ABSTRACT

ESHRAGHI, HADI. An Assessment of the US Energy System under Uncertainty. (Under the direction of Dr. Joseph F. DeCarolis).

The US is the second largest energy-related greenhouse gas producer and thus critical to global efforts to curb greenhouse gas emissions. Despite the current lack of a federal climate policy, 35 states have committed to mandates, such as renewable portfolio standards or cap and trade programs aimed at mitigating the adverse impacts of climate change. In addition to policy, rapid technology innovations will continue to play a key role in shaping the future US energy system over the next several decades. In this thesis, Tools for Energy Model Optimization and Analysis (Temoa), an open-source energy system optimization model, is used to rigorously examine US energy system development separately under two divergent emissions pathways: in the absence of new climate policy and under an aggressive carbon cap. This thesis also considers the sensitivity of seasonal residential electricity demand to climate and therefore offers a way to improve the exogenous future demand projections used in energy system models.

The US withdrawal from the Paris Agreement as well as uncertainty about federal climate policy has raised questions about the country’s future emissions trajectory in the absence of new policy. Chapter 2 includes a framework consisting of a global sensitivity analysis method, a Monte Carlo simulation, and a clustering algorithm, which is used to examine future emission outcomes given uncertainty in fuel prices and energy technology capital costs. The results suggest that market forces are likely to keep US energy-related greenhouse gas emissions relatively flat or produce modest reductions. Natural gas versus coal utilization in the electric sector represents a key trade-off, particularly under conservative assumptions about future technology innovation. The lowest emissions scenarios are produced when natural gas and electric vehicle costs decline, and coal and oil prices increase relative to the baseline.

Chapter 3 considers the opposite extreme to Chapter 2: the technology and cost implications of achieving a 95% system-wide emissions reduction by 2050. A structural uncertainty assessment technique called modeling-to-generate-alternatives (MGA) is used to produce maximally different deep decarbonization pathways under modest budget constraints. This analysis is also performed with Temoa. The model input database embeds several low carbon pathways, including power-to-X pathways that utilize electrolyzed hydrogen to create a variety of
fuels. The results show that this low carbon transition can be achieved using currently commercialized technologies with no more than an 8% increase in system-wide supply cost, assuming a 5% global discount rate. This transition takes place through three mechanisms: (i) energy efficiency, (ii) substituting fossil fuels in the end-use sectors with electricity, biomass, or synthetic fuels, and (iii) full decarbonization of electric sector. The results suggest that there are other system alternatives to nuclear with almost the same cost; a ban on nuclear increases the system costs by less than 1%. By contrast, bio-energy with carbon capture and storage and large-scale hydrogen storage systems are critical to lowering the costs of deep decarbonization.

Chapter 4 examines the sensitivity of residential electricity demand in 48 U.S. states to seasonal climate variations and structural changes in each state’s household electricity demand. The main objective is to quantify the effects of seasonal climate variability on residential electricity demand variability during winter and summer. The results show that interannual climate variability explains a significant share of seasonal household electricity demand variation. The work done in this chapter suggests the need for new datasets to quantify the unexplained variance in electricity demand during the winter and summer. Findings from this study are critical to developing seasonal electricity demand forecasts, which can aid power system operation and management, particularly in a future with greater electrification of end-use demands, as well as providing a basis for residential electricity demand projections used by energy system models.
An Assessment of the U.S. Energy System Under Uncertainty

by
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DEDICATION

I dedicate this work to my kind parents whose unconditional love and inspiring words of encouragement has given me more than I deserved. I cannot wait for the day I will be able to see them again.
ACKNOWLEDGEMENT

I have a special feeling of gratitude to my wonderful advisors Dr. DeCarolis and Dr. de Queiroz for their guidance and continuous support all along. I wish to extend my gratitude also to my committee members: Dr. Sankar Arumugam, Dr. Jeremiah Johnson, and Dr. Christopher Galik.

I thank all my friends in the U.S. for the joy and color they brought into my life. I strive to do the same for you all.
BIOGRAPHY

Hadi Eshraghi was born in 1987 in Tehran, Iran. He received his Bachelor's degree from the Department of Mechanical Engineering at Sharif University of Technology in 2010. During his senior year, he started learning more about climate change and the extent to which it can impact human lives. He became particularly interested in studying higher-level topics related to transformation of energy systems, renewable energy, and energy efficiency. He then chose to study energy systems engineering in his Master’s program, and upon receiving his Master’s degree, he accepted a job offer in an international project on climate change for developing countries funded by the United Nations Development Program (UNDP).

In 2016, he started his doctoral program in the Department of Civil, Construction, and Environmental Engineering in North Carolina State University. He joined a group of researchers who work on an open source energy system optimization model called Temoa. Hadi’s main doctoral work was on developing databases and uncertainty assessment frameworks to examine the U.S. energy system development over the next several decades.
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1 Introduction

The Paris Climate Agreement aims to limit global temperature rise to “well below 2 °C” relative to pre-industrial levels [1]. Accomplishing this goal requires net-zero greenhouse gas (GHG) emissions in the second half of this century. As of 2020, 187 nations have ratified the agreement [2]. The urgency of mitigating climate change along with rapid technology innovation are beginning to drive large-scale transformation of the global energy system [3].

Given the wide array of factors involved in this large scale transformation, computer models provide a self-consistent framework for exploring alternative energy futures. Energy system optimization models (ESOMs) are a widely used type of energy model that enable analysts to explore the future decision landscape and derive insights that inform policy. ESOMs minimize the present cost of total system-wide costs over a user-specified time horizon, typically several decades, by optimizing the installation and utilization of energy technologies across the system. ESOMs include several constraint sets to ensure appropriate system operations and energy flow from upstream sources to points of consumption. Additional user-specified constraints, such as maximum emissions limits can be added to the set of governing constraints. In this thesis, I utilize Tools for Energy Model Optimization and Analysis (Temoa), an open source ESOM developed at NC State. The mathematical formulation of the model is described in Hunter et al. [4] with updates available through the project website [5].

Modeling future energy systems is inherently difficult and complex. Lempert et al. (2003) argues that long-term policy analysis – which includes ESOM-focused analysis – represents a decision making process under deep uncertainty [6]. Decision making under deep uncertainty is a situation where decision makers cannot agree on (i) the exact structure of the models, including the key driving forces that determine the future of a system, (ii) the probability distribution of key model inputs, and (iii) the utility of alternative future outcomes [6]. The literature on uncertainty assessment associated with ESOMs identifies two type of uncertainties: structural and parametric [7]. Structural uncertainty arises from our inability to precisely model the real-world dynamics, and parametric uncertainty refers to the uncertainty in the model’s assumed input parameter values [7]. The collective effect of these uncertainties make ESOMs difficult to validate [8] and as a result, ESOMs should not be used for predicting the future [9]. Numerous examples of poor forecasts produced with ESOMs can be found, and attest to the peril of model-based energy forecasts [10,11].
A number of approaches have been utilized within the energy modeling community to address future uncertainty. Scenario analysis has long been used for the assessment of parametric uncertainty associated with ESOMs. Most modelers assert that their scenario analysis should be interpreted as possible future outcomes under a specific set of assumptions rather than predictions about the future. Nonetheless, scenario results are often interpreted as predictions by many observers [12]. Furthermore, dealing with the three aspects of deep uncertainty necessitates the application of additional methods beyond simple scenario analysis [13]. Approaches that have been used previously include myopic modeling [14], parametric uncertainty assessment [15,16], near-optimal scenarios [17-19], stochastic optimization [20], and multi-objective optimization [21]. Although these studies, taken together, yield insights informed by future uncertainty, they have not focused on US energy system development in its entirety, under deep uncertainty.

The goal of this thesis is to rigorously examine US energy development pathways through midcentury while considering parametric and structural uncertainties. Three main research objectives are defined to accomplish this goal:

1. Explore baseline scenarios for future US GHG emissions in the absence of new federal climate policy and quantify the effects of parametric uncertainty associated with fuel prices and technology costs.
2. Examine deep decarbonization pathways for the US energy system. Modeling to generate alternatives (MGA) is applied in order to assess the structural uncertainties in the model and assess the technological flexibility in achieving deep cuts in GHG emissions.
3. Quantify the relationship between monthly residential electricity demand and climate, which can be used to develop improved electricity demand projections for use in ESOMs.

Meeting these three research objectives allows for a rigorous assessment of potential energy technology pathways for the United States, with scenarios ranging from business-as-usual to a nearly net zero emissions system by mid-century.

In Chapter 2, I present a new framework for parametric uncertainty assessment and use it to explore future US energy-related GHG emissions in the absence of federal climate policy through 2040. The main focus is to examine how technology- and fuel-specific costs affect emissions and to quantify the envelope of future emissions in the absence of climate policy. This framework consists of a method to identify the most sensitive model inputs, a Monte Carlo
simulation, and a clustering algorithm used to group similar results generated by the Monte Carlo simulation.

In Chapter 3, I consider deep decarbonization of the US energy system in terms of costs and system configuration using MGA. MGA allows for the systematic exploration of the decision space, which allows modelers to identify decarbonization pathways that are maximally different in decision space but have nearly the same cost. Although these alternative pathways are all considered suboptimal relative to the cost optimal solution, they may represent a preferred option when uncertainties exogenous to the model are evaluated. In addition, MGA can be used to limit technology selection by the model, a feature used in Chapter 3 to explore low carbon strategies that only include renewables.

Energy system modelers need to understand the factors that shape future demand and its variability at the seasonal time-scale. Chapter 4 considers residential electricity demand and its interannual dependency to climate. I use linear regression to assess the sensitivity of residential electricity demand in the conterminous United States to seasonal climate variations and structural changes in state-level household electricity demand. The dependency of demand on seasonal climate poses challenges for power system operators and has critical implications for both demand- and supply-side planning in the electric sector. Deep decarbonization of the U.S. energy system, which is the subject of Chapter 3, requires, among other measures, large-scale electrification of heating services [22]. Thus understanding the role of climate in shaping electricity demand is critical in future modeling efforts. In addition, improvements in monthly to seasonal electricity demand forecasts can aid in the development of emergency, contingency management, and system maintenance plans, forward fuel purchases, demand-response programs, and scheduling of hydro and thermal power plants.
1.1 References


2.1 Introduction

The US is the second largest energy-related greenhouse gas emitter, and therefore critical to global efforts to mitigate climate change. The US intends to formally withdraw from the Paris Agreement, and key policies aimed at curbing greenhouse gas emissions – in particular the Clean Power Plan and revised CAFE standards – face a highly uncertain fate. Inaction on the federal level is tempered by state-level action, including California’s SB32, the Regional Greenhouse Gas Initiative (RGGI) covering 9 northeastern states, and renewable portfolio standards active in 37 states. In addition to federal and state policy, market forces will play a critical role in shaping the future US energy system over the next several decades. Reasons for optimism include low natural gas prices as well as dramatic drops in the cost of solar photovoltaics and lithium ion batteries used for grid storage and electric vehicles. While prevailing market forces are likely to temper unconstrained greenhouse gas emissions at the national level, the US will eventually need to produce deep emissions reductions in order to avoid the worst effects of climate change. The US had previously acknowledged the need for such reductions. For example, the US nationally determined contribution (NDC) under the Paris Agreement is 26-28% below 2005 levels by 2025, and the Mid-Century Strategy suggests an 80% reduction below 2005 levels by 2050.

Given the anticipated lack of near-term federal action to address climate change, it is critical to evaluate potential baseline emissions scenarios in the absence of federal climate policy. In addition, careful model-based analysis of baseline scenarios can help inform discussions regarding the timing and structure of future climate and energy policy. The US Energy Information Administration (EIA) utilizes the National Energy Modeling System (NEMS) to produce the Annual Energy Outlook (AEO). The AEO includes a Base Case as well as several side cases that typically focus on variations in economic growth, fuel resource cost and availability, and rates of technology innovation. For example, AEO 2017 includes a total of seven cases that are repeated with and without implementation of the EPA Clean Power Plan. While these internally consistent
scenarios provide a sketch of potential midterm energy futures, they belie the underlying market uncertainty that could push the US energy system in different directions in the absence of new policy. Several other recent modeling efforts have projected US energy technology deployment and greenhouse gas emissions, but generally focus on scenarios under proposed or hypothetical federal policy and use a limited number of scenarios to address parametric uncertainty.

In this analysis, we utilize Tools for Energy Model Optimization and Analysis (Temoa) 19, an open source, publicly available energy system optimization model (ESOM) to examine a large set of baseline US energy futures through 2040. Our objective is to rigorously explore the future decision landscape and quantify greenhouse gas (GHG) emissions in a future where energy system changes are driven by market forces rather than top-down federal policy. We employ a sensitivity technique called the Method of Morris 20,21 to rank order the input parameters that produce the largest effect on emissions. We then incorporate the ten most sensitive parameters into a suite of Monte Carlo simulations that indicate how US energy-related GHG emissions may change under different future assumptions. The full set of results are used to identify plausible combinations of assumptions that can lead to either very high or low emissions, which can inform our understanding of future baseline emissions and suggest pathways to lower emissions in the absence of new federal policy.

2.2 Model and Data

The analysis is performed with an open source energy system optimization model (ESOM) called Temoa, which operates on a single regional input database representing the continental United States. The Temoa baseline scenario is designed to be conservative. The baseline assumes that the Clean Power Plan is not implemented, and does not include California’s cap-and-trade system or RGGI. The Temoa baseline results are compared with AEO in Section A.1 of the Appendix A. Key features of the model and input dataset are described here, with additional information provided in Appendix B.

2.2.1 Tools for Energy Model Optimization and Analysis (Temoa)

Temoa 19 is an open source, bottom-up ESOM, similar to MARKAL/TIMES 22, OSeMOSYS 23 and MESSAGE 24. Temoa employs linear optimization to generate the least-cost
pathway for energy system development. The model objective function minimizes the system-wide present cost of energy provision over a user-specified time horizon by optimizing the installation and utilization of energy technologies across the system. Technologies in Temoa are explicitly defined by a set of engineering-economic parameters (e.g., capital costs, operations and maintenance costs, conversion efficiencies) and are linked together in an energy system network through a flow of energy commodities. Model constraints enforce rules governing energy system performance, and user-defined constraints can be added to represent limits on technology expansion, fuel availability, and system-wide emissions. The model formulation is detailed in Hunter et al. 17 and the Temoa source code is publicly available on Github 25. Since the model formulation evolves over time, revised model documentation can be found on the project website 26. The model source code and data used to produce this analysis are publicly archived through zenodo.org, and can be retrieved with the following DOI: 10.5281/zenodo.1140091.

2.2.2 Input Data

The input database used in this analysis is largely drawn from the EPA MARKAL database 27 and represents the US as a single region. The time horizon extends from 2015 to 2040, with 5-year time periods. For example, the 2015 period covers the years 2015 to 2019. The results for each year within a given time period are assumed to be identical. Temporal variation in renewable resource supply and end-use demands is captured through representation of three seasons (summer, winter, intermediate) and four times of day (am, pm, peak, night). Fuel price trajectories are drawn from the Annual Energy Outlook (AEO) 9 and specified exogenously. While assuming a fixed fuel price trajectory does not capture demand-price feedbacks, it simplifies the execution and interpretation of the sensitivity analysis. The model tracks emissions of CO2, NOx and SO2 as well as CH4 leakage rates from natural gas systems. We assume a methane leakage rate equivalent to 1.4% of total natural gas delivered 28, which is lower than both NETL 29 and EDF 30 estimates of 1.6 and 1.65%, respectively. Given the ability to mitigate methane leakage and the multi-decadal timescale of our analysis, use of the EPA estimate was deemed appropriate. Methane emissions are transformed into CO2-equivalents using a global warming potential (GWP) of 25 28. This GWP value complies with the international inventory reporting guideline under the United Nations Framework Convention on Climate Change 28. The input database and baseline assumptions are
publicly available for testing and verification through Github 25. A brief sectoral description of the input dataset is provided in Table 2.1.

The baseline includes the aggregate effect of state-level renewable portfolio standards as well as prevailing tax incentives, including the production tax credit for wind units 31, a 10% tax credit on utility scale solar PV throughout the time horizon, and a 10% tax credit on rooftop solar PV until 2021 32. To orient our baseline to a familiar projection, our input assumptions draw heavily on the AEO 9 and Assumptions to the AEO 33.

Table 2.1 Sectoral-level detail in the Temoa input database.

<table>
<thead>
<tr>
<th>Sector</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel Supply</td>
<td>Fuel prices are specified exogenously. Baseline projections are drawn from the 2017 Annual Energy Outlook 9. There is no limit on fuel availability except for biofuel use in the transportation sector 34.</td>
</tr>
<tr>
<td>Electric</td>
<td>The electric sector includes 34 generating technologies. Air pollution control retrofits for coal include low NOx burners, selective catalytic reduction, selective non-catalytic reduction, and flue gas desulfurization. Costs and performance characteristics are largely drawn from the EPA U.S. nine-region MARKAL database 27, and existing capacity estimates are drawn from the US EIA 9.</td>
</tr>
<tr>
<td>Transportation</td>
<td>The transportation sector is divided into four modes: road, rail, air, and water. Road transport is modeled with greater detail by dividing it into three subsectors: light duty transportation, heavy duty transportation, and off-highway transportation. The light duty sector includes 6 size classes and 9 different vehicle technologies. Data is largely drawn from the EPA U.S. nine-region MARKAL database 27.</td>
</tr>
<tr>
<td>Industrial</td>
<td>Given the high degree of heterogeneity in the industrial sector, it is model simplistically as a set of fuel share constraints that are calibrated to the 2017 Annual Energy Outlook 9.</td>
</tr>
<tr>
<td>Commercial</td>
<td>The commercial sector includes the following end-use demands: space heating, space cooling, water heating, refrigeration, lighting, cooking, and ventilation. A total of 83 demand technologies are included to meet these end-use demands. Data is largely drawn from the EPA U.S. nine-region MARKAL database 27.</td>
</tr>
<tr>
<td>Residential</td>
<td>The residential sector includes the following end-use demands: space heating, space cooling, water heating, freezing, refrigeration, lighting, cooking, and appliances. A total of 69 demand technologies are included to meet these end-use demands. Data is largely drawn from EPA U.S. Nine-region MARKAL database 27.</td>
</tr>
</tbody>
</table>
2.3 Analysis Framework

Our methodological approach shares common elements with previous work. For example, we utilize large scale scenario generation and cluster analysis similar to the Robust Decision Making (RDM) approach \cite{35,36}; however, we are not attempting to identify a policy strategy. In addition, recent studies have used ESOMs to generate a large ensemble of near optimal scenarios to derive policy relevant insights, but such work has focused on European applications \cite{37,38,39}. Below we describe each element of our framework in turn.

2.3.1 Method of Morris

Following work by Usher \cite{40}, we utilize a global sensitivity method called Method of Morris \cite{20,21} to identify the model inputs that produce the largest effect on cumulative GHG emissions over the model time horizon. The method produces a reliable sensitivity measure with a minimum number of runs and can handle a large number of uncertain parameters, making it suitable for use with data-intensive ESOMs \cite{40}. We consider price variation in 6 different fuels and 35 technology-specific capital costs. (See Section A.2 of Appendix A for additional details on the Method of Morris formulation and problem setup used in this analysis.) For simplicity, each parameter is varied within a range representing $\pm$20\% of its baseline value rather than trying to identify specific ranges for each parameter separately, which are subject to considerable future uncertainty. While not shown here, a $\pm$40\% input parameter range produced the same top ten parameters, though their rank order based on cumulative GHG emissions shifted.

2.3.2 Monte Carlo Simulation

Next, we perform a Monte Carlo simulation where we consider variation in the ten most sensitive parameters selected from the Method of Morris analysis. Our objective is to quantify how variation in the ten most sensitive techno-economic parameters can affect the resultant range in GHG emissions. Given the high uncertainty associated with these future parameter values, we do not attempt to quantify different ranges, probability distributions, or correlations between parameters. Rather, a uniform distribution and range is assumed for each parameter, similar to other studies \cite{39,41,42,43}. As a result, the full set of model results indicate the range of future emissions pathways and suggest possible outcomes, but should not be interpreted probabilistically. When
investigating low emissions outcomes relying on specific combinations of realized parameter values, we consider the plausibility of those parameter combinations ex post. The required number of model runs for the Monte Carlo simulation is assumed independent of the number of uncertain inputs; 1000 runs are conducted within the simulation. To minimize the computational time, we created an embarrassingly parallel implementation of the framework. The model runs are parallelized using the “joblib” python library. We run the model using a workstation containing two Multi-Core Intel Xeon E5-2600 series processors, representing a total of 12 compute cores.

2.3.3 K-means Clustering

Rather than examine the raw set of 1000 model runs, we employ k-means clustering to examine a limited number of representative points. The k-means algorithm partitions the dataset by creating groups or clusters with similar features. The algorithm minimizes the Euclidean distance between the centroid of each cluster, where each cluster consists of values representing the 10 uncertain input parameters plus cumulative emissions (see Section A.3 of Appendix A for more details). We separate the data into ten clusters, which provide enough points to identify relationships between input values and the resultant level of cumulative CO2 emissions. Larger numbers of clusters were tested, but the configuration of centroids did yield additional insights.

The k-means cluster algorithm is a well-established methodology applied to separate datasets into homogenous groups of observations. The method was first developed by Lloyd and has been widely used as a non-hierarchical clustering approach. Other methods such as principal component analysis, hierarchical and other non-hierarchical clustering methods, and supervised and unsupervised learning algorithms could also be used for our purpose. However, in this work we make use of the k-means method for clustering due to its simplicity, efficiency, and relevant success in several areas of the literature.

2.3.4 Uncertainty Cases

We develop three different cases to represent different levels of future uncertainty, and repeat the Monte Carlo simulation, consisting of 1000 model runs, for each case. We refer to the first case as ‘Stable World,’ which denotes a relatively stable future in which the ten most sensitive parameters selected from Method of Morris vary within ±20% of their baseline values. The second
case, ‘Uncertain Fuels,’ allows natural gas and oil prices to vary within ±80% of their baseline values, consistent with their longer-term historical range over the last 50 years 52,53. The remaining eight parameters in the Uncertain Fuels case vary within ±20% of their baseline values, as in the Stable World case. The third case, ‘Uncertain World,’ allows natural gas and oil prices to vary within ±80% of their base value, while the other eight uncertain input factors vary within ±40% of their baseline values.

2.4 Results and Discussion

The presentation of results follows the order described in the Analysis Framework section. We begin by presenting results from the Method of Morris sensitivity analysis, followed by the Monte Carlo simulations associated with each of the three uncertainty cases. The raw Monte Carlo results are used to examine the range of future cumulative emissions and the role that natural gas prices play in determining emissions. Finally, we present results from k-means clustering to assess how variations in technology cost and fuel prices lead to different emissions outcomes.

**Identifying key sensitivities.** The Method of Morris results (Figure 2.1) indicate that natural gas prices have the largest overall effect on cumulative GHG emissions. In the electric sector, coal prices and capital costs for solar photovoltaics, wind, and combined-cycle gas turbines also have a measurable effect on total emissions. The inclusion of capital costs associated with battery electric vehicles, conventional gasoline vehicles, and diesel vehicles indicate that the light duty vehicle sector can also have an effect on emissions. Below the tenth most sensitive parameter (heat pump capital cost), the average effect on cumulative GHG emissions is less than 0.25% of the base case cumulative emissions. In general, the small relative changes in cumulative emissions reflect inertia in the energy system: a change in any single parameter takes time to reach its full effect on technology deployment and has a limited effect across the system.
Figure 2.1 Method of Morris results indicating the ten input parameters that produce the largest effect on cumulative GHG emissions (2015-2040), ranked from largest to smallest effect. Parameters labeled “price” represent fuel prices, while all others represent capital costs. The horizontal axis indicates the magnitude of the expected change in cumulative GHG emissions relative to the baseline value. Each input parameter is tested at 25 distinct values over a range representing ±20% of its baseline value. The length of the bar indicates the average effect, while the error bars indicate the 95% confidence intervals.

We repeated the Method of Morris analysis with a ±40% input parameter range and found that it generates the same top ten parameters as shown in Figure 2.1; however, oil price rises to the second rank while the relative order of the other inputs stays the same.

**Baseline GHG emissions under future uncertainty.** The ten parameters with highest sensitivity (Figure 2.1) are selected for inclusion in a suite of Monte Carlo simulations that indicate how US energy-related GHG emissions may change under different future assumptions. The distribution of cumulative GHG emissions from the three cases is shown in Figure 2.2 where kernel density estimation is employed to smooth out the raw histogram results.
Figure 2.2 Kernel density estimates of cumulative GHG emissions from 2015-2040 for three cases: Stable World, Uncertain Fuels, Uncertain World. The modeled baseline GHG emissions are estimated to be 169 Gtonnes of CO₂ equivalent, represented by the black dot on the horizontal axis. Larger ranges in input parameters produce large ranges in cumulative GHG emissions, with results skewed towards cumulative emissions below the baseline value.

In the Stable World case, the distribution of cumulative GHG emissions are clustered around the baseline scenario (169 GtCO₂e), with a range extending to a minimum emissions level (153 GtCO₂e). By comparison, both the Uncertain Fuels and Uncertain World cases exhibit a wider range in cumulative GHG emissions than Stable Word, but both are skewed towards lower emissions. Thus, allowing a wider range in fuel prices (±80%) flattens the distribution of cumulative emissions and increases the proportion of scenarios with emissions lower than the baseline. Moving from Uncertain Fuels to Uncertain World increases the highest emissions scenario by 1% and decreases the lowest emissions scenario by 3.2% relative to the cumulative emissions level in the baseline scenario. Overall, Figure 2.2 indicates that wider input ranges related to fuel costs and technology investment costs increase the proportion of emissions scenarios below the baseline. For reference, our baseline cumulative GHG emissions are 6.2% higher than the AEO reference case without the Clean Power Plan. Part of this discrepancy is due to our consideration of CO₂-equivalent emissions from methane leakage during natural gas production, processing and transport, which AEO does not report. If only CO₂ emissions are compared, the
difference is 3.2%. Across all modeled scenarios, methane leakage range from 1.6% to 4.1% of total CO2e emissions.

The GHG emissions trajectories associated with the three cases are presented in Figure 2.3 and compared with the Mid-Century Strategy (MCS) for deep decarbonization. The MCS outlines a path for the US to meet its commitments under the Paris Accord and ultimately achieve an 80% reduction below 2005 emissions by 2050.

Figure 2.3 indicates that it may be possible to meet the US 2025 commitments in the absence of federal policy; however, market forces alone are not enough to sustain the emissions reductions prescribed by the MCS post-2025.

The effect of fuel prices in the power sector on GHG emissions. In addition to total GHG emissions, we examine the underlying trends in technology deployment that drive the...
emissions shown in Figures 2.2 and 2.3. Since the Method of Morris results indicated that emissions are highly sensitive to natural gas and coal prices, we plot cumulative GHG emissions versus the average ratio of natural gas to coal prices across all model time periods (Figure 2.4). In the Stable World case (Figure 2.4a), there is a linear increase in emissions as the natural gas price increases relative to coal, which is due to the direct substitution of natural gas with coal to produce baseload electricity. Around a price ratio of approximately 1.8, however, the cumulative GHG emissions reach a plateau because baseload electricity production from coal reaches a maximum. At low price ratios, the variation in emissions at a given fixed price ratio is largely explained by variation in the capital cost of advanced natural gas combined cycle capacity. However, at higher price ratios above 1.8, the variability in cumulative emissions increases as variations in other input parameter values begin to exert their influence under high natural gas prices.

