Socially Optimal Replacement of Conventional with Electric Vehicles for the U.S. Household Fleet

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Abstract

In this study a framework is proposed for minimizing the societal cost of replacing gas-powered household passenger cars with battery electric ones (BEVs). The societal cost consists of operational costs of heterogeneous driving patterns' cars, the government investments for charging deployment, and monetized environmental externalities. The optimization framework determines the timeframe needed for conventional vehicles to be replaced with BEVs. It also determines the BEVs driving range during the planning timeframe, as well as the density of public chargers deployed on a linear transportation network over time. We leverage datasets that represent U.S. household driving patterns, as well as the automobile and the energy markets, to apply the model. Results indicate that it takes 8 years for 80% of our conventional vehicle sample to be replaced with electric vehicles, under the base case scenario. The socially optimal all-electric driving range is 204 miles, with chargers placed every 172 miles on a linear corridor. All of the public chargers should be deployed at the beginning of the planning horizon to achieve greater savings over the years. Sensitivity analysis reveals that the timeframe for the socially optimal conversion of 80% of the sample varies from 6 to 12 years. The optimal decision variables are sensitive to battery pack and vehicle body cost, gasoline cost, the discount rate, and conventional vehicles' fuel economy. Faster conventional vehicle replacement is achieved when the gasoline cost increases, electricity cost decreases, and battery packs become cheaper over the years.

Keywords: vehicle replacement; battery electric vehicles (BEVs); internal combustion engine vehicles (ICEVs); charging density; all-electric driving range

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Introduction

Road transportation, along with the sectors of electricity generation and industrial activities, are dominating contributors to worldwide carbon dioxide emissions. The 2005 International Energy Agency data indicate that 33% of U.S. CO_2 emissions come from the transportation sector, and the main contributor of this amount (78%) is on-road transport. These percentages are also high for other countries, such as 30% and 69% for the United Kingdom, 22% and 78% for Germany, and 22% and 75% for Australia (OECD and International Transportation Forum 2010). The introduction of alternative fuel and advanced technology vehicles in the global market promises decoupling personal mobility from petroleum-based fuels, improvement of the fuel economy for the vehicle mix, and potential energy security.

Battery electric vehicles (BEVs) are one of the major alternative fuel cars in the light-duty automobile market, taking up to 0.062% of the global vehicle stock at the end of August 2015 (Cobb 2015). The BEVs sales share in the U.S. reached 0.41% in 2015 (Electric Drive Transportation Association 2016). Countries that participate at the Electric Vehicle Initiative pledged to accelerate adoption of BEVs by setting specific stock and sale goals (Clean Energy Ministerial, Electric Vehicles Initiative, International Energy Agency 2013). Annual growth rates of the BEV market share are encouraging, as, in some cases, those reach more than 100%, e.g., the 2013 market share of BEVs in the U.S. reached 1% after growing approximately 200% compared to 2012; Norway's BEV market share reached 6% in 2013 after growing approximately 90% from the previous year (Mock and Yang 2014). Both Japan and the U.S. led the BEV market with 28% and 26% of the 2012 BEV world sales, respectively. When it comes to the highest sales of BEVs per capita, by July 2016, Norway and the Netherlands reached 21.52 and 5.63 BEVs out of every 1,000 vehicles registered, respectively (HybridCars 2016). Many studies provide evidence of the potential of plug-in electric vehicles (PEVs) to have lower lifecycle and externalities costs compared to their internal combustion engine (ICEV) counterparts, e.g., Michalek et al. (2011) and Aguirre et al. (2012). The data presented above indicate early traits of a global shift to electricity-powered personal mobility, showcase that the BEV market has momentum, and pinpoint the need to further study the electrification of the passenger car fleet.

In the U.S. the tie of personal mobility to petroleum-based fuels is an obstacle towards achieving energy independence, considering that 33% of the oil consumed is imported (Energy Information Administration 2015b). BEV adoption would result in tailpipe emissions reduction and, potentially, in GHG fuel production reductions by substituting petroleum-based fuels with clean grid electricity. Expecting to spur the market for BEVs, the Department of Energy set the goal of one million PEVs (both PHEVs and BEVs) on the U.S. streets by 2015 (U.S. Department of Energy 2013b). However, only

256,385 PEVs were sold from 2011 to 2014 (California Plug-In Electric Vehicle Collaborative 2014). The transition period from ICEVs to PEVs is taking longer than suggested. We are motivated to model this replacement process centrally and assist policymakers with revisiting their target BEV adoption goals for minimizing societal impacts during the electrification of the U.S. household vehicle fleet.

Agent-based and discrete choice models have been popular approaches for modeling alternative fuel vehicle ownership choice and projecting BEV adoption, e.g., Eppstein et al. (2011), Cui et al. (2010), Silva and Moura (2014), Musti and Kockelman (2011), and Krause et al. (2016). These studies capture consumer preferences and pinpoint significant variables that drive automobile ownership decisions in order to forecast PEV market penetration. Due to the presently limited number of PEVs in the passenger car market, models based on existing data might represent innovators and early adopters, and thus their results may not apply to the rest of the population. Moreover, the aforementioned models do not consider the social costs of transitioning from conventional to electric vehicle technology. This gap is addressed in our work.

A utilitarian government would be interested in minimizing the cost of the replacement of conventional with BEVs in order to achieve an optimal transition for society's stakeholders. In this paper, we assume that the central planner has the ability to manage the vehicle fleet by indicating the year of replacement of a household's ICEV with a BEV. The central planner here assumes the role of an agency, such as a national or local government, that is concerned with minimizing society's costs from the transportation sector. We develop a deterministic mixed integer non-linear mathematical program to minimize this social cost, which is incurred during the electrification process of the household vehicle fleet. The proposed model captures relationships between the BEV driving range and the public charging density. Our findings also showcase the evolution of public charging density on a linear transportation network over the planning timeframe.

The purpose of this work is to centrally model the replacement of gas-powered household vehicles with BEVs. The resulting ICEV replacement timeline specifies a socially optimal electrification process, which can serve as guideline for setting targets for BEV market adoption during the planning horizon. For example, if a rebate policy can motivate consumers to make decisions so that the resulting BEV adoption timeline resembles our optimal pathway to electrification, we will know that the policy adopted is an optimal one. To design such a policy, work should be conducted to collect consumer preference data and optimize rebates to incentivize market adoption of BEVs at a pace specified by our socially optimal timeline. In general, the methodology investigated in this paper provides to policymakers the ability to understand the upper limit of electrification for maximizing social benefit and set targets for BEV market share without the need for survey data or agent-based simulation.

The proposed methodology stems from fleet replacement optimization frameworks, which are usually applied to commercial vehicle fleets. Vehicle replacement models have been developed to effectively manage transit and commercial cars. For example, Feng and Figliozzi (2013), Feng and Figliozzi (2014), and Figliozzi et al. (2012) proposed mixed integer non-linear programming frameworks to replace conventional vehicles, trucks, and buses with electric ones, using scenarios of variations of economic and technological factors. Stasko and Gao (2012) used a stochastic dynamic programming formulation to model fleet management decisions under environmental regulations. Suzuki and Pautsch (2005) used a deterministic mixed integer non-linear programming framework to examine commercial fleet replacement modeling adaptations under unstable economies.

Once more, the goal of our study is not to predict the market's transition from ICEVs to BEVs, since we do not capture market behavior. Instead, we consider a best-case scenario for solving the ICEV with BEV replacement model from a societal point of view, which may serve as a compass for policy making. The resulting electrification timeline is useful to set BEV target adoption goals for achieving maximum societal benefits and can assist central planners in designing effective subsidies in order to meet those goals. Specifically, our objective is to answer the following research questions:

1. How long will it take to electrify 80% of household vehicles while minimizing the societal cost of this transition process, under various scenarios?
2. What is the optimal all-electric driving range of the BEVs?
3. What is the optimal density of charging stations to be deployed, subsidized by the government over the planning horizon?

The optimization of the described electrification process from a societal perspective has not been addressed in the literature. Cost components related to vehicle operation capture the heterogeneity among driving patterns and are estimated dynamically. The total social cost accounts for society's spending required to support the travel of households. It consists of costs incurred by road network users while conducting trips, monetized environmental externalities for the passenger car transportation sector, and the government investment for installing public chargers. The base case results provide a policymaking benchmark to plan for a sustainable future of electrified personal mobility. By exploring alternative scenarios we nurture policy dialogue.

The rest of this paper is organized as follows. The second section introduces the methodology developed to answer the research questions. The third section presents the empirical datasets, and the fourth summarizes the results. The final one refers to conclusions.

Methodology

The following subsections present the mathematical programming model and the social cost decomposition for ICEVs and BEVs.

Modeling Framework

The formulation of the programming model is based on the following considerations. The central planner faces the decision to replace ICEVs with BEVs annually. There is no market for new ICEVs during the planning horizon of the transition, so only BEVs can be purchased. Every household owns an ICEV at the beginning of the transition timeframe. The household might own more than one ICEVs, but the ICEV that covers a greater annual mileage is considered the main household vehicle. When the central planner determines the replacement of the household's main ICEV with a BEV, the BEV becomes the main household automobile. When this occurs, each household uses a preowned, leases, or acquires a back-up ICEV exclusively for range-limited days (i.e., days when the all-electric driving range of the BEV is smaller than the daily vehicle miles traveled -VMT-).

