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DATE	APR 24 2012
RECD.	APR 24 2012

To: California Energy Commission
Subject: 2012-2013 Investment Plan Update for the Alternative and Renewable Fuel and Vehicle Technology Program
Docket No.: 11-ALT-01
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Date: April 24, 2012

The *2012-2013 Investment Plan Update for the Alternative and Renewable Fuel and Vehicle Technology Program* provides a broad spectrum of energy alternatives for light, medium, and heavy duty vehicles and their supporting fuels and infrastructure. It provides solid context for the drivers behind the plan to invest $100 million annually for the development and deployment of lower-carbon advanced fuels and vehicle technologies. It also refers to the *2011 Integrated Energy Policy Report*, which summarizes the expected benefits of the program in terms of petroleum reduction, carbon emissions reduction, and jobs created.

Given the importance of these metrics, we suggest that the CEC carefully examine and validate how these quantities are measured and their uncertainties. For example, the Low Carbon Fuel Standard (LCFS) and Life Cycle Analysis (LCA) tools draw upon other data sets for calculating carbon emissions. The CEC should consider how to monitor and validate carbon emissions through direct measurements and systems analysis. Moreover, the deployment projections and potential of each technology should be considered within the overall context of the fuel and vehicle mix. The CEC should seek out unbiased, independent assessments that examine the market, policy, and technology factors that influence the potential deployment of advanced technologies. The recent RFP for Evaluation, Measurement and Verification of the AB 118 Projects and Program may yield analyses that can partially address these issues. Other analyses, such as the enclosed parametric analysis of electric (including battery electric and plug in) and conventional vehicles in the light duty fleet,[1] can also highlight these factors that influence advanced technology deployment and competition with internal combustion engine (ICE) technologies.

While the *Investment Plan* includes support for many advanced fuels and vehicles, the CEC should develop target metrics and a vision for the specific market role of each technology that will enable the CEC to prioritize investments over time. The CEC should encourage continued improvement in ICE efficiency to support near term petroleum consumption and carbon emission reductions, as well as to serve as a continuously improving baseline for assessing alternative technology performance. Metrics for alternative technologies could be tailored based on the time horizon of the technology being developed. For example, drop-in biofuels may be a relatively near-term technology that would serve as a petroleum replacement for all-duty and long distance transport. They could be required to meet specified cost or carbon reduction targets over time. Battery electric vehicles and supporting charging infrastructure could be targeted to denser urban populations for shorter-distance travel. The *Investment Plan* partially raises this issue,

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[1] Barter, G.E., et al., Parametric analysis of technology and policy tradeoffs for conventional and electric light-duty vehicles. Energy Policy (2012), http://dx.doi.org/10.1016/j.enpol.2012.04.013

emphasizing the importance of providing charging access to multiunit dwellings. Range targets and charging infrastructure could be geared toward these goals. The *Investment Plan* also partially addresses these issues for hydrogen infrastructure by highlighting the work that the CEC has done in collaboration with the auto industry, California Fuel Cell Partnership, and ARB in identifying regions for early fuel cell vehicle deployment and recognizing the higher upfront investment for fueling infrastructure. The combination of target metrics and specified market roles would enable the CEC to measure potential and progress, and thus periodically re-evaluate and allocate resources accordingly over time. The decision to reduce support for E85 fueling infrastructure in the *Investment Plan* is an example of shifting priorities given the slow progress in station development and challenge to compete with gasoline prices.

In addition to the high priority investments called out in the plan, we support the CEC decision to reserve funds for emerging opportunities. Supporting innovative technologies, advanced fuels, and federal cost-sharing projects can help stimulate breakthrough ideas. The *Investment Plan* highlights examples of possible partnerships to produce fuels from sunlight and working with the Air Force for PEV deployments. We suggest that the CEC seek input from a broad set of potential partners so that it can invest in the most promising and impactful technologies.

Parametric analysis of technology and policy tradeoffs for conventional and electric light-duty vehicles

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Abstract

A parametric analysis is used to examine the supply-demand interactions between the US light-duty vehicle (LDV) fleet, its fuels, and the corresponding primary energy sources through 2050. The analysis emphasizes competition between conventional internal combustion engine (ICE) vehicles, including hybrids, and electric vehicles (EVs), represented by both plug-in hybrid and battery electric vehicles. We find that EV market penetration could double relative to our baseline case with policies to extend consumers' effective payback period to seven years. EVs can also reduce per vehicle petroleum consumption by up to 5% with opportunities to increase that fraction at higher adoption rates. However, EVs have limited ability to reduce LDV greenhouse gas emissions (GHG) with the current energy source mix. Alone, EVs cannot drive compliance with the most aggressive GHG emission reduction targets, even if the electricity grid shifts towards natural gas powered sources. Since ICEs will dominate the LDV fleet for up to forty years, conventional vehicle efficiency improvements have the greatest potential for reductions in LDV GHG emissions and petroleum consumption over this time. Specifically, achieving fleet average efficiencies of 72 mpg or greater can reduce average GHG emissions by 70% and average petroleum consumption by 81%.

Keywords: Electric vehicle, Greenhouse gas, Oil consumption

1. Introduction

The transportation sector contributes a significant fraction of the total US greenhouse gas (GHG) output and petroleum consumption. Not surprisingly, transportation is the largest consumer of crude oil by economic sector, with 85% of every barrel of oil going to liquid fuels, of which 43% is used by light-duty vehicle (LDV) transportation (U.S. Energy Information Administration, 2011a). In a similar manner, the EPA estimates that in 2008, 27% of the total US GHG emissions were attributable to transportation (36% if

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vehicle manufacturing and gasoline refining are included) (U.S. Environmental Protection Agency, 2011). Thus, improvements to LDV fuel economy, or the substitution of an alternative energy source for petroleum, can exert tremendous leverage over US GHG emissions and petroleum consumption. Of course, the consumption of petroleum-based fuels for personal transportation has environmental effects beyond GHG emissions and demand for petroleum, in general, has far-reaching economic, political, and security effects. However, for this analysis we focus on petroleum usage and GHG emissions as they are well-known metrics and frequently used as targets for policy or legislative action.

The prominence of environmental and security concerns over transportation energy use comes at a time of transition for the LDV fleet. New technologies could have a profound impact on the fleet make-up and diversify the energy sources that power vehicles. The introduction of mass-market plugin-hybrid electric vehicles (PHEVs), such as the Chevy Volt, and battery-electric vehicles (BEVs), such as the Nissan Leaf, offer an opportunity to shift some of the vehicle miles traveled (VMT) away from petroleum-derived energy sources. The current US administration has stated an informal mandate to put one million electric vehicles (EVs, implying both PHEVs and BEVs) on the road by 2015 (Obama, 2011). In this light, a number of other researchers and organizations have published reports examining the future viability and market penetration of these electric vehicles. The National Research Council (2010) concluded that with current policies and technology estimates, EVs will likely be less than 5% of the fleet in 2030. Hence, targeted policies or purchase incentives will be necessary to realize widespread EV adoption amongst consumers. A number of other studies concurred with this finding (Bandivadekar et al., 2008; Plotkin and Singh, 2009; Lin and Greene, 2010). Axsen et al. (2010) noted that while EVs, particularly PHEVs, are attractive for their potential fuel savings, battery performance is still limited in its energy storage capacity, peak power availability, and capacity degradation over the vehicle lifetime. Consumers must also be accepting of the higher purchase costs and lengthy recharge times. BEVs have additional hurdles of range restrictions, again due to limited battery storage capacity, and the lack of a sufficient recharging infrastructure. A compelling economic argument for EVs in the absence of policy-based incentives requires sustained high gasoline prices and low battery costs since conventional internal combustion engine (ICE) vehicles continue to remain cost competitive with EVs (Markel and Simpson, 2007). This is especially true as ICEs become more integrated with hybrid technology to recover energy typically lost in driving cycles.

Although the consensus amongst researchers is that EVs have a meager future without policy intervention, a policy-focused study at Indiana University notes that the seedlings of intervention already exist (Indiana University, 2011). Existing policies such as tax credits for consumers and producers or access to high occupancy vehicle lanes on highways could evolve into grander policies, such as additional taxes imposed on gasoline or carbon emissions, economic encouragement for an electric recharging infrastructure, or additional investment in battery research. One significant obstacle to any alternative vehicle technology is the limited payback period of consumers (i.e. the time over which fuel savings need to recover the higher alternative vehicle purchase cost) (Eppstein et al., 2011). While there is some disagreement over the effective payback period consumers assume when considering alternative vehicles (Greene, 2011; Train, 1985; Calfee, 1985), all concur that it is less than the lifetime of the vehicle.

Regardless of their market viability, EVs could offer GHG emission and fuel consumption improvements over ICEs. The benefit of vehicle electrification on GHG emissions, however, depends on the make-up and evolution of the electricity grid energy sources. As long as electricity production is derived from carbon intensive sources, the impact of EVs on GHG emissions will be limited (Bandivadekar et al., 2008; National Research Council, 2010; Plotkin and Singh, 2009). In fact, Samaras and Meisterling (2008) report that the well-to-wheel GHG emissions of a hybrid ICE could be lower than PHEVs or BEVs with the current mix. However, if future capacity added to the grid is based on lower carbon sources and those sources dispatch to the EV load, then EVs can realize GHG reductions of up to 50–75% compared to conventional vehicles (Samaras and Meisterling, 2008; Greene et al., 2011). To this end, the U.S. Energy Information Administration (2011a) optimistically assumes that most capacity additions to electric generation come from natural gas or renewable sources, yielding significant future GHG savings from EVs.

Although the internal combustion engine and personal automobile have existed for more than 100 years, there is still notable room for efficiency improvements (Bandivadekar et al., 2008). Conventional ICE vehicles will likely be a significant fraction of the LDV fleet through 2050, so important reductions in GHG emissions and fuel consumption can be achieved by focusing technological innovations on ICE vehicles. Potential fuel economy improvements of up to 50% over the next 20–30 years could be achieved by addressing vehicle light-weighting, rolling resistance, aerodynamics, transmission limitations, turbocharging, and combustion cycle inefficiencies (Bandivadekar et al., 2008).

