ABSTRACT

BABAEE, SAMANEH. The Potential Role of Plug-in Electric Vehicles in the U.S. and their Effect on Emissions through Mid-Century. (Under the direction of Dr. Joseph F. DeCarolis.)

Concerns about oil security and availability, greenhouse gas (GHG) emissions, and degraded air quality motivate interest in alternative fuels and vehicles. Plug-in vehicles (PEVs), which include plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs), have received significant attention from the government, research community, and automotive industry. These vehicles have the potential to increase the security of US fuel supply, improve air quality, and reduce GHG emissions by displacing some or all of the gasoline or diesel fuels with electricity and shifting emissions out of dense urban areas to more remotely located power plants.

Increasing PEV deployment will shift market shares in the light duty vehicle (LDV) sector, which can affect prevailing energy prices, technology deployment and utilization, and emissions throughout the energy system. The efficacy of using PEVs to reduce air emissions will depend on a broad set of underlying system-wide conditions that unfold over time. This research employs a bottom-up energy system model (TIMES), along with a U.S. dataset (NUSTD) I developed, to meet the following objectives: (1) identify the conditions under which electric drive vehicles (EDVs; which include PEVs and hybrid electric vehicles) achieve high LDV market penetration in the U.S. and quantify the associated change in CO_2, SO_2, and NO_X emissions through mid-century; (2) quantify the incremental impact of PEV deployment on national U.S. CO_2 emissions through mid-century under alternative electric sector scenarios; and (3) examine the potential impact of different time-of-day PEV charging

scenarios on system-wide CO_2 emissions, electricity prices, and technology deployment in the electric and LDV sectors.

To address future uncertainty and examine PEV deployment within the LDV market through 2050, varying assumptions related to crude oil and natural gas prices, a CO_2 policy, a federal renewable portfolio standard, and vehicle battery cost were combined to create a large set of 108 scenarios. Furthermore, several policy options that could promote dramatic changes in the future electric sector mix were considered to quantify system-wide PEV emissions benefits and test the model response to different PEV charging patterns.

The model results suggest the following high-level insights. First, oil price and battery cost exert the greatest influence on EDV deployment across the modeled scenarios. Second, the model results do not demonstrate a clear and consistent trend towards lower system-wide emissions of CO_2, SO_2, and NO_X in the U.S. as EDV deployment increases. Higher electric sector emissions associated with PEV charging and shifting emissions in other energy sectors can partially offset the lower tailpipe emissions from PEVs. Third, the incremental CO_2 emissions benefit associated with PEV deployment largely depends on marginal changes in electricity generation mix required to charge PEVs. Fourth, time-of-day PEV charging does not produce a significant impact on electricity prices, PEV deployment, or total system-wide CO_2 emissions in the U.S. through 2050. In summary, the net effect of PEVs over time on national emissions will depend on a variety of factors beyond vehicle deployment numbers, including the introduction of new energy and environmental policies, prevailing fuel prices, and technology innovation across the energy system. Policymakers should pay careful attention to prevailing system-wide conditions, as simply incentivizing the purchase of PEVs will not automatically lead to emissions reductions.

The Potential Role of Plug-in Electric Vehicles in the U.S. and their Effect on Emissions through Mid-Century

by
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DEDICATION

تقدیم به مادر و پدرم به خاطر حمایتهای همیشگی و زحمات بی دریغشان

To my mom and dad for their endless support and unstinting devotion

BIOGRAPHY

Samaneh Babaee was born and raised in Tehran, Iran. She received a Bachelor of Science degree in Civil Engineering in 2004 from Shahrood University of Technology in Iran. She started her graduate studies in 2005 and earned her Master of Science in Environmental Engineering in 2007 from Khajeh Nasiredin Toosi University in Tehran. In May 2009, Samaneh joined the Department of Civil, Construction, and Environmental Engineering at North Carolina State University in Raleigh, North Carolina. Her Ph.D. research has focused on the system-level energy and environmental impacts associated with the large scale deployment of electric drive vehicle technologies under the direction of Dr. Joseph DeCarolis.

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Chapter 1: Introduction

Transportation accounts for 70% of U.S. petroleum use and contributes 34% of U.S. CO_2 emissions (EIA, 2014). Internal combustion engines operating on petroleum-based fuels have powered most vehicles for the past century. However, high oil costs, concerns about energy security and availability, greenhouse gas (GHG) emissions, and air quality are driving national interest in alternative fuels and vehicles. Plug-in electric vehicles (PEVs)—plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs)—have the potential to reduce emissions and dependence on oil. In recent years, improved technologies and government tax incentives have helped increase PEV adoption (DOE, 2014; DOE, 2010). Combined U.S. sales of PHEVs and BEVs have increased from 345 in 2010 to approximately 97,000 in 2013. Since 2007, more than 230,000 PEVs have been sold in the U.S. (EDTA, 2014).

Major automobile manufacturers have introduced plug-in electric vehicles (PEVs) into the global market as part of a strategy to develop alternative fuel and vehicle technology options. For example, Toyota, Chevrolet, and Ford have PHEVs on the market; Nissan, Tesla Motors, Mitsubishi, and Fiat have introduced BEVs into the market (PIA, 2014). Research, development, and deployment of the technologies and infrastructure required to enable the widespread deployment of PEVs is also ongoing. Home and workplace electric charging options for PEVs are rapidly expanding and public infrastructure is steadily growing, with 8500 stations and 20,000 outlets operating in cities, suburbs, and along highways nationwide

(EDTA, 2014). A projected 1.5 million charging locations will be available by 2017 (EDTA, 2013).

A large market penetration of PEVs will couple the transportation and electric sectors, changing the system-wide supply of energy and emissions. Electrification of the transportation sector could increase electric generation capacity and shift emissions from millions of individual vehicle tailpipes to large, centralized power plants. Increasing PEV deployment will shift market shares in the light duty vehicle (LDV) sector, which can affect prevailing energy prices, technology deployment and utilization, and emissions throughout the energy system. In this thesis, I utilize an energy system model along with a U.S. dataset I developed, to provide policy-relevant insights related to the interaction of PEVs with the rest of the U.S. energy system through mid-century. This thesis specifically addresses the following questions:

- What effect does electric drive vehicle (EDV) deployment have on the net system-wide emissions of CO_2, SO_2, and NO_X under a variety of different future scenarios?
- What is the incremental change in national CO_2 emissions associated with high PEV deployment levels under several plausible policy scenarios focused on clean electricity?
- How might variation in PEV time-of-day charging affect electricity prices, PEV deployment, and total system-wide CO_2 emissions in the U.S.?

The research in this dissertation is organized into five chapters. Chapters 2-4 each address one of the questions above and represent a self-contained journal article. Chapter 2 is more broadly focused on electric drive vehicles (EDVs), which include hybrid electric vehicles (HEVs) in addition to PHEVs and BEVs. In Chapter 2, an energy system model was utilized to examine 108 scenarios in order to identify the conditions under which EDVs achieve high market penetration in the U.S. LDV sector through 2050. The resultant system-wide changes in U.S. CO_2, SO_2, and NO_X emissions were quantified. Because we did not observe a clear and consistent decline in emissions as a function of EDV deployment across the 108 scenarios tested, we decided to focus on quantifying PEV emissions benefits under different clean electricity scenarios, which is the focus of Chapter 3. For simplicity, Chapters 2 and 3 assume that vehicle charging through the year is constant. Chapter 4 presents the potential impact of different time-of-day PEV charging scenarios on electricity prices, technology deployment, and total system-wide CO_2 emissions under conditions favorable to PEV deployment. The dissertation closes with Chapter 5, which presents key observations and insights drawn from all three analyses as well as directions for future research. The development of a TIMES-compatible dataset represented a large effort underlying the model-based analysis, which is documented in the appendices.

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Chapter 2: How Much Do Electric Drive Vehicles Matter to Future U.S. Emissions?

2.1 INTRODUCTION

Increasing concerns over U.S. oil imports, anthropogenic climate change, and urban air quality motivate interest in alternative fuels and vehicles. Among existing options, electric drive vehicles (EDVs)—hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs)—are receiving increased attention from government, industry, and academia. Current U.S. policies designed to promote EDVs include President Obama's pledge to deploy 1 million BEVs by 2015 (The White House, 2011), a $7500 federal tax credit for BEVs and PHEVs (DOE, 2010), and numerous state-level incentives (DOE, 2014). In addition, the recent passage of aggressive new Corporate Average Fuel Economy (CAFE) standards that will roughly double fuel economy and halve the greenhouse gas emissions produced by cars and light duty trucks in model year 2025 (EPA Federal register, 2012) make the prospect for EDV deployment even more promising.

EDVs offer three key benefits over competing vehicle technologies: (1) reduced consumption of petroleum-based fuels (GREET, 2012), (2) lower refueling infrastructure costs compared to alternatives such as H_2 and compressed natural gas (AEO, 2012), and (3) a shift in energy production from vehicles to the electricity grid, where emissions from large, centralized facilities are cheaper and easier to control (Sioshansi et al., 2010; Peterson et al., 2011). While previous work has applied different methodologies and models to quantify the environmental benefits of EDVs, several consistent insights have emerged. First, HEVs produce less emissions than conventional vehicles (Traut et al., 2012; Shiau et al., 2010; Samaras and Meisterling, 2008). Second, PHEVs with smaller battery packs are more likely to deliver emissions benefits and reduced gasoline consumption at lower lifetime cost compared to those with large battery packs in the short term (Michalek et al., 2011; Peterson and Michalek, 2013; Shiau et al., 2009; ANL, 2009). Third, significant emissions benefits, particularly from vehicles with large battery packs, only begin to accrue with clean electricity (Traut et al., 2012; Samaras and Meisterling, 2008; Michalek et al., 2011; Kammen et al., 2009; Hawkins et al., 2012; EPRI, 2007). Fourth, CO_2 prices as high as 100 $/tonne do not provide sufficient incentive for vehicle electrification (Traut et al., 2012; Shiau et al., 2010; Michalek et al., 2011; Shiau et al., 2009; Kammen et al., 2009).

While these studies (along with Wang et al., 2011; Hadley and Tsvetkova, 2009; Wu and Aliprantis, 2013; NRC, 2013) have made significant contributions to the literature, they only consider a single point in time or employ sector-specific models or calculations that ignore the interaction of EDVs with the rest of the energy system over time. Recent analyses based on energy system models mainly focus on CO_2 emissions and have been run with a limited set of scenarios (AEO, 2012; Yeh et al., 2008; Karplus et al., 2010), which make it difficult to draw insight specific to EDVs.

This paper employs an energy system model to meet the following objectives: (1) identify the conditions under which EDVs achieve high market penetration in the U.S. light duty vehicle (LDV) sector through 2050, and (2) quantify the system-wide changes in CO_2, SO_2, and NO_X emissions at the national level. The model minimizes the system-wide cost of energy over time and links all sectors of the economy together through a consistent set of energy prices. Therefore, rather than characterizing the rest of the energy system through exogenous inputs and isolating the effects of EDV deployment, application of an energy system model can help characterize the broader impacts due to dynamic interactions across the energy system. As such, this paper adds to the existing literature by addressing a fundamental question: Does EDV deployment produce a consistent and measurable decline in emissions relative to other changes that may be induced throughout the system in response to a common set of scenario drivers? This analysis places particular emphasis on the long-run emissions changes that may be produced in the U.S. by 2050. To address future uncertainty, we examine the effect of 5 factors on EDV deployment: crude oil and natural gas prices, a federal CO_2 policy, a federal renewable portfolio standard (RPS), and EDV battery cost. To characterize possible EDV deployment over the next half century, assumed values associated with each factor are blended to create a large set of 108 scenarios that capture a wide range of potential outcomes. Given the highly uncertain role of consumer choice in future vehicle adoption, this analysis is focused on the economic and environmental performance of EDVs assuming minimal behavioral barriers to vehicle adoption. Strong and persistent reluctance on the part of consumers to adopt EDVs will dampen or eliminate the EDV-related effects presented here.

2.2 MODEL DESCRIPTION

The model used for this analysis consists of two components: The Integrated MARKAL-EFOM System (TIMES) (Loulou et al., 2005), which serves as a generic energy optimization framework and operates on the National U.S. TIMES Dataset (NUSTD), a TIMES-compatible dataset constructed specifically for this analysis.

2.2.1 The TIMES model generator

TIMES is a widely used bottom-up, technology rich energy system model, which represents an energy system as a network of technologies linked together via flows of energy commodities (Loulou et al., 2005). TIMES performs linear optimization to identify the least-cost way to satisfy end-use demands, subject to user-imposed constraints such as emissions limits and maximum growth rates on technology capacity. Model outputs by future time period include the optimal installed capacity and utilization by technology, marginal energy prices, and emissions. TIMES assumes rational decision-making, with perfect information and perfect foresight, and optimizes over an entire set of multi-year modeling periods simultaneously. Appendix B provides a simplified algebraic formulation of the TIMES model.

2.2.2 The National U.S. TIMES Dataset (NUSTD)

We developed NUSTD, a TIMES-compatible input dataset containing fuel prices; technology cost and performance estimates; and end-use demands to represent the U.S. as a single region over the next four decades. We adhere to the adage that the best policy-relevant models are "small and simple" in order to maximize transparency (Morgan and Henrion, 1992). As such, NUSTD represents a compromise between capturing enough technological detail to meet the goals of this analysis and eliminating superfluous information that makes the input dataset unnecessarily complex and difficult to manage. We describe the basic design of NUSTD in this section, and provide detailed documentation in Appendices A and B. In addition, the workbooks containing the complete set of input data are publicly available (Energy Modeling, 2014), allowing verification of results by external parties.

The model time horizon is 2010 to 2050, with 5-year time periods. Intra-annual variation in demand and renewable resource availability is represented by specifying 3 seasonal (i.e., summer, winter, and intermediate) and 4 diurnal (i.e., morning, mid-day, afternoon/evening, and night) time segments. The U.S. is modeled as a single region with no interregional trade. A 5% social discount rate is used to convert future expenditures into present cost. As described below, a 10% hurdle rate is applied to all alternative vehicle technologies.

An overview of the energy system representation in NUSTD is provided in Figure A1 of Appendix A. Conceptually, NUSTD can be categorized into 4 parts: fuel supply, electric sector, transport sector, and the remaining end-use sectors (i.e., commercial, residential, industrial). Fuel supply is represented by a set of exogenously specified fuel prices drawn from the output to the Annual Energy Outlook (AEO) 2012 (EIA, 2012). This is in contrast to many other model datasets (Yeh et al., 2008; EIA, 2009; Shay et al., 2006; Sarica and Tyner, 2013), which specify supply curves that represent future fuel price and availability as a set of piece-wise continuous steps. While the AEO utilizes supply curves, a retrospective analysis indicates that the fuel price prediction error more than 1 decade in the future is often greater than 40% compared to the realized value (AEO Retrospective Review, 2011). In addition, a review of the AEO (EIA, 2012) indicates low cross-price elasticities over the next 2 decades: an increase in one fuel price (e.g., coal) has a less than 10% effect on other fuel prices (e.g., oil, natural gas). Although the fuel price interaction effects are non-negligible, the fuel price prediction errors are significantly larger. As a result, we make the simplifying assumption that fuel price trajectories are independent of one another.

Given the focus on EDV deployment, the database contains significant technological detail in the transportation and electric sectors. The electric sector contains 32 generation technologies and 71 pollution control retrofits to reduce NO_X and SO_2 emissions from existing coal-fired power plants. Because the electric sector is modeled explicitly, the price of electricity is determined endogenously.

The transportation sector includes light duty, heavy duty, and off highway vehicles. There are 85 light duty vehicle technologies, which consist of 7 vehicle size classes, 6 fuel types, and 13 vehicle types. Much of the vehicle cost and performance data is derived from EPA (Shay et al., 2006), but vehicle cost information is updated based on AEO (EIA, 2012), and EDV performance data are drawn from the Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) Model (GREET, 2012). The following EDV technologies, ordered by their all-electric range (AER) in kilometers, are modeled: HEV, PHEV20, PHEV60, and BEV160. Hurdle rates are used to adjust the amortized cost of alternative fuel vehicles relative to conventional gasoline vehicles in order to partially capture non-market factors that may affect their deployment. We allow alternative vehicle shares to reach the same levels as in the AEO reference case without a hurdle rate, but additional deployment beyond AEO levels requires the use of alternative vehicles with a hurdle rate.

Studies conducted using surveys have estimated hurdle rates for alternative vehicle purchases in the range of 20-50%, with most estimates closer to the low end of this range

(Peterson and Michalek, 2013; Mau et al., 2008; Horne et al., 2005). However, applying a 20% hurdle rate to all alternative vehicle technologies resulted in zero market share across the 108 scenarios tested. While interesting, we view this result as implausible, as hurdle rates are uncertain and likely to decrease over time as technology improves, market penetration increases, and recharging infrastructure becomes more available. Therefore, in the absence of literature quantifying how hurdle rates may change over time, we simply employ a constant 10% hurdle rate, which is large enough to keep additional alternative vehicles out of the reference case (i.e., reference case fuel prices and battery cost as well as no new policy). As a result, we assume that consumers make decisions based largely on vehicle cost-effectiveness. Details on the hurdle rate calculation are provided in Section A2 of Appendix A. We note that while sophisticated consumer choice models exist and are used to predict future vehicle deployment (NRC, 2013; Lin and Greene, 2010; Heckmann et al., 2013), incorporation of such methodology into an energy system model is beyond the scope of the current analysis.

The remaining end-use sectors (commercial, industrial, residential) each contain a single aggregate energy demand with no explicit representation of demand devices. Instead, base year 2010 fuel consumption is constrained to historical shares, and the projected AEO (EIA, 2012) fuel shares serve as the basis for lower bound fuel share constraints that are gradually relaxed over time (Figures A2-A4 and Equations B.20 and B.21). Because there are minimum required electricity shares in these end-use sectors, the resultant price for electricity is affected not only by transportation demand, but by demand in the other end-use sectors as well. While the lack of technology detail is a key simplification, we assume that technology switching in these end use sectors will have a limited effect on vehicle deployment.

2.3 SCENARIO DESCRIPTION

For decades, scenario analysis has been used as a way to generate insights about the future that lead to improved strategic management (Schwartz, 1996). Scenarios provide a way to systematically organize our perceptions about the future to see how they might play out (Schwartz, 1996). The resultant model-based scenarios can then be used to challenge and inform our mental models about the future (Schwartz, 1996; Kates et al., 1985).

While scenarios provide a self-consistent way to explore future outcomes, a small set of highly detailed scenarios can create compelling storylines that are prone to cognitive biases, which often leads to systematic overconfidence in the presented results (Morgan and Keith, 2008). We try to mitigate the effect of cognitive biases by examining a large number of composite scenarios based on 5 factors likely to affect the cost-effectiveness of EDVs relative to other vehicle technologies: natural gas price, crude oil price, EDV battery cost, a federal cap on CO_2 emissions, and a federal RPS. A key simplifying assumption is that these factors only interact weakly, and therefore can be treated independently. Figure C1 in Appendix C represents an influence diagram that illustrates how scenario parameters affect the marginal price of fuel and electricity, which affect technology deployment and utilization, and ultimately emissions. The total number of modeled scenarios is 108, which represents every combination of assumptions specified in Table 2.1 For example, 1 of the 108 scenarios involves low natural gas prices, high oil prices, a CO_2 policy, a federal RPS, and reference case EDV battery cost. The assumptions made in each set of scenarios are outlined in the subsections below. Table C3 in Appendix C provides a complete enumeration of scenarios.

Table 2.1 Scenario assumptions in 2050

Factor	**Low**	**Reference**	**High**
Natural gas prices ($/GJ)[1]	4.5	7.8	8.7
Crude oil prices ($/bbl)[1]	62	145	200
Battery Cost ($/kWh)[1]	304	135	700
	No	**Yes**	
Federal CO_2 cap[2]	NA	40% reduction below 2010 levels	
Federal RPS[2]	NA	20% renewables	

[1] Drawn from AEO2012 (EIA, 2012)
[2] See Appendix C for more details.

2.3.1 Baseline Assumptions

Several assumptions regarding the domestic U.S. energy market are consistent through all 108 scenarios. Twenty-nine states currently have legal binding renewable portfolio standards (Equation B.10), which require a minimum percentage of electricity to come from renewable sources (DSIRE RPS, 2013). The overall minimum share of renewable energy for all states is 2% in 2010 and it gradually increases to 13% by 2025 (EIA, 2012). The new CAFE standard and the corresponding greenhouse gas (GHG) emissions rate limit (EPA Federal register, 2012) are described by Equations B.17 and B.18 and included in the base case assumptions. LDVs are expected to reach a fleet-wide average fuel economy of 49.6 miles per gallon and GHG emissions of 163 grams CO_2 per mile in model year 2025, per the NHTSA and EPA requirements, respectively (AEO, 2012). Consistent with AEO (AEO, 2012), the NHTSA standard of 49.6 miles per gallon is multiplied by a degradation factor of 80% to approximate on-road fuel economy. To factor out the effects of improved air conditioning which we do not model, the EPA standard is implemented as 185 grams CO_2 per mile to only capture the effects of improved energy efficiency.

The upper bound constraints on SO_2 and NO_x emissions from the electric sector (Equation B.9) are based on AEO (EIA, 2012) and include implementation of the Mercury and Air Toxics Standards (MATS) (U.S. EPA, 2012) and the Cross-State Air Pollution Rule (CSAPR) (U.S. EPA, 2013). The renewable fuel requirements in the transportation sector (Equations B.14, B.15, and B.16) are based on the Energy Independence and Security Act of 2007 (EPA RFS, 2013). The upper bound on cellulosic ethanol availability from 2015-2020 is obtained from the Renewable Fuel Standard (RFS, 2013) and held constant from 2025 to 2050, while the lower bound is based on AEO projections to 2035 (EIA, 2012) and linearly extrapolated to 2050. Finally, the effect of existing fuel subsidies and tax credits for new vehicles, drawn from AEO (AEO, 2012), are included in the baseline cost assumptions.

2.3.2 Natural gas prices

The future price of natural gas is a key factor that will affect future U.S. energy system development. In particular, the recent boom in shale gas exploration has dramatically increased the proved reserves of wet natural gas, rising from approximately 6 trillion m^3 in 2007 to 9 trillion m^3 in 2010 (AEO, 2012). In the AEO (AEO, 2012), the impacts of total recoverable shale gas resources are examined by defining 4 scenarios in which the estimated ultimate recovery (EUR) and well density are varied. To limit the number of scenarios but also explore the full range of projected natural gas prices, we adopt the resultant AEO natural gas prices from the Low EUR, Reference, and High Total Recoverable Resources (TRR) scenarios. Additional information is provided in Appendix C.

2.3.3 Oil Prices

A key determinant of future vehicle deployment in the U.S. will be the prevailing price of crude oil. To explore the effect of different oil price trajectories, we adopt the resultant crude oil price trajectories produced in the Low, Reference, and High Oil Price cases of the AEO (EIA, 2012). The price differences between the three scenarios stem from demand uncertainty in non-OECD countries, the cost of non-OPEC supply, OPEC investment and production decisions, and the economics of alternative liquid fuel supplies (AEO, 2012).

2.3.4 CO_2 policy

A federal cap-and-trade system for greenhouse gas emissions has the potential to produce large impacts throughout the U.S. energy system. While several bills have been introduced in the U.S. Congress, none have been signed into law (U.S. EPA legislative analyses, 2013). Based on a review of 4 proposed federal climate policies, which are outlined in Appendix C, we chose to model a cap on national CO_2 emissions level that requires a 40% reduction in the 2010 energy-related emissions level by 2050 (Equation B.22). For simplicity, we omit consideration of current state-level GHG targets such as California's AB32 (CEPA, 2013) or the Regional Greenhouse Gas Initiative (RGGI) (RGGI, 2013). The federal CO_2 cap enters into force with a 5% reduction in the 2015 model period, and we assume uniform, linear reductions each 5-year period until a 40% reduction is achieved in 2050.

2.3.5 Renewable portfolio standard (RPS)

The federal renewable portfolio standard modeled in this study is based on a recent proposal contained in Title I of the American Clean Energy and Security Act of 2009 (H.R. 2454), which sets forth renewable energy purchase requirements (ACESA, 2009). Because the proposed federal standard is more aggressive than the aggregation of existing state policies (DSIRE state incentives, 2013), we adopt the percentages associated with H.R. 2454 as the lower bound constraint on renewable electricity generation in the RPS scenario and extend the required renewable share in 2039 to 2050 (ACESA, 2009). See Appendix C and Equation B.10 for more details.

2.3.6 Battery Development

Assumptions about the pace and scale of battery innovation will be a key determinant of EDV cost-effectiveness relative to other vehicle technologies. We adopt high, reference, and low battery cost assumptions. The high battery cost scenario assumes constant EDV cost over the entire model time horizon. The reference battery cost scenario is drawn from the AEO Reference case, which assumes a battery cost of 304 $/kWh in 2035 (AEO, 2012). The low cost battery scenario considers attainment of program goals set forth by the DOE's Office of Energy Efficiency and Renewable Energy, which assumes a battery cost of 135 $/kWh in 2035 (EIA Today In Energy, 2013). We only include effects on battery investment cost, not increased efficiency or reduced EDV weight over time, given the uncertainty inherent in such estimates.

2.4 RESULTS AND DISCUSSION

The insights discussed below are drawn from analysis of the 108 scenario results. For reference, the scenario-specific EDV deployment as well as CO_2, SO_2, and NO_X emissions are included in Appendix C (Table C3).

2.4.1 Technology Deployment in Two Extreme Scenarios

Figure 2.1 displays results from the electric and LDV sectors for 2 of the 108 scenarios: the lowest EDV deployment (left) and the highest EDV deployment (right). The lowest EDV deployment corresponds to high natural gas prices, low oil prices, no RPS, no CO_2 policy, and high battery cost. Without a CO_2 policy or RPS, the electric sector is driven largely by generation from combined-cycle natural gas, coal steam, and light water nuclear reactors. The combination of low oil prices and high battery cost prevent EDV deployment.

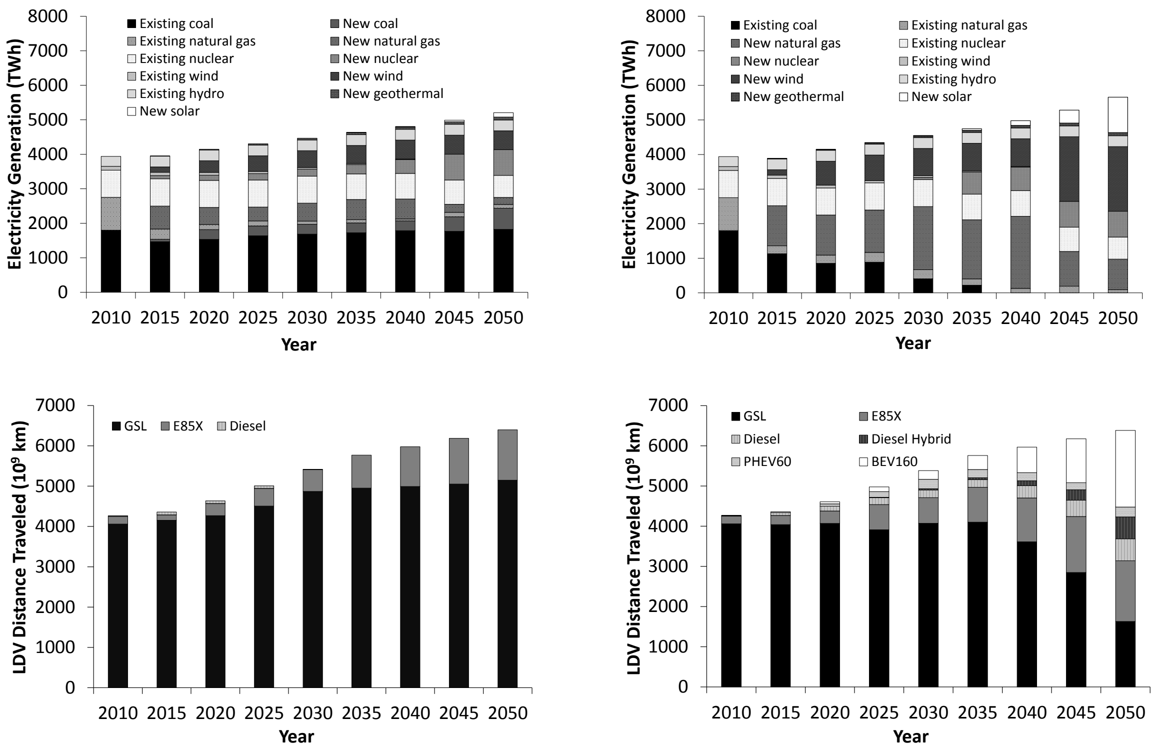

Figure 2.1 Electric generation by plant type (top) and travel demand met by different light duty vehicle types (bottom) over time for the lowest EDV deployment scenario (left) and the highest EDV deployment scenario (right). The lowest EDV deployment corresponds to low oil prices, high natural gas prices, no CO_2 cap or RPS, and high battery cost. The highest EDV deployment corresponds to high oil prices, low natural gas prices, a CO_2 cap and RPS, and low battery cost.

By contrast, the highest deployment of EDVs corresponds to low natural gas prices, high oil prices, the RPS, the CO_2 policy, and low battery cost. In the electric sector, the existing coal power plants are retired by 2040 in favor of natural gas and renewables due to the combined effect of the CO_2 cap and the RPS. In the LDV transportation sector, a combination of BEV160, diesel, and diesel hybrids meet growing demand and replace retired vehicles by 2050. In this scenario, dramatic reductions in battery cost coupled with low electricity prices relative to liquid fuels make BEV160s and PHEV60s the most cost-effective EDV alternatives in the long run. In the remaining end use sectors (i.e., commercial, industrial, and residential), the fuel shares gradually shift from fossil fuel combustion to low carbon electricity.

2.4.2 Effects of Scenario Drivers on EDV Deployment

One metric to assess the role of EDVs is the total share of the LDV market in 2050 met by a combination of hybrid, plug-in hybrids, and electric vehicles. Figure 2.2 summarizes the results across all scenarios as a series of boxplots that represent the total EDV share within the LDV market when a particular scenario parameter is held fixed. For example, the box representing 'NG-Low' represents the EDV deployment across the 36 scenarios in which natural gas prices are assumed low. For each box, the circle represents the median, the edges of the box represent the 25th and 75th percentiles, and the whiskers extend to the maximum and minimum EDV deployment levels. The effects of oil price, battery cost, and CO_2 policy are clearly discernible because the median, quartiles, and range shift as the associated parameter values change. By contrast, the range and median values associated with natural gas (NG) prices and the RPS do not change.

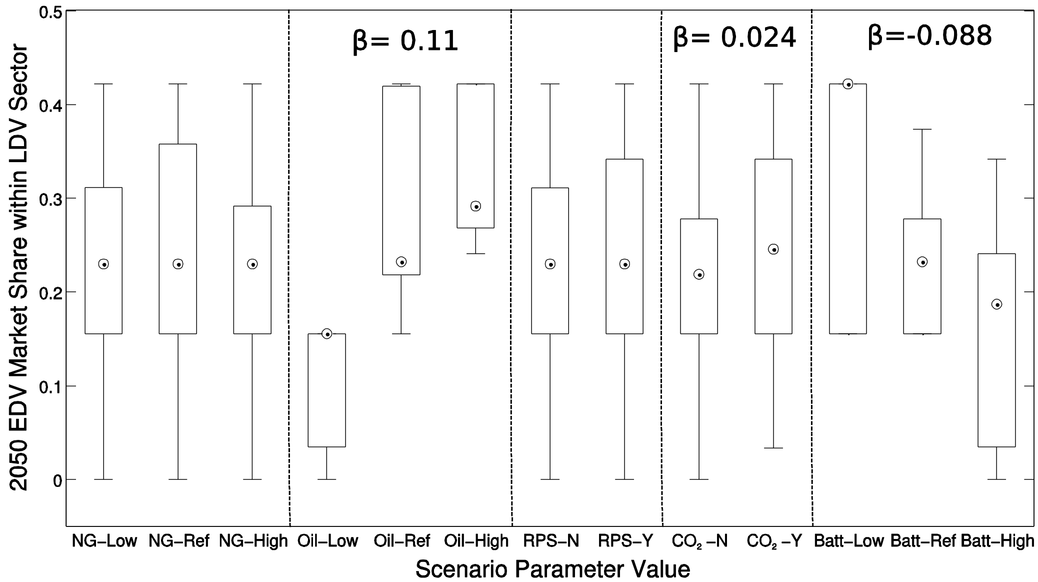

Figure 2.2 The projected range of 2050 EDV market share for each scenario parameter value. Each boxplot represents the variation in EDV market share when the given parameter value is held fixed but the others are allowed to vary. When the boxplots appear similar across all values for a given scenario parameter (i.e., natural gas price, RPS), it indicates that the effect of that scenario parameter is minimal. The β values represent the linear regression coefficients and express the fractional change in the EDV market share per unit change in each scenario parameter selected during the stepwise regression.

No EDV deployment occurs with high battery costs, low oil prices, and no CO_2 policy. At least 1 of these 3 scenario assumptions must change in order for EDVs to achieve some level of market penetration in 2050. As the scenario parameters shift to values more favorable to EDVs (i.e., ‘low’ to ‘high’ oil prices, ‘no’ to ‘yes’ on CO_2 policy, ‘high’ to ‘low’ on battery cost), the median market shares increase. The maximum EDV market penetration is 16% with the low oil price assumption versus 42% with reference or high oil prices. Similarly, high and reference battery costs limit EDV penetration to a maximum of 34% and 37%, respectively, whereas low battery costs enable the maximum market penetration of

42%. The maximum EDV market share is 42% because EDV deployment is largely limited to the compact and full size vehicle classes. EDVs in larger size classes are generally not cost-effective under the broad range of scenario assumptions we tested. The CO_2 cap results in marginal CO_2 prices of 37-125 \$/tCO_2, which all else equal, only increase EDV deployment by approximately 3%. This result is consistent with other studies demonstrating that CO_2 prices less than 100 \$/tCO_2 have little effect on EDV deployment (Traut et al., 2012; Shiau et al., 2010; Michalek et al., 2011; Shiau et al., 2009; Kammen et al., 2009).

A multivariate linear regression model was developed to further quantify the relative degree of scenario parameter influence on EDV deployment in 2050. All scenario parameters were converted into integer scores, starting with values of 0 for scenario parameters designated by ‘low’ or ‘no’. A stepwise linear regression was performed to identify the scenario parameters that improve model fit by increasing R^2. The regression coefficients are presented in Figure 2.2. The order of parameter selection in the stepwise regression was oil price, battery cost, and CO_2 cap, which were all significant at the 5% level. The resultant linear regression equation had an adjusted R^2 of 0.86. The CO_2 policy; however, increased the R^2 value by less than 1% when included. These results are consistent with Kammen et al., 2009 who found that battery cost and oil price are the two most significant factors driving EDV deployment. The natural gas price and RPS scenarios do not have a statistically significant influence on EDV deployment.

Across all scenarios, the total EDV deployment ranges from 0–42% of the LDV market with an average value of 24%, which is broadly consistent with other projections. For comparison, AEO projects 7.5-19% EDVs in 2035 (EIA, 2012), Yeh et al., 2008 project 32-

100% EDVs in 2050, and Wu et al., 2013 predict 100% EDVs in 2050. Within the EDV category, the average market share of HEVs, PHEVs, and BEVs in 2050 is 5%, 1%, and 18%, respectively, across the 108 scenarios in this analysis. The relatively low HEV adoption rate is due in part to the use of conservative GREET EDV efficiency data compared to the higher AEO (AEO, 2012) efficiencies used for conventional gasoline vehicles.

While the average market share of PHEVs and BEVs is roughly the same through 2030, BEV deployment begins to dominate post-2030. The long-run model preference for BEVs over PHEVs and HEVs is due to several factors: higher BEV efficiency, the generally lower cost for electricity compared to liquid fuels, and larger proportional benefits to BEVs associated with battery cost reductions. While the long-term trend towards BEVs differs somewhat from studies that focus on near term deployment (Michalek et al., 2011; Peterson and Michalek, 2013; Shiau et al., 2009; ANL, 2009), it is consistent with modeling studies that make projections to 2035 and beyond and show appreciable shares of BEVs (Wu et al., 2013; EIA, 2012).

2.4.3 Effect of EDV Deployment and Scenario Drivers on Emissions

Figure 2.3 illustrates how 2050 EDV deployment relates to the total system-wide CO_2, NO_X, and SO_2 emissions across the 108 scenarios. While the scenario parameters influence EDV deployment, the EDV deployment does not in turn produce a discernible effect on total system-wide emissions. There are three reasons for this lack of observed effect: at present the overall share of emissions from the LDV sector is only 20% of U.S. CO_2 emissions (EIA, 2012); EDV charging can still produce comparable emissions to conventional vehicles depending on the grid mix; and the effect of other sectors on emissions is significant. Because the CO_2 policy has a large and direct effect on system-wide emissions, the emissions in the CO_2 and no-CO_2 policy cases are discussed in turn.

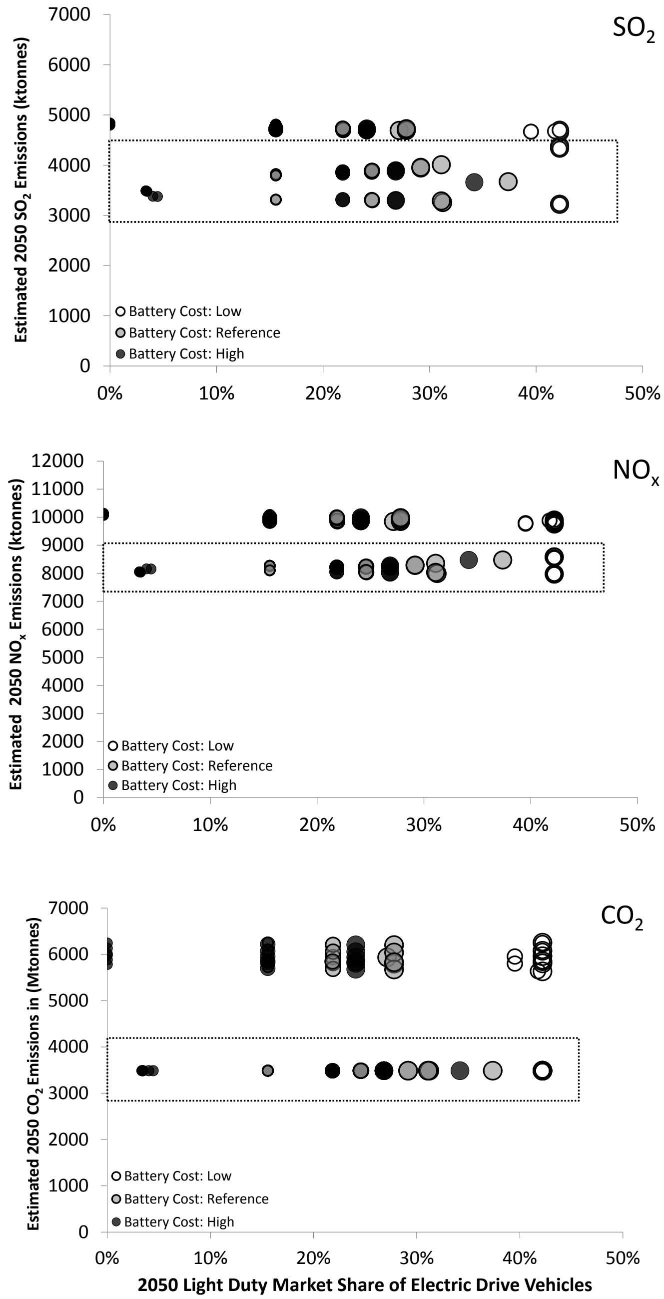

Figure 2.3 The estimated total system-wide SO_2 (top panel), NO_X (middle panel), and CO_2 (bottom panel) emissions in 2050 associated with the 2050 market share of light duty travel demand met by EDVs in each of the 108 scenarios. Scenarios with higher oil prices and lower battery costs are presented with larger bubbles and lighter colors, respectively. Scenarios with a CO_2 policy are enclosed by the dashed boxes. The horizontal spread is largely related to the oil price and battery cost, while the vertical spread is determined by the natural gas price and RPS.

