Life Cycle Cost and Environmental Implications of U.S. Electric Vehicle and Charging Infrastructure Scenarios

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Abstract

This thesis examines life cycle cost, greenhouse gas (GHG) emissions, petroleum use, and policy implications of scenarios for electrified vehicles and charging infrastructure in the U.S., addressing several questions: What mix of vehicles minimizes life cycle cost? GHG emissions? What are the implications of workplace charging in addition to home charging? How much current and potential U.S. residential charging exists? What are the costs and GHG emissions of fast-charging and battery swapping service stations? How sensitive are these results to uncertain parameters? What factors are most critical? and What are the policy implications?

Results indicate that without sufficiently clean electricity, plug-in vehicles (PEVs) with home and workplace charging do not offer substantial reductions in GHG emissions compared to hybrid electric vehicles (HEVs). Benefits improve with low-emission electricity generation. High gas prices ($6/gal) cause PEVs to appear in minimum cost solutions and combined with low vehicle and battery costs (DOE 2030 targets) cause PEVs to dominate.

Currently 79% of households but only 56% of vehicles have home parking where charging could be installed. Excluding renters, who face additional barriers, less than half of U.S. vehicles have reliable access to off-street parking where charging could be installed. This places a major limit on potential penetration of PEVs for the foreseeable future.

Battery swapping stations cost 40% more per vehicle served than fast charging stations without the cost of waiting time during service, but 50% less when it is included. Battery swapping's cost advantage requires vehicle and battery standardization.

Several policy implications are identified. Gas prices and vehicle and battery prices are identified as price levers to encourage adoption and reduce petroleum consumption, but clean electricity is also needed for GHG emissions reductions. Lack of residential charging could curb adoption and needs attention since parking infrastructure turns over more slowly than the vehicle fleet. With clean electricity, dedicated workplace charging further reduces GHGs. Battery electric vehicle (BEV) adoption is restricted by limited range. Rapid BEV refueling options include fast charging, which incurs costly waiting times during service, or battery swapping, which is faster and potentially less costly but requires vehicle and battery standardization.

1 Introduction and Motivation

Electrified vehicles (xEVs), including hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs), are currently of interest both to the U.S. government and to industry as a potential way to reduce greenhouse gas (GHG) emissions and petroleum use of the U.S. personal vehicle fleet, thus helping to alleviate national and global concerns about energy security and climate change (Office of the Press Secretary, 2009). In the U.S., the transportation sector accounted for 27% of GHG emissions in 2009 and 63% of petroleum consumption in 2010 (US EIA, 2011a). Passenger vehicles accounted for 9.5% of 2009 U.S. GHG emissions (US EPA, 2011). Reducing GHG emissions and petroleum consumption in the personal transportation sector is crucial to achieving climate and energy goals.

Electrified transportation helps with both of those goals by shifting transportation energy use from gasoline to electricity, and eventually to low-carbon electricity (Samaras and Meisterling, 2008). xEVs are vehicles that use electric motors for propulsion, either instead of or in addition to traditional internal combustion engines (ICEs). Plug-in vehicles (PEVs) are a subset of xEVs that can be powered by grid electricity and include PHEVs (which use both grid electricity and gasoline) and BEVs (which use only grid electricity). PEVs currently represent well less than 1% of U.S. new vehicle sales (Ohnsman, 2011). The hierarchy of vehicle types and acronyms is shown in Figure 1.1.

There are two main xEVs operating modes: charge sustaining mode and charge depleting mode. Charge depleting mode further consists of either all-electric mode or a blended mode. In charge sustaining mode, the gasoline engine provides all net propulsion energy and the battery is used as a buffer, with battery charge level remaining roughly constant. HEVs always operate in

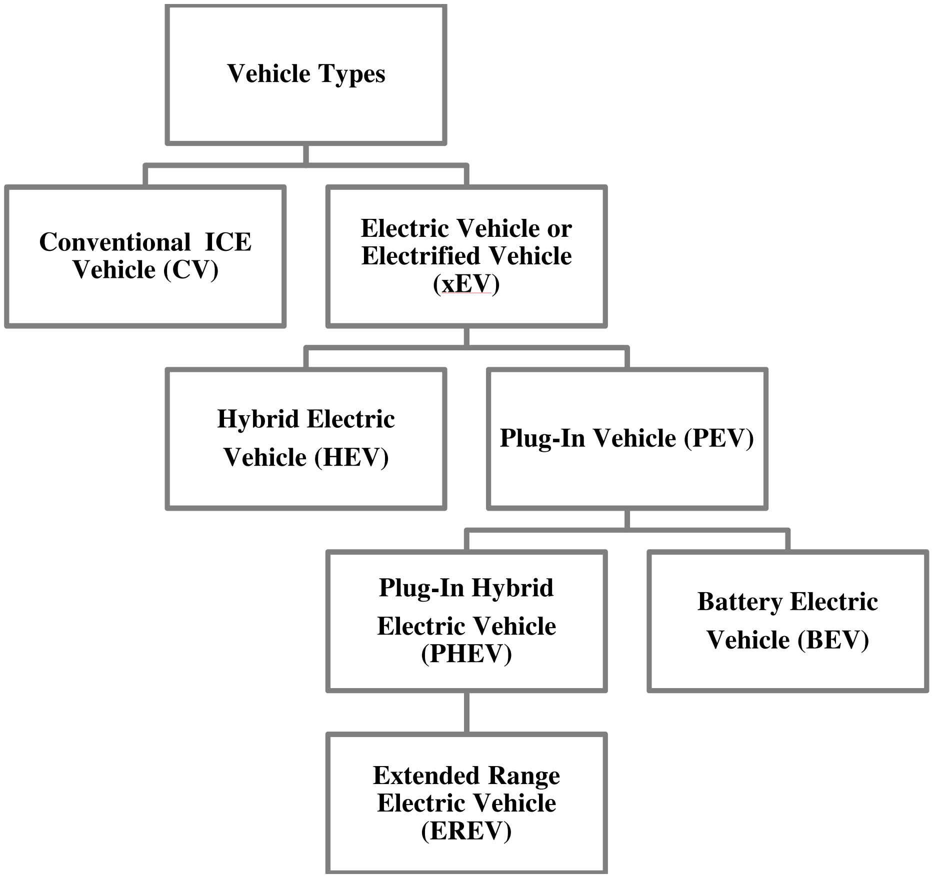

Figure 1.1 Hierarchy of vehicle types with acronyms

charge sustaining mode. In all-electric charge depleting mode, the main power source is the battery. BEVs always operate in all-electric charge depleting mode. In blended charge depleting mode, both the engine and the battery are providing power. PHEVs can operate in any of these modes. PHEVs that only operate in all-electric charge depleting mode or charge sustaining mode, without blending, are also known as extended range electric vehicles (EREVs). The distance that a PHEV can drive in all-electric charge depleting mode before switching to charge sustaining mode, or that a BEV can drive before it needs to stop and charge, is called the all-electric range (AER).

xEVs can have several different powertrain configurations. In conventional vehicles (CVs) with ICEs and without electric motors, the engine provides the propulsion to the wheels. In BEVs with motors and without ICEs, the electric motors provide the propulsion. PHEVs have both an engine and motor(s) and can have several powertrain configurations broadly categorized as series, parallel, and split (or series-parallel). In a series powertrain, the motor provides propulsion and the engine provides power either to the motor or the battery. This is the usual configuration for an EREV, since they usually do not operate in blended mode, and as the name implies, the battery and motor provide the main propulsion (as in a BEV) and the engine provides “extended range” by charging the battery. In a parallel powertrain, the motor and engine both provide propulsion simultaneously. A split powertrain can operate either in series mode or in parallel mode.

Subsequent sections of this thesis will refer to xEVs, CV, HEVs, PEVs, PHEVs, and BEVs. Unless otherwise noted, this thesis will assume that PHEVs have a split powertrain and EREV operation and do not operate in blended mode, but instead operate in charge depleting mode until the battery reaches the lower target SOC and in charge sustaining mode beyond that. This thesis will indicate the AER of a PHEV or BEV by appending the AER in miles to the acronym, so that, for example, a PHEV20 is a PHEV with a 20-mile AER.

The main charging method for PEVs is likely to be slow overnight residential charging. Three levels of charging speeds have been defined by SAE standard J1772 and are shown in Table 1.1 (SAE, 2010). This thesis will refer to AC Level 1 as “Level 1”, AC Level 2 as “Level 2”, and DC Level 3 as “Level 3”. This thesis will also refer to Levels 1 and 2 as “slow charging” and Level 3 as “fast charging”. Another type of DC fast charging is also defined by the Japanese CHAdeMO standard (“CHAdeMO Association,” n.d.). Unless otherwise noted, the terms “Level 3” and “fast charging” can also apply to CHAdeMO standards. Most PHEV or BEV owners will have Level 1 or

Level 2 charging at their home and maybe also at work. Level 2 charging is also likely to be available at some commercial destinations such as retail locations. However, faster charging methods will be needed to allow BEVs to be driven longer distances without stopping for a slow charge, thus addressing consumer "range anxiety" and mitigating a barrier to BEV purchase. With only slow Level 1-2 charging, a drive of 300 miles between two major cities would require a BEV with a typical range of 100 miles to stop at least twice, and for several hours each time.