![Figure 2.4](image)

**Figure 2.4** Cumulative GHG emissions versus the ratio of natural gas to coal prices. Each subplot represents the full set of 1000 runs associated with each case: (a) Stable World, (b) Uncertain Fuels, and (c) Uncertain World. The red circles represent the baseline projection. Each point in the Stable World case is colored by the capital cost of combined-cycle natural gas turbines, while points in the other two cases are colored by the oil price. These factors help explain the variability in cumulative GHG emissions at a given fuel price ratio. The color bar indicates the scalar value used to adjust the input parameter value in the Monte Carlo simulation.
In the Uncertain Fuels case (Figure 2.4b), coal and natural gas prices still largely explain cumulative emissions when the price ratio is below 1.8, as in the Stable World case. However, the wider range associated with input natural gas and oil prices in the Uncertain Fuels case leads to a wider range in cumulative GHG emissions. The maximum variation in GHG emissions at a given fuel price ratio is approximately 33 GtCO₂e in the Uncertain Fuels case, and 18.4 GtCO₂e in the Stable World case. While the spread in cumulative emissions increases in the Uncertain Fuels case, it is largely skewed towards lower emissions. At a given natural gas to coal price ratio, oil prices help explain the variation in cumulative emissions, particularly at price ratios less than two.

In the Uncertain World case (Figure 2.4c), the variability in cumulative emissions as a function of fuel price ratio further increases because other input parameters play a larger role in determining emissions. Compared with the Uncertain Fuels case, oil prices are not as clearly correlated with cumulative emissions at a given price ratio. Emissions in all three cases are skewed towards lower values. In addition, there is a fairly consistent emissions ceiling; cumulative emissions do not exceed 180 GtCO₂e in any of the three cases.

**The effect of all uncertain inputs on GHG emissions.** Figure 2.4 indicates that the cumulative GHG emissions are strongly influenced by input parameters other than natural gas and coal prices in the Uncertain Fuels and Uncertain World cases. K-means clustering is applied to Monte Carlo results to condense the full set of 1000 runs from each case into a more manageable 10 clusters, which can be used to identify other key input parameters influencing cumulative emissions. Each of the ten clusters is defined by ten centroids representing the input parameter scaling factors used in the Monte Carlo simulation and another centroid representing cumulative GHG emissions. The centroids are extracted from their clusters, grouped by input parameter, and plotted versus the associated cumulative emissions in Figure 2.5. Parameter centroids that demonstrate a monotonic relationship with cumulative emissions and a wider spread in centroid values suggest a stronger effect on the emissions outcome.

Spearman rank correlation coefficients are used to quantify the relationship between the centroid values and associated cumulative emissions. Spearman coefficients quantify the correlation between parameter value ranks, and are thus an appropriate choice because they measure the degree of monotonicity between variables and do not require a linear relationship. High Spearman coefficients with low p-values (<0.05) indicate that changing a given input
parameter produces a consistent directional change in emissions. The capital costs of solar PV, wind, electric vehicles, and heat pumps as well as natural gas, coal, and oil prices have high Spearman coefficients (>0.6) and low p-values (<0.05) in at least one of the Uncertain Fuels and Uncertain World cases. Coal and oil prices exhibit negative correlation, while renewable and heat pump capital costs as well as natural gas prices show positive correlation with emissions.

Figure 2.5 Centroid values associated with uncertain inputs (x-axis) versus cumulative GHG emissions (y-axis). The centroid values represent scaling values, which are expressed as a fraction of the assumed baseline value. X-axis ranges correspond to the allowable ranges in the Uncertain Fuels and Uncertain World cases. The Spearman rank correlation coefficients (ρ) and p-values help to identify the degree of monotonicity between each input and emissions. Cumulative baseline emissions are shown by the black dot on the y-axis.

Given the low coefficient of variation (<5%) associated with heat pump capital costs, we investigated the raw scenario results further and found that it had little effect on cumulative emissions.
**Assessment of the highest and lowest emissions outcomes.** The cluster results can also be used to identify the parameter combinations that produce the highest and lowest emissions outcomes, which can inform future policy discussions. Clustering analysis is applied separately to the 50 model runs in both the Uncertain Fuels and Uncertain World cases that produce the highest and lowest 5% cumulative GHG emissions (Figure 2.6). In Figure 2.6, centroids are grouped by cluster to demonstrate how a particular set of centroids comprising a cluster produce a given emissions outcome. We consider the six input parameters with high Spearman correlation coefficients (>0.6) that are statistically significant at the 5% level in either the Uncertain Fuels and Uncertain World cases and whose centroids have a coefficient of variation greater than 10%. Two clusters per case and emissions level (high or low) are generated; more clusters tended to produce redundant results.

![Figure 2.6 Application of k-means clustering to the 5% highest and lowest emission runs from the Monte-Carlo simulation for both the Uncertain Fuels (UF) and Uncertain World (UW) cases. Each horizontally aligned row represents a single parameter cluster (‘C1’ or ‘C2’), and each colored dot represents the centroid value associated with a specific parameter within the given cluster. The centroid values on the x-axis represent the scaling factors applied to baseline estimates and used in the Monte Carlo simulation; cumulative GHG emissions associated with each cluster are plotted on the y-axis. Cumulative baseline emissions are shown by the black dot on the y-axis.](image)

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In the Uncertain Fuels case, both the highest and lowest emissions regimes are characterized by opposing oil and natural gas prices. The centroid values reflect the wider allowable range in natural gas and oil prices (±80%) compared to coal prices and capital costs for alternative technologies (±20%). Since this analysis does not account for correlation between input parameters, we need to consider ex post whether a future with low natural gas prices and high oil prices is plausible. With the advent of shale gas in North American markets, the historically strong correlation between oil and natural gas prices has been weaker since 2007\textsuperscript{52,53}. While there are studies indicating that this decoupling was a temporary phenomenon\textsuperscript{54}, others show that Henry Hub prices are completely decoupled from WTI prices\textsuperscript{55,56}. In general, market forces, policies, and regulations that promote natural gas over coal in the electric sector will lead to lower emissions, though concerted effort is required to minimize upstream methane leakage from natural gas systems\textsuperscript{57}.

In the Uncertain World case, the centroids associated with the highest emissions clusters include low oil prices and high natural gas prices, with a discernable shift towards lower coal prices and higher capital costs for alternative technologies compared to the base case. We investigated the individual scenarios that comprise the two high emissions clusters, and all are consistent with the centroid values. The centroids associated with the lowest emissions clusters in the Uncertain World case merit careful examination, as they suggest ways in which the lowest emissions pathways can be achieved. In the Uncertain World low emissions clusters, capital cost reductions in electric vehicles coupled with low natural gas prices and high coal prices lead to low electric sector emissions, relatively cheap electricity, and therefore a cost-effective deployment of electric vehicles to supplant gasoline vehicles. The comparison between C1 and C2 in Uncertain World is instructive: relative to C1, the C2 cluster achieves lower emissions with higher coal prices and lower electric vehicle costs. Cluster 2 of Uncertain World achieves the lowest observed emissions with low natural gas prices (52% of baseline), low electric vehicle prices (76% of baseline) coupled with high oil (144% of baseline) and coal prices (122% of baseline). Note that these centroid values do not indicate the relative contribution that each parameter makes to emissions reductions. However, inspection of Figure 2.6 indicates that the drop in electric vehicle capital cost from Uncertain Fuels Cluster 1 to Uncertain World Cluster 2 is a significant contributor to the 4% drop in cumulative emissions relative the baseline. By contrast, the total drop in cumulative emissions
from baseline to the lowest emissions scenario is approximately 17%. Thus, electric vehicle deployment is not the dominant factor behind lower emissions, consistent with Babaee et al. 34.

While the $k$-means clustering results strongly suggest the need for low natural gas prices coupled with high oil and coal prices, they obscure some of the underlying variation in the individual scenarios produced by the Monte Carlo simulation. For example, Figure 2.7 shows the variation in electric sector installed capacity between the baseline and two scenarios drawn from the set of 50 lowest emissions scenarios.

**Figure 2.7** Comparison of electric sector capacities in three scenarios: baseline scenario and two scenarios drawn from the set of 50 lowest emissions scenarios. ‘S1’ represents a low emissions drawn from Uncertain World Cluster 2 that is consistent with the centroid values shown in Figure 2.5. ‘S2’ represents a low emissions drawn from Uncertain World Cluster 1 that shows a result significantly different from the associate centroid values.

The electricity capacity results shown in Figure 2.7 illustrate the potential diversity in individual scenario results. ‘S2’ shows a much higher penetration of wind and solar PV compared to either the baseline or ‘S1’, a scenario result with input parameter values consistent with the low emissions centroid values shown in Figure 2.6. The ‘S2’ scenario achieves among the lowest cumulative greenhouse gas emissions (140 GtCO$_2$e) with high fossil fuel prices and high combined-cycle turbine cost coupled with capital costs for wind, solar PV, and electric vehicles that are more than 30% below their baseline value.
2.5 Policy Insights and Caveats

Energy system models are often used to examine a limited number of scenarios that reflect carefully considered states of the world; however, the results often ignore high levels of future uncertainty and can thus be misleading. There is a critical need to introspect energy models to quantify key assumptions, sensitivities, and uncertainties. Real world uncertainty includes a broader array of considerations, such as the prevailing political climate, public acceptance of alternative energy technology, and potential policy actions at the state or regional level that are not captured here. Nonetheless, a careful examination focused on technology cost and performance in a systems context can yield useful insight for policy makers.

Our analysis focuses on techno-economic uncertainty related to fuel prices and technology-specific capital costs, thus providing an indication of how changes in costs can produce different base case outcomes. We do not attempt to model different ranges or correlations among uncertain inputs, which could affect the shape of the emissions distributions shown in Figure 2.2. Even with a more sophisticated representation of input data, we would not expect a fundamental change in the emissions distributions. As indicated in the Method of Morris results, no single parameter will drive results across the entire energy system. Our approach here is to conduct the sensitivity analysis with a simplified representation of input data and then examine key relationships ex post for plausibility. This approach leaves open the possibility for new insights. For example, the lowest emissions scenarios rely on low natural gas prices and high oil and coal prices, which led us to consider the degree of price decoupling between these resources.

Overall, the model results indicate that market forces operating in the absence of new federal climate or energy policy will tend to produce emissions trajectories that remain relatively flat or produce modest reductions: the 2040 emissions range from -23% to +10% of the baseline estimate. By comparison, the 2040 emissions across the AEO 2017 scenarios (without the Clean Power Plan) range from +4% to -5% of the AEO reference scenario 9. Thus the broader consideration of input uncertainty in this analysis produces a wider range in future emissions, but the range skews towards lower emissions. Our results show consistency with results from Barron et al. 56, where most of the scenarios show relatively flat emissions trajectories in comparison with historical levels. By contrast, Clark et al. 59 and Zhu et al. 60 project higher emissions over the next several decades due to greater reliance on fossil fuels. In our analysis, there are more parameter
value combinations that decrease emissions through the deployment of natural gas and renewables than increase emissions through the increased deployment of coal. For perspective, the cumulative difference between the highest and lowest emissions scenario from 2020-2025 is approximately 1.8 times the 2015 emissions level, and the same cumulative difference from 2020-2040 grows to nearly 6.6 times the 2015 emissions level. These variations in emissions are significant and illustrate the importance of considering techno-economic uncertainty in future no-policy scenarios. Applying sensitivity techniques that extend beyond conventional scenario analysis can broaden future energy and emissions pathways, and could help inform subsequent policy efforts.

If technology innovation remains low and technology costs track close to their baseline values, then the key tradeoff will be natural gas versus coal utilization in the electric sector. The model results suggest that the continuation of low natural gas prices will lead to additional coal plant retirements, similar to other studies. The cluster results (Figure 2.5) indicate that coal, oil, and natural gas prices as well as capital costs for wind, solar PV, and electric vehicles produce a statistically significant effect on cumulative emissions. The lowest emissions scenarios generally rely on lower natural gas prices and electric vehicle costs in addition to higher oil and coal prices relative to the baseline. While the centroids associated with renewable capital costs suggest that they do not play a consistent role in the 50 lowest emissions scenarios, their significance in the full set of results indicate that they are playing a meaningful role in lowering emissions. For example, Figure 2.5 indicates that low solar PV costs (20% below the baseline) play a role in achieving cumulative emissions of 160 GtCO\textsubscript{2e}, which is 5% below the baseline level. Our choice of the 50 scenarios with lowest emissions was illustrative; changing the size of the lowest emissions set could also affect centroid values.

We devised our base case to be conservative. More optimistic assumptions about renewables in the baseline could shift the cost threshold at which renewables are deployed at large scale. In addition, our model does not include the EPA Clean Power Plan. While the collective requirement under state-level renewable portfolio standards is included, we did not explicitly model emissions caps in California or the Northeastern states under RGGI. These existing policies, combined with additional state-level efforts to reduce emissions and increase the deployment of renewables, could produce significant GHG reductions beyond those estimated here. Our analysis indicates that energy market forces, operating in the absence of significant new policy, will hold
emissions close to current levels or produce modest reductions. While it is heartening that a hiatus in federal energy and climate policy will not produce a dramatic rise in emissions, aggressive policy action will be required to produce the level of GHG reductions required to avoid the worst effects of climate change.
2.6 References


3 Exploring Technology Pathways to Achieve Deep Decarbonization in the United States

3.1 Introduction

Limiting global temperature rise to 1.5°C requires a 40-60% reduction in anthropogenic greenhouse gas emissions (GHGs) by 2030 and approximately 100% by 2050 [1]. This realization has informed the national debate on climate change, and proposals such as the Green New Deal ultimately aim to reach carbon neutrality [2]. Although the political economy of deep decarbonization remains a significant barrier [3,4], there are still ongoing debates about the cost and performance of different energy system configurations under such an ambitious climate policy. The transition to near carbon-neutral future requires massive changes in the energy system. While there is consensus in the literature about the importance of energy efficiency, electrification of end-use services and transitioning to a carbon-free electric grid [5-15], questions still remain about how best to implement and coordinate these options. For example, a low carbon electric sector can be achieved in a variety of ways. While some studies point out the significant damage costs associated with nuclear and carbon capture and storage (CCS) and emphasize that the electric grid can be run by a mix renewable sources, energy storage, and demand response in a reliable way [14,15], other studies recommend a more diverse portfolio of low carbon options such as nuclear, and carbon capture and storage to enable a more cost-effective and reliable mitigation pathway [16-18].

Energy system optimization models (ESOMs) are used to explore future scenarios and associated outcomes over the next several decades. Several recent modeling efforts have projected energy technology deployment and the costs of deep decarbonization at the national or state-level [5-13], but generally focus on a limited set of scenarios that vary a few key assumptions. Conventional scenario analysis does not adequately address large future uncertainties, including both parametric uncertainties, which reflect uncertainty in assumed input parameter values, and structural uncertainties, which reflect the inadequate nature of ESOMs to represent real-world processes. Methods such Monte Carlo simulation can help address parametric uncertainty, but do not account for structural uncertainty in the model. Overlooking the structural uncertainty in
ESOMs can miss an array of potentially interesting policy solutions [19]. In this paper, we use a technique called modeling to generate alternatives (MGA) to systematically explore the decision space under a stringent cap on U.S. CO₂ emissions. MGA is an algorithm designed to produce solutions that have similar system costs but are very different in decision space [20]. By restructuring the model to search the near-optimal solution space, MGA can account for structural uncertainty in the model.

The significance and application of MGA in the context of energy systems modeling has been demonstrated in various contexts [19,21-26]. Price and Keppo (2017) use MGA to generate a handful of alternatives that have maximally different primary energy supplies under both a carbon cap and a cap-free scenario [16]. In another study, Berntsen and Trutnevyte (2017) use MGA and scenario analysis to generate 520 different scenarios of Swiss electricity futures [22]. DeCarolis et. al. (2016) apply MGA to a model of the U.S. electric and light duty transportation sectors, and suggest different methods to update the MGA algorithm in an energy systems modeling context [25].

This paper is the first study to apply MGA to a U.S. energy system model that embeds plausible pathways to deep decarbonization by mid-century. Our objective is twofold: explore alternative solutions under a CO₂ cap scenario that achieves a 95% reduction in emissions by 2050, and compare the cost and performance of deep decarbonization versus all-renewable scenarios. From a policy perspective, examining deep decarbonization alternatives with approximately the same system cost is worthwhile because sub-optimal solutions may be optimal when weighing factors exogenous to the model. The observed differences between MGA alternatives indicate the degree of flexibility in the system: a highly diverse set of technology deployments across several different MGA runs indicates that there are more paths to meet the deep decarbonization target at the same cost level and therefore the system is more flexible. By contrast, highly similar MGA solutions suggest a narrow technological path to achieve deep decarbonization across the system.

3.2 Methods

The methods section is organized as follows. Section 3.2.1 outlines our research objectives and describes our approach to the analysis. Section 3.2.2 briefly describes the Temoa formulation,
and Section 3.2.3 describes the Temoa-compatible input database. Section 3.2.3 explains how we implemented the MGA algorithm to search the near optimal decision space.

### 3.2.1 Approach to the Analysis

Currently, 15 states have committed to either deep decarbonization or 100% renewables, either through legislation or as explicit goals through executive orders [27]. Our objective is to explore technology pathways that can produce deep decarbonization of the entire U.S. energy system. First, we run an emissions cap (“CCap”) scenario that includes a steep linear reduction in emissions, resulting in a 95% reduction in greenhouse gas emissions below 2017 emission levels by 2050. We then apply MGA to identify technology pathways that are maximally different from one another but are within a prescribed cost range. This exploration of alternatives is used to identify key technology tradeoffs. Second, we examine an “all-renewable electricity” strategy for deep decarbonization (CCap*) and compare it to the equivalent carbon reduction scenario in terms of system costs and technology performance. We keep the same carbon cap constraint for CCap* as we do for the CCap scenario but new deployments from nuclear and CCS are not allowed in the CCap*. Since excluding specific technology options from consideration leads to higher costs, we assess the incremental cost of an all-renewable electricity scenario compared to the equivalent low carbon scenario.

### 3.2.2 Tools for Energy Model Optimization and Analysis

For this analysis we use an open source ESOM called Tools for Energy Model Optimization and Analysis (Temoa). Temoa performs linear optimization to generate the least-cost pathway for energy system development by optimizing the installation and utilization of energy technologies across the system. Technologies in Temoa are explicitly defined by a set of engineering-economic parameters (e.g., capital costs, operations and maintenance costs, conversion efficiencies) and are linked together in an energy system network through the flow of energy commodities. The model formulation is detailed in Hunter et al. [28] and the Temoa source code and input data are publicly available on Github [29]. We are committed to full transparency and openness in order to allow for replication of our analysis.
3.2.3 Input database

The Temoa-compatible input database includes a representation of the residential, commercial, transportation, industrial and electric sectors. The model time horizon spans from 2017 to 2050, with 5-year time periods beginning in 2020. To represent seasonal and diurnal variations in energy supply and demand, the model balances energy commodity flows across a set of time slices, which represent different combinations of seasons and times of day. The results for each year within a given time period are assumed to be identical. Temporal variation in renewable resource supply and end-use demands is captured through representation of three seasons (summer, winter, intermediate) and four times of day (morning (6AM - 12PM), afternoon (12PM - 3PM), evening (3PM - 9PM), and night (9PM - 6AM)). Fuel price trajectories are drawn from the Annual Energy Outlook 2019 (AEO) [30] and specified exogenously. The model tracks emissions of CO$_2$, NO$_x$ and SO$_2$ as well as CH$_4$ leakage rates from coal, petroleum, and natural gas systems. The database was initially developed based on the EPA U.S. nine-region MARKAL database [31], but significant modifications have been made to it. These modifications include, but are not limited to, adding power-to-gas pathways as depicted in Figure 3.1 and incorporating a relatively simple representation of the industrial sector.

A brief sectoral description of the input dataset is provided in the Table 3.1 More detailed information on the database is provided in Appendix B.

**Table 3.1** Sectoral-level detail in the Temoa input database.

<table>
<thead>
<tr>
<th>Sector</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel Supply</td>
<td>Fuel prices are specified exogenously. Baseline projections are drawn from the 2019 Annual Energy Outlook. There is no limit on fuel availability except for biofuel use in the transportation sector. Six types of biomass are modeled and their prices and national availability are drawn from the Billion Ton report [32].</td>
</tr>
<tr>
<td>Electric</td>
<td>The electric sector includes 31 generating technologies. Air pollution control retrofits for coal include low NOx burners, selective catalytic reduction, selective non-catalytic reduction, and flue gas desulfurization. Costs and performance characteristics are largely drawn from the “Mid” scenario of the Annual Technology Baseline (ATB) 2019 [33].</td>
</tr>
</tbody>
</table>
Table 3.1 (continued).

<table>
<thead>
<tr>
<th>Sector</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transportation</td>
<td>The transportation sector is divided into four modes: road, rail, air, and water. Road transport is modeled with greater detail by dividing it into three subsectors: light duty transportation, heavy duty transportation, and off-highway transportation. The light duty sector includes 6 size classes and 9 different vehicle technologies. Data is largely drawn from the EPA U.S. nine-region MARKAL database [31]</td>
</tr>
<tr>
<td>Commercial</td>
<td>The commercial sector includes the following end-use demands: space heating, space cooling, water heating, refrigeration, lighting, cooking, and ventilation. A total of 83 demand technologies are included to meet these end-use demands. Data is largely drawn from the EPA U.S. nine-region MARKAL database [31]</td>
</tr>
<tr>
<td>Residential</td>
<td>The residential sector includes the following end-use demands: space heating, space cooling, water heating, freezing, refrigeration, lighting, cooking, and appliances. A total of 69 demand technologies are included to meet these end-use demands. Data is largely drawn from the EPA U.S. nine-region MARKAL database [31]</td>
</tr>
<tr>
<td>Industrial</td>
<td>Given the high degree of heterogeneity in the industrial sector, it is modeled more simplistically compared to other sectors. The demand for CHP and process heat are drawn from the EPA U.S. nine-region MARKAL [31] while the rest of the industrial demand is calibrated to the 2019 Annual Energy Outlook [30].</td>
</tr>
<tr>
<td>Power-to-X</td>
<td>The power-to-X pathway includes various ways of producing alternative fuels such as hydrogen, synthetic gas and methanol from the electrolysis of water. The resulting products can be used by the end-use sectors, Figure 3.1. We assume that the CO₂ needed to generate synthetic fuels comes from two sources: the CO₂ captured by CCS technologies in the electric sector and direct capture of CO₂ from the atmosphere.</td>
</tr>
</tbody>
</table>

Figure 3.1 Power-to-X pathways in the database. ‘X’ could be hydrogen, methanol or liquid fuels.
3.2.4 MGA formulation

MGA was originally developed to address water and land management problems in the early 1980s [14, 30]. The MGA algorithm changes the structure of the original optimization problem by making the model’s original objective function a constraint and limiting its righthand side to a user-specified value above the value of the model’s original objective function value. The amount by which the user-specified value exceeds the original objection function value is referred to as “slack” [34]. By adding slack to the baseline cost - in our analysis, the CCap scenario cost – and formulating a new objective function, the model is able to search the decision space to find near optimal solutions. The model’s new objective function minimizes a select set of decision variables by applying differing weights to them. The model can then be iterated, where each iteration includes a set of updated objective function coefficients. In this way, MGA can systematically explore the decision space in order to find near optimal solutions to the model.

Hop-Skip-Jump (HSJ) MGA represents a common way to update the MGA objective function coefficients and generate a limited number of alternatives [19]. In HSJ MGA, the decision variable coefficients in the objective function are iteratively updated based on the decision variable values in previous solutions. However, preliminary analysis using HSJ MGA did not result in sufficiently different results from one model iteration to the next. We speculate that the large number of decision variables make it difficult to produce a small number of highly diverse solutions across all modeled sectors. In order to more systematically explore the suboptimal space, I update the MGA objective function coefficients in a different manner. Similar to Berntsen et al. [17], I weight the model’s activity variables with random coefficients with values between zero and one. Similar to previous work, the activity variables are used in the MGA objective function, as they represent the contribution of each technology towards meeting end-use demands [19]. This optimization exercise is repeated a large number of times with different random technology coefficients. In contrast to HSJ MGA, this algorithm produces a large number of iterations in a wide search of the decision space, and then ex-post screening algorithms are used to find the solutions that are maximally different in decision space. A screening algorithm called Distance-to-Selected technique [16,31] is used to select a few maximally different solutions. Philip and Trunoevyte (2017) review the relevant screening methods and conclude that Distance-to-Selected technique has the same efficacy as other methods while its application is simpler and faster [16]. If the total number of iterations is N, Distance-to-Selected technique works by first calculating the
Euclidean distance between the original optimal scenario and all the N other solutions, and picking the solution with the largest Euclidean distance. The next maximally different solution must have the highest harmonic mean of Euclidean distances from these two solutions (i.e., the original optimal solution and the solution picked in the first round). We continue this procedure until a handful of maximally different solutions are picked.

The number of iterations sufficient for a thorough search depends on the slack value, as higher slacks open up a wider decision space that needs to be explored. As a preliminary test, I ran the MGA algorithm with a 50% slack value, using different number of iterations: 50, 100, 200, 300 and 500. Once the full set of results are generated, I return ten maximally different solutions from each of the diagnostic tests. The results stabilized once 200 iterations were produced. Therefore, for this paper I make all the MGA runs with 200 iterations. Since this experiment was made using a 50% slack, 200 iterations are sufficient for slack values less than 50%.

3.3 Results

In Section 3.3.1, we present the key insights of applying MGA on the CCap scenario and in Section 3.3.2 we examine the cost and technology characteristics of a 100% renewable strategy against the same carbon target defined in the CCap scenario, and Section 3.3.3 includes sensitivity analysis on end-use demands.

3.3.1 MGA and US Deep Decarbonization Pathways

The incremental cost associated with the CCap scenario are 7.2% of the BAU total cost, using a 5% global discount rate. The key mechanisms by which decarbonization is achieved in the CCap scenario are (1) a fully decarbonized electric sector through massive deployment of nuclear, renewables and bioenergy with CCS (BECCS), (2) displacement of fossil fuels in the end-use sectors by electricity, hydrogen, synthetic gas, and biofuels, and (3) the deployment of more energy efficient devices in the end-use sectors. The residential and commercial sectors are characterized by a close to full-scale electrification of services. In the transportation and industrial sectors, a combination of electrification and penetration of carbon-free fuels drives down emissions. More sector-wise results from the CCap scenario is shown in Appendix Figure C.1 in the Supplementary Information.
We performed MGA on the CCap scenario for select slack values ranging from 0.01–5%, expressed as a percentage of the CCap scenario total costs. In Figure 3.2, the ranges of technology-specific capacities in the electric sector in 2050 across all 200 MGA iterations are shown. We also ran the CCap scenario with the “low” and “constant” cost projections drawn from the NREL ATB [33]. Sector-specific results under these two sets of future technology cost assumptions are presented in Appendix Figures C.2 and C.3 of the Supplementary Information. Appendix Figure C.4 of the Supplementary Information shows the relative total system costs of the CCap to the baseline scenarios with different assumptions on future technology costs.
A slack equal to 0.01% is not sufficient for any major alternative to emerge. In this case, all the 200 iterations generated solutions that are nearly identical to the optimal solution obtained in the original CCap scenario. But as the slack increases to only 0.05%, new solutions that differ in their utility-scale solar PV, nuclear and combustion turbine capacities begin to emerge. Doubling the amount of slack from 0.05% to 0.1%, allows the algorithm to explore a wider suboptimal space, and as a result, we obtain wider ranges of deployed technology capacity. As the
slack increases to above 1%, a more diverse basket of alternatives, including rooftop solar PV and concentrating solar power (CSP) with thermal storage, are among the solutions.

