Transportation Research Part D 64 (2018) 158–177

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Impact of public electric vehicle charging infrastructure

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ARTICLE INFO

Keywords:
Transportation energy
Battery electric vehicle

ABSTRACT

This work uses market analysis and simulation to explore the potential of public charging infrastructure to spur US battery electric vehicle (BEV) sales, increase national electrified mileage, and lower greenhouse gas (GHG) emissions. By employing both scenario and parametric analysis for policy driven injection of public charging stations we find the following: (1) For large deployments of public chargers, DC fast chargers are more effective than level 2 chargers at increasing BEV sales, increasing electrified mileage, and lowering GHG emissions, even if only one DC fast charging station can be built for every ten level 2 charging stations. (2) A national initiative to build DC fast charging infrastructure will see diminishing returns on investment at approximately 30,000 stations. (3) Some infrastructure deployment costs can be defrayed by passing them back to electric vehicle consumers, but once those costs to the consumer reach the equivalent of approximately 12¢/kWh for all miles driven, almost all gains to BEV sales and GHG emissions reductions from infrastructure construction are lost.

1. Introduction

How many chargers is enough? Current research and media (Singer, 2016; Mooney, 2016; Davies, 2014; Read, 2013) suggest that the prevalence of charging stations is an important factor for consumers' acceptance of electric vehicles (EVs) and that there are currently not enough charging stations in the US to soothe the range concerns of the average car buyer.

Government, utilities, and industry have been hearing this call for more public charging and, spurred by the current market potential of electric vehicles and their potential positive impacts on greenhouse gas (GHG) emissions, have been building, and proposing to build, more public charging infrastructure. Between January 1, 2011 and December 31, 2013, the US Department of Energy built over 17,000 charging stations across the US through the EV Project and the ChargePoint America project (Francfort et al., 2015). Idaho National Laboratory used data from this network of chargers and participating electric vehicles to study electric vehicle use and charging. In July 2016, President Obama announced a new plan to help transition the nation to EVs. The President's plan involves promoting "electric vehicle adoption by increasing access to charging infrastructure", as well as investing in the vehicles and manufacturing (Office of the Press Secretary, 2016). States, cities, and utilities are investing as well. In particular, California is using infrastructure as one of many tools to meet an objective of 1.5 million zero-emission vehicles on the road by 2025: the California Public Utilities Commission approved Southern California Edison to begin a pilot project wherein the utility will support installation of 1500 EV charging stations (Southern California Edison, 2016); San Diego Gas & Electric is similarly approved to install 3500 chargers at 350 locations in its coverage region (SDG&E, 2016); and PG&E is working on an infrastructure deal (John, 2016). Within the greater Kansas City metropolitan area, Kansas City Power & Light built 1000 EV charging stations in advance of demand, creating a small "EV mecca" in Missouri and Kansas (Wernle, 2015; Shelton, 2015). Moreover, automakers are building charging stations as well, both as part of these aforementioned efforts and as part of their own marketing strategies (Sparks, 2015;

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http://dx.doi.org/10.1016/j.trd.2017.10.006
Accepted 7 October 2017
Available online 16 October 2017
1361-9209/ © 2017 Published by Elsevier Ltd.

Boeriu, 2014; NissanNews.com, 2015).

Of course, the construction of all of this infrastructure leads naturally into the question of exactly what everyone is hoping to accomplish by constructing it. Ostensibly EV charging infrastructure will spur EV market growth, but by how much, and to the detriment of sales of which other vehicle types? And at what point is saturation reached? More important for government initiatives are the impacts on GHG emissions. Research indicates that EVs are cleaner than their conventional counterparts in most regions of the US, even including manufacturing emissions, and will continue to get cleaner as electric grids evolve (Nealer et al., 2015). However, the strength of the correlation between the installation of EV charging infrastructure and GHG emissions reductions, especially if other alternative energy vehicle technologies are displaced, deserves study. Next follows the question of cost. Many charging networks are not free, and utilities constructing infrastructure must eventually recoup losses (Berman, 2014; Shelton, 2015). If EV infrastructure must bring with it increases in electricity prices due to station construction costs or required improvements to the electricity grid in order to handle increased loads, how will EV sales respond? Under what combinations of infrastructure deployment and electricity prices will GHG emissions still improve? Last is the question of prioritization. If it becomes prudent to focus EV infrastructure construction efforts on a limited number of states rather than divide efforts nationally, might infrastructure have more impact in some states than others?

Previous works have analyzed the role of out-of-home vehicle charging in various ways. Typical analyses examine the local impacts of charging infrastructure (Andrews et al., 2013; Xi et al., 2013; Zhang et al., 2013; Pan et al., 2017), focusing on optimizing the number of trips that can be completed in a specific metro region assuming the trips are performed by BEVs of various ranges. González et al. (2014) additionally co-optimizes to reduce charging fees given time-of-use rates. While a range buffer is often added to the nominal BEV range to allow for driver range anxiety, the concept of consumer choice is absent from these analyses; drivers are assigned to BEVs, BEVs are assumed to be plugged in at charging locations when chargers are available (if charger congestion is considered in the analysis), and the analyses are designed to show the feasibility or infeasibility of EV ranges and charging power given the implemented networks. In all of the above analyses only level 1 and 2 public charging is considered, neglecting DC fast, and for all analyses save that presented in Pan et al. (2017), at home charging is assumed for all BEV owners. (Pan et al., 2017 considers the opposite extreme of no at-home charging for any vehicles.) A somewhat similar approach from Liu and Lin (2016) models charging availability as a percentage of public parking places installed with chargers that is translated into charging opportunity, defined as the probability that one PEV driver encounters a charger when parking the car. However, Liu and Lin (2016) go a significant step further; in addition to determining the feasibility and infeasibility of trips, this charging opportunity metric feeds into the MA3T consumer choice model for the national light duty vehicle stock (Liu and Lin, 2017). Sutherland (2016) takes a slightly different approach to weighing infrastructure value for a population; rather than creating local charging networks and declaring them feasible or infeasible, this study uses trip data to quantify the value of different levels of EV charging in terms of utility factors for different range EVs. For PHEVs the utility factor is measured as the percentage of miles driven on electricity. For BEVs, the utility factor is measured as the percentage of miles covered by the BEV, assuming that the driver will substitute the BEV with a conventional vehicle if the trip length exceeds the range of the vehicle plus the range enabled by out-of-home charging. This work is laudable in many ways, as it captures potential impact of charging for PHEVs and BEVs in homes with and without charging and potentially with substitute vehicles for BEVs for long trip days. However, it stops at utility factors, and does not extend to determining how those factors influence consumer purchasing and driving behavior as is done in the MA3T model.

In this work we seek to address the above questions concerning national scale implementation and impacts of EV charging through parametric analysis of the vehicle and fuel markets. We use the ParaChoice model, a market analysis simulation tool for the light duty vehicle (LDV) stock that is specifically designed for parametric analysis. The ParaChoice model simulates vehicle stock, sales, fuel use, and emissions from 2015 through 2050 given a wide variety of adjustable input parameters. In this analysis, we parametrically vary the number of level 2 or DC fast EV charging stations available to the consumer starting in 2017, simulating both national and state level policy-driven efforts to jumpstart infrastructure growth. We also parametrically vary the electricity prices in regions where EV infrastructure is constructed in order to test consumer tolerance to increases in electricity prices which may be necessary to support charging infrastructure initiatives. In a penalty model similar in spirit to the utility factors used in Sutherland (2016), EVs become more desirable to the consumer as their effective driving days and electrified mileage are enabled by public charging. However, reflecting the options available to consumers, BEVs and PHEVs must compete against conventional and other alternative powertrain vehicles on the market, and EVs are penalized for their high initial purchase price, time spent charging outside of the home, and other factors relevant to consumer choice.

A description of the ParaChoice model is given in Section 2, detailing the parameters varied and how those parameters might be expected to affect consumer choice and the simulation outcome. The model inputs for the specific scenarios and trade spaces explored in the analyses are outlined in Section 3. In Section 4.2, we analyze LDV sales by powertrain, mileage by fuel type, and fleet average GHG emissions per mile for four scenarios: (1) a baseline scenario, detailed results for which are presented in Section 4.1, (2) a scenario where 500,000 level 2 chargers are deployed nationally, (3) a scenario where 50,000 DC fast chargers are deployed nationally, and (4) a scenario where 50,000 DC fast chargers are deployed nationally and a 10¢/kWh electricity surcharge is imposed to offset the cost of the deployment. We broadly find that the level 2 charging infrastructure has limited impact on battery electric vehicle (BEV)[1] sales and GHG emissions, the more sparsely implemented DC fast charging infrastructure has the most impact on all metrics, and that the 10¢/kWh surcharge negates many of the BEV sales and GHG emissions gains from the DC charging

[1] In this work, we refer to pure battery electric vehicles with no gasohol engine as BEVs and plug-in hybrids as PHEVs. When referring to all vehicles with batteries, independent of the presence of a gasohol engine, we use the all inclusive, EV.

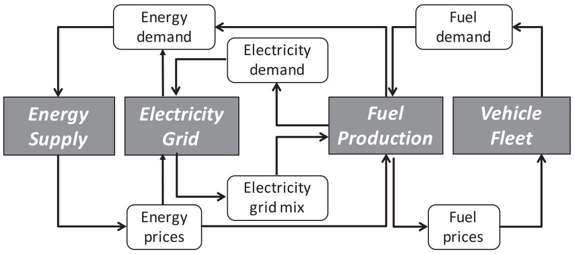


Fig. 1. High level overview of ParaChoice model and sub-models (grey).

infrastructure. In Section 4.3 we explore the tradespace between number of stations injected nationally and the electricity surcharge in greater depth in order to determine both the point of diminishing returns on station injection and the costs which can be tolerated by the consumer. And in Section 4.4 we explore regional station deployment scenarios, focusing on the states with current zero emission vehicle (ZEV) mandates for manufacturers, in order to determine if one might achieve disproportionally favorable sales or emissions targets by deploying infrastructure into select regions only. We conclude in Section 5.

2. Model description

ParaChoice models the dynamic relationship between the light duty vehicle fleet and the oil, coal, natural gas, biomass, and zero-carbon energy that ultimately moves the fleet. As shown in Fig. 1, the relationship between the energy and the fleet is mediated by fuel, including electricity. In the model, information is shared between the sub-models for energy, fleet, and fuel by price and demand information. Energy, electricity, and fuel prices are initialized using data from the U.S. Energy Information Administration (2016a,b). The composition of the LDV fleet is initialized to 2014 values using state motor-vehicle registrations from the U.S. Department of Transportation Federal Highway Administration (2014) and model availability by powertrain from Polk and Co (2015) compiled by SRA International, Inc. Refueling station availability is compiled from the U.S. Department of Energy (2016a) and National Petroleum News Magazine (2012).

