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Optimal design and allocation of electrified vehicles and dedicated charging infrastructure for minimum life cycle greenhouse gas emissions and cost

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HIGHLIGHTS

- ► We pose an MINLP model to minimize cost and GHG emissions of electrified vehicles.
- ► We design PHEVs and BEVs and assign vehicles and charging infrastructure in US fleet.
- ► Under US grid mix, PEVs provide minor GHG reductions and work chargers do little.
- ► HEVs are robust; PEVs and work charging potential improve with a decarbonized grid.
- ► We quantify factors needed for PEVs to enter and dominate the optimal fleet.

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ABSTRACT

Electrified vehicles can reduce greenhouse gas (GHG) emissions by shifting energy demand from gasoline to electricity. GHG reduction potential depends on vehicle design, adoption, driving and charging patterns, charging infrastructure, and electricity generation mix. We construct an optimization model to study these factors by determining optimal design of conventional vehicles, hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs) with optimal allocation of vehicle designs and dedicated workplace charging infrastructure in the fleet for minimum life cycle cost or GHG emissions over a range of scenarios. We focus on vehicles with similar body size and acceleration to a Toyota Prius under government 5-cycle driving conditions. We find that under the current US grid mix, PHEVs offer only small GHG emissions reductions compared to HEVs, and workplace charging is insignificant. With grid decarbonization, PHEVs and BEVs offer substantial GHG emissions reductions, and workplace charging provides additional benefits. HEVs are optimal or near-optimal for minimum cost in most scenarios. High gas prices and low vehicle and battery costs are the major drivers for PHEVs and BEVs to enter and dominate the cost-optimal fleet. Carbon prices have little effect. Cost and range restrictions limit penetration of BEVs.

1. Introduction

Climate change and energy security are among the most pressing issues faced by the world and by the US. In the US, the transportation sector accounted for 28% of GHG emissions in 2009 (US EIA, 2011a) and 71% of petroleum consumption in 2010 (US EIA, 2011b). Passenger vehicles accounted for 9.5% of 2010 US carbon dioxide emissions (US EPA, 2011) and 19% of 2009 nitrous oxide emissions (US EIA, 2011a). Reducing GHG emissions and petroleum consumption in the personal transportation sector is crucial to achieving climate and energy goals. Electrified transportation can help to address both of those issues by shifting transportation energy use from gasoline to electricity, especially when that electricity comes from low-carbon generation sources (Samaras and Meisterling, 2008).

A barrier to widespread adoption of personal electrified vehicles, especially BEVs, is the "chickn and egg" problem: manufacturers do not want to make vehicles that have no market, consumers do not want vehicles that have no refueling infrastructure, and no one wants

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to invest in refueling infrastructure for vehicles that do not exist (Melaina and Bremson, 2008). Policymakers can help break this cycle by putting incentives, taxes, and regulations in place. For instance, the Obama administration has set a target of one million plug-in electric vehicles (PEVs: including PHEVs and BEVs) on the road by 2015 and has provided incentives to manufacturers and consumers as well as support for research and development (Office of the Press Secretary, 2009). However, to promote cost effective GHG reductions, it is important to understand which outcomes should be incentivized, and this study is a step towards addressing this issue by analyzing best possible outcomes.

The Electric Power Research Institute and the National Resources Defense Council found in a 2007 study that PHEVs have substantial potential for reducing GHG emissions and air pollution (EPRI, 2007). However, a 2009 Argonne National Laboratory report finds that PEVs are likely to have "little or no" market penetration by 2050 without government subsidies (Plotkin and Singh, 2009). They estimate that government subsidies of $7500/vehicle (a level matched by current policy (American Recovery and Reinvestment Act of 2009, 2009)) could increase penetration of PHEVs, leading to a 22% reduction in GHG emissions by 2050 compared to their base case. Other studies have concluded that GHG reductions from PEVs are not likely to be cost effective in the near term and that PEVs represent an expensive approach to reducing GHG emissions (Delucchi and Lipman, 2001; Kammen et al., 2009; Plotkin and Singh, 2009; Shiau et al., 2010).

Several trade-offs must be considered to determine the best scenarios to meet cost or GHG emissions goals for electrified vehicles (which include HEVs, PHEVs, and BEVs). One of the major design decisions for PHEVs and BEVs is selecting the battery size. A larger battery pack enables the vehicle to travel a longer distance on electricity alone (the all-electric range, or AER) without the use of gasoline, which reduces use phase GHG emissions (also called operating emissions) over the vehicle life under today's average grid mix. However, a larger battery pack costs more initially, has production implications including additional GHG emissions, and may reduce vehicle efficiency due to its weight (Delucchi and Lipman, 2001; Shiau et al., 2009). Availability of charging infrastructure at the workplace and/or in public locations can enable a longer effective AER with a smaller battery pack. Availability of such infrastructure also affects charge timing, which has implications for marginal electricity generation and resulting emissions (Ferdowsi, 2007; Parks et al., 2007; Samaras and Meisterling, 2008; Sioshansi et al., 2010). In this study, we take a limited scope, ignoring charge timing and focusing on the effect of dedicated workplace charging availability on vehicle mix and on battery sizing in vehicle design.

Prior studies compare and select among a small set of fixed vehicle configurations based on selected commercially available vehicles or a small set of simulated vehicle alternatives (EPRI, 2001; Kammen et al., 2008; Parks et al., 2007; Peterson et al., 2011; Samaras and Meisterling, 2008; Shiau et al., 2009; Sioshansi et al., 2010). However, interactions among engine sizing, motor sizing, and battery sizing can be important in comparing vehicle characteristics, and optimal battery sizing represents a compromise among drivers with different travel patterns. We follow Shiau et al. (2010) and pose a mixed-integer nonlinear programming (MINLP) formulation to determine the best configuration of vehicles in the design space in order to compare the best design of each conventional vehicle (CV), HEV, PHEV, and BEV model under acceleration performance constraints that ensure vehicles are comparable. We further incorporate charging infrastructure decisions that determine which of the PEVs should be only charged at home vs. charged both at home and at the workplace, given charging infrastructure costs and production emissions, and we use driving pattern data to model required BEV ranges and PHEV electricity and gasoline usage. We then address three questions: (1) What mix of vehicles can minimize cost or GHG emissions? (2) What is the cost or GHG reduction potential with and without workplace charging infrastructure? and (3) What effect does workplace charging have on optimal vehicle allocation and battery sizing? We describe our approach in Section 2, present results for a base case and alternative scenarios in Section 3, address model limitations and future work in Section 4, and provide discussion and conclusions in Section 5.

2. Approach

We pose an optimization problem to minimize life cycle cost or GHG emissions over the personal vehicle fleet by jointly determining (1) the optimal design of each CV, HEV, PHEV, and BEV; (2) the optimal allocation of each vehicle design in the fleet based on annual vehicle miles traveled (VMT); and (3) the optimal allocation of workplace charging infrastructure to PEVs in the fleet. Within the fleet, we consider only vehicles of similar size and acceleration performance to the Toyota Prius. We also incorporate vehicle design constraints to ensure comparable acceleration performance and vehicle allocation constraints to ensure BEVs are assigned only if they have sufficient range to accommodate the vehicle's driving distance on most days (base case 95% of days, as discussed in Section 2.4). This formulation represents a best-case scenario for minimizing cost or GHG emissions with these vehicle technologies; market outcomes would likely deviate.