The large number of MGA iterations (200 in this case) allows us to examine the correlations between different solutions generated by the algorithm in a systematic way, and therefore identify key technology tradeoffs. In Figure 3.3, we calculate the Pearson correlation coefficient between the cumulative installed capacities of different technologies through 2050 under three select slack values.

**Figure 3.3** Pearson correlation coefficients between different pairs of technology-specific cumulative installed capacities from 2017-2050. There are 200 observations associated with each technology. The correlation coefficients quantify the relationship between the cumulative capacities of a pair of technologies. Blank rows and columns indicate that one or both of the technologies are not deployed in any of the MGA iterations. The values in the diagonal of each of the three subplots are either blank (no deployment) or 1 (deployment greater than 0).

Figure 3.3 reveals important information about the technology tradeoffs. There is a group of technologies that strongly co-vary and, includes solar PV, electrolysis, synthetic gas production, hydrogen storage and natural gas combustion turbines. Solar PV drives the deployment of other technologies in this group. Natural gas combustion turbines are required to maintain an adequate capacity reserve margin when more solar PV with low capacity credit is on the system. On the other hand, the coupling of solar PV and hydrogen storage, allows generation and storage of hydrogen during the day and discharge of hydrogen during the night. The discharged hydrogen is directly consumed in the end-use sectors or is converted to synthetic gas and then sent to the end-use sectors. Synthetic gas is mainly used to displace natural gas in the end-use sectors. Hydrogen
can also be converted to liquid fuels through the Fischer-Tropsch process to meet the industrial demands (see Figure 3.1).

The deployment of solar PV and the group of power-to-X technologies is strongly and negatively correlated with nuclear deployment. With more nuclear and less solar PV, the need for large-scale hydrogen storage diminishes. Although hydrogen and electricity used to meet end-use service demands remains the same, hydrogen production takes place on a real-time basis from electricity in the higher nuclear scenario. This tradeoff indicates that the same levels of electricity and hydrogen can be generated with a considerably different combination of generators in the electric sector.

To visualize the diversity of solutions generated by the MGA algorithm, we select four maximally different solutions from the set of 200 solutions and compare them against the original CCap scenario for three small slack values, as shown in Figure 3.4.

Figure 3.4 Maximally different solutions in the 2050 electric sector. The left axis shows the technology-specific capacities as stacked bars and the right axis shows electricity generation as red dots.

The diversity of MGA solutions depends on the assigned slack value. But even under a 0.1% slack, two notable decarbonization pathways whose total installed capacities in 2050 differ by about 40%, are found (left-most subplot in Figure 3.4). One solution is the CCap scenario itself with about 3900 GW of power sector capacity in 2050 (excluding underground hydrogen capacities shown by gray bars in Figure 3.4). Total installed capacities in the CCap scenario in 2050 relative to the base year (2017), as also shown by Figure S1, are wind (500 GW), solar PV
(700 GW), rooftop solar PV (180 GW), BECCS (100 GW), and nuclear (1250 GW). The other notable solution (adjacent to the CCap in the left-most subplot of Figure 3.4) has more solar PV capacity (2700 GW) coupled with underground hydrogen storage, and considerably less nuclear capacity (700 GW). In contrast to the CCap scenario, total 2050 electric sector capacity in this MGA solution is 6300 GW. In all the solutions, total electricity generation is almost identical and equal to 14000 TWh, implying that the amount of end-use electrification remains constant. Under a 1% slack, the same trade-off between solar PV and nuclear discussed earlier still exist while other technologies such as natural gas combined cycle with CCS and CSP with thermal storage can as well be deployed at the expense of nuclear. In the 5% slack case, (the right-most subplot in Figure 3.4) there are solutions with zero new nuclear and CCS buildups. This observation indicates that there can be nuclear and CCS free solutions under smaller slacks (<5%). We further examine this possibility in Section 3.3.2.

Interesting insights can be drawn by looking at the different alternatives in the end-use sectors. Figure 3.5 shows four maximally different alternatives against the CCap scenario in the transportation sector for a high slack value (10%). Unlike Figure 3.4, we modified our screening algorithm to select solutions that are maximally different only in terms of their transportation sector fuel mix. The alternatives start with a more diverse set of transportation fuel mixes, but those fuel mixes largely converge by 2050. Because these maximally different pathways have similar end points, we can infer that there is limited technological flexibility to meet the stringent carbon target in 2050.

The main difference between the CCap fuel mix and the four MGA alternatives in 2050 relates to the degree of electrification of heavy-duty vehicles: all five scenarios have fully electrified light-duty vehicles, but more electrification in heavy-duty fleet can be achieved at the expense of bio-diesel. Second, less bio-diesel consumption in the alternative scenarios frees up additional biomass resources to be used for aviation biofuel production, which leads to less use of conventional jet fuels. Third, although limited, light-duty hydrogen fuel cell vehicles are deployed in the alternative scenarios.
While not shown, the residential and commercial sectors exhibit little flexibility in terms of their final energy demand mixes across the MGA iterations. In almost all of the iterations, electrification of heating services via efficient heat pumps, along with more efficient appliances define the building-related transition under a carbon cap.

3.3.2 An All-Renewable Electric Sector

There are a number of studies proposing that deep decarbonization targets should be met through only the deployment of renewables and storage coupled with aggressive demand response measures [22,23]. The MGA algorithm offers a test a system without nuclear and CCS, if we were to accept a marginal cost exceeding the CCap scenario cost. Since we obtained a solution for the 5% slack case in Figure 3.4 that had no CCS and nuclear, we know that the minimum marginal cost associated with all renewables is going to be lower than 5%.

We define a new scenario named CCap* with the same emission reduction target but subject to an investment ban on new nuclear as well as all CCS technologies (natural gas combined cycle with CCS, coal IGCC with CCS and bio-IGCC with CCS). With this new set of constraints, CCap* becomes 3.0% more expensive than CCap (a ban only on nuclear or CCS increases the costs by 0.67% and 1.9%, respectively, relative to CCap). Similar to what was done before, I
perform a new round of MGA iterations on the CCap scenario with a 3.0% slack but this time new investments from nuclear and CCS are disallowed, while existing nuclear capacities are kept operational. The objective is to evaluate system flexibility as well as identify maximally different ways in which the carbon target can be met only through renewables.

In the absence of new nuclear and CCS, the main trade-off is between solar PV and bio-IGCC on the one hand and, CSP with thermal storage on the other hand, as shown in Figure 3.6. Bio-IGCC is the only available renewable to meet baseload electricity in this case and therefore, becomes a complementary option to solar PV. Similar to the previous cases, a strong positive correlation exists between solar PV and electrolysis, seasonal hydrogen storage, and synthesis gas production. This information on electric sector technology tradeoffs is further illustrated in the maximally different alternatives shown in Figure 3.7.

Figure 3.6 Pearson correlation coefficients between the cumulative capacities of renewable technologies in the absence of nuclear and CCS. The data points used to calculate the correlation coefficients are cumulative installed capacities during 2017-2050. There are 200 observations associated with each technology. Blank rows and columns indicate that respective technology is not deployed in any of the MGA iterations.
Compared to the CCap scenario (Figure 3.4), electricity generation in the CCap* scenario and its associated alternatives is considerably higher. In the CCap* scenario, a ban on BECCS, which produces negative emissions in the CCap scenario, requires even more reductions from the industrial sector, and therefore more synthetic gas is needed to replace natural gas. Higher demand for synthetic natural gas in turn requires more electricity generation. There is another system effect associated with a ban on CCS: the CO₂ input to power-to-X is more expensive because in the absence of CCS, the only source of CO₂ is direct air capture. Consequently, unlike nuclear which has cost-effective competitors, when CCS is disallowed, not only does the system need to generate more synthetic fuels, but the unit cost of synthetic fuel production also rises. More sector-wise results from the CCap* scenario are shown in Appendix Figure C.5.

![Power Plant Capacity](image)

**Figure 3.7** CCap* scenario against 4 other maximally different all renewable pathways. All of the five alternatives cost 3.0% more than the CCap scenario. Similar to Figure 3.4, the right axis (red dots) indicate total electricity generation.

Of all the technologies involved in the US deep decarbonization pathways, the cost of underground hydrogen storage is among the most uncertain. Figure 3.8 shows the sensitivity of solar PV, CSP and hydrogen storage generation to the cost of underground hydrogen storage in the CCap* scenario. Total system costs are shown on the secondary axis. Interestingly, CSP and solar PV activities are complementary. With higher hydrogen storage costs, the system shifts away from solar PV to CSP. For a hydrogen cost of 25000 $/kW (~ 11 times the base cost for
underground hydrogen storage in a geologic formation), there is no hydrogen storage deployment, and the lack of storage produces an additional 1.3% extra cost on top of the CCap* costs. In the absence of hydrogen storage, hydrogen is generated on a real-time basis from mostly solar PV and CSP, Figure 3.8.

Figure 3.8 Sensitivity of the CCap* scenario to hydrogen storage costs. The left axis shows the cumulative activities of solar PV, CSP and hydrogen storage in peta joules and the right axis shows the system costs.

3.3.3 End-Use Demand Sensitivities

Thus far, a limit to the model used in this analysis is the assumption of fixed end-use demands that cannot be shifted over time. In order to examine the extent to which our results in the CCap and CCap* scenarios are affected by the way the demand of energy services are modeled, we designed a few diagnostic tests. We ran both the CCap and CCap* scenarios assuming that there is full flexibility in shifting a service demand from one time-slice to another time-slice in a day. Instead of being forced by a specific service demand distribution, the model can optimize the distribution of demand services in a day without any limitations, while preserving the total annual demand. As Appendix Figures C.6 and C.7 show, our hypothetical demand shifting assumption results in a shift in the electric sector capacity away from nuclear in the CCap scenario, and CSP with thermal storage in the CCap* scenario to solar PV. This result is consistent with our overall conclusion about technology tradeoffs shown in Figures 3 and 6. However, the costs of the CCap and CCap* scenarios under this assumption decline by 2.2% and 3.2%, respectively, relative to the
inflexible demand cases. This extreme assumption regarding demand shifting produces an upper bound on the potential of an aggressive demand response program to lower the costs of energy supply in the CCap and CCap* scenarios.

In a separate test case shown by Appendix Figures C.8 and C.9, we ran the two scenarios with different service demand projections. The objective is to examine how technology deployment would differ under a different demand projection. The new set of demand projections have the same values for demand services in 2020, but linearly decline over time such that the new 2050 demand values are 80% of the original 2050 demand values. This lower demand scenario only affects the amount of capacity deployed for technologies at the margin. In the CCap scenario, the model includes lower baseload electricity, and therefore lower total nuclear capacity in 2050. In the CCap* scenario, since baseload electricity demand is met by CSP and CSP is the marginal investment choice, there is less CSP capacity. Some minor differences in the end-use sectors are also observed, but again, the demand does not affect the relative economic advantage of specific technologies.

3.4 Conclusions and Caveats

This chapter includes a detailed exploration of potential technology pathways to achieve deep levels of decarbonization in the United States. Our work demonstrated the application of MGA to a large-scale ESOM in the presence of deep decarbonization targets. The rationale for using MGA is to rigorously exercise a data-intensive ESOM and present a suite of alternative solutions that are constrained to have similar system-wide costs as the original optimal solution. One of our key insights is that even small slack values (e.g., 0.05%) can generate qualitatively different solutions. The MGA algorithm thoroughly explores the decision space to find near-optimal solutions and employs a screening algorithm to generate a user-specified number of maximally different alternatives.

Our results show that a 95% carbon reduction in 2050 can be achieved by a 7.2% increase in total system costs relative to the base no policy scenario. The mechanisms of this transition are: a carbon-free electric sector, energy efficiency in the end-use sectors, and displacing fossil fuels in the end-use sectors through either electrification or bio-energy or synthetic fuels. Due to their relative cost-effectiveness, energy efficiency and renewables deployment in the electric sector are
the key reduction measures in the mid-term. As the carbon cap becomes more stringent after 2030, the electrification of end-use services in the residential, commercial and light-duty vehicle sectors becomes the next most cost-effective measure. Finally, in the last decade (2040-2050), power-to-\textit{X} pathways are the key to achieving deep carbon reductions, particularly in the industrial sector.

While these mechanisms remain consistent across all scenarios, our MGA analysis suggests important tradeoffs within each of these three mechanisms. One tradeoff that emerges is between nuclear and solar PV coupled with hydrogen storage. The results demonstrate that given our assumptions about future technology costs, there are cost-competitive substitutes to nuclear. A ban on new nuclear deployment increases the system costs by 0.6%. CSP with thermal storage becomes cost-competitive under small slacks (<1%). As the slack value reaches 3%, solutions that only rely on hydro, wind, and solar for electricity generation are found. We find that BECCS is often cost-effective and provides free CO\textsubscript{2} needed for synthetic fuels production in which case the storage part of it is not used.

Given the significant structural uncertainties associated with any energy modeling exercise, model results should always be interpreted in the light of real world complexities. A key limit is the spatial and temporal resolution of the model. In general, finding the appropriate spatio-temporal resolution is always a challenge in ESOMs given the tradeoff between model accuracy and computational performance. In this analysis, we only modeled 12 time-slices within a representative year. This limits our ability to model ramping constraints and hourly dispatch in order to meet time-varying demand. As a result, our model tends to underestimate the amount of curtailment from renewables, overestimate solar PV deployments, and underestimate the costs of electricity supply with high renewables penetrations. In addition, we speculate that the lack of battery deployment across scenarios is due to the limited temporal resolution. However, running the CCap scenario with NREL’s ATB “low” scenario assumptions on future electric sector technology costs produces significant deployments of battery storage are obtained at the expense of nuclear to meet baseload electricity demand, as shown in Appendix Figure C.2. In future work, the temporal representation can be improved via sampling of days that yield the right dispatch characteristics [35-37].

We performed this analysis on a single-region database of the US energy system. Having different regions explicitly represented in the database can better reflect variation in renewables
and service demands, which could highlight key regional differences. Another issue is our simplified representation of the industrial sector. The heterogeneity associated with various industrial subsectors, makes it very difficult to fully capture all of the processes in the industrial sector. In this paper, as a backstop, we assumed that all liquid fuels in the industrial sector can be replaced by the outputs of the Fischer-Tropsch process in which hydrogen and carbon dioxide are used to produce liquid fuels. Similarly, we assumed that natural gas can be substituted by the synthetic gas.
3.5 References


[27] https://news.energysage.com/states-with-100-renewable-targets/


4 Quantification of Climate-Induced Interannual Variability of Residential Electricity Demand

4.1 Introduction

US electricity demand has been growing at 1.6% annually since 1990. This rate is higher than other major fuels used in the residential sector (EIAa, 2019). In 2018, 37% of total US electricity demand was consumed in the residential sector, which is the highest among US end-use sectors (EIAb, 2019). Electricity in the residential sector is used to meet various energy services, some of which are subject to high seasonal variations. Recent surveys show that 46% of the total residential electricity consumption in the coterminous United States (CONUS) is used for indoor space conditioning (EIAc, 2015). This dependency of demand on seasonal climate poses challenges for power system operators and has critical implications for both demand and supply-side planning in the electric sector. Improvements in monthly to seasonal electricity demand forecasts can aid in the development of emergency, contingency management, and system maintenance plans (Mukerji et al., 1991), forward fuel purchases, demand-response programs, and scheduling of hydro and thermal power plants (de Queiroz, 2016). For example, improved demand forecasts could support seasonal power generation planning (de Queiroz et al., 2019) and can be used to properly define unit commitment schedules in power systems. Similarly, a 1% reduction in forecasting error for a 10,000 MW utility can provide savings of more than US$ 1.5 million per year (Yamin, 2004). Despite these findings, the role of variability in seasonal temperature on residential electricity demand is not yet fully understood across the CONUS.

Electricity as a heating fuel has been increasing at the expense of other fuels, including natural gas, over the past decade (EIAc, 2015). The Energy Information Administration’s Annual Energy Outlook projects this trend will continue (EIAb, 2019). Further, deep decarbonization of the U.S. energy system requires, among other measures, large-scale electrification of end-use services. Numerous studies on deep decarbonization show that electrification of heating services can play a key role in reducing direct emissions from the end-use sectors (Bataille, 2016; White House, 2016).
The dependency of electricity demand on climate have been studied extensively over different spatio-temporal scales. One class of studies estimate future electricity demand, particularly residential cooling and heating loads, over the long-term considering climate change projections (Frank, 2005; Camilleri et al., 2001; Holmes and Hacker, 2007; Gaterell and McEvoy, 2005, Amato et al., 2005; Ruth and Lin, 2006; Sullivan et al., 2015). Other studies have analyzed the load-temperature relationship at shorter time-scales (from hours to months) (Quayle and Diaz, 1980; Le Comte and Warren, 1981; Downton et al., 1988; Badri, 1992; Lehman, 1994; Sailor and Munoz, 1997; Lam, 1998; Yan, 1998; Morris, 1999; Sailor, 2001; Pardo et al., 2002; Suzara, 2008). Detailed comparison of three types of demand prediction models that include traditional regression, neural networks, and decision trees is discussed in Tso et al. (2007). A review of the common methodologies reveals that regression techniques, mostly due to their ease of application, have been widely used to quantify climate-load relationships (Lehman, 1994; Sforna, 1995; Sailor and Munoz, 1997; Barakat and Al Rashid; 1996; Tripathy, 1997; Robinson, 1997; Lam, 1998; Yan, 1998; Morris, 1999; Sailor, 2001; Pardo et al., 2002; Sailor and Pavlova, 2003; Suzara, 2008; Mukhopadhyay and Nategi, 2017; Wang et al., 2017). Other approaches such as neural networks (Islam et al., 1995; Chen et al., 1996; Al-Saba and El-Amin; 1999; Kermanshahi and Iwamiya, 2000; Tzafestas S and Tzafestas E, 2001; Ringwood et al., 2001; Kialashaki and Reisel, 2013) and decision trees (Yu et al., 2010) are also used, although to a lower extent compared to regression techniques.

Except for the summer per-capita energy consumption study by Wang et al., (2017), the spatial resolution of most studies on load model development and prediction are limited to a given city or a limited number of states. Previous empirical studies support the argument that the load-temperature relationship is highly region-specific. Sailor (2001) found that a 2°C temperature rise results in an 11.6% increase and 7.2% decline in residential per capita electricity used in Florida and Washington respectively. They also found sufficiently different load-temperature sensitivities even in neighboring states such as Louisiana and Texas. This uniqueness of load-temperature response motivates this study, which looks at the seasonal variability impacts of climate on residential electricity demand at the state level over the CONUS. Though Wang et al. (2017) focused on a national predictive model for summer per-capita consumption over the 48 states, the study did not consider the sensitivity of winter electricity demand to climate and other heating sources.
The main objective of this study is to quantify the main drivers of both summer and winter seasonal variability of residential electricity demand over the CONUS. For this purpose, we systematically decompose the explained variance by each driver using linear regression and use that information to explain the spatial difference on the role of different drivers across the nation. *To our knowledge, no previous studies quantify how interannual variation in winter and summer electricity demand at the national scale is affected by population, climate, and alternate heating sources.* The manuscript is organized as follows: Section 4.2 of the paper discusses the methodology and data. Section 4.3 presents the results and Section 4.4 discusses the findings of the paper.

### 4.2 Methods and Materials

This study systematically explains the interannual variability of residential electricity demand during the winter (December, January and February, DJF) and summer (June, July and August, JJA) over the CONUS. We consider only the summer and winter seasons because power systems face more variability in electric loads during summer and winter seasons compared to spring and fall. Figure 4.1 illustrates the conceptual framework adopted for quantifying the role of the four selected variables – population, climate, natural gas substitution effect, and previous month demand – in explaining the winter and summer electricity demand over the CONUS. Monthly electricity demand for the residential sector was obtained from the U.S. Energy Information Administration for the period 2005-2017 (EIA, 2018). Data associated with the proposed explanatory variables are described in Sections 4.2.1 – 4.2.4.

#### 4.2.1 Population

We use state population as a driving factor for the increase in residential electricity demand. A review of electricity demand models by Suganthi and Samuel (2012) identifies population as a driving factor to explain the variability of residential electricity demand. Annual population data and housing unit estimates for each county are obtained from the US Census Bureau (USCB, 2018). Annual data was interpolated linearly to the monthly time scale based on the differences between the annual values.
4.2.2 Population-weighted HDD and CDD

Seasonal climate variabilities are represented by the widely-used heating and cooling degree days (HDD and CDD) (Suganthi and Samuel, 2012; Ranson, 2014). The work of Sailor and Munoz (1997) compares the application of HDD and CDD in a regression model against the application of temperature and conclude that the former better explains the climate-induced variability in electricity demand. Daily HDD and CDD are defined as the number of degrees the daily average temperature is below and above 65 °F respectively. Monthly heating and cooling degree days are obtained by summing the daily HDD and CDD over all days in the month. Monthly HDD and CDD were obtained for each state from 2005 through 2017 through NOAA’s National Climate Data Center (NCDC, 2018).

To understand the role of HDD and CDD in explaining the state-level electricity demand variability, monthly state-level HDD and CDD could be obtained by spatially averaging the monthly HDD and CDD by climate division. However, given the role of population in electricity demand, the climate in more highly populated areas is expected to have a larger impact on electricity demand than the climate in less populated areas (Taylor, 1981). Thus, we calculate state-level HDD and CDD using a population weighted average, which employs the monthly county population data described above. Given that the county data overlaps with the climate division data, we weighted the HDD and CDD based on the population at the climate division level using Equations (1) and (2).

\[
HDD_{t,m}^{s} = \frac{1}{P_{t,m}^{s}} \sum_{i=1}^{n_{cd}} P_{t,m}^{i} \cdot HDD_{t,m}^{i}, \quad (1)
\]

\[
CDD_{t,m}^{s} = \frac{1}{P_{t,m}^{s}} \sum_{i=1}^{n_{cd}} P_{t,m}^{i} \cdot CDD_{t,m}^{i}, \quad (2)
\]

where, \( P_{t,m}^{s} \), \( HDD_{t,m}^{s} \) and \( CDD_{t,m}^{s} \) denote the population and state population weighted average HDD and CDD for month \( m \) in year \( t \) in state ‘s’ with \( n_{cd} \) climate divisions and \( P_{t,m}^{i} \), \( HDD_{t,m}^{i} \) and \( CDD_{t,m}^{i} \) denote the population, HDD, and CDD for each climate division within the state, respectively.
4.2.3 Residential winter natural gas consumption

The space heating market is another structural factor, besides the state population, that affects long-term residential sector electricity demand. This market varies considerably over the CONUS. Over the last decade, natural gas has been the dominant heating fuel in colder areas, and electricity has been used by more homes in milder areas (EIAe). However, the heating fuel mix by state has changed over time. Since 2005, more houses have been using electricity for space heating at the expense of natural gas, except for the Northeast (EIAc, 2015). We incorporate these long-term changes in the space heating market by adding the monthly state residential winter natural gas consumption as one of the explanatory variables. This data for the period 2005-2017 is drawn from the EIA website (EIAf, 2018).

4.2.4 Electricity demand from the previous month

Similar to the previous studies (e.g., Wang et al, 2017), we use the previous month’s electricity consumption as an additional explanatory variable to capture the monthly persistence in the electricity demand time series.

4.2.5 National Analysis of Electricity Consumption

Our intent is to quantify the interannual variability in electricity demand explained by population, climate, substitution effect and previous month demand. Hence, by using a series of linear regression models, we can quantify the contribution of each explanatory variable to the variation in seasonal residential electricity demand (Figure 4.1). We first quantify the role of population and temperature on electricity demand and natural gas consumption. These regressions provide the variability explained by both population and temperature on winter and summer electricity demand for each state over the CONUS. Then, the resulting residuals (i.e., after regressing with population and temperature) from electricity demand and natural gas consumption are regressed against each other to quantify the role of substituting natural gas with electricity in order to further explain the variation in electricity demand.
In the equations below, for ease of exposition, we drop the index $s$, which denotes the state. We only present the equations for the winter season. The summer season analysis is done in a similar fashion except that the CDD time series is used instead of HDDs. First, we extract the population effect from the electricity demand using Equation (3):

$$ED_t = \alpha_P \times P_t + \beta_P + \varepsilon_t|_P \quad (3)$$

Where $P_t$ is the winter population, $ED_t$ is the winter season electricity demand time series, $\alpha_P$ and $\beta_P$ are the regression coefficients, and $\varepsilon_t|_P$ is the residual after regressing against population. We define $R_1^2$ as the explained variance (i.e., coefficient of determination in equation 3) in electricity demand by population. We then regress $\varepsilon_t|_P$ against the HDDs based on Equation (4) and obtain the explained variance, $R_2^2$, by HDDs on electricity demand residuals ($\varepsilon_t|_{P,HDD}$):

$$\varepsilon_t|_P = \alpha_{HDD} \times HDD_t + \beta_{HDD} + \varepsilon_t|_{P,HDD} \quad (4)$$
where $\alpha_{HDD}$ and $\beta_{HDD}$ are the regression coefficients and $\varepsilon_t|_{P,HDD}$ represents the regression residuals, which represent the unexplained variability in electricity demand by population and HDDs. $R_2^2$, is the coefficient of determination from the regression in equation 4.

Since the regression in Equation (4) is performed using the residual electricity variability conditioned on population, the contribution of HDDs to explaining the variability in electricity demand is given as: $R_2^2 \times (1 - R_1^2)$. Thus far, the analysis has a total explained variability of electricity demand equal to $[R_2^2 \times (1 - R_1^2) + R_1^2] \times 100$. Next, we consider the role of the previous month’s demand and the substitution effect between electricity and natural gas.

In order to capture monthly persistence in the electricity demand time series, we perform regression between $\varepsilon_t|_{P,HDD}$ and $ED_{t-1}$:

$$\varepsilon_t|_{P,HDD} = \alpha_{PreMonthELC} \times ED_{t-1} + \beta_{PreMonthELC} + \varepsilon_t|_{P,HDD,PreMonthELC} \quad (5)$$

Again, $\alpha_{PreMonthELC}$ and $\beta_{PreMonthELC}$ are the regression coefficients, $R_3^2$ is the variance explained by the previous month’s demand on $\varepsilon_t|_{P,HDD,PreMonthELC}$, which is the regression residual.

The fourth explanatory variable is natural gas consumption in the residential sector. However, since natural gas consumption, just like electricity consumption, is correlated with population and climate conditions, and the previous month’s (natural gas) demand, we need to calculate the residuals of natural gas consumption conditioned on population, HDDs, and the previous month’s demand, $\nu_t|_{P,HDD,PreMonthNG}$. The steps needed to calculate $\nu_t|_{P,HDD,PreMonthNG}$ are similar to what was done earlier to calculate $\varepsilon_t|_{P,HDD,PreMonthELC}$. Once $\nu_t|_{P,HDD,PreMonthNG}$ is calculated, Equation 6 calculates the substitution effect on electricity demand:

$$\varepsilon_t|_{P,HDD,PreMonthELC} = \alpha_{ELC-NG} \times \nu_t|_{P,HDD,PreMonthNG} + \beta_{ELC-NG} + \varepsilon_{ELC-NG} \quad (6)$$

where $\varepsilon_{ELC-NG}$ is the final unexplained variability in electricity demand, $\alpha_{ELC-NG}$ and $\beta_{ELC-NG}$ are the regression coefficients and $R_4^2$ is the coefficient of determination.