In the 54 scenarios without a CO_2 policy, the horizontal position of the 2050 emissions levels are determined largely by the prevailing oil price and battery cost, while the vertical spread is determined largely by the natural gas price and the RPS. Although low natural gas prices and the presence of the RPS do not produce an effect on EDV deployment, they do affect system-wide emissions. The RPS reduces electric sector emissions by forcing a minimum share of renewables, which produces a modest reduction in system-wide emissions. Similarly, lower natural gas prices lead to higher shares of new natural gas rather than coal capacity in the electric sector. The result is uniformly lower system-wide SO_2, NO_X, CO_2 emissions at lower natural gas prices.

By contrast, the CO_2 policy imposes a binding constraint on system-wide CO_2 emissions, which results in 54 scenarios with 2050 emissions of approximately 3500 $MtCO_2$. In these cases, the SO_2 and NO_X also decrease because much of the conventional coal capacity in the electric sector is retired.

Since oil price and battery cost have the largest effect on EDV deployment, we can better isolate the effect of EDV deployment on emissions by varying these scenario parameters while holding the others constant. Figure 2.4 presents the sector-specific differences in 2050 emissions between high and low EDV deployment scenarios without the CO_2 cap (top panel) and with the CO_2 cap (bottom panel). The high deployment scenario assumes high oil prices and low battery cost, while the low deployment scenario assumes low oil prices and high battery cost. All 4 scenarios assume reference case natural gas prices and no RPS. Without the CO_2 cap, there is no change in electric sector SO_2 and NO_X emissions because the air pollution constraints remain binding. The system-wide net decrease in SO_2 and NO_X

(approximately 3% for each) is largely unrelated to EDV deployment: higher oil prices lead to fuel switching in the fuel supply, heavy duty vehicle (HDV), and end-use sectors. Also without the CO_2 cap, high EDV deployment creates a 21% reduction in LDV CO_2 emissions but a 13% increase in electric sector CO_2 emissions. Accounting for additional changes across the remaining sectors, the net system-wide effect is a slight 0.9% decrease in total CO_2 in 2050. EPRI similarly finds little change in electric sector SO_2 and NO_X emissions due to PHEV deployment and an 11% increase in electric sector CO_2 emissions in 2030 (EPRI, 2007). The CO_2 cap is binding when in effect, so lower tailpipe CO_2 emissions from high EDV deployment are compensated by higher CO_2 emissions in the electric sector. As a result, high EDV deployment can enable the retention of some existing coal in the electric sector, which increases both electric sector SO_2 and NO_X emissions by approximately 24% and 7% respectively in 2050, because the air pollution limits are no longer binding.

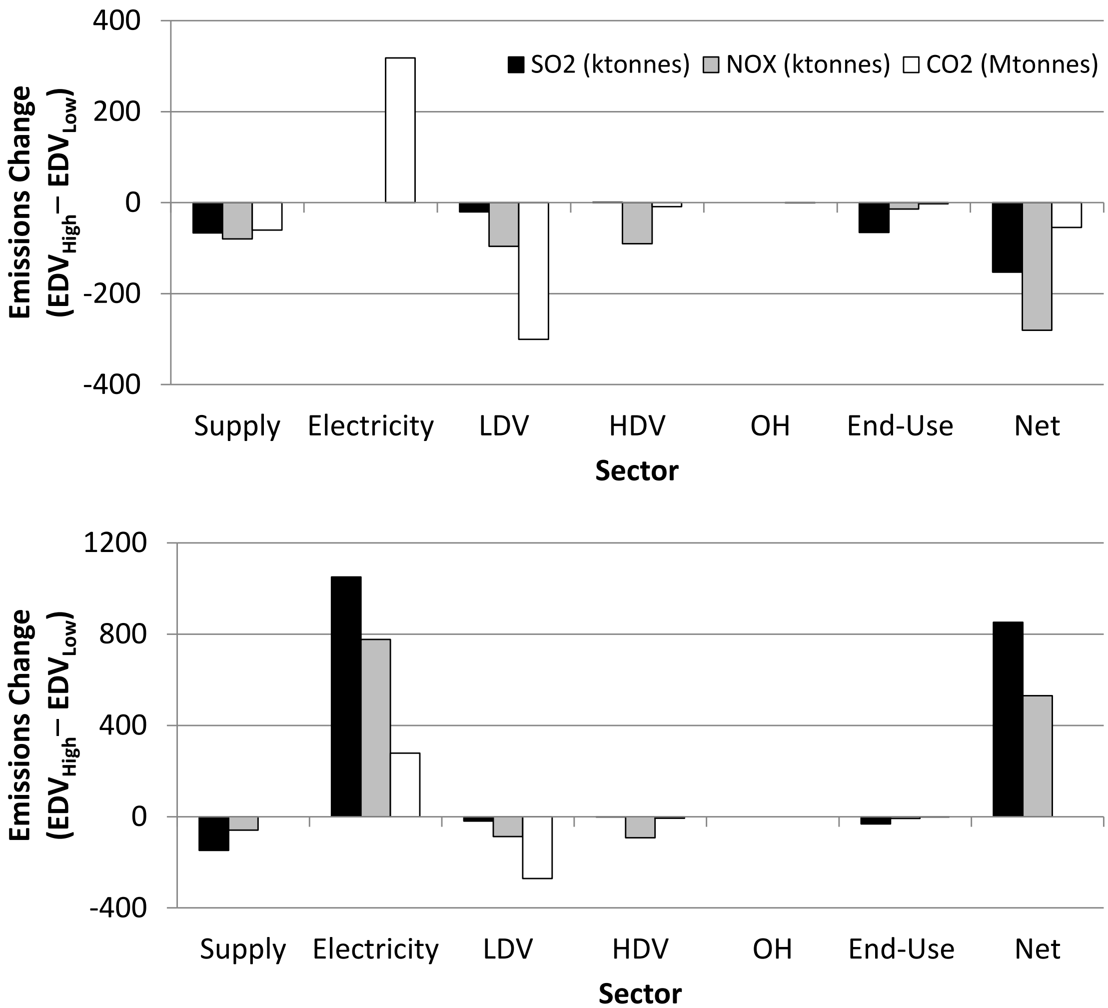

Figure 2.4 Year-2050 sectoral differences in SO_2, NO_X, and CO_2 emissions between high and low EDV deployment scenarios without the CO_2 cap (top panel) and with the CO_2 cap (bottom panel). High EDV deployment assumes high oil prices and low battery cost; low EDV deployment assumes low oil prices and high battery cost. Both sets of scenarios assume reference case natural gas prices and no RPS. 'HDV' represents the heavy duty vehicle sector, 'OH' represents off highway vehicles, and 'End Use' represents the end use sectors other than transport (i.e., commercial, industrial, residential). 'Net' represents the net emissions change across the whole system.

To quantify the benefit of EDV deployment, the model was run again in the CO_2 constrained scenarios exhibiting the highest and lowest EDV deployment, but without the availability of EDVs. Comparing the difference in the marginal CO_2 price between the EDV and no-EDV runs in both scenarios, the cost savings associated with EDV deployment ranges from approximately 30–200 \$/tonne CO_2 in 2050. While there is much uncertainty associated with these price estimates, they nonetheless suggest that EDVs can provide an economic benefit under a CO_2 policy, though their deployment must be driven by other factors such as oil price and battery cost.

2.5 POLICY IMPLICATIONS

The model results do not demonstrate a clear and consistent trend towards lower system-wide emissions as EDV deployment increases. Differences in net emissions among scenarios do not stem exclusively from the tradeoff between lower vehicle tailpipe emissions and higher electric sector emissions; rather, the scenarios can produce systemic effects that mask the effect of EDVs, as shown in Figure 2.4. Therefore, it is not enough to simply incentivize the purchase of EDVs and wait for emissions benefits to accrue. The emissions benefits – if any – will depend on a broad set of future conditions. Therefore, public policies that target EDV deployment should be formulated, reviewed, and revised with careful attention paid to evolving changes to the broader energy system over time.

If the primary objective is to reduce emissions, policy makers should focus on implementing targeted emissions policy rather than the promotion of specific technologies or fuels. Among the scenario variables tested, the CO_2 cap produced the largest and most consistent drop in CO_2, SO_2, and NO_X emissions. Although the observed marginal CO_2 prices do not drive significant EDV deployment, the results indicate that EDVs can help lower the marginal price of CO_2, particularly if scenario variables favorable to EDVs (high oil prices, low battery cost) prevail.

In the absence of a CO_2 policy, the promotion of clean electricity can provide direct emissions reductions and also lower the emissions footprint from vehicle charging. The new EPA proposed carbon pollution standard and the forthcoming proposed rule on existing coal-fired power (due out in 2014) could have a significant impact on national emissions and eliminate some of the potential emissions increases associated with vehicle charging (U.S. EPA Carbon Pollution Standards, 2013).

Finally, other alternative vehicles are worth a mention. First, compressed natural gas (CNG) vehicles are not cost-effective in any scenario, including those with low natural gas prices, because low CNG prices are not enough to overcome the higher investment costs. Second, the model deploys diesel and diesel hybrids in many scenarios, which may be a cost-effective way to reduce CO_2 emissions given their higher efficiency compared to conventional gasoline vehicles.

While this analysis provides useful insight into the role that EDVs may play in the future, a few caveats should be noted. First, we do not capture the potential air quality benefits due to shifting emissions out of dense urban areas to more remotely located power plants where emissions from large point sources are easier to control. Second, we do not explicitly map the all electric range (AER) for plug-in vehicles to the annual distribution of daily trip lengths. However, we note that the highest penetration of BEV160 in the model results is 30%, which can be assumed to meet 87% of the daily trips less than 160km in length (Bradley and Quinn, 2010) in the 59% of households with 2 or more vehicles (NHTS, 2009). Third, as noted above, the 10% hurdle rate applied to alternative vehicle technologies is relatively low compared to the 20-40% rates published in the literature, so EDV deployment should be considered optimistic. We conducted a sensitivity analysis of hurdle rates in the highest EDV deployment scenario and found there is a significant drop in EDV deployment as the hurdle rate increases from 12-14%, with no deployment of hurdle rate EDVs at 15%. While hurdle rates are a crude proxy of consumer choice, the results nonetheless indicate that prevailing consumer preferences pose a potentially serious challenge to large scale EDV deployment. Fourth, we assume vehicle charging is constant throughout the day. We investigate the effects of time-of-day charging on system-wide emissions in Chapter 4.

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Chapter 3: The Effect of Clean Electricity on CO_2 Emissions Reductions from Plug-in Electric Vehicles

3.1 INTRODUCTION

Plug-in vehicles (PEVs), which include both plug-in hybrid electric vehicles (PHEV) and battery electric vehicles (BEVs), have received significant attention from the research community, automotive industry, and policymakers. Annual PEV sales in the U.S. have increased rapidly from 345 in 2010 to approximately 97,000 in 2013, representing 3.8% of the market (EDTA, 2014). This rapid growth is due in part to improvements in battery technology and financial incentives at the federal and state level (DOE, 2010; DOE, 2014). There are currently over 40 different plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) under development or available on the U.S. market (PIA, 2014). By pushing some or all of the input fuel from gasoline or diesel to electricity, these vehicles have the potential to increase the security of US fuel supply, improve air quality, and reduce greenhouse gas emissions.

Given the threat of anthropogenic climate change, the efficacy of using PEVs to reduce national CO_2 emissions is a key concern and will depend in part on three interdependent factors: (1) the degree to which PEVs can penetrate the light duty vehicle (LDV) market, (2) the fraction of tailpipe CO_2 emissions offset by CO_2 emissions from the electric sector incurred through vehicle charging, and (3) the potential effect of changing electricity prices on PEV deployment, and vice versa. The role that these factors play in determining the net reduction in emissions will depend on a broad set of underlying system-wide conditions that unfold over time. While the U.S. Congress is unlikely to pass federal economy-wide climate legislation soon, there is increasing likelihood that more targeted electric sector policy may be implemented. For example, using their regulatory authority under the Clean Air Act, the U.S. EPA recently issued a set of rules pertaining to electric sector CO_2 emissions (U.S. EPA 2014; U.S. EPA 2013). The electric sector has remained a key target for greenhouse gas reductions given that existing power plants represent large, stationary point sources that can be replaced at relatively low abatement costs (Johnson and Keith, 2004). There are a limited number of plausible, targeted electric sector policies that can affect electricity prices and emissions, which can in turn affect PEV deployment and charging-related emissions. A key challenge is to quantify the incremental change in national CO_2 emissions from PEV deployment in response to changes in the electric sector over time.

Given large uncertainties over fuel prices, technological innovation, and potential energy and environmental policy, the future U.S. energy system and associated emissions have previously been modeled with a wide variety of scenarios and methods. Several studies, which treat electric sector emissions through a set of exogenous assumptions, indicate that significant emissions benefits from PEVs only begin to accrue with clean electricity (Traut et al., 2012; Samaras and Meisterling, 2008; Michalek et al., 201; Kammen et al., 2009; Hawkins et al., 2012). However, these studies do not indicate how the electric and transportation sectors may co-evolve over time in response to a set of drivers that can affect the net emissions from PEVs. Energy system models can address such issues by simultaneously optimizing technology capacity and utilization across the entire energy system over time in order to minimize cost, subject to a set of rules that constrain system performance due to technological limits or public policy. Several studies utilize energy system models to analyze changes in transportation over the next several decades. For example, Kyle and Kim (2011) and Wallington et al. (2010) explore the effect of technology deployment and CO_2 policy on alternative vehicle deployment and emissions abatement, but both are focused at the global level. Likewise, McCollum et al. (2012) and Bahn et al. (2013) employ the TIMES model generator to examine the effect of CO_2 policies on the transport sector and the broader energy system; however, these analyses are limited to California and Canada, respectively. EPRI and NRDC (2007) examined the emissions impact of PHEVs using an energy system model coupled to an electric sector model by examining three PHEV deployment scenarios along with three electric scenarios with varying CO_2 intensity. Sarica and Tyner (2013a) utilize a modified EPA MARKAL model to examine the effects of different policy and technology scenarios on the uptake of biofuels. Yeh et al. (2008) explore the effects of an economy-wide and transportation-only CO_2 cap as well as biofuel mandate on the light duty vehicle market. Sarica and Tyner (2013b) also use MARKAL to examine the economy-wide changes in primary energy consumption and CO_2 emissions in response to different policy scenarios, including a new CAFE standard, renewable fuel standard, clean energy standard, and federal carbon tax. AEO (2014) also utilizes the NEMS model to produce a mid-term forecast of the U.S. energy system, but they do not specifically focus on the effect of PEV deployment. While all of these studies make a unique contribution to the literature, none specifically addresses an important question: How might U.S. CO_2 emissions change over time due to PEV deployment under targeted efforts to reduce electric sector emissions?

In addition to these studies, we previously employed an energy system model to examine PEV deployment within the light duty vehicle (LDV) market in response to a broad set of conditions: different projections of oil price, natural gas price, vehicle battery cost, a federal renewable portfolio standard, and a CO_2 cap (Chapter 2; Babaee et al., 2014). We found that the oil and the battery cost exert the greatest influence on PEV deployment, which is consistent with previous studies (e.g., Kammen et al., 2009). Furthermore, across these various scenario conditions, the model results did not demonstrate a clear and consistent trend towards lower system-wide emissions as EDV deployment increased. This result is due to a couple factors. First, LDV emissions represent a relatively small share of the overall total (e.g., 20% of U.S CO_2 emissions in 2010), so emissions changes across the broader energy system induced by the modeled scenarios can partially mask the emissions effects due to PEV deployment. Second, lower tailpipe emissions are partially offset by high electric sector emissions. In the scenarios without a CO_2 cap, the CO_2 intensity of electricity in 2050 only decreased by 10-30% compared to the current value of 1220 lbs/MWh (EPA eGRID, 2007). In the scenarios with a national CO_2 cap, we found that the availability of EDVs reduces the price of CO_2 emissions by 30-200 \$/tCO_2 in 2050. While electricity CO_2 intensity decreased by 90-99% in 2050, the cap was binding in all cases so higher EDV deployment did not lead to larger emissions reductions. These results led us to consider a set of targeted electric sector scenarios that could reduce emissions over time, thereby increasing the efficacy of using PEVs to further reduce CO_2 emissions.

This paper fills a gap in the literature by employing an energy system model to quantify the incremental impact of PEV deployment on national U.S. CO_2 emissions through mid-century under different electric sector scenarios. We consider a base case and three different future electricity policy scenarios: a federal renewable portfolio standard, a clean energy standard, and the proposed EPA power sector rules. In addition, we examine a separate no-policy scenario that assumes accelerated technological innovation in wind and solar technology that drives lower investment costs. Under all scenarios, we assume conditions favorable to PEV deployment in order to quantify the maximum expected emissions benefits. To perform the analysis, we employ the TIMES modeling framework coupled to the National US TIMES Dataset (NUSTD). NUSTD is an open source, TIMES-compatible dataset we developed to examine the impacts of electric drive vehicle deployment on US emissions (Energy Modeling, 2014). TIMES-NUSTD models all sectors of the economy, and therefore captures the system-wide effects induced by policy on technology deployment and utilization as well as the resultant emissions of CO_2, SO_2, and NO_X. The paper is organized as follows. Section 2 presents a set of simple calculations to bound the model-based analysis, Sections 3 and 4 describe the TIMES modeling framework and input dataset used to conduct this analysis, Section 5 presents the modeling results, and Section 6 draws high-level insights regarding the effect of PEVs on national CO_2 emissions under different electricity scenarios.

3.2 BOUNDING THE MODEL-BASED ANALYSIS

We develop a simple set of calculations that bound the potential emissions benefits from PEVs and serve as a check on the model-based analysis presented in Section 3.5. For simplicity, we use current vehicle performance data and reduce the system complexity to two key variables: the CO_2 intensity of electricity used for vehicle charging and the BEV market share within the LDV sector.

Table 3.1 presents data drawn from EPA TRENDS (2013), which is ultimately used to estimate the reduction in national emissions if each LDV size class switches from gasoline to BEVs. The first two rows represent the market share and vehicle fuel economy associated with each vehicle size class, respectively. In Row 3, the fuel economy associated with the gasoline vehicle is then converted to the equivalent electricity requirement for a BEV, assuming a 20% thermal efficiency for the internal combustion engine and an 85% battery charge/discharge efficiency. For simplicity, we do not account for the additional weight associated with the equivalent BEVs, which would increase the electrical energy requirement (Shiau et al., 2010). Rows 4 and 5 present the associated CO_2 emissions per gasoline and electric vehicle if traveled 12,000 miles/year, respectively (ORNL, 2013). For the BEVs, we assume that electricity used for vehicle charging emits 1220 lbs/MWh, corresponding to the national average CO_2 intensity of electricity (EPA eGRID, 2007).

Table 3.1 Average CO_2 emissions per gasoline and electric vehicle in each size class

	Vehicle Class					
	Car	**Wagon**	**Non-Truck SUV**	**Van**	**Truck SUV**	**Pickup**
Market Share	0.531	0.039	0.068	0.051	0.210	0.100
Fuel Economy (km/lit)	11.8	12.0	10.3	8.96	8.59	7.35
Electricity Requirement (kWh/km)	0.178	0.175	0.204	0.234	0.244	0.285
Gasoline: CO_2 emissions (tonnes/yr)	3.85	3.78	4.41	5.05	5.27	6.16
Electric: CO_2 emissions (tonnes/yr)	1.90	1.86	2.17	2.49	2.60	3.03

Using the data in Table 3.1, displacing gasoline with electricity results in an approximately 50% reduction in CO_2 emissions within each vehicle size class. Next, we estimate the reduction in national CO_2 emissions associated with each vehicle class switching from gasoline to electricity, assuming that LDVs are currently responsible for 20% of U.S. CO_2 emissions (EIA, 2012). Figure 3.1 shows the resultant cumulative reduction in national CO_2 emissions as vehicle size classes with progressively lower fuel economy and higher electricity requirements are switched from gasoline to electricity. While BEVs will likely continue to penetrate multiple segments of the vehicle market simultaneously, we generally expect that smaller electric vehicles requiring smaller, less expensive batteries are likely to be deployed in proportionally larger numbers first. Figure 3.1 includes two trajectories: an upper line assuming CO_2-free electricity, and a lower line assuming electricity with the current national average CO_2 intensity. If BEVs took over the entire car and wagon classes representing 57% of the LDV market, the total reduction in total US CO_2 emissions would be 5% with the current electricity mix, and 10% with CO_2-free electricity. An electricity grid with a lower CO_2 intensity than today, perhaps under new policy, will result in a trajectory that falls between the two extremes plotted in Figure 3.1. In addition, non-zero PHEV market share will lead to lower CO_2 reductions, as those vehicles consume some gasoline.

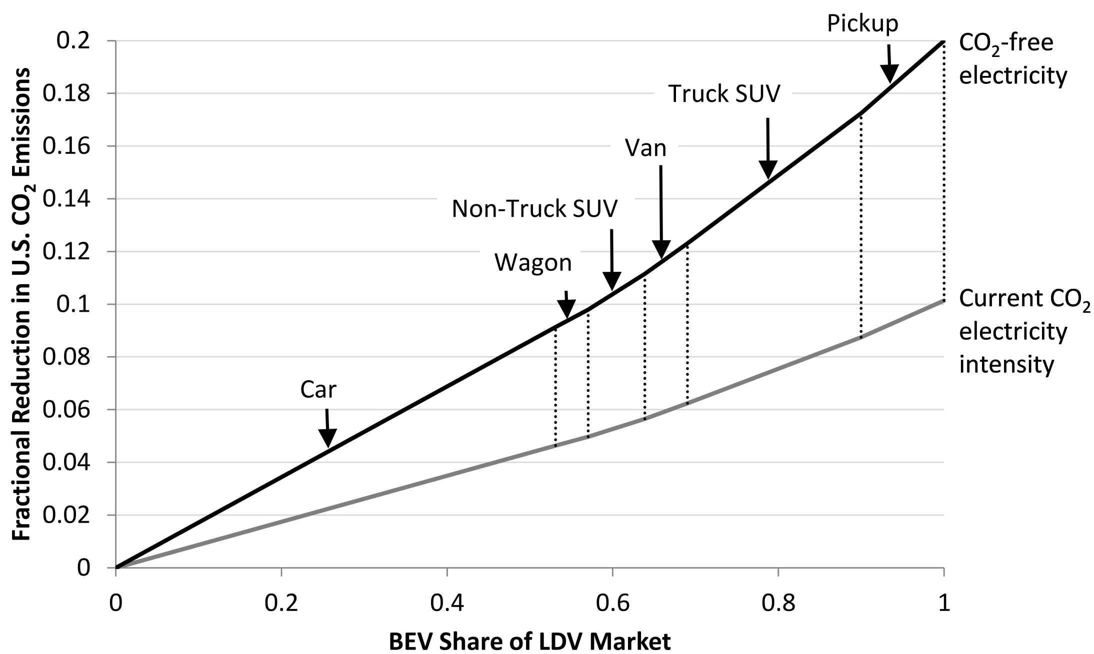

Figure 3.1 The cumulative share of national CO_2 emissions displaced as a function of LDV market share met with electric vehicles. The top line represents the case where electricity used to charge electric vehicles is CO_2-free, and the bottom line represents the case where electricity with the average U.S. CO_2 intensity of 1216 lbs/MWh is used to charge electric vehicles. The label associated with each segment represents the size class added to obtain the given market share; ordering progresses from the highest to lowest fuel economy. Note that wagons have slightly higher overall fuel economy than cars, but we reversed the ordering to more clearly see the effect from cars alone. Market shares in 2012 based on ORNL (2013).

While based on simple calculations, Figure 3.1 provides a useful set of bounds that help ground the model-based results presented in Section 3.5. However, there are several key considerations not addressed by this simple, static analysis. First, although we generally expect PEV market deployment to occur in the smaller size classes first given the lower absolute battery costs, simultaneous deployment across different vehicle size classes will affect the shape of the curves above. Second, the LDV share of total national CO_2 emissions may not remain fixed at 20%, as emissions across the energy system change over time. Third, the shift from gasoline to electricity in the LDV sector will also produce changes across the broader energy system (e.g., a shift in emissions from oil drilling to coal mining or natural gas drilling) that will also affect net emissions. Fourth, electric sector CO_2 intensity will change dynamically in response to a variety of factors that exert their influence over time. Fifth, the marginal CO_2 intensity associated with PEV charging may be quite different from the average CO_2 intensity of the electric sector. Sixth, PEV deployment and associated emissions changes will be driven by the prevailing prices for competing technologies and fuels. Policy or technological change in the electric sector will affect electricity prices, which in turn may affect PEV deployment. Conversely, electric demand associated with PEV charging may affect the electric sector mix and electricity prices. The TIMES-NUSTD model described in Section 3.3 addresses these issues by exploring the dynamic co-evolution of the energy system in response to prevailing market conditions and different energy and environmental policy scenarios.

3.3 MODEL AND DATA DESCRIPTION

The model used for this analysis consists of two components: The Integrated MARKAL-EFOM System (TIMES) (Loulou et al., 2005), which serves as a generic energy optimization framework and operates on the National U.S. TIMES Dataset (NUSTD), a TIMES-compatible dataset constructed specifically for this analysis.

3.3.1 The TIMES model generator

TIMES is a widely used bottom-up, technology rich energy system model, which represents an energy system as a set of networked technologies linked together via flows of energy commodities (Loulou et al., 2005). TIMES employs linear programming techniques to identify the optimal installed technology capacity and utilization in order to meet a set of end-use demands over time, subject to a number of built-in constraints that ensure proper operation of the energy system as well as user-defined constraints such as emissions limits and growth rate limits on specific technologies. Model outputs by future time period include the optimal installed technology capacity, commodity flows, marginal energy prices, and emissions. TIMES assumes rational decision-making, with perfect information and perfect foresight, and optimizes over an entire set of multi-year modeling periods simultaneously.

3.3.2 The National U.S. TIMES Dataset (NUSTD)

We developed NUSTD, a TIMES-compatible input dataset containing fuel prices; technology cost and performance estimates; and end-use demands to represent the U.S. as a single region over the next four decades. NUSTD was carefully documented in Babaee et al. (2014) and the updated workbooks required to run the model are publicly available (Energy

Modeling, 2014). Here we provide a brief summary of key data elements relevant to this study.

The model time horizon is 2010 to 2050, with 5-year time periods. Intra-annual variation in demand and renewable resource availability is represented by specifying 3 seasonal (i.e., summer, winter, and intermediate) and 4 diurnal (i.e., morning, mid-day, afternoon/evening, and night) time segments. The U.S. is modeled as a single region with no interregional trade. A 5% social discount rate is used to convert future expenditures into present cost. As described below, a 10% hurdle rate is applied to all alternative vehicle technologies.

An overview of the energy system representation in NUSTD is provided in Figure 3.2. Conceptually, NUSTD can be categorized into several different sectors: fuel supply, electric, transport, and the remaining end-use sectors (i.e., commercial, residential, industrial). Fuel supply is represented by a set of exogenously specified fuel prices drawn from the output to the Annual Energy Outlook (AEO) 2012 (EIA, 2012).

Given the focus on PEV deployment, the database contains significant technological detail in the transportation and electric sectors. The electric sector contains 32 generation technologies and 71 pollution control retrofits to reduce NO_X and SO_2 emissions from existing coal-fired power plants. Because the electric sector is modeled explicitly, the price of electricity is determined endogenously. As the model only represents 12 timeslices per year, it is impossible to accurately model the potential relaibility effects associated with intermittent renewables such as wind and solar. To represent the need for backup capacity to support intermittent renewables, we added a model constraint (Equation B.8) that requires one capacity unit of simple- or combined-cycle gas turbine capacity to be installed for every capacity unit of wind, solar photovoltaics, or concentrating solar thermal installed. This backup capacity constraint is loosely based on previous modeling work by Greenblatt et al. (2007) and DeCarolis and Keith (2006).

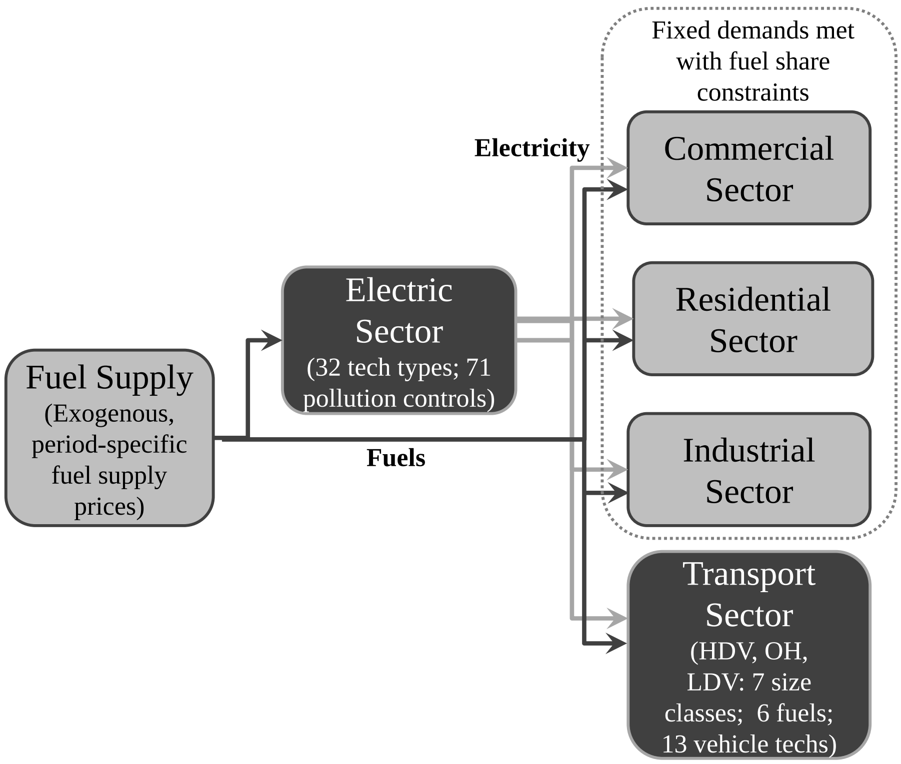

Figure 3.2 Schematic illustrating the design of the National U.S. TIMES Dataset (NUSTD). Given the focus on the emissions effects of PEV deployment, there is significant technology detail in the electric and transportation sectors. Fuel supply is modeled as a set of exogenously specified, period-specific price projections drawn from EIA (2012). The commercial, industrial, and residential sectors are modeled with fixed end-use demands that can be met with fuels whose shares are constrained.

The transportation sector includes light duty, heavy duty, and off highway vehicles. There are 85 light duty vehicle technologies, which consist of 7 vehicle size classes, 6 fuel types, and 13 vehicle types. Much of the vehicle cost and performance data is derived from

EPA (Shay et al., 2006), but vehicle cost information is updated based on AEO (EIA, 2012), and electric drive vehicle performance data are drawn from the Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) Model (GREET, 2012). The following PEV technologies, ordered by their all-electric range (AER) in kilometers, are modeled: PHEV20, PHEV60, and BEV160. Hurdle rates are used to adjust the amortized cost of alternative fuel vehicles relative to conventional gasoline vehicles in order to partially capture non-market factors that may affect their deployment. We allow alternative vehicle shares to reach the same levels as in the AEO reference case without a hurdle rate, but additional deployment beyond AEO levels requires the use of alternative vehicles with a hurdle rate. While studies conducted using surveys have estimated hurdle rates for alternative vehicle purchases in the range of 20-50 (Peterson and Michalek, 2013; Mau et al., 2008; Horne et al., 2005), our previous work in Chapter 2 indicates that applying even a 20% hurdle rate results in zero PEV deployment across a wide range of scenarios (Babaee et al., 2014). As a result, we assume that consumers make decisions based largely on vehicle cost-effectiveness.

The remaining end-use sectors (commercial, industrial, residential) each contain a single aggregate energy demand with no explicit representation of demand devices. Instead, base year 2010 fuel consumption is constrained to historical shares, and the projected AEO (EIA, 2012) fuel shares serve as the basis for lower bound fuel share constraints that are gradually relaxed over time (Figures A2-A4 and Equations B.20 and B.21). Because there are minimum required electricity shares in these end-use sectors, the resultant price for electricity is affected not only by transportation demand, but by demand in the other end-use sectors as well. While the lack of technology detail is a key simplification, we assume that technology switching in these end use sectors will have a limited effect on vehicle deployment.

3.4 SCENARIO INFORMATION

The promotion of clean electricity can provide direct emissions reductions and also lower the emissions footprint from vehicle charging. The effect of clean electricity generation on PEV deployment and total system-wide CO_2 emissions are investigated in 4 low carbon electricity scenarios and compared with a base case scenario.

3.4.1 Base Scenario

To clearly see the effect of PEV deployment on emissions, we focus on scenarios that result in high PEV deployment, which is informed by our previous work. In Chapter 2 (Babaee et al., 2014), we examined electric drive vehicle deployment across 108 different scenarios, where each scenario represents a unique combination of assumptions regarding future oil prices, natural gas prices, vehicle battery cost as well as the presence of a renewable portfolio standard and a national cap on CO_2 emissions. Similar to earlier studies (e.g., Kammen et al., 2009), we found that low battery cost and high oil prices have the greatest influence on PEV deployment. As such, we adopt the scenario from our previous analysis that leads to the highest PEV deployment without new policy, which corresponds to high oil prices, reference natural gas prices, and low battery cost. As a result, all scenarios in the current analysis – including the Base scenario – include these scenario conditions that lead to high PEV deployment. Fuel prices, with the exception of crude oil, are drawn from the EIA (2012) reference case projection. Oil-based commodity prices are drawn from the EIA (2012) High Oil Price Case. The low cost battery scenario considers attainment of program goals set forth by the DOE's Office of Energy Efficiency and Renewable Energy, which assumes a battery cost of 135 $/kWh in 2035 (EIA Today In Energy, 2013). We only include the effects on battery investment cost, not increased efficiency or reduced EDV weight over time, given the uncertainty inherent in such estimates.

Several assumptions regarding policy affecting the U.S. energy system are included in the base case, and therefore apply to the four alternative electricity scenarios as well. We account for the 29 existing state-level renewable portfolio standards (Equation B.10), which require a minimum percentage of electricity to come from renewable sources (DSIRE RPS, 2013). The overall minimum share of renewable energy for all states is 2% in 2010 and it increases to 13% by 2025 (EIA, 2012). The new CAFE standard and the corresponding greenhouse gas (GHG) emissions rate limit (EPA Federal Register, 2012) are included as constraints in the base case (Equations B.17 and B.18). LDVs are expected to reach a fleet-wide average fuel economy of 49.6 miles per gallon and GHG emissions of 163 grams CO_2 per mile in model year 2025, per the NHTSA and EPA requirements, respectively (AEO, 2012). Consistent with AEO (AEO, 2012), the NHTSA standard of 49.6 miles per gallon is multiplied by a degradation factor of 80% to approximate on-road fuel economy. To factor out the effects of improved air conditioning which we do not model, the EPA standard is implemented as 185 grams CO_2 per mile to only capture the effects of improved energy efficiency.

The upper bound constraints on SO_2 and NO_x emissions from the electric sector (Equation B.9) are based on AEO (EIA, 2012) and include implementation of the Mercury and Air Toxics Standards (MATS) (EPA MATS, 2012) and the Cross-State Air Pollution Rule (CSAPR) (EPA CSAPR, 2013). The renewable fuel requirements in the transportation sector (Equations B.14, B.15, and B.16) are based on the Energy Independence and Security Act of 2007 (EPA RFS, 2013). The upper bound on cellulosic ethanol availability from 2015-2020 is obtained from the Renewable Fuel Standard (EPA RFS, 2013) and held constant from 2025 to 2050, while the lower bound is based on AEO projections to 2035 (EIA, 2012) and linearly extrapolated to 2050. Finally, the effect of existing fuel subsidies and tax credits for new vehicles, drawn from AEO (AEO 2012), are included in the baseline cost assumptions. We do not include the recently proposed EPA regulations (EPA, 2014) on power sector CO_2 emissions in the base case, but rather model those in a separate scenario.

3.4.2 Renewable Portfolio Standard (RPS) Scenario

The modeled federal renewable portfolio standard is based on the Title I of the American Clean Energy and Security Act of 2009 (H.R. 2454, 2009). According to this proposal, the minimum requirement for renewable energy generation is 9.5% in 2015, which gradually increases to 20% by 2020 (Equation B.10). Eligible renewables under this policy include wind, solar photovoltaics and concentrating thermal, biomass gasification, and incineration of municipal solid waste. For simplicity, we assume that existing renewables are also eligible as their existing share was only 3% of 2010 electricity supply (EIA, 2012).

3.4.3 The EPA CO_2 Rules scenario

On April 13, 2012, the U.S. EPA proposed a new source performance standard (NSPS) for CO_2 emissions from electric generating units, including new fossil fuel-fired boilers, integrated gasification combined-cycle (IGCC) units, and natural gas-fired stationary combustion turbines (EPA, 2013). A CO_2 standard of 1100 lbs/MWh (499 kg / MWh) is proposed for new fuel-fired boilers, IGCC, and small gas-fired combustion turbines with a heat input rating less than 850 MMBtu/hr (897 GJ/hr). A CO_2 standard of 1000 lbs/MWh (454 kg / MWh) is proposed for large gas-fired combustion turbines with a heat input rating less than 850 MMBtu/hr. In this analysis, these emissions rate limits are applied to applicable new capacity in model year 2015 and remain in place through 2050 (Equation B.24).

In addition, on June 2, 2014, the U.S. EPA proposed emission guidelines for states to follow in developing plans to address greenhouse gas (GHG) emissions from existing fossil fuel-fired EGUs (EPA, 2014). Following Section 111(d) of the Clean Air Act (CAA), the proposed rule contains state-specific goals that reflect EPA's calculation of the achievable emission reductions by applying the "best system of emission reduction" (EPA, 2014). EPA has proposed two options: Option 1 requires larger emissions reductions over a longer timeframe, and Option 2 requires smaller emissions reductions over a shorter timeframe. Each state is expected to meet its target using four basic approaches: plant-level heat rate improvements, utilizing less carbon-intensive generation, and increasing demand-side efficiency improvements. EPA emphasizes that each state should develop its own strategy to meet the required emissions reductions, with the flexibility to act independently or on a regional basis through interstate cooperation. Given the long model timeframe, we chose to adopt Option 1, which requires a 30% reduction in electric sector emissions by 2030 relative to 2005 emissions. Given the nature of the TIMES-NUSTD model employed for this analysis, we do not model electric sector capacity at the plant level, and therefore cannot effectively consider potential heat rate improvements at individual plants. Also, because the end-use sectors include fixed demands, the model cannot employ end-use efficiency measures to help meet the required emissions reductions. Finally, the model is focused at the U.S. national level, so we cannot model state-level options as U.S. EPA does in their regulatory impact analysis (EPA, 2014). Instead, we apply a national-level constraint on electric sector CO_2 emissions that requires a CO_2 emissions reduction below 2005 levels of 26% in 2020, 29% in 2025, and 30% in 2030 (Table 3.2). The 30% upper bound constraint on total CO_2 emissions is extended from 2030 to 2050 in this scenario (Equation B.25). These reduction requirements must be met through the retrofit of existing fossil fuel-fired boilers with carbon capture and sequestration or the deployment of low or zero carbon emitting generating units. Because the emissions reductions must be met exclusively through changes in electric generation in this model scenario, the expected emissions benefit attributable to PEV deployment may be larger than in reality.

3.4.4 Clean Energy Standard Scenario

The Clean Energy Standard (CES) modeled in this study (Equation B.23) is based on Clean Energy Standard Act of 2012, which sets forth a minimum requirement for electricity purchase from clean power plants (S. 2146, 2012). The qualifying clean power technologies include solar, wind, geothermal, municipal solid waste, biomass, new nuclear, coal-based

IGCC-CCS, and NGCC-CCS (S. 2146, 2012). Most existing nuclear and hydro capacity does not qualify under this plan, which only considers plants built after 1992; only 2.5% of existing nuclear and hydro capacity was built after 1992 (EIA, 2011). Under this model scenario, we assume for simplicity that no existing capacity (pre-2010) qualifies under the modeled CES. In addition, since the proposal is now two years old, we delayed the implementation of the plan from 2015 to 2020. Table 3.2 presents clean energy purchase requirements, expressed as a percentage of total electricity generation, for both Clean Energy Standard Act of 2012 and our study.

