

The Future Adoption and Benefit of Electric Vehicles: A Parametric Assessment

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ABSTRACT

We present a parametric analysis of electric vehicle (EV) adoption rates and the corresponding contribution to greenhouse gas (GHG) reduction in the US light-duty vehicle (LDV) fleet through 2050. The analysis is performed with a system dynamics based model of the supply-demand interactions among the fleet, its fuels, and the corresponding primary energy sources. The differentiating feature of the model is the ability to conduct global sensitivity and parametric trade-space analyses. We find that many factors impact the adoption rates of EVs. These include, in particular, policy initiatives that encourage consumers to consider lifetime ownership costs, the price of oil, battery performance, as well as the pace of technological development for all powertrains (conventional internal combustion engines included). Widespread EV adoption can have noticeable impact on petroleum consumption and GHG emissions by the LDV fleet. However, EVs alone cannot drive compliance with the most aggressive GHG emission reduction targets, even as the electricity source mix shifts away from coal and towards natural gas. Since vehicles with traditional internal combustion engines (ICEs) will comprise the majority of the LDV fleet for up to forty years, conventional vehicle efficiency improvements have the greatest potential for reductions in LDV GHG emissions over this time.

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INTRODUCTION

With the introduction of the Chevy Volt and Nissan Leaf in 2011, the electric vehicle (EV) is now part of the mainstream US light-duty vehicle (LDV) fleet. As new EV models are introduced each year, there is an opportunity to shift the source of US transportation energy away from petroleum and towards the electricity grid, which could be driven by renewable sources. This shift could reduce the US reliance on imported oil as well as the greenhouse gas (GHG) emissions from the transportation sector. However, a number of studies have been skeptical of the viability of EVs in the marketplace due to their increased cost and performance shortcomings [1, 2, 3, 4]. In fact, the National Research Council [1] predicted that EVs would still be less than 5% of the fleet in 2030. One significant obstacle to EV adoption is the heavy discounting of future fuel savings by consumers [5]. Consumers implicitly demand a short payback period for their investment in an alternative fuel vehicle [6, 7, 8]. Hence, actions that encourage consumers to consider lifetime ownership costs in their purchasing decisions, such as policy-based incentives, subsidies, and consumer education, could increase EV adoption rates.

It is, of course, impossible to accurately predict the US LDV fleet decades into the future. The future price of oil and other key commodities, the pace of technology innovation in electric and internal combustion powertrains, and a turbulent political environment all introduce significant uncertainty into the problem. Computing the environmental benefit of EVs is also approximate at best, as the future carbon intensity of the electricity grid is also subject to the same sources of uncertainty. It is, in fact, possible for EVs to emit more GHGs than a conventional hybrid vehicle for certain grid mixes [9]. The common analysis approach for making these predictions is to conduct scenario-based studies, where one set of input values is used to generate a *reference* case with a few excursion scenarios also computed (e.g. a high oil price future scenario and a low oil price future scenario). The difficulty with this approach is that small changes in input values can lead to large changes in output metrics, and it yields only a sparse view of the technology and policy trade space to the analyst. 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 [3].

To address these challenges, this work presents a parametric assessment of the value and viability of EVs in the US LDV fleet. Specifically, the analysis presented focuses on the set of market, technology, policy, and economic characteristics that could drive adoption of electric vehicles and/or lead to notable reductions in fleet greenhouse gas emissions. To accomplish this objective, a system dynamics based model of the interactions among the US LDV fleet, its fuels, and the corresponding raw energy sources through the year 2050 was developed. The differentiating feature of the model is the ability to conduct parametric analyses, where probability distributions were considered for input variables. Sensitivity studies were conducted to highlight the key drivers of output metrics, as well as characterize the uncertainty introduced by modeling assumptions. Additionally, iso-performance contours were identified in the trade space that trace the multiple sets of parameter values that can be used to achieve performance goals.

MODEL DESCRIPTION

Our model is implemented using a system dynamics approach to construct a set of interacting algebraic and differential equations using Python and the Numpy library. 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 four modules: an energy supply sub-model, a fuel production sub-model, an electricity grid sub-model, and a vehicle sub-model. The sub-models exchange price and demand points for energy supply stocks and fuels. The model presented here significantly expands on the model described in Barter et al. [10]. A list of model notation is provided at the end of the document.

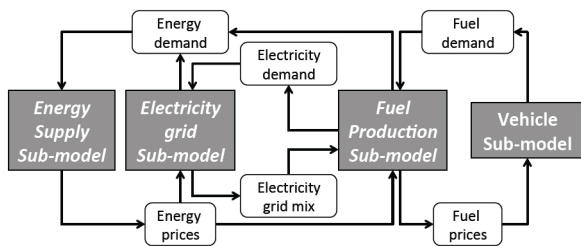


Figure 1. High-level diagram of the model components.