Thus, the total variability explained in the winter season, $TV_{winter}$ due to the four factors can be quantified using equation 7:
\[ TV_{winter} = [R_1^2 + R_2^2 \times (1 - R_1^2) + R_3^2 \times (1 - (R_1^2 + R_2^2 \times (1 - R_1^2))) + R_4^2 \times (1 - (R_1^2 + R_2^2 \times (1 - R_1^2))) \times 100 \] (7)

The total explained variance by all four variables in (7) is simply the \( R^2 \) of the regression between winter electricity demand against the selected four variables. Since we are interested in quantifying the explained variance by each explanatory variable, we performed the regression sequentially on the residuals obtained in each step. A similar procedure is followed with CDDs to obtain the total variability \( TV_{summer} \) explained in the summer. The only difference is that since cooling demand is exclusively met by electricity, we do not consider substitution with natural gas. Results are summarized below on the explained variance by each explanatory variable for both seasons.

### 4.3 Results

Our results indicate that the previous month demand’s makes a negligible contribution to explaining the total variability in electricity demand. Therefore, we only present the results pertaining to variability explained by population, climate, and the natural gas substitution effect. Appendix Tables D.1 and D.2, and Appendix Figures D.1 and D.2 of the Appendix D provide the full regression results for the summer and winter seasons with more details.

#### 4.3.1 Summer Season

Figure 4.2 shows the amount of the variability in electricity demand explained by population and climate for each state in the summer season.
Figure 4.2 Variability in residential electricity demand explained by the population (a) and climate (b) in the summer season. (a) Both the colors and numbers on the states denote the contribution of population to explaining electricity demand variation in the summer season. Generally, population has greater explanatory power in the western states. (b) Raster colors indicate the cumulative share of population and CDD in explaining total variability of electricity demand in the summer season. Number labels by state indicate the CDD share alone in explaining total variability of electricity demand in the summer season.

Figure 4.2-b generally exhibits greater explanatory power than Figure 4.2-a and therefore, the largest portion of the household summer electricity demand variation is explained by interannual climate variability. In order to better understand the residential electricity demand-population relationship, in a separate test case (not shown here) we ran the same model with 1990-2005 (rather than 2005-2017) data and we observed that state residential electricity demand was
more correlated with the state population. The recent divergence between household electricity demand and population (as indicated by the relatively small numbers in Figure 4.2a can be explained by looking at household electricity consumption intensity trends since 2005. This data is available through a nationwide surveys of buildings in selected years (EIAc, 2015). A declining electricity consumption intensity means population growth effects are not translated into electricity demand growth. Figure 4.3 shows that the intensity of electricity consumption in American homes increased from 1993 to 2005. This increase is mainly driven by larger home sizes and increased electrification of household energy services (Hojjati, 2014). After 2005 however, household electricity consumption intensity has been consistently declining across all nine Census Divisions. While the average square foot per household and penetration of electric appliances continued to increase from 2005 to 2015 (EIAc, 2015), their impact is countered by stricter energy efficiency standards as well as technology improvements at the household level (Hojjati, 2014).

![Figure 4.3 Household electricity consumption intensities by US Census Division.](image_url)

To understand how interannual climate variability modulates electricity demand across the country, we plot the standard deviation of CDD against the interannual variability explained by CDD (i.e., state-level estimate drawn from Figure 4.2-b) in Figure 4.4. As Figure 4.4 shows, even a relatively small variation in CDD can cause a large variation in electricity demand in states such as Florida, Colorado and Louisiana. The main observed pattern is that regardless of states’ average temperature, climate-induced variability of household summer electricity demand is correlated with summer climate variability. This is indicated by a 0.3 coefficient of determination. Part of the
spread around the regression line in Figure 4.4 could be due to other state-specific factors, such as humidity and air conditioning penetration levels. The reason for plotting climate-induced demand variability on the vertical axis is that it does not include the effect of other factors, and therefore it isolates the role of climate variability on seasonal load.

Figure 4.4 CDD share in explaining household summer electricity demand variations as a function of standard deviation of CDD for the regression period (2005-2017). Colors indicate the average mean temperature for each state in the summer season. On the vertical axis, only the portion of variability in electricity demand due to climate is plotted. The linear relationship between the two axis is indicated by a 0.3 coefficient of determination. $R^2=0.3$.

4.3.2 Winter Season

Figures 5 shows the variability in winter electricity demand explained by population and climate, for each state. As the Figure shows, in winter, similar to summer, only a small portion of interannual variability in electricity demand is due to population alone.
Figure 4.5 Variability in residential electricity demand explained by the population (a) and climate (b) in the winter season. (a) Both the colors and numbers on the states denote the contribution of population to explaining electricity demand variation in the winter season. (b) Raster colors indicate the cumulative share of population and HDD in explaining total variability of electricity demand in the winter season. Number labels by state indicate the HDD share alone in explaining total variability of electricity demand in the winter season.

The state-specific numbers in Figure 4.5b denote the variability in electricity demand explained by HDD alone. Figure 4.5b indicates that climate information can explain part of the electricity demand in the upcoming winter season, as the demand variation due to the population is known at the beginning of each season.

Similar to the summer season, we plot climate variability against the climate-induced variability in electricity demand in Figure 4.6.
Unlike the summer season where larger climate variations generally translate to larger monthly demand variations, climate-induced winter electricity demand variability does not appear to be a function of HDD variations. Although we can observe some similarities among the states within the same climate region, large differences in climate-load sensitivities persist even in some neighboring states. This lack of correlation is consistent with the findings of other studies and is the result of a number of factors, including income per capita, choice of heating fuels, housing type, appliance efficiency, building envelopes, other climatic parameters such as humidity, and a host of demographic factors (Sailor, 2001). Among these factors, we speculate that the fraction of heating demand met by electricity could vary significantly, even among neighboring states. In such a case, states with high HDD variability could nonetheless exhibit little variability in electricity demand if other less climate sensitive contributors to winter electricity demand are dominant. Ideally, we could test this hypothesis by isolating the portion of state-level electricity demand used for space heating. Unfortunately, this data is not available at the state-level, but the most recent
residential sector energy consumption surveys provide this information for each Census Division (EIAc, 2015); see Appendix Table D.3. We use this Census Division-level data to normalize the variability in electricity demand explained by HDDs (dependent variable in Figure 4.6). The result is shown in Figure 4.7. The normalized estimates now account for the share of households using electricity for space heating, which in Figure 4.7 effectively scales states with less electric heating upward.

Figure 4.7 Winter electricity demand explained by HDD normalized (inflated) by the share of households with electric heating. The household shares are only provided by Census Division, and thus we assigned the same shares to all states in the same Census Division. The coefficient of determination is 0.1, indicating improved explanatory power compared to Figure 4.6. $R^2=0.105$.

As the new coefficient of determination shows, incorporating a measure of states’ space heating market helps to better explain seasonal climate-load sensitivity variations by state. However, this scaling is imperfect because it employs share of household heating met with electricity at the Census Division level. We suspect that there are significant variations in electricity used for space heating among some states within the same Census Division.
The substitution effect explains part of the remaining variability in electricity demand (Figure 4.8). The state-specific values on the map are higher where substitution of natural gas with electricity (or vice versa) has taken place.

![Figure 4.8 Role of natural gas substitution in explaining the winter electricity demand variability. Raster colors indicates the cumulative share of population, HDDs and the substitution effect in explaining total variability of winter electricity demand. Numbers in each state indicate the natural gas substitution effect alone in explaining total variability of electricity demand in the winter season.](image)

From a national perspective, EIA, (2015c) indicates that electricity has a higher market share, in comparison to natural gas, in meeting household heating needs. In addition, there has been a shift from natural gas to electricity as a heating fuel (EIAc, 2015). Part of this shift is due to population migration further south and west, where the electricity share is increasing, and the natural gas share is declining (EIAc, 2015). The choice of electric heating pumps in the South is a key reason for this substitution with natural gas. This substitution is in contrast to colder parts of the country, particularly the Midwest, where natural gas is still the dominant heating fuel, mainly because the application of heat pumps in very cold climates is more expensive than natural gas furnaces. Nevertheless, even in the Midwest, owing to improvements in electric heat pumps, the electricity share continues to increase (EIAc, 2015). In the Northeast, both electric and natural gas heating shares are increasing at the expense of the decline in liquid fuels (EIAc, 2015). To summarize, the ability to explain the variability in winter electricity demand is challenging over the northern states since different fuel types are used for heating. Still, as shown in Figures 4 and
7, interannual temperature variability explains a significant portion of electricity demand in most states across the CONUS.

4.4 Discussion

We assessed the variation of residential electricity demand over the CONUS to population, seasonal climate variation, substitution of electricity for natural gas, and the month-to-month persistence in electricity demand. The main objective of the analysis is to quantify the impact of seasonal climate variability on residential electricity demand during the winter and summer seasons. We sequentially evaluated these explanatory variables’ ability to explain the demand variability separately. Such analysis is critically important, particularly as the share of electricity serving end-use demands continued to increase due to policies aimed at deep decarbonization.

Our general observation from the analysis is that seasonal climate variability has a crucial role in explaining household electricity demand variations. While the ability of climate variability to explain electricity demand is significant, there is substantial spatial variation, especially during winter, across the CONUS. The same level of climate variations in two different states do not necessarily lead to an identical demand-side variation in these states.

With regard to winter electricity demand, no existing dataset provides space heating demand met by electricity at the state level. As a result, we are not able to isolate the effects of climate on the state-level space heating loads met by electricity. Recent residential energy consumption surveys provide some measure of space heating and cooling but only at the Census Division level and for select years (EIAc, 2015). This information is more critical for winter than summer because residential cooling demand is met exclusively with electricity, whereas heating demand is met with a wider range of fuel sources. The Energy Information Administration should consider collecting data on the state-level heating demand met with electricity which would prove valuable in future analyses.

The state-level disparities observed in Figures 5 and 8 stems from several factors, such as income levels, choice of heating fuels, housing type, appliance efficiency, building envelopes. In addition, as discussed in Yang (2014), psychological and behavioral factors are also key to determining thermal comfort zones. As noted by Yang (2014), psychological adaption refers to the effects of cognitive, social and cultural factors in determining human perceptions to thermal
comfort. Behavioral adaption on the other hand, refers to the adjustment of the body temperature balance in order to achieve thermal comfort through actions such as adjusting the physical activity and clothing levels and opening or closing windows and switching on fans (Yang, 2014).

The results of this paper could assist in power system scheduling as well as demand side management. Since the population is not expected to change over the course of a season, having insights over climate-load responses for the upcoming season in a specific region can be of crucial aid to power system operators, especially when climate forecasts have better skill in forecasting temperature. Information on the temperature anomaly can be translated into forecasted electricity demand (Devineni et al., 2010; Devineni and Sankarasubramanian, 2010), and a short-term seasonal hedging strategy could be developed. In addition, this methodology can be adopted to better manage electricity demand under a changing energy system. As countries move to reduce greenhouse gas emissions, a key strategy is to decarbonize the electric sector and then electrify many end-use demands. As the share of electricity meeting end-use demands increases under such a scenario, quantifying the role of seasonal climatic variation on seasonal electricity demand will become even more critical. Such seasonal information gleaned from the regression models could be used to inform demand-response programs aimed at reducing electricity demand during peak periods and develop contingency measures such as fuel stockpiling for the upcoming season. Finally, while this paper is focused exclusively on the residential sector, future work could extend this analysis to include the commercial sector as well, since its electricity consumption is also expected to vary with climatic conditions.
4.5 References


EIAd - Energy Information Administration, 2018, electric power sales, revenue, and energy efficiency Form EIA-861 detailed data files

EIAe, https://www.eia.gov/todayinenergy/detail.php?id=18131

EIAf - https://www.eia.gov/dnav/ng/ng_cons_sum_a_EPG0_vrs_mmcf_m.htm


http://dx.doi.org/10.1016/j.enbuild.2007.02.009
NCDC 2018 National Centers for Environmental Information (formally National Climatic Data
323 Center) found at http://www.ncdc.noaa.gov/

Pardo, A., Meneu, V., Valor, E., 2002. Temperature and seasonality influences on the Spanish

Quayle, R. G., & Diaz, H. F. (1980). Heating degree day data applied to residential heating

Ranson, M., Morris, L., & Kats-Rubin, A. (2014). Climate Change and Space Heating Energy
Demand: A Review of the Literature (No. 201407). National Center for Environmental
Economics, US Environmental Protection Agency.

Ringwood JV, Bofell D, Murray FT. Forecasting electricity demand on short, medium and long

Robinson P. Modeling utility load and temperature relationships for use with long-lead forecasts.

Ruth, Matthias, and Ai-Chen Lin. "Regional energy demand and adaptations to climate change:
methodology and application to the state of Maryland, USA." Energy policy34.17 (2006): 2820-
2833.

Sailor, D.J., 2001. Relating residential and commercial sector electricity loads to

Suzara, H. (2008). Modeling the impact of temperature on peak electricity demand in
California. University of California Berkeley.

Sforna M. Searching for the electric load-weather temperature function by using the group

Sailor D. J., Munoz J. R., Sensitivity of electricity and natural gas consumption to climate in the
USA—methodology and results for eight states. Energy. 1997; 22(10):987–98. DOI:
10.1016/S0360-5442(97)00034-0

residential cooling energy demand to climate change. Energy, 28(9), 941–951.

review. Renewable and sustainable energy reviews, 16(2), 1223-1240.

Sullivan, Patrick, Jesse Colman, and Eric Kalendra. Predicting the response of electricity load to

2016. http://unfccc.int/files/focus/long-


T. Frank, Climate change impacts on building heating and cooling energy demand in Switzerland, Energy Build, 37 (2005), pp. 1175–1185


5 Conclusions and future work

The key contribution of this thesis is to apply rigorous uncertainty analysis methods to an energy system optimization model (ESOM) to produce insights that can inform future US federal policy efforts. Chapter 2 presents a novel framework to examine baseline scenarios of the US energy system in the absence of federal climate policy. Chapter 2 model results quantify a range for future energy-related GHG emissions as well as key parameter combinations that lead to different emission outcomes. Chapter 3 focuses on finding cost-competitive ways in which US energy system can develop under an aggressive carbon cap. Chapter 4 examines the factors that drive residential electricity demand, and quantifies the role that temperature plays in determining demand. Because ESOMs typically represent the full energy system, it is critical for modelers to understand the dynamics that shape both supply and demand. The results obtained from Chapter 4 can be used to improve demand representations in future ESOM-based analyses, which is particularly important in scenarios that involve a high degree of end-use electrification. The remainder of this chapter focuses on cross-cutting insights and directions for future work.

5.1 Cross-cutting insights

The last several decades bore witness to important changes in the US energy system. With the advent of shale gas development in mid-2000s, domestic natural gas is at record low prices [1]. This breakthrough has led to the increased use of natural gas for electricity generation and industrial activities since 2010, largely at the expense of coal. During the same time, the costs of renewables dropped by rates that were very hard to even imagine a decade ago [2], resulting in higher penetrations of renewables in the electric sector. For instance, utility-scale solar PV cost has dropped by 77% since 2010 [3]. In addition, despite federal inaction on climate policy, 35 states have committed to mandates, such as renewable portfolio standards or cap and trade [4].

The collective impact of all these market-driven changes and state-level actions is a modest decline in energy-related GHGs over the past decade. Our analysis shows that the same trend is likely to continue in the mid-term in the absence of new federal climate policy. This future is characterized by a slight increase in electrification and energy efficiency in buildings, and significant increases in natural gas combined cycle capacity and, to a lesser extent, solar PV and onshore wind in the electric sector. In the transportation sector, unless there is a simultaneous large
cost drop for electric vehicles and a large oil price hike, the fuel mix associated with road transport is unlikely to change significantly. The industrial sector is even less sensitive to fuel prices changes, except the fuel mix used for process heating.

Deeper emissions reductions post-2030, for instance at the levels charted by the Obama Mid-Century Strategy [5], will not happen through favorable market forces only, but instead will require unprecedented shifts in energy technology investment patterns. Our model-based analysis shows that this low carbon transition can be achieved using currently commercialized technologies with no more than a 10% increase in system-wide supply cost, assuming a 5% discount rate. This transition takes place through three mechanisms: (i) energy efficiency, (ii) substituting fossil fuels in the end-use sectors with electricity, biomass, or synthetic fuels and (iii) full decarbonization of electric sector. A key enabling fuel to make the second mechanism workable is hydrogen generated via electrolysis with carbon-free electricity. Hydrogen and carbon dioxide can be reacted to generate a variety of synthetic hydrocarbons for the transportation and industrial sectors. Power-to-X processes are relatively expensive compared to other mitigation options, and therefore they are needed only when the required system-wide carbon reductions are above 85%, which in my modeled scenarios occur from 2040 - 2050. While large-scale seasonal hydrogen storage systems are not strictly necessary in a highly decarbonized energy system, they are the key to reducing the costs of deep decarbonization. The same assertion holds valid for bio-energy with CCS (BECCS).

One of the key features of all the deep decarbonization pathways considered in Chapter 3 is that the largest system changes do not take place until 2030. Before 2030, the main decarbonization strategies are limited to end-use energy efficiency, deployment of new utility-scale solar PV (~ 600 GW) and wind turbines (~ 400 GW), and modest increased electrification of heating services in buildings and the light-duty vehicle sector. After 2030 however, the linearly declining carbon cap exerts more pressure on the system and thus, increasingly large shares of carbon-free electricity are required to decarbonize the end-use sectors through either direct electrification of energy services or the conversion of electricity to synthetic fuels, which in turn serve end-use demands. The increased electrification in response to emissions reductions required post-2030 also increase the need for nighttime, baseload electricity, which means more deployment of nuclear, concentrating solar thermal with storage, and CCS.
While there is a high degree of uncertainty regarding the potential for future federal climate policy, the observation that the largest system changes under a carbon constraint take place after 2030 provides an opportunity to align our mid-term actions with the strategies featured under a carbon cap scenario from 2020-2030. The degree of alignment strongly depends on the prevailing market forces. Higher fossil fuel prices and lower renewables costs in the next decade will ease the path to carbon-neutrality by 2050. Further, if we center our efforts on promoting renewables in the electric sector - a combined 1 TW of utility-scale solar PV and onshore wind and the use of efficient appliances and heat pumps in buildings - we will minimize the costs associated with uncertainty in climate policy. State-level efforts, such as the 100% clean electricity targets in nine states plus District of Columbia and Puerto Rico are key to facilitating the transition to a clean energy system [4].

By contrast, low fossil fuel prices coupled with less technology innovation can make investment strategies from 2020-2030 diverge from the path to carbon neutrality. This pathway raises critical concerns in the electric and fuel supply sectors, where infrastructure is long-lived. For instance, combined-cycle gas turbines that are cost competitive in the absence of a climate policy are not featured in the deep decarbonization pathways from 2020-2030. Thus, if we ignore the possibility of a carbon cap in the mid-term, we might end up being locked into a system that is even more expensive to decarbonize by 2050.

Energy systems development on the supply-side is also affected by the growth in final energy demand and its seasonal and diurnal variations. With further electrification of heating services in the residential and commercial sectors in both the baseline and carbon cap cases, the required level of electricity production is projected to increase, and therefore it is important to understand the factors that determine future electricity demand. The effects of US population growth on long-term residential electricity demand have been negated by improvements in appliance energy efficiency and more strict building envelope codes [6]. While climate variations are the key driver of electricity demand variations in the summer and winter seasons, there is a large disparity among different states regarding how electricity production reacts to climate variations. The reason for this state-to-state disparity is not well-known, but could be related to differences in space heating markets, the relative mix of space conditioning devices, air humidity, and perhaps human perception of heating and cooling needs.
Though not analyzed here, there are other forms of uncertainty that can affect future energy system development. For instance, societal acceptance can work in favor or against certain technologies. Windfarms, carbon capture and storage installations, hydrogen refueling stations, and nuclear power plants have been met with public resistance in the past [7]. The issue is made more complicated because public attitudes towards energy systems are not static and can change over time as people’s base knowledge changes [7].

5.2 Limitations and Future work

As part of this thesis, two different databases of the US energy system were assembled: a single region database and a nine region database. Both of the databases were initially developed based on the EPA 9-region MARKAL [8] database, but over time significant changes were made. These changes include, but are not limited to, adding power-to-gas pathways and incorporating a relatively simple representation of the industrial sector. Existing representations of the industrial sector, such as in EPA MARKAL [8] and NEMS [9] are either extremely complicated for the purposes of this work or lack low-carbon options that are critical to a deep decarbonization study. The main difference between our single region and nine region databases is that the latter has region-specific existing capacities, end-use demands, and renewable capacity factors while the former averages over regional variations. The nine-region database includes inter-regional transfer of electricity through high voltage direct current lines as well. All the older versions of the database are archived in a public repository [10]. Under a carbon cap, the two databases show a large degree of similarity in terms of their output results. This observation led me to choose the single-region database for use in Chapters 2 and 3, which produces less computational burden.

With regards to input data development, I did my best to balance the tradeoff between simplicity and transparency on one hand and sufficient complexity to properly model the system on the other. Nonetheless, there are still several areas that can be improved. The list below outlines current database limitations as well as future work to address them.

- Increase the spatial granularity of the database. An improved regional representation is important to capture regionally specific renewables potential and state-level climate policies.
- Increase the temporal granularity of the database. Our current version has only 12 time-slices (3 seasons and 4 times-of-day). This limited number of time-slices is a barrier to properly
capturing key system dynamics, such as ramping constraints as well as hourly variations in end-use demands and renewables availability. One way to improve the temporal representation is to use sample days that yield dispatch characteristics similar to a higher time resolution model.

- Disaggregate the industrial sector into a few energy-intensive industries. This disaggregation would provide a more realistic picture of the processes and mitigation options for an important group of industrial activities.
- Add new low carbon options associated with heavy duty transportation, including electric and hydrogen-based aviation and marine shipping options. Currently there are residual emissions associated with heavy-duty vehicles, and these options would allow for full decarbonization of the transportation sector.
- Add supply curves for coal, natural gas, uranium and biomass. The fuel prices in the current database are exogenously specified and therefore prices are insensitive to demand. Supply curves provide a more realistic representation of fuel markets by establishing feedback between a fuel price and the quantity demanded.
- Include the costs of early retirements of the existing energy infrastructure that will not be used in a highly carbon constrained future, particularly for existing coal and natural gas plants.
- Incorporate behavioral aspects within the energy system representation. These aspects include consumer behavior, consumer willingness to participate in demand-side management programs, and how human behavior can affect aggregate demand under different circumstances.
- Develop and utilize open-source tools that directly convert raw data to model-formatted data. This would add one additional level of transparency to the database.

Given the challenge of modeling the whole US energy system over the next several decades, the process of model and data improvement is never-ending. Incremental improvements, including the ones above, can always be made. In this thesis, I have endeavored to draw insights that are robust to both future uncertainties and existing model limitations.
5.3 References


[10] https://github.com/TemoaProject/data
A Appendix A

In Section 1 of this appendix, Temoa business-as-usual (BAU) scenario is discussed, and in Sections 2 and 3, the Method of Morris and k-means clustering algorithm are described respectively.

A.1 BAU scenario

BAU scenario reflects the continuation of past trends into the future. While no federal climate policy in envisioned, the BAU scenario includes state-level renewable portfolio standards (RPS).

A.1.1 End-use sectors

Figures A.1 and A.2 show energy consumption in the residential and commercial sectors, respectively. For comparison, the same results from the Annual Energy Outlook (AEO) 2017 Reference scenario without CPP \(^{11}\) are also shown.

![Figure A.1 Residential sector baseline energy consumption in AEO (left) and this analysis (right).](image)

\(^{11}\) CPP: Clean Power Plan
In both sectors, a shift to more efficient technologies is observed in the Temoa baseline scenario compared with AEO. Less delivered energy is consumed in our model compared to AEO in order to meet approximately the same end-use services.

Figure A.3 shows the fuel consumption in the transportation sector. When compared to the AEO results, the Temoa baseline scenario shows less consumption of E10 (a gasoline blend containing 10% ethanol) and diesel from 2025 to 2040. While our vehicle cost and performance estimates are aligned with AEO, our model is less complex and tends toward more efficient vehicles in order to minimize cost.
The technological mix in the light duty vehicle sector is shown in Figure A.4. The deployment of electric vehicles is largely due to the constraint that alternative vehicle technologies must make up a minimum 10% market share. Among alternative vehicle technologies, battery electric vehicles are the most cost-effective. Regarding E85, the prevailing AEO prices make ethanol vehicles cost-competitive, however, an upper bound drawn from Renewable Fuel Standard on ethanol availability limits E85 consumption in the transportation sector.
The industrial sector is another major end-use sector represented in Temoa. The current modeling framework of this sector however does not allow flexibility regarding technological and fuel mix change, and simply follows the AEO base scenario projections. As is noted by Barron 14, we recognize that this modeling framework hinders our ability to evaluate technological shifts and policies implementation in the industrial sector.

A.1.2 Electric sector

Base case electric sector results are presented in Appendix Figure A.5.
The Temoa baseline scenario builds more advanced combined cycle plants and utility-scale solar PV and slightly less wind than AEO. The National Energy Modeling System (NEMS), which is used to produce AEO, uses a zip code-level econometric model to project rooftop solar PV adoption. Since our model does not capture all the dynamics relevant to residential solar PV deployment, we adopt the AEO 2018 base case capacities of rooftop solar PV in the form of minimum capacity constraints. Temoa deploys utility-scale solar PV at a higher rate compared to AEO. However, this deployment is largely due to the aggregation of state-level RPSs. Figure 1.6 shows electric sector capacities in the absence of RPS.
Figure A.6 Baseline electric sector installed capacity in AEO (left) and this analysis without the RPS (right).

As is shown in Appendix Figure A.7, both the Temoa and AEO baseline scenarios project nearly similar levels of electricity demand. Coal retains a significant share of electricity generation through the model time horizon in both models. In the first model time period, 2015-2019, existing capacity in 2015 is fixed, but new wind and solar PV capacity in the electric sector are allowed, given their rapid annual growth in recent years.
Figure A.7 Baseline electric sector generation in AEO (left) and this analysis (right).

A.1.3 Emissions

Temoa estimates emissions of CO$_2$, SO$_2$ and NO$_x$ from direct fuel combustion in the energy sector using EPA emission factors. In addition, CO$_2$ equivalent emissions from the upstream natural gas production system (both combustion-related CO$_2$ emissions and fugitive methane emissions) are estimated using actual emissions in 2015. According to EPA, natural gas production in 2015 resulted in 42 million metric tons of combustion-related CO$_2$ and 162.4 million tonnes of CO$_2$e methane, assuming a global warming potential of 25 for methane. Total US natural gas consumption in 2015 was approximately 28,000 PJ, yielding an emissions factor of 7.3 ktons CO$_2$e /PJ for natural gas extraction, processing, storage, transportation and distribution.

