.

What-if scenarios are used to determine potential outcomes based upon different beliefs of input values. Typically, these involve a “business as usual” scenario as well as many other potential scenarios where one input value is changed (i.e. increase in research and development spending or decrease in social support). These have the disadvantage of requiring the analyses to be redone whenever new information on the input variables changes (i.e. the business as usual scenario changes). In addition, another disadvantage coming from them is a strong dependence on the chosen scenario and associated assumed input variables (Haasnoot, Middelkoop, Beek, & Deursen, 2011). In addition, the dependence between the assumed input variables and the calculated scenario outcomes cannot be quantified.

Stochastic programming optimizes a system, given the potential of risky events, to produce a strategy. One strategy is produced until the first instance of an uncertain event. After this event, there is a different strategy to account for each outcome of this uncertain event. This type of uncertainty modeling is useful because it can find a robust strategy that can withstand the uncertain future, rather than selecting the lowest cost option. However, a disadvantage of this type of modeling is that it can be very computationally demanding (Labriet, Kanudia, & Loulou, 2012).

One study accounted for the high computational demand of this stochastic programming by combining stochastic programming with scenario (what-if) analysis. The model handled technology uncertainties with stochastic programming while handling climate uncertainties with “what-if” scenarios. The results from this study (which was focused on Asian regions) showed that natural gas was a robust choice for reduction of climate change effects. It was not only robust across the technological parameter uncertainties but it was also robust across the climate uncertainties. The main reason for this is because natural gas allowed for a cheap “wait and see” approach to installing further low carbon emitting technologies. In other words, it is cheap to install natural gas, which has lower emissions than coal, to reduce carbon emissions in the short term and wait to see which low carbon technology has the appropriate parameters (cost, performance, etc.) in the long run before selecting one of these technologies. Nuclear and carbon capture and sequestration technologies are less robust as they have a high dependence on either the climate or technology uncertainties (Labriet et al., 2012).

Another study uses a stochastic model to look at the effect of uncertainty of geological storage resources as well as the uncertainty of climate radiative forcing targets upon the usefulness of carbon capture and sequestration technology in long-term carbon emission reduction. The study found that the uncertainty in the overall climate radiative forcing target dominated the results over the uncertainty in the geologic storage resources for carbon capture and sequestration. The reason for this is that the most stringent climate targets represent almost the limit of what is feasible to reach with the system modeled and therefore there is little room to consider economics of the system (i.e. there is only one strategy that will work) (Keppo & van der Zwaan, 2012).

Another study uses a bottom-up integrated assessment model called TIMES Integrated Assessment Model (TIAM WORLD) to model the effect of carbon emission reduction policies upon meeting a climate target of limiting warming to 2.1°C by 2100. A limitation identified by the study is that although the model, TIAM WORLD, can account for uncertainty in climate sensitivity, it assumes perfect foresight for the technology and economy parameters. This means that the results are not realistic concerning actual considerations that policymakers must think about when making decisions (i.e. the uncertainties of future conditions). In order to consider the future uncertainties, this study implemented the model in conjunction with a Monte Carlo simulation using Latin hypercube sampling. The uncertainties considered in this study were climate sensitivity (the effect of a doubling of greenhouse gas concentration upon global temperature increase), carbon capture and sequestration parameters (year of commercial viability as well as capture, transportation, and sequestration costs), energy efficiency improvements, elasticity of substitution between technology production, economic growth, as well as oil and gas prices. The study found that the main source of uncertainty in resulting probability distribution functions was a result of climate sensitivities. It also found that the best way to increase the probability of meeting a carbon target is through developing a "basket" of carbon-free technologies to use and that one technology alone (the study considered carbon capture and sequestration technologies) is not sufficient (Babonneau, Haurie, Loulou, & Vielle, 2012).

Another study identifies several economic uncertainties present in climate change models. These include economic growth, population growth, emission intensities, new technologies, the carbon cycle, climate response and damages, as well as the costs and benefits of different policy objectives. The study uses a "two-track" approach to model the effect of three of the economic uncertainty variables (population growth, total factor productivity growth, and equilibrium climate sensitivity) upon major variables such as per capita consumption, output, damages, and the social cost of carbon. In the first "track," a three-dimensional response surface was generated for each of the major variables which each dimension being one of the economic uncertainty variables. In the second "track," probability distribution functions are developed each of the three economic uncertainty variables. The two tracks are then combined using a Monte Carlo simulation which selects from probability distribution functions of the three economic uncertainty variables and finds the corresponding point of the response surface of each major variable in order to generate probability distribution functions for each of the major output variables. One major advantage of this method is replicability. One can reproduce the response surfaces, the input uncertainty variable probability distribution functions, or the Monte Carlo (or all three) very easily. The study used three criteria to determine which economic variables to apply uncertainty to: 1) it must be an influential parameter, 2) it must be able to be altered without significant burden as well as without changing the spirit of the model, and 3) it must be able to be represented with a probability distribution function. The study was interested in finding the relative magnitude of the effects of parametric uncertainty and model uncertainty. It did this by repeating the two-track method for six different climate models and comparing the results. The study concluded that parametric uncertainty plays a much larger role in the uncertainty of the major variables than does model uncertainty. The exception was in the determination of social cost of carbon. This implies that the model choice does not matter as much as the choice of uncertainty input probability distribution functions (Gillingham et al., 2015).

Modeling Decarbonization

According to (Pye & Bataille, 2016), a model of decarbonization pathways must have the following three characteristics to be successful: 1) transparency, 2) practicality, and 3) cognizant of the complex dynamics associated with decarbonization. These complex dynamics include the operation of the energy sector, use of technology, society behavior, relationship with the economy, and infrastructure deployment.

Pye & Bataille (2016) developed a three-step process for selecting the type of model to use when simulating decarbonization pathways. The first step is to "determine policy priorities." By highlighting what the goals of the model are, the necessary qualities of the model can be found. For example, the qualities of a model built to determine the economic costs of decarbonization are different than the qualities of a model built to show the technological progression of decarbonization technologies (Pye & Bataille, 2016).

The second step is to "recognize system characteristics." This means that the model must be built to recognize the circumstances of the country or region that is being modeled. For example, a mostly rural country will require a different handling of transmission of electricity than a mostly urban country. The characteristics need to be handled properly to ensure that each characteristic of the country or region is adequately described and not glossed over (which could lead to inaccurate results) (Pye & Bataille, 2016).

The third and final step is to "evaluate capacity constraints." This means that there are always limitations when modeling a complex system and one needs to recognize the limitations before trying to model something that cannot be modeled. For example, it is impossible to model minute-by-minute output of a solar array if there is no minute-by-minute data on solar irradiance in the region where the solar array is. By recognizing these limitations from the beginning, it allows for the model developer to work around these obstacles to produce a model that still accurately depicts the system (Pye & Bataille, 2016).

From the three step process as well as the three characteristics a model needs in order to be successful, (Pye & Bataille, 2016) define five modelling principles:

1. "Problem driven,"
2. "Transparent, comprehensible and replicable,"
3. "Recognition of uncertainty,"
4. "Necessarily complex, not complication," and
5. "Flexibility for new objectives."

From an exhaustive literature review, (Pye & Bataille, 2016) identify 6 major areas in which future research needs to be focused in order to improve the availability and use of deep decarbonization pathway analyses. Of the six, three bear discussion here.

The first recommended research focus area is a need to have "flexibility to represent diverse energy systems." Lacking from the current research on decarbonization is a method to describe the characteristics of decarbonization in regions that are poorly represented (for example, regions with supply shortages/electrification issues or perhaps regions with a reliance on traditional biofuels) (Pye & Bataille, 2016). It is a goal of this thesis to provide a framework that is flexible and can work for any characteristic set of any region.

The second recommended research focus area is "recognizing wider environmental constraints." Lacking from the current research on decarbonization is the understanding of the relationship between the energy system of a region and the region's water, land, and air systems. These natural systems can play a large role in limiting a country's choices for decarbonization as well as create opportunities for decarbonization. In addition, there is a linkage between climate change and future weather patterns (which will in turn affect resources such as solar and wind which can affect decarbonization potential) (Pye & Bataille, 2016). It is a goal of this thesis to provide a framework that will account for the relationships between the energy system and the natural resources of a region.

The third recommended research focus are that is discussed here is "a focus on transparency, engagement and communication." Many models of decarbonization rely on a great array of assumed parameter inputs. These inputs can have a large influence on the results of a decarbonization pathway (such as economics, feasibility, etc.). The utilization of different assumptions is a reason why there are many models that give different solutions in terms of recommended pathways for decarbonization. The way to compare two different models with two different solutions is to understand all of the modeling and input assumptions, requiring transparency and communication (Pye & Bataille, 2016). It is a goal of this thesis to provide a framework in which all assumptions will not only be transparent, but also the procedure of getting to the assumptions will be transparent. Transparency is important because the conclusions of decarbonization models often are sensitive to input values. In this framework, all assumptions, as well as the rationale for all assumptions, will be explicitly stated.

Summary of Gaps in Previous Studies

Most decarbonization studies come out in support of a given suite of technologies (for example, all renewables, or pro-nuclear). This is because decarbonization research has become entangled with political and societal influences. There is a need for a technology-agnostic approach to analyze decarbonization. For example, the methods of studies on the effectiveness of nuclear power in decarbonization should be transferable to studying the effectiveness of solar or wind or carbon capture. However, the methods most studies of decarbonization include a section where the study eliminates certain technologies from consideration due to safety concerns or economic concerns. In this thesis, I provide two frameworks: one to look at the economic opportunity cost of forgoing a technology and the second to look at the probability of failure of a certain policy. In each of these frameworks, and technology can be analyzed (i.e. technology agnostic).

Another gap in previous decarbonization studies is the robust treatment of uncertainties. Most studies address uncertainty in decarbonization with “high”, “medium” and “low” scenarios. However, this does not show the dynamics in between these scenarios. As stated previously in this chapter, there are non-linearities in decarbonization and climate change and so the continuous (rather than discrete) treatment of uncertainties is needed. This is occurring in some studies (see Uncertainties in Decarbonization section), but these are niche studies. A method for addressing uncertainties should be utilized instead of the “high”, “medium” and “low” scenario strategy. This is the objective of Chapter 4 of this thesis – to provide a simple framework that can be used in any study so the results are not shown as point values, but as continuous distributions. If there are failures associated with the results, then the failure probabilities will be able to be calculated from the continuous distributions. This is a contribution of this thesis.

A final gap identified in decarbonization studies is the lack on global emphasis. Most studies pertain to the United States or some other developed country. However, according to the EIA, developing countries will account for 65% of the world’s energy consumption by 2040 (US EIA, 2018). Methods for analyzing decarbonization must be relevant for both developed countries and developing countries. Developing countries often have different needs than developed countries. For example, in the United States, the required grid resilience is one day loss of load per 10 years (NERC, 2018). From the North American Electric Reliability Corporation (NERC), who is in charge of maintain grid reliability: “Simply stated, customers expect uninterrupted electric service–or nearly so–for their own health and welfare. We know our societies rely on electricity; we needn’t say more.” However, for developing countries, this is often not a priority. Brownouts and loss of load are to be expected. Therefore, in the framework I present in Chapter 4, the failure criteria are not set beforehand. Rather, it is part of the framework to decide the failure criteria. This means that the framework will be able to be used in any country by adapting the failure criteria to that country’s specific needs.

Chapter 3 – Economic Opportunities for Nuclear Technology

The objective of this chapter is to develop a framework to assess the economic benefit of a technology in a decarbonized electricity sector. This is important because investment decisions must be made now for certain technologies to remain an option in the future electricity sector. However, the economic prospects of a technology now may not reflect what the economic prospects will be in a decarbonized electricity sector. For example, it appears that constructing nuclear power plants is not an economically attractive decision currently in the United States. However, if the option of building nuclear power plants in the United States is to exist in the future, then investments are needed today in maintaining the nuclear supply chain and nuclear engineering expertise. Looking at the economic prospects of nuclear power in a decarbonized electricity sector may encourage investment today.

The work in this chapter is also presented in the first chapter of a report entitled The Future of Nuclear Energy in a Carbon-Constrained World (Petti et al., 2018)

Introduction

Decarbonization of the electrical energy sector is needed to mitigate the effects of climate change. There are goals proposed to which carbon emissions must be reduced to in order to keep average global warming within 2°C (Chen et al., 2016). To achieve this decarbonization, there have been many suggested technical pathways proposed to have a substantial reduction in greenhouse gas emissions. Each of these pathways have different likelihoods of succeeding at reaching the carbon emission reductions goal. Cultural, political, and economic factors will play a role in what pathways is ultimately followed in different countries.

Current efforts to reduce carbon emissions in the electrical sector consist of promoting usage of renewable sources of electricity generation (such as solar and wind) as well as energy efficiency and energy conservation methods to reduce overall electric sector demand. However, these efforts are not enough to meet the carbon emission goals needed to keep average global warming within 2°C. Studies that have looked at the extent of measures needed to meet these goals acknowledge that the electric sector should be the prime first target of carbon emission reductions (Williams et al., 2015). This is because the cost of reducing carbon emission in the electric sector is initially lower than the heat or transportation sector. The lowering of carbon emissions in the heat and transportation sector would require more intense infrastructure shifts, which amplify the costs.

In the analysis in this sector, we focus on the carbon emission reduction in the electric sector because this will be where to focus will be first. We consider a wide range of decarbonization targets. Current electric sector carbon emissions in the United States average about 500 gCO2/kWh. In order to meet the goals stated in the Paris Agreement, the carbon emission reductions in the electric sector in the United States need to be at least 97% of this value. This would reduce carbon emissions to below 15 gCO2/kWh. This analysis is the result of estimating the relative scale of emissions reductions that are feasible in the electric and non-electric sectors in order to keep the concentration in the atmosphere to 450 parts per million (Chen et al., 2016).

Similar analyses have been performed for the carbon emission reductions needed in the electric sector of China and the United Kingdom. These are summarized in Table 1. The two analyses presented are the 2050 IEA Energy Technology Perspectives (International Energy Agency, 2017) and the MIT Joint Program Outlook (Chen et al., 2016).

Table 1: Current carbon emissions and carbon emission goals

Country	2017 CO2 Electric Sector Emissions	2050 IEA Energy Technology Perspectives 2°C Scenario	MIT Joint Program Outlook
United States	~470 gCO2/kWh	11 gCO2/kWh	~1 gCO2/kWh
China	~680 gCO2/kWh	24 gCO2/kWh	~1 gCO2/kWh
United Kingdom	~350 gCO2/kWh	11 gCO2/kWh	~1 gCO2/kWh

If the goal is to provide a majority of the electricity in the electric sector in a carbon-free manner, the question then naturally arises: what generating technologies should be used? There are other goals than simply carbon-free emission in the electricity sector, such as electricity security, reliability, resiliency, and affordability. There is disagreement over the relative extent that each low-carbon technology can be used to provide electric generation that meet all of these goals.

However, decisions made today can limit the extent to which the low carbon technologies will be able to contribute to electric generation in the future. For example, the future capital costs of solar and wind will depend upon the research and experience in building solar and wind power plants today. Nuclear technology is particularly susceptible to this because if the supply chain of constructing nuclear power plants is allowed to stagnate, it will be very difficult to construct nuclear power plants in the future. Therefore, it is important to determine which low-carbon technologies will be useful in the future so that, at worst, those technologies are not allowed to die out or, better, are significantly improved.

The goal here then becomes to find a method for determining the usefulness of low-carbon technologies in the future. A subgoal of this is to find what factors play a role in determining the usefulness of a low-carbon technology in the future. We use nuclear technology as the example.

Methods

This section outlines the framework needed to determine the usefulness of low carbon technologies in the future as well as to determine the factors that play important roles in determining the usefulness of nuclear technology in the future. We examine different carbon reduction targets from a “business as usual” case of 500 g/kWh to the MIT Joint Program Outlook proposed U.S. goal of 1 gCO2/kWh. We then expand the analysis to two provinces in China as well as the United Kingdom.

A technology is considered economically useful for meeting a given carbon emission reduction target if it is a part of the optimal installed capacity mix for that given carbon emission reduction target. The optimal installed capacity mix is obtained based upon the objective function of minimizing the average total system cost. The usefulness can be quantified by examining the cost difference between a completely optimized installed capacity mix and an optimized installed capacity mix where the technology examined is not permitted to be in that installed capacity mix.

Calculation of Opportunity Cost

The figure of merit used to quantify the economic usefulness of a technology is the technology's opportunity cost (OC). The opportunity cost is defined as the total system cost (TSC) difference between the lowest cost optimal solution with that technology as an option (LCOS) and the lowest cost optimal solution without that technology as an option (LCOS-i). See **Error! Reference source not found.**,

$$OC_A = TSC_{LCOS,-A} - TSC_{LCOS}. \qquad \text{Eq. 1}$$

The percentage of the total system cost that the opportunity cost represents is found by dividing the opportunity cost by the total system cost with the technology available. See **Error! Reference source not found.**,

$$POC_A = \frac{OC_A}{TSC_{LCOS}} \times 100. \qquad \text{Eq. 2}$$

Optimization Model

In order to find the total system cost, an optimization model (GenX) was utilized (Jenkins & Sepulveda, 2017). GenX is a power system support tool developed by Sepulveda and Jenkins. It varies the installed capacity and dispatch of the capacity's generation to find an optimal solution based on the total system cost (including total fixed and variable operation cost, total investment cost, as well as total fuel cost). It adheres to constraints on 1) technology operating performance, such as ramping, minimum on time, and minimum off time and 2) carbon emission limits. Inputs into the model include a year's hourly demand profile and a year's weather patterns (determining the potential for wind and solar technologies) (Jenkins & Sepulveda, 2017).

GenX considers one full year of operating decisions (with a time step of one hour) to represent a snapshot of a future year. That is to say, the model considers a static scenario (or greenfield situation) with no consideration of the influences of the path that must be taken to get to the scenario. This means that the solution that is generated is truly an optimal solution. It is the best-case scenario. It is possible that the solution will not be feasible due to some path constraint (for example, the required installation rate of a particular technology).

Due to considerations of simplicity and computational speed, I represented the transmission network modeled in GenX as a single node. This is often referred to as a “copper plate” assumption. This means that I do not consider transmission constraints or transmission costs in the model. In addition, I assume that the electricity generated within a region serves only the demand in that region. The modeled scenarios do not account for import or export of electricity from outside regions.

The outputs of GenX are 1) the installed capacity of each available technology, 2) the hourly power production of each available technology, 3) the total carbon emissions, and 4) the total and average system cost. We use this total and average system cost in the calculation of a technology’s opportunity cost.

Cases Tested

In order to determine the opportunity cost of forgoing nuclear technology, we need to find the difference between the lowest cost optimal solution with nuclear as an option and the lowest cost optimal solution without nuclear as an option. Therefore, I examine two alternative pathways in every simulation: one with nuclear and one without nuclear being allowed. It is important to note that even if nuclear is allowed to be in the lowest cost optimal solution, that does not mean it has to be in the lowest cost optimal solution. Nuclear will only be deployed if it is economically efficient for the overall installed capacity of electric generators. In the scenarios in which nuclear is allowed to be deployed but is not deployed, there will be no difference between the two pathways and the opportunity cost of forgoing nuclear will be zero.

The global perspective of carbon emission reductions is important. The opportunity costs of a technology in one region may be different in other regions based on economic, social, and political factors. I focus on the importance of the region’s economic factors in this study. These economic factors include fuel costs, construction costs, as well as demand profile characteristics. I consider three different countries: 1) The United States, 2) China, and 3) The United Kingdom. Within the United States, I considered a region with favorable renewables (Texas) and a region with unfavorable renewables (New England). I do the same in China by considering both the Tianjin, Beijing, and Tangshan (T-B-T) Region as well as Zhejiang province. Due to the smaller relative size of the United Kingdom, I consider the country as a whole in our simulation.

I consider various emission targets ranging from a “business as usual” (or unlimited carbon emissions allowed) scenario where the emissions are close to current emissions down to the MIT Joint Program Outlook goal of 1gCO2/kWh. The specific carbon constraints modeled are Unlimited, 500gCO2/kWh, 100gCO2/kWh, 50gCO2/kWh, 10gCO2/kWh, and 1gCO2/kWh. In the United States and the United Kingdom, the business as usual (unlimited) scenario is the same as the 500gCO2/kWh scenario, and so, it will not be shown in the results.

I utilized a wide range of assumptions about costs and technology characteristics in order to test the sensitivities of the results generated. In addition, I specifically tested a lower capital costs (25% reduction in capital cost) of nuclear technology in order to see the dependence of the opportunity cost of nuclear upon its capital cost. In the three cases most favorable for nuclear (i.e. forgoing nuclear had the highest opportunity cost), I tested a higher capital cost as well (25% increase in capital cost). In addition, I tested an extremely low nuclear capital cost in the Texas case (50% decrease in capital cost).

The results are expressed in terms of 1) the economically optimal installed capacity mix, 2) the economically dispatched generation of the capacity mix, and 3) the average cost of generation (in $/MWh).

In order to make the computation of the simulations feasible, it was necessary to limit the number of technology options for each modeled scenario. I used a large light water reactor (1000 MW) as the surrogate for all nuclear technologies. Table 2 shows all of the technical options that are able to be deployed as part of the economically optimal capacity mix.

Table 2: Technology Options for Each Simulated Pathway

Nuclear Energy IS Allowed Pathway	Nuclear Energy IS NOT Allowed Pathway
Carbon Free Options • **Photovoltaic (PV) Solar** • **On-Shore Wind** • **Light-water Reactor (LWR) Nuclear** • **Coal w Carbon-capture-storage (CCS)** • **Natural Gas with CCS**	Carbon Free Options • PV Solar • On-Shore Wind • ~~LWR Nuclear~~ • Coal with CCS • Natural Gas with CCS
Carbon Options • **Open Cycle Gas Turbine (OCGT)** • **Combined Cycle Gas Turbine (CCGT)** • **Coal (IGCC)**	Carbon Options • OCGT • CCGT • Coal (IGCC)
Storage Options • **Battery Storage** • **Hydro-electric Storage (Fixed)**	Storage Options • Battery Storage • Hydro-electric Storage (Fixed)

Model Inputs

Each region has a different demand profile, weather patterns, and technology costs. I assumed that the operating parameters (i.e. efficiency, ramping capability) were the same across each region. The sources of solar hourly capacity factor, wind hourly capacity factor, and hourly electric demand are in Table 3.

Table 3: Hourly data sources for each region.

	Tianjin, China	Zhejiang, China	United Kingdom	Texas, United States	New England, United States
Solar Hourly Capacity Factor (2016)	Renewables Ninja[a]	Renewables Ninja[a]	Sheffield Solar[d]	Sepulveda 2016	Sepulveda 2016
Wind Hourly Capacity Factor (2016)	Renewables Ninja[a]	Renewables Ninja[a]	EnAppSys[e]	Sepulveda 2016	Sepulveda 2016

Historical Hourly Elec. Demand	CEIC[b] and SWITCH[c]	CEIC[b] and He et al.[c]	Gridwatch[f]	Sepulveda 2016	Sepulveda 2016

[a](Pfenninger & Staffell, 2016, 2017; I. Staffell & Pfenninger, 2016) [b](CEIC, 2017) [c](He et al., 2016) [d](The University of Sheffield, 2017) [e](EnAppSys, 2017) [f](Gridwatch, 2017)

Most technology costs for the United States in 2050 were taken from the National Renewable Energy Laboratory Annual Technology Baseline report (National Renewable Energy Laboratory, 2018). The exception was the cost of batteries which was taken from a Lazard Report (Lazard, 2015). The costs for China and the United Kingdom were adapted from the costs for the United States based upon capital, fuel, and operating cost scaling factors calculated by comparing U.S. data to each respective country's data as reported by the International Energy Agency (International Energy Agency, 2015). The investment costs for each technology are shown in Table 4, Table 6, and Table 8 for the United States, China, and the United Kingdom, respectively. The high and low investment costs are also shown to the technologies in which the investment cost was varied to show the sensitivity of the results. The operational costs and constraints are shown in Table 5, Table 7, and Table 9 for the United States, China, and the United Kingdom, respectively.

Table 4: United States Investment Costs by Technology

Technology	Overnight Cost [$/MW]	Construction Period [years]	Life Time [years]	Interest Rate	Future Cost [$/MW]	Investment Cost [$/MW-yr]
OCGT	$1,038,000.00	2	20	8%	$1,122,191.82	$114,333.51
CCGT	$1,143,000.00	2	20	8%	$1,235,708.33	$125,899.03
Coal	$3,514,839.91	4	40	8%	$4,116,254.00	$345,345.33
Nuclear (High)	$6,875,000.00	7	40	8%	$9,110,863.69	$764,382.92
Nuclear (Nominal)	$5,500,000.00	7	40	8%	$7,288,690.95	$611,506.33
Nuclear (Low)	$4,100,000.00	7	40	8%	$5,433,387.80	$455,850.18
Nuclear (Very Low)	$2,750,000.00	7	40	8%	$3,644,345.47	$305,753.17
Solar (High)	$1,897,747.42	1	20	8%	$1,972,722.65	$200,989.08
Solar (Nominal)	$916,570.16	1	20	8%	$952,781.54	$97,073.29
Solar (Low)	$551,282.53	1	20	8%	$573,062.32	$58,385.94
Wind (High)	$1,714,103.19	1	20	8%	$1,781,823.09	$181,539.45
Wind (Nominal)	$1,553,387.38	1	20	8%	$1,614,757.81	$164,518.15
Wind (Low)	$1,368,619.70	1	20	8%	$1,422,690.42	$144,949.54
Battery (Nominal)	$1,430,000.00	1	10	8%	$1,486,495.70	$221,573.74
Battery (Low)	$715,000.00	1	10	8%	$743,247.85	$110,786.87
Battery (Very Low)	$429,000.00	1	10	8%	$445,948.71	$66,472.12
Coal IGCC+CCS	$5,875,883	6	30	8%	$7,468,797.41	$663,697.50
Gas CCGT+CCS	$2,215,000	3	25	8%	$2,491,723.88	$233,505.55
Gas CCGT+CCS (Low)	$1,720,000	3	25	8%	$1,934,882.65	$181,322.60
Hydro-Electric Storage	n/a[1]	n/a[1]	n/a[1]	n/a[1]	n/a[1]	n/a[1]

[1]Hydro-electric storage was considered to already be built, and so the investment cost is not considered.

Table 5: United States Operation Costs by Technology

Resource	Unit Size (MW_e)	Fixed O&M Cost ($/$MW_e$-yr)	Variable O&M Cost ($/$MWh_e$)	Heat Rate (MMBTU/ MWh_e)	Fuel	Minimum Power (%)	Ramping Capability (%)	Fuel Cost ($/MMBTU)	CO_2 Emissions (tons/MMBTU)
OCGT	200	$7,300	$10.69	9.75	Natural Gas	24%	100%	$7.52	0.053
CCGT	500	$15,800	$3.37	6.43	Natural Gas	38%	70%	$7.52	0.053
IGCC	600	$52,000	$7.34	8.80	Coal	70%	30%	$3.14	0.097
Nuclear	1000	$95,000	$6.89	10.49	Uranium	50%	25%	$1.02	0.000
Wind	1	$51,000	$0.00	n/a	n/a	0%	100%	n/a	n/a
Solar	1	$17,000	$0.00	n/a	n/a	0%	100%	n/a	n/a
Battery	1	$5,000	$0.00	n/a	n/a	0%	100%	n/a	n/a
IGCC (CCS)	600	$73,965	$8.58	8.31	Coal (CCS)	70%	10%	$3.14	0.010
CCGT (CCS)	500	$32,278	$6.89	7.49	Natural Gas (CCS)	30%	70%	$7.52	0.005
Hydro-Electric Storage	(max total = 500)	$4,600	$4.00	n/a	n/a	0%	100%	n/a	n/a

Table 6: China Investment Costs by Technology

Technology	Overnight Cost [$/MW]	Construction Period [years]	Life Time [years]	Interest Rate	Future Cost [$/MW]	Investment Cost [$/MW-yr]
OCGT	$542,971.62	2	20	8%	$587,011.86	$59,807.18
CCGT	$597,896.49	2	20	8%	$646,391.67	$65,857.04
Coal	$1,160,273.19	4	40	8%	$1,358,804.17	$114,000.90
Nuclear (Nominal)	$2,796,046.84	7	40	8%	$3,705,367.50	$310,872.79
Nuclear (Low)	$2,084,325.82	7	40	8%	$2,762,183.05	$231,741.54
Solar (High)	$1,389,408.38	1	20	8%	$1,444,300.41	$147,151.25
Solar (Nominal)	$671,053.61	1	20	8%	$697,565.25	$71,070.81
Solar (Low)	$403,613.55	1	20	8%	$419,559.31	$42,746.42
Wind (High)	$1,398,452.48	1	20	8%	$1,453,701.82	$148,109.11
Wind (Nominal)	$1,267,332.36	1	20	8%	$1,317,401.47	$134,222.27
Wind (Low)	$1,116,589.50	1	20	8%	$1,160,703.14	$118,257.20
Battery (Nominal)	$1,430,000.00	1	10	8%	$1,486,495.70	$221,573.74
Battery (Low)	$715,000.00	1	10	8%	$743,247.85	$110,786.87
Battery (Very Low)	$429,000.00	1	10	8%	$445,948.71	$66,472.12
Coal IGCC+CCS	$1,939,670	6	30	8%	$2,465,502.15	$219,091.18
Gas CCGT+CCS	$1,158,653	3	25	8%	$1,303,405.92	$122,145.36
Gas CCGT+CCS	$899,722	3	25	8%	$1,012,125.59	$94,848.77
Hydro-Electric Storage	n/a[1]	n/a[1]	n/a[1]	n/a[1]	n/a[1]	n/a[1]

[1]Hydro-electric storage was considered to already be built, and so the investment cost is not considered.

Table 7: China Operation Costs by Technology

Resource	Unit Size (MW_e)	Fixed O&M Cost ($/$MW_e$-yr)	Variable O&M Cost ($/$MWh_e$)	Heat Rate (MMBTU/ MWh_e)	Fuel	Minimum Power (%)	Ramping Capability (%)	Fuel Cost ($/MMBTU)	CO_2 Emissions (tons/MMBTU)
OCGT	200	$5,102	$7.47	9.75	Natural Gas	24%	100%	$12.92	0.053
CCGT	500	$11,043	$2.36	6.43	Natural Gas	38%	70%	$12.92	0.053
IGCC	600	$19,032	$2.69	8.80	Coal	70%	30%	$3.78	0.097

Nuclear	1000	$59,677	$4.33	10.49	Uranium	50%	25%	$0.84	0.000
Wind	1	$40,884	$-	n/a	n/a	0%	100%	n/a	n/a
Solar	1	$60,091	$-	n/a	n/a	0%	100%	n/a	n/a
Battery	1	$5,000	$-	n/a	n/a	0%	100%	n/a	n/a
IGCC (CCS)	600	$73,965	$8.58	8.31	Coal (CCS)	70%	10%	$3.78	0.010
CCGT (CCS)	500	$32,278	$6.89	7.49	Natural Gas (CCS)	30%	70%	$12.92	0.006
Hydro-Electric Storage	(max total = 500)	$4,600	$4.00	n/a	n/a	0%	100%	n/a	n/a

Table 8: United Kingdom Investment Costs by Technology

Technology	Overnight Cost [$/MW]	Construction Period [years]	Life Time [years]	Interest Rate	Future Cost [$/MW]	Investment Cost [$/MW-yr]
OCGT	$865,454.07	2	20	8%	$935,650.75	$95,327.94
CCGT	$953,000.00	2	20	8%	$1,030,297.50	$104,970.94
Coal	$3,514,839.91	4	40	8%	$4,116,254.00	$345,345.33
Nuclear (Nominal)	$8,142,682.93	7	40	8%	$10,790,818.06	$905,327.67
Nuclear (Low)	$6,070,000.00	7	40	8%	$8,044,064.38	$674,880.63
Solar (High)	$1,664,524.56	1	20	8%	$1,730,285.74	$176,288.61
Solar (Nominal)	$803,928.66	1	20	8%	$835,689.86	$85,143.51
Solar (Low)	$483,532.90	1	20	8%	$502,636.07	$51,210.62
Wind (High)	$2,363,445.81	1	20	8%	$2,456,819.61	$250,310.86
Wind (Nominal)	$2,141,847.07	1	20	8%	$2,226,466.06	$226,841.50
Wind (Low)	$1,887,085.04	1	20	8%	$1,961,639.02	$199,859.83
Battery (Nominal)	$1,430,000.00	1	10	8%	$1,486,495.70	$221,573.74
Battery (Low)	$715,000.00	1	10	8%	$743,247.85	$110,786.87
Battery (Very Low)	$429,000.00	1	10	8%	$445,948.71	$66,472.12
Coal IGCC+CCS	$5,875,883	6	30	8%	$7,468,797.41	$663,697.50
Gas CCGT+CCS	$1,846,802	3	25	8%	$2,077,526.56	$194,690.11
Gas CCGT+CCS	$1,434,086	3	25	8%	$1,613,248.61	$151,181.48
Hydro-Electric Storage	n/a[1]	n/a[1]	n/a[1]	n/a[1]	n/a[1]	n/a[1]

[1]Hydro-electric storage was considered to already be built, and so the investment cost is not considered.

Table 9: United Kingdom Operation Costs by Technology

Resource	Unit Size (MW_e)	Fixed O&M Cost ($/$MW_e$-yr)	Variable O&M Cost ($/$MWh_e$)	Heat Rate (MMBTU/ MWh_e)	Fuel	Minimum Power (%)	Ramping Capability (%)	Fuel Cost ($/MMBTU)	CO_2 Emissions (tons/MMBTU)
OCGT	200	$10,408	$15.24	9.75	Natural Gas	24%	100%	$15.39	0.053
CCGT	500	$22,528	$4.80	6.43	Natural Gas	38%	70%	$15.39	0.053
IGCC	600	$52,000	$7.34	8.80	Coal	70%	30%	$3.14	0.097
Nuclear	1000	$180,759	$13.11	10.49	Uranium	50%	25%	$1.02	0.000
Wind	1	$54,194	$-	n/a	n/a	0%	100%	n/a	n/a
Solar	1	$91,952	$-	n/a	n/a	0%	100%	n/a	n/a
Battery	1	$5,000	$-	n/a	n/a	0%	100%	n/a	n/a
IGCC (CCS)	600	$73,965	$8.58	8.31	Coal (CCS)	70%	10%	$3.14	0.010
CCGT (CCS)	500	$32,278	$6.89	7.49	Natural Gas (CCS)	30%	70%	$70.41	0.040

Hydro-Electric Storage	(max total = 500)	$4,600	$4.00	n/a	n/a	0%	100%	n/a	n/a

Results

This section outlines the results of the simulated cases.

Figure 8 shows the installed capacity by generation technology for different assumed overnight costs of nuclear in Texas for carbon emission limits of 500g/CO2/kWh, 100 gCO2/kWh, 50 gCO2/kWh, 10 gCO2/kWh, and 1 gCO2/kWh.

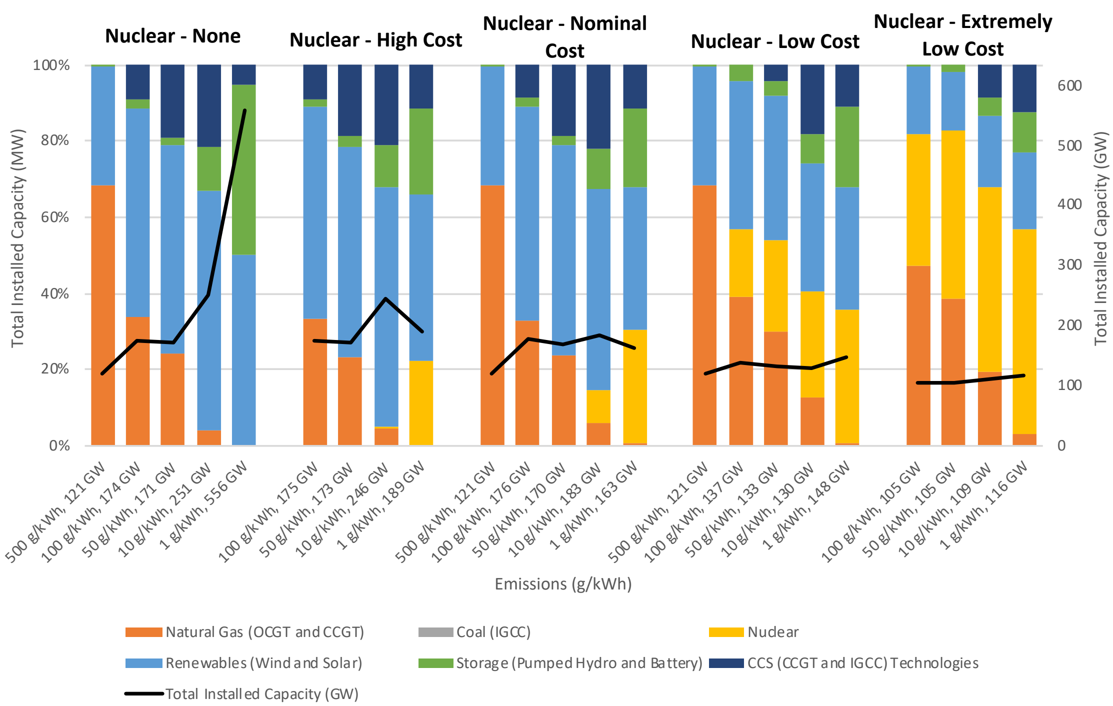


Figure 8: ERCOT Installed Capacity

Texas is a region with high renewable potential (windy and sunny climate) and low costs of natural gas, thus suggesting a region where nuclear may not be competitive or have a large impact. This is confirmed in business as usual case of emissions at 500 gCO2/kWh, which is about the current U.S. emissions level. However, even in Texas, as the emissions targets are decreased, nuclear is deployed in the least-cost generation mix for cases with a CO_2 emissions limit below 50 gCO2/kWh at the nominal capital cost of nuclear. This is due to the value that nuclear energy presents to the system as a zero-emissions dispatchable generation option. If capital costs are reduced to the low-cost scenario (25% reduction), the value of nuclear energy increases and one notes that nuclear capacity begins to contribute to the system mix when the CO_2 emissions limit is 100 gCO2/kWh. As the capital cost is reduced further to the extremely low cost scenario (50% reduction), the penetration of nuclear into the economically optimized capacity mix increases. The converse is true if the capital costs are increased to the high cost scenario (25% increase). In this case, nuclear capacity begins to contribute to the system mix only when the emissions limit is 1 gCO2/kWh.

Figure 9 shows average system cost for different assumed overnight costs of nuclear in Texas for carbon emission limits of 500g/CO2/kWh, 100 gCO2/kWh, 50 gCO2/kWh, 10 gCO2/kWh, and 1 gCO2/kWh.

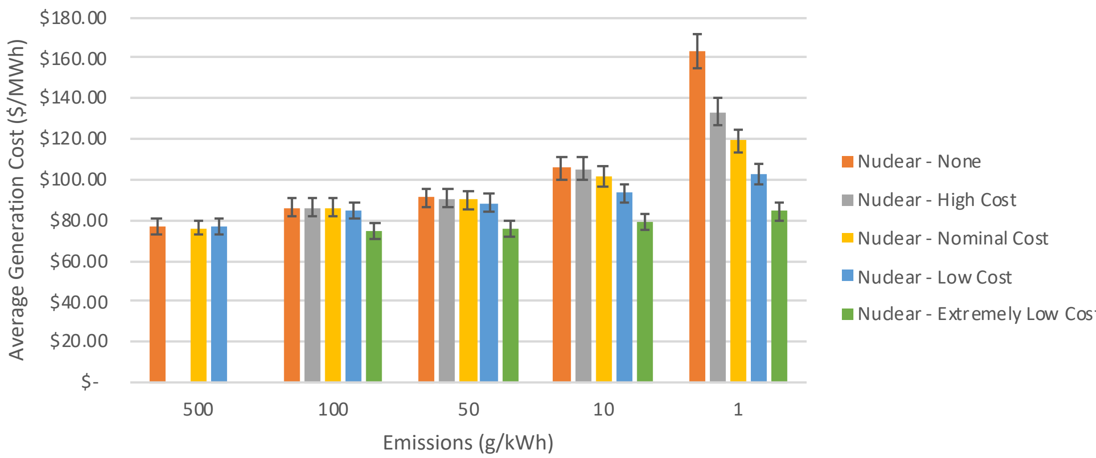


Figure 9: ERCOT Cost of Electricity Generation

As can be seen in Figure 8 and Figure 9, imposing a carbon emission limit to the system reduces the ability for deployment and use of fossil-fueled generation. This constraint, at a certain level, depends on the renewables resource availability and technological costs, and directly affects the value of renewables even in the presence of storage due to the lack of backup capacity to operate during rapidly-changing renewables output and the need to move greater amounts of energy from hours with higher renewables output to hours with lower renewables output. This results in a system of low-carbon generation backup capacity or a system of greater deployment of battery storage and renewables generation to provide backup capacity. Both situations result in a greater cost.

As shown in the Figure 9, limiting the deployment of a carbon-free dispatchable generation resource, like nuclear, greatly increases the system cost by mean of deployment of less efficient forms of generation and backup. This trend is most strongly seen at the carbon emission targets below 50 gCO2/kWh; i.e., 10 gCO2/kWh and 1 gCO2/kWh as required for deep decarbonization. One also notes that reductions in the capital cost for nuclear improves its value and allows it to be deployed not only for near-zero emissions limits but also for more modest emission reduction targets (100 and 50 gCO2/kWh).

A further explanation for the cost escalation without nuclear as an option is found in the amounts of installed capacity, Figure 8. If nuclear is not included in the pathway, large build outs of wind, solar, and battery storage are required to meet the constraint of a low CO_2

emission. This is evident in the 10 gCO2/kWh emission scenario and more so in the 1 gCO2/kWh emission scenario, where the installed capacity of the no nuclear technological scenario is over three times the installed capacity of the nuclear-nominal technological scenario. This installed capacity comes at a large investment cost, which dramatically increases the total system cost.

In addition to the large investment cost of renewables build out, low carbon scenarios without nuclear come at a cost of sizable land usage. For the 1 gCO2/kWh emission target in the "Nuclear – None" case, the land requirements for both solar and wind would be just under 4 million hectares (about 5.5% of the state of Texas). This is the largest build out of renewable energy in any of the Texas scenarios. This land usage is proportionately larger in the other regions analyzed as the renewable capacity factors are lower in the other regions investigated.

Now let us examine New England, which has more modest renewable resource availability than Texas. Figure 10 shows the effect of including nuclear as an option in the optimal total system cost of electricity generation for New England (US).

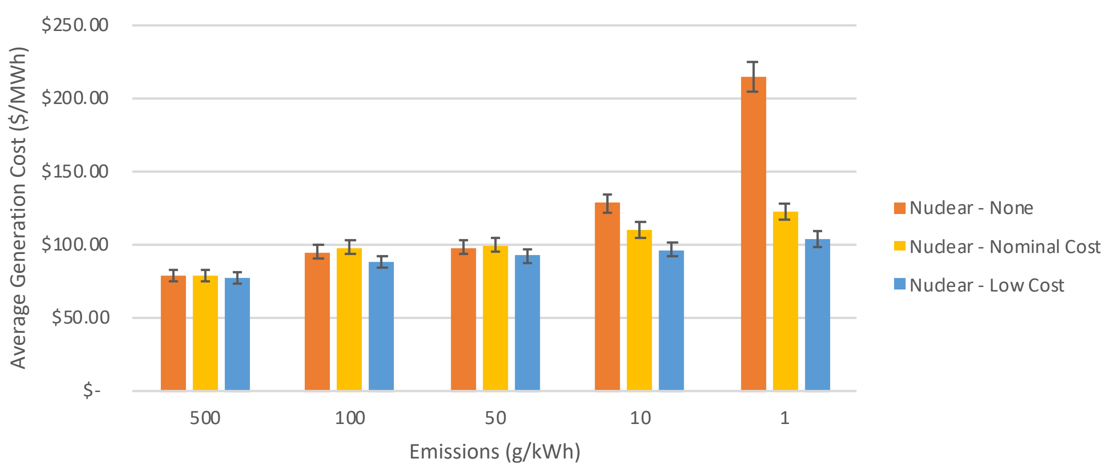


Figure 10: New England Cost of Electricity Generation

In New England, with the cost of nuclear technology at its nominal value, the benefit of having nuclear technology as an option is only seen at CO_2 emission targets of 10 and 1 gCO2/kWh. If we consider the possibility of the cost of nuclear being below this nominal cost (as in the "Nuclear – Low Cost" scenario), then some small benefit of nuclear technology as an option can be seen at the 50 and 100 gCO2/kWh emission targets.

In comparison to Texas, New England sees a higher benefit from nuclear technology in the optimal capacity mix, because there are fewer renewable resources available in New England when demand is high, than there are available when demand is high in Texas. Thus, for New England to generate enough electricity in periods of higher demand, it requires a larger amount of installed renewable capacity and storage. This build out of installed capacity requires a large amount of capital expenditure, which translates into a higher system cost. The combination of less favorable weather conditions and more stringent CO_2 constraint is the reason for the steep increase in the cost of generation. As the emissions constraint decreases from the 'Business as usual' case of 500 gCO2/kWh, the cost of substituting one kWh of the carbon-emitting electricity generation with carbon-free electricity generation increases. At the less strict carbon emission levels, the carbon-emitting energy is displaced by renewable technologies during periods of high renewable potential (i.e., sunny and windy days). However, as the carbon constraint is decreased further, the electricity generation during these high renewable potential times is already carbon-free. The carbon-emitting electricity generation, which must be displaced, is at times with lower renewable potential. Therefore, either a large build out of renewable capacity with storage is needed to compensate for the lower generation potential or a carbon-free dispatchable generation technology is needed (such as nuclear). This means that there is a much higher cost to displace that unit of carbon-emitting energy generation at stricter carbon constraints without nuclear as an option. The build out of renewable capacity is seen in Figure 11.

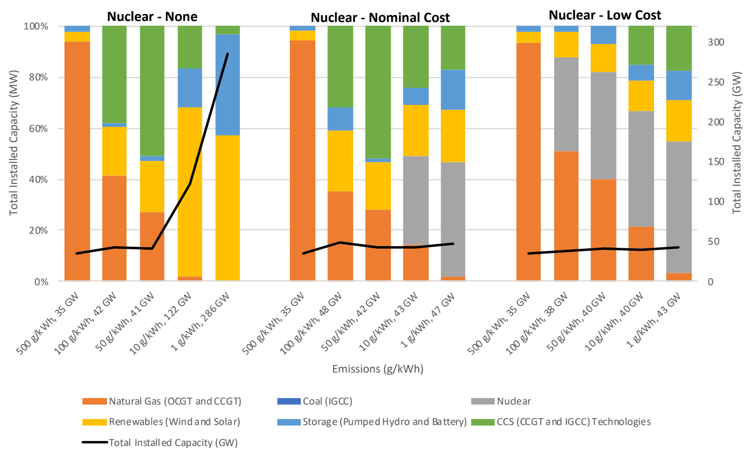


Figure 11: New England Installed Capacity

The required installed capacity of renewables and battery storage in New England is large due to the more limited wind and solar resource potentials in New England during periods of high demand. In addition, a large battery storage capacity must be supplied to compensate for weather variability.

Now let us examine two regions in China – T-B-T and Zhejiang – which have different costs for energy technologies. Figure 12 and Figure 13 show the effect of including nuclear as an option in the optimal total system cost of electricity generation for T-B-T and Zhejiang, respectively.

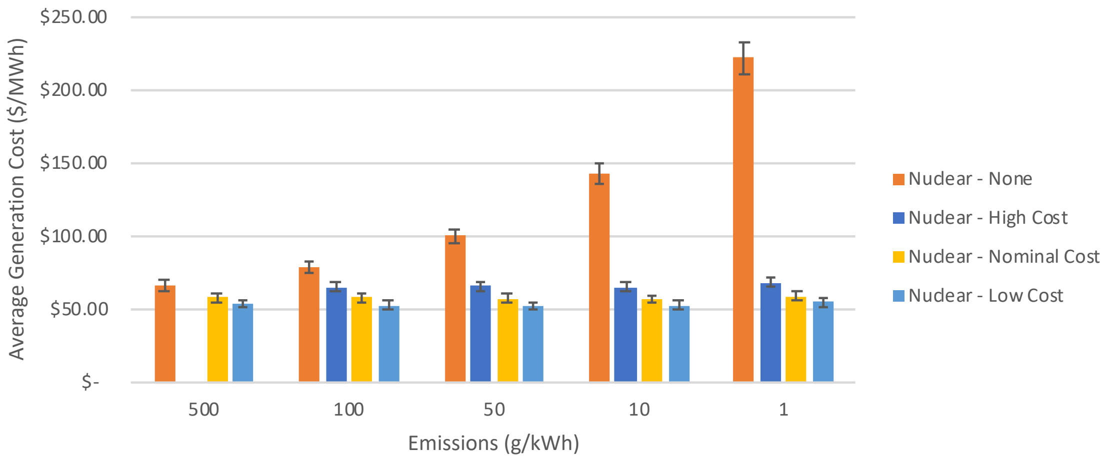


Figure 12: T-B-T Cost of Electricity Generation

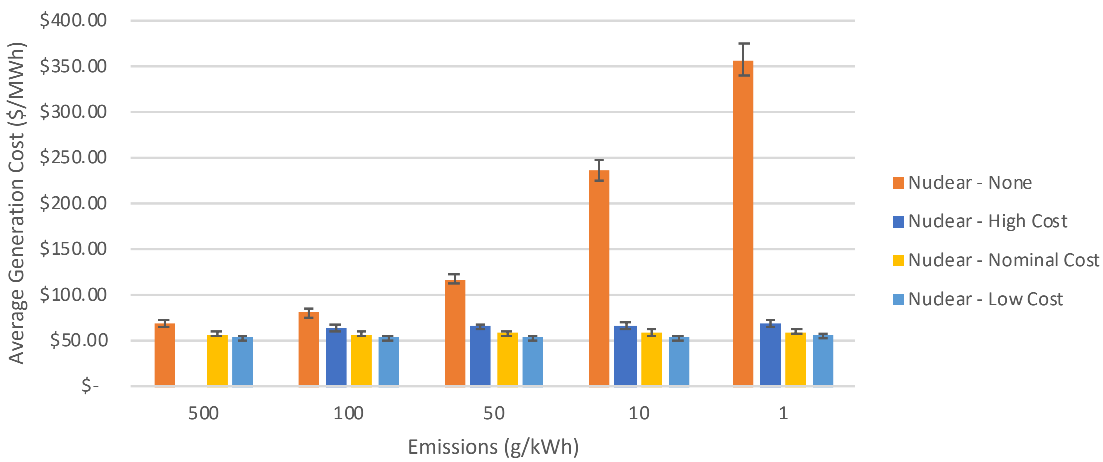


Figure 13: Zhejiang Cost of Electricity Generation

In the two Chinese provinces considered, the benefit of having nuclear technology as an option under nominal conditions for the total system cost is seen over the entire wide range of emission targets modeled: 500 gCO2/kWh, 100 gCO2/kWh, 50 gCO2/kWh, 10 gCO2/kWh, and 1 gCO2/kWh. For example, based on these cost assumptions, the average system cost of generating electricity without nuclear technology as an option at a 10 gCO2/kWh CO_2 emission target is greater than 3 times the electricity generation cost with nuclear technology as an option. This is because the cost of nuclear technology is comparatively less expensive in China. Thus, nuclear is selected to be part of the generation mix even at the least restrictive CO_2 emissions constraint. Even in periods of high renewable potential, nuclear technology is selected because it is the less costly option. This benefit of having nuclear as an option is notable.