This paper presents a system dynamics based model of the interactions between the US LDV fleet, its fuels, and the corresponding raw energy sources through the year 2050. An important capability of our model is the ability to conduct parametric analyses. Others have relied upon scenario-based analysis, where one discrete set of values is assigned to the input variables and used to generate one possible realization of the future (Bandivadekar et al., 2008; Plotkin and Singh, 2009; National Research Council, 2010; Greene et al., 2011). In these studies, there is often a *reference* case, as well as perhaps *optimistic* and *pessimistic* scenarios relative to the reference case. While these scenarios can be illustrative of dominant trends and tradeoffs under certain circumstances, changes in input values or assumptions can have a significant impact on results, especially when output metrics are associated with projections far into the future. For instance, two similar models at Argonne National Laboratories arrived at significantly different predictions of LDV oil consumption in 2050 due to the fact that one was calibrated to reference input values published in 2007 and another was calibrated to 2008 data (Plotkin and Singh, 2009). This type of uncertainty can be addressed by using a parametric study to examine a range of values for the input variables, offering a richer source of data to an analyst. It also enables a sensitivity analysis, which can reveal the underlying sources of uncertainty in a model, as well as identify key drivers of output metrics. Additionally, the n-dimensional shape of the trade space can be characterized to locate points of interest, such as inflection or saddle points, slope changes and asymptotic features. Finally, iso-performance contours can be traced to track the multiple sets of parameter values that can be used to achieve performance goals.

The paper is divided into four sections. This section has introduced the work and motivated our analysis. The following section outlines our model along with its methodology, assumptions, and data sources. Detailed model equations and input data are included in Appendix A. Section 3 presents the numerical results, focusing first on a global sensitivity analysis of the model to give greater insight into its behavior and the

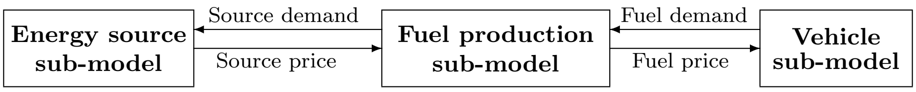


Figure 1: High-level diagram of the model components.

key drivers of uncertainty. Next is a discussion of one- and two-parameter variation studies used to understand the trade space for the impact of the US LDV fleet characteristics and associated policies on GHG emissions and petroleum consumption. This is followed by concluding remarks.

It is worth noting that this analysis focuses on policies that could influence vehicle *buying* behavior, but not *driving* behavior. Population migration away from suburbs and into urban enclaves or mass-transit improvements could decrease VMT, GHG emissions, and petroleum consumption as well, but are not considered here.

2. Model description

This section presents an overview of the modeling approach, key assumptions, and data sources. A more detailed discussion of the model equations and input data is provided in Appendix A.

Our model is implemented using a system dynamics software package with an interactive development environment to construct a set of interacting algebraic and differential equations. Solutions are generated using a third-order Runge-Kutta algorithm with fixed step size. A high-level diagram of the model components is shown in Figure 1. The model is broken down into three modules: an energy supply sub-model, a fuel production sub-model, and a vehicle sub-model. The sub-models exchange price and demand points for energy supply stock and fuels. The model is initialized with an age distribution of existing vehicles representative of the current fleet and then calculates annual vehicle sales and scrapping to determine the evolution of the fleet composition. The sales rate of each vehicle is determined using a choice algorithm that considers vehicle purchase cost, fuel costs, and penalty factors (e.g. range penalties). The cost of fuels and vehicles depends, in part, on the demand and prior sales so that there are both positive and negative feedback effects on the vehicle sales rate. The model tracks vehicles and fuel use in eight geographic regions, approximating the North American Electric Reliability Council (NERC) regional entities (E.H. Pechan & Associates, Inc., 2010). Fuel demand is negotiated with supply using raw energy supply curves at a global, national, or regional scale, depending on the energy stock.

2.1. Vehicle modeling

The model starts in 2010 with 247 million gasoline-fueled ICE light-duty vehicles in service in the United States. We use an age distribution as reported by the US Department of Transportation (Davis et al., 2010). The composition of the vehicle fleet is segmented by vehicle class (small car, large car, and light truck) using distributions of current data (U.S. Department of Transportation Federal Highway Administration, 2009). The fleet is further segmented by geographic region and population density (urban, suburban, and rural) within each region (U.S. Department of Transportation Federal

Highway Administration, 2011). The eight NERC regional entities form the basis for geographic segmentation. Finally, the vehicle fleet is segmented by binning driving intensity (light, medium, heavy) and home recharging availability (Greene and Lin, 2010). The ages of vehicles are tracked using binning with one-year resolution. Age-dependent annual mileage factors are applied to each bin to reflect decreasing annual miles as vehicles age (U.S. Department of Transportation National Highway Traffic Safety Administration, 2008). These factors are normalized to produce an average annual mileage per vehicle (VMT) of 10,959 miles for small cars, 11,731 miles for large cars, and 11,792 miles for light trucks. We assume that the VMT is constant over the course of the simulation. A complete breakdown of vehicle segmentation is provided in Tables A.4–A.7.

We consider four potential fuel and powertrain combinations for vehicles in this work: gasoline-fueled ICE (including gasoline-only hybrids), plug-in hybrid with 10-mile electric drive range (PHEV10), plug-in hybrid with 40-mile electric drive range (PHEV40), and battery electric (BEV). Existing gasoline-fueled vehicles are assigned fuel efficiency based on historical data (U.S. Environmental Protection Agency, 2009). Future gasoline powertrain vehicle efficiencies are taken from an ANL-led study for DOE (Moawad et al., 2011), and are assumed to achieve the regulatory targets proposed by the U.S. Environmental Protection Agency and U.S. Department of Transportation (2011). PHEV and BEV electric powertrain efficiencies and battery storage capacities are also taken from the same source. The amount of electricity and gasoline used by PHEV vehicles is determined by the electric range and driving patterns (Elgowainy et al., 2009). PHEV vehicles are assumed to operate in a serial drive train mode with daily home recharging, such that only on-board electricity is used when daily driving is less than the battery range.

Vehicle purchase costs are calculated using estimates for advanced technology and derived from the same study as the efficiency data (Moawad et al., 2011). The costs include learning over time that captures the decline in manufacturing costs due to process and technological maturation. The cost for electric vehicles is offset through subsidies from the American Clean Energy and Security Act of 2009. The cost for the batteries in electrified vehicles is calculated separately from other purchase costs so that the effect of targeted research in this area can be explored parametrically. The cost for batteries is extracted directly from National Research Council (2010), but allows for the user to adjust the rate of price decline over time associated with technological development. For vehicles that require home recharging, we include charger costs in the vehicle purchase cost calculation. We also include penalty functions to quantify limitations of alternative powertrains as an added cost averaged over the annual mileage. A range penalty is included to represent the reduced utility of a vehicle with a short range and is calculated using the value of the time spent refueling. A station availability penalty is used to capture the lower utility of a vehicle that has limited public refueling options. The dollar values of the penalties are taken from Greene (2001) and the growth trends of refueling infrastructure for alternative vehicles is taken from Yeh (2007). The generalized vehicle purchase costs, including penalties and subsidies, are amortized over a payback period of 3 years (in the baseline case) at 0% discount rate and converted to a per mile cost using the annual vehicle miles traveled (Greene et al., 2005).

Overall sales and scrap rates are kept at a constant percent of fleet size, with sales at 6.7% and scrap rate at 5.8%. The sales rate used is the average sales rate for the period 2000-2009 (Davis et al., 2010). The overall number of vehicles increases at 0.9% per year, the average rate of projected population growth from 2010 through 2050, and thus assumes no change in the number of vehicles per capita (U.S. Census Bureau, Population Division, 2008). While the overall rate of vehicle scrapping is fixed, the scrap rate of vehicles increases as the vehicles age, using rates derived from survival data (Davis et al., 2010). Because only new car sales and final disposal of the vehicles are considered, used vehicle sales are not tracked.

The sales in each time-step are assigned to segments using a logit choice of powertrain options in each vehicle segment (Struben and Sterman, 2008). Aside from the choice of powertrain, we do not assume the migration of consumers from one segment to another. For the recharging availability segment, no BEVs are sold where home recharging is not available. Based on survey data, 45% of drivers could have access to home recharging (Axsen and Kurani, 2010).

2.2. Modeling fuel production and distribution

The fuel model calculates the cost and energy source mix of transportation fuels, given fuel demand from the vehicle model and energy source costs from the energy source submodel. The fuel derived demand in each region is matched with energy sources and allows transport of fuel between regions to satisfy extreme supply or cost imbalances. The fuel model matches this demand with energy sources and allows transport of fuel between regions to satisfy extreme supply or cost imbalances. Two fuels are considered as transportation fuel for the light-duty vehicle fleet: electricity and a gasoline/ethanol blend. The model does not currently consider other fuels such as diesel, natural gas, or hydrogen. Diesel-fueled light-duty vehicles make up a small fraction of the current vehicle fleet (Davis et al., 2010), and the difference between gasoline and diesel with respect to both greenhouse gas emissions and petroleum consumption is small (Wang, 2010). Natural gas and hydrogen are potential future LDV transportation fuels, however this study focuses on electricity, gasoline, and ethanol as those are in mass-market use today.

The liquid-fueled portion of the fleet uses a mixture of gasoline and ethanol, with the ethanol consumption rate programmed to meet the Renewable Fuel Standard (RFS) (Sissine, 2007; Yacobucci and Capehart, 2008; One Hundred and Tenth Congress of the United States of America, 2007). We assume that future liquid-fuel vehicles will be able to use high-ethanol gasoline blends mandated by the RFS. The assumptions in the GREET 1.8d model were used to calculate the energy input requirements for gasoline and ethanol production as well as GHG emissions (Wang, 2010). We allow for ethanol production from five pathways: (1) fermentation of grains, thermochemical production from (2) forest residue or (3) woody energy crops, and biochemical production from (4) herbaceous energy crops or (5) agricultural waste. Taxes, profit margin, production, and delivery costs are cumulatively estimated to be \$1.29/gallon for gasoline, \$0.56/gallon for grain ethanol, \$1.23/gallon for thermochemical cellulosic ethanol, and \$1.33/gallon for biochemical cellulosic ethanol (Humbird et al., 2011; Urbanchuk, 2010; U.S. Energy Information Administration, 2011b).

The model allows for transport of fuels between regions so that regions with lower production cost can supply other regions. The cost of fuel imported from another region is the production cost plus a transportation cost proportional to the transportation distance between approximate region centroids. A distance-based GHG emission rate is also calculated, with a carbon cost added if required by the scenario definition. We assume electricity is not transferred between regions. The fuel supply for each region is chosen by a logit choice function of the same form as the vehicle choice function.