The indices and decision variables are presented here. The driver of the household's main vehicle is $i \in \mathrm{I} = \{1,2,\dots,I\}$, and the time period is denoted by $t \in \mathrm{T} = \{0,1,2,\dots,T\}$. The households' number I is assumed to be constant during the planning horizon. Should a small planning horizon is selected, the replacement decisions are severely affected. Therefore, an adequately long planning horizon is allowed to accommodate at least the 80% target level of household ICEV replacement. All households use passenger cars as their main mode of transport. The central planner at the end of each year t makes the decision of replacing or keeping the old vehicle for each driver i. The replacement of the ICEV for each i can occur at most once during the planning horizon; when this decision is made, the ICEV retires and its residual value is considered. Then, a BEV becomes the main household vehicle. However, the central planner may make the decision to replace the household's BEV with a new BEV, if this results in cost savings. If the old vehicle is kept at year t, the central planner faces a similar replacement decision at year $t+1$. If household i at time t operates a BEV $X_i^{(t)} = 1$ holds, otherwise $X_i^{(t)} = 0$. When household i purchases a BEV at the end of year t then $Y_i^{(t)} = 1$. We allow $Y_i^{(t)}$ to be 1 more than once, in order to enable the planner to replace a BEV with a newer BEV. When entering period t, the vehicle in use depreciates based on an exogenous process.

The all-electric driving range denoted by r is determined by the social planner and is assumed constant during the planning period. The transportation network herein is assumed to resemble a linear city where the density of charging stations can be represented as the distance between stations, denoted as $w^{(t)}$ in miles. Note that public charging is considered a crucial factor for BEV adoption decisions (e.g., Lieven 2015; Carley et al. 2013; Egbue & Long 2012). Given that workplace chargers are found to be an effective method for reducing societal cost in similar studies, e.g., Kontou et al. (2015), it is deemed worthwhile to investigate the benefits of public-charging installation for the electrification process. As the number of public chargers on the network is expected to increase every year of our planning horizon, we allow the capital and installation cost annuity of the charging deployment to be received over the lifetime of the public chargers. The cost component parameters included in this study are either extrapolated based on historical data, or assumed to be constant where appropriate.

The mixed integer non-linear programming formulation is presented here:

$$\min z =$$

$$\sum_{t\in T}\Big(\sum_{i\in I}\Big(\big(B^{(t)}(r)-\Delta_i^{(t)}\cdot(1-X_i^{(t)})\big)\cdot Y_i^{(t)}+\big(O_{EV}{}_i^{(t)}(r)+E_{EV}{}_i^{(t)}(r)+A_{o}{}_i^{(t)}(r)+A_{e}{}_i^{(t)}(r)+ \quad (1)$$

$$I_i^{(t)}(r)+H\big)\cdot X_i^{(t)}+\big(M_i^{(t)}+O_{CV}{}_i^{(t)}+E_{CV}{}_i^{(t)}+F_i^{(t)}\big)\cdot\big(1-X_i^{(t)}\big)\Big)\cdot(1+\delta)^{-t}\Big)+P^{(t)}\cdot(1+\delta)^{-t}\Big)$$

subject to:

$$X_i^{(t+1)} \le X_i^{(t)} + Y_i^{(t)} \quad \forall\, i \in I,\ t \in T \tag{2}$$

$$X_i^{(t+1)} \ge Y_i^{(t)} \quad \forall\, i \in I,\ t \in T \tag{3}$$

$$X_i^{(t+1)} \ge X_i^{(t)} \quad \forall\, i \in I,\ t \in T \tag{4}$$

$$X_i^{(1)} = 0 \quad \forall\, i \in I \tag{5}$$

$$r_l \le r \le r_u \tag{6}$$

$$X_i^{(t)}, Y_i^{(t)} \in \{0,1\} \tag{7}$$

$$w^{(t+1)} \le w^{(t)} \quad \forall\ t \in T \tag{8}$$

where $B^{(t)}(r)$ is the cost of purchasing a BEV; $\Delta_i^{(t)}$ is the cost of trading in the old ICEV; $O_{EV_i}^{(t)}(r)$ is the operational cost of the BEV; $E_{EV}{}_i^{(t)}(r)$ denotes the environmental cost associated with BEV operation; $A_{o_i}^{(t)}(r)$ is the cost of the user associated with the operation of a back-up conventional vehicle while owning a BEV; $A_{e_i}^{(t)}(r)$ is the cost associated with the environmental externalities when operating the back-up ICEV; $I_i^{(t)}(r)$ is the inconvenience cost associated with the time spent while charging the BEV, and H is the home-charger installation cost. For ICEVs, $M_i^{(t)}$ is the maintenance cost for the user i; $O_{CV}{}_i^{(t)}$and $E_{CV}{}_i^{(t)}$ are the operating and environmental costs, respectively, and $F_i^{(t)}$ is the yearly cost of refueling the ICEV's tank. $P^{(t)}$ is the capital and installation cost of deploying public charging on the linear city, which is incurred by the government. The present worth (discount) factor is $(1+\delta)^{-t}$, with δ as the discount rate. Most of the costs associated with BEVs are a function of the all-electric driving range, which is one of the decision variables.

The objective function (1) is the total social cost of the described replacing process that we aim to minimize. The optimization framework determines the replacement of an ICEV with a BEV for each i each year t, the battery size r that the market should provide during the planning period, and the distance between public chargers $w^{(t)}$ that is expected to decrease over the years as the government deploys more stations on the linear corridor road network. Constraints (2), (3), and (4) ensure vehicle preservation. When the social planner determines that a household a at the end of year t_1 purchases a BEV, then $Y_a^{(t_1)} = 1$ holds and a operates a BEV at year $t_1 + 1$ as $X_a^{(t_1+1)} = 1$ holds. If household a has not purchased a BEV at year t_1 as denoted by $Y_i^{(t_1)} = 0$, or it does not use a BEV at t_1 denoted by $X_a^{(t_1)} = 0$, then the household does not operate a BEV at year $t_1 + 1$ and thus $X_a^{(t_1+1)} = 0$. However, this constraint combination allows the household to own a BEV at year t_2 with $X_a^{(t_2)} = 1$, and the central planner to decide to replace it with a new BEV, hence $Y_a^{(t_2)} = 1$, yielding $X_a^{(t_2+1)} = 1$. Constraint (5) demonstrates that at year $t = 1$ all household vehicles are conventional ones. Constraint (6) sets the lower r_l and upper r_u bounds of r to be 40 and 300 miles, based on the smallest and largest range of the latest BEV technology market available (U.S. Department of Energy 2015). Constraint (7) sets $X_i^{(t)}$ and $Y_i^{(t)}$decision variables to be binary. Constraint (8) ensures that public charging infrastructure is being placed more densely on the linear city over the years of the planning horizon. The relative relationship between the all-electric driving range and the spacing between chargers defines the expected extended electric driving range of each BEV after recharging. Therefore, additional constraints should be added to the model in order to account for the extended driving range, as those are presented on the "Battery Electric Vehicle Costs" subsections.

Conventional Vehicle Costs

Cost components introduced in the objective function are related to ICEV and BEV purchase and operation. The ICEV cost in dollars per year consists of a maintenance component as in Eq. (9), an operational as in Eq. (10), an emissions related as in Eq. (11),a refueling related as in Eq. (12), and a trade-in component as in Eq. (13). These costs are a function of the annual VMT and the age of the household ICEV. The driving patterns of each household are assumed to be the same over the planning timeframe, due to the unavailability of time series data at the household level.

The maintenance cost is estimated by:

$$M_i^{(t)} = d_i \cdot m_g \cdot (1 + \theta_m)^{j_i + t}, \tag{9}$$

where d is the annual VMT; m_g is the average yearly maintenance cost in \$ per mile for a medium sedan vehicle considering engine issues, braking, and fluids; θ_m is the average increase rate of the maintenance cost per year; and j_i is the age of the vehicle at the beginning of the planning horizon. Due to the wear and tear of the ICEV components over the years, maintenance cost increases at a rate of $(1+\theta_m)^{j_i+t}$. An upper bound for the vehicle driving years is not considered.

The operational cost of the conventional vehicle is also related to the annual VMT, as shown in Kontou et al. (2015):

$$O_{CV}{}_i^{(t)} = d_i \cdot p_g(t) \cdot \frac{1}{n_g}, \tag{10}$$

where $p_g(t)$ is the pre-tax price of gasoline in \$/gallon, under the assumption that the pre-tax price equals the cost, and n_g is the gasoline efficiency in miles per gallon (mpg), under the assumption that the impact of a vehicle's age on mpg is negligible. The ICEV operational cost is an increasing function of gasoline cost, and is thus increasing over time.