Vehicle Modeling

Vehicle segmentation

The model starts in 2010 with 232 million privately-owned, light-duty vehicles in service in the United States. The initial vehicle fleet is segmented by age, geographic region, vehicle size, vehicle powertrain, population density, driving intensity, and owner housing type,

$$\mathcal{V} = \mathcal{V}_{arsnpdh} \quad (1)$$

The subscripts, which will be used throughout the model description, denote segmentation by a age, r region, s vehicle size, n powertrain, p population density, d driving intensity, and h housing type.

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 [11]. 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 [12]. While the overall rate of vehicle scrapping is fixed, the scrap rate of vehicles increases as the vehicles age [13]. Because only new car sales and final disposal of the vehicles are considered, used vehicle sales are not tracked. The evolution of each vehicle segment is therefore given by,

$$\frac{d\mathcal{V}_{a=0,rsnpdh}}{dt} = \sigma_{rsnpdh}^V \mathcal{S} \sum_{an} \mathcal{V}_{arsnpdh} \quad (2)$$

$$\frac{d\mathcal{V}_{arsnpdh}}{dt} = -\omega_{sa} \mathcal{W} \mathcal{V}_{arsnpdh} \quad (3)$$

where $\mathcal{S}$ is the overall sales rate, $\mathcal{W}$ is the overall scrap rate, ω is the scrap fraction taken from survival data, and σ^V is the consumer sales fraction by powertrain for each vehicle segment such that,

$$\sum_n \sigma_{rsnpdh}^V = 1 \quad (4)$$

The number of initial vehicles segmented by vehicle size and state is taken from vehicle registration data [14]. We include the 48 continental US states as well as the District of Columbia. Vehicle sizes considered are compact, midsize, small SUV, large SUV, and light pickup trucks. The age distribution (0-46 years) is incorporated from the US Department of Transportation [13] based on survival data. Thirteen different powertrains are considered in this analysis. The first 12 powertrains are conventional, hybrid, plug-in hybrid with 10 mile all-electric range (PHEV10), and PHEV40 variants of gasoline-fueled Spark Ignition (SI), diesel-fueled Compression Ignition (CI), and E85 flex-fuel. The final powertrain is a battery-electric vehicle with 150 mile all-electric range (BEV150). The initial vehicles are primarily SI powertrains, but E85, CI, and hybrid SI powertrain vehicles exist as well. The numbers of the alternative vehicles in the initial fleet is based on sales data and state based reporting of hybrid sales [11]. The fleet is further segmented by population density (urban, suburban, and rural) and home housing type (single family house and other), based on census data [12]. Finally, the vehicle fleet is

segmented by binning driving intensity into light, medium, and heavy groups, which relate to an average daily trip distance expressed by a gamma distribution. The bins and gamma distribution parameters for the driving intensity segmentation are shown in Table 1. Through the National Highway Travel Survey data set, population density is also related to vehicle size and driver intensity [15], shown in Table 2.

Table 1. Segmentation of driving intensity in each population density segment and the associated gamma distribution of daily driving distance [16].

Driving intensity	Population density			Gamma params	
	Urban	Suburban	Rural	k	θ
Light	40%	37%	27%	1.68	14.11
Medium	34%	31%	33%	1.90	23.20
Heavy	26%	31%	40%	1.80	43.05

Table 2. Distribution of vehicle size in population density segments [15].

Population density	Vehicle size				
	Compact	Midsize	Small SUV	Large SUV	Pickup
Urban	0.326	0.287	0.137	0.143	0.107
Suburban	0.304	0.268	0.145	0.153	0.129
Rural	0.241	0.213	0.142	0.143	0.262

We assume that the annual vehicle mileage traveled (VMT) is constant for each segment over the course of the simulation. The variation of VMT over vehicle size, region, and population density is initialized using the *BESTMILE* estimate of the National Highway Travel Survey [15]. These averages are apportioned to vehicle age, to reflect decreasing use as vehicles age [13], and also to driving intensity using the gamma distribution bins listed in Table 1.

Initial vehicles in the fleet are assigned fuel efficiency based on historical data [17]. Future vehicle efficiency data for all powertrains and all fuel sources are taken from Moawad et al. [18], which also comply with the CAFE regulatory targets [19]. The same report also provides battery capacity for all of the hybrid, plug-in hybrid, and battery electric vehicles as a function of time. The amount of electricity versus liquid fuel used by the PHEVs is determined by the all-electric range and daily driving distance distribution [20]. PHEV vehicles are thus 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. These electricity use rates are shown in Table 3.