Figure 14 and Figure 15 show the installed capacity mix for T-B-T and Zhejiang, respectively.

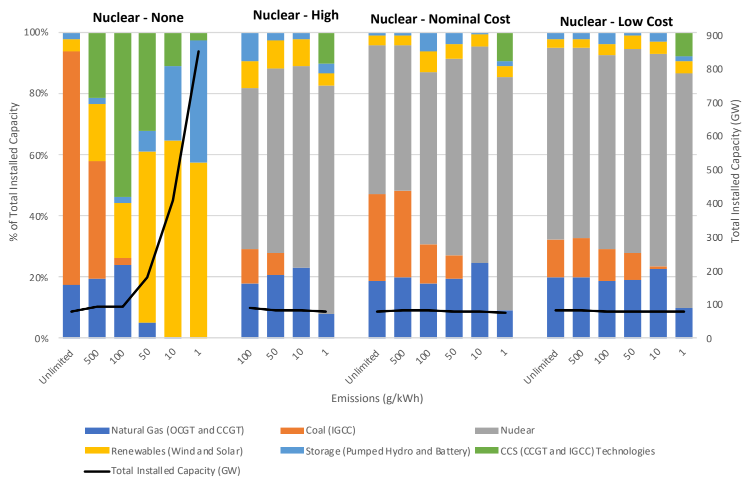


Figure 14: T-B-T Installed Capacity

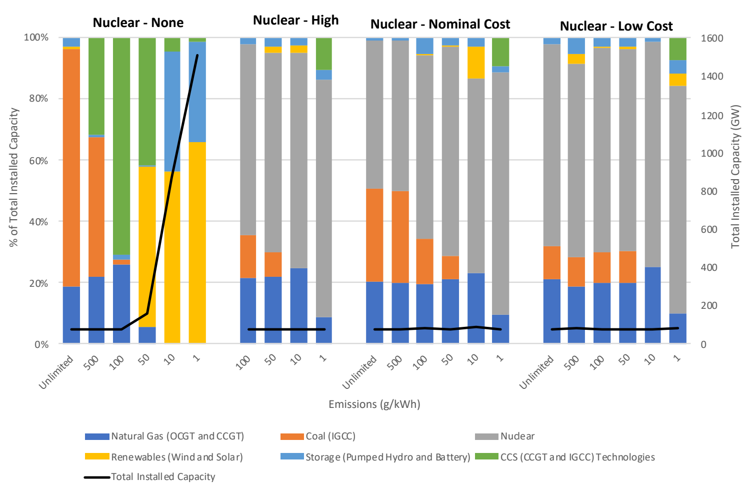


Figure 15: Zhejiang Installed Capacity

The same qualitative capacity trends are noted as in Texas and the New England regions, in that in the absence of nuclear capacity at low carbon emissions there is an overbuild of renewables and battery storage, but even more pronounced.

Now let us examine the United Kingdom. Figure 16 shows the effect of including nuclear as an option in the optimal total system cost of electricity generation for the United Kingdom.

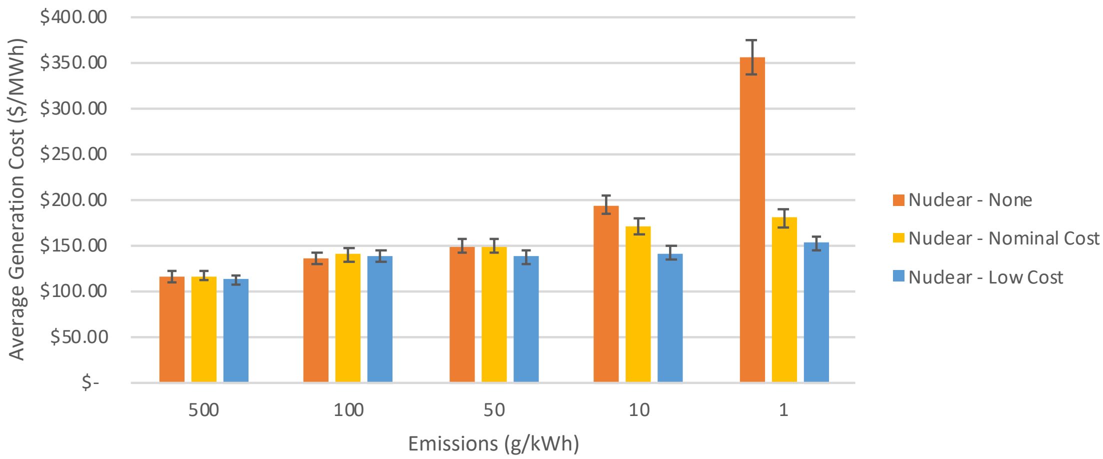


Figure 16: United Kingdom Cost of Electricity Generation

In the United Kingdom, the cost implications of including nuclear as an option is similar to the United States cases with the same steep increase in the average generation cost with increasing strictness of carbon emission constraints. A notable cost benefit with nuclear is seen at CO_2 emissions targets of 10 and 1 gCO2/kWh.

Figure 17 show the installed capacity mix for the United Kingdom.

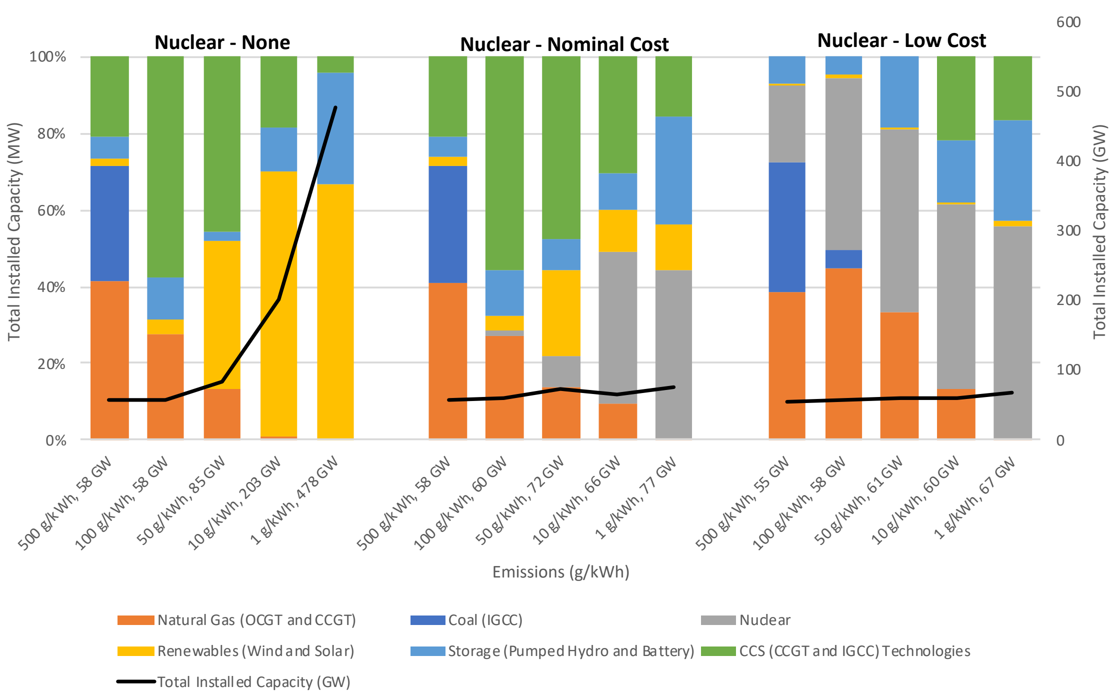


Figure 17: United Kingdom Installed Capacity

The same qualitative capacity trends are noted as in Texas, New England, and the China regions, in that in the absence of nuclear capacity at low carbon emissions there is an overbuild of renewables and battery storage.

By comparing the optimal capacity mixes with the system electricity costs, it is found that higher system costs are always associated with greater amounts of installed renewable capacity (both wind and solar) combined with battery storage. At lower carbon targets without nuclear technology allowed as an option, the electricity generation must come from renewables as the only other completely carbon-free option. Due to renewable generation's intermittent nature, a very large amount of installed renewable and battery storage capacity is needed to ensure that the electricity generation always meets the demand. The large increase in investment cost of the additional installed capacity increases the total system cost. This represents an opportunity for nuclear technology, as the capacity build out for nuclear to generate electricity to meet demand is much less than the build out required for renewables. These differences in required capacity build out are the result of the dispatchable nature of nuclear and the high average operating capacity factor for nuclear technology compared to the lower operating capacity factor for solar and wind without battery storage capacity.

Table 10 below shows the opportunity cost of not including nuclear technology as an option in the optimal capacity portfolio mix for each of the five regions for the nominal and low cost of nuclear. We show both the opportunity cost (**Error! Reference source not found.**) and the p ercentage opportunity cost (**Error! Reference source not found.**).

Table 10: Opportunity Cost of not including Nuclear in the Optimal Installed Capacity Mix. The absolute opportunity cost is shown in $/MWh and the percentage opportunity cost is shown in % in the parentheses.

	Nuclear Costs	500 gCO2/kWh	100 gCO2/kWh	50 gCO2/kWh	10 gCO2/kWh	1 gCO2/kWh
Texas	Nominal	$0.2/MWh (0.3%)[a]	$0.16/MWh (0.2%)[a]	$0.73/MWh (0.8%)[a]	$3.54/MWh (3.5%)[a]	$43.89/MWh (36.9%)
	Low	$0/MWh (0%)[a]	$1.8/MWh (2.1%)[a]	$2.62/MWh (3%)[a]	$12.02/MWh (12.9%)	$60.53/MWh (59.1%)
New England	Nominal	$0.02/MWh (0%)[a]	$-3.09/MWh (-3.1%)[a]	$-1.54/MWh (-1.5%)[a]	$17.93/MWh (16.3%)	$91.73/MWh (75%)
	Low	$1.22/MWh (1.6%)[a]	$6.89/MWh (7.8%)	$5.67/MWh (6.1%)	$31.64/MWh (32.8%)	$110.37/MWh (106.4%)
T-B-T	Nominal	$8.38/MWh (14.5%)	$21.46/MWh (37%)	$42.48/MWh (73.9%)	$84.87/MWh (148.7%)	$162.41/MWh (273.9%)
	Low	$12.73/MWh (23.8%)	$26.55/MWh (50.2%)	$47.19/MWh (89.4%)	$89.03/MWh (168.3%)	$166.97/MWh (305%)
Zhejiang	Nominal	$10.91/MWh (19.2%)	$22.91/MWh (40%)	$59.51/MWh (103.3%)	$176.58/MWh (299.2%)	$296.46/MWh (497.2%)
	Low	$14.39/MWh (26.9%)	$27.49/MWh (52.1%)	$64.15/MWh (121.1%)	$182.97/MWh (347.6%)	$300.66/MWh (542.5%)

United Kingdom	Nominal	\$-0.65/MWh (-0.6%)[a]	\$-3.62/MWh (-2.6%)[a]	\$-0.01/MWh (0%)[a]	\$23.79/MWh (14%)	\$175.34/MWh (97.6%)
	Low	\$3.6/MWh (3.2%)[a]	\$-2.38/MWh (-1.7%)[a]	\$11.53/MWh (8.4%)	\$51.83/MWh (36.5%)	\$202.79/MWh (133.2%)

[a]These results are within the error band, and so are insignificant.

Figure 18, Figure 19, Figure 20, Figure 21, and Figure 22 show the electricity generation for Texas, New England, T-B-T, Zhejiang, and the United Kingdom respectively. As we previously noted, if there is a high electricity demand at a period of low renewable generation potential, this demand must be satisfied through dispatchable generation or a buildout of renewable capacity. While the buildout of renewable capacity is just enough to supply the demand at the times of high demand and low renewable generation potential, it exceeds the supply of demand at times of low demand and/or high renewable potential. Therefore, much of the available generation is curtailed. This is why we see only a modest increase in the percent of generation from renewable sources as the carbon emission limit is restricted as compared to the drastic increase in percent of installed capacity in the installed capacity plots.

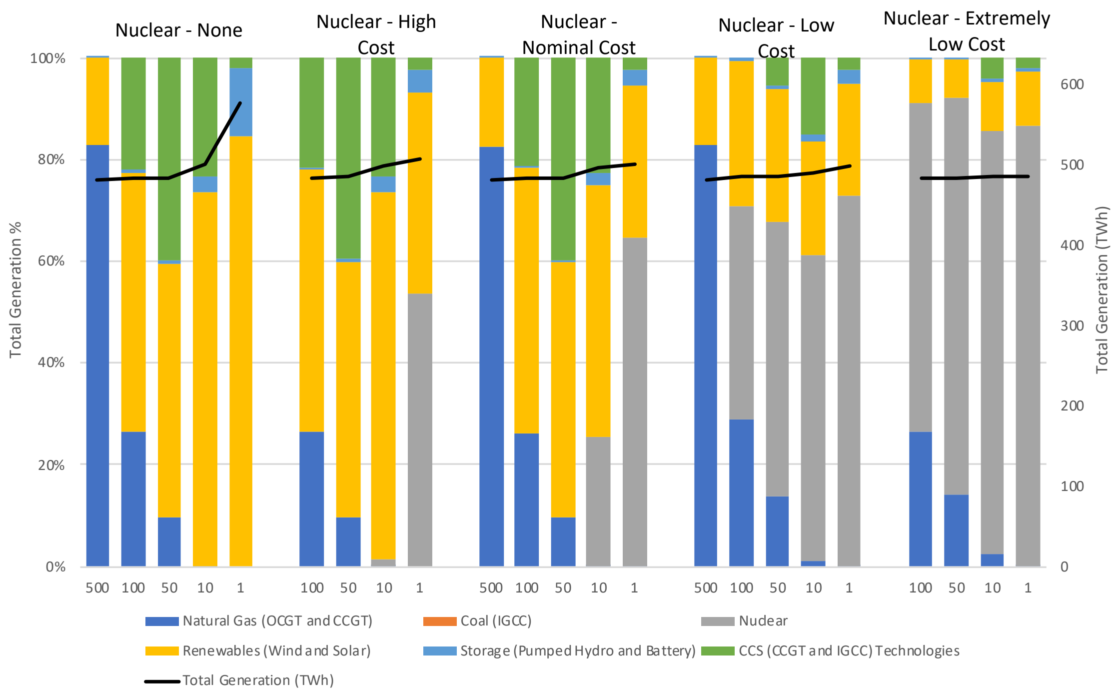


Figure 18: ERCOT Electricity Generation

In Texas, if there is only a modest decarbonization constraint this demand is satisfied with dispatchable technologies. The dispatchable technology will either be fossil fuel or nuclear, depending on the cost of nuclear. For the cases with either no or high cost nuclear technology, CCS technology is selected at higher CO_2 emission targets due to the lower cost of natural gas in that market. For the cases with nominal or lower costs of nuclear technology, nuclear technology is selected to generate power during these demand periods.

However, with a stringent decarbonization constraint, this demand is met with renewable buildout if there are no nuclear technology options. The renewable capacity buildout can be seen in the installed capacity chart (Figure 9). If there is a nuclear technology option this demand is met with nuclear generation. The reason that CCS technology is not selected for this power generation is that it is not 100% efficient, and so it still emits some CO2.

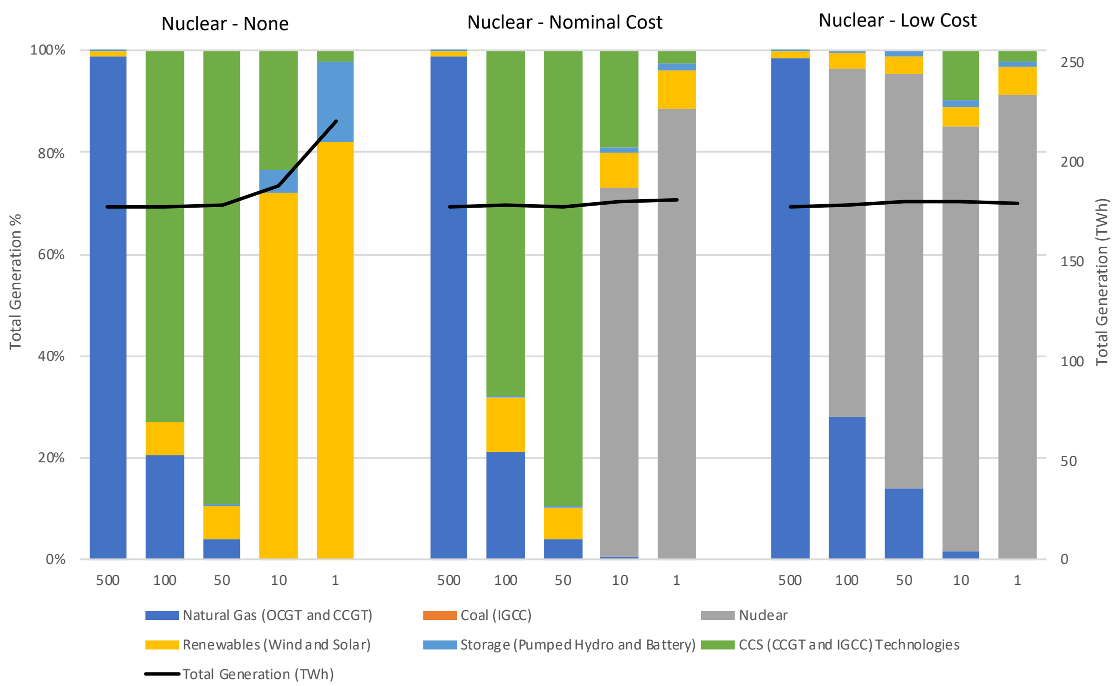


Figure 19: New England Electricity Generation

In New England, the trends are very similar to that of Texas. The difference is that the carbon capture technology plays a larger role in electricity generation.

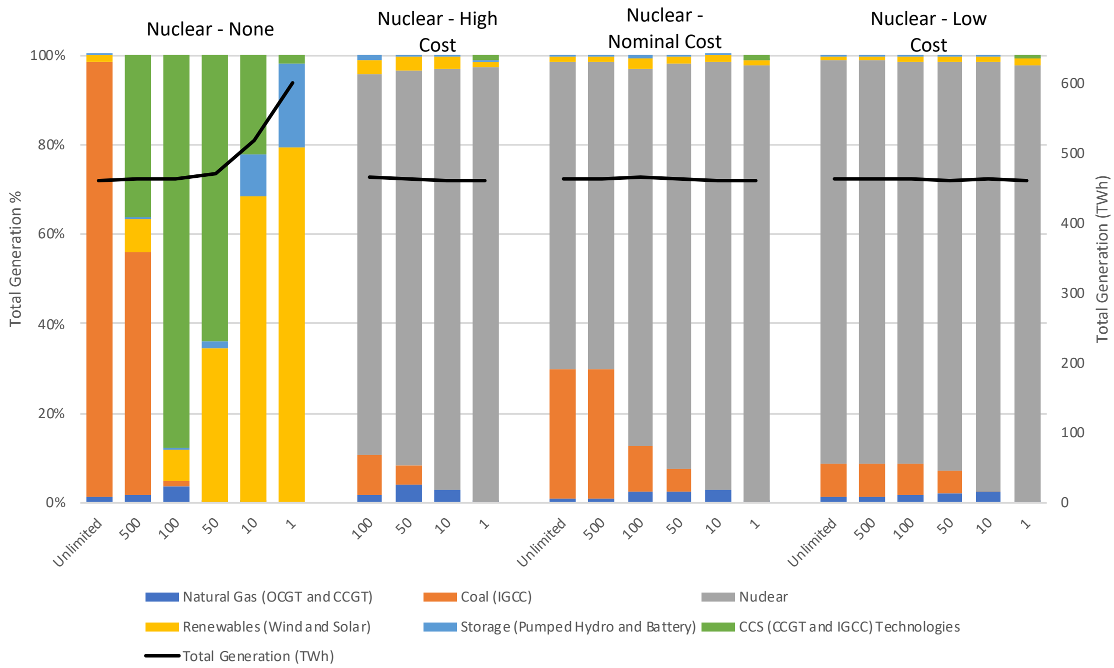


Figure 20: T-B-T Electricity Generation

In the T-B-T cases, if nuclear power generation is not an option, then cases with only a slight decarbonization constraint will use either fossil fuel generation or renewable buildout to satisfy periods with high demand and low renewable generation potential. The cases with a buildout of renewable capacity are confirmed in the installed capacity chart (Figure 14). If nuclear power generation is an option, then nuclear power generation will be used to satisfy these electricity demand periods.

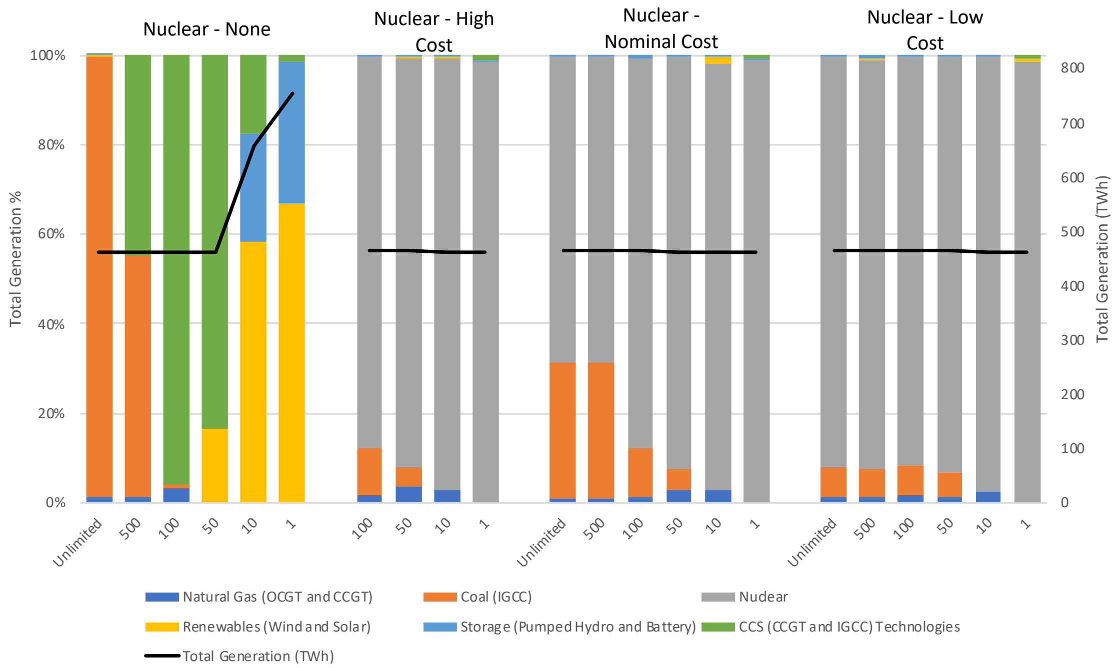


Figure 21: Zhejiang Electricity Generation

The trends in the Zhejiang case are very similar to that of the T-B-T case.

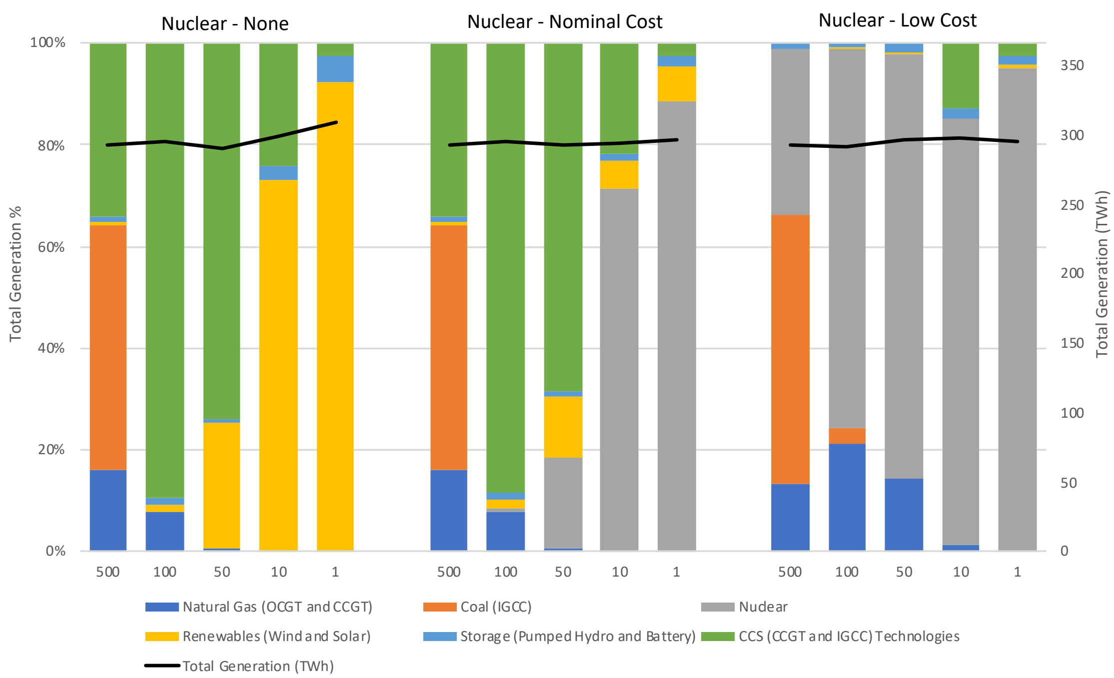


Figure 22: United Kingdom Electricity Generation

The trends in the United Kingdom case are very similar to that of the New England case. The exception is that nuclear plays a role at a higher carbon emission limit because the renewables potential is even lower in the United Kingdom.

A sensitivity study was also performed on the costs and technology parameters that were used in GenX for each region. The following sensitivities were performed based on costs from the 2016 NREL analysis (National Renewable Energy Laboratory, 2018):

- Low Renewables/Storage Cost (60% of nominal costs)
- High Renewables/Storage Cost (200% of nominal costs)[3]
- High CCS Cost (130% of nominal cost)
- Low Natural Gas Cost (75% of nominal cost)
- High Natural Gas Cost (125% of nominal cost)
- 99% Efficient CCS Systems (nominal efficiency is 90%)
- Demand Side Resources Considered [4]
- Extreme Weather Year for Renewable Potential[5]

The results of the sensitivity studies are shown in Figure 23, Figure 24, Figure 25, Figure 26, and Figure 27. We use the same definition of opportunity cost as in Table 10. Very similar trends are seen in the sensitivity studies for all the other regions.

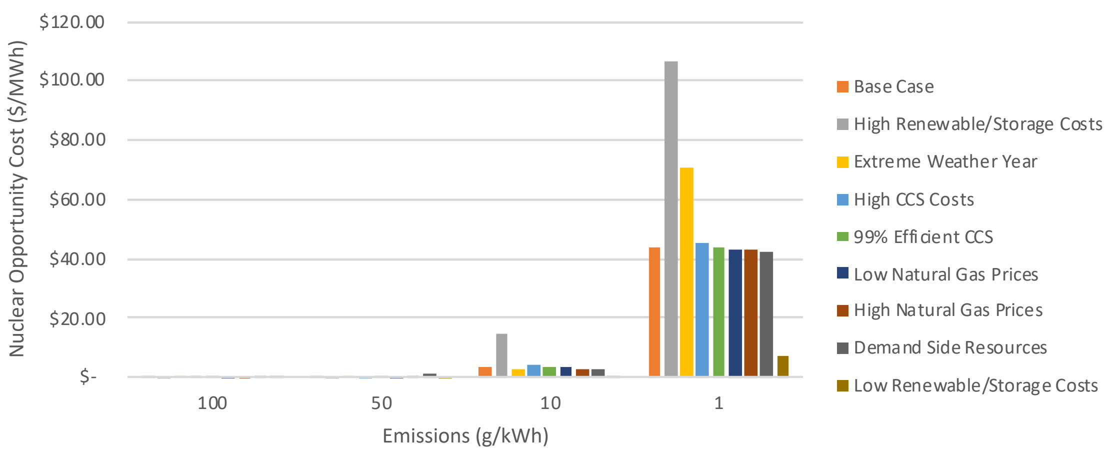


Figure 23: ERCOT Sensitivity Results

---

[3] This is the current cost of renewables and storage as reported in the NREL ATB report (2017). This sensitivity represents the scenario where costs are not reduced in the next 30 years.

[4] Demand side resources are the ability of the grid operator to shift demand when generation is low as well as the ability of electricity consumers to curb demand when prices are too high. It is assumed that the grid operator can shift up to 5% of demand each hour, with a maximum shift of 6 hours. The amount that consumers will curb demand depends on how much they value the electricity.

[5] We have represented an extreme weather year for low renewable potential. We have done this by arbitrarily lowering the renewable potential for both wind and solar during the entire first week of July to 10% of its original value. This time of the year was chosen arbitrarily to illustrate the effect of prolonged cloudy and windless days.

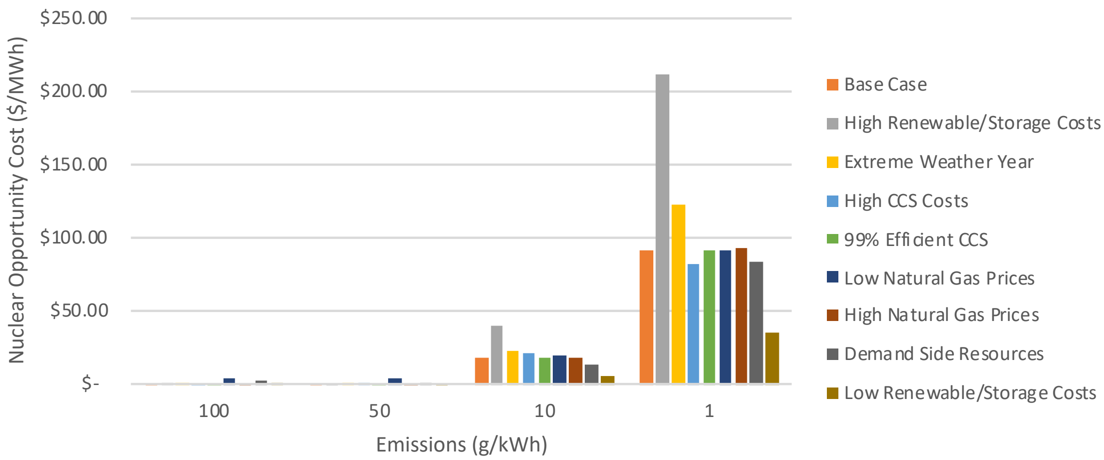


Figure 24: New England Sensitivity Results

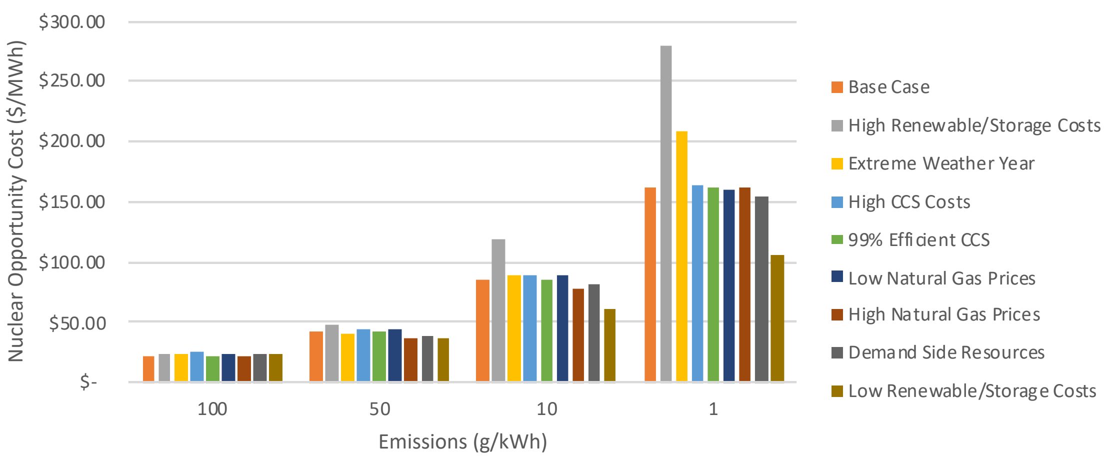


Figure 25: T-B-T Sensitivity Results

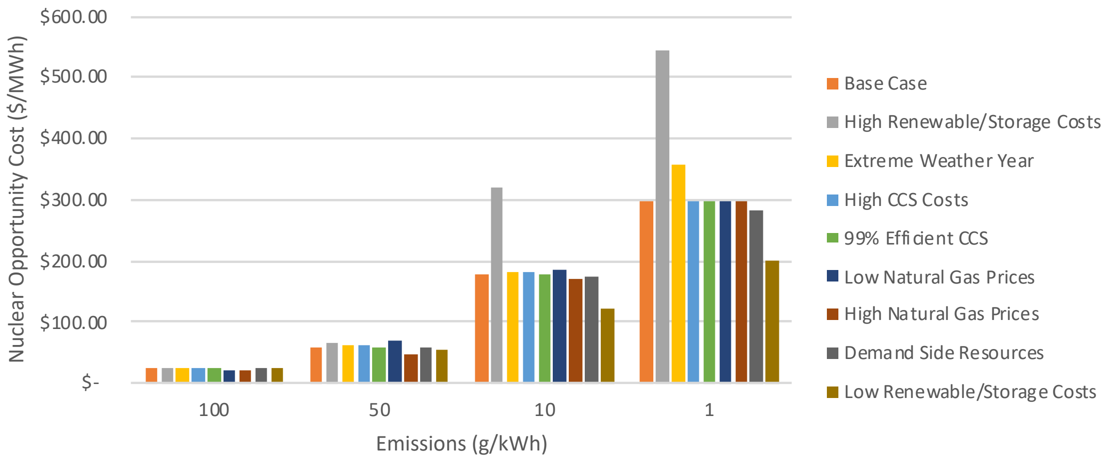


Figure 26: Zhejiang Sensitivity Results

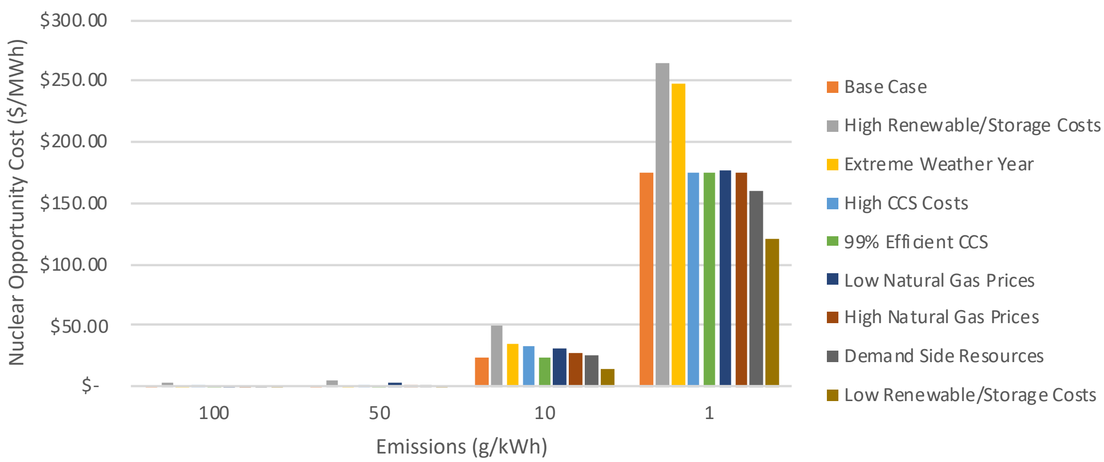


Figure 27: United Kingdom Sensitivity Results

There are only three sensitivities that deviate significantly from the base case (with nominal assumed costs and nominal technology performance). The High Renewable/Storage Costs and the Extreme Weather sensitivity cases will both increase the opportunity cost by excluding nuclear technology. High renewable/storage costs more than double the opportunity cost of nuclear. Conversely, low renewable/storage costs will significantly decrease the opportunity cost of excluding nuclear. This is because with low renewable/storage costs, the build out of installed renewable capacity and associated battery storage, although still significant in magnitude, is less costly and is chosen over building nuclear (nominal cost) in the cost optimization. Very similar trends are seen in the sensitivity studies for all the other regions. To illustrate this point, consider the sensitivity results for T-B-T in China (Figure 25). The opportunity cost for nuclear is notable even at 100 gCO2/kWh and increases at lower CO_2 emissions targets. Again, High Renewable/Storage Costs and the Extreme Weather sensitivity cases both increase the opportunity of including nuclear technology, while low renewable/storage costs decrease the opportunity for nuclear.

Conclusions

I have emphasized that to reach the 2°C Scenario by 2050, 'deep decarbonization' must reach CO_2 emission levels of at least 10 to 25 gCO2/kWh worldwide. For the U.S. I focused on regions representing a range of weather conditions. In both Texas and New England, I found that when the low carbon constraint was reduced to below 50 gCO2/kWh nuclear technology provides a noticeable advantage to the average cost of electricity and the optimal generation system mix. This was particularly the case for target CO_2 emissions levels at and below 10 gCO2/kWh. This advantage increased notably when I considered a decreased overnight cost of nuclear (25% reduction).

Conversely this advantage decreased notably when I considered cost improvements for renewables and battery storage beyond what is already projected for 2050 in the sensitivity analysis. All other sensitivities had a small effect on the optimal generation mix and cost advantage with nuclear technology. These results also indicate that to meet deep-carbonization goals without nuclear requires a substantial build out of renewables and battery storage with significant cost increases. This leads to the following conclusion: *Without a dispatchable, zero carbon-emitting technology, there will need to be a drastic build out of renewables and storage technology.*

In contrast to the United States, for the eastern provinces of China (T-B-T and Zhejiang), substantial cost advantages of including nuclear as part of the capacity mix are seen even at less restrictive CO_2 emission constraints such as 100 gCO2/kWh. These CO_2 emissions targets are far above the 25 gCO2/kWh target needed for China to meet its 2050 goals and nuclear is still needed to minimize system costs. This conclusion is not substantially affected by any of the other cost sensitivities considered.

These results present a comprehensive picture of the opportunity cost of forgoing nuclear energy. I found that the cost of constructing new nuclear power plants is high in the United States and the United Kingdom and therefore there is no opportunity cost of forgoing nuclear power at higher carbon emission limits. This is because renewables and carbon capture technologies provide the lowest system cost. In China, the cost of constructing new nuclear power plants is sufficiently low that there is an opportunity cost of not being able to include nuclear technology in the installed capacity portfolio.

However, at carbon emission constraints needed to keep global temperature rise to within 2°C (1-10 gCO2/kWh), there is an opportunity cost of forgoing nuclear power in each region. This opportunity cost increases if the cost of constructing the nuclear power plants decrease. This shows an important finding: *The opportunity cost of nuclear power is most dependent upon the cost of constructing the nuclear power.*

Chapter 4 – Framework to Assess Uncertainties in Decarbonization

Introduction

A challenge associated with the mitigation of climate change effects is the long time frame associated with the effects as well as with the solutions. Actions (or inactions) taken in the short term can have long-lasting implications for both the climate as well as the availability of technologies in the future decades. Because of this, decision makers should consider all possible futures and all possible implications of the choices that they make (Keppo & van der Zwaan, 2012). An example of this is with the retirement of the U.S. nuclear power plant fleet. If there is no action to preserve the nuclear industry knowledge expertise in the U.S., then the U.S. nuclear supply chain and nuclear engineering human resource pipeline could diminish in size. (Energy Futures Initiative, 2017). This could make it difficult to construct nuclear reactors in the U.S. in the future.

This brings about the following question: given the uncertain future, how do we determine the decarbonization strategies that have the highest probability of success? This chapter seeks to answer this question through the development of an analytical framework that allows for the consideration of technological uncertainties as well as the determination of outcomes in terms of failure criteria of the future states.

There are many advantages of looking for the best decarbonization strategy, which will comprise a portfolio of technologies and decisions that minimize overall risk of failure, rather than simply the lowest cost portfolio. The portfolio will inherently be a compromise between the lowest cost strategy and the minimum chance of making the incorrect decision (Labriet et al., 2012).

There are many challenges associated with modeling the uncertainties in climate change scenarios. The long horizon of climate change policies spans decades (Pye & Bataille, 2016). The uncertainties take on a significant role in determining the outcome of climate change models because the uncertainties (as well as the effect of the uncertainties) grow as the model predicts further and further into the future. It is important to note that a model can never be truly accurate in its predictions. Rather a model is a tool that can be used to improve decisions and draw attention to factors in a decision that may not have been considered.

Compounding the implications of short-term actions upon climate and technology availability in the future is the effect of uncertainties. Given the large time frame, it is no surprise that there exist many uncertainties in the economics, technological states, and climate (just to name a few) of the future. These uncertainties grow as one looks further and further into the future. In the modeling of climate, uncertainties take on an additional role as there are many non-linearities in the modeling of climate and energy systems. In particular, there are many thresholds which, once reached, can be irreversible. These thresholds are also known as tipping elements or tipping points. Examples include large ice sheet melting or large-scale ocean circulation changes (Gillingham et al., 2015).

If the uncertainty range of one input variable used in a model gives response variables on either side of this threshold, it is crucial to not use one possible value for this input. This can lead to conclusions about only one side of the threshold without ever acknowledging the possibility of landing on the opposite side of the threshold. Instead, a more prudent approach is to use not just one value for each desired output variable: but a range of values. This range can show whether the results are entirely on one side of a threshold, or possibly straddling the threshold. Even more useful than a range for each desired output variable is a probability distribution function for each output variable. This can show not only whether the variable straddles a threshold, but also what the estimated probability is for being on either side of the threshold.

Quantifying the probability distribution function for each desired output variable is useful, but another great value in the use of uncertainty in decarbonization models is the potential to find which uncertain variables, if the uncertainty were to be reduced, would give the biggest reward in reducing the failure probability. Doing this can reveal short-term actions that can be taken in order to better affect long term results.

Methodology

The objective of this section is to describe and demonstrate this framework that can be used to address the effects of uncertainty in decarbonization analyses. It draws on methods used in previous work to create a process for identifying the most important uncertainties to include in the analysis, quantifying their effects, identifying the failure criteria, modeling the probability distribution functions of the failure variables, and finally determining the probabilities of successful outcomes.

Scenario Scope and Failure Determination

The first step in the framework will be to identify the failure criteria and pathways to failure. The identification of the failure criteria is typically done when deciding to embark on this framework. The failure is the problem which one wants to solve by using this framework. The failure criteria are the quantifiable variables which will have a threshold at which the failure occurs. For example, in the previous chapter the failure of each simulation was a carbon emission target. The specific value of the threshold comes from what would or would not be societally acceptable.

Once the failure criteria are identified and quantified, the pathways that can lead to this failure must be examined. It is these pathways that must be modeled. The uncertainties (identified and quantified in the following sections) will be propagated along these pathways. In addition, the pathways will give insight into which input variables will be important in determining the value of the variables which have failure criteria and which input variables are not important. For example, if a failure criterion is a specific reduction in emissions, then the variable of amount of global warming per concentration of CO2 in the atmosphere is not important.

Identification of Uncertainties

To determine the procedure for looking at uncertainties, we examined many different uncertainty classification systems from previous studies. The categorization of three such studies are described below:

(Haasnoot et al., 2011) sort uncertainties into 3 main categories:

1. Natural Uncertainties: These are uncertainties that are associated with random, natural processes. An example could be the availability of solar and wind resources in a given year as well as the temporal distribution of these resources throughout the year.
2. Social Uncertainties: These are uncertainties that are associated with human reaction to future events as well as future societal values. An example could be societal support for (or dissent against) nuclear power.
3. Technological Uncertainties: These are uncertainties that are associated with model characteristics due to lack of understanding about the model parameters. An example could be the cost per kilowatt of installed solar panels or the possible ramping rate of nuclear power plants.

(Babonneau et al., 2012) sort uncertainties into 4 main categories:

1. Climate: This category reflects the uncertainty between the concentration of greenhouse gases and the effect upon solar irradiance (and therefore the effect upon global temperature rise).
2. Technology: These are uncertainties related to the parameters (cost, date of availability, technical progress, etc.) of the available technologies.
3. Economy: These are uncertainties associated with economic drivers (GDP growth, etc.).
4. Energy Prices: The price of providing energy

(Gillingham et al., 2015) sort uncertainties into 7 categories:

1. Parametric: These result from uncertainty in input variables to the model.
2. Model or Specification: These result from the specification of the model (for example, the reason why two different models can give two different answers even with all of the same inputs).
3. Measurement Error: These result from inaccurate measurements (such as global temperature level and trends).
4. Algorithmic Error: These result from incorrect solutions to a model.
5. Random Error: These result from shocks that can't be modeled with structural equations (for example, weather shocks).
6. Coding Error: These result from incorrectly coding the model.
7. Scientific: These result from the use of modeling a potentially false scientific theory.

In looking at the similarities between these three methods, we see some common categories – such as natural phenomena, society factors, and developments uncertainties. We also see in (Babonneau et al., 2012) an economic category. (Gillingham et al., 2015) considers several categories that the others do not, such as coding error, measurement error, and algorithm error. While these are important uncertainties, the purpose of this framework is to be able to address uncertainties related to decarbonization and these are the result of human error. Therefore, they will not be considered in this framework.

Overall, I state four categories of uncertainties and variabilities to consider: 1) Natural, 2) Societal, 3) Economic, and 4) Development. I explain these further below.

Natural uncertainties are the aleatory uncertainties associated with the randomness of natural processes. While it may be possible to better predict the randomness of the natural processes, the variabilities of the random processes themselves cannot be decreased (or increased) without changing the process. For example, cloud cover on a given day is a natural variability. There is no way to change this variability, but it will directly affect the availability of solar power production. The timescales of natural variabilities can be short (i.e. cloud cover in a given hour) or long (i.e. 100-year storms).

Societal uncertainties are the result from the unknown societal shifts and reactions. Societal perception of different policies and technologies have an important effect on whether or not those policies and technologies are adapted. For example, societal support of nuclear power plays a large role in whether or not it is deployed in a country. The unknown societal stance on nuclear power in the future makes it uncertain the extent to which nuclear power will be part of a decarbonization solution. Societal uncertainties will become less uncertain the closer in the future the model is analyzing. This is because societal shifts are often slow and so there is good likelihood that the societal stance in the near future is close to the societal stance in present day.

Economic uncertainties are the result of the unknown economic state of the future. This includes both the capacity of the global (or regional) economy but also the relative economies of one region to another. It includes the distribution of wealth and resources that may be required in the future energy sector. It also includes the availability of resources and the cost of extracting and using those resources. Similar to societal uncertainties, economic uncertainties will be become less uncertain the closer in the future the model is analyzing. This is because economic shifts are often slow and so there is good likelihood that economics in the near future are close to the economic in present day. Technology can also decrease economic uncertainties. For example, being able to know the total availability of resources will lower the uncertainty around of those resources will be available in the future. A final aspect of economic uncertainty is in the economic effect of climate change and how this effect will be distributed across and within different regions.

Development uncertainties are the result of using predictions for parameters in technologies that are being developed (i.e. not fully tested). This involves both the costs of the developing technology as well as the performance characteristics of that technology. These uncertainties are not reserved only for non-commercial technologies. Development uncertainties affect any technology in which a technological advance can change any parameter or cost of that technology. For example, nuclear power has tremendous development uncertainty surrounding the construction cost. This is because there are cross-cutting technologies that have the potential to lower the cost of construction (for example, seismic isolation) (Petti et al., 2018).