The monetized environmental externality in \$/year is estimated as:

$$E_{CV}{}_i^{(t)} = d_i \cdot v_g \cdot \frac{1}{n_g} \cdot SCC(t), \tag{11}$$

where v_g is the well-to-wheels gasoline emission factor in average $kgCO_2$-equivalent per gallon and $SCC(t)$ is the social cost of carbon in \$ per $kgCO_2$-equivalent. The social cost of carbon is monetizing "the damages of increasing the levels of CO_2 emissions, considering the economic costs of the climate change" (Environmental Protection Agency 2013). The ICEV emissions are attributed to gasoline consumption and upstream processes (e.g., oil refinement). The Environmental Protection Agency projects an increase in the social cost of carbon, so this cost component is an increasing function of time.

The refueling time cost in \$/year is estimated as:

$$F_i = d_i \cdot \frac{1}{n_g} \cdot \frac{1}{cap} \cdot \tau_f \cdot c_{idle}, \tag{12}$$

where cap is the average capacity of an ICEV's fuel tank in gallons; τ_f is the average rate of refueling in hours per gallon based on the maximum allowable fuel dispensing limit (Environmental Protection Agency 1996) and c_{idle} is the cost of waiting while refueling in \$ per hour (Ayala 2014). There is no literature projecting that cost, hence we assume that it is constant over the years. Note that the value of this cost component is marginal compared to the rest of the ICEV cost values.

The societal cost accounts also for the vehicle's end-of-life residual value. At the end-of-life, scrapped ICEVs might be used as maintenance parts for the rest of the fleet. Therefore, the residual vehicle value (if any, due to vehicle depreciation) is subtracted from the BEV purchase cost. The vehicle residual value is approximately captured by the trade-in cost. Hence, it is a function of the ICEV's age (Feng & Figliozzi 2013). All conventional vehicles are considered eligible for trade-in. The cost of the trading-in process is estimated for all ICEVs as:

$$\Delta_i^{(t)} = p_{c_i} \cdot (1-\theta_{tr})^{j_i+t}, \tag{13}$$

where p_{c_i} is the ICEV cost of purchase in pre-tax dollars and θ_{tr} is the rate that this cost decreases as a function of $j_i + t$. The cost differs for each user depending on the vehicle's age and the years of owning the vehicle. The users who have acquired used ICEVs are identified and p_{c_i} cost is reduced for those accordingly. Due to the depreciation of the owned ICEVs over time, the residual value of each vehicle is a decreasing function of time.

Battery Electric Vehicle Costs

The BEV cost consists of the purchase cost in Eq. (14), the operational cost, and the environmental cost. Additional BEV costs associated with driver range-anxiety and recharging are introduced in the following subsections.

The BEV purchase cost is the summation of the battery pack cost, modified from Lin (2014), and the vehicle body cost c_b:

$$B^{(t)}(r) = r \cdot n_e(r) \cdot B(r) \cdot (1-\theta_{br})^t \cdot \frac{1}{h_b} + c_b, \tag{14}$$

where $n_e(r)$ is the on-board electricity usage rate in kWh/mile; $B(r)$ is the battery pack cost in \$/kWh, which is expected to decrease by a rate of θ_{br} as the battery capacity increases under the assumption of economies of scale, and h_b is the battery utilization factor, i.e., the ratio of usable capacity over the total battery capacity. As the total battery capacity increases, the size of the battery pack increases and the BEV has a greater r. However, the on-board electricity usage rate will increase with r due to its heavier battery pack.

The vehicle body cost c_b is not a function of r. The vehicle body materials and parts are susceptible to changes over the years. Hence, so is the cost. However, due to the unavailability of related data, c_b is assumed to remain constant over the planning horizon.

Financing options regarding vehicle ownership are not considered; such options might be based on various exogenous factors, such as the dealership options or the income of the consumer. In addition, the BEV maintenance cost is not introduced here due to the absence of sufficient datasets that could describe the relationship between this cost component and the driving range r. Given that the majority of the batteries in the market have an 8-year battery pack warranty, the cost of battery swapping (if needed during that period) should be incurred by the manufacturer (Office of Energy Efficiency and Renewable Energy 2016).

The home charging installation cost H is not a function of r. We assume that it remains constant during the planning horizon, even though the cost is expected to decrease with time due to economies of scale. The BEV owner bears the home charging capital and installation cost annuity over the lifetime of the chargers. Therefore, $H = c_{hch} \cdot CRF$, where c_{hch} is the cost in $ per home charger (purchase and installation) and the capital recovery factor $CRF = \gamma \cdot \frac{(1+\gamma)^n}{(1+\gamma)^n - 1}$, where n denotes the charger lifecycle and γ signals the interest rate.

The annual BEV operational, environmental, and range-anxiety costs are a function of the availability of public charging and also depend on the VMT of the households. Public charging placement allows for greater VMT electrification and reduces the range-anxiety cost for range limited days. In order to capture this effect, we assume that both public chargers and travel demand are uniformly distributed along a linear city/corridor, an assumption that was also made in the studies of He et al. (2013) and He et al. (2015). Two cases are investigated, which result in the additional modeling constraints presented below.

P1: Distance between chargers less than or equal to the all-electric driving range

When the spacing distance w between two public chargers for a certain year t', is less than or equal to the all-electric driving range r, BEV drivers can always recharge their batteries before depletion. This implies that they can drive on electricity as far as they want, with extended all-electric driving range $\hat{r}$ equal to the maximum daily distance covered x_m ($\hat{r} = x_m$). However, drivers would avoid recharging constantly due to the high inconvenience cost associated with the idle time during recharging. Hence, drivers set critical ranges $\overline{r}_i$; when the daily driving miles exceed $\overline{r}_i$, they use their back-up ICEV. The lower bound of $\overline{r}_i$ can be estimated using Figure 1.

The distance between two consecutive public chargers on the linear transportation network is w miles. For the P1 case, additional constraints are imposed on the optimization framework, which are presented below:

$$w^{(t)} \leq r, \tag{15}$$

$$\overline{x}_i \geq \overline{r}_i^{(t)}. \tag{16}$$

The annual BEV operating cost, modified from Lin (2014), is presented here:

$$O_{EV\,i}^{(t)}(\overline{r}_i) = 365 \cdot p_e(t) \cdot n_e(r) \cdot \frac{1}{n_c} \cdot \int_0^{\overline{r}_i^{(t)}} x \cdot p_i(x; k_i, \theta_i)\,dx, \tag{17}$$

where $p_e(t)$ is the electricity pre-tax price in $/kWh as a function of time; n_c is the charging efficiency, and $p_i(x; k_i, \theta_i)$ is the probability density function of the random daily VMT denoted as x, with k_i as the shape and θ_i as the scale parameter of the x distribution.

The annual environmental cost of a BEV, associated with the production of the electricity that powers it, is estimated by Eq. (18). Note that BEVs do not produce tailpipe emissions as ICEVs do.

$$E_{EV\,i}^{(t)}(\overline{r_i}) = 365 \cdot SCC(t) \cdot v_e \cdot n_e(r) \cdot \frac{1}{n_c} \cdot \int_0^{\overline{r_i}^{(t)}} x \cdot p_i(x; k_i, \theta_i) dx \tag{18}$$

where v_e is the average kgCO$_2$-equivalent/kWh of electricity consumed.

Range-anxiety is identified as a major deterrent in BEV adoption e.g., Carley et al. (2013) and Egbue & Long (2012). It is defined as the fear of exhausting the all-electric driving range on the road before reaching a charging station. Range-anxiety is captured as the additional cost needed to accommodate travel needs on range-limited days (Lin 2014). The user cost of operating a back-up ICEV during those days is noted in this paper as range-anxiety cost. Eq. (19) estimates the operational cost of usage of a back-up ICEV. The first addend captures the fixed cost of obtaining an ICEV as a back-up and the second the cost of operating it. Eq. (20) captures the monetized environmental externality of operating the back-up vehicle. Eq. (21) presents the inconvenience cost of recharging the BEV. The refueling time is used to capture the inconvenience cost of recharging; this cost component has been also considered in Nie et al. (2016). Time of recharging is considered a cost for the BEV operator. We assume that this time is spent waiting instead of participating in another activity. However, this may be an overestimate of the cost, as drivers may have a productive use of their recharging time.

$$A_{o\,i}^{(t)}(\overline{r_i}) = 365 \cdot \rho_i \cdot \int_{\overline{r_i}^{(t)}}^{x_m} p_i(x; k_i, \theta_i) dx + 365 \cdot p_g(t) \cdot \frac{1}{n_g} \cdot \int_{\overline{r_i}^{(t)}}^{x_m} x \cdot p_i(x; k_i, \theta_i) dx \tag{19}$$

$$A_{e\,i}^{(t)}(\overline{r_i}, t) = 365 \cdot SCC(t) \cdot v_g \cdot \frac{1}{n_g} \cdot \int_{\overline{r_i}^{(t)}}^{x_m} x \cdot p_i(x; k_i, \theta_i) dx \tag{20}$$

$$I_i^{(t)}(r, \overline{r_i}) = 365 \cdot \int_r^{\overline{r_i}^{(t)}} (x - r) \cdot \mu \cdot p_i(x; k_i, \theta_i) dx \tag{21}$$

where ρ is the range limitation cost associated with household vehicle flexibility in daily \$ per mile; x_m are the maximum daily vehicle miles traveled, and $(x - r) \cdot \mu$ is the potential recharging cost, with μ as the cost of time while recharging in \$ per mile.