Figure A.8 shows energy-related CO2 emissions from all sectors. The CO2 emissions nearly level off during 2030-2040 and experience a modest 5% drop during 2015-2030. While electricity-related CO2 emissions remain at their current levels (approximately 1800 million metric tons), the transportation sector experiences the most CO2 reduction due to the improvement in vehicle fuel economy and the partial switch to electric vehicles in the light duty sector.
A.2 Method of Morris

Method of Morris works by calculating a number of incremental ratios called Elementary Effects (EE), sampled on a grid representing the input parameter space $\Omega$. Assuming $k$ input parameters, the sensitivity experiment is based on one-at-a-time changes to each parameter $x_i$, $i = 1, ..., k$, which is assumed to vary across $p$ levels in the discretized input space $\Omega$. As a standard practice, this input space is assumed to be the unit hypercube, in which $k$ independent inputs are uniformly distributed across $p$ discrete levels. The elementary effect of the $i$th input ($EE_i$) is defined by equation (1):

$$EE_i = \frac{f(x_1, x_2, ..., x_i + \Delta, ..., x_k) - f(x_1, x_2, ..., x_i, ..., x_k)}{\Delta}$$

(1)

where $\Delta$ represents a perturbation to $x_i$ and can assume arbitrary values $\{1 \over p-1}, 2 \over p-1, ..., 1 - 1 \over p-1 \}$ and $\mathbf{x} = (x_1, x_2, ..., x_i, ..., x_k)$ is any selected point in the $k$-dimensional $p$-level grid ($\Omega$). Note that $\mathbf{x} + u_i \Delta$ is still in $\Omega$, where $u_i$ is a $k$-dimensional vector with zero elements for all its components but unity for the $i$th one.
To implement the method, the elementary effects associated with each input factor must be sampled. Morris\textsuperscript{16} proposes a sampling strategy based on developing $N$ different trajectories in the $k$-dimensional input parameter space, $\Omega$, each of which consists of $(k + 1)$ points. Each trajectory generates a total number of $k$ elementary effects, one per each input. Thus, a total number of $N \times (k + 1)$ model executions are needed.

Even though the number of trajectories $N$ is exogenously defined, it interacts with the value chosen for $p$. A higher $p$ means a higher resolution $\Omega$, and consequently, to better cover $\Omega$, a larger $N$ is required. Saltelli et al.,\textsuperscript{18} suggests using more than 10 trajectories when $p = 4$. The mean and standard deviation associated with the resultant distribution of elementary effects, $F_i$, reveals information about the $i$th input. A large value for the mean indicates that the input has a high influence on function $f$, and a large measure for the standard deviation suggests that the input interacts with other inputs, has a nonlinear effect, or both.

Campolongo et al.\textsuperscript{17}, as an extension to the original Morris methodology\textsuperscript{16}, proposed that the average of the absolute values of elementary effects, $\mu_i^*$, is in fact a better measure of sensitivity because it rules out the possibility of elementary effects with opposing sign cancelling one another out. In this modification, $\mu_i^*$ as defined by equation (2), is a measure of the expected variance of function $f$ when only the $i$th input can change, given the interactions with other inputs:

$$\mu_i^* = \frac{\sum_{j=1}^{N} |EE_i^j|}{N}$$

(2)

where $EE_i^j$ is the elementary effect associated with the $i$th input along the $j$th trajectory and $N$ is the number of the trajectories. We use the approach suggested by Campolongo et al.\textsuperscript{17}, and Figure 2.1 presents $\mu_i^*$ divided by 2015 emissions.

In this study, $\Omega$ consists of 41 parameter groups (Table A.1), and the range associated with each parameter is $\pm 20\%$ of its baseline value. A single trajectory therefore consists of 42 points, and $N=25$ trajectories are created. Because Temoa is dynamic, parameter values can vary by model time period. As a result, a single parameter indexed by time period constitutes a single parameter group. For example, natural gas prices over the model time horizon constitute a single group, and thus the natural gas price trajectory is uniformly shifted up or down within Method of Morris, rather than allowing prices to shift randomly from one time period to the next. Grouping ensures
consistent trajectories for capital costs and fuel prices, and reduces the computational effort. To conduct this analysis, we make use of SALib v9, an open source Python library, which includes a complete implementation of the Method of Morris.

**Table A.1** Groups of the input parameters for the sensitivity analysis.

<table>
<thead>
<tr>
<th>Group</th>
<th>No. of Included Technologies</th>
<th>Group</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boiler for space heating/water heating</td>
<td>5</td>
<td>Biomass price</td>
</tr>
<tr>
<td>Furnace for space heating</td>
<td>10</td>
<td>Coal price</td>
</tr>
<tr>
<td>Radiative space heating</td>
<td>10</td>
<td>Natural gas price</td>
</tr>
<tr>
<td>Heat pumps</td>
<td>11</td>
<td>Petroleum product prices</td>
</tr>
<tr>
<td>Fluorescent lighting</td>
<td>10</td>
<td>Hydrogen price</td>
</tr>
<tr>
<td>Geothermal heat pumps</td>
<td>2</td>
<td>Uranium price</td>
</tr>
<tr>
<td>HID lighting</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>HID-LED lighting</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>LED lighting</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>Resistive lighting</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Induction cooking</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Convection cooking</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Freezing and refrigeration</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>Solar water heating</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Ventilation</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Coal steam plant</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Combined cycle plants</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Combustion turbine plants</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Carbon Capture and Storage (CCS)</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Integrated Gasification Combined Cycle (IGCC)</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>
Table A.1 (continued).

<table>
<thead>
<tr>
<th>Energy Source</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nuclear plants</td>
<td>1</td>
</tr>
<tr>
<td>Solar PV</td>
<td>2</td>
</tr>
<tr>
<td>Solar thermal</td>
<td>1</td>
</tr>
<tr>
<td>Wind turbine</td>
<td>3</td>
</tr>
<tr>
<td>Geothermal</td>
<td>1</td>
</tr>
<tr>
<td>Compressed Natural Gas (CNG) vehicles</td>
<td>6</td>
</tr>
<tr>
<td>Diesel engines</td>
<td>18</td>
</tr>
<tr>
<td>Diesel engine railroads</td>
<td>6</td>
</tr>
<tr>
<td>Electric railroad</td>
<td>3</td>
</tr>
<tr>
<td>Conventional internal combustion engines</td>
<td>21</td>
</tr>
<tr>
<td>Hybrid vehicles (gasoline-based)</td>
<td>14</td>
</tr>
<tr>
<td>Hybrid vehicles (diesel-based)</td>
<td>8</td>
</tr>
<tr>
<td>Plugin hybrid vehicles (gasoline as the main fuel)</td>
<td>22</td>
</tr>
<tr>
<td>Electric vehicles</td>
<td>3</td>
</tr>
<tr>
<td>Fuel cell vehicles</td>
<td>5</td>
</tr>
</tbody>
</table>

Changing the input parameters uncertainty ranges used by Method of Morris can affect the parameter sensitivity rankings, which in turn affect the Monte Carlo simulation. As a side case, we developed the upper bound of input ranges based on Muratori et al. This led to the removal of wind capital cost and the addition of coal steam investment cost from the Method of Morris rankings. However, after performing the Monte Carlo simulation, we found that this change did not produce a significant change in the shape of the emissions distributions in Figure 2.2. In another test similar to the -+20% input parameter range, we let the input parameters vary by -+40%. This produced the same top ten parameters but this time oil prices ranked second while the relative rank of the rest of the parameters stayed the same. The results support our general insight that the system uncertainty tends to skew emissions towards lower values.
A.3 K-means clustering

K-means clustering partitions a group of $n$ observations $O_1, O_2, ... O_n$ into a set of $k$ ($< n$) clusters: $S = \{S_1, S_1, ..., S_k\}$. Given $n$ observations, each observation $O_i, i = 1, ..., n$ can have $m$ attributes that define the position of that observation in $m$-dimensional space. The goal of $k$-means clustering is to find the centroid associated with each of the $k$ clusters $C_i, i = 1, ..., k$ in the $m$-dimensional space, such that the Euclidean distance $D$ in Equation (3) is minimized:

$$D = \sqrt{\sum_{i=1}^{k} \sum_{j \in S_i} (O_j - C_i)^2}$$

Where $S_i$ belongs to the set of clusters $S = \{S_1, S_1, ..., S_k\}$ and $O_j, C_i \in \mathbb{R}^m$.

Minimizing equation (3) is computationally difficult because it is NP-hard. Instead of solving equation (3) directly, heuristic algorithms are used to find the optimal centroids. The most common approach, and the one used here, is Lloyd's algorithm. The algorithm works iteratively by: (1) initializing the centroids $C_i, i = 1, ..., k$; (2) assigning the $n$ observations to the closest cluster; (3) updating the centroids of each of the clusters with the observations assigned to that cluster; and (4) repeating Steps 1 to 3 until there is no difference in the value of the centroids.
A.4 References


B Appendix B

This document describes the inputs and assumptions to the US regional energy system database. In Sections 1, 2, 3, and 4, sector-specific inputs and assumptions are presented. In Section 5 we expand on cross-sectoral issues, Section 6 describes the Power to X representation, and Section 7 describes the biomass representation. This appendix represents the collective work of several individuals.

B.1 An overview of the database

This database is mostly structured on the US EPA MARKAL database (USEPA) (Lenox, et al., 2013) and US NREL ReEDs database (Eurek et al., 2014). It includes residential, commercial, transportation, industrial, and electric sectors. The model time horizon spans 2017 to 2050, with 5-year time periods. To represent seasonal and diurnal variations in energy supply and demand, the model must perform energy commodity balances across a set of time slices that represent different combinations of seasons and times of day. In the input database used in this analysis, we represent three seasons (summer, winter, intermediate) and four times of times of day: morning (6am-12pm), early afternoon (12-3pm), evening (3-9pm), and night (9-6am).

The residential, commercial, transportation and industrial sectors include demand technologies that convert secondary energy carriers (e.g., electricity, natural gas, liquid fuels) into useful energy services (e.g., space heating, space cooling, vehicle miles traveled). These energy service demands are specified exogenously and are drawn from the USEPA database. For example, the residential sector includes demands for space heating, space cooling, water heating, freezing, refrigeration, lighting, and miscellaneous electricity for appliances.

Data on existing technology capacities in the residential, commercial and transportation sectors as well as their techno-economic parameters are drawn from the USEPA (Lenox, et al., 2013). These parameters include overnight investment costs, conversion efficiencies and technology lifetime. Instead of using USEPA industrial sector data, we developed a more simplified representation. Other electric sector data and assumptions are described in Section 2. A high-level representation of the system is shown in Figure B.1. Fuel prices are specified exogenously and taken from the AEO 2019 Outlook (AEO, 2019).
Fuels are connected to the end-use sectors as well as the electric sector, which includes a large array of renewable, nuclear, and fossil-based generators. Pollution control retrofits, including flue gas desulfurization, low NOx burners, selective catalytic reduction, and selective non-catalytic reduction are available for existing coal-fired capacity. Electricity is generated endogenously within the model, and is connected to the end-use sectors in order to meet a variety of service demands. In the end-use sectors – residential, commercial, industrial, and transport – electricity and other fuels are fed to a variety of demand technologies that convert these inputs into exogenously specified, fixed end-use demands. Because the database is used to explore deep decarbonization pathways, we also include a representation of power-to-X, which allows for the generation of H₂ via water electrolysis. The resultant H₂ can be fed directly into natural gas pipelines up to a concentration of 10% or used to make synthetic natural gas or methanol.
Figure B.1 High-level representation of the modeled system, including key linkages between energy commodities and technologies within each sector.

B.2 The Electric Sector

The electric sector modeled in this analysis includes a representation of existing and new generation technologies. Thermal power plants include coal-fired steam, integrated gasification combined-cycle (IGCC) with and without carbon capture and storage (CCS), oil-based steam plants, natural gas steam plants, open cycle and combined-cycle natural gas turbines with and without CCS, and light water nuclear reactors. Renewable sources include conventional hydro, solar photovoltaics, concentrating solar thermal, wind, biomass IGCC, and geothermal. In addition to these electric generating technologies, the model represents air pollution retrofit technologies for NOx removal, including low NOx burners (LNB), selective catalytic reduction (SCR), and
selective non-catalytic reduction (SNCR). In addition, flue gas desulfurization (FGD) can remove SO₂ associated with coal-fired generation.

In Sections B.2.1 through Section B.2.6, we describe our assumptions and modeling approach to the electric sector. Input parameters not discussed here, are drawn directly from the USEPA database.

**B.2.1 Investment costs of electric sector technologies**

Investment costs of electric sector technologies are drawn from the mid scenario of the National Renewable Energy Laboratory (NREL) Annual Technology Baseline (ATB) 2018 (Cole, et al., 2018). Solar photovoltaic systems are assumed to be single axis tracking with capacity of 100 MW or higher. All wind classes are specified with the techno-resource group 4 of ATB.

**B.2.2 Renewable energies representation**

In this section we describe our key assumptions to calculating solar and wind capacity factors and capacity credits.

**B.2.2.1 Solar**

We include utility-scale photovoltaic (UPV), distributed photovoltaic (DPV) and solar thermal concentrating (STH) technology. UPV and DPV capacity factors come from NREL’s National Solar Radiation Database (NSRDB) (Habte and Sengupta, 2017), and are also used in the ReEDS model (Furek, et al., 2016). NREL’s study represents UPV potential sites in the United States based on multiple criteria for appropriate sites (Habte and Sengupta, 2017). This resource potential is based on large parcels of land outside of urban areas, excluding federally protected lands, roadless areas, areas of environmental concern, and excluding areas with a slope greater than 5%. UPV modules are based on a 100MW system. DPV representation includes fixed tilt systems with a tilt equal to latitude from simulated solar data at 6,000 simulated PV plants (Habte and Sengupta, 2017).

The NREL database provides 5-minute power output data for each of these sites in their respective states (Habte and Sengupta, 2017). The 5-minute power output data is used to calculate the region-specific capacity factors for each time slice. The national capacity factor is then calculated by averaging across the regional capacity factors. STH capacity factors are drawn from
the USEPA by averaging capacity factors of various solar thermal classes and cost categories (Lenox, et al., 2013). The USEPA database defines STH Class 1 to 5, and each class includes 5 different cost categories. Thus, there are 25 different STH technologies, and each technology is represented by an upper bound that indicates available capacities from the technology (Lenox, et al., 2013). By performing a weighted-average across all 25 technologies, we are able to calculate the STHdd capacity factors. Table B.1, Table B.2, and Table B.3 show DC capacity factors of UPV, DPV, and STH, respectively. In the database, we multiply the investment cost and capacity factor associated with solar technologies by an inverter loading ratio of 1.3 to convert the numbers from DC to AC.

Table B.1 UPV capacity factors.

<table>
<thead>
<tr>
<th>Time Slice</th>
<th>Fraction of US</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intermediate-AM*</td>
<td>0.082</td>
</tr>
<tr>
<td>Intermediate-Peak*</td>
<td>0.003</td>
</tr>
<tr>
<td>Intermediate-PM*</td>
<td>0.096</td>
</tr>
<tr>
<td>Intermediate-Night*</td>
<td>0.153</td>
</tr>
<tr>
<td>Summer-AM*</td>
<td>0.098</td>
</tr>
<tr>
<td>Summer-Peak*</td>
<td>0.003</td>
</tr>
<tr>
<td>Summer-PM*</td>
<td>0.109</td>
</tr>
<tr>
<td>Summer-Night*</td>
<td>0.125</td>
</tr>
<tr>
<td>Winter-AM*</td>
<td>0.082</td>
</tr>
<tr>
<td>Winter-Peak*</td>
<td>0.003</td>
</tr>
<tr>
<td>Winter-PM*</td>
<td>0.109</td>
</tr>
<tr>
<td>Winter-Night*</td>
<td>0.138</td>
</tr>
</tbody>
</table>

Table B.2 DPV capacity factors.

<table>
<thead>
<tr>
<th>Time Slice</th>
<th>Fraction of US</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intermediate-AM*</td>
<td>0.082</td>
</tr>
<tr>
<td>Intermediate-Peak*</td>
<td>0.003</td>
</tr>
<tr>
<td>Intermediate-PM*</td>
<td>0.096</td>
</tr>
<tr>
<td>Intermediate-Night*</td>
<td>0.153</td>
</tr>
<tr>
<td>Summer-AM*</td>
<td>0.098</td>
</tr>
<tr>
<td>Summer-Peak*</td>
<td>0.003</td>
</tr>
<tr>
<td>Summer-PM*</td>
<td>0.109</td>
</tr>
<tr>
<td>Summer-Night*</td>
<td>0.125</td>
</tr>
<tr>
<td>Winter-AM*</td>
<td>0.082</td>
</tr>
<tr>
<td>Winter-Peak*</td>
<td>0.003</td>
</tr>
<tr>
<td>Winter-PM*</td>
<td>0.109</td>
</tr>
<tr>
<td>Winter-Night*</td>
<td>0.138</td>
</tr>
</tbody>
</table>
Table B.3 STH capacity factors.

<table>
<thead>
<tr>
<th>Time Slice</th>
<th>Fraction of US</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intermediate-AM*</td>
<td>0.082 0.46</td>
</tr>
<tr>
<td>Intermediate-Peak*</td>
<td>0.003 0.46</td>
</tr>
<tr>
<td>Intermediate-PM*</td>
<td>0.096 0.46</td>
</tr>
<tr>
<td>Intermediate-Night*</td>
<td>0.153 0.23</td>
</tr>
<tr>
<td>Summer-AM*</td>
<td>0.098 0.46</td>
</tr>
<tr>
<td>Summer-Peak*</td>
<td>0.003 0.46</td>
</tr>
<tr>
<td>Summer-PM*</td>
<td>0.109 0.46</td>
</tr>
<tr>
<td>Summer-Night*</td>
<td>0.125 0.23</td>
</tr>
<tr>
<td>Winter-AM*</td>
<td>0.082 0.46</td>
</tr>
<tr>
<td>Winter-Peak*</td>
<td>0.003 0.46</td>
</tr>
<tr>
<td>Winter-PM*</td>
<td>0.109 0.46</td>
</tr>
<tr>
<td>Winter-Night*</td>
<td>0.138 0.23</td>
</tr>
</tbody>
</table>

Similar to Furek et al. (2016), we specify minimum capacity constraints on DPV deployments through 2050. Minimum capacity values were obtained from NREL’s dSolar model (Gangron and Sigrin, 2016). The dSolar model projects the amount of distributed solar capacity on a state-by-state basis, which is aggregated for the US energy system database. Table B.4 shows minimum capacity values from DPV.

Table B.4 Solar outputs of the DPV deployments across the regions (GW).

<table>
<thead>
<tr>
<th>Capacity (GW)</th>
<th>2020</th>
<th>2025</th>
<th>2030</th>
<th>2035</th>
<th>2040</th>
<th>2045</th>
<th>2050</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>29.0</td>
<td>32.3</td>
<td>6.1</td>
<td>98.4</td>
<td>154.3</td>
<td>178.5</td>
<td>178.5</td>
</tr>
</tbody>
</table>

In real-world systems, the capacity credit associated with wind and solar decrease with an increase in their grid penetration. For simplicity, we exogenously reduce the capacity credit of these technologies as a function of time period, under the assumption that solar and wind deployment will increase over time. Hence, the technology-specific capacity credits are indexed by model time period. In future work, we will investigate ways to endogenize the change in capacity credit as a function of deployment level.

For solar PV, we use the capacity credit provided by (Frew et al., 2017) as shown in Figure B.2. This is a simplifying assumption, as the change in capacity credit over time is a function of the solar deployment in a particular scenario.
B.2.2.2 Wind

We use the USEPA database to represent wind resources in our database (Lenox, et al., 2013). Depending on availability of wind resources, various wind classes are defined along with an upper bound on each class. If a particular class represents less than 5% of total wind capacity potentials in USEPA, it is not defined in our database, Table B.5. The capacity factors of the wind classes are taken from USEPA.

<table>
<thead>
<tr>
<th>Wind Class 1</th>
<th>Wind Class 2</th>
<th>Wind Class 3</th>
<th>Wind Class 4</th>
<th>Wind Class 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>272.27</td>
<td>30.96</td>
<td>62.03</td>
<td>119.67</td>
<td>81.89</td>
</tr>
</tbody>
</table>

For the capacity credit of wind resources, we utilize estimates from Voorspools and D'haeseleer (2006), as shown in Figure B.3, which plots the capacity credit as a function of wind share in electricity generation and capacity factor of wind.
The same methodology described above for solar PV is used to project the capacity credit for wind. We interpolate the capacity credit of wind resources based on the capacity factor of wind during summer peak time slice.

Table B.6 provides the capacity credit depending on capacity factor. If the capacity factor during the summer peak time slice is 29% then we use the nearest capacity factor value given in Figure B.3. The capacity credit values for wind are given in Table B.7.

### Table B.6 Capacity credits values from the Figure B.3 (Voorspools and D’haeseleer, 2006).

<table>
<thead>
<tr>
<th>Capacity factor</th>
<th>2017</th>
<th>2020</th>
<th>2025</th>
<th>2030</th>
<th>2035</th>
<th>2040</th>
<th>2045</th>
<th>2050</th>
</tr>
</thead>
<tbody>
<tr>
<td>30%</td>
<td>0.37</td>
<td>0.3</td>
<td>0.23</td>
<td>0.2</td>
<td>0.18</td>
<td>0.16</td>
<td>0.15</td>
<td>0.15</td>
</tr>
<tr>
<td>20%</td>
<td>0.25</td>
<td>0.2</td>
<td>0.16</td>
<td>0.14</td>
<td>0.12</td>
<td>0.11</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>40%</td>
<td>0.51</td>
<td>0.41</td>
<td>0.33</td>
<td>0.26</td>
<td>0.23</td>
<td>0.22</td>
<td>0.2</td>
<td>0.2</td>
</tr>
</tbody>
</table>

### Table B.7 capacity credit for wind resources in the US database.

<table>
<thead>
<tr>
<th>Capacity factor</th>
<th>2017</th>
<th>2020</th>
<th>2025</th>
<th>2030</th>
<th>2035</th>
<th>2040</th>
<th>2045</th>
<th>2050</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Figure B.3** The capacity credit of wind as a function of wind share and capacity factor (Drawn from Voorspools and D’haeseleer, 2006).
Table B.7 (continued).

<p>| | | | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>E_WNDCL1_N</td>
<td>0.29</td>
<td>0.36</td>
<td>0.29</td>
<td>0.22</td>
<td>0.19</td>
<td>0.17</td>
<td>0.15</td>
</tr>
<tr>
<td>E_WNDCL2_N</td>
<td>0.35</td>
<td>0.45</td>
<td>0.36</td>
<td>0.29</td>
<td>0.23</td>
<td>0.20</td>
<td>0.18</td>
</tr>
<tr>
<td>E_WNDCL3_N</td>
<td>0.38</td>
<td>0.49</td>
<td>0.39</td>
<td>0.32</td>
<td>0.25</td>
<td>0.22</td>
<td>0.19</td>
</tr>
<tr>
<td>E_WNDCL4_N</td>
<td>0.402</td>
<td>0.51</td>
<td>0.41</td>
<td>0.33</td>
<td>0.26</td>
<td>0.23</td>
<td>0.22</td>
</tr>
<tr>
<td>E_WNDCL5_N</td>
<td>0.4340</td>
<td>0.55</td>
<td>0.44</td>
<td>0.36</td>
<td>0.28</td>
<td>0.25</td>
<td>0.24</td>
</tr>
</tbody>
</table>

B.2.3 Capacity reserve margin

This constraint requires Temoa to build enough capacity in each period to satisfy the capacity reserve margin. The capacity reserve margin is defined by the North American Electric Reliability Cooperation (NERC) as the amount of unused electric capacity at the time of peak load (NERC, 2009). The capacity reserve requirement ensures that peak demand can be met at all times, thereby maintaining system reliability. Equation 1 defines the constraint for the period $p$:

$$\sum_{t \in T} CC_t \times \text{CAPAVL}_{p,t} \times C2A_t \times SEG^{s^*,d^*} \geq (1 + RES) \times \sum_{t \in T} \text{ACT}_{p,s^*,d^*,t}$$

(1)

Where $t$ denotes the electricity generating technologies in a set $T$, $(s^*, d^*)$ indicates the peak-load time-slice, $CC_t$ represents the technology-specific capacity credit, $C2A_t$ is the conversion factor between capacity and activity respectively, $SEG^{s^*,d^*}$ represents the fraction of peak-load time-slice as a fraction of year, and $RES$ is the region-specific reserve margin. $\text{CAPAVL}_{p,t}$ and $\text{ACT}_{p,s^*,d^*,t}$ are the two decision variables in the inequality. $\text{CAPAVL}_{p,t}$ indicates total available capacity from technology $t$ in period $p$, and $\text{ACT}_{p,s^*,d^*,t}$ indicates activity of technology $t$ in the peak time-slice $(s^*, d^*)$ of period $p$.

While NERC minimum reserve margins vary from 12% to 18% (NERC, 2017), we assume a uniform 15% reserve rate. However, due to the coarse representation of time-slices, our model inherently underestimates peak demand. Our model estimation of summer peak-load for the base year (2017), is 645 GW, while the actual non-coincident peak in summer 2017 has been 20% higher, around 776 GW. To close the gap between our estimate of peak demand and actual peak demand and meet the minimum reserve margin requirement, we assume $RES$ in equation 1 is 35%.
Another important parameter in Equation 1 is the technology-specific capacity credit. Capacity credit indicates the contribution of non-dispatchable technologies to meeting electricity demand at peak-load time (IEA, 2011). The capacity credits of dispatchable plants are drawn from (NERC, 2017). By contrast, as discussed above, wind and solar receive less capacity credit because they are not dispatchable during peak demand periods.

B.2.4 Renewable portfolio standards

State-level renewable portfolio standards (RPSs) are included in our regional dataset in the form of minimum production from renewables. Total state-level electricity generation from renewables are drawn from the AEO 2018 input assumptions (Assumptions to AEO, 2018) and are then aggregated to the national level, as shown in Table B.8. Since the goal of an RPS is to increase the deployment of new renewable technologies, most states restrict existing hydro plants from counting towards the RPS target. The fraction of total hydro generation that counts towards region-specific RPS constraints, are shown in Table B.8. The shares are obtained from the USEPA database (Lenox, et al., 2013).

Table B.8 Minimum generation from renewable energies (RPS)

<table>
<thead>
<tr>
<th>Region</th>
<th>Renewable hydro (as a % of regions’ total hydro)</th>
<th>2020</th>
<th>2025</th>
<th>2030</th>
<th>2035</th>
<th>2040</th>
<th>2045</th>
<th>2050</th>
</tr>
</thead>
<tbody>
<tr>
<td>US</td>
<td></td>
<td>37.3</td>
<td>207.72</td>
<td>230.04</td>
<td>252.36</td>
<td>272.88</td>
<td>293.4</td>
<td>313.56</td>
</tr>
</tbody>
</table>

B.2.5 Cross-State Air Pollution Rule

The Cross-State Air Pollution Rule (CSAPR) limits SO₂ and NOₓ emissions from the electric sector in 22 mostly eastern states (EPA-CSAPR). 2017 State-level budgets for SO₂ and NOₓ are gathered and are then aggregated to the national level. We use 2017 emission budgets to cap SO₂ and NOₓ emissions from 2017 to 2050 (EPA-CSAPR).