Now that the categories of uncertainties have been developed, the next step is to determine to procedure for populating those categories with relevant parameters and down selecting to the specific variables that will be modeled. For this, I looked at many techniques for brainstorming, such as mindmapping, round robin, rapid ideation, etc. Ultimately, there was no one brainstorming technique to populate the uncertainty categories that would work in every situation. Therefore, I pulled out the strengths and weaknesses of each brainstorming technique to form some best practices. These are described as follows:

Working individually to come up with ideas before working in a group setting avoids group think. Group think is a psychological occurrence that happens when a group is making a decision. Individuals tend to prefer to be a part of the group and so will not voice any opinions which stray far from the group's thought process. This tends to decrease creativity. However, if individuals work alone and come up with ideas before the group works together, then there will not be the bias to stay within the group's though process and all avenues will be explored.

Another important practice in deciding the uncertainty variables is to engage a diverse group. The more diverse a group is who decides the uncertainty variables, the more variables will be thought of. For example, government officials will think of different uncertainties than consumers of electricity. The different perspectives will produce a bigger list of uncertainty parameters in each category.

The third best practice is to not think of feasibility when brainstorming. Rather than deciding which specific variables should have uncertainties, the brainstorming should focus on what phenomena have uncertainties regardless of if it is feasible to model that phenomena. After the brainstorming is concluded, the feasibility can be a factor when down selecting variables. For example, rather than having "hourly solar capacity factors" in the brainstorming, one can think of "effect of sunlight." Then when down selecting, a variable of "hourly solar capacity factors" is used to describe the uncertainty of "effect of sunlight."

The final step in identifying the uncertainties is to down select from the lists of uncertain phenomena generated through the brainstorming. The variables selected for propagation through the model should have two characteristics: 1) large influences on the pathway to failure and 2) large uncertainty. Sometimes one variable itself will have a minimal influence but when interacting with another uncertain variable will have a large influence. Both of these variables should be part of the selection. In addition, there is a third important characteristic: the phenomenon must be able to be characterized by a quantitative variable and the uncertainty must be able to be found. Once the variables are selected, then they are ready to be quantified.

Quantification of Uncertainties

Natural uncertainties can typically be quantified by looking at models of the phenomena or by looking at historical data if the variability does not significantly change over time.

The remaining uncertainty categories can be quantified through expert elicitation. Expert elicitation is used in many fields to quantify uncertainties and to make best estimates when there are sparse data. A seven-step procedure was outlined by Knol et al (2010). This is shown in Figure 28 (Knol, Slottje, van der Sluijs, & Lebret, 2010).

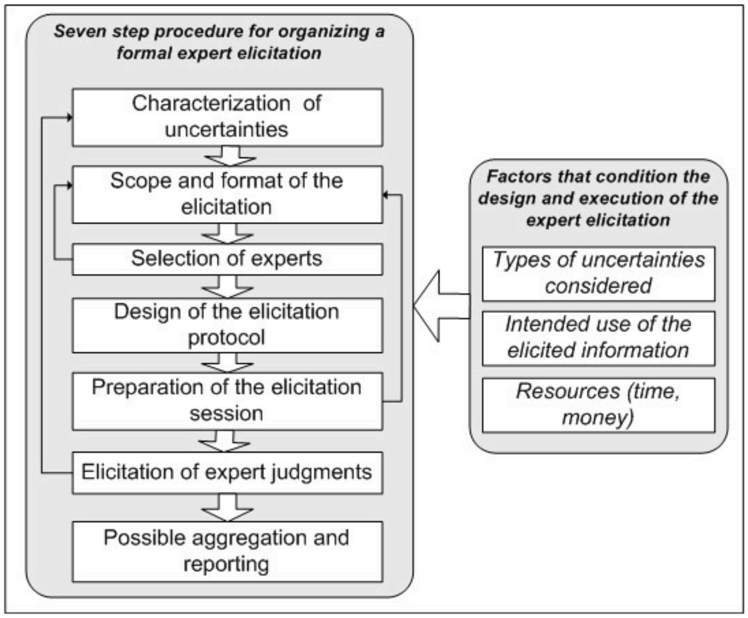


Figure 28. Seven Step Procedure for a Formal Expert Elicitation

It is important to note that there have been many expert elicitations performed in the energy field. Expert elicitation has been used estimating future energy costs. Wiser et al. (2016) shows how expert elicitation can be used to quantify the uncertainties in future wind energy costs (Wiser, et al., 2016). Verdolini et al. (2016) also shows the use of expert elicitation to provide estimates and uncertainties of future energy technology costs (Verdolini, Anadon, Baker, Bosetti, & Reis, 2016). Expert elicitation can be used as part of this framework to generate probability distribution functions of uncertain variables used as inputs into decarbonization pathway analyses.

Propagate Uncertainties and Analysis

The final steps of the framework are to propagate through the uncertainties to the failure criteria variables. The many methods available to do this were described in Chapter 2. A very common method (if the uncertainties cannot be propagated through analytically) is a Monte Carlo. A model must be developed that links the uncertain variables to the failure criteria and this model is iterated through many times (each time a single value is selected from the uncertainty variables) to generate a probability distribution output for the failure criteria variables.

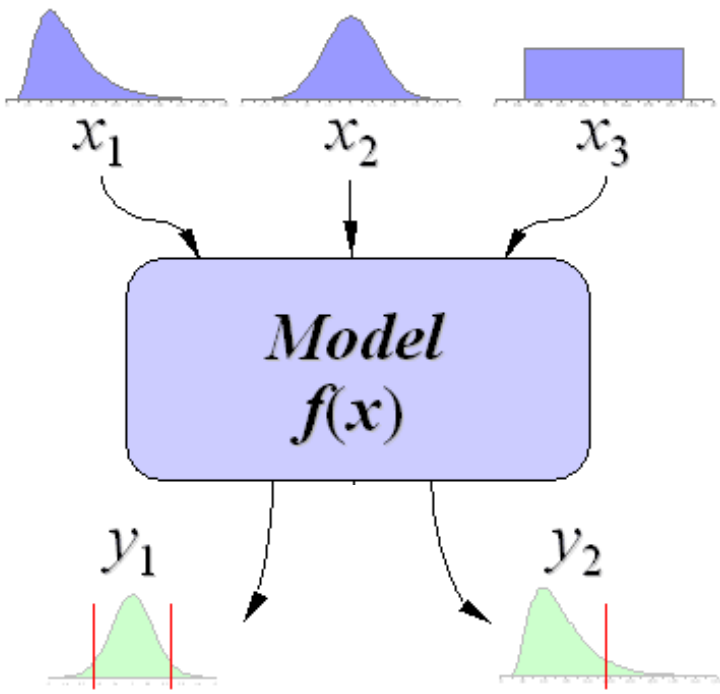


Figure 29: Monte Carlo Diagram

Once output probability distributions are generated, the failure probability can be determined through calculating the probability that the output variable is above/below the failure criterion threshold. In the case of multiple failure criteria, the failure probability is the compound probability.

Once a framework is used, it is simple to now play out "what if" scenarios to better inform the nuances of a decision on what strategy to use for decarbonization.

Framework Summary

In the previous section, I discuss the development process for a six-step process analyzing the uncertainties associated with decarbonization. This framework is summarized in Figure 30, and each step is summarized below.

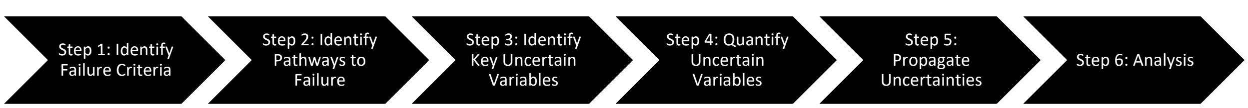


Figure 30: Summary of Six-Step Framework

<u>Step 1: Identify Failure Criteria</u>

In this step, you should think about what would be considered a failure in implementing your solution to decarbonize. Failure can be economic (i.e. implementing a solution being too costly), social (i.e. a solution changes too many social norms), or political (i.e. a solution failing to meet stated goals). It is possible that there are multiple ways of failing or possibly only one criterion satisfied for failure. Each criterion of failure will have both a quantifiable variable as well as a threshold for what is considered a failure and what is considered a success.

Step 2: Identify Pathways to Failure

The next step is to identify all of the ways that the failure criteria can be satisfied. For economic failures, it is important to consider all of the costs associated with the solution. For social failure, it is important to consider all of the social norms which are not allowed to be violated. An example of this in decarbonization of the electricity sector is the expectation of reliability on the grid. In the U.S. for example, brownouts are not acceptable. In other global regions, however, it may be acceptable for there to be brownouts due to lack of adequate installed capacity. For political or goal failures, it is important to consider how to quantify the goal (for example, a goal could be reduction in carbon emissions) and what ways that efforts to meet that goal could be unsuccessful. This can be analyzed through use of an event tree analysis in which critical junctures determining the success of the pathway are identified.

Step 3: Identify Key Uncertain Variables

The next step is to recognize the variables that affect the pathway to failure. This is done by recognizing which variables are present in the identified pathways to failure. A list of variables should be created. Best practices for brainstorming this list include: 1) Work individually first, 2) Engage a diverse group of people, and 3) Don't think of feasibility until the end. From this list, the next step is to select the variables that have two characteristics: 1) plays a large role in the pathway to failure and 2) has a large uncertainty.

Step 4: Quantify Uncertain Variables

Once the key uncertain variables have been identified, their probability distributions need to be quantified so that the uncertainties can be propagated through to the failure criteria variables. This can be done in several different ways. If it is random process (i.e. weather), it is possible that the uncertainty has already been quantified. If not, a good resource to use is historical data. If it is an uncertainty associated with lack of knowledge (i.e. future costs), then expert elicitations can be used.

Step 5: Propagate Uncertainties

With the quantified key uncertain variables and the pathways to failure, it is then possible to propagate the uncertainties. There are many methods of doing this. With simple pathways, analytically propagating the uncertainty may be possible. With more complex pathways, a tool such as a Monte Carlo analysis may be used. The results from this step will be a probability distribution function for each failure criteria variable.

Step 6: Analysis

The last step is to calculate the probability of failure from the probability distribution function(s). If there is more than one, it is necessary to determine the union of failure probabilities. In this stage, it is also possible see the order of influence of each key uncertain variable upon the overall uncertainty.

Chapter 5 – Decarbonization Model to Propagate Uncertainties

Introduction

This chapter outlines the model developed in order to propagate uncertainties in input variables in decarbonization models to two output variables: carbon emissions and cost of electricity generation. In the Methods section, the theoretical basis of the model is explained. In the Model Description section, the model is explained in detail. In the Model Benchmarking section, the benchmarking used to verify the model is shown.

Methods

Monte Carlo Uncertainty Propagation

The model uses a Monte Carlo approach to propagate uncertainties. In a Monte Carlo approach, many iterations of a model are run. For each iteration, values from uncertainty probability distribution functions are selected. This means that each iteration of the model may produce a different output value. After the completion of all of the iterations of the model, the resulting distribution of output values represents the probability distribution of the output variable.

In the model, the input variables can be technology costs, demand characteristics, or any other variable used in the model. The output variables are carbon emissions and cost of generation.

Because there are so many iterations of the model, it is important that the model be non-computationally demanding (i.e. that it not take a long time to run). Unfortunately, due to the complexities of the economics of the electricity sector, most of the current models available to determine optimal installed capacity/dispatch would not be useful in a Monte Carlo simulation due to the length of time needed to run. That is the rational to develop a new model for use in this work. The new model will prioritize important economic market mechanisms to find the optimal installed capacity/dispatch in a manner that requires a smaller amount of computational resources. There are two methods of accomplishing this: a model can be created from the ground up using economic principles determined to be the most important or a more complex model can be broken down into a simpler model using methods such as neural networks or machine learning. The method used in this work is the former. The next sections outline the economic and electricity market principles that are used in the model.

A key component of Monte Carlo simulations is determining the number of iterations to be run. The simulation should have at least the number of iterations needed for the output distributions to converge. The metric used in this work to measure convergence is the coefficient of variation. The coefficient of variation is the standard deviation of the sample mean estimate divided by the sample mean estimate,

$$COV = \frac{1}{U}\sqrt{\frac{\sum_{i=1}^{N}(x_i - U)^2}{N(N-1)}} \qquad \text{Eq. 3}$$

where U is the sample mean estimate, x is a data point from the output distribution, and N is the number of iterations.

Technology costs

There are two cost categories of each generating technology: 1) fixed cost and 2) variable cost

The fixed cost comprises the annual operation and maintenance required (regardless of how much generation the technology produces) as well as the investment cost needed to build the capacity. The investment cost depends both on the capital cost of constructing the power plant as well as the discount rate applied to account for the time value of money. The discount rate accounts for both the rate of return on investment needed for the project as well as other economic values (such as inflation). The equation for fixed cost (FC, per unit capacity per year) for technology A is

$$FC_A = FOM_A + \left(\frac{1-(1+r)^{-L_A}}{r}\right)^{-1} \times CC_A \qquad \text{Eq. 4}$$

where FOM is the fixed operating and maintenance cost per unit capacity per year, r is the discount rate, L is the lifetime of the power plant, and CC is the capital cost of the power plant per unit capacity.

The variable cost comprises the variable operating and maintenance cost required (which is a cost per amount of generation produced) as well as any fuel costs and carbon costs. The fuel cost depends upon the price of fuel as well as the efficiency (or heat rate) of the power plant. The carbon cost depends upon the carbon price, fuel carbon emissions, as well as the efficiency (or heat rate) of the power plant. The equation for variable cost (VC, per unit of generation) for technology A using fuel F is

$$VC_A = VOM_A + FP_F \times HR_A + FE_F \times HR_A \times CP \qquad \text{Eq. 5}$$

where VOM is the variable operating and maintenance cost per unit generation, FP is the fuel price, HR is the heat rate, FE is the fuel emissions, CP is the carbon price and G is the total generation.

Screening Curves

The model uses technology costs, technology parameters, and demand characteristics to find the minimum cost of supplying generation to meet demand. There are two aspects to supplying generation: the first is the amount of installed capacity needed on the grid and the second is how that installed capacity is dispatched.

The screening curve method is used to find the optimal amount of dispatchable capacity and generation. The Renewable Capacity Selection and Storage Capacity Selection sections that follow this explain how the optimal amount of renewable and storage capacity is selected. This is necessary because one of the disadvantages with the screening curve method is that it cannot be used to find the optimal amount of non-dispatchable capacity.

The screening curve method finds the optimal amount of baseload capacity, intermediate load capacity and peaking capacity. Baseload capacity has a high capital investment cost but lower marginal operating cost. Therefore, baseload capacity will need to operate mostly continuously in order to be economical. On the other hand, peaking capacity has a low capital investment cost but higher marginal operating cost. Therefore, peaking capacity will need to operate sporadically in order to be economical.

The total cost of generation for a technology is the sum of the fixed cost and the variable cost. The variable cost depends upon the amount of generation the technology produces. The equation for the total cost (TC, per unit installed capacity per year) of technology A is

$$TC_A = FC_A + VC_A \times 8760 \frac{hours}{year} \times CF \qquad \text{Eq. 6}$$

where CF is the annual capacity factor. This represents a linear function where the total cost is a function of the capacity factor.

The total cost as a function of capacity factor is shown for various dispatchable technologies in Figure 31. For the variable and fixed costs used to generate this figure, it can be seen that is the required capacity factor for a demand segment is above 0.7, then nuclear technology is the most economical way to meet this demand. For capacity factors between 0.2 and 0.7, then natural gas with carbon capture and sequestration (CCS) is the most economical way to meet demand. For capacity factors between 0.05 and 0.2, natural gas (CCGT) is the most economical way to meet demand. For capacity factors between 0.001 and 0.05, natural gas (OCGT) is the most economical way to meet demand. Finally, for capacity factors below 0.001, the most economical option is actually to not meet demand. Unserved demand acts as a generator with no capital cost and with a variable cost equal to the value of lost load. It should be noted that in Figure 31 there is no situation in which coal is the most economic choice.

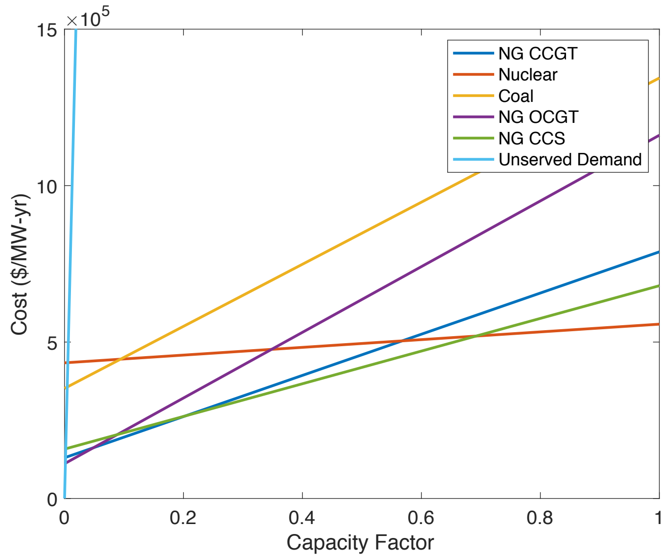


Figure 31: Example Technology Cost Curves

While the total cost for technologies is useful for determining under what capacity factor conditions each technology is the economic choice, it is not useful on its own for determining the optimal installed capacity mix. To do this, the total cost as a function of capacity factor must be used in tandem with a load duration curve. A load duration curve is the annual demand profile ordered from largest demand to smallest demand. There is demand that is needed constantly throughout the entire year, which would require a generator with a capacity factor of 1. Then, as demand becomes less frequently needed, the capacity factor needed to supply the demand also decreases. An example of a load duration curve is in Figure 32.

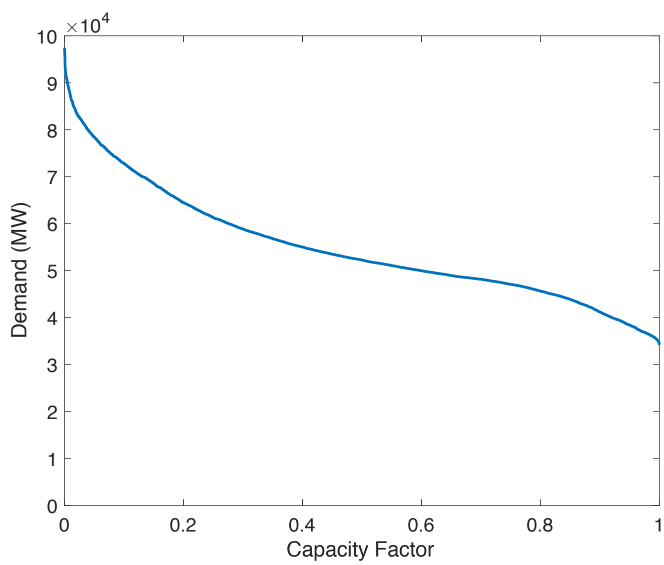


Figure 32: Example Load Duration Curve

To find the optimal installed capacity mix, each capacity factor threshold (as identified using the cost curves in Figure 31) is matched with the corresponding demand from the load duration curve. This segments the demand. Each demand segment has a different economically optimal technology to satisfy that demand. This is shown in Figure 33 and the optimal installed capacities for this example are shown in Table 11.

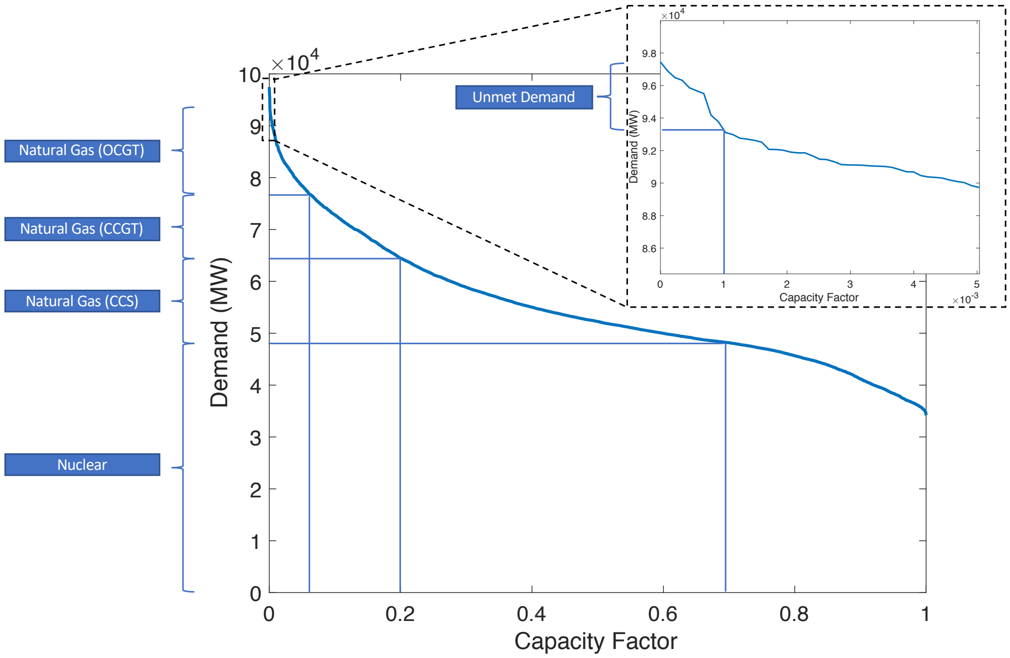


Figure 33: Example Load Duration Curve segmented by optimal installed capacity (ERCOT 2015)

The optimal generation of each technology is the generation is the amount of demand in each demand segment (as segmented from Figure 33). This is shown in Table 11 for the example.

Table 11: Optimal Installed Capacity and Generation for Example

Technology	Optimal Installed Capacity	Optimal Generation
Natural Gas CCGT	16,546 MW	16,700 GWh
Nuclear	47,461 MW	402,240 GWh
Coal	0 MW	0 GWh
Natural Gas OCGT	13,588 MW	2,190 GWh
Natural Gas CCS	17,327 MW	59,870 GWh
Unserved Demand	1,446 MW	10 GWh

There are several disadvantages to the screening curve method beyond the fact that it can only be used for dispatchable generation. The most crucial of the disadvantages is that it only considers the fixed and variable cost and does not consider other costs such as ramping costs, startup/shutdown costs. It also does not consider constraints of technologies such as ramping and minimum stable output power (Sullivan, Margolis, & Eurek, 2014).

Because of these constraints, there are more complex models which find the optimal capacity installation and dispatch using techniques which model dynamic operating constraints (such as ramping and minimum power output) as well as the interaction between generation and transmission. However, these models have large computational requirements and therefore are not well suited for Monte Carlo applications (Iain Staffell & Green, 2015).

Instead, to account for the constraints, a modified version of the screening curve is be used. Incorporating the cost of startups for each technology can be found by examining a given demand value and finding the number of times the demand profile rises above this point. See Figure 34 from (Iain Staffell & Green, 2015). For the red line (representing a demand value of 34.5 GW), there are 4 plant starts required for one week. For the green line (representing 42.5 GW), there are 7 plant starts required for one week. Finally, for the purple line (representing 51.5 GW), there are 4 plant starts required for one week.

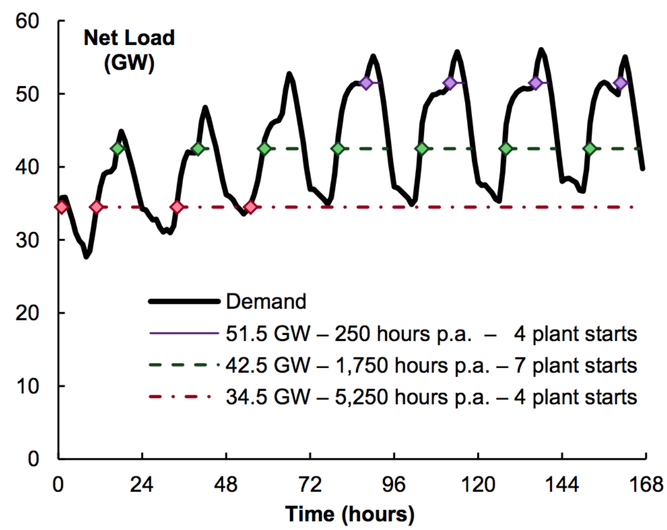


Figure 34: Visual representation of finding the number of startups needed at different demand values, from (Iain Staffell & Green, 2015)

By determining the number of startups required at each demand value as well as the capacity factor needed at that demand value, the relationship between number of startups versus capacity factor can be found. This is shown in Figure 35 for the year 2015 in ERCOT. Baseload generators (with a capacity factor new 1) require very few startups since they are running almost constantly. As the capacity factor decreases to around 0.5, the intermediate load generators are called on to start nearly once per day to provide generation during the higher load part of the day but to turn off at night when the load is lower. As the capacity factor decreases towards 0, the peaking generators are only called on to start a few days out of the year and so the number of startups decreases back towards 1

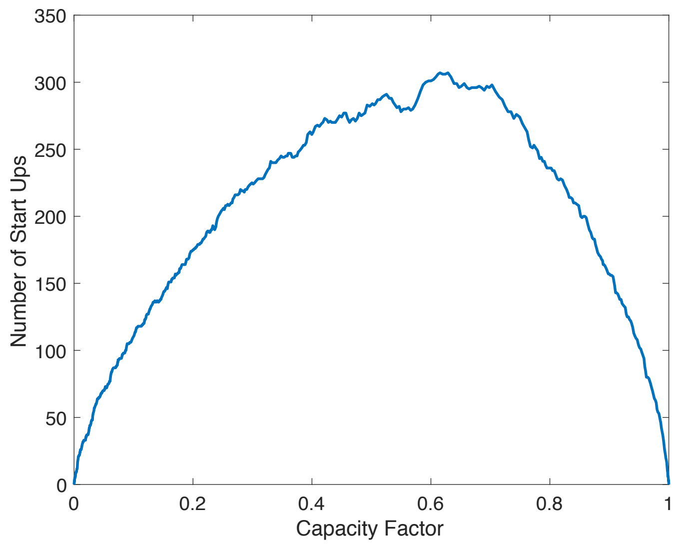


Figure 35: Number of startups versus capacity factor for the year 2015 in ERCOT

Each startup has a cost associated with it which depends upon the power plant technology. Nuclear power plants tend to be very expensive to startup whereas natural gas plants tend to be cheaper to startup. If the cost of starting up is included in the technology cost curves, the total cost equation changes to

$$TC_A = FC_A + VC_A \times 8760 \frac{hours}{year} \times CF + CSU_A \times NSU \qquad \text{Eq. 7}$$

where CSU is the cost of each start up (normalized to the unit capacity) and NSU is the number of startups (which is a function of the capacity factor as seen in Figure 35). It should be noted that the relationship between the number of startups and the capacity factor depends upon the demand profile. Therefore, it is not constant across years and will need to be calculated for every different demand profile.

Using the 2015 ERCOT demand profile, the asset curves from Figure 31 are adjusted to reflect the addition of the startup costs of each technology. This is shown in Figure 36. The most economical capacity factors for nuclear technology shift from above 0.7 to above 0.95. This is because nuclear has a high startup cost and so it is not actually economical to operate between 0.7 and 0.95 because the nuclear power plant would incur a high cost due to the number of startups needed.

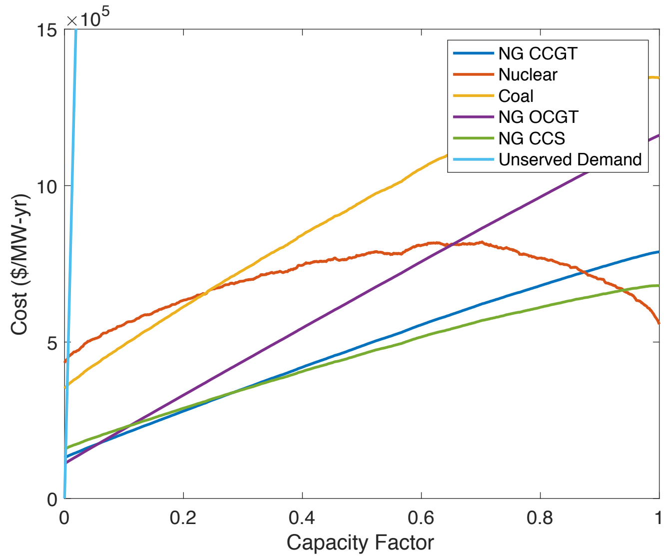


Figure 36: Example technology cost curves with startup costs considered

The optimal installed capacities and generation can be found in the same manner as before (using the load duration curve) and are presented in Table 12.

Table 12: Optimal Installed Capacity and Generation for Example with Startup Costs Considered

Technology	Optimal Installed Capacity	Optimal Generation
Natural Gas CCGT	20,122 MW	26,580 GWh
Nuclear	38,624 MW	337,370 GWh
Coal	0 MW	0 GWh
Natural Gas OCGT	15,053 MW	2,860 GWh
Natural Gas CCS	21,124 MW	114,180 GWh
Unserved Demand	1446 MW	10 GWh

When accounting for the startup costs, the more inflexible generators which has a higher startup cost have a smaller optimal installed capacity. If the startup costs were not considered, the installed capacities of these technologies would be overpredicted by the model.

In reality, if there is more than one generator is a given technology, instead of that one generator choosing to shut down and incurring the shutdown cost, the fleet of generators will choose to ramp down if possible when demand drops and then ramp up as demand rises again. The maximum power that technology A can ramp in an hour (MHR) is

$$MHR_A = IC_A \times MHRP_A \qquad \text{Eq. 8}$$

where IC is the installed capacity and MHRP is the maximum hourly ramping percentage that technology A can do.

In addition to the ramping constraint, generators have a constraint on the minimum stable output power. The minimum power of a fleet of generators (MFSP) of technology A is

$$MFSP_A = MSPP_A \times IC_A \qquad \text{Eq. 9}$$

where MSPP is the minimum stable power percent. As long as an installed technology can ramp without violating either the maximum ramping possible or the minimum stable output power, then the technology can ramp to avoid shutting off and therefore the cost of the startup.

Now the number of startups depends upon not only the capacity factor but also the installed capacity of a technology. This makes it difficult to use a straightforward screening curve to divide the load duration curve into segments. Instead, a chronological load curve can be used in combination with a technology cost curve that are represented in terms of the demand value (Batlle & Rodilla, 2012). These technology cost curves are shown in Figure 37.

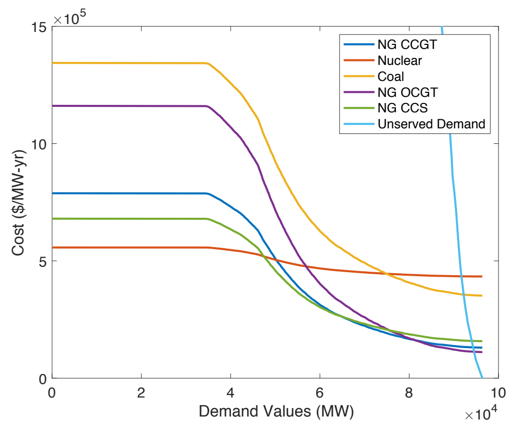


Figure 37: Example technology cost curves as a function of demand value (not including startup costs) for the load profile in ERCOT 2015.

The chronological load curve is divided into load slices. Three such load slices are shown in Figure 38.

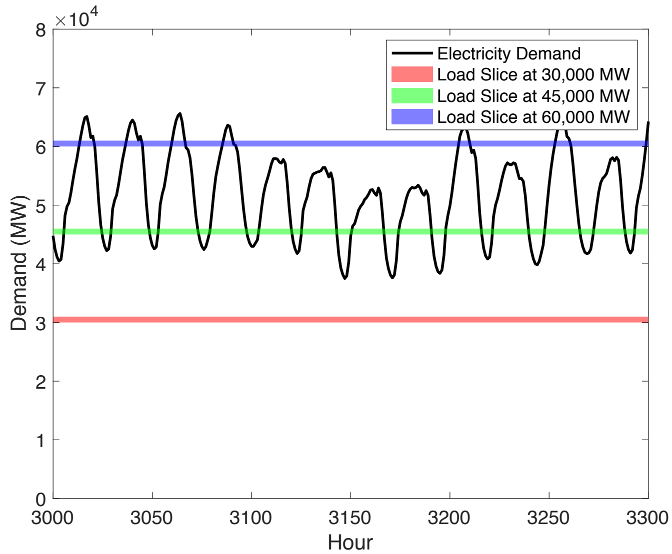


Figure 38: Example of three load slices on the ERCOT 2015 chronological load curve

Each load curve represents a different demand value. Each load slice also has a maximum ramping requirement as well as a number of startups. The number of startups is adjusted by eliminating the startups that can be avoided by ramping down the entire fleet of installed capacity of each technology (making sure not to violate any ramping or minimum power output constraints). Therefore, the number of startups for each different technology may be different. The values from the technology cost curves are adjusted to reflect the additional startup costs and the technology that has the lowest cost for that load value is selected as the most economical to supply generation. This is repeated for each load slice.

Renewable Capacity Selection

One of the major disadvantages associated with the screening curve method is that it can only be used to find the optimal installed capacity portfolio for dispatchable technologies. However, non-dispatchable technologies such as solar and wind are likely to play a large role in a decarbonized electricity grid. Therefore, it is important to find the optimal installed capacity which includes solar and wind.

The traditional method for handling this is to use the screening curve on a net load duration curve. The net load duration curve is the load duration curve minus generation from wind and solar resources. This assumes that since wind and solar have a near zero marginal cost of generation, they will be dispatched first in a merit-order dispatch stack (Sullivan et al., 2014). See Figure 39 for the original load duration curve as well as the net load duration curve for an example with 10,000 MW of wind capacity and 30,000 MW of solar capacity.

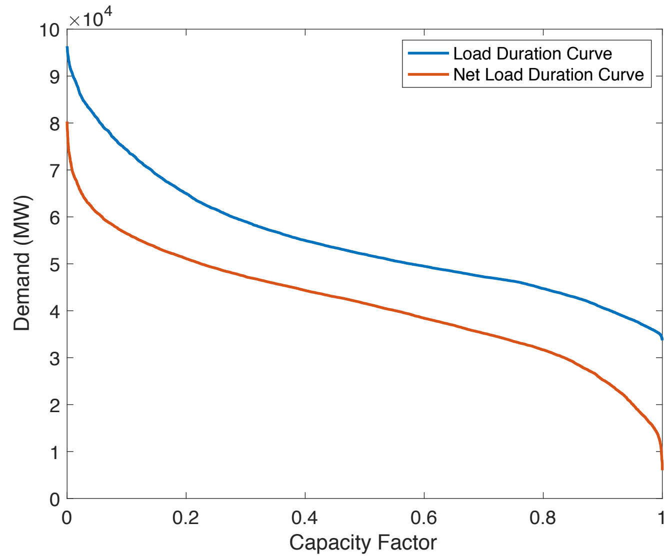


Figure 39: Example load duration curve and net load duration curve with 30,000 MW of solar and 10,000 MW of wind (ERCOT 2015)

However, this traditional method relies on the fact that the installed capacity of renewables is known in advance. The optimal installed capacity of renewables cannot be found. In order to find the lowest system cost configuration of renewable and dispatchable technology, many combinations of solar and wind capacity need to be tried and the lowest system cost among all of the combinations is the optimal configuration of renewable and dispatchable technology. Figure 40 shows the total system cost for 5000 different combinations of solar and wind installed capacity for an example in ERCOT in 2015. It is shown as the total of all renewable installed capacity on the x axis and the percent of that installed capacity that is solar on the y axis.

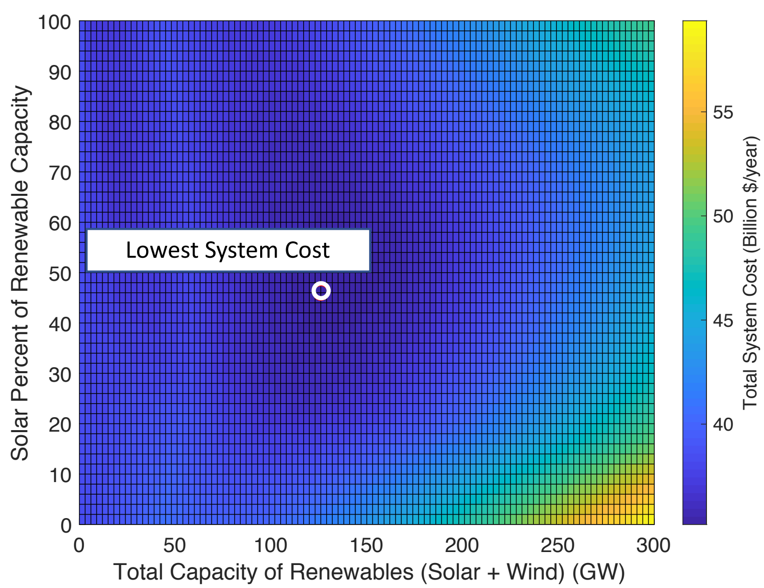


Figure 40: System cost for different combinations of solar and wind capacity

The combination of solar and wind installed capacity which results in the lowest system cost is 126 GW of total renewable installed capacity, 46% of which is solar.

While this method can find the optimal installed renewable and dispatchable capacity, it is computationally intensive because so many different combinations of solar and wind capacity must be tested. Instead, the characteristics of the total system cost as a function of renewable penetration is examined to develop a strategy to find the combination of solar and wind which result in the lowest system cost without testing every possible combination.

The total system cost as a function of the total capacity of renewables for different solar percentages is shown for the same example in ERCOT in 2015 in Figure 41. There are two regions of behavior for the system cost. The boundary between the two regions is dependent upon the percent of the renewable capacity that is solar. The boundary is found at the amount of renewable penetration where curtailment of the renewable generation begins. The reasons for the behavior in each region are due to the behavior of the sum of all fixed dispatchable costs, sum of all variable dispatchable costs, and the sum of all fixed renewable costs. These are shown in Figure 42 to Figure 44 for each of the different solar percentages.

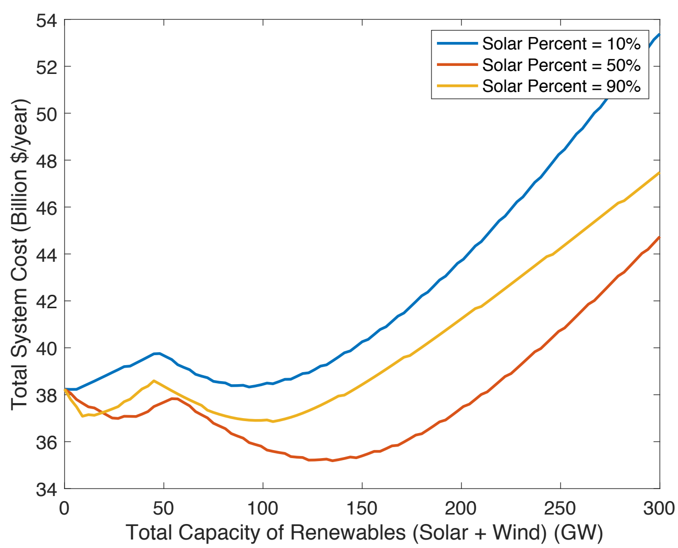


Figure 41: Total system cost as renewable penetration increases

As more renewable capacity is installed, there is less need for dispatchable capacity (the renewable capacity replaces the dispatchable capacity). This is why the dispatchable fixed cost for the system decreases. However, after a certain amount of renewable capacity is installed, the amount of dispatchable capacity that can be replaced by a given amount of additional renewable capacity decreases. This occurs when the renewable generation begins to be curtailed. After this point the slope of the decrease in dispatchable fixed costs becomes shallower.

The generation from the renewable capacity decreases the baseload capacity needed from the dispatchable technologies. Some of the demand that was previously baseload is shifted to being supplied by intermediate or even peaking technology. This increases the dispatchable variable cost. When there is no longer any baseload capacity (the point at which renewable generation begins to be curtailed), the additional generation from the additional installed renewable capacity replaces generation from only intermediate or peaking technologies. This then drives down the dispatchable variable cost.

As more renewable capacity is installed, the renewable fixed cost increases. This is a linear relationship because fixed cost is directly proportional to the amount of installed capacity.

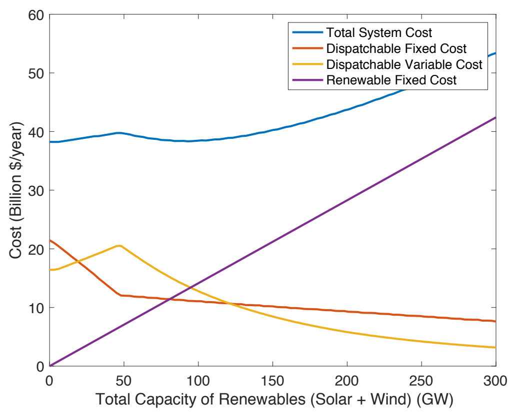


Figure 42: System cost breakdown as a function of renewable penetration for 10% solar percent

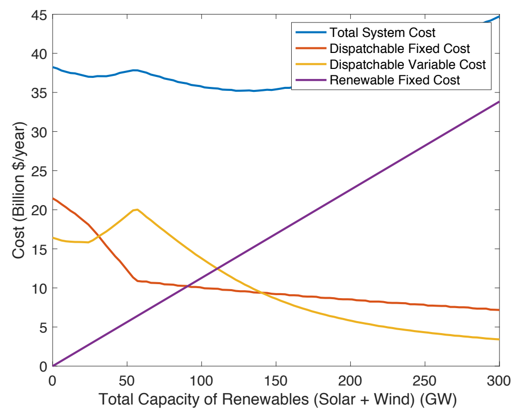


Figure 43: System cost breakdown as a function of renewable penetration for 50% solar percent

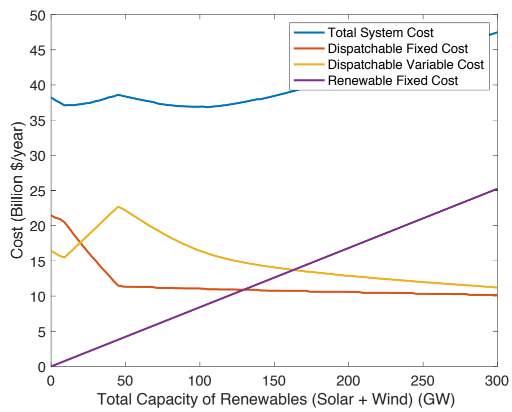


Figure 44: System cost breakdown as a function of renewable penetration for 90% solar percent

Understanding these behaviors shows that for a given percent of solar, there are three possible locations for the minimum system cost. There could be a local minimum in the first or the second behavior region. The absolute minimum is either one of these local minimums or at no installed renewable capacity.

To find the absolute minimum, each of the local minimums can be found through a numerical method. The local minimums and the value at no installed renewable capacity can then be compared. The minimum of these values is the absolute minimum.

Storage Capacity Selection

Installed storage capacity charges at times of low electricity prices and discharges at times of high electricity prices. As with renewable capacity, the screening curve method cannot be used to find the optimal amount of storage capacity.

Instead, a similar method to the modified screening curve method incorporating renewable capacity can be used. The hourly load profile is adjusted by charging at time of low electricity demand (night) and discharging at times of high electricity demand (peak hours). This is shown in Figure 45 for 5000 MW (with total energy storage of 10,000 MWh) installed storage capacity on the ERCOT grid with demand from the year 2015.

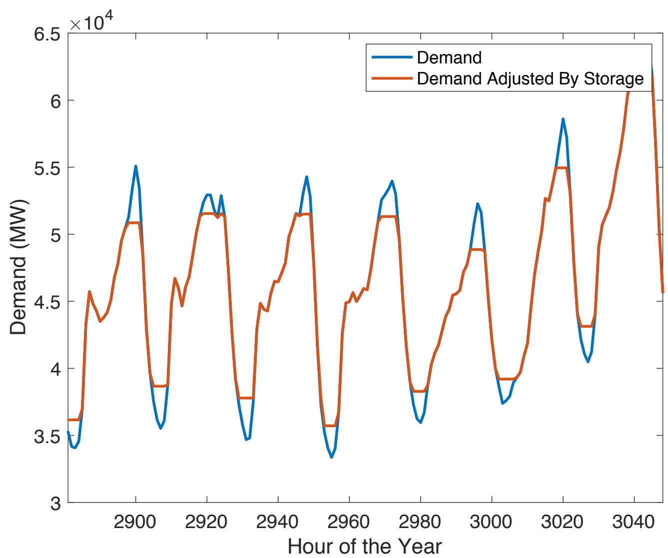


Figure 45: Original demand and demand adjusted by 5000 MW storage for the first week in May in ERCOT 2015

The result of adjusting the demand as a result of storage installed capacity is that the demand profile becomes less peaked. This means that there would be less peaking generation needed, decreasing the overall system cost. Whether or not it is optimal to install storage capacity depends upon whether the decrease in system cost from the adjusted demand is more or less than the fixed cost of the storage capacity itself.

The load duration curve from the case with 5000 MW of installed storage capacity (with 8 hours of storage) on the ERCOT grid using demand data from 2015 is compared to the original load duration curve in Figure 46. This new load duration curve is the one used in the screening curve method (much like the net demand load duration curve used to incorporate renewable capacity into the screening curve method).

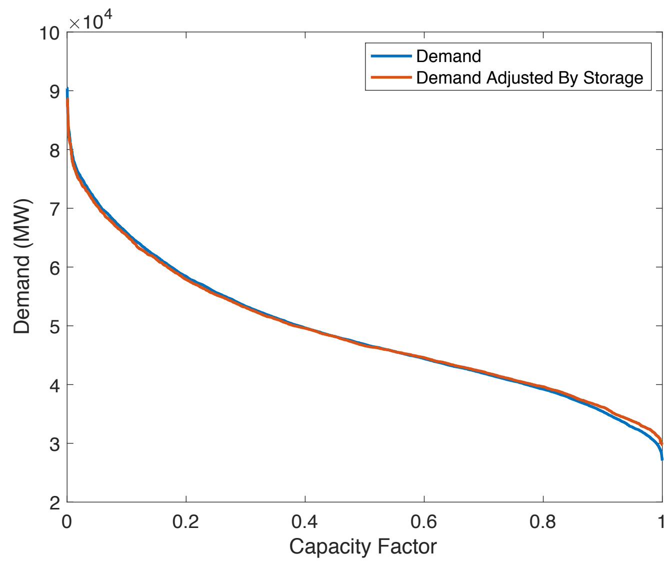


Figure 46: Original load duration curve and load duration curve adjusted by 5000 MW of storage in ERCOT 2015

The total system cost (including the cost of the storage capacity) for an example scenario in ERCOT using 2015 demand data is shown as a function of installed storage capacity in Figure 47

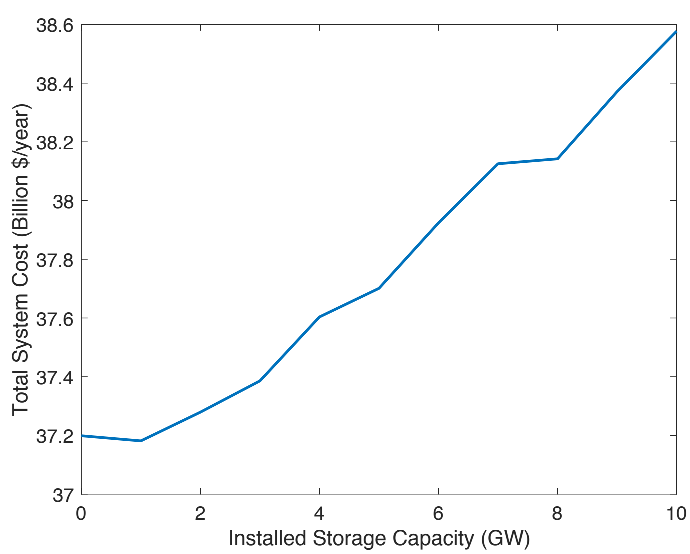


Figure 47: Total system cost as a function of installed storage capacity

From Figure 47, it is seen that the optimal amount of installed storage capacity is 1000 MW. To incorporate this into an overall model, a range of installed storage capacities should be tested and the installed storage capacity that produces minimum system cost from that range should be selected as the optimal amount of storage capacity.

Model Description

The previous section discussed the theories that went into the development of the model used to propagate uncertainties in the electricity market through to overall carbon emissions and system cost. This section will discuss how the theories were applied to this model.

The overview of the Monte Carlo set up is in Figure 48. Descriptions of the input distributions used in the scenarios tested in this work are in the following Chapter. The output distributions are annual carbon emissions and annual system cost.