Table 3. Fraction of miles driven on liquid fuel 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 liquid fuel only).

Driving intensity	PHEV10		PHEV40	
	Liquid	Electricity	Liquid	Electricity
Light	42%	58%	4%	96%
Medium	63%	37%	17%	83%
Heavy	76%	24%	35%	65%

Vehicle purchase model

The segment sales fractions in each time-step, σ^V , are assigned using a nested logit choice model [21], similar to Lin and Greene [4]. Aside from the choice of powertrain, we do not assume the migration of consumers from one segment to another (including vehicle size). The nests are shown in Figure 2 and are evaluated from the bottom-up.

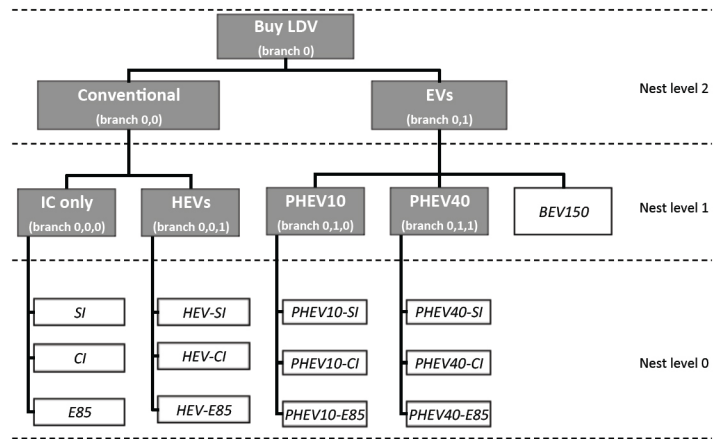


Figure 2. Nested consumer choice diagram.

The sales fraction for a given segment is determined by,

$$\sigma_{rsnpdh}^V = \kappa_n \prod_{i=0}^2 \sigma_{rsnpdh}^{V^i}; \quad (5)$$

$$\kappa_n = \frac{k_1}{1 + 1000 \exp[k_2(t - m_n^0)]}; \quad (6)$$

$$k_1 = \begin{cases} 1, & t \geq m_n^0 \\ 0, & t < m_n^0 \end{cases}; \quad k_2 = -0.3/\text{year} \quad (7)$$

where κ is the market availability fraction, the superscript i denotes the nest branch, σ^{V^i} is the sales fraction of the intermediate nest branch, and m^0 is the market introduction year of a given power-train. The market availability fraction represents a growth curve tracking the availability of a given

powertrain in vehicle manufacturers' fleets. The start year parameter for each powertrain (not necessarily the first year of market introduction), m^0 , is given in Table 4. The intermediate sales fractions are evaluated as,

$$\sigma_{rsnph}^{V^i} = \frac{U_{rsnph}^V \sigma_{rsnph}^{V^{i-1}}}{\sum_{n \in i} U_{rsnph}^V \sigma_{rsnph}^{V^{i-1}}}; \quad (8)$$

$$U_{rsnph}^V = \exp \left(-\beta^i \frac{\mathbb{C}_{rsnph}^G}{\langle \mathbb{C}_{rsnph}^G \rangle_n^i} \right); \quad (9)$$

where U^V is the utility, β^i is the logit exponent of the nest branch, $\mathbb{C}^G$ is the total cost, and $\langle \cdot \rangle_n^i$ is a reference cost taken to be the average cost over powertrains in branch, i , for each segment. The sales fractions for nest level 0 are evaluated assuming $\sigma^{V^{i-1}} = 1$. The logit exponent values vary by level, as depicted in Figure 2. The baseline values, from the lowest to highest nest levels are, $\beta = [15, 12, 9]$, which are 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% in nest level 0 [22].

Table 4. US light-duty vehicle mass market introduction year for each powertrain.