Once the fleet, fuel, and infrastructure are initialized at the beginning of the simulation in the first quarter of 2015, the simulation is marched forward in time. Following Fig. 1, starting from the vehicle fleet sub model on the right, the initialized fleet is used to compute the demand for processed and mixed vehicle fuels, i.e. pump fuels. The fuel production sub-model converts this fuel demand to energy and electricity demand and passes those values to the energy and electricity sub-models respectively. Using these demand values, the energy and electricity sub-models update their prices and the electricity grid mix. The fuel production sub-model converts these new energy and electricity prices into pump fuel prices. The vehicle sub-model evolves the vehicle fleet, retiring old vehicles from the fleet and simulating new vehicle sales, which are influenced by the fuel prices from the fuel production sub-model, among other factors including vehicle costs and infrastructure availability. The simulation then iterates forward quarterly through the end of the simulation in 2050.

The following subsections provide an overview of the vehicle choice sub-model and a detailed description of the modeling decisions specific to plug-in electric vehicles and their infrastructure as these aspects of the ParaChoice simulation are most relevant to the infrastructure analyses reported on in this work. For a more complete description of the ParaChoice model and its workings, we direct the reader to previous works (Barter et al., 2012; Barter et al., 2013; Peterson et al., 2014). Levinson et al. (2016) documents a validation study for the ParaChoice model showing how modeled sales compare to actual sales for alternate energy vehicles 2010–2015. A list of common vehicle choice parameters and assumptions and the values used in this study can be found in the Appendix.

2.1. Vehicle fleet

Consumer choice, the competition of powertrains against one another whereby alternative energy vehicles may flourish or fail in the marketplace, occurs in the vehicle sub-model. In this sub-model, the total amortized cost of each vehicle powertrain to the consumer over the vehicle payback period is used to apportion vehicle sales using a nested multi-nomial logit function. The structure of the segmentation and logic in this sub-model are similar to those found in Struben and Sterman (2008), Lin and Greene (2010) and are detailed in Barter et al. (2012, 2013), Peterson et al. (2014).

For this analysis of EV infrastructure, we model 17 powertrains with ParaChoice including conventional gasoline spark ignition (SI), diesel compression ignition (CI), and flex fuel spark ignition which accepts E85 as well as regular gasohol. For each of the SI, CI, and flex fuel powertrains, hybrid electric vehicle (HEV) configurations and plug-in hybrid electric vehicle configurations with 10 and 40 mile all-electric ranges (PHEV10s and PHEV40s) are also modeled. The model additionally tracks full battery electric vehicles (BEVs) with 75, 100, 200, and 300 mile ranges,[2] and a fuel cell electric vehicle (FCEV). The full list of vehicles, fuels, and

[2] Previous analyses with the ParaChoice model have assessed simulations including BEVs with ranges of 75, 100, 150, and 225 miles. We have switched simulated

Table 1
Vehicles, fuels, and abbreviations.

Abbreviation		fuels
SI Conventional	Conventional spark ignition	Gasohol
SI HEV	Hybrid spark ignition	Gasohol
SI PHEV10	Plug-in hybrid 10mi electric range	Electricity, gasohol
SI PHEV40	Plug-in hybrid 40mi electric range spark ignition	Electricity, gasohol
CI Conventional	Compression ignition	Diesel OR B20 blend
CI HEV	Hybrid compression ignition	Diesel OR B20 blend
CI PHEV10	Plug-in hybrid 10mi electric range compression ignition	Electricity, diesel OR B20 blend
CI PHEV40	Plug-in hybrid 40mi electric range compression ignition	Electricity, diesel OR B20 blend
E85 Conventional	Flex fuel spark ignition	Gasohol OR E85
E85 HEV	Hybrid flex fuel spark ignition	Gasohol OR E85
E85 PHEV10	Plug-in hybrid 10mi electric range flex fuel spark ignition	Electricity, gasohol OR E85
E85 PHEV40	Plug-in hybrid 40mi electric range flex fuel spark ignition	Electricity, gasohol OR E85
BEV75	Battery electric75 mi range	Electricity
BEV100	Battery electric100 mi range	Electricity
BEV200	Battery electric200 mi range	Electricity
BEV300	Battery electric300 mi range	Electricity
FCEV	Fuel cell electric vehicle	Hydrogen

abbreviations is given in Table 1.[3]

For each time step in the simulation, a generalized cost is computed for each powertrain, which is used to compute the powertrain's relative utility. This cost is given by:

$$\begin{aligned}\text{GeneralizedCost} = {} & (\text{PurchasePrice} + \text{AtHomeChargerPrice}_{\text{EVsonly}} \\ & - \text{OneTimeIncentives} + \text{OneTimePenalties})_{\text{Amortizedoverpayback}} \\ & + (\text{YearlyFuelCost}{-}\text{AnnualIncentives} + \text{RecurringPenalties})\end{aligned} \tag{1}$$

Vehicle prices, penalties, incentives, and fuel costs evolve in time and may vary across one or more of: the state in which the vehicle is purchased, vehicle size, vehicle powertrain, and driver demographics including population density, driver intensity, and dwelling type.

2.1.1. Infrastructure, refuel time, and disutility penalties

The penalties for all vehicles save BEVs are those associated with time spent refueling and availability of infrastructure and are adopted from Greene (2001). The refueling time penalty is a simple multiplicative of the value of one's time,

$$\text{Cost R} = a \times t_{refueling} \tag{2}$$

where a is taken from Greene to be \$25.93/h when converted to 2012 dollars,[4] and $t_{refueling}$ is the number of hours spent refueling the vehicle at public refueling stations. The time spent refueling will vary by powertrain, dwelling type (which will determine if at home recharging can lower the requirement for public refueling of EVs), and driver intensity.

For conventional and hybrid vehicles, $t_{refueling}$ is computed as the yearly vehicle miles traveled (VMT) divided by the vehicle range (350 miles), times the duration of a refueling event (5 min). The yearly refueling time will vary depending on the driver's intensity by segment.

For PHEVs in single family dwellings, the vehicle is assumed to be charged every night. Based on this assumption and the distributions of daily driving patterns from Barter et al. (2015), we compute the yearly miles driven on gasoline. The time spent refueling is the yearly miles driven on gasoline, divided by the range of the vehicle (340 miles for PHEV10s, 310 miles for PHEV40s), times the duration of a refueling event (5 min, as external refueling is refueling of the liquid tank).

The refueling time calculation for PHEVs in non-single family dwellings (without the capability to refuel at home), is the same as for conventional and hybrid vehicles. The exception is that the vehicle range is smaller, reflecting the smaller liquid tank and the larger weight of the vehicle given the battery.

The infrastructure availability penalty is also given by Greene (2001)

$$\text{CostI} = \delta \exp[-20.149\phi_f] \tag{3}$$

where the cost of zero station availability, δ, is set to \$7500 for all vehicles fueled exclusively outside of the home, following that same work. For those vehicles with an at home refueling options, the cost drops to \$375. The variable ϕ_f is the ratio of the number of

(*footnote continued*)
BEV ranges to better align with vehicle inputs from Moawad et al. (2016).

[3] The ParaChoice model is also capable of simulating three types of compressed natural gas fuel vehicles (CNGs): standard spark ignition, electric hybrid, and gasoline bi-fuel. As future market availability of CNGs is uncertain, we have excluded this powertrain type from this EV focused study.

[4] The nominal dollar value in the ParaChoice model is 2012 dollars, so all dollar values are referenced to 2012 unless otherwise noted.

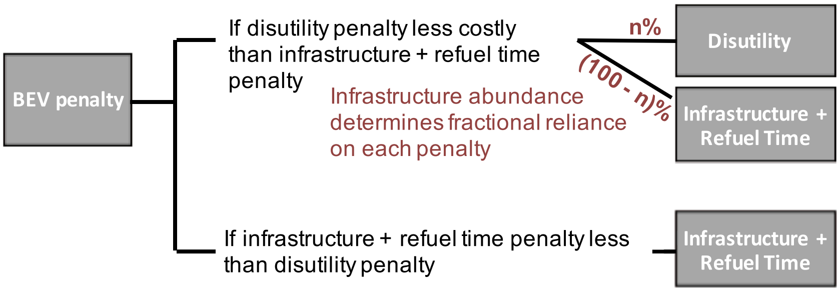


Fig. 2. BEV penalty.

fueling stations for fuel *f* to the number of gasohol stations. This penalty is evaluated individually for each dwelling type for each population density segment within each state. The infrastructure penalty is assessed at the time of vehicle purchase, and its impact is amortized over the vehicle payback period. Refueling infrastructure built after the time of vehicle purchase is not factored into the purchasing decision, as the buyer is not assumed to have market or infrastructure foreknowledge.

Dual fuel vehicles such as PHEVs require special treatment for the infrastructure penalty. PHEVs are assumed to be driven serially with recharging happening in the home once per night in single family dwellings. If the vehicles are drained of charge mid-day, the vehicles are driven on their liquid tank for the remainder of the day. Only the liquid tank is refueled outside of the home as gasoline stations are abundant and gasoline refueling is fast and therefore incurs a minimal penalty as compared to recharging; consumers are assumed to use the most convenient refueling option available to them, which will by default be liquid refueling. Admittedly, this assumption ignores the potential impact of extremely abundant DC fast charging infrastructure, and also the impact of well-placed and thus ‘convenient’ level 2 charging stations (e.g. workplace charging). We will address the impact of the latter in a forthcoming study, focusing this present study on the impact of more general access to public charging.

The penalties applicable to pure battery electric vehicles, BEVs, are slightly different from those applicable to conventional and hybrid vehicles. Depending on the availability of recharging infrastructure and an infrastructure willingness parameter detailed in Barter et al. (2015), BEVs are either penalized for days of vehicle disutility or for the refuel time + infrastructure penalty described above. The use cases for the BEV penalties are depicted in Fig. 2.

As depicted in Fig. 2, the applied BEV penalty is either the weighted average of the vehicle disutility and the refuel time + infrastructure penalty, where the weighting factor n is determined by the infrastructure abundance and the infrastructure willingness parameter, or simply the refuel time + infrastructure penalty if that penalty is smaller than the vehicle disutility penalty. By default, the infrastructure willingness parameter is set to 0.1, indicating that half of the population will be willing to use public charging infrastructure if the density of public charging infrastructure is 10% of the density of gasoline refueling infrastructure. This segregation is applied at the state level, so that if infrastructure in one state is different than infrastructure in another, the penalty is applied appropriately in the different states.