The energy source for electricity generated for transportation is modeled using the marginal source, as estimated from the EPA eGRID database (E.H. Pechan & Associates, Inc., 2010). In each region, coal, natural gas, and oil generation facilities operating between 30–60% of capacity were considered to be the marginal producers that dispatched to the EV load (Kromer and Heywood, 2007). The marginal capacity in each region is allowed to evolve in time according to user input. Existing capacity is assigned a five year mean replacement time and new capacity is added to meet the electricity demand from the vehicle fleet. As specified by the user, this new capacity scales from the initial marginal mix fractions to a 100% natural gas mix or to a 100% renewable (carbon-free) mix. The rapid, five year retirement rate allows for user exploration of alternative grid mix scenarios.

2.3. Modeling energy sources

The US Department of Energy's Annual Energy Outlook was our source for crude oil prices (U.S. Energy Information Administration, 2011a), which was assumed to be a global commodity with a price unaffected by perturbations in US LDV petroleum consumption. The price of coal and natural gas was calculated at a national level by adapting the supply curves from the US Environmental Protection Agency's Integrated Planning Model (U.S. Environmental Protection Agency, 2010). Biomass supply curves were constructed with technically available biomass data from the US Billion-Ton Update analysis (U.S. Department of Energy, 2011). Biomass was categorized as either grain, for fermentative ethanol production, or as foresting residue (farmed trees, herbaceous plants) or agricultural residue (stover) for cellulosic ethanol production. The supply curves were constructed to resemble the Billion-Ton report supply curves that included prices per dry ton of potentially available biomass at \$40, \$45, \$50, \$55, and \$60 USD per dry ton. Biomass supply data was converted from either state or county level to represent the NERC regions based on land area. The model treated all supply curves as look-up tables that input energy source demand and output energy source price.

3. Numerical analysis

This section presents numerical, parametric analysis results conducted using the model. Model parameterization and output metrics of interest are discussed. Results are shown for both a global sensitivity analysis and more focused trade space studies, using the metrics of GHG emissions and petroleum consumption. Parameterization and sensitivity analysis are a useful approach to understand the impact of significant modeling assumptions or uncertain input data on our results. Additionally, a sensitivity analysis can also be leveraged for model verification, where a perturbation in one or more parameters leads to expected changes in output metrics. Finally, parameterization allows for trade-space exploration to identify the multiple sets of input values that can achieve performance targets.

3.1. Model parameterization

Overall, the model parameterization spans variables that could be categorized across multiple conceptual labels, such as inherent modeling assumptions, economic forecasting, technological development, and future policy decisions. It is not feasible to independently parameterize every single input variable in the model both due to variable inter-dependency and also tractability of the sensitivity analysis. Instead of varying the crude oil price in 2030 and 2031 independently, for instance, all oil prices are scaled by a constant multiplier (keeping the initial 2010 value constant). This *multiplier* approach is similarly applied to other energy source supply curves, vehicle efficiencies, conversion efficiencies, and consumer choice penalties. Where appropriate, such as the exponent in the logit choice function, individual variables are parameterized directly. The marginal grid mix is parameterized by imposing a short, five-year lifetime on existing capacity and adding new marginal capacity with a regional blending function to vary the regional carbon intensity of the grid. A blending parameter value of 0 maintains the initial mix throughout the simulation, 0.5 leads to a 100% natural gas marginal mix, and 1 leads to a 100% carbon-free mix.

Uniform distributions are assumed for all parameters in all studies. For the sensitivity analysis, parameter minimums, maximums, and baseline values are described in Table 1. The carbon price parameter appends an additional cost to fuels proportional to the emission of GHG and represents a potential carbon tax policy. For calibration, the maximum carbon price considered, \$1,000 per metric ton of CO_2 equivalent, corresponds to an additional price on gasoline of nearly \$10 per gallon. Two other parameters, the consumer payback period and the BEV penalty multiplier, could also be considered variables subject to policy influence. The biomass, coal, natural gas, and oil price multiplier parameters, as well as the grid mix carbon intensity, address commodity forecasting uncertainty. Additionally, a number of parameters included in the sensitivity analysis characterize the uncertainty in technological development. Technological performance uncertainty is captured by multipliers applied to gasoline powertrain efficiency, electric powertrain efficiency, and electricity generation efficiency. Some of the efficiency multipliers have truncated lower bounds so that future efficiencies do not drop below current day capabilities (since 2010 values were held fixed). Similarly, the variation in battery cost can be thought of as the technological maturation of battery storage and manufacturing. Adjusting the battery cost in 2030 set the exponential decay rate of the associated technological development in an intuitive manner. Finally, the remaining parameters included in the sensitivity analysis are notable model assumptions with the potential for influencing output metrics. These include the two logit choice exponents for vehicle selection and fuel exchange, the overall fleet growth rate, and the overall vehicle sales rate which, together with the fleet growth rate, also determines the overall scrap rate.

It should be noted that all of the input parameters are assumed to be independent. While this assumption is plausible near the baseline values, it is likely less valid at some value extremes. For instance, at high values of oil price or carbon price, consumers would probably have longer payback periods than current estimates. Similarly, battery costs and electric powertrain efficiency are likely coupled, as high efficiencies might be associated with higher battery costs.

Table 1: Baseline values and uniform distribution ranges for sensitivity analysis parameters.

Parameter	Baseline	Min	Max
Carbon price [$/MT CO_2 equivalent]	0	0	1000
Consumer payback period [years]	3	2.48	10.38
BEV penalty multiplier	1	0	1
Battery cost in 2030 [$/kWh]	360	50	500
Gasoline powertrain eff multiplier	1	0.9	2
Electric powertrain eff multiplier	1	0.9	2
Electricity generation eff multiplier	1	0.5	2
Grid mix blending parameter	0	0	1
Vehicle choice logit exponent	14.9	1	20
Fuel transport logit exponent	18	1	20
Fleet growth rate	0.9%	0.5%	2.0%
Vehicle sales rate	6.7%	5%	9%
Oil price multiplier	1	0.5	3
Coal price multiplier	1	0.5	3
Natural gas price multiplier	1	0.5	3
Biomass price multiplier	1	0.5	3

3.2. Output metrics of interest

The first metric of interest is LDV fleet fractions of ICEs and EVs, where EVs are defined as the sum of PHEVs and BEVs. In his 2011 State of the Union address, President Barack Obama promulgated a national goal to have one million EVs on the roads in the US by 2015 (Obama, 2011). Since 1 million vehicles represent less than 1% of the total fleet, small changes in parameter values can have a significant impact on meeting this target. As will be seen below, the fleet fractions are indeed sensitive to variations in key parameters.

To address the environmental perspective of transportation energy, we examine the relationship between the LDV fleet and GHG emissions. The model is capable of tracking GHG emissions, specifically the quantity of carbon dioxide equivalent emissions released into the atmosphere either through direct LDV fleet tailpipe emissions or indirectly through gasoline refinement and electricity production. A number of organizations, states, and countries have set out ambitious GHG reduction goals for 2050. The State of California and the European Commission, for instance, have both targeted an 80% reduction in CO_2 below 1990 emissions levels by 2050 (Schwarzenegger, 2005; European Commission, 2011). A recent study by Grimes-Casey et al. (2009) distributed the IPCC-recommended global carbon reduction targets to individual countries and sectors based on population and economic modeling. They determined that the average US LDV well-to-wheel GHG emissions must be reduced 88% in 2050 over 2002 levels. Despite these mandates, CO_2 emissions have nevertheless increased from 1990 to 2010 (Butler, 2011). We consider GHG reductions per vehicle using a 2010 reference point.

To address the security context of energy use, we examine the total petroleum consumption from the LDV transportation sector, and its corresponding relationship to imported crude oil. According to the latest projections from the U.S. Energy Information Administration (2011a), in 2010 the US produced 37% of its crude oil needs, with

Table 2: Spearman rank correlation coefficients for outputs (columns) with respect to inputs (rows). Output metrics are measured at simulation end, 2050.

Parameter	**GHG emissions**	**Petrol consumption**	**ICE fleet fraction**	**BEV fleet fraction**
Carbon price	-0.04	-0.05	-0.14	0.13
Consumer payback period	-0.13	-0.17	-0.44	0.24
BEV penalty mult	0.01	0.01	0.00	-0.14
Battery cost in 2030	0.07	0.10	0.28	-0.47
Gasoline powertrain eff mult	-0.71	-0.69	0.11	-0.14
Electric powertrain eff mult	-0.05	-0.02	-0.04	0.09
Electricity generation eff mult	-0.06	-0.02	-0.04	0.07
Grid mix blending parameter	-0.07	-0.01	-0.02	0.03
Vehicle choice logit exponent	0.14	0.21	0.72	-0.68
Fuel transport logit exponent	0.00	0.00	0.01	-0.01
Fleet growth rate	0.61	0.58	0.02	-0.01
Vehicle sales rate	-0.04	-0.04	-0.08	0.07
Oil price mult	-0.03	-0.03	-0.09	0.11
Coal price mult	0.00	0.01	0.01	-0.01
Natural gas price mult	0.00	0.00	0.00	-0.02
Biomass price mult	-0.04	0.00	0.01	-0.01

another 22% coming from Canada and Mexico, leaving 41% for OPEC and other countries. Thus, reducing petroleum consumption by these same margins could potentially enhance US energy security by mitigating crude oil dependency on foreign sources.

3.3. Sensitivity analysis

A sensitivity analysis was performed to verify expected model behavior and to reveal the most significant drivers of variability in output metrics of interest. A non-parametric, non-linear global sensitivity analysis was desired. The approach undertaken was crafted to account for complex variable interactions, as well as large changes to non-normalized input and output variables. Specifically, a Monte Carlo simulation allowed 16 uncertain input parameters to vary, where the tabulation of these 16 parameters is found in Table 1. Spearman rank correlation coefficients were then computed between the output metrics of interest and the 16 uncertain input parameters. The magnitude of the correlation coefficient relates the degree to which a given input parameter variance is statistically associated with an output variance. A coefficient value of 1 or -1 represents a perfect positive or negative correlation, respectively. A Monte Carlo simulation with 5,000 model evaluations and Latin hypercube sampling generated the sensitivity analysis sample data. A follow-on Monte Carlo simulation with 10,000 model evaluations produced identical correlation coefficients and confirmed convergence of the results. The sensitivity analysis results are described in Table 2 where each value represents the Spearman rank correlation coefficient of an output metric, listed in columns, with respect to an input parameter, listed by rows.