B.2.6 Hydrogen combustion

Hydrogen at 100 bar pressure (H2_100) can be burned to produce electricity. We introduced a technology E_H2CC_N which has the same techno-economic parameters as E_NGAACC_N. The only difference between the two is that E_H2CC_N doesn’t produce combustion-related emissions.
Table B.9 Techno economic parameters for hydrogen combustion to produce electricity

<table>
<thead>
<tr>
<th></th>
<th>period/vintage</th>
<th>E_H2CC_N</th>
</tr>
</thead>
<tbody>
<tr>
<td>efficiency</td>
<td>all periods</td>
<td>53.0</td>
</tr>
<tr>
<td>CAPEX Mil. $/GW</td>
<td>2020</td>
<td>1048.44</td>
</tr>
<tr>
<td></td>
<td>2025</td>
<td>1024.69</td>
</tr>
<tr>
<td></td>
<td>2030</td>
<td>1001.07</td>
</tr>
<tr>
<td></td>
<td>2035</td>
<td>983.36</td>
</tr>
<tr>
<td></td>
<td>2040</td>
<td>966.43</td>
</tr>
<tr>
<td></td>
<td>2045</td>
<td>950.07</td>
</tr>
<tr>
<td></td>
<td>2050</td>
<td>927.08</td>
</tr>
<tr>
<td>FOM Mil. $/GW-yr</td>
<td>all periods</td>
<td>9.73</td>
</tr>
<tr>
<td></td>
<td>periods/vintages</td>
<td></td>
</tr>
<tr>
<td>Cost, variable Mil. $/PJ</td>
<td></td>
<td>0.54</td>
</tr>
<tr>
<td>Lifetime (year)</td>
<td></td>
<td>40</td>
</tr>
<tr>
<td>Discount rate</td>
<td></td>
<td>6%</td>
</tr>
</tbody>
</table>

B.3 Transportation sector

As Figure B.1 shows, the modeled transport modes are light-duty vehicles, trucks, buses, rail passenger, rail freight, subway, aviation, marine and off-highway. The demands for these transport modes are drawn from the USEPA database (Lenox, et al., 2013) out to 2050 and can be met by various technologies. Light-duty vehicles have the most detailed representation. Seven different size classes are specified for the light-duty vehicles and each size class is constrained to contribute a fraction of total light-duty demand. We optimize the technologies and fuels within each size class. The size classes are mini compact, compact, full, small SUV, large SUV, minivan and pickup and their share in meeting light duty demand is 2.3%, 28%, 36%, 11.5%, 10%, 3.8% and 8.4%. We assume these shares remain the same throughout time.

The main modeled light-duty vehicle types are conventional internal combustion engines, hybrid, plug-in hybrid, battery electric, and fuel cell vehicles. The internal combustion engine vehicles, include gasoline, diesel, liquified petroleum gas (LPG), compressed natural gas (CNG) and ethanol-flex vehicles. Hybrid vehicles have more limited types that include gasoline, diesel and ethanol fueled cars. Plug-in hybrid types can only use gasoline and/or ethanol.
Heavy-duty road transport (i.e. trucks and busses) have a variety of types. The modeled heavy-duty vehicle types in the USEPA database are conventional diesel engines, LPG engines and CNG engines (Lenox, et al., 2013). The cost and performance data for electric trucks and busses are drawn from the “Moderate Advancement” scenario of the NREL Electrification Future Study (Mai, Trieu T., et al., 2018).

B.3.1 Ethanol representation (E10 and E85)

In the current database, similar to the USEPA database (Lenox, et al., 2013), E10 and E85 are each represented as fuels. E10 is defined as gasoline with an up to 10% ethanol blend and is most commonly 10% ethanol. However, E85 is defined as a gasoline blend with 55 to 83% ethanol, which can vary seasonally based on weather. Our modeling of E85 differs from the USEPA database in that E85 blends in the database are represented as 74% minimum ethanol and 9% minimum gasoline. The blend ratio is therefore optimized based on the cost of the respective fuels and also depends on the presence of an emissions constraint. In addition, we explicitly represent two main sources of ethanol, corn-based ethanol and cellulosic ethanol. The Energy Independence and Security Act of 2007 (EISA) specifies where biomass must be sourced (U.S. Congress, 2007). EISA addresses fuel economy and energy efficiency standards, but also incorporates biofuel requirements. It requires the use of “renewable biomass” to produce renewable fuels. Feedstocks sourced from new farmland cultivated after December 2007, tree crops and tree residues and biomass produced on federal lands or rangeland are all excluded from the “renewable biomass” designation (U.S. Congress, 2007). This constrains the land available for the production of biofuels. The EISA updates the renewable fuels standards (RFS) with annual biofuel requirements, culminating in a requirement of at least 36 billion gallons of biofuels to be used in the US by 2022 (U.S. Congress, 2007). Additionally, by 2022, at least 16 billion gallons of this total biofuel requirement must be supplied by cellulosic biofuels, and a cap of 15 billion gallons is placed on corn-based biofuel (U.S. Congress, 2007).

The database includes these constraints with regard to corn ethanol, cellulosic ethanol, and total ethanol production. For simplicity, the EISA corn-biofuel cap is applied exclusively to ethanol, though biodiesel is also considered a renewable fuel. The bio-based diesel requirement includes a minimum of 1 billion gallons by 2012, representing 2.8% of the total standard (U.S. Congress, 2007). Values for the 2017, 2020, and 2025 time periods are included in Table B.10.
Except for the maximum total ethanol use constraint that accounts for land availability, the rest of the constraints come from EISA (U.S. Congress, 2007). Numerous scenarios of land availability were considered when designing the maximum total ethanol use constraint, ranging from converting all existing cropland in 2007 to biofuel feedstocks to the use of only residual lands for feedstock production. Residual lands are abandoned or degraded cropland, typically not suitable for typical food crops (Cai et al., 2010). The implemented land constraint is based on the land requirements for current ethanol production, plus the addition of minimum estimated residual lands on which biofuel feedstocks could be grown at a minimum yield value (Cai et al., 2010; Hay, 2015; National Agricultural Statistics Service, 2016). This produced a total biofuel potential of 42 million gallons per year – the current 14 billion gallons plus an additional 32 billion from residual lands.

**Table B.10** Constraints imposed on ethanol use. Numbers are in PJ.

<table>
<thead>
<tr>
<th>Year</th>
<th>Minimum cellulosic ethanol use</th>
<th>Maximum corn-based ethanol use</th>
<th>Minimum total ethanol use</th>
<th>Maximum total ethanol use (land constraint)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015</td>
<td>240.6</td>
<td>1203.0</td>
<td>1644.1</td>
<td>3689.0</td>
</tr>
<tr>
<td>2020</td>
<td>842.1</td>
<td>1203.0</td>
<td>2406.0</td>
<td>3689.0</td>
</tr>
<tr>
<td>2025</td>
<td>1283.2</td>
<td>1203.0</td>
<td>2887.2</td>
<td>3689.0</td>
</tr>
</tbody>
</table>

Note: The 2025 time period reflects the federal government requirements to be implemented by 2022. The 2025 values are maintained for all of the subsequent time periods. The energy content of each ethanol type was assumed the same and equal to 80.2 MJ/gallon (Lenox, et al., 2013).

**B.3.2 Production of cellulosic ethanol from corn stover**

Figure B.4 below shows the cellulosic ethanol production pathway.

![Diagram of cellulosic ethanol production](image)

**Figure B.4** Structure of cellulosic ethanol production in Temoa.

The corn stover biomass (STV) is fed to the CELL_ETH_SYN technology, which includes a gasifier. The resultant syngas is then cleaned and passed through a catalyst bed at high temperatures to produce cellulosic ethanol (ETH_CEL). ETH_CEL is then mixed with corn
ethanol (ETH_CORN) to produce Ethanol (ETH), which is then used to produce E10 or E85 blends. Techno-economic parameters for ethanol production are given in Table B.11.

### B.3.3 Production of corn ethanol from corn
In the Temoa database, corn ethanol (ETH_CORN) is produced from corn (CORN) using a similar framework to that of cellulosic ethanol (ETH_CEL), as shown in Figure B.5. The technology used is dry milling (DRY_MILL), which involves grinding the corn into a fine granular powder, which is then treated with enzymes, and the resulting fermentation produces ethanol. ETH_CORN is then blended with ETH_CEL to produce ethanol (ETH), which is subsequently used in the transportation sector.

![Figure B.5 Structure of cellulosic ethanol production in Temoa.](image)

Corn production estimates from the Billion-Ton Study are detailed in the Biomass section B.8. Techno-economic parameters for the corn ethanol production is described in Table B.11.

**Table B.11 Techno-economic data for corn ethanol production**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Efficiency</td>
<td>48%</td>
<td>52%</td>
<td>(GREET, 2018)</td>
</tr>
<tr>
<td>Emissions</td>
<td>27.69</td>
<td>15.16</td>
<td>g/MJ</td>
</tr>
<tr>
<td></td>
<td>0.038</td>
<td>0.03549</td>
<td>g/MJ</td>
</tr>
<tr>
<td></td>
<td>0.028</td>
<td>0.126</td>
<td>g/MJ</td>
</tr>
<tr>
<td>Investment cost</td>
<td>36.38</td>
<td>99.68</td>
<td>M$/PJ</td>
</tr>
</tbody>
</table>
Table B.11 (continued).

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed cost</td>
<td>2.41</td>
<td>24.57</td>
<td>M$/PJ</td>
<td>(Tao et al, 2014)</td>
</tr>
<tr>
<td>Variable cost</td>
<td>14.61</td>
<td>9.67</td>
<td>M$/PJ</td>
<td>(Tao et al, 2014)</td>
</tr>
</tbody>
</table>

B.3.4 Jet fuel and biodiesel

In the Temoa database, there are several different types of biomass that are fed into various processes to produce aviation biofuel and biodiesel. The abbreviations used for the biomass commodities are given in Table B.12.

Table B.12 Biomass related commodities

<table>
<thead>
<tr>
<th>Commodity name in Temoa</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>STV</td>
<td>Corn Stover</td>
</tr>
<tr>
<td>ECW</td>
<td>Energy Crops (Woody)</td>
</tr>
<tr>
<td>FSR</td>
<td>Forest Resources</td>
</tr>
<tr>
<td>UWW</td>
<td>Urban wood waste</td>
</tr>
<tr>
<td>AGR</td>
<td>Agricultural Residues</td>
</tr>
<tr>
<td>ECG</td>
<td>Energy Crops (Grass)</td>
</tr>
<tr>
<td>ECA</td>
<td>Energy Crop (Annual) - Sorghum</td>
</tr>
<tr>
<td>SOY</td>
<td>Soybeans</td>
</tr>
<tr>
<td>FISCH_TROP</td>
<td>Fischer-Tropsch process</td>
</tr>
<tr>
<td>HEFA</td>
<td>Hydro processed esters and Fatty acids</td>
</tr>
</tbody>
</table>

B.3.4.1 Description

Two methods of aviation biofuel production are incorporated into the model. The structure of the process as incorporated in the Temoa database is shown in Figure B.6.
B.3.4.2 Fischer-Tropsch (FISCH_TROP) process

Woody biomass is passed through a gasifier. The resultant syngas is then transformed into hydrocarbons by means of the Fischer-Tropsch process as follows:

\[(2n + 1) \text{H}_2 + n \text{CO} \rightarrow C_n\text{H}_{2n+2} + n \text{H}_2\text{O}\]

The hydrocarbons are then processed to produce jet fuel and biodiesel, of roughly the same quality as conventional jet fuel and conventional diesel.

B.3.4.3 Hydro-processed esters and fatty acids (HEFA) and transesterification

Soybeans (SOY) are hydrotreated (treated with hydrogen), then isomerized through a cracking process, and subsequently refined to produce gasoline, jet fuel, diesel and various other light hydrocarbons (e.g., naphtha).

This process has been commercially implemented, with several companies producing HEFA jet fuel for aviation use. It is ASTM certified, and allows for a maximum of 50% of biojet fuel to be blended with conventional jet fuel. Hence, there is a TechInputSplit of 0.5 associated with the blending technology BLEND_BIOJTF_JTF, which blends bio-jet fuel and conventional jet fuel.

In the database, SOY is imported, then fed to HEFA. It produces both BIOJTF and BIODSL. The other products are ignored, since it is assumed that the process conditions are tailored to favor biodiesel and bio-jet fuel production.
Biodiesel is typically produced from vegetable oils using the transesterification process. Since the same feedstocks are used for both transesterification and HEFA, both processes are linked using a common feedstock (SOY). In this database, BIODSL is also produced using TRANSEST. Techno-economic parameters for the above mentioned processes are given in Tables B.13 and B.14.

**Table B.13** Techno-economic data for FISCH_TROP AND HEFA.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>FISCH_TROP</th>
<th>HEFA</th>
<th>Unit</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Efficiency</td>
<td>50%</td>
<td>84%</td>
<td></td>
<td>(GREET, 2018; de Jong, 2018)</td>
</tr>
<tr>
<td>Emissions</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CO₂</td>
<td>3.67</td>
<td>19.47</td>
<td>g/MJ</td>
<td>(GREET, 2018)</td>
</tr>
<tr>
<td>NOₓ</td>
<td>0.02329</td>
<td>0.0142</td>
<td>g/MJ</td>
<td>(GREET, 2018)</td>
</tr>
<tr>
<td>SOₓ</td>
<td>0.00571</td>
<td>0.0038</td>
<td>g/MJ</td>
<td>(GREET, 2018)</td>
</tr>
<tr>
<td>Investment cost</td>
<td>137.46</td>
<td>76.63</td>
<td>M$/PJ</td>
<td>(Pavlenko et al., 2019; Bann et al., 2017; de Jong, 2018; Wormslev, 2016)</td>
</tr>
<tr>
<td>Fixed cost</td>
<td>16.37</td>
<td>10.16</td>
<td>M$/PJ</td>
<td>(Pavlenko et al., 2019; Bann et al., 2017; de Jong, 2018; Wormslev, 2016)</td>
</tr>
<tr>
<td>Variable cost</td>
<td>5.52</td>
<td>5.52</td>
<td>M$/PJ</td>
<td>(Pavlenko et al., 2019; Bann et al., 2017; de Jong, 2018; Wormslev, 2016)</td>
</tr>
<tr>
<td>LCOE</td>
<td></td>
<td></td>
<td>€/kWh</td>
<td>jet fuel</td>
</tr>
</tbody>
</table>
Table B.14 Techno-economic data for TRANSEST

<table>
<thead>
<tr>
<th>Parameter</th>
<th>FISCH_TROP</th>
<th>HEFA</th>
<th>Unit</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Efficiency</td>
<td>90%</td>
<td>84%</td>
<td></td>
<td>(Huang et al., 2016)</td>
</tr>
<tr>
<td>Emissions</td>
<td>CO₂</td>
<td>7.22</td>
<td>19.47 g/MJ</td>
<td>(GREET, 2018)</td>
</tr>
<tr>
<td></td>
<td>NOx</td>
<td>0.0369</td>
<td>0.0142 g/MJ</td>
<td>(GREET, 2018)</td>
</tr>
<tr>
<td></td>
<td>SOx</td>
<td>0.00242</td>
<td>0.0038 g/MJ</td>
<td>(GREET, 2018)</td>
</tr>
<tr>
<td>Investment cost</td>
<td>29.1</td>
<td>76.63</td>
<td>M$/PJ</td>
<td>(Huang et al., 2016)</td>
</tr>
<tr>
<td>Fixed cost</td>
<td>2.59</td>
<td>10.16</td>
<td>M$/PJ</td>
<td>(Huang et al., 2016)</td>
</tr>
<tr>
<td>Variable cost</td>
<td>4.39</td>
<td>5.52</td>
<td>M$/PJ</td>
<td>(Huang et al., 2016)</td>
</tr>
<tr>
<td>LCOE</td>
<td></td>
<td></td>
<td>€/kWh</td>
<td>jet fuel</td>
</tr>
</tbody>
</table>

Table B.15 Techno-economic data for ethanol

<table>
<thead>
<tr>
<th>Parameter</th>
<th>FISCH_TROP</th>
<th>HEFA</th>
<th>Unit</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Efficiency</td>
<td>52%</td>
<td>84%</td>
<td></td>
<td>(Luo et al., 2009)</td>
</tr>
<tr>
<td>Emissions</td>
<td>CO₂</td>
<td>15.16</td>
<td>19.47 g/MJ</td>
<td>(GREET, 2018)</td>
</tr>
<tr>
<td></td>
<td>NOx</td>
<td>0.03549</td>
<td>0.0142 g/MJ</td>
<td>(GREET, 2018)</td>
</tr>
<tr>
<td></td>
<td>SOx</td>
<td>0.126</td>
<td>0.0038 g/MJ</td>
<td>(GREET, 2018)</td>
</tr>
<tr>
<td>Investment cost</td>
<td>99.68</td>
<td>76.63</td>
<td>M$/PJ</td>
<td>(Zhao et al., 2015)</td>
</tr>
<tr>
<td>Fixed cost</td>
<td>24.57</td>
<td>10.16</td>
<td>M$/PJ</td>
<td>(Zhao et al., 2015)</td>
</tr>
<tr>
<td>Variable cost</td>
<td>9.67</td>
<td>5.52</td>
<td>M$/PJ</td>
<td>(Zhao et al., 2015)</td>
</tr>
<tr>
<td>LCOE</td>
<td></td>
<td></td>
<td>€/kWh</td>
<td>jet fuel</td>
</tr>
</tbody>
</table>

B.3.5 Calculations

Economic calculations pertaining to the various biofuel technologies are provided below.

B.3.5.1 HEFA

Density of jet fuel = 0.804 kg/l
Energy content of jet fuel = 44 MJ/kg (GREET, 2018)
Discount rate = 6%

From (de Jong, 2018), Investment cost = 560 million $/500 ton of jet fuel production per day (average of 265 and 855 M$)
Total energy generated in a year = (0.5 x 106 kg) x 365\frac{days}{year} x 44\frac{MJ}{kg} = 8030 TJ

\Rightarrow \frac{560 \times 10^6 $}{8030 TJ \times 10^8 \frac{PJ}{TJ}} = 69.738 \frac{MS}{PJ}

Converting to 2018 dollars,

\textbf{Investment cost} = \frac{69.738 \frac{MS}{PJ}}{0.91} = 76.64 \frac{MS}{PJ}

Fixed cost = 10.2\% \ of \ Investment \ cost + Labor + Waste disposal

= 0.102 \times 69.738 + (0.65+1.26) \frac{€}{GJ} \times 1.12

(1.12 = \text{conversion factor from euros to dollars})

= 9.25 \frac{MS}{PJ}

Converting to 2018 dollars,

\textbf{Fixed cost} = \frac{9.25 \frac{MS}{PJ}}{0.91} = 10.16 \frac{MS}{PJ}

Variable cost = Electricity + Catalyst + Hydrogen + Natural gas

= (0.59+0.51+0.46+2.92) \frac{€}{GJ} \times 1.12

= 5.02 \frac{MS}{PJ}

Converting to 2018 dollars,

\textbf{Variable cost} = \frac{5.02 \frac{MS}{PJ}}{0.91} = 5.52 \frac{MS}{PJ}

\textbf{B.3.5.2 Fischer-Tropsch}

From (de Jong, 2018), Investment cost = 1004.5 M$/500 ton jet fuel (average of 434 and 1575 M$)

Total energy generated in a year = (0.5 \times 106 kg) \times 365\frac{days}{year} \times 44\frac{MJ}{kg} = 8030 TJ

\Rightarrow \frac{1004.5 \times 10^6 $}{8030 TJ \times 10^8 \frac{PJ}{TJ}} = 125.09 \frac{MS}{PJ}

Converting to 2018 dollars,

\textbf{Investment cost} = \frac{125.09 \frac{MS}{PJ}}{0.91} = 137.46 \frac{MS}{PJ}

Fixed cost = 10.2\% \ of \ Investment \ cost + Labor + Waste disposal
\[
= 0.102 \times 125.09 + (0.65 + 1.26) \frac{e}{GJ} \times 1.12
\]

(1.12 = conversion factor from euros to dollars)

\[
= 14.899 \frac{MS}{PJ}
\]

Converting to 2018 dollars,

**Fixed cost** = \(\frac{14.899 \frac{MS}{PJ}}{0.91} = 16.37 \frac{MS}{PJ}\)

Variable cost for FT is the same as that of HEFA.

### B.3.5.3 Transesterification

Density of biodiesel = 0.874 kg/l (Biodiesel)

Energy content = 37.8 MJ/kg (Energy content)

Lifetime = 20 years

From (Huang et al., 2016), Investment cost = 84 M$ / 96 million liters of biodiesel production per year

Total energy generated in a year = 96 \* 106 \(\frac{litres}{yr}\) \times 0.874 \(\frac{kg}{lit}\) \times 37.8 \(\frac{MJ}{kg}\) = 3.171 \(\frac{PJ}{yr}\)

\[
\Rightarrow \frac{84 \frac{MS}{PJ}}{3.171 \frac{PJ}{yr}} = 26.49 \frac{MS}{PJ}
\]

Converting to 2018 dollars,

**Investment cost** = \(\frac{26.49 \frac{MS}{PJ}}{0.91} = 29.1 \frac{MS}{PJ}\)

Fixed cost = Labor + capital depreciation

\[
= (3.5 + 4) \frac{MS}{3.171 \frac{PJ}{yr}}
\]

\[
= 2.36 \frac{MS}{PJ}
\]

Converting to 2018 dollars,

**Fixed cost** = \(\frac{2.36 \frac{MS}{PJ}}{0.91} = 2.59 \frac{MS}{PJ}\)

Variable cost = Other chemical costs + Utilities + Supplies + General Works

\[
= (6.5 + 4 + 1.3 + 0.9) \frac{MS}{3.171 \frac{PJ}{yr}}
\]
\begin{equation}
\frac{4 \text{ MS}}{\text{PJ}}
\end{equation}

Converting to 2018 dollars,

\begin{equation}
\text{Variable cost} = \frac{4 \frac{\text{MS}}{\text{PJ}}}{0.91} = 4.39 \frac{\text{MS}}{\text{PJ}}
\end{equation}

### B.4 Residential and commercial sectors

We made some minor changes to the USEPA representation of end-use technologies by removing the alternative technologies from the same family of technologies. In the USEPA database, four demand services – space heating, space cooling, water heating and refrigeration – can be met by various “versions” of a single technology type. For instance, there are four different versions of a heat pump in the USEPA database that vary in their coefficient of performance and overnight capital costs (Lenox, et al., 2013). To limit the size of our input database, we keep the “version one” of each of the technology with multiple versions. In all cases, “version one” has the closest cost and performance to the products found in the market today.

### B.5 Industrial sector

#### B.5.1 Background

The industrial sector accounts for the second-largest share (32%) of primary energy consumption in the United States (33,000 PJ in 2015). Within the industrial sector, 10,500 PJ (24%) of primary energy come from the electric sector. Besides electricity, industrial energy demands rely on a mix of fossil fuels and biomass (EIA, 2017). The industrial sector in Temoa disaggregates energy consumption into non-manufacturing and manufacturing industry. The majority of the energy consumption in the non-manufacturing industry comes from agriculture, mining, and construction while major energy consumers in manufacturing are food, paper, bulk chemical, cement, iron, steel and aluminum industry.

#### B.5.2 Structure

One of the side effects of deep decarbonization scenarios is electrification of end use sectors. The previous representation of the industrial sector considered fixed fuel shares, which did not allow the substitution of fossil fuels with electricity or renewable sources. In order to enable
substitution between fuels under high renewable penetration scenarios or other deep decarbonization scenarios, while at the same time keeping the complexity at a minimal level, we choose a simplified representation of the industrial sector.

The industrial sector in Temoa estimates energy consumption by energy source for manufacturing and non-manufacturing industries. The manufacturing subsector is subdivided further by end use. The non-manufacturing industries are modeled with less detail because processes are simpler and limited data is available.

In order to simplify the manufacturing industry representation in Temoa, the energy consumption is classified by source and three end uses: process heat, combined heat and power (CHP), and other. We also combine petroleum coke, lease, plant fuel, metallurgical coal, coke, and road oil into a single fuel commodity called ‘other fuels’ because of their significantly smaller share in energy consumption (EIA, 2017). We combined all end uses for non-manufacturing industry into one combined non-manufacturing demand commodity. Note that the type of fuel consumed is dependent on the end-use process. For example, asphalt is only consumed in the non-manufacturing industry. The framework for the industrial sector representation in Temoa is shown in Figure B.7.

![Figure B.7 Conceptual framework for the industrial sector representation in the Temoa database.](image)

In the USEPA database, the end uses in the manufacturing sector are classified into 13 categories: conventional boiler use, combined heat and power (CHP), process heating, process
cooling, machine drive, electro-chemical process, other process uses, facility HVAC, facility lighting, onsite transportation, conventional electricity generation, other non-process uses, and end use not reported. We consider end use categories other than process heat and CHP as ‘other’ end uses. As shown in Figure B.8, process heating and CHP account for 45% of final energy use in manufacturing.

![Energy use chart]

**Figure B.8** Energy use in U.S. manufacturing (MECS, 2014).

Approximately 6,200 PJ of natural gas, 1,550 PJ of biomass and 820 PJ of coal were used directly by manufacturing industries in 2014, with most occurring in process heating and CHP. There is a potential interchangeability in fuels used for process heat and CHP. For example, natural gas can be replaced by electricity and biomass in process heat and CHP, respectively. Figure B.9 shows the industrial subsectors and end uses that have the potential for electrification.
The major energy source for non-manufacturing industry is asphalt, which contributes to 60% of energy consumption. Natural gas, electricity, and LPG contribute 20%, 12%, and 4% to final energy consumption, respectively. There might be a potential for fuel substitution for non-manufacturing industry, however, due to lack of data, we assume a fixed fuel share.

### B.5.3 Key assumptions about the manufacturing sector

Total energy consumption data for manufacturing industry is available for our assumed time horizon of 2017 to 2050. However, we do not have energy consumption data by fuel and end use. To obtain the required data, we use data from MECS (2014) and EIA (2010). The MECS (2014) provides the fuel consumption by source and end use for 2014. EIA (2010) provides energy consumption by fuel and end use for 2010.

Figure B.10 gives the share of various end-uses which are combined to form a single category called ‘other’ end uses. Fifty-two percent of the energy consumption for ‘other’ end uses is reported by fuel type. The exact end use process is not reported in EIA (2017). Moreover, 92% of the fuel consumption is from ‘other fuels which are from a variety of fuels, including petroleum coke, lease, and plant fuel. So, there is lack of information and relevant data for potential fuel substitution for 52% of the energy consumption within the manufacturing sector. Furthermore, process cooling, machine drive, electro-chemical processes, and facility lighting demand account...
for 25% of the energy consumption for ‘other’ end uses, more than 90% of which is satisfied by electricity. There might be a fuel substitution potential for the remaining 23% energy consumption in ‘other’ end uses, however, for simplicity, we assume that potential for electrification in ‘other’ end uses is negligible. Note that 23% of ‘other’ end uses is equivalent to 10.6% of the total industrial sector energy consumption (=1969/19748). Hence, we fix the fuel share of other end uses for the entire time horizon. We also fix the fuel share of the entire manufacturing industry for the base year in order to calibrate the database to a historical year. Natural gas accounts for 90% and 55% of the process heat and CHP energy consumption, respectively.

Figure B.10 Share of energy consumption by end-uses which are included in ‘other’ end uses.

We assume that biomass in industrial sector is a byproduct of the paper industry, which is used for combined heat and power (CHP). Since it is a byproduct, we assume that the cost of biomass for CHP is zero. The biomass use in the industrial sector has remained approximately constant since 1979 as shown in Figure B.11. Hence, to avoid unlimited utilization of biomass for CHP, we set a maximum activity constraint on biomass based on its historical share. We let the cost of technology and fuels determine the optimal fuel mix for the process heat and CHP end use.
Figure B.11 Historical renewable energy consumption for industrial sector.