The disutility penalty is detailed in Barter et al. (2015) and we summarize it here. The motivation behind this penalty is that, for low density infrastructure coupled with long and thus inconvenient refuel times, some BEV drivers will simply choose to use an alternate, conventional vehicle on days where their driving range exceeds the range of their BEV. The penalty applied for each day of vehicle disutility is the cost of a rental vehicle for the urban, suburban, or rural region in which the vehicle is located. Moreover, for these days of BEV disutility, the BEV is not credited for having electrified the driver’s miles traveled on that day. The miles instead are attributed to gasohol.

To compute the number of days of disutility for the BEVs, we use real world daily driving cycles scaled to produce a distribution of daily driving distances for different population segments (Barter et al., 2015). BEV disutility penalties will differ for different driver intensities and for different regions with different refueling infrastructure. Disutility will also differ for those with and without at home charging access (dwelling type); those without at home charging access will be ‘inconvenienced’ every driving day by this model. Therefore there is a switch in the model that insists that the infrastructure + refuel time penalty will be used if it is ever less than the disutility penalty. This logic also holds intuitively as, all things being equal, one tends to prefer to retain use of one’s own vehicle if at all practical rather than to revert to a rental vehicle.[5]

The structure of the infrastructure + refuel time penalty for BEVs is nearly the same as that described for non-BEV vehicles. However, there exist multiple levels of charging infrastructure that must be accounted for in the simulation in order to give an accurate representation of actual EV charging availability. At present, there are three levels of charging infrastructure: level 1, level 2, and DC fast.[6] Level 1 and level 2 chargers are available for at-home installation, lowering their maximum total infrastructure penalty in Eq. (3), though at the expense of an additional cost at time of purchase for level 2 charging equipment, see Eq. (1). Assumptions for the speed, installation cost, and maximum infrastructure penalty costs of chargers are given in Table 2.

We assume that all public charging stations will contribute to the reduction of the infrastructure + refuel time penalty for BEVs.

[5] The model does not take into account the potential impact of multiple vehicle households. It is possible, if not likely, that the penalty for BEV disutility in a multiple vehicle household is lower than that simulated here.

[6] Tesla Supercharging infrastructure is grouped with DC fast infrastructure. However, in initializing the infrastructure in the model, the number of DC fast chargers are penalized to account for the incompatibility of Tesla, CHAdeMO, and J1772Combo plug types.

Table 2
EV charging infrastructure levels.

Charger Level	Recharge speed/power [a]		Cost to build [b]	δ [c]
Level 1	5 mi/h	1.4 kW		\$350
Level 2	20 mi/h	5.5 kW	\$1,354, \$3,108[d]	\$350
DC Fast	210 mi/h	57 kW[e]	\$22,626	\$7500

[a] U.S. Department of Energy (2016b), assuming $19.2kW \approx 70$ mi/h.
[b] Costs from Francfort et al. (2015).
[c] Max infrastructure penalty δ in Eq. (3).
[d] Home and public installation costs respectively.
[e] Current max power outputs for CHAdeMO and SAE Combo chargers are 50 kW. Tesla Superchargers are 120 kW. We have aimed high to be consistent with the upper charging rate estimates of U.S. Department of Energy (2016b), consistent with modeled rates for level 1 and 2 charging.

In order to fairly capture the impact of each charger type on lowering consumer resistance to public refueling, we use a parallel resistor model to aggregate their effects. In this model, the total impact of the combined EV infrastructure is the inverse sum of the penalties from the individual charger types. Thus, for each charger type j, the refueling time penalty R_j, as given by Eq. (2), and infrastructure penalty I_j, as given by Eq. (3), are computed assuming that only charger type j is available. The total infrastructure + refuel time penalty, CostIR, across all charger levels is then computed as the sum of the inverse penalties,

$$\mathrm{CostIR} = (\Sigma_j (I_j + R_j)^{-1})^{-1}. \tag{4}$$

The above penalty formulation has the virtue of always being less than the individual charger penalties. Moreover, in the case where infrastructure is effectively infinite, the penalty reduces to the refuel time penalty for DC fast chargers times $1-\Delta$, where Δ is a coefficient of the order of the ratio of the level 2 and DC fast charger rates. This matches intuitive understanding that, given an abundance of charging infrastructure of all levels, DC fast charging times would be the limiting 'inconvenience' in recharging.

We note that there is no penalty or 'negative penalty' based on the value provided by refueling stations in simply creating awareness of a vehicle powertrain. Analysis by Singer (2016) shows that charging infrastructure is linked to consumer willingness to consider purchase of EVs, even if they may not end up not relying upon the infrastructure after purchase (as is suggested by Francfort et al. (2015)). However, this 'soft' value is difficult to quantify, and thus it is not captured in the model.

2.1.2. Refueling station growth

At the beginning of the simulation, known gasohol and alternative fueling station availabilities from National Petroleum News Magazine (2012) and U.S. Department of Energy (2016a) respectively are loaded into the model by state. Linearly interpolated station data from September 2014, August 2015, April 2016, and July 2016 are used to supply the station fractions for all dates up until third quarter 2016. Beyond third quarter 2016, refueling stations in the simulation grow with the vehicle market; refueling stations increase in proportion to state vehicle sales of the associated powertrain at a rate of 0.7 stations per thousand vehicles sold.[7][8]

BEV and PHEV40 powertrains both contribute to the endogenous growth of public EV charging stations. For each time step and within each state and population density zone (urban, suburban, rural) within the state, the simulation selects which type of public charging to add, level 2 or DC Fast. This simulation's selection is designed to optimize the reduction of the infrastructure + refuel time cost penalty to medium intensity BEV100 and BEV200 drivers, subject to the constraint that one DC fast charging station is approximately ten times as expensive as a public level 2 charging station and thus must be compared to the benefit of building ten times as many level 2 stations. The ten to one ratio in the constraint is based on the pricing of the DC fast chargers and public level 2 chargers in Francfort et al. (2015),[9] the current ratio of existing DC fast stations to existing non-home level 2 stations (U.S. Department of Energy, 2016a), and also reports from Tesla for their announced infrastructure plans (Sparks, 2015).

Thus, for each time step t, if m_{rt} EVs are sold in state and density region r, $(0.7m_{rt})/1000$ DC fast stations will be built in that region if DC fast stations reduce the penalty optimally. Alternately $10 \times (0.7m_{rt})/1000$ level 2 charging stations will be built in that region, if level 2 stations will reduce the penalty optimally.

For internal consistency in the model, we use the number of DC fast stations plus 1/10 the number of level 2 charging stations to compute the ratio of charging stations to gasohol stations for the infrastructure willingness computation, which decides the fractional BEV disutility penalty and infrastructure + refuel time penalty, see Fig. 2.

The number of level 1 public charging stations remains fixed to present values throughout the simulation. As the recharge time for charging at level 1 chargers is quite long compared to level 2 and DC fast stations, and preliminary evidence shows that most EV drivers don't seem to use level 1 infrastructure outside of their homes Francfort et al. (2015), the impacts of low station density for level 1 stations are quite small.

[7] This in an adjustable parameter, the structure and nominal value of which is taken from Yeh (2007). For this analysis we retain the nominal value of 0.7.
[8] Refueling station sizes are not considered in the model. For the sake of the simulation, the utility of a refueling station is to lower range anxiety. We assume that the market will build infrastructure of adequate size to meet demand at a given location, if demand exists. Therefore a recharging station in the model could consist of one or multiple chargers. We use charger and charging station interchangeably.
[9] While ten to one is not an exact ratio, Francfort et al. (2015) states that the price of the DC fast chargers may be artificially low as bids to build DC fast chargers that were over \$50,000 were rejected. Schroeder and Traber (2012) finds cost ratios of approximately 20 to one.

In addition to market-driven station growth, the ParaChoice model has an option for a one-time station injection of any number of level 2 or DC fast stations (a) nationally, (b) by state, or (c) into multiple states in 2017. This station injection is in addition to the endogenous growth described above. These station injection options allow the user to test the impact of dedicated national, state, or multi-state programs to spur electrification technologies through the build-out of EV charging stations. The model can also simulate a surcharge on electricity prices for electric vehicles in the states where there is injected station growth, simulating scenarios where the costs of refueling station programs are placed in part or whole back on EV consumers. For these scenarios we assume that EV drivers alone will bear the electricity surcharges (both for at home recharging as well as at public recharging stations), but that the other fuel prices will not be affected. We do not simulate electricity price increases at public refueling stations exclusively, nor do we simulate an increase to industrial electricity costs that would raise the prices of all fuels.

If the optional station injection parameter is used, charging stations will be injected into the model in mid-2017 and market driven growth will continue thereafter. While instantaneous station growth of this nature is infeasible in practice, the station injection parameters are designed to test the long term impacts of station availability, so the specific details of construction duration were deemed to be less important. We do note for comparison the relatively short time scales in which other charging station initiatives have been completed once they had been decided upon. Tesla built 1500 ‘destination chargers’ in 1.5 years after announcing an initiative to have them ‘virtually everywhere’ (U.S. Department of Energy, 2016a; Sparks, 2015). Kansas City Power and Light Company installed 1000 chargers in just over a year (Loveday, 2014; Wernle, 2015). Nissan and BMW partnered to build 120 DC fast stations across 19 states, announcing the project in December 2014 and announcing its completion the following December (Boeriu, 2014; NissanNews.com, 2015).

In cases of national station injection or injection into multiple states in the simulation, the charging station distribution follows the distribution of gasohol stations; states with a greater number of gasohol stations receive a greater number of EV charging stations. This distribution roughly follows potential market demand and proportionally lowers the EV infrastructure penalty in each state.

3. Baseline, scenario, and parametric model inputs

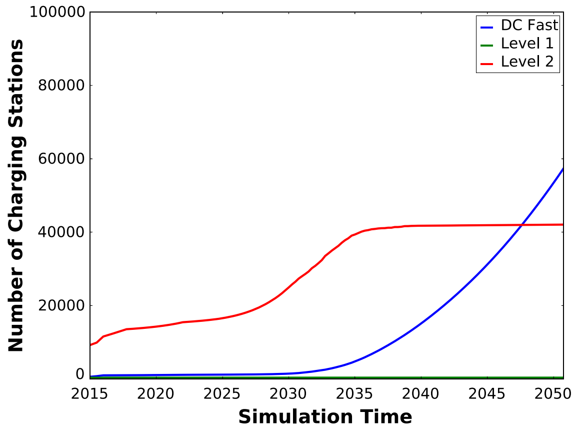
For all simulations in this work, the ParaChoice model relies on ‘baseline’ or ‘business-as-usual’ assumptions for all energy price and technology price projections. Energy prices are taken from U.S. Energy Information Administration (2016a). Vehicle prices and efficiencies are taken from the Moawad et al. (2016) low case which is “aligned with original-equipment-manufacturer improvements [to technologies] based on regulations.” The low case is chosen in alignment with other ‘baseline’ modeling assumptions, namely that the only modeled policies and initiatives are those currently written into law. For detailed assumptions used in the baseline case see Barter et al. (2012, 2013) and Peterson et al. (2014).