The sensitivity analysis for total LDV GHG emissions in 2050 shows that gasoline powertrain efficiency and fleet growth rate are the most influential parameters. Consumer payback period and the vehicle choice exponent only show minor influence. It is worth noting which parameters had little impact on LDV GHG emissions. Grid carbon intensity, electric powertrain efficiency, oil price, and carbon price have little correlation with LDV GHG emissions, which prompted deeper inspection. The grid carbon intensity and electric powertrain efficiency have little influence due to the limited market penetration of EVs. Oil price and carbon price both serve to dissuade consumers from buying inefficient vehicles in general, but do not directly impact average trip length, VMT, or vehicle efficiencies in this analysis. These relationships will continue to be explored in later sections.

Table 2 also lists the sensitivity analysis results for total LDV petroleum consumption in 2050. The results largely mirror those for LDV GHG emissions with slightly stronger correlations for consumer payback period, battery cost, and the vehicle choice exponent as those can augment the market penetration of EVs and reduce overall petroleum consumption. The oil price multiplier again shows little correlation. Even at extreme values of the oil price range considered, three times EIA projections, ICEs are still cheaper than EVs at the baseline consumer payback period. The oil price would have to be nearly five times as high as baseline projections for ICEs to be more expensive. It should be noted that consumer payback periods would likely be longer than current baseline values in such an extreme oil price environment.

A sensitivity analysis result for the final fleet fractions of ICE vehicles is similarly detailed in Table 2. Since only ICEs and EVs were considered in the model, final ICE fractions are sensitive to parameters that encourage or discourage either of those powertrains. This includes chiefly the vehicle choice exponent, consumer payback period, carbon price, and battery cost. To a lesser extent, gasoline powertrain efficiency and carbon price are also correlated. It is interesting to note that consumer payback period rises above all other parameters except the vehicle choice exponent.

Although the sensitivity analysis results for the total EV fleet fraction are identical to the ICE results, the BEV fleet fraction in 2050 is extracted and shown in Table 2. In this case, a few additional parameters, in addition to those correlated with ICE fleet fractions, show signs of influence. These include consumer penalties, electric powertrain efficiency, and the price of oil. This larger suite of parameters perhaps reflects that a potential BEV customer must both choose not to purchase an ICE, and also to single out BEVs from the PHEVs. One conclusion that could be drawn from this sensitivity analysis is that there are many factors that contribute to the adoption of BEVs, and EVs in general. Technology improvements or policy initiatives in isolation cannot effect widespread change. Only through the combination of improvements in multiple technologies with broad policy incentives will EVs play a significant role in the LDV fleet.

3.4. Trade space analysis

3.4.1. Baseline predictions and metrics of interest

Before presenting the parametric analysis, it is helpful to understand the baseline model state about which variations are taken. As stated above and illustrated in Figure 2a, the average LDV fleet efficiency is projected to improve markedly from 2010 to 2050, with a more than 30% increase in electric powertrain efficiencies and more than 60% increase in gasoline powertrain efficiencies. Concurrently, battery costs are expected to decrease by more than 60%, shown in Figure 2b, due to technological maturation. Similar to the sensitivity analysis, these cost and efficiency values are scaled parametrically through the multiplier approach to explore their dynamics, critical points, and tradeoffs.

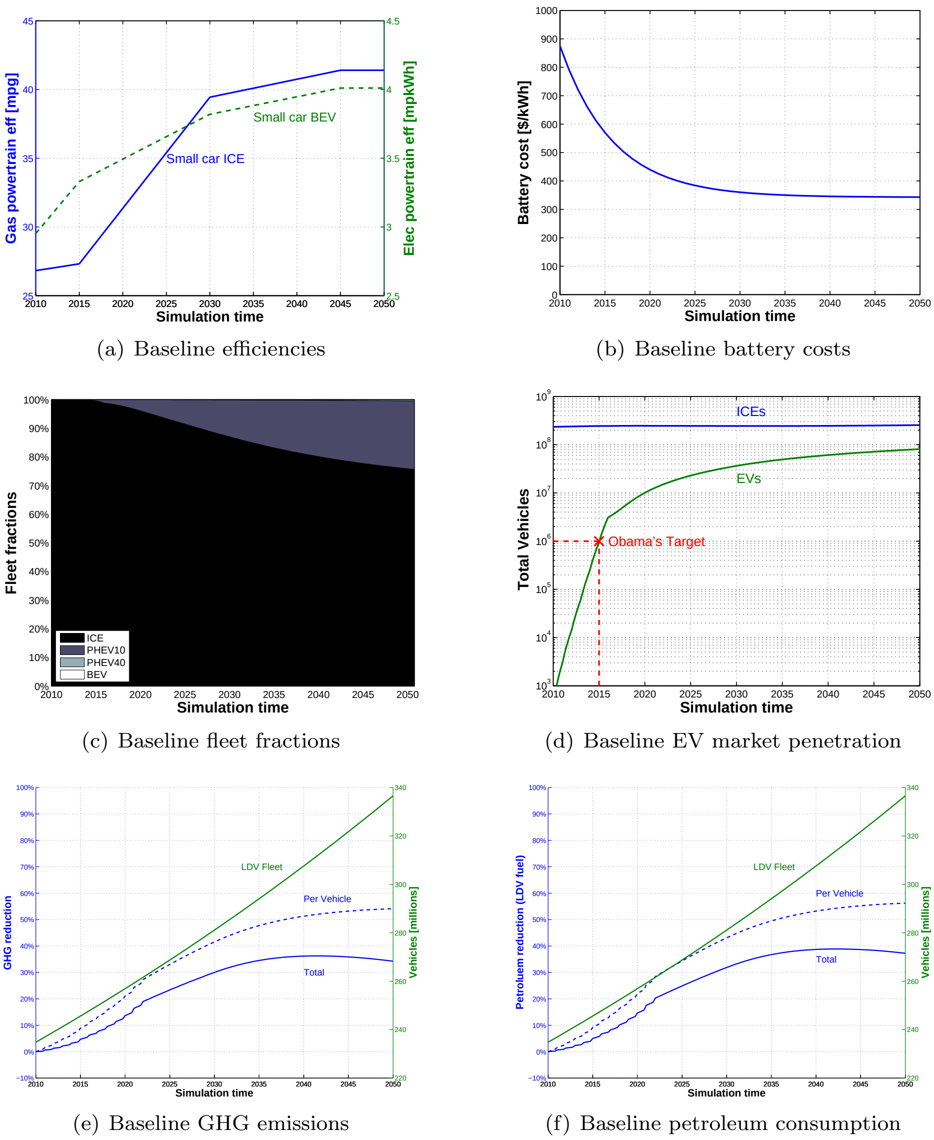
The baseline model outputs are also shown in Figure 2. For the baseline model state, fleet breakdown by vehicle powertrain over time is drawn in Figure 2c. In this projection, ICEs are more than 70% of the LDV fleet in 2050, with most of the other vehicles being PHEV10s; PHEV40 and BEV fleet fractions in 2050 are negligible. This pace of EV growth is nevertheless sufficient to meet Obama's EV target in 2015, shown in Figure 2d.

As a fraction of 2010 quantities, baseline GHG emissions reductions are shown in Figure 2e. Since the sensitivity analysis showed total GHG emissions to be heavily dependent on fleet growth rate, we normalize by number of vehicles to examine the annual GHG output per LDV in the model. For this quantity, the model projects a baseline reduction of more than 50% by 2050. Similar to the GHG case, petroleum consumption from the LDV is also normalized by number of vehicles and framed as a relative reduction from 2010 levels. As shown in Figure 2f, the baseline scenario projects a reduction in petroleum consumption per vehicle of 55% by 2050.

3.4.2. Electric vehicle adoption targets

More detailed parametric studies, beyond the sensitivity analysis, were conducted to understand the penetration of electric vehicles into the LDV fleet. Figure 3a depicts the impact of two market-based adjustments that might be available to policy makers to influence the fleet fraction of EVs in 2050. The consumer payback period can be influenced by media campaigns, consumer education, and even direct incentives. In fact, adjusting consumers' perceived payback period from 3 to 7 years can more than double the EV fleet fraction. Carbon price, as a disincentive for fossil fuel consumption, can change the EV fleet fraction by approximately 25 percentage points for the range of values considered, a slightly less influential parameter in this respect than the payback period.

It is interesting to compare the competing influences of electric powertrain efficiency and the cost of batteries upon the adoption rates of EVs, which is displayed in Figure 3b. As mentioned above, these two parameters are likely not independent since higher electric powertrain efficiency will likely coincide with more expensive batteries. Surprisingly, the contour lines are almost chiefly aligned with the battery cost-axis. Even if electric powertrain efficiency is twice baseline projections, our model predicts that the impact on EV sales rates will be negligible. Essentially, the difference in price between traditional ICE vehicles and EVs stems from the batteries themselves, immature manufacturing processes, and perceived range and infrastructure penalties for BEVs. Improving electric powertrain efficiency, without concurrently altering the payback period, only addresses the BEV range penalty component of the cost differential since we assumed that the total battery pack capacity remained constant. In contrast, significant reductions to battery costs make all EVs much more competitive with ICEs. This message is reiterated in the comparison of battery cost and gasoline powertrain efficiency, shown in Figure 3c. While increased gasoline powertrain efficiency decreases the EV fleet fraction, since EVs become less attractive, the cost of batteries is a more influential parameter. Increasing gasoline powertrain efficiency, perhaps contrary to common opinion, is not entirely antithetical to increased EV adoption as gasoline powertrain efficiency gains benefit PHEVs as well.



(a) Baseline efficiencies

(b) Baseline battery costs

(c) Baseline fleet fractions

(d) Baseline EV market penetration

(e) Baseline GHG emissions

(f) Baseline petroleum consumption

Figure 2: Baseline efficiencies, battery costs, fleet fractions, GHG emissions, and petroleum consumption. Note that final fleet fractions in (c) are 75.6% ICE, 24.0% PHEV10, 0.4% PHEV40, and < 0.01% BEV.