Table 3.2 Minimum annual requirements for a clean energy standard and a federal EPA CO_2 cap on the electric sector

Year	Percent Clean Energy		EPA CO_2 Cap (% reduction from 2005 levels)
	CES 2012	**This study**	**This study**
2015	24.0	NA	NA
2020	39.0	24.0	26.0
2025	54.0	39.0	29.0
2030	69.0	54.0	30.0
2035	84.0	69.0	30.0
2040	NA	84.0	30.0
2045	NA	84.0	30.0
2050	NA	84.0	30.0

3.4.5 Low Wind and Solar Cost Scenario

In addition to the three electric sector policy scenarios described above, we also wanted to examine a scenario in which technology innovation drives higher deployments of wind and solar electric generators in the absence of new policy. Since 2000, electricity generation from both wind and solar photovoltaics has grown at annual average rates of 30% (EIA, 2014).

With rapid growth and innovation that drives down investment costs, it is possible that the accelerated deployment of wind, solar photovoltaics, and concentrating solar thermal could lead to significant reductions in electric sector CO_2 emissions without additional policy.

To capture the effects of technology innovation in TIMES-NUSTD, we apply technology learning rates to wind and solar, which represent the average reduction in capital cost associated with a doubling of capacity. Azevedo et al. (2013) performed a comprehensive literature review of historical learning rates for wind and photovoltaics, and found that the mean learning rate for wind is 16% and for solar PV is 22%. They also note that while learning curves may be reasonable at explaining the past, the use for forecasting or modeling future cost trends is likely to be inadequate and the judgment of technology modelers is still required to use the appropriate learning rate (Azevedo et al., 2013). Since we do not use learning rates in the base case and only apply learning rates to wind, solar photovoltaics, and concentrating solar thermal in this model scenario, we assume the rates cited above for wind and solar photovoltaics. Given the paucity of data, we also apply the solar PV learning rate of 22% to concentrating solar thermal. Since we do not consider learning associated with other electric generation technology, application of the average historical learning rates for wind and solar relative to other technologies with unchanging capital costs represents an aggressive but plausible renewable development scenario. Using these rates, a four-fold increase in wind and solar capacity would produce a capital cost reduction of 30% and 40%, respectively. While there is a high degree of uncertainty in future learning rates, this scenario is simply meant to illustrate the possible effects of accelerated renewable deployment within the electric sector and the consequent effect on CO_2 emissions.

In addition, the capacity constraint requiring one unit of gas turbine capacity for each unit of wind or solar (described in Section 3.3.2) is lifted under this scenario to further increase the cost-effectiveness of renewables relative to other generation options.

3.5 RESULTS

We present several results from the TIMES-NUSTD analysis that highlight the effect of alternative electricity scenarios on electric sector technology deployment, prices, CO_2 intensity, PEV deployment, and the overall effect on system-wide CO_2 emissions. Each electric sector scenario includes assumptions favorable to PEV deployment, including high oil prices and low battery cost to maximize the deployment of PEVs. To quantify the marginal effects of PEV deployment, we also ran each of the five scenarios without PEVs. We begin by presenting the results from the light duty vehicle sector, followed by electric sector results, and finally the incremental effect of PEV deployment on national CO_2 emissions.

Figure 3.3 illustrates the light duty vehicle market share with and without PEVs in the future. Without PEVs included in the model, gasoline vehicles remain dominant, but the market shares of ethanol, diesel, and diesel hybrid vehicles increase over time. With PEVs, the vehicle deployment is the same across the base case and all three policy scenarios, indicating that the effects of electric sector policy do not increase the electricity price enough to affect the economics of PEVs relative to other vehicle technologies. As a result, the feedback of more costly, lower CO_2-intensive electricity on PEV deployment is negligible. Likewise, the availability of low cost wind and solar does not lower the price of electricity enough to push PEV deployment levels higher than those in the base case. The market share of BEVs begins to dominate the alternative vehicle share post-2030. The higher BEV efficiency, larger proportional battery cost reductions in BEVs, and lower cost for electricity compared to liquid fuels makes BEVs more cost-effective than PHEVs in the long-run. The market share of BEVs and PHEVs in 2050 is 30% and 4%, respectively. As noted in Chapter 2, diesel and diesel hybrids also make a significant contribution given their high fuel economy relative to gasoline vehicles.

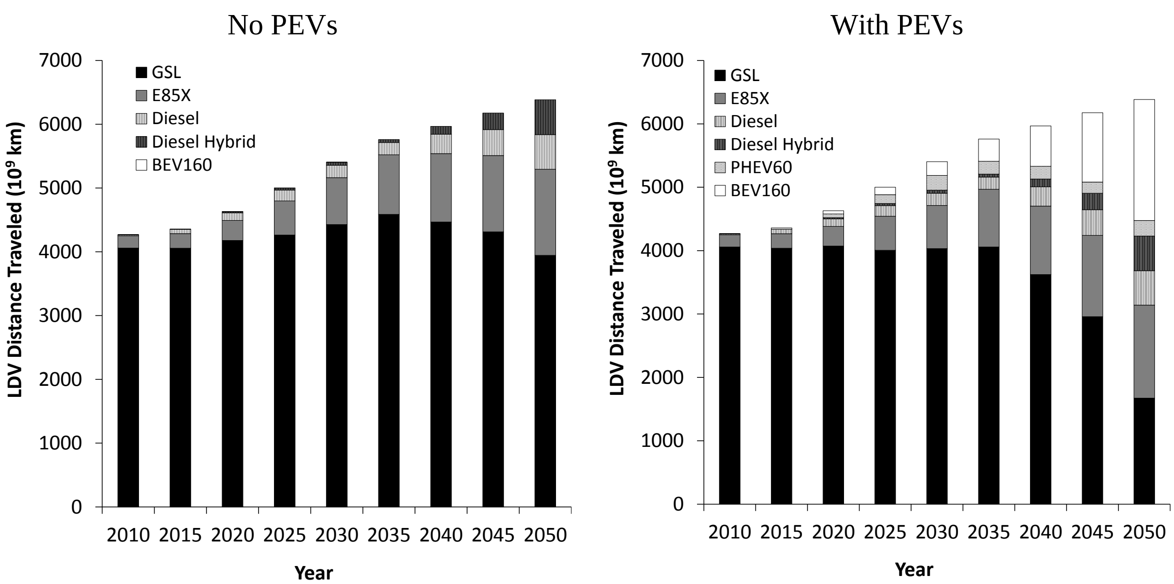

Figure 3.3 Market share in the LDV sector when no PEVs are included in the model (left panel) and PEVs are allowed to enter the market (right panel). As battery costs fall over time, the BEV market share accelerates, reaching a 30% market LDV share in 2050. No differences in LDV market share are observed across the various electricity scenarios.

As discussed above, PEV deployment does not change with the assumed electric sector scenarios. Figure 3.4 presents the average cost of electricity across the five studied scenarios with PEVs, which varies from approximately 73-100 $/MWh over the 40-year time horizon. The three policy scenarios show an increase in electricity price relative to the base case because they apply binding constraints on technology deployment in the electric sector. The RPS scenario has a negligible effect on electricity price compared to the base case, as the former only supplants a modest amount of new coal and natural gas with additional wind power, totaling 364 TWh of wind-generated electricity in 2050 (Figure 3.5). Similar to the RPS, the EPA Rules scenario has a small effect on electricity prices, resulting in a 3% increase in the 2050 electricity cost relative to the base scenario. The CES has the largest effect on electricity prices, resulting in a 16% increase in 2050 relative to the base scenario. The CES requires an aggressive deployment of 84% clean energy by 2040, but as the requirement is held constant from 2040 to 2050, the deployment rate of more expensive renewables slows down considerably and the electricity price remains nearly constant for the last decade. The low wind and solar cost scenario does not add a policy constraint to the model and features lower renewable costs, so the prevailing price of electricity is 5% lower in 2050 compared to the base case.

To better understand why these variations in electricity price across the 5 scenarios do not affect PEV deployment, we calculate the present cost of gasoline and non-hurdle rate battery electric vehicles purchased in 2050 across the four vehicle sizes classes in which BEVs are available: minicompact, compact, full size, and small SUV. Using the lowest (82 $/MWh) and highest (100 $/MWh) electricity prices across the 5 scenarios in 2050, the electricity portion of the BEV present cost varies from 5-12%, indicating that the bulk of the BEV present cost comes from the investment cost. The present cost of the BEVs is 25-36% lower than their gasoline vehicle counterparts across the high and low electricity prices, which suggests that electricity prices do not have a strong effect on the economic tradeoff between different vehicle technologies. Because PHEVs derive their motive power from a combination of electricity and gasoline, their present cost will be less sensitive to electricity prices than BEVs.

While we have demonstrated that electricity prices do not have a significant effect on PEV cost-effectiveness, it is possible that PEV deployment may affect electricity prices, since more electric generating capacity is needed to support vehicle charging. Comparing the average 2050 electricity prices with and without PEV availability for each scenario, the price difference is negligible and ranges from 0.004% to 1.2%.

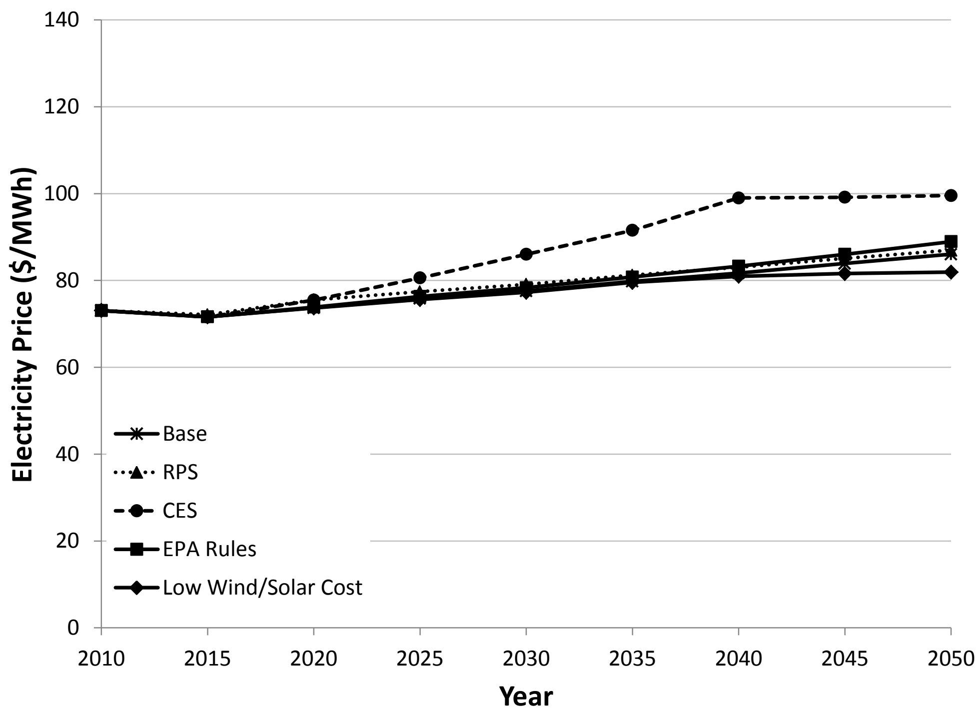

Figure 3.4 Average annual electricity price ($/MWh) in each of the five studied scenarios. When the same scenarios were run without PEVs, the change in average annual price was negligible.

Each of the five scenarios leads to different electric sector mixes, as summarized in Figure 3.5. Future reductions in electric sector CO_2 emissions will hinge critically on the retirement of existing coal-fired power plants and the deployment of new low carbon sources. In the CES scenario, existing coal-based electricity generation is pushed to nearly zero by 2050. Because the CES scenario requires more than 80% of U.S. electricity supply post-2030 to be provided from clean sources, it effectively forces the retirement of existing coal and requires the most aggressive deployment of new clean capacity. In addition, the CES scenario suggests that wind and solar can compete favorably against fossil alternatives with carbon capture and sequestration, as it leads to the highest deployments of wind and solar across the five scenarios. The EPA Rules and Low Cost Wind/Solar scenarios reduce the utilization of existing coal by 24% and 47%, respectively, compared to the base scenario in 2050. Given the increasing price of natural gas over time and the low marginal costs associated with coal-fired electricity, coal persists in the U.S. electric sector in the absence of aggressive policy such as the CES. Wind plays a large role in all four alternative electricity scenarios, and solar makes a significant contribution to electricity supply in the CES and Low Cost Wind/Solar scenarios. The model prefers concentrating solar thermal over solar photovoltaics given its slightly lower cost. However, this distinction is not robust because the two solar technologies have similar cost and performance characteristics given their simplified representation with the model.

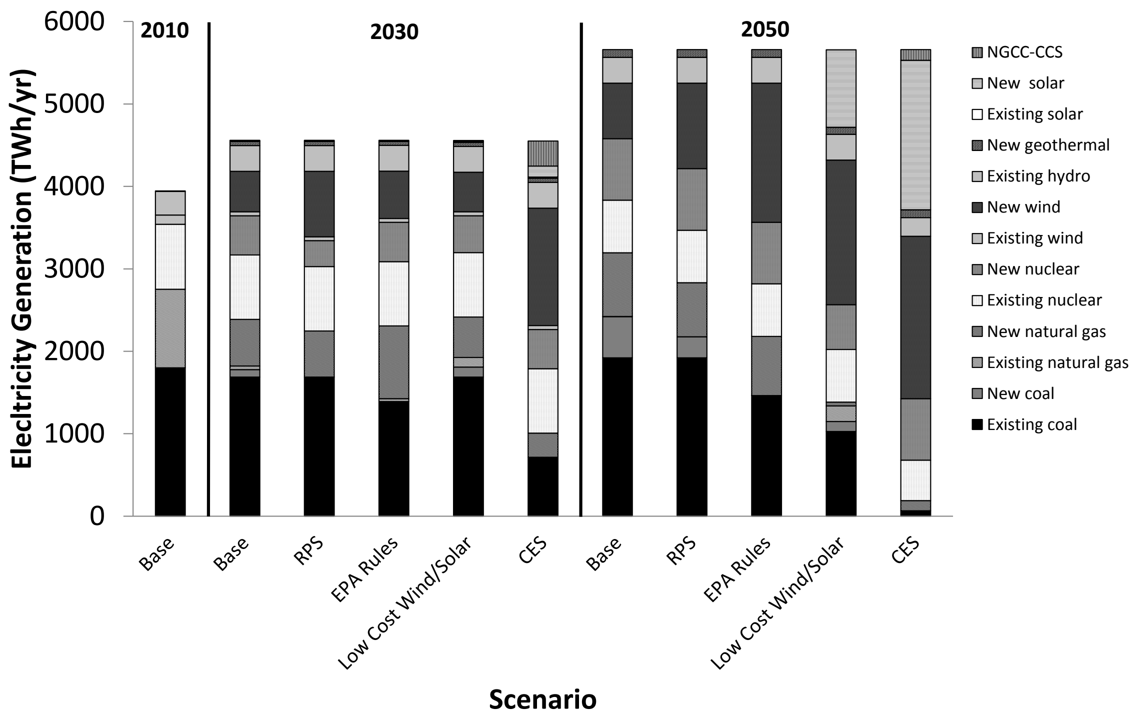

Figure 3.5 Electricity production in representative model periods 2010, 2030, and 2050. Note that the CES scenario produces the most dramatic cut in existing coal and the largest deployment of wind and solar.

The effect of existing coal retirement is also evident in Figure 3.6, which presents the CO_2 emissions intensity (kg/MWh) across the five scenarios, with and without the availability of PEVs. All four alternative electricity scenarios lead to a reduction in CO_2 intensity compared to the base scenario by 2050. In both the CES and EPA rules scenarios, the CO_2 intensity pathway is largely determined by the policy requirements over time. Although the CES does not directly regulate CO_2 emissions, the aggressive requirements for low carbon energy lead to a 52% reduction in 2050 CO_2 intensity compared to the base case. The EPA Rules scenario directly regulates CO_2 emissions, but overall produces less technology switching in the electric sector, resulting in a 35% reduction in 2050 CO_2

intensity compared to the base case. The RPS scenario enables a 9.5% cut in CO_2 intensity relative to the base scenario in 2050 without increasing the average price of electricity. In the Low Wind/Solar Cost scenario, the CO_2 intensity is nearly the same as the Base scenario through 2040, but then drops below the base scenario in the last decade as the low costs of solar and wind plants accelerate wind and solar deployment levels. The CO_2 intensity in the Base case increases from 2040 to 2050, indicating that in the absence of electric sector policy, new coal capacity is cost-effective, particularly in later time periods as the projected price of natural gas increases.

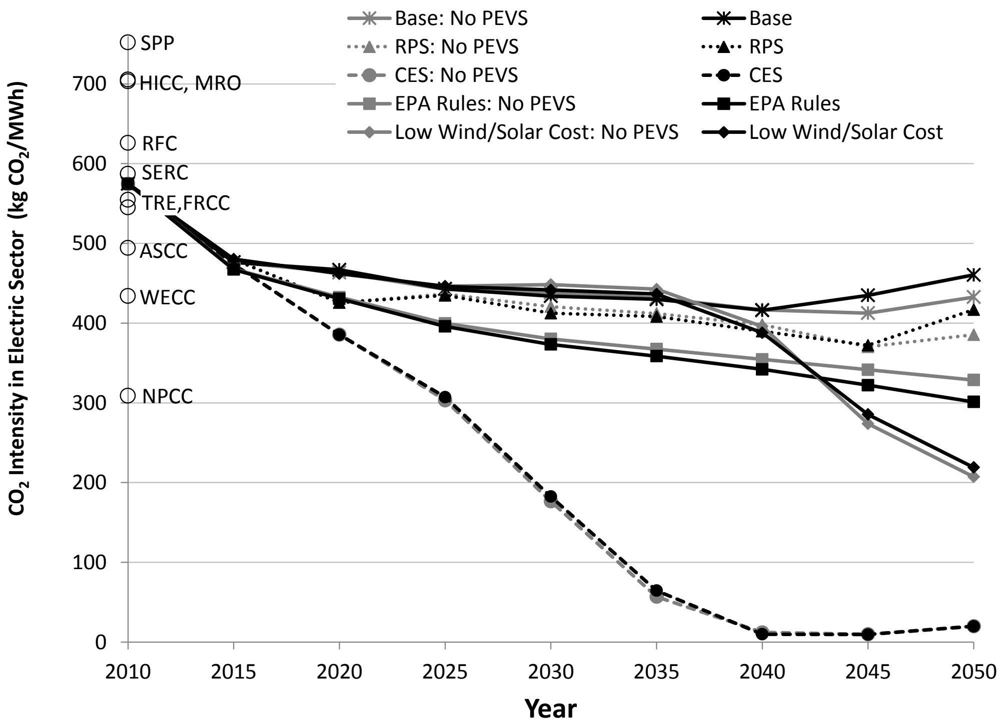

Figure 3.6 Electric sector CO_2 intensity across the five studied scenarios. Results without PEV availability are plotted in gray; those with PEVs are plotted in black. For reference, current CO_2 intensities by NERC region are plotted as open circles in 2010. Note that in the base and RPS scenarios, PEV deployment leads to higher CO_2 intensities in the last decade.

One of the most interesting features of Figure 3.6 is the difference in CO_2 intensity – particularly in last decade – between each scenario version with and without PEV availability in the model. In the Base and RPS scenarios, the increased electricity demand associated PEV charging leads to higher CO_2 intensity than without PEVs. In both cases, steadily increasing natural gas prices over the model time horizon make new pulverized coal capacity a viable option in the last decade. Because the RPS mandates a minimum share of renewables without regard to emissions, the model can replace natural gas turbines with new coal and still meet the requirement, despite the shift towards higher CO_2 intensity. In the EPA Rules scenario, the upper limit on absolute CO_2 emissions means that increasing electricity demand will simply require more low carbon electricity generation, thereby dropping the overall CO_2 intensity as electricity demand from PEV charging ramps up in later periods.

Figure 3.7 presents national U.S. CO_2 emissions under all 5 scenarios with and without PEV availability, which illustrates the net effect of PEV deployment, electric sector CO_2 intensity, and broader effects across the energy system. Figure 3.7 also splits the changes in 2050 national CO_2 emissions into two components: (1) the CO_2 emissions change between the Base and each scenario without PEVs, and (2) the incremental change in CO_2 emissions within each scenario due to PEV deployment.

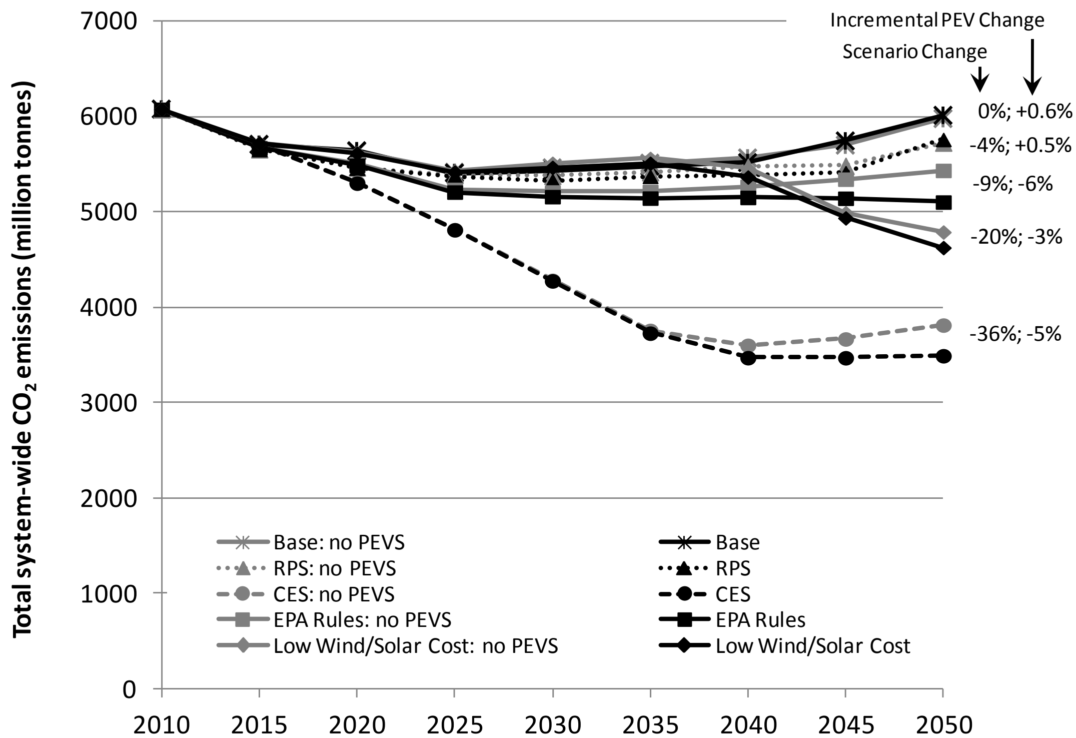

Figure 3.7 CO_2 emissions pathways for all five scenarios with and without the availability of PEVs, which are represented by black and gray lines, respectively. The percentages to the left represent the 2050 emissions change between the Base and each scenario without the availability of PEVs, and the percentages to the right represent the incremental change in 2050 emissions within each scenario due to PEV deployment.

Figure 3.7 indicates that the PEV deployment in the Base and RPS scenarios actually produce a slight increase (less than 1%) in 2050 CO_2 emissions. Because the EPA Rules scenario effectively provides a cap on CO_2 emissions, the increased electricity demand from PEV charging does not lead to higher CO_2 emissions, but rather an additional 6% drop by 2050. The incremental emissions benefit under the Low Cost Wind/Solar scenario is a more modest 3% in 2050, as a higher share of existing coal is retained in later time periods in order to meet the increased demand from vehicle charging. Finally, PEV deployment under the

CES scenario also results in an additional 5% decrease in 2050 CO_2 emissions, similar to the EPA Rules scenario. As PEV charging demand ramps up, the share of clean electricity under the CES must be preserved, so the absolute amount of renewables rises and CO_2 intensity remains relatively constant. For comparison to these modeled scenarios, the simple calculations in Section 2 indicate that carbon-free electricity used to charge a 100% electric LDV fleet would produce a 20% reduction in national CO_2 emissions. In the alternative electricity scenarios tested here, the largest reductions in national CO_2 emissions due to PEV deployment are on the order of 5-6%.

To understand the effects of PEV deployment on future CO_2 mitigation costs, the 2050 difference in total system cost and CO_2 emissions was calculated between the PEV and no-PEV deployment cases within the EPA Rules, CES, and Low Cost Wind/Solar scenarios. The difference in system cost divided by the difference in system-wide CO_2 emissions (yielding $/tonne CO_2) provides a rough estimate of CO_2 mitigation cost associated with deploying PEVs. The resultant CO_2 mitigation costs are 270, 290, 620 $/tonne CO_2 in 2050 for the EPA Rules, CES, and Low Cost Wind/Solar scenarios, respectively. The higher mitigation cost in the low cost wind and solar scenario occurs because the additional electricity load associated with vehicle charging is partially met by new coal, which leads to higher electric sector CO_2 emissions compared to the EPA Rules and CES scenario, which have stringent requirements for new capacity with low CO_2 emissions. For comparison, these CO_2 mitigation costs are an order of magnitude higher than EPA's social cost of carbon, which has an average value of 28 $/tonne CO_2 in 2050 using a 5% discount rate (EPA, 2013).

3.6 DISCUSSION

We have quantified the incremental change in CO_2 emissions associated with PEV deployment under different electric sector scenarios over time. Rather than focus on parametric variation of electricity CO_2 intensity, we modeled the entire energy system in order to explore how changes in the national grid mix could affect PEV-related emissions. We focus attention on scenarios that are favorable to PEV deployment, including high oil prices, low battery cost, and use of a relatively low 10% hurdle rate for alternative vehicle purchases, which collectively result in a 34% share of PEVs within the LDV market. As shown in Figure 3.7, the alternative electric sector scenarios without PEVs result in national CO_2 emissions reductions ranging from 4-36% in 2050. Allowing PEV deployment changes emissions by an additional +0.5% to -6% in 2050. Thus the direct effect of electric sector policies in reducing electricity-related CO_2 emissions is much larger than the effect produced by PEV deployment.

The model results suggest the following policy-relevant insights. First, the alternative electricity scenarios produce a wide range of emissions reductions. Given the threat of anthropogenic climate change, policymakers would be wise to revisit the CES, which produced the largest emissions reductions, or perhaps an aggressive, system-wide cap-and-trade system. Second, PEV deployment is relatively robust to changes in electricity price. So reducing electric sector CO_2 emissions will improve the efficacy of using PEVs to further reduce emissions without producing a significant effect on PEV cost-effectiveness. Third, wind, and to a lesser extent solar, compete favorably against other low carbon options in the CES scenario, suggesting that continued support for these technologies through government research & development as well as the production tax credit is warranted. Fourth, pulverized coal remains a viable generation option, particularly as natural gas prices increase over time, leading to generally higher carbon intensities from 2040-2050 in the absence of policy constraints. As a result, incremental changes in electricity supply to meet PEV charging requirements can produce a significant increase in marginal CO_2 emissions. For instance, in the Base and RPS scenarios, changes in electricity supply to meet PEV charging requirements actually lead to a slight 0.5-0.6% increase in overall 2050 CO_2 emissions. Interestingly, the EPA Rules scenario inoculates the electric sector to this possibility by effectively capping electric sector CO_2 emissions. As a result, electricity demand for PEV charging leads to a decrease in electric sector CO_2 intensity, producing a significant 6% incremental reduction in CO_2 emissions due to PEV deployment. These results highlight a key point: Policymakers must be attentive to electric sector developments when considering policy related to PEV deployment, as the marginal changes to electricity supply to accommodate vehicle charging can produce a range of effects on net CO_2 emissions.

There are several underlying uncertainties that can affect the CO_2 projections shown in Figure 3.7. The first uncertainty relates to the projected level of PEV deployment. In this analysis we assume conditions favorable to PEV deployment, including high oil prices and low battery prices. Under less favorable conditions – such as the continuation of current low crude oil prices around 70 $/barrel (EIA, 2014) – fewer PEVs will be deployed and their ability to affect national CO_2 emissions will be reduced. By contrast, surging oil prices, the rapid development of battery technology, aggressive investment in public charging infrastructure, and increased consumer acceptance of driving range limitations can push PEV deployment to levels well beyond the 34% of the LDV fleet shown here. All else equal, higher PEV deployment levels will magnify the CO_2 emissions effects from PEVs shown in Figure 3.7.

A second key uncertainty relates to natural gas and coal prices, which can affect electric sector technology deployment and utilization. As shown in Figure 3.5, the base and RPS scenarios include increased coal development towards mid-century as natural gas prices continue to rise. The model results suggest that the marginal generation used to charge a future PEV fleet could partially come from new coal plants. If instead natural gas prices remain low and/or coal prices increase over several decades, new NGCC generation could supplant coal generation, lowering the emissions footprint of both PEVs and the broader electric sector.

A third key uncertainty relates to technology innovation. Capital cost reductions in wind, solar, nuclear, and grid-scale storage could enable lower electric sector CO_2 intensities and push Base Case CO_2 emissions due to PEV deployment from a modest increase to a decrease. By contrast, stagnant innovation of low carbon electric generators in the absence of new policy could result in higher Base Case CO_2 emissions than projected here, which could increase the marginal CO_2 emissions associated with PEV charging.

A fourth uncertainty pertains to policy implementation. For example, an RPS or CES can vary widely based on its timeline for implementation and the stringency of the requirements. Aggressive, coordinated low carbon electric sector policy along with high levels of PEV deployment could maximize the CO_2 emissions benefit of PEVs while weak, uncoordinated electric sector policy along with high levels of PEV deployment could produce marginal increases in CO_2 emissions.

Given the complexity of the system we are trying to model, several caveats should be noted. First, as with all energy system models, ours is a radical simplification of the real world. Second, the scenarios analyzed here are not predictions but rather stylized pathways from which useful insight about future possibilities can be derived. For example, given the model granularity, we do not model the possibility of boiler retrofits to increase thermal efficiency or increased end use efficiency in the EPA Rules scenario, which may overstate the effects of EPA's proposed rules on the U.S. generation portfolio. Third, we do not account for regional variation in resource availability or generation mix; consideration of which could lead to additional insight regarding regional policy strategies. Fourth, while we do not consider radical technological breakthroughs or geopolitical developments that could push PEV deployment beyond 34%, we nonetheless consider the deployment levels and associated effects to be on the optimistic side because we assume high oil prices, low battery cost, and a low hurdle rate of 10% across all modeled scenarios. Fifth, for simplicity, we assume that electricity demand from vehicle charging is constant throughout the day. Preliminary work on our part indicates that stacking vehicle charging demand in a more limited daily time window (e.g., 8 hours) does not have a significant effect on PEV deployment or emissions. Finally, while we focus attention on CO_2 emissions, the deployment of PEVs can also produce a significant reduction in crude oil consumption and improvements in air quality, particularly in urbanized areas, which we do not address. As such, the results from this study should not be used to pass judgment on the overall utility of PEV deployment.

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Chapter 4: The Effect of Time-of-Day Plug-in Electric Vehicle Charging on U.S. Power Generation and CO_2 Emissions

4.1 INTRODUCTION

Vehicle electrification is often identified as an effective strategy to reduce oil dependence, greenhouse gas (GHG) emissions, and air pollution (Michalek et al., 2011; Silva et al., 2009; and EPRI, 2007). The transport and electric sectors have evolved independently over the last several decades because they use different fuel sources. Plug-in electric vehicles (PEVs), which include both plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs), directly couple the electric and transport sectors through the process of vehicle charging. Time-of-day PEV charging may have a significant effect on the diurnal distribution of electricity demand, which in turn can affect the electricity generation mix, electricity price, and technology deployment across the broader energy system.

Several previous studies have investigated the impacts of charging power requirements, time, or PEV location on hourly electricity load patterns over the course of a day or week (Harris and Webber, 2014; Yao et al., 2013; Kelly et al., 2012; Weiller, 2011; Wang et al., 2011; Zhang et al., 2011; Clement et al., 2010; Tate and Savagian, 2009; EPRI, 2007; Kintner-Meyer et al., 2007; Parks et al., 2007; Denholm et al., 2006).

Sioshansi et al. (2010), Hadley and Tsvetkova (2009), and Parks et al. (2007) provide comprehensive analyses of the fuel and plant types used to generate the required electricity for PEVs based on different charging scenarios. Kim and Rahimi (2014), Peterson et al.

(2011), Axen et al. (2011), and Shiau et al. (2009) examine the effect of different charging strategies on hourly electricity load, energy consumption, GHG emissions, and lifetime cost associated with PEVs. Peterson and Michalek (2013), NRC (2013a), and Morrow (2008) estimate the lifetime gasoline consumption and charging infrastructure cost of PEVs associated with different charging times and locations. Yao et al. (2013), Traut et al. (2012), and Kristofferson et al. (2011) minimize life cycle cost or GHG emissions for the fleet of PEVs based on different charging times, locations, and electricity prices. All of these studies employ sector-specific electric and transportation models, but do not indicate how the electric and transportation sectors may co-evolve over time in response to a set of scenario drivers and charging strategies that can affect PEV deployment. The various charging strategies (e.g., time-of-day vehicle charging) when combined with policy scenarios (e.g., a federal CO_2 cap) may affect electricity prices, technology deployment, and fuel use throughout the energy system.

A growing body of literature has also focused on PEV smart charging. For instance, one strategy is to charge PEVs when the electricity demand is lowest to make maximal use of existing power plants (Iversen et al., 2014; Weis, 2014; Richardson, 2013). Several studies investigate the effects of smart charging on the electricity transmission and distribution network (Kiviluoma et al., 2011; Green II et al., 2011; Denholm et al., 2006). These studies treat the electricity generation mix through a set of exogenous assumptions and do not account for the potential effects of smart charging through the broader energy system over time and in response to different policy and technology scenarios. For example, charging

PEVs over night, when electricity demand is lowest, may have a significant effect on electricity prices if combined with a CO_2 cap that requires more expensive baseload plants.

Previous analyses based on energy system models do not consider charging strategies (McCollum et al., 2012; AEO, 2012; Van Vliet et al., 2010; Yeh et al., 2008; Turton et al., 2007). They explore technology deployment in the transportation and electric sectors for several scenarios assuming constant charging demand from PEVs. Yet time-of-day charging can exert influence over power system development over time as PEV deployment increases.

The goal of this paper is to examine the potential impact of time-of-day PEV charging on electricity prices, generation mix, and total system-wide CO_2 emissions under several scenarios that consider different PEV deployment levels, time-of-day charging patterns, and policy options that could promote dramatic changes in the future electric sector mix. To perform the analysis, we use, the Integrated MARKAL-EFOM System (TIMES), a bottom-up, technology rich energy system model generator, which allows us to account for coupled electric and transport system development as well as interactions across the energy system over time. We developed the TIMES-compatible National US TIMES Dataset (NUSTD) (Energy Modeling, 2014) as an input dataset, which is specifically designed to look at the effects of PEV deployment under different future scenarios. This analysis draws from and builds on our previous work in Chapter 2, which examined 108 future scenarios and the resultant PEV deployment, electric generation mix, and system-wide emissions. The next section provides a brief overview of the model and dataset employed in this analysis, followed by a description of the charging time scenarios in Section 4.3. Sections 4.4 and 4.5 present key results and draw conclusions, respectively.

4.2 MODEL AND DATABASE DESCRIPTION

The model used for this analysis consists of two components: The Integrated MARKAL-EFOM System (TIMES) (Loulou et al., 2005), which serves as a generic energy optimization framework and operates on the National U.S. TIMES Dataset (NUSTD), a TIMES-compatible dataset constructed for this analysis.

4.2.1 The TIMES Model Generator

TIMES is a widely used bottom-up, technology rich energy system model, which represents an energy system as a set of networked technologies linked together via flows of energy commodities (Loulou et al., 2005). TIMES employs linear programming techniques to identify the optimal installed technology capacity and utilization in order to meet a set of end-use demands over time, subject to a number of built-in constraints that ensure proper operation of the energy system. In addition, user-defined constraints, such as emissions caps or growth rate limits on specific technologies, can be used to represent particular systems or scenarios. The model is driven by an objective function that minimizes the system-wide cost of energy supply over the user-specific time horizon. Model outputs by future time period include the optimal installed capacity and utilization of each technology, marginal energy prices, and emissions. TIMES assumes perfect information and perfect foresight, optimizing over an entire set of multi-year modeling periods simultaneously.

4.2.2. The National U.S. TIMES Dataset (NUSTD)

We developed NUSTD, a TIMES-compatible input dataset containing fuel prices, technology cost and performance estimates, and end-use demands to represent the U.S. as a single region over the next four decades. NUSTD was carefully documented in Babaee et al. (2014) and the updated workbooks required to run the model are publicly available (Energy Modeling, 2014). Here we provide a brief summary of key data elements relevant to this study.

The model time horizon is 2010 to 2050, with 5-year time periods. The U.S. is modeled as a single region with no interregional trade. A 5% social discount rate is used to convert future expenditures into present cost. As described below, a 10% hurdle rate is applied to all alternative vehicle technologies.

NUSTD is organized into several different sectors: fuel supply, electric, transport, and the remaining end-use sectors (i.e., commercial, residential, industrial). Fuel supply is represented by a set of exogenously specified fuel prices drawn from the output to the Annual Energy Outlook (AEO) 2012 (EIA, 2012). Given the focus on PEV deployment, the database contains significant technological detail in the electric and transportation sectors. The electric sector contains 32 generation technologies and 71 pollution control retrofits to reduce NO_X and SO_2 emissions from existing coal-fired power plants. Because the electric sector is modeled explicitly, the price of electricity is determined endogenously. To represent the need for backup capacity to support intermittent renewables such as wind and solar, we added a model constraint that requires one capacity unit of simple- or combined-cycle gas turbine capacity to be installed for every capacity unit of wind, solar photovoltaics, or concentrating solar thermal installed (Equation B.8). This backup capacity constraint is loosely based on previous modeling work by Greenblatt et al. (2007) and DeCarolis and Keith (2006).

The transportation sector includes light duty, heavy duty, and off highway vehicles. There are 85 light duty vehicle technologies, which consist of 7 vehicle size classes, 6 fuel types, and 13 vehicle types. Much of the vehicle cost and performance data is derived from EPA (Shay et al., 2006), but vehicle cost information is updated based on AEO (EIA, 2012). Hybrid vehicle and PEV performance data are drawn from the Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) Model (GREET, 2012). The following PEV technologies, ordered by their all-electric range (AER) in kilometers, are modeled: PHEV20, PHEV60, and BEV160.

A 10% hurdle rate is used to adjust the amortized cost of alternative fuel vehicles relative to conventional gasoline vehicles in order to partially capture non-market factors that may affect their deployment. We allow alternative vehicle shares to reach the same levels as in the AEO reference case without a hurdle rate, but additional deployment beyond AEO levels requires the use of alternative vehicles with the 10% hurdle rate. While studies conducted using surveys have estimated hurdle rates for alternative vehicle purchases in the range of 20-50 (Peterson and Michalek, 2013; Mau et al., 2008; Horne et al., 2005), previous work in Chapter 2 indicates that applying even a 20% hurdle rate results in zero PEV deployment across a wide range of scenarios. As a result, we assume that consumers make decisions based largely on vehicle cost-effectiveness.

The remaining end-use sectors (commercial, industrial, residential) each contain a single aggregate energy demand with no explicit representation of demand devices. Instead, base year 2010 fuel consumption is constrained to historical shares, and the projected AEO (EIA, 2012) fuel shares serve as the basis for lower bound fuel share constraints that are gradually relaxed over time (Figures A2-A4 and Equations B.20 and B.21). Because there are minimum required electricity shares in these end-use sectors, the resultant price for electricity is affected not only by transportation demand, but by demand in the other end-use sectors as well. While the lack of technology detail is a key simplification, we assume that technology switching in these end use sectors will have a limited effect on vehicle deployment.

4.2.3 Time-Slices Used in NUSTD

The TIMES model generator optimizes the flow of energy commodities over a set of user-defined seasons and times-of-day. The combination of each season and time-of-day (e.g., winter-night) is referred to as a “time-slice” (Loulou et al., 2005). The commodity flows within each time-slice are used to determine the optimal technology capacity and activity associated with a representative year within each user-defined model time period.