Changes to the baseline assumptions will change the absolute values of the reported sales fractions, mileages, and GHG emissions in each of the scenarios and parametric analyses. However, exploration of ‘optimistic’ and ‘pessimistic’ technology and energy price parameters for alternative energy vehicle (AEV) adoption suggests that the trends reported here hold for a range of energy and technology assumptions, see Section A.1 for details. We have not explored the range of behavioral parameters here, though one might expect the results to change if drivers changed their sensitivity to cost, refueling availability, or significantly changed their driving habits. A sensitivity analysis of the model to the a wide range of parameters, including behavioral parameters and the BEV penalty multiplier, can be found in Barter et al. (2012). Barter et al. (2013) examines the impacts of changing the BEV penalty structure altogether. A reanalysis of the penalty sensitivity with the current BEV penalty modifications is outside of the scope of the present work.

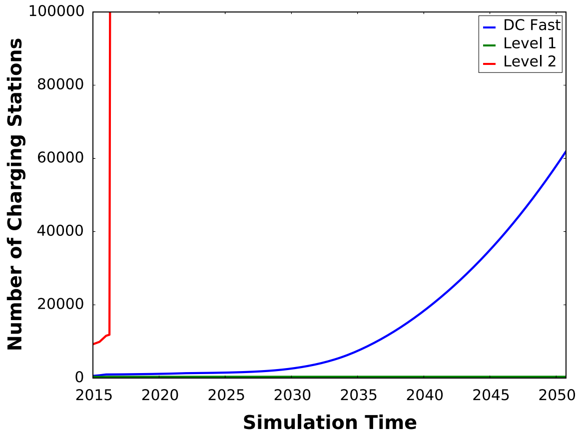
Incentives and policies are implemented at the state level. All policy assumptions are assumed to be only those currently written into law, with end dates in place where mentioned in the law. The exception is the station injection scenarios explicitly stated and analyzed here and the associated parametric analyses. They are:

1. Baseline. No station injection.
2. 500,000 level 2 charging stations injected nationally in 2017.
3. 50,000 DC fast charging stations injected nationally in 2017.
4. 50,000 DC fast charging stations injected nationally in 2017, and an additional 10¢/kWh electricity surcharge applied to all electrified miles driven by EV drivers. This approximates a scenario where some of the cost of building and maintaining the EV infrastructure has been passed back to EV drivers.
5. A tradespace analysis comparing DC fast infrastructure and electricity surcharge. 0–120,000 DC fast stations injected nationally in 2017 and 0 - 80¢/kWh electricity surcharge.
6. Three parametric analyses comparing
   (a) 0–200,000 DC fast stations injected nationally in 2017
   (b) 0–150,000 DC fast stations injected in 2017, but only in the ten states with a ZEV mandate (as of August 2016), namely California, Connecticut, Maine, Maryland, Massachusetts, New Jersey, New York, Oregon, Rhode Island, and Vermont
   (c) 0–100,000 DC fast stations injected in 2017, but only in California.
7. 25 parametric analyses of station injection impacts in collections of non-ZEV mandated states. 0–50,000 DC fast stations injected in randomly selected groups of ten states whose total number of vehicles is within 1% of the total number of vehicles in the ZEV states.

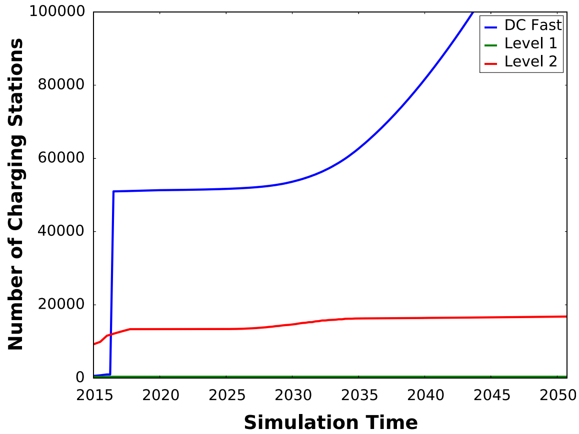
The number of DC fast charging stations to add in the DC fast scenario case (3) approximates a scenario whereby each state takes



(a) Baseline scenario. Market driven station growth only.



(b) 500,000 level 2 stations injected in 2017 followed by marked driven station growth. Scenario (2)



(c) 50,000 DC fast stations injected in 2017 followed by marked driven station growth. Scenario (3)

Fig. 3. Simulation inputs for charging station availability in baseline and station injection scenarios. Level 1 station availability beyond present day installations are not modeled.

up an initiative to install, on average, 1,000 public DC fast stations. States with more vehicles, such as Texas and California would be obligated to install more charging stations, and states with fewer vehicles would be obligated to install fewer. The 500,000 level 2 charging stations were selected for scenario (2) based on the (admittedly crude) ratio of ten level 2 chargers equating one DC fast (in construction cost and charging rate). The evolution of infrastructure in the baseline, level 2 station injection, and DC fast station injection scenarios are depicted in Fig. 3. Notice the historical, injected, and endogenous station growth phases before, during, and after 2017.

With the exception of the scenario in case (4) and the parametric analysis in case (5), electricity grid evolution and pricing follows the baseline scenarios described in Barter et al. (2012). For the electricity price surcharge scenario and parametric analysis, the same electricity pricing and evolution holds with the addition of a surcharge on the price of electricity for EV users only. This surcharge is applied at a per kWh rate for all miles driven electrically by BEVs and PHEVs. For the scenario in case (4), this value is fixed to 10¢/kWh. For the parametric analysis, it is varied from the baseline 0¢/kWh to an upper bound of 80¢/kWh.

We acknowledge that there are many possible payment models to offset the cost of infrastructure construction and grid enhancements that may be necessary for infrastructure deployment on a large scale. Electricity prices may increase for everyone (Shelton, 2015), including commercial and industrial users, thus driving up the cost of other fuels. The prices may be borne exclusively by the public charging stations and not impact residential pricing. Charging networks may implement a subscription fee rather than a charge per kWh as Aerovironment and EVGO have done (Berman, 2014). There also may be membership discounts, following Blink (2016). Alternately, charging may be free or discounted if the OEMs or states back such an initiative (Berman, 2014; Nissan, 2015). There is certainly room for a future analysis of the impacts of different electricity charging models on the adoption of EVs. However, such an analysis is beyond the scope of this current work, and so we only examine the impacts of one such charging model here.

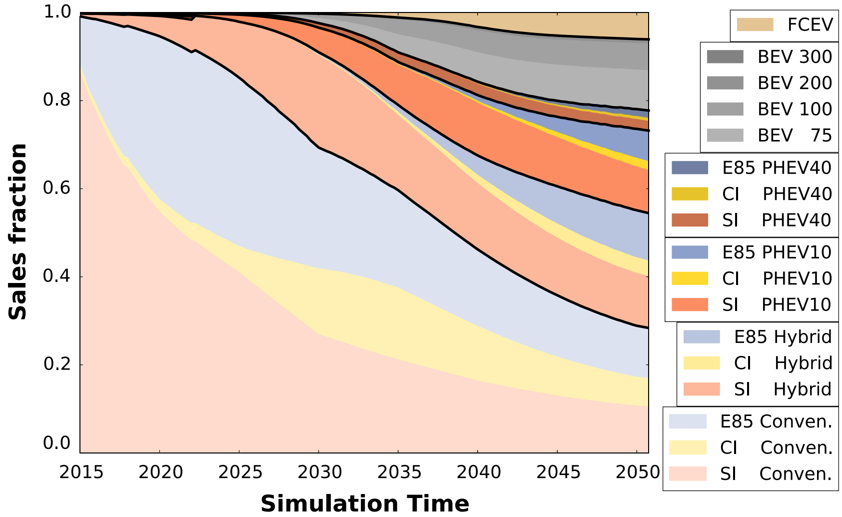


Fig. 4. Sales projections for the baseline scenario. Corresponding numeric values for 2050 sales percentages by powertrain are given in Table 3 alongside stock numbers.

The surcharge per kWh cost structure modeled here reflects the cost of the charging stations and grid improvements needed to support the increased stress on the grid due to mass EV adoption being passed onto EV consumers proportionally by usage.[10] 80¢ per kWh is twice Blink's average current member rate surcharge for DC fast charging,[11] and thus we use it as an extreme, though not unimaginable, upper bound for parametric analysis in this study.

4. Results

4.1. Baseline

In the baseline scenario, BEVs comprise 16% of new vehicle sales and 11% of the vehicle stock by 2050. PHEV40 sales comprise an additional 5% of sales and 3% of the stock. Sales evolution and 2050 sales and stock values in the baseline case are shown in Fig. 4 and Table 3 respectively. Pump fuel prices per mile, reflecting both the fuel price evolution and the vehicle efficiency evolution are shown in Fig. 5 alongside the fleet fuel use evolution. The fleet transitions from almost entirely gasohol and diesel use in 2015 to 15% electricity use in 2050 in this baseline scenario with only market-driven electric charging station growth. The net impact of both the adoption of electrification technologies and higher fuel efficiency across the powertrains leads to a drop in vehicle average GHG emissions per mile by 47% over 2015 values by the end of the simulation in 2050.

4.2. National station injection scenarios

We compare the relative impact of three station injection scenarios with the baseline case. These scenarios are cases (2–4) described in Section 3 and all describe instances of national station injection in 2017. 2050 results for vehicle sales by powertrain and fleet average mileage by pump fuel in these three scenarios and the baseline case are shown in Tables 4 and 5. Because one might expect charging infrastructure to have a different impact on vehicles in different dwelling types, (i.e. in single family homes with recharging infrastructure potential and in non-single family homes without), the results are broken down by dwelling type. The time series evolution of powertrain sales for the three scenarios are shown in Fig. 6.