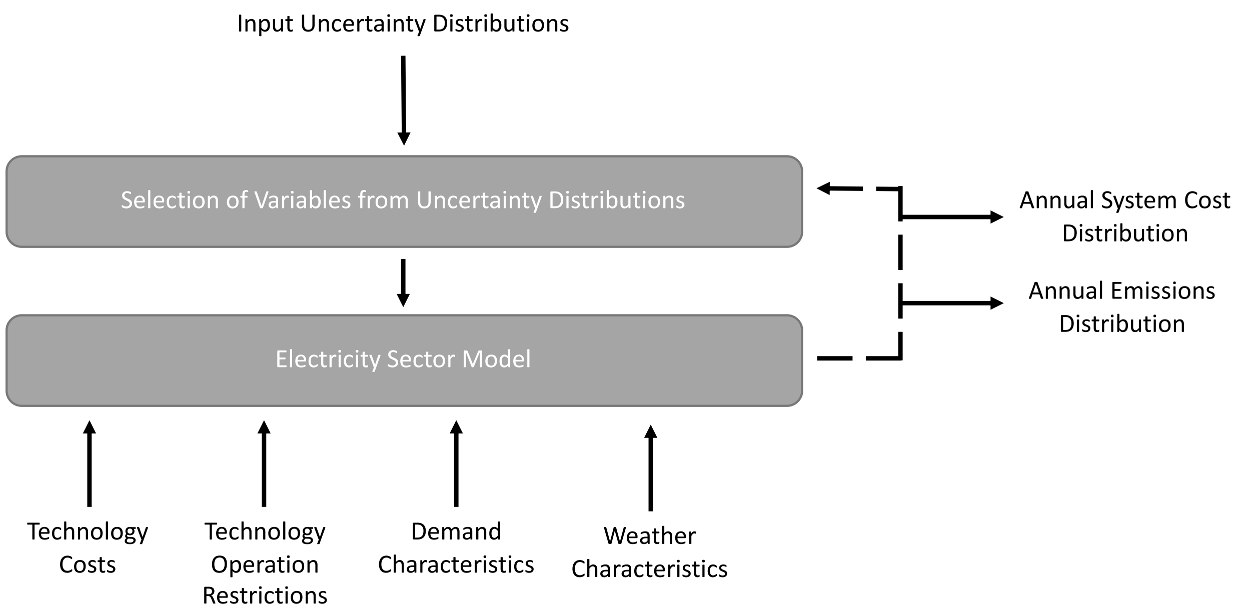


Figure 48: Monte Carlo model overview

The overview of the electricity sector model is in Figure 49. The optimal solar, wind, and storage capacities are found through an optimal capacity model (described below). This is used to create a net demand curve by subtracting the available renewable generation from the original demand curve. Then, the storage capacity adjusts this demand by charging at time of low electricity demand (night) and discharging at times of high electricity demand (peak hours). See description of Figure 45 for the more details of this. Then, the screening curve method (modified to account for ramping and minimum power constraints as well as startup costs as described in the previous section) is used to find the optimal dispatchable installed capacity and generation. These are used, with the renewable and storage installed capacity, to calculate the total annual system cost. In addition, the generation is used to determine the total annual emissions.

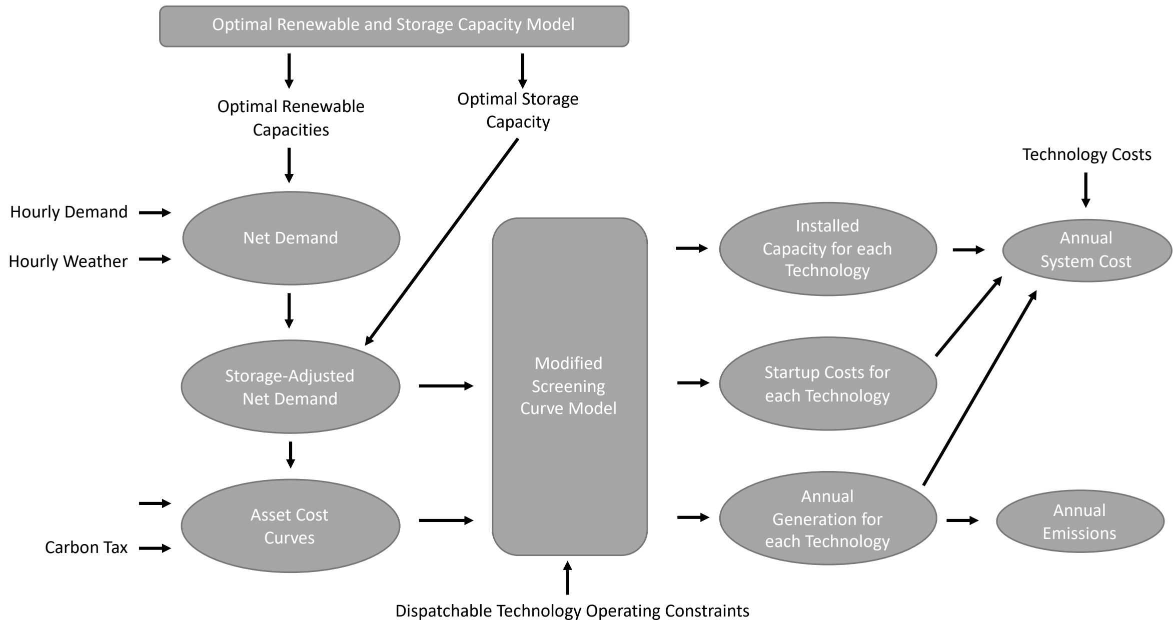


Figure 49: Overview of electricity sector model

A numeric scheme is used in the "Optimal Renewable and Storage Capacity Model" to find the renewable capacity, fraction of that capacity that is solar, and storage capacity that provides the lowest system cost. This scheme was tested against the matrix solutions (testing all possible combinations of renewable capacity, solar fractions, and storage capacities and selecting the combination that produces the lowest system cost) for 150 different scenarios (varying capital costs and natural gas price). The error of the numeric scheme versus the matrix scheme are in Figure 50. This highest discrepancy is -0.6%.

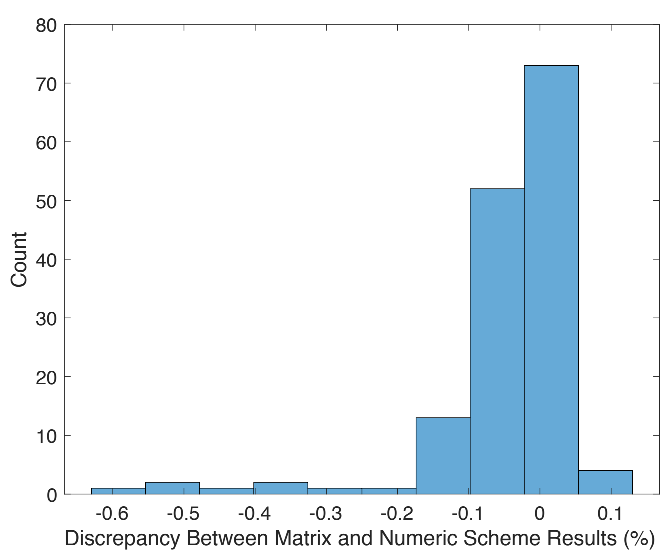


Figure 50: Histogram of discrepancy between matrix solution and numeric scheme.

The numeric scheme finds the optimal capacity of installed renewables and storage. It does this in three layers.

The bottom layer is finding the optimal capacity of storage for a given solar and wind installed capacity. This is done by

- Varying the amount of installed storage capacity,
- Finding the optimal capacity of dispatchable technology for the net demand curve resulting from the total renewable capacity and adjusted for the amount of storage capacity installed, and
- Selecting the amount of installed storage capacity that produces the minimum total system cost.

For any given input of solar and wind installed capacity, the output is the optimal system cost and storage capacity.

The middle layer finds the optimal total capacity of renewables for a given fraction of solar capacity. It does this by varying the total amount of renewable capacity and utilizing the bottom layer to find the two local minimums of total system cost as a function of total renewable capacity (see Renewable Capacity Selection section for description of the local minimums). The lowest of these and the total system cost of no installed renewable capacity is the absolute minimum for the system cost and the total renewable capacity that produces this absolute minimum is the optimal installed capacity of renewables.

The top layer finds the optimal fraction of installed renewable capacity that is solar. It does this by varying the fraction of solar capacity and finding the optimal system cost using the middle layer. The optimal solar fraction is the one that produces the lowest system cost. The total renewable capacity and storage capacity from the bottom and middle layer that produce this system cost for the optimal solar fraction are the optimal renewable capacity and storage capacity.

Model Benchmarking

The Electricity Sector Model performance was tested against the model used in Chapter 3 of this thesis, GenX, using the same cost inputs as in Chapter 3. GenX is a power system support tool developed by Sepulveda and Jenkins. It varies the installed capacity and dispatch of the capacity's generation to find an optimal solution based on the total system cost (including total fixed and variable operation cost, total investment cost, as well as total fuel cost). It adheres to constraints on 1) technology operating performance, such as ramping, minimum on time, and minimum off time and 2) carbon emission limits. Inputs into the model include a year's hourly demand profile and a year's weather patterns (determining the potential for wind and solar technologies) (Jenkins & Sepulveda, 2017).

The five different carbon emission constraints from Chapter 2 were tested as scenarios and labeled as follows:

- A: 500 g/kWh

- B: 100 g/kWh
- C: 50 g/kWh
- D: 10 g/kWh
- E: 1 g/kWh.

Since the model described in this chapter relies on a carbon price input rather than a carbon limit input, each of the carbon limits was translated into a carbon price (CP) using the following equation

$$CP = \frac{\Delta \mathrm{SC}}{\Delta \mathrm{SE}}. \qquad \text{Eq. 10}$$

where SC is system cost and SE is system emissions.

The scenarios with nuclear technology available and no nuclear technology available are tested for the benchmark. The equivalent carbon price for each scenario is in Table 13.

Table 13: Equivalent carbon price for each GenX benchmarking scenario

	Without Nuclear	**With Nuclear**
A (500 g/kWh)	$0/ton	$0/ton
B (100 g/kWh)	$24.57/ton	$24.65/ton
C (50 g/kWh)	$92.42/ton	$81.06/ton
D (10 g/kWh)	$362.68/ton	$292.46/ton
E (1 g/kWh)	$6,390.85/ton	$1,907.03/ton

The comparison between the system cost from the GenX simulations and the simulations using the Electricity Sector Model are in Figure 51 for the case with nuclear and in Figure 52 for the case without nuclear.

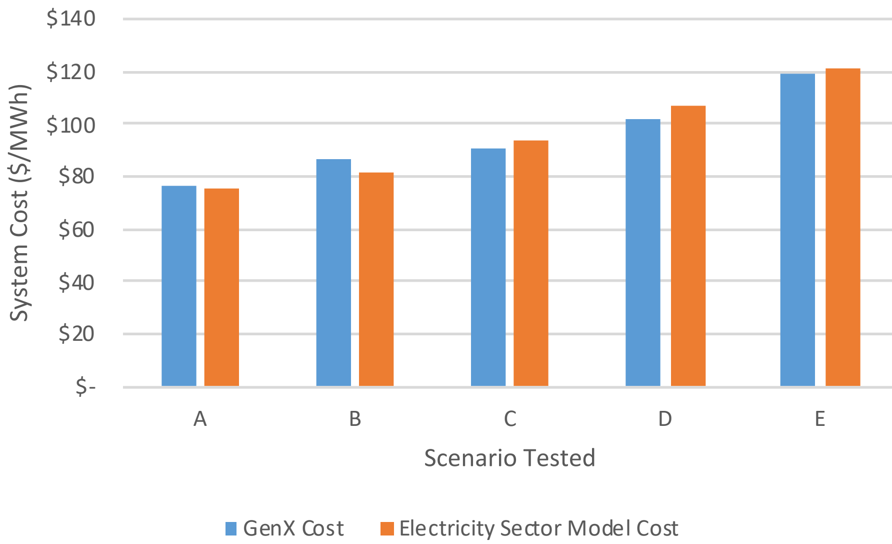


Figure 51: Comparison of the GenX and Electricity Sector Model system costs for the case with nuclear

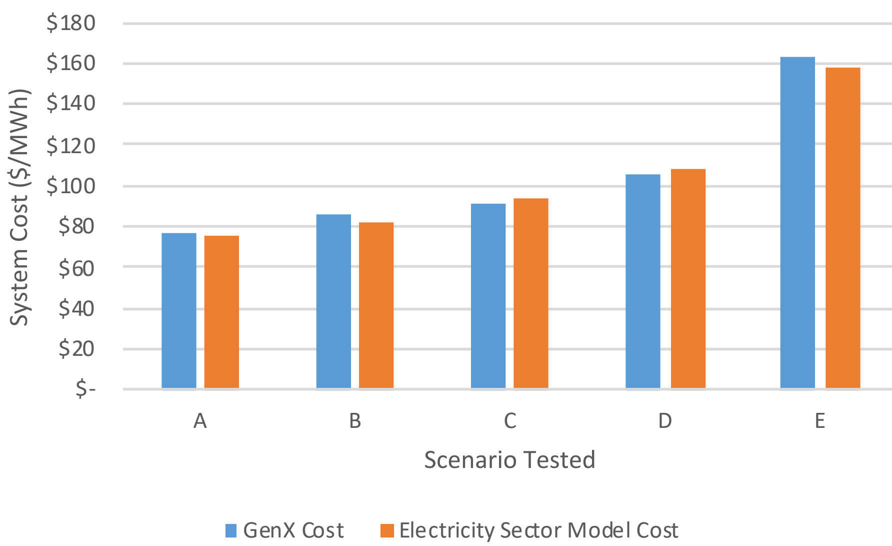


Figure 52: Comparison of the GenX and Electricity Sector Model system costs for the case without nuclear

As seen in Figure 51 and Figure 52, the total system cost between the GenX and Electricity Sector Model are very similar.

The comparison between the installed capacity portfolio from the GenX simulations and the simulations using the Electricity Sector Model are in Figure 53 for the case with nuclear and in Figure 54 for the case without nuclear.

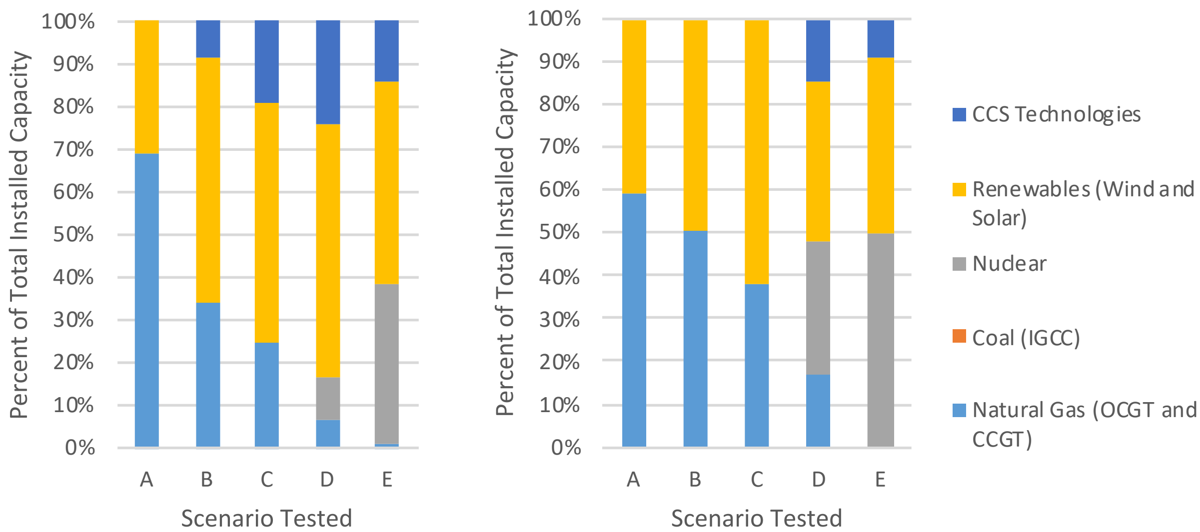


Figure 53: Comparison of the GenX (left) and Electricity Sector Model (right) installed capacity portfolio for the case with nuclear

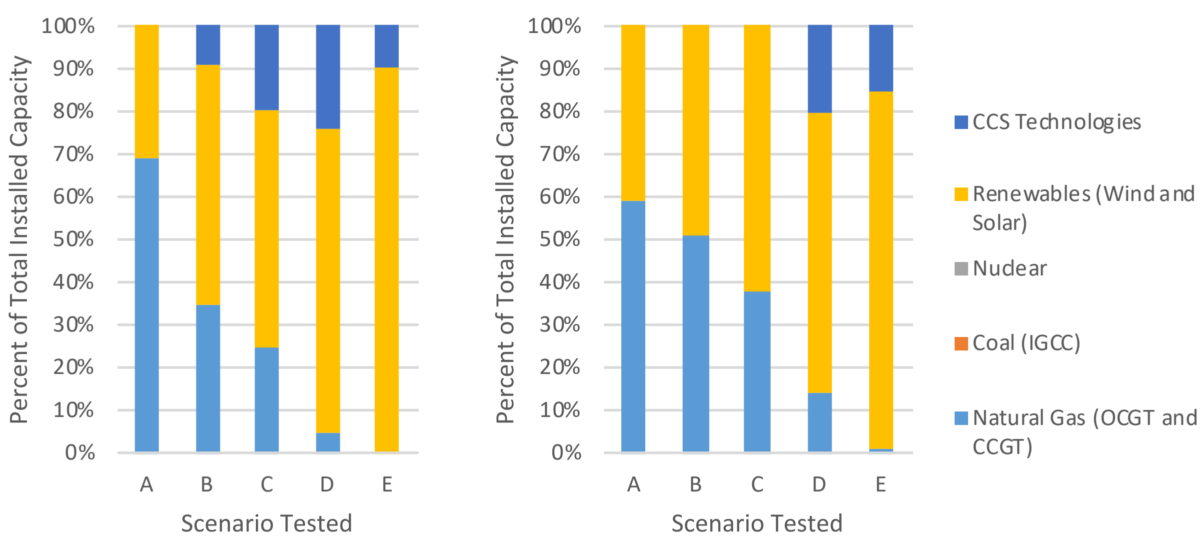


Figure 54: Comparison of the GenX (left) and Electricity Sector Model (right) installed capacity portfolio for the case without nuclear

The major difference between the GenX model results and the Electricity Sector Model results is that natural gas with CCS is not installed in the Electricity Sector Model in the cases where the carbon emission limit is 50 g/kWh or above. Instead, regular natural gas is installed. This could be due to the fact that the GenX model has more constraints on thermal technologies (efficiency losses when ramping, etc.) which were not able to be utilized in the Electricity Sector Model due to computational complexity.

Chapter 6 – Decarbonization Risk-Mitigation Opportunities for Nuclear Technology

Introduction

It is shown in Chapter 3 that nuclear technology has a role to play in lowering the cost of generating electricity if carbon emissions were limited. However, it is also shown that the role that nuclear technology plays depends upon many different factors, such as the capital cost of nuclear technology, the capital cost of other low-carbon technologies as well as regional characteristics. This is shown through a "scenario analysis," where input variables that have higher uncertainty are modified to have a "nominal", "low", and "high" value. While it can be possible to show the range of possible outcomes through scenario analysis, the details of how the variables with higher uncertainty interact with each other is lacking. In other words, the edges can be drawn but nothing is colored in.

The purpose of this chapter is to illuminate the characteristics of what goes on in between the edges drawn by the scenario analysis. This chapter will answer the following questions:

1. What does the distribution of possible carbon emissions look like at different carbon prices?
2. How does the exclusion of nuclear technology from possible options change this distribution?

The answers to these questions hold important information for decisions pertaining to mitigate carbon emissions. From the answer to the first question, one can see what the probability of meeting certain carbon emission targets is. From the answer to the second question, the role of nuclear technology in reducing carbon emissions can be determined.

Methods

The model described in Chapter 5 is used to propagate uncertainties in input values through to two important output distributions: carbon emissions and cost of generation. This section will go through the uncertainty distributions selected for use in the Monte Carlo model as well as the case conditions considered. The region considered is Texas because it has favorable renewable resources (solar and wind). The year considered is 2050. It should be noted that this represents a case that is unfavorable to nuclear. For other regions, a similar analysis to the one in this chapter would show a larger opportunity for nuclear technology.

Input Uncertainty Distributions

The uncertainty in modeling the future energy sector is split between the four main uncertainty categories: Natural, Societal, Economic, and Development. A literature search as well as communications with experts in the field populated each of these categories. For each category, a comprehensive list of the uncertainties considered, the reasoning for consideration, and the ultimate decision of whether or not to include the uncertainty are below. If the uncertainty was included, then there is a decision of which variable(s) were considered to be used to reflect the uncertainty.

Natural Uncertainties

Natural uncertainties are the aleatory uncertainties associated with the randomness of natural processes. A summary of the variables that were considered in this category are in Table 14.

Table 14: Summary of Natural Uncertainties

Uncertainty	Reason for Consideration	Included/Not Included	Variable(s) to Depict Uncertainty if Included
Hourly Weather	The hourly weather will affect the outputs of solar and wind and therefore the ability to generate revenue.	Included	Hourly Availability Factors of Wind
Storm Frequency	Storms can prevent installed capacity from being able to generate electricity, thereby increasing the required reserves (in order to guarantee adequate supply).	Not Included	N/A
Hourly Demand Profile	The hourly demand profile sets the required generation at each hour and therefore the required total installed capacity.	Included	Hourly Demand Fractions

Societal Uncertainties

Societal uncertainties are the result from the unknown societal shifts and reactions. Societal perception of different policies and technologies have an important effect on whether or not those policies and technologies are adapted. A summary of the variables that were considered in this category are in Table 15.

Table 15: Summary of Societal Uncertainties

Uncertainty	Reason for Consideration	Included/Not Included	Variable(s) to Depict Uncertainty if Included
Electricity Demand Growth	The electricity demand growth affects how much new installed capacity will be needed each year to satisfy demand.	Not Included	N/A

Electricity Demand Profile	The characteristics (i.e. peak/average demand ratio) of the electricity demand profile affect how many fast ramping assets are needed on the grid.	Not Included	N/A
Electricity Demand Elasticity	The elasticity of demand affects the flexibility of which generating assets need to quickly ramp up and down to match demand.	Not Included	N/A
Power Plant Siting Restrictions	Siting restrictions can add cost to generation (if sited in areas where construction cost is high) or can limit the maximum installed capacity of certain technology types.	Not Included	N/A
Power Plant Security Requirements	Power plant security requirements can affect the cost of operating the power plants.	Not Included	N/A

Economic Uncertainties

Economic uncertainties are the result of the unknown economic state of the future. This includes both the capacity of the global (or regional) economy but also the relative economies of one region to another. It includes the distribution of wealth and resources that may be required in the future energy sector. A summary of the variables that were considered in this category are in Table 16.

Table 16: Summary of Economic Uncertainties

Uncertainty	Reason for Consideration	Included/Not Included	Variable(s) to Depict Uncertainty if Included
Project Finance	Project finance can affect the overall capital cost of constructing power plants (as well as whether or not capital-intensive technologies are favored over operation cost intensive technologies).	Included	Discount Rate
Available Capital	Available capital limits the number of capital-intensive	Not Included	N/A

	projects that can be financed.		
Cost of Natural Gas Generation	This affects what the marginal cost of natural gas is (and also the clearing price when natural gas sets the clearing price).	Included	Natural Gas Fuel Price
Available Land for Power Plants	This limits the amount of installed capacity that can be built for technologies with ah large land requirement (i.e. solar and wind).	Not Included	N/A

Development Uncertainties

Development uncertainties are the result of using predictions for parameters in technologies that are being developed (i.e. not fully tested). This involves both the costs of the developing technology as well as the performance characteristics of that technology. A summary of the variables that were considered in this category are in Table 17.

Table 17: Summary of Development Uncertainties

Uncertainty	Reason for Consideration	Included/Not Included	Variable(s) to Depict Uncertainty if Included
Cost of Nuclear Generation	This affects the marginal cost of nuclear.	Not Included	N/A
Cost of Solar Capacity	This affects the capital cost of solar.	Included	Solar Capital Cost
Cost of Wind Capacity	This affects the capital cost of wind.	Included	Wind Capital Cost
Cost of Nuclear Capacity	This affects the capital cost of nuclear.	Included	Nuclear Capital Cost
Cost of Carbon Capture Installation	This affects the capital cost of carbon capture.	Not Included	N/A
Cost of Carbon Capture Generation	This affects the marginal cost of carbon capture.	Included	Natural Gas (CCGT) Carbon Capture and Sequestration Capital Cost
Availability of Solar	This affects the overall ability for solar to generate	Not Included	N/A

	electricity and therefore the revenue of solar.		
Availability of Wind	This affects the overall ability for wind to generate electricity and therefore the revenue of wind.	Not Included	N/A
Availability of Nuclear	This affects the overall ability for nuclear to generate electricity and therefore the revenue of nuclear.	Not Included	N/A
Availability of Carbon Capture	This affects the overall ability for carbon capture to generate electricity and therefore the revenue of carbon capture.	Not Included	N/A
Cost of Storage Generation	This affects the marginal cost of storage.	Not Included	N/A
Cost of Storage Capacity	This affects the capital cost of storage.	Included	Battery Capital Cost
Storage Efficiency	This affects how much storage can generate per amount that storage charges (and therefore the marginal cost per unit generated of storage).	Not Included	N/A
Storage Duration	This affects how often storage will need to charge.	Not Included	N/A
Ultra-High Voltage Electricity Transmission Cost	This affects transmission cost.	Not Included	N/A
Ultra-High Voltage Electricity	This affects how far from consumers a	Not Included	N/A

Transmission Maximum Length	power plant can be located.		
Ultra-High Voltage Electricity Transmission Losses	This affects transmission cost.	Not Included	N/A

Uncertainty Variable Quantification

I selected seven uncertain variables in this example:

1. Hourly Availability Factors of Wind
2. Hourly Availability Factors of Solar
3. Hourly Demand Fractions
4. Natural Gas Fuel Price
5. Solar Capital Cost
6. Wind Capital Cost
7. Nuclear Capital Cost
8. Battery Capital Cost
9. Natural Gas CCGT Carbon Capture and Sequestration Capital Cost
10. Discount Rate

These uncertainty distributions will be used in the analyses presented in Chapters 7 to 9 as well.

The uncertainty quantifications of hourly availability factors of wind and hourly demand were generated from Texas historical data (ERCOT, 2019b) (ERCOT, 2019a). 18 years of hourly demand data were found. 39 years of wind hourly generation were found. 18 years of solar hourly generation were found. The uncertainty distribution for selecting which weather year to select from is uniform (i.e. all years are equally likely to occur). Because the weather and demand data are selected from the same year, only years which have solar, wind, and demand data can be selected from. These years are 1999-2000, and 2002-2015. There was missing hourly demand data from 2001 and so that year was not considered.

The hourly demand data for each year is divided by the total demand to give hourly demand fractions. This way, the demand fractions for different years can be used for one value of overall annual demand. The distributions of hourly demand fractions are in Figure 55 for each year as a boxplot. The top and the bottom of each whisker represent the maximum and minimum values. The upper and bottom lines of the box represent the third and first quartile. The horizontal line in the box represents the median.

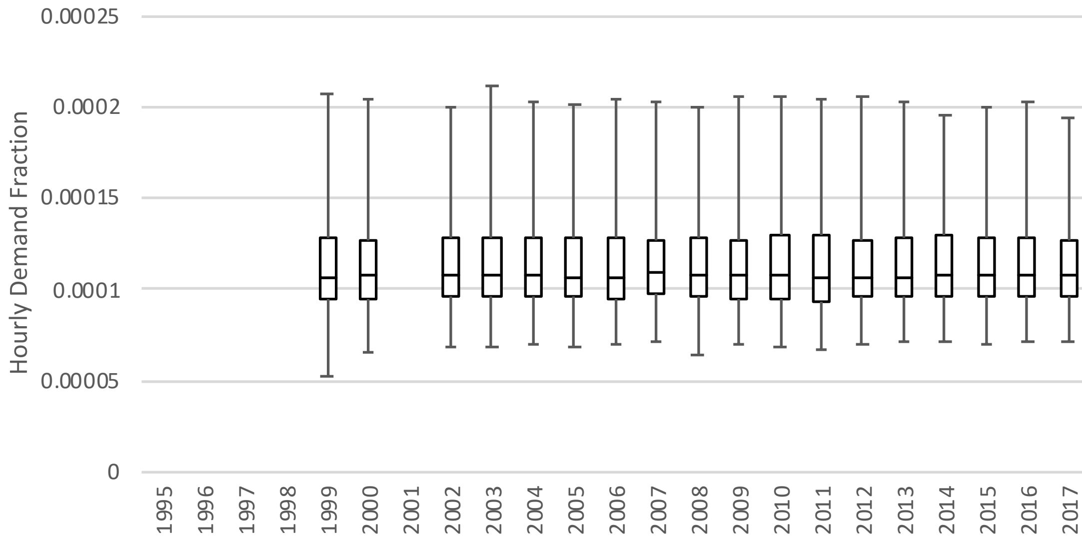


Figure 55: Hourly Demand Fractions

The wind/solar hourly generation is divided by the total installed wind/solar capacity. This gives the fraction of the total wind/solar capacity that was used for generation each hour, or the wind/solar hourly availability factors. The distributions of hourly wind availability factors are in Figure 56 for each year as a boxplot. The distributions of hourly solar availability factors are in Figure 57 for each year as a boxplot.

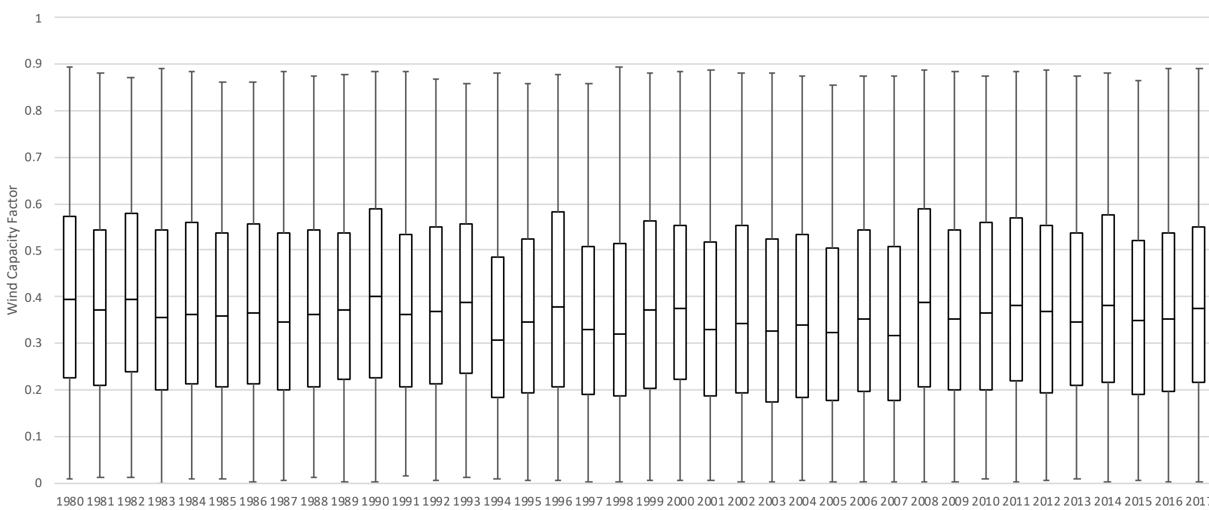


Figure 56: Hourly Wind Availability Factors

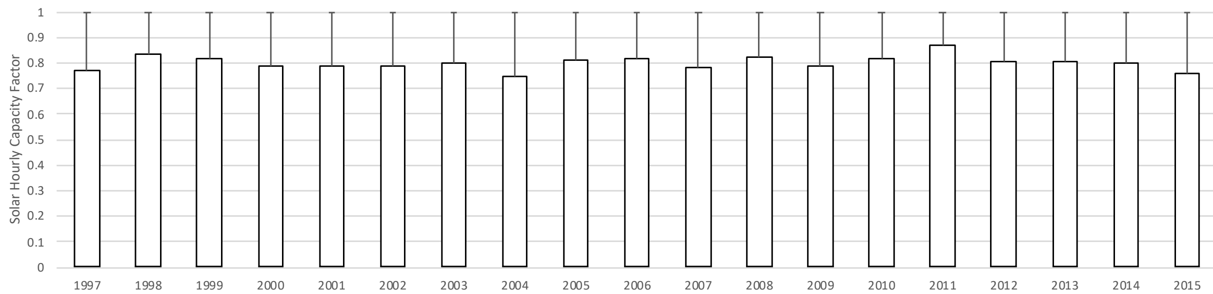


Figure 57: Hourly Solar Availability Factors

The uncertainty distributions of the natural gas fuel price as well as the capital costs of solar, wind, and batteries were taken from the Annual Technology Baseline report put out by the National Renewable Energy Laboratory (NREL) (National Renewable Energy Laboratory, 2018). The upper, lower and middle values in the report were selected for each of the technologies for the year 2050. Because there are only three points given, a triangular distribution is used to represent the uncertainty of the variables. The upper and lower values from the report became the maximum and minimum for the distribution. The middle value was the median of the distribution. From there, the mode was calculated. The probability distribution functions for the natural gas fuel price is shown in Figure 58. The probability distribution functions for the solar capital cost, wind capital cost, natural gas CCS capital cost, nuclear capital cost, and battery capital cost are shown in Figure 59

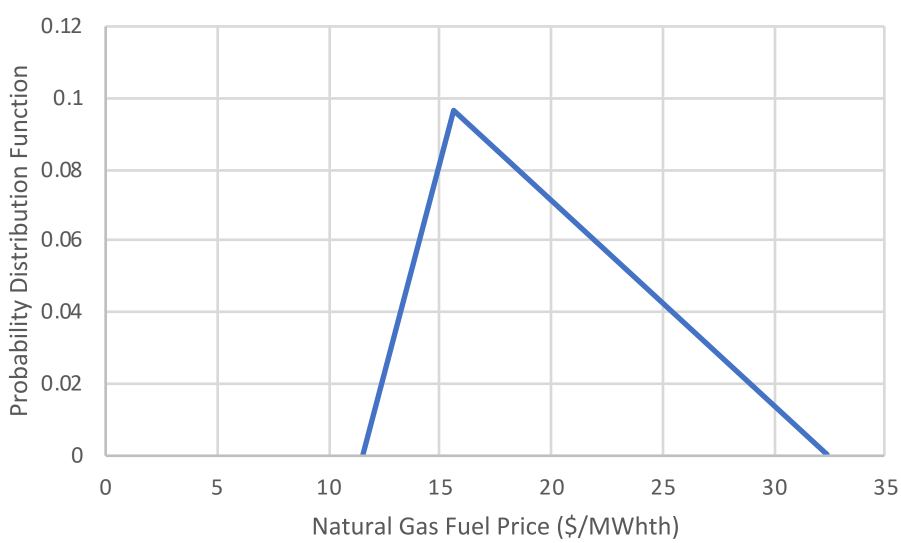


Figure 58: Probability distribution functions for the price of natural gas fuel

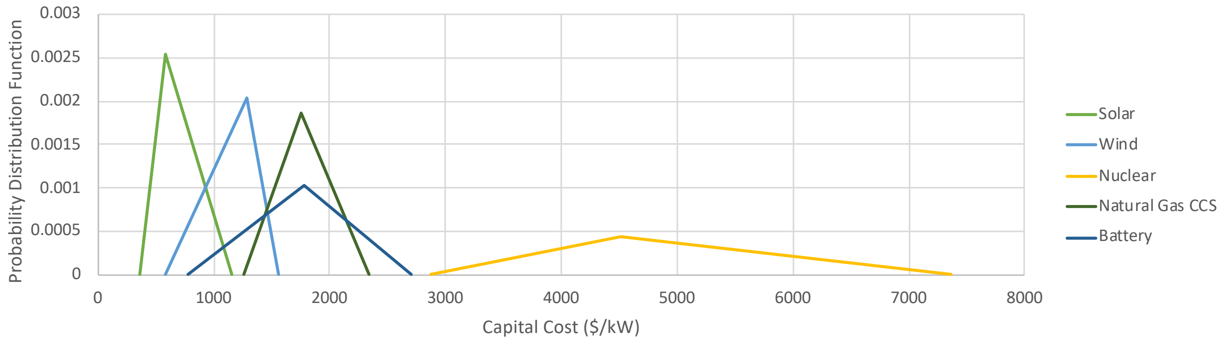


Figure 59: Probability distribution functions for the capital cost of low-carbon technologies

A triangular probability distribution is used for the capital cost of nuclear as well. There is no range of values given in the Annual Technology Baseline report for nuclear capital cost, only a middle value. This middle value was selected to be the median for the nuclear capital cost uncertainty distribution. The upper and lower values were selected from a study of historical capital costs of nuclear done by Riesz et al. (2016). In this study, a lognormal distribution was created from the historical capital costs. The 5th percentile and 95th percentiles were selected as the minimum and maximum values on the triangular distribution.

The uncertainty in the discount rate was modeled using a uniform distribution ranging from 3.5% to 10%. This is following the work from (Keirstead & Calderon, 2012).

The distributions of each inputted uncertainty variable are below in Table 18.

Table 18: Uncertainty Distribution Summary for Uncertain Input Variables

Variable	Distribution	Distribution Characteristics
Weather/Demand Year	Discrete, Uniform	1999-2000; 2002-2015
Natural Gas Fuel Cost	Triangular	a = \$11.56/MWh$_{th}$ b = \$15.67 /MWh$_{th}$ c = \$32.36/MWh$_{th}$
Solar Capital Cost	Triangular	a = \$367/kW b = \$585/kW c = \$1,156/kW
Wind Capital Cost	Triangular	a = \$580/kW b = \$1,285/kW c = \$1,561/kW
Natural Gas CCS Capital Cost	Triangular	a = \$1,264/kW b = \$1,760/kW c = \$2,334/kW
Nuclear Capital Cost	Triangular	a = \$2,877/kW b = \$4,514/kW c = \$7,357/kW

Battery Capital Cost	Triangular	a = $776/kW b = $1,780/kW c = $2,700/kW
Discount Rate	Uniform	Min: 3.5% Max: 10%

Case Matrix

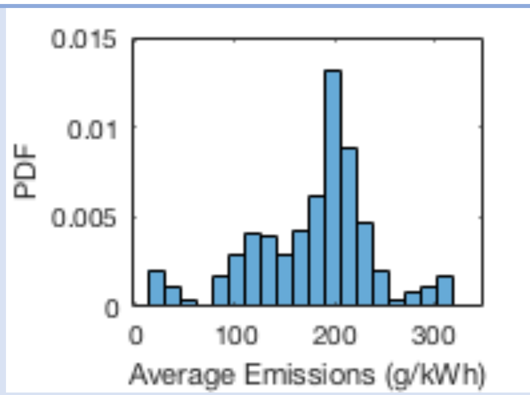
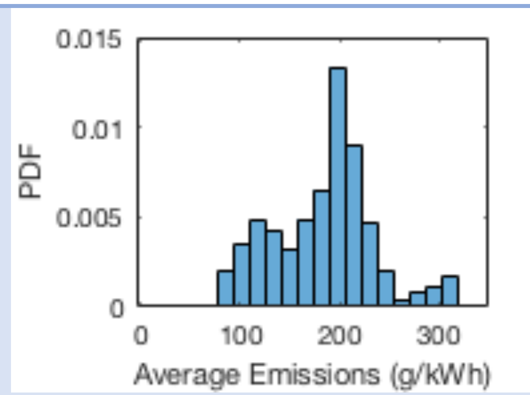
The Monte Carlo model is used to find the output distribution for carbon emissions and cost of generating electricity for different carbon prices. In addition, for each carbon price, a simulation is run in which all technologies are available and in which nuclear technology is not available.

Results

As the carbon price increases, the average emissions decrease and the average system cost increases. In addition, the uncertainty of the emissions decreases as the carbon price increases. The uncertainty of the average system cost increases slightly.

The distributions of the average emissions for each carbon price tested for both the cases where nuclear is available and the case where nuclear is not available are in Table 19. The distributions of the average system cost are in Table 20. In each table the distribution is shown for carbon prices of $0/ton, $100/ton, and $400/ton. The distributions for the remaining tested carbon prices are shown in Appendix A.

Table 19: Carbon Emission Distributions

	Nuclear is Available	**Nuclear is Not Available**
Carbon Price = $0/ton		

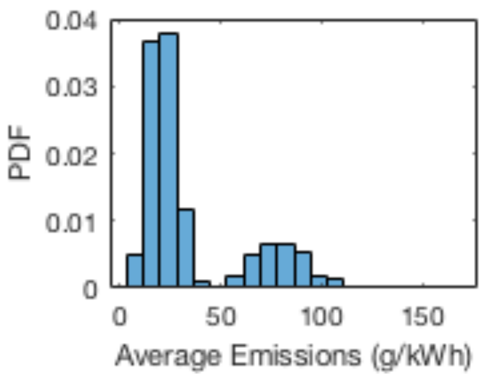
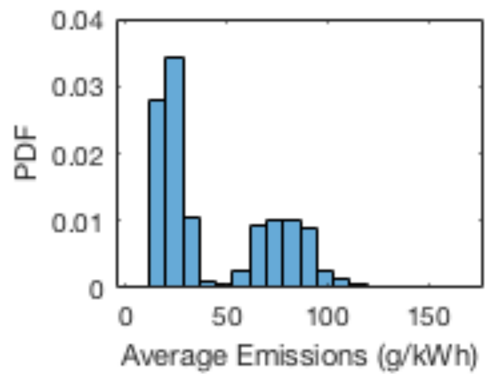
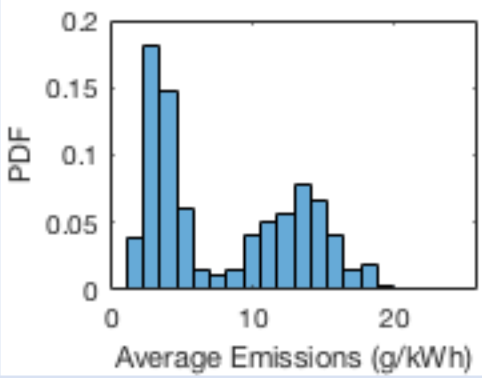
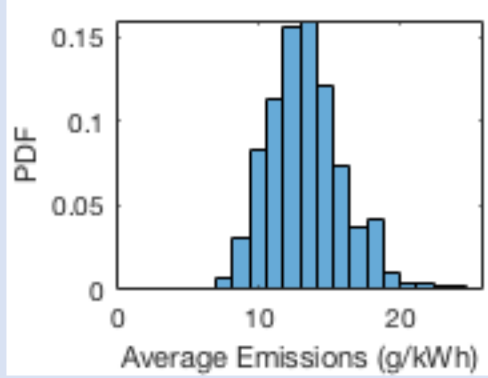
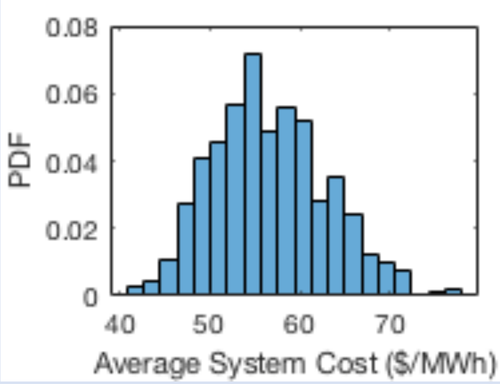
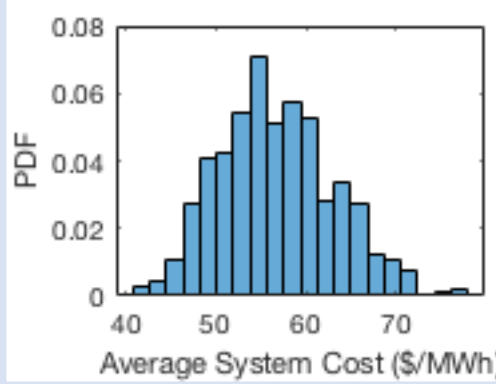
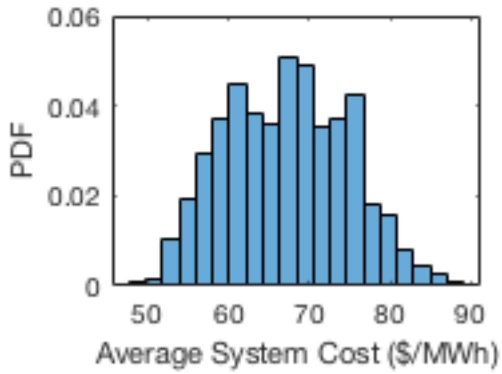
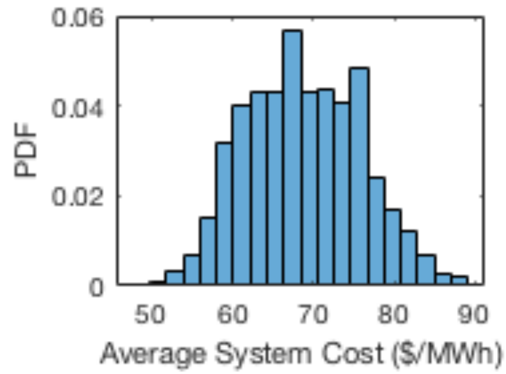
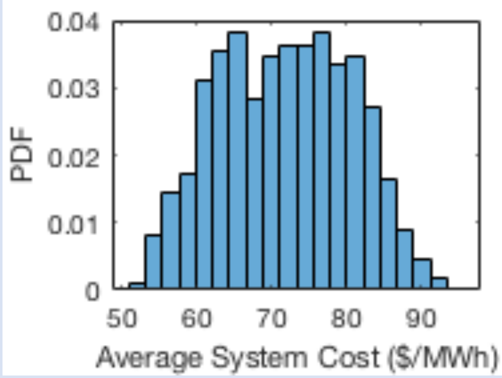
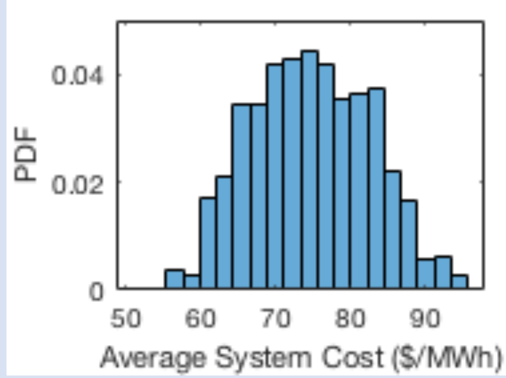
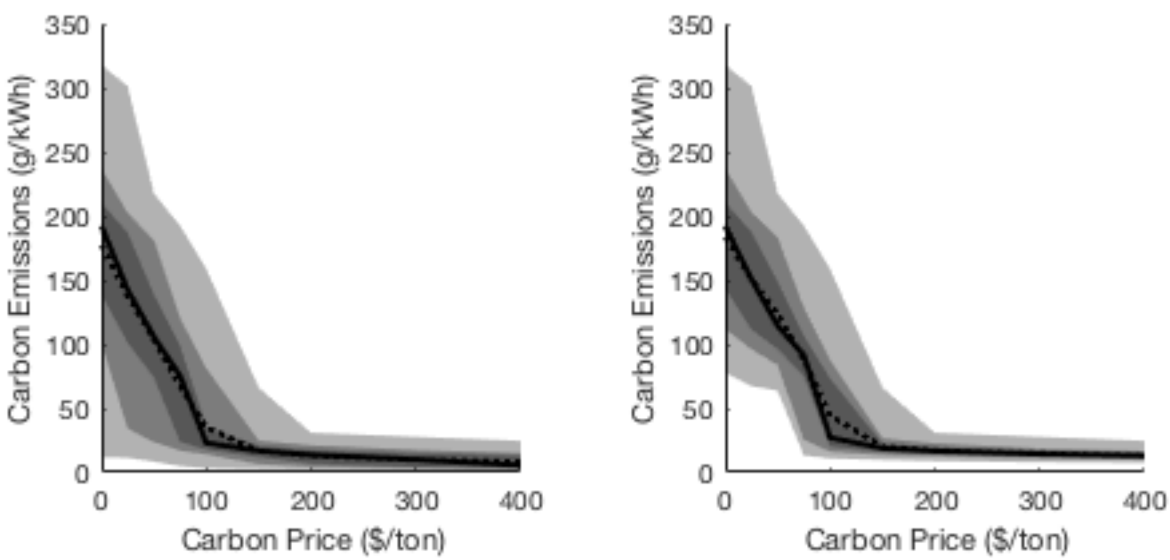
<table>
<tr><td>Carbon Price = $100/ton</td><td>
</td><td>
</td></tr>
<tr><td>Carbon Price = $400/ton</td><td>
</td><td>
</td></tr>
</table>

Table 20: Cost of Electricity Generation Distributions

<table>
<tr><th></th><th>Nuclear is Available</th><th>Nuclear is Not Available</th></tr>
<tr><td>Carbon Price = $0/ton</td><td>
</td><td>
</td></tr>
</table>

<table>
<tr>
<td>**Carbon Price = $100/ton**</td>
<td>
</td>
<td>
</td>
</tr>
<tr>
<td>**Carbon Price = $400/ton**</td>
<td>
</td>
<td>
</td>
</tr>
</table>

The carbon emission distributions plotted as a function of the carbon price are in Figure 60. The carbon emission distributions plotted as a function of the carbon price are in Figure 61. The different shaded regions refer to different percentiles. The left-hand plot is the case where nuclear technology is available. The right-hand plot is the case where nuclear technology is not available.



