DECISION-MAKING IN CLIMATE AND ENERGY POLICY

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And I urge you to please notice when you are happy,

and exclaim or murmur or think at some point,

”If this isn’t nice, I don’t know what is.”

Kurt Vonnegut, A Man Without a Country

To Kaci, for her neverending love, support, and belief in me.

To Grant and Van, for their hilarity, mischief, and refusal to let me forget how to play.

To my parents, Don and Felicia, for their encouragement, optimism, and patience.

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Now to him who by the power at work within us is able to accomplish abundantly far more than all we can ask or imagine, to him be the glory in the church and in Christ Jesus to all generations, forever and ever. Amen.

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SUMMARY

As many governments at local, state, and national levels seek to lessen their impacts on climate change, carbon dioxide emissions reduction targets are becoming increasingly common. Many of these plans set goals based on a combination of the feasibility and economics of the policies and actions available and the necessary emissions reduction levels identified by the scientific community.

Due to the intertemporal nature of analyses relating to climate and energy, many cost inputs are more easily ingested as and are more clearly presented as annualized costs. In Chapter II, a formalized methodology for the calculation of the levelized cost of electricity is presented. The levelized cost is widely used as a concise estimate of the cost of electricity generation or comparison between different technologies, incorporating the full lifecycle costs of electricity generation into a unit price over the lifetime of the plant. Several issues persist when these calculations are presented. First, the source and reliability of the cost inputs are often unverifiable if they are based on insider information or models that lack transparency. Second, the method typically involves projection of future fuel costs throughout the projected lifetime of the project. These cost streams are highly uncertain and have a significant effect on the result. Third, single point estimates are frequently used for inputs, which results in point estimates for the levelized cost that do not reflect the wide range of potential costs associated with electricity generation technologies. These issues show a continuing need for a formalized approach for comparing the costs of generation technologies.

In Chapter III, a model is presented to evaluate the cost of meeting carbon dioxide emissions targets using an electricity generation planning model incorporating natural gas and transportation fuels with simultaneous selection of efficiency investments in order to satisfy consumer service levels and policy-makers' desired carbon dioxide emissions targets. This model bridges the gap between two sets of existing literature. The first set uses scenario-

based analysis to generate feasible paths for efficiency in order to meet an emissions target and then calculates the resulting costs. The second set uses optimization techniques to minimize either costs or emission, thereafter calculating the other metric based on the results. The framework presented herein allows a specific target to be met at minimum cost by allowing the user to define the efficiency portfolios and directly incorporate them into the cost structure of the optimization model. This framework is intended to be tractable and easily extended to specific applications.

In Chapter IV, the model presented in Chapter III is validated by performing a case study on the United States state of Georgia. Considering electricity, natural gas, and transportation fuel emissions, the case study examines three scenarios. The first involves only business-as-usual considerations; the second incorporates efficiency investments; the third adds a carbon dioxide emissions constraint along with the efficiency investments. By analyzing these three scenarios, the study finds that a 40% reduction in carbon dioxide emissions from 2015 levels is achievable by 2050 at present value costs 17.5% below that of business-as-usual, with the carbon dioxide emissions target itself accounting for costs being 4% above what would otherwise be achieved with efficiency investments alone.

The thesis illustrates a formalized, tractable approach to decision-making in climate and energy policy, while providing the flexibility needed for future work requiring extensions and application to specific contexts. The full source code is provided in order to assist in this endeavor.

CHAPTER 1

INTRODUCTION

The seed of this thesis began on a Saturday in the spring of 2008. Dr. Valerie Thomas put out a call to assemble a group of PhD students to spend a couple of hours on a Saturday to help the City of Atlanta, then under the direction of Mayor Shirley Franklin, to calculate their first Greenhouse Gas Emissions Inventory. This one-day project became a multi-year project, including updates to the Emissions Inventory, which led to work on the City's first Climate Action Plan under Mayor Kasim Reid. It became clear that I could use my mathematical modeling skillset to provide assistance in aiding the planning and course of action in situations like these.

The decisions made today surrounding energy and climate policy will have lasting effects on society, both at the micro and macro levels. The outcomes of these individual decisions are inherently dependent upon each other across both space and time, and the decision-maker must consider both economic and political aspects of the problem. In recent history, many societies have preferred myopic, low cost solutions over long-term, sustainable solutions. This trend is shifting as governing bodies from international to local levels gain a better understanding of the long-term impacts of these near-term decisions.

In increasingly divided political and economic settings, it is growing more important to have a level of transparency, tractability, and flexibility when presenting the basis for decisions that have been and need to be made [1], [2]. There is no doubt that differing viewpoints will be present, but the scientific community will need to become more persuasive and connected with the political and business realms if lasting change is to occur. Transparency, tractability, and flexibility are steps in this direction. This thesis provides a framework that moves towards this end.

In Chapter II, a formalized methodology for the calculation of the levelized cost of electricity is presented. The levelized cost is widely used as a concise estimate of the cost of electricity generation or comparison between different technologies, incorporating the full lifecycle costs of electricity generation into a unit price over the lifetime of the plant. Several issues persist when these calculations are presented. First, the source and reliability of the cost inputs are often unverifiable if they are based on insider information or models that lack transparency. Second, the method typically involves projection of future fuel costs throughout the projected lifetime of the project. These cost streams are highly uncertain and have a significant effect on the result. Third, single point estimates are frequently used for inputs, which results in point estimates for the levelized cost that do not reflect the wide range of potential costs associated with electricity generation technologies. These issues show a continuing need for a formalized approach for comparing the costs of generation technologies.

In Chapter III, a model is presented to evaluate the cost of meeting carbon dioxide emissions targets using an electricity generation planning model with simultaneous selection of efficiency investments in order to satisfy consumer service levels and policy-makers' desired carbon dioxide emissions targets. This model bridges the gap between two sets of existing literature. The first set uses scenario-based analysis to generate feasible paths for efficiency in order to meet an emissions targets and then calculates the resulting costs. The second set uses optimization techniques to minimize either costs or emission, thereafter calculating the other metric based on the results. The framework presented herein allows a specific target to be met at minimum cost by allowing the user to define the efficiency portfolios and directly incorporate them into the cost structure of the optimization model. This framework is intended to be tractable and easily extended to specific applications.

In Chapter IV, the model presented in Chapter III is validated by performing a case study on the United States state of Georgia. Considering electricity, natural gas, and transportation fuel emissions, the case study examines three scenarios. The first involves only business-as-usual considerations; the second incorporates efficiency investments; the third adds a carbon dioxide emissions constraint along with the efficiency investments. By analyzing these three scenarios, the study finds that a 40% reduction in carbon dioxide emissions from 2015 levels is achievable by 2050 at present value costs 13% below that of business-as-usual, with the carbon dioxide emissions target itself accounting for costs being 2% above what would otherwise be achieved with efficiency investments alone.

CHAPTER 2
THE LEVELIZED COST OF ELECTRICITY

2.1 Introduction

The levelized cost is widely used as a concise estimate of the cost of electricity generation or comparison between different technologies, incorporating the full lifecycle costs of electricity generation into a unit price. The levelized cost (C_L) is the cost that, when applied to each unit over the lifetime of the asset, is equivalent to the present value of the cost stream. It is calculated by taking the present value of total lifecycle costs and dividing by the present value of total lifetime electricity generation as shown in Equation 2.1.

$$C_L = \frac{PV[Costs]}{PV[ElectricityGeneration]} \tag{2.1}$$

The levelized cost in isolation does have limitations in its potential for being used for power planning. The levelized cost assumes each unit of electricity to be of equal value, which particularly comes into effect when comparing dispatchable and baseload generation technologies with intermittent technologies. This omits a key component in determining why a certain type of technology is chosen over another, as the variations in output and electricity price play significant roles in this decision (Joskow 2011) [3]. Along these same lines, the value of having control over the output at specific times of day or within a season is not factored into this framework. The cost and requirements for frequency and voltage control and support are not included in the calculation. Reactive power planning, which allocates reactive power sources considering location and size to maintain optimal power flow, is a critical component in power planning (Zhang 2007) [4]. The levelized cost is also dependent upon a projected utilization rate, which will vary depending on the times of day and season for which the capacity is needed. The existing resource mix will also affect the decision of which technology to install. The current generation resources will determine the value of displacing the electricity generated by these resources. Portfolio diversification is an important factor when making power planning decisions, as the price of fuels can be volatile and projections over the entire lifespan of a plant are highly uncertain. The levelized avoided cost of electricity (LACE), which measures what it would cost the grid to generate the electricity otherwise displaced by a newly installed technology, is one alternative metric. In theory, when the LACE exceeds the LCOE, the value outweighs the cost, and thus the installation would be economically beneficial (EIA 2016) [5].

In addition to the planning element itself, a number of issues arise within the calculation of the levelized cost as seen in practice. First, the source and reliability of the cost inputs are often unverifiable if they are based on insider information or models that lack transparency. Second, the method typically involves projection of future fuel costs throughout the projected lifetime of the project. These cost streams are highly uncertain and have a significant effect on the result. Third, single point estimates are frequently used for inputs, which results in point estimates for the levelized cost that do not reflect the wide range of potential costs associated with electricity generation technologies. These issues show a continuing need for a formalized approach for comparing the costs of generation technologies. This paper specifically addresses the first two issues by developing more transparent capital cost and fuel cost estimates, and seeks more clarity in presentation of cost ranges and sensitivities.

Levelized cost analyses depend heavily on the capital cost and fuel cost associated with a given technology. In this analysis, capital costs are based on publicly available cost estimates for real, commercial plants, published within the past five years. Fuel costs are projected based on past and current prices and account for the effect of discounted future costs. This approach avoids projecting exactly how fuel costs and technologies will change in the future. While projections of future price changes can be credible and useful in evaluations of electricity generating technologies, this less prediction-dependent approach can provide a baseline for evaluation of technologies and for evaluation of the implications of future price changes. This approach does have limitations in that cost estimates for new technologies for which commercial plants are not yet under construction need to be developed differently. Sensitivity analysis provides a basis for understanding the implications of uncertain parameters.

We demonstrate this approach with a case study of new electricity generation in the United States and calculate estimated levelized cost ranges for three different electricity generation technologies: supercritical pulverized coal, natural gas combined cycle, and nuclear fission. An implementation of this approach is available online [1]; a review of the calculation of the levelized cost of electricity is provided in the appendix.

Our calculation includes five costs: capital costs, fuel costs, fixed operation and maintenance (O&M) costs, variable O&M costs, and the cost of carbon dioxide emissions. Capital costs are assumed to occur over the book life of the plant while the other costs occur over the entire operational life of the plant. The levelized cost is calculated for three technologies: supercritical pulverized coal, natural gas combined cycle, and nuclear fission.

2.2 Literature Review

Levelized cost analyses have been developed by many academic, governmental, and private entities; the history of levelized cost analyses shows increasing application to a wide range of electricity technologies, cost types and externalities, in combination with continuing work to clarify and improve the methods. In 1990, Bemis and DeAngelis, building on substantial previous work in levelized cost analyses, calculated levelized costs for 70 electricity generating technologies and two facility ownership scenarios [6]. In 1995, the National Renewable Energy Laboratory released a report outlining a set of equations for calculating levelized costs [7]. In 2000, Vatavuk compared the levelized cost method to the EPAs OAQPS Control Cost Manual, noting that the two methods are different and unlikely

[1] http://www2.isye.gatech.edu/esns/lcoe/

to converge completely [8]. In 2004, Roth and Ambs presented levelized cost calculations including externalities for 14 generation technologies using fixed charge rates [9]; Previsic et al. presented two methodologies for calculating levelized costs: one for utility generators and one for non-utility generators [10]. Also in 2004, Kammen and Pacca reviewed four focus areas for comparing costs of electricity generation: busbar costs, market-based costs that include risk premiums and cost variability, market costs including subsidies, and monetization of externalities within energy costs. They also address a range of other issues including the costing of combined heat and power systems, and the cost of conserved energy [11]. In 2005, Rosenberg et al. calculated the levelized cost of integrated gasification combined cycle coal, including a derivation of the carrying charge [12]. In 2008, the Congressional Budget Office detailed the equations used for calculating the levelized cost using comprehensive financial parameters [13]. Also in 2008, Cambell calculated levelized costs for solar photovoltaic electricity including a system degradation rate [14]. In 2009, the California Energy Commission calculated the levelized cost of 18 technologies for merchants, independently owned utilities, and publicly owned utilities [15]. In 2010, the International Energy Association calculated levelized costs for technologies throughout many countries. Cost inputs were obtained by a questionnaire and sensitivity analyses were performed on costs and input parameters [16]. The Electric Power Research Institute (EPRI) frequently releases updates to their Renewable Energy Technical Assessment [17]. In 2011, Islegen and Reichelstein, noting that there does not seem to be a commonly accepted formula for calculating this average cost, use the levelized cost to calculate the break-even emissions charges that justify investing in carbon capture and sequestration technology [18]. The literature indicates growing acceptance and application of LCOE calculations; we relegate a basic methods review to the appendix. Yet calculations of similar systems by different authors may have considerably different results. The focus of this work is on development of a reference approach to key data inputs.

2.3 Estimating Fuel Costs and Other Uncertain Future Cost Streams

2.3.1 Discounted Average Fuel Costs

The market price of fuel will not remain constant over time, and therefore, the cost stream will fluctuate from year to year. A levelized cost calculation, as detailed in the appendix, requires calculation of fuel costs throughout the lifetime of the plant. Projecting these fuel costs introduces substantial uncertainty and potential for deviation among analysts. Operation and maintenance costs will recur over time and can be expected to fluctuate. The approach developed below can be applied to any recurring cost stream; fuel costs are emphasized here because of their substantial contribution to electricity costs.

As shown in Equation 2.1, only the present value of a cost stream is included in a levelized cost calculation. All cost streams with the same discounted present cost will have the same levelized cost. Specifically, for a projected fuel cost stream that fluctuates in time, there is a constant fuel cost stream with the same present value. Given a variable fuel cost $(z_1 \ldots z_L)$ throughout the plant life (L) of a generation facility, we define the discounted average cost $(\bar{z})$ as the value that satisfies this relationship, as shown in Equation 2.2.

$$\sum_{i=1}^{L} \frac{z_i}{(1+r_0)^i} = \frac{\bar{z}}{r_0} \cdot \left[1 - \frac{1}{(1+r_0)^L}\right] \tag{2.2}$$

where r_0 is a constant discount rate. Solving for $\bar{z}$, we find

$$\bar{z} = r_0 \cdot \frac{\sum_{i=1}^{L} \frac{z_i}{(1+r_0)^i}}{\left[1 - \frac{1}{(1+r_0)^L}\right]} \tag{2.3}$$

A particular value of $\bar{z}$ may correspond to an infinite number of different fuel cost projections or other cost streams. However, it is the only parameter necessary to fully characterize a particular time-variable cost stream for a levelized cost calculation. Therefore, the discounted average cost provides a single metric for comparing the total cost impact of differing cost streams.

A similar concept can be applied to past cost streams, with costs in the distant past weighted less heavily than recent ones; we refer to this as the historical discounted average fuel price ($\bar{h}$) . The calculation, shown in Equation 2.4, is similar to an explicitly normalized form of exponential smoothing, where t is the index present year and $h(i)$ is the historical price in index year i.

$$\bar{h} = \frac{\sum_{i=1}^{t-1} \frac{h_i}{(1+r_0)^{t-1}}}{\sum_{i=1}^{t-1} \frac{1}{(1+r_0)^{t-1}}} \tag{2.4}$$

2.3.2 Fuel Cost Examples

Coal

The cost of coal for a power plant depends on the type of coal used and the transportation cost. Prices for coal used for electricity in the US for 1980 through 2009 are shown in Figure 1. During this period, the use of Appalachian coal decreased, while the use of Powder River Basin coal increased [19]; both the type of coal and the transportation distance have changed over time. The historical prices shown are free-on-board weighted averages for bituminous, sub-bituminous, lignite, and anthracite coal. Figure 1 also shows the discounted average fuel price from 2009 back to 1980. A $0.50/MMBtu cost of transportation was added to the historical prices in order to provide a more direct comparison between these prices and forecasts made for delivered prices. Rail transportation costs about $.02/ton-mile in 2010 dollars [20]. The longest distance from either the Powder River Basin located in Wyoming and Montana or Central Appalachia to any other location in the United States is roughly 2,000 miles or 3,200 km. The minimum distance that the coal would be transported is assumed to be 200 miles or 320 km. Thus, transportation adds between $4/ton and $40/ton to the fuel cost [21].

Forecasting techniques are often scenario based, as with the Department of Energys Annual Energy Outlook (AEO) [22]. Three scenarios from the Annual Energy Outlook, are shown in Figure 2.1, the high coal cost and low coal cost scenarios and the reference scenario. The discounted average fuel price of these scenarios is $2.75, $1.82, and $2.20, respectively, when calculated over the 25 year horizon provided by the AEO.

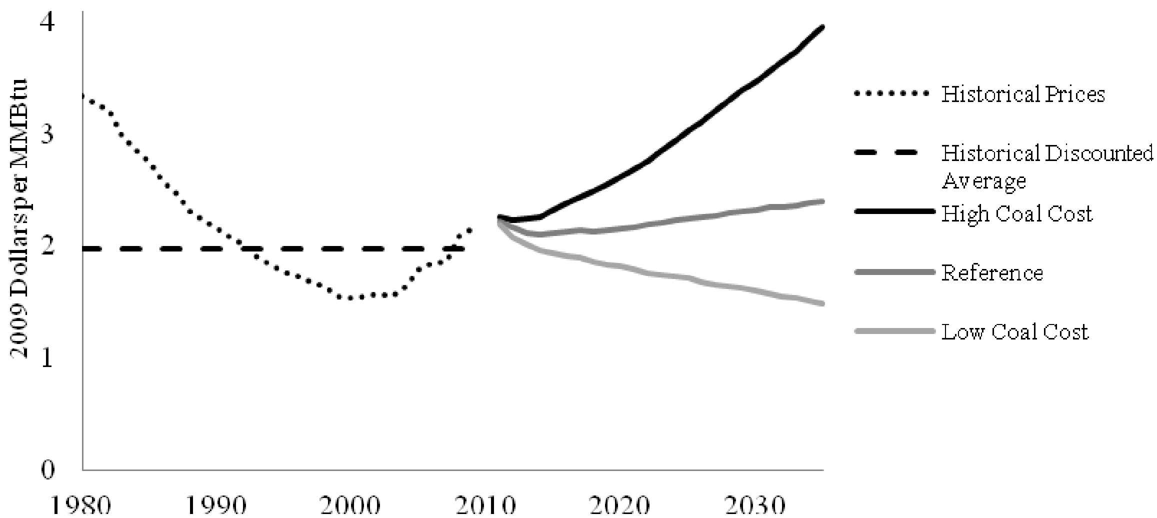

Figure 2.1: Historical U.S. Coal Prices, AEO Forecast Scenarios, and the Historical Discounted Average [23],[22]

The historical discounted average is $1.98/MMBtu when discounted at a real rate of 4.9%. Comparing these discounted average fuel values: $1.82, $2.20 and $2.75 for the AEO low, reference, and high cases respectively, to the historical discounted average of $1.98/MMBtu provides some perspective on how various fuel price projections affect the levelized fuel cost of electricity generation. Our case study uses a price of $2.25/MMBtu in 2010 dollars for the baseline discounted average price of coal.

Natural Gas

Natural gas prices, shown in Figure 2, dropped significantly in 2010 after peaking above $12/thousand cubic feet in mid 2008 (1000 cubic feet = 1.039 MMBtu) [23]. Three scenarios from the Annual Energy Outlook, along with their discounted average fuel prices, are shown in Figure 2.2. The slow technology development and rapid technology development scenarios were selected since they are among the upper and lower range scenarios for natural gas prices, respectively. When calculated over the 25 year horizon projected by the AEO, these scenarios have discounted average fuel prices of $4.85, $5.20, and $5.71 per MMBtu in 2009 dollars for the rapid technology, reference, and slow technology scenarios, respectively.

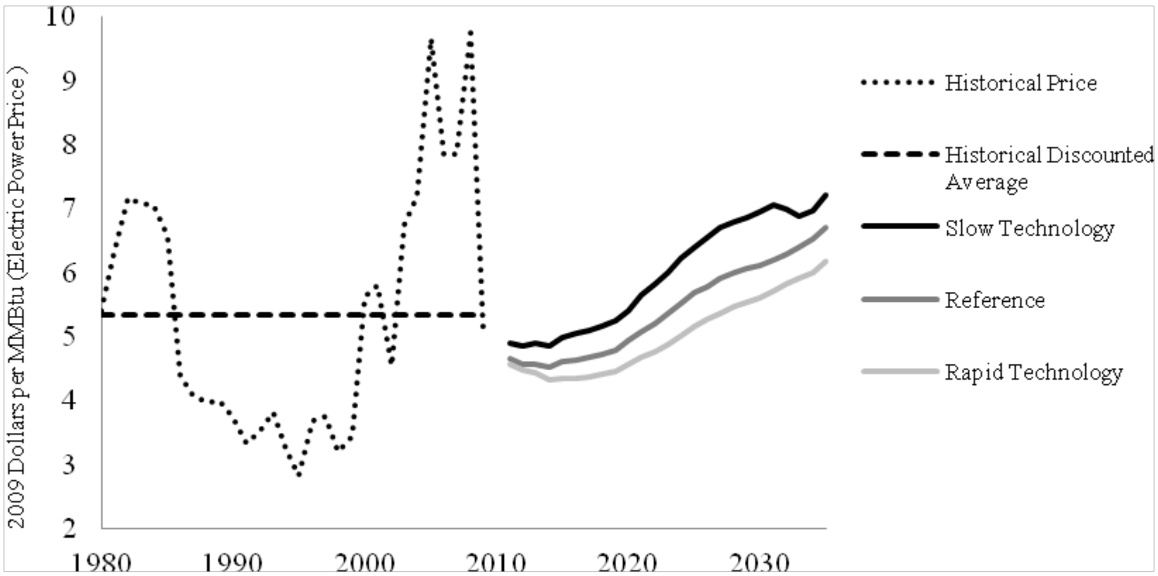

Figure 2.2: Historical U.S. Natural Gas Prices, AEO Forecast Scenarios, and the Historical Discounted Average [23],[22]

The historical discounted average price shown in Figure 2.2 is $5.34/MMBtu when discounted at a real rate of 4.9% from 1980 to 2009. The selection of the discount rate and years included can significantly affect the historical discounted average. This is particularly important for natural gas, both because of its historic price volatility, and because fuel cost is a substantial portion of the cost of electricity derived from natural gas. Figure 2.3 shows the historical discounted average for various discount rates as a function of the first year of price data included. For the 2% discount rate the low natural gas prices from 1920 to 1970 result in a low historical discounted average price, whereas for a 25% discount rate, the prices in the past have less weight and thus the historical discounted average price reflects recent higher prices.

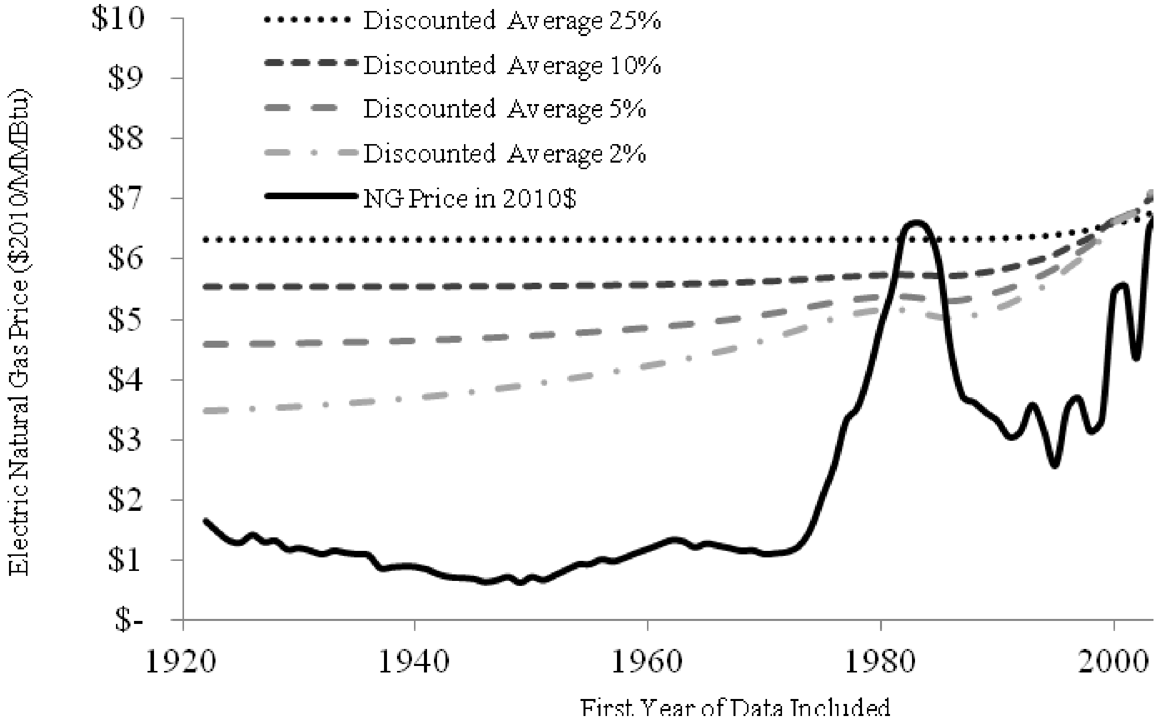

Figure 2.3: Historical U.S. Natural Gas Prices, AEO Forecast Scenarios, and the Historical Discounted Average [23]

Recognizing that the substantial variation in post and potential future prices precludes confidence in projection of future fuel prices, we simply select a price of $5.50/MMBtu in 2010 dollars as the baseline discounted average price for natural gas, and focus the analysis on the effect of the uncertainty of natural gas prices on the levelized cost of electricity.

Nuclear

Nuclear fuel costs include the purchase of uranium oxide and its conversion, enrichment, and fabrication to obtain a high enough concentration of ^{235}U to be used as nuclear fuel. The weighted average price of imported and domestically produced uranium oxide from 1983 to 2008 is shown in Figure 2.4.

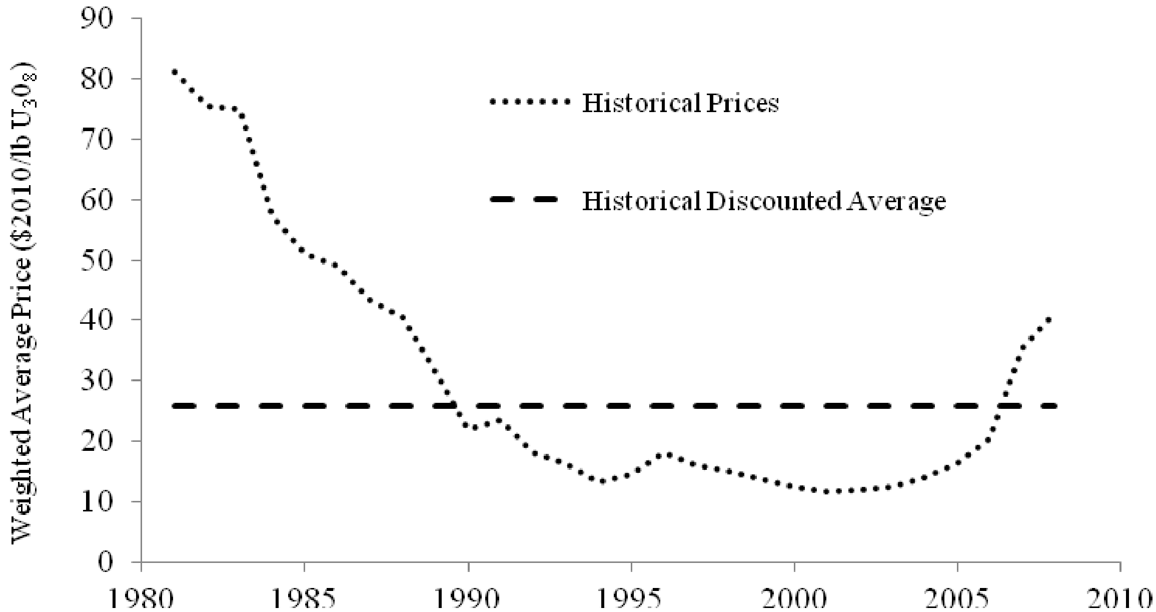

Figure 2.4: Historical U.S. Nuclear Fuel Prices and the Corresponding Historical Discounted Average [23]

Average prices in nominal dollars and total quantities for purchased imports and domestic concentrate production were obtained from the Energy Information Administrations Annual Energy Review 2009 Table 9.3 [23]. The weighted average price was then updated to 2010 dollars using the Consumer Price Index from the Bureau of Labor Statistics [24]. Approximately 2.6 lbs of U_3O_8 are required to produce one lb of nuclear fuel [25]. The historical discounted average price of one lb of U_3O_8 is $25.70.

When purchased, the nuclear fuel is 60 to 85 percent U_3O_8. In the conversion process, the fuel becomes 99.95 percent pure uranyl nitrate for light water reactors. The cost of conversion is between $10 and $18 per kg nuclear fuel in 2010 dollars, updated from 1991 dollars. The fuel is then enriched from approximately 0.7% $^{2}35$U to 3 to 4% $^{2}35$U. The cost of enrichment is between $130 and $210 per SWU (separative work unit). The fuel is fabricated for use in the reactor by conversion to a powder, pelletization, and then sintering into ceramic fuel. The cost of fabrication is between $320 and $560 per kg nuclear fuel and the energy density of the fuel is 1032 MWh/kg [26]. Section 302 of the Nuclear Waste Policy Act of 1982 requires civilian nuclear power reactors to pay a spent fuel fee of 1.0 mil/kWh ($1/MWh) [27]. These full life-cycle costs of nuclear fuel material, conversion, enrichment and fabrication are equivalent to a final cost of $0.37 to $0.57/MMBtu. Other studies use fuel costs of $0.53/MMBtu with an escalation rate of 2.5% [28], $0.68/MMBtu levelized [29], and $0.73/MMBtu with a real escalation rate of 0.5% [30]. These conversion costs indicate a conversion factor of approximately 80 MMBtu/lb U_3O_8. Using this scaling factor, the historical discounted average price is $0.35/MMBtu.

2.4 Capital Cost Examples

For each generation technology, publicly available costs are used to identify a range of possible capital costs. This allows for consistency among modelers and reduced bias for or against specific technologies.

Even for established electricity generating technologies, only a small number of plants may have been built or proposed within recent years. With a small number of data points, there is little basis for determining the distribution of the costs or the cause of variation in costs. Accordingly, we use the range of capital costs for new and proposed plants for each technology as a range for sensitivity analysis.

2.4.1 Coal

Public filings are available for Duke Energy Carolinas' Cliffside Generating Station, SWEPCOs John W. Turk power plant, Florida Power and Lights Glades power plant, and AMP Ohios American Municipal Power generating station. Table 2.1 shows the projected overnight costs including and excluding transmission costs for the four proposed coal-fired power plants.

We use an average of $2,450/kW for the capital cost of coal power plants.

Table 2.1: Overnight Costs for Proposed Supercritical and Ultra-Supercritical Coal Plants (2010$)

Owner	Name	Design	Capacity(MW)	Projected Commercial Operation Date	Overnight Cost($/kW) Excluding Transmission	Overnight Cost($/kW) Including Transmission
Duke Energy	Cliffside	SCPC	800	2012	N/A	1,500
SWEPCO	Turk	USCPC	600	2012	2,300	2,700
FP&L	Glades	USCPC	1,960	2013-2014	2,300	2,500
AMP Ohio	Meigs County	SCPC	960	2014	N/A	3,400

Sources:[31], [32], [33], [34]

2.4.2 Natural Gas

Table 2.2 shows the projected overnight costs for proposed gas-fired combined cycle power plants, as of 2011.

Based on these estimates, we use an average value for the overnight cost of natural gas combined cycle plants of $950/kW.

2.4.3 Nuclear

Public filings for two new nuclear power plants being built by South Carolina Energy and Gas and Georgia Power are available through state Public Service Commissions. Of the several plants under consideration in 2011, these are the two that appear likely to move forward with construction [36]. To provide some consistency among the estimates, we have identified the overnight capital cost, that is, the capital cost excluding financing costs, and then we have explicitly included the same financing costs, fuel costs, and other costs for all the plants to provide an estimate of wholesale electricity costs on a consistent basis. Table 2.3 summarizes the projected overnight costs with and without transmission costs for the two proposed US nuclear power plants, both of which are Westinghouse AP1000s.

The costs shown in Table 2.3 reflect a considerable increase in costs over the past 15 years. Data on nuclear power plants built in Japan and in the Republic of Korea from 1994 to 2006 are consistent with a 15% annual increase in capital costs [30].

Based on the projected costs of the US nuclear power plants shown in Table 2.3, we use an average value of $4,100/kW as the overnight capital cost of new nuclear power plants excluding transmission costs.

2.5 Operation and Maintenance (O&M) Costs and Other Costs

Estimates of O&M costs from various sources are shown in Table 2.4. Note that these values are not utility data, but rather reflect information or estimates from the authors of

Table 2.2: Overnight Costs for Proposed Natural Gas Power Plants(2010$)

Owner	Name	Design	Capacity(MW)	Projected Commercial Operation Date	Overnight Cost($/kW)
PE Carolinas	Richmond	2-on-1	570	2011	1,300
NCPA	Lodi	1-on-1	255	2012	1,100
CPV	Vaca Station	2-on-1	660	2013	740
Macquarie	Avenal Energy Project	2-on-1	600	2012	800
NV Energy	Harry Allen	2-on-1	500	2012	1,300
FP&L	West County	3-on-1	1,219	2011	600

All estimates made in 2008. Sources:[30], [35]

Table 2.3: Overnight Costs for Proposed Nuclear Power Plants(2010$)

Primary Owner	Name	Capacity(MW)	Project Commercial Operation Date	Overnight Cost($/kW)
SCE&G	VC Summer 2 & 3	2,234	2016-2019	4,600
Georgia Power	Vogtle 3 & 4	2,200	2016-2017	3,600

Sources:[37], [38]

the cited studies. For nuclear O&M costs, Du and Parsons use a real escalation rate for O&M costs of 1.0%, and Lazard, Ltd uses an annual escalation rate of 2.5% [30],[28].

Several other costs are sometimes considered when calculating the levelized cost of electricity, including incremental capital costs, waste fees, and decommissioning costs. FPL certified that financial assurance of approximately $376 million per unit would be provided for decommissioning [39]. Du and Parsons assume an incremental capital cost of $27/kW/year, $10/kW/year, and $40/kW/year for coal, natural gas, and nuclear, respectively [30]. We do not assume any additional costs in our case study calculations. The effect of including a cost associated with carbon dioxide emissions from power generation on the levelized cost is analyzed in Section 2.6.3.

We use fixed O&M costs of $30, $13.5, and $80 per kW for coal, natural gas, and nuclear, respectively. Variable O&M costs used in this study are $2.80, $3.00, and $0.50 per MWh for coal, natural gas, and nuclear, respectively.

2.6 Results of the Case Study

2.6.1 Baseline Values

Table 2.5 shows our estimate of the levelized busbar cost of electricity from the technologies analyzed. Since the levelized cost is heavily tied to the capacity factor, any actual construction should be reevaluated based on its actual production.

An annual inflation rate of 2% is used for the above calculation. The percentage of the levelized cost associated with each cost component for nuclear, coal, and natural gas is shown in Figure 2.5.

Table 2.4: Fixed and Variable O&M Costs in $/kW and $/kWh, Respectively(2010$)

Source	Coal		Natural Gas		Nuclear	
	$/kW	$/MWh	$/kW	$/MWh	$/kW	$/MWh
Du,[30]	26.2	3.9	14.2	4.5	61	0.46
Black & Veatch,[29]	35.3	1.7	16.2	3.4	101	0.56
Lazard,[28]	–	–	–	–	14	11.67
NETL,[40]	25.2	4.9	11.1	1.5	–	–
Katzer,[41]	–	8.7	–	–	–	–

Table 2.5: Baseline Estimated Levelized Costs of Electricity from New Generation Capacity

	Coal	Natural Gas	Nuclear
Nameplate Capacity (MW)	1,000	600	2,200
Capacity Factor	85%	85%	90%
Nominal Discount Rate	7%	7%	7%
Book Life (years)	30	20	30
Plant Life (years)	50	50	60
Heat Rate (Btu/kWh)	9,000	6,800	10,400
Capital Cost ($/kW)	2,450	950	4,100
Fixed O&M ($/kW)	30	13.5	80
Variable O&M ($/MWh)	2.8	3.0	0.5
Fuel Cost ($/MMBtu)	2.25	5.50	0.50
Carrying Charge Rate	15%	15%	18%
Levelized Cost ($/MWh)	68	55	91

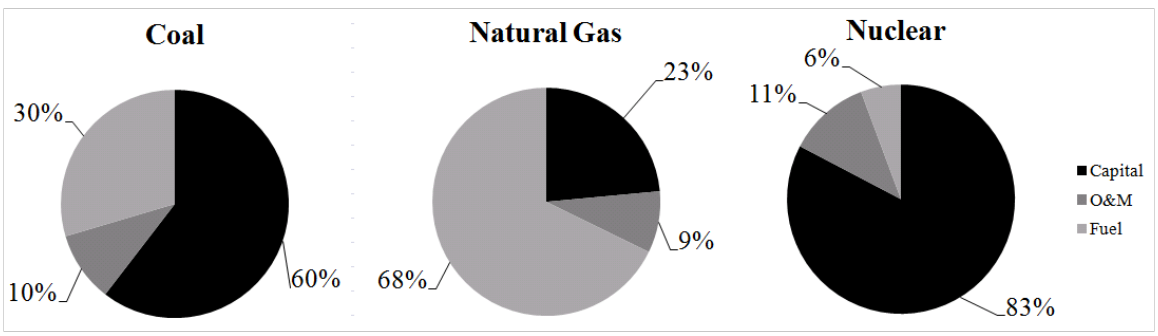

Figure 2.5: Levelized Cost Components by Technology

2.6.2 Sensitivity Analysis

Figures 2.6 through 2.8 show the sensitivity of the levelized cost to three financial parameters: nominal discount rate, plant life, and carrying charge rate. The sensitivities are based on the baseline values shown in Table 2.5.

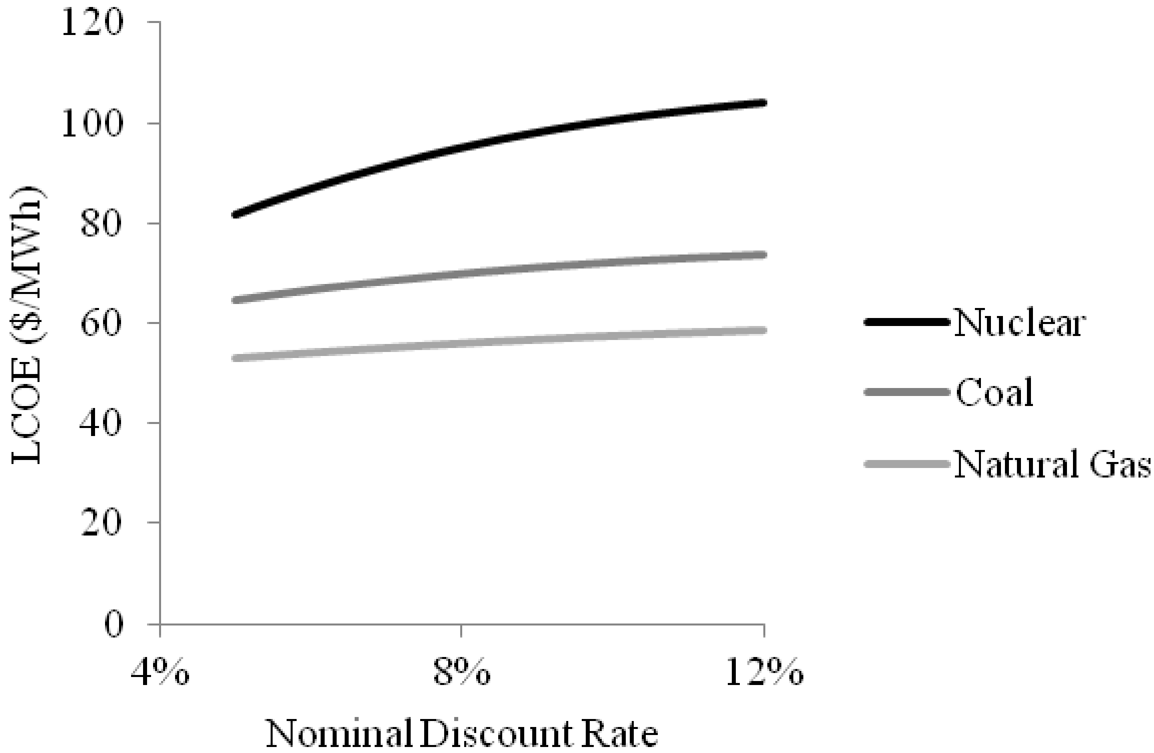

Figure 2.6: Levelized Cost Sensitivity to Nominal Discount Rate

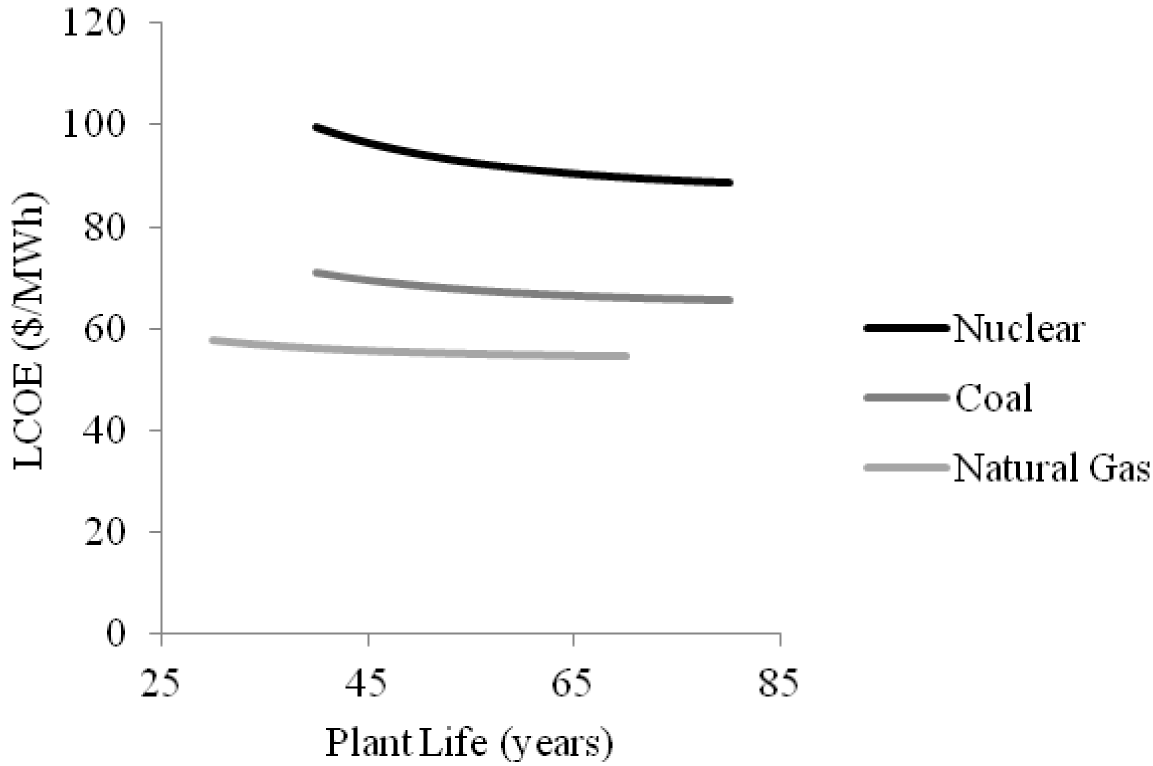

Figure 2.7: Levelized Cost Sensitivity to Plant Life

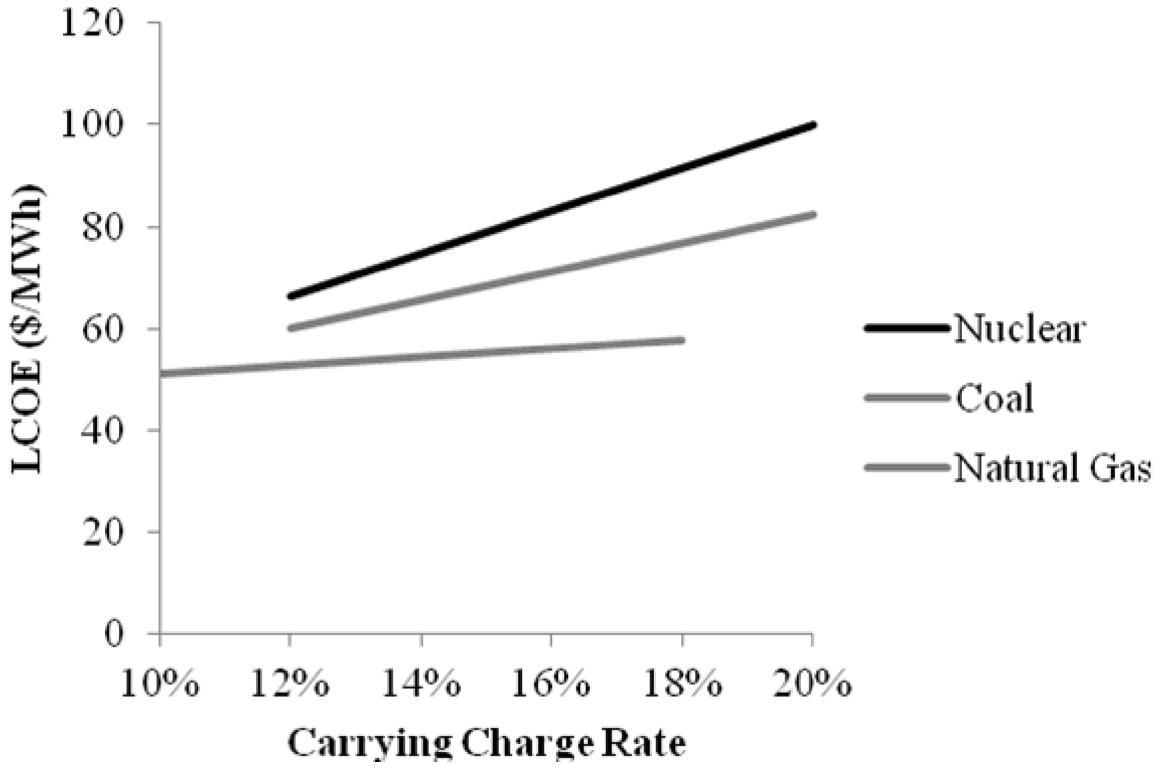

Figure 2.8: Levelized Cost Sensitivity to Carrying Charge Rate

There is a considerable range in both the potential capital cost and the potential fuel costs. Figure 2.9 shows the sensitivity of the levelized cost from nuclear, coal, and natural gas with respect to discounted average fuel costs and capital costs. Capitals costs range from \$3,600 to \$4,600, \$1,500 to \$3,400, and \$600 to 1,500 per KW for nuclear, coal, and natural gas, respectively. The figure indicates that at todays prices, nuclear is more expensive than coal, and coal is more expensive than natural gas. However, the figure also indicates that if both the coal price and the capital cost of a coal-fired power plant are at the upper ranges shown here, electricity from coal can be more expensive than electricity from nuclear power. Also, at sufficiently high natural gas prices and sufficiently low coal prices, electricity from natural gas can be more expensive than electricity from coal.