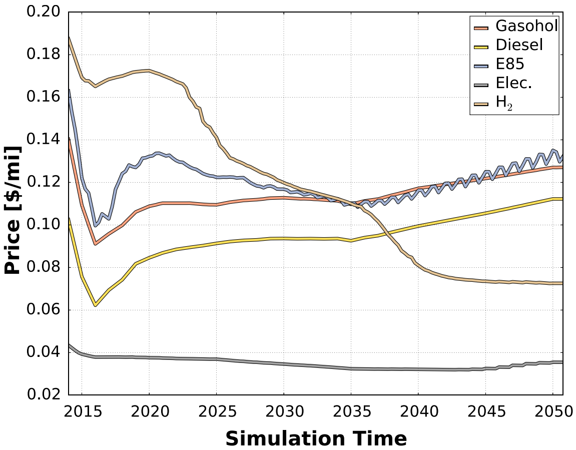
Public level 2 charging infrastructure has minimal impact on powertrain sales distributions and mileage by fuel type. In both single and non-single-family homes, the level 2 infrastructure changes vehicle sales distributions by one percent or less. Electrified mileage is likewise minimally impacted. We note again that the current EV penalty model may not be a perfect representation of drivers' responses to the availability of level 2 charging infrastructure as the penalty does not capture (a) the auxiliary benefits of chargers in creating visibility and advertising for EVs, (b) potential benefits to PHEV drivers, or (c) the potential for 'convenient' or 'workplace-type' level 2 charging outside of the home. However, we believe that the broader result presented in this section, that *public* DC fast infrastructure can have a much greater impact on BEV sales and fleet-wide electrified mileage than public level 2 infrastructure, holds for the general construct of the penalty model presented in Section 2, i.e it holds for an aware consumer minimizing cost and inconvenience to himself.[12] The impacts of *private* charging, whereby drivers may have regular and prolonged

[10] An analysis of whether this billing method is fair or attainable is also beyond the scope of this work.

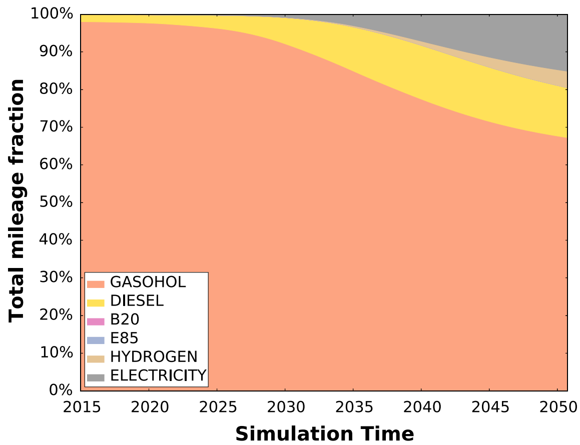
[11] Surcharge computed from Blink's advertised member rates per kWh by state in states with per kWh charging from Blink (2016) minus the average residential cost of electricity in that state from U.S. Energy Information Administration (2016b). Non-member surcharges are 10¢/kWh higher.

Table 3
Simulated 2050 stock and sales percentages by powertrain in the baseline case, corresponding to sales depicted in Fig. 4.

Powertrain	% Sales	% Stock
SI Conven.	11	26
CI Conven.	6	10
E85 Conven.	11	14
SI HEV	12	13
CI HEV	4	2
E85 HEV	11	6
SI PHEV10	10	9
CI PHEV10	2	1
E85 PHEV10	7	2
SI PHEV40	2	2
CI PHEV40	1	0
E85 PHEV40	2	1
BEV 75	9	6
BEV 100	6	4
BEV 200	1	1
BEV 300	0	0
FCEV	6	3



(a) National average fuel prices



(b) Fleet wide mileage fractions

Fig. 5. (a) National average fuel prices in dollars per mile for representative midsize vehicles in the baseline case. Conventional spark ignition vehicles, compression ignition vehicles, flex fuel vehicles, and BEV100s are used to compute gasoline, diesel, E85, and electricity costs per mile respectively. Fuel economy projections are taken from Moawad et al. (2016) and fuel price projections from U.S. Energy Information Administration (2016a). (b) National vehicle miles driven by fuel type. 2050 values are: gasohol 67%, diesel 13%, B20 0%, E85 0%, Hydrogen 4%, and electricity 15%.

access to convenient level 2 chargers during the day, may be different, but that is a subject for future work.[13]

DC fast charger implementation leads to much larger 2050 BEV sales and fleet wide electrified mileage than level 2 charging station injection, even though we model only 1/10 as many injected DC fast stations in this scenario than we had modeled injected level 2 stations in the previous scenario. Total BEV sales increase from 16% to 23% of the market, and electrified mileage jumps from 15% to 23%. In single family homes, BEVs gain 7% of sales, pulling sales from across the other powertrains. BEV sales share in non-single family homes gain 5%. Electrified mileage fraction follows the same trend as BEV sales; 9% more miles driven by vehicles in single family homes are driven on electricity in this scenario over the baseline, and 5% more miles driven by vehicles in non-single family homes are driven on electricity. While the impact of infrastructure in non-single family homes is more modest than the gains

[12] We note in particular that PHEV drivers gain less obviously from public EV infrastructure of either type than BEV drivers. When using public EV infrastructure, PHEV drivers reduce their fuel costs but do so at the inconvenience of slowly and/or frequently charging a relatively small battery. This option may or may not be superior to using the gasoline tank. BEVs don't have this option. Thus, while the introduction of level 2 or DC fast infrastructure may have different impacts on PHEV sales and electrified mileage as compared to BEV sales and mileage, the effect of including the potential benefits of *public* infrastructure to PHEV drivers in the penalty model might be expected to be small compared to the effect of including the benefits to BEV drivers. Additionally, the little data available on EV charging suggests that most EV drivers do not use public (non-workplace) level 2 infrastructure (Francfort et al., 2015).

[13] As a temporary measure, one could look to the work of Sutherland (2016) who computes the utility value of home and workplace charging, finding that workplace charging is of most utility to vehicles with smaller batteries, and high power and workplace charging have limited utility for long range (200+ range) BEVs. The analysis only considers level 1 and level 2 charging and does not consider a consumer choice element.

Table 4
2050 Vehicle Sales %.

Powertrain	Baseline	500 K Level 2	50 K DC Fast	50 K DC Fast & 10¢/kWh Elec. Surcharge
		Fleet average		
Conventional	29	28	27	29
HEV	26	26	25	27
PHEV10	19	18	17	19
PHEV40	5	4	4	4
BEV	16	17	23	15
FCEV	6	6	5	6
		Single Family Homes Only		
Conventional	27	27	25	28
HEV	25	25	23	26
PHEV10	18	17	16	17
PHEV40	5	5	4	4
BEV	20	20	27	19
FCEV	6	6	5	6
		Non-Single Family Homes Only		
Conventional	31	31	30	31
HEV	28	28	27	28
PHEV10	20	20	18	21
PHEV40	4	4	4	4
BEV	10	11	15	10
FCEV	7	7	6	7

Table 5
2050 Fleet Mileage %.

Powertrain	Baseline	500 K Level 2	50 K DC Fast	50 K DC Fast & 10¢/kWh Elec. Surcharge
		Fleet Average		
Gasohol	67	67	62	67
Diesel	13	13	12	13
Hydrogen	4	4	4	4
Electricity	15	16	23	16
		Single Family Homes Only		
Gasohol	63	63	56	62
Diesel	13	13	11	13
Hydrogen	4	4	3	4
Electricity	20	21	29	21
		Non-Single Family Homes Only		
Gasohol	74	74	70	74
Diesel	14	14	14	14
Hydrogen	5	5	4	5
Electricity	7	7	12	7

made in single family homes, even these smaller contributions from non-single family homes are significant. DC fast infrastructure can electrify mileage in the non-single family home population segment, even if the impacts are not as extreme as those observed in single family homes.

In the scenario where a 10¢/kWh surcharge is imposed on all EV electricity consumption in order to offset the costs of the DC fast charger station injection, BEV sales shares only reach 15% compared to 16% in the baseline. PHEV40s also lose market share in this scenario, as they experience the increased electricity costs felt by BEVs, but do not feel the reduced penalty from the increase in EV station availability as they already have an extremely low infrastructure and refuel time penalty due to their ability to use gasohol infrastructure. Even though there are fewer EV sales due to the higher electricity price, the increased infrastructure still enables more long distance trips for existing BEV owners in single family homes to be driven electrically rather than replaced by trips with conventional vehicles. The result is a slight gain in electrified mileage. In net, fleet-wide electrified mileage only increases by 1%, indicating that the 10¢/kWh surcharge nearly negates the positive impact of the 50,000 added DC fast charging stations.[14]

We additionally weigh the impact of the charging station injection scenarios by comparing their respective impact on GHG emissions, Fig. 7. The DC fast station injection scenario produces a 50% emissions reduction over 2015 values, compared to a 47% reduction in the baseline case. This result is expected, as the DC fast station injection scenario results in a significantly higher fraction

[14] To better show how vehicle prices, infrastructure, and fuel prices affect final sales distributions in the various scenarios, we have provided breakdowns of generalized vehicle costs for representative vehicles in the baseline, 50 K DC fast, and 50 K DC fast with 10¢/kWh electricity price surcharge scenarios in the Appendix.