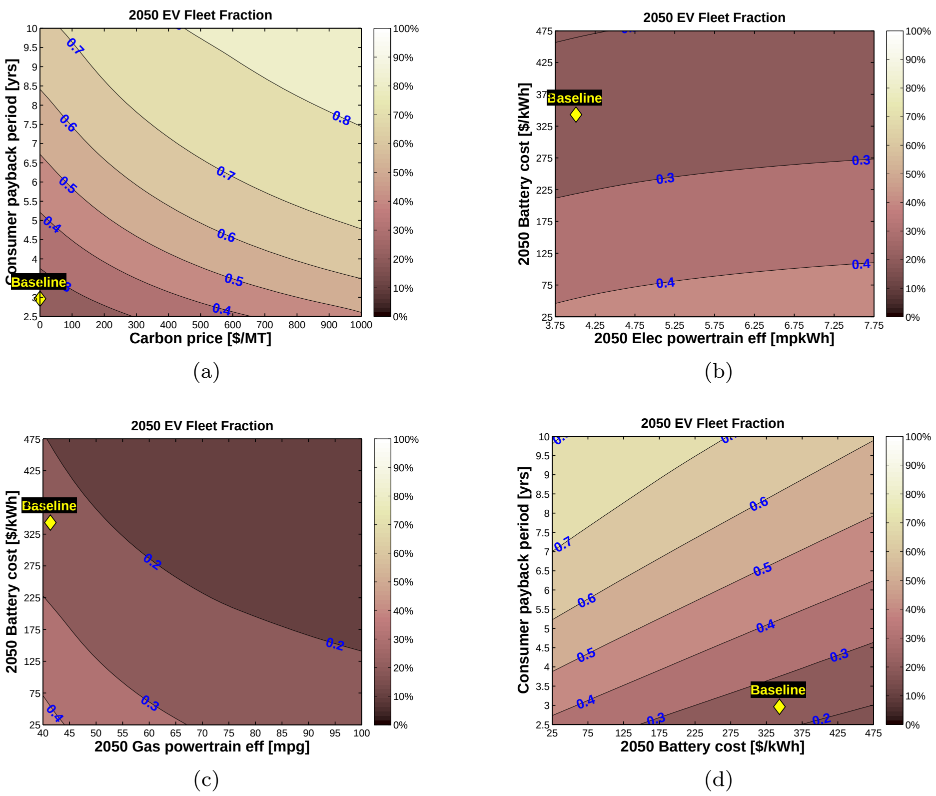


Figure 3: Contours of electric vehicle fleet fractions. Efficiencies listed are for small cars.

As one would expect, and shown in Figure 3d, large EV adoption rates occur when reduction in battery costs is coupled with adjustments to consumers' payback period. At extreme values of these parameters, the fleet fraction of EVs can reach nearly 80%. While these tradeoffs can guide decision makers to encourage EV sales, one must also question if EV fleet penetration is a worthy goal in its own right, or if environmental or security objectives should be targeted directly. To that end, our model can simulate a future with and without EVs by effectively turning them on or off. This comparison uncovers the benefit of EVs upon other metrics of interest. Figure 4 shows the reduction in GHG emissions and LDV petroleum consumption per vehicle for this tradeoff versus variations in gasoline powertrain efficiency and grid carbon intensity. The first observation from these plots is that the value of EVs is somewhat subject to the performance uncertainty of ICEs, but nearly independent of the grid mix. If unanticipated technological leaps are made in gasoline powertrain efficiency, then EVs will indeed have limited utility. Second, EVs indeed have limited capacity to impact GHG emissions or LDV petroleum consumption per vehicle. There is only a 0-5% reduction in GHG emissions per vehicle and a 0-7% reduction in LDV petroleum consumption across the entire range of gasoline powertrain efficiencies and grid carbon intensities considered. While not captured by the range of values considered here, it is possible for the lines in Figure 4a to cross; at extreme gasoline powertrain efficiencies EVs produce more GHG emissions than ICEs (with the current electricity generation mix).

3.4.3. Reduction in greenhouse gas emissions per vehicle

The model baseline already projects a GHG per vehicle reduction of more than 50% below 2010 values by 2050, but the LDV segment must do more if the 80% reduction targets below 1990 levels are to be achieved. If policy makers relied upon market-based influences only, as shown in Figure 5a, then little benefit beyond the baseline scenario can be expected. Both carbon price and consumer payback period have little leverage over GHG reductions per vehicle, as both parameters primarily incentivize EV adoption, but do not impact vehicle efficiencies directly. Even broad adjustments to EV efficiency projections, shown in Figure 5b, have little impact on GHG emissions. Noteworthy reductions in GHG reductions in this case only occur when extreme values of electric powertrain efficiency are combined with extreme values for consumer payback period. Similar levels of reduction can also be seen in Figure 5c, but also only at extreme values of carbon price and grid carbon intensity.

The impacts of gasoline powertrain efficiency and battery cost changes are shown in Figure 5d. As one would expect, the contour lines are nearly aligned with the gasoline powertrain efficiency axis. This suggests that meeting the most ambitious GHG reduction targets requires, chiefly, improvement in gasoline powertrain efficiencies and that battery costs have little impact on GHG emissions. Additionally, the 80% reduction target falls at gasoline powertrain efficiencies beyond 80 mpg for small cars (71.6 mpg fleet average), almost double the baseline projection. Thus, meeting the most aggressive targets might be dependent upon realizing technological leaps or currently unforeseen advances, rather than incremental changes. At these efficiencies, while the per vehicle GHG emission reduction is 80%, the absolute reduction across the LDV fleet is 70%.

Under our baseline assumptions, significant gasoline powertrain efficiency improvements are indispensable to meeting GHG reduction targets due to the small proportion of EVs in the LDV fleet. To examine the conditions where the gasoline powertrain ef-

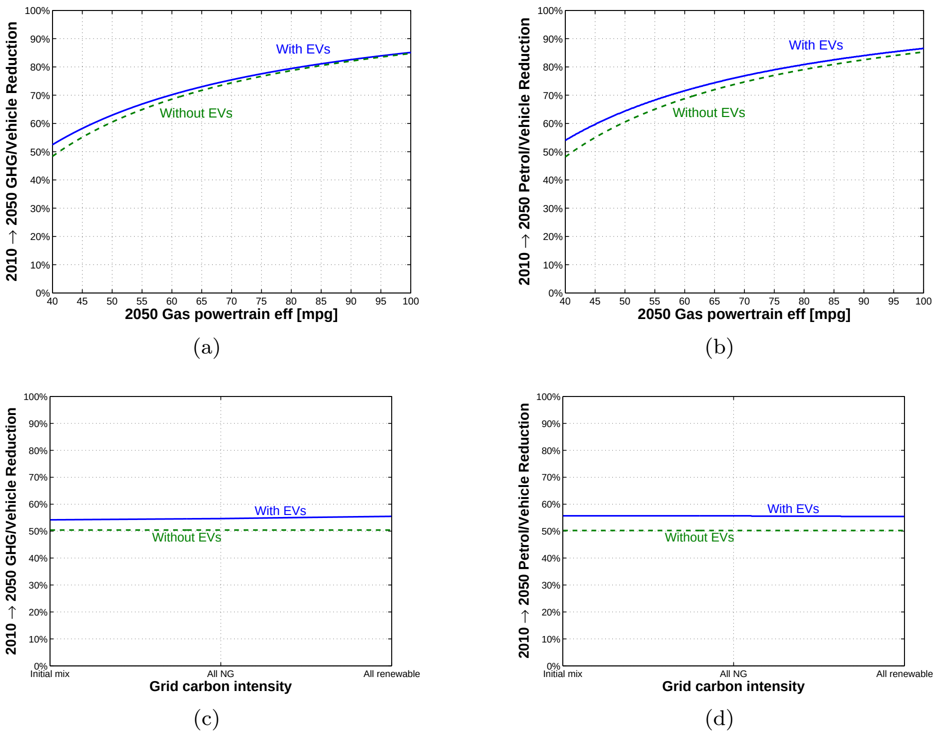


Figure 4: Overall contribution of electric vehicles to reductions in GHG and petroleum consumption per vehicle in 2050, relative to 2010. Efficiencies listed are for small cars.

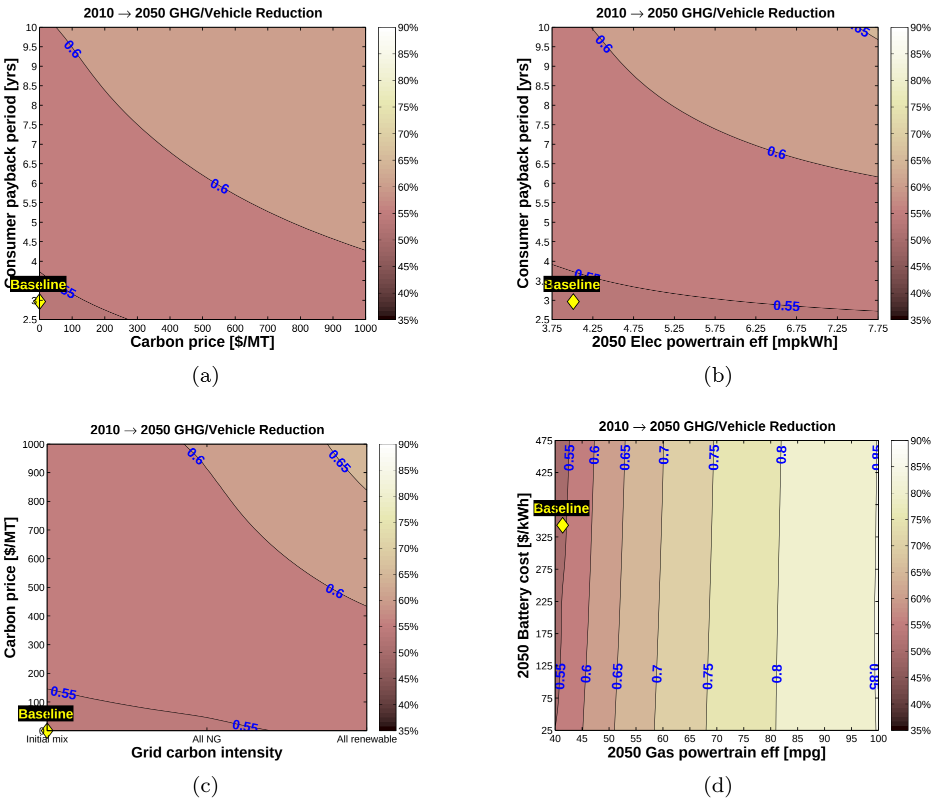


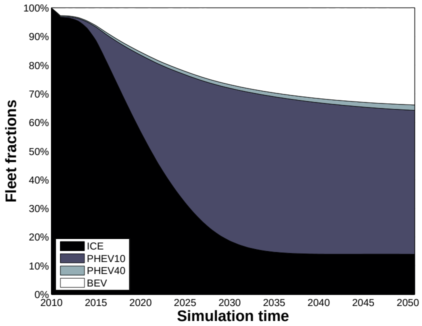
Figure 5: Contours of LDV GHG reduction per vehicle in 2050 relative to 2010. Efficiencies listed are for small cars.

ficiency parameter might be less important, we explore parameter ranges that would result in a higher prevalence of EVs. We consider a world that is ideal for the purchase of EVs: consumer payback periods are doubled, batteries are free, consumer range and infrastructure penalties for BEVs are eliminated, and a high vehicle turnover rate ensures that the oldest, least efficient vehicles are replaced with higher efficiency models quickly. Furthermore, this ideal environment rapidly retires the coal intensive sources of electricity in favor of natural gas, consistent with some projections (U.S. Energy Information Administration, 2011a). In this setting, depicted in Figure 6, ICEs still remain 14% of the fleet in 2050, and the EVs are dominated by PHEV10s and BEVs since PHEV40s are the most expensive powertrain. Additionally, of all of the vehicle-miles traveled, 40% of them are still powered by gasoline due to the prevalence of PHEV10s. Therefore, the GHG per vehicle reduction in 2050 is only 70% over 2010 values, still short of the available improvement offered by the range of gasoline powertrain efficiencies considered. Thus, to meet the most aggressive GHG reduction targets, gasoline powertrain efficiency improvements beyond current projections are critical even for a fleet that consists of nearly 85% EVs. Only by recharging the EVs with carbon free sources, such as wind or solar, can the 80% GHG reduction target per vehicle be achieved using default projections for gasoline powertrain efficiency. In short, many unlikely parameter values must be realized for EVs to have a significant impact on GHG emissions.