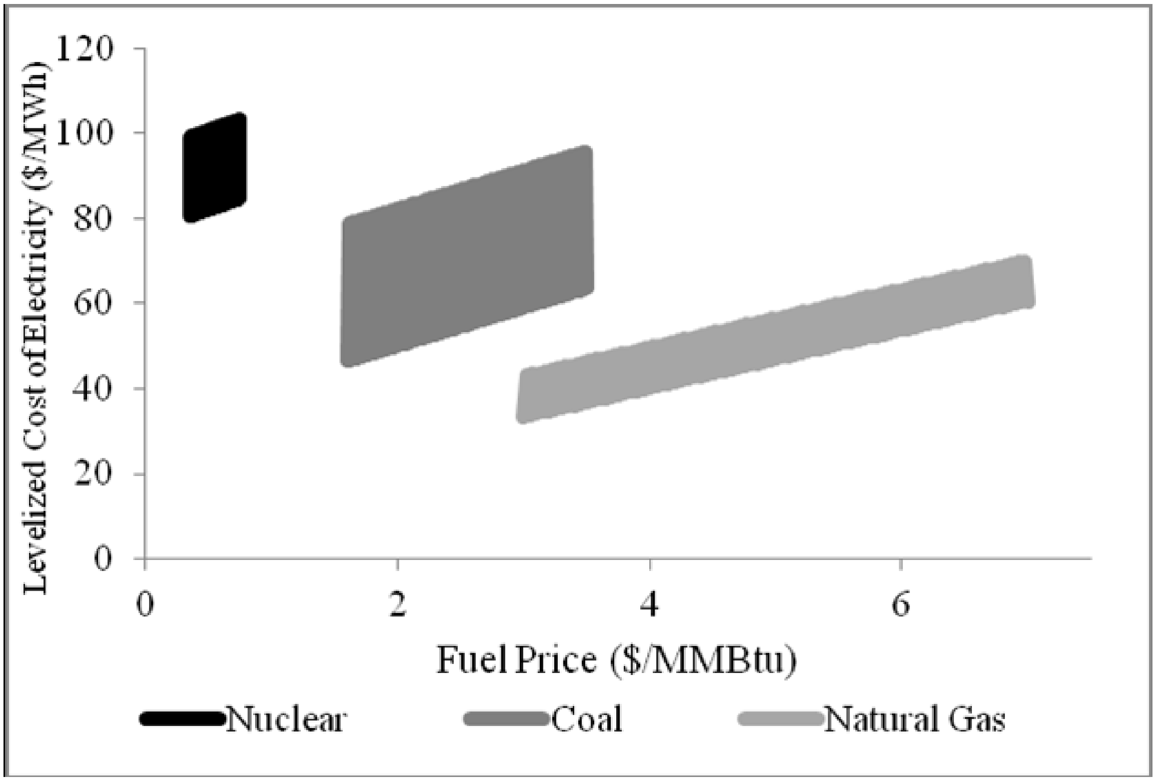

Figure 2.9: Levelized Cost Sensitivity to Capital Cost and Fuel Price

2.6.3 Carbon Dioxide Costs

The production of 1 MWh of electricity results in approximately 1 tonne of CO2-equivalent lifecycle greenhouse gas emissions for coal-fired power plants and approximately 0.57 tonnes for natural gas fired power plants [42]. Although production of electricity from nuclear power results in no net direct emissions of carbon dioxide, the activities required to produce the fuel do result in some small net emissions, on the order of 0.05 tonnes/MWh for nuclear generation. The effect of carbon prices on levelized costs are shown in Figure 2.10, with the ranges reflecting the minimum and maximum reported capital costs.

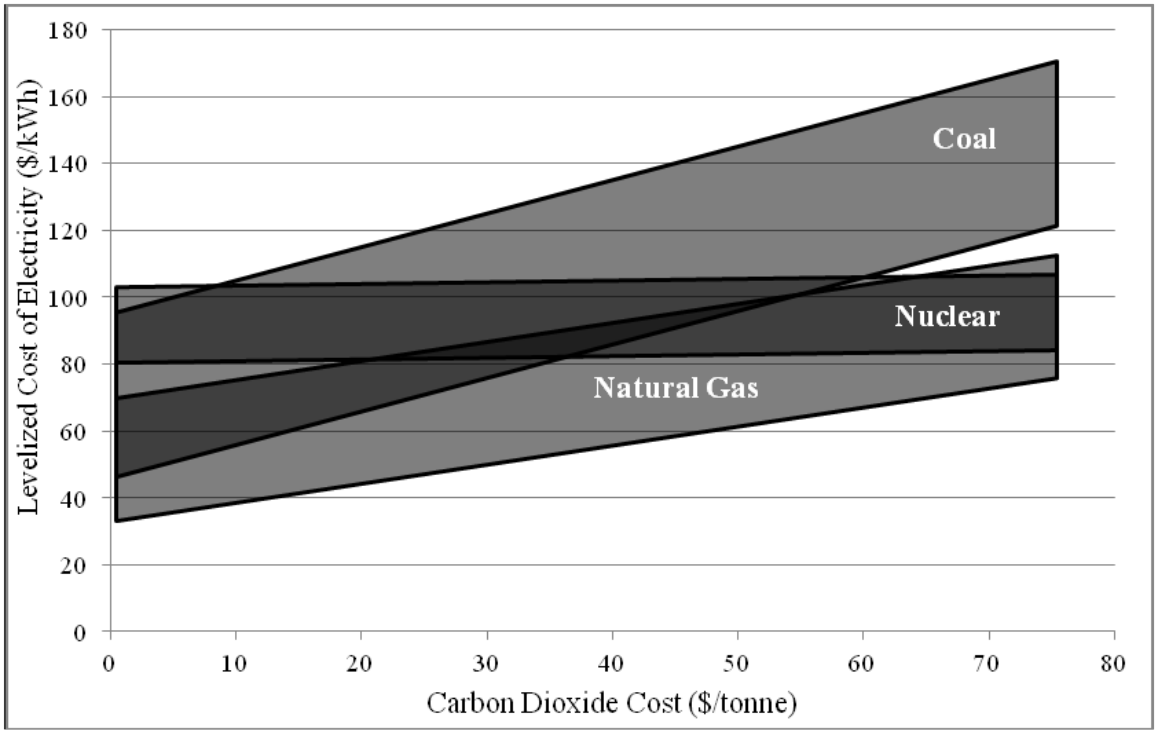

Figure 2.10: Effect of a Cost of Carbon Dioxide on the Levelized Cost of Electricity

Although there is significant range in the cost of all the options, at about $20/tonne of CO2, coal-derived electricity becomes as expensive as nuclear electricity. At about $70/tonne, natural gas derived electricity becomes as expensive as nuclear electricity and coal is more expensive than both nuclear and natural gas electricity. Historically, the price of coal and natural gas have been independent of one another [43].

2.6.4 Comparison with Other Studies

The levelized cost of electricity as reported by other sources is shown in Table 2.6 and Figure 2.11. Transmission costs are excluded where possible. Costs are updated to 2010 dollars using the Consumer Price Index.

Table 2.6: Comparison of Levelized Cost Result to Previous Studies

	Study	Year	Coal	Natural Gas	Nuclear
	NETL[40]	2007	67.0	71.9	–
	MIT[41]	2007	53.4	–	–
	Black & Veatch[29]	2007	73.6	80.0	96.3
	MIT[44]	2009	65.2	68.4	88.3
Levelized Cost ($/MWh)	EPRI[45]	2009	66.8	82.5	85.1
	MIT[46]	2010	60.3	62.5	98.3
	IEA[16]	2010	73.4	77.5	49.4
	EIA[22]	2010	103.3	77.7	109.9
	EIA[47]	2010	95.4	64.9	114.9
	This Study		68	55	91

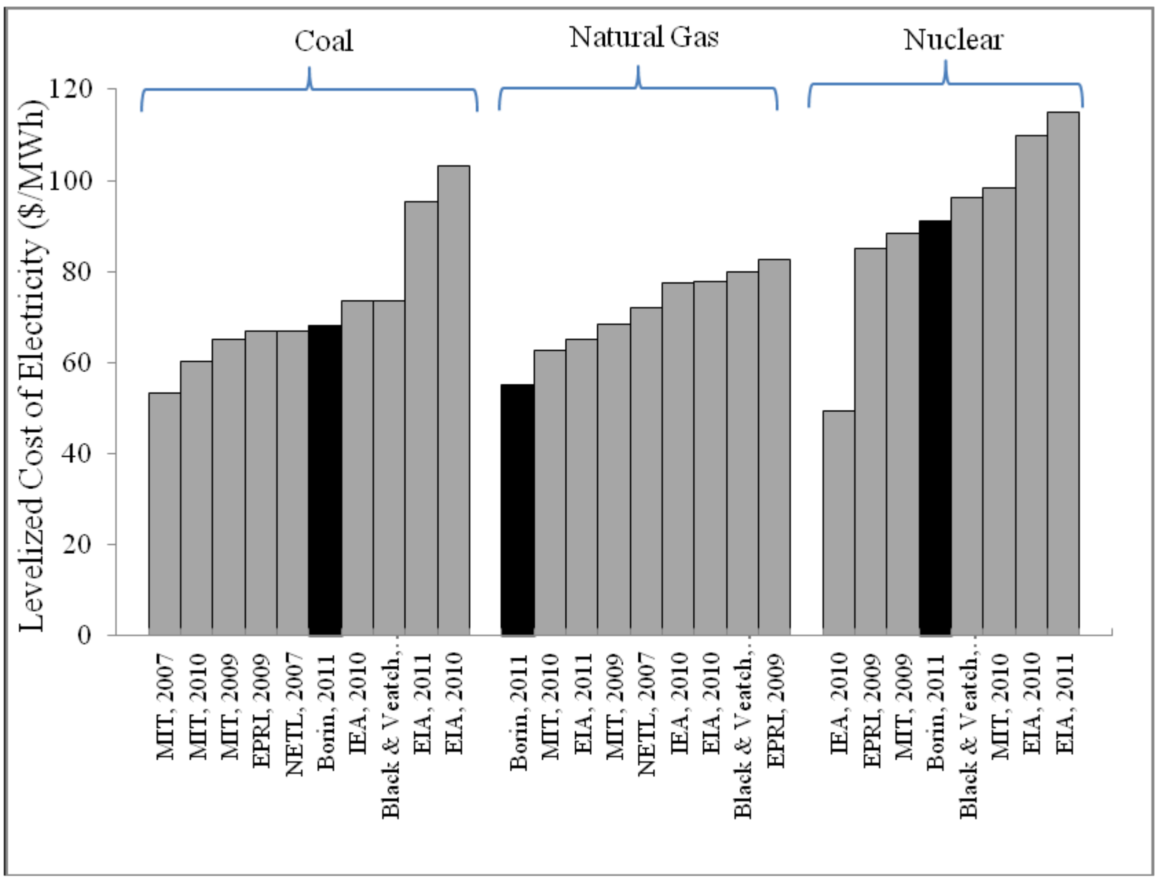

Figure 2.11: Levelized Cost Comparison with Other Studies

The use of the methodology results in levelized cost values that are comparable with values reported by other studies, while avoiding specific projections of future fuel prices and technological change.

2.7 Conclusions

Fuel costs and technology costs will change over time. Cost projections can be credible, and are an important component of decision-making and policy analysis. However, it can also be useful to separate assumptions about future cost changes from the analysis of levelized costs. The methodology presented in this paper provides a straightforward and transparent way to calculate the levelized cost of electricity for various technologies, and is intended as a complement to analyses of expected future price changes. Using publicly-available data for capital costs, and considering discounted average fuel prices with sensitivity analysis allows for technologies to be compared in a straightforward manner. The case study shows that the methodology produces results consistent with other studies while avoiding assumptions about future price changes. The methodology allows for additional costs and externalities to be incorporated with minimal alteration. To provide perspective on fuel prices, we have used historical data to develop a discounted average fuel price; other values, such as the current price or projections of future fuel prices, can be used to develop the discounted average fuel price.

The similarity of the results with other studies suggests that other analyses are in essence assuming that capital costs in the future will be about what they are now, and that future fuel prices will be, in effect, the same as in the recent past. By adopting this somewhat clearer and more explicit approach to calculating levelized electricity costs, the approach developed here could clarify future calculations and provide a basis for understanding how assumptions about future technology and fuel cost changes affect projections of future electricity costs.

CHAPTER 3

MINIMIZING THE COST OF MEETING A CARBON DIOXIDE EMISSIONS TARGET BY SIMULTANEOUS SELECTION OF SUPPLY AND EFFICIENCY

3.1 Introduction

As many governments at local, state, and federal levels seek to lessen their impacts on climate change, carbon dioxide emissions reduction targets are becoming increasingly common. Many of these plans set goals based on a combination of the feasibility and economics of the policies and actions available and the necessary emissions reduction levels identified by the scientific community. This study evaluates the cost of meeting carbon dioxide emssions targets using an electricity generation planning model with simultaneous selection of efficiency investments in order to satisfy consumer service levels and desired emissions targets. Additionally, this model provides the investment magnitudes and timing required to guide the decision-maker down a path to meet the targeted levels.

3.2 Literature Review

Jacobson, et al. examine the technical and econmical feasibility of replacing New York state's current infrastructure with wind, water, and solar energy [48]. They find that this conversion will reduce end-use electricity demand by 37% due to an increase in efficiency gained from not using oil and gas for transportation and heating/cooling. The resulting cost of electricity is estimated to be 4 to 8.8 cents/kWh. When these costs include externalities at 5.7 cents/kWh, the cost is 12 cents/kWh less than fossil fuel generation in 2030.

Bosetti, et al. use a dynamic optimal growth general equilibrium model of the climate, energy, and economic sectors to determine the optimal combination of technical progress and alternative enrgy investment paths to achieve atmospheric carbon dioxide stabilization targets [49]. Equilibrium strategies are found between twelve regions of the world as the result of a dynamic game. They conclude that concentrations of CO_2 can be sustained at levels set by the Intergovernmental Panel on Climate Change's Fourth Assessment Report at reasonible economic costs. This would require significant changes in the energy sector, a large investment in R&D, and the pursuit of energy efficiency and de-carbonization of energy.

Deetman, et al. use the TIMER model of the IMAGE Integrated Assessment modeling framework to analzye specific mitigation options in the industry, transport, and residential sectors [50]. This model focuses on long-term dynamic relationships within the energy system and models energy demand as a function of changes in population, economic activity, and price-induced changes. They use the Power ACE model, which combines a policy-driven diffusion model with optimization techniques, to analyze the power generation sector. The PowerACE-ResInvest model, an agent-based renewable energy investment model, is used to describe the diffusion of technologies. Finally, the full IMAGE model is used to analyze emission reduction options not included in the energy sector. The authors find that GHG emissions can be reduced below European 1990 levels by 2050. Although some of the most tangible measures have a very limited effect, technological advancement and high energy prices in Europe ensure some actions will be already be taken. They note that trade-offs exist between measures within and between sectors. Lastly, they conclude that bottom-up modeling of climate change mitigation options provides a starting point for exploring explicit dynamics and policy choices.

An integer-valued minimax regret analysis method, a hybrid of inverval parameter programming and minimax regret analysis, is proposed for planning greenhouse gas abatement under uncertainty in Li, et al. (2011) [51]. They note that in real world problems, the quality of information is not satisfactory to determine probabilistic specifications for uncertain parameters. They find that the optimal abatement strategy found using this method can reduce the worst regret level of any outcome under an uncertain greenhouse gas abatement targets.

Martinez, et al. (2012) propose a methodology using mixed integer linear programming to select and determine operating loads for electricity generation plants in Argentina to minimize greenhouse gas emissions and operating costs [52]. They compare costs and greenhouse gas emissions when the objective is to minimize greenhouse gas emissions or to minimize costs, but they do not look at these objectives simultaneously.

Costs and emissions are minimized simultaneously in Tekiner, et al. (2010) using a weighted objective function [53]. They find a Pareto frontier for the multi-objective generation expansion planning problem. Then Monte-Carlo simulation is used to generate scenarios for optimal solutions under a weighted objective function. A Pareto frontier is then found by varying these weights.

A multi-stage interval-stochastic integer programming model is used to manage greenhouse gas emissions and plan electric-power systems under uncertainty in Li and Huang (2012) [54]. They perform a case study, suggesting that a greenhouse gas emissions target could be achieved by low-emission energy technologies but at a high cost.

Pacala and Socolow (2004) find a feasible way to lower atmospheric carbon dioxide levels to the stabilizing level of 254 GtC/year [55]. This is accomplished using current technologies through the year 2054. Fifteen options are proposed in two categories: energy efficiency and conservation and decarbonization of electricity and fuels. The energy efficiency and conservation options include improved fuel economy, reduced reliance on cars, and more efficient buildings. The decarbonization options are as follows: substituting natural gas for coal electricity production; storage of carbon captured in power plants, hydrogen plants, and synfuels plants; nuclear fission, wind, and solar photovoltaic electricity; renewable hydrogen and biofuels for vehicles; natural sinks, forest management, and agricultural soils management. They conclude that, as these options are already implemented at industrial scales, they could feasibly be scaled up to reduce carbon dioxide emissions to the desired level. They do not calculate costs for these options.

Williams, et al. (2012) claim that technically feasible levels of energy efficiency and decarbonization of the energy supply are insufficient to reduce California's greenhouse gas emissions levels to 80 percent below 1990 levels [56]. This is likely to be untrue for states with more carbon intense energy and low levels of penetration for energy efficiency such as those in the Southeast.

This study employs an optimization framework to explore the potential for cost reductions under carbon dioxide emissions targets when the electricity generation mix and demand side efficiency investments are chosen simultaneously by a state-level government. Unlike other methods, the electricity generation mix is determined by an electricity generation capacity planning model rather than being established a priori and appended with renewable energy in structured ways. Given this additional flexibility, costs will be no higher than using a more structured method. Additionally, the scope of this study matches a reasonable operational scope. Some methods deal with global-level solutions to the global problem. This approach requires cooperative strategies at macro and micro levels that are difficult to negotiate and enforce. While analyses of this sort allow for high level goal and strategy setting, more localized implementation strategies allow lower levels of government and individuals to act upon realizable, relatively short-term actions that aim toward long-term global progress.

3.3 Model

In this study, we seek to minimimze the total social cost of reaching target emissions levels by choosing the electricity generation mix and the level of investment in efficiency measures to meet consumer service levels. The study focuses on carbon dioxde due to its position as the dominant anthropogenic greenhouse gas.

3.3.1 Parameters and Data

Calculations are based on the period of interest, 2015 to 2050, but the model is run from 2015 to 2085 in order to achieve steady state behavior for latter years. This is necessary due to the annualization of costs, particularly with respect to capital costs. Ten electricity generation technologies, natural gas, and three transportation fuels are considered.

Sets and Indices

T: years in the planning horizon

T_{run}: years in the model run horizon

H: hours per day

S: seasons (winter, summer, and intermediate)

M: sectors (commercial, industrial, residential, and transportation)

I: technologies for electricity generation

L: petroleum transportation fuels (gasoline, diesel, and jet fuel)

r: real discount factor

Demand

$d^{e}_{m,t}$: electricity demand for sector m at time t (MWh)

$d^{ng}_{m,t}$: natural gas demand for sector m at time t (million therms)

$d^{tf}_{l,t}$: transportation fuel demand for fuel l at time t (thousand barrels)

Electricity Capacity

$\widehat{x}_{i,0}$: initial generation capacity for technology i

$\underline{y}_i$: lower bound annual capacity expansion for technology i

$\overline{y}_i$: upper bound annual capacity expansion for technology i

$\widehat{y}^{ret}_{i,t}$: planned retirements for electricity generation technology i at time t

$\widehat{y}^{inst}_{i,t}$: planned installation for electricity generation technology i at time t

τ_i: plant life for technology i

R: reserve margin for capacity during peak demand

Electricity Generation

π_i: maximum annual capacity factor of technology i

$\sigma^{solar}_{i,s,h}$: maximum capacity factor for technology i in season s at hour h

Electricity Supply

ρ_s: seasonal factor for season s

$\mu_{s,h}$: demand factor for season s and hour h

λ_s: maximum hourly demand factor for season s

δ_s: peak demand ratio for season s

θ_s: days in season s

η: electricity reserve margin

Electricity Costs

Electricity costs included in the model are shown below. The variable O&M and fuel costs are dependent upon the heat rate of a specific technology. These are held constant in this formulation but could be varied throughout time as technologies become more efficient or as less efficient plants retire.

f_i^C: annualized capital investment cost of electricity technology i (\$/MW)

f_i^O: fixed cost of O&M (\$/MW)

v_i: variable cost of O&M for technology i(\$/MWh)

$c_{i,t}^e$: cost of fuel for technology i at time t (\$/MWh)

$c_{m,t}^{ng}$: cost of natural gas for sector m at time t (\$/million therms)

$c_{l,t}^{tf}$: cost of transportation fuel l at time t (\$/thousand gallons)

Emissions

The emissions rate is currently held constant throughout time. This could be varied through time if the emissions rates for certain technologies were expected to change due to research and development efforts, governmental policies, or retirement of older, less efficient plants.

ω_i^e: emissions rate for electricity generation technology i

ω^{ng}: emissions rate for natural gas

ω_l^{tf}: emissions rate for transportation fuel l

Efficiency Investments

K_m^e: index for electricity efficiency investment for sector m

K_m^{ng}: index for natural gas efficiency investment for sector m

K_l^{tf}: index for transportation efficiency investment actions for fuel l

$MC_{m,k}^{e}$: marginal cost for electricity efficiency investment in sector m for segment k

$MC_{m,k}^{ng}$: marginal cost for natural gas efficiency investment in sector m for segment k

$MC_{l,k}^{tf}$: marginal cost for transportation fuel efficiency investment in fuel l for segment k

$q_{m,k}^{e}$: efficiency investment available for sector m for investment k (MWh)

$q_{m,k}^{ng}$: efficiency investment available for sector m for investment k (million therms)

$q_{m,k}^{tf}$: efficiency investment (MWh) available for sector l for investment k (MWh)

max_q: maximum annual implementation for efficiency investment (% of total available)

3.3.2 Variables

Decision Variables

$y_{i,t}$: additional capacity for electricity technology i at time t

$b_{i,t}$: binary variable for additional capacity for electricity technolgy i at time t

$z_{i,s,h,t}^{e}$: hourly electricity generation by technology i for season s in hour h at time t

$z_{m,t}^{ng}$: annual natural gas supply for sector m at time t

$z_{l,t}^{tf}$: annual transportation fuel supply for fuel l at time t

$gs_{m,k,t}^{e}$: annual electricity demand in sector m met by efficiency investment $k \in K_m^e$

$gs_{m,k,t}^{ng}$: annual natural gas demand in sector m met by efficiency investment $k \in K_m^{ng}$

$gs_{l,k,t}^{tf}$: annual transportation fuel demand in fuel l met by efficiency investment $k \in K_l^{tf}$

Intermediate Variables

$x^e_{i,t}$: total capacity of technology i at time t

$y^{ret}_{i,t}$: additional capacity constructed by the model and then retired for technology i at time t

$g^e_{m,t}$: annual electricity demand met by efficiency investment in sector m at time t

$g^{ng}_{m,t}$: annual natural gas demand met by efficiency investment in sector m at time t

$g^{tf}_{l,t}$: annual petroleum transportation demand met by efficiency investment for fuel l at time t

TC^e_t: total electricity generation cost at time t

TC^{ng}_t: total natural gas cost at time t

TC^{tf}_t: total transportation fuel cost at time t

$TC^{efficiency}_t$: total cost of demand reduction efficiency investment at time t

$TC^{efficiency,e}_{m,t}$: total cost of demand reduction efficiency investment for sector m at time t

$TC^{efficiency,ng}_{m,t}$: total cost of demand reduction efficiency investment for sector m at time t

$TC^{efficiency,tf}_{l,t}$: total cost of demand reduction efficiency investment for sector m at time t

3.3.3 Objective Function

The goal of the model is to find the least cost for reducing greenhouse gas emissions to target levels. Costs included in this formulation are limited to the cost of supplying the fuel by the producer and the cost of investments in efficiency programs and policies. This does not include costs such as the purchase of new equipment by the consumer corresponding to implemented policies and programs, energy efficiency premiums paid by the consumer, health impacts resulting from the decisions made, or macroeconomic costs including job creation and loss.

Accounting for energy efficiency costs can be particularly complex due to the dispersion of costs across the government, suppliers, and consumers. Costs for energy efficiency fall into four categories: financial incentives; information and technical assistance; program administration; and capital. Financial incentives include subsidies, rebates, tax credits, low-interest loans, and loan guarantees. These are attributable to the cost of energy efficiency investments, as the incremental cost of the investment relates directly to the energy saved. Information and technical assistance may be needed to disseminate and promote the policies, which could account for a significant portion of the costs. Program administration costs may be difficult to estimate, as the resources needed may be shared among differing programs. Lastly, capital is required to begin most ventures and thus the cost of acquiring and holding the capital should be included, although this is typically not the case. Where possible, all four categories of costs should be included in the cost of energy efficiency in order to provide fair comparisons to supplying energy services (Brown and Wang 2015) [57].

The objective function is shown in Equation 3.1.

$$\text{minimize} \quad \sum_{t} \left(TC_t^{e} + TC_t^{ng} + TC_t^{tf} + TC_t^{efficiency} \right) \cdot r^t \tag{3.1}$$

where

$$
\begin{aligned}
TC_t^e = &\quad \sum_i \left[f_i^C \cdot \left(x_{i,t}^e + q_{i,t}^{e,inst}\right) + f_i^O \cdot x_{i,t}^e\right] + \left(v_i + c_{i,t}^e\right) \cdot \sum_{i,s,h} \left(\theta_s * z_{i,s,h,t}^e\right) && \forall t \\
TC_t^{ng} = &\quad \sum_m \left(c_{m,t}^{ng} \cdot z_{m,t}^{ng}\right) && \forall t \\
TC_t^{tf} = &\quad \sum_l \left(c_{l,t}^{tf} \cdot z_{l,t}^{tf}\right) && \forall t \\
TC_t^{efficiency} = &\quad \sum_m TC_{m,t}^{efficiency,e} + \sum_m TC_{m,t}^{efficiency,ng} + \sum_l TC_{l,t}^{efficiency,tf} && \forall t
\end{aligned}
\tag{3.2}
$$

3.3.4 Constraints

Electricity Capacity

Electricity generation may not be installed in year 0, as these are already incorporated into planned installations, $\widehat{y}_{i,t}^{inst}$. Thus the total unplanned installed is zero at time 1. Total capacity for any year is equal to previous total capacity, minus planned retirements, plus planned and chosen installations.

$$
\begin{aligned}
x_{i,0} &= \widehat{x}_{i,0} + y_{i,0} + \widehat{y}_{i,0}^{inst} - \widehat{y}_{i,0}^{ret} && \forall i \\
x_{i,t} &= x_{i,t-1} + y_{i,t} - y_{i,t}^{ret} + \widehat{y}_{i,t}^{inst} - \widehat{y}_{i,t}^{ret} && \forall i, t = 1 \ldots T \\
y_{i,t}^{ret} &= y_{i,t-\tau_i} && \forall i, t = \tau_i \ldots T \\
y_{i,t} &\geq b_{i,t} \cdot \underline{y}_i \forall i, t \\
y_{i,t} &\leq b_{i,t} \cdot \overline{y}_i \forall i, t
\end{aligned}
\tag{3.3}
$$

Electricity Generation

$$
\begin{aligned}
z_{i,s,h,t}^e &\leq x_{i,t}^e \cdot \pi_{i,s,h} && \forall i, s, h, t \\
\sum_{s,h} z_{i,s,h,t}^e \cdot \theta_s &\leq \pi_i \cdot x_{i,t} * \sum_s \theta_s \cdot H && \forall i, t
\end{aligned}
\tag{3.4}
$$

Supply

Electricity demand must be met on an hourly basis and the maximum capacity must be sufficient to meet peak demand for every season for electricity and year for natural gas and transportation fuels.

$$\begin{aligned}
\sum_i z^e_{i,s,h,t} &\geq \frac{\rho_s \cdot \mu_{s,h}}{\theta_s} \sum_m \left(d^e_{m,t} - g^e_{m,t}\right) && \forall s,h,t \\
\sum_i \left(\pi_i \cdot x_{i,t}\right) &\geq \frac{\rho_s \cdot \lambda_s \cdot \delta_s}{\theta_s R} \sum_m \left(d^e_{m,t} - g^e_{m,t}\right) && \forall s,t \\
\sum_m z^{ng}_{m,t} &\geq \sum_m \left(d^{ng}_{m,t} - g^{ng}_{m,t}\right) && \forall t \\
z^{tf}_{l,t} &\geq d^{tf}_{l,t} - g^{tf}_{l,t} && \forall l,t
\end{aligned} \tag{3.5}$$

Energy Efficiency Investment Constraints

The investments in efficiency are calculated below.

$$\begin{aligned}
TC^{efficiency,e}_{m,t} &= \sum_k \left(gs^e_{m,k,t} \cdot MC^e_{m,k}\right) && \forall m,t \\
TC^{efficiency,ng}_{m,t} &= \sum_k \left(gs^{ng}_{m,k,t} \cdot MC^{ng}_{m,k}\right) && \forall m,t \\
TC^{efficiency,tf}_{l,t} &= \sum_k \left(gs^{tf}_{l,k,t} \cdot MC^{tf}_{l,k}\right) && \forall l,t
\end{aligned} \tag{3.6}$$

The total level of investment in efficiency for each source and sector is calculated below.

$$\begin{aligned}
g^e_{m,t} &= \sum_k gs^e_{m,k,t} && \forall m,t \\
g^{ng}_{m,t} &= \sum_k gs^{ng}_{m,k,t} && \forall m,t \\
g^{tf}_{l,t} &= \sum_k gs^{tf}_{l,k,t} && \forall l,t
\end{aligned} \tag{3.7}$$

Efficiency investments do not have hourly load profiles in this formulation. By including hourly load profiles for each investment, there is potential to decrease the variation in the supply needed throughout the day. This would potentially lead to lower peaks, which would require less capital investment for the installation of infrastructure. Specifically for electricity, less generation capacity would need to be installed to meet the same annual demand.

Since cost functions and demand met with efficiency are annualized, we require that they be nondecreasing as a percentage of the total demand. Thus we do not allow the percentage of demand met with investment in efficiency for any year to be less than that of the preceding years.

$$\begin{aligned} g^{e}_{m,t} &\geq g^{e}_{m,t-1} \cdot \left(\frac{d^{e}_{m,t}}{d^{e}_{m,0}} \right) \quad \forall m, t \\ g^{ng}_{m,t} &\geq g^{ng}_{m,t-1} \cdot \left(\frac{d^{ng}_{m,t}}{d^{ng}_{m,0}} \right) \quad \forall m, t \\ g^{tf}_{l,t} &\geq g^{tf}_{l,t-1} \cdot \left(\frac{d^{tf}_{l,t}}{d^{tf}_{l,0}} \right) \quad \forall l, t \end{aligned} \tag{3.8}$$

Efficiency measures cannot be implemented to its maximum level in a single year even if the full investment were made. Since these costs are annualized, efficiency investments are constrained by a maximum implementation for all years. In the first year, efficiency implementation is limited by the maximum. In following years, the annual increase must be less than the maximum percent implementation. Given sufficient data, this could be incorporated into the model explicitly for each efficiency investment across all periods or for each specific period rather than as a general parameter.

$$\begin{aligned}
gs^{e}_{m,k,t} &\leq max_g \cdot q^{e}_{m,k} && \text{for } t = 0 \\
gs^{ng}_{m,k,t} &\leq max_g \cdot q^{ng}_{m,k} && \text{for } t = 0 \\
gs^{tf}_{m,k,t} &\leq max_g \cdot q^{tf}_{l,k} && \text{for } t = 0 \\
gs^{e}_{m,k,t} - gs^{e}_{m,k,t-1} &\leq max_g \cdot q^{e}_{m,k} && t = 1 \dots T \\
gs^{ng}_{m,k,t} - gs^{ng}_{m,k,t-1} &\leq max_g \cdot q^{ng}_{m,k} && t = 1 \dots T \\
gs^{tf}_{m,k,t} - gs^{tf}_{m,k,t-1} &\leq max_g \cdot q^{tf}_{l,k} && t = 1 \dots T
\end{aligned} \tag{3.9}$$

Emissions Target Constraints

The emissions target set by the Climate Action Plan is enforced below.

$$\sum_{i,s,h,t} \left(\omega^{e}_{i} \cdot z^{e}_{i,s,h,t}\right) + \omega^{ng} \cdot \sum_{m} z_{m,t} + \sum_{l} \left(\omega^{tf}_{l} \cdot z^{tf}_{l,t}\right) \leq E_t \quad \forall t \tag{3.10}$$

3.3.5 Solution Time

Using the Gurobi solver in a Python environment on a business-grade laptop, the fully constrained model solves in approximately 90 seconds. Relaxing the carbon dioxide target constraint reduces the solution time to less than 15 seconds.

3.4 Conclusion

Here we have developed a framework that will allow for both the assessment of the cost of a carbon dioxide emissions cap and a model that shows the timeline and investment path that will make it achievable. This framework is similar to other optimization-driven decision models and is able to encompass the nuances of studies using scenario-based emissions targets. This framework contrasts with assessments built around technical and economic feasibility independent of one another. This approach would be particularly useful in situations where the scope of the decision-maker extends into the electricity generation sector, although the general philosophy - that of using a precise objective function to establish best alternatives within large sets of possibilities - is useful in many circumstances that exist within and beyond the example presented herein.

Behavioral effects for consumers are not taken into account in the model. In particular, rebound effects, both direct and indirect, are not accounted for in the model. As production decreases, the marginal cost of supplying electricity decreases. Should this translate into decreased prices to consumers, price effects are likely to lead to increased consumption of energy and income effects may lead to the purchase of additional products requiring energy. The extent to which these actually effect savings from energy efficiency remains a subject of disagreement (Brown and Wang 2017) [58]. The model also assumes that demand response at a macro level has been already taken into account and that effects at a state level will not cause significant disruption. One possible area of further research is including this, as shown in Choi (2012) [59]. These realities are partially incorporated by using data inputs from models such as the National Energy Modeling System (NEMS) which incorporates the rebound and macroeconomic effects.

The models assumes that all decisions are made at the current point in time using deterministic forecasts. In reality, a high level of uncertainty is present in forecasts for demand and prices, and the horizon for which decisions must be made is likely to be less than the full time horizon of the model. In its present form, the model would need to be run with the updated future expectations for each period when a decision is to be made as demand and prices are realized. The model lends itself well to a few extensions that address these issues. One possibility is to use Monte Carlo simulation to extend the problem into the realm of stochastic optimization. In this setting, uncertainty would be introduced into the model by sampling from distributions of inputs. This makes particular sense for future costs and demands. The set of outcomes and their accompanying decisions would then be analyzed to lead to a decision that fits the modelers desired objective, such as minimizing the maximum cost of achieving a carbon dioxide emissions target. A second option is to incorporate a rolling horizon approach where decisions made in each period consider the current state of the system and forecasts for the time horizon needed for making decisions in that period. The previous two extensions could be combined to incorporate both the Monte Carlo simulation as well as the rolling horizon, incorporating both the uncertainty in forecasts and the horizon for which decisions must be made at each point in time. One additional extension would be using mutli-stage dynamic programming, whereby each periods decision would be dependent the expected optimal solutions for future periods, as shown in Shapiro (2007) [60].

Brown and Wang (2017) note a growing appreciation for designing energy efficiency technologies and systems around the types of service, as opposed to linking them directly to the energy source [58]. Another interesting extension would be to flex this model to become driven by service types, such as thermal comfort, productivity, lighting, mobility, nutrition, and entertainment. In this setting, energy services and efficiency would be an input to consumer service demands.

CHAPTER 4

CASE STUDY - UNITED STATES STATE OF GEORGIA

4.1 Introduction

In this chapter, the model developed in Chapter 3 is applied to the United States state of Georgia. The selection of this state was based on previous work with the City of Atlanta Office of Sustainability in developing a Greenhouse Gas Emissions Inventory and Climate Action Plan for the city. For the situation outlined, we find that carbon dioxide emissions for Georgia could feasibly be reduced to 40% of 2015 emissions by 2050 at a net present value cost savings of 17.5% relative to the business-as-usual baseline scenario. The actual cost of meeting the carbon dioxide target is effectively 4% above the total cost of the scenario where efficiency investments are utilized in the absence of a carbon dioxide target.

4.2 Scenarios

In order to provide bounds for the cost of the Climate Action Plan, three scenarios are run: business as usual (BAU) without efficiency actions or a target, efficiency investment without a carbon target, and efficiency investment with a carbon target. An annual discount rate of 5% is used in all scenarios.

4.3 Data and Inputs

4.3.1 Demand

EIA data are used for Georgia's energy consumption for each source and sector. Projections are from the EIA's Annual Energy Outlook 2016 Reference Case Scenario for the South Atlantic Region in Supplemental Table 3.5 which runs from 2015 to 2040 [61]. These values were normalized to 2014 levels and then scaled by 2014 consumption for Georgia from the EIA's State Energy Data System (SEDS) [62]. In years 2040 to 2085, growth rates from 2015 to 2040 are used to extrapolate the projections. These values are shown in Figures 4.1, 4.2, and 4.3 for electricity, natural gas, and transportation fuels, respectively. The figures show only the period of interest rather than the entire run length of the model.

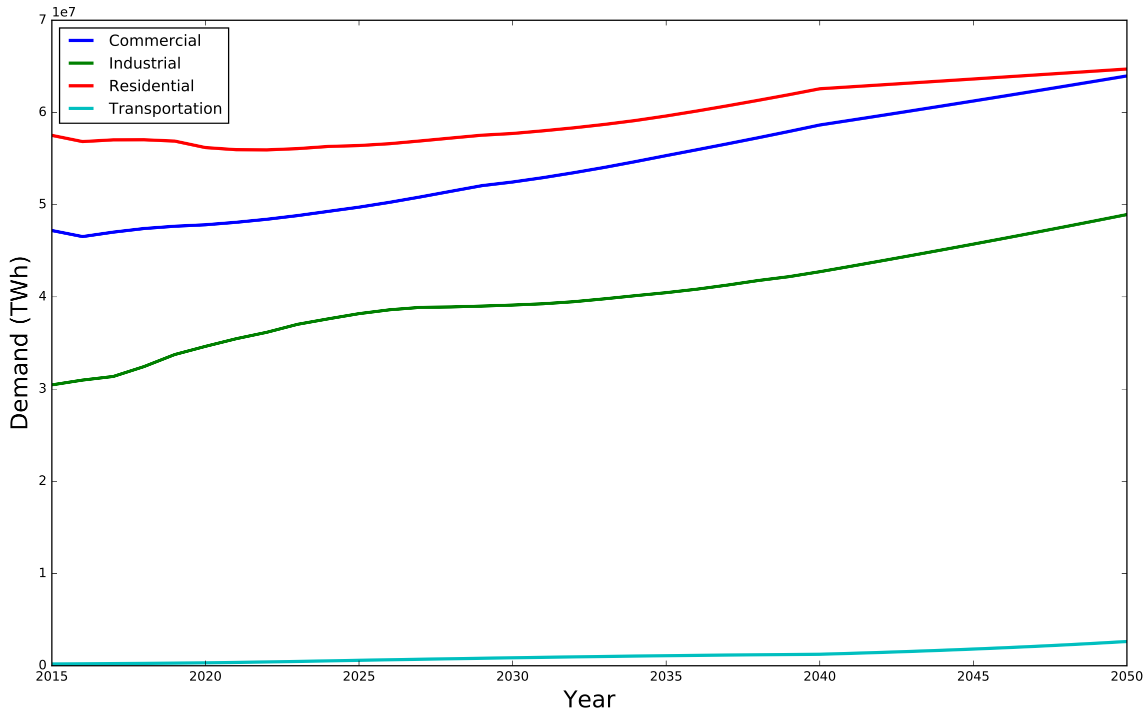

Figure 4.1: Projected Electricity Demand for the U.S. State of Georgia, Based on EIA Projections(MWh)

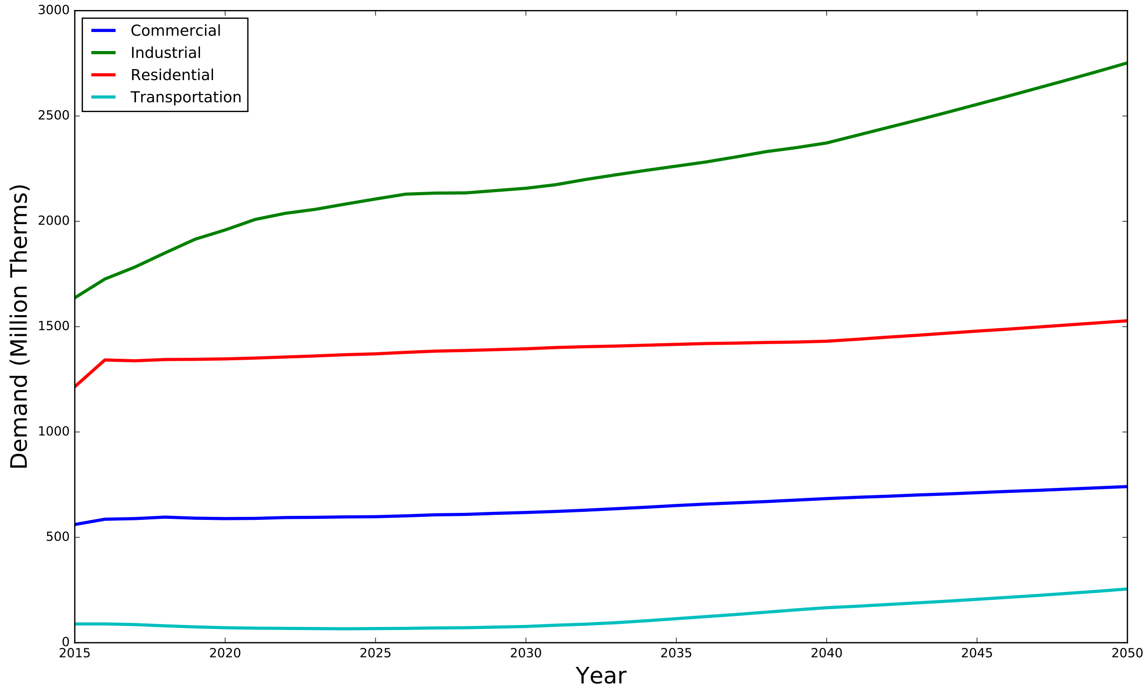

Figure 4.2: Projected Natural Gas Demand for the U.S. State of Georgia, Based on EIA Projections(MMTherms)

Table 4.1: 2014 Electricity and Natural Gas Demand for Georgia [62]

Sector	Electricity (GWh)	Natural Gas (MMTherms)
Commercial	46,608	609
Industrial	31,849	1,660
Residential	57,167	1,387
Transportation	16.5	84

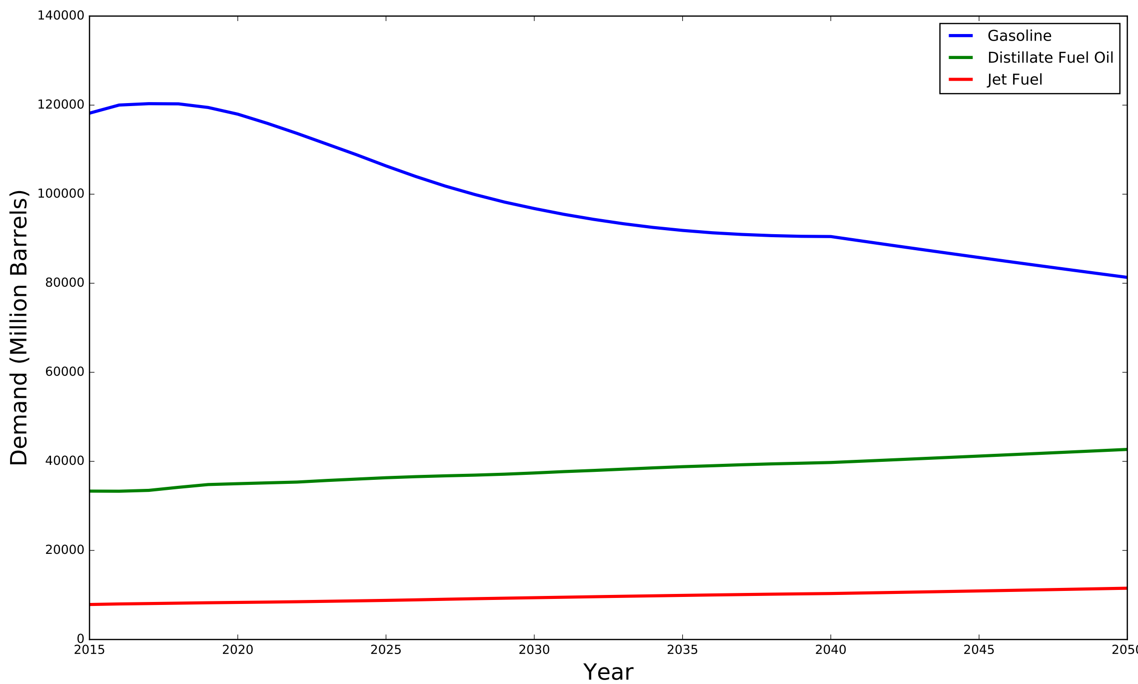

Figure 4.3: Projected Transportation Fuel Demand for the U.S. State of Georgia, Based on EIA Projections (Thousand Barrels)

Table 4.1 shows Georgia's 2014 consumption of electricity and natural gas, and Table 4.2 shows Georgia's 2014 consumption of transportation fuels. Figures 4.4, 4.5, and 4.6 show demand projections normalized to 2014 consumption for electricity, natural gas, and transportation fuels, respectively.