Powertrain	Year	Powertrain	Year
SI	1920	PHEV10-SI	2012 ^g
CI	2009 ^a	HEV10-CI	2025 ^h
E85	1996 ^b	PHEV10-E85	2018 ⁱ
HEV-SI	2000 ^c	PHEV40-SI	2011 ^j
HEV-CI	2020 ^d	PHEV40-CI	2025 ^k
HEV-E85	2015 ^e	PHEV40-E85	2013 ^l
BEV150	2011 ^f		

^a Re-introduction of compact, non-luxury CIs (Volkswagen and others)

^b Davis et al. [11]

^c Honda Insight and Toyota Prius

^d Estimated

^e Estimated

^f Nissan Leaf

^g Toyota Prius ZVW35

^h Estimated

ⁱ Estimated

^j Chevrolet Volt

^k Estimated

^l Chevrolet Volt

^m Honda Civic GX

ⁿ Chevrolet Silverado, GMC Sierra

The generalized vehicle purchase costs, including penalties and subsidies, are amortized over a payback period and converted to a per mile cost using the annual vehicle miles traveled [23].

$$\mathbb{C}_{rsnph}^G = \mathbf{A} \left(\frac{\mathbb{C}_{sn}^B + \mathbb{C}_{nh}^H + \mathbb{C}_{sn}^V + \mathbb{C}_{rsnph}^P - \mathbb{C}_{rsnph}^{Y^1}}{\mathcal{M}_{a=0,rsph}} \right) + \mathbb{C}_{rsnph}^F - \frac{\mathbb{C}_{rsnph}^{Y^2}}{\mathcal{M}_{a=0,rsph}}, \quad (10)$$

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, $\mathbb{C}^F$ is the fuel

cost per mile, $\mathbb{C}^Y$ is the value of subsidies, 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) with no discounting. $\mathbb{C}^{Y,1}$ are national and state subsidies and incentives that are realized once, when the customer purchases a vehicle, and $\mathbb{C}^{Y,2}$ are recurring subsidies, such as fuel discounts or recurring tax rebates. The list of federal and state-based subsidies and incentives is lengthy and is compiled by the U.S. Department of Energy [24]. The individual cost components are discussed in the following paragraphs.

Vehicle purchase costs, $\mathbb{C}^V$, are calculated using estimates for advanced technology from Moawad et al. [18]. The cost for the batteries in electrified vehicles, $\mathbb{C}^B$ and the battery capacity in each vehicle, are also taken from the same source, but are included separately from other purchase costs so that the effect of targeted research in this area can be explored parametrically.

For vehicles that require home recharging, we include a charger cost with each vehicle,

$$\mathbb{C}_{nh}^H = \delta_{nh}^H (1 - Q)^t; \quad (11)$$

$$\delta_{nh}^H = \begin{cases} \$878, & \text{PHEV10, single family house} \\ \$2146, & \text{PHEV40, BEV, single family house} \\ \$0, & \text{else} \end{cases} \quad (12)$$

where Q is the rate of price decline per year and t is the years since 2010. The charger cost assumes a Level 1 charger for PHEV10s and a Level 2 charger for PHEV40s and BEVs.

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 over the course of the year. A station availability penalty captures the lower utility of a vehicle that has limited public refueling options. The penalties are expressed as,

$$\mathbb{C}_{rsnph}^P = \mathbb{C}_{snd}^{P^1} + \mathbb{C}_{rnp}^{P^2}; \quad (13)$$

$$\mathbb{C}_{rsnph}^{P^1} = \delta^{P^1} \mathcal{H}_n \frac{\mathcal{M}_{a=0,rsph}}{\mathcal{R}_n}; \quad \mathbb{C}_{rnp}^{P^2} = \delta_{nh}^{P^2} e^{-20.15\phi_{rnp}}; \quad (14)$$

$$\mathcal{H}_n = \begin{cases} 30 \text{ min}, & \text{BEV} \\ 5 \text{ min}, & \text{else} \end{cases}; \quad \mathcal{R}_n = \begin{cases} 150 \text{ mi}, & \text{BEV} \\ 350 \text{ mi}, & \text{else} \end{cases} \quad (15)$$

$$\delta^{P^1} = \$35.3/\text{hour}; \quad (16)$$

$$\delta_{nh}^{P^2} = \begin{cases} \$375, & \text{EVs in single family house} \\ \$7500, & \text{else} \end{cases} \quad (17)$$

where $\mathbb{C}^{P^1}$ is the range penalty, $\mathbb{C}^{P^2}$ is the refueling penalty, $\mathcal{H}$ is the vehicle refueling time at a public station, $\mathcal{R}$ is the vehicle range, and ϕ is the ratio of public fueling stations for an alternative powertrain to gasoline fueling stations in a given area. The cost constant dollar values of the penalties, $\delta_n^{P^1}$ and $\delta_n^{P^2}$, and the estimated recharging times are taken from Greene [22]. The growth trends of refueling infrastructure for alternative vehicles is taken from Yeh [25], which assumes new refueling stations are added as new alternative vehicles are built,

$$\frac{d\Phi_{rpf}}{dt} = \alpha \sum_{sdh, n \in f} \frac{d\mathcal{V}_{a=0,rsnpdh}}{dt}; \quad \phi_{rnp} = \frac{\sum_{f \in n} \Phi_{rpf}}{\Phi_{rpf, f=gas}}, \quad (18)$$

where Φ is the number of refueling stations for a given fuel, α is the rate of new stations added per new vehicle sold, and the f subscript denotes type of fuel. The initial refueling station distribution by region and fuel type is taken from U.S. Department of Energy [26].