P2: Distance between chargers greater than the all-electric driving range

When $w > r$ the BEV range is less than the distance between chargers; thus, the expected extended driving range $\hat{r}$ is calculated based on Figure 2. The expected extended all-electric driving range is estimated as the summation of the stripped area of Figure 2 $\left(\int_0^r (x + r) \cdot \frac{1}{w} dx\right)$ and the dotted area $\left(\int_r^w r \cdot \frac{1}{w} dx\right)$ as $\hat{r} = \frac{r^2}{2w} + r$, for a specific year t'. The former integral denotes the portion of the average extended range contributed while conducting a trip shorter than the all-electric driving range, considering encountering a charger within the all-electric driving range of the vehicle, much like the previous case in Fig. 1. The latter integral captures the portion of the average extended range that accounts for the case when a driver, while covering her or his daily VMT, might encounter a charger after the battery has been depleted.

The additional constraint that needs to be added here is $r < w^{(t)}$. The strict inequality is relaxed in order for the feasible region to be closed. Regarding P2, the constraints added to the set of Eqs. (1-8) to complete the described framework are:

$$w^{(t)} \geq r, \tag{22}$$

$$\hat{r}^{(t)} = \frac{r^2}{2w^{(t)}} + r. \tag{23}$$

In this case, the BEV operational, environmental, range-anxiety and inconvenience costs are estimated by Eq. (17), (18), (19-20), and (21), respectively, but expected extended range $\hat{r}$ replaces $\overline{r_l}$.

Public Charging Infrastructure Cost

The objective function incorporates the capital cost of the public charging stations P. A linear city/corridor is considered. The size of it is estimated as the maximum driving distance x_m of the sample multiplied by the size of the data sample N. Therefore, the number of chargers on the network can be calculated as $N \cdot \frac{x_m}{w^{(t)}}$. This number is expected to increase annually. The annuity collected over the lifetime of the chargers represents the government investment, which is introduced in Eq. (23):

$$P^{(t)} = N \cdot \frac{x_m}{w^{(t)}} \cdot c_l \cdot CRF, \tag{23}$$

where c_l is the cost of the appropriate level public charging infrastructure in \$ per charger and CRF is the capital recovery factor.

Data

The proposed framework is applied to a sample dataset that pertains to the National Household Travel Survey 2009 data (U.S. Department of Transportation and Federal Highway Administration 2009). In order to generate a sample, data filtering is performed based on the following criteria:

- The main vehicle of the household is identified; users from the same household are not included in the study due to potential correlation of their driving patterns.
- The household vehicle is a passenger car such as a compact, sedan, or station wagon; pick-up trucks, SUVs, and larger vehicles are excluded from this study.
- The vehicle is not carrying a commercial license plate.

- The household driver is a worker; the number of days working from home are equal to or less than five.
- The working trip is conducted by the main automobile and not with other means of transport, such as transit, bike, etc.
- The workplace location is not the same location as the location of residence.
- All entries contain complete information.

We assume that each household's VMT follow a gamma distribution. Various literature sources support this assumption, e.g., Greene (1985) and Lin et al. (2012). However, some studies fit a log-normal distribution (Plötz 2014), while others propose the superposition of a broad exponential distribution and a narrow Gaussian that require more than two parameters (Tamor et al. 2013).

Due to the absence of trip chain data, the circle distance from home to work and work to home is assumed to be the most common trip of each household and, thus, the mode of gamma distribution. The mean of gamma distribution is assumed to be the daily VMT, denoted by $\overline{x_i} = \frac{d_i}{365}$. By solving the system of Eq. (21), (22), and (23), we calculate the shape (k_i) and scale (θ_i) parameters for each household i:

$$mode_i = (k_i - 1) \cdot \theta_i, \forall_i \tag{21}$$

$$\overline{x_i} = k_i \cdot \theta_i, \forall_i \tag{22}$$

$$k_i > 0, \theta_i > 0, \forall_i \,. \tag{23}$$

The fixed daily range limitation cost in Eq. (24) is associated with the vehicle flexibility of each household. The vehicle flexibility H_{vf} in Eq. (25) captures the ease of obtaining a back-up ICEV. The H_{vf} notion stems from the study of Lin (2014).

$$\rho_i = \begin{cases} \rho_1 \,, & H_{vf} \leq 1 \\ \rho_2 + (\rho_1 - \rho_2) \cdot \left(2 - H_{vf_i}\right), & 1 < H_{vf} < 2 \\ \rho_2, & H_{vf} \geq 2 \end{cases} \tag{24}$$

where ρ_1 is the upper bound and ρ_2 is the lower bound of the daily fixed range limitation cost.

$$H_{vf_i} = \frac{H_{vno_i}}{\min\left(H_{wno_i}, H_{dno_i}\right)}, \tag{25}$$

where H_{vno_i} is the number of vehicles, H_{wno_i} is the number of workers, and H_{dno_i} is the number of drivers in the household. As the number of workers or drivers in a household increases, it is harder to obtain a back-up vehicle within the household, and since $H_{vf} \leq 1$, the fixed limitation cost is the cost of a rental ICEV, denoted as ρ_1. As the number of vehicles owned in a household increases, the indicator value increases. When $H_{vf} \geq 2$, ρ_i equals ρ_2, denoted as the amortized discounted cost of a purchased back-up ICEV. Descriptive statistics of the sample household dataset are presented in Table 1.

Figure 3 presents the cost parameter trends fitted on data projections. All inputs are “valued in efficiency and not in market prices,” as we capture costs and not prices (Newbery and Strbac 2014).

Figure 3a shows that as the battery size increases, the battery pack cost is expected to decrease in $ per kWh. Figure 3b portrays that the bigger the battery, the heavier the vehicle and the lower the efficiency in kWh per miles. Parameters on Figure 3a and 3b are from the Environmental Protection Agency et al. (2010). Figure 3c depicts the trend of the battery cost, corresponding to an 80-mile driving range, over time. As the θ_{br} rate increases, the battery pack cost decreases at a faster pace over the years of the planning horizon due to economies of scale. Figure 3d and 3e portray the electricity and the gasoline pre-tax prices evolution, respectively. The base case utilizes 2015 Energy Outlook data (U.S. Department of Energy 2013a), and the low and high value scenarios come from Newbery and Strbac (2014) projections. Figure 3f shows the trajectory of the social cost of carbon from the Environmental Protection Agency (2013). In that graph, a higher discount rate leads to a decreased net present social cost of carbon value. Overall, an optimistic case is the one that leads to lower social costs; otherwise, the projection is considered pessimistic.

Note that the social cost of electricity depends on the time and location of recharging, e.g., He et al. (2015) and He et al. (2013); however, addressing this is beyond the scope of this study.

The average cost of the electric vehicle body is the average sticker price of the 2015 BEV models from the U.S. Department of Energy (2015) minus the average state tax, multiplied by the percentage corresponding to the vehicle body without the battery pack cost. The purchase price of the conventional vehicle pc_i is estimated through time series data of average pre-tax new or used ICEV market prices for each year (Kelley Blue Book 2015). We assume that all households have the capability of installing home chargers, although this might not hold (Traut et al. 2013). Residential charging infrastructure is assumed to be residential level 2, and the public charging infrastructure is assumed to be public level 2. There are significant differences in the installation and capital costs for those charging equipment (Idaho National Laboratory 2015). The capital recovery factor for chargers is estimated with a $\gamma = 7\%$ interest rate and a compound period of n =25 years, which is essentially the projected lifecycle of the charging stations. Table 2 presents the parameters of the base case and the alternative scenarios, along with their sources.

Results

Figure 4 portrays the cost curves, considering an annual VMT value of 12,422 for a medium sedan conventional vehicle. For Figures 4(b, c, d, e, f, g), $r \in [1,300]$ and the distance between chargers on the linear city road network is assumed to be $w^{(t)}$ =150 miles $\forall\, t$. Figures 4(b, c, d, e, f, g) portray the cost curves for years 1, 10, 20, and 30. Figure 4 costs are estimated using the average data values of our sample, as those are presented in Table 1.

The environmental externalities and the refueling cost are at a maximum 5% and 3% of the operational cost of the ICEV, which is portrayed in Figure 4a. These costs are not expected to play a vital role in ICEV replacement decisions. ICEV maintenance and trade-in costs increase and decrease respectively over time due to vehicle depreciation. The operational cost growth rate is 1.07% and is only affected by the gasoline cost trajectory, which is increasing over time for the base case.

The BEV battery pack cost is the largest cost component in the case of large batteries. As smaller batteries may cause range-anxiety, the cost associated with operating a back-up ICEV becomes larger than the battery pack cost. This occurs due to the necessity of owning a back-up ICEV vehicle for range-limited days. The operational and environmental cost curves are estimated both for $r < w^{(t)}$ and $r \geq w^{(t)}$. The curves are continuous at $r = w^{(t)}$ where the two cost branches meet, estimated from $P1$ and $P2$. Figures 4e and 4f show that small all-electric driving ranges are penalized compared to larger ones, as drivers of such vehicles are more susceptible to experiencing range-anxiety and pay more for a back-up, gasoline-fueled, vehicle. In Figure 4e, the operational anxiety cost has little variation over the years since the fixed, annual "limitation" cost of obtaining a back-up ICEV is the largest addend. In Figure 4g the inconvenience cost increases exponentially when $r < 150$ miles. The branch that corresponds to $r \geq 150$ indicates that for all-electric driving ranges larger than 200 miles the cost decreases, since the probability of driving above that mileage is low due to gamma's distribution thin tail.