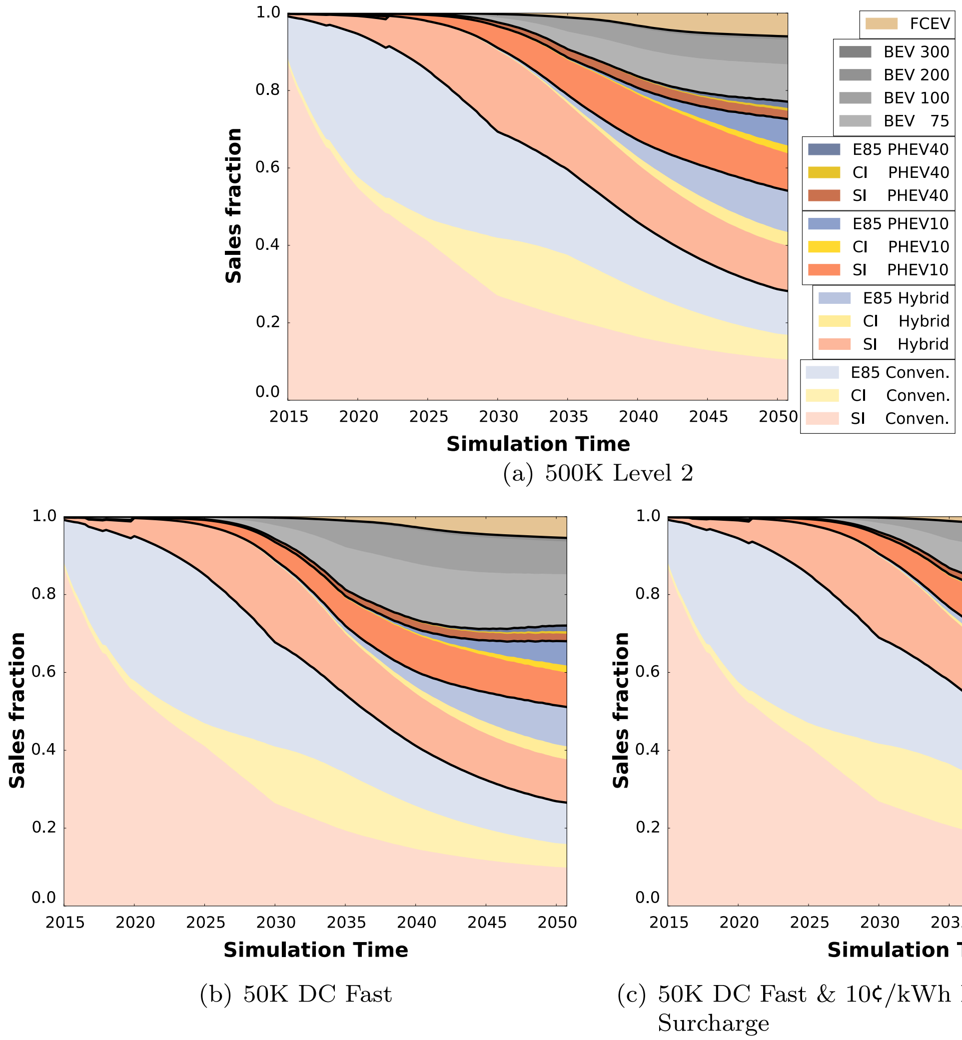


Fig. 6. (a) Simulated sales projections by powertrain for three scenarios of charging station injection in 2017. Corresponding numeric values for 2050 sales projections and mileages by pump fuel are given in Tables 4 and 5.

of fleet wide electrified miles and lower fraction of miles driven on gasohol and diesel as compared to the baseline case. In comparison, the level 2 station injection scenario and the 10¢/kWh electricity surcharge scenario result in fleets with emissions only marginally better than emissions in the baseline.

4.3. DC fast station injection and electricity surcharge tradespace

To more thoroughly explore the relationship between DC fast station injection and EV consumer electricity pricing, we perform a tradespace analysis between number of stations injected nationally and electricity surcharge imposed to pay for the station injection. A simple parametric analysis of the number of nationally injected DC fast charging stations demonstrates that the impact of DC fast station injection starts to have diminishing returns after approximately 30,000 and returns level off nearly completely at approximately 80,000 stations, see Fig. 9. Based on this finding we explore a potential DC fast station injection range of 0–120,000 in increments of 3,000. As stated in Section 3, 80¢/kWh is twice the computed member surcharge for a Blink DC fast charging station, and thus we use it as an upper bound for this tradespace study, exploring the parameter range in increments of 2.5¢/kWh.

Fig. 8 shows the sensitivity of BEV sales and GHG emissions reduction to number of DC fast stations injected and electricity cost surcharge up to 40¢/kWh. The general behaviors of BEV sales and emissions reductions in response to the parameters are as expected-as more stations are injected in 2017 there are more BEV sales and greater emissions reductions. However, diminishing returns are observed after approximately 30,000–80,000 stations are injected, depending on the electricity surcharge. Likewise, the greater the surcharge on electricity, the lesser the GHG reduction and the fewer the BEV sales. BEV sales max out at ~ 23% in the limit of maximal stations and no electricity surcharge. Outside the range of Fig. 8, BEV sales drop to 0% for an 80¢/kWh surcharge regardless of the number of EV charging stations built.

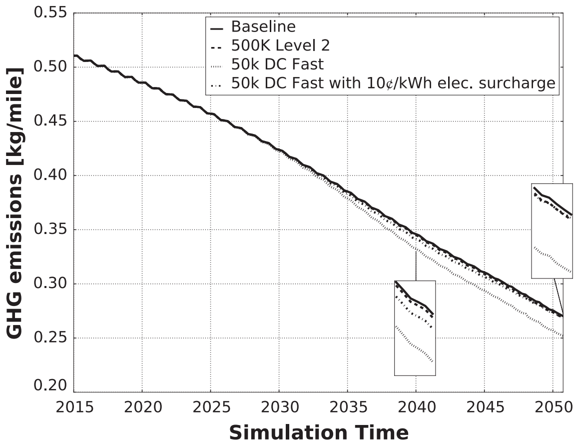
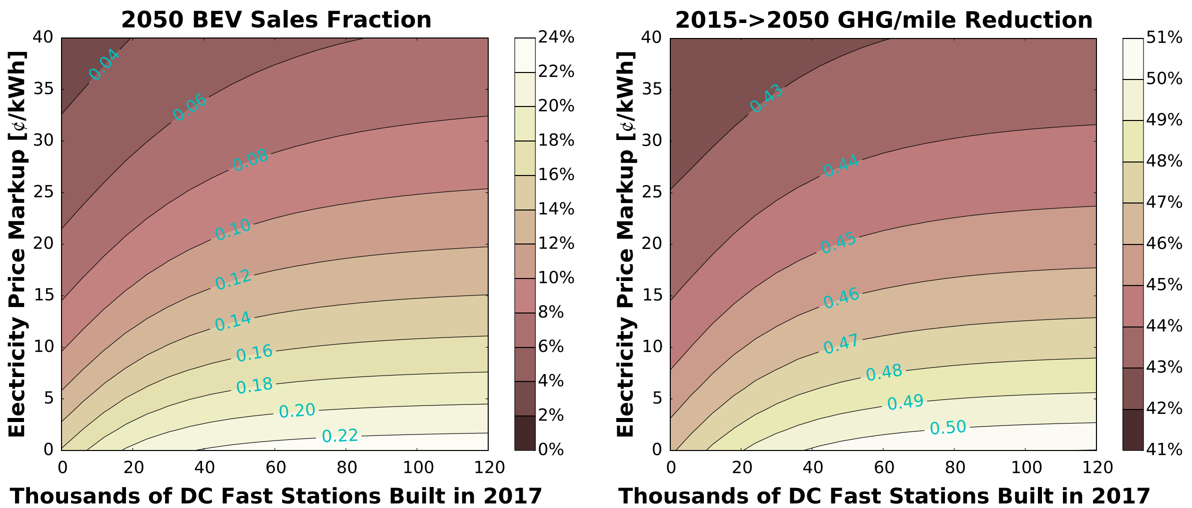


Fig. 7. Fleet average GHG emissions per vehicle mile for scenarios with and without nation wide policy driven charging station injection in 2017. The injection of 50,000 DC fast charging stations has a much greater impact on GHG emissions than an injection of 500,000 Level 2 charging stations. Insets show magnification around years 2040 and 2050.



(a) Sales fraction of BEVs in 2050.

(b) Fleet average 2050 GHG emissions reduction per mile compared to 2015 values.

Fig. 8. Tradespace between impact of number of DC fast charging stations injected nationally in 2017 and the electricity cost surcharge borne by EV drivers.

A feature of note in Fig. 8 is that the contours that pass through the origins do not exceed ~ 12¢/kWh on either the BEV sales or GHG reduction plots, even at maximal DC fast station injection. This result would indicate that there exist no number of DC fast public charging stations that can be built that would alleviate the damages to BEV sales or GHG emissions reductions that would be caused by electricity surcharges greater than ~ 12¢/kWh. Plans to build out EV charging infrastructure can achieve GHG emissions reductions and BEV sales increases and may do so while passing some of the costs back onto EV drivers, but those costs should remain below ~ 12¢/kWh to EV drivers in order to achieve these goals.

While this analysis provides a broad, national brush stroke view, it shows that there are pathways by which national DC fast station injection can contribute to the goals of increasing BEV sales and lowering GHG emissions, even with some of the costs shared by EV consumers. Determining exactly what the cost structure should be, and whether the cost which can be passed to consumers is sufficient to defray the expense of building the infrastructure, will require much more detailed studies.

4.4. Targeted injection

The impact of a national station injection initiative for DC fast charging stations levels off at approximately 80,000 stations. If

80,000 stations are injected nationally in 2017, by 2050 BEVs comprise 23% of powertrain sales and emissions reductions per mile over 2015 values reach 51%. The question remains, could a policy do equally well with a smaller number of stations injected into a more targeted region? Or, given a more limited budget, could one maximize returns by injecting stations preferentially into some regions rather than others.

We first examine the impact of DC fast station injection in the ten states with a ZEV mandate implemented as of August 2016 (Section 3, analysis (6b)), comparing it to the baseline national station injection (analysis (6a)). While we do not simulate manufacturer incentives in the ParaChoice model and thus do not enforce ZEV mandate compliance, we do model consumer purchasing incentives by state. We chose to explore targeted station injection in the ZEV states as it follows logically that states with a ZEV mandate might be friendly to BEV adoption and its potential impacts in other ways. For example, the ZEV states already have a head start for number of EV charging stations, currently possessing 42% of the approximately 1900 DC fast stations deployed nationally. Other significant examples of BEV and ZEV incentives in the ZEV states are.

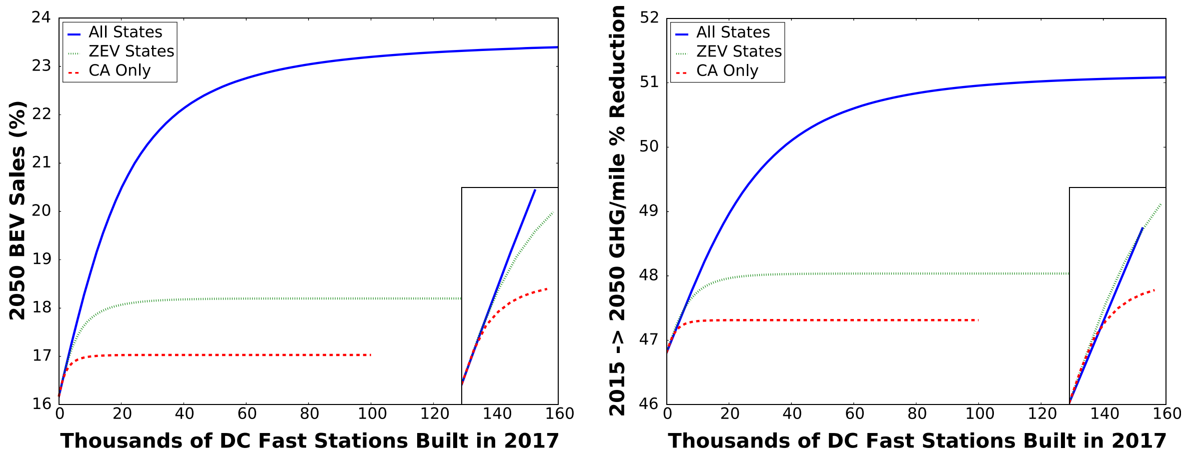
- CA: PHEV and ZEV rebates of up to $5000
- CT: EV rebate of $3000 for a vehicle with a battery capacity of 18 kWh or greater, $1500 for capacity of 7–18 kWh, or $750 for capacity less than 7 kWh
- MD: EV rebate up to $3000, calculated as $125 per kWh of battery capacity
- MA: EV rebate up to $2500
- NJ: ZEV sales tax (7%) exemption from purchase
- NY: PHEV and ZEV rebate up to $2000
- RI: EV rebate of $2500 for any vehicle with a battery capacity of 18kWh or greater, $1500 for capacity between 7 and 18 kWh, or $500 for capacity less than 7 kWh
- CA, MD, NJ, NY: High occupancy vehicle lane access incentives for EVs

We also examine the impact of DC fast station injection into California only, as California tends to lead the nation in clean vehicle adoption. California also has 11% of the nation's light duty vehicles.