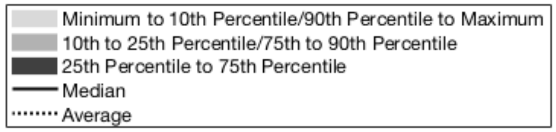


Figure 60: Distribution of carbon emissions as a function of carbon price with nuclear available (left) and without nuclear available (right)

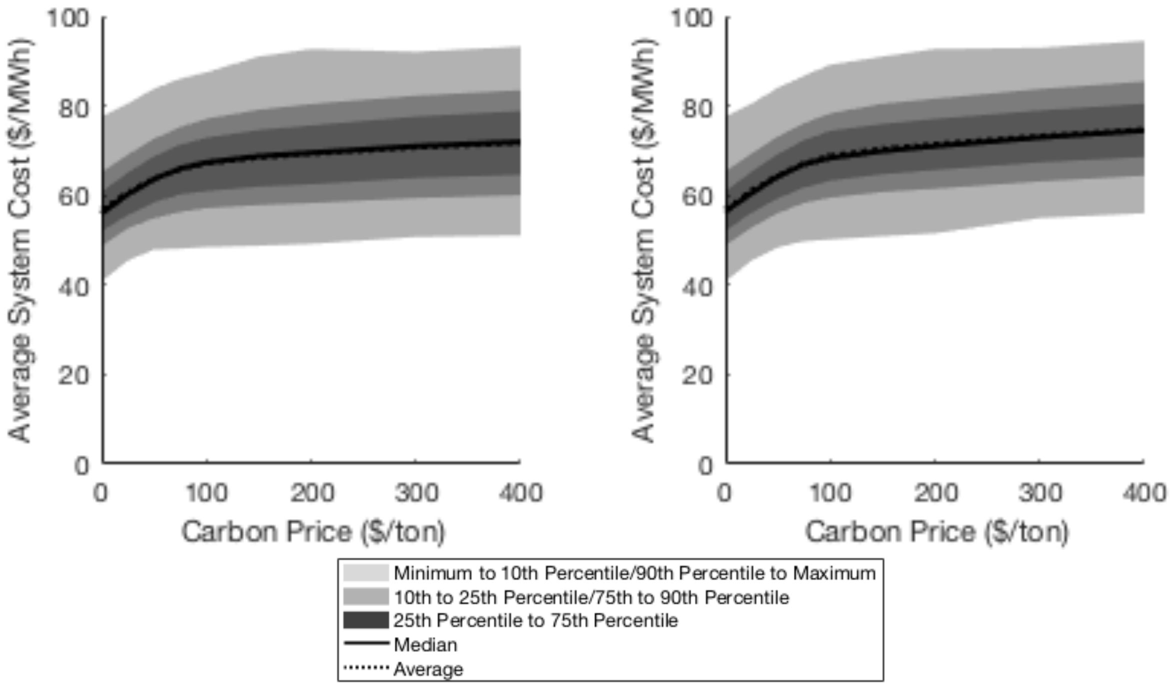


Figure 61: Distribution of average system cost as a function of carbon price with nuclear available (left) and without nuclear available (right)

The probability of reducing carbon emissions below a given target is shown as a function of carbon price is plotted in Figure 62. The left-hand plot is the case where nuclear technology is available. The right-hand plot is the case where nuclear technology is not available.

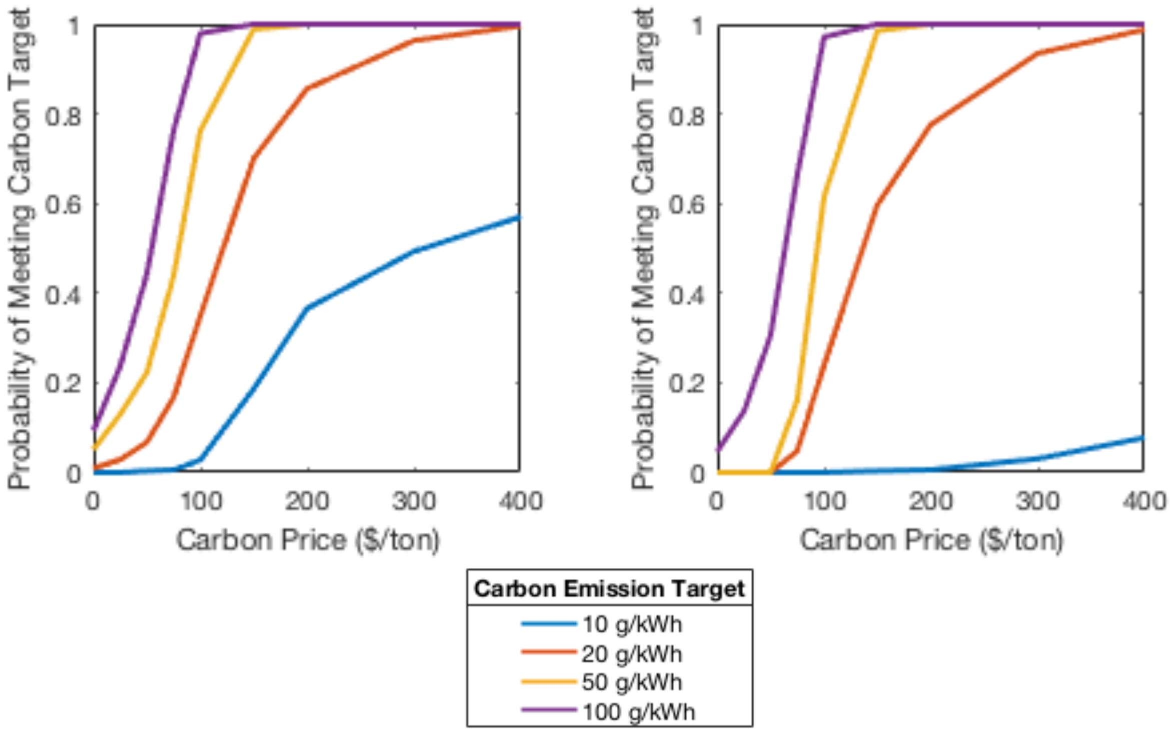


Figure 62: Probability of reducing carbon emissions below a given target as a function of carbon price with nuclear available (left) and without nuclear available (right)

The relative influence of each of the uncertainty inputs upon the variance of the output distributions (carbon emissions and average system cost) was measured using the Sobol index. The higher a Sobol index is for a given parameter, the more influence that parameter has upon the variance of the output distribution. It shows which parameters are most important in shaping the output distribution. The Sobol indices for carbon emissions and average system cost for the cases with and without nuclear are shown in Figure 63 and Figure 64.

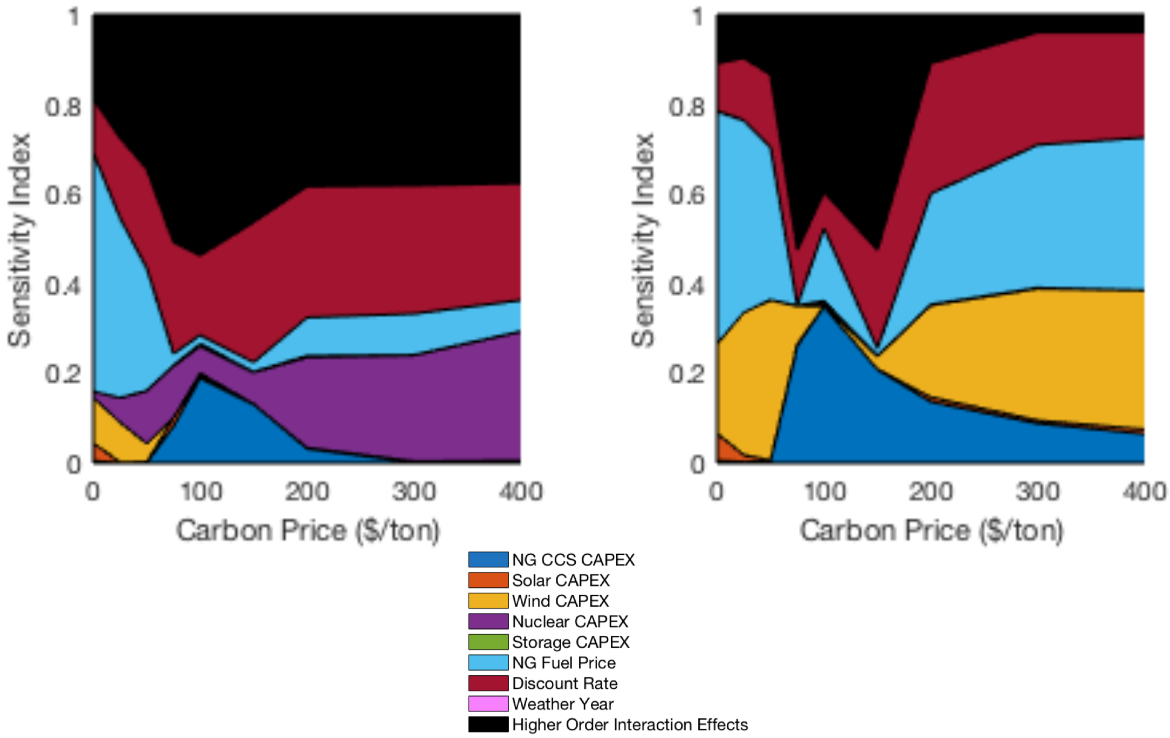


Figure 63: Relative Sobol indices of the uncertain inputs' first-order effects upon carbon emissions as a function of carbon price with nuclear available (left) and without nuclear available (right)

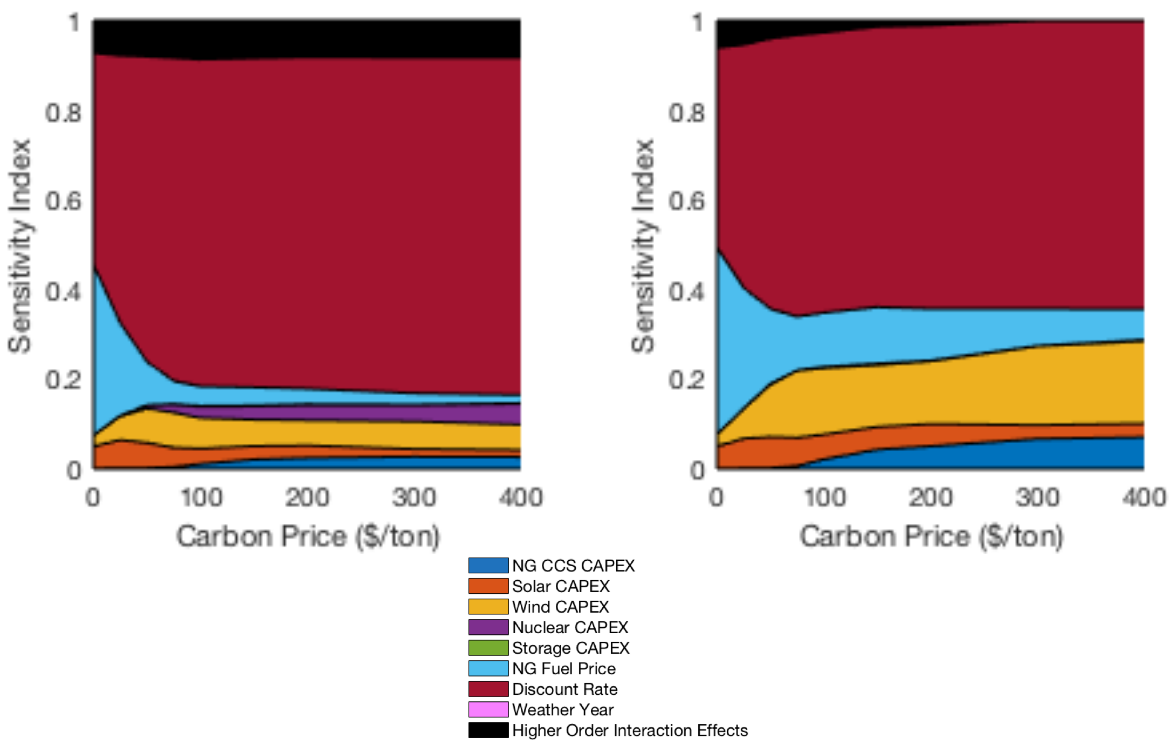


Figure 64: Relative Sobol indices of the uncertain inputs' first-order effects upon average system cost as a function of carbon price with nuclear available (left) and without nuclear available (right)

Discussion

As the carbon price increases, the average carbon emissions decrease. This is due to the carbon price increasing the marginal cost of fossil fuel electricity generation. As the marginal cost of fossil fuel generation increases, non-carbon emitting technology becomes the more economical option to meet demand. The non-carbon emitting technology that replaces the fossil fuel technology is nuclear, carbon capture natural gas, or renewables (solar and wind). The amount of fossil fuel generation that is replaced depends upon the price of natural gas. If the price of natural gas is cheap, the natural gas technologies can absorb more of the carbon price into its marginal cost before it is more economical to replace the natural gas technologies with non-carbon emitting technologies.

The amount of each non-carbon emitting technologies that makes up the replacement for the fossil fuel generation depends upon the investment costs of the non-carbon emitting technology. In each iteration of the Monte Carlo simulation, the most economical portfolio of these non-carbon emitting technologies is chosen to be the replacement capacity. If nuclear technology is not available as a replacement option, then even if it would have been the most economical option, it will not be part of the replacement capacity portfolio. This means that replacement portfolio will be more expensive than it would have been if nuclear was an option and therefore less of the fossil fuel will be replaced. In addition, the system cost of generating will increase. This is observed in Figure 60 and Figure 61.

As a consequence of the decreasing emissions with increasing carbon price, the probability of meeting a carbon target increases with increasing carbon price (as observed in Figure 62). If nuclear technology is not available as an option, the probability of meeting a carbon target decreases with respect to the scenario where nuclear technology is available. This highlights an important consequence if not all available non-carbon emitting options are not available to be deployed as the electricity sector is decarbonized. The chances of successfully decarbonizing down to a given carbon emission target decrease if not all non-carbon emitting technologies are available to be used.

The Sobol indices show the relative importance that each of the uncertainty inputs have upon the uncertainty in the output distributions (carbon emissions and system cost). In examining the importance of the input variables upon the output carbon emission distribution, the most important input uncertainty at no carbon price is the natural gas fuel price regardless if nuclear is available or not. It is more important, however, in the case where nuclear is available. The discount rate is also important. As the carbon price increases, the capital cost of natural gas with CCS becomes important. As the carbon price increases further, the capital cost of natural gas with CCS then becomes less important. This is because CCS is not a zero-carbon emitting technology, it is a low carbon emitting technology. It becomes more attractive at moderate carbon prices as a replacement for natural gas without CCS, but at high carbon prices it is not favorable because zero-carbon emitting technologies will be preferred over low carbon emitting technologies. The importance of nuclear capital cost grows with an increasing carbon price in the case where nuclear technology is available. In the case where nuclear technology is not available, wind capital cost and natural gas fuel price instead grow more important with an increasing carbon price.

The relative importance of the input variables upon the output average system cost distribution are different than the importance of the input variables upon the output carbon emissions distribution. At no carbon price, the most important input uncertain variables are the discount rate and the natural gas fuel price regardless if nuclear is available or not. As the carbon price increases, in the case with nuclear available, the discount rate becomes more important as does the capital cost of nuclear technology. The importance of natural gas fuel price decreases. In the case without nuclear available, the discount rate becomes more important as does the capital cost of wind technology. The natural gas price becomes less important, but not as unimportant as the case with nuclear available. This is because natural gas is needed as a backup to the intermittent solar and wind generators.

Conclusion

This chapter shows that there is uncertainty in the amount of emissions that will occur in 2050 in ERCOT. The uncertainty is highest for carbon prices below $200/ton. The uncertainty is lower if nuclear is not available as an option to be part of the optimal capacity portfolio. However, if nuclear is not available to as an option to be part of the optimal capacity portfolio, the expected carbon emissions will be higher. This is because the system cannot take advantage of the scenarios where nuclear is favorable and instead build more natural gas.

This analysis shows a role for nuclear technology in decreasing carbon emissions for all carbon price values (even at no carbon price). This would not have been seen in a deterministic scenario. This shows the advantage of considering uncertainties in decarbonization analyses.

In addition, the uncertainty treatment of this analysis shows that nuclear has a role in increasing the probability of meeting carbon emission targets. In the cases where nuclear is not available, the probability of meeting these carbon emission targets decreases. This is especially true for more aggressive carbon emission targets such as 10 g/kWh.

The uncertainty treatment also shows that the discount rate is the most important uncertainty in the future in determining both carbon emissions and the total system cost. This is because the discount rate affects the investment cost of technologies, which has more of an influence upon non-carbon emitting technologies due to high capital costs (solar, wind, and nuclear). If the discount rate is high, then carbon emitting technologies (with a low capital cost) will be preferred over non-carbon emitting technologies (with a high capital cost).

Chapter 7 – Heat and Transportation Electrification

Introduction

In this chapter, the effect of the electrification of the heat sector as well as passenger vehicles in the transportation sector is examined. As explained in Chapter 2, there is the potential for these markets to become electrified. However, that has the potential of changing the characteristics of electricity demand. Electrification of the heat sector will increase the amount of baseload generation – particularly in the winter months. Electrification of the transportation sector will add or accentuate the peaks already present in the daily load profile. The effect of this electrification is tested using the model developed for this thesis (as described in Chapter 5) using the uncertainties quantified in Chapter 6. Two separate cases were analyzed: 1) 30% electrification of the heat sector and 2) 30% electrification of passenger cars and passenger trucks. Both cases were set in the ERCOT electricity grid in the year 2050.

Methods

This section described how the electricity demand is adjusted to account for either the partial electrification of the heat or the transportation demand. There are two steps to adjust the electricity demand: 1) find the total annual demand for the heat/transportation sector and 2) apply this annual demand to an hourly profile.

Total Annual Passenger Vehicle Transportation Demand

The annual passenger vehicle transportation demand is found using a bottom up approach and verified using a top down approach.

The historical annual passenger vehicles mileage was taken from the Texas Department of Transportation (TxDOT) Roadway Inventory database (TxDOT, 2019). The annual passenger miles for the years 2005 to 2017 are shown in Figure 65. There is a compound annual growth rate (CAGR) of 1.32% during this period. If the growth rate is assumed to be constant between 2017 and 2050, the annual passenger miles in the year 2050 is 377.6 billion miles.

Figure 65: Annual passenger vehicle miles for the years 2005 to 2017 in Texas

To find the annual electricity demand resulting from the annual miles drive, the efficiency of the passenger vehicles (miles per MWh) must be known. However, passenger vehicles comprise many different categories – from sedans to light-duty trucks. Not all of these categories will have the same efficiency. Therefore, the total amount of passenger vehicles driven is separated into two categories – passenger cars and passenger trucks. Data from the United States Department of Transportation shows that the annual miles driven in 2015 for passenger cars is 2,984 billion and the annual miles driven in 2015 for passenger trucks is 844 billion (USDOT, n.d.). If the same ratio is assumed for Texas in 2050, that would mean there are 294.4 billion annual passenger car miles and 83.3 billion passenger truck miles.

According to the US Office of Energy Efficiency and Renewable Energy, the highest rated electric passenger car currently available is the Hyundai Ioniq Electric which has a rated mileage of 136 miles per electric gallon[6] (Office of Energy Efficiency and Renewable Energy, 2019b). This is equivalent to 4,000 miles per MWh. The Rivian R1T electric pick-up truck is projected to have a 180 kWh battery that allows for 400 miles of range (O'Kane, 2018). This is equivalent to 2,200 miles per MWh.

Using these mileages for the passenger car and passenger truck categories and the annual miles driven by the passenger car and passenger truck categories, the total annual additional electric demand is determined to be 111,000 GWh.

The annual additional electric demand of 110,000 GWh from the bottom up approach was verified using a top-down approach. In this approach, the entire energy demand of the transportation sector was broken down into segments. The segment that contains passenger

[6] There are 33.7 kWh in one electric gallon

cars represents the total additional energy demand that would have to be satisfied by the electric grid of those vehicles were electrified.

The US Energy Information Agency (EIA) estimates that there will be 25.57 quadrillion BTUs of energy used by the transportation sector in the United States in 2050. This represents about a quarter of energy use from all sectors. Of the 25.57 quadrillion BTUs from the transportation sector, 11.27 quadrillion BTUs (44%) are the result of light-duty (i.e. passenger) vehicles. For the West South Central region[7] of the United States, it is estimated that 4.724 quadrillion BTUs will be used by the transportation sector (US EIA, 2019). Applying the same 44% passenger car percent, this means that in the West South Central region, approximately 2.082 quadrillion BTUs are used for passenger car energy needs. Assuming that Texas accounts for about half of this total energy demand, this means that 1.041 quadrillion BTUs of energy demand are used for passenger cars in Texas. This is equivalent to 305,100 GWh. Assuming that the vehicles have on average a thermal efficiency of 20% and the electric efficiency 60% (Office of Energy Efficiency and Renewable Energy, 2019a), this means that the 305,100 GWh of transportation demand will require 101,700 GWh of electric demand.

The bottom up approach led to the conclusion of an additional 110,000 GWh of electric demand if all passenger cars are electrified. The top down approach led to the conclusion of an additional 101,700 GWh of electric demand if all passenger cars are electrified. Therefore, it is approximated that about 105,000 GWh of additional electric demand annually will be added to the electric grid of all passenger vehicles are electrified.

Hourly Annual Passenger Vehicle Transportation Demand

The additional annual electric demand resulting from the electrification of passenger vehicles is not uniformly applied over the entire year. Instead, there are times where demand from charging vehicles peaks. As discussed in Chapter 2, there will be typical times that people will plug in and charge their electric vehicles. The California Energy Commission produced a report in which they estimated the electric demand from charging cars for an entire weekday and weekend, as seen in Figure 66 (from the report) (Bedir et al., 2019).

[7] Texas, Oklahoma, Arkansas, Louisiana

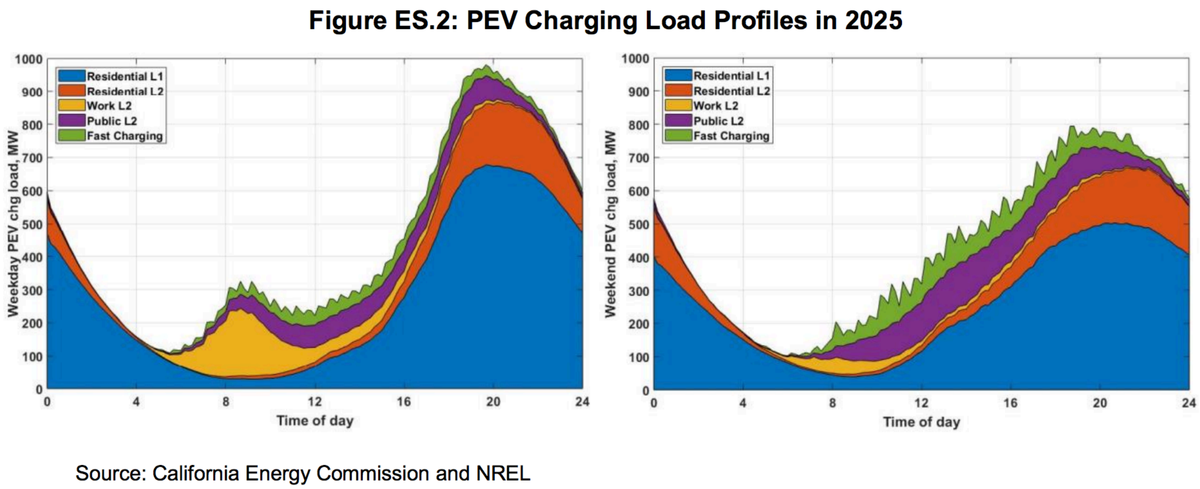


Figure 66: Electric car charging load anticipated in 2025 in California

If these residential load profiles are assumed for the entire year, then the fraction of total passenger vehicle transportation annual electric demand in any given hour can be determined. To find the additional electric demand from the electrification of passenger vehicles in each hour, the fraction in each hour is multiplied by the annual electric passenger vehicle demand.

Total Annual Heat Demand

The annual heat demand is found using a top down approach. The electrified heat demand is assumed to come from residential and commercial space-heating In the West South Central region[8] of the United States, the US EIA estimates that there will be 0.717 quadrillion BTUs of residential and commercial heating annually. If it is estimated that half of this demand comes from Texas, this means that there is 0.359 quadrillion BTUs of heat demand that has the potential to be electrified. This is equivalent to 105,000 GWh of additional demand to the electric grid if it were to be electrified.

Hourly Heat Demand Profile

The space-heating demand varies based on the season. Historical data on heating degree days[9] in Texas was used to scale the total amount of residential and commercial heating for each month. The average heating degrees per day for each month was calculated from 2017 heating degree day data for Texas from the National Oceanic and Atmospheric Administration (National Oceanic and Atmospheric Administration, 2019). This is shown in Figure 67.

[8] Texas, Oklahoma, Arkansas, Louisiana

[9] The number of heating degrees in a day is 65°F minus the average temperature of that day

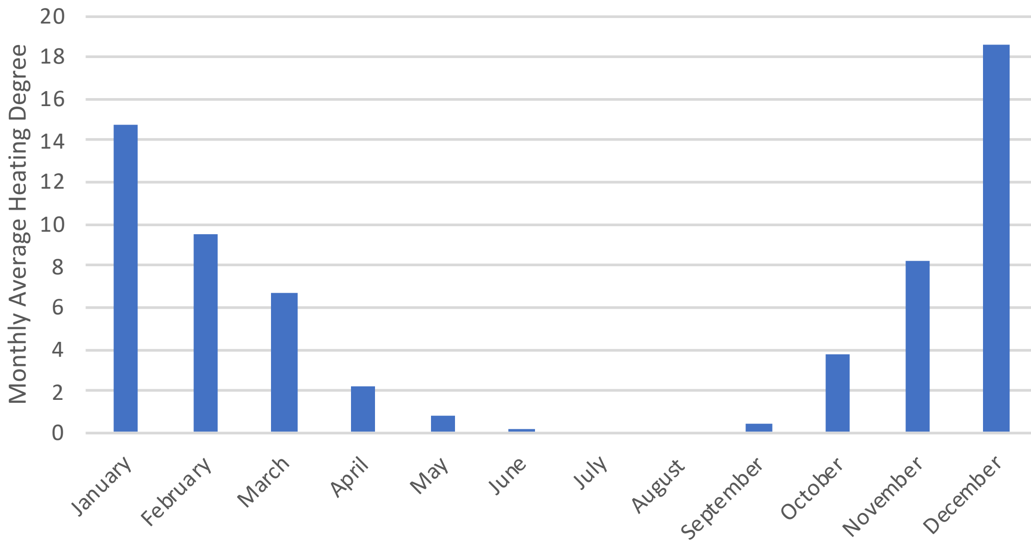


Figure 67: Average heating degrees per day in Texas for each month in 2017

The percent of residential and commercial heating demand that is used for each month is scaled in accordance to that month's average heating degrees per day.

Case Matrix

The Monte Carlo model is used to find the output distribution for carbon emissions and cost of generating electricity for different carbon prices. In addition, for each carbon price, two other simulations are run: in the first, 30% of passenger vehicles are electrified and in the second 30% of space heating is electrified.

Transportation Electrification Results

The distributions of the average emissions for each carbon price tested for both the cases where the electricity demand is its nominal value and where there is 30% electrification of passenger vehicles added to the electricity demand are in Table 21. Both cases have all technologies available. The distributions of the average system cost are in

Table 22. In each table the distribution is shown for carbon prices of \$0/ton, \$100/ton, and \$400/ton. The distributions for the remaining tested carbon prices are shown in Appendix A.

Table 21: Carbon Emission Distributions

	Nominal Electricity Demand	30% Passenger Vehicles Electrified

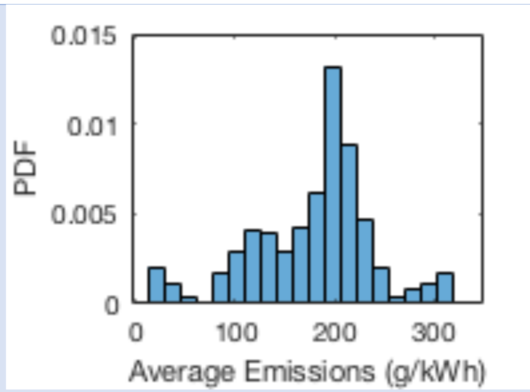
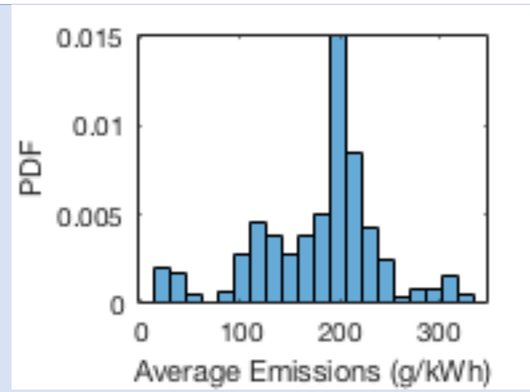
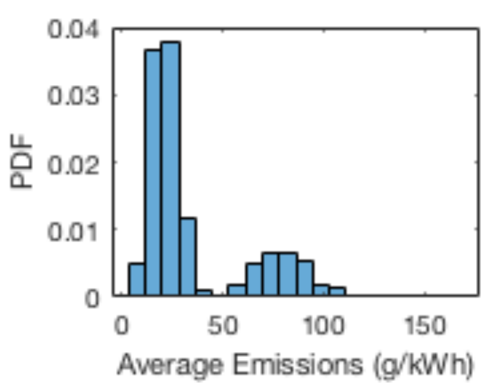
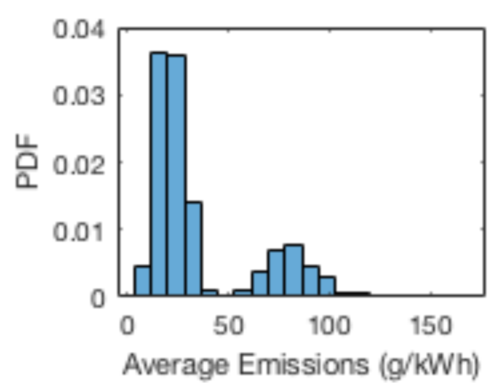
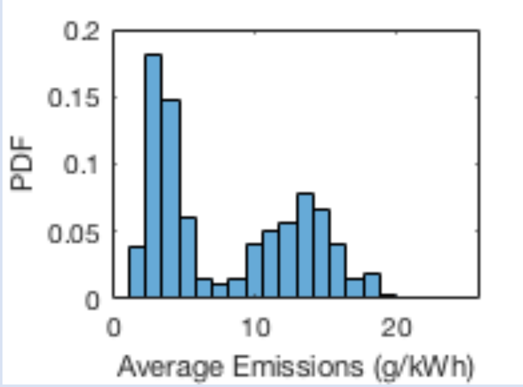
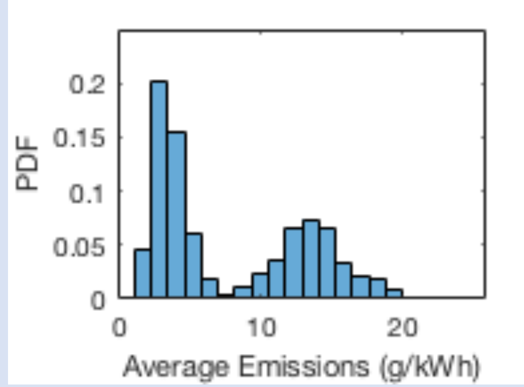
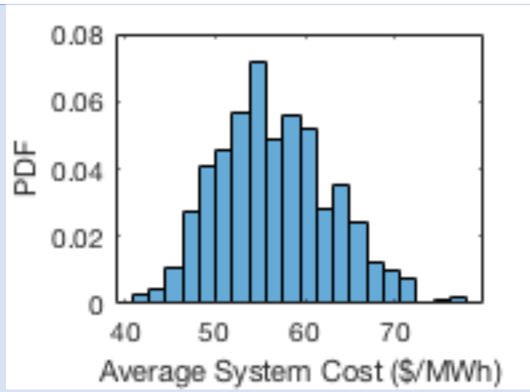
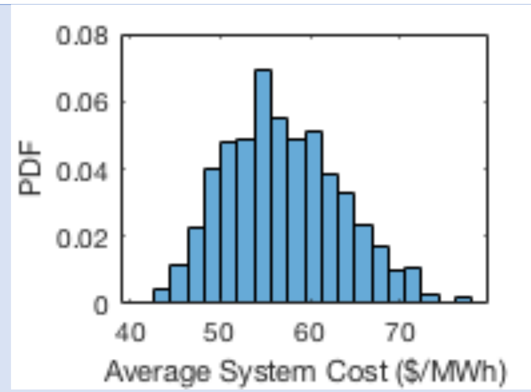
Carbon Price = $0/ton		
Carbon Price = $100/ton		
Carbon Price = $400/ton		

Table 22: Cost of Electricity Generation Distributions

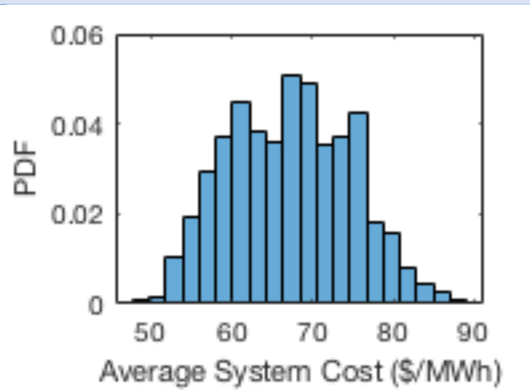
	Nominal Electricity Demand	**30% Passenger Vehicles Electrified**

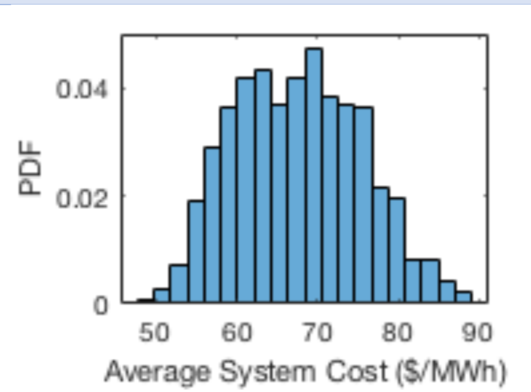
Carbon Price = \$0/ton



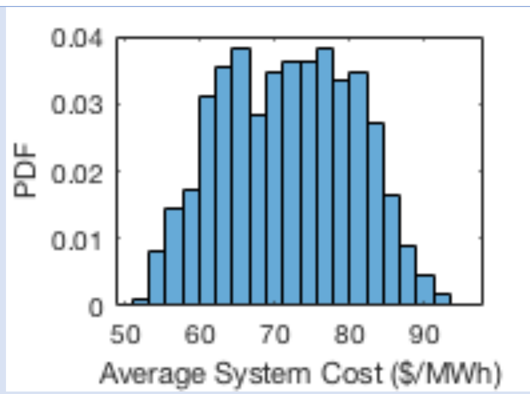


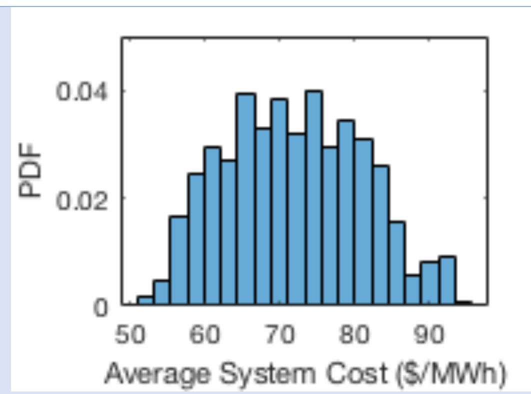
Carbon Price = \$100/ton





Carbon Price = \$400/ton





The carbon emission distributions plotted as a function of the carbon price are in Figure 68. The carbon emission distributions plotted as a function of the carbon price are in Figure 69. The different shaded regions refer to different percentiles. The left-hand plot is the case with nominal electricity demand. The right-hand plot is the case with 30% electrification of passenger vehicles added to the electricity demand.

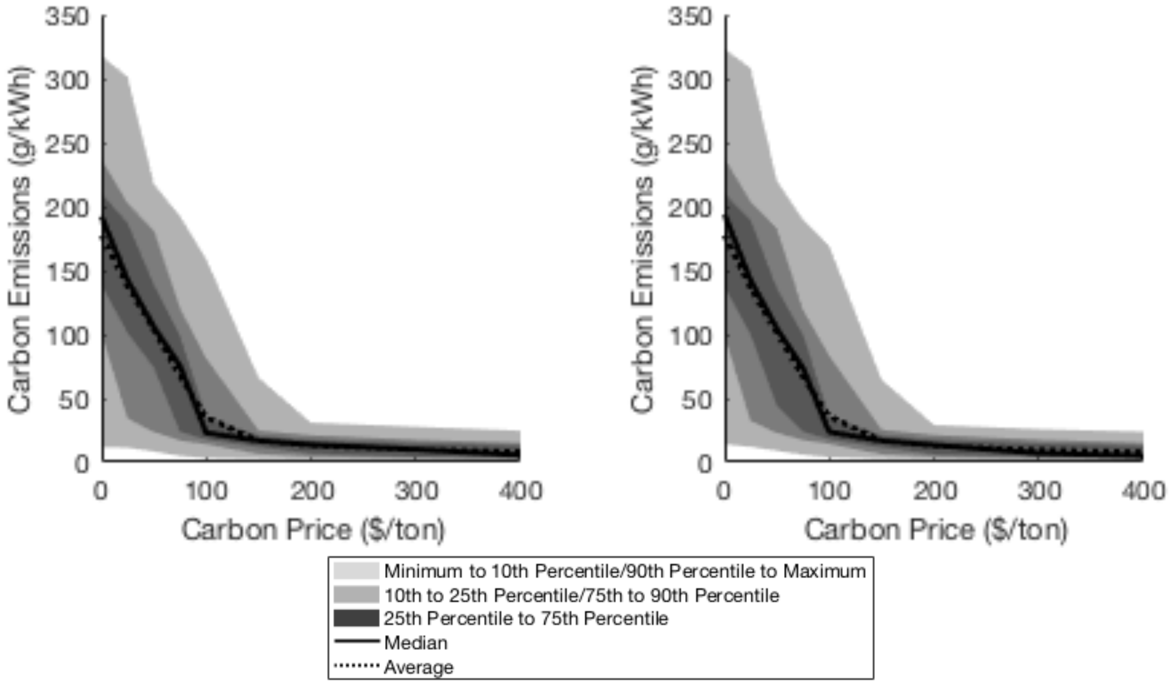


Figure 68: Distribution of carbon emissions as a function of carbon price with nominal electricity demand (left) and with 30% of passenger vehicles electrified (right)

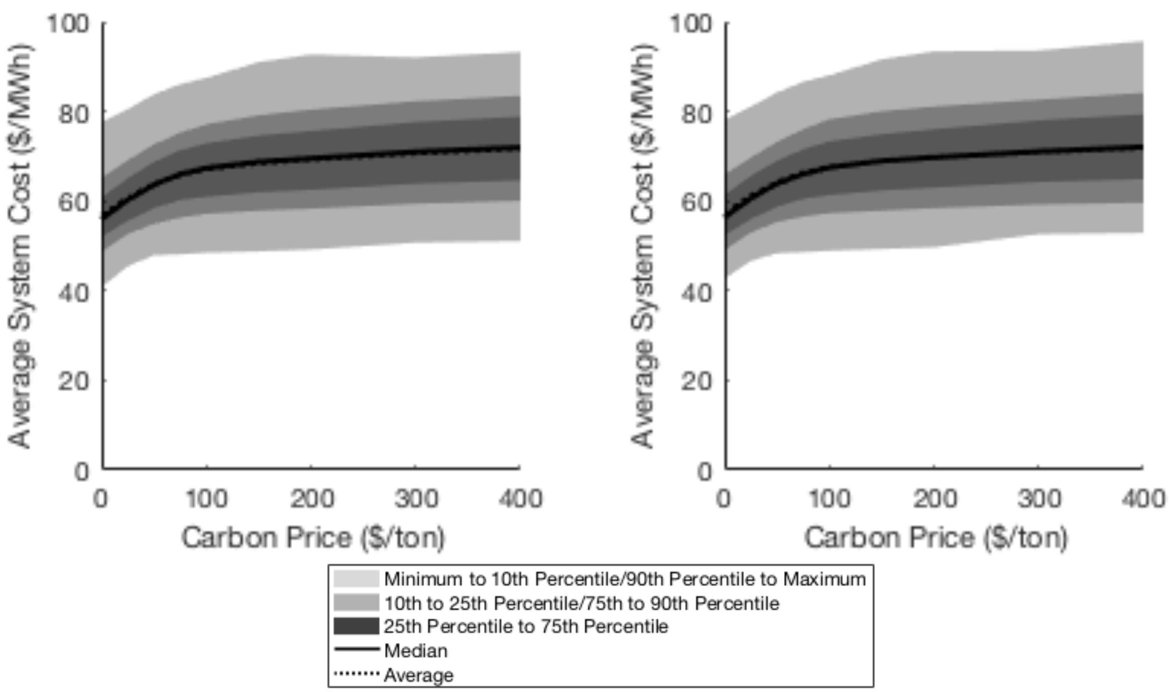


Figure 69: Distribution of average system cost as a function of carbon price with nominal electricity demand (left) and with 30% of passenger vehicles electrified (right)

The probability of reducing carbon emissions below a given target is shown as a function of carbon price is plotted in Figure 70. The left-hand plot is the case with nominal electricity demand. The right-hand plot is the case with 30% electrification of passenger vehicles added to the electricity demand.

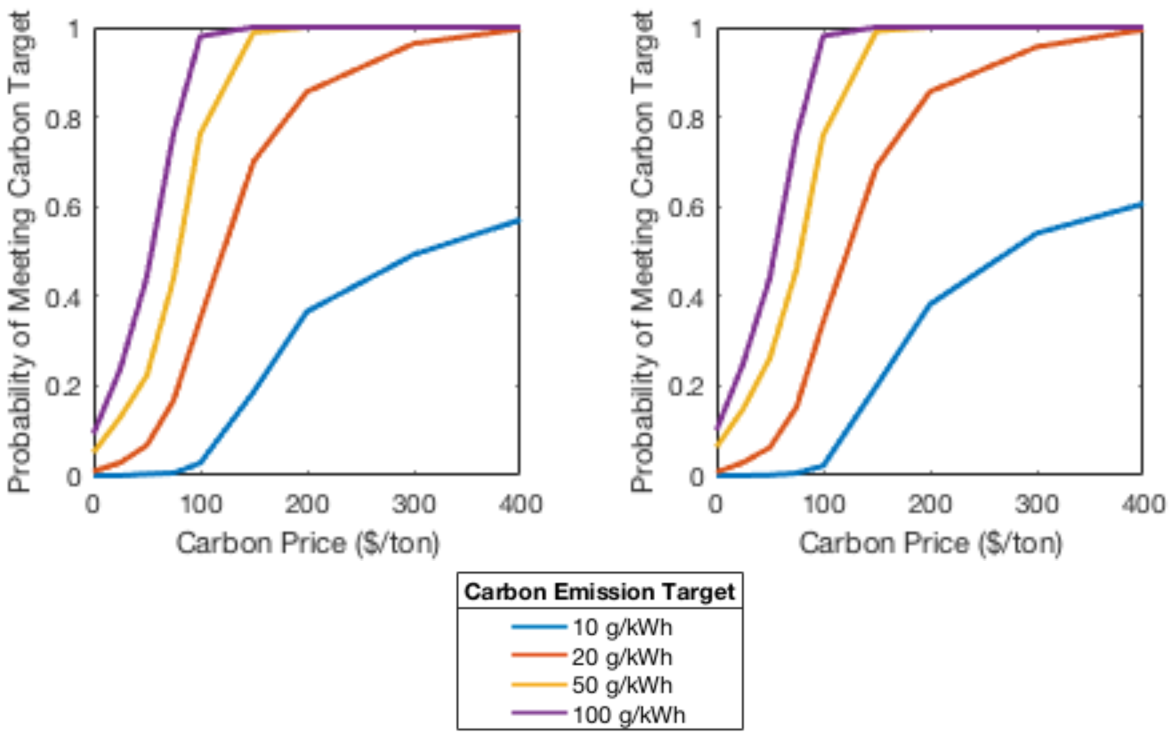


Figure 70: Probability of reducing carbon emissions below a given target as a function of carbon price with nominal electricity demand (left) and with 30% of passenger vehicles electrified (right)

The relative influence of each of the uncertainty inputs upon the variance of the output distributions (carbon emissions and average system cost) was measured using the Sobol index. The higher a Sobol index is for a given parameter, the more influence that parameter has upon the variance of the output distribution. It shows which parameters are most important in shaping the output distribution. The Sobol indices for carbon emissions and average system cost for the cases with nominal demand and nominal plus 30% electrification of passenger vehicles are shown in Figure 71 and Figure 72.

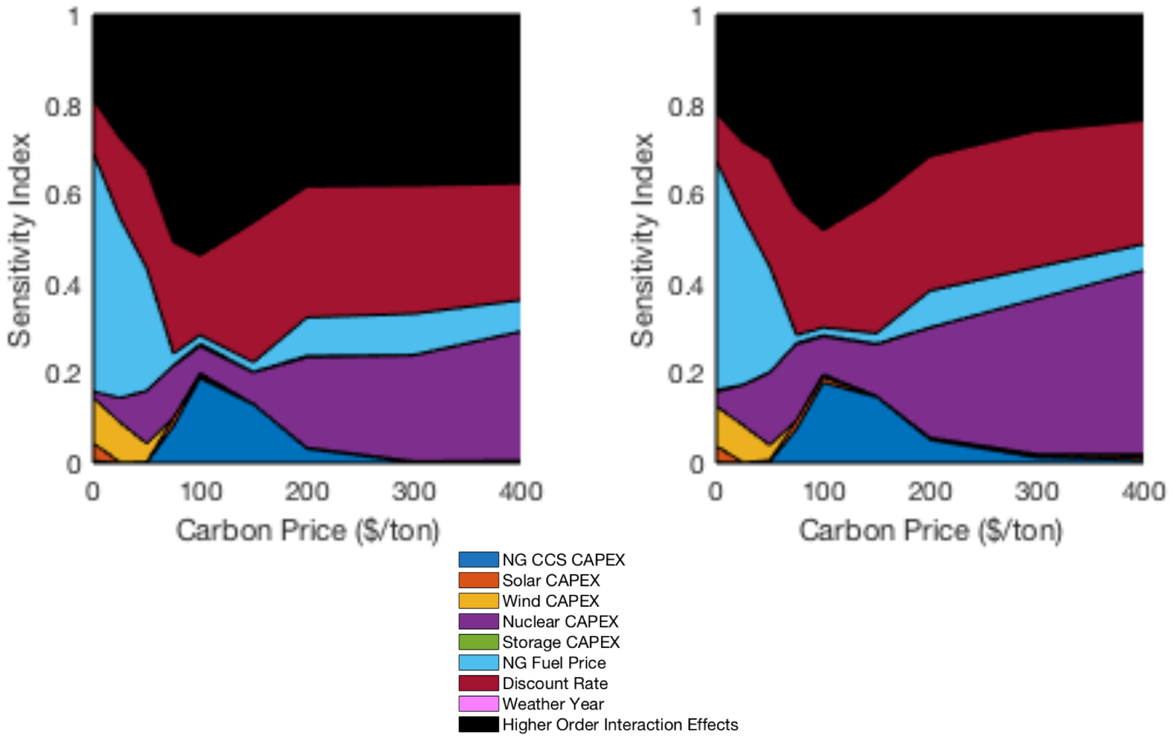


Figure 71: Relative Sobol indices of the uncertain inputs' first-order effects upon carbon emissions as a function of carbon price with nominal electricity demand (left) and with 30% of passenger vehicles electrified (right)

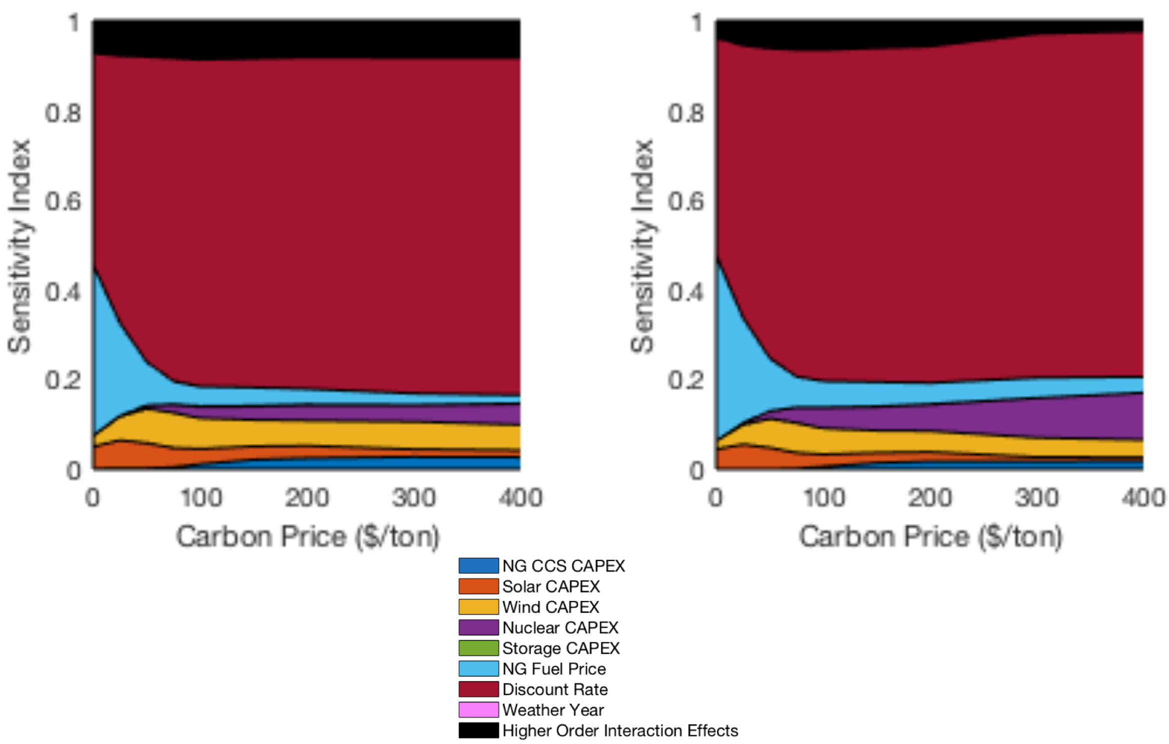


Figure 72: Relative Sobol indices of the uncertain inputs' first-order effects upon average system cost as a function of carbon price with nominal electricity demand (left) and with 30% of passenger vehicles electrified (right)

Transportation Electrification Discussion

Adding the demand for charging electric vehicles to the nominal demand changes the shape of the load profile. Charging is not uniform across all hours of the year (see Figure 66). Instead, it peaks in the evening. Adding the demand for charging electric vehicles increases the peaks of the electric demand. This addition to the peaks must be met with a flexible, dispatchable generator if it is not at a time when renewable potential is high. Depending on the carbon price, this will either be natural gas or natural gas with CCS. This is why the expected emissions increases as well as the variance of the emissions increases. The probability of successfully meeting carbon targets stays relatively constant.