Table 1.1 Vehicle charging levels defined by SAE J1772, with the time to charge a Nissan LEAF at that level (Roper, 2013).

Charge Method	Nominal Supply Voltage	Max. Current	Max. Power	Time to Charge Nissan LEAF
AC Level 1	120 V AC, 1-phase	12 A (15A breaker)	1.44 kW	20 hours
	120 V AC, 1-phase	16 A (20A breaker)	1.92 kW	
AC Level 2	208 to 240 V AC, 1-phase	≤ 80 A	19.2 kW	7 hours
DC Level 3	200 – 600 V	≤ 400 A	240 kW (more commonly 50-100kW)	30 min (to 80%)

PEV charging can also be divided into three types depending on location and how it is used, as shown in Table 1.2. Dedicated charging is charging with guaranteed access so that travel can be planned around it. The most common types will be Level 1 and 2 charging at home or at work, and BEVs and PHEVs will use it every day. Public use charging such as Level 1 or 2 charging at street parking or in shopping center parking lots will be for occasional use when convenient, but drivers would not be able to count on having access. BEVs and PHEVs would use public charging as "opportunity charging". Service station charging will be the most similar to what we are currently used to with gasoline service stations. They will be available for relatively fast refueling during trips and the two main options are Level 3 fast charging or battery swapping. These are unlikely to be used by PHEVs because those drivers can continue using gasoline; they will not need to wait 30 minutes to charge and their batteries are unlikely to be swappable. The customers for PEV service station charging will mostly be BEVs, and since drivers will purchase BEVs with enough range for most of their travel, they will stop only on the exceptional days when the usual range is exceeded.

Table 1.2 Types of PEV charging by location and use

	Dedicated	***Public Use***	***Service Station***
Location	Home, work with dedicated parking spot	Parking meters, commercial, retail	Service station
Speed	Slow: Level 1-2 120V-240V, 1.4-3.3 kW	Slow: Level 2 240V, 2.5-19.2 kW	Fast: Level 3 charging Or: Battery swapping with Level 1-3 inventory charging
Customers	BEV, PHEV	BEV, PHEV	Primarily BEV
Use	Daily	"Opportunity charging" as convenient	Exceptional days
Chapters	Chapters 2 and 3		Chapter 4

Options for rapid recharging of BEVs include Level 3 fast charging at specialized service stations – which has issues with efficiency, safety, cost, and increased battery degradation, and impacts the electricity grid – or battery swapping service stations – which physically switch a depleted battery for a charged battery but have challenges in cost, battery inventory requirements, standardization, wear, location, and operations. Fast-charging or battery swapping stations may offer refueling speeds of anywhere from 2 minutes to 30 minutes and are likely to be used mainly by BEVs on days when normal driving ranges are exceeded or normal overnight charging methods are unavailable. Since PHEVs can achieve longer daily driving ranges using gasoline, they will not need to stop for a fast charge, although they may still choose to do so if the opportunity is available.

A problem with BEVs is that in order to match the range of a conventional gasoline-powered vehicle they require very large, heavy battery packs. The weight of the battery packs reduces the vehicle efficiency, and the size reduces useable vehicle space for passengers and cargo. A vehicle with a smaller battery pack can be more efficient and versatile, but it needs to charge more often (Shiau et al., 2009).

A barrier to widespread adoption of xEVs is the “chicken 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 to invest in refueling infrastructure for vehicles that do not exist (Melaina and Bremson, 2008). Policy incentives can help speed market adoption of xEVs, but we would like to know which scenarios of xEV designs and charging infrastructure should be incentivized to meet cost, energy, or environmental goals. Engineering tradeoffs between xEV design, fleet penetration, and charging infrastructure deployment also need to be understood. Engineering tradeoffs in xEV design include the tradeoff between battery size and charging frequency and the tradeoff between different charging infrastructure types and scenarios. Outcomes depend on additional factors including vehicle adoption (market penetration), vehicle charging patterns, charging infrastructure availability, and public policy. Implementation of appropriate public policy (taxes, incentives, regulations) regarding xEVs can potentially decrease GHG emissions, petroleum use, and the cost of personal transportation by incentivizing desired scenarios. However, it is critical to understand which scenarios should be incentivized. An important part of analyzing those scenarios is modeling the cost and environmental effects of the vehicles and different types of vehicle charging infrastructure. Since many of the engineering tradeoffs just discussed have significant costs and emissions implications not just for vehicle operation but also upfront (purchase price, production emissions), it is important to consider both cost and GHG emissions on a life cycle basis. Throughout this thesis I will refer to life cycle cost as including both the production cost and the operation cost. Production cost includes the cost of the vehicle, batteries including replacement batteries if applicable, and charging infrastructure. Operation cost is the fuel price (gasoline or electricity). To combine production and operation costs into life cycle cost, they will both be annualized. Similarly, life cycle GHG emissions includes production emissions, which are from vehicle production, battery production, and charging infrastructure production, and operation GHGs, which include the production and combustion of gasoline and the production, transmission, and distribution of electricity.

This thesis examines potential and optimal scenarios for sustainable personal transportation through electrified personal vehicles, with a focus on the life cycle cost and GHG emissions of different types of charging infrastructure. I examine the cost, GHG emissions, petroleum use, and policy implications of future scenarios for xEVs and charging infrastructure in the U.S., addressing several sets of research questions:

(1) What mix of vehicles can minimize life cycle cost or GHG emissions of the midsize vehicle fleet, assuming availability of overnight slow charging? What is the cost or GHG reduction potential with and without daytime workplace charging infrastructure? What effect does workplace charging have on optimal vehicle allocation and battery sizing? What effect does carbon-intensity of the electricity grid have on these results? Under what conditions are PEVs part of the cost-optimized fleet?

(2) What opportunities exist for PEVs to be charged in U.S. residential areas, and what are the implications for potential and optimal fleet penetration of those vehicles?

(3) What are the cost, energy, and environmental effects of fast-charging? How sensitive are these results to parameters such as vehicle AER, driving patterns, fuel costs, charging efficiency, and carbon intensity of the electric grid, and what factors and uncertainties are most critical?

(4) What are the cost and environmental impacts of battery swapping service stations in comparison to fast-charging? How sensitive are these results to parameters such as vehicle AER, driving patterns, fuel costs, charging efficiency, and carbon intensity of the electric grid, and what factors and uncertainties are most critical? and

(5) What are the implications for policy related to xEVs and charging infrastructure?

Studies have addressed the effects of vehicle charging on the grid (Kelly et al., 2012; Parks et al., 2007; Peterson et al., 2011; Sioshansi et al., 2010; Weiller, 2011) and have studied the overall cost and emissions of PEVs (Bandivadekar et al., 2008; EPRI, 2001; Kammen et al., 2008; Michalek et al., 2011; Peterson et al., 2011; Samaras and Meisterling, 2008; Shiau et al., 2010, 2009), although most have focused on slow-charging and excluded costs and production emissions of charging infrastructure (Bandivadekar et al., 2008; Parks et al., 2007; Peterson et al., 2011; Samaras and Meisterling, 2008; Shiau et al., 2010, 2009; Sioshansi et al., 2010), and most also compare and select among a small set of fixed vehicle configurations which may not be optimal and therefore may not allow fair comparison between powertrains (Bandivadekar et al., 2008; 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; Weiller, 2011). Three studies do include slow charging infrastructure costs: an EPRI study includes costs for onboard vehicle chargers, household circuit upgrades, and charging cords (EPRI, 2001); and two other studies include costs of offboard chargers (Delucchi and Lipman, 2001; Michalek et al., 2011). All three of these studies that include slow charging infrastructure costs include only a small set of fixed vehicle configurations (Delucchi and Lipman, 2001; EPRI, 2001; Michalek et al., 2011), and one considered only PHEVs, not HEVs or BEVs (Delucchi and Lipman, 2001). Some studies in the literature also make simplifying assumptions about driving patterns or about electricity consumption that may make their results less realistic, such as assuming vehicles drive the same distance every day (Shiau et al., 2010, 2009) or consume the same amount of electricity every day (Schroeder and Traber, 2012). Studies in the literature have also addressed a business plan for fast charging (Schroeder and Traber, 2012), business plans for combining slow-charging with battery swapping (Avci et al., 2012; Lidicker et al., 2011), operation and inventory of a battery swapping station (Worley and Klabjan, 2011), and forecasted potential consumer adoption of BEVs under a battery subscription model with battery swapping (Becker et al., 2009), but these studies do not directly compare the costs or emissions of fast charging with battery swapping and have simplistic assumptions about the amount of fast charging or battery swapping infrastructure needed to support a fleet of vehicles (Lidicker et al., 2011; Worley and Klabjan, 2011). The presented work examines the impacts of availability of daytime charging on optimal vehicle designs for cost and GHG emissions objectives and will compare fast-charging to battery swapping for BEVs on cost and GHG emissions metrics. Necessary amounts of fast charging and battery swapping infrastructure will be informed by driving pattern models including variability across vehicles and across days, incorporating some geography-related bounds, and the sensitivity analysis will examine the effects of these parameters on the cost and emissions of a fleet including PEVs. Further literature relevant to each individual topic will be discussed in subsequent sections.