Fig. 9 shows the GHG emissions reductions which result from station injection in the ZEV states and CA as compared to a national station injection initiative. The results are summarized numerically in Table 6, which shows: (a) the percent change from 0 station injection to maximal station injection for each case, (b) how that change compares to the total possible gains from a national station injection scenario, and (c) the number of stations at which additional stations begin to provide diminishing returns in GHG emissions reductions.

Fig. 9 informs us that, for a DC fast injection initiative of greater than a few thousand stations, the effort must be spread over more than just CA and the ZEV states to have greatest national GHG emissions impact. These regions will hit points of diminishing return where additional DC fast stations do not help increase BEV sales or reduce GHG emissions. However, for station injection initiatives of a few thousand or less, injection of stations into the ZEV states only will yield at least the same impact as a more widespread, national initiative.

According to the model, the maximal nation-wide GHG emissions reduction that can be achieved through DC fast station injection in the ZEV states alone is 1%. The max impact that can be made by CA alone is half that. To provide perspective, a national station



(a) Percent of new vehicle sales in 2050 which are BEVs

(b) Fleet average 2050 GHG emissions reduction (%) per mile compared to 2015 values.

Fig. 9. National impact of national and regional policy driven station injection plans. Horizontal axis depicts total number of DC fast charging stations built in 2017. Total charging stations are split across all states (blue, solid), only those states currently with a ZEV mandate in place (green, dash dot), only within California (red, dash). Inset figures show magnification of parameter space with fewer than 10,000 stations injected. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 6
National and regional DC fast station injection impact above baseline case of no station injection.

Region	% Vehicles	Max GHG/mile gain		stations needed for 1/2 max GHG gains	
		% over baseline	% of natl. gains	#	% of natl.
National	100	4.3		20,200	
ZEV States	25.3	1.2	28.6	6,060	30
CA	11.1	0.5	11.8	2,020	10

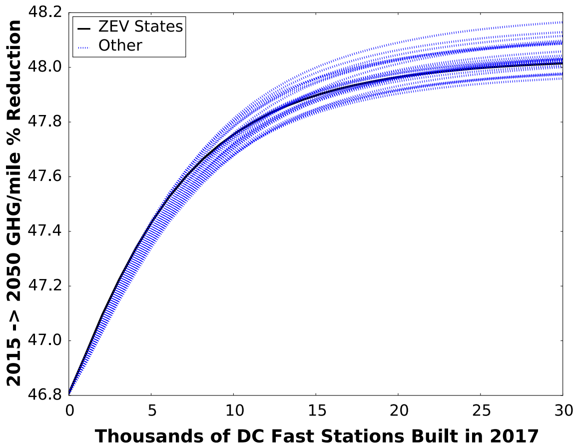


Fig. 10. Comparison of impact of targeted station injection in ZEV states (black) and twenty-five other possible collections of randomly selected non-ZEV states (blue) with a similar number of total vehicles as the ZEV states. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 7
2050 Vehicle Sales % in Pessimistic Scenario.

Powertrain	No Station Injection	500 K Level 2	50 K DC Fast	50 K DC Fast & 10¢/kWh Elec. Surcharge
		Fleet Average		
Conventional	39	39	37	39
HEV	24	24	23	25
PHEV10	20	19	17	19
PHEV40	4	4	4	4
BEV	9	10	15	10
FCEV	3	3	3	3
		Single Family Homes Only		
Conventional	38	38	36	39
HEV	24	24	23	25
PHEV10	18	18	16	17
PHEV40	4	4	4	3
BEV	12	12	19	13
FCEV	3	3	3	3
		Non-Single Family Homes Only		
Conventional	40	40	39	40
HEV	25	25	25	25
PHEV10	21	21	19	21
PHEV40	5	5	4	4
BEV	5	6	9	6
FCEV	4	4	4	4

injection initiative could achieve a 4% gain in emissions reductions over the baseline case of no station injection initiative. Thus, the maximal GHG reduction impact achievable by CA and the ZEV states is approximately proportional to the percentage of vehicles in those regions respectively. The impact is also approximately proportional to the required investment in number of stations needed to

Table 8
2050 Fleet Mileage % in Pessimistic Scenario.

Powertrain	No Station Injection	500 K Level 2	50 K DC Fast	50 K DC Fast & 10¢/kWh Elec. Surcharge
		Fleet Average		
Gasohol	72	72	67	71
Diesel	15	15	14	15
Hydrogen	3	3	2	3
Electricity	11	11	17	12
		Single Family Homes Only		
Gasohol	69	68	63	67
Diesel	14	14	13	14
Hydrogen	2	2	2	2
Electricity	15	15	22	16
		Non-Single Family Homes Only		
Gasohol	78	77	74	77
Diesel	16	16	15	16
Hydrogen	3	3	3	3
Electricity	4	4	8	5

Table 9
2050 Vehicle Sales % in Optimistic Scenario.

Powertrain	No Station Injection	500 K Level 2	50 K DC Fast	50 K DC Fast & 10¢/kWh Elec. Surcharge
		Fleet Average		
Conventional	11	11	11	11
HEV	21	21	21	23
PHEV10	11	11	11	11
PHEV40	5	5	5	5
BEV	24	24	27	20
FCEV	28	28	25	30
		Single Family Homes Only		
Conventional	10	10	9	10
HEV	20	20	19	21
PHEV10	11	11	10	11
PHEV40	6	6	6	5
BEV	29	29	33	25
FCEV	25	25	22	28
		Non-Single Family Homes Only		
Conventional	12	12	12	13
HEV	24	24	24	25
PHEV10	12	12	12	13
PHEV40	5	5	5	5
BEV	15	15	18	12
FCEV	32	32	29	33

achieve maximal gains in those states.

A feature of note in Fig. 9 is that both CA and the ZEV states have greater GHG reductions returns for low numbers of stations injected than the national average, see figure insets. In order to determine if the ZEV states are a superior place to inject stations or if targeted station injection into any ten states of approximately the same vehicle footprint (25.3% of the national stock) would have similar impact as station injection into the ZEV states, we ran an additional 25 parametric analyses where we recreated the ZEV curve in Fig. 9b for non-ZEV states. The non-ZEV states were randomly selected subject to the constraint that the fraction of vehicles in those states summed to the fraction of the vehicles in the ZEV states ± 1%. We also excluded the ten ZEV states from the random selection pool. The results of this random draw analysis are shown in Fig. 10.

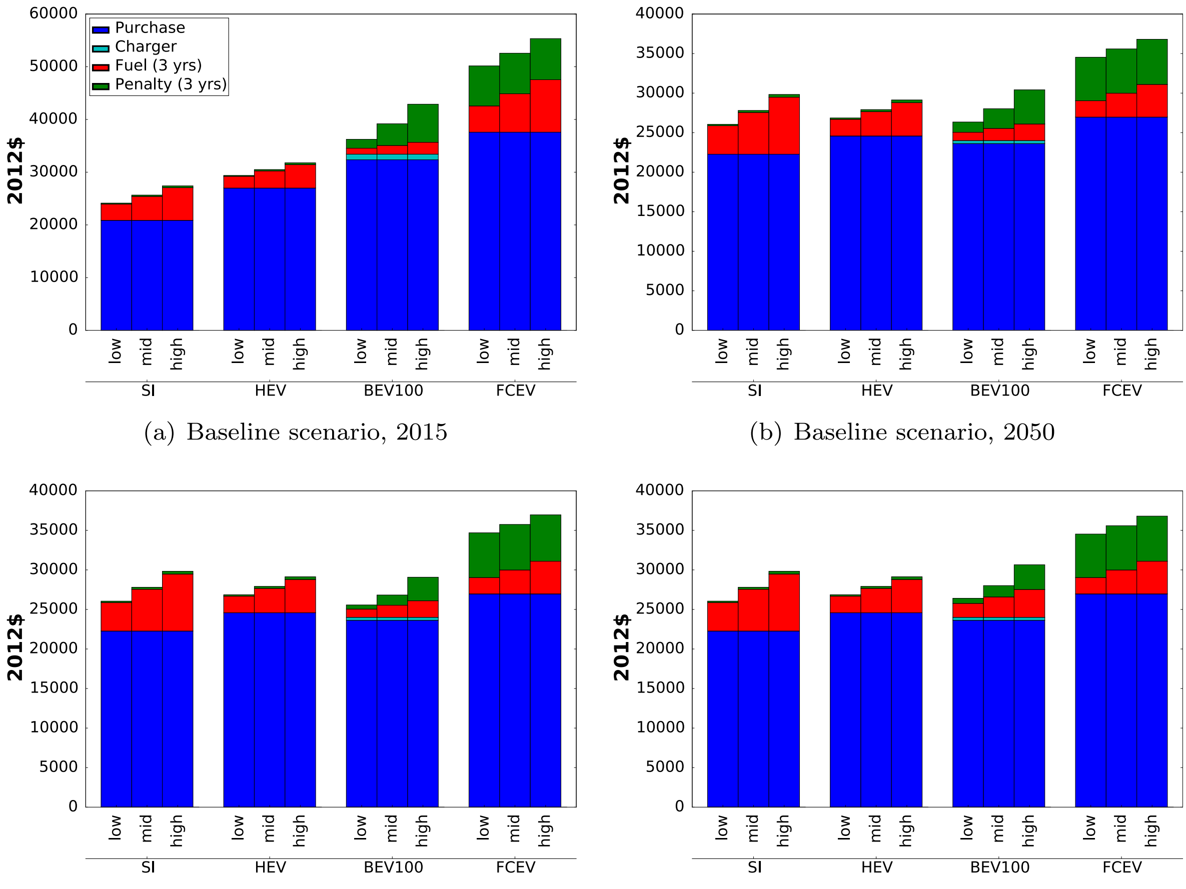
For fewer than ~5,000 injected stations, targeted station injection into the ZEV states produces the greatest returns in GHG emissions reductions, echoing the result observed in Fig. 9. This is likely due to the fact that states such as CA currently have a relatively clean electric grid as compared to the US average. However, for larger numbers of injected stations, the ZEV states start to show no obvious superiority to the other states. This result suggests that, with the support of infrastructure, EV technology can have an impact in those states as well.