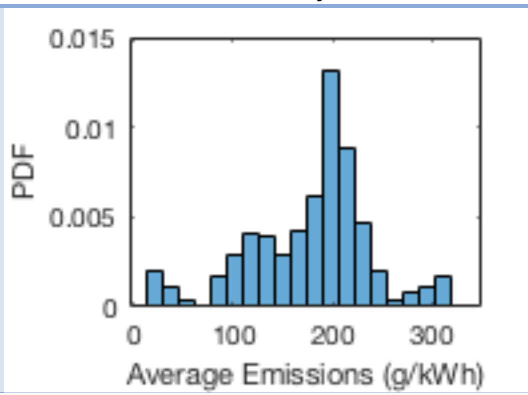
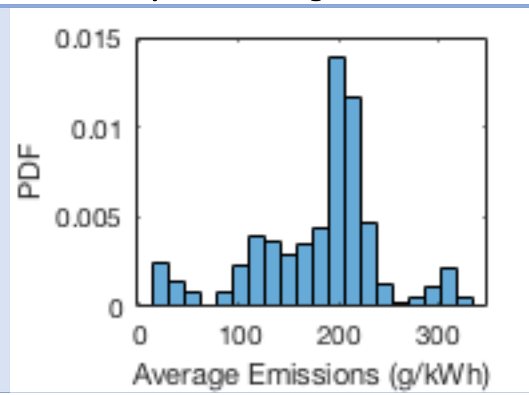
The influence of the input uncertain variables upon the output distribution of carbon emissions changes with the addition of the charging vehicle demand to the nominal electric demand. Again, this is an effect from the increase in the peaks in the demand profile. The importance of the natural gas with CCS capital cost is higher at larger carbon prices when there is additional charging vehicle demand. This is because the natural gas with CCS is providing generation during the peaks when renewable potential is low at higher carbon prices.

The influence of the input uncertain variables upon the output distribution of average system cost also changes with the addition of the charging vehicle demand to the nominal electric demand. Natural gas becomes more of an important player and therefore the importance of the natural gas price with respect to average system cost increases.

Heat Electrification Results

The distributions of the average emissions for each carbon price tested for both the cases where the electricity demand is its nominal value and where there is 30% electrification of space heating added to the electricity demand are in Table 23. The distributions of the average system cost are in
Table 24. In each table the distribution is shown for carbon prices of $0/ton, $100/ton, and $400/ton. The distributions for the remaining tested carbon prices are shown in Appendix A.

Table 23: Carbon Emission Distributions

	Nominal Electricity Demand	**30% Space Heating Electrified**
Carbon Price = $0/ton		

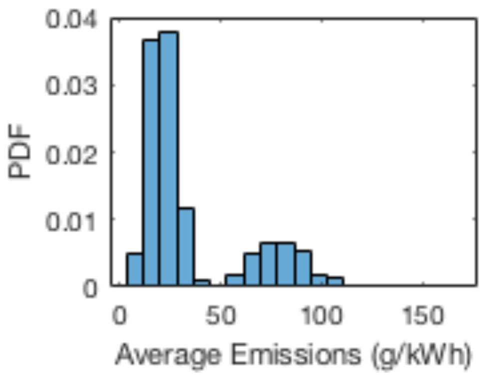
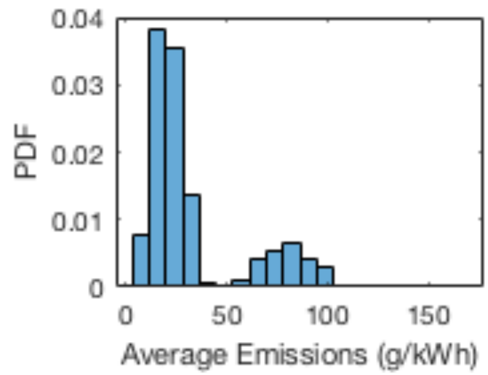
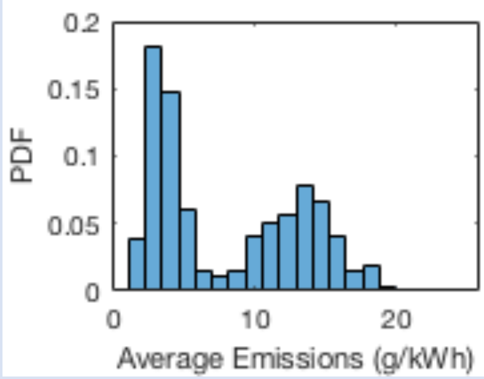
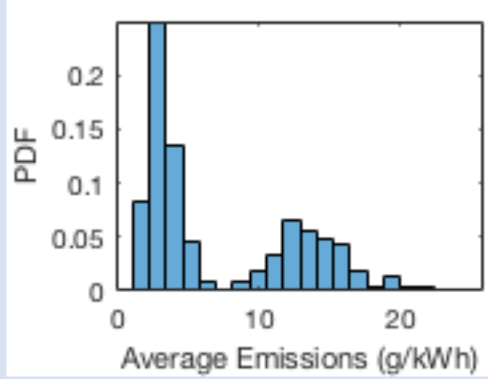
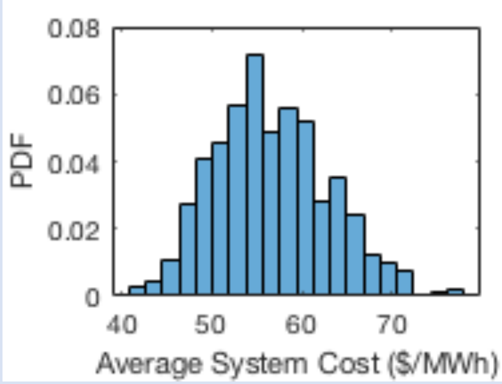
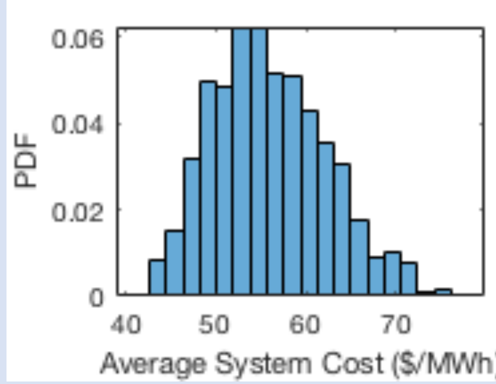
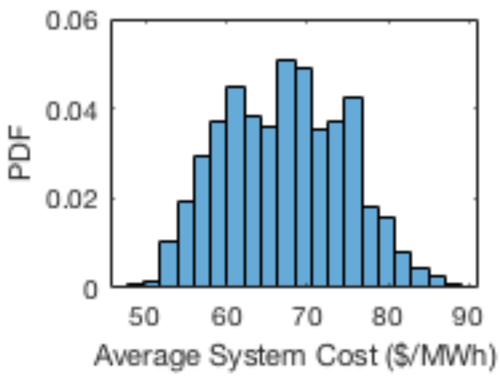
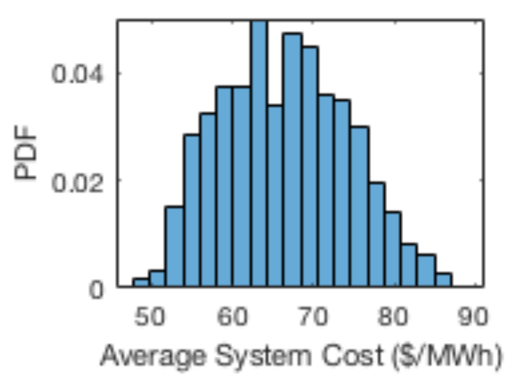
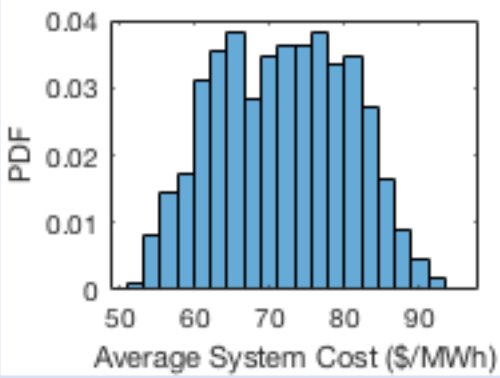
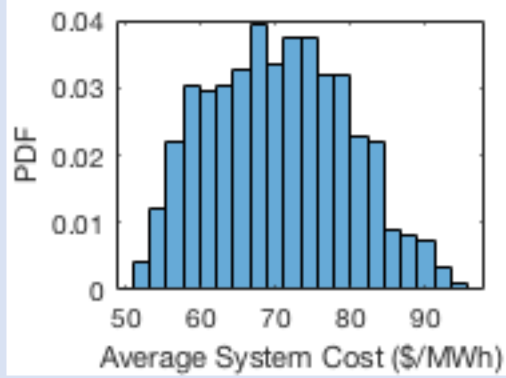
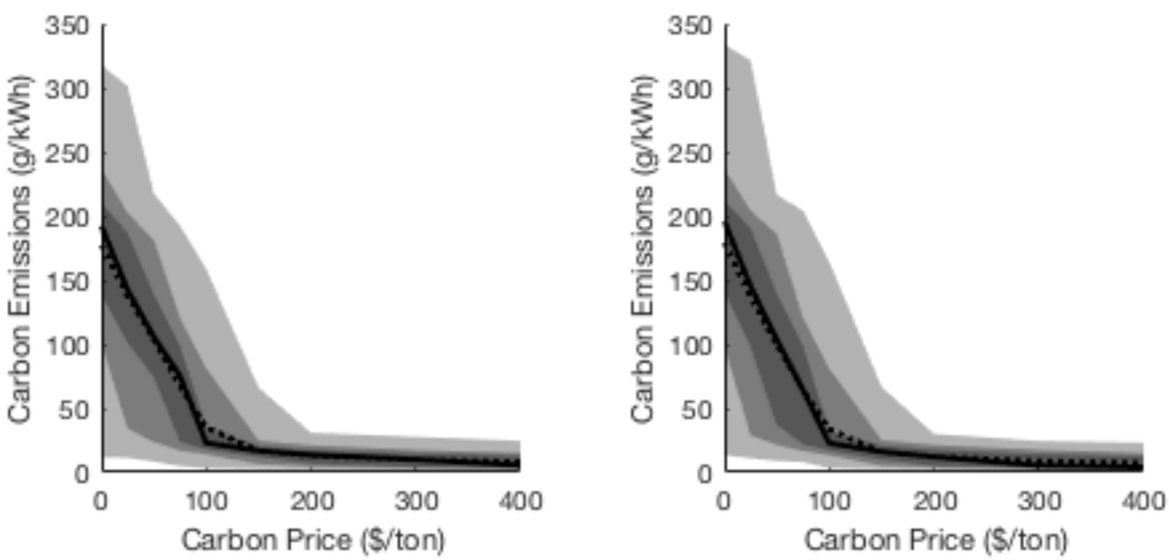
<table>
<tr><th></th><th></th><th></th></tr>
<tr><td>Carbon Price = $100/ton</td><td></td><td></td></tr>
<tr><td>Carbon Price = $400/ton</td><td></td><td></td></tr>
</table>

Table 24: Cost of Electricity Generation Distributions

<table>
<tr><th></th><th>Nominal Electricity Demand</th><th>30% Space Heating Electrified</th></tr>
<tr><td>Carbon Price = \$0/ton</td><td></td><td></td></tr>
</table>

Carbon Price = $100/ton		
Carbon Price = $400/ton		

The carbon emission distributions plotted as a function of the carbon price are in Figure 73. The carbon emission distributions plotted as a function of the carbon price are in Figure 74. The different shaded regions refer to different percentiles. The left-hand plot is the case with nominal electricity demand. The right-hand plot is the case with 30% electrification of space heating added to the electricity demand.



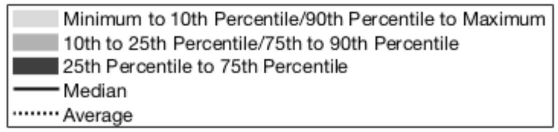


Figure 73: Distribution of carbon emissions as a function of carbon price with nominal electricity demand (left) and with 30% of space heating electrified (right)

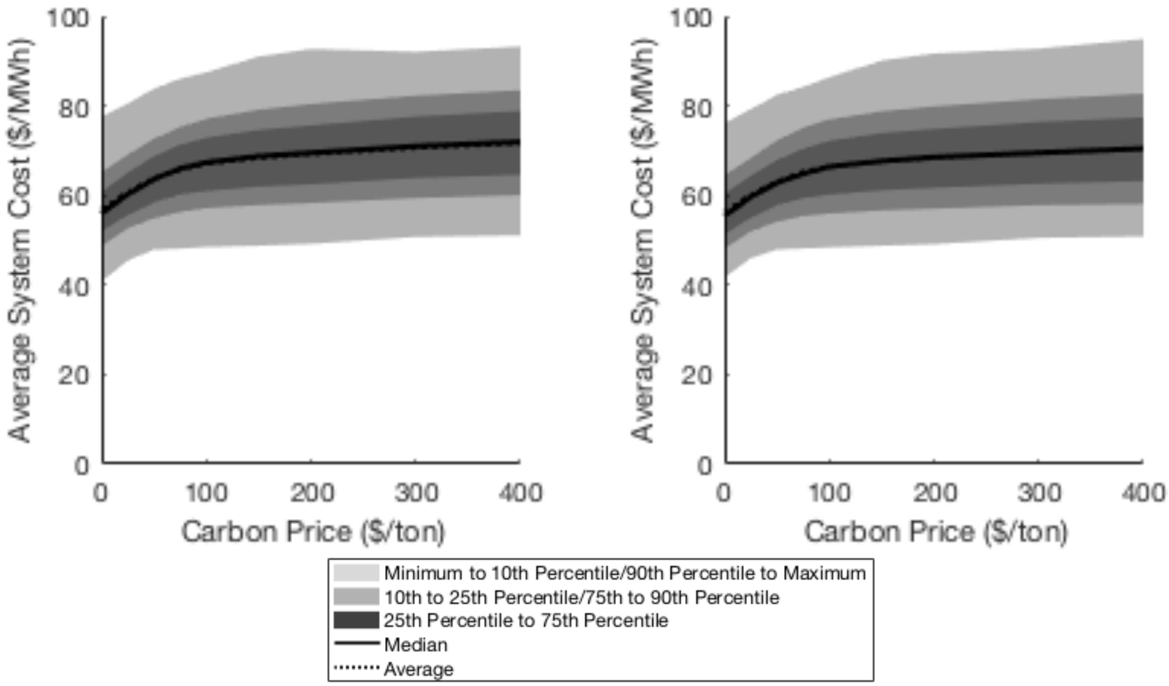


Figure 74: Distribution of average system cost as a function of carbon price with nominal electricity demand (left) and with 30% of space heating electrified (right)

The probability of reducing carbon emissions below a given target is shown as a function of carbon price is plotted in Figure 75. The left-hand plot is the case with nominal electricity demand. The right-hand plot is the case with 30% electrification of space heating added to the electricity demand.

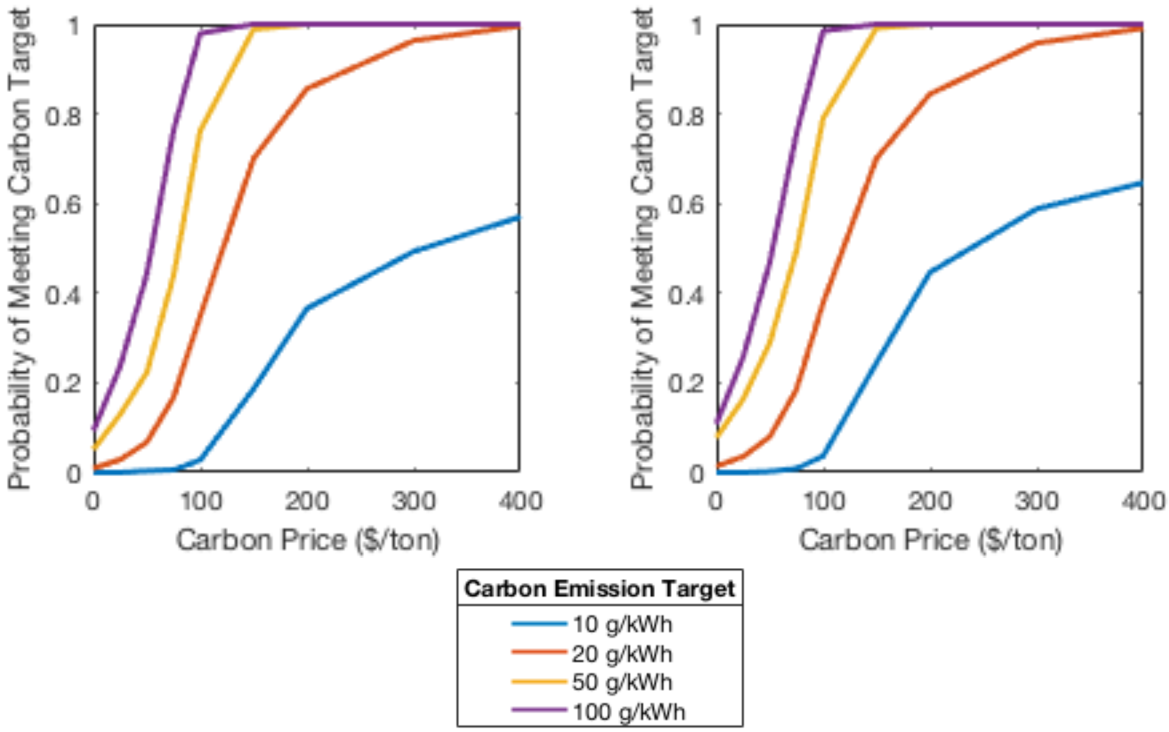


Figure 75: Probability of reducing carbon emissions below a given target as a function of carbon price with nominal electricity demand (left) and with 30% of space heating electrified (right)

The relative influence of each of the uncertainty inputs upon the variance of the output distributions (carbon emissions and average system cost) was measured using the Sobol index. The higher a Sobol index is for a given parameter, the more influence that parameter has upon the variance of the output distribution. It shows which parameters are most important in shaping the output distribution. The Sobol indices the output distributions of carbon emissions and average system cost are shown for the cases with nominal demand and nominal plus 30% electrification of space heating are shown in Figure 76 and Figure 77.

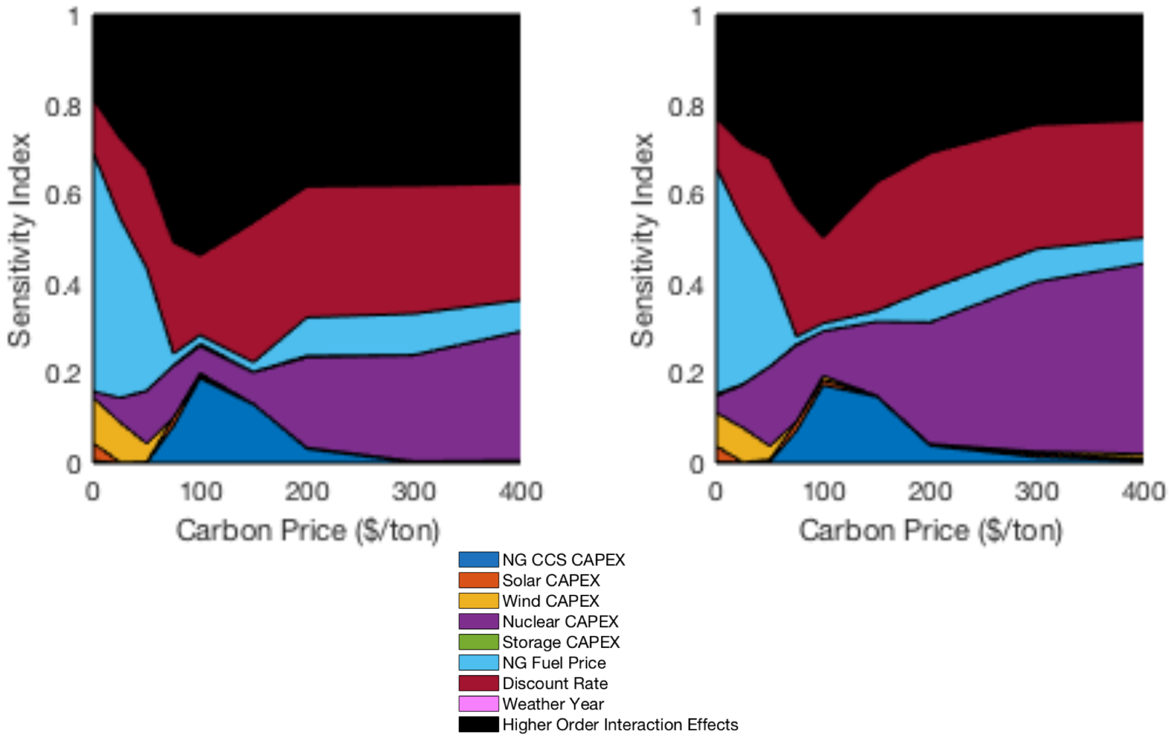


Figure 76: Relative Sobol indices of the uncertain inputs' first-order effects upon carbon emissions as a function of carbon price with nominal electricity demand (left) and with 30% of space heating electrified (right)

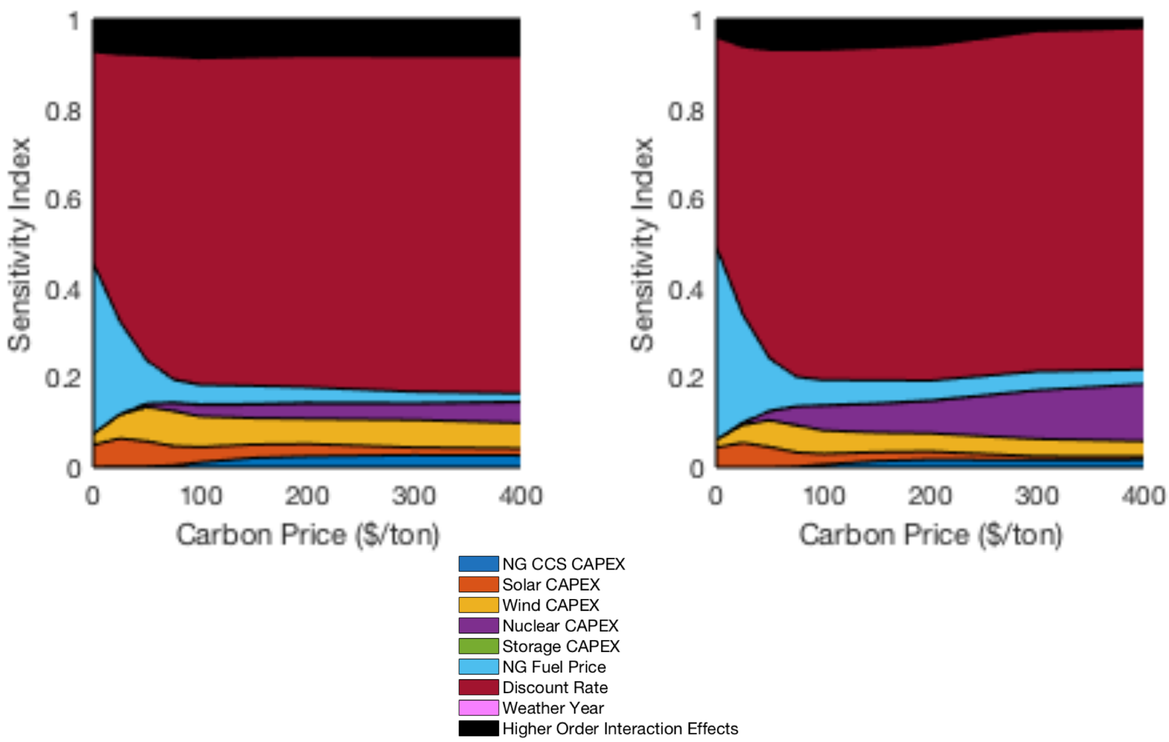


Figure 77: Relative Sobol indices of the uncertain inputs' first-order effects upon average system cost as a function of carbon price with nominal electricity demand (left) and with 30% of space heating electrified (right)

Heat Electrification Discussion

Adding the space heating demand to the nominal electric demand increases the base load in the winter. As winter typically has lower base load than the summer, increasing the base load in the winter increases the annual base load. This is advantageous for nuclear technology which is a baseload generator. However, if nuclear technology is too expensive, then there may be no low-cost baseload generating technology and the additional baseload will be supplied with natural gas, natural gas with CCS, or a build out of renewable capacity. In the first case, this will increase carbon emissions. This is seen in Figure 73 and Table 23 where the upper part of the emissions distribution increases.

On the other hand, if nuclear technology is not too expensive, then more of the annual demand will be met with nuclear technology because the annual baseload demand increases. Since nuclear technology is a non-carbon emitting technology, this will decrease emissions. This is also seen in Figure 73 and Table 23 where the lower part of the emissions distribution increases.

The overall effect of the increase in both the upper and lower part of the emissions distribution is to increase the variance of carbon emissions. For carbon emission targets of 100 g/kWh, 50 g/kWh, and 20 g/kWh, this has minimal effect upon the probability of successfully meeting the target. However, for the emission target of 10 g/kWh, the effect of adding space heating demand to the nominal demand increases the probability of successfully meeting the target.

As expected, the importance of the uncertainty in nuclear capital cost upon the output carbon emission distribution as well as the output average system cost distribution increases as space heat demand is added to the nominal electric demand. This is because, as previously stated, the annual baseload demand increases. The importance of the capital cost of natural gas with CCS decreases.

Conclusion

This chapter showed the implications of the electrification of part of the transportation sector and the space heating sector upon the system cost and carbon emissions of the electric sector. In the case of electrification of the transportation sector, the demand profile changes to be more peaked. The added demand is met with either renewables (if it is at time when renewable potential is high) or with natural gas (CCS if the carbon price is high enough). This can increase the annual emissions.

In the case of electrification of the space heat sector, the demand profile changes to have a higher annual baseload demand. This is beneficial for nuclear technology and if nuclear technology is not too expensive then the additional demand will be supplied with nuclear generation. This decreases carbon emissions. However, if nuclear technology is too expensive then the additional demand will be met with natural gas or renewables. This has the potential of increasing emissions. In this case, the uncertainty around the capital cost of nuclear becomes more important.

Chapter 8 – The Role of a Flexible Electricity Market in Decarbonization

Introduction

In this chapter, the effect of a low-price flexible electricity market is examined. This market is able to add to the nominal electricity demand as needed. This market could be electricity to a flexible process or perhaps electricity converted to heat and stored in a heat storage technology such as FIRES (Forsberg, Stack, Curtis, & Sepulveda, 2017).

The effect of this market is adding flexibility to electricity demand. This is in contrast to flexibility within the generating assets (such as ramping capability). The idea is that there will be added flexibility to nonflexible technologies (such as nuclear). Instead of needing to ramp or shut off, the nuclear power plant can supply electricity to the flexible market.

To test the effect of this low-price flexible electricity market, a case with a market of 20,000 MW of flexible demand is added to the nominal electric demand and compared to the case with only nominal electric demand from Chapter 6. Both of the cases are set in ERCOT in 2050.

Methods

The flexible market was added on top of the nominal electric demand. This demand is not required to be met. The electric "buyer" in the flexible market pays $10/MWh for the electricity. This is shown as the gray area above the load duration curve in Figure 78.

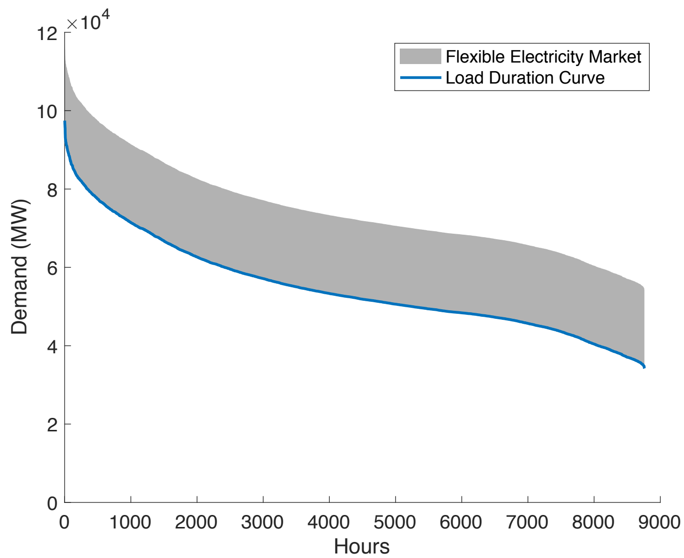


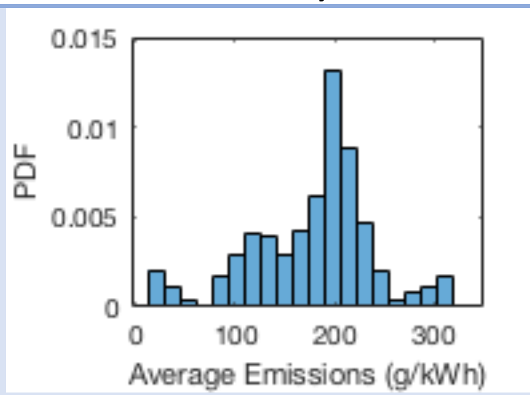
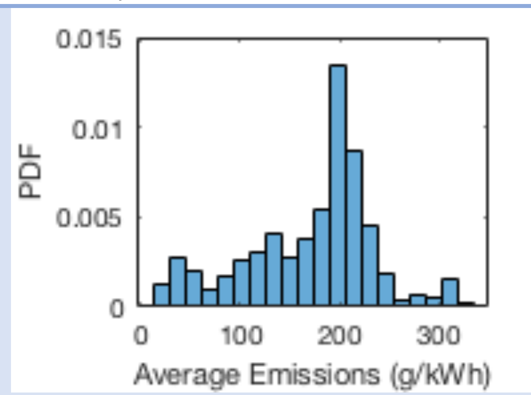
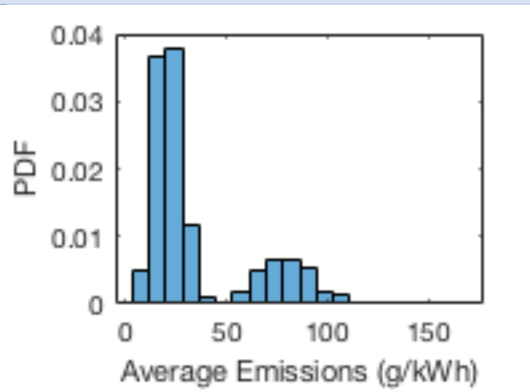
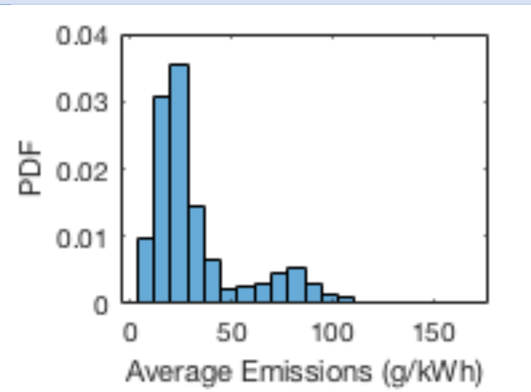
Figure 78: Load duration curve with flexible electricity market

If it is more economical to supply electricity to the flexible market in addition to the nominal demand rather than only supply the nominal, then electricity will be supplied to the flexible market. This is determined separately for each load slice (see description about Figure 38 from Chapter 5). The cost (per MW) for the case where only the nominal demand is met and the case where the nominal and flexible market demand is met (including the $10/MWh payment) are evaluated. The case which produces the lowest cost (per MW) is the case that is selected to be the most economical. For this case, nuclear technology was assumed to have access to this flexible market.

Results

The distributions of the average emissions for each carbon price tested for both the cases where there is only the nominal demand and where there is a flexible market in addition to the nominal demand are in Table 25. The distributions of the average system cost are in Table 26. In each table the distribution is shown for carbon prices of $0/ton, $100/ton, and $400/ton. The distributions for the remaining tested carbon prices are shown in Appendix A.

Table 25: Carbon Emission Distributions

<table>
<tr><th></th><th>Nominal Electricity Demand</th><th>20,000 MW Flexible Market</th></tr>
<tr><td>Carbon Price = $0/ton</td><td>
</td><td>
</td></tr>
<tr><td>Carbon Price = $100/ton</td><td>
</td><td>
</td></tr>
</table>

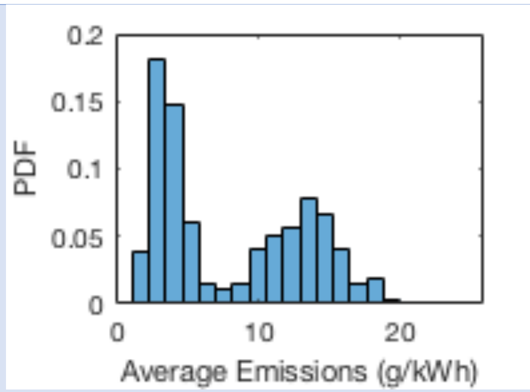
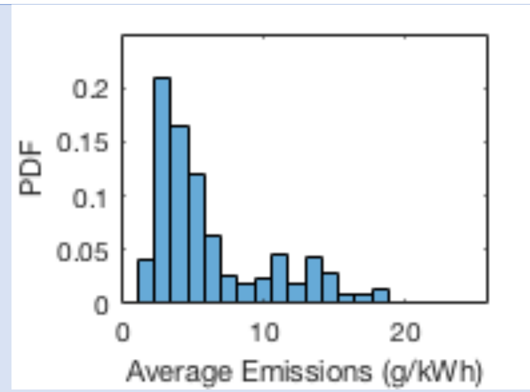
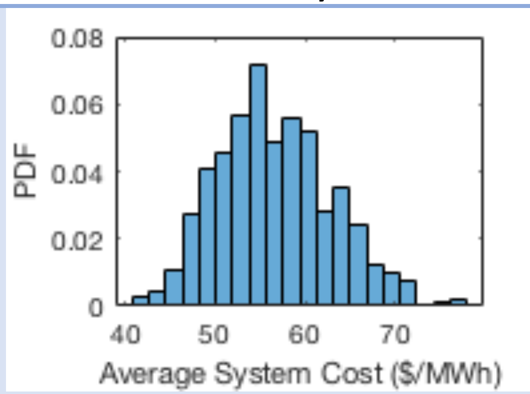
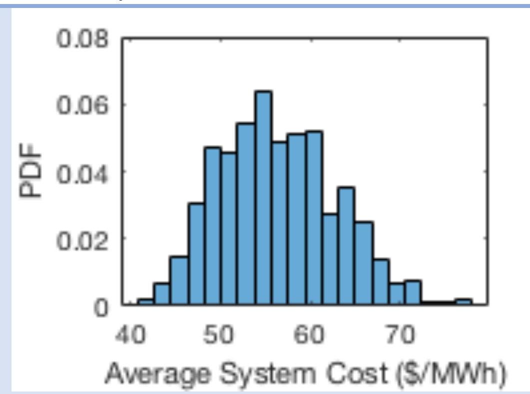
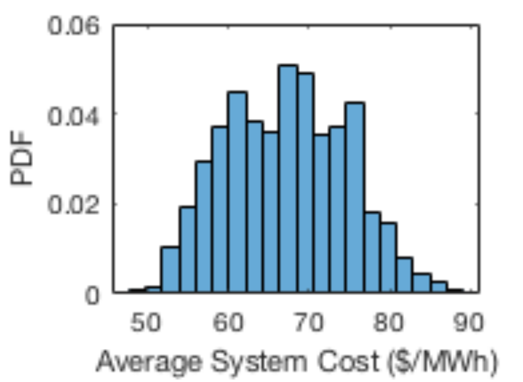
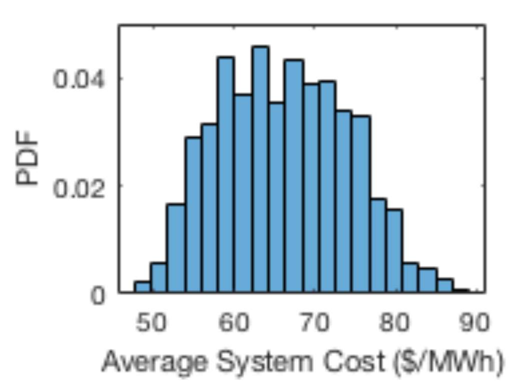
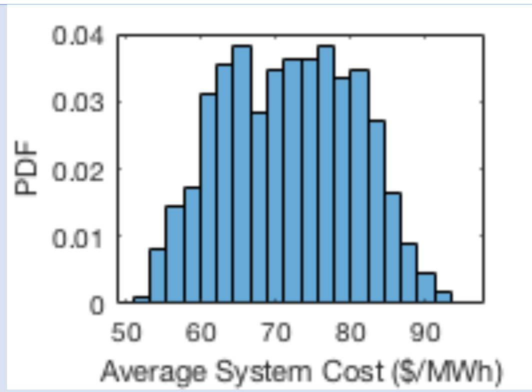
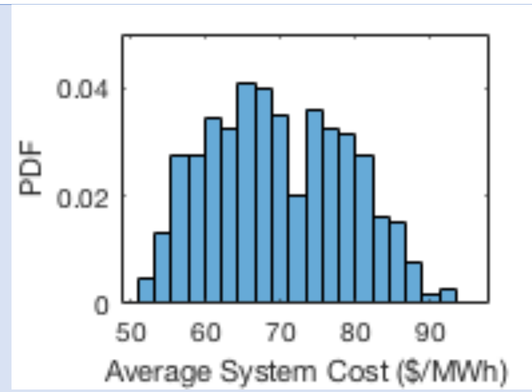
Carbon Price = \$400/ton		

Table 26: Cost of Electricity Generation Distributions

	Nominal Electricity Demand	**20,000 MW Flexible Market**
Carbon Price = \$0/ton		
Carbon Price = \$100/ton		

Carbon Price = $400/ton		

The carbon emission distributions plotted as a function of the carbon price are in Figure 79. The carbon emission distributions plotted as a function of the carbon price are in Figure 80. The different shaded regions refer to different percentiles. The left-hand plot is the case with only nominal electricity demand. The right-hand plot is the case with the flexible market in addition to nominal demand.

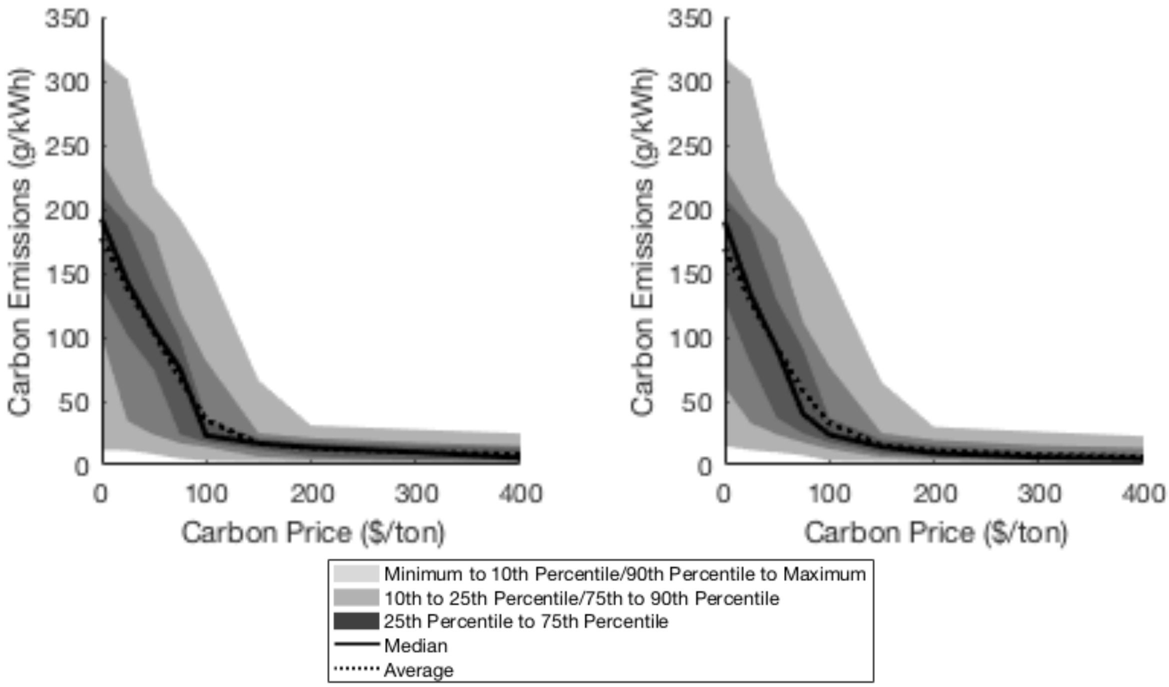


Figure 79: Distribution of carbon emissions as a function of carbon price with nominal electricity demand (left) and with 20,000 MW flexible market (right)

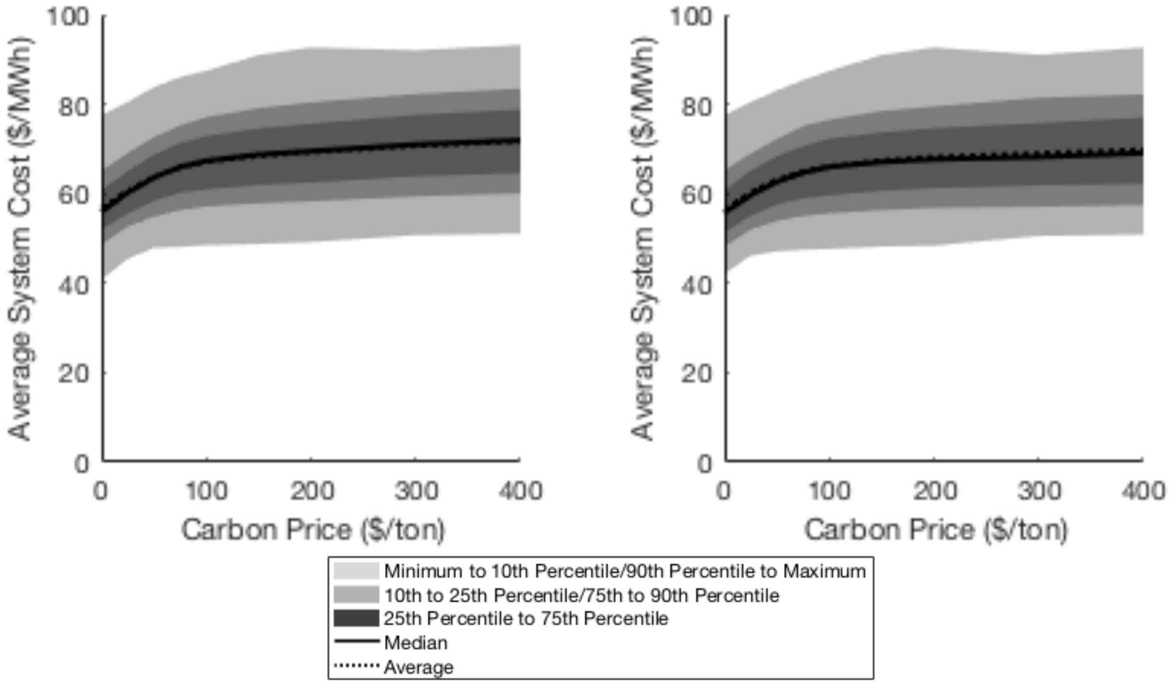
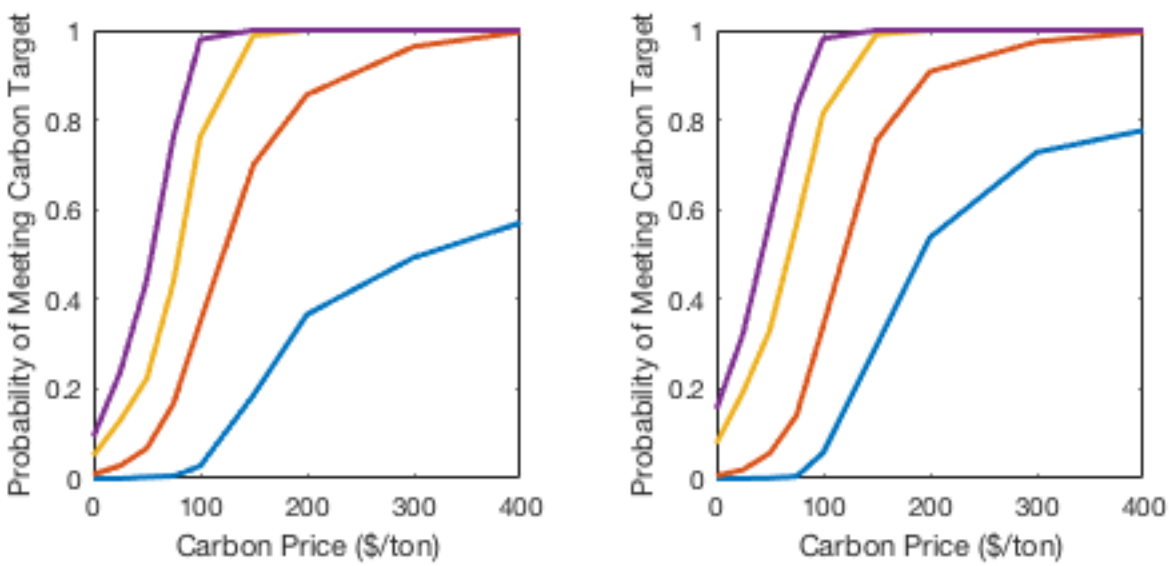


Figure 80: Distribution of average system cost as a function of carbon price with nominal electricity demand (left) and with 20,000 MW flexible market (right)

The probability of reducing carbon emissions below a given target is shown as a function of carbon price is plotted in Figure 81. The left-hand plot is the case with nominal electricity demand. The right-hand plot is the case with 30% electrification of space heating added to the electricity demand.



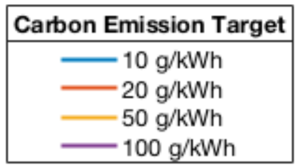


Figure 81: Probability of reducing carbon emissions below a given target as a function of carbon price with nominal electricity demand (left) and with 20,000 MW flexible market (right)

The relative influence of each of the uncertainty inputs upon the variance of the output distributions (carbon emissions and average system cost) was measured using the Sobol index. The higher a Sobol index is for a given parameter, the more influence that parameter has upon the variance of the output distribution. It shows which parameters are most important in shaping the output distribution. The Sobol indices of carbon emissions and average system cost for the cases with nominal demand and nominal plus a 20,000 MW flexible electric market are shown in Figure 82 and Figure 83.