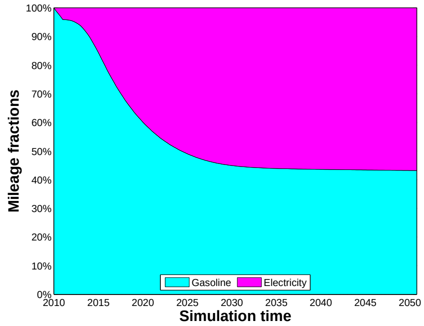
3.4.4. Reduction in petroleum consumption

The model baseline projects a 55% reduction in petroleum consumption per vehicle in 2050 over 2010 levels, due to improved vehicle efficiencies and electrification of the fleet. The parametric variations that further increase either vehicle efficiency or EV sales will therefore result in even lower petroleum consumption. For instance, market-based influences such as consumer payback period and carbon price both serve to encourage vehicle electrification and reduce petroleum consumption. As depicted in Figure 7a, at the extreme values of consumer payback period and carbon price, petroleum consumption reduction per vehicle can reach nearly 70%.

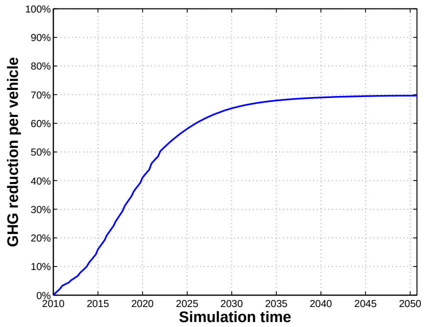
Technological influences upon LDV petroleum consumption are shown in Figure 7b. As one would expect, gasoline powertrain efficiency improvements offer significant opportunity for reducing petroleum consumption, but unlike the GHG reduction case, the contour lines are not wholly aligned with the gasoline powertrain efficiency-axis. In this case, lower battery costs also augment EV sales rates, especially at lower values of gasoline powertrain efficiency, and therefore reduce average vehicle petroleum consumption. Thus, the US can meet aggressive petroleum consumption reduction targets without relying chiefly on improvements to gasoline powertrain efficiency. This is underscored in Figure 7c where consumer payback period incentives are combined with battery technology improvements. At low battery costs and long consumer payback periods, 2050 average vehicle petroleum consumption is reduced by 68% over 2010, corresponding to a 54% reduction in absolute consumption, a significant improvement over the baseline value, and in-line with US energy independence objectives. For reference, the 71.6 mpg fleet average efficiency mentioned above to meet GHG reduction targets yields an 73% reduction in absolute petroleum consumption.



(a)

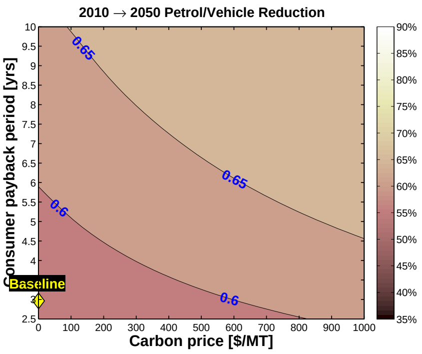


(b)

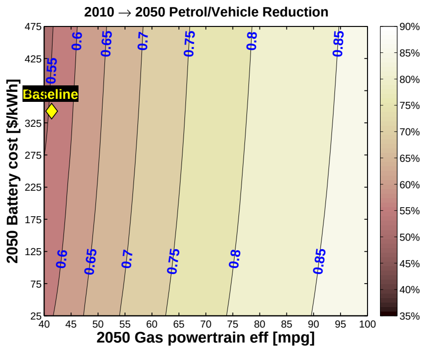


(c)

Figure 6: Fleet fractions, energy mileage fractions, and GHG reductions per vehicle under ideal conditions for electric vehicle adoption. Efficiencies listed are for small cars. Final fleet fraction in (a) are 14% ICE, 50% PHEV10, 2% PHEV40, and 34% BEV.



(a)



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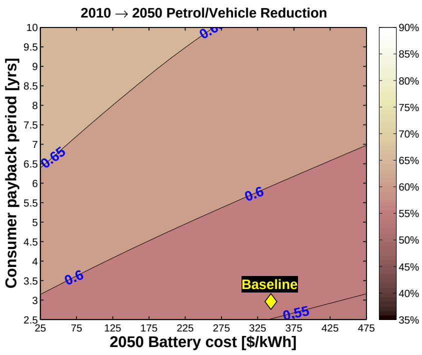

(c)

Figure 7: Contours of LDV petroleum consumption reduction per vehicle in 2050 relative to 2010. Efficiencies listed are for small cars.

4. Conclusions

The parametric analysis capability of the model presented here is new to this application space. This capability has enabled a comprehensive sensitivity analysis and trade space exploration, with emphasis on factors that influence the adoption rates of EVs, the reduction of GHG emissions, and the reduction of petroleum consumption within the US LDV fleet.

Many factors contribute to the adoption rates of EVs. These include the pace of technological development for the electric powertrain, battery performance, as well as gasoline powertrain efficiency. Policy initiatives can also have a dramatic impact on the degree of EV adoption. The consumer payback period, in particular, can more than double the EV fleet fraction if extended beyond seven years. Widespread EV adoption can have noticeable impact on petroleum consumption by the LDV fleet and can assist in reducing US reliance on imported crude oil. However, widespread EV adoption has little impact on GHG emissions, especially if the electricity grid continues to rely on fossil fuel based power. Even if all of the coal in the current electric mix were replaced by natural gas, GHG emissions reduction would fall short of stated targets.

The conventional gasoline vehicle will remain the core of the LDV fleet for many years to come. This conclusion seems robust even if global oil prices rise to two to three times current projections. Thus, investment in improving the internal combustion engine might be the cheapest, lowest risk avenue towards meeting ambitious GHG emission and petroleum consumption reduction targets out to 2050. Vehicle efficiency improvements, however, will have to be negotiated with historical consumer and manufacturer preferences for large, powerful cars with many energy-hungry cabin features.

5. Acknowledgments

The authors would like to thank Dr. Andrew Lutz, Dr. Benjamin Wu, Prof. Joan Ogden and Dr. Christopher Yang for their suggestions over the course of this project. This work was funded by the Laboratory Directed Research and Development program at Sandia National Laboratories. Sandia National Laboratories is a multi-program laboratory managed and operated by Sandia Corporation, a wholly owned subsidiary of Lockheed Martin Corporation, for the U. S. Department of Energy's National Nuclear Security Administration under Contract DE-AC04-94AL85000.

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Appendix A. Detailed model description

This section contains an expanded description of our modeling approach, the mathematical equations, and the input data used. This section should be read as a supplement rather than a replacement to Section 2, which outlines the general approach, key assumptions, and data sources. The notation and variables used in this model description are listed in Table A.3.

Appendix A.1. Vehicle modeling

The initial vehicle fleet is segmented by age, vehicle class (small car, large car, and light truck), vehicle powertrain (ICE, PHEV10, PHEV40, and BEV), geographic region (eight NERC regions), population density (urban, suburban, and rural), home recharging availability, and driving intensity (light, medium, heavy). The driving intensity relates to an average daily trip distance expressed by a gamma distribution, which has a cumulative distribution function of the form,

$$F(x; k, \theta) = \frac{\gamma(x, \frac{k}{\theta})}{\Gamma(k)},$$

where $\gamma(\cdot)$ is the lower, incomplete gamma function, $\Gamma(\cdot)$ is the gamma function, k is the shape parameter, and θ is the scale parameter. The detailed segmentation fraction breakdowns are presented in Tables A.4–A.6, as well as the age-dependent annual mileage in Table A.7.

Table A.3: Symbol guide for model equations.

Demand variables

$\mathbb{D}^E$	Energy source demand
$\mathbb{D}^F$	Fuel use demand
$\mathbb{D}^{F^P}$	Fuel production demand

Vehicle cost variables

$\mathbb{C}^G$	Generalized vehicle ownership cost
$\mathbb{C}^F$	Vehicle fuel costs
$\mathbb{C}^B$	Electric vehicle battery capital cost
$\mathbb{C}^H$	Electric vehicle charger cost
$\mathbb{C}^P$	Penalty costs
$\mathbb{C}^V$	Vehicle capital cost minus battery
$\mathbb{C}^Y$	Electric vehicle subsidy
δ	Dollar cost constant
$\mathbf{A}(\cdot)$	Amortization function

Logit choice variables

$\mathcal{U}^V$	Vehicle logit choice utility
$\mathcal{U}^F$	Fuel region logit choice utility
β	Logit choice exponent
$\mathbb{C}_0$	Reference cost
$\mathbb{P}_0$	Reference price

Subscript segmentation

a	Subscript for vehicle age
e	Subscript for energy source
f	Subscript for fuel
r	Subscript for geographic region
s	Subscript for vehicle size class
p	Subscript for population density
d	Subscript for driving intensity
n	Subscript for vehicle powertrain

Price variables

$\mathbb{P}^E$	Energy source price
$\mathbb{P}^F$	Fuel price
$\mathbb{P}^C$	Price for carbon emissions

Vehicle fleet variables

$\mathcal{V}$	Number of vehicles
$\mathcal{S}$	Overall vehicle sales rate
$\mathcal{W}$	Overall vehicle scrap rate
σ	Segment sales fraction
ω	Segment scrap fraction
$\mathcal{Q}$	Battery energy capacity
$\mathcal{R}$	Vehicle range
$\mathcal{M}$	Annual VMT
η	Vehicle fuel economy
ρ	Vehicle fuel use rate
ϕ	Recharging availability fraction
κ	Market availability fraction