Table 4.2: 2014 Transportation Fuel Consumption for Georgia [62]

Sector	**Thousand Barrels**
Gasoline	116,590
Diesel	32,050
Jet Fuel	7,806

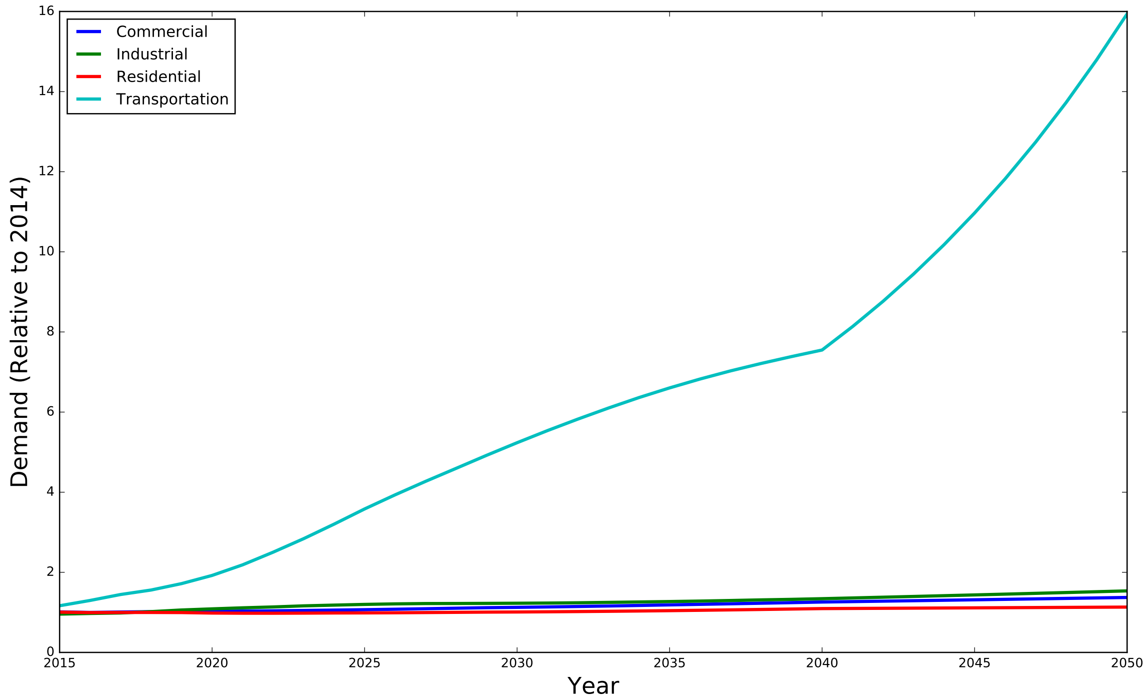

Figure 4.4: Electricity Demand Projections Normalized to 2014, Based on EIA Projections

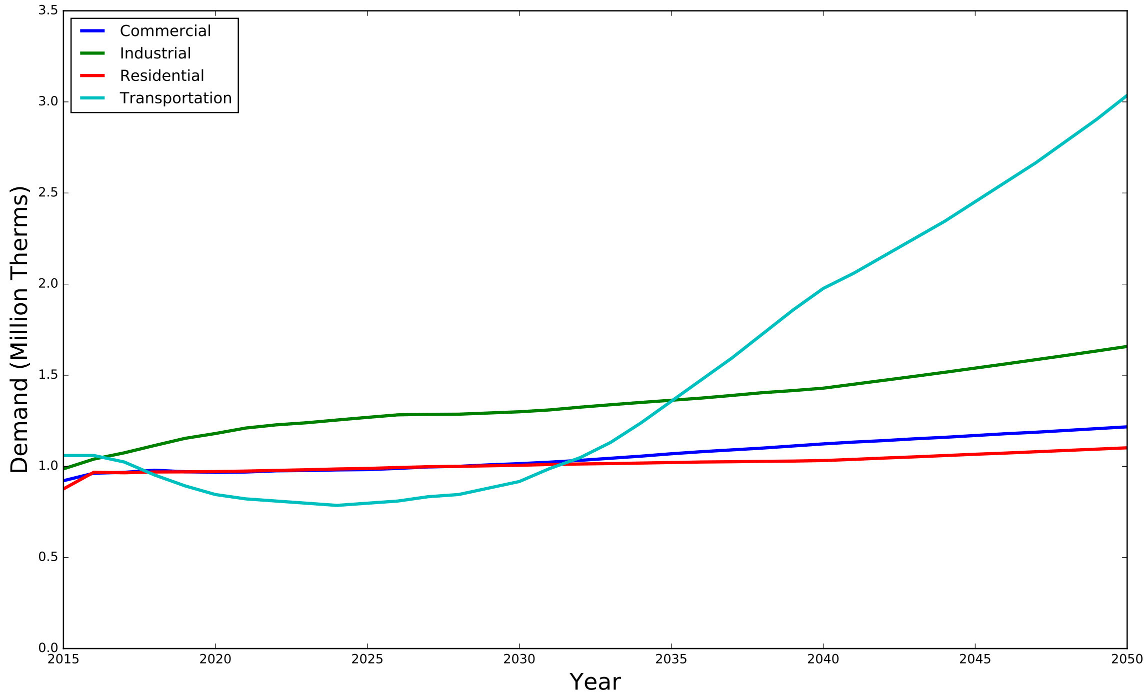

Figure 4.5: Natural Gas Demand Projections Normalized to 2014, Based on EIA Projections

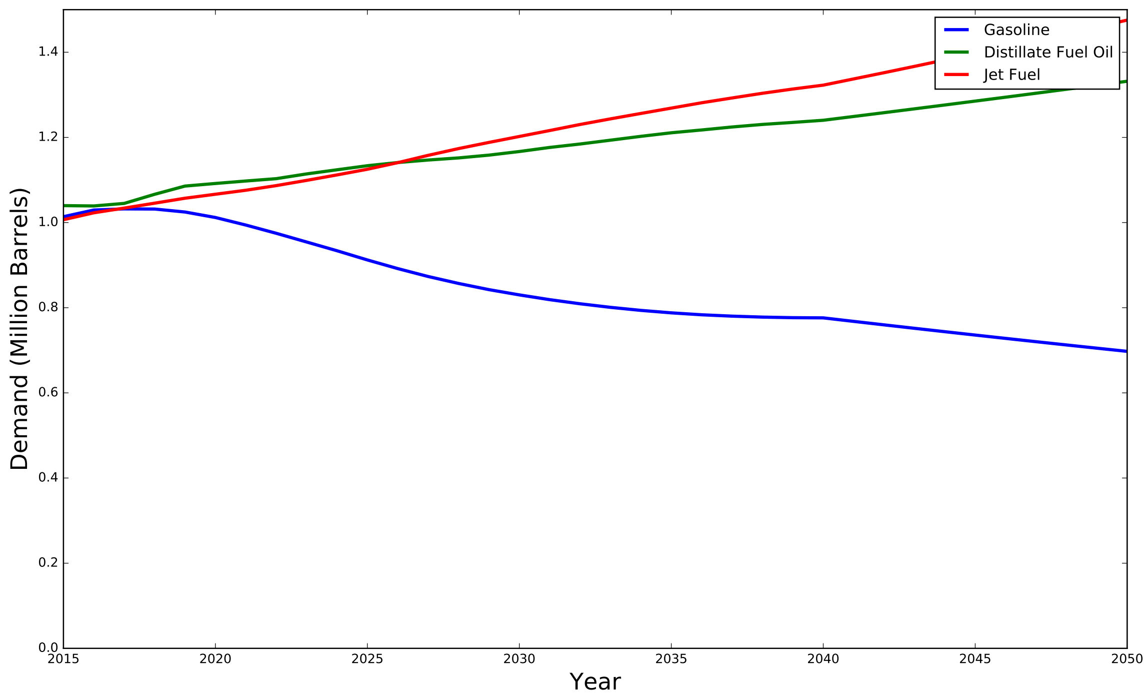

Figure 4.6: Transportation Fuel Demand Projections Normalized to 2014, Based on EIA Projections

4.3.2 Initial Electricity Generation Capacity

The initial electricity generation capacity of each technology is based on data from the US Environmental Protection Agency's eGRID2012, which uses 2012 data [63]. The initial capacities used in this analysis are shown in Table 4.3.

4.3.3 Electricity Generation Capacity Factor

Maximum capacity factors by fuel type are from Borin et. al (2010) as shown in Table 4.4 [64]. Solar hourly capacity factors are used from Choi and Thomas (2012) [59].

Table 4.3: Electricity Capacity Generation in Georgia, 2015

Technology	Initial Capacity(MW)
Coal	14,782
Nuclear	4,042
Natural Gas	17,512
Hydro	3,354
Wood Waste Solids	147
Oil	1,230
Landfill Gas	27
Biomass	632
Solar	11
Wind	0

Table 4.4: Capacity Factor by Generation Technology in Georgia

Technology	Capacity Factor
Coal	0.85
Nuclear	0.89
Natural Gas	0.85
Hydro	0.44
Wood Waste Solids	0.80
Oil	0.85
Landfill Gas	0.50
Biomass	0.85
Solar	0.20
Wind	0.30

4.3.4 Electricity Generation Capacity Expansion and Demand Factors

Although generation decisions in this model are made at the annual level, one must account for the variation of demand throughout the day and across seasons. Hourly demand factors are the percentage of daily demand associated with each hour and are used to ensure sufficient capacity is available at peak consumption times. Seasonal demand factors account for the percentage of demand occurring in each season in order to ensure, along with the hourly demand factor, that sufficient generation capacity is available at peak consumption. For this study, three seasons are used: winter, summer, and intermediate. A representative day from each season is segmented into 24 one hour periods. Lower and upper bounds on capacity expansion, as shown in Table 4.5, and seasonal and hourly demand factors, shown in Table 4.6 and Figure 4.7, are based on 2006 hourly load data from Georgia Power [65]. Biomass and wind capacity expansion are capped at 9 GW and 3 GW, respectively.

Table 4.5: Capacity Bounds by Generation Technology

Technology	Lower Bound (MW, Annual)	Upper Bound (MW, Total)
Coal	500	-
Nuclear	1000	-
Natural Gas	250	-
Hydro	0.1	2565
Wood Waste Solids	0.1	58
Oil	0.1	-
Landfill Gas	0.01	45
Biomass	10	2800
Solar	1	-
Wind	2	1000

Table 4.6: Seasonality and Demand Factors [65]

Season	Seasonality Factor	Days (Annually)	Maximum Demand Factor	Peak Ratio
Winter	0.24	90	0.047	1.27
Summer	0.48	153	0.050	1.23
Intermediate	0.28	122	0.046	1.25

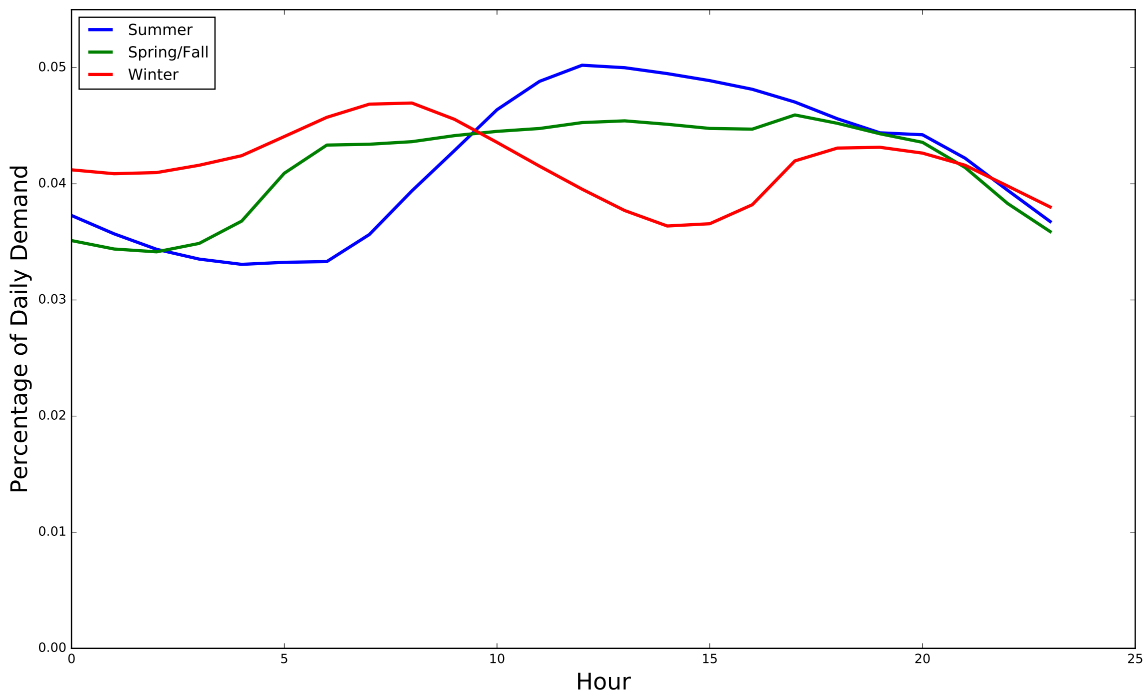

Figure 4.7: Hourly Demand Factor - Percentage of Consumption Occurring Each Hour by Season [65]

4.3.5 Fixed Electricity Costs

Capital costs are from the EIA's Annual Energy Outlook 2016 as shown in Table 4.7 [61] annualized at a 5% discount rate using plant lifespans shown in 4.8.

Table 4.7: Annualized Capital Costs by Generation Technology [61]

Technology	Capital Cost (2015$/MW/year)
Coal	58,995
Nuclear	322,675
Natural Gas	62,189
Hydro	120,630
Wood Waste Solids	70,060
Oil	62,189
Landfill Gas	553,653
Biomass	70,060
Solar	199,002
Wind	106,945

Table 4.8: Plant Lifespans by Technology

Generation Technology	Plant Life (Years)
Coal	50
Nuclear	60
Natural Gas	30
Hydro	150
Wood Waste Solids	30
Oil	30
Landfill Gas	30
Biomass	30
Solar	20
Wind	30

Fixed O&M costs are from the EIA's Annual Energy Outlook 2016 as shown in Table 4.9 [61]. Wood waste solids are assumed to have the same costs as natural gas combined cycle.

Table 4.9: Fixed O&M Costs by Generation Technology [61]

Technology	Fixed O&M Cost (2015 $/MW/Year)
Coal	17,120
Nuclear	98,110
Natural Gas	10,760
Hydro	14,700
Wood Waste Solids	10,760
Oil	10,760
Landfill Gas	403,970
Biomass	108,630
Solar	21,330
Wind	45,980

4.3.6 Variable Electricity Costs

Variable O&M costs are from the EIA's Annual Energy Outlook 2016 as shown in Table 4.10 [61]. Wood waste and biomass are assumed to have the same variable O&M cost as coal, and oil and landfill gas are assumed to have the same variable O&M cost as natural gas combined cycle. Heat rates, which directly effect the variable O&M and fuel costs, are assumed to be constant throughout time.

Table 4.10: Variable O&M Costs by Generation Technology (2015 $/MWh)[61]

Technology	Variable O&M Cost (2015 $/MWh)
Coal	3.42
Nuclear	2.25
Natural Gas	3.42
Hydro	2.62
Wood Waste Solids	3.42
Oil	3.42
Landfill Gas	9.00
Biomass	3.42
Solar	0.0
Wind	0.0

4.3.7 Fuel Costs

Fuel costs for electricity generation technologies are shown in Figure 4.8. Coal, natural gas, and distillate fuel oil prices for the electricity sector are from the EIA's Annual Energy Outlook 2016 Reference Case Scenario [61]. The average cost growth rate from 2015 to 2040 is used for years beyond 2040. The heat rates for coal, combined cycle natural gas, oil, and biomass are 9,800, 6,600, 9,960, and 13,500 Btu/kWh, respectively, from the Assumptions to the Annual Energy Outlook 2016 [66]. Nuclear prices per MWh are from Borin, et al. (2010) [64].

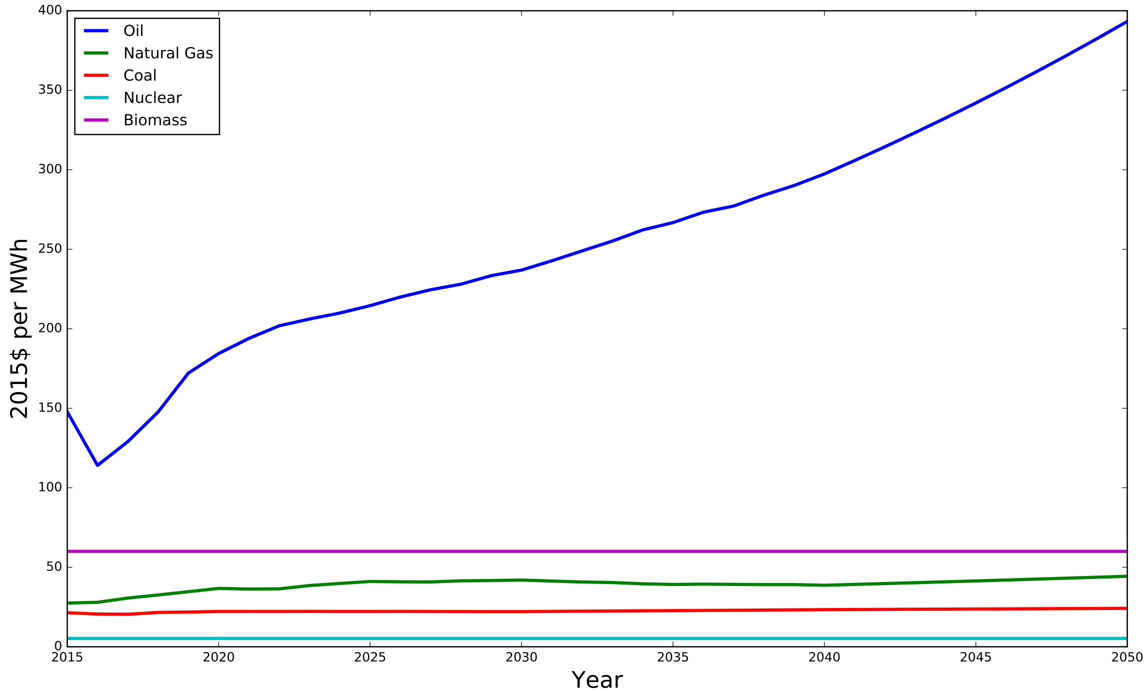

Figure 4.8: Fuel Costs for Electricity for the U.S. State of Georgia, Based on EIA Projections ($2015/MWh)

Feedstock availability and prices for biomass generation in Georgia are aggregated from Levin et. al (2011) [67]. The marginal and average costs per MMBtu are adjusted to 2015 dollars using the United States Bureau of Labor Statistics Consumer Price Index, as shown in Figure 4.9 [68]. For this analysis, the cost of biomass fuel over time is held constant at $4.45/MMBtu, or $60/MWh.

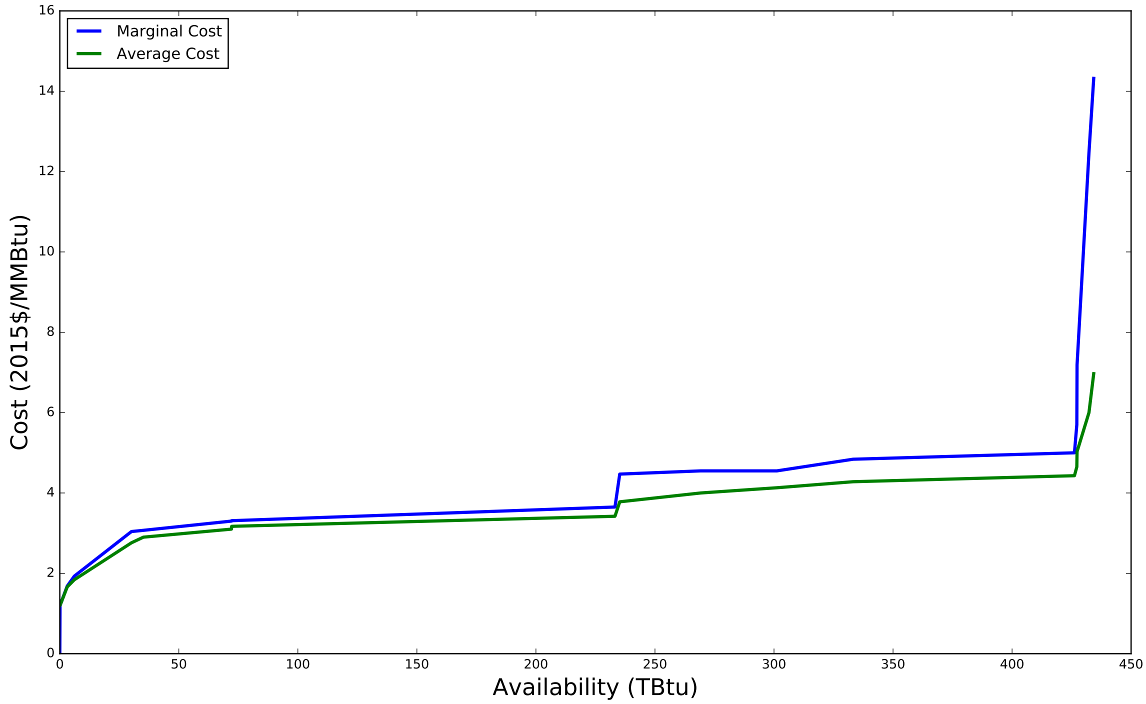

Figure 4.9: Biomass Feedstock Costs for the U.S. State of Georgia, Based on Levin et. al (2011) [67]

Natural gas and transportation fuel price forecasts by sector are from the EIA's Annual Energy Outlook 2016 as shown Figures 4.10 and 4.11 [61]. The average growth rate from 2015 to 2040 is used for years beyond 2040.

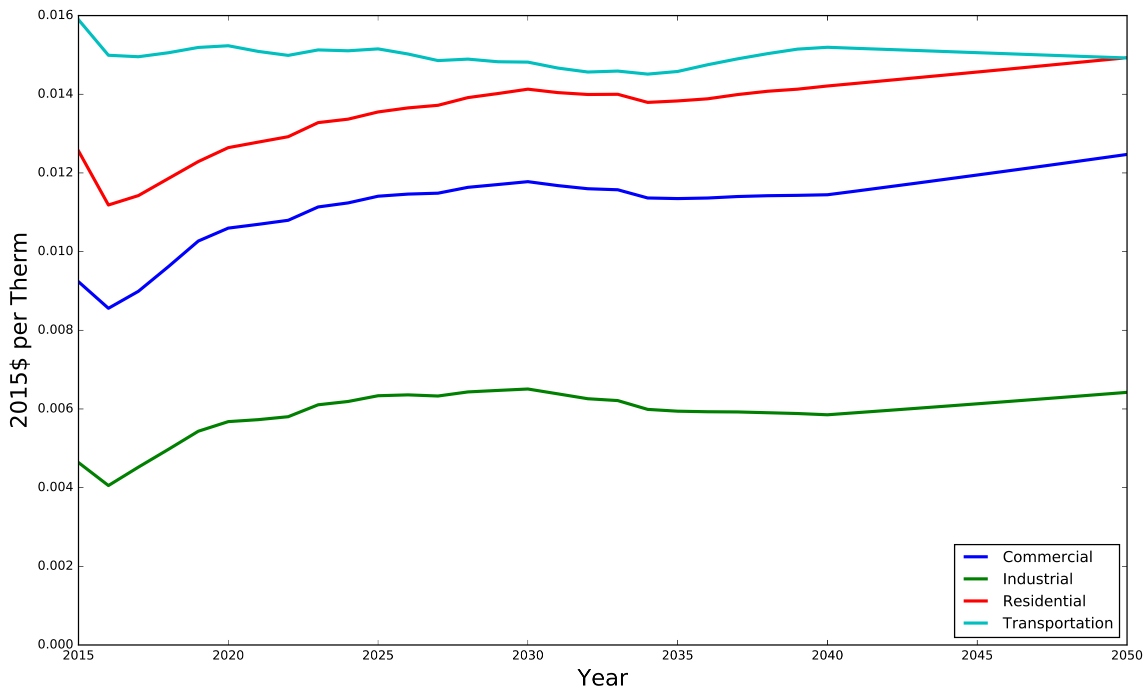

Figure 4.10: Natural Gas Costs for the South Atlantic Region, Based on EIA Projections [61]

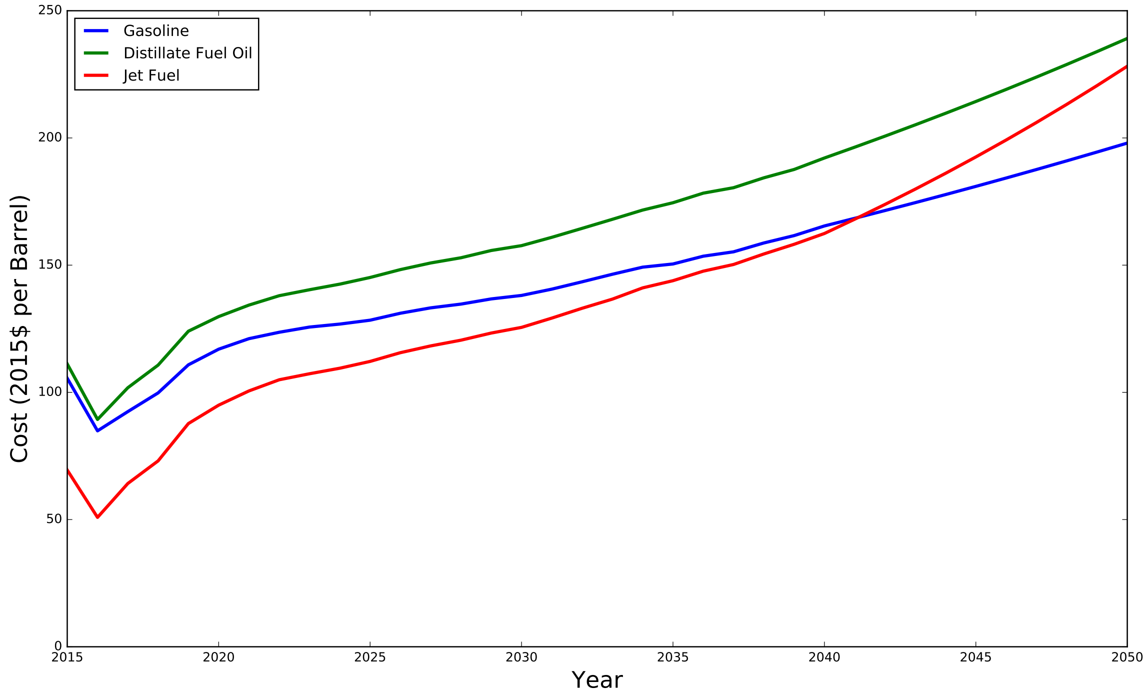

Figure 4.11: Transportation Fuel Costs for the South Atlantic Region, Based on EIA Projections [61]

4.3.8 CO_2 Emissions Rates

Emissions rates for technologies used are from eGRID 2012 [63]. Net emissions rates for nuclear, hydro, wood waste solids, landfill gas, biomass, and solar generation are assumed to be negligible.

Table 4.11: CO_2 Emissions Rates by Generation Technology [63]

Technology	Emissions Rate (tonnes/MWh)
Coal	1.141
Natural Gas	0.442
Oil	0.805

4.3.9 Efficiency Measures

A significant issue in modeling efficiency investments is the availability of demand that can be met with efficiency and the associated costs. Efficiency costs and quantities have been developed using the best available sources. Fuel switching is not included in the model but, given sufficient data on the substitutability and system dynamics of the sources, could be incorporated into the model without. In future work, this could be incorporated into the model without updating the base structure of the model.

Literature Review

Much work has been done to quantify costs and availability of efficiency investments, particularly for electricity programs.

Researchers at Lawrence Berkeley National Laboratory have analyzed estimates of energy efficiency programs funded by customers of investor-owned utilities to establish the full cost of saving electricity [69]. They find the average cost for the U.S. to be \$0.046 per kWh, as shown in Table 4.12 with ranges shown in Figure 4.12. The total cost includes program administrator costs and participant costs. Lost revenue recovery and performance incentives for the program administrator, participant transaction costs, and tax credits were excluded from the study. Programs for Georgia are not available in the report. Figure 4.13 shows the reported total levelized cost of saved energy for North Carolina and South Carolina, the two states geographically closest to Georgia, to be \$0.041 per kWh.

Table 4.12: Savings-weighted average total cost of saved electricity at the national level by market sector [69]

Sector	Total Cost of Saved Electricity (2012$/kWh)	Program Administrator Cost of Saved Electricity (2012$/kWh)	Participant Cost of Saved Electricity (2012$/kWh)
All Sectors	$0.046	$0.023	$0.022
Residential	$0.033	$0.019	$0.014
Commercial, Industrial, and Agricultural	$0.055	$0.025	$0.030
Low Income	$0.142	$0.134	$0.008

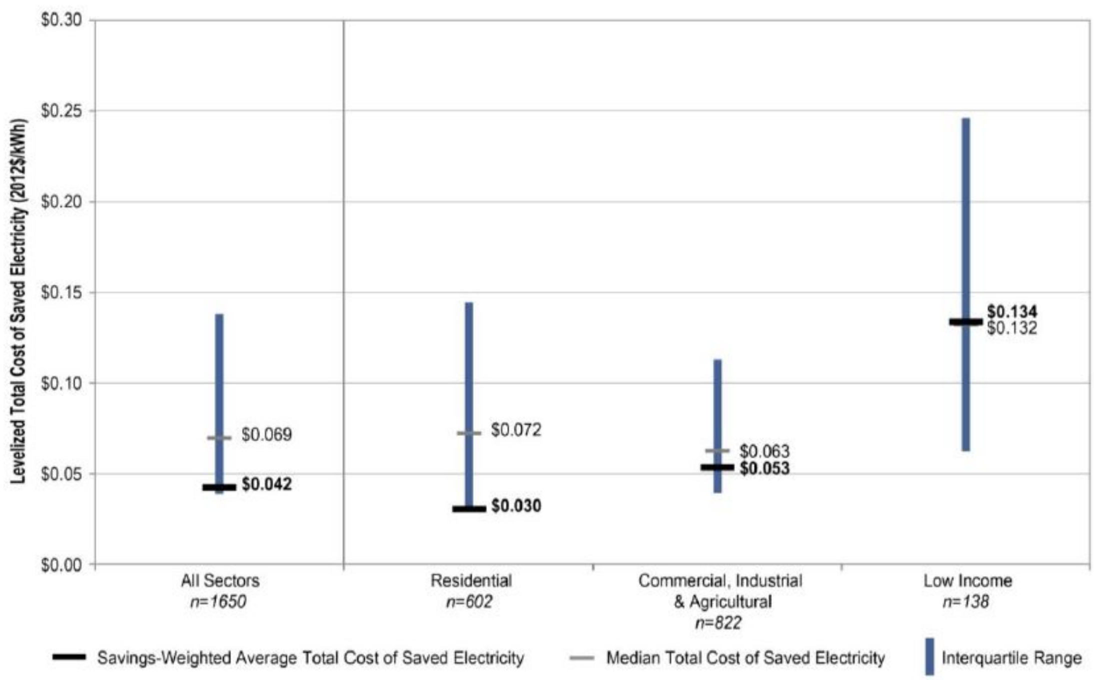

Figure 4.12: Savings-weighted average, median and interquartile range of total cost of saved electricity values for all sectors. Only programs with claimed savings are included. [69]

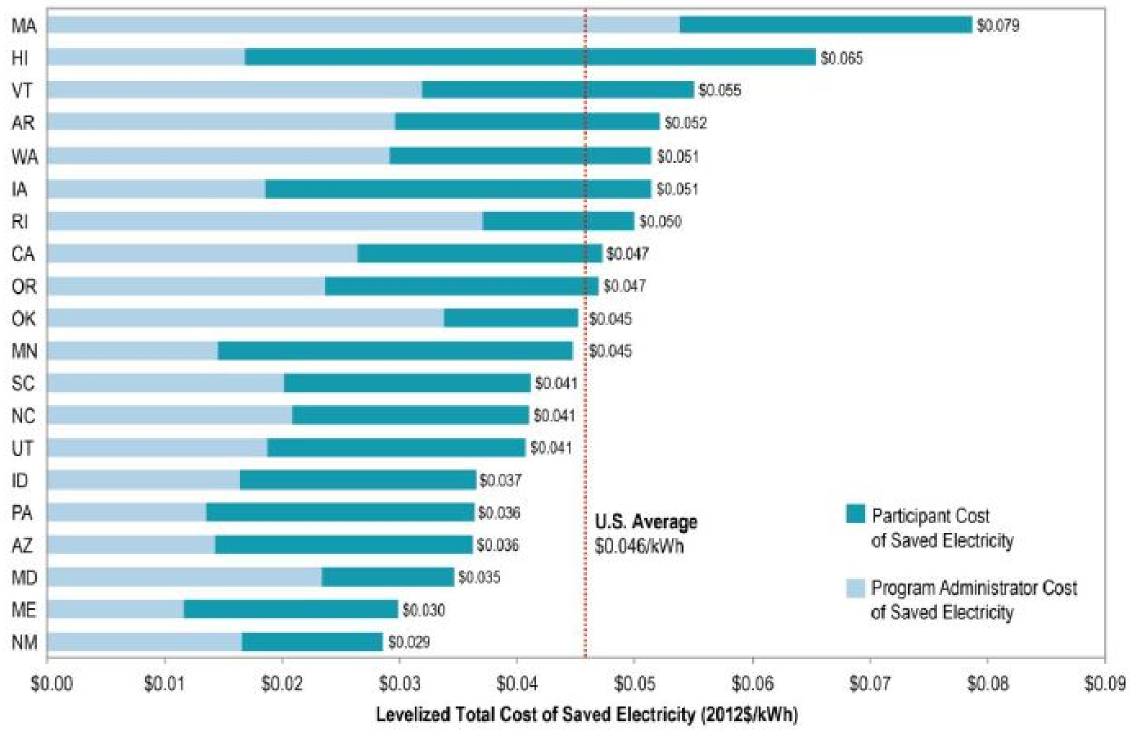

Figure 4.13: Savings-weighted average total cost of saved electricity, by state [69]

Methods for assessing the costs of energy efficiency programs are presented in Southworth and Fox (2015) [70]. This supports use of the levelized cost of energy efficiency as a means to establish the least cost path to meeting emissions regulations, including the U.S. Clean Power Plan. In order to demonstrate the levelized cost methodology, they report the cost of saved energy as shown in Table 4.13. The costs are calculated based on utility spending and savings as reported in energy efficiency dockets filed with the state Public Service Commissions for each year.

In Billingsley, et. al (2014), the authors focus on the savings and costs to program administrators for energy efficiency programs [71]. Since these are not total costs, they are not directly applicable to the model presented here, but these values can serve as a lower bound on the cost of energy efficiency. Table 4.14 shows these values for electricity efficiency programs, and Table 4.15 presents values for natural gas efficiency programs. They

Table 4.13: LCSE for Select Southeastern Utilities, 2011-2013 (2011$) [70]

Utility	Levelized Cost of Saved Energy		
	2011	2012	2013
Entergy Arkansas	$0.03	$0.03	$0.03
LG&E/KU(projected)	$0.02	$0.02	$0.03
Tennessee Valley Authority	$0.02	$0.02	$0.02
Duke Energy Carolinas	$0.01	$0.01	$0.01
Gulf Power	$0.04	$0.03	$0.02

Table 4.14: The program administrator CSE for electricity efficiency programs by sector: national savings-weighted average [71]

Sector	Levelized CSE (6% Discount) ($/kWh)	Levelized CSE (3% Discount) ($/kWh)	Lifetime CSE ($/kWh)	First Year CSE ($/kWh)
Commerical & Industrial (C&I)	$0.021	$0.018	$0.015	$0.188
Residential	$0.018	$0.016	$0.014	$0.116
Low Income	$0.070	$0.059	$0.049	$0.569
Cross Sectoral/Other	$0.017	$0.014	$0.012	$0.120
National CSE	$0.021	$0.018	$0.015	$0.162

conclude that program administrator costs account for roughly one-third to one-half of the total costs associated with energy efficiency programs. Participant costs were available for a limited number of programs and are shown in order to provide the total resource cost. Due to the small sample size and uncertainty in how the costs were derived, the total resource costs are presented for illustrative purposes only.

In 2016, Nadel of the American Council for an Energy-Efficiency Economy updated a

Table 4.15: The program administrator CSE for natural gas efficiency programs by sector: national savings-weighted averages ($/therm) [71]

Sector (Natural Gas)	Levelized CSE (6% Discount) ($/therm)	Levelized CSE (3% Discount) ($/therm)	Lifetime CSE ($/therm)	First Year CSE ($/therm)
C&I	$0.17	$0.14	$0.11	$1.61
Residential	$0.56	$0.43	$0.32	$6.44
Low Income	$0.59	$0.47	$0.36	$6.26
Cross Sectoral/Other	$1.78	$1.55	$1.34	$12.37
National CSE	$0.38	$0.31	$0.24	$3.93

previous report published in 2012 to assess opportunities for decreasing 2050 U.S. energy use [72]. Nadel finds that the energy efficiency measures considered in the study could reduce energy use by 34% by 2040, reducing carbon dioxide emissions by 35%. Savings were largest in the transportation, commercial, industrial, and residential sectors.

Wang and Brown (2014) provides estimates for the economically achievable potential for the availability of electricity end-use efficiency and the associated levelized costs using GT-NEMS for the entire United States of America [73]. In this study, the authors focus on assessing policies rather than technologies with resultant costs ranging from 0.005 to 0.081 $/kWh. They report a total savings of 0.45% per year, while other studies cited range from 0.36% to 2.26% per year, with an achievable energy efficiency potential of 10.2% in 2035. The savings potentials and LCOE's by policy are shown in Table 4.16. The supply curve generated by these potentials and costs is shown in Figure 4.14. Since the authors assess policies, the scope of the decision-maker fits well with the framework presented in this paper. Having reported their results directly as levelized costs, these values provide a direct fit with the parameters required for the model presented here.

Table 4.16: Savings potential and LCOE by policy [73]

Policy	Electricity efficiency potential (TWh) in 2020	Electricity efficiency potential (TWh) in 2035	LCOE* (cents/kWh)
Residential			
Appliance incentives	17.6	35.5	6.7-8.0
On-bill financing	20.2	33.4	6.6-7.4
Building codes	27.0	51.0	0.5-0.8
Aggressive appliance policy	23.4	59.2	0.6-0.7
Market priming	136.9	164.1	2.7-3.6
Commercial			
Financing	22.6	82.6	7.8-8.1
Building codes	11.1	46.3	3.4-4.6
Benchmarking	44.3	107.0	0.9-1.4
Industrial			
Motor standard	8.4	12.3	2.4-3.9
Plant and technology upgrade	7.6	21.7	3.0-4.8
CHP incentives	33.4	39.3	1.5-2.3

*The ranges for levelized costs result from discounting private cost at different rates, 7 and 3%. For details of the levelized cost calculation, see Appendix of [73].

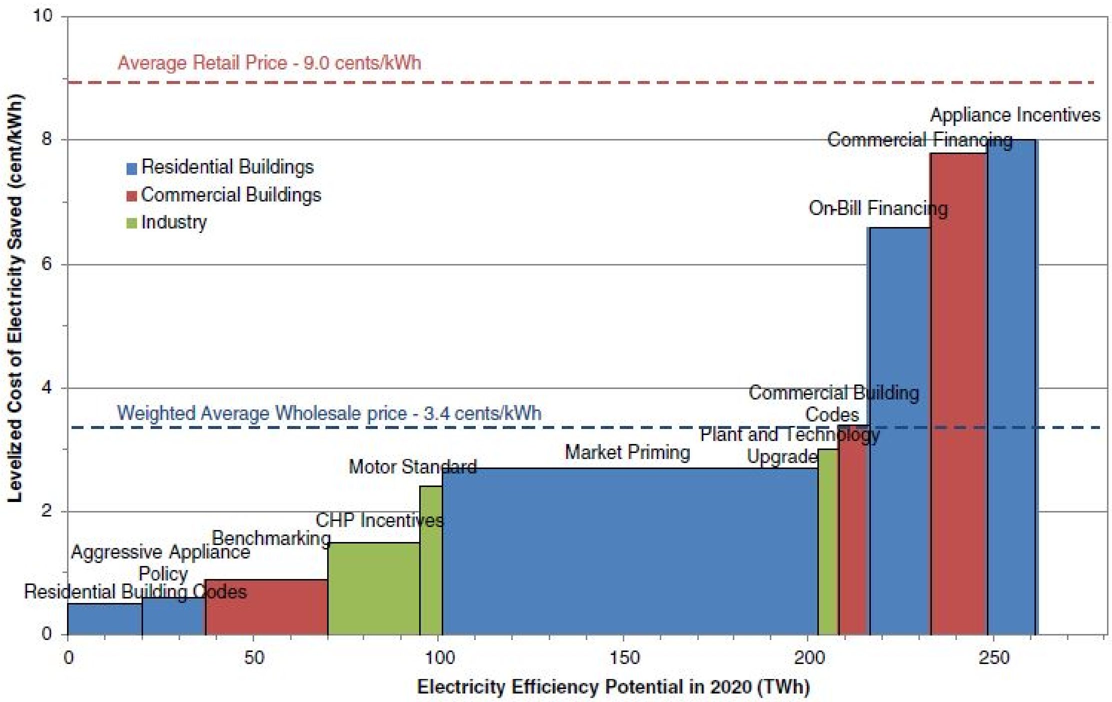

Figure 4.14: Supply curve for electricity efficiency resources in 2020. The weighted average wholesale price is derived from the Intercontinental Exchange data which reports price and volume information for daily transactions among the 10 largest hubs in the USA[73]

As part of their Certified Demand-Side Management Programs Report, Georgia Power reported costs and savings for residential and commercial demand-side management programs [74]. Table 4.17 is adapted from this filing.

Mary Shoemaker at the American Council for an Energy Efficient Economy confirmed that additional energy efficiency resource analyses specific to the state of Georgia or the southeast were not available in the public realm [75].

Baatz, et. al (2016) reviews fourteen leading electricity efficiency program administrators [76]. They find the levelized cost of saved energy (LCSE), equivalent to cost measure used in this study, to have been flat since 2010. This supports use of levelized cost for efficiency investments developed since 2010. Figure 4.15 shows the levelized cost of saved

Table 4.17: 4Q 2015 Summary [74]

Program Name	YTD Savings (Million kWh)	YTD Costs (Million $)	Cost/kWh
Lighting	16.6	$1.3	$0.08
Appliance	6.9	$1.8	$0.26
Refrigerator Recycling	17.2	$2.4	$0.14
New Homes	7.3	$3.6	$0.49
Home Energy Improvements	12.7	$9.5	$0.75
Residential Programs	**60.7**	**$18.6**	**$0.31**
Custom Incentive	235.4	$11.5	$0.05
Prescriptive Incentive	42.0	$6.4	$0.15
Small Commercial	10.2	$2.4	$0.23
Commercial Programs	**287.7**	**$20.3**	**$0.07**
Total	**348.3**	**$38.9**	**$0.11**

electricity from 2007 to 2014. Figure 4.16 shows that the LCSE does not inherently increase when the total savings increase for savings percentages in a range of of roughly 0.8% to 1.8%.