Less temporal resolution (i.e., fewer seasons and time-of-day segments) decreases model run time, however, greater temporal resolution can more accurately represent demand, which can be critical when modeling electricity supply. The original time-slice fractions, which are drawn from Shay et al. (2006), are based on 3 seasonal (i.e., summer, winter, and intermediate) and 4 diurnal (i.e., morning, mid-day, afternoon/evening, and night) time segments, thus creating a total set of 12 time-slices. To study the effect of time-of-day charging on electricity prices and PEV deployment with greater temporal resolution, we increase the number of diurnal time segments from 4 to 12 in order to represent two-hour intervals, resulting in a total of 36 time slices when applied across all three modeled seasons (summer, winter, intermediate). We do not increase the number of seasons, as we expect seasonal variations in charging demand to be a second order effect.

These time slices provide the flexibility to look at three different diurnal charging scenarios: constant, night (12am-4am), and an extreme scenario where all charging demand occurs in the 2-hour time slice associated with peak daily electricity demand within each season. We model the latter 2-hour charging case because it represents an extreme upper bound on how vehicle charging can affect grid development and performance. For reference, two hours of charging at a 240 volt charging station (Level 2 charger) can fully charge a Toyota Prius (PHEV20), charge a Chevrolet Volt (PHEV60) to more than 50%, and a Nissan Leaf (BEV160) to approximately 25% (Toyota, 2014; Chevrolet, 2015; Nissan, 2015).

In order to parameterize these new time-slices within the model, we need to calculate the fraction of a year represented by each time slice, which can be obtained by multiplying the fraction of a day associated with each diurnal slice (i.e., 2/24) with the fraction of a year associated with each season (i.e., winter = 0.3315; summer = 0.3342; intermediate =0.3343) (Shay et al., 2006). The resultant time-slice fractions used in this analysis are presented in Table 4.1.

Table 4.1 The sub-annual time-slice fraction

Time-slice Name[a]	**Fraction of a Year**
S0-2, S2-4, S4-6, S6-8, S8-10, S10-12, S12-14, S14-16, S16-18, S18-20, S20-22, S22-24	0.02785
W0-2, W2-4, W4-6, W6-8, W8-10, W10-12, W12-14, W14-16, W16-18, W18-20, W20-22, W22-24	0.02763
I0-2, I2-4, I4-6, I6-8, I8-10, I10-12, I12-14, I14-16, I16-18, I18-20, I20-22, I22-24	0.02786

[a] S: Summer, W: Winter, I: Intermediate; Numerical ranges correspond to the two-hour intervals within a day

As discussed in Section 4.2.2, each end-use sector (residential, commercial, and industrial) contains a single aggregate demand which is distributed across time-slices to represent the amount of demand occurring within a given time-slice. The following subsection describes how demand in each end-use sector is reallocated from the original 12 EPA time-slices to the 36 two-hour time-slices shown in Table 4.1.

4.2.4 Demand Reapportionment in the Residential, Commercial, and Industrial Sectors

In this analysis, the total end-use demand for the residential, commercial, and industrial sectors is partitioned into dedicated electricity demand and “other” demand. For each end-use sector, the dedicated electricity demand represents the sum of all end-use demands in each time period that can only be met with electricity (e.g., lighting, freezing, and cooling demand). By contrast, the “other” demand is the sum of other end-use demands (e.g., space heating and water heating) that can be met with other fuels as well as electricity. The end-use demand data are obtained from EIA (2012) for each end-use sector and are distributed throughout the EPA time-slices based on the annual fraction of each end-use demand occurring within each time-slice drawn from Shay et al. (2006). Both the dedicated electricity and “other” demands are then reallocated to the new 2-hour time-slices. A step-by-step description of the demand reapportionment process in the end-use sectors is provided in Appendix D.

4.3 SCENARIO DESCRIPTION

We focus on three scenarios with high PEV deployment and compare the results with the base scenario. Focusing on high deployment scenarios allow us assess the upper bound impacts of time-of-day charging across the energy system, which can help determine whether additional analysis at different PEV deployment levels is warranted. We assume three time-of-day charging scenarios: constant, peak, and night. In all cases, we assume no seasonal variation in charging patterns, only diurnal. In the constant charging scenarios, the PEV charging occurs at a constant rate throughout the day. In the peak charging scenarios, the PEV charging occurs during the 2-hour interval with the highest electricity demand throughout the system, corresponding to 2pm to 4pm each day. In the night charging scenarios, PEV charging occurs over the 4-hour interval spanning midnight to 4am every day. As described below, we examine four different deployment scenarios, which include a base case, a high deployment case, and a high deployment case coupled with new policies related to CO_2 reduction and clean energy deployment. The total number of model scenarios is 12, which represents every combination of four PEV deployment scenarios and three charging times. The assumptions made in each set of PEV deployment scenarios are outlined in the subsections below.

4.3.1 Base Scenario

The base and high PEV deployment scenarios are based on our previous work in which we examined electric drive vehicle deployment across 108 different scenarios (Babaee et al., 2014). Each scenario represents a unique combination of assumptions regarding future oil prices, natural gas prices, vehicle battery cost as well as the presence of a renewable portfolio standard (RPS) and a national cap on CO_2 emissions. For our base case in this analysis, we adopt the scenario corresponding to reference oil prices, reference natural gas prices, reference battery cost, no RPS, and no CO_2 policy, which resulted in a 15.6% PEV market share in the light duty vehicle (LDV) sector in 2050 (Babaee et al., 2014). Several existing policies that affect baseline system performance, including CAFE standards (EPA Federal register, 2012), the Mercury and Air Toxics Standards (MATS) (EPA MATS, 2012), the Cross-State Air Pollution Rule (CSAPR) rules (EPA CSAPR, 2013), state-level renewable portfolio standards (DSIRE RPS, 2013), and the Renewable Fuel Standard (EPA RFS, 2013), are described in Chapter 2 and are included in all the scenarios tested in this analysis (Equations B.9, B.10, and B.14 to B.18).

4.3.2 High PEV scenario [PEV]

We adopt the highest PEV deployment scenario drawn from Chapter 2 that excludes new policy. The highest PEV market share achievable without new policy is 34% in 2050, and includes high oil prices, reference natural gas prices, and low battery cost (Babaee et al., 2014).

4.3.3 High PEV with CO_2 cap scenario [PEV(CO_2)]

A federal cap on national U.S. CO_2 emissions is based on a review of four proposed federal climate bills introduced in the US Congress in the last 7 years (U.S. EPA legislative analyses, 2013). We chose to model a cap on national CO_2 emissions assuming uniform, linear reductions in each 5-year period until a 40% reduction in the 2010 energy-related emissions level is achieved by 2050 (Equation B.22). The high PEV with CO_2 cap scenario includes the same assumptions as the high PEV scenario, but with the addition of the CO_2 cap.

4.3.4 High PEV with Clean Energy Standard (CES) scenario [PEV(CES)]

The Clean Energy Standard (CES) modeled in this study (Equation B.23) is based on the Clean Energy Standard Act of 2012, which sets forth a minimum requirement for electricity purchase from clean power plants (S. 2146, 2012). The qualifying clean power technologies include solar, wind, geothermal, municipal solid waste, biomass, new nuclear, coal-based IGCC-CCS, and NGCC-CCS (S. 2146, 2012). Most existing nuclear and hydro capacity does not qualify under this plan, which only considers plants built after 1992; only 2.5% of existing nuclear and hydro capacity has been built since 1992 (EIA, 2011). Under this model scenario, we assume for simplicity that no existing capacity (pre-2010) qualifies under the modeled CES. In addition, since the proposal is now two years old, we delayed the implementation of the plan from 2015 to 2020. Table 4.2 presents clean energy purchase requirements, expressed as a percentage of total electricity generation, for both the Clean Energy Standard Act of 2012 and our study.

Table 4.2 Minimum annual requirements for the modeled CES

Year	Percent Clean Energy	
	CES 2012	**This study**
2015	24.0	NA
2020	39.0	24.0
2025	54.0	39.0
2030	69.0	54.0
2035	84.0	69.0
2040-2050	NA	84.0

Table 4.3 summarizes the 12 modeled scenarios based on the PEV deployment level, new policy, and assumed time-of-day charging.

Table 4.3 Charging Scenarios

Scenario Name[a]	Brief Scenario Description
Base-C	Base PEV deployment with constant charging
Base-P	Base PEV deployment with peak charging
Base-N	Base PEV deployment with night charging
PEV-C	High PEV deployment with constant charging
PEV-P	High PEV deployment with peak charging
PEV-N	High PEV deployment with night charging
PEV(CO_2)-C	High PEV deployment with a CO_2 cap and constant charging
PEV(CO_2)-P	High PEV deployment with a CO_2 cap and peak charging
PEV(CO_2)-N	High PEV deployment with a CO_2 cap and night charging
PEV(CES)-C	High PEV deployment with a CES and constant charging
PEV(CES)-P	High PEV deployment with a CES and peak charging
PEV(CES)-N	High PEV deployment with a CES and night charging

[a]-C: Constant charging, -P: Peak charging, -N: Night charging

4.4 RESULTS

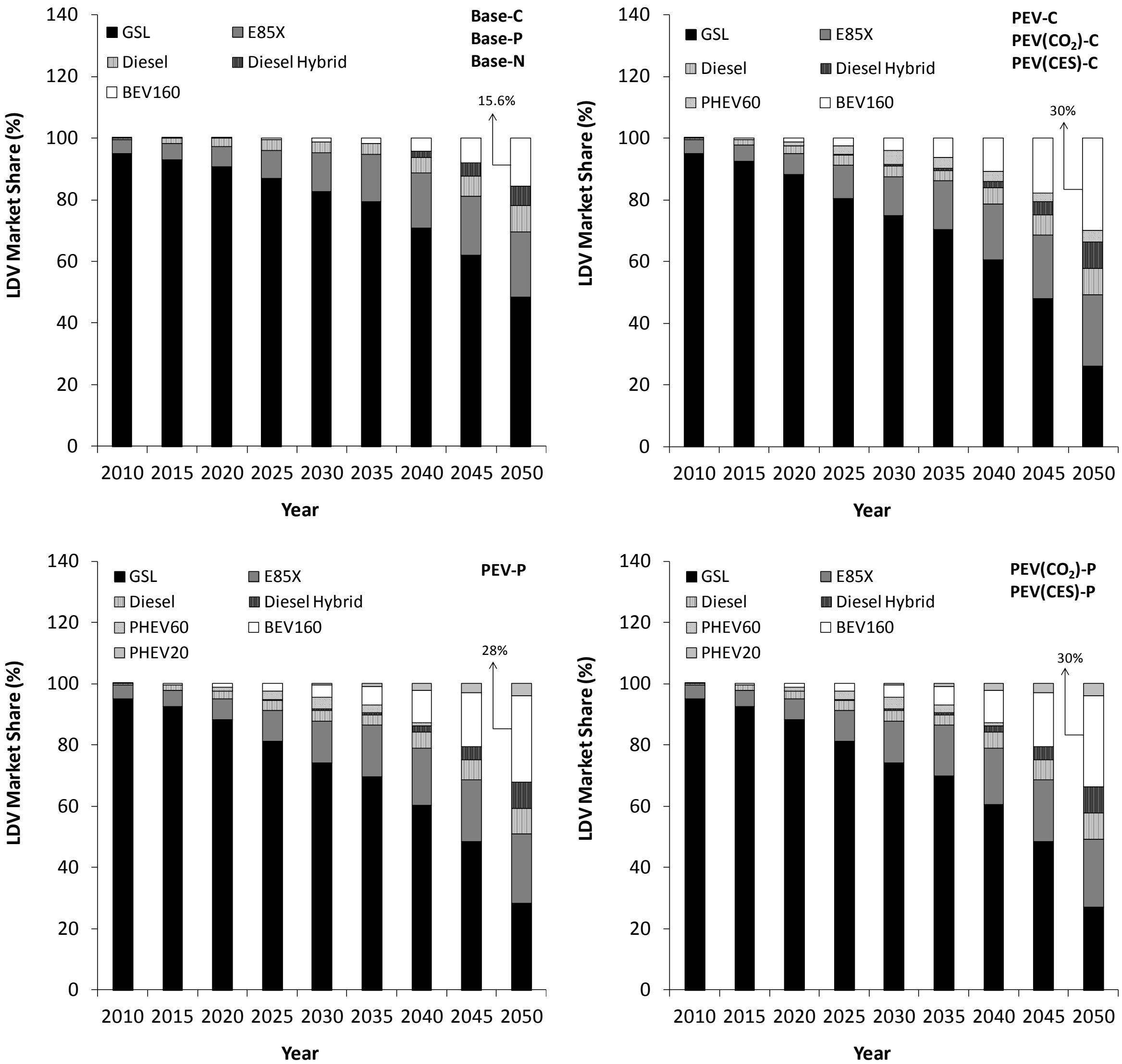
We present LDV deployment, electricity mix, average electricity prices, and system-wide CO_2 emissions associated with all 12 tested scenarios. Figure 4.1 displays the LDV market share for the 12 modeled scenarios through 2050. In the Base scenarios (top left), the vehicle deployment is the same with constant, peak, and night charging, implying that the electricity price does not fluctuate enough to affect PEV deployment. The market penetration of BEVs, which is the only PEV technology in the Base scenarios, is 1% in 2030 and increases to 15.6% by 2050.

Differences in time-of-day charging can produce modest changes in deployment when the high PEV deployment scenario is examined under different policy futures. The PEV market share is identical in the PEV-C, PEV(CO_2)-C, and PEV(CES)-C scenarios through 2050, indicating that the effect of different policy futures does not change vehicle market shares when vehicle charging remains constant through the day. In all three cases, the 2050 share of PHEV60 and BEV160 is 4% and 30%, respectively.

The middle plots in Figure 4.1 illustrate the results with peak charging. LDV shares under the PEV-P (left) as well as PEV(CO_2)-P and PEV(CES)-P scenarios (right) are almost the same through 2045. However, the 2050 market penetration of BEVs is 2% lower in the PEV-P (no policy) scenario. This result indicates that the need to use low carbon, clean energy under the policy scenarios drives slightly higher demand for PEVs, despite the higher cost of electricity, as shown in Figure 4.2. As a result, the model tends to build larger amounts of more efficient BEVs in the smaller size classes in the policy scenarios versus smaller amounts of larger BEVs in the no policy scenario. Across all three peak charging scenarios, PHEV60 gradually disappears by 2045 and is replaced by PHEV20, which has 4% of LDV market share in 2050, in part due to increasing electricity prices.

In the night charging scenarios with high PEV deployment (Figure 4.1, bottom), the LDV market share across all three policy scenarios is almost the same through 2050. Similar to the constant charging scenarios with high PEV deployment, the market penetration of BEVs increases to 30% by 2050. However, there are slight differences in the market share of PHEVs. In the PEV-N and PEV(CO_2)-N scenarios, the market share of PHEV60 declines by 3% from 2030 to 2050 while the share of PHEV20 increases by 2.6% over the same period. In the PEV(CES)-N scenario, the market share of PHEV60 declines by 3.75% from 2030 to 2050 while the share of PHEV20 increases by 3.5% over the same period. As shown in Figure 4.2, the slight shift from PHEV60 to PHEV20 deployment in the PEV(CES)-N scenario is due to higher electricity prices compared to the PEV-N and PEV(CO_2)-N scenarios.

Figure 4.1 LDV market shares associated with all 12 scenarios, organized by time-of-day PEV charging: constant (top row), peak (middle row), and nighttime (bottom row).



Base-C
Base-P
Base-N
GSL
E85X
Diesel
Diesel Hybrid
BEV160
15.6%
LDV Market Share (%)
Year
PEV-C
PEV(CO2)-C
PEV(CES)-C
PHEV60
30%
PEV-P
PHEV20
28%
PEV(CO2)-P
PEV(CES)-P
30%

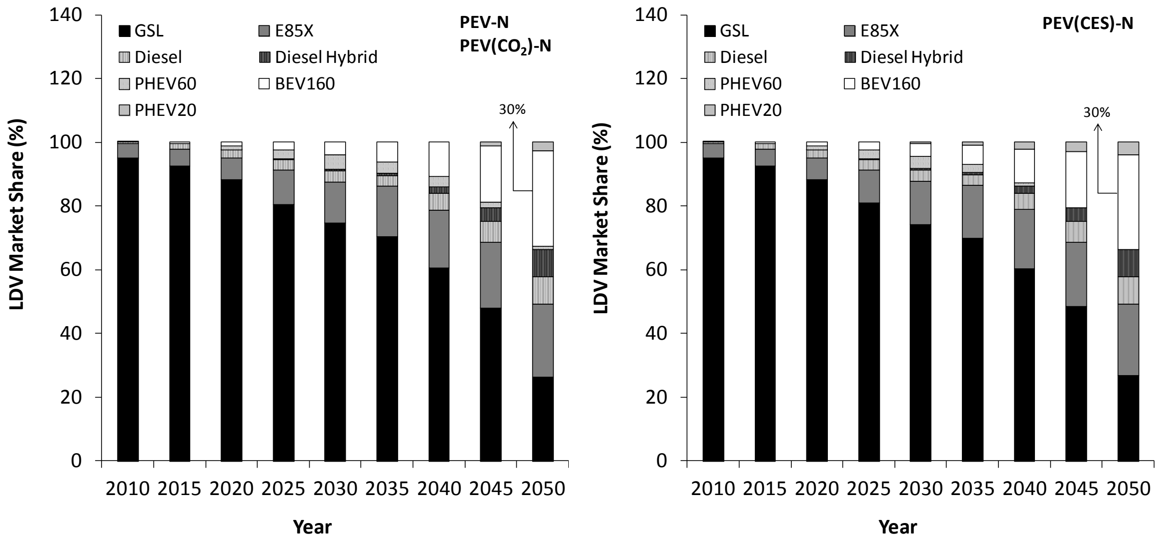


Figure 4.2 presents the average annual electricity price in \$/MWh across the 12 scenarios from 2010-2050. Over the 40-year model time horizon, the average annual electricity cost varies from 73 to 107 \$/MWh across 12 charging scenarios. The PEV(CES)-P scenario shows the largest effect on electricity prices, resulting in a 22% increase in the 2050 electricity price relative to the Base-C scenario. Because the CES requires an aggressive deployment of 85% clean electricity by 2040, the electricity price increases significantly until 2040. The CES requirement is held constant from 2040 to 2050 and the electricity price only increases 5% for the last 10 years in the PEV(CES)-P scenario.

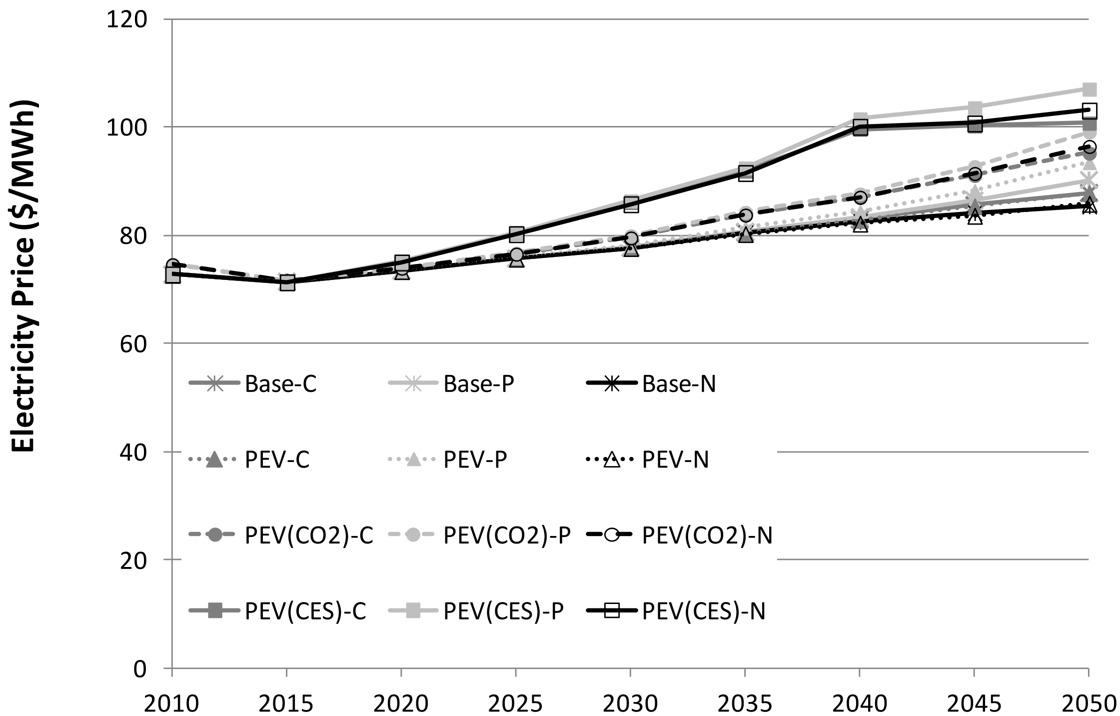
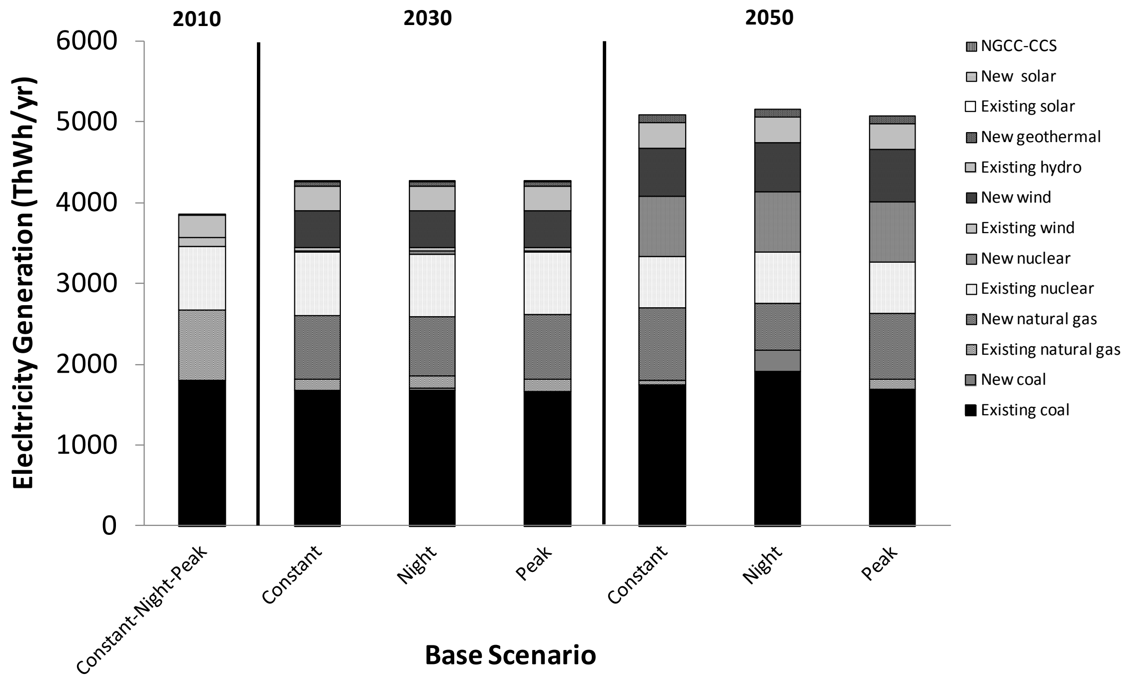


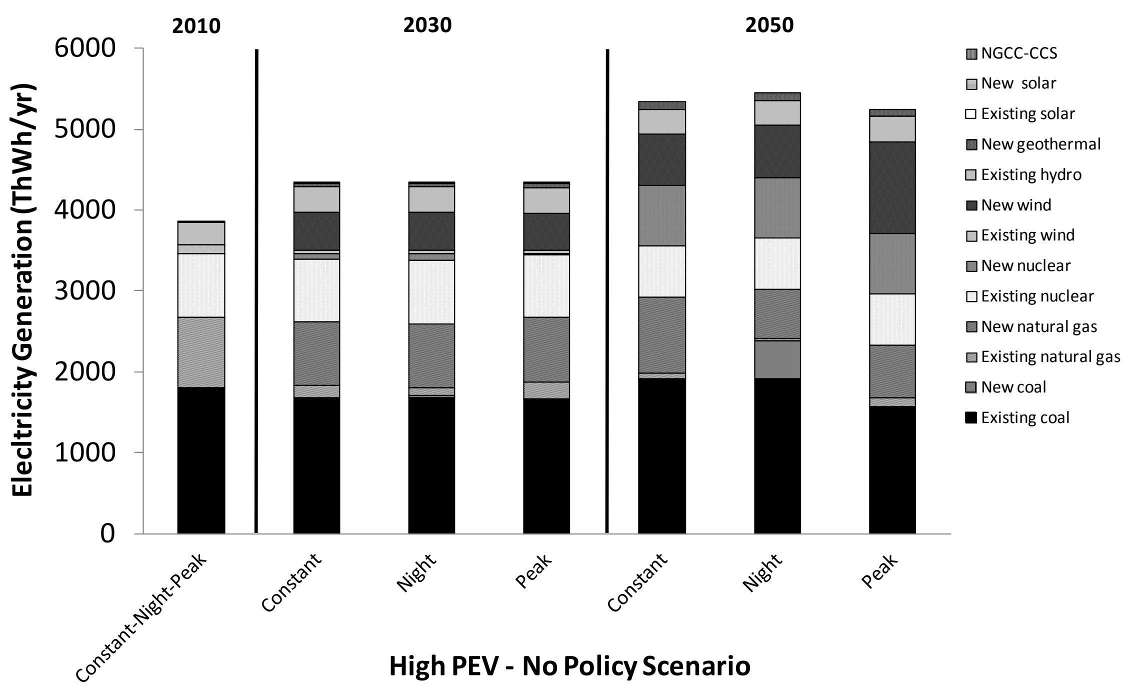
Figure 4.2 Average annual electricity price ($/MWh) for each charging scenario. The highest and lowest electricity price corresponds to the PEV(CES)-P and Base-N scenarios, respectively.

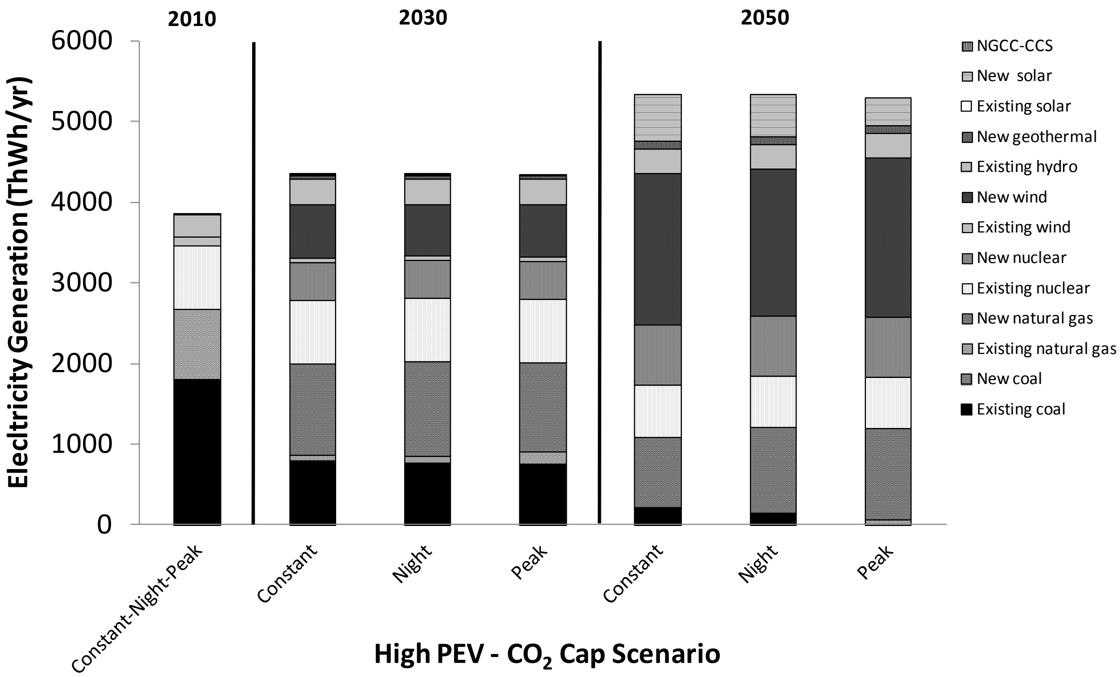
The annual average electricity price for the Base-N and PEV-N scenarios is 2.7% lower than the Base-C scenario in 2050. The electricity generation associated with the night charging scenarios is largely provided by existing and new coal steam power plants, which are more cost-effective than new combined-cycle natural gas (NGCC) power plants, resulting in lower electricity prices associated with night charging. By contrast, coupling either the CO_2 cap or CES with the night charging scenario requires significant retirement of existing baseload coal. The presence of low carbon technology options under the policy scenarios increases the electricity cost by 3% and 11% in PEV(CES)-N and PEV(CO_2)-N scenarios in the last decade, respectively. Looking beyond the electric sector, variations in electricity prices across the 12 modeled scenarios are not large enough to shift the share of electricity consumed (relative to other fuels) in the residential, commercial, and industrial sectors.

Figure 4.3 illustrates the electricity generation mix associated with each modeled scenario, grouped by time-of-day charging. In the Base scenarios (top), the electricity generation from new baseload coal steam begins to increase in Base-N after 2035 and electricity production from NGCC plant decreases, unlike the pattern of NGCC deployment exhibited in Base-C and Base-P. The NGCC deployment level for the Base-N scenario is 38% less relative to the Base-C scenario in 2050.

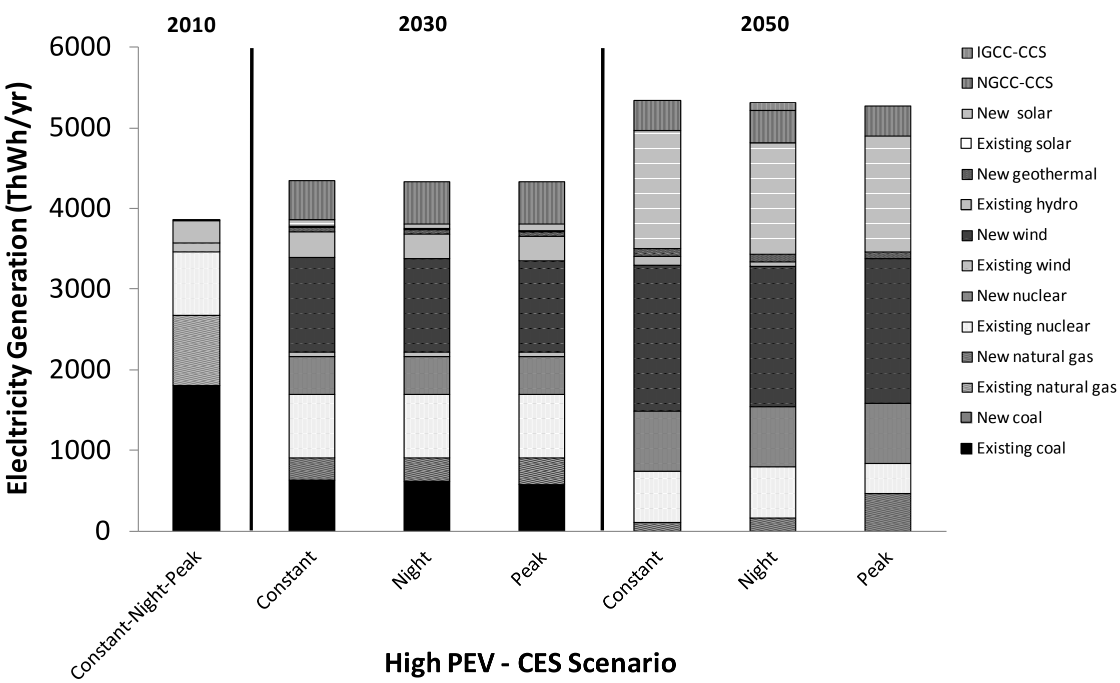
Figure 4.3 Total electricity generation by plant type, time period, and time-of-day charging for Base scenarios (top panel), high PEV deployment scenarios with no policy (second middle panel), high PEV deployment scenarios with a CO_2 cap (third middle panel), and high PEV deployment scenarios with a CES (bottom panel). The night charging scenarios have higher coal power plant deployment levels than peak charging scenarios. By contrast, the peak charging scenarios have higher natural gas and wind power plant deployment levels than the night charging scenarios.


2010
2030
2050
6000
5000
4000
3000
2000
1000
0
Elecltricity Generation (ThWh/yr)
Constant-Night-Peak
Constant
Night
Peak
Constant
Night
Peak
Base Scenario
NGCC-CCS
New solar
Existing solar
New geothermal
Existing hydro
New wind
Existing wind
New nuclear
Existing nuclear
New natural gas
Existing natural gas
New coal
Existing coal


2010
2030
2050
6000
5000
4000
3000
2000
1000
0
Elecltricity Generation (ThWh/yr)
Constant-Night-Peak
Constant
Night
Peak
Constant
Night
Peak
High PEV - No Policy Scenario
NGCC-CCS
New solar
Existing solar
New geothermal
Existing hydro
New wind
Existing wind
New nuclear
Existing nuclear
New natural gas
Existing natural gas
New coal
Existing coal



High PEV - CO_2 Cap Scenario



High PEV - CES Scenario

In the PEV-N scenario (second panel from top), we found a similar deployment pattern to the Base-N scenario post-2035, only with twice the new coal steam generation in 2050. In the PEV-P scenario, wind generation significantly increases after 2035 and replaces retired coal and NGCC. The 2050 coal and NGCC deployment levels in the PEV-P scenario are 18% and 30% less compared to the PEV-C scenario, respectively, because PEVs are being charged with non-baseload renewables during the peak charging window.

In the PEV(CO_2) scenarios (third panel from top), a dramatic decline in electricity generation from coal power plants coupled with a modest reduction in NGCC electricity generation for the constant, night, and peak charging occurs over the entire model time horizon. The 40% reduction in total CO_2 emissions by 2050 leads to significant retirement of existing coal across all three charging times compared to the base and high PEV deployment scenarios with no policy. The electricity generation from wind and solar thermal power plants significantly increases in the PEV(CO_2)-C, PEV(CO_2)-N, and PEV(CO_2)-P scenarios after 2035. However, the growth rate of solar thermal deployment in the PEV(CO_2)-P scenario is lower than in the PEV(CO_2)-C scenario, which results in 40% less solar deployment by 2050.

In the PEV(CES) scenarios (bottom), the existing coal power plants are retired by 2040 in the constant, night, and peak charging times. The aggressive requirement of 85% clean energy by 2040 in the CES scenario leads to significant retirements of existing coal across the three modeled charging times. Similar to the PEV(CO_2) scenarios, there is a dramatic increase in electricity generation from wind and solar thermal power plants in the PEV(CES)-C, PEV(CES)-N, and PEV(CES)-P scenarios post-2035. The more stringent requirements under the CES compared to the system-wide CO_2 cap lead to higher deployments of NGCC-CCS in the former. However, in all the high PEV deployment scenarios with a CES, wind and solar compete favorably against NGCC-CCS as the projected price of natural gas increases in later time periods. In the PEV(CES)-N scenario, 92 TWh of coal IGCC-CCS displaces NGCC-CCS in the last decade due to the increased baseload electricity demand.

Figure 4.4 illustrates the estimated total system-wide CO_2 emissions across the 12 charging scenarios from 2010-2050. Across the PEV(CO_2) scenarios, there is no variation in total CO_2 emissions associated with time-of-day charging because the CO_2 policy imposes a binding constraint on system-wide CO_2 emissions. Across all the no-policy scenarios, the variation in total CO_2 emissions is approximately 5% in 2045 and less than 12% in 2050. The PEV(CES)-C scenario produces the largest drop in system-wide CO_2 emissions relative to Base-C (40%). The PEV-N scenario produces a modest 5% increase in total CO_2 emissions compared to the Base-C scenario by 2050. In the Base-N and PEV-N scenarios, nighttime charging leads to higher system-wide CO_2 emissions relative to peak and constant charging due to the higher utilization of coal steam power plants, particularly in the last decade.

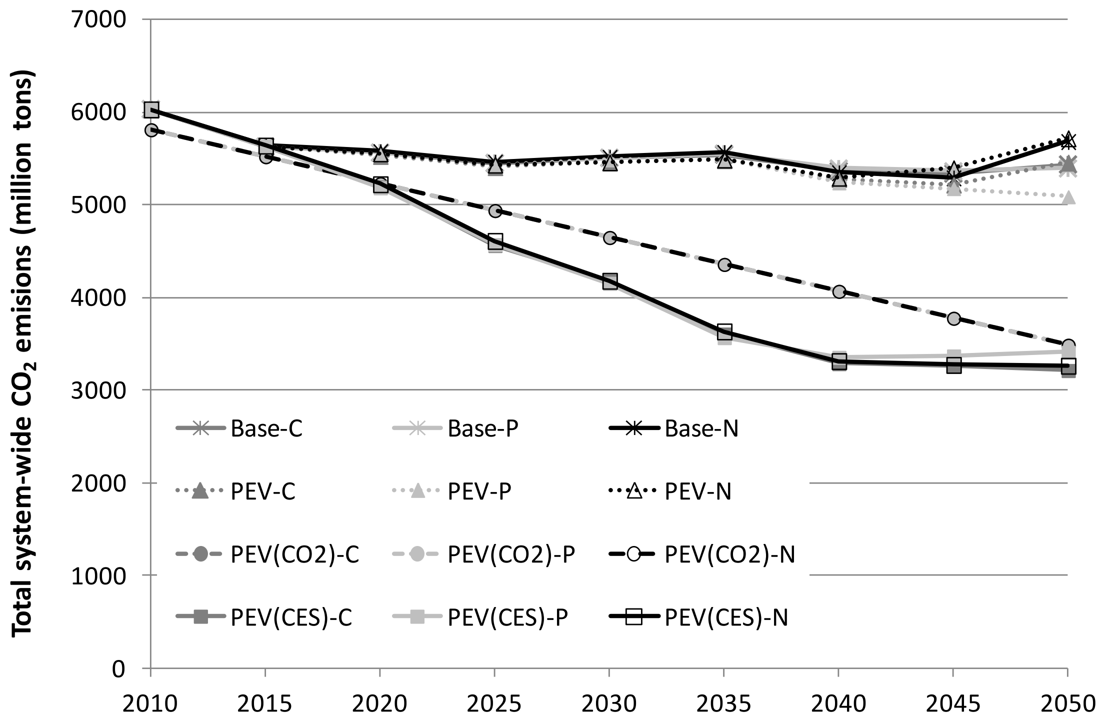


Figure 4.4 CO_2 emissions pathways for the 12 charging scenarios over the model time horizon. The lowest and highest 2050 system-wide CO_2 emissions corresponds to PEV(CES)-C and PEV-N scenarios, respectively.

In the PEV(CES) scenarios, total CO_2 emissions in the peak charging time are higher than in the constant and night charging times post-2040 because the existing coal power plants are retired by 2040 in all three charging times and electricity generation from NGCC is higher with peak charging relative to constant and night charging from 2040 to 2050 (Figure 4.3). NGCC is a backup power plant for wind and solar, which are utilized to a larger extent in the PEV(CES)-P than the equivalent constant and night charging scenarios.

To to understand the effects of time-of-day charging on future CO_2 mitigation costs within each PEV deployment scenario, the 2050 difference in total system cost and CO_2

emissions was calculated between pairs of scenarios. The different in system cost divided by the difference in system-wide CO_2 emissions (yielding \$/tonne CO_2) provides a rough estimate of how switching from a charging scenario with higher emissions to one with lower emissions affects the cost of CO_2 mitigation. Three cases involving a switch from peak to constant, night to constant, and peak to night charging were examined. The estimated 2050 mitigation cost in the CES scenario due to switching from peak to constant charging is 184 \$/tonne CO_2, from night to constant charging is 256 \$/tonne CO_2, and from peak to night charging is 159 \$/tonne CO_2. While it is not possible to control when owners charge their vehicles, these CO_2 prices nonetheless indicate that switching the time-of-day charging does not provide a cheap means to lower CO_2 emissions when compared to EPA's social cost of carbon (EPA, 2013) or improvements in end use efficiency (McKinsey, 2009) .