The general form of the optimization problem that we would like to solve is

$$\begin{array}{lll}
\underset{\mathbf{x}=[\mathbf{x}_1,\mathbf{x}_2,\ldots,\mathbf{x}_n]}{\text{minimize}} & \int_{S=0}^{\infty} f_{\mathrm{O}}(\mathbf{x},S) f_{\mathrm{S}}(S)\,dS & \begin{array}{l}\textit{minimize life cycle cost}\\ \textit{or GHG emissions,}\end{array} \\
\text{subject to} & \begin{array}{l}\mathbf{g}_j^{\mathrm{D}}(\mathbf{x}_j) \le \mathbf{0},\ \forall j \in J\\ \mathbf{x}_j \in \Re^{p_j},\ \forall j \in J\end{array} & \textit{s.t. design constraints,} \\
\text{where} & f_{\mathrm{O}}(\mathbf{x},S) = \min\limits_{\left\{ j \in J \mid \mathbf{g}_j^{\mathrm{A}}(\mathbf{x}_j,S) \le \mathbf{0} \right\}} \left\{ f_{\mathrm{O}j}(\mathbf{x}_j,S) \right\} & \begin{array}{l}\textit{where vehicles are optimally}\\ \textit{allocated based on VMT}\\ \textit{subject to allocation constraints}\end{array}
\end{array} \tag{1}$$

where S is the annual VMT for a specific vehicle in the fleet; $f_{\mathrm{S}}(S)$ is the probability density function of annual VMT over the fleet; $J=\{1,2,\ldots,n\}$ is the set of indices for all vehicle alternatives; $f_{\mathrm{O}j}(\mathbf{x}_j,S)$ is the equivalent annualized life cycle cost or annualized life cycle GHG emissions of vehicle j defined by the vehicle design vector $\mathbf{x}_j$ when driven S miles per year (daily variation is discussed later); $\mathbf{g}_j^{\mathrm{D}}(\mathbf{x}_j)$ is the vector of vehicle design constraints; $\mathbf{g}_j^{\mathrm{A}}(\mathbf{x}_j,S)$ is the vector of allocation constraints; and p_j is the size of vector $\mathbf{x}_j$.

This formulation presents two key difficulties for mathematical optimization: (1) the objective function contains an integral, and (2) the objective function contains a minimum function, which has derivative discontinuities. To avoid these difficulties, we reformulate the problem using numerical integration and binary selection variables. First, we select a finite upper limit for the integral S_{MAX} (73,000 mi.) and partition $[0,S_{\mathrm{MAX}}]$ into m equal adjacent bins $i \in \{1,2,\ldots,m\}$, each of size S_{MAX}/m. We introduce binary selection variables, $\alpha_{ij} \in \{0,1\}$, for each bin i and vehicle alternative j that define which vehicle is assigned to each bin ($\Sigma_j \alpha_{ij}=1$: only one vehicle alternative can be selected for each bin), and we further partition each bin into $K=S_{\mathrm{MAX}}/m\Delta$ segments of size Δ for numerical integration using the midpoints of f_{O} and F_{S} in each segment, where F_{S} is the cumulative distribution function (CDF) of f_S. The resulting formulation is

$$\begin{aligned}&\underset{\substack{\mathbf{x}_j,\alpha_{ij},\forall j\in J,\\ \forall i\in\{1,..,m\}}}{\text{minimize}} \quad \sum_{i=1}^{m}\sum_{k=K(i-1)}^{iK-1}\left(\frac{\sum_{j=1}^{n}\alpha_{ij}\begin{pmatrix}f_{Oj}(\mathbf{x}_j,k\Delta)\\+f_{Oj}(\mathbf{x}_j,(k+1)\Delta)\end{pmatrix}}{2}\begin{pmatrix}\dfrac{F_S((k+1)\Delta)-F_S(k\Delta)}{\Delta}\end{pmatrix}\right)\Delta\\ &\text{subject to} \quad \sum_{j\in J}\alpha_{ij}=1,\ \mathbf{g}_j^{D}(\mathbf{x}_j)\le\mathbf{0},\ \mathbf{x}_j\in\Re^{p_j},\ \alpha_{ij}\in\{0,1\},\\ &\qquad \forall i\in\{1,..,m\},\ \forall j\in J\\ &\qquad \mathbf{g}_{ij}^{A}(\mathbf{x}_j,\alpha_{ij})\le\mathbf{0},\ \forall i\in\{1,\ldots,m\},\ \forall j\in J_{BEV}\\ &\text{where} \quad \Delta=\frac{S_{MAX}}{mK}\end{aligned} \tag{2}$$

We relax the binary allocation variables α_{ij} into the continuous domain, $\alpha_{ij}\in\Re$, $0\le\alpha_{ij}\le1$, making this into a nonlinear programming problem to ease computation. For any set of fixed designs $\mathbf{x}^*=[\mathbf{x}_1,\ldots,\mathbf{x}_n]^*$, the optimization formulation in (2) is linear in α_{ij} and totally unimodular, so we expect that the optimal solution set will always contain a corner solution with integer values for the allocation variables α_{ij} (Nemhauser and Wolsey, 1999).

In our application, the set of vehicle alternatives J is partitioned into CVs, HEVs, PHEVs and BEVs, so that $J=J_{CV}\cup J_{HEV}\cup J_{PHEV}\cup J_{BEV}$. The decision variable vector $\mathbf{x}_j=[x_{Ej}, x_{Mj}, x_{Bj}, x_{SWj}]^T$ for each vehicle $j\in J$ includes x_E=gasoline internal combustion engine peak power (kW), x_M=electric motor peak power (kW), x_B=battery size (number of cells), and x_{SW}= battery swing window (portion of total energy capacity) for each vehicle j, where $x_M=x_B=x_{SW}=0\forall j\in J_{CV}$ and $x_E=0\forall j\in J_{BEV}$. The function $f_{Oj}(\mathbf{x}_j,S)$ in the objective function of Eq. (2) is replaced by either $f_{Cj}(\mathbf{x}_j,S)$, equivalent annualized life cycle cost in 2010 US dollars (USD2010) per vehicle-year, discussed in Section 2.1.1, or $f_{Gj}(\mathbf{x}_j,S)$, annualized life cycle GHG emissions in kilograms of CO_2-equivalent ($kgCO_2e$) per vehicle-year, discussed in Section 2.1.2. The Supplemental information summarizes model variables, functions, and parameters and defines base case and sensitivity values.

The design constraint vector $\mathbf{g}_j^D(\mathbf{x}_j)=\{g_{1\ j}^D(\mathbf{x}_j),g_{2\ j}^D(\mathbf{x}_j)\}$ ensures that each vehicle satisfies comparable acceleration performance criteria. These include a maximum 0–60 miles per hour (mph) acceleration time $t_{MAX}=11$ s for all vehicles, in both gasoline and electric mode: $g_{1\ j}^D(\mathbf{x}_j)=t_G(\mathbf{x}_j)-t_{MAX}\le0\forall j\in J_{CV}\cup J_{HEV}\cup J_{PHEV}$, $g_{1\ j}^D(\mathbf{x}_j)=0\forall j\in J_{BEV}$, $g_{2\ j}^D(\mathbf{x}_j)=t_E(\mathbf{x}_j)-t_{MAX}\le0\forall j\in J_{PHEV}\cup J_{BEV}$, and $g_{2\ j}^D(\mathbf{x}_j)=0\forall j\in J_{CV}\cup J_{HEV}$, where $t_G(\mathbf{x}_j)$ and $t_E(\mathbf{x}_j)$ are the 0–60 mph acceleration time of vehicle $\mathbf{x}_j$ in gasoline and electric mode, respectively, as discussed in Section 2.2. We also incorporate simple bounds $30\text{ kW}\le x_{Ej}\le60\text{ kW}$, $50\text{ kW}\le x_{Mj}\le110\text{ kW}$, and $200\text{ cells}\le x_{Bj}\le1000\text{ cells}\ \forall j\in J_{PHEV}$ and $x_{Ej}=0$ kW, $70\text{ kW}\le x_{Mj}\le250\text{ kW}$, and $200\text{ cells}\le x_{Bj}\le9000\text{ cells}\ \forall j\in J_{BEV}$ to avoid extrapolation beyond our simulation data. The battery swing window constraints are $0.1\le x_{SWj}\le0.8\ \forall j\in J/J_{CV}$ to ensure safe battery operation and avoid excessive degradation. Finally, the allocation constraints $\mathbf{g}_{ij}^A(\mathbf{x}_j,\alpha_{ij})=\alpha_{ij}f_{Aij}(\mathbf{x}_j)\le0$, where $f_{Aij}(\mathbf{x}_j)=s_\phi((k+1)\Delta)-s_{AER}(\mathbf{x}_j)$ $\forall i\in\{1,\ldots,m\}\forall j\in J_{BEV}$, and $f_{Aij}(\mathbf{x}_j)=0\forall i\in\{1,\ldots,m\}\forall j\in J/J_{BEV}$ ensure that BEVs are only allocated to vehicles if ϕ percent of days have VMT lower than the vehicle's range. We discuss the $s_{AER}(\mathbf{x}_j)$ function in the Supplemental Information and the s_ϕ function in Section 2.4.