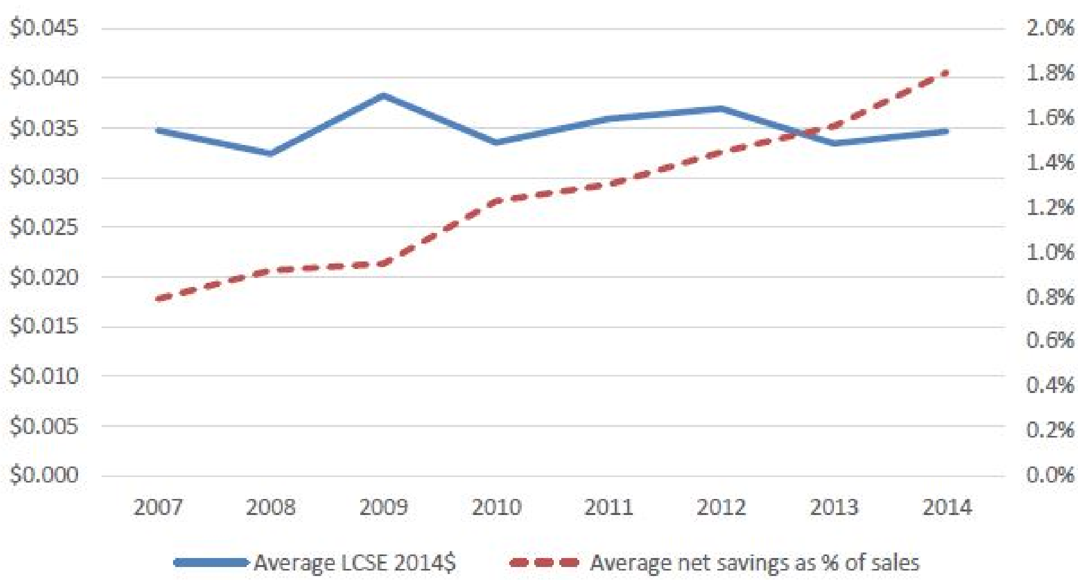

Figure 4.15: Annual average value of LCSE at portfolio level for the United States in 2014 dollars, and average net energy savings as percentage of sales [76]

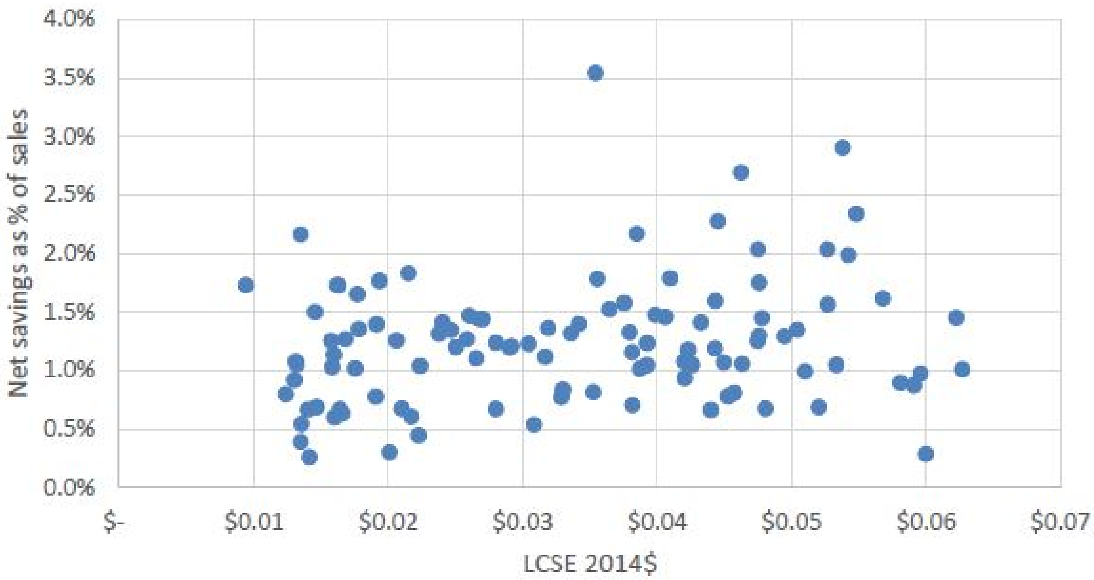

Figure 4.16: All sector LCSE values for the United States relative to electric savings as a percentage of sales [76]

In Molina (2014), the costs and cost effectiveness of utility energy efficiency programs for 20 states from 2009 to 2012 are shown [77]. Electricity and natural gas efficiency programs are reported to have an average cost of $0.028/kWh and $0.35/therm, respectively. Figure 4.17 and Table 4.18 shows the range of costs reported. None of the states included in the study are located in the southeastern United States. The author finds only a very weak correlation between the cost of saved electricity and energy savings levels, which implies that costs may not increase substantially as investments in electricity efficiency increase from currently observed levels. Savings as a percentage of retail sales is shown in Figure 4.18. The weak correlation between the cost of saved electricity and energy savings holds for a range of roughly 0.25% to 2.6% of the total retail sales.

Table 4.18: Summary of results for four-year averages (2009-2012) for all states in dataset [77]

	Electricity program ($/kWh)	Natural gas programs ($/therm)
Average	$0.028	$0.35
Median	$0.026	$0.37
Minimum	$0.016	$0.10
Maximum	$0.048	$0.59

2011$ per levelized net kWh or therm at meter. 5% real discount rate. Each state's four-year average is a distinct data point. The complete data set for individual years has lower minimum and higher maximum values.

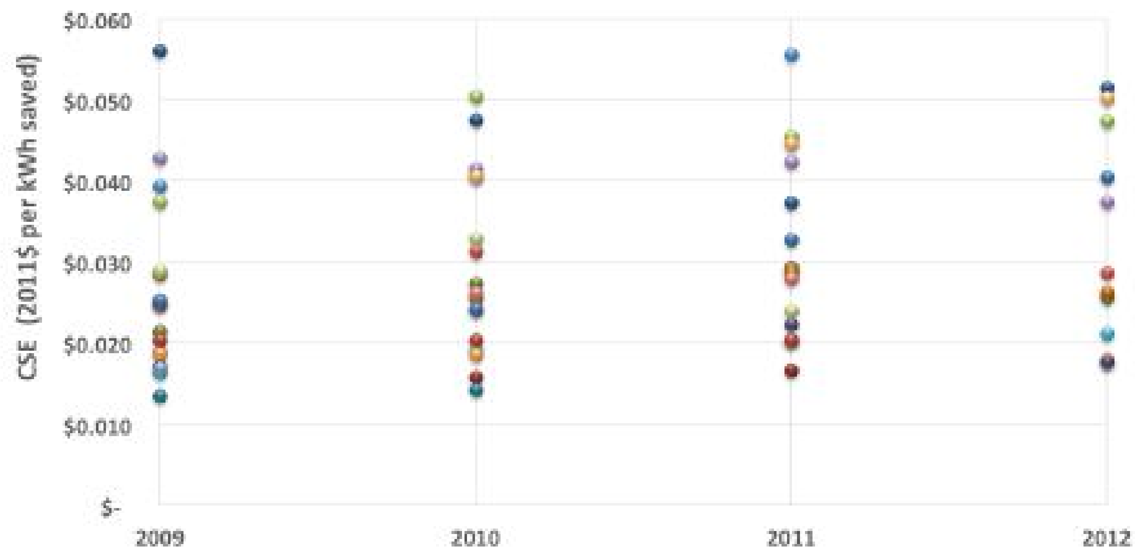

Figure 4.17: Electricity energy efficiency program CSE by year. Each dot represents average costs for each state in a given year. 2011$ per levelized net kWh at meter. Assumes 5% real discount rate [77]

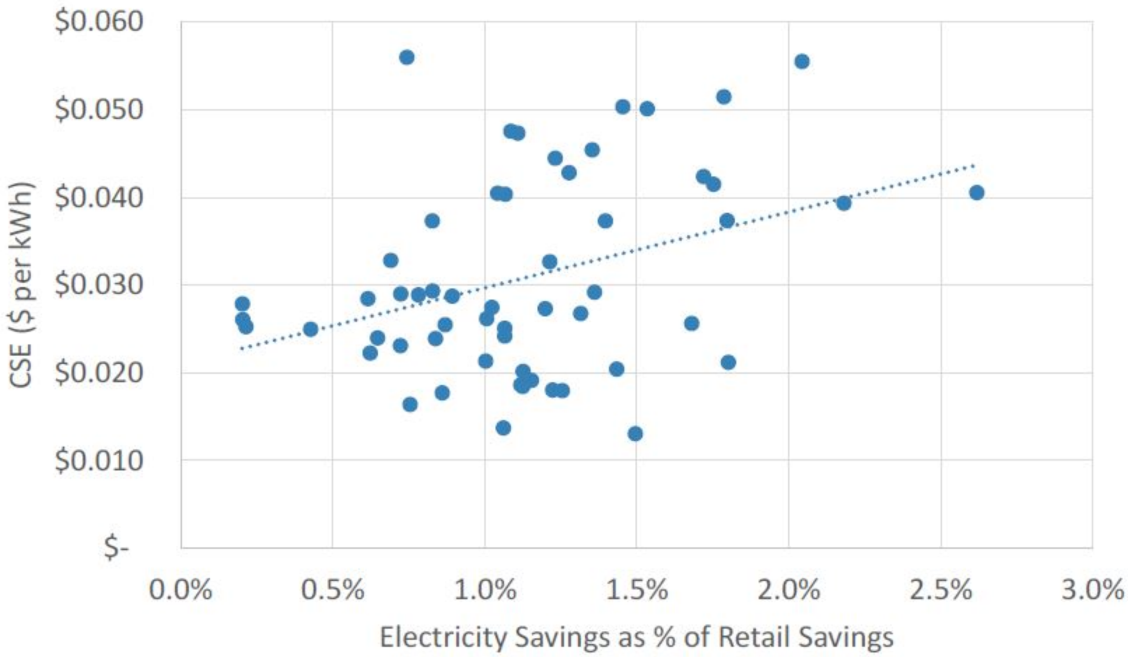

Figure 4.18: CSE values relative to electricity savings as a percentage of sales [77]

The values used in this study for efficiency investments for electricity, natural gas, and transportation fuels are show in Figure 4.19.

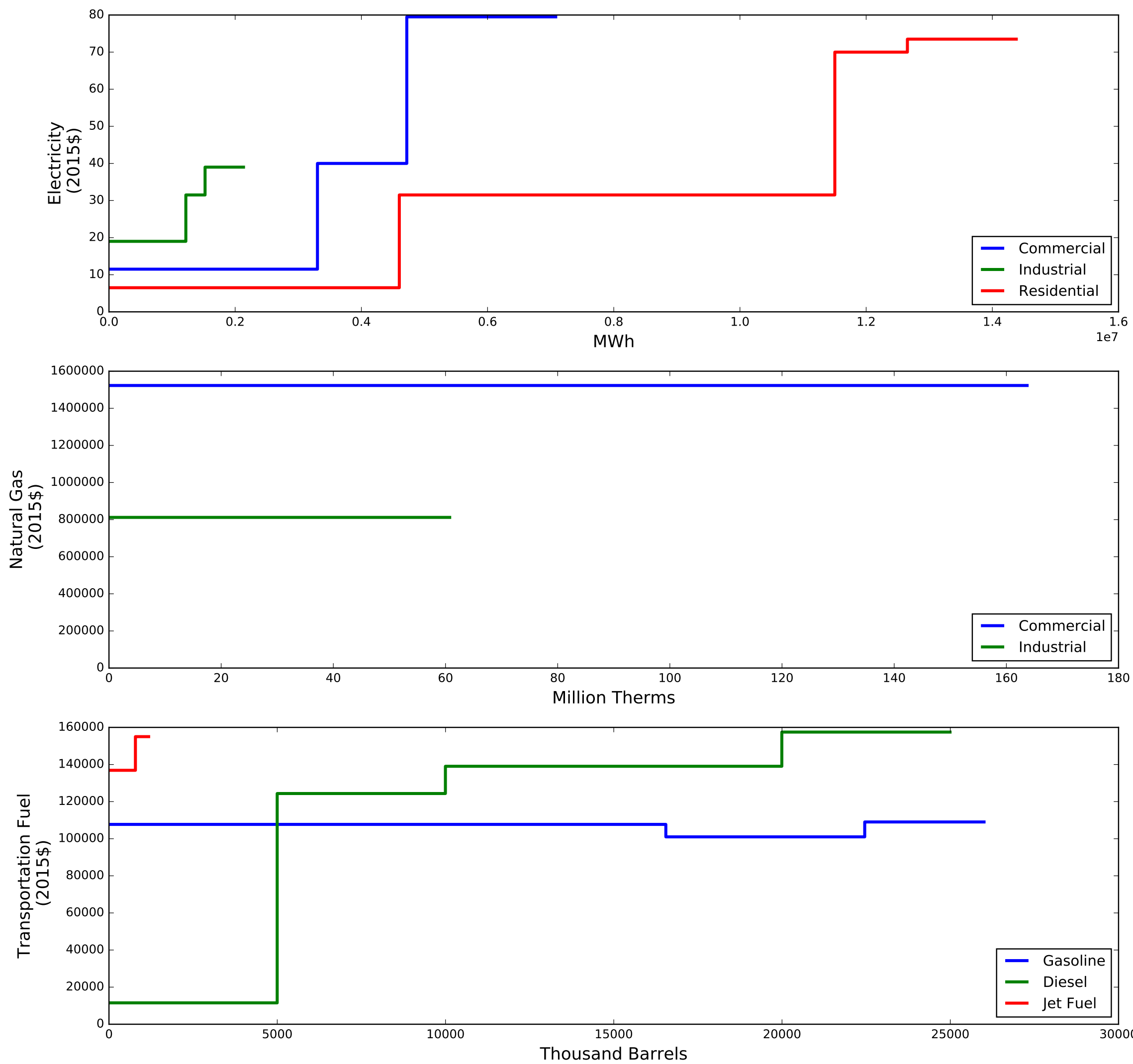

Figure 4.19: Efficiency Investments

Electricity

Electricity efficiency availability is based on availability presented in Wang and Brown (2014), updated to percentages by sources and sectors by using national consumption for 2035 presented in the Annual Energy Outlook 2011 [73], [78]. Values used in this study are shown in Table 4.19.

Table 4.19: Energy Efficiency Availability and Costs for Electricity

Sector	Policy	Electricity Efficiency Potential (%)	LCOE($/MWh)
Commercial	Benchmarking	6.9%	11.5
	Building codes	3.0%	40
	Financing	5.3%	79.5
Industrial	CHP incentives	3.8%	19
	Motor standard	1.2%	31.5
	Plant and technology upgrade	2.1%	39
Residential	Building codes	3.6%	6.5
	Aggressive applicance policy	4.2%	6.5
	Market priming	11.7%	31.5
	On-bill financing	2.4%	70
	Appliance incentives	2.5%	73.5

Table 4.20: Energy Efficiency Availability and Costs for Natural Gas

Sector	Measure No	2050 End Use Reduction (Mtherms)	% 2015 Demand	Incremental levelized annual measure cost ($/Mtherms)
Residential	2	1869	0.16%	812,000
Industrial	29	759	0.05%	1,523,000

Natural Gas

Marginal costs and available quantities of demand side management for industrial and residential sectors are scaled to the United States state of Georgia from [56]. Williams, et al. does not include demand side management for commercial and transportation sectors directly, but rather through fuel switching, which is excluded from this study. The costs and quantities used in this study are shown in Table 4.20. No savings directly related to natural gas for the residential sector were available. A broader set of all efficiency investments in natural gas would provide an opportunity for reaching the desired carbon dioxide targets at a lower cost than presented herein.

Table 4.21: Energy Efficiency Availability and Costs for Transportation Fuels

Fuel	Measure No	2050 End Use Reduction (thousand barrels)	Incremental levelized annual measure cost ($/barrel)
Diesel	21	5216	11.52
Diesel	22	5216	124.36
Diesel	23	10432	139.05
Diesel	25	3599	157.48
Diesel	26	10954	157.48
Diesel	51	313	157.48
Diesel	53	26	157.48
Diesel	54	104	157.48
Gas	19	14458	30.81
Gas	20	892	30.81
Gas	31	15172	76.91
Gas	49	5950	101.00
Gas	50	2975	109.03
Jet Fuel	24	10598	136.87
Jet Fuel	52	583	155.02

Transportation Fuels

Marginal costs and reduction levels for efficiency investments for transportation fuel, shown in Table 4.21, are scaled to the United States state of Georgia from Williams (2012) [56].

4.3.10 Carbon Dioxide Target

For this study, carbon dioxide targets are relative to the 2015 resultant emissions from the scenario in which no efficiency investments are available and no carbon dioxide target is in place. Targets are set to 80% by 2020, 50% by 2035, and 40% by 2050. These were established based on the availability of efficiency investments used in this study. Targets are graduated between years as opposed to being step-wise targets for specific years as shown for select years in Table 4.22.

Table 4.22: Carbon Dioxide Emissions Targets

Year	Carbon Dioxide Target (% of 2015 BAU Emissions)
2020	80%
2025	70%
2030	60%
2035	50%
2040	47%
2045	43%
2050	40%

4.4 Results

4.4.1 Electricity

Capacity

Figures 4.20 and 4.21 show the total electricity generation capacity for years 2015 to 2050. For the scenario in which a carbon dioxide target is enforced, coal capacity is significantly decreased and nuclear capacity is significantly increased. Natural gas capacity remains roughly in line with the scenario in which efficiency investments are made available but a carbon target is not enforced. Capacity from hydroelectric power, wood waste solids, landfill gas, biomass, and solar are constant across all scenarios. Oil capacity is installed in the scenarios where a carbon target is not enforced, and the carbon target drives the economic installation of wind capacity.

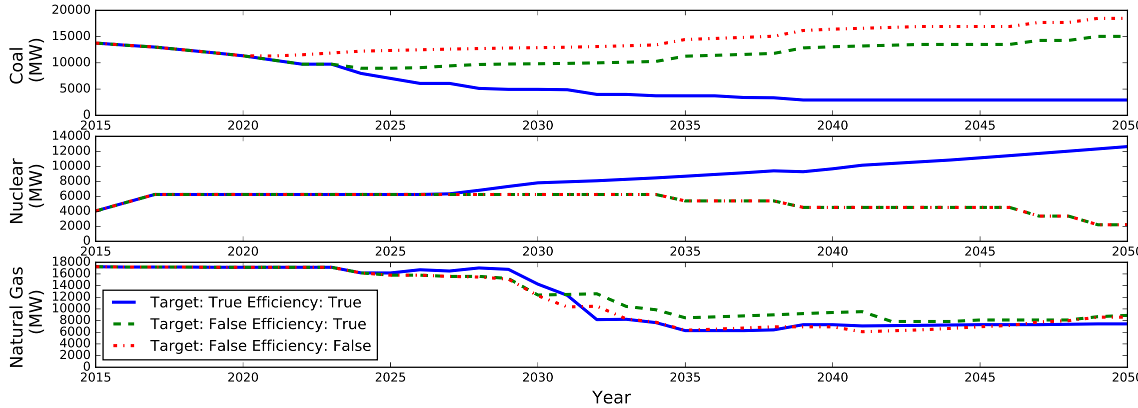

Figure 4.20: Total Electricity Capacity - Coal, Natural Gas, and Nuclear (MW)

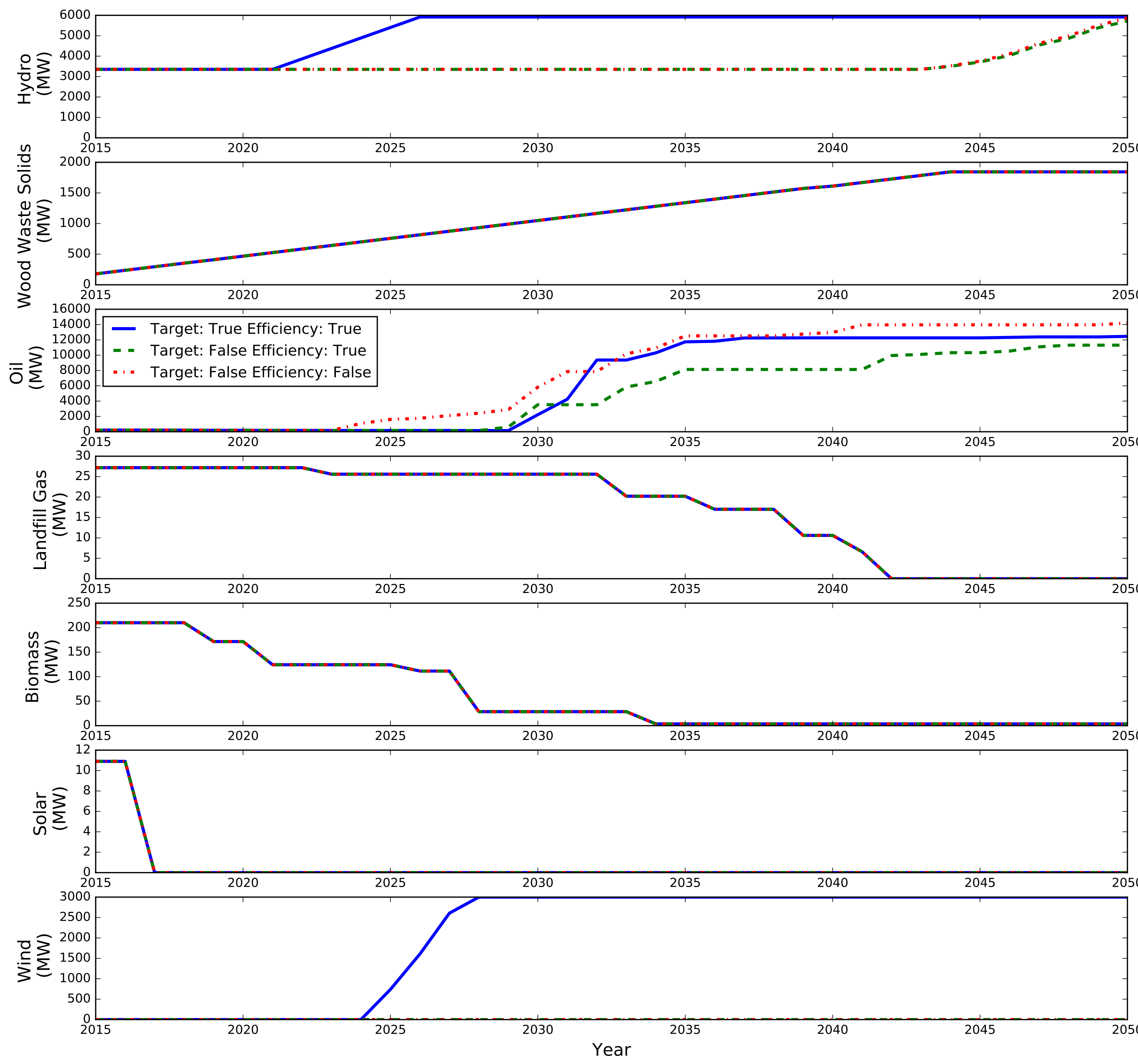

Figure 4.21: Total Electricity Capacity - Other Generation Technologies (MW)

Figures 4.22 and 4.23 show the generation capacity expansion that occurs each year. This is affected by the retirement schedule for existing generation facilities and capacity constructed as a result of the model. When a carbon dioxide constraint is in place, coal power plants continue to be constructed but to a much lesser extent than in the other scenarios, natural gas installations slightly decrease, and nuclear installations increase. The carbon dioxide targets make the expansion of hydroelectric power occur sooner and the installation of wind cost effective.

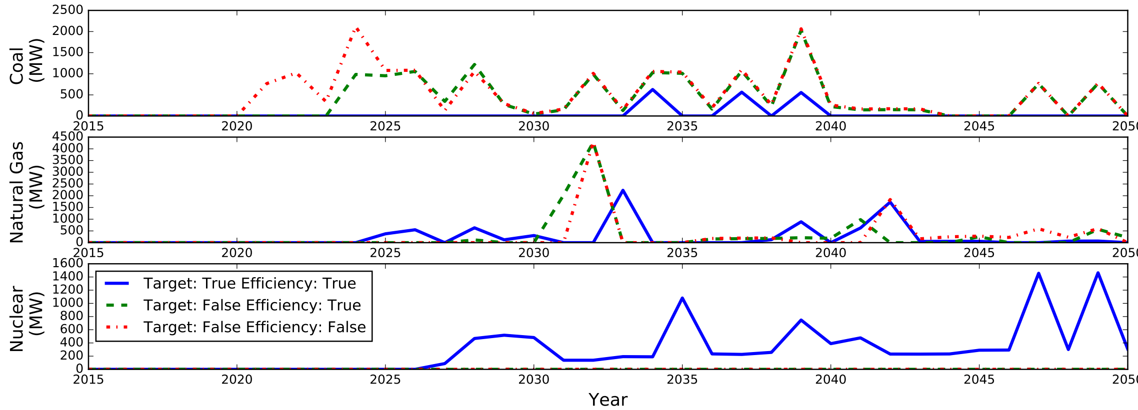

Figure 4.22: Electricity Capacity Expansion - Coal, Natural Gas, and Nuclear (MW)

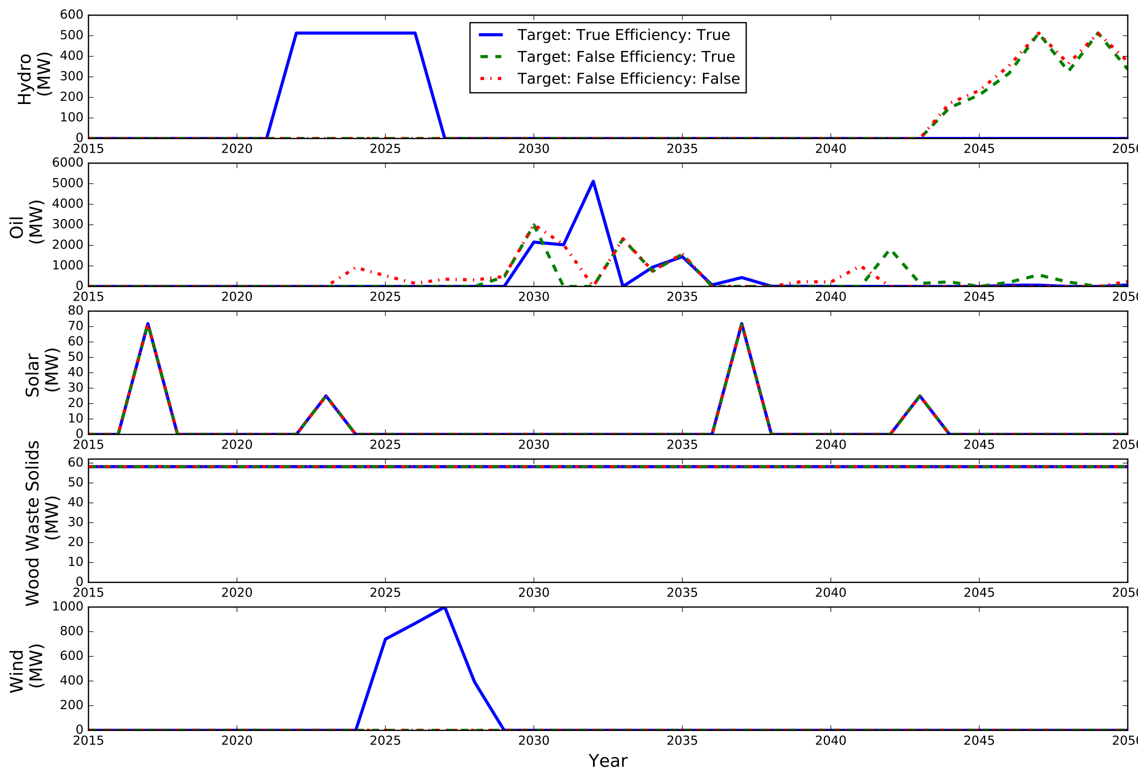

Figure 4.23: Electricity Capacity Expansion - Other Generation Technologies (MW)

Supply

Figures 4.24 and 4.25 show the total electricity supply generated by each fuel source by scenario. As might be expected, the electricity supply corresponds well to the increase or decrease in each generation technology's change in capacity.

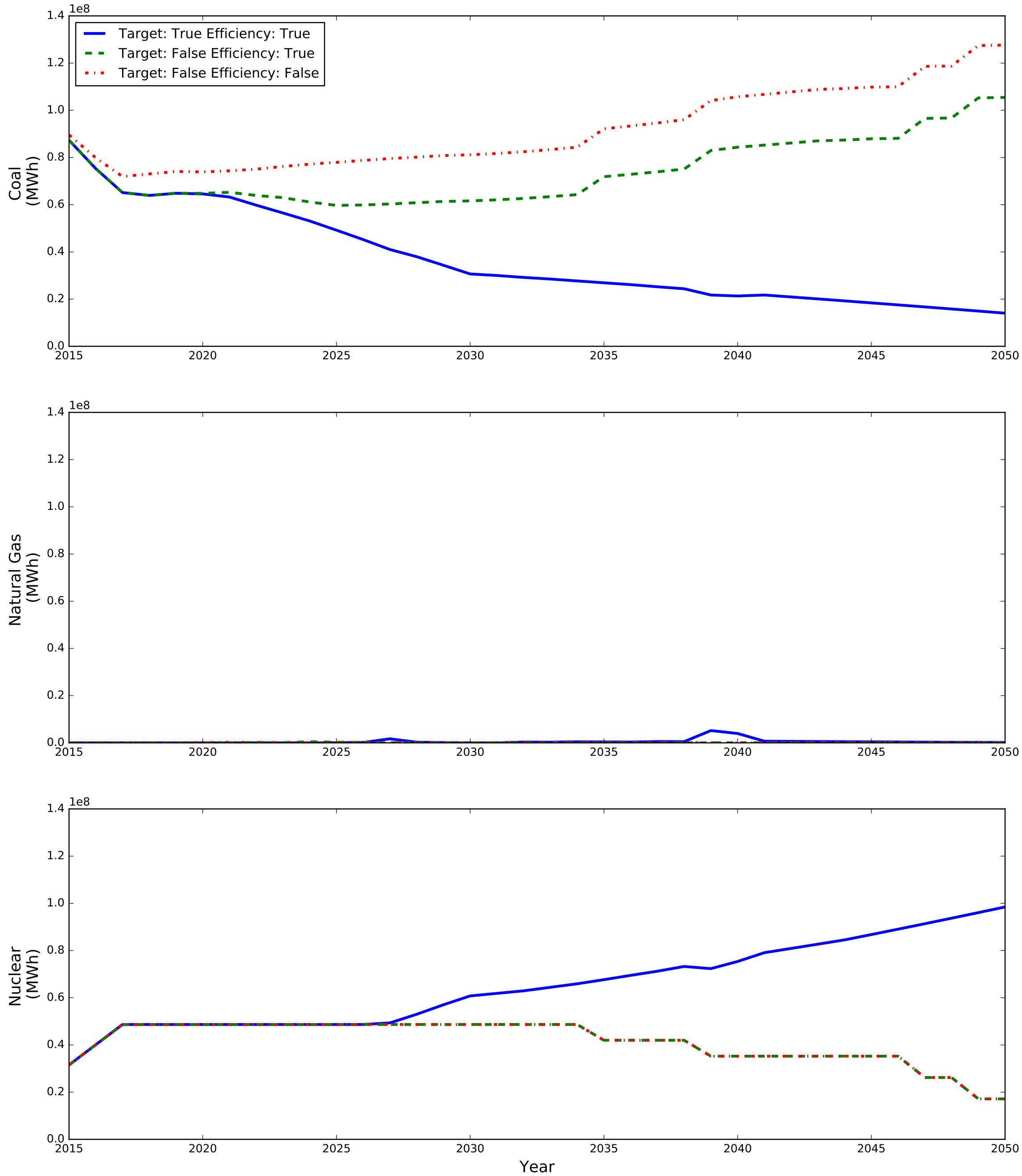

Figure 4.24: Electricity Supply - Coal, Natural Gas, and Nuclear (MWh)

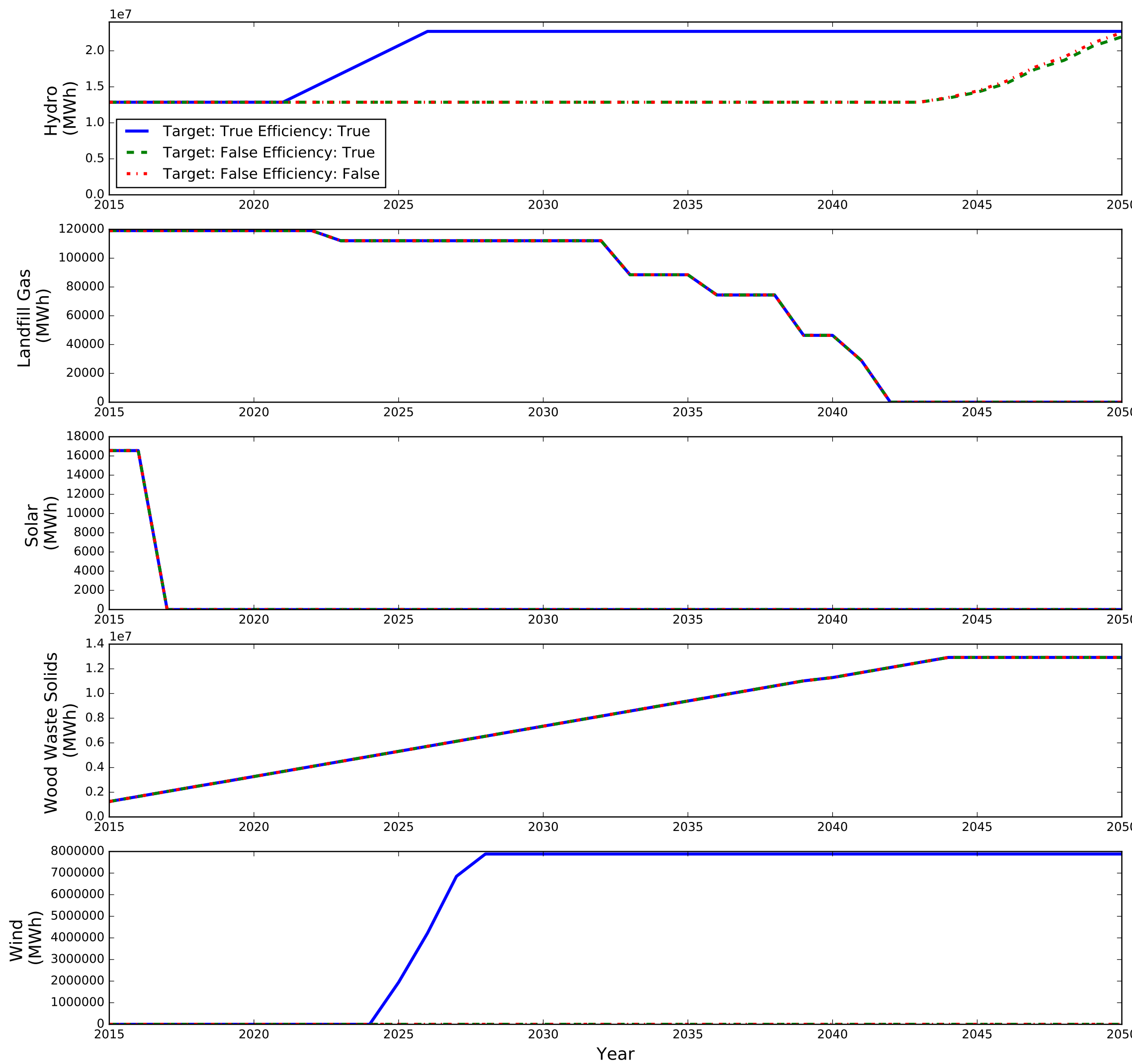

Figure 4.25: Electricity Supply - Other Generation Technologies (MWh)

The total electricity supply is reduced in scenarios where efficiency investments are available, as shown in Figure 4.26. By 2050, electricity consumption is decreased by 12.6% when efficiency investments are included and an additional 0.7% when a carbon target is in place.

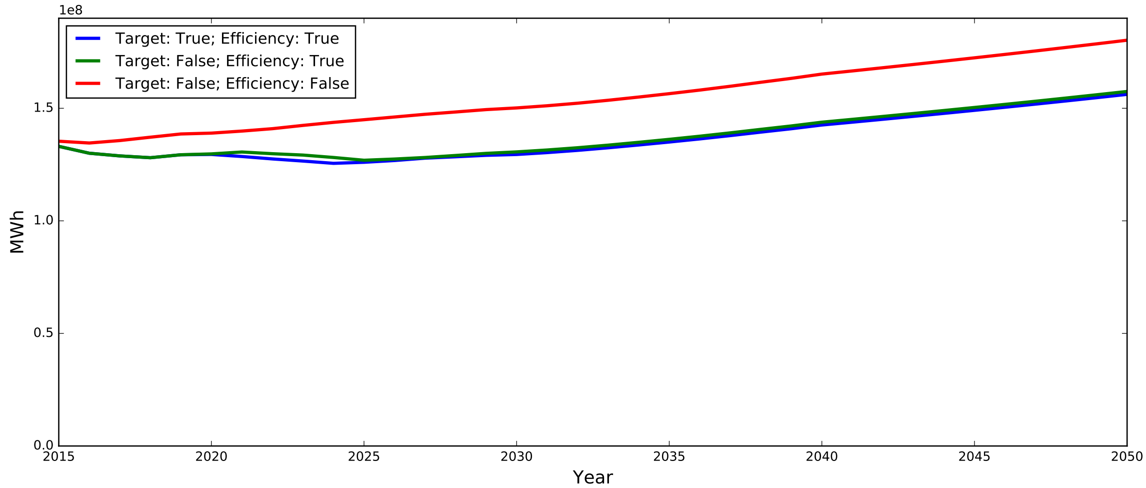

Figure 4.26: Annual Electricity Supply (MWh)

4.4.2 Natural Gas

The amount of natural gas supplied in each scenario is the same as shown in Figure 4.27. As will be shown later, this is due to a lack of investment in efficiency measures.

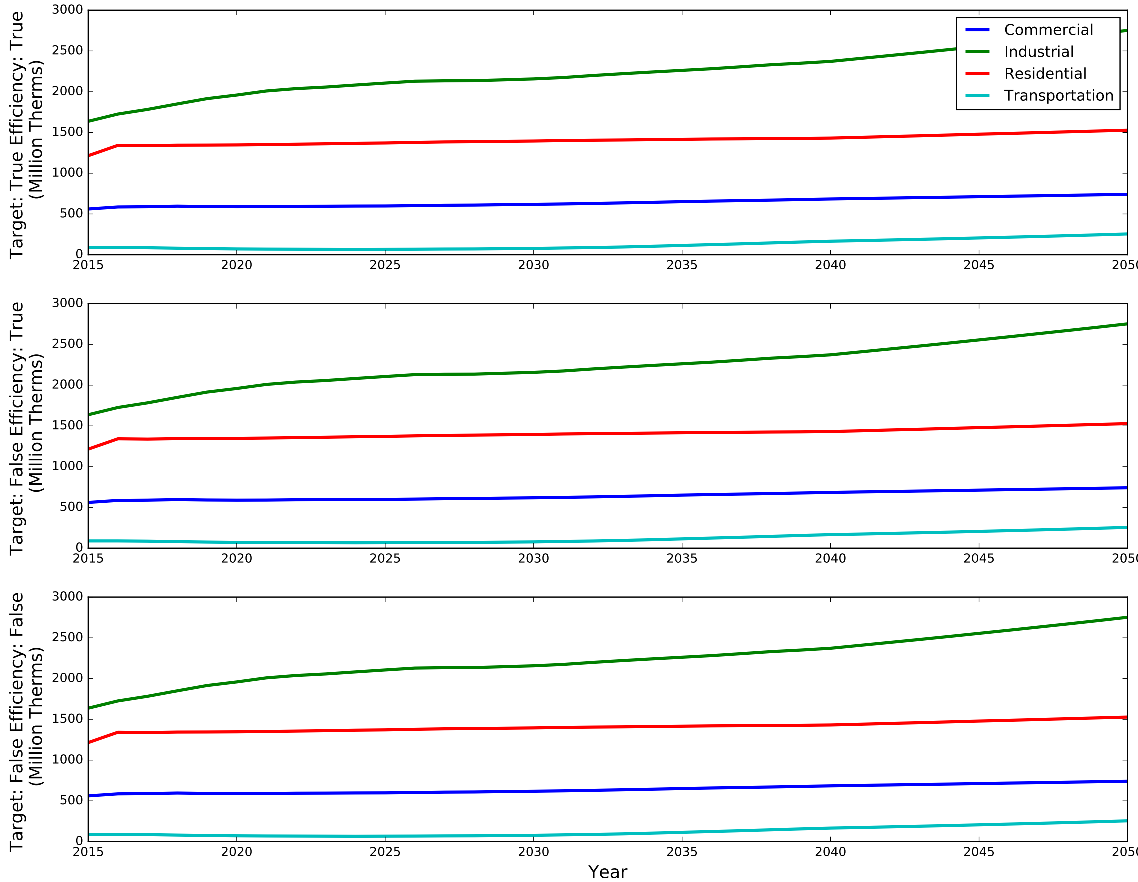

Figure 4.27: Natural Gas Supply (Million Therms)

4.4.3 Transportation Fuel

Both gasoline and diesel show decreased supply when efficiency investments are available. Since the full efficiency investment is chosen, the carbon dioxide target does not decrease the supply further. By 2050, supply is decreased by 75%, 36%, and 15% for diesel, gasoline, and jet fuel, respectively, as shown in Figure 4.28. If demand decreases, then costs of fuels are likely to decrease. This in turn would make efficiency investments relatively less attractive, which might then increase the need for a carbon dioxide target to achieve desired emissions levels.

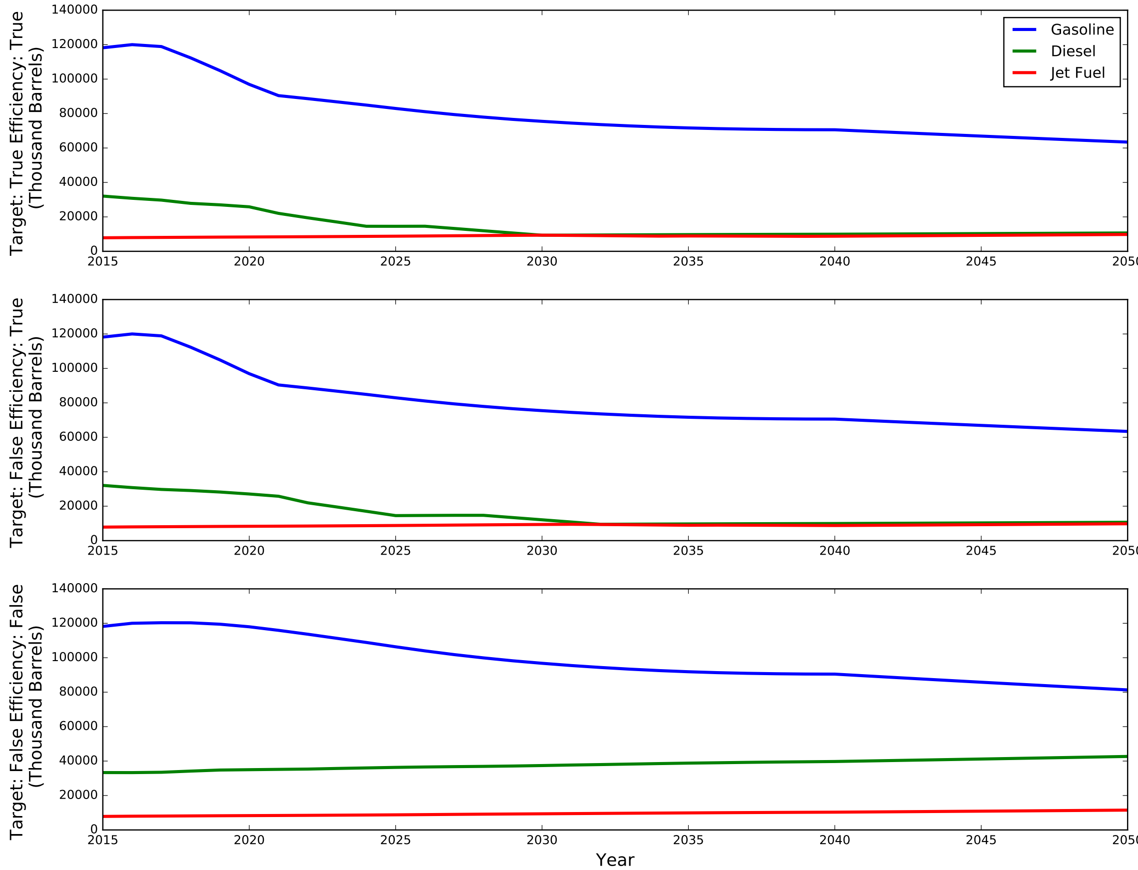

Figure 4.28: Transportation Fuel Supply (Thousand Barrels)

4.4.4 Efficiency Investment

In both scenarios where efficiency investments are available to satisfy consumer demand, significant quantities are invested in electricity efficiency as shown in Figure 4.29. For the scenario in which the carbon dioxide target is enforced, efficiency investments are 6% higher than without the carbon dioxide target in 2050.