4.5 DISCUSSION

We have examined the effect of constant, night, and peak PEV charging times coupled to different PEV deployment levels (i.e., base, high) and policy futures (i.e., no new policy, CO_2 cap, CES). The model results demonstrate that PEV market penetration is not strongly affected by time-of-day charging. Within the base and each alternative electricity scenario, the variation in electricity demand due strictly to variations in PEV deployment and therefore charging requirements is less than 4% in 2050. In addition, there is a 6% increase in electricity demand between the base and high PEV deployment levels with nighttime charging in 2050. Even in the presence of a system-wide CO_2 cap or CES, the price of electricity does not increase enough to adversely affect the cost-effectiveness of PEVs relative to other vehicle technologies. The highest and lowest electricity prices occur in the PEV(CES)-P and Base-N scenarios, respectively. In the PEV(CES)-P scenario, the 2050 average electricity price is 107$/MWh, which is ~26% higher than in the Base-N scenario.

In the high PEV deployment scenarios with night charging, the electricity price increases significantly when either the CES or CO_2 policy is implemented in the model. Night charging with a CO_2 cap or CES forces the retirement of existing baseload coal that operates with low marginal cost, which has a significant effect on electricity prices. Under the CES and CO_2 policies, the need for clean and cost-effective electricity leads to a dramatic increase in electricity generation from wind and solar thermal plants in the last decade.

The night charging scenarios generally have higher coal power plant deployment levels than the peak charging scenarios. The peak charging scenarios have higher natural gas and wind power plant deployment levels than the night charging scenarios. National CO_2 emissions reductions under different charging times are largely driven by the carbon intensity of the electric sector in the last decade rather than different time-of-day PEV charging scenarios.

Many of the same uncertainties mentioned in Chapter 3 also apply in this chapter, including uncertainty in PEV deployment levels, fuel prices, technology innovation in the electric sector, and the timing and magnitude of policy requirements. Though we assume conditions favorable to PEV deployment, we do not consider future policies or technology innovations that may dramatically increase the market penetration of PEVs. In this work, we observe that PEV charging does not have a significant effect on annual average electricity prices, even in the peak charging scenario, which serves as an upper bound and assumes all

PEV charging across the U.S. takes place in the same 2-hour window. Nonetheless, higher levels of PEV deployment beyond those considered here could have a larger impact on electric sector technology deployment and utilization, which could in turn affect prices and emissions. Second, fuel prices and technology development in the electric sector can have an effect on which power plants operate at the margin and serve the incremental electricity demand to meet PEV charging requirements. For example, the Base-N and PEV-N scenarios partially utilize new coal steam to meet PEV charging demand. An approximate 40% drop in the capital cost for new light water nuclear reactors by mid-century could provide carbon-free baseload power to charge PEVs, thereby reducing the CO_2 emissions associated with nighttime charging. Finally, changes to the timing and stringency of the policy scenarios would affect the resultant electricity prices and emissions. For example, a more stringent CO_2 cap could have dramatic effects in the electric sector, and electricity prices may become more sensitive to the incremental effect of PEV charging.

Use of an energy system model to look at the effect of PEV time-of-day charging can only provide limited insight into the consequent effects on electricity prices, technology deployment, and emissions. Quantifying the effects of different vehicle charging patterns can be refined by applying more detailed and regionally specific models. For example, running the same scenarios presented here through a unit commitment and dispatch model would provide a more accurate picture of how PEV charging affects hour-by-hour power system operation. Nonetheless, our analysis indicates that time-of-day vehicle charging, even under high deployment scenarios, is unlikely to produce dramatic effects on PEV deployment or electric sector capacity deployment and utilization.

Several model simplifications suggest important caveats to this work. We apply a low hurdle rate (10%) to alternative vehicle technologies compared to 20-40% hurdle rates used in other studies, which may result in optimistic PEV deployment. In the end-use sectors, we do not include explicit representation of demand technologies, which can create additional opportunities for fuel switching, and which in turn can affect overall electricity demand, electricity prices, and PEV deployment under different time-of-day charging scenarios. Finally, we assume fixed end-use demands that are unresponsive to price, which may lead to an overestimation of the electricity price effects associated with PEV deployment.

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Chapter 5: Summary and Future Work

The research presented in this dissertation represents the most comprehensive study to date of U.S. electric drive vehicle (EDV) deployment with an energy system model. Using the TIMES model coupled to the National U.S. Technology Database (NUSTD) that I developed, changes in electricity prices, technology and fuel shares, and emissions across the energy system were quantified in response to changing EDV deployment under a variety of different scenarios. Such model-based analysis serves a critical role by identifying potential feedbacks and system effects associated with technology deployment that might not be captured by simplified calculations or sector-specific models.

The model results in Chapter 2 illustrate that high EDV deployment in the light duty vehicle (LDV) sector does not produce a clear and consistent decline in total system-wide emissions of CO_2, SO_2, and NO_X in the U.S. through 2050. There are a broad set of future conditions that can mask the effect of lower EDV tailpipe emissions, including high electric sector emissions and shifting emissions in the heavy duty vehicle, supply, and end-use sectors. However, the study also demonstrates that EDVs can produce a significant decline in marginal CO_2 prices under a federal CO_2 cap. Overall, policy makers must pay careful attention to prevailing system-wide conditions; they cannot simply incentivize EDV purchases through tax credits and wait for the emissions benefits to accrue.

Based on the results from Chapter 2, I decided to investigate plausible, clean electricity scenarios that could potentially magnify the CO_2 emissions benefit from plug-in electric vehicle (PEV) deployment. The Chapter 3 model results demonstrate that the incremental

CO_2 emissions benefit associated with PEV deployment is largely determined by the marginal emissions rates associated with the power plants used to meet the PEV charging requirements. We find that the incremental change in national CO_2 emissions ranges from +0.6% (Base case) to -5% (Clean Energy Standard). In scenarios where electric sector emissions are not constrained, it is possible to produce high marginal CO_2 emissions from vehicle charging, particularly towards mid-century as natural gas prices increase relative to coal. As such, the CO_2 emissions benefit from an increasing PEV market share depends on the evolving electric sector generation mix and to a lesser extent changes across the broader energy system. Since the emissions footprint of PEVs is contingent on electric sector developments over time, auto manufacturers should be engaged in policy discussions that can affect electric sector emissions.

Another critical issue related to PEV deployment is the distribution of demand for vehicle charging over the course of a day, which can affect the deployment and utilization of different electricity generation technologies over time. Chapter 4 addresses this issue by exploring a set of bounding scenarios related to vehicle charging. The model results indicate that time-of-day charging does not have a large impact on electricity prices, PEV deployment, or total system-wide CO_2 emissions. However, interesting system effects were observed. In the night charging scenarios, increased baseload electricity demand can increase the deployment of new pulverized coal plants in the base case. When instead emissions are limited or clean energy is required by new electric sector policy, new low carbon capacity can produce a significant rise in electricity cost, which is amplified by increases in vehicle charging demand. Therefore, policies aimed at shifting to low carbon power plants along with an increase in baseload electricity demand can prove challenging and must be examined carefully.

The analyses described in Chapters 2-4 suggest a broad set of policy relevant lessons. First, estimating the effect of PEVs on national emissions is complex; simple back-of-the-envelope analyses assuming a fixed deployment level and using average emissions rates from electricity production are likely to be misleading. When considering the emissions effect of PEVs, it is important to consider the marginal changes to the system rather than the prevailing average conditions. For example, as illustrated in Chapter 4, it is possible to have a business-as-usual electric sector with a low average CO_2 intensity that meets the incremental nighttime PEV charging demand with coal generation that has a high CO_2 intensity. Marginal changes in electricity production and associated emissions are sensitive to system conditions, including fuel prices, the implementation of new energy and environmental policy, the relative economic performance of different vehicle and electric generation technologies, and the distribution of PEV charging demand across the day. The only way to capture the effects of such factors is to perform detailed modeling exercises, such as the ones presented in this thesis.

Overall, we find that the net effect of PEV deployment on national CO_2 emissions strongly depends on prevailing system conditions. For example, in a base case assuming no new policy, PEV deployment may actually produce an increase in CO_2 emissions. On the other hand, PEV deployment in the presence of constrained electric sector CO_2 emissions can produce additional reductions in national CO_2 emissions on the order of 3-6%. Because PEV deployment produces emissions reductions that are contingent on prevailing system conditions, federal policymakers should work on coordinated policy measures that ensure clean electricity for vehicle charging as PEV deployment continues.

While the high level insights drawn from this thesis work are robust, several caveats to this work should be noted. First, the energy system model developed in this study represents a radical simplification of the underlying real world complexity. Any exercise with an energy system model at the national scale necessarily involves distilling very complex socioeconomic and technical issues into a manageable set of equations and input data. All discussion of model-based insight implicitly takes these limitations into account. Second, we did not consider fundamental technological breakthroughs or major geopolitical developments that could affect PEV market penetration. Third, we applied a low hurdle rate of 10% across all modeled scenarios. The 10% hurdle rate is an approximate estimate of consumer expectations towards alternative vehicles use, which depend on a variety of factors, including convenience of refueling or charging infrastructure, travel range on a single charge, or desired payback periods. Consumer choice in future vehicle adoption can also be affected by several other factors, such as vehicle design, safety, and comfort, driver's income, age, and education, driving habits, household size and location (urban, suburban, or rural), social media coverage, the opinion of peers, and subjective aspects such as prestige or style. The application of a scalar hurdle rate to represent the reluctance to adopt alternative vehicle technologies is a key simplification in this modeling work. Fourth, we did not capture the potential effects of vehicle smart charging and vehicle-to-grid power on electricity prices and PEV market share. Fifth, we did not consider the environmental life cycle impacts of competing vehicle technologies. For example, we did not consider potential shortages in battery raw materials such as lithium, the environmental impacts associated with battery recycling and disposal, or resource consumption and emissions associated with building charging infrastructure. Sixth, there are several macroeconomic aspects of PEV deployment that were not captured by our energy system model. For example, the widespread adoption of PEVs can exert an influence on total U.S. employment, household income, gross domestic product (GDP), federal budget, and the U.S. trade balance.

The work in this dissertation could be extended in several ways. Future efforts are needed to develop a U.S. regional energy system database. Regional variations in energy resources, electricity supply, energy and emissions policies, air quality regulations, and inter-regional trade of fossil fuels and electricity could produce important region-specific energy and emissions impacts. Furthermore, while emissions of SO_2 and NO_X are tracked in addition to CO_2, we were not able to assess the impact on regional air quality. Linking the output of a regional energy system model to an air quality model would help quantify the potential air quality benefits associated with PEV deployment and associated shift in emissions from urban transportation to more rural power plants. Finally, it would be worthwhile to extend the assessment to include the effects of large scale PEV deployment on crude oil consumption, imports, and overall energy security. Only through a holistic examination of PEV deployment and its effect on CO_2 emissions, local and regional quality, and energy security can we judge the overall efficacy of this promising vehicle technology.

APPENDICES

APPENDIX A. National US TIMES Dataset (NUSTD) Description

Section A1. Overview of the National US TIMES Dataset (NUSTD)

The National US TIMES Dataset (NUSTD) was designed and built to conduct this analysis. Given the focus on electric drive vehicles (EDVs), NUSTD contains significant technology detail in both the electric and transportation sector, while the industrial, commercial, and residential sectors are each represented by a fixed total demand and a set of fuel share constraints (Equations B.20 and B.21) that are gradually relaxed over time. The organization of NUSTD is provided below in Figure A1.

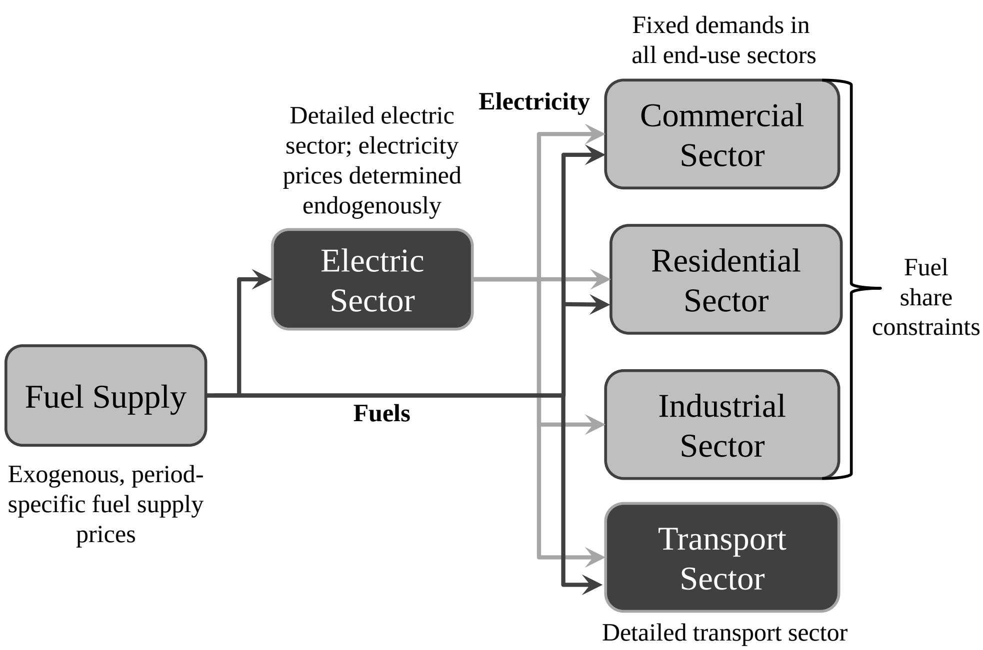

Figure A1. Design details associated with the NUSTD. The electric and transport sectors contain significant technology detail in order to capture the effects of EDVs in both sectors. Conceptually, energy commodities flow left-to-right through a series of transformations in order to meet a set of fixed end-use demands. Capacity installation and utilization of technology over time is determined in both the electric and transport sectors.

We started with the U.S. EPA National Model Database (EPANMD) as a data source for transportation and electric sectors (Shay et al., 2006), but then incorporated a series of technology updates and assumptions largely based on the Annual Energy Outlook (AEO) 2012 (EIA, 2012), GREET (GREET, 2012), and eGRID (eGRID, 2010). Key data and assumptions are described in the following sections, organized by model sector: transportation (A2), electric (A3), end-use sectors (A4), and resource supply (A5). While we provide a description of NUSTD in sections A2-A5, the complete set of input workbooks is publicly accessible online (Energy Modeling, 2014).

Section A2. Transportation sector

The transport sector consists of three subsectors: light duty vehicles (LDV), heavy duty vehicles (HDV), and off-highway (OH). All of the parameters used to characterize HDV and OH technologies in NUSTD are obtained from EPANMD-2010-V1.0 (Shay et al., 2006). This section is focused on the LDV sector, which is most relevant to the current analysis. An overview of the LDV sector is provided first, followed by vehicle-specific energy efficiency, special considerations associated with EDVs, and the use of hurdle rates for alternative vehicles.

Vehicles Costs, stock, tailpipe emissions, and demand

Table A1 lists all of the light duty vehicles, categorized by size and fuel type according to the EPANMD (Shay et al., 2006). Vehicle lifetimes and the fixed operation and maintenance costs (in units of million 2010 $ per billion vehicle miles traveled [bnvmt]) are based on

EPANMD-2010-V1.0 (Shay et al., 2006). The investment costs associated with light duty vehicles and start years (i.e., the first year of technology availability) are drawn from the AEO (EIA, 2012). While the National Energy Modeling System (NEMS) (EIA-NEMS, 2009) assumes that vehicle price is subject to endogenous technological learning at the vehicle component level, for simplicity, we adopt the resultant EDV prices from AEO and use them to specify the vehicle cost exogenously in NUSTD. The cost of refueling infrastructure for alternative fuel vehicles is added to the capital cost of PHEVs and BEVs and to the fuel price of CNG, E85X, and hydrogen fuel cell vehicles (EIA, 2012; Peterson and Michalek, 2013).

Table A1. Start year, lifetime, fixed operation and maintenance cost, and capital cost of LDVs

Technology Name	Start Year	Lifetime	Fixed Operation & Maintenance Cost (M$/bnvmt)	Investment Cost (million 2010 $ per bnvmt)							
				2015	2020	2025	2030	2035	2040	2045	2050
Compact Diesel	2015	15	38.49	2034	2139	2216	2222	2222	2222	2222	2222
Full Diesel	2015	15	43.30	2389	2470	2556	2556	2556	2556	2556	2556
Minivan Diesel	2015	15	43.30	2586	2637	2764	2784	2784	2784	2784	2784
Pickup Diesel	2015	15	48.12	2310	2362	2448	2448	2448	2448	2448	2448
Small SUV Diesel	2015	15	43.30	2330	2380	2513	2538	2538	2538	2538	2538
Large SUV Diesel	2015	15	43.30	3390	3448	3549	3582	3582	3582	3582	3582
Compact Diesel Hybrid	2020	15	40.42		2488	2463	2446	2446	2446	2446	2446
Full Diesel Hybrid	2025	15	45.52			2757	2728	2728	2728	2728	2728
Minivan Diesel Hybrid	2015	15	45.47	2947	2964	2939	2931	2931	2931	2931	2931
Small SUV Diesel Hybrid	2020	15	45.52		2780	2780	2764	2764	2764	2764	2764
Large SUV Diesel Hybrid	2020	15	45.52		3858	3833	3816	3816	3816	3816	3816
Compact Ethanol Flex Fuel	2015	15	38.49	1863	1973	2080	2080	2080	2080	2080	2080
Full Ethanol Flex Fuel	2015	15	43.30	2249	2347	2467	2467	2467	2467	2467	2467
Minivan Ethanol Flex Fuel	2015	15	43.30	2160	2236	2375	2403	2403	2403	2403	2403
Pickup Ethanol Flex Fuel	2015	15	48.12	1878	1963	2066	2080	2080	2080	2080	2080
Small SUV Ethanol Flex Fuel	2015	15	43.30	2029	2121	2263	2271	2271	2271	2271	2271
Large SUV Ethanol Flex Fuel	2015	15	43.30	3056	3148	3265	3281	3281	3281	3281	3281

Table A1 Continued

Compact Hybrid Ethanol	2015	15	40.42	2406	2399	2383	2374	2374	2374	2374	2374
Full Hybrid Ethanol	2015	15	45.52	2810	2804	2784	2776	2776	2776	2776	2776
Pickup Hybrid Ethanol	2015	15	48.12	2597	2374	2349	2332	2332	2332	2332	2332
Minivan Hybrid Ethanol	2015	15	45.52	2653	2650	2630	2617	2617	2617	2617	2617
Large SUV Hybrid Ethanol	2015	15	45.52	3666	3649	3624	3615	3615	3615	3615	3615
Small SUV Hybrid Ethanol	2015	15	45.52	2605	2597	2580	2563	2563	2563	2563	2563
Compact Ethanol plugin hybrid (20km)[a]	2015	15	40.42	2581	2523	2443	2421	2413	2413	2413	2413
Full Ethanol plugin hybrid (20km)	2020	15	45.52		2841	2809	2784	2772	2772	2772	2772
Pickup Ethanol plugin hybrid (20km)	2025	15	48.12			2636	2621	2602	2602	2602	2602
Minivan Ethanol plugin hybrid (20km)	2020	15	45.52		2766	2691	2685	2663	2663	2663	2663
Large SUV Ethanol plugin hybrid (20km)	2025	15	45.52			3643	3609	3593	3593	3593	3593
Small SUV Ethanol plugin hybrid (20km)	2015	15	45.52	2657	2657	2582	2557	2540	2540	2540	2540
Compact Ethanol plugin hybrid (60km)[a]	2015	15	40.42	3140	2967	2861	2772	2714	2714	2714	2714
Full Ethanol plugin hybrid (60km)	2015	15	45.52	3524	3357	3235	3129	3068	3068	3068	3068
Pickup Ethanol plugin hybrid (60km)	2025	15	48.12			3269	3123	2991	2991	2991	2991
Minivan Ethanol plugin hybrid (60km)	2020	15	45.52		3431	3361	3219	3081	3081	3081	3081
Large SUV Ethanol plugin hybrid (60km)	2025	15	45.52			4583	4366	4177	4177	4177	4177
Small SUV Ethanol plugin hybrid (60km)	2015	15	45.52	3375	3228	3176	3028	2902	2902	2902	2902
Minicompact Electric[b]	2015	15	25.98	8435	7141	6390	6022	6022	6022	6022	6022
Compact Electric[b]	2015	15	25.98	2908	2825	2683	2551	2551	2551	2551	2551
Full Electric[b]	2020	15	25.98		3225	3075	2925	2925	2925	2925	2925
Small SUV Electric[b]	2015	15	25.98	3517	3200	3025	2858	2858	2858	2858	2858
Mini compact conventional gasoline	2015	15	38.49	3565	3692	3792	3789	3789	3789	3789	3789
Compact conventional gasoline	2015	15	38.49	1855	1965	2074	2074	2074	2074	2074	2074
Full conventional gasoline	2015	15	43.30	2241	2338	2459	2459	2459	2459	2459	2459
Minivan conventional gasoline	2015	15	43.30	2152	2227	2367	2395	2395	2395	2395	2395
Pickup conventional gasoline	2015	15	48.12	1869	1961	2057	2066	2066	2066	2066	2066
Small SUV conventional gasoline	2015	15	43.30	2021	2113	2254	2263	2263	2263	2263	2263
Large SUV conventional gasoline	2015	15	43.30	3048	3140	3256	3273	3273	3273	3273	3273
Compact gasoline hybrid	2015	15	40.42	2399	2392	2375	2367	2367	2367	2367	2367
Full gasoline hybrid	2015	15	45.47	2801	2795	2776	2767	2767	2767	2767	2767
Minivan gasoline hybrid	2015	15	45.52	2645	2642	2622	2609	2609	2609	2609	2609
Pickup gasoline hybrid	2015	15	48.12	2588	2365	2340	2323	2323	2323	2323	2323
Small SUV gasoline hybrid	2015	15	45.52	2597	2588	2572	2555	2555	2555	2555	2555
Large SUV gasoline hybrid	2015	15	45.52	3657	3641	3615	3607	3607	3607	3607	3607
Compact gasoline plugin hybrid (20km)[a]	2015	15	40.42	2574	2515	2435	2414	2405	2405	2405	2405
Full gasoline plugin hybrid (20km)	2020	15	45.52		2833	2800	2775	2764	2764	2764	2764
Pickup gasoline plugin hybrid (20km)	2025	15	48.12			2628	2613	2594	2594	2594	2594
Minivan gasoline plugin hybrid (20km)	2020	15	45.52		2758	2682	2676	2655	2655	2655	2655
Large SUV gasoline plugin hybrid (20km)	2025	15	45.52			3634	3601	3584	3584	3584	3584
Small SUV gasoline plugin hybrid (20km)	2015	15	45.52	2649	2649	2574	2549	2532	2532	2532	2532
Compact gasoline plugin hybrid (60km)[a]	2015	15	40.42	3133	2960	2853	2765	2707	2707	2707	2707
Full gasoline plugin hybrid (60km)	2015	15	45.52	3516	3349	3227	3121	3059	3059	3059	3059

Table A1 Continued

Pickup gasoline plugin hybrid (60km)	2025	15	48.12			3260	3115	2983	2983	2983	2983
Minivan gasoline plugin hybrid (60km)	2020	15	45.52		3423	3352	3210	3072	3072	3072	3072
Large SUV gasoline plugin hybrid (60km)	2025	15	45.52			4575	4358	4168	4168	4168	4168
Small SUV gasoline plugin hybrid (60km)	2015	15	45.52	3367	3220	3168	3020	2893	2893	2893	2893
Compact hydrogen fuel cell	2015	15	40.42	5327	4736	4195	3850	3850	3850	3850	3850
Full hydrogen fuel cell	2015	15	45.47	6356	5435	4790	4391	4391	4391	4391	4391
Minivan hydrogen fuel cell	2015	15	47.63	7114	6070	5185	4651	4651	4651	4651	4651
Small SUV hydrogen fuel cell	2015	15	45.52	6563	5611	4885	4392	4392	4392	4392	4392
Large SUV hydrogen fuel cell	2025	15	45.52			6813	6179	6179	6179	6179	6179
Compact compressed natural gas	2015	15	34.64	2505	2613	2730	2730	2730	2730	2730	2730
Full compressed natural gas	2015	15	38.97	3073	3165	3307	3307	3307	3307	3307	3307
Minivan compressed natural gas	2015	15	38.97	2847	2922	3031	3048	3048	3048	3048	3048
Pickup compressed natural gas	2015	15	48.12	2705	2780	2864	2889	2889	2889	2889	2889
Existing Mini compact conventional gasoline	2010	15	38.49								
Existing Compact conventional gasoline	2010	15	38.49								
Existing Full Diesel	2010	15	43.30								
Existing Full conventional gasoline	2010	15	43.30								
Existing Small SUV conventional gasoline	2010	15	43.30								
Existing Large SUV conventional gasoline	2010	15	43.30								
Existing Minivan conventional gasoline	2010	15	43.30								
Existing Pickup conventional gasoline	2010	15	48.12								
Existing Pickup Diesel	2010	15	48.12								
Existing any Ethanol Flex Fuel	2010	15	43.30								
Existing any CNG	2010	15	38.97								
Existing any Electric	2010	15	25.98								
Blending process to collect conventional gasoline and ethanol for E10 for LDV	2010	50									
Blending process to collect conventional gasoline and ethanol for E85X for LDV	2010	50	2.08								
Collector: DSLU to DSL for LDV	2010	55									
Collector: NGA to CNG for LDV	2010	55	1.95								

[a] The distance in parentheses represents the all-electric range (AER)

[b] All new electric cars have 160 kilometers all-electric range battery.

Table A2 presents the assumed existing stock of light duty vehicles by size class and fuel type. Note that the total distance traveled (bnvmt) can be converted to the total number of light duty vehicles by assuming 12,500 mi/yr/vehicle traveled. The cumulative retirement percentages of the 2010 existing capacity are 30%, 59%, 84%, and 92% for 2015, 2020, 2025, and 2030, respectively. Both the existing stock and the estimated retirement rates are drawn from EPANMD-2010-V1.0 (Shay et al., 2006).

Table A2. Existing capacity of light duty vehicles (bnvmt)

Technology Name	2010	2015	2020	2025	2030
Existing Mini compact conventional gasoline	43.18	30.22	17.70	6.908	3.454
Existing Compact conventional gasoline	728.3	509.8	298.6	116.5	58.26
Existing Full Diesel	4.906	3.400	1.992	0.777	0.389
Existing Full conventional gasoline	604.2	423.0	247.7	96.68	48.34
Existing Small SUV conventional gasoline	187.1	130.9	76.69	29.93	14.96
Existing Large SUV conventional gasoline	159.4	111.6	65.34	25.50	12.75
Existing Minivan conventional gasoline	281.0	196.7	115.21	44.96	22.48
Existing Pickup conventional gasoline	519.3	363.5	212.9	83.09	41.55
Existing Pickup Diesel	4.944	3.461	2.027	0.791	0.396
Existing any Ethanol Flex Fuel	119.2	83.46	48.88	19.08	9.538
Existing any CNG	3.301	2.310	1.353	0.528	0.264
Existing any Electric	0.300	0.210	0.123	0.048	0.024

The total demand for vehicle miles associated with light duty transportation, shown in Table A3, is drawn from AEO (EIA, 2012) and linearly extrapolated from 2035 to 2050.

Table A3. Demand values for light duty transportation sector (billion vehicle miles)

Commodity Description	Abbreviation	2010	2015	2020	2025	2030	2035	2040	2045	2050
Total miles demanded for LDV	TMDLDV	2655	2711	2882	3113	3365	3586	3716	3846	3975

CO_2 emission coefficients for transportation fuels are drawn from the AEO (EIA, 2012) and are shown in Table A4. CO_2 emissions are provided per unit of primary fuel input, whereas SO_2 and NO_X emissions depend not only on the input fuel but also on vehicle engine technology and performance. For brevity, only the CO_2 emissions factors are shown in Table A4; however, emissions factors for SO_2 and NO_X can be found in the NUSTD spreadsheets (Energy Modeling, 2014).

Table A4. CO_2 emission factor of transportation fuels

Commodity Name	**CO_2 Emissions Factor (Thousand ton/PJ)**
Conventional gasoline	67.6
Ethanol	67.6
Ultra low sulfur diesel	69.4
Natural gas	50.3

Vehicle energy efficiency

We represent vehicle performance through two key parameters: (1) the vehicle efficiency, expressed in units of PJ/bnvmt, and (2) the fuel ratio, which characterizes the ratio of fuel inputs required to generate 1 bnvmt. The latter only applies to vehicles that operate on more than one fuel type, such as PHEVs and flex fuel vehicles (i.e., vehicles that use blended fuels, such as ethanol and gasoline).

Non-electric drive vehicles

The efficiencies of existing and new non-electric drive LDVs (conventional gasoline, ethanol (E85), diesel, compressed natural gas, and hydrogen fuel cell) are taken from EPANMD-2010-V1.0 (Shay et al., 2006), but were updated based on the AEO (EIA, 2012). Table A5 shows the period-specific efficiencies associated with all of the light duty technologies in NUSTD. The commodity abbreviations are described in Table A12.

Table A5. Light duty vehicle energy efficiency (bnvmt per PJ)

Technology Name	Commodity In	Commodity Out	2010	2015	2020	2025	2030	2035	2040	2045	2050
Compact Diesel	TRNDSLLDV	TMDLDV		0.2672	0.3259	0.3796	0.3798	0.3798	0.3798	0.3798	0.3798
Full Diesel	TRNDSLLDV	TMDLDV		0.2536	0.2989	0.3466	0.3467	0.3467	0.3467	0.3467	0.3467
Minivan Diesel	TRNDSLLDV	TMDLDV		0.2167	0.2418	0.2944	0.3026	0.3026	0.3026	0.3026	0.3026
Pickup Diesel	TRNDSLLDV	TMDLDV		0.1838	0.2027	0.2323	0.2368	0.2368	0.2368	0.2368	0.2368
Small SUV Diesel	TRNDSLLDV	TMDLDV		0.2221	0.2472	0.3037	0.3122	0.3122	0.3122	0.3122	0.3122
Large SUV Diesel	TRNDSLLDV	TMDLDV		0.1793	0.2028	0.2359	0.2427	0.2427	0.2427	0.2427	0.2427
Compact Diesel Hybrid	TRNDSLLDV	TMDLDV			0.3883	0.3883	0.3883	0.3883	0.3883	0.3883	0.3883
Full Diesel Hybrid	TRNDSLLDV	TMDLDV				0.3883	0.3883	0.3883	0.3883	0.3883	0.3883
Minivan Diesel Hybrid	TRNDSLLDV	TMDLDV		0.2700	0.2763	0.2763	0.2763	0.2763	0.2763	0.2763	0.2763
Small SUV Diesel Hybrid	TRNDSLLDV	TMDLDV			0.2763	0.2763	0.2763	0.2763	0.2763	0.2763	0.2763
Large SUV Diesel Hybrid	TRNDSLLDV	TMDLDV			0.2406	0.2656	0.2656	0.2656	0.2656	0.2656	0.2656
Compact Ethanol Flex Fuel	E85XLDV	TMDLDV		0.2205	0.2707	0.3340	0.3351	0.3351	0.3351	0.3351	0.3351
Full Ethanol Flex Fuel	E85XLDV	TMDLDV		0.2098	0.2519	0.3109	0.3112	0.3112	0.3112	0.3112	0.3112
Minivan Ethanol Flex Fuel	E85XLDV	TMDLDV		0.1800	0.2087	0.2595	0.2702	0.2702	0.2702	0.2702	0.2702
Pickup Ethanol Flex Fuel	E85XLDV	TMDLDV		0.1516	0.1757	0.2044	0.2096	0.2096	0.2096	0.2096	0.2096
Small SUV Ethanol Flex Fuel	E85XLDV	TMDLDV		0.1863	0.2184	0.2794	0.2832	0.2832	0.2832	0.2832	0.2832
Large SUV Ethanol Flex Fuel	E85XLDV	TMDLDV		0.1484	0.1761	0.2140	0.2231	0.2231	0.2231	0.2231	0.2231
Compact Hybrid Ethanol	E85XLDV	TMDLDV		0.2888	0.3126	0.3126	0.3126	0.3126	0.3126	0.3126	0.3126
Full Hybrid Ethanol	E85XLDV	TMDLDV		0.2888	0.3126	0.3126	0.3126	0.3126	0.3126	0.3126	0.3126
Pickup Hybrid Ethanol	E85XLDV	TMDLDV		0.1784	0.1798	0.1798	0.1798	0.1798	0.1798	0.1798	0.1798
Minivan Hybrid Ethanol	E85XLDV	TMDLDV		0.2096	0.2145	0.2145	0.2145	0.2145	0.2145	0.2145	0.2145
Large SUV Hybrid Ethanol	E85XLDV	TMDLDV		0.1784	0.1798	0.1798	0.1798	0.1798	0.1798	0.1798	0.1798
Small SUV Hybrid Ethanol	E85XLDV	TMDLDV		0.2096	0.2145	0.2145	0.2145	0.2145	0.2145	0.2145	0.2145
Compact Ethanol plugin hybrid 20 km	E85XLDV	TMDLDV		0.3494	0.3811	0.3811	0.3811	0.3811	0.3811	0.3811	0.3811
	ELC	TMDLDV		0.3494	0.3811	0.3811	0.3811	0.3811	0.3811	0.3811	0.3811
Full Ethanol plugin hybrid 20 km	E85XLDV	TMDLDV			0.3811	0.3811	0.3811	0.3811	0.3811	0.3811	0.3811
	ELC	TMDLDV			0.3811	0.3811	0.3811	0.3811	0.3811	0.3811	0.3811
Pickup Ethanol plugin hybrid 20 km	E85XLDV	TMDLDV				0.2256	0.2256	0.2256	0.2256	0.2256	0.2256
	ELC	TMDLDV				0.2256	0.2256	0.2256	0.2256	0.2256	0.2256
Minivan Ethanol plugin hybrid 20 km	E85XLDV	TMDLDV			0.2480	0.2480	0.2480	0.2480	0.2480	0.2480	0.2480
	ELC	TMDLDV			0.2480	0.2480	0.2480	0.2480	0.2480	0.2480	0.2480
Large SUV Ethanol plugin hybrid 20 km	E85XLDV	TMDLDV				0.2256	0.2256	0.2256	0.2256	0.2256	0.2256
	ELC	TMDLDV				0.2256	0.2256	0.2256	0.2256	0.2256	0.2256
Small SUV Ethanol plugin hybrid 20 km	E85XLDV	TMDLDV		0.2393	0.2480	0.2480	0.2480	0.2480	0.2480	0.2480	0.2480
	ELC	TMDLDV		0.2393	0.2480	0.2480	0.2480	0.2480	0.2480	0.2480	0.2480

Table A5 Continued

Compact Ethanol plugin hybrid 60 km	E85XLDV	TMDLDV	0.3855	0.4189	0.4189	0.4189	0.4189	0.4189	0.4189	0.4189
	ELC	TMDLDV	0.3855	0.4189	0.4189	0.4189	0.4189	0.4189	0.4189	0.4189
Full Ethanol plugin hybrid 60 km	E85XLDV	TMDLDV	0.3855	0.4189	0.4189	0.4189	0.4189	0.4189	0.4189	0.4189
	ELC	TMDLDV	0.3855	0.4189	0.4189	0.4189	0.4189	0.4189	0.4189	0.4189
Pickup Ethanol plugin hybrid 60 km	E85XLDV	TMDLDV			0.2419	0.2419	0.2419	0.2419	0.2419	0.2419
	ELC	TMDLDV			0.2419	0.2419	0.2419	0.2419	0.2419	0.2419
Minivan Ethanol plugin hybrid 60 km	E85XLDV	TMDLDV		0.2734	0.2734	0.2734	0.2734	0.2734	0.2734	0.2734
	ELC	TMDLDV		0.2734	0.2734	0.2734	0.2734	0.2734	0.2734	0.2734
Large SUV Ethanol plugin hybrid 60 km	E85XLDV	TMDLDV			0.2419	0.2419	0.2419	0.2419	0.2419	0.2419
	ELC	TMDLDV			0.2419	0.2419	0.2419	0.2419	0.2419	0.2419
Small SUV Ethanol plugin hybrid 60 km	E85XLDV	TMDLDV	0.2535	0.2734	0.2734	0.2734	0.2734	0.2734	0.2734	0.2734
	ELC	TMDLDV	0.2535	0.2734	0.2734	0.2734	0.2734	0.2734	0.2734	0.2734
Mini Compact Electric	ELC	TMDLDV	0.5500	0.7831	0.9882	1.0131	1.0131	1.0131	1.0131	1.0131
Compact Electric	ELC	TMDLDV	0.8251	0.8932	0.8932	0.8932	0.8932	0.8932	0.8932	0.8932
Full Electric	ELC	TMDLDV		0.8932	0.8932	0.8932	0.8932	0.8932	0.8932	0.8932
Small SUV Electric	ELC	TMDLDV	0.6209	0.6355	0.6355	0.6355	0.6355	0.6355	0.6355	0.6355
Mini compact conventional gasoline	E10LDV	TMDLDV	0.1964	0.2489	0.2972	0.2982	0.2982	0.2982	0.2982	0.2982
Compact conventional gasoline	E10LDV	TMDLDV	0.2191	0.2711	0.3320	0.3331	0.3331	0.3331	0.3331	0.3331
Full conventional gasoline	E10LDV	TMDLDV	0.2078	0.2494	0.3077	0.3081	0.3081	0.3081	0.3081	0.3081
Minivan conventional gasoline	E10LDV	TMDLDV	0.1783	0.2069	0.2567	0.2672	0.2683	0.2683	0.2683	0.2683
Pickup conventional gasoline	E10LDV	TMDLDV	0.1501	0.1743	0.2025	0.2073	0.2098	0.2098	0.2098	0.2098
Small SUV conventional gasoline	E10LDV	TMDLDV	0.1844	0.2165	0.2764	0.2802	0.2809	0.2809	0.2809	0.2809
Large SUV conventional gasoline	E10LDV	TMDLDV	0.1470	0.1747	0.2119	0.2207	0.2219	0.2219	0.2219	0.2219
Compact gasoline hybrid	E10LDV	TMDLDV	0.2888	0.3126	0.3126	0.3126	0.3126	0.3126	0.3126	0.3126
Full gasoline hybrid	E10LDV	TMDLDV	0.2888	0.3126	0.3126	0.3126	0.3126	0.3126	0.3126	0.3126
Minivan gasoline hybrid	E10LDV	TMDLDV	0.2096	0.2145	0.2145	0.2145	0.2145	0.2145	0.2145	0.2145
Pickup gasoline hybrid	E10LDV	TMDLDV	0.1784	0.1798	0.1798	0.1798	0.1798	0.1798	0.1798	0.1798
Small SUV gasoline hybrid	E10LDV	TMDLDV	0.2096	0.2145	0.2145	0.2145	0.2145	0.2145	0.2145	0.2145
Large SUV gasoline hybrid	E10LDV	TMDLDV	0.1784	0.1798	0.1798	0.1798	0.1798	0.1798	0.1798	0.1798
Compact gasoline plugin hybrid 20 km blended	E10LDV	TMDLDV	0.3701	0.4034	0.4034	0.4034	0.4034	0.4034	0.4034	0.4034
	ELC	TMDLDV	0.3701	0.4034	0.4034	0.4034	0.4034	0.4034	0.4034	0.4034
Full gasoline plugin hybrid 20 km blended	E10LDV	TMDLDV		0.4034	0.4034	0.4034	0.4034	0.4034	0.4034	0.4034
	ELC	TMDLDV		0.4034	0.4034	0.4034	0.4034	0.4034	0.4034	0.4034
Pickup gasoline plugin hybrid 20 km blended	E10LDV	TMDLDV			0.2256	0.2256	0.2256	0.2256	0.2256	0.2256
	ELC	TMDLDV			0.2256	0.2256	0.2256	0.2256	0.2256	0.2256
Minivan gasoline plugin hybrid 20 km blended	E10LDV	TMDLDV		0.2633	0.2633	0.2633	0.2633	0.2633	0.2633	0.2633
	ELC	TMDLDV		0.2633	0.2633	0.2633	0.2633	0.2633	0.2633	0.2633
Large SUV gasoline plugin hybrid 20 km blended	E10LDV	TMDLDV			0.2256	0.2256	0.2256	0.2256	0.2256	0.2256
	ELC	TMDLDV			0.2256	0.2256	0.2256	0.2256	0.2256	0.2256
Small SUV gasoline plugin hybrid 20 km blended	E10LDV	TMDLDV	0.2540	0.2633	0.2633	0.2633	0.2633	0.2633	0.2633	0.2633
	ELC	TMDLDV	0.2540	0.2633	0.2633	0.2633	0.2633	0.2633	0.2633	0.2633
Compact gasoline plugin hybrid 60 km series	E10LDV	TMDLDV	0.4063	0.4409	0.4409	0.4409	0.4409	0.4409	0.4409	0.4409
	ELC	TMDLDV	0.4063	0.4409	0.4409	0.4409	0.4409	0.4409	0.4409	0.4409
Full gasoline plugin hybrid 60 km series	E10LDV	TMDLDV	0.4063	0.4409	0.4409	0.4409	0.4409	0.4409	0.4409	0.4409