2.1. Objective functions

The function $f_{Oj}(\mathbf{x}_j,S)$ in the objective function of Eq. (2) is replaced by either $f_{Cj}(\mathbf{x}_j,S)$, equivalent annualized life cycle cost (USD2010/vehicle-year), or $f_{Gj}(\mathbf{x}_j,S)$, annualized life cycle GHG emissions ($kgCO_2e$/vehicle-year), depending on the case.

2.1.1. Equivalent annualized life cycle cost

When the goal is to minimize equivalent annualized life cycle cost, the function $f_{Oj}(\mathbf{x}_j,S)$ in the objective function of Eq. (2) is replaced with $f_{Cj}(\mathbf{x}_j,S)$ (USD2010/vehicle-year), defined as

$$\begin{aligned}f_{Cj}(\mathbf{x}_j,S)=&\left(\begin{matrix}\underbrace{c_{Vj}+\rho\nu_{Vj}}_{\text{base vehicleproduction}}+\underbrace{c_E(x_{Ej})+\rho\nu_E(x_{Ej})}_{\text{engineproduction}}\\ \underbrace{+c_M(x_{Mj})+\rho\nu_M(x_{Mj})}_{\text{motorproduction}}\end{matrix}\right)f_{A|P}(r_N,l_V(S))\\ &+\left(\underbrace{(c_B(x_{Bj})+\rho\nu_{Bj})x_{Bj}\kappa_{Bj}}_{\text{battery production}}\right)f_{A|P}(r_N,l_V(S))\\ &+\left(\underbrace{(c_C+\rho\nu_C)q_{Cj}}_{\text{chargerproduction}}\right)f_{A|P}(r_N,l_C(S))\\ &+\left(\underbrace{\frac{(p_G+\rho\nu_G)S_G(\mathbf{x}_j,S)}{\eta_G(\mathbf{x}_j)}}_{\text{gasoline usage}}\right)\frac{f_{A|P}(r_N,l_V(S))}{f_{A|P}(r_{AG},l_V(S))}\\ &+\left(\underbrace{\frac{(p_{ELEC}+\rho\nu_{ELEC})S_E(\mathbf{x}_j,S)}{\eta_E(\mathbf{x}_j)}}_{\text{electricity usage}}\right)\frac{f_{A|P}(r_N,l_V(S))}{f_{A|P}(r_{AE},l_V(S))}\end{aligned} \tag{3}$$

where c_{Vj} is the cost of producing the base vehicle excluding engine, motor, and batteries; ρ is the carbon price in dollars per $kgCO_2e$ (zero in the base case); ν_{Vj} is the GHG emissions from production of the base vehicle excluding engine, motor, and batteries; $c_E(x_{Ej})$ is the cost of engine production; $\nu_E(x_{Ej})$ is the GHG emissions from engine production; $c_M(x_{Mj})$ is the cost of motor production; $\nu_M(x_{Mj})$ is the GHG emissions from production of the motor; $f_{A|P}(r,n)=r(1+r)^n((1+r)^n-1)^{-1}$ is the capital recovery factor; r_N is the nominal discount rate; $l_V(S)=S_{LIFE}/S$ is the life of the vehicle, including the engine and motor (and, for simplicity, the battery), in miles; S_{LIFE} is 150,000 miles; $c_B(x_{Bj})$ is the cost per kWh of battery production; ν_B is the GHG emissions per kWh of battery production; κ_B is the battery cell energy capacity (0.0216 kWh/cell for the lithium ion batteries in the PHEVs and BEVs and 0.00774 kWh/cell for the nickel metal hydride pack (NiMH) in the HEV); c_C is the cost of charger production; ν_C is the GHG emissions of charger production; q_{Cj} is the number of chargers allocated to vehicle j (treated as separate design types to avoid adding a binary vehicle design decision variable); l_c is the charger life in years, which we assume is equal to the life of the vehicle; p_G is the gasoline price in dollars per gallon; ν_G is the life cycle GHG emissions from gasoline consumption per gallon, including both production and combustion; $S_G(\mathbf{x}_j,s)$ is the annual distance for which the vehicle is powered by gasoline (charge sustaining mode); $\eta_G(x_j)$ is the vehicle 5-cycle combined gasoline efficiency in miles per gallon (mpg); p_{ELEC} is the electricity price per kWh; ν_{ELEC} is the life cycle GHG emissions from electricity consumption per kW; $S_E(\mathbf{x}_j,s)$ is the annual distance for which the vehicle is powered by electricity (charge depleting mode); $\eta_E(x_j)$ is the vehicle 5-cycle combined electrical efficiency in mi./kWh; $r_{AG}=(1+r_N)(1+r_{NG})^{-1}-1$ is the adjusted gasoline price growth rate, where r_{NG} is the nominal gasoline price growth rate, accounting for inflation and other factors affecting gasoline prices; $r_{AE}=(1+r_N)(1+r_{NE})^{-1}-1$ is the adjusted electricity price growth rate, where r_{NE} is the nominal electricity price growth rate, accounting for inflation and other factors affecting gasoline prices (see Supplemental Information for a description of the adjusted growth rates). We focus on the all-electric control strategy (in which PHEVs travel the entire AER distance in charge depleting mode without using gasoline), and we ignore PHEVs with blended control strategies. In Eq. (3), the motor, battery, charger, and electricity terms drop out for CVs; the charger and electricity terms drop out for HEVs; and the engine and gasoline terms drop out for BEVs. We also ignore battery degradation and replacement. We discuss cost functions and parameters below in this section and GHG functions and parameters in Section 2.1.2. We discuss vehicle fuel efficiency functions $\eta_G(x_j)$ and $\eta_E(x_j)$ in Section 2.2 and driving pattern functions $f_S(s)$, $S_E(\mathbf{x}_j,s)$, and $S_G(\mathbf{x}_j,s)$ in Section 2.4.

Vehicle production costs and equations are derived from a 2009 Argonne National Laboratories report (Plotkin and Singh, 2009). Base case values come from their literature review predictions for 2015 and other cases are used for sensitivity analysis. All costs have been converted to USD2010 using the Consumer Price Index (US DOL, 2010). Resulting battery costs are in the range of \$380–570/kWh rated capacity. Other details of vehicle cost parameter values appear in the Supplemental Information. Charger production cost c_C is \$1500 in the base case. This represents the approximate average cost of a Level 2 charger including installation (240 V AC, up to 3.3 kW (Morrow et al., 2008)).

Gasoline and electricity prices and price growth rates come from the EIA Annual Energy Outlook 2011 (US EIA, 2011c). We use EIA's high oil price case as our base case because their reference case is generally optimistic. The base case gasoline price p_G is \$2.22 per gallon, the 2009 US sales-weighted average price for all grades. The nominal gasoline price growth rate, r_{NG}, including inflation and other factors, is 5.2%. Details of other cost parameters appear in the Supplemental information.