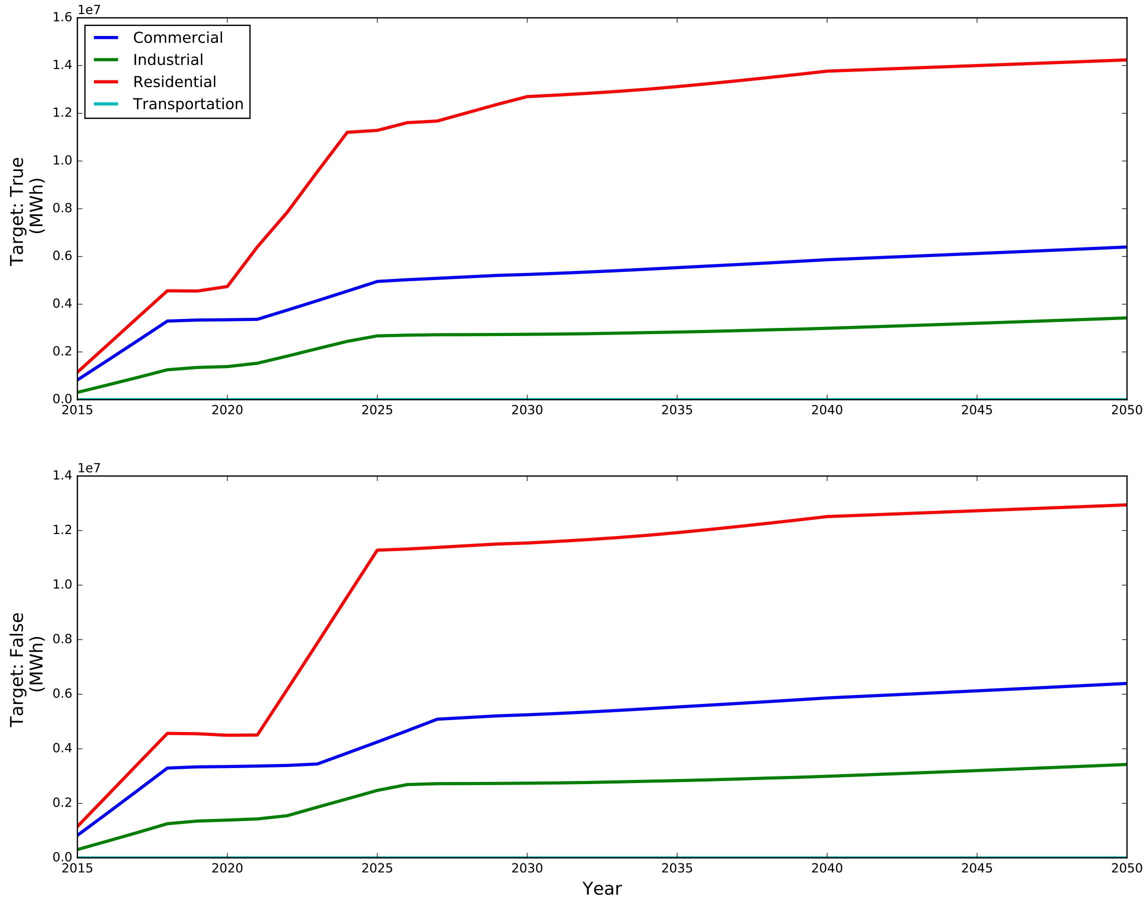

Figure 4.29: Electricity Efficiency (MWh)

No efficiency investment is made in natural gas. This is due both to the economics of the price relative cost of efficiency investment and the cost of reducing carbon dioxide emissions associated with natural gas relative to other reduction options.

Figure 4.30 shows the efficiency investment for transportation fuels for the two scenarios in which efficiency investments are available. By 2045, the efficiency investments are equivalent for both scenarios for all three fuels. The carbon dioxide target forces a few discrepancies on when the investments begin for diesel and jet fuel. For jet fuel, efficiency investments are slightly elevated for years 2030 to 2040 as a result of the carbon dioxide target.

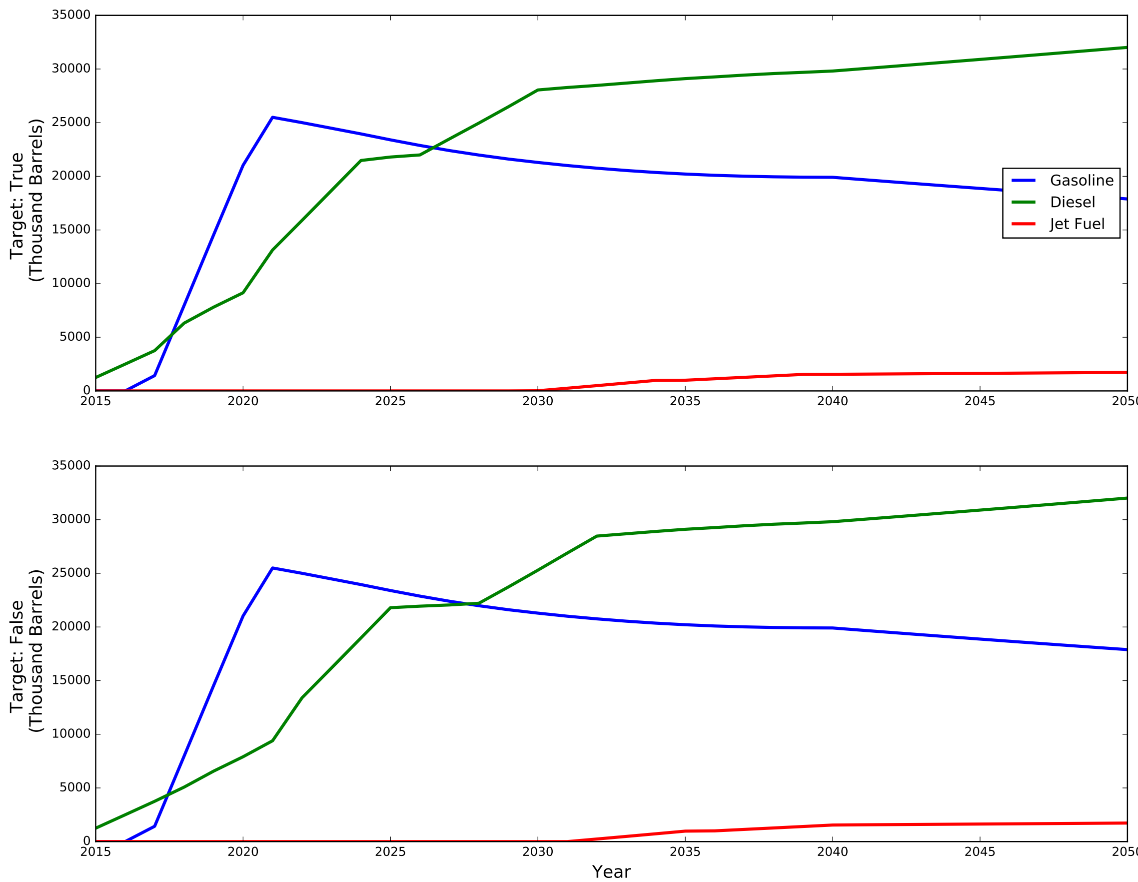

Figure 4.30: Transportation Fuel Efficiency (Thousand Barrels)

Figures 4.31 and 4.32 show the investment in efficiency for electricity and transportations fuels, respectively. The corresponding policies and programs can be seen in tables 4.19 and 4.21. For commercial and residential sectors in electricity and jet fuel in transportation fuels, investment in segments is strictly ordered by cost. That is, before an investment is made in a segment, the entire potential of the lower costs segments are chosen. For industrial electricity and gasoline, contiguous segments show simultaneous efficiency investment. If the maximum annual investment were decreased to create longer rollout periods, one could expect more simultaneous investment in multiple segments within a source and sector or fuel.

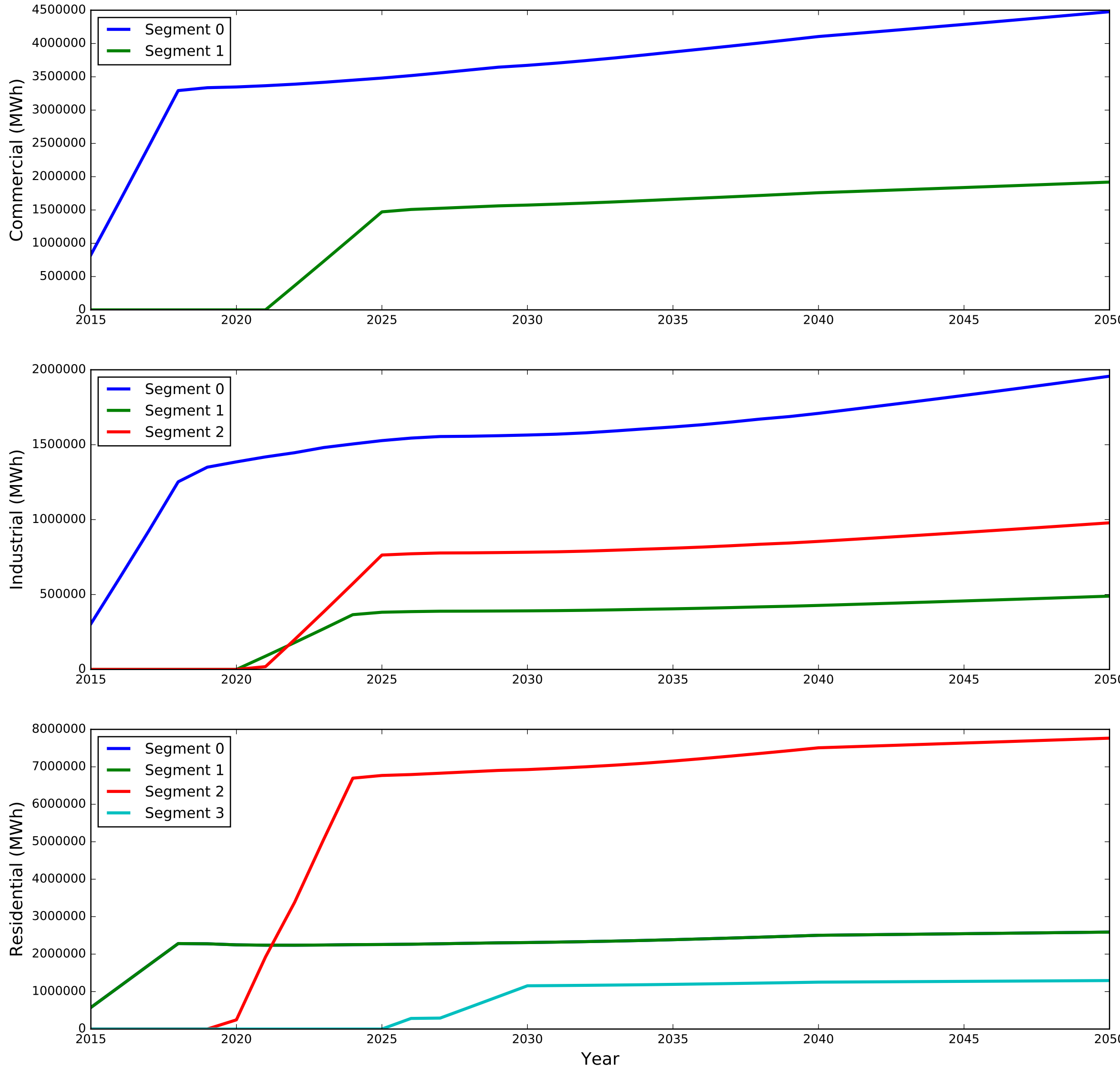

Figure 4.31: Electricity Efficiency by Segment (MWh)

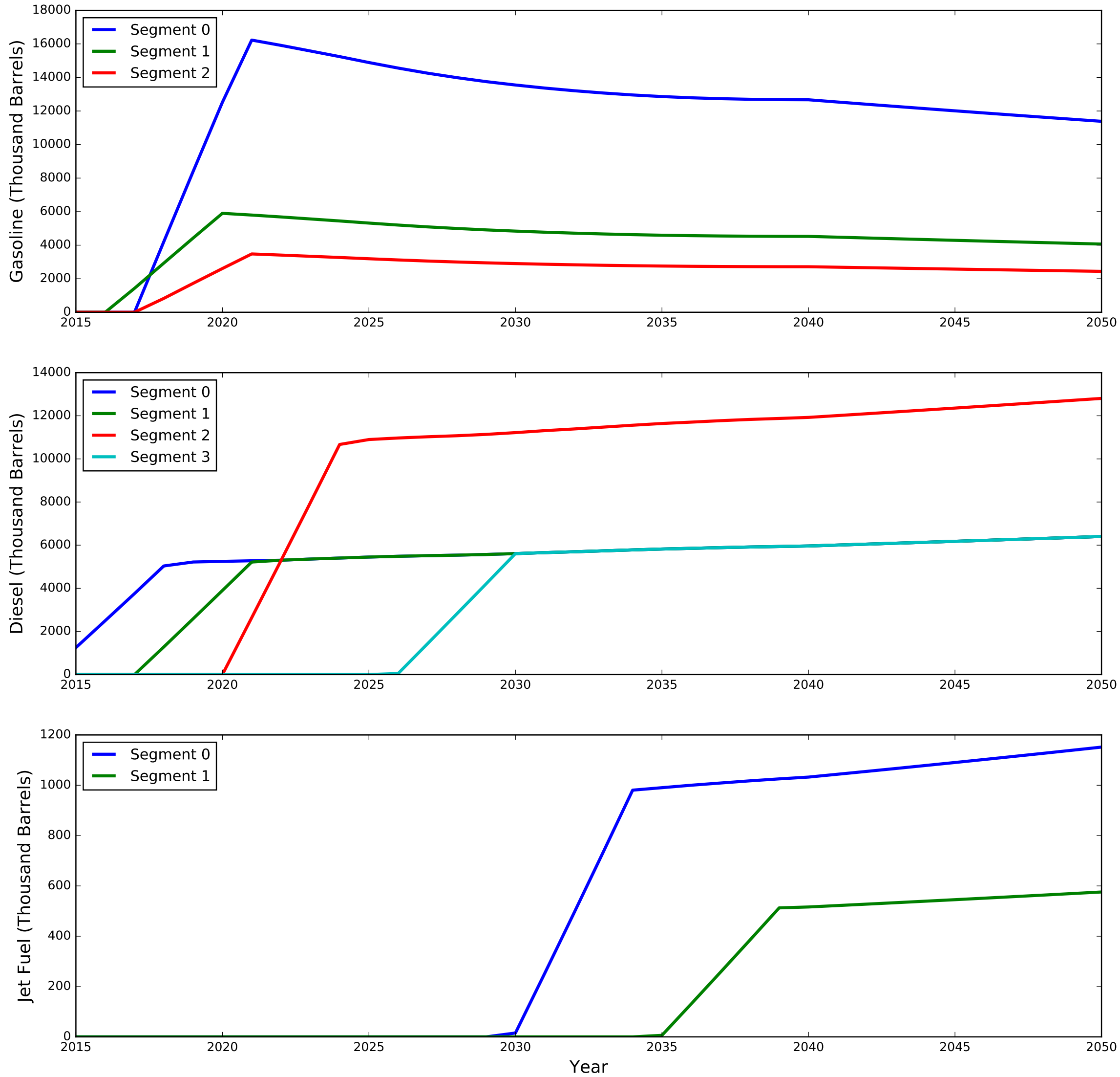

Figure 4.32: Transportation Fuel Efficiency by Segment (Thousand Barrels)

Emissions

Figure 4.33 shows the total annual emissions by source and scenario. The economics of efficiency investments drive decreased emissions for electricity and transportation fuels. The carbon target has a significant effect on the emissions resulting from electricity generation, reducing carbon dioxide emission from 82% of the baseline scenario to 31% of the baseline

Table 4.23: Energy Efficiency Costs by Segment for Electricity

Sector	Segment	Policy	LCOE($/MWh)
Commercial	0	Benchmarking	11.5
	1	Building codes	40
	2	Financing	79.5
Industrial	0	CHP incentives	19
	0	Motor standard	31.5
	1	Plant and technology upgrade	39
Residential	0	Building codes Aggressive appliance policy	6.5
	1	Market priming	31.5
	2	On-bill financing	70
	3	Appliance incentives	73.5

Table 4.24: Energy Efficiency Costs by Segment for Transportation Fuels

Fuel	Segment	Measure No.	Description	Incremental levelized annual measure cost ($/barrel)
Diesel	0	21	Freight Truck	11.52
	1	22	Freight Rail	124.36
	2	23	Domestic Shipping	139.05
	3	25	Bus	157.48
	3	26	Passenger Rail	157.48
	3	51	Freight Truck VMT	157.48
	3	53	Passenger Rail VMT	157.48
	3	54	Boats & Other VMT	157.48
Gas	0	19	Passenger Light Duty	30.81
	0	20	Commercial Light Duty	30.81
	1	31	Gas Efficiency	76.91
	2	49	Passenger Light Duty VMT	101.00
	3	50	Commercial Light Duty VMT	109.03
Jet Fuel	0	24	Air Travel	136.87
	1	52	Air Travel VMT	155.02

scenario by 2050. Transportation fuels are slightly impacted by the carbon dioxide target, which matches the discrepancy in efficiency investments.

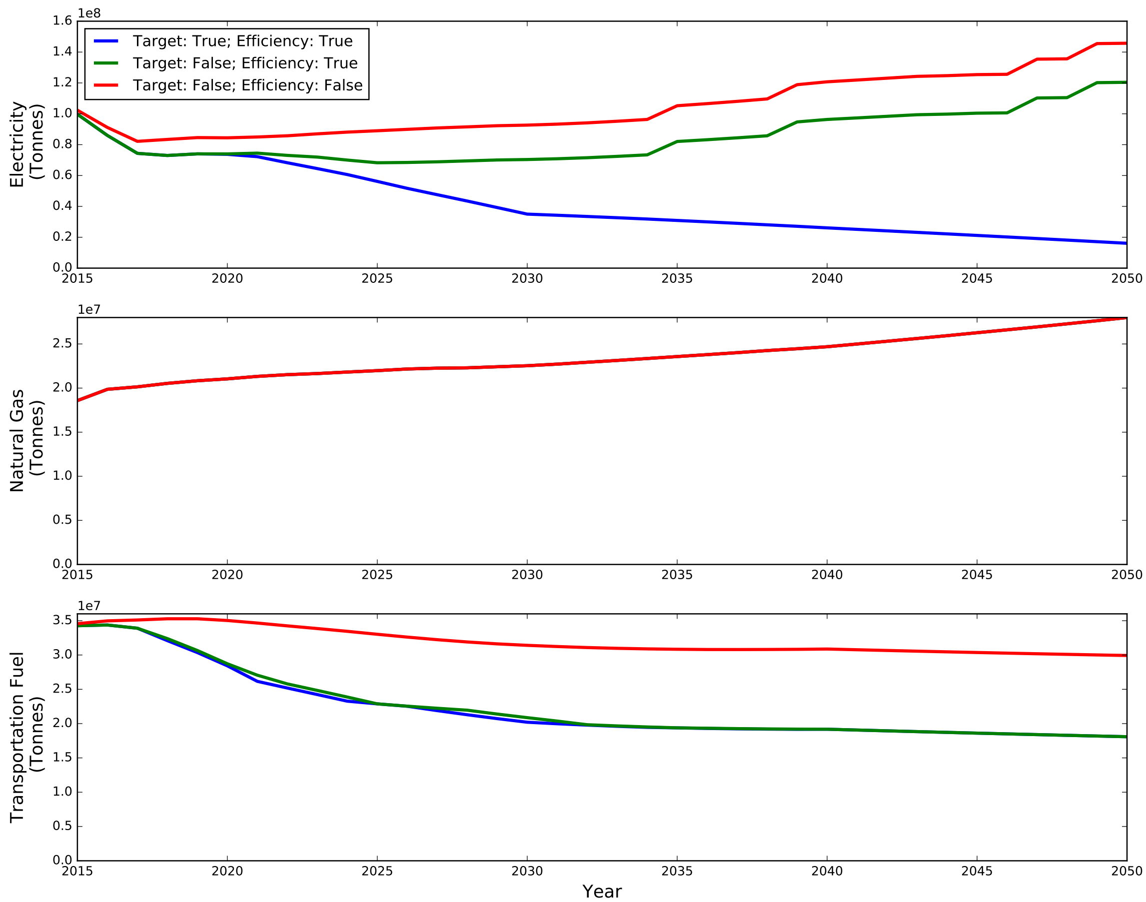

Figure 4.33: Annual Emissions by Source and Scenario (Tonnes)

Annual carbon dioxide emissions for each scenario are shown in Figure 4.34. Over the course of the 35 year time horizon, carbon dioxide emissions are reduced by 2.6 billion tonnes, resulting in decreased emissions of 141 million tonnes annually in 2050. Efficiency investments alone account for 1.1 billion tonne decreases over the entire time horizon and 37 million tonnes annually in 2050. This leaves the carbon dioxide target to account an emissions reduction of 1.5 billion tonnes in total and 104 million tonnes annually by 2050.

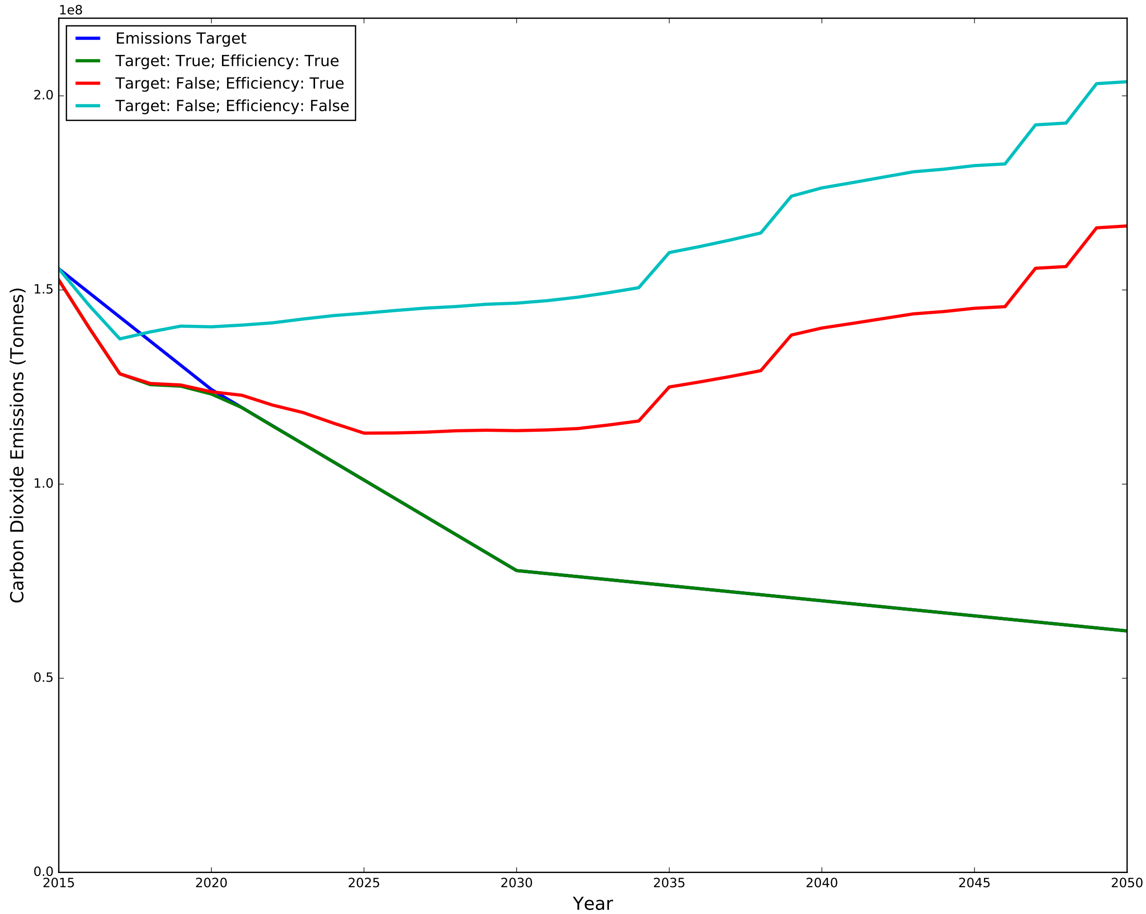

Figure 4.34: Total Annual Emissions (Tonnes)

Costs

Figure 4.35 shows the annual costs by scenario and source. For both supply and efficiency, transportation fuels make up a significant portion of the total costs. Natural gas plays an insignificant role in total costs. The total annual costs for each scenario are shown in Figure 4.34. As shown, the total cost for the scenario in which efficiency investments are available with a carbon dioxide target are significantly lower than the baseline cost and slightly higher than the scenario in which a carbon dioxide target is not enforced. The total change in net present value is shown in Table 4.25. The cost difference between scenarios where efficiency investment is available, that is, with or without enforcing the emissions constraint, provides an estimate for the total cost of meeting the carbon dioxide target. In this study it is found to increase costs by 10% for electricity and 2% across all sources. In relation to the baseline scenario, this is a savings of 14% in total.

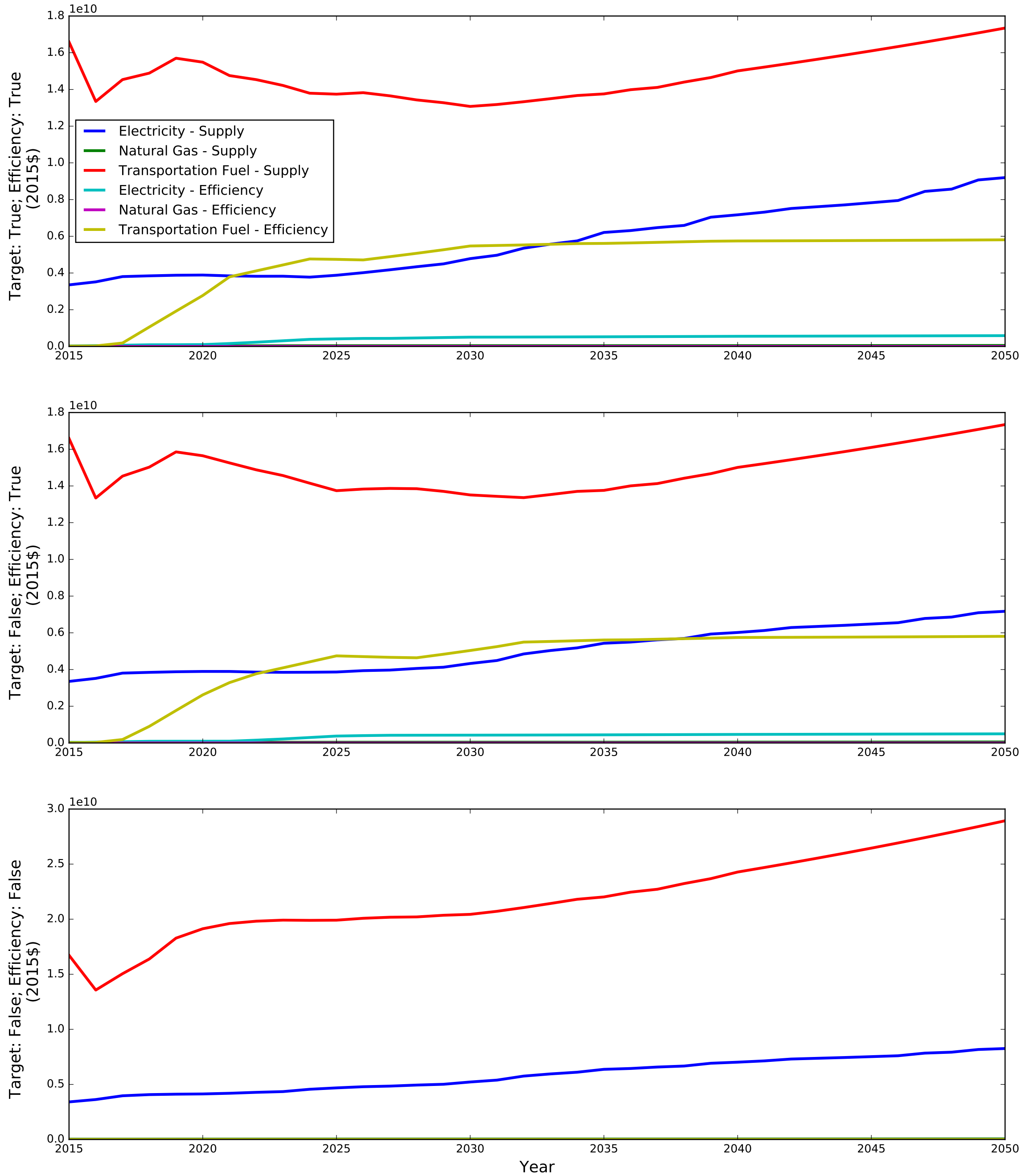

Figure 4.35: Annual Costs

Table 4.25: Percent Change in Net Present Value from the Baseline Scenario

	Efficiency Investments, No Emissions Target	Efficiency Investments, Emissions Target
Electricity	-7.2%	7.7%
Natural Gas	0.0%	0.0%
Transportation Fuels	-20.3%	-20.3%
Total	**-17.5%**	**-14.4%**

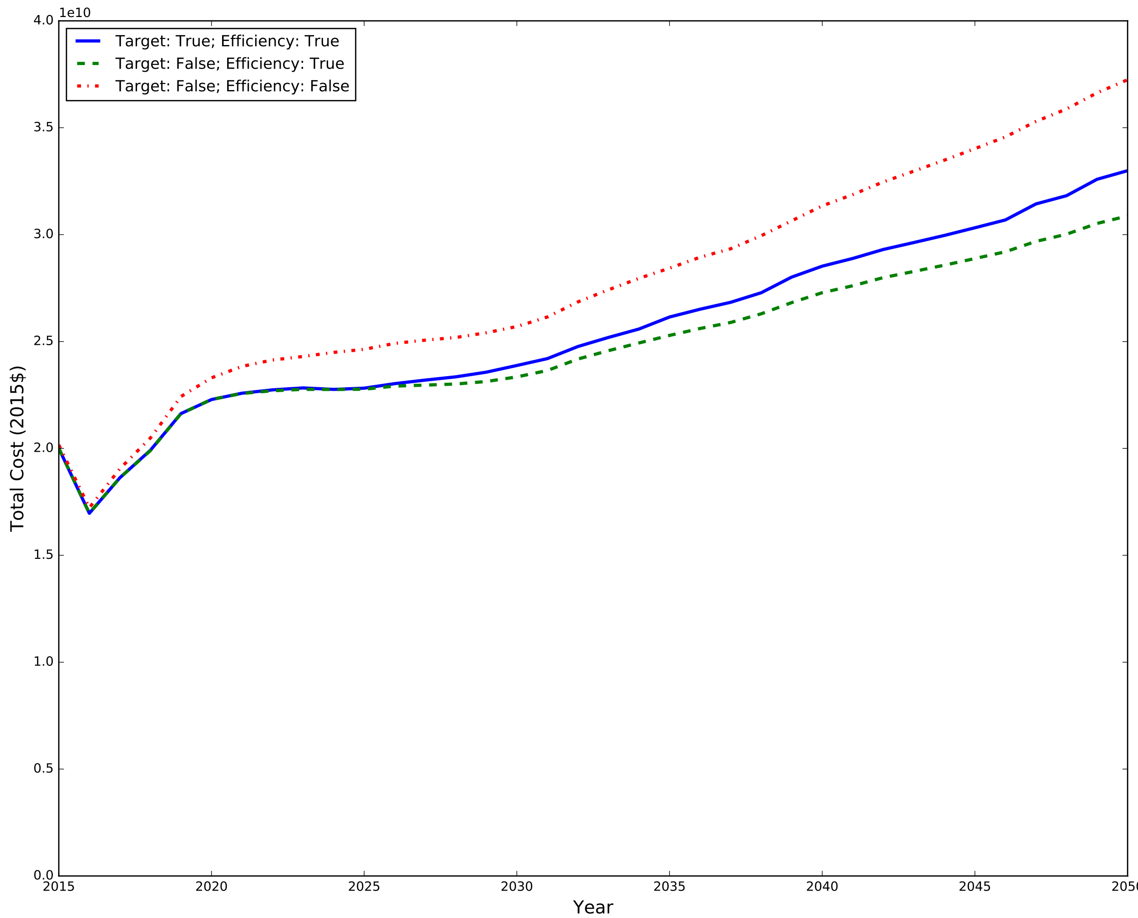

Figure 4.36: Total Annual Costs

4.5 Scenario - No New Nuclear Expansion

Due to the cost overruns and extended deadlines associated with nuclear plants currently under construction, one interesting alternative is to see what the effect of preventing new nuclear installation would have on the overall outcome. The data and parameters were held constant with the preceeding scenario, but no new capacity was allowed to be installed for nuclear.

Figures 4.37 and 4.37 show that the nuclear capacity installed the in the original scenario is replaced by a combination of natural gas, oil, and biomass capacity.

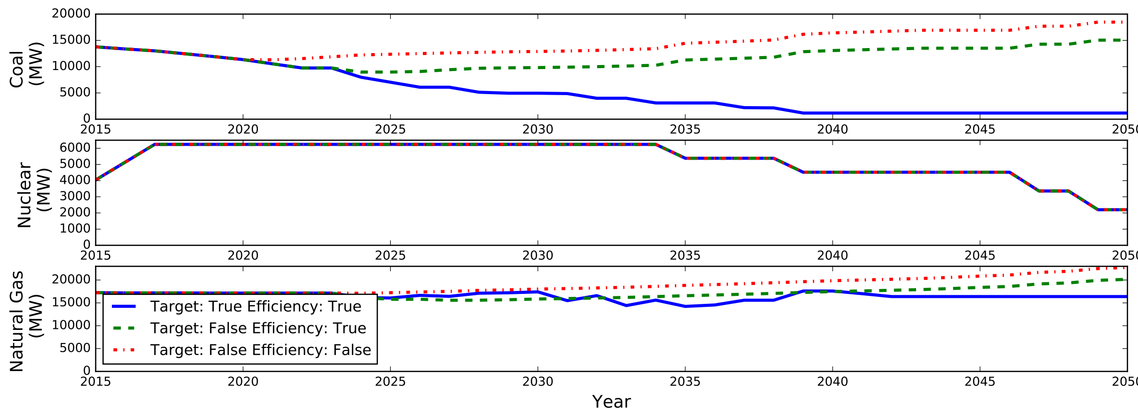

Figure 4.37: Total Electricity Capacity - Coal, Natural Gas, and Nuclear - No Nuclear Expansion (MW)

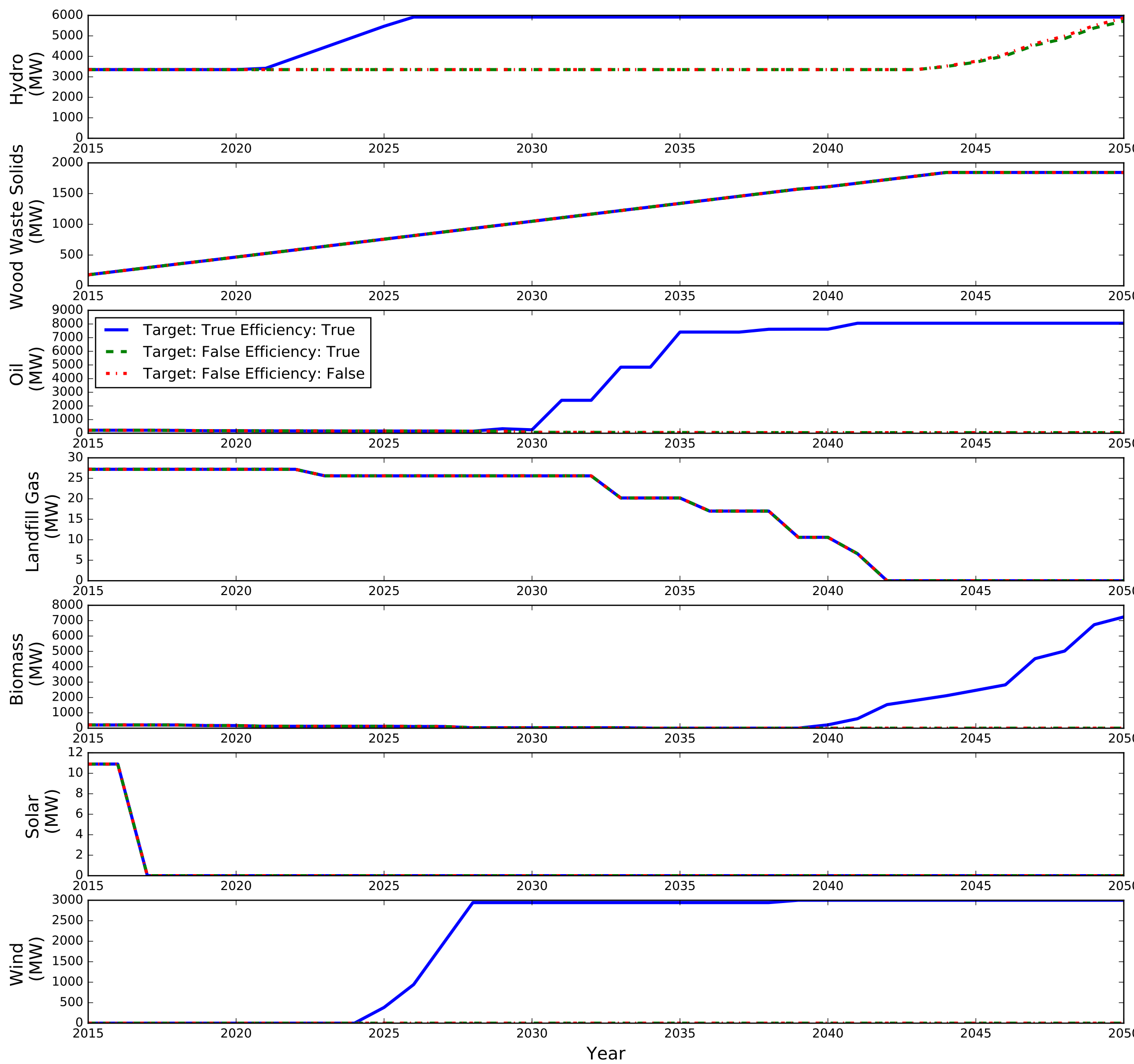

Figure 4.38: Total Electricity Capacity - Other Generation Technologies - No Nuclear Expansion (MW)

Figures 4.39 and 4.40 show that supply follows same trajectory as installed capacity, with natural gas, oil, and biomass filling the gap left when nuclear capacity cannot supply additional electricity.

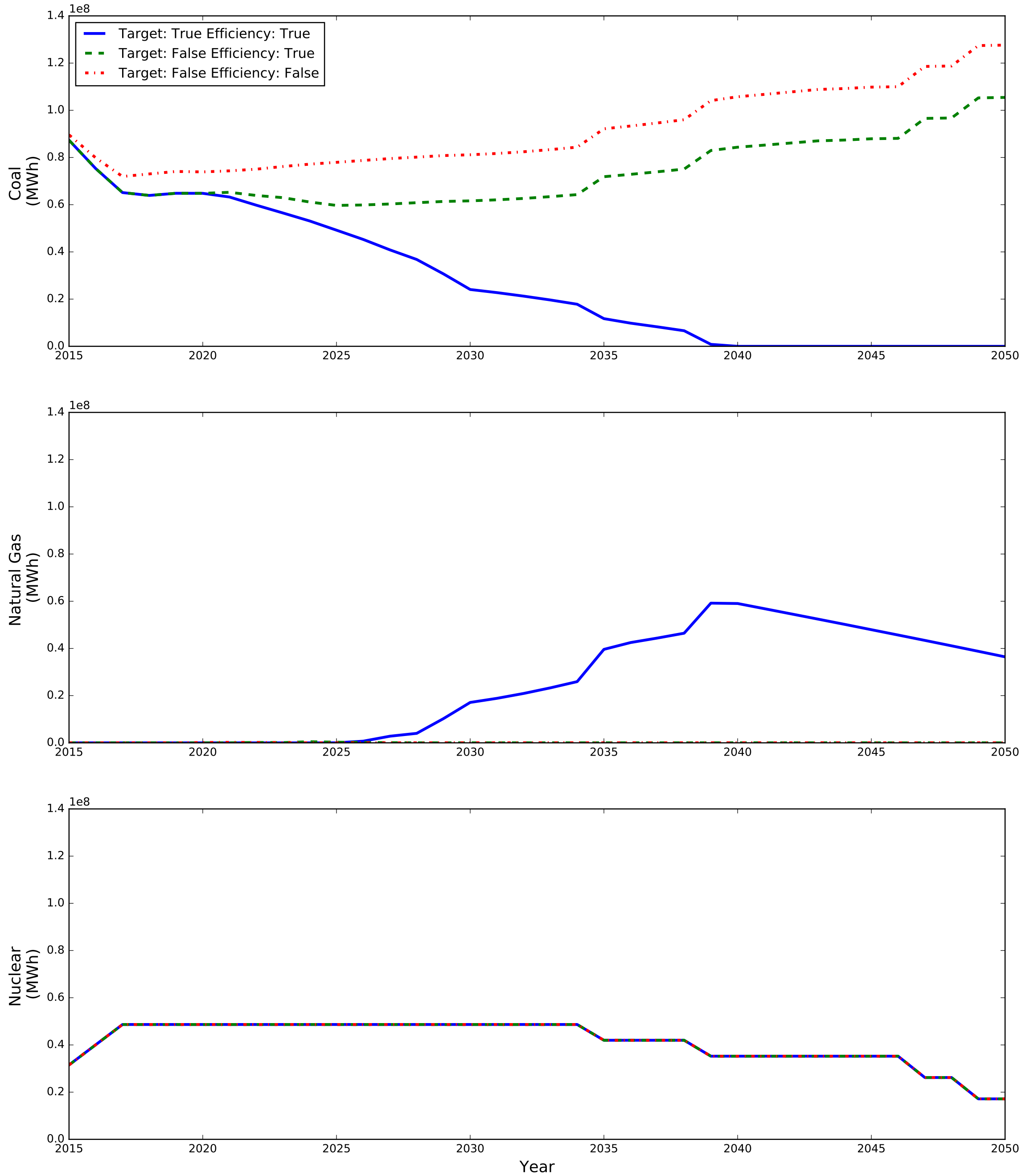

Figure 4.39: Electricity Supply - Coal, Natural Gas, and Nuclear - No Nuclear Expansion (MWh)

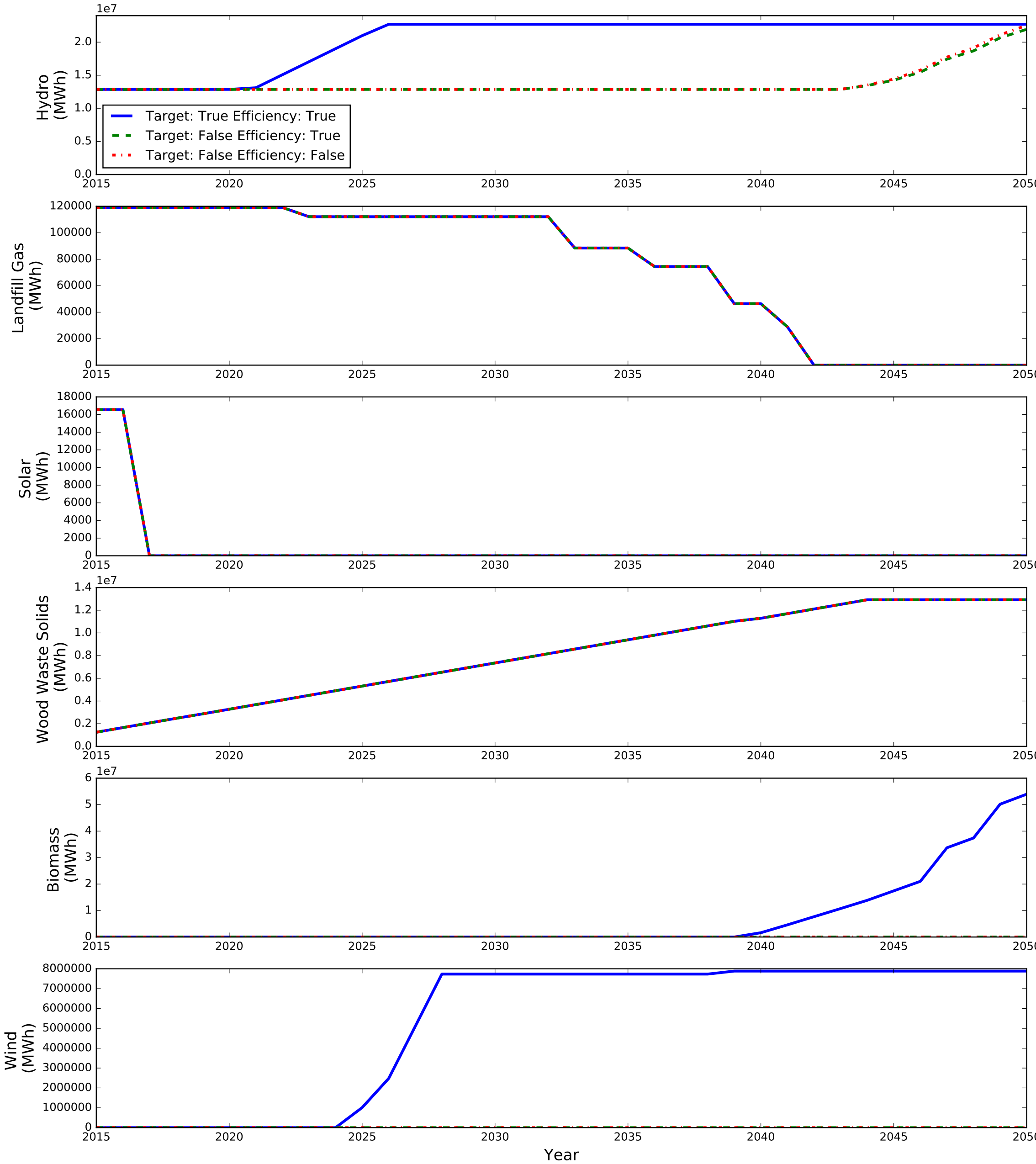

Figure 4.40: Electricity Supply - Other Generation Technologies - No Nuclear Expansion (MWh)

The amount of electricity supply is slightly decreased in the scenario without nuclear expansion, and natural gas and transportation fuel supplies are identical in both scenarios. Without nuclear, less coal is used to generate electricity in the scenario with the carbon dioxide target. The emissions difference is accounted for by switching from coal to natural gas.