Table A5 Continued

	ELC	TMDLDV		0.4063	0.4409	0.4409	0.4409	0.4409	0.4409	0.4409	0.4409
Pickup gasoline plugin hybrid 60 km series	E10LDV	TMDLDV				0.2419	0.2419	0.2419	0.2419	0.2419	0.2419
	ELC	TMDLDV				0.2419	0.2419	0.2419	0.2419	0.2419	0.2419
Minivan gasoline plugin hybrid 60 km series	E10LDV	TMDLDV			0.2890	0.2890	0.2890	0.2890	0.2890	0.2890	0.2890
	ELC	TMDLDV			0.2890	0.2890	0.2890	0.2890	0.2890	0.2890	0.2890
Large SUV gasoline plugin hybrid 60 km series	E10LDV	TMDLDV				0.2419	0.2419	0.2419	0.2419	0.2419	0.2419
	ELC	TMDLDV				0.2419	0.2419	0.2419	0.2419	0.2419	0.2419
Small SUV gasoline plugin hybrid 60 km series	E10LDV	TMDLDV		0.2674	0.2890	0.2890	0.2890	0.2890	0.2890	0.2890	0.2890
	ELC	TMDLDV		0.2674	0.2890	0.2890	0.2890	0.2890	0.2890	0.2890	0.2890
Compact hydrogen fuel cell	H2	TMDLDV		0.3784	0.4017	0.4193	0.4193	0.4193	0.4193	0.4193	0.4193
Full hydrogen fuel cell	H2	TMDLDV		0.3335	0.3465	0.3639	0.3639	0.3639	0.3639	0.3639	0.3639
Minivan hydrogen fuel cell	H2	TMDLDV		0.2527	0.2623	0.2814	0.2866	0.2866	0.2866	0.2866	0.2866
Small SUV hydrogen fuel cell	H2	TMDLDV		0.2814	0.2930	0.3062	0.3122	0.3122	0.3122	0.3122	0.3122
Large SUV hydrogen fuel cell	H2	TMDLDV				0.2349	0.2385	0.2385	0.2385	0.2385	0.2385
Existing Mini compact conventional gasoline	E10LDV	TMDLDV	0.1607	0.1607	0.1607	0.1607	0.1607	0.1607	0.1607	0.1607	0.1607
Existing Compact conventional gasoline	E10LDV	TMDLDV	0.1951	0.1951	0.1951	0.1951	0.1951	0.1951	0.1951	0.1951	0.1951
Existing Full Diesel	TRNDSLLDV	TMDLDV	0.1752	0.1752	0.1752	0.1752	0.1752	0.1752	0.1752	0.1752	0.1752
Existing Full conventional gasoline	E10LDV	TMDLDV	0.1714	0.1714	0.1714	0.1714	0.1714	0.1714	0.1714	0.1714	0.1714
Existing Small SUV conventional gasoline	E10LDV	TMDLDV	0.1452	0.1452	0.1452	0.1452	0.1452	0.1452	0.1452	0.1452	0.1452
Existing Large SUV conventional gasoline	E10LDV	TMDLDV	0.1213	0.1213	0.1213	0.1213	0.1213	0.1213	0.1213	0.1213	0.1213
Existing Minivan conventional gasoline	E10LDV	TMDLDV	0.1576	0.1576	0.1576	0.1576	0.1576	0.1576	0.1576	0.1576	0.1576
Existing Pickup conventional gasoline	E10LDV	TMDLDV	0.1301	0.1301	0.1301	0.1301	0.1301	0.1301	0.1301	0.1301	0.1301
Existing Pickup Diesel	TRNDSLLDV	TMDLDV	0.1364	0.1364	0.1364	0.1364	0.1364	0.1364	0.1364	0.1364	0.1364
Existing any Ethanol Flex Fuel	E85XLDV	TMDLDV	0.1596	0.1596	0.1596	0.1596	0.1596	0.1596	0.1596	0.1596	0.1596
	E10LDV	TMDLDV	0.1596	0.1596	0.1596	0.1596	0.1596	0.1596	0.1596	0.1596	0.1596
Existing any CNG	CNGLDV	TMDLDV	0.1712	0.1712	0.1712	0.1712	0.1712	0.1712	0.1712	0.1712	0.1712
Existing any Electric	ELC	TMDLDV	0.7225	0.7225	0.7225	0.7225	0.7225	0.7225	0.7225	0.7225	0.7225
Compact compressed natural gas	CNGLDV	TMDLDV		0.2349	0.2919	0.3581	0.3593	0.3593	0.3593	0.3593	0.3593
Full compressed natural gas	CNGLDV	TMDLDV		0.2155	0.2610	0.3282	0.3283	0.3283	0.3283	0.3283	0.3283
Minivan compressed natural gas	CNGLDV	TMDLDV		0.1895	0.2164	0.2608	0.2709	0.2709	0.2709	0.2709	0.2709
Pickup compressed natural gas	CNGLDV	TMDLDV		0.1574	0.1786	0.2025	0.2122	0.2122	0.2122	0.2122	0.2122

Light Duty Electric Drive Vehicles

Electric drive vehicles (EDVs) include hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs). EDV efficiencies are drawn from GREET (GREET, 2012). The NUSTD includes 6 LDV vehicle size classes (compact, full, minivan, small SUV, pickup, and large SUV), whereas GREET only includes 3 size classes (passenger car and two light duty truck sizes categorized by weight). According to the GREET size definitions, ‘passenger cars’ have a gross vehicle weight of less than 2721 kg; ‘light duty truck 1’ also has a gross vehicle weight of less than 2721 kg; ‘light duty truck 2’ has a gross vehicle weight of 2722-3855 kg (ANL, 2001). As a result, the ‘passenger car’ fuel economy from GREET is used in NUSTD for the compact and full size vehicles, ‘light duty truck 1’ for small SUVs and minivans, and ‘light duty truck 2’ for large SUVs and pickup trucks. No improvement in battery efficiency is assumed from 2020 to 2050, as GREET projections do not extend beyond 2020. Further extrapolation of battery improvements is highly speculative and could unintentionally drive model results.

Because PHEVs operate in both charge-depleting (CD) and charge-sustaining (CS) modes, their representation in the NUSTD requires some explanation. A PHEV at full charge operates in CD mode until the battery reaches a minimum state of charge, at which point the vehicle switches to CS mode. There are two basic control strategies for vehicles in CD mode: all-electric or blended operation. PHEVs with an all-electric control strategy derive all of their propulsion energy from the battery during CD mode, whereas PHEVs with a blended control strategy derive their propulsion energy from a combination of the engine and the battery during CD mode. For PHEVs with a blended control strategy, the distance traveled in CD mode exceeds the all-electric range (AER). With either control strategy, the PHEV operates like an HEV with regenerative braking during CS mode.

NUSTD includes 2 types of PHEVs, which are differentiated by the specified AER of 20 km or 60 km, which is consistent with other studies (Michalek et al., 2011; Weiller, 2011; Axen et al., 2011; Wang et al., 2011). The PHEV20 has a blended control strategy, with an all-electric range of 20 km, while the PHEV60 has an all-electric control strategy. PHEVs in the model can use electricity in combination with gasoline or E85 (ethanol with 15% gasoline).

GREET provides separate efficiencies for CD and CS mode for both the PHEV20 and PHEV60 (GREET, 2012). Because vehicle assumptions are harmonized with Michalek et al. (2011) their estimates of the fractional distance traveled annually in CD mode for PHEV20 (28%) and PHEV60 (47%) are utilized. Given the PHEV energy efficiency for the fuel and electricity inputs (in PJ per bnvmt) in each mode and the distance traveled in each mode, the gasoline and electricity consumption (in PJ) is estimated for each mode. The overall fuel ratio of gasoline to electricity for the PHEV is then calculated as follows:

$$\text{Ratio}_{\text{(gasoline/electricity)}} = \frac{\text{Total gasoline consumption in } (\text{CD} + \text{CS}) \text{ modes}}{\text{Total electricity consumption in } (\text{CD} + \text{CS}) \text{ modes}} \quad \text{(A.1)}$$

Table A6 lists the fuel ratios for the PHEV20, PHEV60, and the blending technologies (i.e., processes that blend two fuels; for example ethanol and gasoline to make E85). The commodity abbreviations are explained in Table A12.

Table A6. Fuel share of ethanol, gasoline, and electricity for the PHEV20, PHEV60, and blending processes

Technology Name	Commodity In	Commodity Out	2010	2015	2020	2025	2030	2035	2040	2045	2050
Compact Ethanol plugin hybrid 20 km	E85XLDV	TMDLDV		0.9327	0.9262	0.9262	0.9262	0.9262	0.9262	0.9262	0.9262
	ELC	TMDLDV		0.0673	0.0738	0.0738	0.0738	0.0738	0.0738	0.0738	0.0738
Full Ethanol plugin hybrid 20 km	E85XLDV	TMDLDV			0.9262	0.9262	0.9262	0.9262	0.9262	0.9262	0.9262
	ELC	TMDLDV			0.0738	0.0738	0.0738	0.0738	0.0738	0.0738	0.0738
Pickup Ethanol plugin hybrid 20 km	E85XLDV	TMDLDV				0.9536	0.9536	0.9536	0.9536	0.9536	0.9536
	ELC	TMDLDV				0.0464	0.0464	0.0464	0.0464	0.0464	0.0464
Minivan Ethanol plugin hybrid 20 km	E85XLDV	TMDLDV			0.9450	0.9450	0.9450	0.9450	0.9450	0.9450	0.9450
	ELC	TMDLDV			0.0550	0.0550	0.0550	0.0550	0.0550	0.0550	0.0550
Large SUV Ethanol plugin hybrid 20 km	E85XLDV	TMDLDV				0.9536	0.9536	0.9536	0.9536	0.9536	0.9536
	ELC	TMDLDV				0.0464	0.0464	0.0464	0.0464	0.0464	0.0464
Small SUV Ethanol plugin hybrid 20 km	E85XLDV	TMDLDV		0.9466	0.9450	0.9450	0.9450	0.9450	0.9450	0.9450	0.9450
	ELC	TMDLDV		0.0534	0.0550	0.0550	0.0550	0.0550	0.0550	0.0550	0.0550
Compact Ethanol plugin hybrid 60 km	E85XLDV	TMDLDV		0.8157	0.8042	0.8042	0.8042	0.8042	0.8042	0.8042	0.8042
	ELC	TMDLDV		0.1843	0.1958	0.1958	0.1958	0.1958	0.1958	0.1958	0.1958
Full Ethanol plugin hybrid 60 km	E85XLDV	TMDLDV		0.8157	0.8042	0.8042	0.8042	0.8042	0.8042	0.8042	0.8042
	ELC	TMDLDV		0.1843	0.1958	0.1958	0.1958	0.1958	0.1958	0.1958	0.1958
Pickup Ethanol plugin hybrid 60 km	E85XLDV	TMDLDV				0.8179	0.8179	0.8179	0.8179	0.8179	0.8179
	ELC	TMDLDV				0.1821	0.1821	0.1821	0.1821	0.1821	0.1821
Minivan Ethanol plugin hybrid 60 km	E85XLDV	TMDLDV			0.8248	0.8248	0.8248	0.8248	0.8248	0.8248	0.8248
	ELC	TMDLDV			0.1752	0.1752	0.1752	0.1752	0.1752	0.1752	0.1752
Large SUV Ethanol plugin hybrid 60 km	E85XLDV	TMDLDV				0.8179	0.8179	0.8179	0.8179	0.8179	0.8179
	ELC	TMDLDV				0.1821	0.1821	0.1821	0.1821	0.1821	0.1821
Small SUV Ethanol plugin hybrid 60 km	E85XLDV	TMDLDV		0.8248	0.8248	0.8248	0.8248	0.8248	0.8248	0.8248	0.8248
	ELC	TMDLDV		0.1752	0.1752	0.1752	0.1752	0.1752	0.1752	0.1752	0.1752
Compact gasoline plugin hybrid 20 km blended	E10LDV	TMDLDV		0.9283	0.9216	0.9216	0.9216	0.9216	0.9216	0.9216	0.9216
	ELC	TMDLDV		0.0717	0.0784	0.0784	0.0784	0.0784	0.0784	0.0784	0.0784
Full gasoline plugin hybrid 20 km blended	E10LDV	TMDLDV			0.9216	0.9216	0.9216	0.9216	0.9216	0.9216	0.9216
	ELC	TMDLDV			0.0784	0.0784	0.0784	0.0784	0.0784	0.0784	0.0784
Pickup gasoline plugin hybrid 20 km blended	E10LDV	TMDLDV				0.9536	0.9536	0.9536	0.9536	0.9536	0.9536
	ELC	TMDLDV				0.0464	0.0464	0.0464	0.0464	0.0464	0.0464
Minivan gasoline plugin hybrid 20 km blended	E10LDV	TMDLDV			0.9416	0.9416	0.9416	0.9416	0.9416	0.9416	0.9416
	ELC	TMDLDV			0.0584	0.0584	0.0584	0.0584	0.0584	0.0584	0.0584
Large SUV gasoline plugin hybrid 20 km blended	E10LDV	TMDLDV				0.9536	0.9536	0.9536	0.9536	0.9536	0.9536
	ELC	TMDLDV				0.0464	0.0464	0.0464	0.0464	0.0464	0.0464
Small SUV gasoline plugin hybrid 20 km blended	E10LDV	TMDLDV		0.9432	0.9416	0.9416	0.9416	0.9416	0.9416	0.9416	0.9416
	ELC	TMDLDV		0.0568	0.0584	0.0584	0.0584	0.0584	0.0584	0.0584	0.0584
Compact gasoline plugin hybrid 60 km series	E10LDV	TMDLDV		0.8058	0.7939	0.7939	0.7939	0.7939	0.7939	0.7939	0.7939
	ELC	TMDLDV		0.1942	0.2061	0.2061	0.2061	0.2061	0.2061	0.2061	0.2061
Full gasoline plugin hybrid 60 km series	E10LDV	TMDLDV		0.8058	0.7939	0.7939	0.7939	0.7939	0.7939	0.7939	0.7939

Table A6 Continued

	ELC	TMDLDV		0.1942	0.2061	0.2061	0.2061	0.2061	0.2061	0.2061	0.2061
Pickup gasoline plugin hybrid 60 km series	E10LDV	TMDLDV				0.8179	0.8179	0.8179	0.8179	0.8179	0.8179
	ELC	TMDLDV				0.1821	0.1821	0.1821	0.1821	0.1821	0.1821
Minivan gasoline plugin hybrid 60 km series	E10LDV	TMDLDV			0.8152	0.8152	0.8152	0.8152	0.8152	0.8152	0.8152
	ELC	TMDLDV			0.1848	0.1848	0.1848	0.1848	0.1848	0.1848	0.1848
Large SUV gasoline plugin hybrid 60 km series	E10LDV	TMDLDV				0.8179	0.8179	0.8179	0.8179	0.8179	0.8179
	ELC	TMDLDV				0.1821	0.1821	0.1821	0.1821	0.1821	0.1821
Small SUV gasoline plugin hybrid 60 km series	E10LDV	TMDLDV		0.8152	0.8152	0.8152	0.8152	0.8152	0.8152	0.8152	0.8152
	ELC	TMDLDV		0.1848	0.1848	0.1848	0.1848	0.1848	0.1848	0.1848	0.1848
Blending process to collect gasoline and ethanol for E10 for LDV	CONVGSL	E10LDV	0.9316	0.9316	0.9316	0.9316	0.9316	0.9316	0.9316	0.9316	0.9316
	EthtoGSLorE85XLDV	E10LDV	0.0684	0.0684	0.0684	0.0684	0.0684	0.0684	0.0684	0.0684	0.0684
Blending process to collect gasoline and ethanol for E85X for LDV	CONVGSL	E85XLDV	0.2107	0.2107	0.2107	0.2107	0.2107	0.2107	0.2107	0.2107	0.2107
	EthtoGSLorE85XLDV	E85XLDV	0.7893	0.7893	0.7893	0.7893	0.7893	0.7893	0.7893	0.7893	0.7893
Truck using diesel to transport cellulosic ethanol between regions for LDV	Celleth	EthtoGSLorE85XLDV	0.9882	0.9882	0.9882	0.9882	0.9882	0.9882	0.9882	0.9882	0.9882
	TRNDSLLDV	EthtoGSLorE85XLDV	0.0118	0.0118	0.0118	0.0118	0.0118	0.0118	0.0118	0.0118	0.0118

Alternative LDVs with hurdle rates

Bottom-up, technology rich models such as TIMES minimize direct costs and do not directly consider consumer expectations related to the convenience of refueling or charging infrastructure, travel range on a single charge, or desired payback periods. Without such considerations, some alternative vehicles, such as BEVs, have lower present cost compared to conventional options, and are therefore preferred by the model. In NUSTD, we approximate consumer behavior by applying hurdle rates (i.e., technology-specific discount rates) to the alternative LDVs: EDVs, CNG, hydrogen fuel cell vehicles, and diesel vehicles. The hurdle rates replace the 5% global discount rate used by the model when amortizing capital cost over the vehicle lifetime. Hurdle rates increase the annual payment on capital investments, thereby making the technology to which they are applied more expensive. As explained in the main narrative, we derived hurdle rates that were just large enough to keep alternative vehicles out of the reference case solution[1] rather than utilize behaviorally realistic hurdle rates.

To estimate the hurdle rate for the alternative vehicle technologies, the present cost for each vehicle is compared to a conventional gasoline vehicle. The capital cost is amortized using a hurdle rate over the uniform 15-year vehicle lifetime, and brought back to present dollars using the 5% global discount rate. Fixed O&M costs and annual fuel costs assuming 12,500mi/yr traveled over the 15-year lifetime are also converted to present dollars using the 5% global discount rate. In many cases, the alternative vehicles have higher capital costs but lower fuel costs compared to a conventional gasoline vehicle. As the alternative vehicle hurdle rate is increased, it has the effect of raising the vehicle's present cost. The vehicle-specific hurdle rate is set such that the present cost of the alternative vehicle just exceeds that of the gasoline vehicle in the reference scenario. Since BEVs are the most cost-effective, they require the highest hurdle rate of 10%. This 10% hurdle rate is then applied uniformly to all alternative vehicles (HEV, PHEV, BEV, CNG, and H_2-fuel cell vehicles).

All of the LDVs in Table A1, with the exception of conventional gasoline and ethanol vehicles, have both a hurdle rate and non-hurdle rate version. Both sets of LDVs (i.e., with and without the hurdle rate) have identical characteristics, as specified in Tables A1 through A6. The only difference is the higher effective cost associated with the hurdle rate versions.

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[1] The assumed reference case includes reference case natural gas, oil, and battery prices, and no RPS or CO_2 policy.

The non-hurdle rate versions of the LDVs are subject to an upper bound constraint that limits their deployment to the levels found in the AEO reference case (EIA, 2012). In order to further deploy alternative vehicles across the 108 scenarios, the model must utilize the hurdle rate versions. By choosing the minimum hurdle rate to keep high levels of alternative vehicles out of the market in the reference case, we are representing some degree of consumer reluctance to switch to new vehicle technology.

Section A3. Electric sector

Thirty-two existing and new power plants along with 71 emission retrofit technologies are included in the electric sector. Emission retrofit technologies can capture NO_X, SO_2, and CO_2 emissions from coal, oil, and natural gas to reduce air pollution and greenhouse gas emissions. Flue Gas Desulfurization (FGD) is available for SO_2 emissions control while Low NO_X Burners (LNB), Selective Catalytic Reduction (SCR), and Selective Non-Catalytic Reduction (SNCR) are available for NO_X control. SO_2 and NO_X controls can be installed in series, and LNB can be combined with either NO_X flue gas control (SCR or SNCR). The existing capacities of NO_X and SO_2 retrofit technologies were updated based on eGRID (eGRID, 2010). The organization of NO_X, SO_2, and CO_2 retrofit technologies is the same as EPANMD-2010-V1.0 (Shay et al., 2006). The cost and performance data for the electric generators and emissions control technologies (shown in Tables A7 to A9) as well as the emission factors associated with the fuels consumed in the power plants are taken from EPANMD-2010-V1.0 (Shay et al., 2006). The investment costs and existing capacities of the electric generators are updated based on AEO (EIA, 2012). All of these data are available online in the NUSTD workbooks (Energy Modeling, 2014). Table A7 includes the list of power plants and their key characteristics.

Table A7. Commodity input/output, start year, lifetime, annual availability factor, investment cost, fixed and variable operation and maintenance costs for electric generators

Technology Name	Commodity In	Commodity Out	Start Year	Lifetime	AAF[a]	Investment Cost (million 2010$/GW)	Fixed Operation & Maintenance Cost (M2010$/GW)	Variable Operation & Maintenance Cost (M2010$/PJ)[c]
Oil Steam (Residual Fuel Oil LS), Existing	ELCRFLEA	ELC	2010	10	0.833		18.86	12.92
Natural Gas Steam, Existing	ELCNGSEA	ELC	2010	10	0.825		12.77	12.99
Diesel Oil Combustion Turbine, Existing	ELCDSLEA	ELC	2010	16	0.873		4.47	20.32
Natural Gas Combustion Turbine, Existing	ELCNGAEA	ELC	2010	29	0.877		3.01	18.81
Diesel Oil Combined-Cycle, Existing	ELCDSLEA	ELC	2010	23	0.823		3.18	13.07
Natural Gas Combined-Cycle, Existing	ELCNGCEA	ELC	2010	25	0.841		4.12	12.47
Wood/Biomass Steam, Existing	ELCBIOSTM	ELC	2010	27	0.819		10.93	15.69
Municipal Solid Waste Steam, Existing	ELCMSWEA	ELC	2010	29	0.788		13.05	16.72
Geothermal, Existing	ELCGEO	ELC	2010	26	0.806		11.96	16.22
Hydroelectric, Conventional, Existing	ELCHYD	ELC	2010	10	0.456		9.35	15.10
Hydroelectric, Reversible, Existing	ELC	ELC	2010	18	0.371		11.96	16.11
Wind, Existing	WND	ELC	2010	35	0.319		13.65	12.57
Solar Thermal, Existing	SOL	ELC	2010	27	0.858		12.00	13.01
Solar Photovoltaic, Existing	SOL	ELC	2010	31	0.150		12.00	13.01
Residual Coal Steam, Existing	COALSTM	ELC	2010	17	0.863		20.15	12.93
Pre-Existing Nuclear LWRs	URNA	ELC	2010	50	0.890		78.41	11.56
		USPTA	2010	50				
Nuclear LWRs in 2015	URNA	ELC	2015	45	0.850	4134	52.72	11.22
		USPTA	2015	45				
Integrated Coal Gasification Combined Cycle CO_2 Capture	COALIGCC	ELC	2015	50	0.850	4852	63.88	13.17
Natural Gas Combined Cycle CO_2 Capture	ELCNGCEA	ELC	2015	50	0.850	1834	27.88	12.76
Solar PV Centralized Generation[b]	SOL	ELC	2015	30		4528	15.39	11.11
Solar Thermal Centralized Generation[b]	SOL	ELC	2015	30		4384	59.00	11.11
Wind Generation Class 4 [b]	WND	ELC	2015	30		2278	19.46	12.78
Wind Generation Class 5 [b]	WND	ELC	2015	30		2278	19.46	12.78
Wind Generation Class 6 [b]	WND	ELC	2015	30		2278	19.46	12.78
Natural Gas - Advanced Combined-Cycle (Turbine)	ELCNGCEA	ELC	2015	30	0.900	929	13.48	11.91
Natural Gas - Advanced Combustion Turbine	ELCNGAEA	ELC	2015	30	0.950	634	6.18	13.64
Geothermal - Binary Cycle and Flashed Steam	ELCGEO	ELC	2015	25	0.640	2393	100.13	13.58
Biomass Integrated Gasification Combined-Cycle	ELCBIGCCEA	ELC	2015	35	0.800	3519	92.69	12.39
Pulverized Coal Steam – 2015	COALSTMCC	ELC	2015	45	0.850	2658	27.35	12.20
Integrated Coal Gasification Combined Cycle	COALIGCCCC	ELC	2015	40	0.850	3010	45.08	12.87
Natural Gas - Combined Cycle (Turbine)	ELCNGCEA	ELC	2015	25	0.900	931	13.26	11.99
Natural Gas - Combustion Turbine	ELCNGAEA	ELC	2015	25	0.950	927	6.43	14.88

[a] AAF=Annual availability factor
[b] Availability factors for the new solar and wind power plants are based on season and time of day.
[c] 4 cents/kWh was added to the VAROM of the power plants because of the transmission and distribution cost of electricity based on AEO2012

The existing capacity of the power plants in 2010 is derived from the AEO (EIA, 2012). The amount of capacity to be retired from 2010 to 2035 is also based on the AEO (EIA, 2012). These retirement capacities were linearly extrapolated to 2050 and subtracted from existing capacity in 2010 to estimate the amount of preexisting power plant capacity in each time period. The existing electric sector capacity is shown in Table A8, while the peak factor (i.e., fraction of capacity that can be relied upon during the peak demand time slice) and conversion efficiencies are presented in Table A9.

Table A8. The existing capacity of electric power plants (in GW)

Technology Name	2010	2015	2020	2025	2030	2035	2040	2045	2050
Oil Steam (Residual Fuel Oil LS), Existing	29.31	24.51	24.26	24.12	23.85	23.47	23.18	22.87	22.55
Natural Gas Steam, Existing	78.09	65.29	64.64	64.28	63.55	62.53	61.75	60.93	60.07
Diesel Oil Combustion Turbine, Existing	26.37	25.02	24.86	24.39	24.00	23.87	23.45	22.96	22.39
Natural Gas Combustion Turbine, Existing	108.43	102.88	102.24	100.31	98.70	98.13	96.41	94.41	92.06
Diesel Oil Combined-Cycle, Existing	6.83	5.46	4.10	2.73	1.37	0.00			
Natural Gas Combined-Cycle, Existing	164.87	164.87	164.67	164.67	164.67	164.67	164.67	164.67	164.67
Wood/Biomass Steam, Existing	7.95	6.36	4.77	3.18	1.59	0.00			
Municipal Solid Waste Steam, Existing	5.04	4.20	3.36	2.52	1.68	0.84	0.00		
Geothermal, Existing	3.50	2.80	2.10	1.40	0.70	0.00			
Hydroelectric, Conventional, Existing	78.20	78.20	78.20	78.20	78.20	78.20	78.20	78.20	78.20
Hydroelectric, Reversible, Existing	22.20	22.20	22.20	22.20	22.20	22.20	22.20	22.20	22.20
Wind, Existing	39.52	33.87	28.23	22.58	16.94	11.29	5.64	0.00	
Solar Thermal, Existing	0.49	0.39	0.29	0.20	0.10	0.00			
Solar Photovoltaic, Existing	0.42	0.35	0.28	0.21	0.14	0.07	0.00		
Residual Coal Steam, Existing	308.10	266.90	260.10	260.10	260.10	259.90	257.97	255.97	253.88
Pre-Existing Nuclear LWRs	101.20	101.20	100.60	100.60	100.10	95.10	95.10	90.31	81.75

Table A9. The peak factor and efficiency of electric power plants

Technology Name	Commodity In	Commodity Out	Peak	Efficiency (2010-2040)	Efficiency (2045)	Efficiency (2050)
Oil Steam (Residual Fuel Oil LS), Existing	ELCRFLEA	ELC	0.98	0.260	0.260	0.260
Natural Gas Steam, Existing	ELCNGSEA	ELC	0.96	0.286	0.286	0.286
Diesel Oil Combustion Turbine, Existing	ELCDSLEA	ELC	0.92	0.221	0.221	0.221
Natural Gas Combustion Turbine, Existing	ELCNGAEA	ELC	0.96	0.246	0.246	0.246
Diesel Oil Combined-Cycle, Existing	ELCDSLEA	ELC	0.96	0.322	0.322	0.322
Natural Gas Combined-Cycle, Existing	ELCNGCEA	ELC	1.00	0.369	0.369	0.369
Wood/Biomass Steam, Existing	ELCBIOSTM	ELC	0.84	0.206	0.206	0.206
Municipal Solid Waste Steam, Existing	ELCMSWEA	ELC	0.95	0.213	0.213	0.213
Geothermal, Existing	ELCGEO	ELC	0.95	0.162	0.162	0.162
Hydroelectric, Conventional, Existing	ELCHYD	ELC	0.94	0.338	0.338	0.338
Hydroelectric, Reversible, Existing	ELC	ELC	0.95	0.338	0.338	0.338
Wind, Existing	WND	ELC	0.50	0.338	0.338	0.338
Solar Thermal, Existing	SOL	ELC	0.30	0.328	0.328	0.328
Solar Photovoltaic, Existing	SOL	ELC	0.30	0.338	0.338	0.338
Residual Coal Steam, Existing	COALSTM	ELC	0.96	0.326	0.326	0.326
Pre-Existing Nuclear LWRs (PJ elec/ton-input)	URNA	ELC		1.43	1.43	1.43
		USPTA	0.90			
Nuclear LWRs in 2015 (PJ elec/ton-input)	URNA	ELC		1.53	1.53	1.53
		USPTA	0.90			
Integrated Coal Gasification Combined Cycle CO_2 Capture	COALIGCC	ELC		0.411	0.411	0.411
Natural Gas Combined Cycle CO_2 Capture	ELCNGCEA	ELC	0.96	0.455	0.455	0.455
Solar PV Centralized Generation	SOL	ELC	1.00	1.000	1.000	1.000
Solar Thermal Centralized Generation	SOL	ELC	0.30	1.000	1.000	1.000
Wind Generation Class 4	WND	ELC	0.30	1.000	1.000	1.000
Wind Generation Class 5	WND	ELC	0.34	1.000	1.000	1.000
Wind Generation Class 6	WND	ELC	0.34	1.000	1.000	1.000
Natural Gas - Advanced Combined-Cycle (Turbine)	ELCNGCEA	ELC	0.34	0.531	0.531	0.531
Natural Gas - Advanced Combustion Turbine	ELCNGAEA	ELC	0.95	0.350	0.350	0.350
Geothermal - Binary Cycle and Flashed Steam	ELCGEO	ELC	0.92	0.350	0.350	0.350
Biomass Integrated Gasification Combined-Cycle	ELCBIGCCEA	ELC	0.63	0.253	0.253	0.253
Pulverized Coal Steam - 2010	COALSTMCC	ELC	0.84	0.388	0.388	0.388
Integrated Coal Gasification Combined Cycle	COALIGCCCC	ELC	0.96	0.392	0.392	0.392
Natural Gas - Combined-Cycle (Turbine)	ELCNGCEA	ELC	0.96	0.484	0.484	0.484
Natural Gas - Combustion Turbine	ELCNGAEA	ELC	0.95	0.314	0.318	0.318

Section A4. End-use demand sectors (commercial, industrial, residential)

The end-use sectors (excluding transportation) are comprised of three major components: (1) time-sliced demand, (2) fuel share constraints (Equations B.20 and B.21), and (3) emission factors associated with in-sector fossil fuel combustion. The simplified representation of the end-use sectors does not include an explicit representation of demand technologies, since such technology detail is unlikely to have a large impact on vehicle deployment, which is the focus of this analysis. Table A10 provides the total amount of demand (in PJ) for the three end-use sectors (commercial, residential, and industrial), based on the AEO (EIA, 2012). The NUSTD workbooks contain the time-sliced demand and the emission factors associated with the fuel consumption in end-use sectors (Energy Modeling, 2014).

Table A10. Total demands in the non-transportation related end-use sectors (PJ)

Demand Commodity Name	Abbreviation	2010	2015	2020	2025	2030	2035	2040	2045	2050
Residential	RESDEM	12291	11838	11985	12154	12386	12587	12711	12863	13043
Commercial	COMDEM	9179	9284	9696	10012	10435	10825	11229	11668	12142
Industrial	INDDEM	19814	20384	20869	21354	21196	21122	21441	21765	22093

In each end-use sector, the 2010 fuel shares and their projection to 2035 are drawn from the AEO (EIA, 2012). These lower bound shares are linearly extrapolated from 2035 to 2050 and then linearly relaxed to 70% of the extrapolated values in 2050 for all of the fuels shown in Table A11, except electricity. Since it is hard to envision a scenario in which electricity is replaced by other fuels, no relaxation rate is applied to the electricity share. The 70% relaxation rate applied to the other fuel share constraints is chosen to give the model sufficient flexibility to fuel switch in these end-use sectors in response to price signals. Because distributed wind and solar have no fuel costs, their shares are determined by upper bound constraints. Table A11 and Figures A2 through A4 illustrate how fuel shares get relaxed over time in the commercial, industrial, and residential sectors.

Table A11. Fuel share constraints by end-use sector

End-use Demand Sector	Commodity Name*	2010	2015	2020	2025	2030	2035	2040	2045	2050
Residential	LPG (L)	4.80%	4.55%	4.29%	4.04%	3.79%	3.53%	3.28%	3.02%	2.77%
	LPG (U)	4.80%	4.80%	4.80%	4.80%	4.80%	4.80%	4.80%	4.80%	4.80%
	Distillate fuel oil (L)	5.40%	4.85%	4.31%	3.76%	3.21%	2.66%	2.11%	1.56%	1.02%
	Natural Gas (L)	43.40%	41.28%	39.16%	37.05%	34.93%	32.81%	30.69%	28.58%	26.46%
	Renewables (U)	3.58%	3.45%	3.32%	3.19%	3.05%	2.92%	2.79%	2.66%	2.52%
	Electricity (L)	42.45%	43.79%	45.12%	46.45%	47.79%	49.12%	50.45%	51.79%	53.12%
	Coal (U)	0.09%	0.08%	0.08%	0.08%	0.07%	0.07%	0.06%	0.06%	0.06%
Commercial	LPG (L)	1.61%	1.54%	1.47%	1.41%	1.34%	1.27%	1.20%	1.14%	1.07%
	LPG (U)	1.61%	1.61%	1.61%	1.61%	1.61%	1.61%	1.61%	1.61%	1.61%
	Distillate fuel oil (L)	4.92%	4.48%	4.04%	3.60%	3.16%	2.73%	2.29%	1.85%	1.41%
	Distillate fuel oil (U)	4.92%	4.92%	4.92%	4.92%	4.92%	4.92%	4.92%	4.92%	4.92%
	Natural Gas (L)	37.70%	36.03%	34.37%	32.70%	31.03%	29.37%	27.70%	26.03%	24.37%
	Renewables (U)	1.26%	1.19%	1.12%	1.04%	0.97%	0.89%	0.82%	0.74%	0.67%
	Electricity (L)	52.18%	53.01%	53.84%	54.67%	55.50%	56.32%	57.15%	57.98%	58.81%
	Coal (U)	0.69%	0.65%	0.61%	0.57%	0.53%	0.49%	0.45%	0.40%	0.36%
	Motor Gasoline (L)	0.57%	0.55%	0.53%	0.51%	0.49%	0.47%	0.45%	0.43%	0.41%
	Motor Gasoline (U)	0.57%	0.57%	0.57%	0.57%	0.57%	0.57%	0.57%	0.57%	0.57%
	Residual fuel oil (L)	0.92%	0.87%	0.81%	0.76%	0.70%	0.65%	0.59%	0.54%	0.49%
	Residual fuel oil (U)	0.92%	0.92%	0.92%	0.92%	0.92%	0.92%	0.92%	0.92%	0.92%
Industrial	LPG (L)	10.60%	10.22%	9.84%	9.46%	9.09%	8.71%	8.33%	7.95%	7.58%
	LPG (U)	10.60%	10.60%	10.60%	10.60%	10.60%	10.60%	10.60%	10.60%	10.60%
	Motor Gasoline (L)	1.33%	1.30%	1.28%	1.25%	1.23%	1.20%	1.17%	1.15%	1.12%
	Motor Gasoline (U)	1.33%	1.33%	1.33%	1.33%	1.33%	1.33%	1.33%	1.33%	1.33%
	Distillate fuel oil (L)	6.09%	5.83%	5.58%	5.32%	5.06%	4.80%	4.55%	4.29%	4.03%
	Distillate fuel oil (U)	6.09%	6.09%	6.09%	6.09%	6.09%	6.09%	6.09%	6.09%	6.09%
	Kerosene (L)	13.31%	12.69%	12.07%	11.45%	10.83%	10.20%	9.58%	8.96%	8.34%
	Kerosene (U)	13.31%	13.31%	13.31%	13.31%	13.31%	13.31%	13.31%	13.31%	13.31%
	Natural Gas (L)	35.62%	34.42%	33.21%	32.01%	30.81%	29.60%	28.40%	27.19%	25.99%
	Coal (U)	7.99%	7.56%	7.12%	6.69%	6.26%	5.83%	5.40%	4.97%	4.53%
	Renewables (U)	7.99%	7.94%	7.89%	7.85%	7.80%	7.75%	7.70%	7.66%	7.61%
	Electricity (L)	16.45%	16.29%	16.13%	15.96%	15.80%	15.63%	15.47%	15.31%	15.14%

L=Lower bound constraint, U=Upper bound constraint

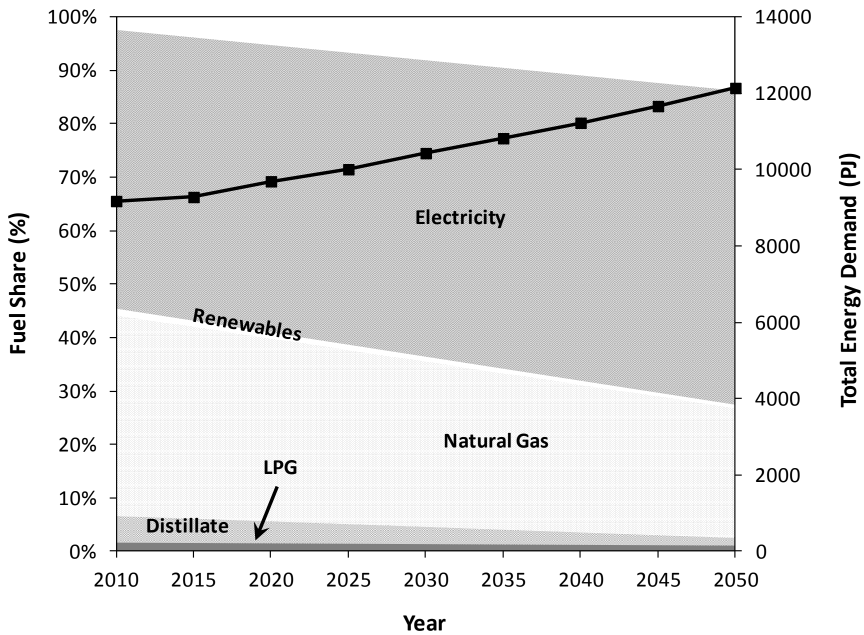

Figure A2. Total energy demand (squares) and minimum fuel shares (stacked area) in the commercial sector. Note that the share pertaining to wind and solar (grouped under 'Renewables') represents an upper bound, as the fuel cost is zero.