2.1.2. Annualized life cycle GHG emissions

When the goal is to minimize annualized life cycle GHG emissions, the function $f_{Oj}(\mathbf{x}_j,S)$ in the objective function of Eq. (2) is replaced with $f_{Gj}(\mathbf{x}_j,S)$ (kgCO$_2$e/vehicle-year), defined as

$$f_{Gj}(\mathbf{x}_j,S) = \underbrace{\frac{v_{Vj}}{l_V(S)}}_{\text{base vehicle production}} + \underbrace{\frac{v_E(x_{Ej})}{l_V(S)}}_{\text{engine production}} + \underbrace{\frac{v_M(x_{Mj})}{l_V(S)}}_{\text{motor production}} + \underbrace{\frac{v_{Bj}x_{Bj}\kappa_{Bj}}{l_V(S)}}_{\text{battery production}} + \underbrace{\frac{v_C q_{Cj}}{l_C(S)}}_{\text{charger production}} + \underbrace{\frac{v_G S_G(\mathbf{x}_j,S)}{\eta_G(\mathbf{x}_j)}}_{\text{gasoline usage}} + \underbrace{\frac{v_{ELEC} S_E(\mathbf{x}_j,S)}{\eta_E(\mathbf{x}_j)}}_{\text{electricity usage}} \tag{4}$$

where all parameters have been previously defined. In Eq. (4), the motor, battery, charger, and electricity terms drop out for CVs; the charger and electricity terms drop out for HEVs; and the engine and gasoline terms drop out for BEVs. Parameter values appear in the Supplemental information.

This equation represents a hybrid life cycle assessment (LCA) approach to calculating the annualized life cycle GHG emissions of personal vehicles. Values for the GHG emission parameters come both from Economic Input–Output LCA (EIO-LCA) and from process-based LCAs. The hybrid approach to LCA for applications such as emissions from personal vehicles is supported in the literature (Suh et al., 2004) and in standards (BSI, 2011). The scope of this LCA is cradle-to-gate GHG emissions plus the use phase, but excluding end-of-life.

2.2. Vehicle performance models

To estimate the electrical $\eta_E(\mathbf{x}_j)$ and gasoline $\eta_G(\mathbf{x}_j)$ efficiencies and the acceleration performances $t_G(\mathbf{x}_j)$ and $t_E(\mathbf{x}_j)$ of vehicle j defined by design variables $\mathbf{x}_j$, we utilize Argonne National Laboratory's Powertrain System Analysis Toolkit (PSAT) vehicle simulation software (ANL, 2008) and construct a metamodel fit to a discrete set of simulation points in the design space $\mathbf{x}_j$ to find the US Environmental Protection Agency (EPA) 5-cycle combined highway and city efficiency and 0–60 mph acceleration time for a range of vehicle designs. We use the 2004 Toyota Prius model (with a power-split or series-parallel HEV powertrain) as the baseline vehicle and our HEV model. We construct our PHEV model by substituting Li-ion batteries for the Prius NiMH batteries, increasing the pack size, and increasing the SOC range for regenerative braking. One kilogram of structural weight is added to the vehicle per kilogram of battery, engine, and motor to support the weight of those components (Shiau et al., 2009). We base our CV model on a scaled Honda Civic powertrain (engine, gearbox, and final drive), adjusted to have a Toyota Prius vehicle body for fair comparison to the HEV, PHEV, and BEV (Shiau et al., 2010). Our BEV model has a generic BEV drive train modified to use the same body, motor, and batteries as the PHEV. We ignore the possibility of using different battery designs on BEVs vs. PHEVs. The error for all metamodels is within 0.5 s, 0.03 miles per gallon equivalent (mpge), and 0.06 mi./kWh over the set of data points used for fitting. Further details of the vehicle designs, vehicle simulation models, metamodel construction, and AER calculations appear in the Supplemental information.

2.3. Charging infrastructure scenarios

We consider the following two charging scenarios: (1) only Level 2 home charging (240 V AC, up to 3.3 kW (Morrow et al., 2008)), and (2) Level 2 home charging with additional dedicated workplace Level 2 charging: we do not consider additional charging methods such as DC fast charging, battery swapping, smart charging, or vehicle to grid power. The Level 2 charger is represented by a single cost parameter that includes equipment and installation and by a single production emissions factor (see Supplemental information for details).

We implement these two charging scenarios in the model by partitioning J_{PHEV} and J_{BEV} each into two subsets $J_{PHEV}=J_{PHEV(1)}\cup J_{PHEV(2)}$ and $J_{BEV}=J_{BEV(1)}\cup J_{BEV(2)}$, where the numbers indicate 1 charger (home) or 2 chargers (home+work). Each 2-charger partition is identical to the corresponding 1-charger partition (equal design variables) except that $q_C=2$ instead of 1. This allows each vehicle design to be assigned to some drivers with one charger and also to other drivers with two chargers. Allocation of charging infrastructure in this model refers to whether each PEV is allocated with or without workplace charging.

2.4. Driving patterns

To find the CDF $F_S(S)$ for annual VMT, we use data on the weighted annual distance traveled (based on odometer readings) of each vehicle in the US from the 2001 National Household Travel Survey (NHTS) (US DOT, 2003). The resulting histogram is shown in Fig. 1. This distribution accounts for the variability in average daily VMT across the US vehicle fleet (across vehicles), but does not account for variability in VMT of each vehicle across days (within vehicle). NHTS data do not contain information on within-vehicle variability, since each household was only surveyed on one day. We use detailed trip data collected for 133 vehicles in Minnesota in 2004–2005 to estimate this variability across days (Sierra Research, 2005). Since the average annual VMT is similar across the two data sets (11,800 mi. in NHTS odometer readings (US DOT, 2003) and 11,900 mi. in the Minnesota data set (Sierra Research, 2005)), we believe the Minnesota data set is reasonably representative for providing an estimate of US within-vehicle variability.

We represent the variability in daily driving distance for each vehicle in two separate ways. In both cases we remove days in which the vehicle was not driven, leaving an average of $D=243.8$

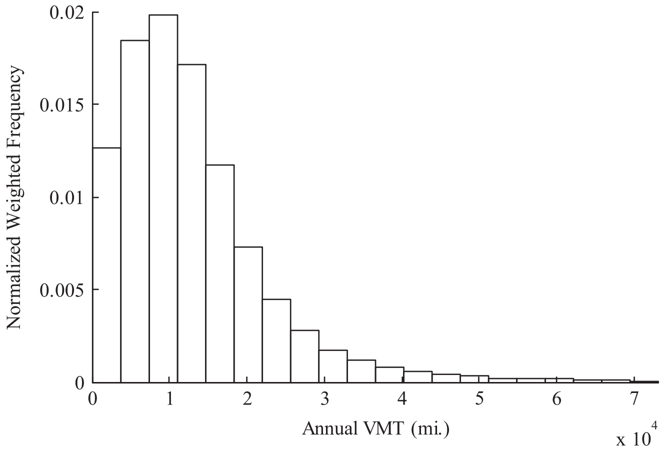

Fig. 1. Histogram of odometer-based annual VMT from NHTS 2001 data (US DOT, 2003).

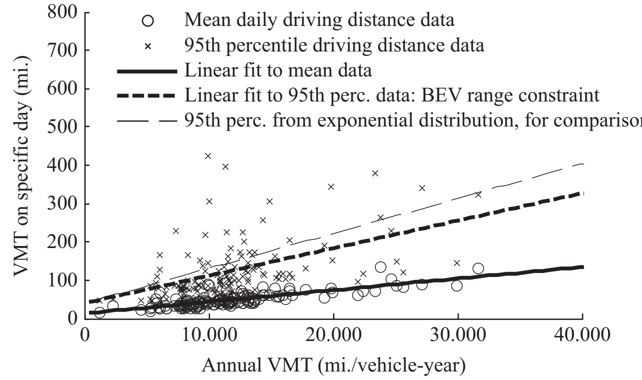

Fig. 2. Mean and 95th percentile driving-day distances for 133 vehicles vs. annual VMT, with linear fits and with 95th percentile implied by the family of exponential distributions calibrated to match a linear fit to the mean. The linear fit to the 95th percentile data is used as the BEV range constraint.

driving days per year (we observed no clear trend in D vs. annual VMT S, so D is assumed constant across S; Sierra Research, 2005).

First, we enforce a BEV range allocation requirement for each bin on S by computing the length of the 95th percentile longest driving-day distance traveled for each vehicle in the Minnesota data set. We fit a curve to these data to produce $s_{95\%}(S)=2.62(S/d)+40.3$ miles, where $d=365$ day per year, and we permit BEV allocation to a bin only if the AER is greater than the greatest 95th percentile distance for that bin (implying that driving and charging behavior or household vehicle allocation would need to change on the remaining 5% of driving days to avoid full battery depletion, which we ignore). We also perform sensitivity analysis by instead constraining allocation of BEVs to satisfy only the average driving distances of each bin $\mu(S)$.