I present three studies to address the five sets of research questions posed above. Chapters 2 through 4 of this thesis discuss these three studies in more detail. Chapter 2, Optimal Design and Allocation of Electrified Vehicles and Dedicated Charging Infrastructure for Minimum Life Cycle Cost and GHG Emissions, discusses the first study, which addresses the research questions in (1) above by analyzing what vehicles should be assigned (perhaps by a benevolent dictator) to what drivers in the U.S. midsize personal vehicle fleet to meet cost and GHG emissions goals. Chapter 3, U.S. Residential Charging Potential for PEVs, presents a study to address the research question in (2) above by using multiple imputation to combine parking availability data from two publicly available datasets and by performing sensitivity analysis on the necessary assumptions where data is not available. Chapter 4, Comparative Implications of Electric Vehicle Fast Charging and Battery Swapping Stations for Life Cycle GHG Emissions and Cost, presents a study addressing the research questions in (3) and (4) above by modeling life cycle costs, GHG emissions, and station operation of fast charging and battery swapping service stations along a highway. Chapter 5 summarizes these studies and their implications for question (5) above.

2 Optimal Design and Allocation of Electrified Vehicles and Dedicated Charging Infrastructure for Minimum Life Cycle Cost and GHG Emissions

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 CVs, HEVs, PHEVs, and 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 U.S. 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.

The study presented in this chapter has been completed and has appeared in Energy Policy (Traut et al., 2012).

2.1 Introduction

Climate change and energy security are among the most pressing issues faced by the world and by the U.S. In the U.S., the transportation sector accounted for 28% of GHG emissions in 2009 (US EIA, 2011b) and 71% of petroleum consumption in 2010 (US EIA, 2011a). Passenger vehicles accounted for 9.5% of 2010 U.S. carbon dioxide emissions (US EPA, 2011) and 19% of 2009 nitrous oxide emissions (US EIA, 2011b). 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 “chicken 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 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 chapter 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 (Duvall and Knipping, 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 $7,500/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 chapter, 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 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 versus 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 2.2, present results for a base case and alternative scenarios in Section 2.3, address model limitations and future work in Section 2.4, and provide discussion and conclusions in Section 2.5.

2.2 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 2.2.4). 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

$$\begin{aligned}
&\underset{\mathbf{x}=[\mathbf{x}_1,\mathbf{x}_2,\ldots,\mathbf{x}_n]}{\text{minimize}} && \int_{S=0}^{\infty} f_{\mathrm{O}}(\mathbf{x},S)\, f_{\mathrm{S}}(S)\, dS && \textit{minimize life cycle cost or GHG emissions,}\\
&\text{subject to} && \mathbf{g}_j^{\mathrm{D}}(\mathbf{x}_j) \le \mathbf{0},\ \forall j \in J && \textit{s.t. design constraints,}\\
& && \mathbf{x}_j \in \Re^{p_j},\ \forall j \in J \\
&\text{where} && f_{\mathrm{O}}(\mathbf{x},S) = \min_{\{j\in J \mid \mathbf{g}_j^{\mathrm{A}}(\mathbf{x}_j,S)\le \mathbf{0}\}} \left\{ f_{\mathrm{O}j}(\mathbf{x}_j,S) \right\} && \textit{where vehicles are optimally allocated based on VMT subject to allocation constraints}
\end{aligned} \tag{2.1}$$

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); $\mathbf{g}^{\mathrm{D}}_j(\mathbf{x}_j)$ is the vector of vehicle design constraints; $\mathbf{g}^{\mathrm{A}}_j(\mathbf{x}_j,S)$ 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 min 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 $i\in\{1,2,...,m\}$, 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

$$\begin{aligned}
&\underset{\substack{\mathbf{x}_j,\alpha_{ij},\forall j\in J,\\ \forall i\in\{1,..,m\}}}{\text{minimize}} && \sum_{i=1}^{m}\sum_{k=K(i-1)}^{iK-1}\left(\frac{\sum_{j=1}^{n}\alpha_{ij}\begin{pmatrix} f_{\mathrm{O}j}\left(\mathbf{x}_j,k\Delta\right)\\ +f_{\mathrm{O}j}\left(\mathbf{x}_j,(k+1)\Delta\right)\end{pmatrix}}{2}\left(\frac{\begin{matrix}F_{\mathrm{S}}\left((k+1)\Delta\right)\\ -F_{\mathrm{S}}\left(k\Delta\right)\end{matrix}}{\Delta}\right)\right)\Delta \\
&\text{subject to} && \sum_{j\in J}\alpha_{ij}=1,\ \mathbf{g}_j^{\mathrm{D}}\left(\mathbf{x}_j\right)\le\mathbf{0},\ \mathbf{x}_j\in\Re^{p_j},\ \alpha_{ij}\in\{0,1\}, \\
& && \forall i\in\{1,..,m\},\ \forall j\in J \\
& && \mathbf{g}_{ij}^{\mathrm{A}}\left(\mathbf{x}_j,\alpha_{ij}\right)\le\mathbf{0},\ \forall i\in\{1,...,m\},\ \forall j\in J_{\mathrm{BEV}} \\
&\text{where} && \Delta=\frac{S_{\mathrm{MAX}}}{mK}
\end{aligned}\tag{2.2}$$

We relax the binary allocation variables α_{ij} into the continuous domain, $\alpha_{ij}\in\Re$, $0\le\alpha_{ij}\le 1$, making this into a nonlinear programming problem to ease computation. For any set of fixed designs $\mathbf{x}^* = [\mathbf{x}_1, ..., \mathbf{x}_n]^*$, 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 $J = J_{\mathrm{CV}} \cup J_{\mathrm{HEV}} \cup J_{\mathrm{PHEV}} \cup J_{\mathrm{BEV}}$. The decision variable vector $\mathbf{x}_j = [x_{\mathrm{E}j}, x_{\mathrm{M}j}, x_{\mathrm{B}j}, x_{\mathrm{SW}j}]^{\mathrm{T}}$ 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 $x_{\mathrm{M}} = x_{\mathrm{B}} = x_{\mathrm{SW}} = 0 \ \forall \ j \in J_{\mathrm{CV}}$ and $x_{\mathrm{E}} = 0 \ \forall \ j \in J_{\mathrm{BEV}}$. The function $f_{\mathrm{O}j}(\mathbf{x}_j,S)$ in the objective function of Eq. (2.2) is replaced by either $f_{\mathrm{C}j}(\mathbf{x}_j,S)$, equivalent annualized life cycle cost in 2010 U.S. dollars (USD2010) per vehicle-year, discussed in Section 2.2.1.1, or $f_{\mathrm{G}j}(\mathbf{x}_j,S)$, annualized life cycle GHG emissions in kilograms of CO_2-equivalent (kgCO_2e) per vehicle-year, discussed in Section 2.2.1.2. Appendix 7.1 summarizes model variables, functions, and parameters and defines base case and sensitivity values.

The design constraint vector $\mathbf{g}^{\mathrm{D}}_j(\mathbf{x}_j)=\{\mathrm{g}_1{}^{\mathrm{D}}_j(\mathbf{x}_j),\mathrm{g}_2{}^{\mathrm{D}}_j(\mathbf{x}_j)\}$ ensures that each vehicle satisfies comparable acceleration performance criteria. These include a maximum 0-60 miles per hour (mph) acceleration time t_{MAX} = 11 seconds for all vehicles, in both gasoline and electric mode: $\mathrm{g}_1{}^{\mathrm{D}}_j(\mathbf{x}_j) = t_{\mathrm{G}}(\mathbf{x}_j) - t_{\mathrm{MAX}} \le 0 \ \forall \ j \in J_{\mathrm{CV}} \cup J_{\mathrm{HEV}} \cup J_{\mathrm{PHEV}}$, $\mathrm{g}_1{}^{\mathrm{D}}_j(\mathbf{x}_j) = 0 \ \forall \ j \in J_{\mathrm{BEV}}$, $\mathrm{g}_2{}^{\mathrm{D}}_j(\mathbf{x}_j) = t_{\mathrm{E}}(\mathbf{x}_j) - t_{\mathrm{MAX}} \le 0 \ \forall \ j \in J_{\mathrm{PHEV}} \cup J_{\mathrm{BEV}}$, and $\mathrm{g}_2{}^{\mathrm{D}}_j(\mathbf{x}_j) = 0 \ \forall \ j \in J_{\mathrm{CV}} \cup J_{\mathrm{HEV}}$, where $t_{\mathrm{G}}(\mathbf{x}_j)$ and $t_{\mathrm{E}}(\mathbf{x}_j)$ are the 0-60 mph acceleration time of vehicle $\mathbf{x}_j$ in gasoline and electric mode, respectively, as discussed in Section 2.2.2. We also incorporate simple bounds 30kW $\leq x_{Ej} \leq$ 60kW, 50kW $\leq x_{Mj} \leq$ 110kW, and 200 cells $\leq x_{Bj} \leq$ 1000 cells $\forall j \in J_{PHEV}$ and x_{Ej} = 0 kW, 70 kW $\leq x_{Mj} \leq$ 250 kW, and 200 cells $\leq x_{Bj} \leq$ 9000 cells $\forall j \in J_{BEV}$ to avoid extrapolation beyond our simulation data. The battery swing window constraints are $0.1 \leq x_{SWj} \leq 0.8 \; \forall \; j \in J \backslash J_{CV}$ to ensure safe battery operation and avoid excessive degradation. Finally, the allocation constraints $\mathbf{g}^{A}_{ij}(\mathbf{x}_j,\alpha_{ij}) = \alpha_{ij} f_{Aij}(\mathbf{x}_j) \leq 0$ 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 $f_{Aij}(\mathbf{x}_j) = 0 \; \forall \; i \in \{1,\ldots,m\} \; \forall \; j \in J \backslash J_{BEV}$ 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 Appendix 7.1 and the s_{ϕ} function in Section 2.2.4.