Fuel production variables

Ω	Energy source to fuel conversion rate
$\mathcal{G}$	CO_{2e} GHG emissions
λ^F	GHG emission rate for fuel use
λ^C	GHG emission rate for fuel conversion
$\mathcal{Y}$	Marginal electricity grid capacity
ψ	Marginal grid mix blending parameter
τ	Regional fuel exchange matrix
η^F	Fuel economy for tanker transport
$\mathcal{X}$	Regional fuel exchange distance
ϵ	Taxes, fees, and profit margin

Gamma distribution variables

$\Gamma(\cdot)$	Gamma function
$\gamma(\cdot)$	Lower incomplete gamma function
k	Shape parameter
θ	Scale parameter

Table A.4: Initial number of vehicles and population density in 2010 by geographic region (NERC regional entities): Florida Reliability Coordinating Council (FRCC), Midwest Reliability Organization (MRO), Northeast Power Coordinating Council (NPCC) Reliability First Corporation (RFC), SERC Reliability Corporation (SERC), Southwest Power Pool (SPP), Texas Reliability Entity (TRE), Western Electricity Coordinating Council (WECC). Source, U.S. Department of Transportation Federal Highway Administration (2009)

	Vehicle size			**Population density**		
Region	Small cars	Large cars	Light trucks	Urban	Suburban	Rural
RFC	24586590	18622043	7240337	24%	55%	22%
TRE	5747139	4909310	3517145	46%	34%	19%
MRO	7401322	5725430	3662847	26%	40%	34%
NPCC	12582536	7260541	2038209	40%	43%	18%
FRCC	5825576	4930174	1934916	22%	67%	11%
SERC	25133312	18851264	11413276	26%	42%	33%
SPP	3672440	3145111	2738557	35%	36%	29%
WECC	25392229	19087251	9395291	37%	51%	12%

Table A.5: Distribution of vehicle size in population density segments (U.S. Department of Transportation Federal Highway Administration, 2011).

	Vehicle size		
Population density	Small car	Large car	Light trucks
Urban	56%	29%	15%
Suburban	49%	27%	24%
Rural	43%	28%	29%

Table A.6: Segmentation of driving intensity in each population density segment and the associated gamma distribution of daily driving distance (Greene and Lin, 2010).

Driving	**Population density**			**Gamma distribution**	
intensity	Urban	Suburban	Rural	k	θ
Short	40%	37%	27%	1.68	14.11
Average	34%	31%	33%	1.90	23.20
Long	26%	31%	40%	1.80	43.05

Table A.7: Vehicle lifetime and annual per vehicle mileage as a function of age (U.S. Department of Transportation National Highway Traffic Safety Administration, 2008).

Vehicle age	**Average Annual Miles Driven**			**Fraction Surviving to Age**		
[years]	Small car	Large car	Light truck	Small car	Large car	Light truck
1	12885	14255	15229	0.995	0.995	0.995
2	12641	13874	14688	0.990	0.978	0.974
3	12377	13495	14157	0.983	0.966	0.960
4	12094	13117	13637	0.973	0.950	0.942
5	11796	12743	13128	0.959	0.929	0.919
6	11484	12371	12630	0.941	0.903	0.891
7	11160	12003	12146	0.919	0.874	0.859
8	10825	11638	11674	0.892	0.840	0.823
9	10483	11278	11216	0.860	0.802	0.783
10	10135	10923	10772	0.825	0.761	0.740
11	9783	10574	10344	0.787	0.718	0.696
12	9429	10230	9930	0.717	0.666	0.650
13	9075	9893	9533	0.613	0.606	0.640
14	8722	9563	9153	0.509	0.542	0.552
15	8374	9241	8789	0.414	0.480	0.501
16	8032	8927	8444	0.331	0.423	0.452
17	7698	8622	8117	0.260	0.371	0.406
18	7374	8326	7809	0.203	0.324	0.363
19	7061	8040	7521	0.157	0.283	0.324
20	6763	7765	7253	0.120	0.246	0.287
21	6481	7500	7006	0.092	0.215	0.254
22	6217	7248	6781	0.070	0.187	0.224
23	5972	7007	6577	0.053	0.163	0.198
24	5750	6780	6396	0.040	0.141	0.174
25	5551	6566	6239	0.030	0.122	0.152
26	5379	6366	6105	0.023	0.106	0.133
27	5379	6215	5996	0	0.089	0.117
28	5379	6073	5912	0	0.077	0.102
29	5379	5938	5853	0	0.067	0.089
30	5379	5813	5821	0	0.058	0.077
31	5379	5813	5821	0	0.051	0.067
32	5379	5813	5821	0	0.045	0.059
33	5379	5813	5821	0	0.039	0.051
34	5379	5813	5821	0	0.033	0.044
35	5379	5813	5821	0	0.030	0.039
36	5379	5813	5821	0	0.025	0.033
37	5379	5813	5821	0	0.022	0.029
38	5379	5813	5821	0	0	0
All years	10964	11788	11804	0	0	0

Distributions of vehicles, $\mathcal{V}$, are tracked according to the above segmentation. The evolution of each vehicle segment is given by,

$$\frac{\mathrm{d}\mathcal{V}_{rspdn}}{\mathrm{d}t} = \overline{\sigma}_{rspdn}\mathcal{V}_{rspd} - \sum_{a} \overline{\omega}_{sa}\mathcal{V}_{rspda},$$

where $\overline{\sigma}$ is the segment sales rate and $\overline{\omega}$ is the vehicle class scrap rate as a function of age. The subscripts, which will be used throughout the model description, denote segmentation by r region, s vehicle class, p population density, d driving intensity, n powertrain, and a age.

The sales and scrap rates are scaled such that overall fleet growth is constant,

$$\overline{\sigma}_{rspdn} = \mathcal{S}\sigma_{rspdn}, \qquad \overline{\omega}_{sa} = \mathcal{W}\omega_{sa},$$

where $\mathcal{S}$ is the overall sales rate, $\mathcal{W}$ is the overall scrap rate, σ is the consumer sales fraction by powertrain for each vehicle segment (described below), and ω is the scrap fraction taken from survival data (Table A.7). An overall sales rate of 6.7% is used, the average value for the 2000-2009 period, along with an overall scrap rate of 5.8% (Davis et al., 2010).

The segment sales fractions in each time-step, σ, are assigned using a logit function (Struben and Sterman, 2008),

$$\sigma_{rspdn} = \frac{\mathcal{U}^V_{rspdn}\phi_n\kappa_n}{\sum_n \mathcal{U}^V_{rspdn}\phi_n\kappa_n}; \qquad \mathcal{U}^V_{rspdn} = \exp\left(-\beta\frac{\mathbb{C}^G_{rspdn}}{\mathbb{C}^G_0}\right); \tag{A.1}$$

$$\kappa_n = \frac{1}{1+m_n e^{-0.35t}}; \quad m_n = \begin{cases} 0, & \text{ICE} \\ 1000, & \text{else} \end{cases}; \qquad \phi_n = \begin{cases} 0.45, & \text{BEV} \\ 1, & \text{else} \end{cases},$$

where ϕ is the recharging availability fraction, κ is the market availability fraction, $\mathcal{U}^V$ is the utility, β is the logit exponent, $\mathbb{C}^G$ is the total cost, and $\mathbb{C}^G_0$ is a reference cost taken as the 2010 small car ICE cost. The baseline logit exponent value of $\beta = 14.9$ is calibrated to give a price elasticity of -9 (a 9% drop in demand for a 1% increase in price) at a market share of 50% (Greene, 2001). Based on survey data, 45% of drivers could have access to home recharging (Axsen and Kurani, 2010). The market availability fraction represents a growth curve tracking the availability of a given powertrain in vehicle manufacturers' fleets.

The generalized vehicle purchase costs are expressed in dollars per annual VMT (Greene et al., 2005),

$$\mathbb{C}^G_{rspdn} = \mathbf{A}\left(\frac{\mathbb{C}^B_{sn} + \mathbb{C}^H_n + \mathbb{C}^V_{sn} - \mathbb{C}^Y_{sn}}{\mathcal{M}_{sd}}\right) + \frac{\mathbb{C}^P_{rspdn} + \mathbb{C}^F_{rsdn}}{\mathcal{M}_{sd}}, \tag{A.2}$$

where $\mathbb{C}^P$ is the penalty costs, $\mathbb{C}^B$ is the battery cost, $\mathbb{C}^H$ is the charger cost, $\mathbb{C}^V$ is the vehicle capital cost, $\mathbb{C}^Y$ is the subsidy value, $\mathbb{C}^F$ is the fuel cost, and $\mathcal{M}$ is the VMT. The function, $\mathbf{A}(\cdot)$, amortizes the cost to the consumer over a payback period of 3 years (in the baseline case) at a 0% discount rate. The individual cost components are discussed in the following paragraphs.

Vehicle purchase costs, $\mathbb{C}^V$, are calculated using estimates for advanced technology (Moawad et al., 2011). The costs, which are listed in Table A.8, include learning over time that captures the decline in manufacturing costs due to process and technological maturation. The cost for electric vehicles is offset through subsidies, $\mathbb{C}^Y$, from the American Clean Energy and Security Act of 2009. The cost for the batteries in electrified vehicles, $\mathbb{C}^B$, is calculated separately from other purchase costs so that the effect of targeted research in this area can be explored parametrically. The cost for batteries is extracted directly from National Research Council (2010) and is given by,

$$\mathbb{C}^B_{sn} = \mathcal{Q}_{sn}\left[1.035\delta^B\left(1 - e^{-0.17t}\right) + 905e^{-0.17t} - 30\right],$$

where δ^B is the battery price in 2030 ($/kWh), t is the years since 2010, and $\mathcal{Q}$ is the battery capacity (kWh). The 2030 price point parameter allowed for adjustment of the price decline over time associated with technological development in an intuitive manner. The battery capacity as a function of vehicle size and time is detailed in Table A.8. For vehicles that require home recharging, we include a charger cost applied to the rate of new EV sales in the fleet,

$$\mathbb{C}^H_n = \delta^H_n \sum_{n=EVs} \frac{1}{\overline{\sigma}_n \mathcal{V}_n} \frac{\mathrm{d}\mathcal{V}_n}{\mathrm{d}t}; \quad \delta^H_n = \begin{cases} \$0, & \text{ICE} \\ \$878, & \text{PHEV10} \\ \$2146, & \text{PHEV40, BEV} \end{cases},$$

which assumes a Level 1 charger for PHEV10s and a Level 2 charger for PHEV40s and BEVs. Note that we do not explicitly track repeat EV purchases and charger re-use.