Overall, the high cost of a BEV acquisition indicates that the savings from operating the BEV for users over the planning horizon should be at least in the magnitude of tens of thousands. This would imply that those covering a greater annual VMT would benefit society more when switching from ICEVs to BEVs and potentially drive the market to provide higher BEV ranges to maximize benefits from the transition. However, considering the high cost of purchasing BEVs with greater r in the beginning of the planning phase, an estimation of the optimal r value is a conundrum.

Figure 5 shows the plots of the costs associated only with BEVs. Compared to Figure 4, Figure 5 cost components are drawn for $w \in [10, 400]$, for $t = 1$, and for some indicative values of the all-electric driving range r in miles (specifically 50, 100, 150, 200).

Figure 5 costs are also calculated using the average data values. The cost component calculations are different when $r \geq w^{(1)}$ for $P1$ and $r < w^{(1)}$ for $P2$, as we presented in the "Methodology" section and also pointed out in Figure 4. The curves change trajectory at point $r = w$, as expected. Figure 5a shows that the BEV operational cost increases exponentially when the range is less than the spacing distance between public chargers and decreases exponentially as the public charging spacing increases relative to the range of the BEV. When the range is less than the distance between chargers, as the spacing increases, the probability of finding a charger decreases. This causes the operational cost to increase. However, when the range is greater than the spacing, the driver can potentially electrify the whole trip, in which case the cost associated with the operation decreases. A similar trajectory follows the BEV environmental externality in 5b due to the production of the electricity that powers the BEVs, and the inconvenience cost in 5e due to recharging. As expected, 5c and 5d mirror Figures 5a and 5b because they portray the cost associated with operating back-up ICEVs.

The mixed integer non-linear *P1* and *P2* programs are solved using CONOPT solver (Drud 1994) in GAMS 23.3 (Rosenthal 2015). The all-electric driving range space is discretized, and the optimization problem was solved for each discrete electric driving range r that belongs to the interval $[40, 300]$ in order to avoid running out of memory. Discussion on the results is presented in the following subsections.

Base Case Results

The base case results indicate that the optimal solution is obtained when $r \geq w^{(t)}$ from $P1$. Figure 6a portrays the optimal cumulative penetration rate of BEVs for base and fuel cost alternative scenarios. Figure 6b shows the minimum average annual social costs of each household vehicle technology for the base case parameters. Figure 6c shows the average VMTs of the ICEVs being replaced, as well as those being used, for the base case scenario.

Specifically, our findings indicate that approximately 8 years are needed for 80% of the US household ICEVs in our sample to be replaced by BEVs. For 9,952 households, the replacement process lasts a total of 31 years. By allowing for a large planning horizon we essentially force a 100% ICEV replacement rate. We chose to comment on an 80% BEV penetration achievement as a more realistic electrification goal. The BEV adoption rate increases rapidly in the beginning of the planning years, as it is socially optimal to replace 50% of the ICEVs by the 2nd planning year, and then the rate decreases gradually, as portrayed in Figure 6a. Our findings support that it is in society's best interest to achieve a fast transition from conventional technologies to electric ones. On the other hand, behavioral studies that model BEV market acceptance show that such a transition might occur slowly, e.g., Greene et al. (2014) estimates the market share of BEVs as only 38% by 2050.

For the base case, the optimal all-electric driving range of the BEVs is r=204 miles. The optimal distance between public chargers is 172 miles at year 1 and stays constant for the rest of the years ($w^{(t)} = 172, \forall\, t$). This result indicates that all deployed public charging stations should be in place as early as possible in order to receive greater savings later in the planning horizon. This finding is well-aligned with Nie et al.'s (2016) results, a study also describing a central-planner's optimization model for determining the government's investments on public charging infrastructure and electric vehicle subsidies. The optimal extended all-electric driving range is $\overline{r_i}^{(t)}$ ≥290 miles for every year t.

BEVs become more attractive under the scenario of increased gasoline cost, which results in reaching 80% BEV diffusion in just 7 years. Under the assumption of decreased gasoline costs, the ICEV product becomes more attractive and the replacement process reaches 80% in approximately 9 years. Increased electricity cost projection causes reaching the cumulative BEV 80% penetration goal 1 year after the base case, whereas optimistic projection of electricity cost results in faster BEV diffusion, reaching the goal of 80% 1 year earlier.

Figure 6b showcases the base case scenario annual costs. Note that the BEV purchase cost consists of the battery pack and vehicle body costs minus the ICEV trade-in cost. The BEV operation cost portrayed there is the summation of operational, environmental, range-anxiety and inconvenience costs, and the ICEV operation cost accounts for maintenance, operation, environmental, and refueling costs. The average cost of purchasing a BEV is approximately the same during the years portrayed; the trend slightly varies because the battery pack cost decreases over time and the trade-in cost varies according to the ICEV population replaced. ICEV operational costs increase over time due to depreciation of the vehicles. BEV costs increase over the years due to the cost components projections, which increase over time.

Interestingly, the average VMT of ICEVs that are not replaced by BEVs in our model and remain in the market decrease over time. This indicates that society benefits more from replacing first household vehicles that cover greater annual mileages because this results in lower cumulative operational and environmental costs.

The socially optimal BEV penetration rates can be compared with the findings from market-based models. It should be noted that the assumptions of each model vary significantly, and thus comparisons are primarily presented to raise further discussion.

The annual energy outlook provides vehicle stock projections as references for the penetration of alternative fuel vehicles, such as battery electric ones, in the years to come. Those are based on the National Energy Modeling System (NEMS), “a market-based approach subject to regulations and standards” (Energy Information Administration 2009). Findings showcase that BEVs would account for 1.33% of the market in a 15 year span and 2.10% in 25 years (Energy Information Administration 2015a). Another modeling approach, named Market Adoption of Advanced Automotive Technologies (MA^{3}T), is a multi-variable nested-logit model, which also aims to provide insights on the penetration of various passenger car technologies. This model projects that BEVs might take up approximately 15% of the total market share by 2050 (Oak Ridge National Laboratory 2015). Findings of this work showcase that faster battery pack cost reduction can significantly increase BEV diffusion over time, similarly to our findings.

In a similar manner, Greene et al. (2014) utilize a consumer behavior model with various feedback loops to project BEV diffusion. There researchers show that in an approximately 25 year-span the BEV diffusion will take up 5% of the total market share, reaching eventually 38% by 2050. Nie et al.

(2016) numerical examples, using a model that captures consumer behavior, projects BEVs reaching approximately 10% of the market share in a 30-year planning horizon. After optimizing incentives, the market share in a 30-years span, for the consumer segment of frequent drivers, is found to exceed 20%. This study concludes that increasing gas prices over time can significantly favor BEV adoption, which is in accordance with our findings. Consumers stated preferences results are more optimistic; for instance, Krause et al. (2016) showcase that 44% of the sample intent to adopt BEVs under the scenario of cost parity. In line with our findings, the aforementioned study also points out that the new electric vehicle's cost has the greatest impact on BEV diffusion.

Obviously, there is a wide gap in terms of the BEV adoption rates projected when comparing behavioral and market results to our findings. This gap was anticipated because: (a) various socio-economic characteristics play an important role in vehicle ownership decisions (e.g., Carley et al. 2013), (b) most consumers resist switching to innovative products immediately, apart from market niches (Green et al. 2014), (c) consumers might not have complete information on the savings they can achieve through BEVs operation (e.g., Carley et al. 2013), and (d) incentives currently might not be designed optimally in order to effectively promote this product (e.g., Nie et al. 2016).

Alternative Scenario Results

More results for alternative scenarios are presented on Figure 7. The differences between the optimal all-electric driving ranges and the optimal distances between charging stations, for each of the parameters in Table 2, are presented in Figure 7a and 7b, respectively.

For all sensitivity analysis cases, the optimal approach is to place all public chargers on the linear network from the 1st year of the planning horizon. Thus, $w^{(t)}$ is constant over the years. Moreover, in all cases is socially optimal to place chargers in distance shorter than the all-electric driving range of the BEVs.