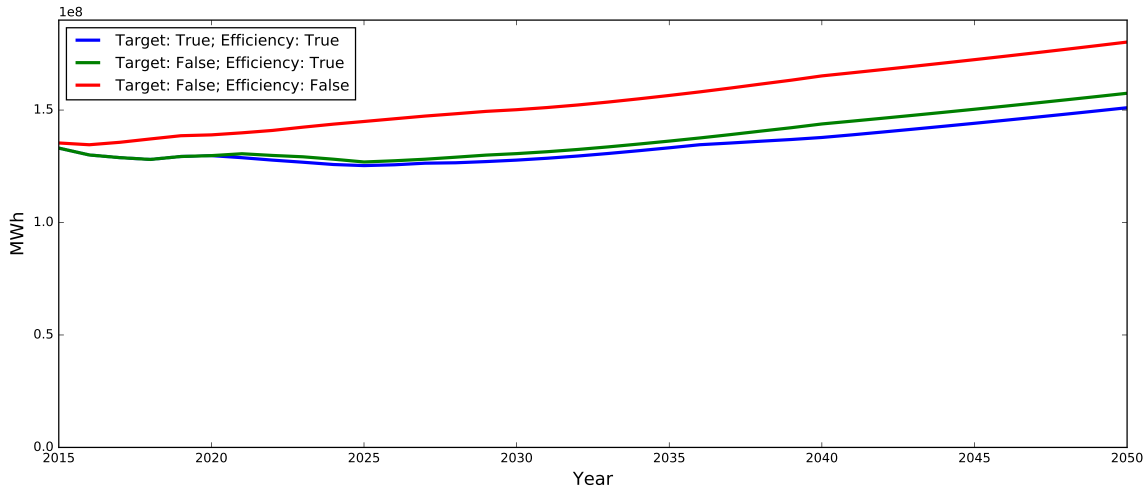

Figure 4.41: Annual Electricity Supply - No Nuclear Expansion (MWh)

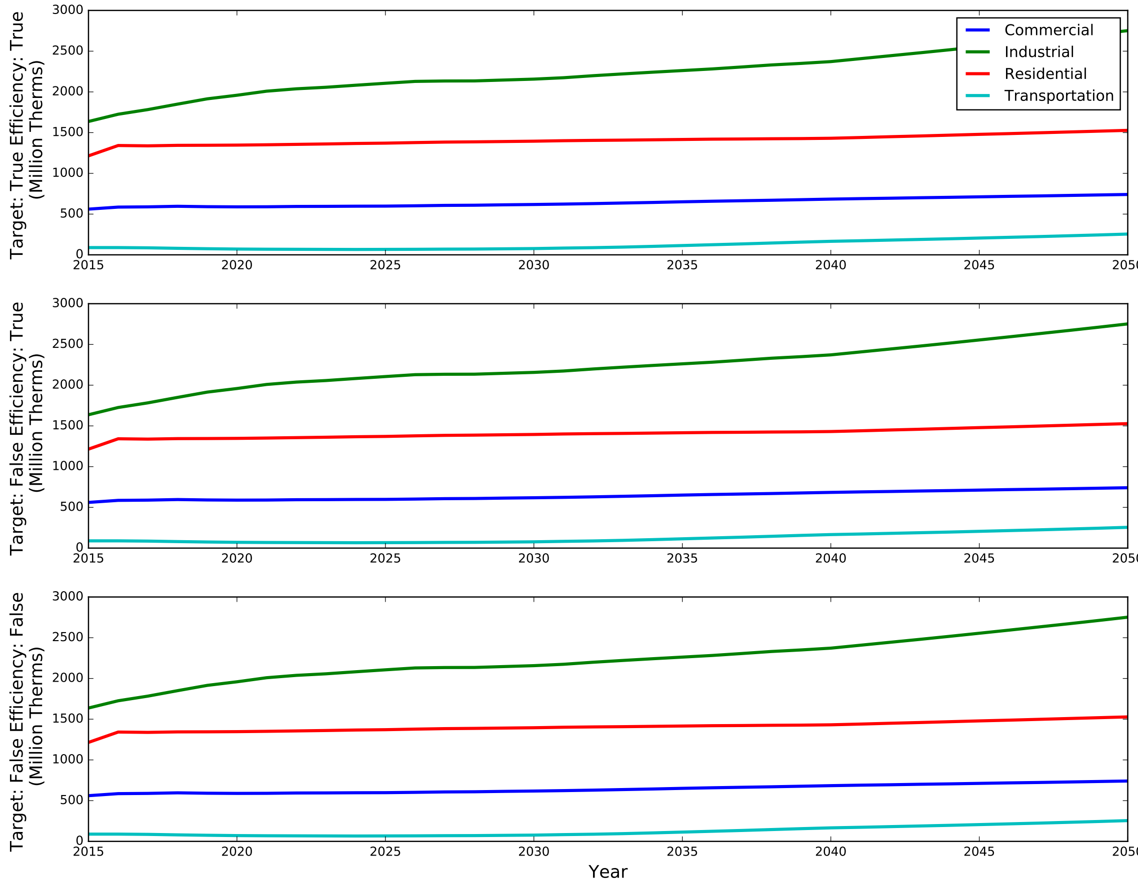

Figure 4.42: Natural Gas Supply - No Nuclear Expansion (Million Therms)

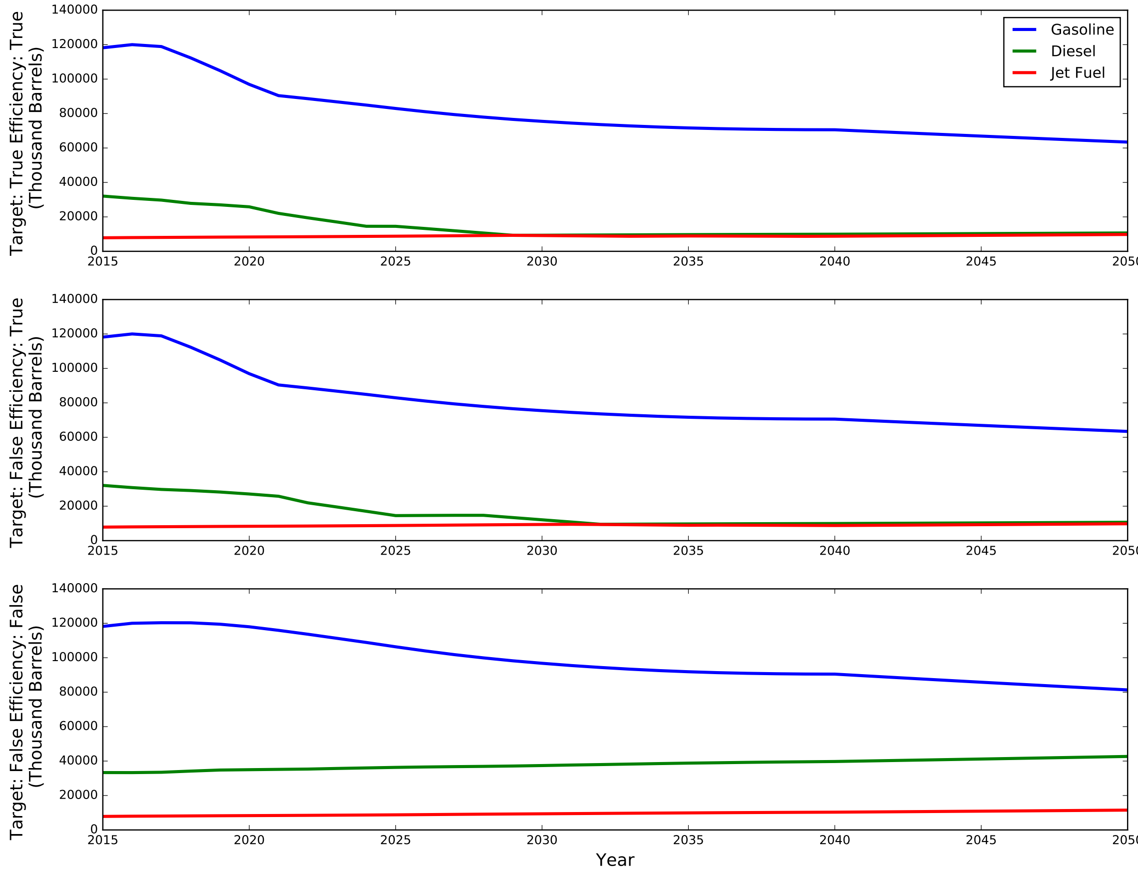

Figure 4.43: Transportation Fuel Supply - No Nuclear Expansion (Thousand Barrels)

In relation to the full technology set scenario, commercial electricity efficiency investments drop between 1% and 3% for year 2020 through 2024, but new policies are invested in beginning in 2025. These lead to increases of 15% by 2038 and 21% by 2050. Natural gas fuel efficiency remains constant. Diesel and jet fuel efficiency investments both begin sooner when nuclear capacity is not allowed to expand.

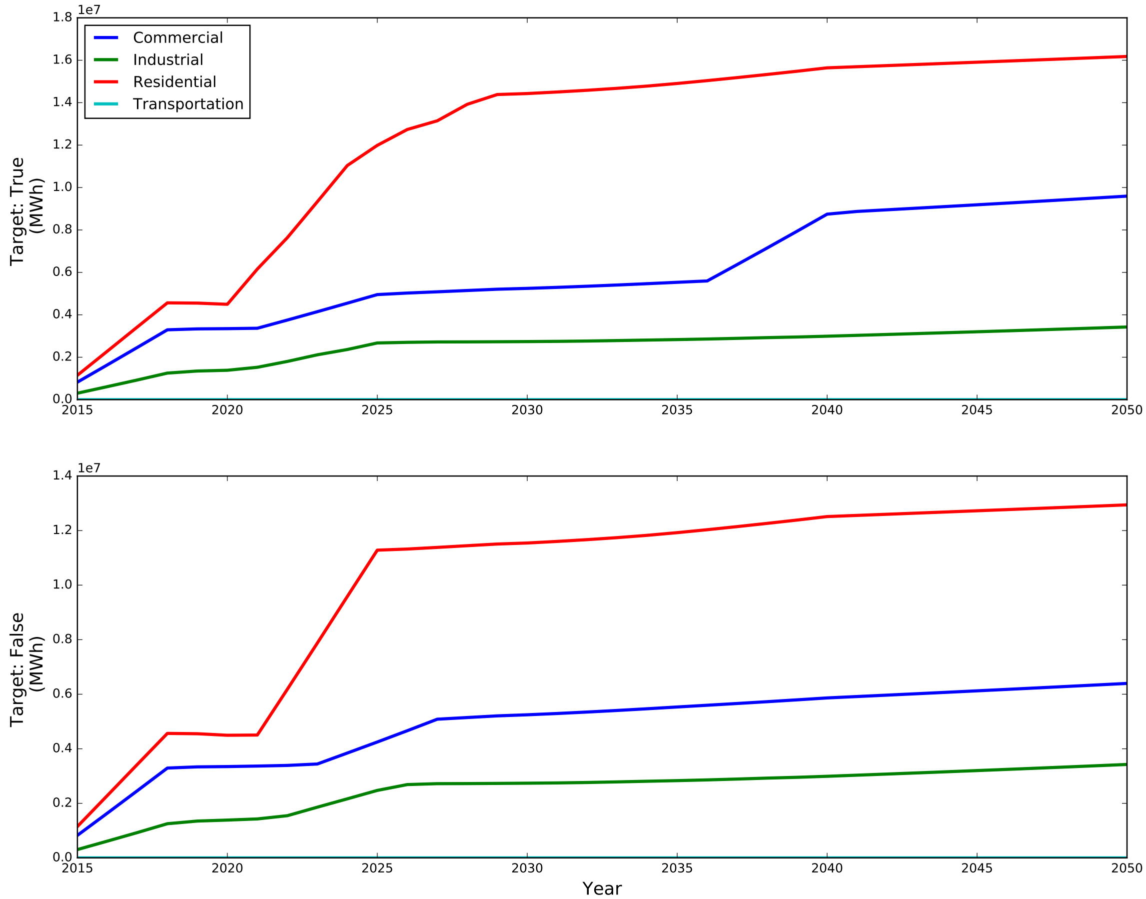

Figure 4.44: Electricity Efficiency - No Nuclear Expansion (MWh)

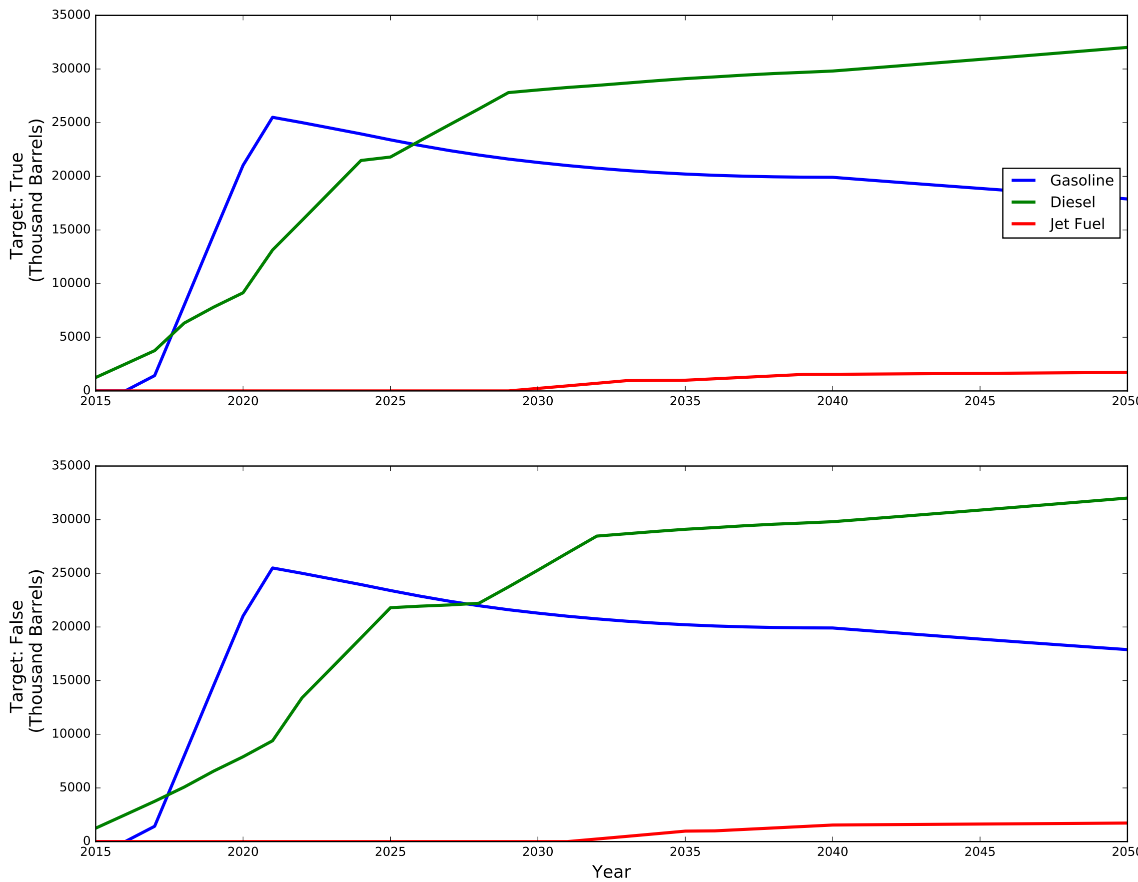

Figure 4.45: Transportation Fuel Efficiency - No Nuclear Expansion (Thousand Barrels)

Since generation from newly constructed nuclear capacity was only significant in the carbon constrained case and that the carbon target constraint was tight in the original scenario, emissions remain consistent in both cases as shown in Figures 4.46 and 4.47.

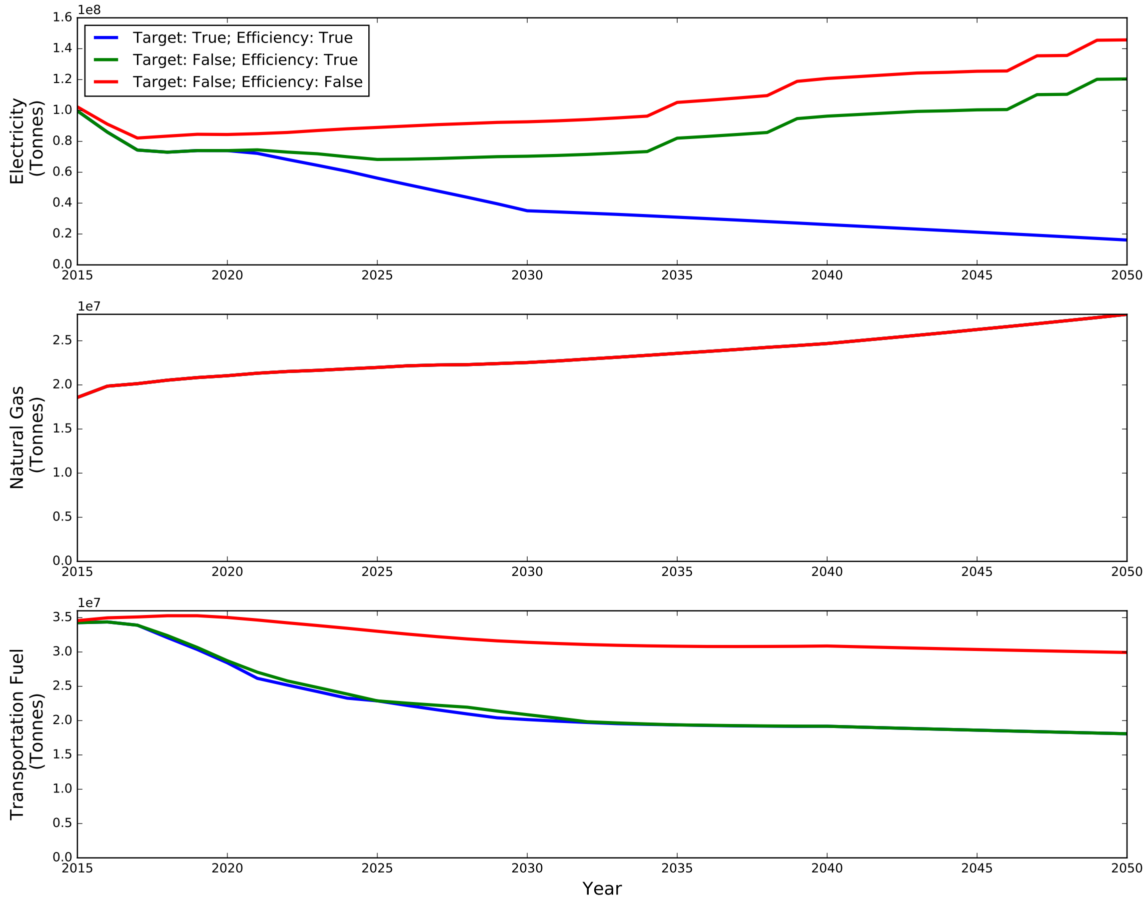

Figure 4.46: Annual Emissions by Source and Scenario - No Nuclear Expansion (Tonnes)

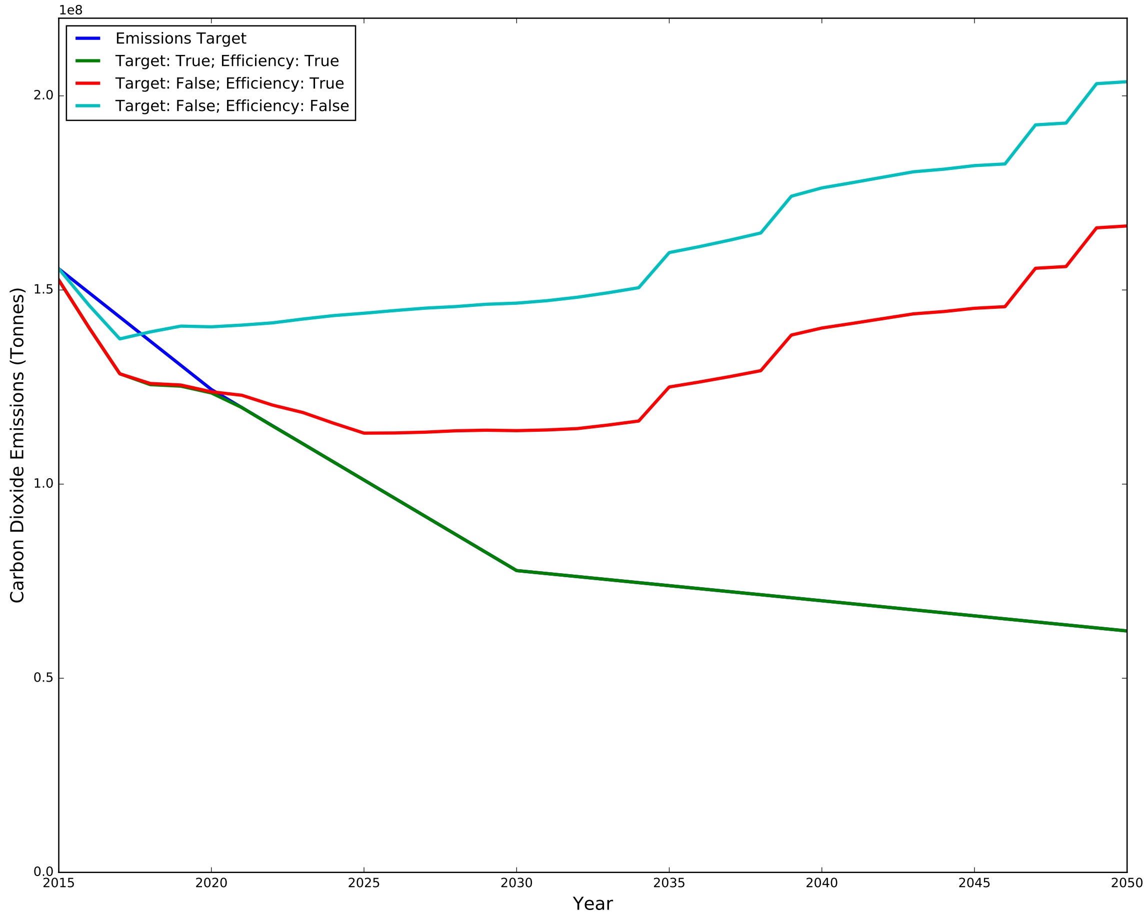

Figure 4.47: Total Annual Emissions - No Nuclear Expansion (Tonnes)

Electricity

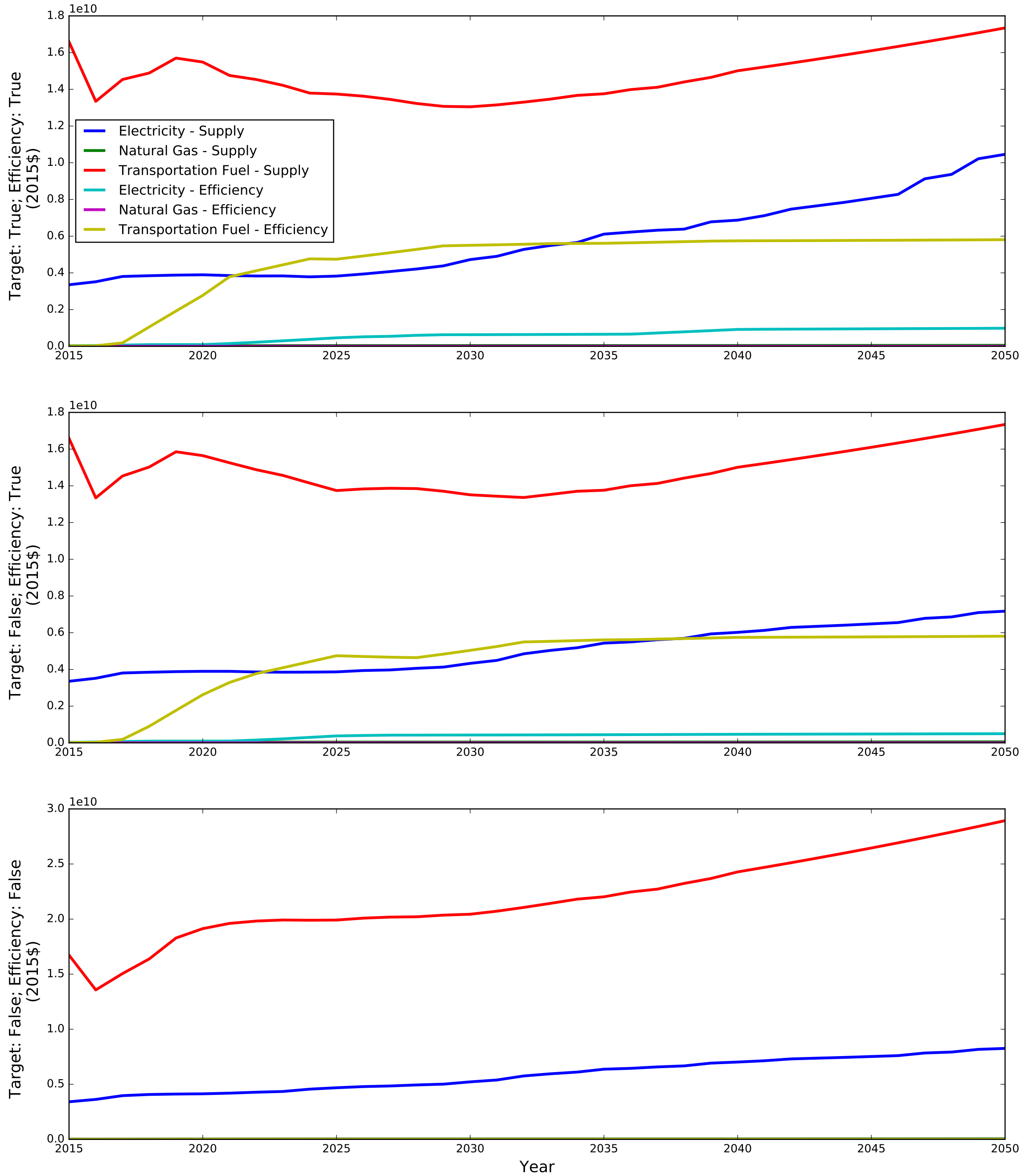

Figure 4.48: Annual Costs - No Nuclear Expansion

Table 4.26: Percent Change in Net Present Value from the Baseline Scenario - No Nuclear Expansion

	Efficiency Investments, No Emissions Target	Efficiency Investments, Emissions Target
Electricity	-7.2%	9.5%
Natural Gas	0.0%	0.0%
Transportation Fuels	-11.7%	-11.7%
Total	**-10.7%**	**-7.2%**

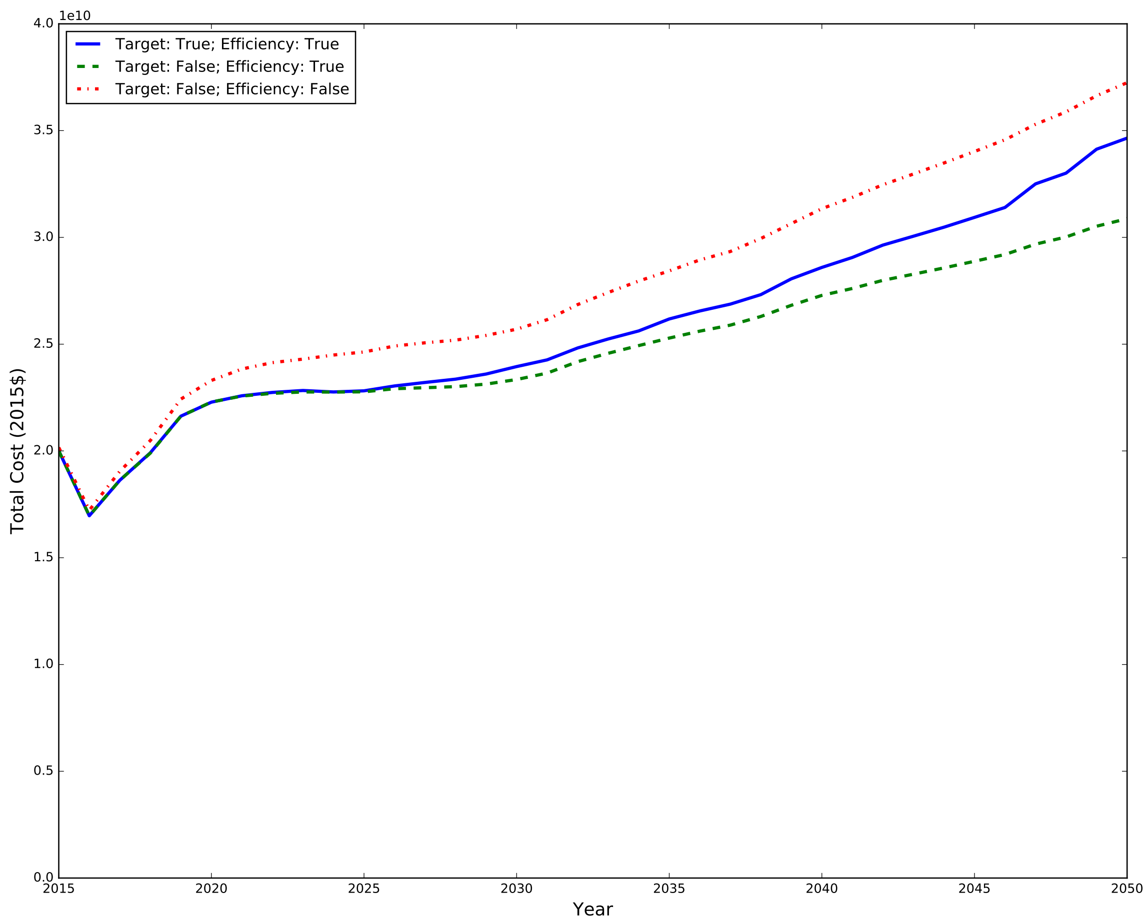

Figure 4.49: Total Annual Costs - No Nuclear Expansion

When nuclear capacity expansion is prohibited, the cost of the carbon target remains roughly 4% below the cost of business as usual. Overall, removing the option to expand nuclear capacity has no effect on the scenarios where a carbon dioxide target is not enforced. For the scenario in which a carbon target is met, a 1% increase in the net present value results from not allowing the expansion of nuclear capacity.

4.6 Conclusion

In the case study of Georgia, this analysis shows that, under a centralized decision maker, efficiency measures are sufficient to drive the majority of the carbon dioxide emissions reductions to meet a desired target. The total cost is approximately 18% less than the baseline scenario and only 4% above the scenario in which efficiency investments are available without a carbon dioxide target that must be met.

The results indicate that there is an energy efficiency gap since energy efficiency investments lead to decreased costs. Brown and Wang (2017) reviews the arguments made by both advocates and skeptics in order to answer three areas of contention: 1) whether an energy efficiency gap exists; 2) the size of the energy efficiency gap; and 3) how the size energy efficiency gap can be decreased [58]. In this review, they argue that market barriers exist that interfere with assumptions made by economists about markets. If the assumptions of a free market hold, which requires rational consumers with complete information maximizing their personal utility, then all cost-effective energy efficiency investments have already been made. Brown and Wang use ten questions to examine where market failures and energy efficiency barriers potentially interfere with the concept of a perfect market. Relevant issues are addressed as follows. Prices may not reflect the full cost of energy, particularly in relation to climate change, air quality, and solid waste pollution. If accounted for in this study, it would be expected that investment in energy efficiency would increase. Another issue is that local markets may have differing levels of efficiency investments. Since this study is at the state level, future work could include the positive externalities associated with energy efficiency and negative externalities associated with fossil fuel combustion. This study assumes that naturally occurring efficiency is already accounted for by using results from the National Energy Modeling System as inputs. It would be appropriate to ensure that any naturally occurring efficiency that was achieved inside the simulation model is not available in this formulation prior to solidifying a plan. Discount rates will also affect the attractiveness of an investment. Sensitivity analysis is useful in determining the potential effect on outcomes under differing valuations of the future. The rebound effect is likely to decrease the net savings from energy efficiency seen in this model for some of the policies. The magnitude of the rebound effect is still a matter of debate. For some policies, there is no latent demand to provide a direct rebound effect. Brown and Wang provide the example of vacuum cleaners which, if made more efficient, are not likely to induce consumers to vacuum more frequently. This study does not account for the rebound effect, but the use of inputs from the National Energy Modeling System negates part of this effect on the outputs of this model. The difficulty of deploying energy efficiency is another barrier that could create an energy efficiency gap. This is difficult to model, both in quantifying the transaction costs and in establishing the adoption rate. This creates a perceived energy efficiency gap that may not be realizable in this study. To partially account for this difficulty, a maximum annual adoption rate is included and where possible program and policy costs are included in the levelized cost of the electricity efficiency investment. Utilities sometimes have difficulty building energy efficiency into their current business models, which can lead to disincentives for implementing efficiency programs. Decoupling utility revenue from profits is one approach to correcting the misalignment of incentives.

One option for decreasing demand is to increase the cost to consumers of the price of energy services. Rate increases are not included in this study, but this would present an alternative lever for decreasing consumption, thus likely decreasing emissions. This could be in the form of restructured tariffs for regulated electricity producers or Pigouvian-style taxes on energy services for consumers to internalize some of the negative externalities. This would lead to a lessened need for carbon dioxide targets. The model also does not account for the electricity producers' ability to maintain profitability. Should demand decrease due to efficiency investments, electricity rates will need to increase in order to cover the large capital investment associated with electricity generation. In situations where decreased demand leads to decreased prices, efficiency investments will become relatively less attractive, at which point the carbon dioxide targets may be required to decrease emissions to desired levels.

The approach used in this study could be enhanced by allowing for fuel switching, for instance intentionally moving from gasoline-powered vehicles to vehicles powered by natural gas or electricity beyond where business-as-usual economics would drive change in consumption behavior, and by incorporating a broader set of efficiency investments. Fuel switching can be incorporated in a straightforward and tractable manner given good data on a realistic adoption rate. As global climate change becomes an increasingly studied topic, more reliable values for efficiency investments will become available at the state level.

CHAPTER 5
CONCLUSION

Borne from a desire to aid the City of Atlanta in planning and executing their Climate Action Plan, this thesis uses optimization and economic decision analysis principles to develop a framework for evaluating the cost of achieving a carbon dioxide target at the state level. Initially, a formalized framework is developed for assessing the levelized cost of electricity for coal, natural gas, and nuclear power generation. This provides a key input to the many energy decisions and models. A model is then developed to analyze the decisions that would lead to least-cost paths to achieving a carbon dioxide emissions target, and the model is then applied to the United States state of Georgia.

By bridging the gap between scenario-based assessments and optimization models that do not simultaneously address supply and efficiency, this thesis provides a new approach to decision-making in the realm of climate and energy policy. The model evaluates the cost of meeting carbon dioxide emissions targets using an electricity generation planning model incorporating natural gas and transportation fuels with simultaneous selection of efficiency investments in order to satisfy consumer service levels and policy-makers' desired carbon dioxide emissions targets. By requiring the decision-maker to clarify the decisions that can or must be made, their objective function, their desired results (e.g. a carbon dioxide target), and the system's inherent constraints, a more transparent view of the model and the modelers intentions is made available. This framework aims to help move these types of analyses in the direction of transparency, tractability, and flexibility.

The Python code is provided in Georgia Tech's GitHub repository which will allow others to run the optimization model, to generate figures that show inputs to the model, and to generate figures that show outputs from the model. Should you find it valuable, please use it freely to drive this methodology forward in assisting policy-makers in achieving their climate and energy objectives.

Appendices

APPENDIX A

REVIEW OF LEVELIZED COST OF ELECTRICITY CALCULATION

We briefly reveiw the calculation fo the levelized cost of electricity.

A.1 Financial Parameters

The present value of a cash flow stream accounts for the time value of money by converting the stream into its equivalent value at a single point in time. Cash flows in future years are rolled back to a specific time period by applying a discount rate. The use of a real discount rate (r_0) adjusts the nominal discount rate for inflation.

$$r_0 = \frac{(1+r)}{(1+f)} - 1 = \frac{r-f}{1+f} \tag{A.1}$$

Here r is the nominal discount rate, or the interest rate at which future cash flows are discounted by the investor and f is the expected rate of inflation. The present value (PV) of a cost stream ($x_0, x_1, \ldots, x_n$) is thus,

$$PV = x_0 + \frac{x_1}{1+r_0} + \frac{x_2}{(1+r_0)^2} + \ldots + \frac{x_n}{(1+r_0)^n} = \sum_{i=0}^{n} \frac{x_i}{(1+r_0)^i} \tag{A.2}$$

When annual costs are fixed in real terms over the life of the plant, the above equation can be represented in closed form.

$$PV_{Fixed} = \frac{x}{r_0} \cdot \left[1 - \frac{1}{(1+r_0)^n}\right] \tag{A.3}$$

where x is a constant annual cost for years i=1 $\ldots n$. If costs escalate by a given rate,

g, each year, the present value is

$$PV_{Gradient} = \frac{x}{r_0 - g} \cdot \left[1 - \frac{1+g)^n}{1+r_0)^n}\right] \tag{A.4}$$

where g is less than r_0.

A.2 Investment Costs

Costs such as capital costs, periodic maintenance, or infrastructure upgrades only occur in certain years of the life of the plant. The present values of costs of this nature are calculated using Equation A.2.

Capital costs can account for a large portion of the total levelized cost of electricity. In order to provide the present value of capital costs from an investors perspective, many parameters must be known. These include the percentage of the total investment that is from debt and equity, the interest rate on debt, the required return on equity, income tax rates, property taxes, insurance costs, construction time, tax life, and others. Estimating these parameters to a high level of accuracy is important for a decision maker analyzing a single plant. However, these parameters can vary greatly by location, technology, company, and regulatory scheme. For this reason, we use a carrying charge approach when calculating the present value of capital costs. The carrying charge approach is also used by Katzer et al. [41] and Rosenberg et al. [12]. The carrying charge rate exchanges the variable cost stream of capital costs for a fixed annual cost stream over the book life of the plant. The total investment (I) is the cost of constructing the plant without consideration of financing and discounting. The cost of construction without financing, also known as the overnight cost (C_o), is often expressed in \$/kW. The total investment is

$$I = C_0 \cdot Cap \tag{A.5}$$

where Cap is the nameplate capacity expressed in units of power (e.g., kW). The carrying charge is applied each year over the book life of the plant and the annual capital cost (C_C) calculated by multiplying the total investment by the carrying charge rate (y).

$$C_C = I \cdot y \tag{A.6}$$

Thus, the present value of capital costs is

$$PV_{CapitalCosts} = \frac{y}{r_0} \cdot \left[1 - \frac{1}{(1 + r_0)^{BL}}\right] \tag{A.7}$$

where BL is the book life of the plant. The book life and plant life are not necessarily equivalent. The book life is the length of time over which initial capital costs affect the operational finances of a company. This includes the time for the plant to fully depreciate and for all financing to be paid in full. The plant life is the operational life of the plant, which generally exceeds the book life of a plant by a decade or more for most power plants. The book life and plant life may be treated as equal from an investment perspective, but this provides inaccurate information when determining the costs of technologies. For instance, nuclear power plants will be financed and depreciated for less than the length of the original 40 year operating permit. Most nuclear plants are then granted another 20 year extension to their operating permit during which they operate without costs or tax benefits associated with the initial construction. The present value of other investment costs, such as periodic maintenance and infrastructure upgrades, can be calculated using Equation A.2.

A.3 Operational Costs

Some costs, including fuel costs and O&M costs, occur each year that the plant is in operation.

A.3.1 Fuel Costs

Given the heat rate (HR) of a plant in units of electricity per input energy (e.g. kWh/MMBtu), the annual electricity output (EO) and a constant fuel price per unit energy (p_F) (e.g., $/MMBtu), the annual fuel cost (C_F) is

$$C_F = p_F \cdot HR \cdot EO \tag{A.8}$$

The present value of fuel costs can be found by letting x equal the annual fuel cost in Equation A.2.

A.3.2 Operation and Maintenance Costs

Operation and maintenance (O&M) costs often have fixed and variable components. The annual fixed O&M (C_{FOM}) costs are determined by the nameplate capacity of the plant in kW and the fixed O&M cost per kW ($c_F OM$).

$$C_{FOM} = Cap \cdot c_{FOM} \tag{A.9}$$

The annual variable O&M costs (C_{VOM})are determined by the annual electricity output in kWh and the variable O&M cost per kWh (c_{VOM}).

$$C_{VOM} = EO \cdot c_{VOM} \tag{A.10}$$

Under the assumption that annual real costs of fixed and variable O&M are constant, the present value of O&M costs can be found by letting x equal this constant total annual cost in Equation A.3.

A.3.3 Emissions Costs

Legislation has been considered in the United States that would place a price on carbon emissions. The annual carbon cost is then

$$C_{CO_2} = p_{CO_2} \cdot ER \cdot EO \tag{A.11}$$

where the CO2 price (p_{CO_2}) is in, for example, \$/ton CO_2 and the CO_2 emissions rate (ER) is in tons CO_2/kWh. The carbon price could be fixed, as with a carbon tax, or it could be variable with the calculation of a discounted average present cost as discussed in section 2.3.1. This includes carbon costs that may start at a future date. The constant, or discounted average, carbon price can be applied to all years of operation using Equation A.3 to find the present value of carbon costs.