2.2.1 Objective Functions

The function $f_{Oj}(\mathbf{x}_j,S)$ in the objective function of Eq. (2.2) 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.

2.2.1.1 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. (2.2) is replaced with $f_{Cj}(\mathbf{x}_j,S)$ (USD2010/vehicle-year), defined as

$$
\begin{aligned}
f_{\mathrm{C}j}\left(\mathbf{x}_j,S\right)=&\left(\begin{array}{l}\underbrace{c_{\mathrm{V}j}+\rho v_{\mathrm{V}j}}_{\substack{\text{base vehicle}\\ \text{production}}}+\underbrace{c_{\mathrm{E}}\left(x_{\mathrm{E}j}\right)+\rho v_{\mathrm{E}}\left(x_{\mathrm{E}j}\right)}_{\substack{\text{engine}\\ \text{production}}}+\\ \underbrace{c_{\mathrm{M}}\left(x_{\mathrm{M}j}\right)+\rho v_{\mathrm{M}}\left(x_{\mathrm{M}j}\right)}_{\substack{\text{motor}\\ \text{production}}}\end{array}\right)f_{\mathrm{A|P}}\left(r_{\mathrm{N}},l_{\mathrm{V}}\left(S\right)\right)+\\
&\left(\underbrace{\left(c_{\mathrm{B}}\left(x_{\mathrm{B}j}\right)+\rho v_{\mathrm{B}j}\right)x_{\mathrm{B}j}\kappa_{\mathrm{B}j}}_{\text{battery production}}\right)f_{\mathrm{A|P}}\left(r_{\mathrm{N}},l_{\mathrm{V}}\left(S\right)\right)+\\
&\left(\underbrace{\left(c_{\mathrm{C}}+\rho v_{\mathrm{C}}\right)q_{\mathrm{C}j}}_{\substack{\text{charger}\\ \text{production}}}\right)f_{\mathrm{A|P}}\left(r_{\mathrm{N}},l_{\mathrm{C}}\left(S\right)\right)+\\
&\left(\underbrace{\frac{\left(p_{\mathrm{G}}+\rho v_{\mathrm{G}}\right)S_{\mathrm{G}}\left(\mathbf{x}_j,S\right)}{\eta_{\mathrm{G}}\left(\mathbf{x}_j\right)}}_{\text{gasoline usage}}\right)\frac{f_{\mathrm{A|P}}\left(r_{\mathrm{N}},l_{\mathrm{V}}\left(S\right)\right)}{f_{\mathrm{A|P}}\left(r_{\mathrm{AG}},l_{\mathrm{V}}\left(S\right)\right)}+\\
&\left(\underbrace{\frac{\left(p_{\mathrm{ELEC}}+\rho v_{\mathrm{ELEC}}\right)S_{\mathrm{E}}\left(\mathbf{x}_j,S\right)}{\eta_{\mathrm{E}}\left(\mathbf{x}_j\right)}}_{\text{electricity usage}}\right)\frac{f_{\mathrm{A|P}}\left(r_{\mathrm{N}},l_{\mathrm{V}}\left(S\right)\right)}{f_{\mathrm{A|P}}\left(r_{\mathrm{AE}},l_{\mathrm{V}}\left(S\right)\right)}
\end{aligned}
\tag{2.3}
$$

where $c_{\mathrm{V}j}$ is the cost of producing the base vehicle excluding engine, motor, and batteries; ρ is the carbon price in dollars per $\mathrm{kgCO_2e}$ (zero in the base case); $v_{\mathrm{V}j}$ is the GHG emissions from production of the base vehicle excluding engine, motor, and batteries; $c_{\mathrm{E}}(x_{\mathrm{E}j})$ is the cost of engine production; $v_{\mathrm{E}}(x_{\mathrm{E}j})$ is the GHG emissions from engine production; $c_{\mathrm{M}}(x_{\mathrm{M}j})$ is the cost of motor production; $v_{\mathrm{M}}(x_{\mathrm{M}j})$ is the GHG emissions from production of the motor; $f_{\mathrm{A|P}}(r,n) = r(1+r)^n((1+r)^n - 1)^{-1}$ is the capital recovery factor; r_{N} is the nominal discount rate; $l_{\mathrm{V}}(S) = S_{\mathrm{LIFE}}/S$ is the life of the vehicle, including the engine and motor (and, for simplicity, the battery), in miles; S_{LIFE} is 150,000 miles; $c_{\mathrm{B}}(x_{\mathrm{B}j})$ is the cost per kWh of battery production; v_{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; v_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; v_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; v_{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 Appendix 7.1 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. (2.3), 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 2.2.2 and driving pattern functions $f_S(s)$, $S_E(\mathbf{x}_j,s)$, and $S_G(\mathbf{x}_j,s)$ in Section 2.2.4.

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 USD 2010 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 Appendix 7.1. Charger production cost c_C is \$1500 in the base case. This represents the approximate average cost of a Level 2 charger including installation (120 or 240 volts 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 U.S. 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 Appendix 7.1.

2.2.1.2 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. (2.2) is replaced with $f_{Gj}(\mathbf{x}_j,S)$ ($kgCO_2e$/vehicle-year), defined as

$$f_{\mathrm{G}j}\left(\mathbf{x}_j,S\right)=\underbrace{\frac{v_{\mathrm{V}j}}{l_{\mathrm{V}}\left(S\right)}}_{\text{base vehicle production}}+\underbrace{\frac{v_{\mathrm{E}}\left(x_{\mathrm{E}j}\right)}{l_{\mathrm{V}}\left(S\right)}}_{\text{engine production}}+\underbrace{\frac{v_{\mathrm{M}}\left(x_{\mathrm{M}j}\right)}{l_{\mathrm{V}}\left(S\right)}}_{\text{motor production}}+\underbrace{\frac{v_{\mathrm{B}j}x_{\mathrm{B}j}\kappa_{\mathrm{B}j}}{l_{\mathrm{V}}\left(S\right)}}_{\text{battery production}}+$$
$$\underbrace{\frac{v_{\mathrm{C}}q_{\mathrm{C}j}}{l_{\mathrm{C}}\left(S\right)}}_{\text{charger production}}+\underbrace{\frac{v_{\mathrm{G}}S_{\mathrm{G}}\left(\mathbf{x}_j,S\right)}{\eta_{\mathrm{G}}\left(\mathbf{x}_j\right)}}_{\text{gasoline usage}}+\underbrace{\frac{v_{\mathrm{ELEC}}S_{\mathrm{E}}\left(\mathbf{x}_j,S\right)}{\eta_{\mathrm{E}}\left(\mathbf{x}_j\right)}}_{\text{electricity usage}} \tag{2.4}$$

where all parameters have been previously defined. In Eq. (2.4), 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 Appendix 7.1.

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.

2.2.2 Vehicle Performance Models

To estimate the electrical $\eta_{\mathrm{E}}(\mathbf{x}_j)$ and gasoline $\eta_{\mathrm{G}}(\mathbf{x}_j)$ efficiencies and the acceleration performances $t_{\mathrm{G}}(\mathbf{x}_j)$ and $t_{\mathrm{E}}(\mathbf{x}_j)$ 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 U.S. 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 seconds, 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 Appendix 7.1.

2.2.3 Charging Infrastructure Scenarios

We consider the following two charging scenarios: (1) only Level 2 home charging (240 volts 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 Appendix 7.1 for details).

We implement these two charging scenarios in the model by partitioning J_{PHEV} and J_{BEV} each into two subsets $J_{\text{PHEV}} = J_{\text{PHEV(1)}} \cup J_{\text{PHEV(2)}}$ and $J_{\text{BEV}} = J_{\text{BEV(1)}} \cup J_{\text{BEV(2)}}$, 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.