Penalty costs, $\mathbb{C}^P$, are also included to quantify limitations of alternative powertrains. A range penalty represents the reduced utility of a vehicle with a short range and is calculated using the value of the time spent refueling per daily mileage. A station availability penalty captures the lower utility of a vehicle that has limited public refueling options. The penalties are expressed as,

$$\begin{aligned}
\mathbb{C}^P_{rspdn} &= \mathbb{C}^{P^1}_{sdn} + \mathbb{C}^{P^2}_{rpn} \\
\mathbb{C}^{P^1}_{sdn} &= \delta^{P^1}_n \frac{\mathcal{M}_{sd}}{365\mathcal{R}_n}; \quad \delta^{P^1}_n = \begin{cases} \$798, & \text{BEV} \\ \$814, & \text{else} \end{cases}, \quad \mathcal{R}_n = \begin{cases} 100\,\text{mi}, & \text{BEV} \\ 350\,\text{mi}, & \text{else} \end{cases} \\
\mathbb{C}^{P^2}_{rpn} &= \delta^{P^2}_n \left(\frac{\sum\limits_{n=EV} \mathcal{V}_{rpn}}{\sum\limits_{n} \mathcal{V}_{rpn}} \right) e^{-20.15}; \quad \delta^{P^2}_n = \begin{cases} \$7500, & \text{BEV} \\ \$0, & \text{else} \end{cases}
\end{aligned}$$

where $\mathbb{C}^{P^1}$ is the range penalty, $\mathbb{C}^{P^2}$ is the refueling penalty, and $\mathcal{R}$ is the vehicle range. The cost constant dollar values of the penalties, $\delta^{P^1}_n$ and $\delta^{P^2}_n$, are taken from Greene (2001) and the exponential growth trends of refueling infrastructure for alternative vehicles is taken from Yeh (2007). The fuel cost per mile, $\mathbb{C}^F$, is simply the ratio of the fuel

Table A.8: Vehicle efficiency, cost and batter capacity parameters. Capital costs are relative to a baseline of $0 for each size class and do not include battery costs.

Year	Parameter	Vehicle Size	ICE	PHEV10	PHEV40	BEV
2010	Efficiency (gas.) [MPG]	Small car	27	41	31	0
		Large car	22	31	22	0
		Light truck	17	24	17	0
	Efficiency (elec.) [MPGe]	Small car	0	122	97	100
		Large car	0	102	71	72
		Light truck	0	80	55	0
	Battery capacity [kWh]	Small car	0	3	17	24
		Large car	0	4	22	32
		Light truck	0	5	29	0
	Relative costs [$]	Small car	-39	3573	8332	5586
		Large car	-5	4240	9712	7024
		Light truck	-63	5918	12149	0
2015	Efficiency (gas.) [MPG]	Small car	27	46	36	0
		Large car	24	35	26	0
		Light truck	18	27	20	0
	Efficiency (elec.) [MPGe]	Small car	0	131	109	113
		Large car	0	111	81	83
		Light truck	0	91	62	0
	Battery capacity [kWh]	Small car	0	3	16	23
		Large car	0	4	21	31
		Light truck	0	5	27	0
	Relative costs [$]	Small car	787	2904	6107	3641
		Large car	1048	2974	6646	4224
		Light truck	823	3775	8037	0
2030	Efficiency (gas.) [MPG]	Small car	39	50	40	0
		Large car	36	38	30	0
		Light truck	24	29	22	0
	Efficiency (elec.) [MPGe]	Small car	0	140	119	130
		Large car	0	115	89	94
		Light truck	0	106	67	0
	Battery capacity [kWh]	Small car	0	3	13	17
		Large car	0	4	17	23
		Light truck	0	4	21	0
	Relative costs [$]	Small car	1797	2739	5337	2566
		Large car	2071	2601	5606	2772
		Light truck	1844	3085	6674	0
2045	Efficiency (gas.) [MPG]	Small car	41	52	42	0
		Large car	38	39	31	0
		Light truck	24	30	23	0
	Efficiency (elec.) [MPGe]	Small car	0	145	124	136
		Large car	0	118	92	99
		Light truck	0	108	69	0
	Battery capacity [kWh]	Small car	0	2	12	15
		Large car	0	3	15	20
		Light truck	0	4	19	0
	Relative costs [$]	Small car	1780	2662	4986	2137
		Large car	1942	2531	5135	2160
		Light truck	1732	3081	6117	0

Table A.9: Fraction of miles driven on gasoline or electricity (fuel use rates). Note that serial drive train mode is assumed for PHEVs (vehicles use electricity up to the electric powertrain range limit and then gasoline only).

Driving	**PHEV10**		**PHEV40**	
intensity	Gasoline	Electricity	Gasoline	Electricity
Short	62%	38%	11%	89%
Average	78%	22%	32%	68%
Long	87%	13%	55%	45%

price and fuel economy of a vehicle,

$$\mathbb{C}^F_{rsdn} = \sum_f \frac{\mathbb{P}^F_{rf}}{\eta_{sdnf}},$$

where $\mathbb{P}^F$ is the price of fuel, η is the fuel economy, and the subscript, f, denotes type of fuel. Gasoline and electric powertrain efficiency are drawn from the same source as the cost data and similarly listed in Table A.8.

As shown in Figure 1, the vehicle sub-model outputs the total fuel use demand, $\mathbb{D}^F$. This is computed by an accounting of the total mileage covered by the fleet, the fuel use rates, ρ (listed in Table A.9), and the fuel economy,

$$\mathbb{D}^F_{rf} = \sum_{spdna} \frac{\mathcal{V}_{rspdna}\mathcal{M}_{sna}\rho_{dnf}}{\eta_{sdnfa}} \quad .$$

Appendix A.2. Modeling fuel production and distribution

The model allows for transport of fuels between regions so that regions with lower production cost can supply other regions. We assume electricity is not transferred between regions. The fuel supply for each region is chosen by a logit choice function of the same form as Equation A.1, with an exponent value of $\beta = 18$,

$$\tau_{rr'f} = \frac{\mathcal{U}^F_{rr'f}}{\sum_{r'} \mathcal{U}^F_{rr'f}}; \qquad \mathcal{U}^F_{rr'f} = \frac{\mathbb{P}^{F^P}_{rr'f}}{\mathbb{P}_0}; \qquad \mathbb{P}^{F^P}_{rr'f} = \mathbb{P}^F_{rf} + \frac{\mathcal{X}_{rr'}}{\eta^F}\left(\mathbb{P}^F_{r,gas} + \mathbb{P}^C\lambda^F_{gas}\right),$$

where τ is the inter-region fuel exchange matrix from production region, r, to demand region, r', $\mathbb{P}^{F^P}$ is the fuel price after regional exchange is accounted for, $\mathcal{X}$ is the distance between region centroids, η^F is the fuel economy of the transport mode (taken to be the average of tanker trucks and rail), $\mathbb{P}^C$ is the carbon price, and λ^F is the GHG production rate from fuel use (GHG bookkeeping is described below). The total fuel *production* demand, $\mathbb{D}^{F^P}$, after accounting for inter-region exchange is,

$$\mathbb{D}^{F^P}_{rf} = \sum_{r'} \tau_{rr'f}\mathbb{D}^{F}_{r'f}$$
$$\mathbb{D}^{F^P}_{r,gas} = \sum_{r'} \tau_{rr'f}\mathbb{D}^{F}_{r'.gas} + \sum_{f} \frac{\mathcal{X}_{rr'}}{\eta^F}\mathbb{D}^{F^P}_{rf},$$

where the gasoline production demand is listed separately due to the additional demand stemming from the inter-region fuel exchange.

The fuel production sub-model translates the regional fuel production demand to regional energy source demand via the relationship,

$$\mathbb{D}^{E}_{re} = \sum_{f} \Omega_{ef}\mathbb{D}^{F^P}_{rf},$$

where $\mathbb{D}^E$ is the energy source demand and Ω_{ef} is a matrix relating quantities of energy source, e, required to produce one unit of fuel, f.

As alluded to above, the fuel production sub-model also does an accounting of the GHG emissions due to fuel use and production, $\mathcal{G}$,

$$\mathcal{G}_{rf} = \lambda^F_f\mathbb{D}^{F^P}_{rf} + \sum_{e} \lambda^C_{ef}\Omega_{ef}\mathbb{D}^{F^P}_{rf}$$

where λ^F is the CO_2-equivalent emissions rate for fuel use and λ^C is the emissions rate for fuel production processes. The first term captures the emissions from fuel use by the fleet and the second term represents emissions from fuel production processes. Note that this is not a life-cycle GHG accounting as contributions from vehicle manufacturing and energy source production are not included. Lastly, the fuel production sub-model outputs the price of fuel in each region. This is calculated as,

$$\mathbb{P}^{F}_{rf} = \sum_{e} \mathbb{P}^{E}_{re}\Omega_{ef}\mathbb{D}^{F^P}_{rf} + \mathbb{P}^C\mathcal{G}_{rf} + \epsilon_{rf},$$

where $\mathbb{P}^E$ is the energy source price, $\mathbb{P}^C$ is a user-specified price on GHG emissions, and ϵ is the total accumulation of taxes, fees, and profit margin.

The initial marginal power mix is summarized in Table A.10. The marginal capacity in each region, $\mathcal{Y}$, is allowed to evolve in time according to user input. Existing capacity is assigned a five year mean replacement time and new capacity is added to meet the electricity demand from the vehicle fleet,

$$\frac{\mathrm{d}\mathcal{Y}_{re}}{\mathrm{d}t} = \psi_{re}(\mathbb{D}^{F}_{r,elec} - \sum_{e} \mathcal{Y}_{re}) - \frac{\mathcal{Y}_{re}}{5},$$

where ψ is a user input parameter that blends the initial marginal mix fraction with other bounding cases, such as a 100% natural gas mix or a 100% renewable (carbon-free) mix.

Table A.10: Electricity generation source mix by NERC region (E.H. Pechan & Associates, Inc., 2010).

Regions	**Oil**	**Coal**	**Natural gas**
RFC	0%	84%	16%
TRE	0%	13%	87%
MRO	3%	87%	10%
NPCC	7%	17%	76%
FRCC	11%	12%	77%
SERC	0%	75%	25%
SPP	0%	53%	47%
WECC	0%	15%	85%