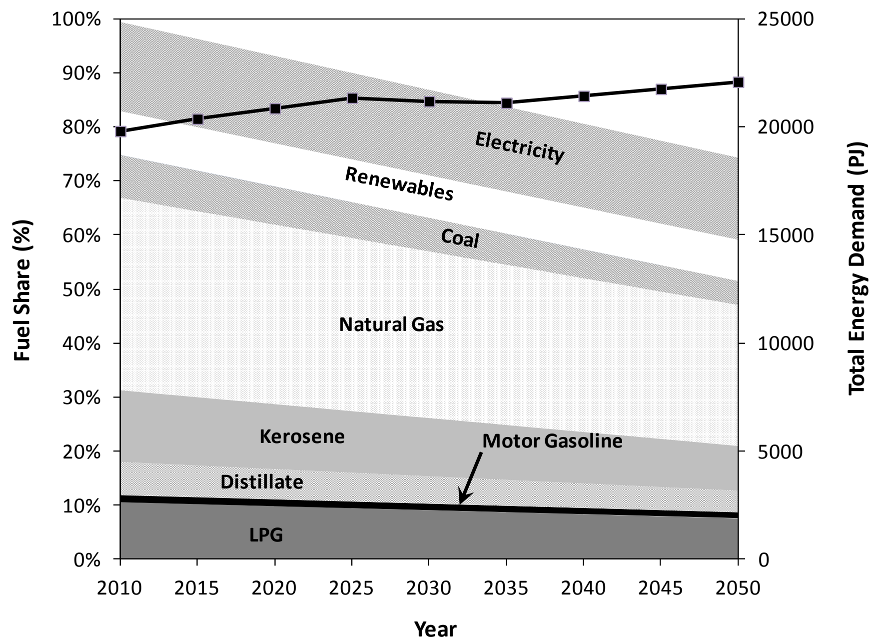

Figure A3. Total energy demand (squares) and minimum fuel shares (stacked area) in the industrial sector. Note that the share pertaining to wind and solar (grouped under 'Renewables') represents an upper bound, as the fuel cost is zero.

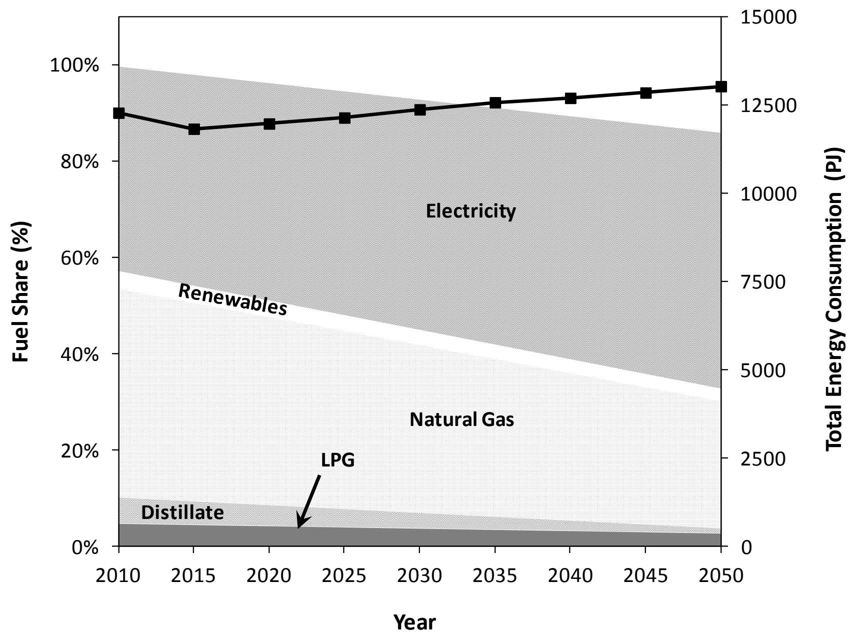

Figure A4. Total energy demand (squares) and minimum fuel shares (stacked area) in the residential sector. Note that the share pertaining to wind and solar (grouped under 'Renewables') represents an upper bound, as the fuel cost is zero.

Section A5. Supply sector

The supply sector includes the cost and emission factors associated with all energy resources and material used as commodity inputs to the transportation, electric, and end-use sectors. The fuel prices, shown in Table A12, are derived from the AEO for fuels delivered to different energy sectors (EIA, 2012). Non-biomass renewables have zero cost, but resource quality is parameterized by the availability factor.

Table A12. Fuel price in base scenario (millions of 2010 US$/PJ)

Commodity Description	Abbreviation	2010	2015	2020	2025	2030	2035	2040	2045	2050
Biomass	ELCBSTMEA	3.39	3.39	3.39	3.39	3.39	3.39	3.39	3.39	3.39
Municipal solid waste	ELCMSW	2.70	2.70	2.70	2.70	2.70	2.70	2.70	2.70	2.70
Cellulosic ethanol to TRN sector	Celleth	39.56	39.56	39.56	39.56	39.56	39.56	39.56	39.56	39.56
Hydrogen fuel to TRN sector	H2	27.65	27.65	27.65	27.65	27.65	27.65	27.65	27.65	27.65
Coal to RESCOMIND sectors	COAL	2.84	3.35	3.39	3.48	3.61	3.76	3.86	3.97	4.09
Wood to RESIND sectors	Wood	2.67	2.67	2.67	2.67	2.67	2.67	2.67	2.67	2.67
Waste to COM sector	Waste	2.70	2.70	2.70	2.70	2.70	2.70	2.70	2.70	2.70
Biomass to bio IGCC power plant	ELCBIO	3.39	3.39	3.39	3.39	3.39	3.39	3.39	3.39	3.39
Bituminous high sulfur coal	ELCCOABH	2.69	2.81	2.93	3.06	3.19	3.33	3.48	3.63	3.79
Bituminous low sulfur coal	ELCCOABL	2.69	2.81	2.93	3.06	3.19	3.33	3.48	3.63	3.79
Bituminous medium sulfur coal	ELCCOABM	2.69	2.81	2.93	3.06	3.19	3.33	3.48	3.63	3.79
Lignite high sulfur coal	ELCCOALH	2.14	2.24	2.33	2.44	2.54	2.65	2.77	2.89	3.02
Lignite medium sulfur coal	ELCCOALM	2.14	2.24	2.33	2.44	2.54	2.65	2.77	2.89	3.02
Sub-bituminous low sulfur coal	ELCCOASL	1.30	1.35	1.41	1.47	1.54	1.60	1.67	1.75	1.82
Sub-bituminous medium sulfur coal	ELCCOASM	1.30	1.35	1.41	1.47	1.54	1.60	1.67	1.75	1.82
Biodiesel to TRNHDV	TRNBDSL	17.47	17.47	17.47	17.47	17.47	17.47	17.47	17.47	17.47
Natural gas steam to electric sector	ELCNGA	4.85	4.29	4.46	5.29	5.86	6.80	7.63	8.56	9.61
Natural gas to RES sector	NGRES	10.48	9.75	10.25	11.38	12.07	13.23	14.27	15.41	16.63
Natural gas to COM sector	NGCOM	8.60	8.14	8.50	9.48	10.02	11.01	11.87	12.81	13.81
Natural gas to IND sector	NGIND	5.21	4.61	4.85	5.71	6.21	7.13	7.96	8.87	9.89
Natural gas to TRN sector	NGTRN	11.09	10.72	11.14	12.24	12.75	14.12	15.13	16.20	17.36
Distillate oil to electric sector	ELCDSL	17.75	21.58	22.92	24.03	25.05	26.35	27.70	29.12	30.61
Residual fuel oil to electric sector	ELCRFL	11.27	21.80	23.11	24.08	24.22	24.38	25.07	25.78	26.51
Conventional gasoline to TRN sector	CONVGSL	22.72	29.17	30.57	31.78	32.69	33.26	34.37	35.51	36.70
Diesel ultra low sulfur to TRN sector	TRDSLU	22.09	26.12	27.47	28.83	29.74	30.71	31.98	33.30	34.67
Ethanol to IND sector	Ethanol	24.47	30.91	31.97	29.09	28.52	26.92	26.01	25.12	24.27
Ethanol to LDV gasoline or E85X vehicles	EthtoGSLorE85XLDV	24.47	30.91	31.97	29.09	28.52	26.92	26.01	25.12	24.27
Ethanol to HDV gasoline or E85X vehicles	EthtoGSLorE85XHDV	24.47	30.91	31.97	29.09	28.52	26.92	26.01	25.12	24.27
Ethanol to off-highway gasoline or E85X vehicles	EthtoGSLorE85XOH	24.47	30.91	31.97	29.09	28.52	26.92	26.01	25.12	24.27
Distillate fuel oil to RESCOMIND sectors	DistOil	20.00	23.84	25.29	26.61	27.74	28.89	30.31	31.81	33.37
Kerosene to RESCOMIND sectors	Kerosene	21.67	21.67	21.67	21.67	21.67	21.67	21.67	21.67	21.67
LPG to RES sector	LPGRES	25.61	29.10	29.45	30.59	31.55	32.83	33.84	34.88	35.95
LPG to COM sector	LPGCOM	22.29	25.99	26.33	27.46	28.40	29.67	30.67	31.70	32.76
LPG to IND sector	LPGIND	20.66	26.00	26.31	27.72	28.89	30.50	31.74	33.04	34.38
LPG to TRN sector	LPGTRN	25.48	30.27	30.53	31.64	32.58	33.88	34.85	35.84	36.87
Motor gasoline to COMIND sectors	Motorgsl	22.63	29.07	30.64	31.60	32.40	32.82	33.83	34.88	35.95
Residual fuel oil to COMIND sectors	ResOil	10.42	16.77	18.07	18.71	19.31	19.22	19.88	20.57	21.28
Jet fuel to TRNHDV sector	TRNJTF	15.37	22.50	23.94	25.07	26.14	27.61	29.06	30.59	32.19
High sulfur residual fuel oil to TRNHDV	TRNRFH	9.88	17.36	18.56	19.55	19.68	19.86	20.54	21.24	21.96
Natural uranium (Units: M$/tonne)	NURN	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13

RES=Residential, COM=Commercial, IND=Industrial, TRN=Transportation (light and heavy duty vehicles and off-highway technologies), TRNHDV=Heavy duty transportation, E85X=85% ethanol blended with 15% gasoline, E10=10% ethanol blended with 90% gasoline, LPG=Liquefied petroleum gas, CNG=Compressed natural gas, GSL=Gasoline, DSL=Diesel, TRNDSLLDV=Diesel to transportation light duty vehicles, TMDLDV=Total miles demand for light duty vehicles, ELC=Electricity

The emissions rates, shown in Table A13, are based on EPANMD-2010-V1.0 (Shay et al., 2006). See Table A12 for commodity descriptions. These emissions factors are associated with the fuel production process, such as refinery emissions. Note that the negative emission coefficients are due to the CO_2 uptake from corn production used to produce corn ethanol. These negative emissions coefficients are balanced by positive emissions coefficients downstream associated with fuel combustion.

Table A13. Emission factors associated with the fuel production (10^3 metric tons/PJ)

Commodity Name	Emission	2010	2015	2020	2025	2030	2035	2040	2045	2050
LPGRES, LPGCOM, LPGIND, LPGTRN, CONVGSL, Motorgsl, TRNJTF, DistOil, ResOil, ELCRFL, TRNRFH, Kerosene, TRDSLU, ELCDSL	SO_2	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019
	NO_X	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020
	CO_2	11.948	11.948	11.948	11.948	11.948	11.948	11.948	11.948	11.948
ELCNGA, NGRES, NGCOM, NGIND	SO_2	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011
	NO_X	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018
	CO_2	4.329	4.329	4.329	4.329	4.329	4.329	4.329	4.329	4.329
ELCBSTMEA	SO_2	0.243	0.243	0.243	0.243	0.243	0.243	0.243	0.243	0.243
ELCBSTMEA	CO2	-108.31	-108.31	-108.31	-108.31	-108.31	-108.31	-108.31	-108.31	-108.31
ELCBIO	CO2	-94.680	-94.680	-94.680	-94.680	-94.680	-94.680	-94.680	-94.680	-94.680
TRNBDSL	CO2	-69.346	-69.346	-69.346	-69.346	-69.346	-69.346	-69.346	-69.346	-69.346
EthtoGSLorE85XLDV,EthtoGSLorE85XHDV,EthtoGSLorE85XOH	CO2	-67.554	-67.554	-67.554	-67.554	-67.554	-67.554	-67.554	-67.554	-67.554
ELCCOABH, ELCCOABL, ELCCOABM, ELCCOALH, ELCCOALM, ELCCOASL, ELCCOASM	SO_2	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006
ELCCOABH, ELCCOABL, ELCCOABM, ELCCOALH, ELCCOALM, ELCCOASL, ELCCOASM	NO_X	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
ELCCOABH, ELCCOABL, ELCCOABM, ELCCOALH, ELCCOALM, ELCCOASL, ELCCOASM	CO_2	0.440	0.440	0.440	0.440	0.440	0.440	0.440	0.440	0.440

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APPENDIX B. Simplified TIMES Formulation

The Integrated MARKAL-EFOM[2] System (TIMES) is a model generator for national or multi-regional energy systems, which provides a technology-rich basis for simulating energy dynamics over a long-term, multi-period time horizon (Loulou et al., 2005). It is usually applied to the analysis of an entire energy system, but may also be applied to the detailed study of individual energy sectors (e.g., electricity or transportation) (Loulou et al., 2005).

The user provides estimates of end-use energy service demands (e.g., vehicle miles traveled per year), the existing stock of energy related equipment in all sectors (e.g., installed capacity of pulverized coal plants), and the characteristics of available future technologies (e.g., capital cost, thermal efficiency) as well as present and projected primary energy prices and potentials (Loulou et al., 2005). TIMES performs linear optimization to supply energy service demands at minimum global cost, subject to user-imposed constraints such as emissions limits and maximum growth rates on technology capacity (Loulou et al., 2005).

The energy system is described algebraically as a network of linked processes that convert primary energy commodities (e.g., natural gas, oil, uranium, biomass) into intermediate energy forms (e.g., enriched uranium, gasoline, ethanol) and finally end-use demands (e.g., lighting, transport, space heating) (Hunter et al., 2013). TIMES is considered a ‘technology rich’ model because it supports the representation of numerous energy

[2] The MARKAL (MARket Allocation) model (Fishbone et al. 1981, 1983; Berger et al., 1992) and EFOM (Van Voort et al., 1984) are two bottom-up energy models which inspired the development of TIMES.

technologies, where each energy technology-related process is defined by a set of engineering, economic, and environmental characteristics (e.g., capital cost, efficiency, capacity factor, emissions rate) associated with converting an energy commodity from one form to another. Processes are linked together in a network via flows of energy commodities. Figure B1 depicts a simplified reference energy system (RES) in TIMES containing processes represented as boxes and commodities as vertical lines. Commodity flows are represented as links between process boxes and commodity lines.

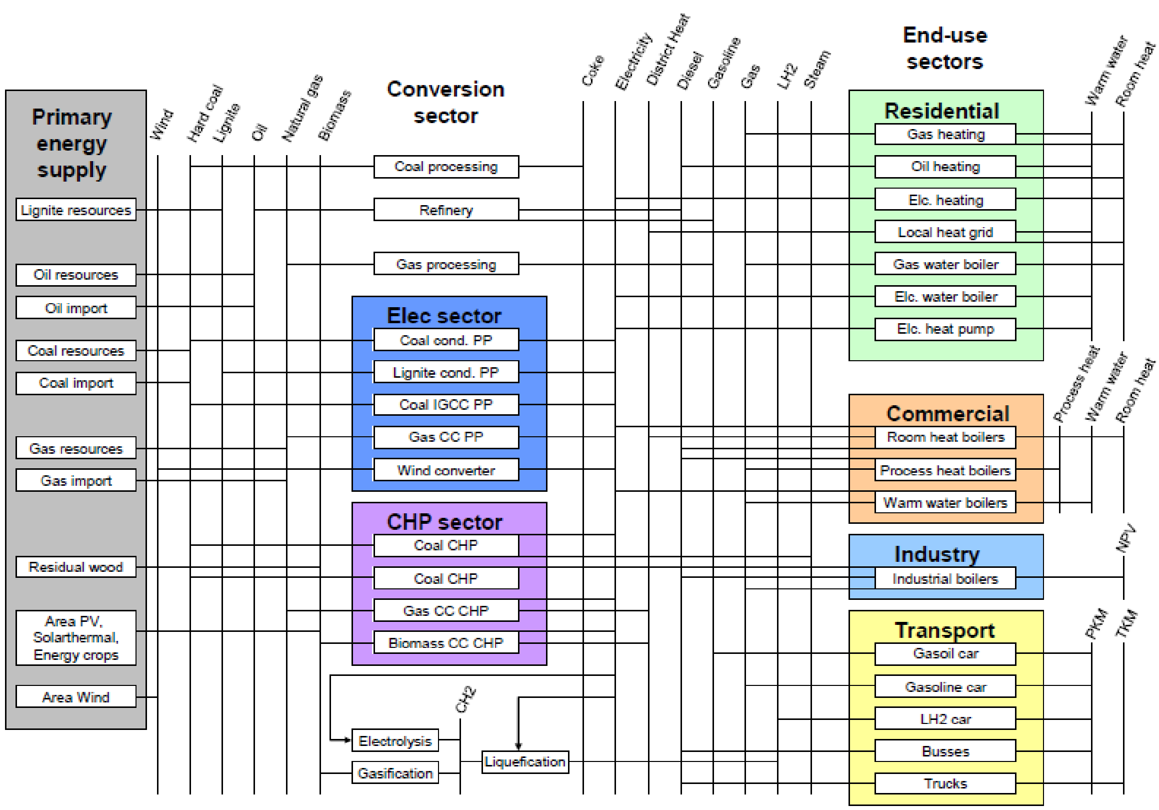

Figure B1. A simplified representation of the reference energy system in TIMES drawn from Gargiulo et al. (2011).

The TIMES model optimizes energy system infrastructure and performance across a time horizon which may range over many decades (Loulou et al., 2005). The time horizon is usually split into several time periods. Each time period represents a point in time where decisions can be taken by the model, (e.g., installation of a new capacity to meet growing demand). The time periods are further divided into sub-annual time-slices to describe how loads vary seasonally and diurnally within a year, which can affect commodity flows and installed process capacities. Time-slices may be organized into four hierarchical levels: annual, seasonal, weekly, and day-night (Loulou et al., 2005). Figure B2 illustrates a user-define time-slice tree, in which a year is divided into four seasons consisting of working days and weekends, and each day is further divided into day and night time-slices.

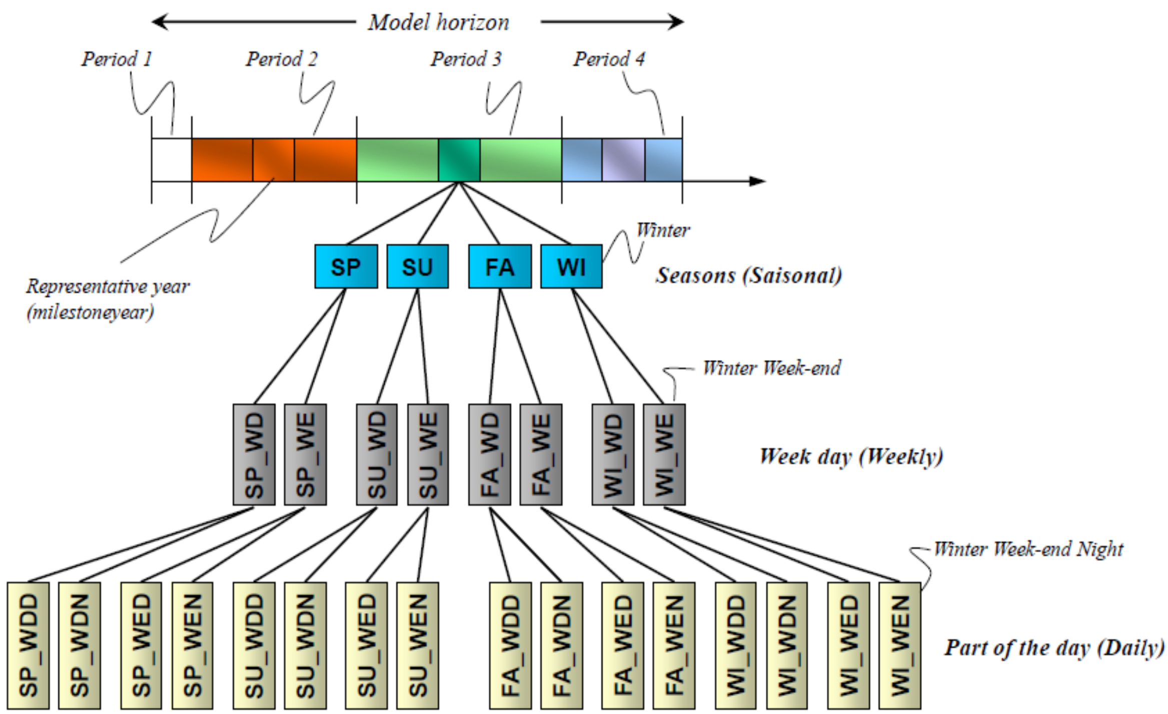

Figure B2. Example of a time-slice tree in TIMES drawn from Gargiulo et al. (2011).

This appendix contains a simplified algebraic formulation of the TIMES model and ignores many exceptions and complexities that are not essential to a basic understanding of the core model principles. Additional details on general linear programming (LP) concepts are provided in the TIMES documentation (Loulou et al., 2005). A mathematical model consists of three key entities: (1) the decision variables, including unknowns or endogenous quantities to be determined by the optimization; (2) the objective function expressing the criterion to be minimized or maximized; and (3) constraint equations or inequalities involving the decision variables that must be satisfied by the optimal solution (Loulou et al., 2005).

TIMES is formulated as an LP problem consisting of an objective function that minimizes the present cost of energy supply over the user-specified model time horizon and subject to a number of constraints that ensure the energy system functions properly (Loulou et al., 2005). The equations that make up the objective function and constraints represent algebraic expressions that include both decision variables and parameters, both of which are indexed by sets that represent unordered collections of items (e.g., model time periods, technologies, and commodities).

The algebraic formulation of TIMES is implemented in the General Algebraic Modeling System (GAMS) language, which is an algebraic modeling language that combines the TIMES source code and user-created database into an LP matrix, which is then passed to a solver that finds the optimal solution (Loulou et al., 2005). Tables B1, B2, and B3 explain the main nomenclature in the TIMES formulation, which is drawn from Loulou et al. (2005).

Table B1. Sets: List and description of TIMES nomenclature

Set	Description
c	Commodity (energy, material, emission, demand)
cg	Commodity group (user-defined list of commodities in a region)
p	Process (technology)
r	Region
s	Time-slice (this index is relevant only for user-designated commodities and processes that are tracked at finer than annual level (e.g., electricity)
t	Time period
v	Technology vintage year is defined by the model time period (*t*) in which a technology (*p*) is installed.

Table B2. Parameters: List and description of TIMES nomenclature

Variable	Description
$AF_{r,v,t,p,s}$	Availability factor of a process that can vary by season and time of day
$FR_{r,s}$	Fraction of year represented by each time-slice *s*
$DEM_{c,t}$	End-use demands specified by commodity *c* and time period *t*
$FLO\text{-}FUNC_{r,t,p,cg_1,cg_2,s}$	Efficiency of process *p* with input commodity group cg_1 and output commodity group cg_2 in time period *t* (optionally with time-slice *s*)
$COM\text{-}IE_{r,t,c,s}$	Efficiency of commodity *c* (e.g., transport losses)
$FLO\text{-}SHAR_{r,t,p,cg,c,s}$	Share of flow commodity *c* from the sum of all commodity flows in group *cg* belonging to process *p*

Table B3. Variables: List and description of TIMES nomenclature

Variable	Description
$ACT_{r,v,t,p,s}$	Total commodity consumption or production of technology *p*, in region *r*, and period *t* (optionally vintage *v* and time-slice *s*)
$CAP_{r,v,t,p}$	Process capacity required to support all associated activity
$NCAP\text{-}COM_{r,t,p,c(io),s}$	New capacity investment on commodity *c* (as input *i* or output *o*) of process *p*, in region *r*, period *t*, and time-slice *s*
$FLOW_{r,v,t,p,c,s}$	The quantity of commodity *c* consumed or produced by process *p*, in region *r* and period *t* (optionally with vintage *v* and time-slice *s*)

While the general TIMES formulation above includes a regional index '*r*' for multi-regional models, NUSTD only represents the U.S. as a single region. As a result, the regional index can be ignored in the generalized algebraic formulation provided below.

Decision variables

The flow variables ($FLOW_{r,v,t,p,c,s}$) are the fundamental quantities defining the detailed operation of a process. The technology activity ($ACT_{r,v,t,p,s}$) and capacity ($CAP_{r,v,t,p}$) represent derived variables based on the FLOW variable. While the ACT and CAP variables are derived from the underlying FLOW variables, they represent critical quantities that get tracked though the model analysis; hence the constraints that define these derived variables are included in this section. In TIMES, the total commodity input to or output from a process (based on the user definition of the activity variable) is referred to as its "activity" and is represented by an equality constraint.

Process activity:

$$\mathrm{ACT}_{r,v,t,p,s} = \sum_c \mathrm{FLOW}_{r,v,t,p,c,s} \qquad \forall\, r,v,t,p,s \qquad \text{(B.1)}$$

In addition, the activity of a process is used to define the associated process capacity through an inequality constraint. For each technology *p*, period *t*, vintage *v*, region *r*, and time-slice *s*, the activity of the technology may not exceed its available capacity.

Technology capacity:

$$\mathrm{ACT}_{r,v,t,p,s} \leq \mathrm{AF}_{r,v,t,p,s} \,.\, \mathrm{CAPUNIT}_{r,p} \,.\, \mathrm{FR}_{r,s} \,.\, \mathrm{CAP}_{r,v,t,p} \qquad \forall\, r,v,t,p,s \qquad \text{(B.2)}$$

The availability factor (AF) represents the maximum availability of a process by season and time-of-day, as determined by resource availability (e.g., as with intermittent renewables) as well as outage rates. The time-slice fraction (FR) is required because it specifies the amount of time over which the specified production must occur. $\mathrm{CAPUNIT}_{r,p}$ is the conversion factor between units of capacity and activity (e.g., activity of 31.536 PJ/yr is equivalent to 1 GW).

Objective function

The TIMES objective is to minimize the total discounted cost of the modeled energy system over the user-specified time horizon (Loulou et al., 2005). The total discounted cost is based on the calculation of costs incurred in each model time period. Within each time period, the model optimizes the energy system for a representative year. The total annual cost for the representative year with a model time period includes the following elements: (1) capital costs incurred for investing into and/or dismantling processes; (2) fixed and variable annual operation and maintenance (O&M) costs; (3) costs incurred for exogenous imports and for domestic resource production; (4) revenues from exogenous exports; (5) delivery costs for required commodities consumed by processes; (6) taxes and subsidies associated with commodity flows and process activities or investments; and (7) salvage values associated with processes and embedded commodities at the end of the planning horizon (Loulou et al., 2005). TIMES computes a net present value (NPV) associated with the stream of annual costs, discounted to a user-selected reference year. These regional discounted costs are then aggregated into a single total cost, which constitutes the objective function to be minimized by the model in its equilibrium computation (Loulou et al., 2005).

$$\mathrm{NPV} = \sum_r \sum_t \frac{\mathrm{Cost\_Ann}_{\mathrm{r,t}}}{(1+d_{r,t})^{(\mathrm{t-REFYR})}} \qquad \text{(B.3)}$$

To estimate the total annual cost of energy supply across the system ($Cost\_Ann_{r,t}$), all annual costs are added to the annualized capital cost payments, minus salvage value and export revenue in region *r* and time period *t*. The model discount rate is represented by *d*. Though a scalar discount rate of 5% is assumed for all model runs in this thesis, the TIMES model generator provides flexibility to vary the discount rate by region and model time period. *REFYR* is the reference year for discounting.

<u>*Constraint equations*</u>

There are several constraints required to represent the critical physical and operational requirements associated with an energy system. If any constraint is not satisfied, the model will be infeasible.

Commodity balance:

$$\sum_{p,c(out)} \mathrm{FLOW}_{r,v,t,p,c,s} \,.\, \mathrm{COM\text{-}IE}_{r,t,c,s} \geq \sum_{p,c(in)} \mathrm{FLOW}_{r,v,t,p,c,s} + \mathrm{FR}_{c,s} \,.\, \mathrm{DEM}_{c,t} \quad \forall r,v,t,s \qquad (B.4)$$

For each time period *t*, time-slice *s*, input commodity *c(in)*, and output commodity *c(out)*, the left and right sides represent the total commodity produced and consumed (including end-use demands), respectively. Equation (B.4) requires that the consumption of each commodity balances its production in each model period and time-slice. For example, total electricity supplied by electric generators (possibly with an adjustment for transportation losses) must be greater than or equal to total electricity consumed by demand devices in each time-slice. This inequality constraint is binding for all commodities that have non-zero production costs.

Transformation equation:

$$\sum_{(c\ in\ cg2)} \mathrm{FLOW}_{r,v,t,p,c,s} \leq \mathrm{FLO\text{-}FUNC}_{r,t,p,cg1,cg2,s} \cdot \sum_{(c\ in\ cg1)} \mathrm{FLOW}_{r,v,t,p,c,s} \quad \forall r,v,t,p,s \qquad (B.5)$$

The transformation equation (B.5) establishes a relationship between the flow of input commodity group cg_1 and output commodity group cg_2 in process p and ensures that the commodity output of a process cannot exceed the product of the commodity input and efficiency of the technology (FLO-FUNC).

Flow share constraint:

$$\mathrm{FLOW}_{r,v,t,p,c,s} \leq \text{FLO-SHAR}_{r,t,p,cg,c,s} \cdot \sum_{(c\ in\ cg)} \mathrm{FLOW}_{r,v,t,p,c,s} \qquad \forall r,v,t,p,s \qquad (B.6)$$

$$\mathrm{FLOW}_{r,v,t,p,c,s} \geq \text{FLO-SHAR}_{r,t,p,cg,c,s} \cdot \sum_{(c\ in\ cg)} \mathrm{FLOW}_{r,v,t,p,c,s} \qquad \forall r,v,t,p,s \qquad (B.7)$$

Equation (B.6) limits the share of commodity flow c within commodity group cg on the input or output side of process p. For instance, refinery output might consist of three refined products: c_1=light distillate, c_2= medium distillate, and c_3= heavy distillate. If the user intends to limit the production of commodity c_3 to 40% of total commodity output, the resultant flow share constraint is $\mathrm{FLOW}_{C3} \leq 0.4 \cdot \{\mathrm{FLOW}_{C1} + \mathrm{FLOW}_{C2} + \mathrm{FLOW}_{C3}\}$. Equation (B.7) was specifically used to set a lower bound on the share of electricity in the end-use sectors, as described on Appendix A, Section A4 (p. 130).

In addition to the internal model constraints described above, several additional constraints were formulated to represent the specific scenarios modeled in Chapters 2-4. These scenario-specific constraints are presented in Equations (B.8) to (B.25). Since the constraints below are applied to the single region dataset NUSTD, the region index is dropped for ease of exposition.

New solar and wind backup constraint:

$$CAP_{v,t,p1} + CAP_{v,t,p2} \leq CAP_{v,t,p3} \qquad \forall v,t,p \qquad (B.8)$$

Where *CAP* represents the installed technology capacity, p_1 is the set of new wind power plants, p_2 is the set of new solar power plants, and p_3 is the set of new natural gas power plants (consisting of either combustion or combined cycle turbines).

Electric sector NOx and SO_2 emissions constraint:

$$\sum_{p,c(out),s} FLOW_{v,t,p,c,s} \leq E_t \qquad \forall v,t \qquad (B.9)$$

Where the commodity FLOW variable is summed over all vintages (v) of processes (p) that produce NO_X or SO_2, which is denoted by the commodity subset *c(out)*. These period-specific total emissions must be less than or equal to the period-specific upper bound values on SO_2 and NO_x emissions from the electric sector E_t specified in Table B4.

Table B4. The upper bound values on electric sector NOx and SO_2 emissions (Equation B.9)

Time Period (t)	Et: NOx (Kt)	Et: SO_2 (Kt)
2010	2060	5110
2015	1571	3988
2020	1479	1378
2025	1557	1544
2030	1590	1580
2035	1597	1590
2040-2050	1604	1611

Based on AEO (EIA, 2012) and include implementation of the Mercury and Air Toxics Standards (MATS) (U.S. EPA, 2012) and the Cross-State Air Pollution Rule (CSAPR) (U.S. EPA, 2013)

Renewable Portfolio Standard (RPS) constraint:

$$\sum_{p1,c(out),s} FLOW_{v,t,p,c,s} \leq PR_t \cdot \sum_{p2,c(out),s} FLOW_{v,t,p,c,s} \qquad \forall v,t \qquad (B.10)$$

Where the *FLOW* variable on the left side represents the total electricity generation from renewable power plant technologies, p_1 (existing and new solar, wind, geothermal, biomass, and municipal solid waste), the *FLOW* variable on the right side represents the electricity generation from all power plant technologies p_2, and PR_t is the minimum percentage of electricity to come from renewable sources presented in Table B5. The percentages in the middle column of Table B5 represent the existing state-level renewable portfolio standards included in all of the scenarios in all three chapters (DSIRE, 2013). The percentages on the right side represent renewable energy purchase requirements, based on Title I of the American Clean Energy and Security Act of 2009 (H.R. 2454) and are only included in the scenarios with the proposed federal RPS (Sections 2.3.5 and 3.4.2).

Table B5. Requirements set for a renewable portfolio standard, old RPS (left) and new RPS (right) (Equation B.10)

Time Period (t)	PRt: Percent Renewable	PRt: Percent Renewable
2010	2.00	NA
2015	7.55	9.50
2020	11.00	20.00
2025	13.24	20.00
2030	13.36	20.00
2035	13.41	20.00
2040	13.46	20.00
2045	13.51	20.00
2050	13.56	20.00

Biomass to coal constraint:

$$\sum_{p1,c(out)} \mathrm{FLOW}_{v,t,p,c,s} \leq 0.1 \,.\, \sum_{p2,c(in)} \mathrm{FLOW}_{v,t,p,c,s} \qquad \forall\, v,t,s \qquad (B.11)$$

Equation (B.11) ensures that biomass co-firing in coal plants does not exceed operational limits. The commodity *FLOW* variable on the left side represents the production of biomass *c(out)* by technologies p_1 that is suitable for co-firing in coal plants p_2. The commodity *FLOW* variable on the right side represents the total flow of coal into the coal-fired power plants and the 0.10 represents the fractional limit on the amount of biomass that can be supplied to coal plants on a per unit energy basis.

Clean power plants capacity constraint:

$$\mathrm{CAP}_{v,t,p} \leq \mathrm{AC}_t \qquad \forall\, v,t,p \qquad (B.12)$$

Equation (B.12) represents the upper bound constraints on the annual capacity (*CAP*) of geothermal, biomass, nuclear, and wind power plants drawn from AEO and EPA (EIA, 2012 and Shay et al., 2006). Table B6 contains the annual upper bound values (AC_t) in GW for these power plants for each time period.

Table B6. The upper bound values on electric generation capacity (Equation B.12)

Time Period (t)	ACt (GW): Geothermal[1]	ACt (GW): Biomass[1]	ACt (GW): New Nuclear	ACt (GW): Wind Class 4	ACt (GW): Wind Class 5	ACt (GW): Wind Class 6
2015	4	8.2	12	2562	468	108
2020	6	8.6	20	2562	468	108
2025	8	8.9	48	2562	468	108
2030	10	9.2	64	2562	468	108
2035	11	9.5	86	2562	468	108
2040	13	9.9	92	2562	468	108
2045	15	10.2	100	2562	468	108
2050	17	10.5	100	2562	468	108

[1] The upper bound constraints are for the sum of existing and new capacity of geothermal and biomass power plants.

Solar capacity growth constraint:

$$CAP_{v,t,p} \,/\, CAP_{v,t-1,p} \leq 1.3 \qquad \forall v,t,p \qquad (B.13)$$

Equation (B.13) requires a maximum annual growth rate of 30% for new solar thermal and photovoltaic capacity *CAP*, based on AEO projections to 2035 (EIA, 2012). The installed capacity of new solar thermal or PV starts with a maximum of 2 GW in any time period that the model decides to start building new solar power plant capacity (EIA, 2012).

Biofuels constraint:

$$\sum_{p1,c1(in)} FLOW_{v,t,p,c,s} \leq ICEU_t \qquad \forall v,t,s \qquad (B.14)$$

$$\sum_{p1,c1(in)} FLOW_{v,t,p,c,s} \geq ICEL_t \qquad \forall v,t,s \qquad (B.15)$$

$$\sum_{p2,c2(in)} FLOW_{v,t,p,c,s} = IOBF_t \qquad \forall v,t,s \qquad (B.16)$$

Equations (B.14) and (B.15) impose upper and lower bound constraints, respectively, on cellulosic ethanol imports to the transportation sector. The *FLOW* variable in both equations represents the cellulosic ethanol imports to technology p_1, which provides ethanol to the transportation sector. $ICEU_t$ and $ICEL_t$, presented in Table B7, are the upper bound and lower bound constraints on cellulosic ethanol imports, respectively. Equation (B.16) sets a fixed bound constraint on imported corn ethanol and other advanced biofuels to the transportation sector. In this case, the *FLOW* variable represents corn ethanol and other advanced biofuels imports to technology p_2, which provides corn ethanol and other advanced biofuels to the transportation sector. $IOBF_t$, presented in Table B7, is the fixed bound constraint value on corn ethanol and other advanced biofuels imports. The upper bound on cellulosic ethanol availability and the fixed bound constraint on corn-based ethanol and other advanced biofuels from 2015-2025 are obtained from the Renewable Fuel Standard (RFS, 2013) and held constant from 2030 to 2050, while the lower bound is based on AEO projections to 2035 (EIA, 2012) and linearly extrapolated to 2050.

Table B7. The upper and lower bound values on cellulosic ethanol imports and the fixed bound constraints on imported corn-based ethanol and other advanced biofuels (Equations B.14, B.15, and B.16)

Time Period (t)	ICEUt (PJ): Upper Bound	ICELt (PJ): Lower Bound	IOBFt (PJ): Fixed Bound
2015	269	11	1482
2020	943	32	1661
2025	1437	137	1706
2030	3318	422	1706
2035	3318	644	1706
2040	3318	783	1706
2045	3318	953	1706
2050	3318	1159	1706

CAFE constraint:

$$\sum_{p,c1(out)} FLOW_{v,t,p,c,s} \leq TLE_t \qquad \forall v,t,s \qquad (B.17)$$

$$\sum_{p,c2(in)} FLOW_{v,t,p,c,s} \leq TLFC_t \qquad \forall v,t,s \qquad (B.18)$$

Equations (B.17) and (B.18) represent the upper bound constraints on total CO_2 emissions and fuel consumption associated with light duty vehicle (LDV) technologies, respectively. To avoid non-linearities in the TIMES model formulation, it was necessary to place constraints on total estimated CO_2 and energy consumption from the LDV sector rather than model the EPA emissions rate limits (EPA Federal Register, 2012) and required NHTSA fuel economies (AEO, 2012) directly.

In Equation (B.17), for each time period t, the *FLOW* of tailpipe CO_2 emissions $c_1(out)$ from LDV technologies p must be less than or equal to the estimated greenhouse gas (GHG) emissions limits TLE_t listed in Table B.8 based on the CAFE standard (EPA Federal register, 2012). In Equation (B.18), for each time period t, the total *FLOW* of input fuel $c_2(in)$ to LDV technologies p must be less than or equal to the maximum fuel consumption in the LDV sector, $TLFC_t$, which is listed in Table B.8 and is based on the fleet-wide average fuel economy drawn from the CAFE standard (AEO, 2012).

According to the new CAFE standard and the corresponding greenhouse gas (GHG) emissions rate limit (EPA Federal Register, 2012), LDVs are expected to reach a fleet-wide average fuel economy of 49.6 miles per gallon and GHG emissions of 163 grams CO_2 per mile in model year 2025, respectively (AEO, 2012). Consistent with AEO (AEO, 2012), the 49.6 miles per gallon is multiplied by a degradation factor of 80% to approximate on-road fuel economy. To factor out the effects of improved air conditioning which we do not model, the EPA standard is implemented as 185 grams CO_2 per mile to only capture the effects of improved energy efficiency.