A.4 Levelized Cost of Electricity

The levelized cost, C_L, is calculated by finding a constant cost per kWh that when applied to every unit of generated electricity is equal to the present value of the sum of all costs. That is,

$$\begin{aligned} PV[Costs] =& PV\left[C_C + C_F + C_{FOM} + C_{VOM} + C_{CO_2}\right] \\ &= \sum_{i=1}^{n} \frac{C_L \cdot y_i}{(1+r_0)^i} = C_L \cdot \sum_{i=1}^{n} \frac{y_i}{(1+r_0)^i} \end{aligned} \tag{A.12}$$

where y_i is the quantity of electricity generated in year i. This gives a levelized cost of

$$C_L = \frac{PV[Costs]}{\sum_{i=1}^{n} \frac{y_i}{(1+r_0)^i}} = \frac{PV[Costs]}{PV[ElectricityGeneration]} \tag{A.13}$$

If y_i is constant and equal to y for all i ,the then levelized cost can be expressed as

$$C_L = \frac{PV[Costs]}{\frac{y}{r_0} \cdot \left(1 - \frac{1}{(1+r_0)^n}\right)} \tag{A.14}$$

APPENDIX B

LINEAR OPTIMIZATION MODEL - MINIMIZING THE COST OF MEETING A CARBON DIOXIDE EMISSIONS TARGET BY SIMULTANEOUS SELECTION OF SUPPLY AND EFFICIENCY INVESTMENTS

```
from gurobipy import *
import numpy as np
import matplotlib.pyplot as plt
from pylab import *
import csv
import datetime
import time
import os
import pandas as pd

### Notes:
#base directory for local execution
#cd C:\Users\Seth\Dropbox\Borin.Thesis\Gurobi

#set to True if running on GT's server
run_condor = False
#Prints variables if True
print_var = True

date_string = datetime.datetime.now().strftime("%m%d%H%M%S")
time_stamp = str(int(time.time()))
```

```
#carbon_target = True
#DSM_actions = True

if run_condor == True :
data_dir = r'/home/stu/sborin3/Data/'
out_dir = r'/home/stu/sborin3/Output/'
else :
data_dir = r'C:/Users/Seth/Dropbox/Borin.Thesis/Gurobi/Data/
    '
out_dir = r'C:/Users/Seth/Dropbox/Borin.Thesis/Gurobi/Output
    /'

#Create new directory for output
new_out_dir = out_dir + date_string
os.makedirs(new_out_dir)

file_name = new_out_dir + r'/obj' + '.csv'
with open(file_name,'w') as csvfile :
csvwriter = csv.writer(csvfile)
csvwriter.writerow(('Target','DSM','Value'))

file_name = new_out_dir + r'/var' + '.csv'
with open(file_name,'w') as csvfile :
csvwriter = csv.writer(csvfile)
csvwriter.writerow(('Target','DSM','Name','Type','Source','
    Tech','Sector','Fuel','Segment','Year','Season','Hour','
```

```
    Units','Value'))

file_name = new_out_dir + r'/tgt' + '.csv'
with open(file_name,'w') as csvfile :
csvwriter = csv.writer(csvfile)



#optimization model function
def opt(tgt,dsm,data_dir,new_out_dir,r,num_years,
    max_yearly_implementation,dsm_cost_multiplier,
    dsm_seg_multiplier,first_target_year,second_target_year,
    third_target_year,first_target_percentage,
    second_target_percentage,third_target_percentage) :

#####   sets   #####
sources = ['electricity',
'natural_gas',
'transportation_fuel'] #e, ng, and tf

seasons = ['winter',
'summer',
'intermediate'] #S

elec_techs = ['coal',
'nuclear',
'natural_gas',
'hydro',
```

```
'wood_waste_solids',
'oil',
'landfill_gas',
'biomass',
'solar',
'wind'] #I

sectors = ['commercial',
'industrial',
'residential',
'transportation'] #M

fuels = ['gasoline',
'diesel',
'jet_fuel'] #L



years = list(range(num_years))

num_hours = 24 #H, number of hours in load curve
hours = list(range(num_hours))

##### parameters #####



discount_factor = {} #r
for year in years:
```

```
discount_factor[year] = float((1 / ((1 + r) ** year)))

#Reserve margin for electricity generation
elec_res_margin = 0.85 #\eta

#emissions targets
baseline_emissions = 155464338.96 #False/False Year 2015
    Results from 9/14/2015 - consistent with results from
emissions_target = {} #E_t

#Use linear interpolation between targets - i.e. targets
    change each year, hitting the predefined targets at the
    desired year
for year in years :
emissions_target[year] = None
if year == 0 :
emissions_target[year] = baseline_emissions
elif 0 < year <= first_target_year :
emissions_target[year] = baseline_emissions * (1 - (1 -
    first_target_percentage)*(year - 0)/(first_target_year -
    0))
elif first_target_year < year <= second_target_year :
emissions_target[year] = baseline_emissions * (
    first_target_percentage - (first_target_percentage -
    second_target_percentage) * (year-first_target_year)/(
    second_target_year - first_target_year))
elif second_target_year <= year < third_target_year :
```

```
emissions_target[year] = baseline_emissions * (
   second_target_percentage - (second_target_percentage -
   third_target_percentage) * (year-second_target_year)/(
   third_target_year - second_target_year))
elif year >= third_target_year :
emissions_target[year] = baseline_emissions *
   third_target_percentage

if tgt == True and dsm == True :
file_name = new_out_dir + r'/tgt.csv'
with open(file_name,'a') as csvfile :
csvwriter = csv.writer(csvfile)
csvwriter.writerow(('Year','Emissions_Target'))
for year in years:
csvwriter.writerow((year,emissions_target[year]))

##### forecasts + data #####

#create dictionaries for demand and cost
demand = {} #d^e_{m,t}, d^{ng}_{m,t,0 $d^{tf}_{l,t}$
cost = {} #$c_{m,t}^{ng}$, $c_{l,t}^{tf}$

for source in sources :
demand[source] = {}
cost[source] = {}
for sector in sectors :
if source == 'electricity' :
```

```
demand[source][sector] = {}
for year in years:
demand[source][sector][year] = None
elif source == 'natural_gas' :
for sector in sectors:
demand[source][sector] = {}
cost[source][sector] = {}
for year in years:
demand[source][sector][year] = None
cost[source][sector][year] = None
elif source == 'transportation_fuel' :
for fuel in fuels:
demand[source][fuel] = {}
cost[source][fuel] = {}
for year in years:
demand[source][fuel][year] = None
cost[source][fuel][year] = None

#read demand
for source in sources :
if source == 'electricity':
filename = data_dir + 'electricity_demand.csv'
with open(filename, mode = 'r') as infile :
reader = csv.reader(infile)
header = next(reader)
for line in reader :
year = int(line[0])
```

```
com_read = float(line[1])
ind_read = float(line[2])
res_read = float(line[3])
tra_read = float(line[4])
demand[source]['commercial'][year] = com_read
demand[source]['industrial'][year] = ind_read
demand[source]['residential'][year] = res_read
demand[source]['transportation'][year] = tra_read
elif source == 'natural_gas':
filename = data_dir + 'natural_gas_demand.csv'
with open(filename, mode='r') as infile:
reader = csv.reader(infile)
header = next(reader)
for line in reader:
year = int(line[0])
com_read = float(line[1])
ind_read = float(line[2])
res_read = float(line[3])
tra_read = float(line[4])
demand[source]['commercial'][year] = com_read
demand[source]['industrial'][year] = ind_read
demand[source]['residential'][year] = res_read
demand[source]['transportation'][year] = tra_read
elif source == 'transportation_fuel':
filename = data_dir + 'transportation_fuel_demand.csv'
with open(filename, mode='r') as infile:
reader = csv.reader(infile)
```

```
header = next(reader)
for line in reader :
year = int(line[0])
gas_read = float(line[1])
die_read = float(line[2])
jet_read = float(line[3])
demand[source]['diesel'][year] = gas_read
demand[source]['gasoline'][year] = die_read
demand[source]['jet_fuel'][year] = jet_read

### costs
#create electricity cost dictionaries
capital_cost = {} #f_i^C
fixed_om_cost = {} #f_i^{O}
variable_om_cost = {} #v_i
fuel_cost = {} #$c_{i,t}^e$

for tech in elec_techs:
capital_cost[tech] = None
fixed_om_cost[tech] = None
variable_om_cost[tech] = None
fuel_cost[tech] = {}
for year in years:
fuel_cost[tech][year] = 0

#read costs
for source in sources:
```

```
if source =='electricity':
filename = data_dir + 'electricity_fuel_costs.csv'
with open(filename, mode='r') as infile:
reader = csv.reader(infile)
header = next(reader)
for line in reader:
tech = line[0]
year = int(line[1])
fc_read = float(line[2])
fuel_cost[tech][year] = fc_read
filename = data_dir + 'electricity_costs.csv'
with open(filename, mode='r') as infile:
reader = csv.reader(infile)
header = next(reader)
for line in reader:
tech = line[0]
cap_read = float(line[1])
fom_read = float(line[2])
vom_read = float(line[3])
capital_cost[tech] = cap_read
fixed_om_cost[tech] = fom_read
variable_om_cost[tech] = vom_read
elif source == 'natural_gas':
filename = data_dir + 'natural_gas_costs.csv'
with open(filename, mode='r') as infile:
reader = csv.reader(infile)
header = next(reader)
```

```
for line in reader :
year = int(line[0])
com_read = float(line[1])
ind_read = float(line[2])
res_read = float(line[3])
tra_read = float(line[4])
cost[source]['commercial'][year] = com_read
cost[source]['industrial'][year] = ind_read
cost[source]['residential'][year] = res_read
cost[source]['transportation'][year] = tra_read
else :
filename = data_dir + 'transportation_fuel_costs.csv'
with open(filename, mode='r') as infile :
reader = csv.reader(infile)
header = next(reader)
for line in reader :
year = int(line[0])
die_read = float(line[1])
gas_read = float(line[2])
jet_read = float(line[3])
cost[source]['diesel'][year] = die_read
cost[source]['gasoline'][year] = gas_read
cost[source]['jet_fuel'][year] = jet_read

### emissions rate
# create dictionary
```

```
emissions_rate = {} #\omega_i^e, \omega^{ng}, \omega_l^{tf}

for source in sources:
if source == 'electricity':
emissions_rate[source] = {}
for tech in elec_techs :
emissions_rate[source][tech] = None
elif source == 'natural_gas':
emissions_rate[source] = None
elif source == 'transportation_fuel' :
emissions_rate[source] = {}
for fuel in fuels:
emissions_rate[source][fuel] = None

#define dictionary, default to zero
for tech in elec_techs :
emissions_rate['electricity'][tech] = 0

#include emissions rates for specified sources and fuels
emissions_rate['electricity']['coal'] = 1.141772461 #tonnes/
    MWh
emissions_rate['electricity']['natural_gas'] = 0.442026346 #
    tonnes/MWh
emissions_rate['electricity']['oil'] = 0.29599316 #tonnes/
    MWh

emissions_rate['natural_gas'] = 5306 #tonnes/million therms
```

```
emissions_rate['transportation_fuel']['gasoline'] =
    209.5238095 #tonnes/thousand barrels
emissions_rate['transportation_fuel']['diesel'] =
    240.4761905 #tonnes/thousand barrels
emissions_rate['transportation_fuel']['jet_fuel'] =
    227.8571429 #tonnes/thousand barrels

###electricity parameters

#create general technology dictionaries
initial_capacity = {} #x_i{i,0}^e
capacity_factor = {} #\pi_i
min_expansion = {} #\underline{x}_i^e
max_expansion = {} #\overline{x}_i^e
plant_life = {} #\tau_i
for tech in elec_techs:
initial_capacity[tech] = None
capacity_factor[tech] = None
min_expansion[tech] = None
max_expansion[tech] = None
plant_life[tech] = None

filename = data_dir + 'electricity_parameters.csv'

#read general technology inputs
with open(filename, mode='r') as infile:
```

```
reader = csv.reader(infile)
header = next(reader)
for line in reader:
tech = line[0]
in_cap_read = float(line[1])
cap_fac_read = float(line[2])
min_exp_read = float(line[3])
max_exp_read = float(line[4])
life_read = int(line[5])
initial_capacity[tech] = in_cap_read
capacity_factor[tech] = cap_fac_read
min_expansion[tech] = min_exp_read
max_expansion[tech] = max_exp_read
plant_life[tech] = life_read

#create technology-specific dictionaries
hourly_capacity_factor = {} #\lambda_s
planned_retirements = {} #y_{i,t}^{e,ret}
planned_installations = {} #y_{i,t}^{e,inst}

for tech in elec_techs:
hourly_capacity_factor[tech] = {}
for season in seasons:
hourly_capacity_factor[tech][season] = {}
for hour in hours:
hourly_capacity_factor[tech][season][hour] = 1
```

```
#read hourly capacity factor
filename = data_dir + 'hourly_cap_fac.csv'
with open(filename, mode='r') as infile:
reader = csv.reader(infile)
header = next(reader)
for line in reader:
tech = line[0]
season = line[1]
hour = int(line[2])
hcf_read = float(line[3])
hourly_capacity_factor[tech][season][hour] = hcf_read

for tech in elec_techs:
if tech != 'solar' and tech != 'wind':
for season in seasons:
for hour in hours:
hourly_capacity_factor[tech][season][hour] = 1

#create retirements/installations dictionaries
for tech in elec_techs:
planned_retirements[tech] = {}
planned_installations[tech] = {}
cap_year = 0
while cap_year < 71:
planned_retirements[tech][cap_year] = 0
planned_installations[tech][cap_year] = 0
cap_year += 1
```

```
#read retirements/installations
filename = data_dir + 'planned_capacity.csv'

with open(filename, mode = 'r') as infile:
reader = csv.reader(infile)
header = next(reader)
for line in reader :
tech = line[0]
year = int(line[1])
ret_read = float(line[2])
inst_read = float(line[3])
planned_retirements[tech][year] = ret_read
planned_installations[tech][year] = inst_read

seasonal_factor = {}
days = {}
max_demand_factor = {}
peak_demand_ratio = {}

for season in seasons:
seasonal_factor[season] = {}
days[season] = {}
max_demand_factor[season] = {}
peak_demand_ratio[season] = {}

filename = data_dir + 'demand_factors_seasonality.csv'
```

```
with open(filename, mode = 'r') as infile:
reader = csv.reader(infile)
header = next(reader)
for line in reader :
season = line[0]
sf_read = float(line[1])
days_read = int(line[2])
max_dem_read = float(line[3])
peak_dem_read = float(line[4])
seasonal_factor[season] = sf_read
days[season] = days_read
max_demand_factor[season] = max_dem_read
peak_demand_ratio[season] = peak_dem_read

#create seasonal demand factor dictionary
demand_factor = {} #\mu_{s,h}
for season in seasons:
demand_factor[season] = {}
for hour in hours :
demand_factor[season][hour] = None

#read seasonal demand dictionary
filename = data_dir + 'demand_factor.csv'

with open(filename, mode='r') as infile :
reader = csv.reader(infile)
```

```
header = next(reader)
for line in reader :
season = line[0]
hour = int(line[1])
df_read = float(line[2])
demand_factor[season][hour] = df_read

#create demand multipliers
peak_seasonal_adjustment = {}
hourly_demand_adjustment = {}

for season in seasons:
peak_seasonal_adjustment[season] = None
hourly_demand_adjustment[season] = {}
for hour in hours:
hourly_demand_adjustment[season][hour] = None

#define demand multipliers
for season in seasons:
#adjusts annual demand to the maximum hourly demand for that
    year - % by season * max % by hour / days in season *
   peak/average ratio / reserve margin for capacity
peak_seasonal_adjustment[season] = seasonal_factor[season] *
    max_demand_factor[season] / days[season] *
   peak_demand_ratio[season] / elec_res_margin
for hour in hours :
#adjusts annual demand to hourly demand - % by season * % by
```

```
    hour / days in season
hourly_demand_adjustment[season][hour] = seasonal_factor[
    season] * demand_factor[season][hour] / days[season]

#maximum number of segments for all sources, sectors, and
    years
num_segments = 5
segments = list(range(num_segments))

#create action cost function dictionaries by creating bin
    sizes and marginal action costs by source, sector, and
    year - defaulting to 0 length and large cost
seg_percent = {}
seg_size = {}
marg_ac = {}
for source in sources :
seg_percent[source] = {}
seg_size[source] = {}
marg_ac[source] = {}
if source == 'transportation_fuel':
for fuel in fuels:
seg_percent[source][fuel] = {}
seg_size[source][fuel] = {}
marg_ac[source][fuel] = {}
for year in years :
seg_percent[source][fuel][year] = {}
seg_size[source][fuel][year] = {}
```

```
marg_ac[source][fuel][year] = {}
for seg in segments :
seg_percent[source][fuel][year][seg] = {}
seg_size[source][fuel][year][seg] = {}
marg_ac[source][fuel][year][seg] = {}
else:
for sector in sectors:
seg_percent[source][sector] = {}
seg_size[source][sector] = {}
marg_ac[source][sector] = {}
for year in years:
seg_percent[source][sector][year] = {}
seg_size[source][sector][year] = {}
marg_ac[source][sector][year] = {}
for seg in segments :
seg_percent[source][sector][year][seg] = {}
seg_size[source][sector][year][seg] = {}
marg_ac[source][sector][year][seg] = {}

#default to 0 size and
for source in sources :
for year in years :
for seg in segments:
if source == 'transportation_fuel' :
for fuel in fuels :
seg_percent[source][fuel][year][seg] = 0
seg_size[source][fuel][year][seg] = 0
```

```
marg_ac[source][fuel][year][seg] = 1
else :
for sector in sectors :
seg_percent[source][sector][year][seg] = 0
seg_size[source][sector][year][seg] = 0
marg_ac[source][sector][year][seg] = 1

#read dsm segment sizes
filename = data_dir + 'dsm_action_seg.csv'

with open(filename, mode='r') as infile :
reader = csv.reader(infile)
header = next(reader)
for line in reader :
dsm_source = line[0]
dsm_sector_fuel = line[1]
dsm_year = int(line[2])
dsm_seg = int(line[3])
seg_percent_read = float(line[4])
seg_cost_read = float(line[5])
seg_percent[dsm_source][dsm_sector_fuel][dsm_year][dsm_seg]
   = seg_percent_read * dsm_seg_multiplier
marg_ac[dsm_source][dsm_sector_fuel][dsm_year][dsm_seg] =
   seg_cost_read * dsm_cost_multiplier #for sensitivity
   analysis purposes
#constant segment percentages throughout forecast period
constant_dsm_percents = True
```

```
if constant_dsm_percents == True :
for year in years :
for source in sources :
if source == 'transportation_fuel' :
for fuel in fuels :
for seg in segments :
seg_percent[source][fuel][year][seg] = seg_percent[source][
    fuel][0][seg]
else :
for sector in sectors :
for seg in segments :
seg_percent[source][sector][year][seg] = seg_percent[source
    ][sector][0][seg]

for year in years :
for source in sources :
if source == 'transportation_fuel' :
for fuel in fuels :
for seg in segments :
seg_size[source][fuel][year][seg] = seg_percent[source][fuel
    ][year][seg] * demand[source][fuel][year]
else :
for sector in sectors :
for seg in segments :
seg_size[source][sector][year][seg] = seg_percent[source][
    sector][year][seg] * demand[source][sector][year]
```

```
#if costs are annualized, set to true - else, write new code
    , fill in new values
annualized_marg_ac = True
if annualized_marg_ac == True :
for year in years :
for seg in segments:
for source in sources :
if source == 'transportation_fuel' :
for fuel in fuels :
marg_ac[source][fuel][year][seg] = marg_ac[source][fuel][0][
    seg]
else :
for sector in sectors :
marg_ac[source][sector][year][seg] = marg_ac[source][sector
    ][0][seg]
if tgt == True and dsm == True :
with open(new_out_dir + r'/marg_ac.csv','w') as file :
file.write('Year,Source,Sector_Fuel,Segment,Size,Percent,
    Marginal_Cost\n')
for year in years :
for seg in segments:
for source in sources :
if source == 'transportation_fuel' :
for fuel in fuels :
file.write("%s,%s,%s,%s,%f,%f,%f\n" %
(year,source,fuel,seg, seg_size[source][fuel][year][seg],
    seg_size[source][fuel][year][seg]/demand[source][fuel][
```

```
    year],marg_ac[source][fuel][year][seg]))
else :
for sector in sectors :
file.write("%s,%s,%s,%s,%f,%f,%f\n" %
(year,source,sector,seg, seg_size[source][sector][year][seg
    ],seg_size[source][sector][year][seg]/demand[source][
    sector][year],marg_ac[source][sector][year][seg]))

try:
##### Create a new model #####
m = Model("cost_CAP")

mip_gap = 0.00001 #optimality gap - 0.0025 as default
m.setParam("MIPGap", mip_gap)
m.setParam("LogFile", out_dir + "/" + str(tgt) +"_" + str(
    dsm) + ".log")


##### Create variables
#Decision variables
b = {} #binary variable for electricity
y = {}  #electricity capacity installed
y_retired = {} #electricity capacity retired, costs assumed
    to be included in capital cost
w = {} #total newly installed capacity
x = {}  #total electricity capacity
z = {}  #source supply
```

```
g = {}  #action supply
#Intermediate variables
annual_e_supply = {} #annual electricity supply by
    technology
total_annual_emissions = {} #total emissions
source_annual_emissions = {} #total emissions by source
total_annual_cost = {} #total annual cost
source_annual_cost = {} #source annual cost
source_annual_efficiency_cost = {} #source annual cost

#Variables for electricity
source = 'electricity'
for tech in elec_techs :
for year in years :
# binary variable - installed = 1, not installed = 0
b[tech,year] = m.addVar(vtype = GRB.BINARY,
name = "expansion,binary,%s,%s,,,,%s,,," % (source,tech,year
    ))
# new capacity installed - MW by technology and year
y[tech,year] = m.addVar(lb=0.0,
ub=GRB.INFINITY,
vtype = GRB.CONTINUOUS,
name = 'expansion,continuous,%s,%s,,,,%s,,,MW' % (source,
    tech,year))
# new capacity installed - MW by technology and year
y_retired[tech,year] = m.addVar(lb=0.0,
ub=GRB.INFINITY,
```

```
vtype = GRB.CONTINUOUS,
name = 'retirement,continuous,%s,%s,,,,%s,,,MW' % (source,
    tech,year))
# total new capacity requiring payment of capital costs - MW
w[tech,year] = m.addVar(lb=0.0,
ub=GRB.INFINITY,
vtype = GRB.CONTINUOUS,
name = 'tot_expansion,continuous,%s,%s,,,,%s,,,MW' % (source
    ,tech,year))
# total capacity - MW by technology and year
x[tech,year] = m.addVar(lb=0.0,
ub=GRB.INFINITY,
vtype = GRB.CONTINUOUS,
name = 'total_capacity,continuous,%s,%s,,,,%s,,,MW' % (
    source,tech,year))

#Supply variables
for source in sources:
if source == 'electricity':
for tech in elec_techs:
for hour in hours:
for season in seasons:
for year in years:
# generation - MWh by technology for a single representative
     hour in a season by year
z[source,tech,season,hour,year] = m.addVar(lb=0.0,
ub=GRB.INFINITY,
```

```
vtype = GRB.CONTINUOUS,
name = 'supply,continuous,%s,%s,,,,%s,%s,%s,MWh' % (source,
   tech, year, season, hour))
for year in years :
# total annual generation by technology
annual_e_supply[source,tech,year] = m.addVar(lb=0.0,
ub=GRB.INFINITY,
vtype = GRB.CONTINUOUS,
name = 'annual_e_supply,continuous,%s,%s,,,,%s,,,MWh' % (
   source, tech, year))
elif source == 'natural_gas' :
for sector in sectors :
for year in years :
# supply - million therms
z[source,sector,year] = m.addVar(lb=0.0,
ub=GRB.INFINITY,
vtype = GRB.CONTINUOUS,
name = 'supply,continuous,%s,,%s,,,%s,,,Mtherms' % (source,
   sector, year))
elif source == 'transportation_fuel' :
for fuel in fuels :
for year in years :
# supply - thousand barrels
z[source,fuel,year] = m.addVar(lb=0.0,
ub=GRB.INFINITY,
vtype = GRB.CONTINUOUS,
name = 'supply,continuous,%s,,,%s,,%s,,,1000gal' % (source,
```

```
    fuel, year))

#DSM Action Variables by Source and Sector
for source in sources:
if source == 'transportation_fuel':
for fuel in fuels:
for year in years:
for seg in segments:
g[source,fuel,year,seg] = m.addVar(lb=0.0,
ub=GRB.INFINITY,
vtype = GRB.CONTINUOUS,
name = 'action_supply,continuous,%s,,,%s,%s,%s,,,' % (source
    , fuel, seg, year))

else:
for sector in sectors:
for year in years:
for seg in segments:
g[source,sector,year,seg] = m.addVar(lb=0.0,
ub=GRB.INFINITY,
vtype = GRB.CONTINUOUS,
name = 'action_supply,continuous,%s,,%s,,%s,%s,,,' % (source
    , sector, seg, year))

#Emissions variables
for year in years:
total_annual_emissions[year] = m.addVar(vtype = GRB.
```

```
    CONTINUOUS,
name = 'total_annual_emissions,continuous,,,,,,%s,,,tonnes'
    % year)
total_annual_cost[year] = m.addVar(vtype = GRB.CONTINUOUS,
name = 'total_annual_cost,continuous,,,,,,%s,,,dollars' %
    year)
for source in sources:
source_annual_emissions[source,year] = m.addVar(vtype = GRB.
    CONTINUOUS,
name = 'source_annual_emissions,continuous,%s,,,,,%s,,,
    tonnes' % (source, year))
source_annual_cost[source,year] = m.addVar(vtype = GRB.
    CONTINUOUS,
name = 'source_annual_cost,continuous,%s,,,,,%s,,,dollars' %
    (source, year))
source_annual_efficiency_cost[source,year] = m.addVar(vtype
    = GRB.CONTINUOUS,
name = 'source_annual_efficiency_cost,continuous,%s,,,,,%s
    ,,,dollars' % (source, year))


m.update()

##### Constraints #####

### Electricity Capacity
#Initial Capacity
```

```
init_cap = {}
init_add_cap = {}
for tech in elec_techs :
#Initial capacity
init_cap[tech] = (m.addConstr(x[tech,0] == initial_capacity[
    tech] + y[tech, 0] + planned_installations[tech][0]-
    planned_retirements[tech][0],
"Initial_Capacity_%s" % tech))

#Expansion
tot_cap_installed = {}
tot_new_cap = {}
for tech in elec_techs :
inst_year = 1
while inst_year < num_years :
#Change in capacity
tot_cap_installed[tech,inst_year]=(m.addConstr(x[tech,
    inst_year]
== (x[tech,(inst_year - 1)] + y[tech, inst_year] - y_retired
    [tech,inst_year] + planned_installations[tech][inst_year]
     - planned_retirements[tech][inst_year]),
"Total_Capacity_Installed_%s_%i" % (tech, inst_year)))
#Change in installed capacity
tot_new_cap[tech,inst_year] = (m.addConstr(w[tech,inst_year]
== (w[tech, (inst_year - 1)] + y[tech,inst_year] - y_retired
    [tech,inst_year] + planned_installations[tech][inst_year
    ])))
```

```
inst_year += 1
tot_new_cap[tech,0] = (m.addConstr(w[tech,0]
== y[tech,0] - y_retired[tech,0] + planned_installations[
    tech][0]))

#Retirement/Installation
cap_retired = {}
cap_retired_0 = {}
for tech in elec_techs :
plant_year = plant_life[tech]
while plant_year < num_years :
year_built = plant_year - plant_life[tech]
cap_retired[tech,plant_year] = m.addConstr(y_retired[tech,
    plant_year]
== y[tech,year_built] + planned_installations[tech][
    year_built])
plant_year += 1
plant_year = 0
while plant_year < plant_life[tech] :
if plant_year < num_years :
cap_retired_0[tech,plant_year] = m.addConstr(y_retired[tech,
    plant_year] == 0)
plant_year += 1

#Minimum yearly expansion/maximum total expansion
bin_exp_1 = {}
bin_exp_2 = {}
```

```
for year in years :
for tech in elec_techs:
bin_exp_1[tech,year] = (m.addConstr(y[tech, year] >= b[tech,
    year] * min_expansion[tech],
"Min_%s_%d" % (tech, year)))
bin_exp_2[tech,year] = (m.addConstr(y[tech, year] <= b[tech,
    year] * max_expansion[tech],
"Max_%s_%d" % (tech, year)))

#Maximum total hydro expansion
max_tot_exp = {}
max_tot_exp['hydro'] = (m.addConstr(sum(y['hydro',year] for
   year in years) <= 5 * min_expansion['hydro'],
"Max_total_hydro"))

#Hourly capacity factors
hour_cap = {}
for year in years :
for season in seasons :
for hour in hours :
for tech in elec_techs :
hour_cap[tech, season, hour, year] = (m.addConstr(z['
   electricity',tech,season,hour,year]
<= x[tech,year] * hourly_capacity_factor[tech][season][hour
   ],
"Hourly_Capacity_%s_%s_%d_%d" % (tech, season, hour, year)))
```

```
#Yearly capacity factors
cap_fac = {}
for year in years :
for tech in elec_techs :
cap_fac[tech, year] = (m.addConstr(sum(sum(z['electricity',
   tech,season,hour,year] for hour in hours) * days[season]
    for season in seasons)
<= capacity_factor[tech] * x[tech,year] * num_hours * sum(
   days[season] for season in seasons),
"Capacity_Factor_%s_%s_%d" % ('electricity', tech, year)))

#Meet energy demand
season_elec_demand = {}
hourly_elec_demand = {}
annual_ng_demand = {}
annual_tf_demand = {}
ann_e_supp = {}

#Note: if dsm == False, DSM actions are forced to zero
for source in sources:
for year in years :
if source == 'electricity' :
for season in seasons :
#Sufficient capacity to meet peak hourly seasonal demand
season_elec_demand[season, year] = (m.addConstr(sum((x[tech,
   year] * capacity_factor[tech]) for tech in elec_techs) #
   available MW for peak hour in season
```

```
# MW of capacity * capacity factor (* one hour) = capability
    of meeting demand for one specific hour slot given
    capacity limits
>= sum((demand[source][sector][year] - sum(g[source,sector,
    year,seg] for seg in segments)) for sector in sectors) *
    peak_seasonal_adjustment[season],
#(demand - offsets) * peak seasonal adjustment = highest
    hourly demand for a season
"Peak_Seasonal_%s_Demand_%s_%d" % (source, season, year)))
for hour in hours:
#Sufficient generation to meet hourly demand
hourly_elec_demand[season,hour,year] = (m.addConstr(sum(z[
    source,tech,season,hour,year] for tech in elec_techs)
# MWh generated for one hour x days for season = total MWh
    for one hour of a season
>= sum((demand[source][sector][year] - sum(g[source,sector,
    year,seg] for seg in segments)) for sector in sectors) *
    hourly_demand_adjustment[season][hour],
# total (MWh demanded - offset MWh) * hourly demand
    adjustment = total MWh for one hour of season
"Hourly_%s_Demand_%s_%d_%d" % (source, season, hour, year)))
elif source == 'natural_gas':
for sector in sectors:
annual_ng_demand[source,sector, year] = (m.addConstr(z[
    source,sector,year] >= demand[source][sector][year] - sum
    (g[source,sector,year,seg] for seg in segments),
"Annual_%s_Demand_%s_%d" % (source, sector, year)))
```

```
else :
for fuel in fuels :
annual_tf_demand[source,fuel,year] = (m.addConstr(z[source,
    fuel,year] >= demand[source][fuel][year] - sum(g[source,
    fuel,year,seg] for seg in segments),
"Annual_%s_Demand_%s_%d" % (source, fuel, year)))

for year in years :
for tech in elec_techs :
ann_e_supp['electricity',tech,year] = (m.addConstr(
    annual_e_supply['electricity',tech,year]
== sum(sum((z['electricity',tech,season,hour,year] * days[
    season]) for season in seasons) for hour in hours)))

#
    ######################################################################

### DSM Constraints
#force DSM to zero if not available
if dsm == False :
DSM_off = {}
for source in sources :
if source == 'transportation_fuel' :
for fuel in fuels:
for year in years :
for seg in segments:
DSM_off[source,fuel,year,seg] = (m.addConstr(g[source,fuel,
```

```
    year , seg ] == 0))
else :
for sector in sectors :
for year in years :
for seg in segments :
DSM_off[ source , sector , year , seg ] = (m. addConstr(g[ source ,
    sector , year , seg ] == 0))
else :
###Actions nondecreasing
action_nondec = {}
dsm_per_year = {}
dsm_constr = {}
for source in sources :
if source == 'transportation_fuel' :
for fuel in fuels:
for seg in segments:
for year in years :
if year > 0 :
action_nondec[ source , fuel , year , seg ] = (m. addConstr(g[ source ,
    fuel , year , seg ] >= g[ source , fuel ,( year - 1) , seg ]*demand[
    source ][ fuel ][ year ]/demand[ source ][ fuel ][( year - 1) ]))
else :
for sector in sectors:
for seg in segments:
for year in years :
if year > 0 :
action_nondec[ source , sector , year , seg ] = (m. addConstr(g[
```

```
    source,sector,year,seg] >= g[source, sector,(year - 1),
    seg]*demand[source][sector][year]/demand[source][sector
    ][(year - 1)]))

#max dsm implementation per year per segment
for year in years:
if year == 0 :
for source in sources :
if source == 'transportation_fuel' :
for fuel in fuels :
for seg in segments :
dsm_per_year[source,fuel,year,seg] = (m.addConstr(g[source,
    fuel,year,seg]
<= max_yearly_implementation * seg_size[source][fuel][year][
    seg]))
else:
for sector in sectors :
for seg in segments :
dsm_per_year[source,sector,year,seg] = (m.addConstr(g[source
    ,sector,year,seg]
<= max_yearly_implementation * seg_size[source][sector][year
    ][seg]))
else:
for source in sources :
if source == 'transportation_fuel' :
for fuel in fuels :
for seg in segments :
```

```
dsm_per_year[source,fuel,year,seg] = (m.addConstr(g[source,
    fuel,year,seg] - g[source,fuel,(year-1),seg]
<= max_yearly_implementation * seg_size[source][fuel][year][
    seg]))
dsm_constr[source,fuel,year,seg] = (m.addConstr(g[source,
    fuel,year,seg] <= seg_size[source][fuel][year][seg]))
else:
for sector in sectors :
for seg in segments :
dsm_per_year[source,sector,year,seg] = (m.addConstr(g[source
    ,sector,year,seg] - g[source,sector,(year-1),seg]
<= max_yearly_implementation * seg_size[source][sector][year
    ][seg]))
dsm_constr[source,sector,year,seg] = (m.addConstr(g[source,
    sector,year,seg] <= seg_size[source][sector][year][seg]))

###Emissions
#calculate annual emissions by source and year for
    simplified checking and calculation
ann_emiss = {}
source_emiss = {}
for year in years:
source_emiss['electricity', year] = (m.addConstr(
    source_annual_emissions['electricity',year]
== sum((annual_e_supply['electricity',tech,year] *
    emissions_rate['electricity'][tech]) for tech in
    elec_techs)))
```

```
source_emiss['natural_gas', year] = (m.addConstr(
   source_annual_emissions['natural_gas',year]
== sum(z['natural_gas',sector,year] for sector in sectors) *
    emissions_rate['natural_gas']))
source_emiss['transportation_fuel', year] = (m.addConstr(
   source_annual_emissions['transportation_fuel',year]
== sum((z['transportation_fuel', fuel, year] *
   emissions_rate['transportation_fuel'][fuel]) for fuel in
   fuels)))


for year in years :
ann_emiss[year] = (m.addConstr(total_annual_emissions[year]
==      sum(source_annual_emissions[source,year] for source
   in sources)))

#emissions target enforced when tgt = True

if tgt == True :
emiss_constr = {}
for year in years:
if year > 0 :
emiss_constr[year] = (m.addConstr(total_annual_emissions[
   year] <= emissions_target[year],
"Emissions_Constraint_%s" % year))
else :
None
```

```
#generate_costs
tot_ann_cost = {}
source_cost = {}
source_emi_cost = {}
for year in years :
tot_ann_cost[year] = (m.addConstr(total_annual_cost[year] ==
sum((x[tech, year] * fixed_om_cost[tech]) for tech in
    elec_techs)
+ sum((w[tech,year] * capital_cost[tech]) for tech in
    elec_techs)
+ sum(sum(sum((z['electricity',tech,season,hour,year] * (
    variable_om_cost[tech] + fuel_cost[tech][year]) * days[
    season]) for tech in elec_techs) for season in seasons)
    for hour in hours)
+ sum((z['natural_gas',sector,year] * cost['natural_gas'][
    sector][year]) for sector in sectors)
+ sum((z['transportation_fuel',fuel,year] * cost['
    transportation_fuel'][fuel][year]) for fuel in fuels)
+ sum(sum(g['electricity',sector,year,seg] * marg_ac['
    electricity'][sector][year][seg] for sector in sectors)
    for seg in segments)
+ sum(sum(g['natural_gas',sector,year,seg] * marg_ac['
    natural_gas'][sector][year][seg] for seg in segments) for
     sector in sectors)
+ sum(sum(g['transportation_fuel',fuel,year,seg] * marg_ac['
    transportation_fuel'][fuel][year][seg] for seg in
    segments) for fuel in fuels)
```

```
,"total_annual_cost_%s" % year))
source_cost['electricity', year] = (m.addConstr(
    source_annual_cost['electricity',year] ==
sum((x[tech, year] * fixed_om_cost[tech]) for tech in
    elec_techs)
+ sum((w[tech,year] * capital_cost[tech]) for tech in
    elec_techs)
+ sum(sum(sum((z['electricity',tech,season,hour,year] * (
    variable_om_cost[tech] + fuel_cost[tech][year]) * days[
    season]) for tech in elec_techs) for season in seasons)
    for hour in hours)))
source_cost['natural_gas', year] = (m.addConstr(
    source_annual_cost['natural_gas',year] ==
sum((z['natural_gas',sector,year] * cost['natural_gas'][
    sector][year]) for sector in sectors)))
source_cost['transportation_fuel', year] = (m.addConstr(
    source_annual_cost['transportation_fuel',year] ==
sum((z['transportation_fuel',fuel,year] * cost['
    transportation_fuel'][fuel][year]) for fuel in fuels)))
if dsm == True :
source_emi_cost['electricity', year] = (m.addConstr(
    source_annual_efficiency_cost['electricity',year] ==
sum(sum(g['electricity',sector,year,seg] * marg_ac['
    electricity'][sector][year][seg] for sector in sectors)
    for seg in segments)))
source_emi_cost['natural_gas', year] = (m.addConstr(
    source_annual_efficiency_cost['natural_gas',year] ==
```

```
sum(sum(g['natural_gas',sector,year,seg] * marg_ac['
    natural_gas'][sector][year][seg] for seg in segments) for
     sector in sectors)))
source_emi_cost['transportation_fuel', year] = (m.addConstr(
    source_annual_efficiency_cost['transportation_fuel',year]
     ==
sum(sum(g['transportation_fuel',fuel,year,seg] * marg_ac['
    transportation_fuel'][fuel][year][seg] for seg in
    segments) for fuel in fuels)))

##### Set Objective #####
obj = sum(
(
sum((x[tech, year] * fixed_om_cost[tech]) for tech in
    elec_techs)
+ sum((w[tech,year] * capital_cost[tech]) for tech in
    elec_techs)
+ sum(sum(sum((z['electricity',tech,season,hour,year] * (
    variable_om_cost[tech] + fuel_cost[tech][year]) * days[
    season]) for tech in elec_techs) for season in seasons)
    for hour in hours)
+ sum((z['natural_gas',sector,year] * cost['natural_gas'][
    sector][year]) for sector in sectors)
+ sum((z['transportation_fuel',fuel,year] * cost['
    transportation_fuel'][fuel][year]) for fuel in fuels)
+ sum(sum(g['electricity',sector,year,seg] * marg_ac['
    electricity'][sector][year][seg] for sector in sectors)
```

```
    for seg in segments)
+ sum(sum(g['natural_gas',sector,year,seg] * marg_ac['
    natural_gas'][sector][year][seg] for seg in segments) for
     sector in sectors)
+ sum(sum(g['transportation_fuel',fuel,year,seg] * marg_ac['
    transportation_fuel'][fuel][year][seg] for seg in
    segments) for fuel in fuels)
)
* discount_factor[year] for year in years)

m.setObjective(obj, GRB.MINIMIZE)

#####  Optimize model  #####
m.optimize()

print_stats = False
if print_stats == True :
m.printStats

print_quality = False
if print_quality == True :
m.printQuality()

##### Print model
#mod_file = new_out_dir + r'/mod' + date_string + '.lp'
#m.write(mod_file)
```

```
##### Print objective function values
obj_file = new_out_dir + r'/obj.csv'
with open(obj_file,'a') as csvfile:
obj_writer = csv.writer(csvfile)
obj_writer.writerow((tgt,dsm,m.ObjVal))

##### Print variables

var_attr = {}
var_name_list = []
for v in m.getVars():
var_name = v.VarName
var_name_list.append(var_name)
var_attr[var_name] = {}
var_attr[var_name]['Name'] = {}
var_attr[var_name]['Type'] = {}
var_attr[var_name]['Source'] = {}
var_attr[var_name]['Tech'] = {}
var_attr[var_name]['Sector'] = {}
var_attr[var_name]['Fuel'] = {}
var_attr[var_name]['Segment'] = {}
var_attr[var_name]['Year'] = {}
var_attr[var_name]['Season'] = {}
var_attr[var_name]['Hour'] = {}
var_attr[var_name]['Units'] = {}
var_attr[var_name]['Value'] = {}
```

```
for v in m.getVars() :
var_name = v.VarName
attr = v.VarName.split(',')
var_attr[var_name]['Name'] = attr[0]
var_attr[var_name]['Type'] = attr[1]
var_attr[var_name]['Source'] = attr[2]
var_attr[var_name]['Tech'] = attr[3]
var_attr[var_name]['Sector'] = attr[4]
var_attr[var_name]['Fuel'] = attr[5]
var_attr[var_name]['Segment'] = attr[6]
var_attr[var_name]['Year'] = attr[7]
var_attr[var_name]['Season'] = attr[8]
var_attr[var_name]['Hour'] = attr[9]
var_attr[var_name]['Units'] = attr[10]
var_attr[var_name]['Value'] = ("{0:.2f}".format(v.x))

var_file = new_out_dir + r'/var.csv'
with open(var_file, 'a') as csvfile:
for name in var_name_list :
var_writer = csv.writer(csvfile)
var_writer.writerow((tgt,dsm, var_attr[name]['Name'], var_attr
    [name]['Type'], var_attr[name]['Source'], var_attr[name]['
    Tech'], var_attr[name]['Sector'], var_attr[name]['Fuel'],
    var_attr[name]['Segment'], var_attr[name]['Year'], var_attr
    [name]['Season'], var_attr[name]['Hour'], var_attr[name]['
    Units'], var_attr[name]['Value']))
```

```
except GurobiError :
m.printStats()
print ('Error reported - %s, %s' % (tgt,dsm))
print ("Message: %s" % GurobiError.message)

#call opt() and output() functions
def execute() :
#######Input parameters
#Thesis range : 71 years
num_years = 71 #T, length of model run
#Maximum yearly dsm implementation by segment
max_yearly_implementation = 0.25
#Discount rate and discount factor
r = 0.05
dsm_cost_multiplier =  1.0
dsm_seg_multiplier = 1.0
first_target_year = 5 #2020
second_target_year = 15 #2030
third_target_year = 35  #2050
first_target_percentage = 0.8
second_target_percentage = 0.5
third_target_percentage = 0.4

params_file = open(new_out_dir + r'/params.txt','a')
params_file.write('%s : %s \n' % ('num_years',num_years))
params_file.write('%s : %s \n' % ('max_yearly_implementation
    ',max_yearly_implementation))
```

```
params_file.write('%s : %s \n' % ('r',r))
params_file.write('%s : %s \n' % ('dsm_cost_multiplier',
    dsm_cost_multiplier))
params_file.write('%s : %s \n' % ('dsm_seg_multiplier',
    dsm_seg_multiplier))
params_file.write('%s : %s \n' % ('first_target_year',
    first_target_year))
params_file.write('%s : %s \n' % ('second_target_year',
    second_target_year))
params_file.write('%s : %s \n' % ('third_target_year',
    third_target_year))
params_file.write('%s : %s \n' % ('first_target_percentage',
    first_target_percentage))
params_file.write('%s : %s \n' % ('second_target_percentage'
    ,second_target_percentage))
params_file.write('%s : %s \n' % ('third_target_percentage',
    third_target_percentage))

params_file.close()
#######Scenarios
opt(False,False,data_dir,new_out_dir,r,num_years,
    max_yearly_implementation,dsm_cost_multiplier,
    dsm_seg_multiplier,first_target_year,second_target_year,
    third_target_year,first_target_percentage,
    second_target_percentage,third_target_percentage)
opt(False,True,data_dir,new_out_dir,r,num_years,
    max_yearly_implementation,dsm_cost_multiplier,
```

```
    dsm_seg_multiplier, first_target_year, second_target_year,
    third_target_year, first_target_percentage,
    second_target_percentage, third_target_percentage)
opt(True, True, data_dir, new_out_dir, r, num_years,
    max_yearly_implementation, dsm_cost_multiplier,
    dsm_seg_multiplier, first_target_year, second_target_year,
    third_target_year, first_target_percentage,
    second_target_percentage, third_target_percentage)

execute()



# coding: utf-8

# In[1]:

import numpy as np
import matplotlib.pyplot as plt
import matplotlib.cm as cm
import pandas as pd
from pylab import figure
from pandasql import sqldf

pd.set_option('display.width', 200)
get_ipython().magic('matplotlib inline')

base_dir = r'C:/Users/Seth/Dropbox/Borin.Thesis/Gurobi/Data/
```

```
    '
output_dir = r'C:/Users/Seth/Dropbox/Borin.Thesis/Gurobi/'
fig_format = '.pdf'

fig_years = 35
linestyles = ['-', '--', '-.', ':']



# In[2]:


def generate_electricity_demand_projection():
df = pd.read_csv(base_dir+'electricity_demand.csv',
    index_col=False, header=0)
sources = list(df.columns.values)
df1 = df[df.year <= fig_years]
plt.figure(figsize=(15,9))

labels = []

x = df1.year + 2015

y = df1.commercial
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Commercial')

y = df1.industrial
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
```

```
labels.append('Industrial')

y = df1.residential
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Residential')

y = df1.transportation
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Transportation')

plt.ylabel('Demand (TWh)',fontsize=18)
plt.gca().set_ylim(bottom=0)
plt.legend(labels,loc='upper left')
plt.xlabel('Year',fontsize=18)
plt.savefig(output_dir+'Figures/'+'electricity_demand' +
    fig_format,
dpi=1000,bbox_inches='tight')
plt.close()
generate_electricity_demand_projection()


# In[3]:

def generate_electricity_demand_projection_normalized() :
df = pd.read_csv(base_dir+'electricity_demand.csv',
    index_col=False, header=0)
sources = list(df.columns.values)
```

```
df1 = df[df.year <= fig_years]
plt.figure(figsize=(15,9))

labels = []

commercial_2014 = 46608000
industrial_2014 = 31849000
residential_2014 = 57167000
transportation_2014 = 165000

x = df1.year + 2015

y = df1.commercial/commercial_2014
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Commercial')

y = df1.industrial/industrial_2014
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Industrial')

y = df1.residential/residential_2014
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Residential')

y = df1.transportation/transportation_2014
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Transportation')
```

```
plt.ylabel('Demand (Relative to 2014)',fontsize=18)
plt.gca().set_ylim(bottom=0)
plt.legend(labels,loc='upper left')
plt.xlabel('Year',fontsize=18)
plt.savefig(output_dir+'Figures/'+'
    electricity_demand_normalized' + fig_format,
dpi=1000,bbox_inches='tight')
#plt.show()
plt.close()
generate_electricity_demand_projection_normalized()


# In[4]:


def generate_ng_demand_projection() :
df = pd.read_csv(base_dir+'natural_gas_demand.csv',
    index_col=False, header=0)
sources = list(df.columns.values)
df1 = df[df.year <= fig_years]
plt.figure(figsize=(15,9))

labels = []

x = df1.year + 2015

y = df1.commercial
```

```
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Commercial')

y = df1.industrial
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Industrial')

y = df1.residential
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Residential')

y = df1.transportation
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Transportation')

plt.ylabel('Demand (Million Therms)',fontsize=18)
plt.gca().set_ylim(bottom=0)
plt.legend(labels,loc='upper left')
plt.xlabel('Year',fontsize=18)
plt.savefig(output_dir+'Figures/'+'ng_demand' + fig_format,
dpi=1000,bbox_inches='tight')
plt.close()
generate_ng_demand_projection()


# In[5]:
```

```python
def generate_ng_demand_projection_normalized():
df = pd.read_csv(base_dir+'natural_gas_demand.csv',
   index_col=False, header=0)
sources = list(df.columns.values)
df1 = df[df.year <= fig_years]
plt.figure(figsize=(15,9))

labels = []

x = df1.year + 2015

commercial_2014 = 609
industrial_2014 = 1660
residential_2014 = 1387
transportation_2014 = 84

y = df1.commercial/commercial_2014
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Commercial')

y = df1.industrial/industrial_2014
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Industrial')

y = df1.residential/residential_2014
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Residential')
```

```
y = df1.transportation/transportation_2014
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Transportation')

plt.ylabel('Demand (Million Therms)',fontsize=18)
plt.gca().set_ylim(bottom=0)
plt.legend(labels ,loc='upper left')
plt.xlabel('Year',fontsize=18)
plt.savefig(output_dir+'Figures/'+'ng_demand_normalized' +
    fig_format,
dpi=1000,bbox_inches='tight')
plt.close()
generate_ng_demand_projection_normalized()


# In[6]:


def generate_tf_demand_projection() :
df = pd.read_csv(base_dir+'transportation_fuel_demand.csv',
    index_col=False, header=0)
sources = list(df.columns.values)
df1 = df[df.year <= fig_years]
plt.figure(figsize=(15,9))

labels = []
```

```
x = df1.year + 2015

y = df1.gasoline
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Gasoline')

y = df1.diesel
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Distillate Fuel Oil')

y = df1.jet_fuel
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Jet Fuel')

plt.ylabel('Demand (Million Barrels)',fontsize=18)
plt.gca().set_ylim(bottom=0)
plt.legend(labels,loc='upper right')
plt.xlabel('Year',fontsize=18)
plt.savefig(output_dir+'Figures/'+'tf_demand' + fig_format,
dpi=1000,bbox_inches='tight')
plt.close()
generate_tf_demand_projection()


# In[7]:


def generate_tf_demand_projection_normalized() :
```

```
df = pd.read_csv(base_dir+'transportation_fuel_demand.csv',
    index_col=False, header=0)
sources = list(df.columns.values)
df1 = df[df.year <= fig_years]
plt.figure(figsize=(15,9))

labels = []

x = df1.year + 2015

gasoline_2014 = 116590
diesel_2014 = 32050
jet_fuel_2014 = 7806

y = df1.gasoline/gasoline_2014
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Gasoline')

y = df1.diesel/diesel_2014
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Distillate Fuel Oil')

y = df1.jet_fuel/jet_fuel_2014
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Jet Fuel')

plt.ylabel('Demand (Million Barrels)',fontsize=18)
```

```
plt.gca().set_ylim(bottom=0)
plt.legend(labels,loc='upper right')
plt.xlabel('Year',fontsize=18)
plt.savefig(output_dir+'Figures/'+'tf_demand_normalized' +
    fig_format,
dpi=1000,bbox_inches='tight')
plt.close()
generate_tf_demand_projection_normalized()



# In[8]:


def generate_hourly_demand_factor() :
df = pd.read_csv(base_dir+'demand_factor.csv', index_col=
    False, header=0)
plt.figure(figsize=(15,9))

labels = []

x = df.hour[df.season == 'winter']

y = df.demand_factor[df.season == 'summer']
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Summer')

y = df.demand_factor[df.season == 'intermediate']
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
```

```
labels.append('Spring/Fall')

y = df.demand_factor[df.season == 'winter']
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Winter')

plt.ylabel('Percentage␣of␣Daily␣Demand',fontsize=18)
plt.gca().set_ylim(bottom=0)
plt.legend(labels,loc='upper␣left')
plt.xlabel('Hour',fontsize=18)
plt.savefig(output_dir+'Figures/'+'hourly_demand_factor' +
    fig_format,
dpi=1000,bbox_inches='tight')
plt.close()
generate_hourly_demand_factor()


# In[9]:

#need to add the remaining technologies
def generate_electricity_fuel_costs() :
df = pd.read_csv(base_dir+'electricity_fuel_costs.csv',
    index_col=False, header=0)
df1 = df[df.year <= fig_years]
techs = df.tech.dropna().unique()
plt.figure(figsize=(15,9))
```

```
labels = []
x = df1.year[df1.tech == 'coal'] + 2015
for t in techs:
y = df1.fuel_cost[df1.tech == t]
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append(t.title().replace("_"," "))

plt.ylabel('2015$ per MWh',fontsize=18)
plt.gca().set_ylim(bottom=0)
plt.legend(labels,loc='upper left')
plt.xlabel('Year',fontsize=18)
plt.savefig(output_dir+'Figures/'+'electricity_fuel_costs' +
    fig_format,
dpi=1000,bbox_inches='tight')
plt.close()
generate_electricity_fuel_costs()



# In[10]:


def generate_ng_fuel_costs():
df = pd.read_csv(base_dir+'natural_gas_costs.csv', index_col
   =False, header=0)
df1 = df[df.year <= fig_years]
plt.figure(figsize=(15,9))

labels = []
```

```
x = df1.year + 2015

y = df1.commercial
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Commercial')

y = df1.industrial
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Industrial')

y = df1.residential
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Residential')

y = df1.transportation
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Transportation')

plt.ylabel('2015$ per Million Therms',fontsize=18)
plt.gca().set_ylim(bottom=0)
plt.legend(labels,loc='lower right')
plt.xlabel('Year',fontsize=18)
plt.savefig(output_dir+'Figures/'+'ng_fuel_costs' +
    fig_format,
dpi=1000,bbox_inches='tight',fontsize=18)
plt.close()
```

```
generate_ng_fuel_costs()


# In[11]:

def generate_tf_fuel_costs() :
df = pd.read_csv(base_dir+'transportation_fuel_costs.csv',
    index_col=False, header=0)
df1 = df[df.year <= fig_years]
plt.figure(figsize=(15,9))

labels = []

x = df1.year + 2015

y = df1.gasoline
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Gasoline')

y = df1.diesel
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Distillate Fuel Oil')

y = df1.jet_fuel
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[0])
labels.append('Jet Fuel')
```

```
plt.ylabel('Cost␣(2015$␣per␣Million␣Barrels)',fontsize=18)
plt.gca().set_ylim(bottom=0)
plt.legend(labels,loc='upper␣left')
plt.xlabel('Year',fontsize=18)
plt.savefig(output_dir+'Figures/'+'tf_fuel_costs' +
    fig_format,
dpi=1000,bbox_inches='tight')
plt.close()
generate_tf_fuel_costs()


# In[12]:


def generate_biomass_feedstock_costs() :
plt.figure(figsize=(15,9))
labels = []
#TBtu_to_MMBtu = float((10**12)/(10**6))
#MMBtu_to_MWh = 13.5

x =
    [0,0.1,3.1,6.1,30.1,35.1,72.1,72.2,233.2,235.2,269.2,301.2,333.2,426

#x[:] = [i*TBtu_to_MMBtu for i in x]
y_mc =
    [0,1.2,1.68,1.93,3.04,3.07,3.3,3.31,3.65,4.47,4.55,4.55,4.84,5,5.7,7

#y_mc[:] = [i*MMBtu_to_MWh for i in y_mc]
```

```
labels.append('Marginal Cost')
plt.plot(x,y_mc,linewidth=2.5,linestyle=linestyles[0])
y_ac =
    [1.2,1.2,1.66,1.84,2.76,2.9,3.1,3.17,3.42,3.78,4,4.13,4.28,4.43,4.65

#y_ac[:] = [i*MMBtu_to_MWh for i in y_ac]
labels.append('Average Cost')
plt.plot(x,y_ac,linewidth=2.5,linestyle=linestyles[0])
plt.gca().set_ylim(bottom=0)
plt.legend(labels,loc='upper left')
plt.xlabel('Availability (TBtu)',fontsize=18)
plt.ylabel('Cost (2015$/MMBtu)',fontsize=18)
plt.savefig(output_dir+'Figures/'+'biomass_fuel_costs' +
    fig_format,
dpi=1000,bbox_inches='tight')
#plt.show()
plt.close()
generate_biomass_feedstock_costs()
```