We define technologies only for process heat and CHP since these end uses have the highest potential for fuel substitution (Jadun et al., 2017). These technologies are distinguished by fuel and the end use demand served. We assume that the demand for the base year is satisfied by existing technology. For simplicity, we assume the existing technology has the same fixed operations and maintenance cost as new technology. EIA (2010) provides the technology cost by manufacturing industry subsectors. Process heat and CHP are common to many industrial subsectors. Using the USEPA database as a starting point, we calculate the average investment cost, fixed cost, and variable cost of the technologies over all the manufacturing industry subsectors. Efficiency and capacity factor of all technologies is assumed to be 1 since we assume end-use demand in PJ and the input fuel is also in PJ. The lifetime of all technologies is assumed to be 50 years. Table B.16 shows the techno-economic parameters for the technologies.
### Table B.16 Techno-economic parameters for the technologies (EIA, 2010).

<table>
<thead>
<tr>
<th>Energy Source</th>
<th>Investment Cost ($M/PJ)</th>
<th>Fixed Cost ($M/PJ)</th>
<th>Variable Cost ($M/PJ)</th>
<th>Efficiency</th>
<th>Capacity Factor</th>
<th>Life Time (years)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Process Heat</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Electricity</td>
<td>45.060</td>
<td>2.960</td>
<td>N/A</td>
<td>1</td>
<td>1</td>
<td>50</td>
</tr>
<tr>
<td>Residual Fuel Oil</td>
<td>51.620</td>
<td>3.240</td>
<td>N/A</td>
<td>1</td>
<td>1</td>
<td>50</td>
</tr>
<tr>
<td>Distillate Fuel Oil</td>
<td>55.760</td>
<td>3.470</td>
<td>N/A</td>
<td>1</td>
<td>1</td>
<td>50</td>
</tr>
<tr>
<td>Natural Gas</td>
<td>42.390</td>
<td>2.770</td>
<td>N/A</td>
<td>1</td>
<td>1</td>
<td>50</td>
</tr>
<tr>
<td>LPG</td>
<td>42.310</td>
<td>3.140</td>
<td>N/A</td>
<td>1</td>
<td>1</td>
<td>50</td>
</tr>
<tr>
<td>Coal</td>
<td>44.470</td>
<td>3.120</td>
<td>N/A</td>
<td>1</td>
<td>1</td>
<td>50</td>
</tr>
<tr>
<td>Renewables</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Others</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>CHP</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Electricity</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Residual Fuel Oil</td>
<td>N/A</td>
<td>0.946</td>
<td>0.011</td>
<td>1</td>
<td>1</td>
<td>50</td>
</tr>
<tr>
<td>Distillate Fuel Oil</td>
<td>17.448</td>
<td>1.120</td>
<td>0.013</td>
<td>1</td>
<td>1</td>
<td>50</td>
</tr>
<tr>
<td>Natural Gas</td>
<td>18.255</td>
<td>0.867</td>
<td>0.025</td>
<td>1</td>
<td>1</td>
<td>50</td>
</tr>
<tr>
<td>LPG</td>
<td>31.802</td>
<td>1.039</td>
<td>0.016</td>
<td>1</td>
<td>1</td>
<td>50</td>
</tr>
<tr>
<td>Coal</td>
<td>N/A</td>
<td>4.355</td>
<td>0.050</td>
<td>1</td>
<td>1</td>
<td>50</td>
</tr>
<tr>
<td>Renewables</td>
<td>7.571</td>
<td>0.470</td>
<td>0.013</td>
<td>1</td>
<td>1</td>
<td>50</td>
</tr>
<tr>
<td>Others</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
</tbody>
</table>

The EPA data has no technology representation for coal and RFO used for CHP. Biomass is used only for CHP and other fuels, which are used only for ‘other’ end uses. The USEPA database has no variable cost for technologies used for process heating.

#### B.5.4 Key assumptions about non-manufacturing sector

Table ‘TechData_OTR’ in the USEPA input worksheet provides residual capacity for the year 2005 and 2010 by energy source. The mining and refining industry consumption is approximately 2 quads. Total energy consumption for the non-manufacturing sector is taken from the USEPA database for the model time horizon. We do not explicitly model mining in the US Temoa database. Instead, we include the cost of mining in the imported fuel cost. Hence, for simplicity, mining and refining energy consumption are removed from the total energy consumption. The EPA worksheet provides the energy consumption for the year 2010, which we
use to estimate non-manufacturing industry demand over the model time horizon. Note that the non-manufacturing demand is met with a fuel share constraint, with a dummy technology used to represent the energy transfer from fuels to end-use demand.

**B.5.5 Fuel Cost**

Fuel cost projections taken from the Annual Energy Outlook are given in Table B.17 (AEO, 2018).

**Table B.17** Fuel cost projections from AEO ($Million/PJ).

<table>
<thead>
<tr>
<th></th>
<th>Distillate</th>
<th>Residual</th>
<th>Natural</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LPG</td>
<td>Fuel Oil</td>
<td>Fuel Oil</td>
</tr>
<tr>
<td>2017</td>
<td>10.069</td>
<td>11.852</td>
<td>4.309</td>
</tr>
<tr>
<td>2025</td>
<td>11.625</td>
<td>18.853</td>
<td>11.526</td>
</tr>
<tr>
<td>2050</td>
<td>15.331</td>
<td>22.324</td>
<td>14.630</td>
</tr>
</tbody>
</table>

**B.5.6 Hydrogen in industrial sector**

There are four ways to use hydrogen in the industrial sector. The first option is to blend at most 3.4% hydrogen with natural gas. The second option is to use synthetic natural gas to replace conventional natural gas. The third option is to blend at most 75% methanol with industrial gasoline. The description of all the above options is given in the power-to-X section. In this section, we discuss the fourth option where “other” fuels are replaced with Fischer-Tropsch fuels in the industrial sector.

We assume that Fischer-Tropsch can serve as a backstop option to produce “other fuels” using hydrogen and carbon dioxide as inputs. The sources of carbon dioxide are explained in Section B.7. We use Fischer-Tropsch to convert hydrogen at 100 bar pressure to “other fuels” in the industrial sector. The costs and performance data for producing synthetic liquid fuels from hydrogen is taken from Tremel et al. (2015). The capital costs for a 14,000 tons product/day facility
is 43 million Euros. It is assumed that the plant generates hydrocarbons that have a similar molecular structure to diesel fuel. The technical efficiency of the plant is 69% and the annual operational hours are assumed to 6000.

B.6 Cross-sectoral issues

B.6.1 Hurdle rate

Hurdle rates represent the technology-specific discount rates used to amortize capital costs and can be used to represent non-economic costs such as time preference, risk, and uncertainty (DeCarolis et al., 2017).

Without hurdle rates on new technologies in the residential and commercial sectors, the majority of existing end-use technologies are retired in the first time period and replaced with new capacity. For simplicity, Temoa does not consider the remaining capital payments on existing technology, which often makes it cost-effective to simply replace older, less efficient vintages with new ones. To remedy this issue, we assigned a uniform hurdle rate of 30% to all new technologies in the residential and commercial sector. This rate is high enough to keep existing technologies active until they reach the end of their useful lifetimes. Since the hurdle rate is uniform for all new technologies, it doesn’t incentivize one technology over another. In the electric sector, all generating technologies except nuclear use a uniform 6% rate, which is the rate for renewable and natural gas-fired technologies in AEO 2018 (AEO, 2018). Since nuclear buildup has historically been tied to significant cost overruns, we used a higher hurdle rate for nuclear. This rate is based on the information drawn from Table 1 of Gilbert et al. (2018). The mean cost overrun associated with nuclear plants has been 117%. This means that if nuclear plant costs 100 units, the cost overruns can drive it up to 217 units. If we amortize 217 units over the 60-year assumed lifetime of nuclear at a 5% discount rate, the annual amortized values will be 11.46 unit. In order to find the hurdle rate associated with nuclear cost overruns, we need to find the rate that amortizes 100 units to 11.46 units annually over 60 years. This rate is approximately 11%.

We used a uniform 10% hurdle rate for all the alternative vehicles in the light duty vehicle sector and 5% for conventional internal combustion engines. All the other technologies in the transportation sector have 5% hurdle rates. The assumed 10% hurdle rate is relatively low; surveys
have estimated hurdle rates associated with alternative vehicle purchases in the range of 20-50% (Peterson and Michalek, 2013; Mau et al., 2008; Home et al., 2005).

B.7 Power-to-X

The increasing share of renewable energies like solar and wind power for generation of electricity results in higher fluctuations in power production. It will become a challenge to balance demand and production of electricity in future energy systems providing a high share of renewables.

Electricity storage is a way to overcome this challenge, and various technologies are available like batteries, compressed air, or pumped hydro. Power-to-X represents an alternative storage mechanism, converting electricity to hydrogen (H2), which can then be used directly or converted to other fuels (hence the “X”). Power-to-X incorporates the generation of gaseous hydrogen from electricity. This hydrogen can either be used directly for electricity generation, i.e., by the use of fuel cells, or it can be converted by a chemical process in conjunction with CO2 to synthetic natural gas (SNG), which can be fed to gas turbines in order to yield electricity again or used in place of natural gas elsewhere in the energy system. In any case, either hydrogen or SNG serve as the energy storage medium, and the timely separation of production and utilization of the gases enables improved balancing of renewable electricity production and electrical load.

The advantage of generating SNG via chemical processes is twofold. First, SNG can be fed into the existing pipeline network for natural gas with no restrictions, and existing technologies can utilize the fuel. Second, the chemical process for converting hydrogen to SNG utilizes CO2 as a byproduct from the CCS technologies in the electric sector or from the atmosphere. In either case, the CO2 utilized in the conversion process does not increase the flux of greenhouse gases to the atmosphere. However, the higher cost and efficiency loss associated with SNG generation needs to be evaluated carefully compared to the direct utilization of hydrogen.

A key advantage to Power-to-X is its ability to supplement non-electrical fuel demands across the energy system. Hydrogen or SNG can serve as heating in the residential, commercial or industrial sectors. Similarly, hydrogen and SNG can be used to power fuel cell or gas vehicles and thereby create an alternative pathway for integrating renewable electricity into the transport sector,
in addition to electric vehicles. In addition, hydrogen can be converted to methanol or even synthetic gasoline, which opens additional options, including large trucks and airplanes.

**B.7.1 The Power-to-X technology**

As already outlined in the introduction, Power-to-X incorporates different pathways for the conversion of electricity to gaseous and liquid fuels. Figure B.12 illustrates the conversion pathways included in the database.

![Figure B.12 Basic pathways for conversion of renewable electricity to gaseous and liquid fuels by Power-to-X.](image)

The following Appendix Figure B.13 gives the schematic of the power to gas structure in Temoa.
Figure B.13 Power-to-X representation in US database. The “Z1” used for the names of technologies and commodities is a region index. The power-to-X representation for other regions follows the same structure.

Initially, electricity is utilized to separate water into hydrogen and O2 by electrolysis. We assume that the water needed is available at no cost and that no revenue is generated from the produced O2. We neglect the potential revenue from O2 production, as its value will decrease as the scale of production increases.

Figure 14 indicates that hydrogen from electrolysis is used in four different ways. First, hydrogen can be used directly in fuel cell vehicles. Second, hydrogen can be directly blended into...
natural gas, with an upper limit of 10% by volume based on Dörr (2016). Further efforts in R&D are intended to yield an increase of this limit (Müller-Syring et al. 2013). A separate technology for hydrogen distribution is considered.

The two additional pathways for hydrogen utilization involve a further chemical process where hydrogen reacts with CO2 to make either SNG or Methanol. The water leaving is not assumed to have an economic value. CO2, however, is considered to be a side product of a CCS-plant, and by this means available for free. Another source of CO2 input to synthetic fuel production is direct air capture. The techno-economic parameters of direct air CO2 capture technology is drawn from the Table 2 of Keith et al. (2018). The capital cost and variable O&M costs are 793 $/t-CO2/year and 30 $/tCO2 respectively. Assuming a 25 year lifetime and a 7.5% capital recovery factor, gives a levelized CO2 capture cost of 126 $/t-CO2.

The SNG generated from the chemical process is almost pure methane, and for this reason there is no restriction to directly feed SNG into the natural gas distribution network. Methanol can be blended into gasoline. Various simulations as well as experimental studies verify the feasibility of a high percentage of methanol in gasoline for Otto engines (Farkade and Pathre, 2012; Iliev, 2015). From 1980-2000, a sizable vehicle fleet ran on 85% methanol (M85) in California (Wuebben, 2015) with no major technical problems. The program was discontinued for economic and political reasons: the price of gasoline dropped under the limit where any blending of methanol was cost-effective, and ethanol grew in popularity given its support by American farmers (Falco, webpage). Based on this experience, the upper limit for blending methanol into gasoline for any transportation purpose is fixed at 85% by volume.

B.7.2 Implementing Power-to-X into Temoa

This section includes an introduction to all technologies and commodities related to power-to-X, including parameter values related to costs, efficiency, emission activity, and lifetime. ENEA (2016) served as a key reference for the technology characterization, but we conducted a further literature review in order to verify the data from the report as well as to gather more recent data. Starting from the input of electricity to Power-to-X, Figure B.14 shows this pathway.
B.7.3 Transformation of electricity from AC to DC (E_TRS_DC)

Since the electrolysis is driven by DC electricity, the AC current from the grid has to be converted to DC beforehand. This might not be always necessary having small units directly coupled to solar-PV in mind, but in general the renewable electricity needs be transferred to the Power-to-X plant by using standard AC transmission lines.

In the ENEA report (Götz et al., 2016) an efficiency of 97.5% is given for the transformation from AC to DC, and this value has been adapted to Temoa as well as the lifetime of 40 years. Regarding investment cost a value of 0.2 Mio €/MW (= 0.24 Mio $/MW) was taken from a report for planning the reinforcement of the German transmission grid from 2016 (Felix et al., 2016). However, this value for CAPEX is in good agreement to the data from the ENEA report (ENEA, 2016). OPEX and variable cost are neglected.

The resulting output commodity is DC electricity ELCP_DC, which is fed to the electrolysis technologies.

---

Figure B.14 Implementation of the processes for hydrogen generation in Temoa (textured commodities/technologies already existing in Temoa, fully colored commodities/technologies new to Temoa).

B.7.4 Technologies for electrolysis (E_ELECAL and E_ELECPEM)

For hydrogen generation from electrolysis three different technologies are currently discussed: Alkaline, PEM and High temperature (SOEC). Alkaline electrolysis is arguably the only mature technology, while PEM electrolysis is being field tested and SOEC is still in the lab. However, PEM and SOEC technologies offer higher efficiencies and lower cost compared to alkaline electrolysis, and thus major R&D efforts being pursued with regard to the first two. For
alkaline and PEM electrolysis, estimates for capital and operating costs already exist, while only rough estimates exist for SOEC. Hence, we decided to implement alkaline and PEM electrolysis into Temoa.

To derive estimates for cost, lifetime, and efficiency, we reviewed several sources (Götz et al., 2016; Schiebahn et al., 2015; Ahern et al., 2015; Smolinka et al., 2016; Bertuccioli et al., 2014; Smolinka et al., 2010). While the data from these different sources does not coincide entirely, they are in the same range. In many cases, the data included in these publications have been taken and averaged from various other sources.

Regarding efficiencies, data is taken from Bertuccioli et al. (2014), applying one correction for alkaline electrolysis as follows: since hydrogen should be supplied at a pressure level of 10 bar after electrolysis, the additional energy for compression needs to be accounted for in the efficiency estimate. Since PEM electrolysis works at elevated pressure, no correction is necessary for this type. In contrast, the efficiency for alkaline electrolysis drops from 74 to 66%, if pressure is increased from ambient to 10 bar according to (ENEA, 2016). For that reason, all efficiencies for alkaline electrolysis taken from Bertuccioli et al. (2014) were corrected by a factor of 66/74.

Investment cost estimates are also taken from Bertuccioli et al. (2014). Since costs in Temoa are based on output, the costs based on output from Bertuccioli et al. (2014) need to be divided by efficiency. In addition, factors of 1.1 and 1.2 are applied; the former for taking installation cost into account, the latter for currency conversion from € to US$. Operating and maintenance cost are calculated at 3% of the capital cost, taken as mean value from ENEA (2016), and variable costs are neglected. The assumed lifetime is 25 years for both types of electrolysis. This accounts for low numbers of operational hours, if the technologies are applied in the near future, and for technical improvement, if applied later on. Table B.18 summarizes all relevant data for the two technologies for electrolysis E_ELECAL and E_ELECPEM.
Table B.18 Data for electrolysis technologies “E_ELECAL” and “E_ELECPEM” entered to Temoa. There is a significant reduction in the capital costs over time.

<table>
<thead>
<tr>
<th>period/vintage</th>
<th>E_ELECAL</th>
<th>E_ELECPEM</th>
</tr>
</thead>
<tbody>
<tr>
<td>efficiency / %</td>
<td>2017: 66.3</td>
<td>75.8</td>
</tr>
<tr>
<td></td>
<td>2020: 67.6</td>
<td>82.1</td>
</tr>
<tr>
<td></td>
<td>2025: 68.9</td>
<td>82.1</td>
</tr>
<tr>
<td></td>
<td>2030: 70.3</td>
<td>83.8</td>
</tr>
<tr>
<td></td>
<td>2035: 71.0</td>
<td>83.8</td>
</tr>
<tr>
<td></td>
<td>2040: 71.7</td>
<td>85.6</td>
</tr>
<tr>
<td>CAPEX / Mio. $/GWout</td>
<td>2017: 1852</td>
<td>2736</td>
</tr>
<tr>
<td></td>
<td>2020: 1231</td>
<td>1609</td>
</tr>
<tr>
<td></td>
<td>2025: 1169</td>
<td>1399</td>
</tr>
<tr>
<td></td>
<td>2030: 1090</td>
<td>1197</td>
</tr>
<tr>
<td></td>
<td>2035: 1060</td>
<td>1055</td>
</tr>
<tr>
<td></td>
<td>2040: 1031</td>
<td>925</td>
</tr>
<tr>
<td>OPEX / Mio. $/GWout</td>
<td>2017: 55.6</td>
<td>82.1</td>
</tr>
<tr>
<td></td>
<td>2020: 36.9</td>
<td>48.3</td>
</tr>
<tr>
<td></td>
<td>2025: 35.1</td>
<td>42.0</td>
</tr>
<tr>
<td></td>
<td>2030: 32.7</td>
<td>35.9</td>
</tr>
<tr>
<td></td>
<td>2035: 31.8</td>
<td>31.7</td>
</tr>
<tr>
<td></td>
<td>2040: 30.9</td>
<td>27.7</td>
</tr>
<tr>
<td>Cost, variable</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Lifetime / a</td>
<td>25</td>
<td>25</td>
</tr>
</tbody>
</table>

B.7.5 Technology for compression of hydrogen to 100 bar

From the 10 bar pressure level after electrolysis, hydrogen is compressed to 100 bar, serving as a sufficient pressure for any further utilization, including feed into high pressure pipelines. However, this assumption prevents any cost savings from delivering hydrogen at the specific pressure level needed for each individual purpose.

In order to derive the efficiency for technology H2_COMP10100, the equation for the electric power necessary to drive an adiabatic compressor is introduced:
\[ P_{el} = \dot{m}_{H_2} \cdot \frac{c_p T_i}{\eta_{mot} \eta_{mech} \eta_{SC}} \cdot \left( \pi \frac{R_i}{c_p} - 1 \right) \]  

(2)

Dividing this number by output activity yields the related loss. Hence, efficiency calculates as follows:

\[ \eta_{compr} = 1 - \frac{P_{el}}{\dot{m}_{H_2} \cdot HHV_{H_2}} \]  

(3)

Using the property data of hydrogen for \( c_p, R_i \) and \( HHV_{H2} \), setting input temperature \( T_i = 30^\circ C \) and pressure ratio \( \pi = 100 \text{ bar} / 10 \text{ bar} = 10 \) and selecting efficiencies for the driving electric motor including controls \( \eta_{mot} = 0.8 \), for mechanical drive \( \eta_{mech} = 0.9 \) and for isentropic compression \( \eta_{SC} = 0.7 \), an efficiency \( \eta_{compr} = 0.94 \) for compressor technology H2_COMP101000 can be derived. It is assumed that compressor efficiency stays constant for all periods.

In order to account for the electricity consumed to run the electrolysis process, grid electricity (ELC) is connected to hydrogen_COMP10100, as shown in Figure 16. The flow of electricity to the compressor should stay constant, as long as hydrogen is treated as an ideal gas where pressure does not account for enthalpy. In order to satisfy both constraints, ELC and hydrogen input activity (H2_10) must be rated with compressor efficiency when connecting to H2_COMP10100. In addition, we add a fixed input ratio between electricity and hydrogen entering H2_COMP10100.

In terms of setting the capital and operating costs, Niaz et al. (2015) reports a price range of 1000 – 1500 €/kWe for large scale (> 100 kWe) hydrogen compressors. Scaling this cost to output activity of hydrogen, factor (1- \( \eta_{compr} \)) is applied, yielding 60 - 90 €/kW\( H_2 \). Taking the average and multiplying by a factor of 1.15 for installation (based on ENEA (2016), and a second factor of 1.2 for currency conversion to US dollars finally results in a capital cost of 103.5 M$/GW for hydrogen_COMP10100. Since hydrogen compression can be considered a mature technology and no information about the potential for cost reduction in the future is available, the capital cost is kept constant for all periods. Similarly, the fixed operations and maintenance cost is assumed to be a constant 4% of the capital cost, which is an average between the 6% reported by ENEA (2016) and 2% reported by Ferreroa et al. (2016). Variable operations and maintenance costs are neglected.
The lifetime of the technology is set at 15 years as suggested by ENEA (ENEA, 2016). In Table B.19 all relevant data for compressor technology H2_COMP10100 is listed:

<table>
<thead>
<tr>
<th>period/vintage</th>
<th>H2_COMP10100</th>
</tr>
</thead>
<tbody>
<tr>
<td>efficiency ELC / %</td>
<td>94.0</td>
</tr>
<tr>
<td>efficiency H2_10 / %</td>
<td>94.0</td>
</tr>
<tr>
<td>Tech_input_split ELC / %</td>
<td>6.0</td>
</tr>
<tr>
<td>Tech_input_split H2_10 / %</td>
<td>94.0</td>
</tr>
<tr>
<td>CAPEX / Mio. $/GWout</td>
<td>103.5</td>
</tr>
<tr>
<td>OPEX / Mio. $/GWout</td>
<td>4.14</td>
</tr>
<tr>
<td>Cost, variable</td>
<td>0</td>
</tr>
<tr>
<td>Lifetime / a</td>
<td>15</td>
</tr>
</tbody>
</table>

As stated in the beginning of this section, the pressure level of 100 bar after compression technology H2_COMP 10100 serves as common basis for all pathways for further processing or utilization of hydrogen in terms of Power-to-X according to Figure B.13. In addition, a hydrogen storage is connected to this pressure level, which will be explained next.

**B.7.6 Technology for hydrogen storage at 150 bar (H2_STO150)**

Hydrogen can be stored in the depleted gas reservoirs at a significantly lower cost compared to above ground storage facilities. Regarding the roundtrip efficiency of hydrogen storage in underground reservoirs (Colbertaldo et al., 2019) notes the following on p. 9564: "These leakage losses are neglected here, as both the studies on Lined Rock Caverns (LRC) [49] and the available measures from existing underground facilities have shown very low leakage rates (further investigation is expected with operation of the first installations, e.g., in the Houston, Texas area) [50]."

As such, we assume the hydrogen storage efficiency is 100%. Given the lack of experience with this means of hydrogen storage, we tested two hurdle rates for hydrogen storage (6 and 10%). The higher hurdle rate did not make a significant difference in the results. So, the hurdle rate for the underground hydrogen storage technology is 6%. We assume that underground hydrogen is
stored at 150 bar pressure which is the same as the above ground storage assumptions. This assumption can be updated in the future.

The above ground storage (i.e., engineered tank) is estimated to cost $12/kWh. It is possible to store hydrogen in underground caverns (e.g., depleted gas reservoirs) at costs that are two orders of magnitude lower at ~$0.1-0.4/kWh. For example, Amos (1999) indicates a cost range between $2-30 / kg. Conservatively taking the upper end of $30/kg, the cost is approximately $0.35/kWh (corrected for inflation). Given these larger geologic reservoirs for hydrogen storage, the assumed duration can be much longer than in the engineered tanks.

To see how the storage duration affects the results, we added a few different versions of the technology with different durations. Note that in each case, the storage cost (we assumed 1.05 $/kWh stored) is multiplied by the hours of duration to get the $/kW investment cost specified in the model. We tested the model with the following durations: 10 hours, 300 hours, 1000 hours. (At 300 hours of duration, the cost per kW is $0.35/kWh*300 = 100 $/kW, which is close to the engineered tank estimate. For reference, the longest time slice in the database is intermediate night, SegFrac=0.1532, which is 1342 hours. Different storage durations did not make a significant difference in the results since we can build a fraction of the hydrogen storage with any duration. The current US data has only one hydrogen storage technology with 2000 hr duration. We do not have any above the ground storage since the model would not choose it over the cheaper underground storage option. Life time of underground hydrogen storage is 40 years. Fixed and variable cost are assumed to be negligible, Table B.20.

Table B.20 Data for hydrogen storage technology H2_STO150 entered to Temoa.

<table>
<thead>
<tr>
<th>period/vintage</th>
<th>H2_STO150</th>
</tr>
</thead>
<tbody>
<tr>
<td>efficiency / %</td>
<td>all periods</td>
</tr>
<tr>
<td>CAPEX / Mio. $/GWout</td>
<td>all vintages</td>
</tr>
<tr>
<td>Duration</td>
<td>all periods/vintages</td>
</tr>
<tr>
<td>Lifetime / a</td>
<td>40</td>
</tr>
</tbody>
</table>

B.7.7 Technology for compression of hydrogen to 100 bar (H2_COMP100700)

As the first pathway in Figure 14, the hydrogen generated by electrolysis is utilized for in hydrogen vehicles. In the current version of the database, hydrogen can only be used to power fuel
cell vehicles. To utilize hydrogen in vehicles, onboard storage is crucial. In order to achieve a reasonable mileage, onboard compressed hydrogen tanks operating at 700 bar are currently state-of-the-art. For that reason, additional compression is required in order to connect fuel cell vehicles to the 100 bar pressure level associated with transported hydrogen.

For utilization of hydrogen in vehicles storage is crucial. In order to reach a reasonable mileage, tanks for compressed hydrogen at 700 bar are currently state of the art. For that reason, another compression is needed, in order to connect these technologies to the 100 bar pressure level provided by the Power-to-X technologies introduced so far. It should be noted, that within this study any additional efforts in terms of establishing hydrogen refueling technology and infrastructure are not included.

Hydrogen compression from 100 to 700 bar is implemented in Temoa in the same way as for technology H2_COMP10100 as described above. The pressure ratio of 700 bar / 100 bar = 7 yields an efficiency of 95%. Similarly, the electricity needed to drive the compressor (H2_COMP10100) is included as an input.

Regarding the capital cost, an additional factor of 1.2 is applied in order to account for the high pressure that the compressor must endure. Thus, estimated capital cost is 124.2 M$/GW and the fixed operations and maintenance cost is 5.0 M$/GW. These costs remain constant in future time periods, and the lifetime is again fixed at 15 years. Table 23 lists all relevant data for compressor technology H2_COMP100700

Table B.21 Data for Compressor technology H2_COMP100700 entered to Temoa.