2.2.4 Driving Patterns

To find the CDF $F_S(S)$ for annual VMT, we use data on the weighted average daily distance traveled (based on odometer readings) of each vehicle in the U.S. from the 2001 National Household Travel Survey (NHTS) (US DOT, 2003). The resulting histogram is shown in Figure 2.1. This distribution accounts for the variability in average daily VMT across the U.S. 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 miles in NHTS odometer readings (US DOT, 2003) and 11,900 miles in the Minnesota data set (Sierra Research, 2005)), we believe the Minnesota data set is reasonably representative for providing an estimate of U.S. 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

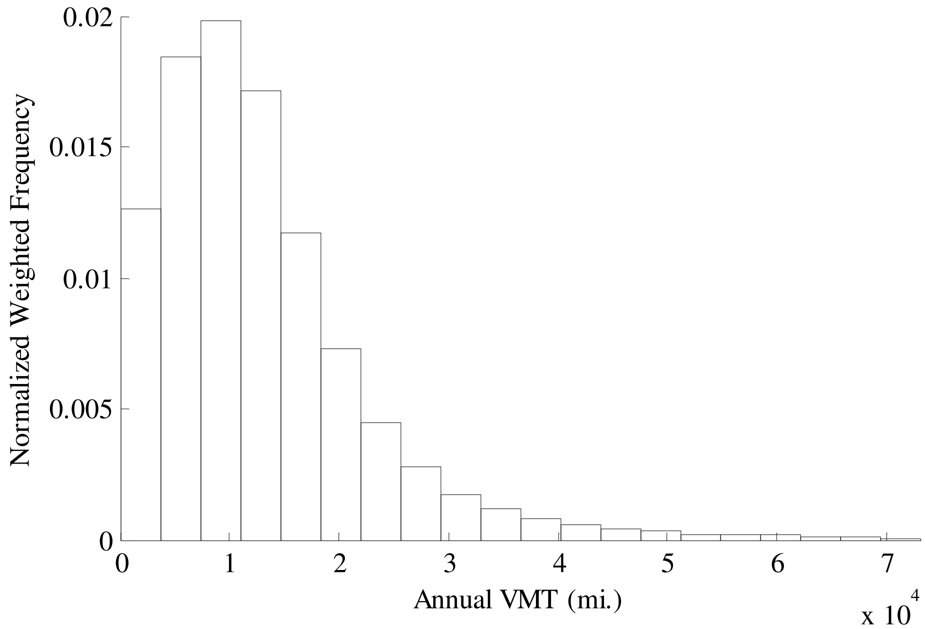

Figure 2.1 Histogram of odometer-based annual VMT from NHTS 2001 data (US DOT, 2003)

average of D = 243.8 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 days 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 $F_{\sigma}^{\mathrm{V}}(\sigma, S) = 1 - \exp(-\sigma/\mu(S))$, where σ is a random variable indicating distance driven on a particular day.

Figure 2.2 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 $S_{\mathrm{G}}(\mathbf{x}_j, S)$, the annual distance powered by gasoline, and $S_{\mathrm{E}}(\mathbf{x}_j, S)$, the annual distance powered by electricity as

$$S_{\mathrm{E}}(\mathbf{x}_j, S) = S\left(1 - \exp\left(\frac{-q_{\mathrm{C}j} s_{\mathrm{AER}}(\mathbf{x}_j)}{\mu(S)}\right)\right) \tag{2.5}$$

$$S_{\mathrm{G}}(\mathbf{x}_j, S) = S \exp\left(\frac{-q_{\mathrm{C}j} s_{\mathrm{AER}}(\mathbf{x}_j)}{\mu(S)}\right) \tag{2.6}$$

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"

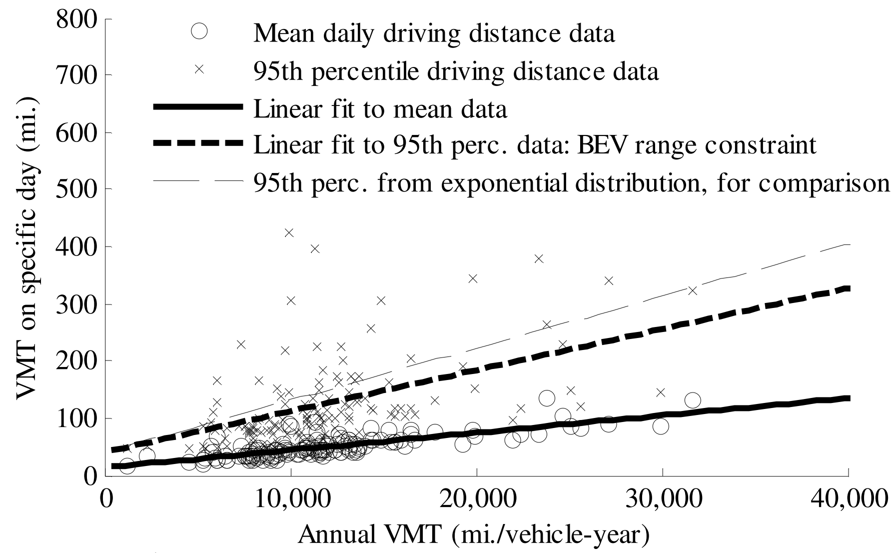

Figure 2.2 Mean and 95th percentile driving-day distances for 133 vehicles versus annual VMT, with linear fits and with 95th percentile implied by the family of exponential distributions calibrated to match a linear fit to the mean. The linear fit to the 95th percentile data is used as the BEV range constraint.

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).

2.2.5 Allocation Method

Figure 2.3(a) shows an example plot of $f_{Oj}(\mathbf{x}_j,S)/S$ (either GHG emissions or cost per mile) versus 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. Figure 2.3(b) 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. (2.1). The area under each vehicle curve in Figure 2.3(b) 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.

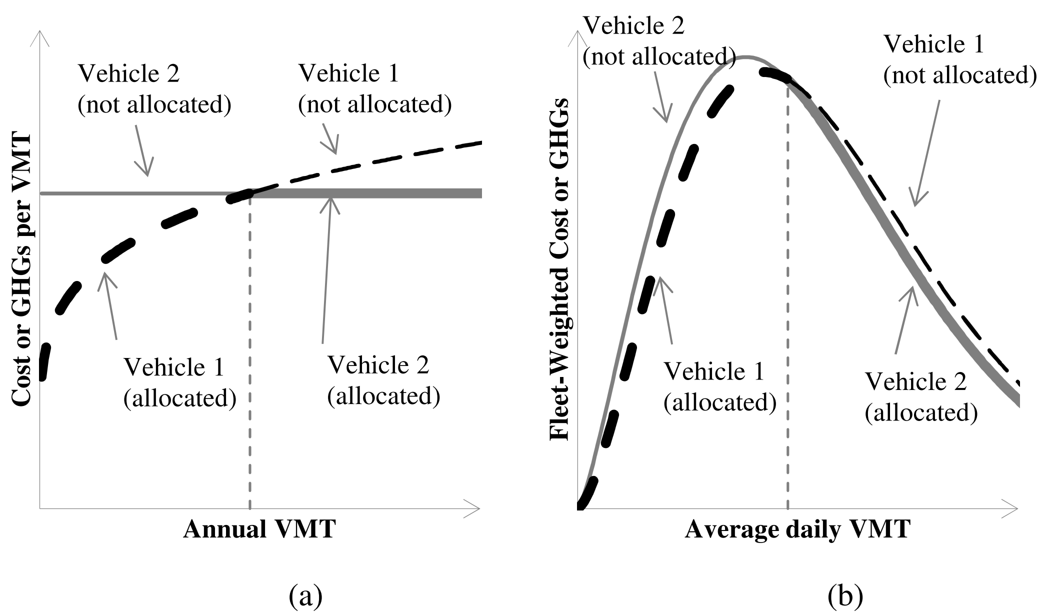

Figure 2.3 Example illustrative plots of (a) cost or GHGs per VMT vs. annual VMT and (b) fleet-weighted cost or GHGs vs. annual VMT. The area under the curve in (b) is the objective function value.

2.2.6 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 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 2.1 summarizes assumptions for our base case and sensitivity cases, and details of sensitivity cases can be found in Appendix 7.1.

Finally, we also ran some additional cases for sensitivity analysis where the PHEV and BEV metamodels had higher efficiency. These updated metamodels were calculated (1) with the PHEV PSAT model used to model BEVs, since the BEV model was less efficient and (2) with the method of calculating 5-cycle efficiency updated so that both PHEVs and BEVs are more efficient. See Appendix 7.1 Section 7.1.1.3.1 for details.

Table 2.1 Summary of base case and sensitivity cases

	Base case	**Sensitivity cases**
Electricity grid mix	U.S. 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, \$.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/kgCO_2e	\$0.02, \$0.1/kgCO_2e (\$20, \$100 per metric ton CO_2 equivalent (tCO_2e))

2.3 Results

In this section, we describe the results obtained from the optimization formulation defined in Eq. (2.2). First in Section 2.3.1, we show lifecycle cost and GHG emission results for several example vehicle designs, disaggregated to illustrate the contributing factors. Then in Section 2.3.2, 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 Appendix 7.1.