APPENDIX C

FIGURE GENERATION FROM MODEL OUTPUTS

```
# coding: utf-8

# In[40]:

import numpy as np
import matplotlib.pyplot as plt
import matplotlib.cm as cm
import pandas as pd
from pylab import figure
from pandasql import sqldf

pd.set_option('display.width', 200)
get_ipython().magic('matplotlib inline')

base_dir = r'C:\Users\Seth\Dropbox\Borin.Thesis\Gurobi/'
folder_num = '0224190334'
fig_format = '.pdf'

df_var = pd.read_csv(base_dir+r'Output/'+folder_num+r'/'+'
    var.csv', index_col=False, header=0)
```

```
df_tgt = pd.read_csv(base_dir+r'Output/'+folder_num+r'/'+'
    tgt.csv', index_col=False, header=0)
df_obj = pd.read_csv(base_dir+r'Output/'+folder_num+r'/'+'
    obj.csv', index_col=False, header=0)
df_eff = pd.read_csv(base_dir+r'Output/'+folder_num+r'/'+'
    marg_ac.csv', index_col=False, header=0)

var_list = []
source_list = []
sector_list = []
fuel_list = []

var_list = df_var.Name.dropna().unique()
source_list = df_var.Source.dropna().unique()
sector_list = df_var.Sector.dropna().unique()
fuel_list = df_var.Fuel.dropna().unique()
tech_list = df_var.Tech.dropna().unique()
linestyles = ['-', '--', '-.', ':','*','^']

dsm_scenarios = [True,False]
tgt_scenarios = [True,False]
fig_years = 35

print (var_list)
print (source_list)
print (tech_list)
print (tgt_scenarios)
```

In[41]:

```
def generate_total_capacity(v,s,df) :
q = """select df.Target, df.DSM, df.Tech, df.Year, sum(df.
    Value) as Total
from df group by df.Target, df.DSM, df.Tech, df.Year;"""
df1 = sqldf(q,locals())



plt.figure(figsize=(15,18))
i=1
for tech in tech_list :
if tech in ['coal','nuclear','natural_gas']:
plt.subplot(10,1,i)
labels = []
j = 0
for tgt in tgt_scenarios :
for dsm in dsm_scenarios :
if df1[(df1.Tech == tech) & (df1.Target == tgt) & (df1.DSM
    == dsm)].empty == False :
x = df1.Year[(df1.Tech == tech) & (df1.Target == tgt) & (df1
    .DSM == dsm)] + 2015
y = df1.Total[(df1.Tech == tech) & (df1.Target == tgt) & (
    df1.DSM == dsm)]
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[j])
```

```
labels.append('Target: %s Efficiency: %s'%(str(tgt),str(dsm)
    ))
j += 1
plt.ylabel('%s' % str(tech).title().replace("_"," "),
    fontsize=14)
plt.gca().set_ylim(bottom=0)
if i == 3 :
plt.legend(labels,loc='lower left')
i+=1
plt.xlabel('Year',fontsize=14)
plt.savefig(base_dir+'Figures/'+'%s_%s_1' % (v,s) +
    fig_format,
dpi=1000,bbox_inches='tight')
#plt.show()
plt.close()

plt.figure(figsize=(15,21))
i=1
for tech in tech_list :
if tech not in ['coal','nuclear','natural_gas']:
plt.subplot(10,1,i)
labels = []
j = 0
for tgt in tgt_scenarios :
for dsm in dsm_scenarios :
if df1[(df1.Tech == tech) & (df1.Target == tgt) & (df1.DSM
    == dsm)].empty == False :
```

```
x = df1.Year[(df1.Tech == tech) & (df1.Target == tgt) & (df1
    .DSM == dsm)] + 2015
y = df1.Total[(df1.Tech == tech) & (df1.Target == tgt) & (
    df1.DSM == dsm)]
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[j])
labels.append('Target: %s Efficiency: %s'%(str(tgt),str(dsm)
    ))
j += 1
plt.ylabel('%s' % str(tech).title().replace("_"," "),
    fontsize=14)
plt.gca().set_ylim(bottom=0)
if i == 1 :
plt.legend(labels,loc='lower left')
i+=1
plt.xlabel('Year',fontsize=14)
plt.savefig(base_dir+'Figures/'+'%s_%s_2' % (v,s) +
    fig_format,
dpi=1000,bbox_inches='tight')
#plt.show()
plt.close()

#generate total_electricity_capacity
v = 'total_capacity'
s = 'electricity'
df_v = df_var[(df_var['Type'] =='continuous')
& (df_var['Year'] <= fig_years)
& (df_var['Name'] == v)
```

```
& (df_var['Source'] == s)
]
generate_total_capacity(v,s,df_v)



# In[42]:


def generate_expansion(v,s,df) :
q = """select df.Target, df.DSM, df.Tech, df.Year, sum(df.
    Value) as Total
from df group by df.Target, df.DSM, df.Tech, df.Year;"""
df1 = sqldf(q,locals())
t_list = df1.Tech[df1.Total > 0].unique()

plt.figure(figsize=(15,18))
i=1
for tech in t_list :
if tech in ['coal','nuclear','natural_gas']:
plt.subplot(10,1,i)
labels = []
j = 0
for tgt in tgt_scenarios :
for dsm in dsm_scenarios :
if df1[(df1.Tech == tech) & (df1.Target == tgt) & (df1.DSM
    == dsm)].empty == False :
x = df1.Year[(df1.Tech == tech) & (df1.Target == tgt) & (df1
    .DSM == dsm)] + 2015
```

```
y = df1.Total[(df1.Tech == tech) & (df1.Target == tgt) & (
    df1.DSM == dsm)]
labels.append('Target: %s Efficiency: %s'%(str(tgt),str(dsm)
    ))
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[j])
j += 1
plt.ylabel('%s' % str(tech).title().replace("_"," "),
    fontsize=14)
plt.gca().set_ylim(bottom=0)
if i == 3 :
plt.legend(labels,loc='upper left')
i+=1
plt.xlabel('Year',fontsize=14)
plt.savefig(base_dir+'Figures/'+'%s_%s_1' % (v,s) +
    fig_format,
dpi=1000,bbox_inches='tight')
#plt.show()
plt.close()


plt.figure(figsize=(15,21))
i=1
for tech in t_list :
if tech not in ['coal','nuclear','natural_gas']:
plt.subplot(10,1,i)
labels = []
j = 0
for tgt in tgt_scenarios :
```

```
for dsm in dsm_scenarios :
if df1[(df1.Tech == tech) & (df1.Target == tgt) & (df1.DSM
    == dsm)].empty == False :
x = df1.Year[(df1.Tech == tech) & (df1.Target == tgt) & (df1
    .DSM == dsm)] + 2015
y = df1.Total[(df1.Tech == tech) & (df1.Target == tgt) & (
    df1.DSM == dsm)]
labels.append('Target: %s Efficiency: %s'%(str(tgt),str(dsm)
    ))
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[j])
j += 1
plt.ylabel('%s' % str(tech).title().replace("_"," "),
    fontsize=14)
plt.gca().set_ylim(bottom=0)
if i == 1 :
plt.legend(labels,loc='upper center')
i+=1
plt.xlabel('Year',fontsize=14)
plt.savefig(base_dir+'Figures/'+'%s_%s_2' % (v,s) +
    fig_format,
dpi=1000,bbox_inches='tight')
#plt.show()
plt.close()

#generate electricity capacity expansion
v = 'expansion'
s = 'electricity'
```

```
df_v = df_var[(df_var['Type'] =='continuous')
& (df_var['Year'] <= fig_years)
& (df_var['Name'] == v)
& (df_var['Source'] == s)
]
generate_expansion(v,s,df_v)



# In[43]:


def generate_tot_expansion(v,s,df) :
q = """select df.Target, df.DSM, df.Tech, df.Year, sum(df.
    Value) as Total
from df group by df.Target, df.DSM, df.Tech, df.Year;"""
df1 = sqldf(q,locals())
t_list = df1.Tech[df1.Total > 0].unique()

plt.figure(figsize=(15,20))
i=1
for tech in t_list :
if tech in ['coal','nuclear','natural_gas']:
labels = []
j = 0
for tgt in tgt_scenarios :
for dsm in dsm_scenarios :
if df1[(df1.Tech == tech) & (df1.Target == tgt) & (df1.DSM
    == dsm)].empty == False :
```

```
x = df1.Year[(df1.Tech == tech) & (df1.Target == tgt) & (df1
    .DSM == dsm)] + 2015
y = df1.Total[(df1.Tech == tech) & (df1.Target == tgt) & (
    df1.DSM == dsm)]
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[j])
labels.append('Target: %s Efficiency: %s'%(str(tgt),str(dsm)
    ))
j += 1
plt.ylabel('%s' % str(tech).title().replace("_"," "),
    fontsize=14)
plt.gca().set_ylim(bottom=0)
if i == 1 :
#plt.legend(labels,loc='upper left')
plt.legend(bbox_to_anchor=(0, 1), loc='upper left', ncol=1)
i+=1

plt.xlabel('Year',fontsize=14)

#plt.savefig(base_dir+'Figures/'+'%s_%s_1' % (v,s) +
    fig_format,
#                dpi=1000,bbox_inches='tight')
plt.show()
plt.close()

#generate total electricity capacity expansion
v = 'tot_expansion'
s = 'electricity'
```

```
df_v = df_var[(df_var['Type'] =='continuous')
& (df_var['Year'] <= fig_years)
& (df_var['Name'] == v)
& (df_var['Source'] == s)
]
#generate_tot_expansion(v,s,df_v)



# In[44]:


def generate_retirement(v,s,df) :
q = """select df.Target, df.DSM, df.Tech, df.Year, sum(df.
    Value) as Total
from df group by df.Target, df.DSM, df.Tech, df.Year;"""
df1 = sqldf(q,locals())
plt.figure(figsize=(15,20))
t_list = df1.Tech[df1.Total > 0].unique()

i=1
for tech in t_list :
plt.subplot(10,1,i)
labels = []
j = 0
for tgt in tgt_scenarios :
for dsm in dsm_scenarios :
if df1[(df1.Tech == tech) & (df1.Target == tgt) & (df1.DSM
    == dsm)].empty == False :
```

```
x = df1.Year[(df1.Tech == tech) & (df1.Target == tgt) & (df1
    .DSM == dsm)] + 2015
y = df1.Total[(df1.Tech == tech) & (df1.Target == tgt) & (
    df1.DSM == dsm)]
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[j])
labels.append('Target: %s Efficiency: %s'%(str(tgt),str(dsm)
    ))
j += 1
plt.ylabel('%s' % str(tech).title().replace("_"," "),
    fontsize=14)
plt.gca().set_ylim(bottom=0)
if i == 1 :
plt.legend(labels ,loc='best')
#plt.legend(bbox_to_anchor=(0, 1), loc='upper left', ncol=1)
i+=1
plt.xlabel('Year',fontsize=14)
plt.show()
#plt.savefig(base_dir+'Figures/'+'%s_%s' % (v,s) +
    fig_format,
#               dpi=1000,bbox_inches='tight')
plt.close()

#generate electricity capacity retirement
v = 'retirement'
s = 'electricity'
df_v = df_var[(df_var['Type'] =='continuous')
& (df_var['Year'] <= fig_years)
```

```
& (df_var['Name'] == v)
& (df_var['Source'] == s)
]
#generate_retirement(v,s,df_v)



# In[45]:


def generate_annual_e_supply(v,s,df) :
q = """select df.Target, df.DSM, df.Tech, df.Year, sum(df.
    Value) as Total
from df group by df.Target, df.DSM, df.Tech, df.Year;"""
df1 = sqldf(q,locals())
plt.figure(figsize=(15,24))
t_list = df1.Tech[df1.Total > 0].unique()

i=1
for tech in t_list :
plt.subplot(10,1,i)
labels = []
j = 0
for tgt in tgt_scenarios :
for dsm in dsm_scenarios :
if df1[(df1.Tech == tech) & (df1.Target == tgt) & (df1.DSM
    == dsm)].empty == False :
x = df1.Year[(df1.Tech == tech) & (df1.Target == tgt) & (df1
    .DSM == dsm)] + 2015
```

```
y = df1.Total[(df1.Tech == tech) & (df1.Target == tgt) & (
    df1.DSM == dsm)]
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[j])
labels.append('Target: %s Efficiency: %s'%(str(tgt),str(dsm)
    ))
j += 1
plt.ylabel('%s' % str(tech).title().replace("_"," "),
    fontsize=14)
plt.gca().set_ylim(bottom=0)
if i == 1 :
plt.legend(labels,loc='upper right')
i+=1
plt.xlabel('Year',fontsize=14)
#plt.show()
plt.savefig(base_dir+'Figures/'+'%s_%s' % (v,s) + fig_format
    ,
dpi=1000,bbox_inches='tight')
plt.close()

#generate annual electricity supply
v = 'annual_e_supply'
s = 'electricity'
df_v = df_var[(df_var['Type'] =='continuous')
& (df_var['Year'] <= fig_years)
& (df_var['Name'] == v)
& (df_var['Source'] == s)
]
```

```
generate_annual_e_supply(v,s,df_v)



# In[46]:


def generate_annual_e_supply_2(v,s,df) :
q = """select df.Target, df.DSM, df.Tech, df.Year, sum(df.
    Value) as Total
from df group by df.Target, df.DSM, df.Tech, df.Year;"""
df1 = sqldf(q,locals())
plt.figure(figsize=(15,18))
t_list = df1.Tech[df1.Total > 0].unique()

i=1
for tech in t_list :
if tech in ['coal','nuclear','natural_gas']:
plt.subplot(3,1,i)
labels = []
j = 0
for tgt in tgt_scenarios :
for dsm in dsm_scenarios :
if df1[(df1.Tech == tech) & (df1.Target == tgt) & (df1.DSM
    == dsm)].empty == False :
x = df1.Year[(df1.Tech == tech) & (df1.Target == tgt) & (df1
    .DSM == dsm)] + 2015
y = df1.Total[(df1.Tech == tech) & (df1.Target == tgt) & (
    df1.DSM == dsm)]
```

```
plt.plot(x,y,linewidth=2.5,  linestyle=linestyles[j])
labels.append('Target: %s Efficiency: %s'%(str(tgt),str(dsm)
    ))
j += 1
plt.ylabel('%s' % str(tech).title().replace("_"," "),
    fontsize=14)
plt.gca().set_ylim(bottom=0)
if i == 1 :
plt.legend(labels,loc='upper left')
i+=1
plt.xlabel('Year',fontsize=14)
#plt.show()
plt.savefig(base_dir+'Figures/'+'%s_%s_1' % (v,s) +
    fig_format,
dpi=1000,bbox_inches='tight')
plt.close()


plt.figure(figsize=(15,21))
i=1
for tech in t_list :
if tech not in ['coal','nuclear','natural_gas']:
plt.subplot(7,1,i)
labels = []
j = 0
for tgt in tgt_scenarios :
for dsm in dsm_scenarios :
```

```
if df1[(df1.Tech == tech) & (df1.Target == tgt) & (df1.DSM
    == dsm)].empty == False :
x = df1.Year[(df1.Tech == tech) & (df1.Target == tgt) & (df1
    .DSM == dsm)] + 2015
y = df1.Total[(df1.Tech == tech) & (df1.Target == tgt) & (
    df1.DSM == dsm)]
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[j])
labels.append('Target: %s Efficiency: %s'%(str(tgt),str(dsm)
    ))
j += 1
plt.ylabel('%s' % str(tech).title().replace("_"," "),
    fontsize=14)
plt.gca().set_ylim(bottom=0)
if i == 1 :
plt.legend(labels,loc='lower left')
i+=1
plt.xlabel('Year',fontsize=14)
#plt.show()
plt.savefig(base_dir+'Figures/'+'%s_%s_2' % (v,s) +
    fig_format,
dpi=1000,bbox_inches='tight')
plt.close()

#generate annual electricity supply
v = 'annual_e_supply'
s = 'electricity'
df_v = df_var[(df_var['Type'] =='continuous')
```

```
& (df_var['Year'] <= fig_years)
& (df_var['Name'] == v)
& (df_var['Source'] == s)
]
generate_annual_e_supply_2(v,s,df_v)


# In[47]:


def generate_tot_annual_e_supply(v,s,df) :
q = """select df.Target, df.DSM, df.Year, sum(df.Value) as
    Total
from df group by df.Target, df.DSM, df.Year;"""
df1 = sqldf(q,locals())
plt.figure(figsize=(15,6))
labels = []
j = 0
for tgt in tgt_scenarios :
for dsm in dsm_scenarios :
if df1[(df1.Target == tgt) & (df1.DSM == dsm)].empty ==
    False :
x = df1.Year[(df1.Target == tgt) & (df1.DSM == dsm)] + 2015
y = df1.Total[(df1.Target == tgt) & (df1.DSM == dsm)]
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[j])
labels.append('Target: %s; Efficiency: %s'%(str(tgt),str(dsm
    )))
plt.ylabel('MWh',fontsize=14)
```

```
plt.gca().set_ylim(bottom=0)
plt.xlabel('Year',fontsize=14)
plt.legend(labels,loc='upper left')
plt.savefig(base_dir+'Figures/'+'total_%s_%s' % (v,s) +
    fig_format,
dpi=1000,bbox_inches='tight')
#plt.show()
plt.close()

#generate total annual electricity supply
v = 'annual_e_supply'
s = 'electricity'
df_v = df_var[(df_var['Type'] =='continuous')
& (df_var['Year'] <= fig_years)
& (df_var['Name'] == v)
& (df_var['Source'] == s)
]
generate_tot_annual_e_supply(v,s,df_v)



# In[48]:


def generate_natural_gas_supply(v,s,df) :
q = """select df.Target, df.DSM, df.Sector, df.Year, sum(df.
    Value) as Total
from df group by df.Target, df.DSM, df.Sector, df.Year;"""
df1 = sqldf(q,locals())
```

```
plt.figure(figsize=(15,12))
i=1
for tgt in tgt_scenarios :
for dsm in dsm_scenarios :
if df1[(df1.Target == tgt) & (df1.DSM == dsm)].empty ==
    False :
plt.subplot(3,1,i)
j = 0
labels = []
for sector in sector_list :
x = df1.Year[(df1.Sector == sector) & (df1.Target == tgt) &
    (df1.DSM == dsm)] + 2015
y = df1.Total[(df1.Sector == sector) & (df1.Target == tgt) &
     (df1.DSM == dsm)]
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[j])
labels.append(str(sector).title())
plt.ylabel('Target: %s Efficiency: %s'%(str(tgt),str(dsm)),
    fontsize=14)
plt.gca().set_ylim(bottom=0)
if i == 1 :
plt.legend(labels,loc='upper right')
i+=1
plt.xlabel('Year',fontsize=14)
plt.savefig(base_dir+'Figures/'+'%s_%s' % (v,s) + fig_format
    ,
dpi=1000,bbox_inches='tight')
plt.close()
```

```
#generate total annual natural gas supply
v = 'supply'
s = 'natural_gas'
df_v = df_var[(df_var['Type'] =='continuous')
& (df_var['Year'] <= fig_years)
& (df_var['Name'] == v)
& (df_var['Source'] == s)
]
generate_natural_gas_supply(v,s,df_v)


# In[49]:


def generate_transportation_fuel_supply(v,s,df) :
q = """select df.Target, df.DSM, df.Fuel, df.Year, sum(df.
    Value) as Total
from df group by df.Target, df.DSM, df.Fuel, df.Year;"""
df1 = sqldf(q,locals())
plt.figure(figsize=(15,12))
i=1
for tgt in tgt_scenarios :
for dsm in dsm_scenarios :
if df1[(df1.Target == tgt) & (df1.DSM == dsm)].empty ==
    False :
plt.subplot(3,1,i)
j = 0
```

```
labels = []
for fuel in fuel_list :
x = df1.Year[(df1.Fuel == fuel) & (df1.Target == tgt) & (df1
    .DSM == dsm)] + 2015
y = df1.Total[(df1.Fuel == fuel) & (df1.Target == tgt) & (
    df1.DSM == dsm)]
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[j])
labels.append(str(fuel).title().replace("_"," "))
plt.ylabel('Target: %s Efficiency: %s'%(str(tgt),str(dsm)),
    fontsize=14)
plt.gca().set_ylim(bottom=0)
if i == 1 :
plt.legend(labels,loc='upper right')
i+=1
plt.xlabel('Year',fontsize=14)
plt.savefig(base_dir+'Figures/'+'%s_%s' % (v,s) + fig_format
    ,
dpi=1000,bbox_inches='tight')
plt.close()

#generate total annual transportation fuel supply
v = 'supply'
s = 'transportation_fuel'
df_v = df_var[(df_var['Type'] =='continuous')
& (df_var['Year'] <= fig_years)
& (df_var['Name'] == v)
& (df_var['Source'] == s)
```

```
]
generate_transportation_fuel_supply(v,s,df_v)



# In[50]:


def generate_electricity_efficiency(v,s,df) :
q = """select df.Target, df.DSM, df.Sector, df.Year, sum(df.
    Value) as Total
from df group by df.Target, df.DSM, df.Sector, df.Year;"""
df1 = sqldf(q,locals())
plt.figure(figsize=(15,12))
i=1
for tgt in tgt_scenarios :
if df1[(df1.Target == tgt) & (df1.DSM == True)].empty ==
    False :
plt.subplot(2,1,i)
j = 0
labels = []
for sector in sector_list :
x = df1.Year[(df1.Sector == sector) & (df1.Target == tgt)] +
    2015
y = df1.Total[(df1.Sector == sector) & (df1.Target == tgt)]
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[j])
labels.append(str(sector).title().replace("_"," "))
plt.ylabel('Target: %s'%str(tgt),fontsize=14)
plt.gca().set_ylim(bottom=0)
```

```
if i == 1 :
plt.legend(labels ,loc='upper left')
i+=1
plt.xlabel('Year',fontsize=14)
plt.savefig(base_dir+'Figures/'+'%s_%s' % (v,s) + fig_format
    ,
dpi=1000,bbox_inches='tight')
#plt.show()
plt.close()

#generate total electricity efficiency by sector
v = 'action_supply'
s = 'electricity'
df_v = df_var[(df_var['Type'] =='continuous')
& (df_var['Year'] <= fig_years)
& (df_var['Name'] == v)
& (df_var['Source'] == s)
& (df_var['DSM'] ==  True)
]
generate_electricity_efficiency(v,s,df_v)


# In[51]:

def generate_natural_gas_efficiency(v,s,df) :
q = """select df.Target, df.DSM, df.Sector, df.Year, sum(df.
    Value) as Total
```

```
from df group by df.Target, df.DSM, df.Sector, df.Year;"""
df1 = sqldf(q,locals())
plt.figure(figsize=(15,12))
i=1
for tgt in tgt_scenarios :
if df1[(df1.Target == tgt) & (df1.DSM == True)].empty ==
    False :
plt.subplot(2,1,i)
j = 0
labels = []
for sector in sector_list :
x = df1.Year[(df1.Sector == sector) & (df1.Target == tgt)] +
     2015
y = df1.Total[(df1.Sector == sector) & (df1.Target == tgt)]
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[j])
labels.append(str(sector).title().replace("_"," "))
plt.ylabel('Target: %s'%str(tgt),fontsize=14)
plt.gca().set_ylim(bottom=0)
if i == 1 :
plt.legend(labels,loc='upper left')
i+=1
plt.xlabel('Year',fontsize=14)
plt.savefig(base_dir+'Figures/'+'%s_%s' % (v,s) + fig_format
    ,
dpi=1000,bbox_inches='tight')
plt.close()
```

```
#generate natural gas efficiency by sector
v = 'action_supply'
s = 'natural_gas'
df_v = df_var[(df_var['Type'] =='continuous')
& (df_var['Year'] <= fig_years)
& (df_var['Name'] == v)
& (df_var['Source'] == s)
& (df_var['DSM'] ==  True)
]
generate_natural_gas_efficiency(v,s,df_v)



# In[52]:


def generate_transportation_fuel_efficiency(v,s,df) :
q = """select df.Target, df.DSM, df.Fuel, df.Year, sum(df.
    Value) as Total
from df
group by df.Target, df.DSM, df.Fuel, df.Year;"""

df1 = sqldf(q,locals())
plt.figure(figsize=(15,12))
i=1
for tgt in tgt_scenarios :
plt.subplot(2,1,i)
j = 0
labels = []
```

```
for fuel in fuel_list :
x = df1.Year[(df1.Fuel == fuel) & (df1.Target == tgt)] +
    2015
y = df1.Total[(df1.Fuel == fuel) & (df1.Target == tgt)]
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[j])
labels.append(str(fuel).title().replace("_"," "))
plt.ylabel('Target: %s'%str(tgt),fontsize=14)
plt.gca().set_ylim(bottom=0)
if i == 1 :
plt.legend(labels,loc='center right')
i+=1
plt.xlabel('Year',fontsize=14)
plt.savefig(base_dir+'Figures/'+'%s_%s' % (v,s) + fig_format
    ,
dpi=1000,bbox_inches='tight')
#plt.show()
plt.close()

#generate natural gas efficiency by sector
v = 'action_supply'
s = 'transportation_fuel'
df_v = df_var[(df_var['Type'] =='continuous')
& (df_var['Year'] <= fig_years)
& (df_var['Name'] == v)
& (df_var['Source'] == s)
& (df_var['DSM'] == True)
]
```

```
generate_transportation_fuel_efficiency(v,s,df_v)



# In[53]:

def generate_annual_emissions_source(v,df) :
q = """select df.Target, df.DSM, df.Year, df.Source, sum(df.
    Value) as Total
from df group by df.Target, df.DSM, df.Year, df.Source;"""
df1 = sqldf(q,locals())
plt.figure(figsize=(15,12))
i=1
for source in source_list :
plt.subplot(3,1,i)
j = 0
labels = []
for tgt in tgt_scenarios :
for dsm in dsm_scenarios :
if df1[(df1.Target == tgt) & (df1.DSM == dsm)].empty ==
    False :
x = df1.Year[(df1.DSM == dsm) & (df1.Target == tgt) & (df1.
    Source == source)] + 2015
y = df1.Total[(df1.DSM == dsm) & (df1.Target == tgt) & (df1.
    Source == source)]
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[j])
labels.append('Target: %s; Efficiency: %s'%(str(tgt),str(dsm
    )))
```

```
plt.ylabel(str(source).title().replace("_"," "),fontsize=14)
plt.gca().set_ylim(bottom=0)
if i == 1 :
plt.legend(labels,loc='upper right')
i+=1
plt.xlabel('Year',fontsize=14)
#plt.savefig(base_dir+'Figures/'+'%s' % v + fig_format,
#             dpi=1000,bbox_inches='tight')
plt.close()

#generate annual emissions by source
v = 'source_annual_emissions'
df_v = df_var[(df_var['Type'] =='continuous')
& (df_var['Year'] <= fig_years)
& (df_var['Name'] == v)
]
generate_annual_emissions_source(v,df_v)



# In[54]:


def generate_annual_emissions_total(v,df) :
q = """select df.Target, df.DSM, df.Year, sum(df.Value) as
    Total
from df group by df.Target, df.DSM, df.Year;"""
df1 = sqldf(q,locals())
plt.figure(figsize=(15,12))
```

```
labels = []
x = df_tgt.Year[df_tgt.Year <= 35] + 2015
y = df_tgt.Emissions_Target[df_tgt.Year <= 35]
plt.plot(x,y,linewidth=2.5)
labels.append('Emissions Target')
for tgt in tgt_scenarios :
for dsm in dsm_scenarios :
if df1[(df1.Target == tgt) & (df1.DSM == dsm)].empty ==
    False :
x = df1.Year[(df1.DSM == dsm) & (df1.Target == tgt)] + 2015
y = df1.Total[(df1.DSM == dsm) & (df1.Target == tgt)]
plt.plot(x,y,linewidth=2.5)
labels.append('Target: %s; Efficiency: %s'%(str(tgt),str(dsm
    )))
plt.xlabel('Year',fontsize=14)
plt.ylabel('Tonnes CO_2',fontsize=14)
plt.gca().set_ylim(bottom=0)
plt.legend(labels,loc='upper left')
plt.savefig(base_dir+'Figures/'+'%s' % v + fig_format,
dpi=1000,bbox_inches='tight')
plt.close()

#generate annual emissions by scenario
v = 'total_annual_emissions'
df_v = df_var[(df_var['Type'] =='continuous')
& (df_var['Year'] <= fig_years)
& (df_var['Name'] == v)
```

```
]
generate_annual_emissions_total(v,df_v)



# In[55]:

'''
def generate_annual_costs_source(v,df) :
q = """select df.Target, df.DSM, df.Year, df.Source, sum(df.
    Value) as Total
from df group by df.Target, df.DSM, df.Year, df.Source;"""
df1 = sqldf(q,locals())
plt.figure(figsize=(15,12))
i=1
for source in source_list :
plt.subplot(3,1,i)
j = 0
labels = []
for tgt in tgt_scenarios :
for dsm in dsm_scenarios :
if df1[(df1.Target == tgt) & (df1.DSM == dsm)].empty ==
    False :
x = df1.Year[(df1.DSM == dsm) & (df1.Target == tgt) & (df1.
    Source == source)] + 2015
y = df1.Total[(df1.DSM == dsm) & (df1.Target == tgt) & (df1.
    Source == source)]
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[j])
```

```
labels.append('Target: %s; Efficiency: %s'%(str(tgt),str(dsm
    )))
plt.ylabel(str(source).title().replace("_"," "),fontsize=14)
plt.gca().set_ylim(bottom=0)
if i == 1 :
plt.legend(labels,loc='upper left')
i+=1
plt.xlabel('Year',fontsize=14)
plt.savefig(base_dir+'Figures/'+'%s' % v + fig_format,
dpi=1000,bbox_inches='tight')
plt.close()

#generate annual emissions by source
v = 'source_annual_emissions'
df_v = df_var[(df_var['Type'] =='continuous')
& (df_var['Year'] <= fig_years)
& (df_var['Name'] == v)
]
generate_annual_costs_source(v,df_v)

'''



# In[56]:

def generate_annual_costs_source(v,df) :
q = """select df.Target, df.DSM, df.Year, df.Source, sum(df.
```

```
    Value) as Total
from df group by df.Target, df.DSM, df.Year, df.Source;"""
df1 = sqldf(q,locals())
plt.figure(figsize=(15,12))
i=1
for source in source_list :
plt.subplot(3,1,i)
j = 0
labels = []
for tgt in tgt_scenarios :
for dsm in dsm_scenarios :
if df1[(df1.Target == tgt) & (df1.DSM == dsm)].empty ==
    False :
x = df1.Year[(df1.DSM == dsm) & (df1.Target == tgt) & (df1.
    Source == source)] + 2015
y = df1.Total[(df1.DSM == dsm) & (df1.Target == tgt) & (df1.
    Source == source)]
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[j])
labels.append('Target: %s; Efficiency: %s'%(str(tgt),str(dsm
    )))
plt.ylabel(str(source).title().replace("_"," "),fontsize=14)
plt.gca().set_ylim(bottom=0)
if i == 3 :
plt.legend(labels,loc='upper left')
i+=1
plt.xlabel('Year',fontsize=14)
plt.savefig(base_dir+'Figures/'+'%s' % v + fig_format,
```

```
dpi=1000,bbox_inches='tight')
plt.close()

#generate annual emissions by source
v = 'source_annual_cost'
df_v = df_var[(df_var['Type'] =='continuous')
& (df_var['Year'] <= fig_years)
& (df_var['Name'] == v)
]
generate_annual_costs_source(v,df_v)



# In[ ]:


def generate_total_annual_cost(v,df) :
q = """select df.Target, df.DSM, df.Year, df.Source, sum(df.
    Value) as Total
from df group by df.Target, df.DSM, df.Year, df.Source;"""
df1 = sqldf(q,locals())
plt.figure(figsize=(15,12))
j = 0
labels = []
for tgt in tgt_scenarios :
for dsm in dsm_scenarios :
if df1[(df1.Target == tgt) & (df1.DSM == dsm)].empty ==
    False :
x = df1.Year[(df1.DSM == dsm) & (df1.Target == tgt)] + 2015
```

```
y = df1.Total[(df1.DSM == dsm) & (df1.Target == tgt)]
plt.plot(x,y,linewidth=2.5, linestyle=linestyles[j])
labels.append('Target: %s; Efficiency: %s'%(str(tgt),str(dsm
    )))
j += 1
plt.ylabel('Total Cost',fontsize=14)
plt.gca().set_ylim(bottom=0)
plt.xlabel('Year',fontsize=14)
plt.legend(labels,loc='upper left')
plt.savefig(base_dir+'Figures/'+'%s' % v + fig_format,
dpi=1000,bbox_inches='tight')
#plt.show()
plt.close()

#generate total annual costs
v = 'total_annual_cost'
df_v = df_var[(df_var['Type'] =='continuous')
& (df_var['Year'] <= fig_years)
& (df_var['Name'] == v)
]
generate_total_annual_cost(v,df_v)



# In[ ]:


def generate_annual_costs_scenario(v,df) :
q = """select df.Name, df.Target, df.DSM, df.Year, df.Source
```

```
    , sum(df.Value) as Total
from df
group by df.Name, df.Target, df.DSM, df.Year, df.Source;"""
df1 = sqldf(q,locals())
df1.to_csv(r'C:\Users\Seth\Desktop\ann_cost.csv')
plt.figure(figsize=(15,18))
names = df1.Name.unique()
i = 1
for t in tgt_scenarios:
for d in dsm_scenarios:
if df1[(df1.Target == t) & (df1.DSM == d)].empty == False:
plt.subplot(3,1,i)
labels = []
for n in names:
for s in source_list:
x = df1.Year[(df1.Target == t) & (df1.DSM == d) & (df1.Name
    == n) & (df1.Source == s)] + 2015
y = df1.Total[(df1.Target == t) & (df1.DSM == d) & (df1.Name
     == n) & (df1.Source == s)]
plt.plot(x,y,linewidth=2.5)
if n == 'source_annual_cost':
labels.append(str(s).title().replace("_"," ") + ' - Supply')
else:
labels.append(str(s).title().replace("_"," ") + ' - 
    Efficiency')
plt.ylabel('Target: %s; Efficiency: %s'%(str(t),str(d)),
    fontsize=14)
```

```
plt.gca().set_ylim(bottom=0)
if i == 1 :
plt.legend(labels,loc='center left')

i+=1
plt.xlabel('Year',fontsize=14)
plt.savefig(base_dir+'Figures/'+'%s_scenario' % v +
    fig_format,
dpi=1000,bbox_inches='tight')
#plt.show()
plt.close()

#generate annual efficiency costs by scenarios
v = 'annual_costs'
df_v1 = df_var[(df_var['Type'] =='continuous')
& (df_var['Year'] <= fig_years)
]
df_v = df_v1[(df_v1['Name'] == '
    source_annual_efficiency_cost')
| (df_v1['Name'] == 'source_annual_cost')
]
generate_annual_costs_scenario(v,df_v)



# In[ ]:


def generate_efficiency_curves() :
```

```
plt.figure(figsize=(15,15))
eff_sources = df_eff.Source.unique()

df1 = df_eff[(df_eff.Year == 0)]
i = 1
for source in eff_sources :
plt.subplot(3,1,i)
labels = []
eff_sector_fuels = df_eff.Sector_Fuel[df_eff.Source ==
    source].unique()
for sf in eff_sector_fuels :
eff_segs = df_eff.Segment[(df_eff.Source == source) & (
    df_eff.Size > 0) & (df_eff.Sector_Fuel == sf)].unique()
labels.append(sf.title().replace('_',' '))
x = [0]
y = []
x1 = 0
for seg in eff_segs :
x_max = eff_segs.max()
x1 += float(df1.Size[(df1.Source == source) & (df1.
    Sector_Fuel == sf) & (df1.Segment == seg)])
x.append(x1)
y.append(float(df1.Marginal_Cost[(df1.Source == source) & (
    df1.Sector_Fuel == sf) & (df1.Segment == seg)]))
y.append(float(df1.Marginal_Cost[(df1.Source == source) & (
    df1.Sector_Fuel == sf) & (df1.Segment == seg)]))
if seg < x_max :
```

```
x.append(x1)
if len(y) > 0 :
plt.plot(x,y,linewidth=2.5)
if source == 'electricity' :
plt.ylabel(source.title().replace('_',' '),fontsize=14)
plt.xlabel('MWh',fontsize=14)
elif source == 'natural_gas' :
plt.ylabel(source.title().replace('_',' '),fontsize=14)
plt.xlabel('Million Therms',fontsize=14)
else:
plt.ylabel(source.title().replace('_',' '),fontsize=14)
plt.xlabel('Thousand Barrels',fontsize=14)
plt.gca().set_ylim(bottom=0)
plt.legend(labels,loc='lower right')
i += 1
plt.savefig(base_dir+'Figures/'+'efficiency_curves' +
    fig_format,
dpi=1000,bbox_inches='tight')
plt.close()

generate_efficiency_curves()



# In[ ]:


#check baseline year 0 emissions
print (df_var.Value[(df_var.Name == 'total_annual_emissions'
```

```
    ) & (df_var.Year == 0) & (df_var.Target == False)
& (df_var.DSM == False)])


# In[ ]:
```

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