Secondly, to estimate the portion of VMT that a PHEV is driven using gasoline vs. electric power, we require an estimate of the distribution of daily driving distances for each bin of vehicles. The shape of the distribution of daily distance driven in the Minnesota data set varies from vehicle to vehicle, including unimodal and multimodal distributions. However, for simplicity and tractability, we assume a family of exponential distributions. This model specification provides a useful approximation of the general trend in daily variability while offering a closed form CDF to facilitate estimation of the portion of miles driven beyond a PHEV's all-electric range. To estimate this relation, we fit a curve through the mean driving-day distance: $\mu(S)=1.110(S/d)+13.33$ and define a family of exponential distributions that follow $\mu(S)$, with CDF of $F^{V}_{\sigma}(\sigma,S)=1-\exp(-\sigma/\mu(S))$, where σ is a random variable indicating distance driven on a particular day.

Fig. 2 shows both of these functions, along with the 95th percentile of the family of exponential distributions, for comparison. The 95th percentile found from the exponential assumption deviates somewhat from the linear fit, and our use of the linear fit as the BEV allocation constraint is more optimistic toward electrification. The 95th percentile found from the exponential distribution is shown only for comparison.

Using the exponential fit, we calculate $S_{G}(\mathbf{x}_j,S)$, the annual distance powered by gasoline, and $S_{E}(\mathbf{x}_j,S)$, the annual distance powered by electricity

$$S_{E}(\mathbf{x}_j,S)=S\left(1-\exp\left(\frac{-q_{Cj}s_{AER}(\mathbf{x}_j)}{\mu(S)}\right)\right)$$
$$S_{G}(\mathbf{x}_j,S)=S\exp\left(\frac{-q_{Cj}s_{AER}(\mathbf{x}_j)}{\mu(S)}\right) \tag{5}$$

We assume here that the presence of workplace charging will provide a charging opportunity sufficient to effectively double the AER. In this sense, "workplace charging" can represent any dedicated (guaranteed) daytime charging opportunity away from home (since it requires a second charger) that occurs at a distance between the AER and the halfway point of the day's driving distance. This assumption is optimistic for estimating the benefits of PHEVs and of workplace charging, since daily distance variability typically reflects trips taken to locations other than the workplace, rather than variable distance to the workplace, so it is likely that a workplace charging opportunity may not occur in the specified distance range. We ignore workplace charging for the purpose of calculating the BEV range constraint, since the 5% of longest days that make the allocation constraint binding are unlikely to be normal commute days with dedicated charging available. Because we use the same driving cycle for all drivers, we also do not account for the correlation between driving distance and driving style (and therefore efficiency).

2.5. Allocation method

Fig. 3a shows an example plot of $f_{Oj}(\mathbf{x}_j,S)/S$ (either GHG emissions or cost per mile) vs. annual VMT (S) for two hypothetical vehicles. At any point along the S-axis, the lowest vehicle curve represents the best vehicle for a driver with annual VMT of S. Fig. 3b shows $f_{Oj}(\mathbf{x}_j,S)f_S(S)$, the fleet-weighted value per vehicle-year and the integrand of the objective function in Eq. (1). The area under each vehicle curve in Fig. 3b represents the total objective function value if all vehicles in the fleet were of the corresponding design and charging scenario. In each graph, the horizontal axis is divided into two bins, and the best vehicle is allocated in each bin. The area under the resulting piecewise smooth curve defined by the thicker lines represents the total objective function value if the two vehicles are allocated optimally.

2.6. Scenarios and sensitivity analysis

We solved the optimization model for several scenarios and performed sensitivity analysis on the key model parameters. For each objective function (cost or GHGs), the base case is the least restricted scenario, in which all vehicle types are included for a total of 6 designs (CV, HEV, 2 PHEV designs, and 2 BEV designs) with both home and workplace charging available. We also considered scenarios with fewer vehicle designs (such as PHEVs only) and scenarios restricted to home charging only.

We performed sensitivity analysis on several major parameters in both the cost and GHG objective functions. For all parameters, we

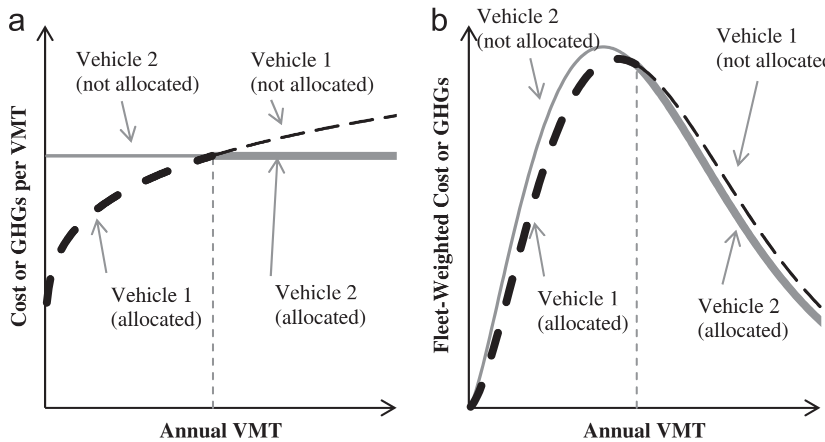

Fig. 3. Example illustrative plots of (a) cost or GHGs per VMT vs. annual VMT and (b) fleet-weighted cost or GHGs vs. annual VMT. The area under the curve in (b) is the objective function value.

Table 1
Summary of base case and sensitivity cases.

	Base case	Sensitivity cases
Electricity grid mix	US average	Nuclear, natural gas, integrated gasification combined cycle plant with carbon capture and sequestration (IGCC-CCS), coal
Potential vehicle fleet	Fleet of CV, HEV, 2 PHEVs, 2 BEVs	CV only, HEV only, 2 PHEVs only, 2 BEVs only
Charging potential	Home, home+work	Home charging only
BEV range constraint	Range $\geq$ 95% of daily VMT	Range $\geq$ average daily VMT
Gas price	$2.22/gal+5.2%/year	$3, $3.25, $4, $5, $6, $7, $8/gal+5.2%/year
Electricity prices	$0.12/kWh+1.9%/year	$0.06, $0.30/kWh+1.9%/year
Vehicle and battery costs	Plotkin and Singh 2015 literature review (LR2015) estimates ($380–$570/kWh rated capacity for batteries)	Plotkin and Singh 2045 lit review (LR2045) estimates ($190–$350/kWh for batteries), 2030 program goals (PG2030) ($130–$180/kWh for batteries)
Charger costs	$1500 installed	$0, $475, $500, $2500
Discount rate	5%	0%, 10%
CV efficiency	25 mpg	32 mpg
CO_2 price	$0/kg$CO_2$e	$0.02, $0.1/kg$CO_2$e ($20, $100 per metric ton CO_2 equivalent (tCO_2e))

identify a base case representing a reasonable current value, based either on recent historical values or near-future projections. For most parameters we also identify a low and high value representing bounds on the likely variation of that parameter in the next several decades. For some parameters, such as gas price, we also examine a range of values to identify critical points. Table 1 summarizes assumptions for our base case and sensitivity cases, and details of sensitivity cases can be found in the Supplemental information.

3. Results

In this section, we describe the results obtained from the optimization formulation defined in Eq. (2). First in Section 3.1, we show lifecycle cost and GHG emission results for several example vehicle designs, disaggregated to illustrate the contributing factors. Then in Section 3.2, we present lifecycle cost and GHG emissions results for several scenarios in which vehicles are optimally designed and allocated, including sensitivity analysis. Further results are available in the Supplemental information.