2.3.1 Cost and GHG Emissions Breakdown

Figure 2.4 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 Eq. (2.3) and (2.4). For illustration purposes, the example vehicle designs shown in Figure 2.4 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 7.9 scenarios 25 and 26 and Table 7.10 scenarios 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.

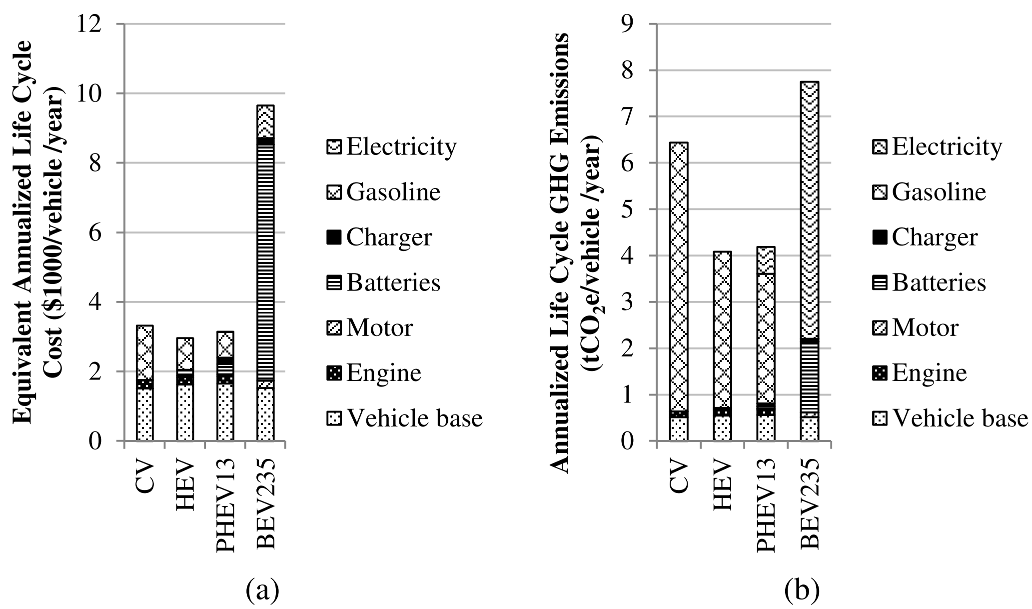

Figure 2.4 Breakdown of (a) equivalent annualized life cycle cost and (b) life cycle GHG emissions for four independently cost-optimized vehicle designs.

As shown in Figure 2.4(a), 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. Figure 2.4(b) 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 chapter HEVs produce 37% less life cycle GHG emissions than CVs. Samaras & 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 tradeoffs between producing additional chargers and electrifying additional miles.

2.3.2 Optimal Design and Allocation

Results are summarized in two figures: Figure 2.5 shows selected results for minimizing annualized life cycle GHG emissions, and Figure 2.6 shows selected results for minimizing equivalent annualized life cycle cost. Further results, including more details for each of the cases shown, are included in Appendix 7.1. 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 estimates defined in the Section 2.2 and tabulated in Appendix 7.1, including average U.S. grid mix and energy prices. Following the base case, each sensitivity analysis scenario is defined by the major differences from the base case.

Figure 2.5 and Figure 2.6 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

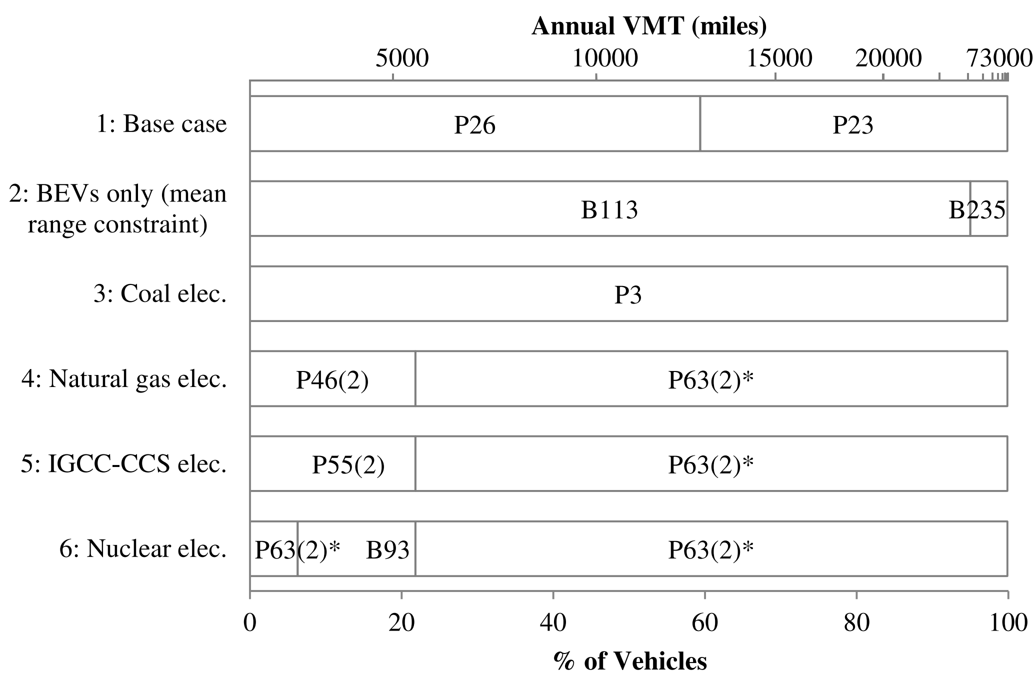

Figure 2.5 Optimal vehicle allocations for minimizing annualized life cycle GHG emissions in selected scenarios. "P" indicates PHEV and "B" indicates BEV. Numbers after vehicle abbreviations indicate the AER in miles, and "(2)" indicates workplace charging in addition to home charging. Asterisks indicate vehicle designs with battery sizes (and AERs) at the bounds of our model. Base case details appear in Table 2.1.

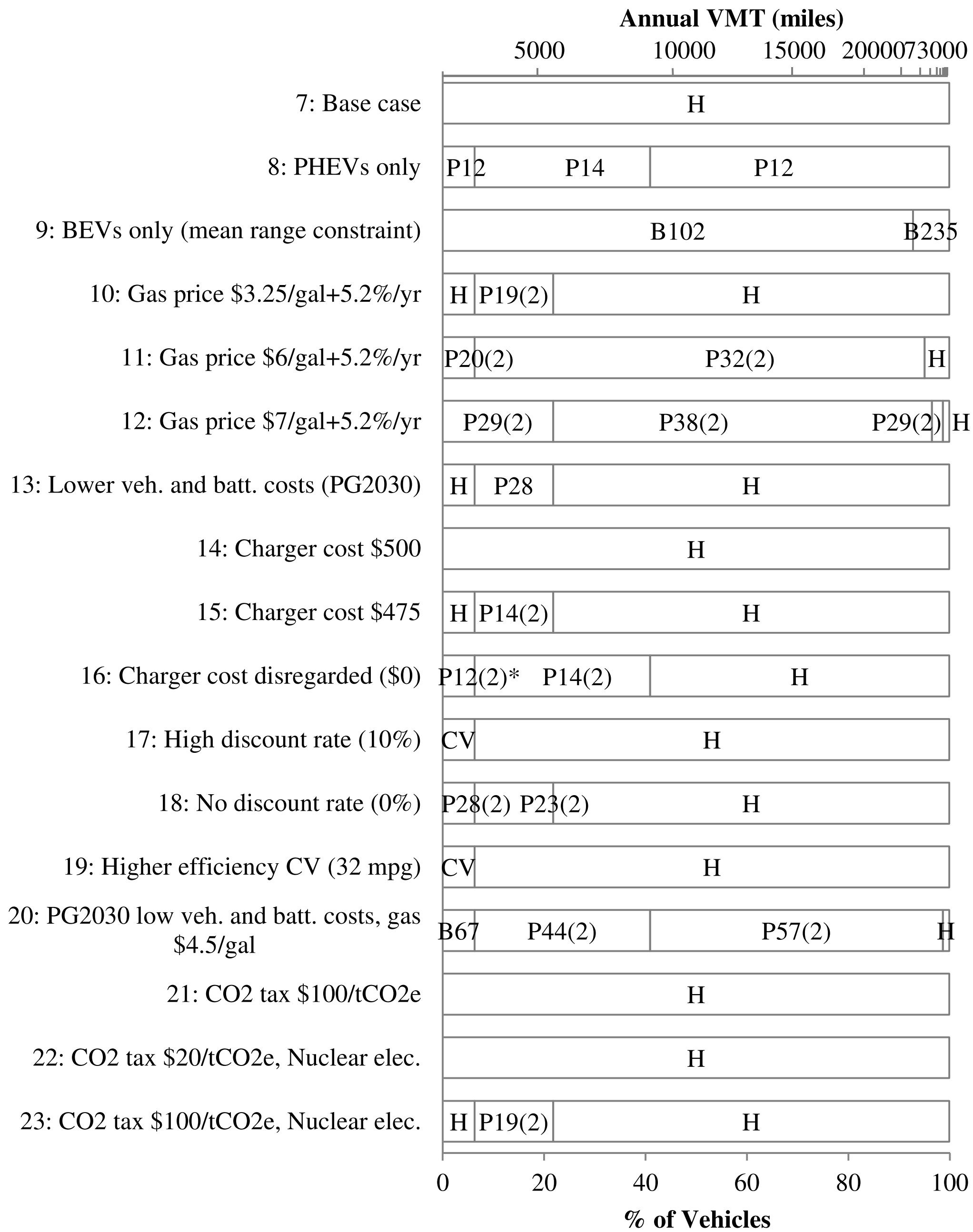

Figure 2.6 Optimal vehicle allocations for minimizing equivalent annualized life cycle cost in selected scenarios. "C" indicates CV, "H" indicates HEV, "P" indicates PHEV, and "B" indicates BEV. Numbers after vehicle abbreviations indicate the AER in miles, and "(2)" indicates workplace charging in addition to home charging. Asterisks indicate vehicle designs with battery sizes (and AERs) at the bounds of our model. Base case details appear in Table 2.1.