Increased gasoline efficiency means BEV usage becomes cheaper and results in decreasing the all-electric driving range by 6.3%. It also places chargers slightly scarcer, as the optimal value of w increases by 3.4%. Lower ICEV maintenance cost leads to 1.98% smaller optimal $r,$ without significantly impacting w. Faster depreciation of ICEVs (i.e., decrease rate of trade-in cost becomes greater) results in a 3% decrease of the all-electric driving range because purchasing a BEV becomes more expensive; society places chargers more densely on the linear city in this case. A higher battery utilization factor implies that users have to pay less for larger batteries; r increases by 2.45% and w increases by approximately 1.7% in this case. The vehicle body cost impacts severely the optimal r decision; a 50% increase in c_b results in 8.8% decrease in $r,$ as smaller ranges would make BEVs more competitive with ICEV in the beginning of the planning horizon. When it takes longer to transition to economies of scale for battery packs, r decreases by almost 3.9% and the distance between chargers on the network increases by 4.65%. The discount rate has a significant impact on the decision variables of the electric driving range and the distance between chargers. Cheaper home chargers result in savings and make larger battery and longer range BEVs more affordable. A dramatic 63% increase of public charging equipment cost results in 12.2% increase of the distance between chargers. Unsurprisingly, r increases by 10.7% in this case in order to offset high range-anxiety costs; the electrification rate in this case slows down as years go by. Increased gasoline cost results in decreased electric driving range and public charger spacing to make BEVs attractive in the beginning of the planning phase. Under the scenario of optimistic electricity cost projection, r rises only by approximately 1%. The impact of social carbon cost change is marginal relatively to the aforementioned effects for the rest of the parameters.

We further investigate the impact of gasoline cost projection on this vehicle technology transition by accounting for the rebound effect. There the elasticity of the VMT with respect to the gasoline cost is captured. Under the base case, gasoline costs are expected to rise during the next years and VMT are expected to follow a downward trajectory (Greene 2012; Hymel & Small 2015). Our model considers the heterogeneity of daily driving patterns and the daily VMT for each driver follow a gamma distribution but data is not available so as to account for the rebound effect impacts on each individual driver. However, we assume a generalized trend that affects all the vehicle drivers uniformly, leveraging other literature insights. We assume that a conservative 10% increase in the gasoline cost will lead to a short-run 5% decrease in the VMT. We further assume that this relationship is linear, based on the conservative values of the first table in Greene (2012). However, we note that Hymel & Small (2015) suggest that rebound effect is greater when gasoline prices go up rather than when going down, implying a non-linear relationship. Results of our findings are presented in Figure 8.

The results shown in Figure 8 suggest that the rebound effect, on top of the gasoline cost changes, does not have a significant impact on the BEV penetration results. As expected, this effect leads to shifting the curve right, decelerating slightly the BEV penetration under the base and the pessimistic scenario of gasoline cost. On the contrary, under the optimistic scenario, where gas cost decreases over time and VMT increase, the rebound effect leads to a slight acceleration of the BEV penetration by shifting the curve left.

Conclusions

This paper presents a framework that optimizes the replacement of household ICEVs with BEVs by minimizing the social cost during this transition phase without modeling consumer behavior. Therefore, we eliminate the need for a costly behavioral modeling process while enabling policymakers to comprehend the societal cost over the electrification timeframe.

In this study, we account for traveling patterns heterogeneity by introducing operational cost of the households' vehicles based on their daily VMT. We also consider the impact of public charging infrastructure on a linear transportation network, as the density of chargers greatly affects the mileage electrified. We demonstrate the framework empirically using U.S. household, energy, and vehicle market data.

Results underline the sensitivity of the optimal set of BEVs' driving range, public charging density, and the BEV penetration under alternate parameters' projections. Base case results indicate that societal cost is minimized for an all-electric range greater than the distance between charges; costs associated with BEV operation and range-anxiety are minimized this way. Targeting the electrification of 80% of the household fleet, the transition lasts approximately 6 to 12 years under alternative scenarios. Faster transition is achieved when gasoline cost is projected to increase, electricity is projected to decrease, discount rate is higher, batteries are cheaper and ICEVs depreciate faster. Decision variables are more sensitive to gasoline costs, discount rate, battery pack and vehicle body costs, and ICEVs fuel economy.

Limitations of the proposed methodology are discussed here. Obviously, the model proposed in this work cannot be used to infer BEV market penetration, which is driven by consumer preferences. Socio-economic factors and market considerations impact such ownership decisions (Krause et al. 2016). Also, word-of-mouth and social network influences (Eppstein et al. 2011), which might impact the diffusion of innovative products, such as BEVs, are not accounted for in this work, because adoption decisions are made centrally. In addition, the modeling framework is based on certain assumptions that significantly affect the resulting BEV adoption timeline, which is generally the case for any modeling framework. However, this work is successful in pinpointing BEV adoption target goals by minimizing costs incurred by stakeholders who comprise society, such as the users and the government. Defining socially optimal BEV penetration target levels is the first step towards the development of a plan for sustainable electrification of the vehicle fleet. Therefore, the BEV penetration timeline resulting from our model can be utilized by policymakers to set targets for BEV market share over the planning horizon when, e.g., designing subsidies to be distributed to consumers, so as to accelerate the adoption of BEVs.

Future research should focus on comparing the social optimum electrification rate of this study with the actual trends of vehicle ownership decisions that household drivers make on a national level and quantify the magnitude of societal gains or losses resulting from consumer behavior. The framework can be modified to add more vehicle types as replacement challengers, such as BEVs with diverse all-electric driving ranges or plug-in hybrid electric vehicles and hybrid vehicles.

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Figure 1. Expected extended driving range estimation when $r \geq w^{(t)}$.

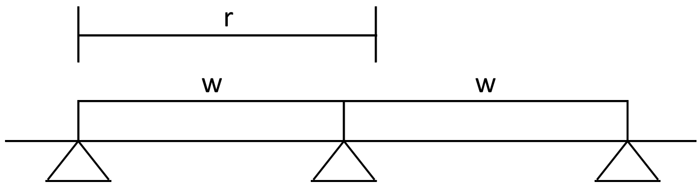

Figure 2. Expected extended driving range estimation when $r < w^{(t)}$.

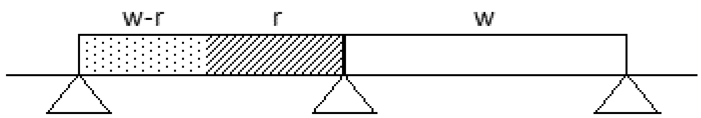

Table 1. Descriptive Statistics of the NHTS 2009 Data Sample (1mile ≈ 1.609km)

	d_i	H_{dno_i}	H_{wno_i}	H_{vno_i}	Hvf_i	ρ	$\overline{x_i}$	$mode_i$	j
Mean	12422	1.99	1.54	2.16	1.52	35.49	38.44	6.89	5.26
Std. Dev.	7779	0.74	0.66	0.99	0.74	16.16	48.75	9.49	3.48
Max	90024	7.00	5.00	11.00	9.00	50.00	246.64	181.00	15.00
Min	369	1.00	1.00	1.00	0.33	15.00	1.01	0.00	1.00
Sample Size	9952								

Figure 3. Fitted equations of the model parameters (1 mile ≈ 1.609 km).

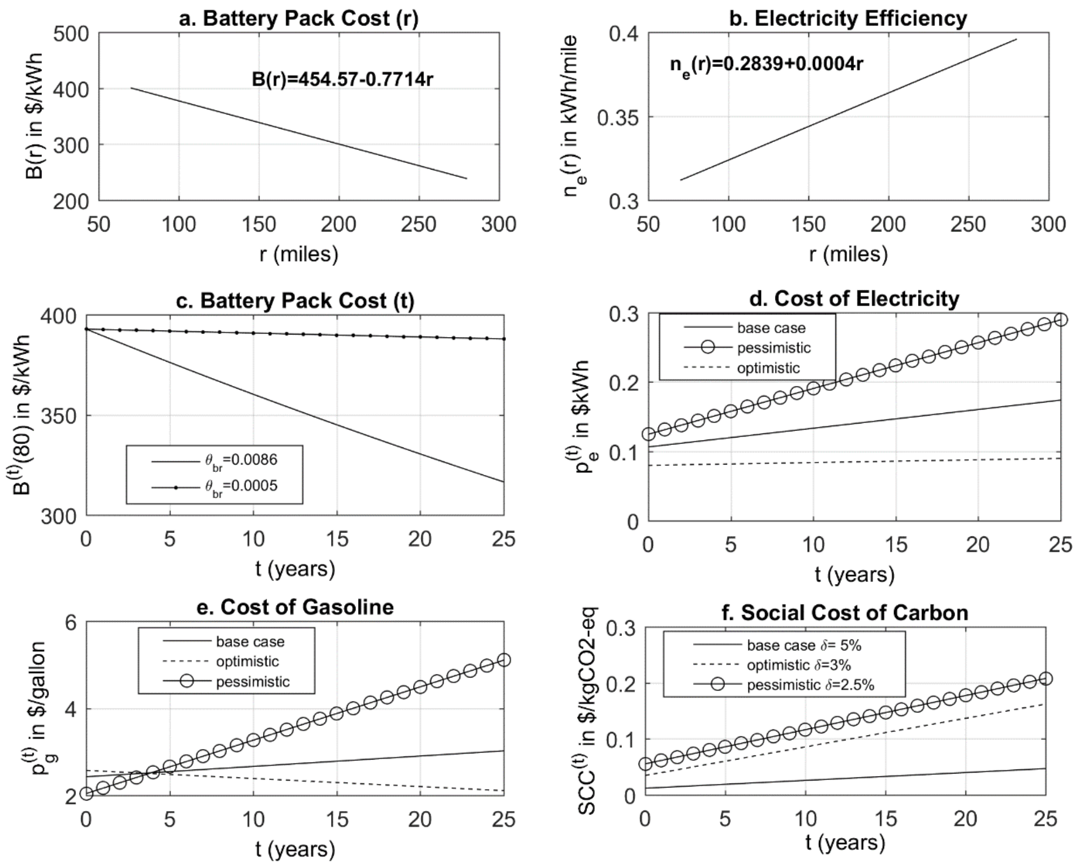

Table 2. Base Case and Alternative Scenarios Parameters (1 mi ≈ 1.609 km; 1 gallon ≈ 3.785 liters)