3.1. Cost and GHG emissions breakdown

Fig. 4 shows a breakdown of the contributing factors to (a) life cycle cost and (b) GHG emissions for example vehicles of each type. These factors also correspond to terms in Eqs. (3) and (4). For illustration purposes, the example vehicle designs shown in Fig. 4 have been optimized for minimum cost when that vehicle design is allocated across the entire fleet. Further details on these vehicles are shown in Table SI5 scenarios 25 and 26 and Table SI6scenarios 33 and 34. In order to obtain a feasible solution with a BEV allocated to the entire fleet, the range constraint was reduced to mean travel distances instead of 95th percentile longest distances. The PHEV and BEV are shown with one charger allocated. Results will vary for different vehicle designs.

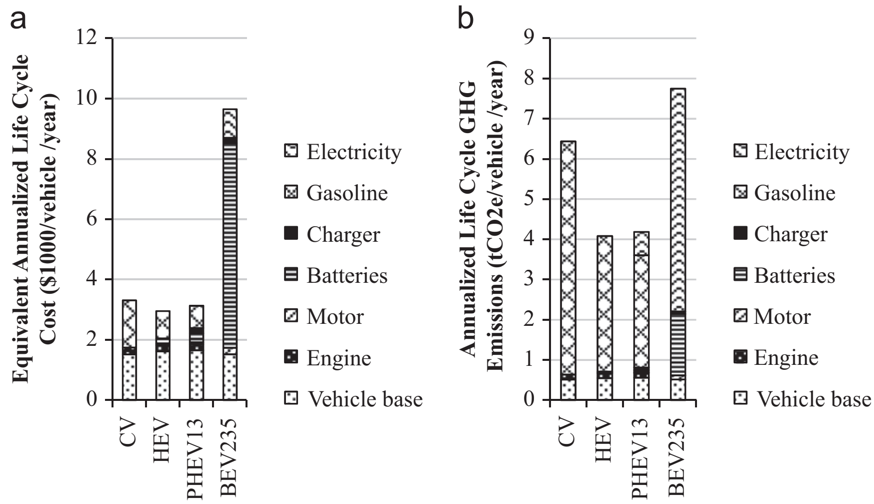

Fig. 4. Breakdown of (a) equivalent anualized life cycle cost and (b) life cycle GHG emissions for four independently cost-optimized vehicle designs.

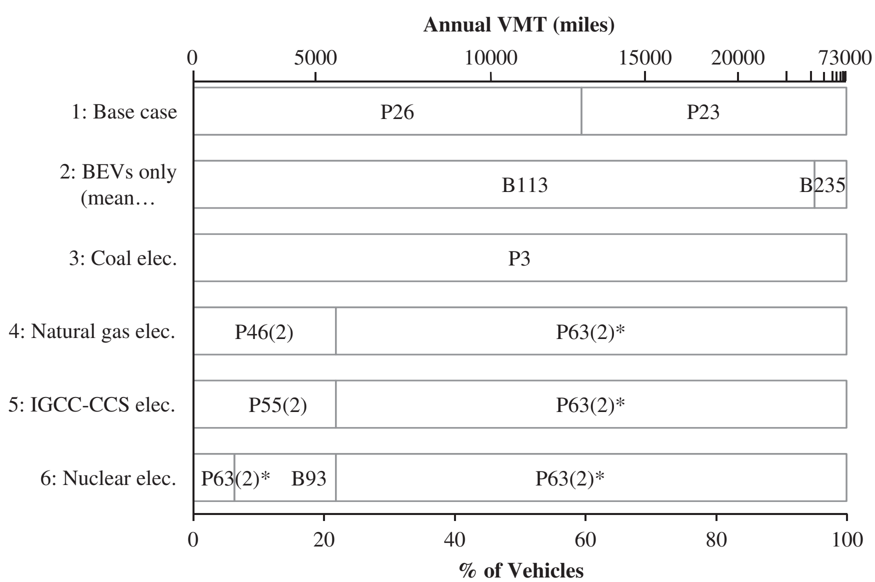

Fig. 5. Optimal vehicle allocations for minimizing annualized life cycle GHG emissions in selected scenarios. "P" indicates PHEV and "B" indicates BEV. Numbers after vehicle abbreviations indicate the AER in miles, and "(2)" indicates workplace charging in addition to home charging. Asterisks indicate vehicle designs with battery sizes (and AERs) at the bounds of our model. Base case details appear in Table 1.

As shown in Fig. 4a, allocating BEVs (with a 235-mile AER) to the entire population is significantly more costly than any of the other vehicle types, mainly due to battery costs. The large battery pack used here is needed to provide enough range for the average daily travel of all driving bins, but smaller battery packs could be used when allocating vehicles to a subset of driving bins, as will be shown in the following sections. CVs have the largest gasoline cost, but the gasoline cost savings from switching to HEVs or PHEVs (with a 13-mile AER) are partially offset by motor, battery and charger costs. HEVs are least expensive overall. Although base vehicle, engine, and motor costs vary across vehicle types, differences in gasoline and battery costs drive comparisons. Fig. 4b shows that more GHG emissions occur when CVs are allocated across the entire fleet than when HEVs or PHEV13s are allocated, and most emissions are from gasoline production and combustion. HEVs have significantly lower emissions from gasoline, and some additional emissions from motor and battery production. Our results agree with the literature both on the range of overall emissions from CVs and HEVs and on their relation to each other: in this study HEVs produce 37% less life cycle GHG emissions than CVs. Samaras and Meisterling (2008) find that HEVs produces 30% less life cycle GHGs than CVs, and Shiau et al. (2010) find that HEVs produce 44% less. PHEVs provide further reductions in GHG emissions from gasoline, but they are offset by an increase in emissions from electricity. BEVs have more GHG emissions than the other vehicle types. Most BEV emissions are from electricity and battery production. Although both the cost and GHG emissions of the chargers are small, including them allows us to model trade-offs between producing additional chargers and electrifying additional miles.

3.2. Optimal design and allocation

Results are summarized in two figures: Fig. 5 shows selected results for minimizing annualized life cycle GHG emissions, and Fig. 6 shows selected results for minimizing equivalent annualized life cycle cost. Further results, including more details for each of the cases shown, are included in the Supplemental information.