Table B8. The upper bound values on tailpipe CO_2 emissions and fuel consumption associated with LDV technologies (Equations B.17 and B.18)

Time Period (t)	TLEt: LDV CO_2 Emissions (Mt)	TLFCt: LDV Fuel Input (PJ)
2010	NA	17154
2015	1376	16618
2020	1218	15961
2025	949	14919
2030	946	14081
2035	933	13699
2040	959	14108
2045	984	14512
2050	1009	14910

LDV size class share constraint:

$$\sum_{p1,c(out)} FLOW_{v,t,p,c,s} \geq SCS_t \,.\, \sum_{p2,c(out)} FLOW_{v,t,p,c,s} \qquad \forall v,t,s \qquad \text{(B.19)}$$

Equation (B.19) represents the lower bound share constraint for each vehicle size class in the LDV sector. For each time period *t*, the total *FLOW* of commodity *c(out)* represents billion vehicle miles traveled associated with vehicle technologies in the LDV sector, p_1 represents the set of vehicle technologies in a certain size class, p_2 represents the set of all LDV technologies, and SCS_t corresponds to the minimum percentage share of each vehicle size class in the LDV sector presented in Table B9 and based on U.S. EPA (Shay et al., 2006). A similar constraint is applied to vehicle technologies in the heavy duty sector.

Table B9. The lower bound values on LDV size class share (Equation B.19)

Time Period (t)	SCSt (%): Mini-Compact	SCSt (%): Compact	SCSt (%): Full	SCSt (%): Mini-Van	SCSt (%): Small SUV	SCSt (%): Large SUV	SCSt (%): Pickup
2015	1.7	19.0	28.5	5.7	17.4	14.3	13.2
2020	1.8	20.2	29.5	5.4	16.6	13.6	12.6
2025	1.9	21.5	30.6	5.2	15.7	13.0	12.0
2030	1.9	22.7	31.6	4.9	14.9	12.3	11.3
2035	2.0	24.0	32.7	4.6	14.0	11.7	10.7
2040	2.1	25.2	33.7	4.4	13.2	11.0	10.0
2045	2.2	26.4	34.8	4.1	12.4	10.3	9.4
2050	2.3	27.6	35.8	3.9	11.6	9.7	8.8

Fuel share constraint in end-use sectors:

$$\sum_{c1} \mathrm{FLOW}_{v,t,p,c,s} \leq \mathrm{FS}_t \, . \, \mathrm{DEM}_{c,t} \qquad \forall v,t,p,s \qquad \text{(B.20)}$$

$$\sum_{c1} \mathrm{FLOW}_{v,t,p,c,s} \geq \mathrm{FS}_t \, . \, \mathrm{DEM}_{c,t} \qquad \forall v,t,p,s \qquad \text{(B.21)}$$

Equations (B.20) and (B.21) represent the upper and lower bound fuel share constraints in the end-use sectors (commercial, residential, and industrial). Note that this constraint set is an implementation of Equations (B.6) and (B.7) specifically applied to fuel shares in the end-use sectors. The lower bound constraint (Equation (B.21)) is only applied to electricity in the end-use sectors, as we do not anticipate the possibility for a shrinking share of end-use electricity demand in the future. For each time period t, the total *FLOW* of commodity c_1 represents the fuel energy required to meet the total amount of end-use demand $DEM_{c,t}$ (in PJ) for each end-use sector, drawn from Tables A10 and D5. FS_t is the percentage fuel share from total demand in each end-use sector based on Tables A11 and D3. Note that end-use demands and fuel share constraints for Chapters 2 and 3 are drawn from Tables A10 and

A11. End-use demands and fuel share constraints for Chapter 4 are based on Tables D5 and D3, respectively.

CO_2 cap constraint:

$$\sum_{p,c(out)} \mathrm{FLOW}_{v,t,p,c,s} \leq \mathrm{TE}_t \qquad \forall v,t,s \qquad \text{(B.22)}$$

Equation (B.22) represents a federal cap on total system-wide CO_2 emissions, where the left side represents the sum of CO_2 emissions over all technologies *p* and the right side (TE_t) is the cap on total system-wide CO_2 emissions listed in Table B.10. The values listed in Table B.10 are based on a review of four proposed federal climate bills introduced in the US Congress over the last 7 years (U.S. EPA legislative analyses, 2013). The federal CO_2 cap enters into force with a 5% reduction in the 2015 model period, with assumed uniform, linear reductions in each 5-year period until a 40% reduction is achieved in 2050. Additional information is provided in Appendix C.

Table B10. A federal cap on system-wide CO_2 emissions (Equation B.22)

Time Period (t)	TEt: Total CO_2 Emissions Cap (Mt)
2010	5811
2015	5520
2020	5230
2025	4939
2030	4649
2035	4358
2040	4068
2045	3777
2050	3487

Clean Energy Standard (CES) constraint:

$$\sum_{p1,c(out),s} \text{FLOW}_{v,t,p,c,s} \leq \text{CES}_t \,.\, \sum_{p2,c(out),s} \text{FLOW}_{v,t,p,c,s} \qquad \forall v,t \qquad \text{(B.23)}$$

Equation (B.23) represents a minimum requirement for electricity purchase from clean power plants based on the Clean Energy Standard Act of 2012 (S. 2146, 2012), where the *FLOW* variable on the left side represents the electricity generation from clean power plant technologies p_1 (solar, wind, geothermal, municipal solid waste, biomass, new nuclear, coal-based IGCC-CCS, and NGCC-CCS). The *FLOW* variable on the right side represents total electricity production from all power plants p_2, including the portion from clean power plants, and CES_t is the minimum percentage of electricity that must come from clean sources, as shown in Table B11. See Section 3.4.4 for more information.

Table B11. Minimum annual requirements for the clean energy standard (Equation B.23)

Time Period (t)	CESt: Percent Clean Power Plants
2020	24.0
2025	39.0
2030	54.0
2035	69.0
2040	84.0
2045	84.0
2050	84.0

EPA CO_2 cap constraint on the electric sector:

$$\sum_{p1,c1(out),s} \text{FLOW}_{v,t,p,c,s} \leq \text{NSPS}_t \,.\, \sum_{p1,c2(out),s} \text{FLOW}_{v,t,p,c,s} \qquad \forall v,t \qquad \text{(B.24)}$$

$$\sum_{p2,c1(out),s} \text{FLOW}_{v,t,p,c,s} \leq \text{EC}_t \qquad \forall v,t \qquad \text{(B.25)}$$

Equation (B.24) represents the upper bound constraint on CO_2 emissions from new coal and natural gas power plants based on the U.S. EPA new source performance standard (NSPS) proposed on April 13, 2012 (EPA, 2013). For each time period *t,* the *FLOW* variable on the left side is summed over commodities $c_1(out)$ and represents the total CO_2 emissions from new fossil fuel-fired power plants p_1. The *FLOW* variable on the right side is summed over commodities $c_2(out)$ and represents the electricity generation from new fossil fuel-fired power plants p_1. $NSPS_t$ is the proposed CO_2 standard (in kt/PJ) for p_1 technologies listed in Table B12. A CO_2 standard of 1100 lbs/MWh (~138 kt/PJ) is applied for new coal steam and IGCC power plants (EPA, 2013). A CO_2 standard of 1000 lbs/MWh (~126 kt/PJ) is applied for gas-fired combustion turbines and combined cycle (EPA, 2013). In this analysis, these emissions rate limits are applied to applicable new capacity in model year 2015 and remain in place through 2050.

Equation (B.25) requires a national-level constraint on electric sector CO_2 emissions based on the U.S. EPA proposed emission guidelines to address greenhouse gas emissions from existing fossil fuel-fired power plants (EPA, 2014). The FLOW variable represents total electric sector CO_2 emissions summed over the set of all of power plant technologies p_2 and EC_t is the CO_2 cap limit on the electric sector emissions shown in Table B12 (EPA, 2013 and 2014). We apply a national-level constraint on electric sector CO_2 emissions that requires a CO_2 emissions reduction below 2005 levels of 26% in 2020, 29% in 2025, and 30% in 2030 (EPA, 2014). The 30% upper bound constraint on total CO_2 emissions is extended from 2030 to 2050. Section 3.4.3 provides more information on the U.S. EPA proposed emission guidelines for the electric sector CO_2 emissions.

Table B12. A federal EPA CO_2 cap on the electric sector (Equations B.24 and B.25)

Time Period (t)	NSPSt: CO_2 Emissions Cap(Kt/PJ)		ECt: Electric Sector CO_2 Cap (Mt)
	New Coal Steam and IGCC	**New Natural Gas Combustion Turbine and Combined Cycle**	
2015	138	126	NA
2020	138	126	1801
2025	138	126	1728
2030-2050	138	126	1704

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APPENDIX C. Scenario Information and Results for Chapter 2

This appendix includes additional background information on the hypothetical CO_2 policy and federal renewable portfolio standard (RPS) that are incorporated into the model scenarios as well as the characteristics of the scenarios analyzed in Chapter 2.

In addition to the baseline data, NUSTD contains scenario data related to 5 key factors likely to affect electric drive vehicle (EDV) deployment: oil prices, natural gas prices, the presence of a federal renewable portfolio standard (RPS), the presence of a federal CO_2 cap, and EDV battery costs. Figure C1 provides an influence diagram that illustrates how each factor affects the marginal electricity and fuel prices as well as vehicle cost, which taken together, determine the deployment of EDVs relative to other light duty vehicle (LDV) technologies as well as the fuel shares in the commercial, industrial, and residential sectors.

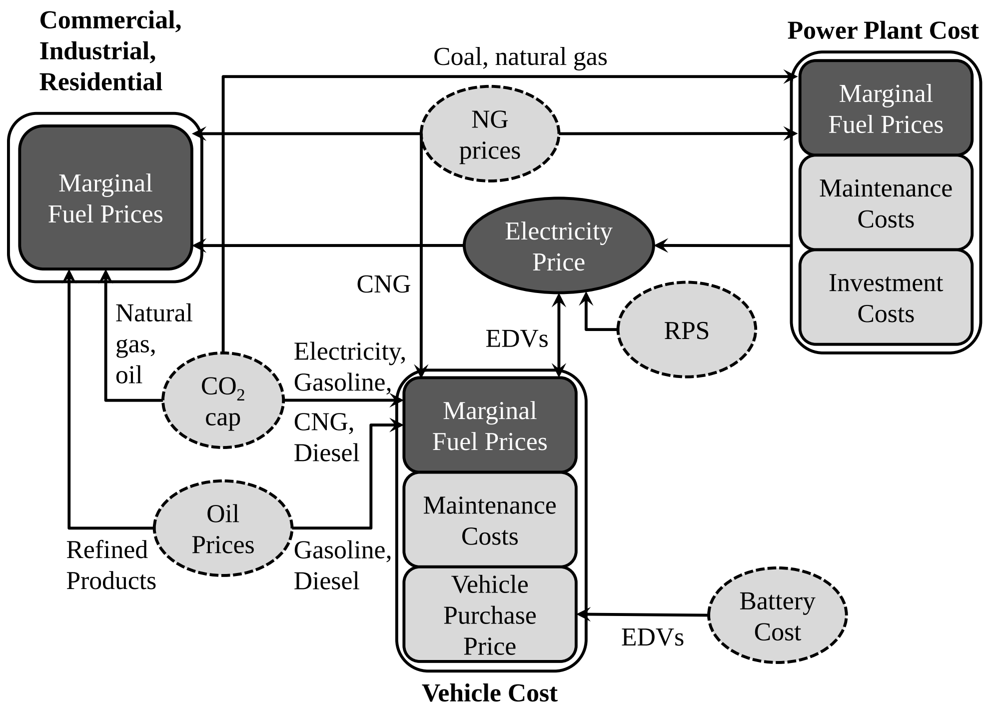

Figure C1. Influence diagram illustrating how scenario parameters related to natural gas prices, oil prices, EDV battery cost, a CO_2 policy, and a renewable portfolio standard ('RPS') affect marginal fuel and electricity prices as well as vehicle cost. The quantities in dark gray are determined endogenously in response to scenario-specific parameters, which are represented by the dashed ovals. The RPS affects the mix of electric generators, which is not represented in the diagram, but it ultimately influences electricity price.

It is important to note that the marginal price of a fuel represents its marginal value to the economy and is given by the change in total system cost per unit increase of the fuel. As a result, although the fuel supply prices are specified exogenously, the associated marginal prices, as determined by the model, can be affected by other scenario-specific assumptions such as the presence of the CO_2 policy. While most of the scenario-specific assumptions are provided in the manuscript, additional information related to the natural gas price scenarios, federal RPS, and system-wide CO_2 cap is provided below.

National gas prices

As noted in Chapter 2, 3 scenarios are drawn from the AEO (EIA, 2012): low estimated ultimate recovery (EUR), reference EUR, and High Total Recoverable Resource (TRR). In the low EUR case, the EUR per shale gas well is 50% lower than the reference case, the high EUR case assumes a 50% higher EUR compared to the reference case, and the TRR case assumes a 136% higher EUR compared to the reference case and a higher well density.

Note that the AEO scenarios above also include changes to the EUR and TRR of tight oil, which affects crude oil supply and prices. However, the variation in the 2035 price of low sulfur, light crude oil is only 5% relative to the reference case, whereas the 2035 variation in natural gas price is 55% (EIA, 2012). As a result, given the 5% price variation compared to much larger fuel price uncertainties, the effects of the variations in tight oil supply are ignored in this analysis.

CO_2 cap

Table C1 below presents a list of several climate bills introduced in the last 5 years and it provides the mid-century emissions targets associated with four pieces of climate legislation introduced in the U.S. Congress (U.S. EPA legislative analyses, 2013). While none of these measures were passed, they nonetheless provide an indication of the level at which greenhouse gas emissions might be capped under an eventual federal policy. For ease of comparison, all emissions reductions are based on emissions levels in 2010, which is the base year for our model. All four bills include provisions for domestic offsets and international emissions credits, which are not explicitly included in our model. As a result, the final column in Table C1 reflects the emissions target whereby the maximum international allowable offsets are added to the 2050 emissions target.

Table C1. Select US Congressional bills creating a federal cap and trade system for greenhouse gas emissions

Bill Name	Bill No.	Offsets	2050 Target (% reduction from 2010 levels)
Bingaman-Specter, "Low Carbon Economy Act of 2007	S1766	100% of cap can be domestic offsets; 10% can be international offsets	38%
Lieberman-Warner Climate Security Act of 2008	S2191	30% of cap level per year	60%
American Clean Energy and Security Act of 2009	H.R.2454	2,000 metric $MtCO_2e$/yr	45%
The Clean Energy Jobs and American Power Act of 2009	S1733	2,000 metric $MtCO_2e$/yr	45%

Renewable portfolio standard (RPS)

Table C2 presents renewable energy purchase requirements, expressed as a percentage of total generation, based on Title I of the American Clean Energy and Security Act of 2009 (H.R. 2454). For comparison, the average annual renewable requirement across the states with existing renewable portfolio standards is also presented for reference (DSIRE, 2013).

Table C2. Requirements set for a renewable portfolio standard as set forth in H.R. 2454

Year	Percent Renewable	
	H.R. 2454	**State Average**
2012	6.0	4.3
2013	6.0	4.4
2014	9.5	4.7
2015	9.5	5.7
2016	13.0	5.8
2017	13.0	6.0
2018	16.5	6.1
2019	16.5	6.4
2020 – 2039	20.0	10.6 [a]

[a] This estimate represents the average percentage from 2020-2030

As described in Chapter 2, 108 scenarios were analyzed, which combine assumptions related to oil and natural gas prices, vehicle battery cost, and the presence of RPS or a federal cap on CO_2 emissions. Table C3 illustrates the various assumptions associated with each of the 108 scenarios analyzed in Chapter 2. The model results for EDV share within the LDV market and associated system-wide emissions are also presented for each scenario.

Table C3. Scenario characteristics and the resultant EDV market share and emissions of CO_2, NO_X, and SO_2

Scenario	Nat Gas Price	Oil Price	RPS	CO_2 Policy	Battery Cost	EDV (% LDV market)	CO_2 emission (Mtons)	NOx emission (Ktons)	SO_2 emission (Ktons)
1	High	High	Yes	Yes	Low	0.42	3487	8578	4378
2	High	High	Yes	Yes	Ref	0.29	3487	8280	3943
3	High	High	Yes	Yes	High	0.27	3487	8232	3875
4	High	High	Yes	No	Low	0.42	5961	9757	4660
5	High	High	Yes	No	Ref	0.27	5935	9848	4693
6	High	High	Yes	No	High	0.24	5939	9855	4695
7	High	High	No	Yes	Low	0.42	3487	8579	4378
8	High	High	No	Yes	Ref	0.29	3487	8290	3957
9	High	High	No	Yes	High	0.27	3487	8242	3890

Table C3 Continued

10	High	High	No	No	Low	0.42	6252	9760	4681
11	High	High	No	No	Ref	0.28	6202	9847	4710
12	High	High	No	No	High	0.24	6205	9858	4713
13	High	Ref	Yes	Yes	Low	0.42	3487	8565	4355
14	High	Ref	Yes	Yes	Ref	0.25	3487	8224	3868
15	High	Ref	Yes	Yes	High	0.22	3487	8208	3841
16	High	Ref	Yes	No	Low	0.40	5954	9763	4667
17	High	Ref	Yes	No	Ref	0.22	5941	9846	4697
18	High	Ref	Yes	No	High	0.16	5953	9849	4702
19	High	Ref	No	Yes	Low	0.42	3487	8564	4359
20	High	Ref	No	Yes	Ref	0.25	3487	8234	3882
21	High	Ref	No	Yes	High	0.22	3487	8218	3857
22	High	Ref	No	No	Low	0.42	6246	9751	4681
23	High	Ref	No	No	Ref	0.22	6207	9849	4715
24	High	Ref	No	No	High	0.16	6220	9852	4721
25	High	Low	Yes	Yes	Low	0.16	3487	8256	3808
26	High	Low	Yes	Yes	Ref	0.16	3487	8256	3808
27	High	Low	Yes	Yes	High	0.03	3487	8038	3479
28	High	Low	Yes	No	Low	0.16	5988	9982	4789
29	High	Low	Yes	No	Ref	0.16	5988	9982	4789
30	High	Low	Yes	No	High	0.00	6016	10062	4826
31	High	Low	No	Yes	Low	0.16	3487	8266	3823
32	High	Low	No	Yes	Ref	0.16	3487	8266	3823
33	High	Low	No	Yes	High	0.03	3487	8038	3479
34	High	Low	No	No	Low	0.16	6255	9985	4808
35	High	Low	No	No	Ref	0.16	6255	9985	4808
36	High	Low	No	No	High	0.00	6244	10066	4842
37	Ref	High	Yes	Yes	Low	0.42	3487	8580	4340
38	Ref	High	Yes	Yes	Ref	0.37	3487	8473	3672
39	Ref	High	Yes	Yes	High	0.34	3487	8474	3660
40	Ref	High	Yes	No	Low	0.42	5806	9798	4661
41	Ref	High	Yes	No	Ref	0.28	5800	9884	4693
42	Ref	High	Yes	No	High	0.24	5808	9894	4696
43	Ref	High	No	Yes	Low	0.42	3487	8581	4341
44	Ref	High	No	Yes	Ref	0.31	3487	8353	4009
45	Ref	High	No	Yes	High	0.27	3487	8274	3899
46	Ref	High	No	No	Low	0.42	6078	9811	4684
47	Ref	High	No	No	Ref	0.28	6042	9897	4714
48	Ref	High	No	No	High	0.24	6055	9906	4717
49	Ref	Ref	Yes	Yes	Low	0.42	3487	8542	4328

Table C3 Continued

50	Ref	Ref	Yes	Yes	Ref	0.25	3487	8239	3890
51	Ref	Ref	Yes	Yes	High	0.22	3487	8223	3865
52	Ref	Ref	Yes	No	Low	0.40	5801	9791	4668
53	Ref	Ref	Yes	No	Ref	0.22	5812	9872	4698
54	Ref	Ref	Yes	No	High	0.16	5824	9875	4704
55	Ref	Ref	No	Yes	Low	0.42	3487	8543	4331
56	Ref	Ref	No	Yes	Ref	0.25	3487	8240	3892
57	Ref	Ref	No	Yes	High	0.22	3487	8224	3868
58	Ref	Ref	No	No	Low	0.42	6074	9789	4685
59	Ref	Ref	No	No	Ref	0.22	6059	9884	4719
60	Ref	Ref	No	No	High	0.16	6071	9887	4725
61	Ref	Low	Yes	Yes	Low	0.16	3487	8266	3796
62	Ref	Low	Yes	Yes	Ref	0.16	3487	8267	3798
63	Ref	Low	Yes	Yes	High	0.03	3487	8051	3489
64	Ref	Low	Yes	No	Low	0.16	5855	10004	4781
65	Ref	Low	Yes	No	Ref	0.16	5855	10004	4781
66	Ref	Low	Yes	No	High	0.00	5884	10079	4815
67	Ref	Low	No	Yes	Low	0.16	3487	8266	3796
68	Ref	Low	No	Yes	Ref	0.16	3487	8267	3797
69	Ref	Low	No	Yes	High	0.03	3487	8051	3489
70	Ref	Low	No	No	Low	0.16	6105	10016	4802
71	Ref	Low	No	No	Ref	0.16	6102	10016	4802
72	Ref	Low	No	No	High	0.00	6132	10091	4837
73	Low	High	Yes	Yes	Low	0.42	3487	7972	3222
74	Low	High	Yes	Yes	Ref	0.31	3487	7988	3256
75	Low	High	Yes	Yes	High	0.27	3487	8025	3292
76	Low	High	Yes	No	Low	0.42	5632	9876	4674
77	Low	High	Yes	No	Ref	0.28	5675	9950	4704
78	Low	High	Yes	No	High	0.24	5681	9960	4707
79	Low	High	No	Yes	Low	0.42	3487	7972	3222
80	Low	High	No	Yes	Ref	0.31	3487	8031	3287
81	Low	High	No	Yes	High	0.27	3487	8043	3305
82	Low	High	No	No	Low	0.42	5853	9899	4697
83	Low	High	No	No	Ref	0.28	5832	9982	4727
84	Low	High	No	No	High	0.24	5842	9991	4730
85	Low	Ref	Yes	Yes	Low	0.42	3487	7971	3223
86	Low	Ref	Yes	Yes	Ref	0.25	3487	8031	3299
87	Low	Ref	Yes	Yes	High	0.22	3487	8047	3311
88	Low	Ref	Yes	No	Low	0.42	5638	9882	4676
89	Low	Ref	Yes	No	Ref	0.22	5686	9965	4709

Table C3 Continued

90	Low	Ref	Yes	No	High	0.16	5698	9968	4715
91	Low	Ref	No	Yes	Low	0.42	3487	7971	3224
92	Low	Ref	No	Yes	Ref	0.25	3487	8044	3309
93	Low	Ref	No	Yes	High	0.22	3487	8051	3315
94	Low	Ref	No	No	Low	0.42	5849	9904	4698
95	Low	Ref	No	No	Ref	0.22	5847	9996	4732
96	Low	Ref	No	No	High	0.16	5859	9999	4738
97	Low	Low	Yes	Yes	Low	0.16	3487	8102	3311
98	Low	Low	Yes	Yes	Ref	0.16	3487	8102	3311
99	Low	Low	Yes	Yes	High	0.04	3487	8152	3377
100	Low	Low	Yes	No	Low	0.16	5725	10047	4757
101	Low	Low	Yes	No	Ref	0.16	5725	10047	4757
102	Low	Low	Yes	No	High	0.00	5784	10129	4797
103	Low	Low	No	Yes	Low	0.16	3487	8106	3314
104	Low	Low	No	Yes	Ref	0.16	3487	8106	3314
105	Low	Low	No	Yes	High	0.04	3487	8155	3380
106	Low	Low	No	No	Low	0.16	5886	10078	4780
107	Low	Low	No	No	Ref	0.16	5886	10079	4780
108	Low	Low	No	No	High	0.00	5978	10141	4814

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APPENDIX D. NUSTD Modifications for Chapter 4

Because Chapter 4 tests the model response to different vehicle charging patterns, it was necessary to develop new time-slices with finer time resolution and reapportion the end-use demands from the previous time-slice configuration based on U.S. EPA (Shay et al., 2006) to the new time-slice configuration. This appendix is organized into four sections, which address the following issues: (1) reapportioning dedicated electricity demand to the new time-slices, (2) reapportioning ‘other’ (i.e., non-exclusive electricity) demand to the new time-slices, (3) mapping vehicle demand to the new time-slices to represent constant, night, and peak charging, and (4) adjustments to the renewable resource characterization.

Section D1. Dedicated electricity demand reapportionment in the end-use sectors

In each end-use sector, the total dedicated electricity demand for each time period is ultimately distributed across the 36 time-slices using the TIMES ‘FR’ parameter, as defined in Equation (D.1):

$$\text{FR (Time-slice)} = \frac{\text{Electricity demand } i \text{ in each time-slice}}{\text{Total electricity demand } i \text{ for each time period}} \tag{D.1}$$

Mapping the EPA demands (Shay et al., 2006) from the original 12 time-slices to the new 36 time-slices is done in a two-step process. First, the demands are mapped to revised EPA time-slices similar to the original, but assuming each revised time-slice contains an integer number of hours. Second, the 12 revised EPA time-slices are mapped to the new 36 time-slices. We construct Tables D1 and D2 to demonstrate how electricity demand is calculated for each 2-hour time-slice in the intermediate season. The electricity demand corresponds to the residential sector in the intermediate season in 2010. The first row represents the EPA original time-slices for the intermediate season, where 'I' represents the intermediate season, 'AM' represents the morning, 'P' represents the peak slice, 'PM' represents the afternoon, and 'N' represents night (Shay et al., 2006). The dedicated electricity demand in Petajoules (PJ) and the length of the original EPA time-slices, drawn from AEO and EPANMD (EIA, 2012; Shay et al., 2006), are presented in rows 2 and 3, respectively. In row 4, the PJ electricity demand from row 2 is converted into a rate of consumption (PJ/hr) for each original EPA time-slice. Using the data in row 3 and assuming intermediate AM (IAM) begins at 6:00am, the start and end time of each EPA time-slice is calculated in row 5. We extended the length of the peak time-slice to 2 hours in order to have each time-slice correspond to an integer number of hours while making the least number of changes in the original time-slices. Rows 6 and 7 present the revised (denoted by 'R') EPA time-slices and the resultant length of time in hr/day, respectively. The start and end time of each revised time-slice is calculated in row 8. To estimate the electricity demand for each revised time-slice in row 11, we compare the length of the revised and original EPA time-slices in rows 9 and 10. For example, the start time of revised intermediate peak (R-IP) is 6 minutes (0.1hr) ahead of IP and the end time of R-IP is 112 min (1.87 hr) ahead of IP. The electricity demand associated with the additional 1.87 hr in the revised intermediate peak slice (R-IP) is taken from the adjacent time-slice, which is intermediate PM (I-PM). The PJ electricity demand for R-IP is then adjusted based on Equation (D.2):

$$\text{Electricity demand for R} - \text{IP (PJ)} =$$

$$\text{electricity demand for IP (PJ)} - 0.1\text{hr} \,.\, \text{electricity demand for IP (PJ/hr)}$$

$$+ 1.87\text{hr} \,.\, \text{electricity demand for IPM (PJ/hr)} \qquad \text{(D.2)}$$

We generate the same equations for other time-slices and estimate the electricity demand for all revised EPA time-slices based on the data in rows 2, 4, and 9.

Table D1. The electricity demand distribution throughout the original and revised EPA time-slices

1	**Original EPA time-slice**	**IAM**	**IP**	**IPM**	**IN**
2	Dedicated-electric demand (PJ)	315	17.9	489.3	492.9
3	EPA original time-slice (hr/day)	5.9	0.23	6.87	11
4	Dedicated-electric demand (PJ/hr)	53.4	78.1	71.2	44.8
5	Start time-end time	6:00-11:54am	11:54-12:08pm	12:08-7:00pm	7:00-6:00am
6	**Revised EPA time-slice**	**R-IAM**	**R-IP**	**R-IPM**	**R-IN**
7	EPA new time-slice (hr/day)	6	2	7	9
8	Start time-end time	6:00-12:00pm	12:00-2:00pm	2:00-9:00pm	9:00-6:00am
9	Time difference between length of original and new time-slices (hr)	+0.1	-0.1,+1.87	-1.87,+2	-2
10	IAM= 6am-11:54am IP=11:54-12:08pm IPM=12:08-7pm IN=7pm-6am R-IAM= 6am-12pm R-IP=12pm-2pm R-IPM=2pm-9pm R-IN=9pm-6am				
11	New Dedicated-electric demand (PJ)	322.8	143.3	445.8	403.3

IAM: Intermediate AM, IP: Intermediate Peak, IPM: Intermediate PM, IN: Intermediate Night

Table D2 illustrates how the demand distribution (FR) parameter is estimated for all 2-hour time-slices in the intermediate season based on the electricity demand from the revised

EPA time-slices shown in Table D1. The first row presents the twelve 2-hour time-slices in the intermediate season. The second row represents the fraction of each revised EPA time-slice associated with each 2-hour time-slice. In row 3, the residential electricity demands from the revised EPA time-slices (last row of Table D1) are distributed across the 2-hour time-slices using the fractions in row 2. Assuming 4607 PJ for the total dedicated electricity demand in the residential sector in 2010, the FR parameter is estimated for all 2-hour time-slices of the intermediate season in row 4 based on Equation (D.1). Note that the sum of dedicated electricity demands in row 3 corresponds to dedicated electricity demand for the intermediate season in the residential sector in 2010.

Table D2. The reapportionment of electricity demand to 2-hour time-slices in the intermediate (I) season

1	**2-hour time-slice**	**I(6-8am), I(8-10am), I(10-12pm)**	**I(12-2pm)**	**I(2-4pm), I(4-6pm), I(6-8pm)**	**I(8-10pm)**	**I(10pm-12am), I(12-2am), I(2-4am), I(4-6am)**
2	Fraction of new 2-hour diurnal time segment coming from each revised EPA diurnal time segment[a]	1/3 (R-IAM)	1 (R-IP)	2/7 (R-IPM)	1/7 (R-IPM), 1/9 (R-IN)	2/9 (R-IN)
3	Dedicated-electric demand (PJ)	107.6	143.3	127.4	108.5	89.6
4	FR (time-slice)	0.023	0.031	0.028	0.024	0.019

[a] Length of revised EPA time-slice drawn from Table D1, Row 7. For example, the demand for the new intermediate time-slice from 8-10pm ('I(8-10pm)') is based on 1/7 of the demand from the revised EPA R-IPM time-slice and the 1/9 of the demand from the revised EPA R-IN time-slice.

Section D2. The reapportionment of 'other' demand in the end-use sectors

The end-use demands (e.g., space heating and water heating) that can be met by either fossil fuels or electricity in the residential, commercial, and industrial sectors are included in a separate demand category called ‘other’ demand. In the industrial sector, the ‘other’ demand is only met by coal, petroleum products, and natural gas, whose prices do not vary by time-slice. As a result, a single aggregate energy demand is specified for ‘other’ industrial demand in each time period, which does not change across time-slices. However, in the residential and commercial sectors, some portion of ‘other’ demand can be met by electricity based on AEO (EIA, 2012). Therefore, the total ‘other’ demand in the residential and commercial sectors is distributed over the 2-hour time slices in the same way as shown in Tables D1 and D2.

Table D3 illustrates how fuel shares get relaxed over time in the commercial, industrial, and residential sectors. The share of the “electricity-other” commodity in the end-use sectors is calculated based on Equation (D.3) for each time period. The total and dedicated electricity demand for each end-use sector in Equation (D.3) is drawn from AEO projections to 2035 (EIA, 2012) and linearly extrapolated to 2050.

$$\text{“Electricity-other” Share} = \frac{\text{Total electricity demand} - \text{dedicated electricity demand}}{\text{Total energy demand} - \text{dedicated electricity demand}} \qquad \text{(D.3)}$$

The 20% and 5% projected electricity share within ‘other’ demand in the residential and commercial sectors, respectively, are specified as lower bound constraints from 2010 to 2050 (Table D3). The 2010 fuel shares and their projection to 2035 for other fuels are drawn from the AEO (EIA, 2012). These lower bound shares are linearly extrapolated from 2035 to 2050 and then linearly relaxed to 70% of the extrapolated values in 2050 for all of the fuels shown in Table D3. The 70% relaxation rate gives the model sufficient flexibility to fuel switch in these end-use sectors in response to price signals. Equation (B.20) represents the fuel share constraint for ‘other’ demand in end-use sectors.

Table D3. Fuel share constraints by end-use sector

End-use Demand Sector	Commodity Name*	2010	2015	2020	2025	2030	2035	2040	2045	2050
Residential	LPG (L)	6.60%	6.26%	5.93%	5.59%	5.26%	4.92%	4.59%	4.25%	3.92%
	LPG (U)	6.60%	6.60%	6.60%	6.60%	6.60%	6.60%	6.60%	6.60%	6.60%
	Distillate fuel oil (L)	7.42%	6.68%	5.93%	5.19%	4.45%	3.70%	2.96%	2.22%	1.47%
	Natural Gas (L)	59.60%	56.82%	54.05%	51.27%	48.50%	45.72%	42.95%	40.17%	37.39%
	Renewables (U)	4.92%	4.75%	4.58%	4.41%	4.24%	4.07%	3.90%	3.73%	3.56%
	Electricity-other (L)	20.97%	21.29%	21.62%	21.95%	22.28%	22.60%	22.93%	23.26%	23.59%
	Coal (U)	0.12%	0.11%	0.11%	0.10%	0.10%	0.10%	0.09%	0.09%	0.08%
Commercial	LPG (L)	3.14%	3.05%	2.97%	2.88%	2.80%	2.71%	2.63%	2.54%	2.45%
	LPG (U)	3.14%	3.14%	3.14%	3.14%	3.14%	3.14%	3.14%	3.14%	3.14%
	Distillate fuel oil (L)	9.59%	8.83%	8.07%	7.31%	6.54%	5.78%	5.02%	4.26%	3.50%
	Distillate fuel oil (U)	9.59%	9.59%	9.59%	9.59%	9.59%	9.59%	9.59%	9.59%	9.59%
	Natural Gas (L)	73.54%	71.36%	69.19%	67.01%	64.83%	62.65%	60.47%	58.30%	56.12%
	Renewables (U)	2.47%	2.35%	2.24%	2.13%	2.01%	1.90%	1.78%	1.67%	1.56%
	Electricity-other (L)	6.73%	6.30%	5.87%	5.44%	5.02%	4.59%	4.16%	3.73%	3.31%
	Coal (U)	1.35%	1.28%	1.22%	1.16%	1.10%	1.04%	0.97%	0.91%	0.85%
	Motor Gasoline (L)	1.12%	1.10%	1.08%	1.05%	1.03%	1.01%	0.99%	0.97%	0.94%
	Motor Gasoline (U)	1.12%	1.12%	1.12%	1.12%	1.12%	1.12%	1.12%	1.12%	1.12%
	Residual fuel oil (L)	1.79%	1.71%	1.63%	1.55%	1.46%	1.38%	1.30%	1.22%	1.13%
	Residual fuel oil (U)	1.79 %	1.79%	1.79%	1.79%	1.79%	1.79%	1.79%	1.79%	1.79%
Industrial	LPG (L)	12.68%	12.21%	11.74%	11.28%	10.81%	10.34%	9.87%	9.40%	8.93%
	LPG (U)	12.68%	12.68%	12.68%	12.68%	12.68%	12.68%	12.68%	12.68%	12.68%
	Motor Gasoline (L)	1.59%	1.56%	1.53%	1.49%	1.46%	1.42%	1.39%	1.35%	1.32%
	Motor Gasoline (U)	1.59%	1.59%	1.59%	1.59%	1.59%	1.59%	1.59%	1.59%	1.59%
	Distillate fuel oil (L)	7.29%	6.97%	6.66%	6.34%	6.02%	5.70%	5.38%	5.06%	4.75%
	Distillate fuel oil (U)	7.29%	7.29%	7.29%	7.29%	7.29%	7.29%	7.29%	7.29%	7.29%
	Kerosene (L)	15.93%	15.17%	14.41%	13.64%	12.88%	12.11%	11.35%	10.58%	9.82%
	Kerosene (U)	15.93%	15.93%	15.93%	15.93%	15.93%	15.93%	15.93%	15.93%	15.93%
	Natural Gas (L)	42.64%	41.14%	39.64%	38.14%	36.64%	35.13%	33.63%	32.13%	30.63%
	Coal (U)	9.56%	9.03%	8.50%	7.98%	7.45%	6.92%	6.39%	5.86%	5.33%
	Renewables (U)	9.56%	9.49%	9.42%	9.34%	9.27%	9.20%	9.13%	9.05%	8.98%
	Electricity-other (L)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

L=Lower bound constraint, U=Upper bound constraint

For reference, Tables D4 and D5 provide the dedicated electricity and "other" demands (in PJ) for the three end-use sectors (commercial, residential, and industrial), based on the AEO (EIA, 2012). The NUSTD workbooks contain the complete set of demand fractions associated with each 2-hour time-slice for each time period in each end-use sector (Energy Modeling, 2014).

Table D4. Total dedicated electricity demands in the non-transportation related end-use sectors (PJ)

Demand Commodity Name	Abbreviation	2010	2015	2020	2025	2030	2035	2040	2045	2050
Residential electricity demand	RESDEMELC	3345	3112	3176	3281	3429	3577	3645	3720	3802
Commercial electricity demand	COMDEMELC	4473	4547	4864	5170	5507	5834	6199	6602	7048
Industrial electricity demand	INDDEMELC	3260	3429	3439	3524	3429	3302	3319	3335	3352

Table D5. Total "other" demands in the non-transportation related end-use sectors (PJ)

Demand Commodity Name	Abbreviation	2010	2015	2020	2025	2030	2035	2040	2045	2050
Residential other demand	RESDEMOTH	8947	8725	8799	8873	8957	9010	9052	9109	9183
Commercial other demand	COMDEMOTH	4706	4727	4843	4843	4917	5001	5084	5173	5266
Industrial other demand	INDDEMOTH	16554	16955	17430	17830	17767	17820	14770	15026	15287

Section D3. Apportionment of light duty vehicle demand to represent vehicle charging scenarios

As described in Appendix B, TIMES balances commodity consumption and production associated with each process over each time slice. As such, vehicle charging and driving is assumed to balance over each time-slice. To represent vehicle charging with different time-slice distributions, the light duty vehicle (LDV) demand is distributed over different time-slices to represent constant, peak, and night charging scenarios. While reapportioning vehicle travel demand effectively assumes that the distribution of travel demand can change over a daily cycle, it is a modeling kluge that allows us to capture the effect of different charging patterns and does not have any other effect on the model results.

The annual demand for vehicle miles associated with light duty transportation, shown in Table A3, is distributed across time-slices for the night and peak charging time by the fractions presented in Tables D6 and D7, respectively. In the constant charging scenarios, the annual LDV demand is constant throughout the year.

Table D6. The fraction of annual LDV demand associated with each time-slice for night charging scenarios

Time-slice name	Demand fraction for each time-slice
I0-2am, I2-4am	0.250
S0-2am, S2-4am, W0-2am, W2-4am	0.125
W4-6, W6-8, W8-10, W10-12, W12-14, W14-16, W16-18, W18-20, W20-22, W22-24, I4-6, I6-8, I8-10, I10-12, I12-14, I14-16, I16-18, I18-20, I20-22, I22-24, S4-6, S6-8, S8-10, S10-12, S12-14, S14-16, S16-18, S18-20, S20-22, S22-24	0.000

S: Summer, W: Winter, I: Intermediate

Table D7. The fraction of annual LDV demand associated with each time-slice for peak charging scenarios

Time-slice name	Demand fraction for each time-slice
I14-16	0.50
W14-16, S14-16	0.25
W0-2, W2-4, W4-6, W6-8, W8-10, W10-12, W12-14, W16-18, W18-20, W20-22, W22-24, I0-2, I2-4, I4-6, I6-8, I8-10, I10-12, I12-14, I16-18, I18-20, I20-22, I22-24, S0-2, S2-4, S4-6, S6-8, S8-10, S10-12, S12-14, S16-18, S18-20, S20-22, S22-24	0.00

S: Summer, W: Winter, I: Intermediate

Section D4. Adjustments to renewable resource characterization

In the electric sector, the existing capacity of concentrating solar thermal and photovoltaic (PV) is updated based on the most recent estimates (1.75GW for solar thermal and 18 GW for solar PV) (EIA, 2013; Greentechsolar, 2014).

In addition, the availability factors (AFs) for the new solar and wind power plants had to be modified for consistency with the new 2-hour time-slices. The NUSTD workbooks contain the availability factors associated with each 2-hour time-slice for the new solar and wind power plants in each time period (Energy Modeling, 2014).

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