The fuel cost per mile, $\mathbb{C}^F$, is simply the product of the fuel price and the fuel consumption per mile of a vehicle,

$$\mathbb{C}_{rsnd}^F = \sum_f \mathbb{P}_{rhf}^F \Xi_{a=0,rsnpdhf}; \quad \Xi_{arsnpdhf} = \frac{\rho_{rsnpdhf}}{\eta_{asnf}}, \quad (19)$$

where $\mathbb{P}^F$ is the price of fuel, Ξ is the fuel consumption per mile, ρ is the fuel use rate, and η is the fuel economy.

Total fuel demand and FFVs

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, and the fuel economy,

$$\mathbb{D}_{rf}^F = \sum_{asnpdh} \mathcal{V}_{arsnpdh} \mathcal{M}_{arspd} \Xi_{arsnpdhf} \quad (20)$$

The fuel use rate for most powertrains is static, with the breakdown between electricity and liquid fuel for the PHEVs shown in Table 3. However, the E85 flex-fuel vehicles can use either the ubiquitous E10 or the more limited E85 gasohol blends. Similarly, the CI powertrains can use diesel or B20 (blendstock of 20% biodiesel by volume). The use rate of a secondary fuel is dynamic and a function of the likelihood of visiting a station with the fuel and a choice by the consumer based on price per unit energy density. The choice is also cast as a logit model, with an exponent value of $\beta^F = 18$. For the E85 powertrains it is,

$$\rho_{rpdh, n \in f = E85} = \phi_{rnp} \sigma_{rh, E85}^F; \quad (21)$$

$$\sigma_{rh, E85}^F = \frac{\mathcal{U}_{rh, E85}^F}{\mathcal{U}_{rh, E10}^F + \mathcal{U}_{rh, E85}^F} \mathcal{U}_{rhf}^F = \exp \left(-\beta^F \frac{\mathbb{P}_{rhf}^F}{\langle \mathbb{P}_{rhf}^F \rangle_f} \right), \quad (22)$$

where σ^F is the E85 logit choice rate based on price, $\mathcal{U}^F$ is the logit choice utility, and the reference price, $\mathbb{P}_0$, is taken as the average of initial fuel prices.

Modeling Fuel Production and Distribution

The fuel module 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 sub-model. The module deconstructs the demand for pump-fuel blends consumers use, such as E10 and E85, into pure fuel demand. Note that E85 fuel is not truly 85% ethanol by volume, but varies seasonally from 51% in the winter to 83% in the summer [27]. The set of pure fuels considered in the model are motor gasoline, diesel, ethanol, compressed natural gas, hydrogen, and electricity. The fuel derived demand in each state is matched with the corresponding raw energy feedstocks using conversion efficiencies specified by Wang [28]. State-by-state pricing variations are enforced for gasoline, diesel, and natural gas due to the complexities of the supply and refining network for those fuels. Ethanol may be transported from one state to another to satisfy extreme supply or cost imbalances due to the uneven distribution of biomass through the continental US. Well-to-pump CO_2 -equivalent GHG emissions are computed using process estimates from Wang [28]. Pump-to-tailpipe GHG emissions are computed using the CO_2 -equivalent content of the fuel and the total fuel demand.

The Renewable Fuel Standard (RFS) [29] is moderately enforced, in that the ethanol fraction by volume in the gasohol blendstock is assumed to rise to satisfy increased use of ethanol in transportation. However, this rise is capped at E15 due to skepticism that higher blend levels will be allowed. Furthermore, the quantity of ethanol produced from corn and other grains, as specified by RFS, is assumed to be satisfied first. Ethanol demand beyond the grain-based RFS limits is assumed to come from cellulosic sources. It is there implicitly assumed that the cellulosic and advanced bio-fuel categories of the mandate will be met with ethanol only, as more complex fuels cannot yet be made economically at scale. Finally, the RFS mandated quantities of biofuel in 2022 are maintained throughout the remainder of the simulation until 2050.

The ethanol supply state for each region is chosen by a logit choice model with an exponent value of $\beta^R = 18$,