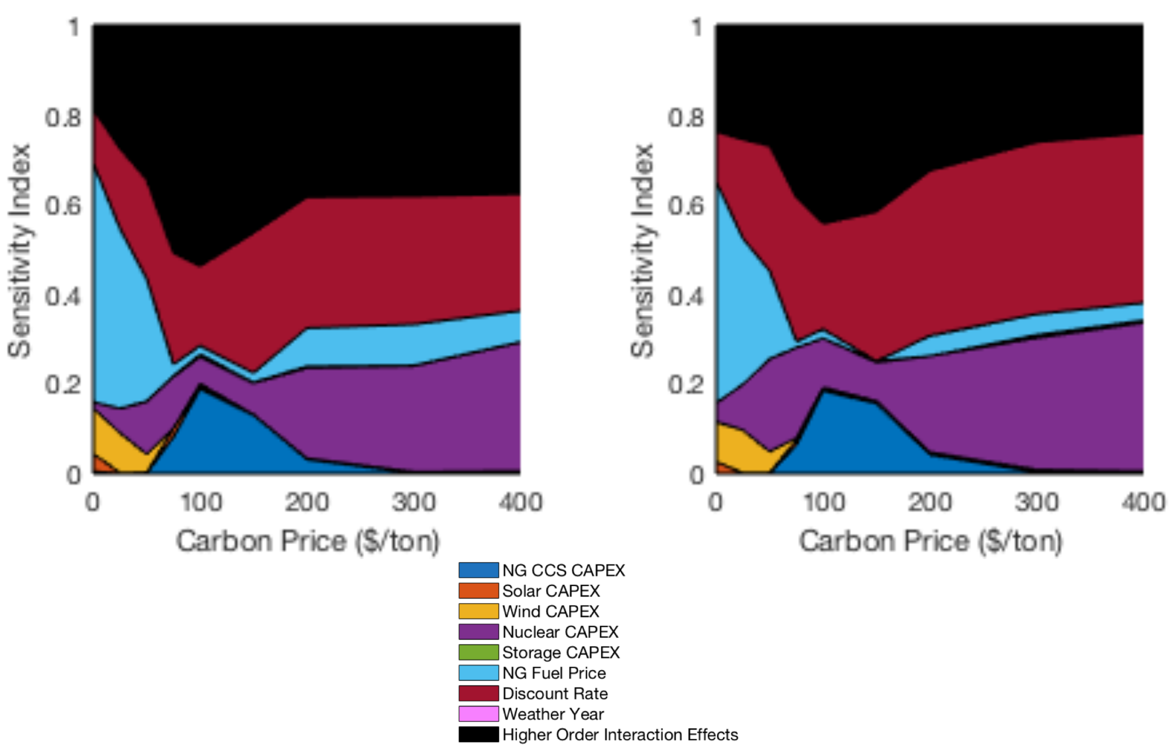


Figure 82: Relative Sobol indices of the uncertain inputs' first-order effects upon carbon emissions as a function of carbon price with nominal electricity demand (left) and with 20,000 MW flexible market (right)

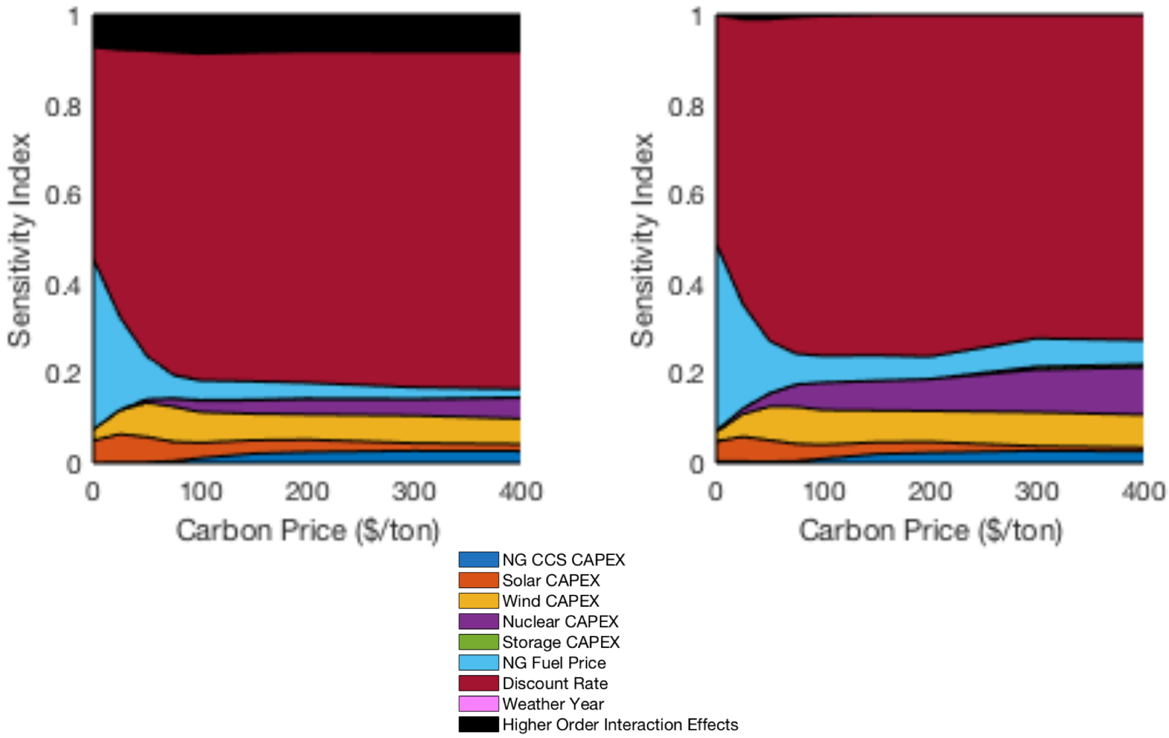


Figure 83: Relative Sobol indices of the uncertain inputs' first-order effects upon average system cost as a function of carbon price with nominal electricity demand (left) and with 20,000 MW flexible market (right)

Discussion

The flexible electricity market allows generation technologies that do not have flexibility in operations (but can provide low marginal cost power) to have flexibility in how to meet demand. This is beneficial to nuclear power. Instead of ramping or shutting down (which is expensive) during periods of low electricity demand, the nuclear power plant can switch to provide electricity to the flexible market. This increases the role of nuclear technology and allows nuclear technology to replace more flexible technologies (such as natural gas) in meeting the nominal electric demand. If natural gas is the technology replaced, then carbon emissions will decrease. This is seen in Table 25 and Figure 79 where the lower part of the emissions distribution increases.

Because the lower part of the emissions distribution increases, the probability of successfully meeting carbon emission targets increases if there was a flexible electricity market. This shows the benefit of this market in decarbonizing the electricity sector. This increase in success probability is higher for more ambitious carbon emission targets. This further demonstrates that a flexible market would be very useful in increasing the probability of achieving deep decarbonization.

In addition, the flexible electric market shifts the importance of the uncertainty inputs. The natural gas fuel price becomes less important in determining the shape of the carbon emission distribution because the flexible market enables nuclear technology to be a more flexible generator and therefore take over some of the electric generation that would have been from natural gas. The flexible market decreases the importance of the uncertainty in capital cost of natural gas CCS upon the carbon emission distribution for the same reasons.

Conclusion

The presence of a flexible market for low price electricity increases the probability of meeting carbon emission targets, especially as the carbon emission target becomes more ambitious. This is because it allows nuclear technology to be more flexible and therefore replace some of the generation from natural gas. This demonstrates that the establishment of the flexible market will be beneficial to the goal of decarbonization.

The addition of the flexible market decreases the importance of the uncertainty in natural gas fuel price and the uncertainty in the natural gas CCS capital cost in determining the carbon emission distribution. This means that because nuclear technology will be enabled to supply demand during more demand periods that are traditionally supplied by flexible generators (natural gas), there is less reliance of the electricity sector upon these flexible generators.

Chapter 9 - Conclusions

This chapter provides a discussion of the usefulness of the two frameworks illustrated in Chapters 3 and 4 and of how the use of them can benefit and transform discussions on decarbonization methods. It also discusses the implications of the results from the cases considered in Chapters 3, 6, 7, and 8.

Decarbonization Decisions

There is opportunity to improve the debate on what are the best pathways is to lower carbon emissions. The current debate is a mix of scientific research with large biases based upon societal or political influences. This is unlikely to result in a wise decision on how to decarbonize successfully.

However, the necessary timescale to decarbonize, including all research and development, infrastructure replacement, and policy implementation, is around 60 years. This means that the discussion about which pathways to decarbonization that we need to pursue will need to occur soon, and will likely be difficult to correct later (Solomon, Plattner, Knutti, & Friedlingstein, 2008). This means that society needs to make the right decision the first time.

The frameworks that I present in this thesis address this core issue of how to improve the discussions of decarbonization strategies. The frameworks are technology agnostic. The results of the framework are not an answer to the question of how to decarbonize. Rather, the results of the frameworks add information to the discussion of how to decarbonize in the best way with the highest likelihood of success.

These frameworks can be very useful for many of the stakeholders in the decarbonization discussion. Governments can use the frameworks to show what is the cost of neglecting timely research and development funding of a particular technology. For example, there is significant cost if nuclear is not able to be deployed at low carbon emission limits. One can also use the framework to see the probability of success for different policies.

Investors can use the framework to see what technologies can be valuable in the future (even if they are not valuable today). Conversely, investors can use the framework to see what technologies will not be valuable in the future even if that technology is valuable today. In addition, the frameworks can show what factors contribute most to either the success likelihood of a strategy or the economic value of a technology. For example, capital cost of nuclear played a large role in at what carbon emission limit it was deployed.

Nuclear Role in Decarbonization

The framework examples show a key role that nuclear power can play in a low carbon electricity sector. Nuclear power decreases the total system cost and improves the economics of solar and wind. This is largely the result of installed capacity mixes with nuclear power require less building out of solar and wind in order to guarantee that electricity demand is met. The building out of solar and wind causes two things:

1. The capital costs of solar and wind contributing to the large growth in energy costs at low carbon emission levels (without nuclear) and
2. A lowering the of capacity factor of solar and wind because much of the capacity of the building out is only utilized for a few hours of the year.

The uncertainty framework also shows that nuclear technology has a role in lowering the expected carbon emissions. Nuclear technology increases the probability of succeeding at meeting a given carbon emission target. It was also demonstrated in an example where there was a flexible, low-price electricity market further enhanced the role of nuclear technology and also increased the probability of succeeding at meeting a given carbon emission target.

The framework examples support the idea that while nuclear may not be economic now, it can be crucial in the future. Support to keep nuclear industry knowledge available (such as how to construct nuclear power plants and how to operate nuclear power plants) is critical so that if the electricity sector is decarbonized, nuclear choices will be available.

Future Work

There is much work that can be done to expand upon the two frameworks that I present in this thesis.

The uncertainty framework example was limited by resources. Therefore, a true expert elicitation could not be performed. In addition, there were only 8 variables that were able to be transformed into probability distributions for propagation through the Monte Carlo analysis. The first elaboration of the work reported here that should be done is to expand the case example set. More technologies can be deployed and analyzed, such as heat storage or concentrated solar power production. More input variables can be treated using probability distribution functions, such as the availability factors of nuclear and natural gas.

The next expansion of this work has to do with the technologies assessed. This thesis concentrates on the effects of nuclear technologies. In Chapter 3, the framework example found the economic cost of excluding nuclear power from being deployed. In Chapter 6, the framework example assessed the effect upon the risk of not meeting carbon emission targets if nuclear was not available. The same analyses can be performed for carbon capture or any other technology. With all of these analyses, one begins to get a bigger sense of how each technology interacts with others in different strategies for lowering carbon emissions.

Third, the uncertainty framework can be used to assess goals other than carbon emission targets. The carbon emissions can be translated into either temperature rise or another damage function. Then, instead of a failure to meet a carbon emission target, a failure to keep global warming within a temperature range can be evaluated.

Finally, the uncertainty framework can be expanded beyond just being a calculation of failure probabilities. There are many other uses for output probability distribution functions. For example, for investors in power plants, it is important to know what the risks are for the future profit of that power plant. This can be used in financial analyses such as real options calculations.

Works Cited

Babonneau, F., Haurie, A., Loulou, R., & Vielle, M. (2012). Combining Stochastic Optimization and Monte Carlo Simulation to Deal with Uncertainties in Climate Policy Assessment. *Environmental Modeling and Assessment*, *17*(1–2), 51–76. https://doi.org/10.1007/s10666-011-9275-1

Batlle, C., & Rodilla, P. (2012). AN ENHANCED SCREENING CURVES METHOD FOR CONSIDERING THERMAL. *IEEE Transactions on Power Systems*, 1–17.

Bedir, A., Crisostomo, N., Allen, J., Wood, E., & Rames, C. (2019). *California Plug-In Electric Vehicle Infrastructure Projections : 2017-*. Retrieved from https://www.nrel.gov/docs/fy18osti/70893.pdf

Carney, P. G., Abdurrahman, M., Robertson, K., & Evans-mongeon, B. (2016). Reliability Considerations for Clean Power Plan Development, (January).

CEIC. (2017). China Premium Database.

Chen, H., Ejaz, Q., Gao, X., Huang, J., Morris, J., Monier, E., & Paltsev, S. (2016). *Food Water Energy Climate Outlook*.

EnAppSys. (2017). GB Power Market. Retrieved from https://www.enappsys.com/gb-power-market

Energy Futures Initiative. (2017). *The U . S . Nuclear Energy Enterprise : A Key National Security Enabler*. Retrieved from https://static1.squarespace.com/static/58ec123cb3db2bd94e057628/t/5992f7e0bf629ad8f9d575ec/1502803938248/EFI+Nuclear+Report+FINAL+08.2017.pdf

ERCOT. (2019a). Generation. Retrieved from http://www.ercot.com/gridinfo/generation

ERCOT. (2019b). Hourly Load Data Archives. Retrieved from http://www.ercot.com/gridinfo/load/load_hist/

Forsberg, C. W., Stack, D. C., Curtis, D., & Sepulveda, N. A. (2017). Converting excess low-price electricity into high-temperature stored heat for industry and high-value electricity production ☆, *30*(August), 42–52. https://doi.org/10.1016/j.tej.2017.06.009

Gillingham, K., Nordhaus, W. D., Anthoff, D., Blanford, G., Bosetti, V., Christensen, P., … Sztorc, P. (2015). Nber Working Paper Series Modeling Uncertainty in Climate Change: a Multi-Model Comparison. Retrieved from http://www.nber.org/papers/w21637

Gridwatch. (2017). G.B. National Grid Status. Retrieved from http://www.gridwatch.templar.co.uk

Haasnoot, M., Middelkoop, H., Beek, E. Van, & Deursen, W. P. A. Van. (2011). Management Strategies for an Uncertain Future. *Sustainable Development*, *19*, 369–381. https://doi.org/10.1002/sd

He, G., Avrin, A., Nelson, J. H., Johnston, J., Mileva, A., Tian, J., & Kammen, D. M. (2016). SWITCH-China: A Systems Approach to Decarbonizing China's Power System. *Environmental Science and Technology*, *50*, 5467–5473.

Hirsch, A., Parag, Y., & Guerrero, J. (2018). Microgrids : A review of technologies , key drivers , and outstanding issues. *Renewable and Sustainable Energy Reviews*, *90*(April), 402–411. https://doi.org/10.1016/j.rser.2018.03.040

IDDRI. (2019). Deep Decarbonization Pathway Project. Retrieved from http://deepdecarbonization.org/

International Energy Agency. (2015). *Projected Costs of Generating Electricity*. Retrieved from https://www.oecd-nea.org/ndd/pubs/2015/7057-proj-costs-electricity-2015.pdf
International Energy Agency. (2017). *Energy Technology Perspectives 2017*.
IPCC. (2014). *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Geneva, Switzerland.
IPCC. (2018). *Global Warming of 1.5°C.An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change,*. Retrieved from https://www.ipcc.ch/site/assets/uploads/sites/2/2019/07/SR15_Full_Report_Low_Res.pdf
Jacobson, M. Z., Mark, A., Bauer, Z. A. F., Wang, J., Weiner, E., Yachanin, A. S., … Yachanin, A. S. (2017). 100 % Clean and Renewable Wind , Water , and Sunlight All-Sector Energy Roadmaps for 139 Countries of the World 100 % Clean and Renewable Wind , Water , and Sunlight All-Sector Energy Roadmaps for 139 Countries of the World. *Joule*, *1*(1), 108–121. https://doi.org/10.1016/j.joule.2017.07.005
Jenkins, J. D., & Sepulveda, N. A. (2017). *Enhanced Decision Support for a Changing Electricity Landscape : The GenX Configurable Electricity Resource Capacity Expansion Model Enhanced Decision Support for a Changing Electricity Landscape : The GenX Configurable Electricity Resource Capacity Expan*. Retrieved from http://energy.mit.edu/wp-content/uploads/2017/10/Enhanced-Decision-Support-for-a-Changing-Electricity-Landscape.pdf
Keirstead, J., & Calderon, C. (2012). Capturing spatial effects, technology interactions, and uncertainty in urban energy and carbon models: Retrofitting newcastle as a case-study. *Energy Policy*, *46*, 253–267. https://doi.org/10.1016/j.enpol.2012.03.058
Keppo, I., & van der Zwaan, B. (2012). The Impact of Uncertainty in Climate Targets and CO 2 Storage Availability on Long-Term Emissions Abatement. *Environmental Modeling and Assessment*, *17*(1–2), 177–191. https://doi.org/10.1007/s10666-011-9283-1
Labriet, M., Kanudia, A., & Loulou, R. (2012). Climate mitigation under an uncertain technology future: A TIAM-World analysis. *Energy Economics*, *34*(SUPPL. 3), S366–S377. https://doi.org/10.1016/j.eneco.2012.02.016
Lazard. (2015). *Lazard's Levelized Cost of Storage Analysis - Version 1.0*.
National Oceanic and Atmospheric Administration. (2019). Degree Day Statistics. Retrieved from ftp://ftp.cpc.ncep.noaa.gov/htdocs/degree_days/weighted/daily_data/
National Renewable Energy Laboratory. (2018). Annual Technology Baseline 2018. Retrieved from https://atb.nrel.gov/
NERC. (2018). *Probabilistic Adequacy and Measures*.
O'Kane, S. (2018, November 26). The all-electric Rivian R1T is a Dream Truck for Adventurers.
Office of Energy Efficiency and Renewable Energy. (2019a). All-Electric Vehicles. Retrieved July 21, 2019, from https://www.fueleconomy.gov/feg/evtech.shtml
Office of Energy Efficiency and Renewable Energy. (2019b). *Fuel Economy Guide Model Year 2019*. Retrieved from https://www.fueleconomy.gov/feg/pdfs/guides/FEG2019.pdf
Penn State. (2019). The Fundamentals of Electricity Markets. Retrieved from https://www.e-education.psu.edu/ebf200/node/151

Petti, D., Buongiorno, J., Corradini, M., & Parsons, J. (2018). *The Future of Nuclear Energy in a Carbon-Constrained World*.

Pfenninger, S., & Staffell, I. (2016). Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data. *Energy*, *114*, 1251–1265.

Pfenninger, S., & Staffell, I. (2017). Renewables.ninja. Retrieved from https://www.renewables.ninja

Prinn, R., Paltsev, S., Sokolov, A., Sarofim, M., Reilly, J., & Jacoby, H. (2011). Scenarios with MIT integrated global systems model : significant global warming regardless of different approaches, 515–537. https://doi.org/10.1007/s10584-009-9792-y

Pye, S., & Bataille, C. (2016). Improving deep decarbonization modelling capacity for developed and developing country contexts. *Climate Policy*, *16*(May), S27–S46. https://doi.org/10.1080/14693062.2016.1173004

Ricke, K., Drouet, L., Caldeira, K., & Tavoni, M. (2018). Country-level social cost of carbon. *Nature Climate Change*, *8*(October). https://doi.org/10.1038/s41558-018-0282-y

Staffell, I., & Green, R. (2015). Is There Still Merit In The Merit Order Stack ? The Impact of Dynamic Constraints on Optimal Plant Mix, 1–21.

Staffell, I., & Pfenninger, S. (2016). Using Bias-Corrected Reanalysis to Simulate Current and Future Wind Power Output. *Energy*, *114*, 1224–1239.

Sullivan, P., Margolis, R., & Eurek, K. (2014). *Advanced Methods for Incorporating Solar Energy Technologies into Electric Sector Capacity-expansion Models : Literature Review and Analysis*.

The University of Sheffield. (2017). PV_Live. Retrieved from https://www.solar.sheffield.ac.uk/pvlive

TxDOT. (2019). Roadway Inventory. Retrieved from https://www.txdot.gov/inside-txdot/division/transportation-planning/roadway-inventory.html

US Department of Energy. (2015). *United States Electricity Industry Primer*.

US EIA. (2018). International Energy Outlook 2018, (July).

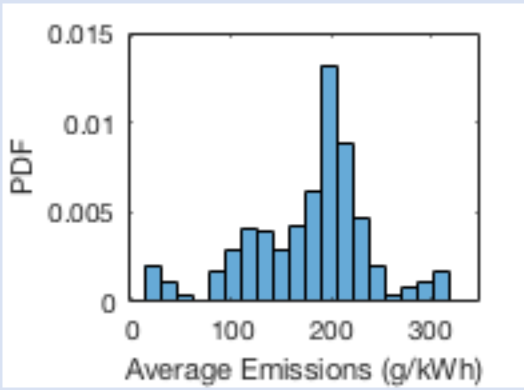
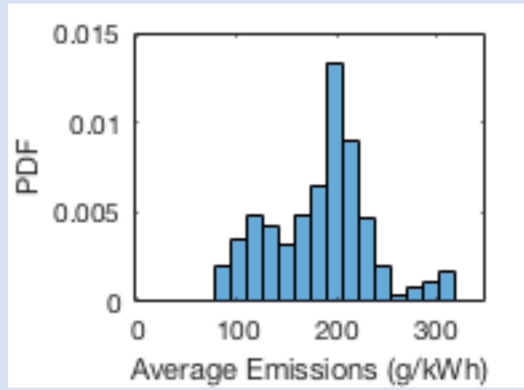
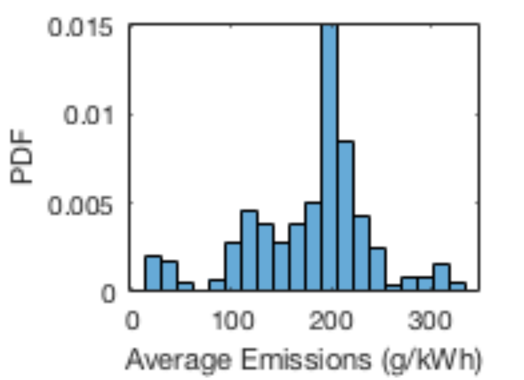
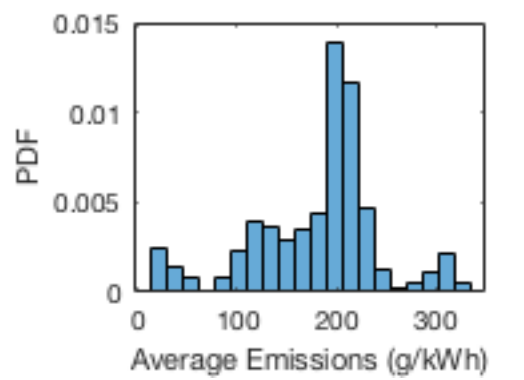
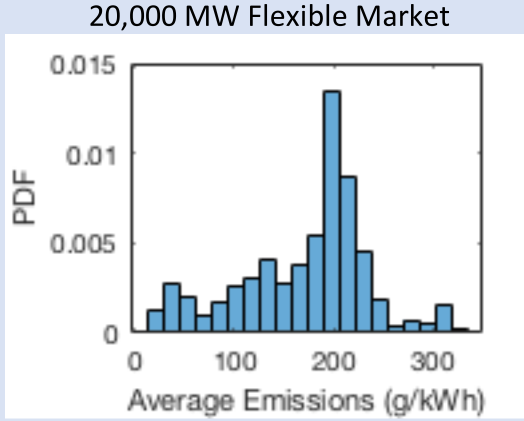
US EIA. (2019). *Annual Energy Outlook 2019*.

USDOT. (n.d.). Table 1-40: U.S. Passenger-Miles (Millions). Retrieved from https://www.bts.gov/archive/publications/national_transportation_statistics/table_01_40

Williams, J., Haley, B., Kahrl, F., Moore, J., Jones, A. D., Torn, M. S., & Mcjeon, H. (2015). *Pathways to Deep Decarbonization in the United States*.

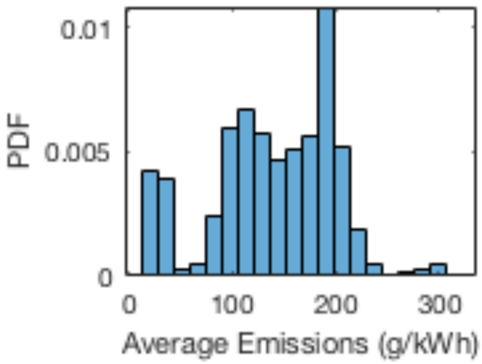
Appendix A: All Result Histograms

Table 27: Average Emission Distributions

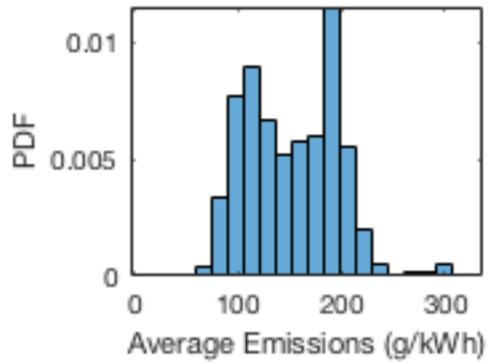
<table>
<tr>
<td rowspan="3">Carbon Price = $0/ton</td>
<td>Base Case