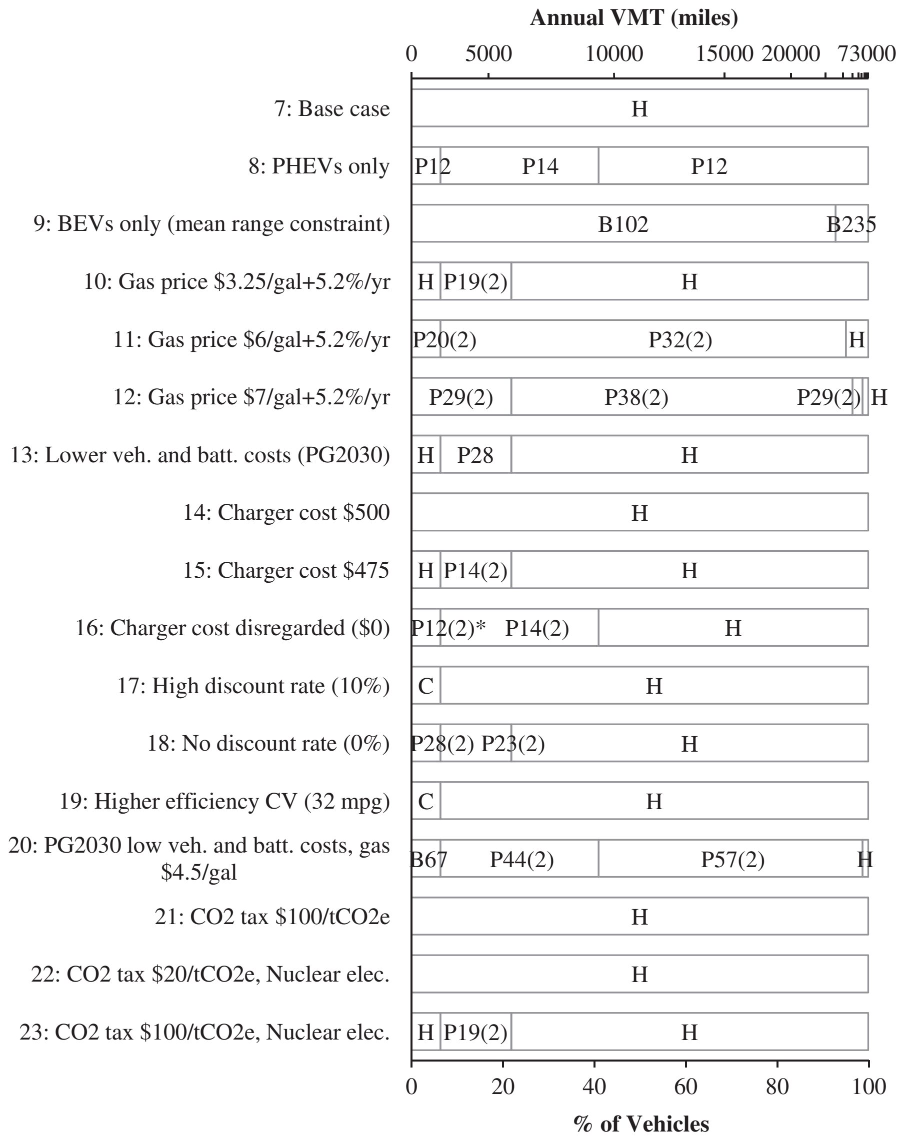

Fig. 6. Optimal vehicle allocations for minimizing equivalent annualized life cycle cost in selected scenarios. "C" indicates CV, "H" indicates HEV, "P" indicates PHEV, and "B" indicates BEV. Numbers after vehicle abbreviations indicate the AER in miles, and "(2)" indicates workplace charging in addition to home charging. Asterisks indicate vehicle designs with battery sizes (and AERs) at the bounds of our model. Base case details appear in Table 1.

For both objective functions, the base case is shown first. The base case is the least restrictive scenario, allowing the CV design, the HEV design, up to 2 PHEV designs, and up to 2 BEV designs to be allocated with home charging only or with home and workplace charging. The base case uses the base case parameter estimated defined in the approach section and tabulated in the Supplemental information, including average US grid mix and energy prices. Following the base case, each sensitivity analysis scenario is defined by the major differences from the base case.

Figs. 5 and 6 show the vehicle allocations at each optimal scenario. The lower x-axis indicates the cumulative percentage of vehicles, and the upper x-axis indicates the corresponding annual VMT of that portion of the fleet. The upper and lower x-axes are related to each other by the distribution of annual VMT across the fleet, shown in Fig. 1. Within each bar, the vehicle designs are indicated, e.g. P46(2), where P stands for "PHEV", 34 indicates the AER, and "(2)" indicates that workplace charging is allocated in addition to home charging. So, for example, the first bar in Fig. 5 shows that in the base case for GHG minimization, a PHEV with an AER of 26 miles is allocated to the first 60% of vehicles that drive up to 14,600 miles per year, and a PHEV with an AER of 23 miles is allocated to the remaining 40% of vehicles with longer annual VMTs. Since this scenario allows workplace charging to be allocated and it is not allocated, we know that the GHG reduction from a second charge (and therefore more electrified miles) is not enough to offset the production GHGs of the second charger. The PHEV with the smaller range is allocated to the vehicles with longer distances because for those vehicles the charge-sustaining mode efficiency matters more, and larger battery packs increase production emissions and reduce efficiency due to weight.

The other cases shown in Fig. 5 are as follows: forcing all vehicles to be BEVs requires large battery packs to satisfy range constraints (even when we require BEV range to satisfy only the average day, shown here, rather than the 95th percentile day), and net GHGs are increased. When charged with coal electricity, GHG benefits of PEVs disappear, and a PHEV3 minimizes GHGs for the fleet. This is practically an HEV, but our model selects a PHEV with the shortest possible range (smallest permitted PHEV battery pack size and swing) because the PHEV is slightly more efficient in charge sustaining mode than our HEV model. Optimizing the HEV design is beyond the scope of this paper, but if it were allowed, it is likely that an optimized HEV would exist that is more efficient than this PHEV3, and coal electricity would therefore remove PEVs from the GHG-optimal fleet. When charging with natural gas or from an integrated gasification combined cycle plant with carbon capture and sequestration (IGCC-CCS), we observe allocation of larger capacity PHEVs with workplace charging. Marginal dispatch electricity associated with PEV charging will vary by location and charge timing, but the grid scenarios examined here provide a bounding analysis over a wide range of grid GHG intensities.

Further details for each case, such as the overall cost and GHG emissions, as well as additional cases appear in the Supplemental Information. These cases show that (1) workplace charging offers no GHG benefits under the average U.S. grid mix, but under decarbonized grid scenarios workplace charging is allocated, providing optimistically up to 21% additional GHG reductions when the workplace charge occurs at the halfway point of daily distance for each vehicle each day. Under more realistic conditions, the benefit of workplace charging would be lower, suggesting that availability of dedicated workplace charging is not a significant factor in reducing overall life cycle GHG emissions unless combined with significant levels of grid decarbonization; (2) under decarbonized grid scenarios, greater penetration of vehicles with larger battery packs are observed in GHG-minimized solutions, including BEVs, and GHG emissions are reduced substantially; however, costs increase; (3) availability of workplace charging in decarbonized grid scenarios affects the vehicle design by allowing some PHEVs to have smaller AERs and by reducing the allocation of larger capacity BEVs in favor of smaller capacity BEVs and more large capacity PHEVs; and (4) even when charged with zero-emission electricity, BEVs are not GHG-minimizers for the entire fleet; minimizing GHGs, even if the grid were entirely decarbonized and cost were not a factor, would involve continued use of gasoline (and/or other liquid fuels not studied here).

Fig. 6 shows that in the base case, the cost-minimizing solution is to assign HEVs to all vehicles. When restricted to allocating PHEVs, they are low capacity, with 12–14 miles AER. When restricted to allocating BEVs, battery packs are large, even when constraining their range to meet only average trip requirements rather than 95th percentile, and costs increase substantially. Gas prices above \$3.25/gal (with 5.2% growth rate) are required to bring PHEVs into the minimum cost solution, and prices as high as \$7/gal (with 5.2% growth rate) are required for PHEVs to almost entirely replace HEVs, and these prices are still not high enough for BEV penetration. Lower vehicle and battery costs that meet DOE 2030 program goals (including optimistic battery costs of \$134–176/kWh) are sufficient for a small penetration of PHEVs but must be combined with \$4.5/gal gasoline (with 5.2% growth rate) to trigger allocation of PHEVs predominately. Charger costs below \$475 are needed to encourage PHEV penetration, and if chargers are free, PHEVs (with workplace charging) are allocated to about 40% of vehicles. While some households can charge a vehicle at 120 V with little or no installation cost, most households will incur at least some equipment, installation, and/or inspection cost before being able to charge at Level 2 (240 V), and Level 2 charging is necessary to charge large battery pack vehicles overnight. Low discount rates drive greater adoption of PHEVs, although consumers are known to use high discount rates in practice (Horne et al., 2005; Mau et al., 2008). Carbon taxes do little to encourage adoption of PHEVs unless high carbon prices (\$100 per metric ton CO_2 equivalent (tCO_2e)) are combined with decarbonized electricity. Studies have indicated that a reasonable range for a carbon price is \$20/tCO_2e to \$100/tCO_2e (Interagency Working Group on Social Cost of Carbon, United States Government, 2010; IPCC, 2007), although some have argued that higher prices are justified (Kopp and Mignone, 2011). Prices on the order of \$100/tCO_2e would induce major changes in the electricity sector before doing much to promote vehicle electrification.

Further details for each case, such as the overall cost and GHG emissions, as well as additional cases appear in the Supplemental Information. These cases show that (1) HEVs are an optimal or near-optimal solution for minimizing cost across many scenarios, including our sensitivity analysis cases with low or base case gas prices, high discount rates, high charger costs, and reduced vehicle and battery prices to the LR2045 levels; (2) cases that lead PEVs to dominate the fleet include \$7/gal gasoline (with 5.2% growth rate), \$6/gal gasoline (with 5.2% growth rate) combined with \$100/tCO_2e carbon prices, or \$4.50/gal gasoline (with 5.2% growth rate) combined with DOE 2030 targets for low vehicle and battery costs.