Parameters	Base	Sensitivity Analysis		Parameter References
		Optimistic	Pessimistic	
Increase rate of maintenance cost θ_m	0.25	0.20	0.30	Kelley Blue Book (2015) (data analysis)
Average annual maintenance cost in $ per mile m_g	0.0492	n.a.		AAA (2013)
Gasoline efficiency in mpg n_g	28	36	20	DOT (2009)
GHG emissions in kgCO$_2$-eq/gallon v_g	11.8	n.a.		Yawitz et al. (2013)
Average capacity of ICEV fuel tank in gallons cap	10.8	n.a.		DOE (2015)
Average rate of refueling in gallons per hour τ_f	0.0396	n.a.		EPA (1996)
Cost of waiting while refueling in $/hour c_{idle}	24.85	n.a.		Ayala (2014)
Decrease rate of trade-in cost θ_{tr}	0.16	0.1	0.2	Kelley Blue Book (2015) (data analysis)
Battery utilization factor h_b	0.9	1	0.8	Lin (2014)
Vehicle body cost in $ c_b	12,000	8,000	18,000	DOE (2015)
Decrease rate of battery pack cost θ_{br}	0.0086	0.01	0.0005	EPA (2010)
Charging efficiency n_c	1	n.a.	0.9	Lin (2014)
GHG emissions in kgCO$_2$-eq/kWh v_e	0.73	n.a.		EIA (2013)
Upper bound of daily fixed limitation cost ρ_1	50	n.a.		Lin (2014)
Lower bound of daily fixed limitation cost ρ_2	15	n.a.		Lin (2014)
Cost of time while recharging in $/mile μ	1.66	n.a.		Ayala (2014)
Discount rate δ	0.03	0.10	0.025	EIA (2013)
Maximum distance covered daily x_m	390	n.a.		DOT (2009)
Residential Level 2 charging cost in $/charger c_{hch}	1354	300	8,000	INL (2015)
Public Level 2 charging cost in $/charger c_l	3,108	600	12,600	INL (2015)

Note: n.a. stands for not applicable.

Figure 4. Indicative ICEV and BEV cost component values for $w = 150$ miles $\forall t$ (1 mi ≈ 1.609 km).

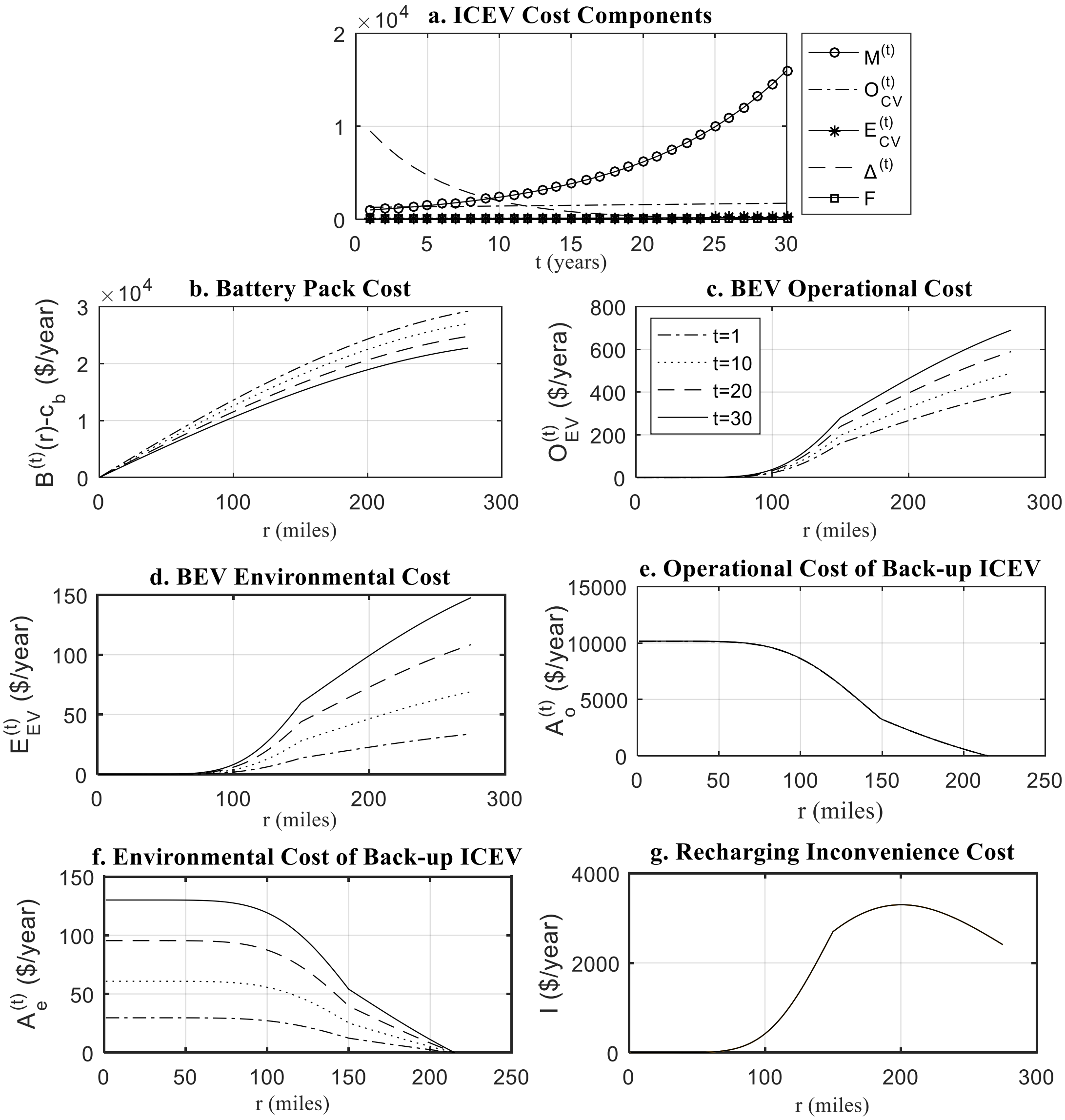

Figure 5. Indicative BEV cost components varying with w for $t = 1$ (1 mi ≈ 1.609 km).