</td>
<td>No Nuclear

</td>
</tr>
<tr>
<td>30% Passenger Vehicles Electrified

</td>
<td>30% Space Heating Electrified

</td>
</tr>
<tr>
<td colspan="2">20,000 MW Flexible Market

</td>
</tr>
</table>

Carbon Price = $25/ton

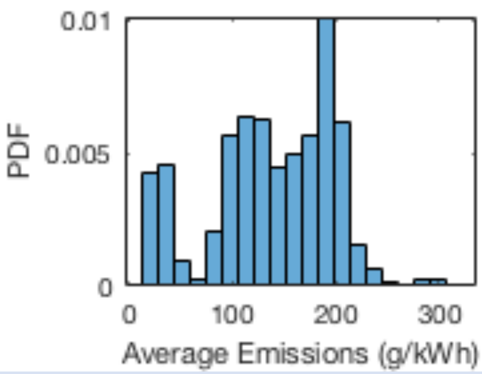
Base Case



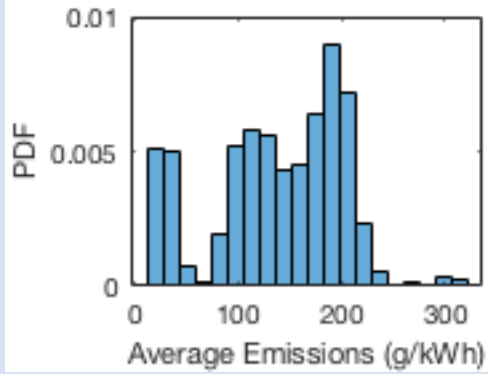
No Nuclear



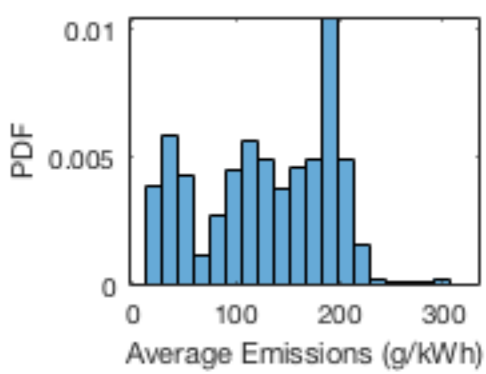
30% Passenger Vehicles Electrified



30% Space Heating Electrified

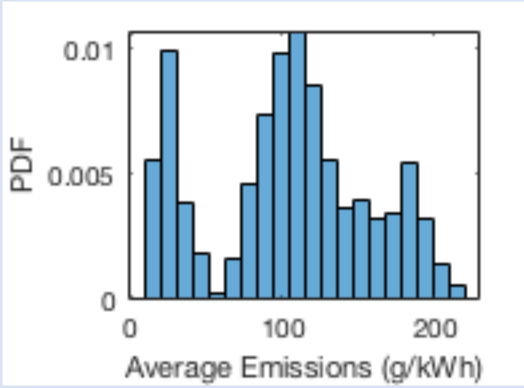


20,000 MW Flexible Market

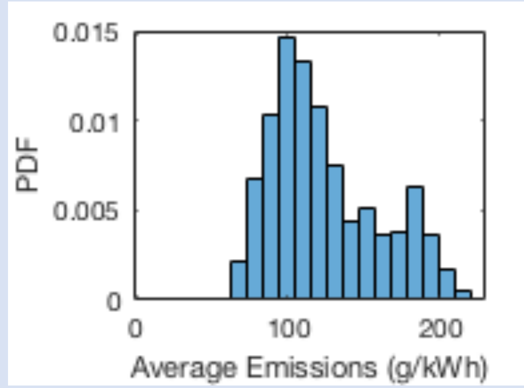


Carbon Price = $50/ton

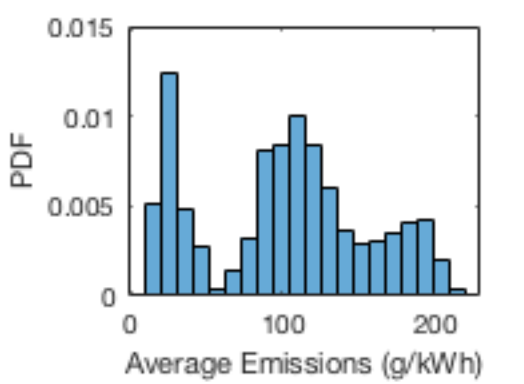
Base Case



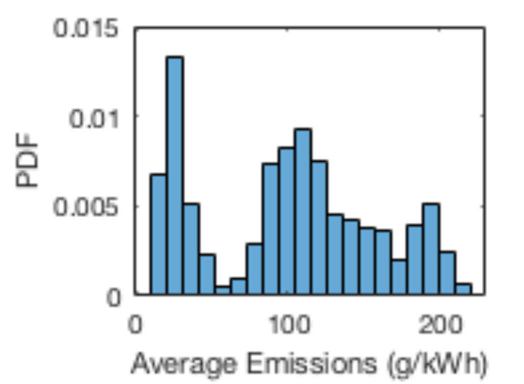
No Nuclear



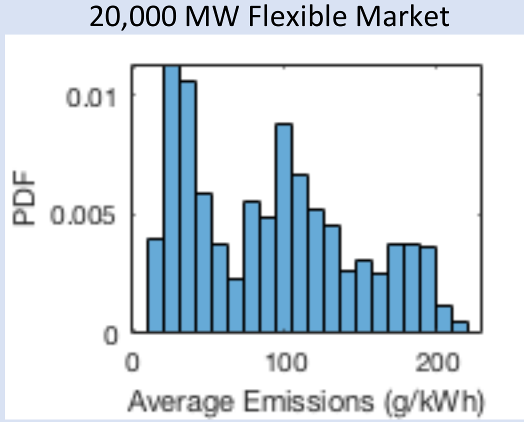
30% Passenger Vehicles Electrified



30% Space Heating Electrified

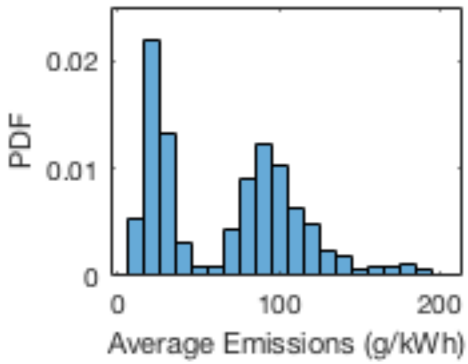


20,000 MW Flexible Market

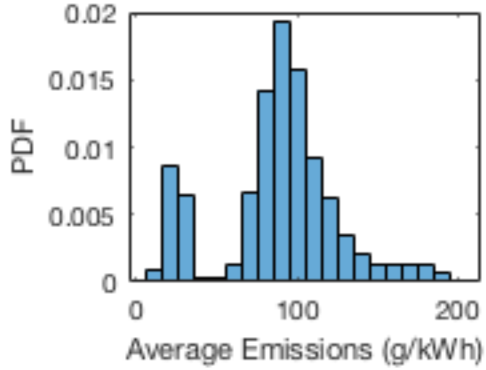


Carbon Price = $75/ton

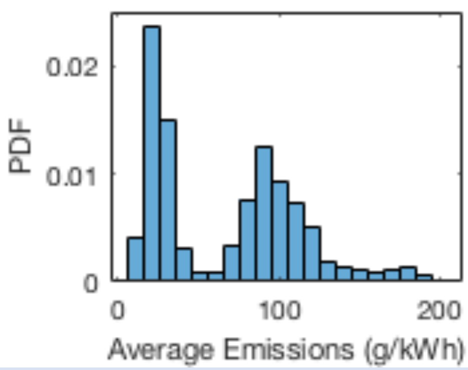
Base Case



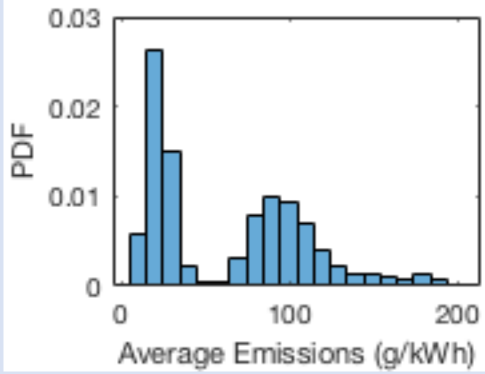
No Nuclear



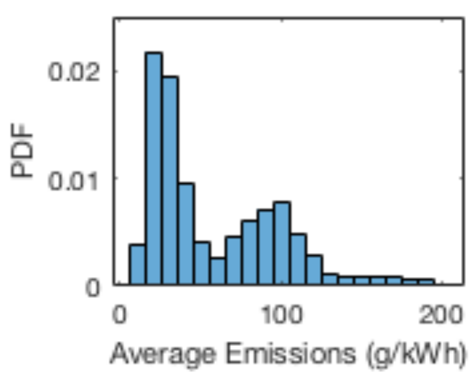
30% Passenger Vehicles Electrified



30% Space Heating Electrified

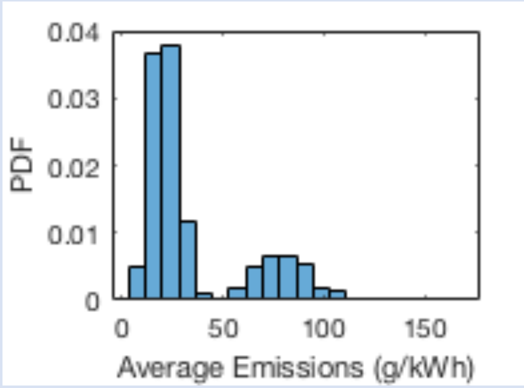


20,000 MW Flexible Market

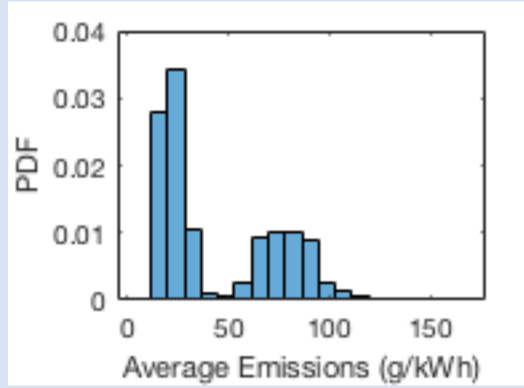


Carbon Price = $100/ton

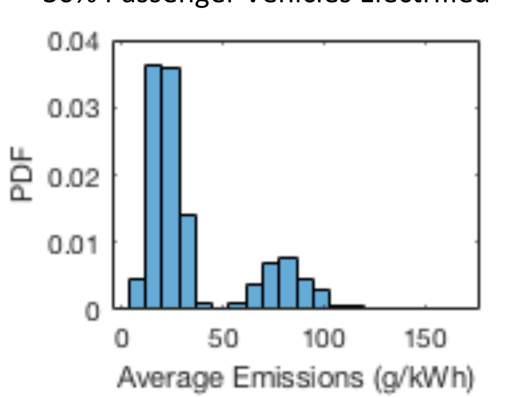
Base Case



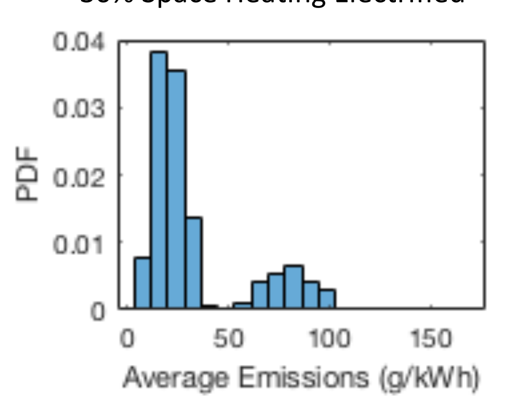
No Nuclear



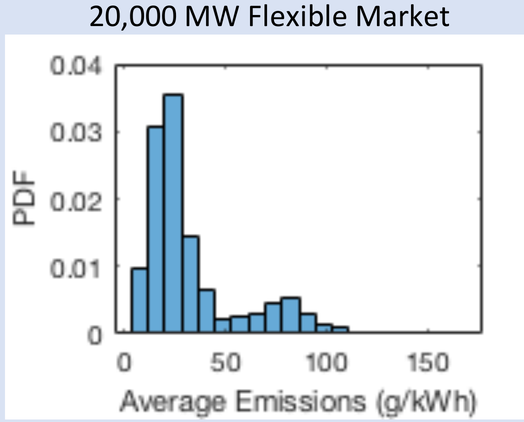
30% Passenger Vehicles Electrified



30% Space Heating Electrified

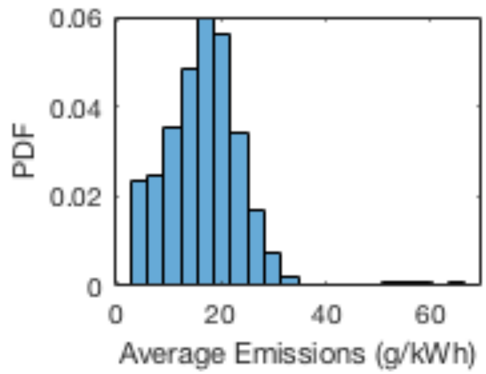


20,000 MW Flexible Market

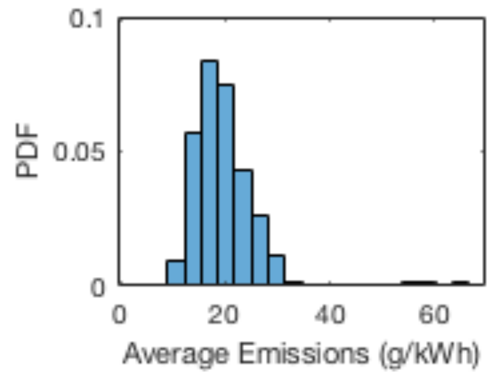


Carbon Price = $150/ton

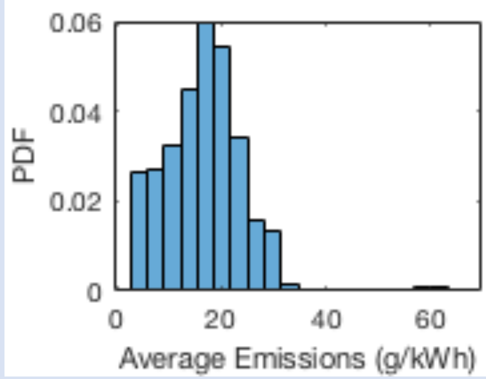
Base Case



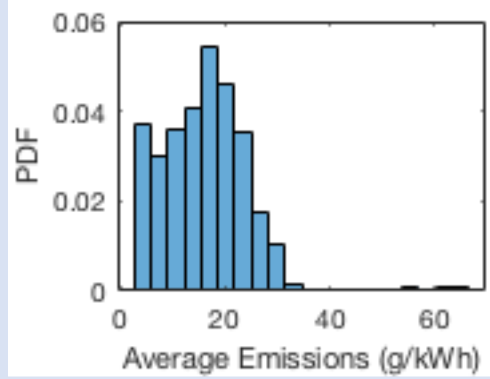
No Nuclear



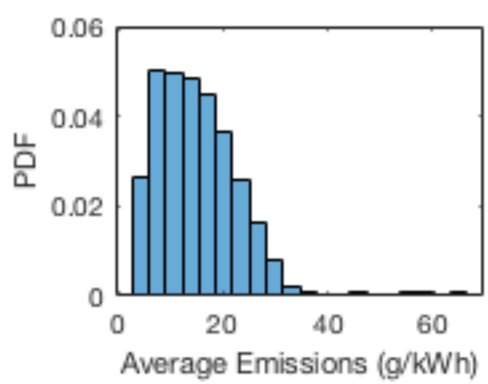
30% Passenger Vehicles Electrified



30% Space Heating Electrified

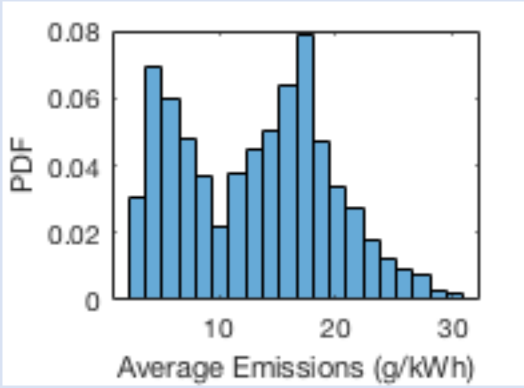


20,000 MW Flexible Market

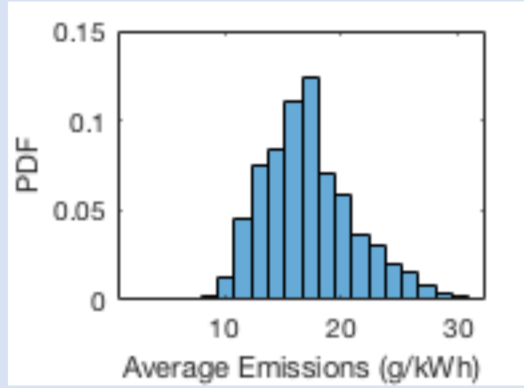


Carbon Price = $200/ton

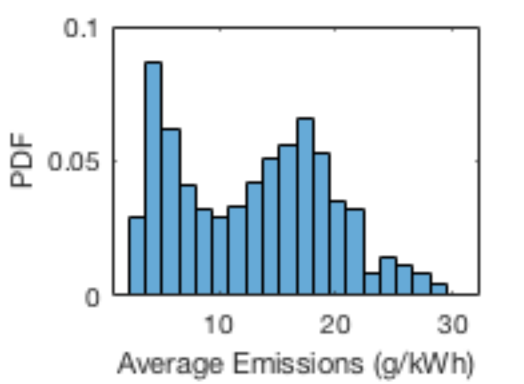
Base Case



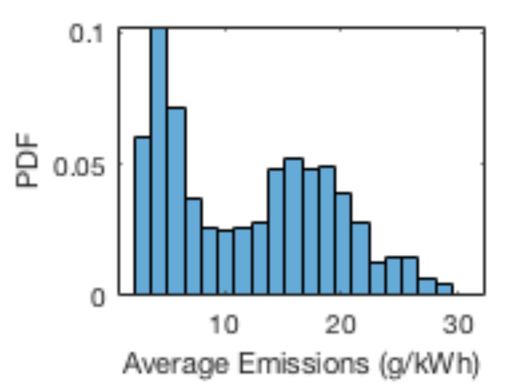
No Nuclear



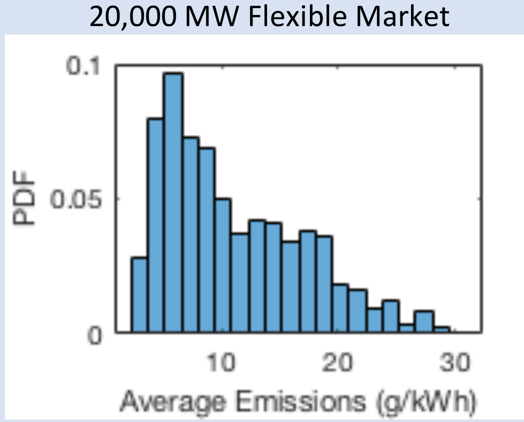
30% Passenger Vehicles Electrified



30% Space Heating Electrified

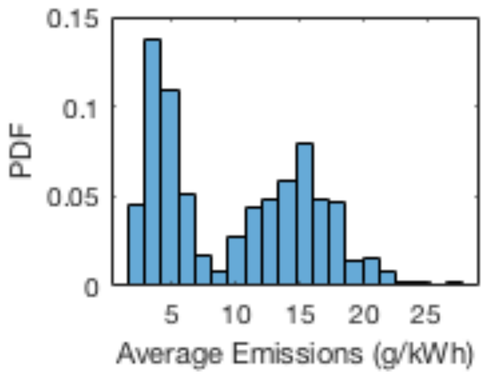


20,000 MW Flexible Market

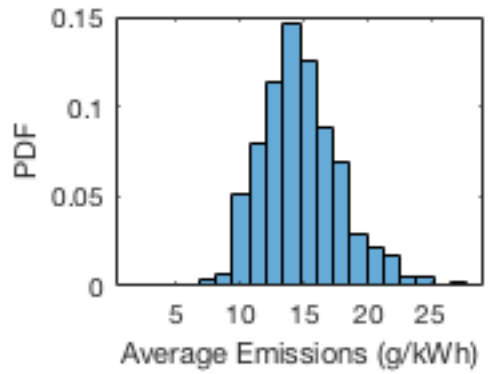


Carbon Price = $300/ton

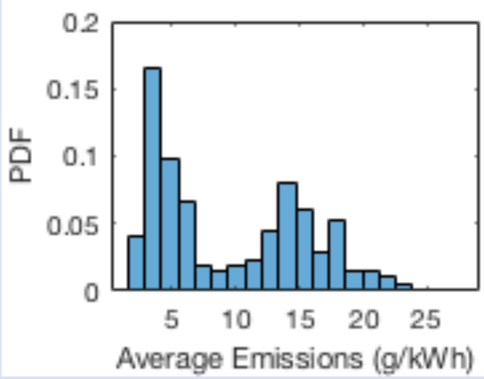
Base Case



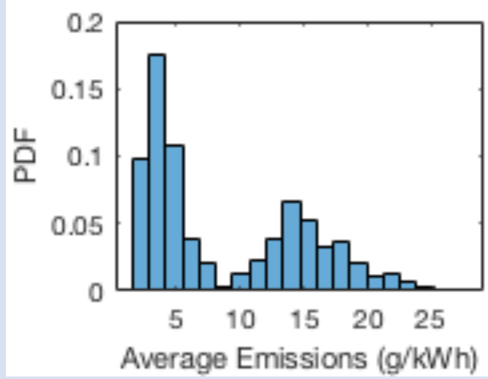
No Nuclear



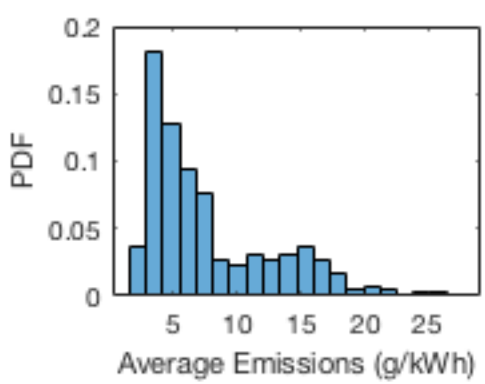
30% Passenger Vehicles Electrified



30% Space Heating Electrified

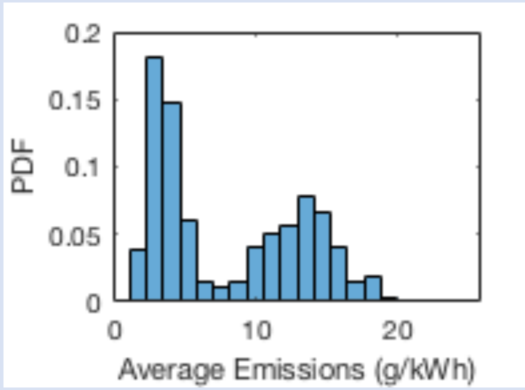


20,000 MW Flexible Market

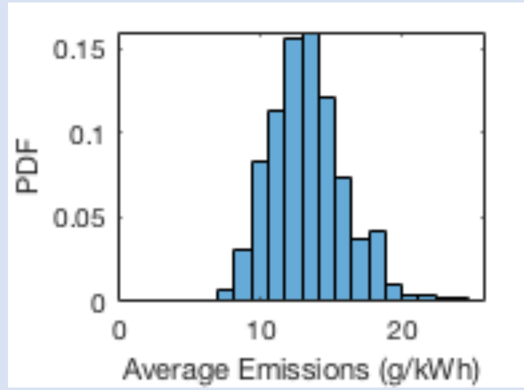


Carbon Price = $400/ton

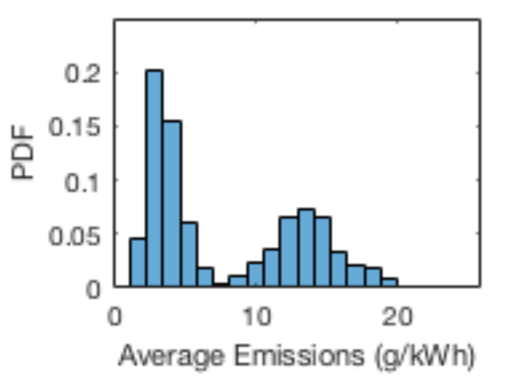
Base Case



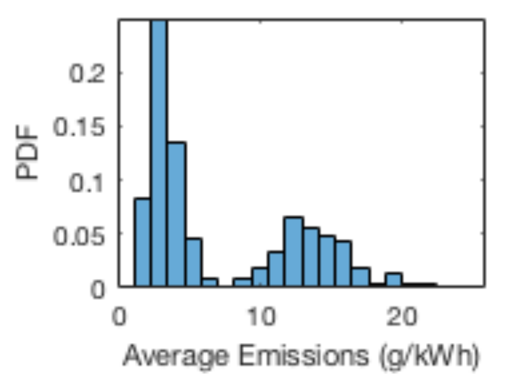
No Nuclear



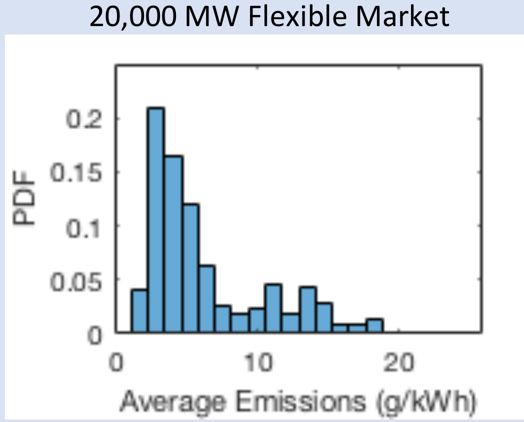
30% Passenger Vehicles Electrified



30% Space Heating Electrified

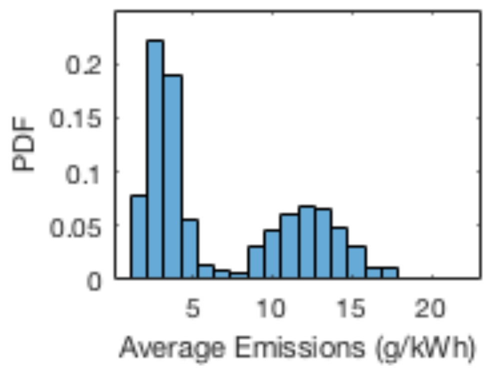


20,000 MW Flexible Market

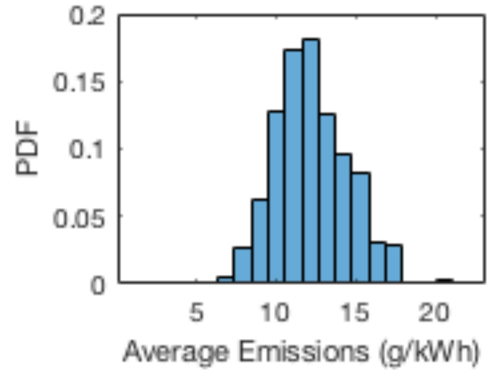


Carbon Price = $500/ton

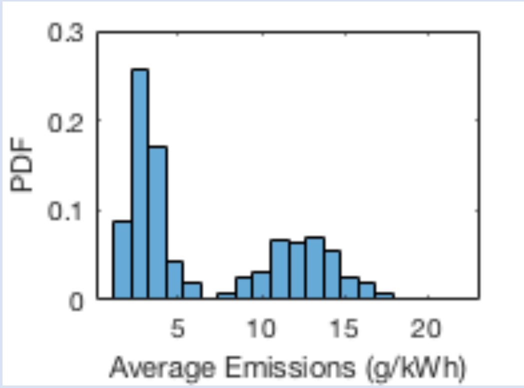
Base Case



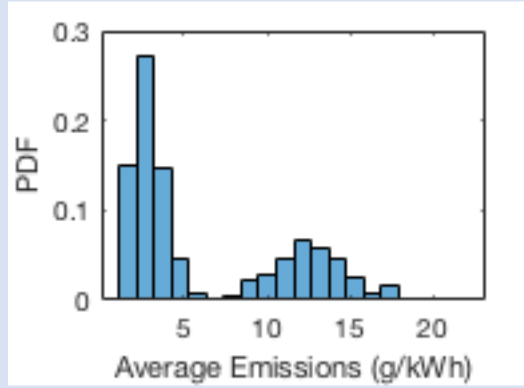
No Nuclear



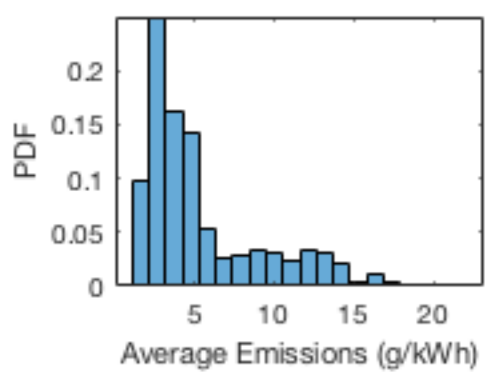
30% Passenger Vehicles Electrified



30% Space Heating Electrified

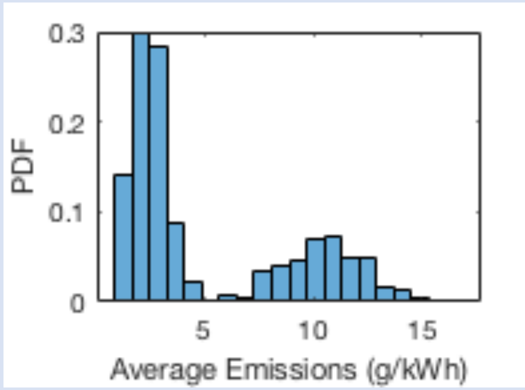


20,000 MW Flexible Market

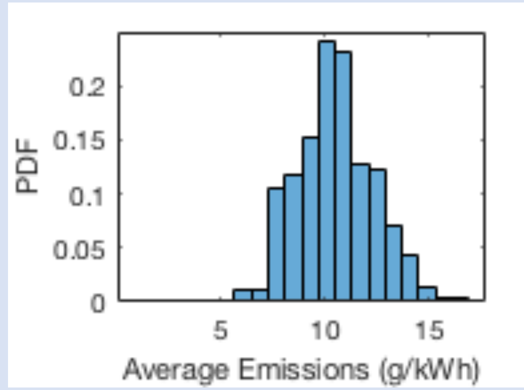


Carbon Price = $750/ton

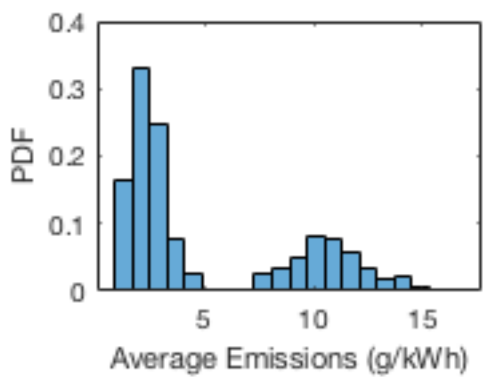
Base Case



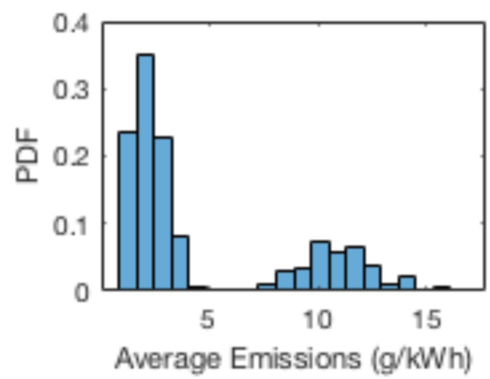
No Nuclear



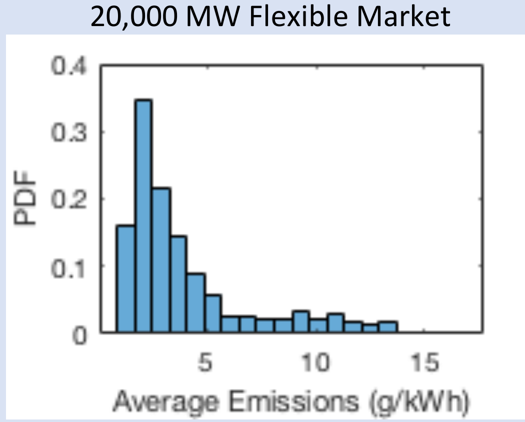
30% Passenger Vehicles Electrified



30% Space Heating Electrified

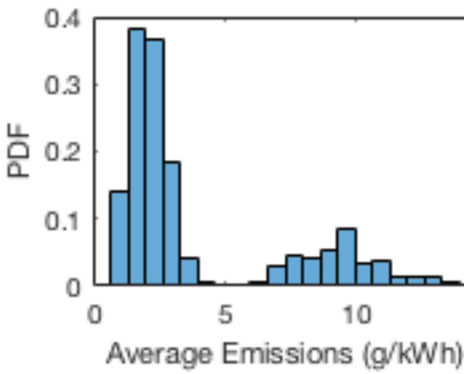


20,000 MW Flexible Market

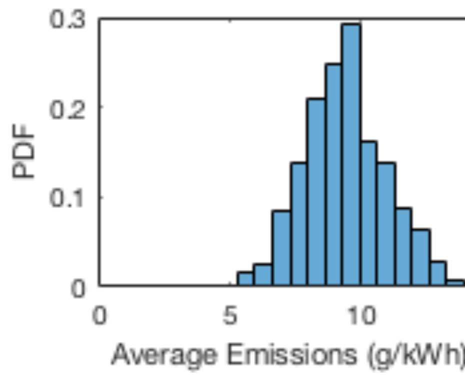


Carbon Price = $1000/ton

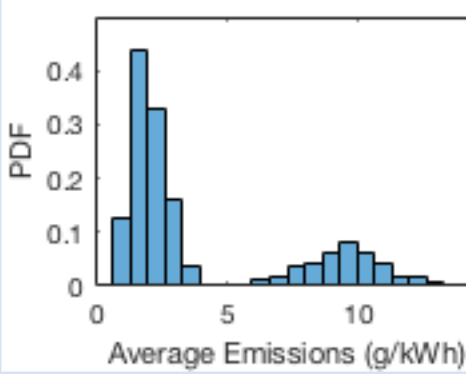
Base Case



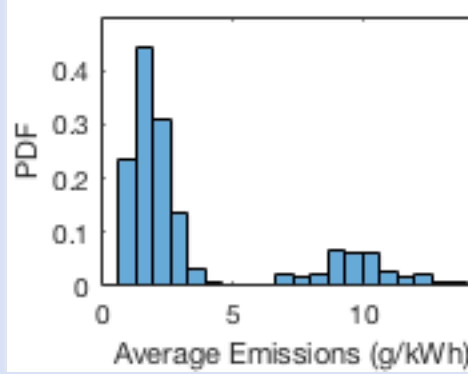
No Nuclear



30% Passenger Vehicles Electrified



30% Space Heating Electrified



20,000 MW Flexible Market

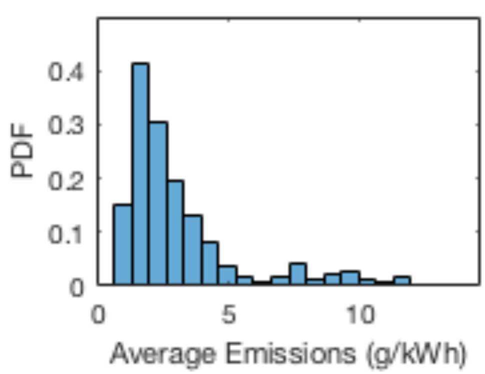
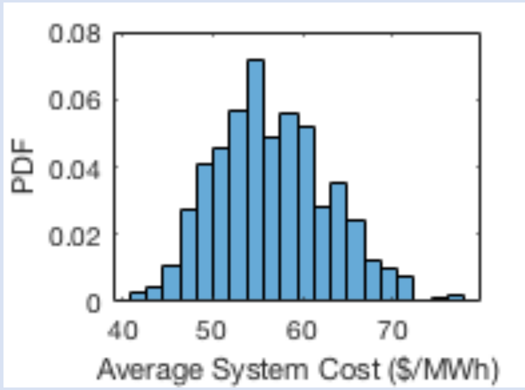
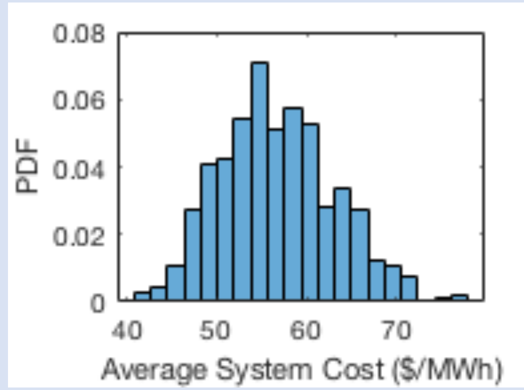
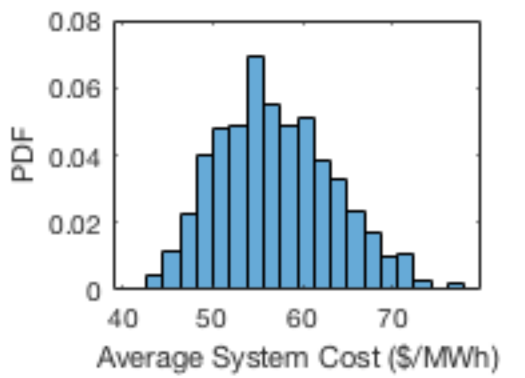
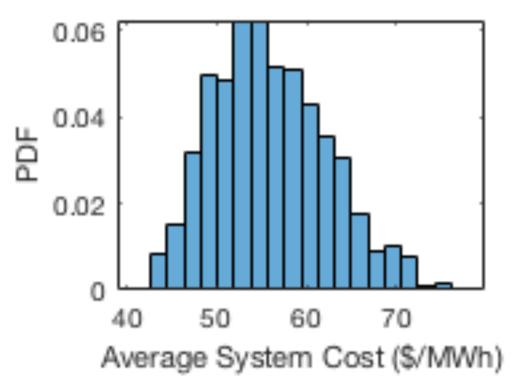
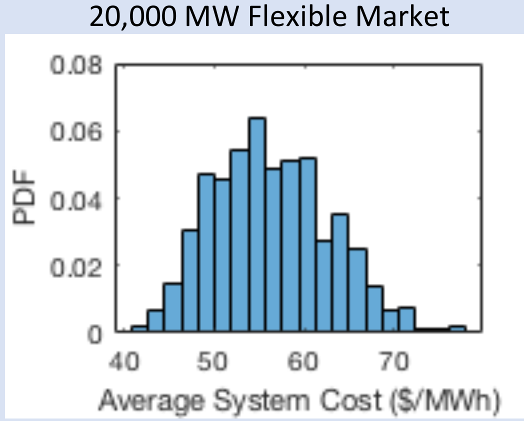
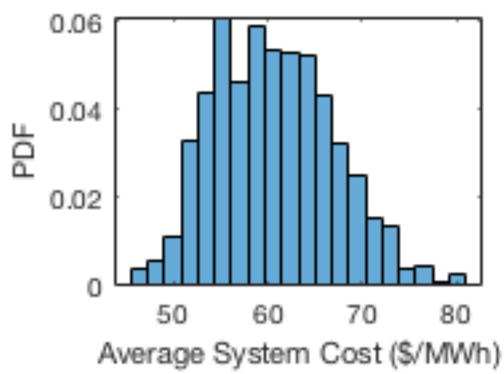


Table 28: Cost of Electricity Generation Distributions

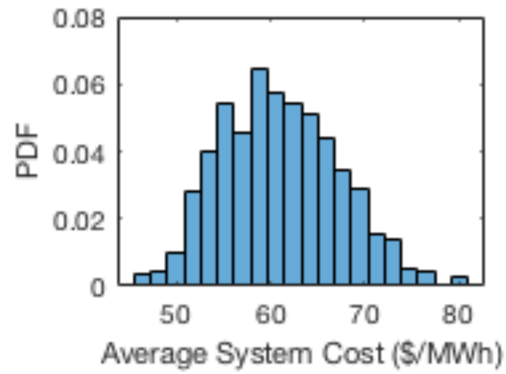
<table>
<tr>
<td rowspan="3">**Carbon Price = $0/ton**</td>
<td>Base Case

</td>
<td>No Nuclear

</td>
</tr>
<tr>
<td>30% Passenger Vehicles Electrified

</td>
<td>30% Space Heating Electrified

</td>
</tr>
<tr>
<td colspan="2">20,000 MW Flexible Market

</td>
</tr>
</table>

Carbon Price = $25/ton

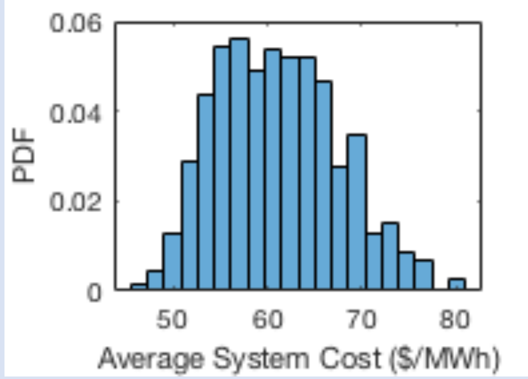
Base Case



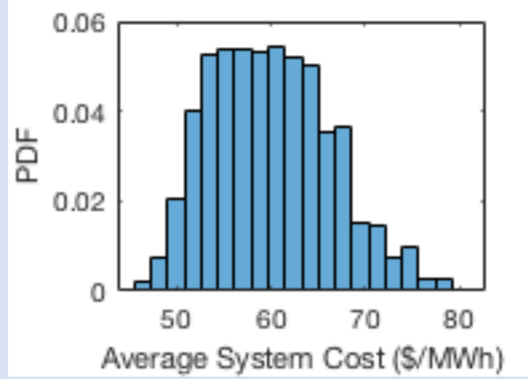
No Nuclear



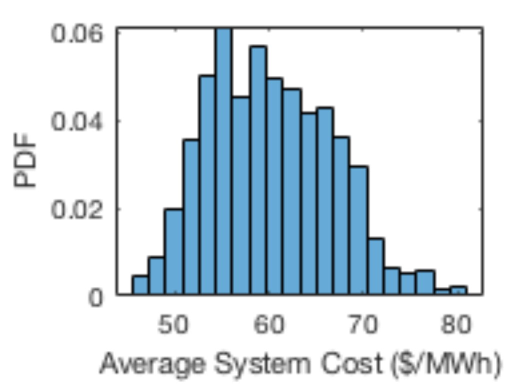
30% Passenger Vehicles Electrified



30% Space Heating Electrified

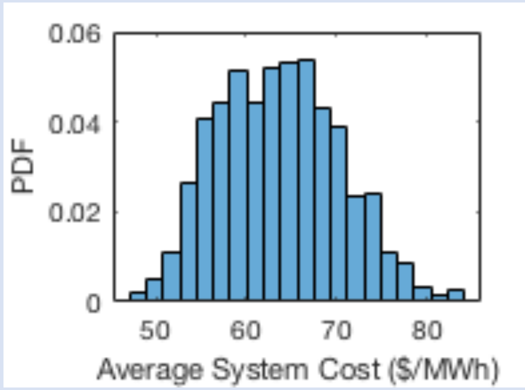


20,000 MW Flexible Market

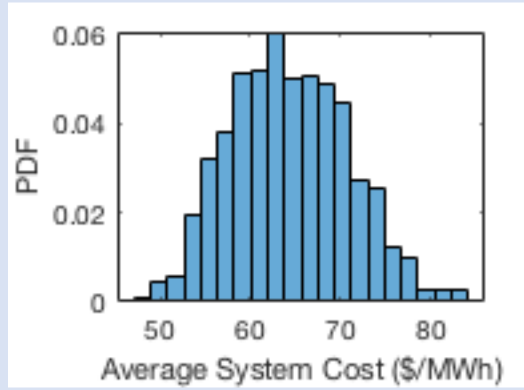


Carbon Price = $50/ton

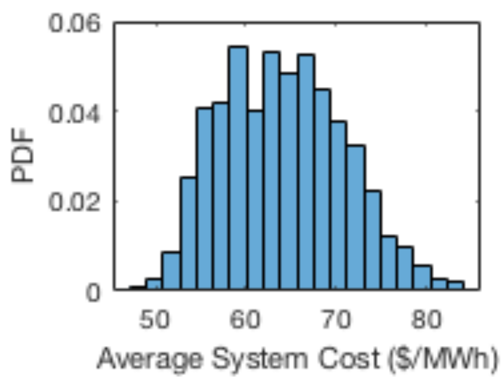
Base Case



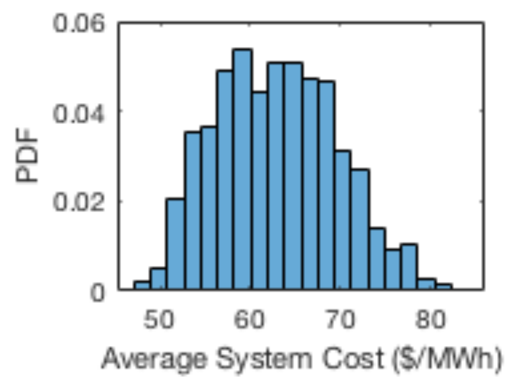
No Nuclear



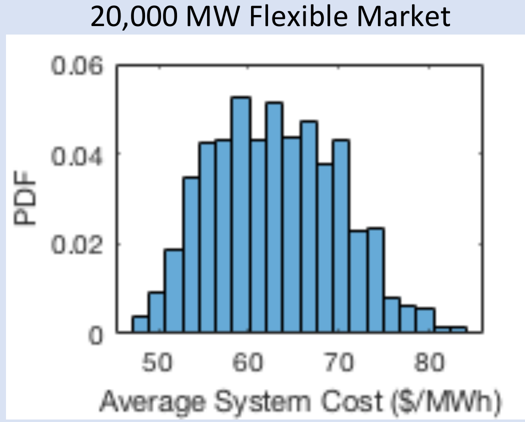
30% Passenger Vehicles Electrified



30% Space Heating Electrified

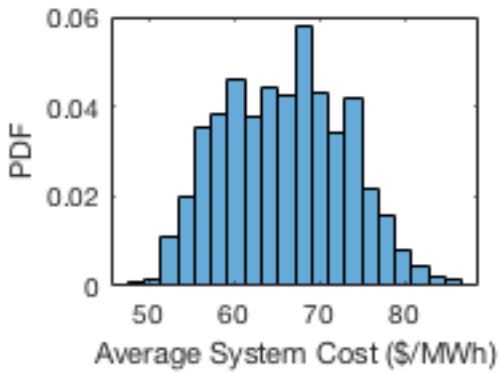


20,000 MW Flexible Market

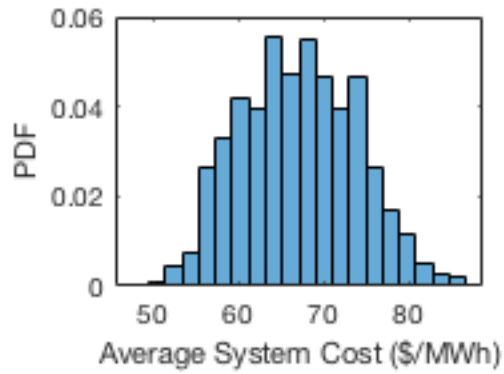


Carbon Price = $75/ton

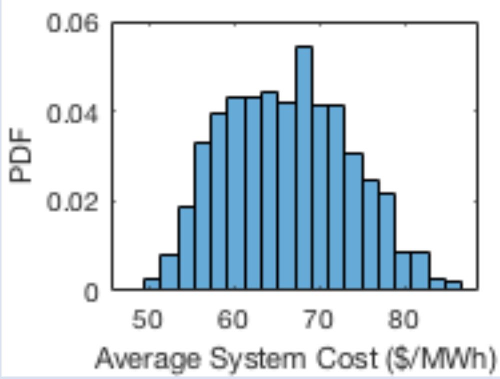
Base Case



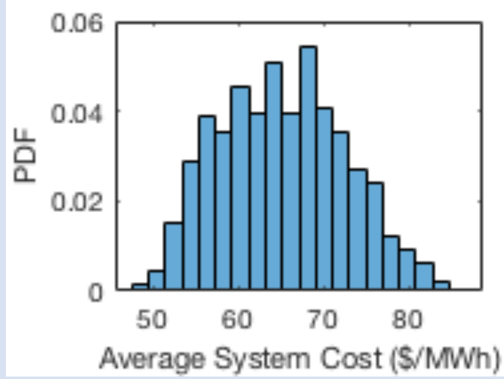
No Nuclear



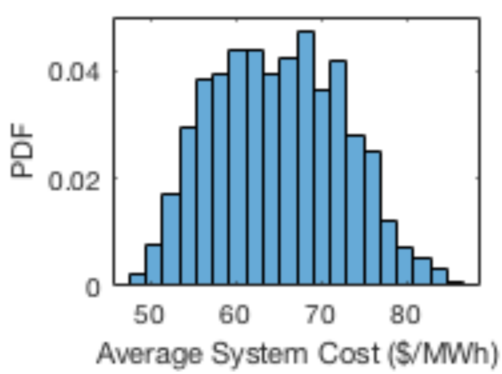
30% Passenger Vehicles Electrified

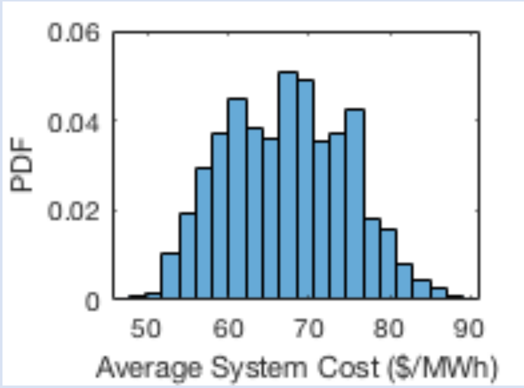
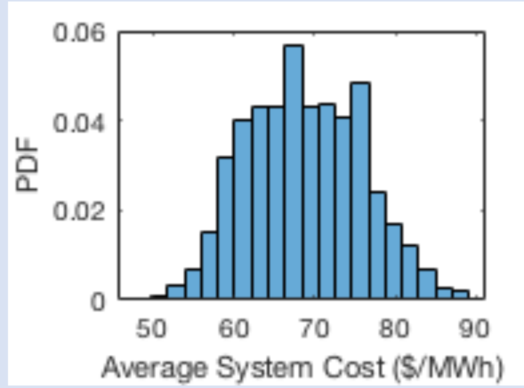
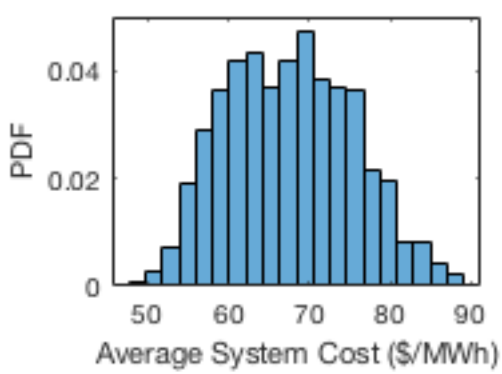
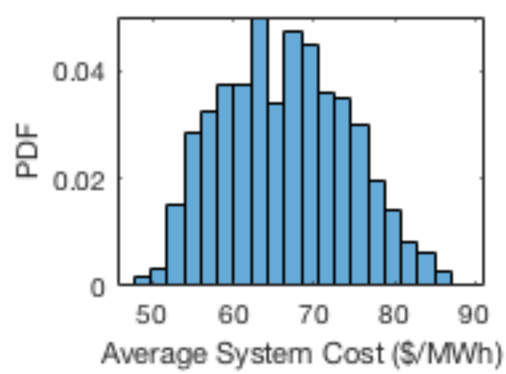
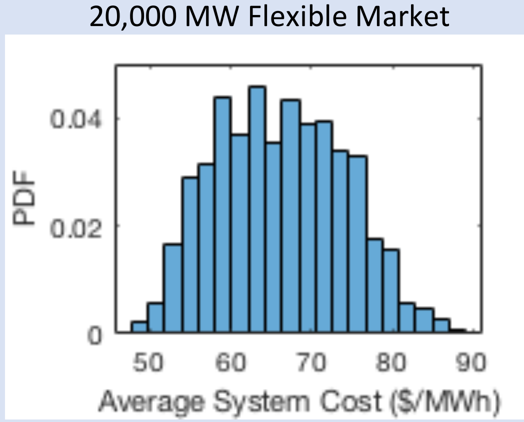


30% Space Heating Electrified



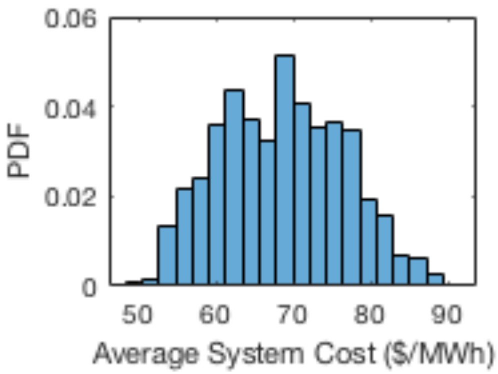
20,000 MW Flexible Market



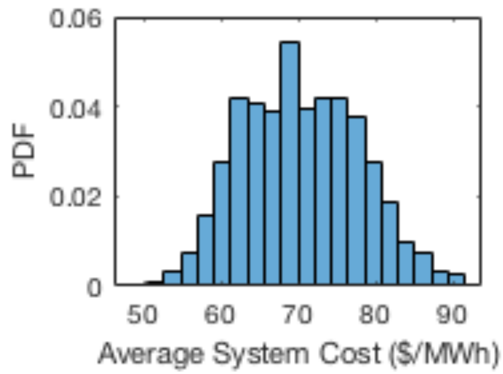
<table>
<tr><td rowspan="3">Carbon Price = $100/ton</td><td>Base Case

</td><td>No Nuclear

</td></tr>
<tr><td>30% Passenger Vehicles Electrified

</td><td>30% Space Heating Electrified

</td></tr>
<tr><td colspan="2">20,000 MW Flexible Market

</td></tr>
</table>

Carbon Price = $150/ton

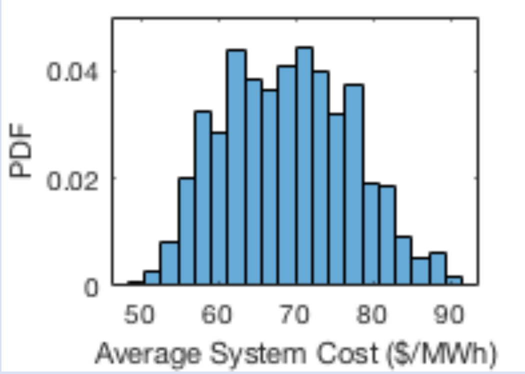
Base Case



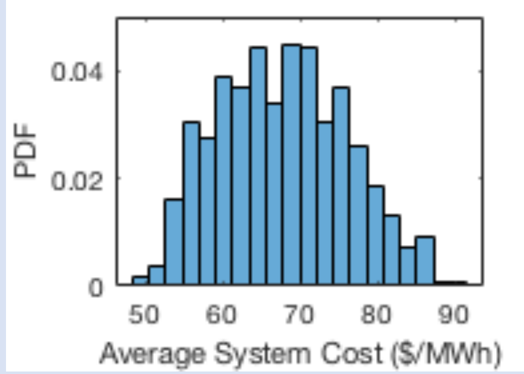
No Nuclear



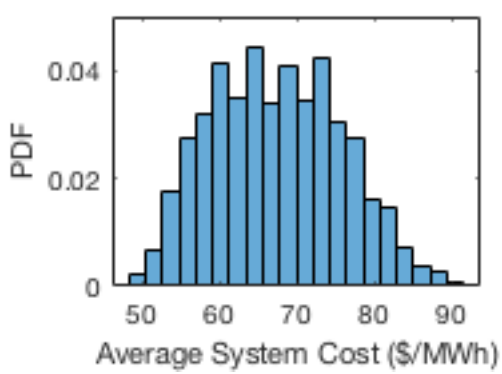
30% Passenger Vehicles Electrified



30% Space Heating Electrified

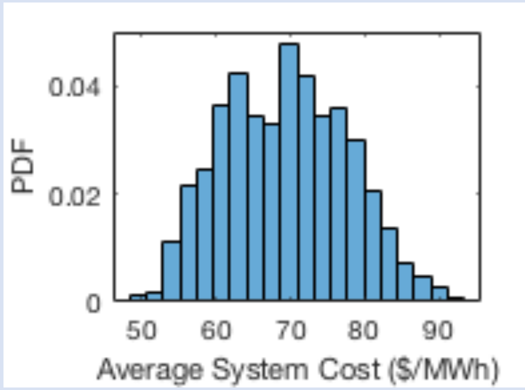


20,000 MW Flexible Market

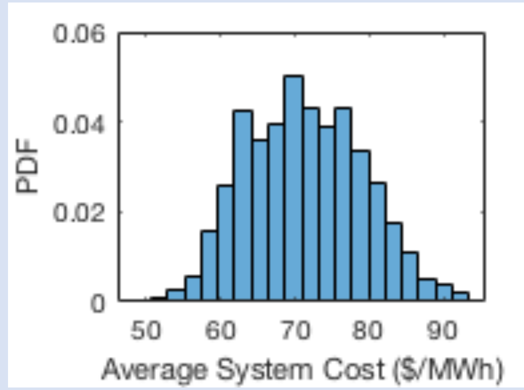


Carbon Price = $200/ton

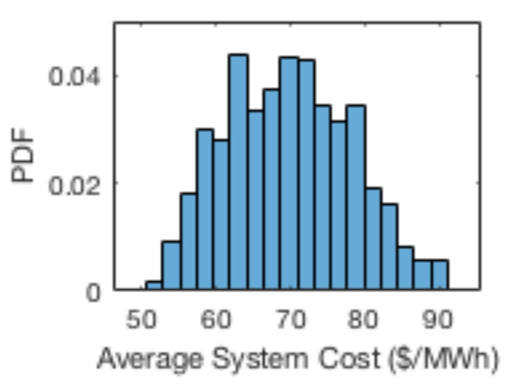
Base Case



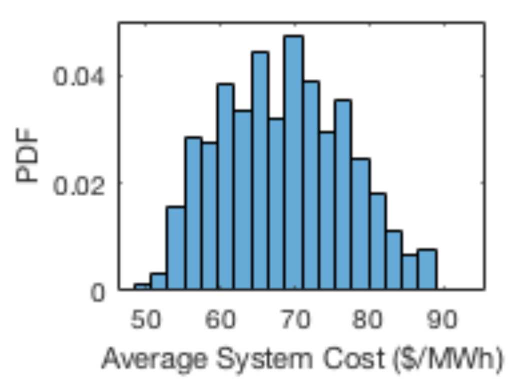
No Nuclear



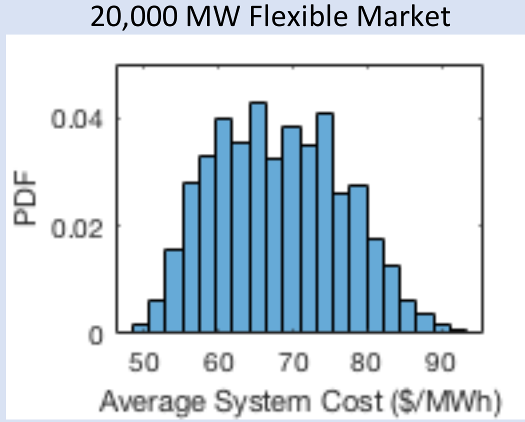
30% Passenger Vehicles Electrified



30% Space Heating Electrified

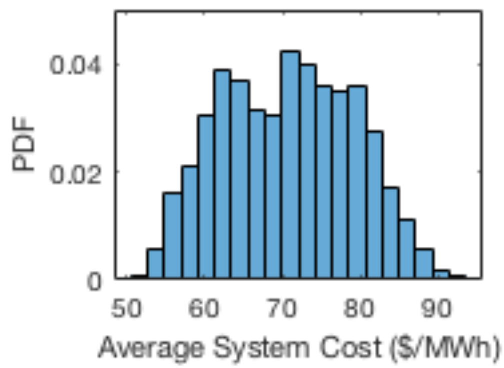


20,000 MW Flexible Market

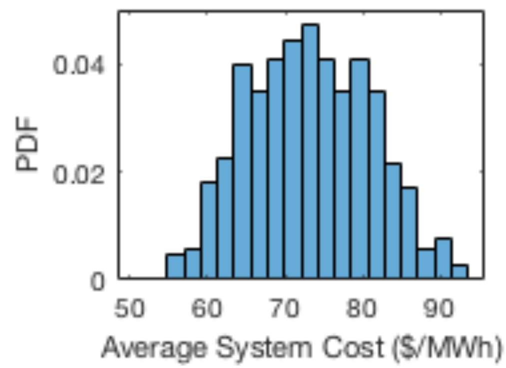


Carbon Price = $300/ton

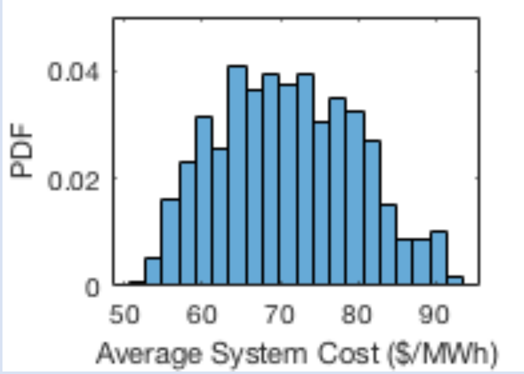
Base Case



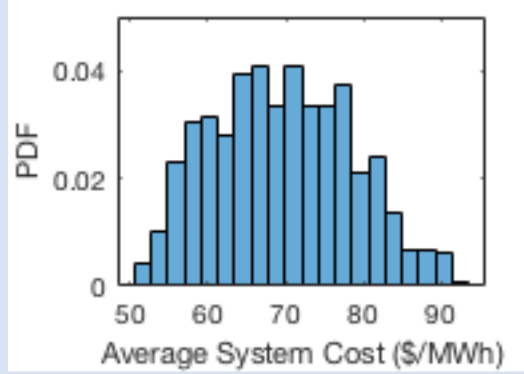
No Nuclear



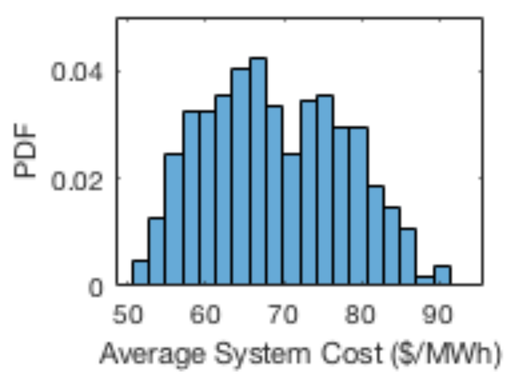
30% Passenger Vehicles Electrified



30% Space Heating Electrified

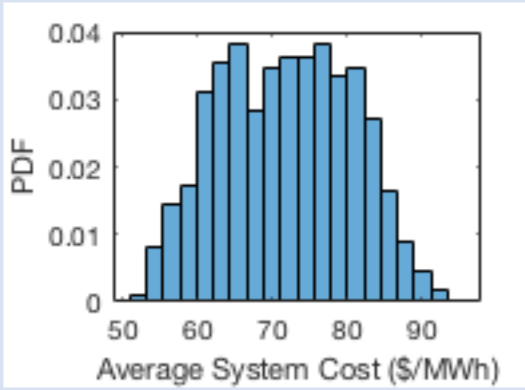


20,000 MW Flexible Market

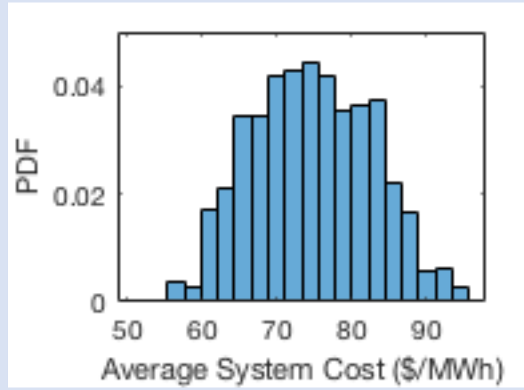


Carbon Price = $400/ton

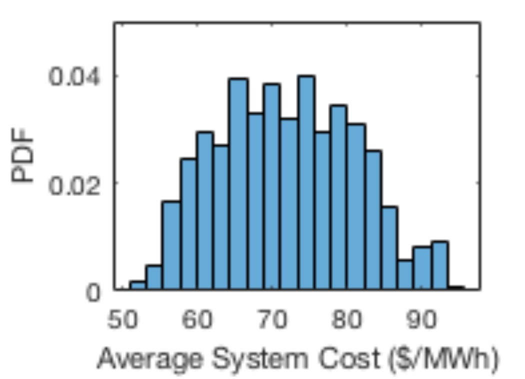
Base Case



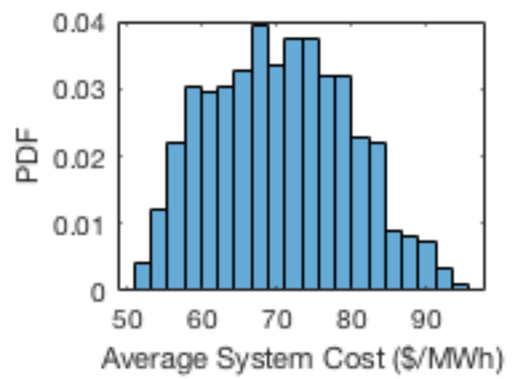
No Nuclear



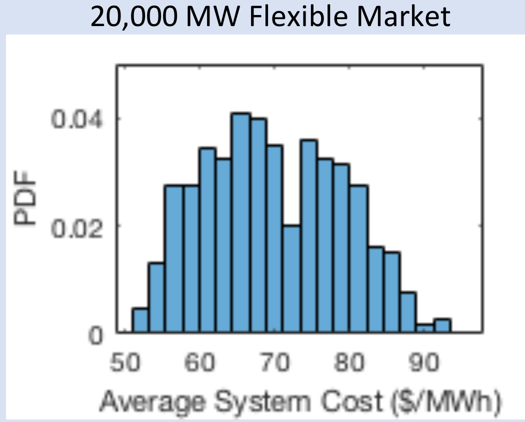
30% Passenger Vehicles Electrified



30% Space Heating Electrified

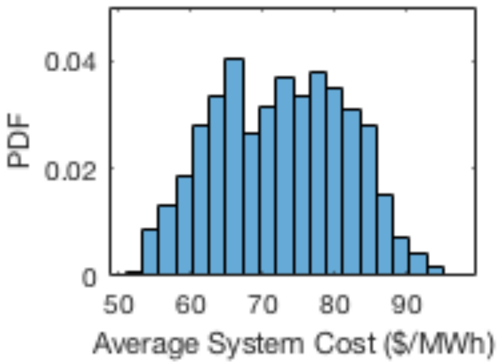


20,000 MW Flexible Market

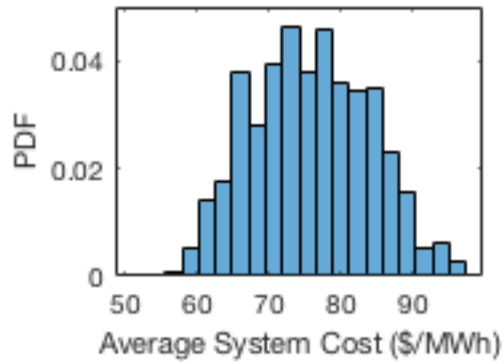


Carbon Price = $500/ton

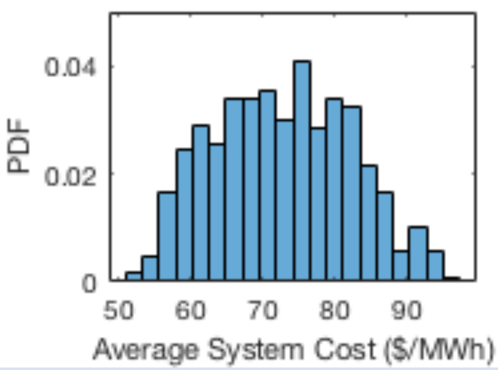
Base Case



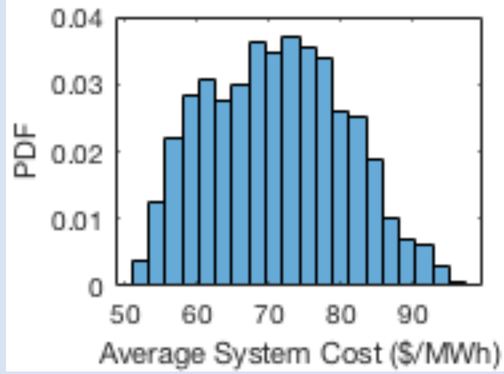
No Nuclear



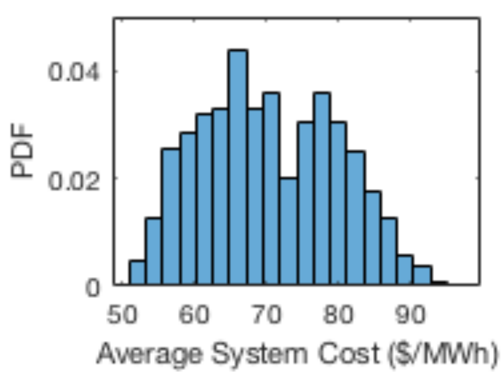
30% Passenger Vehicles Electrified



30% Space Heating Electrified

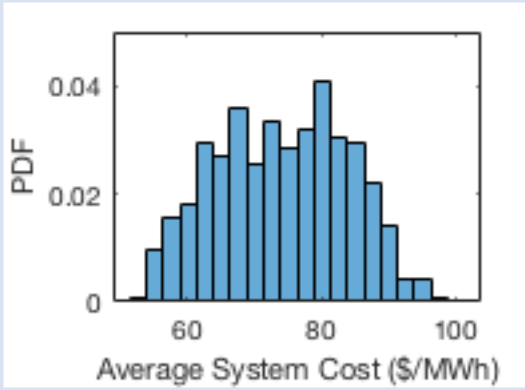


20,000 MW Flexible Market

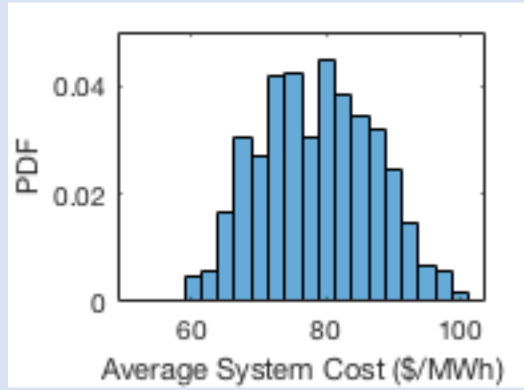


Carbon Price = $750/ton

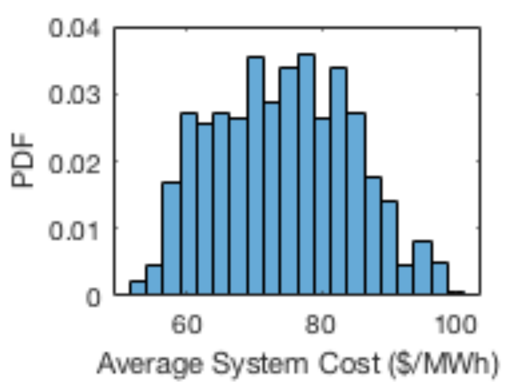
Base Case



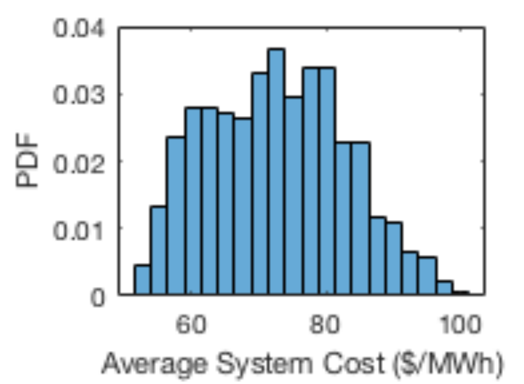
No Nuclear



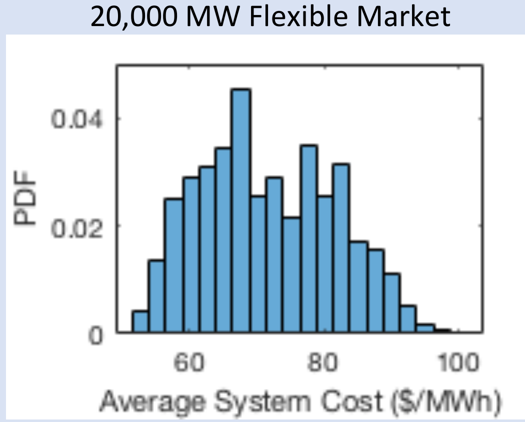
30% Passenger Vehicles Electrified



30% Space Heating Electrified

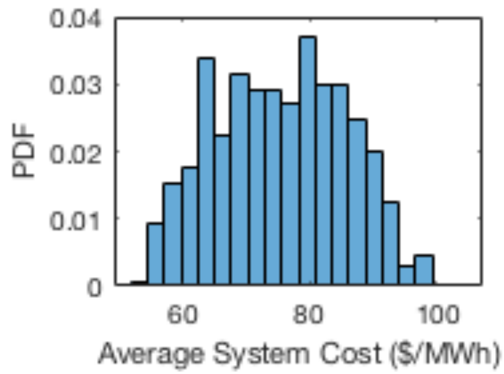


20,000 MW Flexible Market

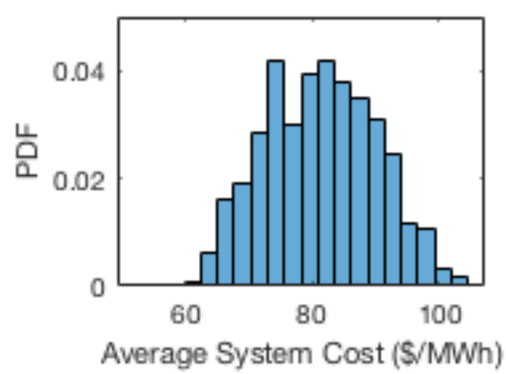


Carbon Price = $1000/ton

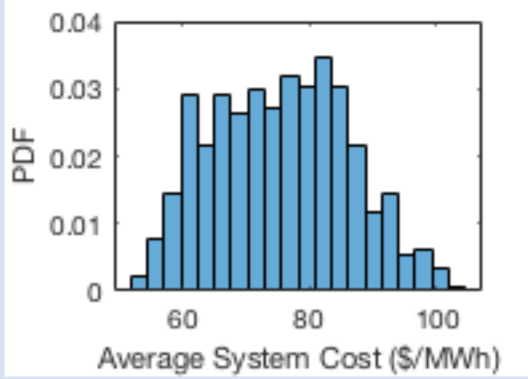
Base Case



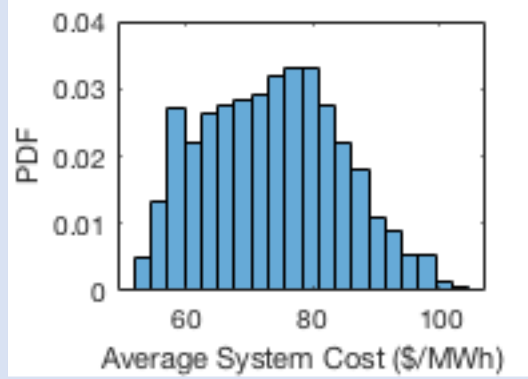
No Nuclear



30% Passenger Vehicles Electrified



30% Space Heating Electrified



20,000 MW Flexible Market