This analysis finds the fleet with the minimum equivalent annualized life cycle cost overall, not the minimum cost to consumers, so no government incentives such as tax credits are considered. Tax credits are still costs incurred by the government and the tax payer if not by the consumer.

These findings are robust to the definition of the CV and HEV models. We find similar results when the CV efficiency increases to as high as 32 mpg, as shown in scenario 19. In the base case the HEV is 58% more efficient than the CV (43 mpg and 25 mpg, respectively), and when the CV reaches 32 mpg the HEV is only 34% more efficient. Real-world HEVs tend to be around 48% more efficient than the same model CV, which falls within the range of our sensitivity analysis and does not change our base case results (Ford Motor Company, 2011).

In a future with low-emission electricity, low vehicle and battery costs, and higher gasoline prices, we may expect high penetration of BEVs for lower-distance vehicles and PHEVs for higher-distance vehicles. However, in near-term scenarios, HEVs and low-range PHEVs are preferable for both cost and GHG reduction. Because HEVs are the cost-minimizing solution, and because GHGs from HEVs are also within 3% of the GHG-minimizing solution under today's US grid energy mix, we find that the cost-minimized base case solution has only 3% more GHG emissions than the GHG-minimized base case solution and costs 12% less (see Tables SI5 and SI6).

Relative to the base case solution for minimizing GHGs, GHG emissions would increase by 63% if all vehicles were CVs of comparable size and acceleration performance, by 3% if all vehicles were HEVs, by 0% if all vehicles were PHEVs (see Table SI5), and by 36% if all vehicles were BEVs with only enough range to support the average trip (BEVs with enough range to support the 95th percentile trip require battery capacity larger than our model permits for long distance vehicles). In practice, range anxiety may cause consumers to demand even greater range from BEVs than the 95th percentile distance (and almost certainly more than the mean) in the absence of widespread, convenient, rapid public charging infrastructure, since accommodation of the 95th percentile longest daily driving range still leaves 18–19 days each year where daily driving distance exceeds vehicle range. It is also possible that consumers will change their driving patterns to accommodate BEVs with shorter ranges than we have assumed, especially since the majority of US households have multiple vehicles (US DOT, 2003), but it would take significantly reduced range requirements to make BEVs competitive across the entire fleet. Neubauer et al. (2012) present one alternate method of treating BEV range restrictions based on adapting driving patterns.

4. Limitations and future work

Several important assumptions and model limitations should be understood to support appropriate interpretation of results. Key assumptions include vehicle driving and charging patterns, vehicle design options and size class considered, and electricity generation mix. We discuss each in turn.

First, assuming that workplace charging is available for all vehicles and allows a charge exactly halfway through daily travel is optimistic for PHEVs, although GHG reduction potential is marginal even under this optimistic assumption except in decarbonized grid scenarios. Assuming that home charging is available for all vehicles may also be optimistic. Additionally, we use the EPA 5-cycle combined city and highway drive cycle to calculate efficiency for all vehicles and do not account for the correlation between driving distance and driving cycle characteristics. Benefits of electrified vehicles can be substantially larger in city traffic conditions than in highway conditions (Karabasoglu and Michalek, 2011), and longer driving distances are likely to involve a greater portion of highway travel, where conventional vehicles are more competitive. We also do not account for other factors such as heating and air conditioning use that can affect vehicle energy use differently for electric vehicles. We would expect these factors to make PHEVs and BEVs somewhat less attractive. We also do not account for any changes in driving behavior that occur alongside electrification, such as households with multiple vehicles adjusting their driving habits to accommodate short-range BEVs in their household fleets.

A second important set of assumptions is the space of design options, such as the use of a single scaled engine design, similar to the Toyota Prius to model each electrified powertrain alternative. In particular, we do not examine advancements to ICEs that improve fuel economy, such as direct injection, low friction lubricants, variable valve timing, etc. (NHTSA, 2008), and we do not optimize the design of the PHEV control strategy or include PHEVs with blended control strategies due to complexity in modeling the control variable space (Bradley and Frank, 2009). Additionally, we do not account for degradation requiring replacement of batteries and chargers prior to the end of vehicle life. Battery degradation will tend to affect smaller battery packs more severely than large packs because processed energy is spread over a larger number of cells in a larger pack, although the thin-electrode design of high-energy cells used in small battery packs may counteract this tendency (Fuller et al., 1994; Li et al., 2011; Wang et al., 2011). If battery life is shorter than vehicle life, it will make PHEVs and BEVs less competitive on both cost and GHGs than this analysis suggests. We do not include vehicle maintenance costs, which may differ by vehicle type. We also consider only vehicles similar in body size to the 2004 Toyota Prius—vehicles well-suited for electrification. The full fleet includes many larger vehicles that are less likely to be electrified in the near term due to cost, range, and technical issues.

Third, while we do consider a wide range of possible electricity generation scenarios, we vary these independently in the sensitivity analysis and do not consider the effect that vehicle allocation might have on marginal grid mix. If assigning vehicles with larger battery packs leads to greater charging demand, it may have systematic effects on the electricity grid mix that vary by region and time and would be expected to change in future scenarios with high penetration of electrified vehicles (EPRI, 2007; Parks et al., 2007; Sioshansi et al., 2010). Marginal electricity associated with charging PHEVs at night may often be more coal-heavy than regional averages, although night charging, and the use of smart chargers that control charge timing, may also support integration of renewables. The impacts of carbon prices on the electric grid are exogenous to our model, so electricity generation scenarios and carbon prices are also varied independently. Across regions and assumptions, grid implications should be bounded by our sensitivity scenarios.

This formulation represents a best-case scenario for minimizing cost or GHG emissions with these vehicle technologies; market outcomes would likely deviate, and we do not attempt to predict firm or consumer behavior.

5. Conclusions

We pose an optimization model to minimize annual life cycle GHG emissions and cost from the personal vehicle fleet by selecting (1) engine, motor, battery size, and battery swing window for midsize conventional, hybrid, plug-in hybrid, and battery electric vehicles and (2) allocation of those vehicles and of home and workplace charging stations to the vehicle fleet based on annual VMT. Results indicate best-possible scenarios for cost and GHG reductions given existing driving patterns, rather than likely market outcomes.

We find, in agreement with the literature, that without sufficient grid decarbonization plug-in vehicles do not offer substantial GHG emissions reductions compared to HEVs. GHG reductions improve with low-carbon electricity. Thus, grid decarbonization is needed to make plug-in vehicles a relevant means of reducing GHG emissions beyond grid-independent HEVs. Compared to CVs, HEVs offer cost and emissions reductions in almost all scenarios and are an optimal or near-optimal solution for minimizing cost across many scenarios.

We further find that under the current US electricity generation mix, workplace charging availability provides no GHG emissions benefit in the optimized solution, but workplace charging does provide additional benefits of optimistically up to 21% in combination with low-carbon electricity. Workplace charging availability changes the GHG-minimized vehicle allocation slightly, allocating smaller capacity PHEVs and BEVs. Gas prices above \$3.25/gal (plus 5.2% per year) cause PHEVs to appear in the minimum cost solution, but for plug-in vehicles to dominate over HEVs, either gas prices of \$7/gal (plus 5.2% per year) or gas prices of \$4.5/gal (plus 5.2% per year) in combination with low vehicle and battery costs (DOE 2030 program goal levels, including battery costs under \$200/kWh) are needed. High carbon prices (over \$100/tCO_2e) do little to drive plug-in vehicles to appear in the cost-minimizing solution.

We find that BEVs are restricted by range requirements from being a significant part of the minimum cost or GHG solutions. Even when range requirements are dramatically reduced, requiring BEV range adequate for only the average trip rather than the 95th percentile trip, a fleet of entirely BEVs is much more expensive and GHG-intensive than the other vehicle types, and BEVs are not GHG-minimizers for the full fleet even when charged with zero-emissions electricity. BEVs enter the GHG-optimal fleet only for short-range vehicles and only in cases with grid decarbonization.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.enpol.2012.08.061.

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