x-axes are related to each other by the distribution of annual VMT across the fleet, shown in Figure 2.1. 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 Figure 2.5 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 Figure 2.5 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 trip, shown here, rather than the 95th percentile trip), 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 chapter, 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 Appendix 7.1. 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).

Figure 2.6 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 mile 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 Appendix 7.1. 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 U.S. 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 Table 7.9 and Table 7.10).

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 7.9), 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 U.S. 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.

2.3.3 Additional Sensitivity Analysis Cases with Improved PHEV and BEV Efficiency

Since our BEV metamodel derived from PSAT resulted in BEVs that were less efficient than the PHEVs, we ran sensitivity analysis cases with improved BEVs efficiency. PHEV efficiency is also improved in these cases due to a change in the 5-cycle calculation method (described in Appendix 7.1) and BEV efficiencies are comparable to PHEV efficiencies with the same AER. Results are shown in Figure 2.7 and Table 7.11. As shown, BEVs now appear in the base case solution for minimizing GHGs. However, their allocation is still limited by range requirements to only the 22% of vehicles with the shortest average driving distances. Their AERs are the same as BEVs allocated in previous cases because these are the minimum required AERs to meet range requirements, but since these vehicles are more efficient, their batteries can be smaller. The allocated PHEV changes only slightly in design but its rated AER is higher due to its increased efficiency. HEVs still dominate the minimum cost solution. Additional sensitivity cases with these more efficient PHEV and BEV metamodels are left for future work.

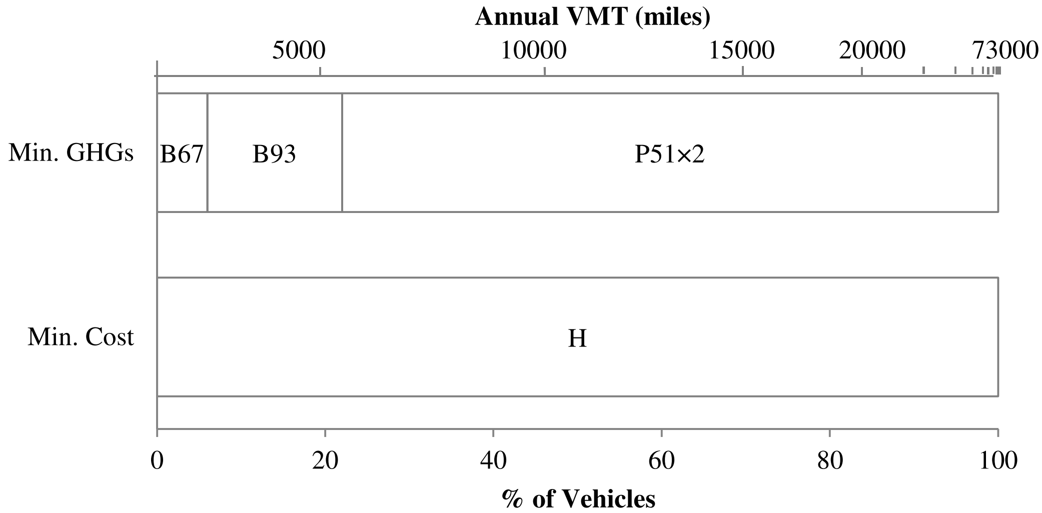

Figure 2.7 Optimal vehicle allocations for minimizing equivalent annualized life cycle cost and annualized life cycle GHG emissions in cases with improved efficiency of PHEV and BEV models and all other parameters at base case values. "H" indicates HEV, "P" indicates PHEV, and "B" indicates BEV. Numbers after vehicle abbreviations indicate the AER in miles, and "(2)" indicates workplace charging in addition to home charging. Detailed results appear in Table 7.11.

2.4 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, 2013), 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 electrified 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. We account for possible higher PHEV and BEV efficiencies in a small number of sensitivity analysis cases, but the impacts of improved PEV efficiency on other cases, especially the decarbonized grid scenarios, is left for future work.

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 electricity grid mix that vary by region and time and would be expected to change in future scenarios with high penetration of electrified vehicles (Duvall and Knipping, 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.

2.5 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 mid-size 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 (Bandivadekar et al., 2008; Samaras and Meisterling, 2008). 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 U.S. 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 gasoline (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.

3 U.S. Residential Charging Potential for PEVs

Availability of residential charging infrastructure could be a limiting factor for fleet penetration of plug-in vehicles in the U.S. We assess existing and potential charging infrastructure for plug-in electric vehicles in U.S. households using data from the American Housing Survey (AHS) and the Residential Energy Consumption Survey (RECS). We estimate that about 38% of households and 22% of vehicles have access to a dedicated home parking spot within reach of an outlet (at least Level 1, 120V) sufficient to recharge a small plug-in vehicle battery pack overnight. Access to faster (Level 2, 240V) charging, required for vehicles with longer electric range, will usually require infrastructure investment (costing from several hundred dollars up to $10,000 depending on electrical panel and construction requirements). Installing multiple vehicle chargers at the same household increases the cost and the likelihood of requiring a costly breaker panel upgrade. We estimate that 79% of households but only 56% of vehicles have access to a dedicated home parking spot where charging infrastructure could be installed. The percentage of vehicles with access is lower than for households due to multi-vehicle households and limited garage/driveway space. Urban areas have the lowest charging and parking availability. Additionally, 33% of U.S. households (38% in urban areas) are rentals, where regular tenant turnover and split incentives between landlords and tenants create additional barriers to infrastructure investment. We discuss sensitivity of results to uncertain factors. Future scenarios of plug-in vehicle penetration that ignore the limited availability of U.S. residential charging infrastructure opportunities are likely to overestimate the potential market for plug-in vehicles.

3.1 Introduction

In the current new light duty vehicle market, CVs have the vast majority of market share. HEVs represent less than 4% of the market (EDTA, 2012; HybridCars.com, 2012). PEVs have been available since 2010 and have received up to 0.3% of the market through October 2012 (EDTA, 2012; HybridCars.com, 2012). PEVs available in the marketplace include PHEVs (e.g. the Chevy Volt and the plug-in Prius) and BEVs (e.g. the Nissan Leaf and the Ford Focus Electric). Several studies have forecast potential future market share of PEVs. For example, the Electric Power Research Institute (EPRI) suggests that PHEVs may have a market share of 60% by 2050 (Duvall and Knipping, 2007), and the Pacific Northwest National Laboratory estimates that PHEVs could reach as much as 70% market share by 2045 (Balducci, 2008). The Center for Entrepreneurial & Technology (CET) forecasts that BEVs may have more than 80% of market share by 2030 (Becker et al., 2009). These and other PEV penetration forecasts are shown in Figure 3.1 (Heckmann et al., 2013; US EIA, 2011c). Factors influencing market penetration of plug-in vehicles are varied, including gasoline prices, battery costs and life, charging infrastructure availability, government incentives, vehicle design, and vehicle availability (Axsen and Kurani, 2008). One potentially significant limiting factor for PEV market penetration is the ability of U.S. households to charge vehicles at home. This chapter uses available housing stock data to quantify current and potential future home charging opportunities in the U.S.