<table>
<thead>
<tr>
<th>period/vintage</th>
<th>H2_COMP100700</th>
</tr>
</thead>
<tbody>
<tr>
<td>efficiency ELC / %</td>
<td>95.0</td>
</tr>
<tr>
<td>efficiency H2_10 / %</td>
<td>95.0</td>
</tr>
<tr>
<td>Tech_input_split ELC / %</td>
<td>5.0</td>
</tr>
<tr>
<td>Tech_input_split H2_10 / %</td>
<td>95.0</td>
</tr>
<tr>
<td>CAPEX / Mio. $/GWout</td>
<td>124.2</td>
</tr>
<tr>
<td>OPEX / Mio. $/GWout</td>
<td>5.0</td>
</tr>
<tr>
<td>Cost, variable</td>
<td>0</td>
</tr>
<tr>
<td>Lifetime / a</td>
<td>15</td>
</tr>
</tbody>
</table>
B.7.8 Technology for hydrogen distribution

A technology named “hydrogen_dist_Z*” is added to account for the costs of building the hydrogen infrastructure. The capital cost is drawn from the EPA MARKAL database (Lenox, et al., 2013) and is the average of hydrogen delivery costs for three categories: rural areas, urbanized areas, and urban cluster.

B.7.9 Technologies for blending hydrogen into natural gas

According to Figure B.15, another option is to blend hydrogen into the natural gas grid. As discussed above, a 10% concentration by volume is introduced as an upper limit for the concentration of hydrogen within the natural gas pipeline network.

For implementation in Temoa, the technologies for feeding natural gas into the five sectors of interest – residential, industrial, commercial, transport and electrical – have been doubled by a blending technology (R_NGA_H2BL, O_NG_H2BL, C_NGA_H2BL, CNG_H2BL and NGA_H2BL), as shown in Figure B.15. By applying the tech_input_split parameter to each technology, an upper bound of 10% hydrogen by volume is maintained. Keeping in mind that the input data for tech_input_split in Temoa is based on energy and not volume, the ratio translates to 3.43% hydrogen and 96.57% natural gas, using the higher heating value of the two gases.

Figure B.15 Implementation of the processes for blending hydrogen in natural gas in Temoa (textured commodities/technologies already existing in Temoa, fully colored commodities/technologies new to Temoa).
B.7.10 Technology for generating SNG from hydrogen and CO₂ (SNGSYN)

Figure B.16 displays the different technologies involved in SNG production and the way they are linked and incorporated in Temoa.

![Diagram of SNG production technologies](image)

Figure B.16 Implementation of the processes for generating SNG and methanol in Temoa (textured commodities/technologies already existing in Temoa, fully colored commodities/technologies new to Temoa).

The process of forming SNG from hydrogen and CO₂ is based on the following chemical reaction also known as Sabatier or methanation process:

\[
4 \, H_2 + CO_2 \rightarrow CH_4 + 2 \, H_2O \tag{4}
\]

It is a catalytic, 2-stage chemical reaction, running at 250-550°C and 1-100 bar (Götz et al., 2016). In the first, endothermic reaction hydrogen and CO₂ are converted to CO and water. The second reaction is exothermic and meant to convert CO with further hydrogen to methane and another molecule of water, and it is exothermic. Since the energy release from the second reaction is higher than needed for the first.

Currently, a biological option to form methane from hydrogen and CO₂ by microorganisms is under investigation. Biological methanation does not require high temperatures and pressures, it runs between 20 and 70°C and at a pressure below 10 bar, and it is more tolerant in terms of impurities, which in the Sabatier process can deactivate the catalyst. However, the reaction rate of
biological methanation is still small and requires large reactors compared to the Sabatier process, which prevents the near-term deployment of this technology in a larger scale. For that reason, the Sabatier process working at a pressure level of 20 bar is considered in the database.

Regarding the efficiency of the Sabatier process, Götz et al. (2016) reports 78%, which is in good correspondence to ENEA (2016) (79.4%) and to Ahern et al. (2015) (80%). According to Schiebahn et al. (2015), the maximum efficiency of the Sabatier process can reach 83%; thus, we allow the efficiency to rise slightly up to 81% in 2040.

Information about current investment cost for the methanation vary a lot; a good overview is given by Götz (Götz et al., 2016). He reports about a range from 130 to 175 €/kW for bigger plants at the lower end up to 1500 €/kW given by (ENEA, 2016). Since Götz refers to other sources at 300-500 €/kW and 600 €/kW, an intermediate value for CAPEX of 450 €/kW (SNG) is implemented in Temoa, which is equivalent to 540 $/kW (SNG) applying the conversion rate of 1.2 between € and US$. For future periods a significant drop of CAPEX seems plausible, ENEA assumes only 1/3 of current investment prices in 2050 (ENEA, 2016). According to this information CAPEX is allowed to decrease by ½ (down to 270 $/kW (SNG)) until 2040 within this study. As an indicator for OPEX a fraction of 7.5% of CAPEX is taken from the ENEA report (ENEA, 2016) resulting in 40.5 $/kW (SNG) in 2015 and 20.25 $/kW (SNG) in 2040.

Variable cost is mainly attributed to the source of CO₂ available, and the potential cost for CO₂ have been already discussed in chapter 2. Within this study the impact of CO₂ cost will be studied by parameter variation. At this point it should be noted that for the Sabatier process, where the cost is based on output activity SNG, specific cost of 10 $/to (CO₂) convert to 0.5 Mio. $/PJ (SNG). Additional variable cost beside CO₂ cost are not considered.

Finally, expected lifetime of the methanation technology is 20 years as indicated in (ENEA, 2016).

Table B.22 displays all relevant data for technology SNGSYN to represent the generation of SNG from hydrogen and CO₂ in Temoa.
Table B.22 Data for SNG generation technology SNGSYN entered to Temoa.

<table>
<thead>
<tr>
<th>period/vintage</th>
<th>SNGSYN</th>
</tr>
</thead>
<tbody>
<tr>
<td>efficiency / %</td>
<td></td>
</tr>
<tr>
<td>2015</td>
<td>79.0</td>
</tr>
<tr>
<td>2020</td>
<td>80.0</td>
</tr>
<tr>
<td>2025</td>
<td>80.5</td>
</tr>
<tr>
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<td>81.0</td>
</tr>
<tr>
<td>2035</td>
<td>81.0</td>
</tr>
<tr>
<td>2040</td>
<td>81.0</td>
</tr>
<tr>
<td>CAPEX / Mio. $/GW (out)</td>
<td></td>
</tr>
<tr>
<td>2015</td>
<td>540</td>
</tr>
<tr>
<td>2020</td>
<td>486</td>
</tr>
<tr>
<td>2025</td>
<td>432</td>
</tr>
<tr>
<td>2030</td>
<td>378</td>
</tr>
<tr>
<td>2035</td>
<td>324</td>
</tr>
<tr>
<td>2040</td>
<td>270</td>
</tr>
<tr>
<td>OPEX / Mio. $/GW (out)</td>
<td></td>
</tr>
<tr>
<td>2015</td>
<td>40.5</td>
</tr>
<tr>
<td>2020</td>
<td>36.45</td>
</tr>
<tr>
<td>2025</td>
<td>32.4</td>
</tr>
<tr>
<td>2030</td>
<td>28.35</td>
</tr>
<tr>
<td>2035</td>
<td>24.3</td>
</tr>
<tr>
<td>2040</td>
<td>20.25</td>
</tr>
</tbody>
</table>

Cost, variable \( \text{CO}_2 \) cost, variable

Lifetime / a 20

B.7.11 Technology for compression of SNG from 20 to 100

In order to feed SNG into the gas grid, its pressure must be elevated to the pressure level of the pipeline, which may vary between 16 and 100 bar depending on the location in the pipeline network and the distance the gas needs to be transferred to the consumers (American Gas Association, 2017). In order to be able to meet the highest pressure, a compression from 20 bar after methanation up to 100 bar is considered for technology SNG_COMP20100. This pressure level change also applies to hydrogen blended into the gas grid.

Due to the differing properties of SNG compared to hydrogen, compressor efficiency is higher in terms of SNG. Applying equations 1 and 2 to the compression of SNG together with the
relevant pressure ratio 100 bar / 20 bar = 5, and using similar data for hydrogen compression (input temperature T1 = 30°C, efficiencies for the driving electric motor including controls is assumed to be 80%, for mechanical drive 90% and for isentropic compression of 0.7), yields an efficiency equal to 98% for SNG_COMP20100.

Incorporating the compressor technology for SNG into Temoa follows the same procedure as already introduced and discussed for hydrogen compression. In addition, and for the sake of simplicity, the data for cost and lifetime derived for technology hydrogen _COMP10100 is adopted for technology SNG_COMP20100, which is a reasonable assumption since output pressure is the same for both technologies. Similarly, all data is assumed constant for all periods and vintages. This yields the data for compressor technology SNG_COMP20100 as listed in Table B.23.

Table B.23 Data for Compressor technology SNG_COMP20100 entered to Temoa.

<table>
<thead>
<tr>
<th>period/vintage</th>
<th>SNG_COMP20100</th>
</tr>
</thead>
<tbody>
<tr>
<td>efficiency ELC / %</td>
<td>98.0</td>
</tr>
<tr>
<td>efficiency H2_10 / %</td>
<td>98.0</td>
</tr>
<tr>
<td>Tech_input_split ELC / %</td>
<td>2.0</td>
</tr>
<tr>
<td>Tech_input_split H2_10 / %</td>
<td>98.0</td>
</tr>
<tr>
<td>CAPEX / Mio. $/GWout</td>
<td>103.5</td>
</tr>
<tr>
<td>OPEX / Mio. $/GWout</td>
<td>4.14</td>
</tr>
<tr>
<td>Cost, variable</td>
<td>0</td>
</tr>
<tr>
<td>Lifetime / a</td>
<td>15</td>
</tr>
</tbody>
</table>

B.7.12 Technologies for emission accounting in Power-to-X

Even though SNG is carbon neutral, we need to make sure that the CO2 that is needed to produce SNG is coming from somewhere. Specially in the deep decarbonization or high renewable penetration scenario where the emissions are going almost to zero in 2050, we need a way to capture CO2 from the atmosphere.

We need 1 mole of CO2 and 4 moles of hydrogen to produce 1 mole of SNG. When we convert CO2 to kt and hydrogen to PJ, it turns out that we need 38.46 kt of CO2 per PJ of hydrogen to produce 1 PJ of SNG. We input this number via the TechInput Split constraint. The Appendix Figure B.17 shows the flow of the process.
The CO2 input to the both SNG and synthetic fuels production technologies is assumed to come from two sources. The first is the CO2 produced by the generators with CCS in the electric sector. If these generators produce electricity, we assume they generate as much from an emission commodity named “CO2_CCS_Z*” as they capture the global emission commodity “CO2”. “CO2_CCS_Z*” is then connected as an input to a technology, “CCS_EA”. This technology provides two paths: the upper path in Figure 19 becomes active when the emissions from the CCS generators are used for synthetic fuels production. This path generates the same amount of CO2 that was capture before by the CCS technology (this accounts for the combustion-related emissions of synthetic fuels in the end-use sectors). However, there might be a case where only CCS technology is selected by the model without any downstream synthetic fuels production processes. In this case, the lower path becomes active and no new emissions are generated and commodity “CO2_CCS_Z*” is taken out of the system (buried underground).

B.7.13 Technology for generating methanol from hydrogen and CO2

There is also a fuel pathway in the database that generates methanol from hydrogen and CO2, which can be used as liquid fuel, and is typically discussed as a carbon-free fuel in the transportation sector. A good overview of the process, including technical and economic data is given by Atsonios et al. (2016) and Pérez-Fortes et al. (2016). ENEA (2016) also includes some information about the process as well.

Equation 4 presents the basic chemical reaction, which splits in two separate reactions: First, CO is created from hydrogen and CO2 in an endothermic reaction under dismissal of water. In a second exothermic step, CO reacts with hydrogen to make methanol and water:

\[ 3 \text{H}_2 + \text{CO}_2 \rightarrow \text{CH}_3\text{OH} + \text{H}_2\text{O} \] (5)
The methanol reactor is typically operated at 250°C and a pressure of 65 bar (Atsonios et al., 2016). Obviously, a high pressure shifts the reaction displayed by eq. 4 to the right hand side. An estimated state-of-the-art conversion efficiency of 75.5% is taken from ENEA (2016). The more advanced CCU process yields an efficiency of 80.4% according to Pérez-Fortes et al. (2016), which is considered for 2020. For the following periods until 2040 only a minor increase in efficiency up to 82% is considered.

Atsonios et al. (2016) provides a levelized cost of 133.4 €/ton MeOH. With fixed operations and maintenance cost and insurance cost of 5% and 2% of the capital cost, respectively, a capital recovery factor of 0.11, and the higher heating value of methanol, this converts to 1575 €/kW MeOH for capital cost. This value is in good agreement with ENEA (2016), where 1500 €/kW MeOH is stated for the year 2015. Since Atsonios et al. (2016) provides more details on the cost analysis, their estimated capital cost is considered in this study, resulting in 1890 $/kW MeOH for MEOHSYN after conversion of currency from € to US$ by a factor of 1.2.

Regarding potential capital cost reductions in the future, only ENEA (2016) provides an estimate. According to ENEA (2016), the capital cost for MEOHSYN should decline by one-third until 2030 and by 53.3% until 2050. We have adopted this decline in the database. OPEX is as well taken from the ENEA report (ENEA, 2016) with 7.5% of CAPEX. The value suggested by Atsonios is close by, if their data for OPEX (5%) and insurance (2%) is added.

Similarly, as in case of technology SNGSYN, the variable cost of MEOHSYM is mainly attributed to CO2 utilization. In contrast to the process of generating SNG, the methanol production cost of 10 $/ton CO2 converts to 0.6 M$/PJ MeOH due to the different stoichiometric of the chemical reactions (compare eqs. 3 and 4). Other variable cost besides the cost for CO2 are neglected. Finally, lifetime of technology MEOHSYN is fixed at 20 years as indicated ENEA (2016). Table B.24 summarizes all relevant data for MEOHSYN, which generates methanol.
Table B.24 Data for Methanol generation technology MEOHSYN entered to Temoa.

<table>
<thead>
<tr>
<th>period/vintage</th>
<th>MEOHSYN</th>
</tr>
</thead>
<tbody>
<tr>
<td>efficiency / %</td>
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</tr>
<tr>
<td>2015</td>
<td>75.5</td>
</tr>
<tr>
<td>2020</td>
<td>80.4</td>
</tr>
<tr>
<td>2025</td>
<td>81.0</td>
</tr>
<tr>
<td>2030</td>
<td>81.5</td>
</tr>
<tr>
<td>2035</td>
<td>82.0</td>
</tr>
<tr>
<td>2040</td>
<td>82.0</td>
</tr>
<tr>
<td>CAPEX / Mio. $/GW (out)</td>
<td></td>
</tr>
<tr>
<td>2015</td>
<td>1890</td>
</tr>
<tr>
<td>2020</td>
<td>1650</td>
</tr>
<tr>
<td>2025</td>
<td>1440</td>
</tr>
<tr>
<td>2030</td>
<td>1260</td>
</tr>
<tr>
<td>2035</td>
<td>1120</td>
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<tr>
<td>2040</td>
<td>1000</td>
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<td>OPEX / Mio. $/GW (out)</td>
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<td>2020</td>
<td>123.75</td>
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<tr>
<td>2025</td>
<td>108.0</td>
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<tr>
<td>2030</td>
<td>94.5</td>
</tr>
<tr>
<td>2035</td>
<td>84.0</td>
</tr>
<tr>
<td>2040</td>
<td>75.0</td>
</tr>
<tr>
<td>Lifetime / a</td>
<td></td>
</tr>
<tr>
<td></td>
<td>20</td>
</tr>
</tbody>
</table>

B.7.14 Technology for storing Methanol (MEOH_STO)

While for SNG the gas grid and the storages associated to it are accessible, in case of Methanol a separate storage should be available at the production site. For that reason, technology MEOH_STO is implemented in Temoa in order to serve in this way. However, the technology itself is quite simple, because Methanol is stored as a liquid at ambient or slightly elevated pressure. Therefore, any cost for the storage of Methanol are neglected at this early stage of the analysis, since they are small compared to the cost of all other technologies involved. In addition, energy losses mainly caused by pumping are small in this terms and by this means negligible as well, resulting in an efficiency of 1 for technology MEOH_STO in Temoa. Expected lifetime of the technology is fixed to 20 years.
B.7.15 Technologies for blending Methanol into gasoline in the transport sector

As mentioned above, methanol can be blended to a high share into gasoline. Methanol can be blended into gasoline commodities E10, E85, JTF and O_GSL, as shown in Figure B.16. Consequently, blending technologies T_E10MEOHBL, T_E85MEOHBL, T_JTFMEOHBL and O_GSLMEOHBL are implemented. By applying the tech_input_split parameter, the upper bound 85% share of methanol is maintained for each type of gasoline. As in case of blending hydrogen into natural gas, it must be kept in mind that the specified shares are based on energy rather than on volume. Therefore, the percentages need to be converted based on the high heating values of the liquids involved. In the case of E10, JTF, and O_GSL, the same higher heating value is assumed, resulting in an upper bound of 75.69% methanol in the gasoline blend. In the case of E85, the lower higher heating value due to the high percentage of ethanol is considered, resulting in an upper bound 80.32% methanol in the E85 blend. We note that any blending with a smaller percentage of methanol is feasible, because the pathway of direct utilization of the gasoline fuels is still active, as displayed in Figure 16.

Again, similar to implementing the blending technologies for hydrogen in Temoa, they are used for emission accounting as well. Since methanol from Power-to-X is produced with CO2 either from the atmosphere or as a combustion byproduct of the CCS generators in the electric sector, it does not produce additional CO2 emissions. Therefore, methanol reduces CO2 emissions in proportion to its blending share, which is incorporated in technologies T_E10MEOHBL, T_E85MEOHBL, T_JTFMEOHBL and O_GSLMEOHBL.

B.8 Biomass

We have following 8 types of biomasses going to power plant and transportation sector. All the types have a maximum activity constraint. The variable cost of the biomass is taken from (DoE BTS, 2016) using the following query:

Filter the data by year and feedstock. For 2017 use the data for the base case all energy crop. For all subsequent year use the data from 4% yield increase scenario. Download the dataset as .csv file. Sum over the data by time period and unit price. If the unit of production is in bushels, then convert it to dry tons by multiplying by 0.0254. The BTS (DoE BTS, 2016) reports out the feedstock values as cumulative amount for each step. So, subtract out the values from the previous
step to get the incremental amount that the model can use at each price step to avoid double counting. For example, Table B.25 shows the calculation for corn stover (IMPSTV).

Table B.25 sample calculation for IMPSTV.

<table>
<thead>
<tr>
<th>IMPSTV (MMt)</th>
<th>USD (Mil. $)</th>
<th>2017</th>
<th>2020</th>
<th>2025</th>
<th>2030</th>
<th>2035</th>
<th>2040</th>
</tr>
</thead>
<tbody>
<tr>
<td>(before) R4</td>
<td>30</td>
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<td>0</td>
<td>6.2</td>
<td>16.29</td>
<td>27.3</td>
<td>31.64</td>
</tr>
<tr>
<td></td>
<td>40</td>
<td>22.92</td>
<td>25.55</td>
<td>29.98</td>
<td>33.21</td>
<td>37.39</td>
<td>40.99</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>50.36</td>
<td>55.86</td>
<td>65.67</td>
<td>75.29</td>
<td>83.12</td>
<td>91</td>
</tr>
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<td></td>
<td>60</td>
<td>57.24</td>
<td>62.96</td>
<td>72.77</td>
<td>80.12</td>
<td>88.02</td>
<td>95.96</td>
</tr>
<tr>
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<td>70</td>
<td>60.06</td>
<td>65.6</td>
<td>76.19</td>
<td>84.72</td>
<td>92.8</td>
<td>99.92</td>
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<td></td>
<td>80</td>
<td>63.17</td>
<td>69.43</td>
<td>79.49</td>
<td>87.34</td>
<td>96.47</td>
<td>103.82</td>
</tr>
<tr>
<td></td>
<td>90</td>
<td>65.05</td>
<td>70.77</td>
<td>81.7</td>
<td>90.15</td>
<td>98.14</td>
<td>104.31</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>66.63</td>
<td>71.75</td>
<td>82.58</td>
<td>90.49</td>
<td>98.13</td>
<td>104.22</td>
</tr>
<tr>
<td>(After) R4</td>
<td>30</td>
<td>0</td>
<td>0</td>
<td>6.2</td>
<td>16.29</td>
<td>27.3</td>
<td>31.64</td>
</tr>
<tr>
<td></td>
<td>40</td>
<td>22.92</td>
<td>25.55</td>
<td>23.71</td>
<td>16.92</td>
<td>10.09</td>
<td>9.35</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>27.44</td>
<td>30.31</td>
<td>35.69</td>
<td>42.08</td>
<td>45.73</td>
<td>50.01</td>
</tr>
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<td>60</td>
<td>6.88</td>
<td>7.1</td>
<td>7.1</td>
<td>4.83</td>
<td>4.9</td>
<td>4.96</td>
</tr>
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<td>70</td>
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<td>2.64</td>
<td>3.42</td>
<td>4.6</td>
<td>4.78</td>
<td>3.96</td>
</tr>
<tr>
<td></td>
<td>80</td>
<td>3.12</td>
<td>3.83</td>
<td>3.3</td>
<td>2.63</td>
<td>3.67</td>
<td>3.9</td>
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<td>90</td>
<td>1.88</td>
<td>1.34</td>
<td>2.21</td>
<td>2.8</td>
<td>1.66</td>
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<td>0.98</td>
<td>0.88</td>
<td>0.34</td>
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<td>0.09</td>
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<td>82.57</td>
<td>90.49</td>
<td>98.13</td>
<td>104.22</td>
</tr>
<tr>
<td>(MMt)</td>
<td>Mil. USD</td>
<td>52.155</td>
<td>51.196</td>
<td>50.103</td>
<td>48.378</td>
<td>46.680</td>
<td>45.534</td>
</tr>
<tr>
<td>Mil. $/MMT</td>
<td>Mil. $/PJ</td>
<td>3.863</td>
<td>3.792</td>
<td>3.711</td>
<td>3.584</td>
<td>3.458</td>
<td>3.373</td>
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</table>
Following Table B.26 shows the energy content of all the biomasses which is used for the above calculations.

**Table B.26 Energy content of the biomass.**

<table>
<thead>
<tr>
<th>Biomass</th>
<th>Energy Content (PJ/Mt)</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>UWW</td>
<td>15</td>
<td>Tillman, (2000)</td>
</tr>
</tbody>
</table>

For IMPSOY, cost was an order of magnitude off with the above calculations. The above cost might not consider the transportations cost. This part needs more research and is currently left for future students. The IMPSOTY cost comes from (Market Insider).
B.9 References


EIA, U.S. Electric Power Monthly (February 2017), Tables 6.2.B and 6.2.C


EPA-CSAPR https://www.epa.gov/csapr/overview-cross-state-air-pollution-rule-csapr


Mau, P.; Eyzaguirre, J.; Jaccard, M.; Collins-Dodd, C.; Tiedemann, K. The neighbor effect: Simulating dynamics in consumer preferences for new vehicle technologies. Ecological Economics, 2008, 68, 504-516. DOI: j.ecolecon.2008.05.007


Smolinka, T., Thomassen, M., Oyarce, A., Marchal, F.: “Cost benefit analysis and cost and performance target for large scale PEM electrolyser stack”, public summary from the project MEASTACK, 2016


The TEMOA Project, www.temoaproject.org


This appendix shows the figures to which I made a reference in Chapter 3.

![Figure C.1 Changes to the US energy system by sector in the CCap scenario. The assumptions on future technology costs is drawn from “Mid” scenario of the NREL’s ATB 2019.](image)

Figure C.1 Changes to the US energy system by sector in the CCap scenario. The assumptions on future technology costs is drawn from “Mid” scenario of the NREL’s ATB 2019.
Figure C.2 Changes to the US energy system by sector in the CCap scenario where electric sector technology costs out to 2050 are drawn from the “mid scenario” of the NREL’s ATB 2019. Significant amount of battery storage is deployed at the expense of nuclear to meet baseload electricity demand.
Figure C.3 Changes to the US energy system by sector in the CCap scenario where electric sector technology costs out to 2050 are drawn from the “constant scenario” of the NREL’s ATB 2019.

Appendix Figure C.4 shows the ranges of the system costs using three different assumptions on future technology costs. The costs represented by the dotted lines, assume NREL’s ATB “mid” scenario. The highest and lowest costs in each scenario are associated with ATB’s “constant” and “low” scenarios respectively.
Figure C.4 Cost ranges of the BAU, CCap and CCap⁺ scenarios using three ATB cost scenarios. System costs in the BAU-low scenario is assumed to be 100 (bottommost line of the yellow box), and other costs are calculated relative to it. Each box shows total system costs ranges associated with ATB’s “low” and “constant” scenarios on future technology costs and the dotted line represent ATB’s “mid” scenario.
Figure C.5 Changes to the US energy system by sector in the CCap* scenario.
Figure C.6 Changes to the US energy system by sector in the CCap scenario where the distribution of the 38 demand services are optimized. The total system costs under this assumption declines by 2.2% compared to the original CCap scenario. This scenario was tested to examine the impact of full demand side flexibility on the system costs and system configuration in the CCap scenario.
Figure C.7 Changes to the US energy system by sector in the CCap scenario where the distribution of the 38 demand services are optimized. The total system costs under this assumption declines by 3.2% compared to the original CCap scenario. This scenario was tested to examine the impact of full demand side flexibility on the system costs and system configuration in the CCap scenario.
Figure C.8 Changes to the US energy system by sector in the CCap scenario with a new vector for service demands. The new vector has the same values for the demand services in 2020 but it linearly declines demands over time such that in 2050 the new demand values are 80% of original demand values in 2050. This scenario was tested to examine the impacts of elastic demands on the system configurations.
Figure C.9 Changes to the US energy system by sector in the CCap+ scenario with a new demand vector. The new vector has the same values for the demand services in 2020 but it linearly declines demands over time such that in 2050 the new demand values are 80% of original demand values in 2050.
## Appendix D

**Table D.1** Winter season results. The numbers show the share of each variable to explaining winter electricity demand variations.

<table>
<thead>
<tr>
<th>State</th>
<th>Total Variability</th>
<th>Population</th>
<th>Climate</th>
<th>Substitution effect</th>
<th>Previous Month Demand</th>
</tr>
</thead>
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<tr>
<td>AL</td>
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<td>81</td>
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</tr>
<tr>
<td>AR</td>
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<td>2</td>
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</tr>
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<td>41</td>
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<td>CO</td>
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<td>0</td>
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Table D.2 Summer season results. The numbers show the share of each variable to explaining summer electricity demand variations.

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Table D.3 Share of households using electricity as their heating fuels (EIA, 2015).

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Figure D.1 Raster colors show total winter variability explained by the model, and the numbers show the contribution of the previous month’s demand to explaining total variability of electricity demand in the winter season.

Figure D.2 Raster colors show total summer variability explained by the model, and the numbers show the contribution of the previous month’s demand to explaining total variability of electricity demand in the summer season.
D.1 References