5. Conclusions

Based on the analyses from the previous section, we conclude the following about a national initiative to build public charging infrastructure if the intent of that initiative is to spur the growth of long term EV sales and reduce GHG emissions:

Table 10
2050 Fleet Mileage % in Optimistic Scenario.

Powertrain	No Station Injection	500 K Level 2	50 K DC Fast	50 K DC Fast & 10¢/kWh Elec. Surcharge
		Fleet Average		
Gasohol	47	47	44	47
Diesel	8	7	7	8
E85	6	6	6	6
Hydrogen	17	17	15	18
Electricity	22	23	29	22
		Single Family Homes Only		
Gasohol	42	42	38	42
Diesel	7	7	6	7
E85	6	6	5	6
Hydrogen	16	16	13	16
Electricity	30	30	38	29
		Non-Single Family Homes Only		
Gasohol	54	54	52	54
Diesel	9	9	8	9
E85	7	7	7	7
Hydrogen	20	20	18	20
Electricity	11	11	15	10



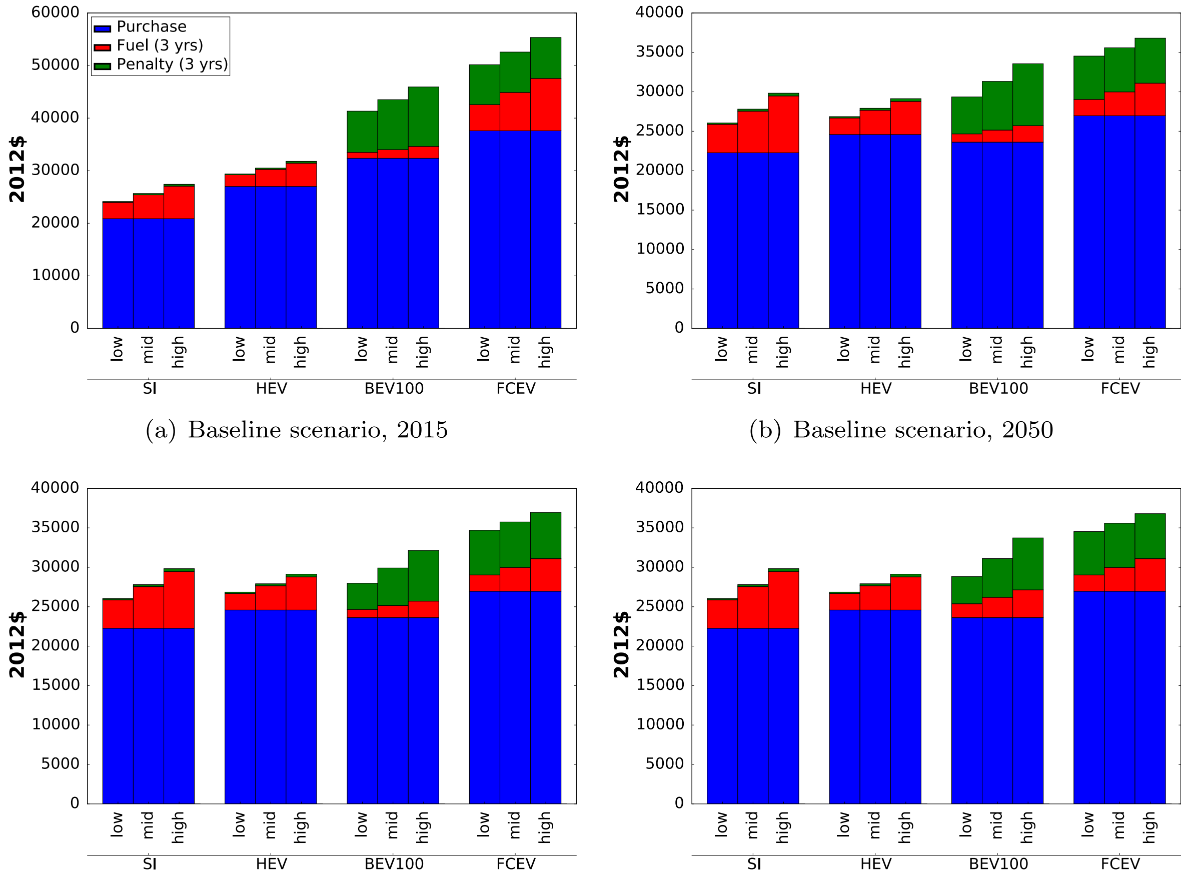
(a) Baseline scenario, 2015

(b) Baseline scenario, 2050

(c) 50,000 DC fast station injection scenario, 2050

(d) 50,000 DC fast station injection plus 10¢/kWh electricity surcharge scenario, 2050

Fig. 11. Generalized vehicle costs in single family homes for different powertrains, including charger costs, fuel costs, and inconvenience penalties. Costs are shown for low, mid, and high intensity drivers. Subfigures show different scenarios and different simulation years.



(a) Baseline scenario, 2015
(b) Baseline scenario, 2050
(c) 50,000 DC fast station injection scenario, 2050
(d) 50,000 DC fast station injection plus 10¢/kWh electricity surcharge scenario, 2050

Fig. 12. Same as Fig. 11, but for non-single family homes, without at home recharging capability.

Table 11
ParaChoice basic parameters assumptions and defaults.

Parameter	Default Assumption
Multinomial logit exponents [top, mid, & bottom] level nests	[9,12,15]
Vehicle payback period	3 years
Amortization rate	0%
Total vehicle sales rate	0.067
Fleet growth rate	Tied to population growth
Infrastructure growth (per 1000 vehicles sold)	0.7
Regional variation	state (48 contiguous + DC) & population density (urban, suburban, rural)
Vehicle classes modeled	Compact, Midsize, Small SUV Large SUV, Pickup
Evolution of vehicle class distribution	Fixed
VMT segregation	Low, medium, high within each region
Evolution of VMT	Fixed
Percent with access to household charging	62%
Percent with access to workplace charging	0
Multi-vehicle households	Not modeled
ZEV mandate	Not modeled
CAFE compliance	Not enforced
Federal & state AEV incentives	Modeled only if currently written into law, including end dates
Reduced value of rebate based incentives	0%
Carbon tax	$0

1. In the baseline scenario, a national initiative to build 50,000 DC fast stations increases 2050 fleet-wide electrified mileage by 8%.
2. For large scale national deployment, public DC fast chargers will be more effective than public level 2 chargers at increasing BEV sales, increasing electrified mileage, and lowering GHG emissions, even if only one DC fast charging station is built for every ten level 2 charging stations.
3. The impact of public DC fast infrastructure rollout on BEV sales and electrified mileage will be largest in single family homes with at-home charging capability.
4. A portion of the cost of EV infrastructure can be defrayed by passing it along to EV drivers while still reaping GHG emissions reductions and BEV sales gains. However, under baseline assumptions for vehicle technology evolution and non-EV fuel costs, once the surcharge to EV drivers reaches ~ 12¢/kWh for all electrified miles driven, many of the gains from the added infrastructure are lost.
5. A national injection of DC fast infrastructure in 2017 will have sharp returns for BEV sales and GHG emissions reduction through ~30,000 stations. However, after 30,000 stations returns begin to diminish. Full saturation on returns is seen at ~80,000 stations.
6. For infrastructure deployment scenarios of less than ~5,000 DC fast stations, injection of those stations into states with ZEV mandates might provide better return on investment for GHG emissions reductions than injections into non-ZEV states.
7. For infrastructure deployment scenarios of greater than a few thousand DC fast stations, the greatest returns will be seen from spreading stations nationally.

Acknowledgments

Financial support was provided by the United States Department of Energy, Vehicle Technologies Office. Sandia National Laboratories is a multimission laboratory managed and operated by National Technology and Engineering Solutions of Sandia LLC, a wholly owned subsidiary of Honeywell International Inc. for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

Appendix A

A.1. A: Optimistic & Pessimistic AEV Adoption Scenarios

For completeness, we provide the results of the 'National Station Injection Scenarios' analysis from Section 4.2 performed with 'optimistic' and 'pessimistic' technology and energy price parameters for AEV adoption. The pessimistic scenario uses the same, low technology success case from Moawad et al. (2016) used in the baseline case, but assumes that oil and coal prices will be half as expensive as projected by the U.S. Energy Information Administration, 2016a by 2050, thus driving down the demand for AEVs. The optimistic scenario uses the high case, "aligned with aggressive technology advancement," from Moawad et al. (2016) and assumes that oil and coal prices will be twice as expensive as projected by U.S. Energy Information Administration (2016a) by 2050.

In both the optimistic and pessimistic cases, the trends for EV infrastructure construction from the baseline, or 'business as usual' case hold. In both the optimistic and pessimistic cases, level 2 infrastructure has little impact; DC fast infrastructure creates 6–7% gains in fleet average miles driven on electricity and more significant gains in single family homes; and a 10¢/kWh electricity surcharge negates many of the gains of added EV infrastructure. However, a significant difference in the optimistic case as compared to the pessimistic and baseline cases exists in the prevalence of hydrogen and fuel cell vehicles in the fuel and vehicle mix. This difference is caused by the low cost of FCEVs in the 'high case' of Moawad et al. (2016).

Tables 7–10.

A.2. B: Generalized vehicle costs

Figs. 11 and 12.

A.3. C: ParaChoice basic assumptions, parameters, and default values

The table below is meant to be a guide to the parameter values and assumptions used in the choice modeling for ParaChoice. It is not comprehensive, but rather addresses some of the most commonly asked questions about the model. For a full model description detailing the sources for the parameter defaults and how these parameters are applied, we direct the reader to (Barter et al., 2012, 2013; Peterson et al., 2014). Some of these parameters and their values are originally sourced from Struben and Sterman (2008), Lin and Greene (2010) as documented in the aforementioned works.

Table 11.

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