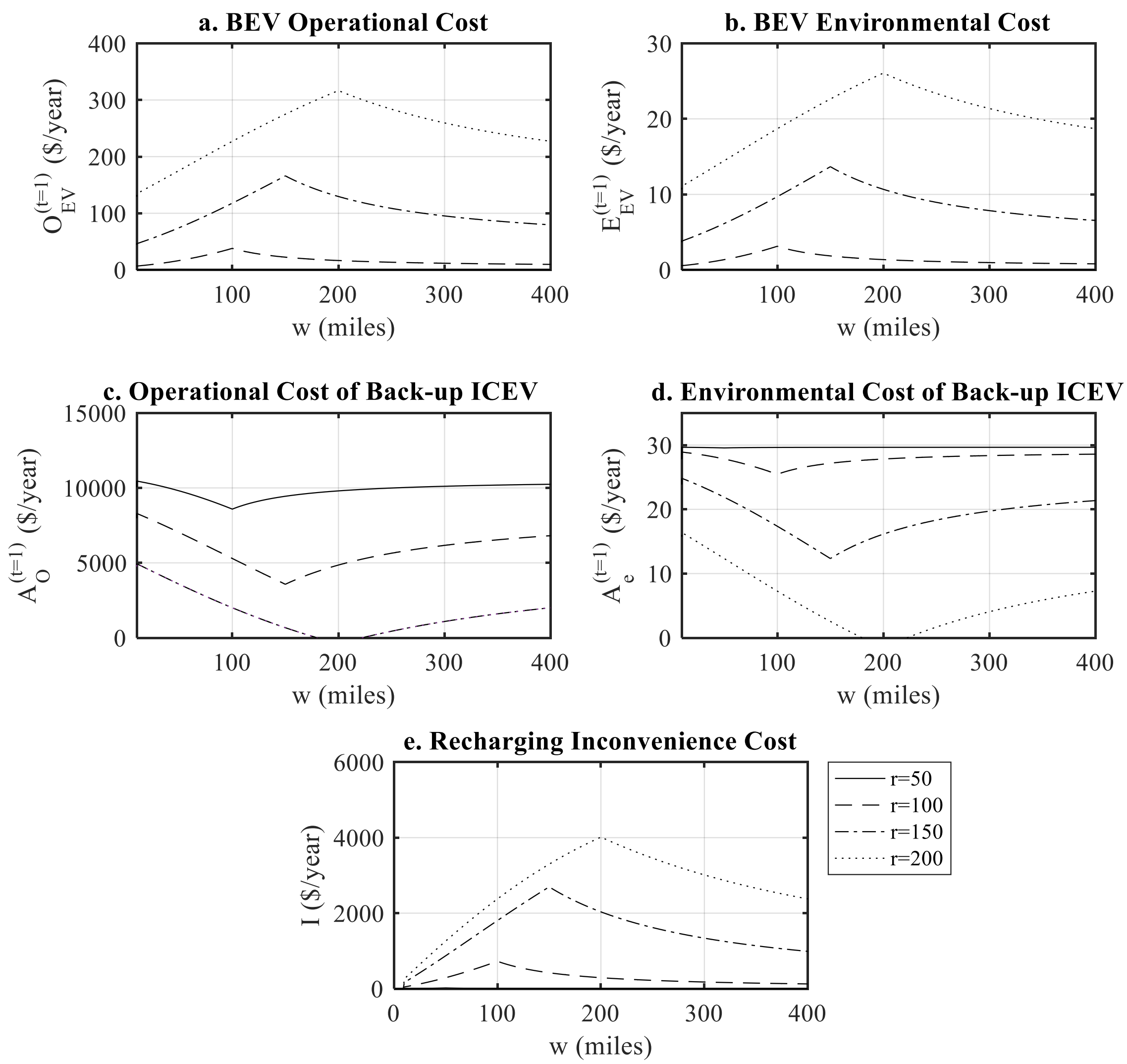

Figure 6. Cumulative BEV penetration (a), base case costs (b) and VMT of ICEVs replaced and used (c) (1 mi ≈ 1.609 km).

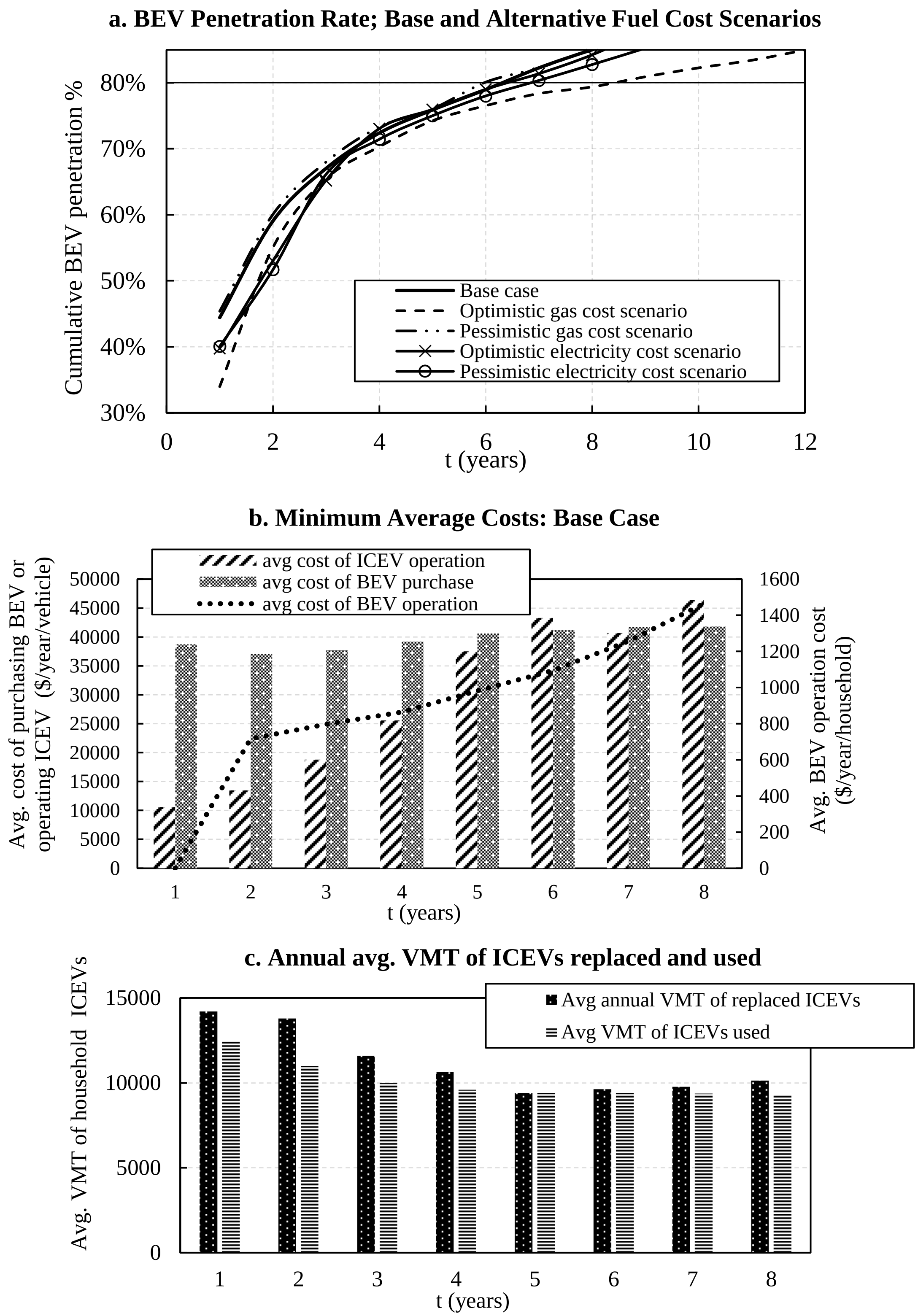

Figure 7. Alternative scenario decision variables, r and w results (1 mi ≈ 1.609 km).

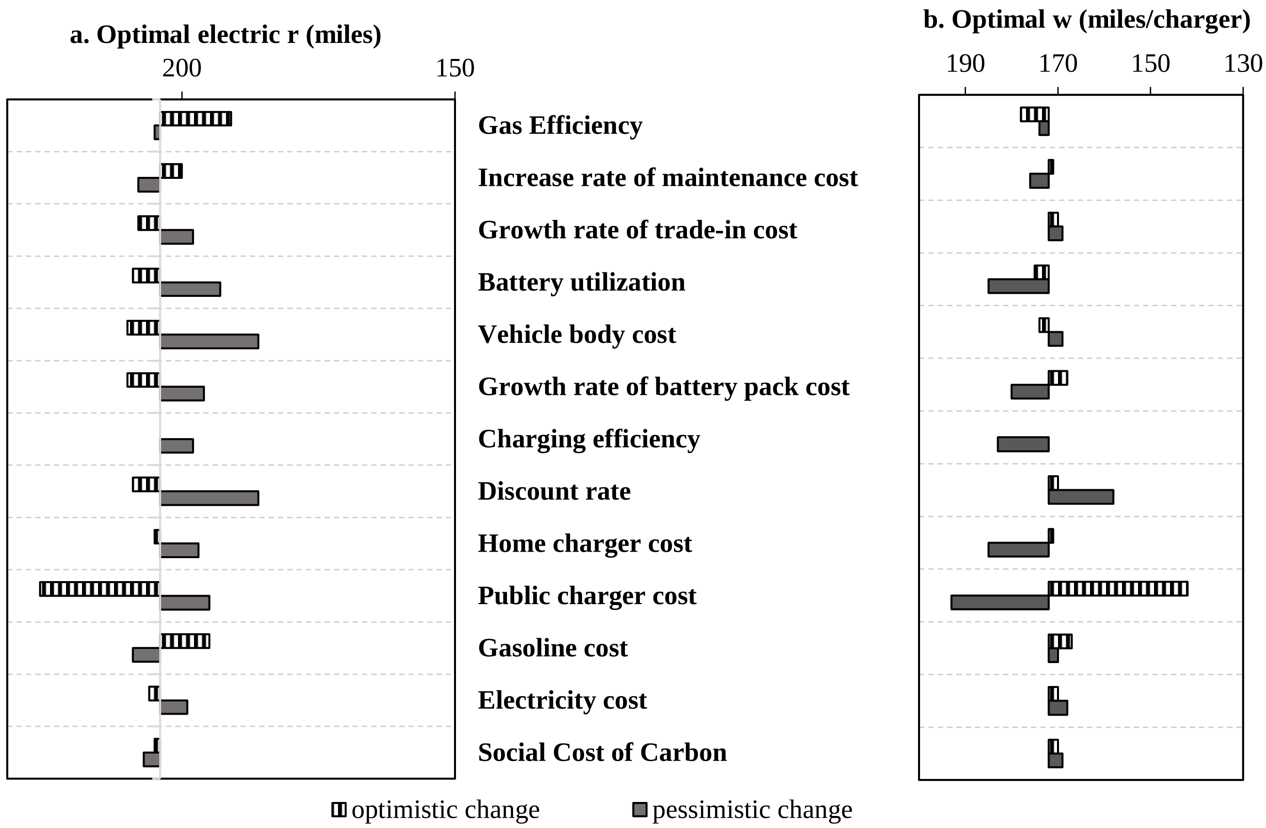

Figure 8. Replacement of ICEV with BEV cumulative rates when accounting for the rebound effect.