Although HEVs, PHEVs, and BEVs are all electrified vehicles (xEVs), BEVs and PHEVs have different battery charging mechanisms than HEVs. An HEV combines a conventional internal combustion engine (ICE) propulsion system with an electric propulsion system; a PHEV has additional battery storage capacity to support a range

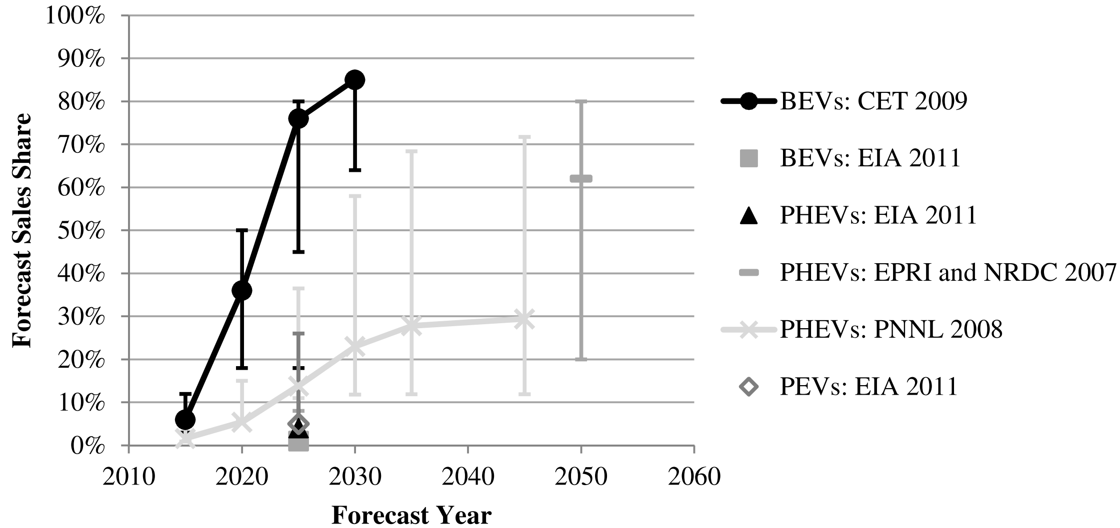

Figure 3.1 PEV Market Penetration Forecasts (Heckmann et al., 2013). Error bars indicate range of forecasted scenarios.

(typically 10 to 40 miles) of driving in electric mode (Li, 2007), while longer distance can be achieved by using an ICE; a BEV is an electric vehicle that is propelled only by electricity. PHEVs can charge their batteries directly from a wall outlet, and BEVs must charge this way, while HEVs charge their batteries only from power generated onboard by the ICE. Therefore PHEVs and BEVs require charging infrastructure that HEVs do not.

While both BEVs and PHEVs both benefit from electric propulsion, BEVs require relatively frequent charging (Electrification Coalition, 2009). Residential charging is likely to be important for adoption of both PHEVs and BEVs, not only because consumers without home charging may be less likely to purchase them, but also because off-peak electric load times are overnight. Research from Oak Ridge National Laboratory (ORNL) and National Renewable Energy Laboratory (NREL) indicates that a large penetration of PHEVs would require additional generation capacity to be built unless most charging happens in off-peak periods (Hadley, 2006; Parks et al., 2007; Shao et al., 2009). According to Dominion Virginia Power (DOM) (Virginia Electric and Power Company, 2011), the off-peak hours during summer months are from 10pm to 10am, and off-peak hours during winter months are from 10pm to 1am and 11am to 5pm. Moreover, Samaras et al. suggest that the existence of several different types of charging connections and the tendency of each vehicle to have only 1-2 specific connection types may limit utility of public charging and require users to have a specific home charger (Samaras et al., 2009). In addition, a survey from EV Customer Strategy Research Council and Electric Vehicle Program Summit indicates that 81% of consumers prefer to charge at home (EV Customer Strategy Research Council and Electric Vehicle Programs Summit, 2011). Thus, residential charging opportunities could be a significant limiting factor for PHEV market penetration.

Electric vehicle charging, whether at home or in public places, can include Level 1, Level 2, or Level 3 charging. According to the SAE J1772 standard for charge couplers, Level 1 charging is at 120 V and 12 A or 16 A, and Level 2 charging is the preferred method for BEV charging using 240 V outlet at 16 to 80 A (NPC, 2012; SAE, 2010). For example, the Chevy Volt charges in about 10 hours using Level 1 charging and 4 hours using Level 2 (Chevrolet, 2010). SAE's Level 3 DC charging standard was approved in October 2012 (Ponticel, 2012). It is the fastest charging method, but it requires high voltage power and will not be an option for residential charging, so we address only Level 1 and Level 2 residential charging in this chapter.

Many studies in the literature have addressed xEV related topics, such as battery pack evaluation for PHEVs, electric grid impacts of PEVs, energy and environmental impacts (Michalek et al., 2011; Peterson et al., 2011), and xEV technology trends (Duvall, 2011;

Mahalik et al., 2010; Tuttle and Kockelman, 2011). Some studies have assessed how much public or workplace vehicle charging might be needed (Capar et al., 2011; Peterson and Michalek, 2013; Traut et al., 2012). However, little has been done to quantify current and future residential charging opportunities. The Electrification Coalition (Electrification Coalition, 2009) estimates availability of residential charging based on residential parking availability, with data from the American Housing Survey (AHS) (US Census Bureau, 2009). Axsen and Kurani have taken steps towards quantifying home charging opportunities in the U.S., especially in the San Diego area (Axsen and Kurani, 2012a). They conducted a nationwide survey of 2373 new car buyers, asking questions about PEVs in general and home charging specifically (Axsen and Kurani, 2008), and they have two published studies that characterize access to Level 1 and Level 2 residential charging (Axsen and Kurani, 2012a, 2012b). The first study shows that around half of the respondents can park a vehicle within 25 feet of a Level 1 outlet in the U.S. and the second study shows that about two thirds of respondents currently have Level 1 charging access in the San Diego area (Axsen and Kurani, 2012a, 2012b). All of these studies in the literature address charging opportunities on a per household basis, and none compare urban versus rural access to parking and charging.

In this chapter, we examine several questions by analyzing data from AHS and combining it with data from the Residential Energy Consumption Survey (RECS) (US EIA, 2011d):

(1) How many U.S. households currently have Level 1 charging access for at least one vehicle?

(2) How many U.S. households have dedicated parking for at least one vehicle, and could therefore charge that vehicle in the future, after some investment in charging infrastructure?

(3) How many U.S. personal vehicles currently have access to Level 1 charging when they are parked at home?

(4) How many U.S. personal vehicles have a dedicated parking space at home and could therefore charge at home in the future, after some investment in charging infrastructure?

(5) How sensitive are these results to the assumptions?

(6) What are the demographics of households that can potentially charge a PEV?

(7) How much do charging and parking opportunities vary between urban and rural areas? and

(8) What implications does the availability of home charging opportunities have for future market penetration of BEVs and for studies that assume universal residential charging access?

3.2 Data, Assumptions, and Sensitivity Analysis

Data are drawn from two main sources: the Residential Energy Consumption Survey (RECS) (US EIA, 2011d) and the American Housing Survey (AHS) (US Census Bureau, 2009). Since each of these data sets contains some but not all of the data needed for this analysis, we combine them to obtain the most complete data possible. For some parameters, data are unavailable. In those cases we make assumptions and perform sensitivity analysis to determine the impact of those assumptions.

RECS is a U.S. nationwide household energy consumption survey conducted every 4 years by the U.S. Energy Information Administration. The 2009 RECS survey is the most recent one available at the time of this analysis. The 2009 RECS survey has data on over 12,000 U.S. households and is designed to be a representative sample, including weighting factors to account for sampling bias and nonresponse bias.

AHS is a U.S. nationwide housing stock survey conducted every 2 years by the U.S. Census Bureau. Although some 2011 AHS data are available at the time of this analysis, 2009 data were used for consistency with the 2009 RECS data. The 2009 AHS survey has data on over 73,000 U.S. households and is designed to be a representative sample of housing stock, although the large number of non-responses may affect the representativeness. AHS includes weighting factors that attempt to adjust for both sampling bias and nonresponse bias, but nonresponses could still have a significant effect on estimates if the nonresponses were systematic in ways that could not be corrected for in determining the weighting factors (e.g.: if respondents who would have given certain answers systematically refrained from answering the questions). Our analysis uses multiple imputation (MI), a Monte-Carlo analysis method, to account for the potential impact of these non-responses (see Section 3.3.1 Data Preparation).

Some of the variables used in this chapter appear in both AHS and RECS. These include housing unit type (single family detached home, single family attached home, apartment, or mobile home), occupancy status (owned, rent, or occupied without rent), population density (urban or rural), year the home was built, household gross annual income, number of household members age 20 or older, presence of a garage or carport, and number of rooms in the home. Variables used in this chapter that are only available in RECS include presence and size (up to 3 spots) of an attached garage, presence and size (up to 3 spots) of a detached garage, presence of a carport, and presence of an outlet within 20 feet of vehicle parking, Variables used in this chapter that are only available in AHS include presence of off-street parking if there is no garage or carport, number of cars owned by the household, and number of light trucks owned by the household.

Figure 3.2 summarizes available data from AHS 2009 and RECS 2009 on the number of light duty vehicles (cars and light trucks) per U.S. household, the number of parking spots available in garages at households, and the portion of households that have an outlet within 20 feet of vehicle parking. Since the maximum number of reported spots per garage is three and each household has at most one garage reported, the maximum number of garage spots per household is also three. Figure 3.2 shows that more U.S. households have vehicles than have garages, and most of those have multiple vehicles. Further details of the AHS and RECS data are provided in Appendix 7.2.

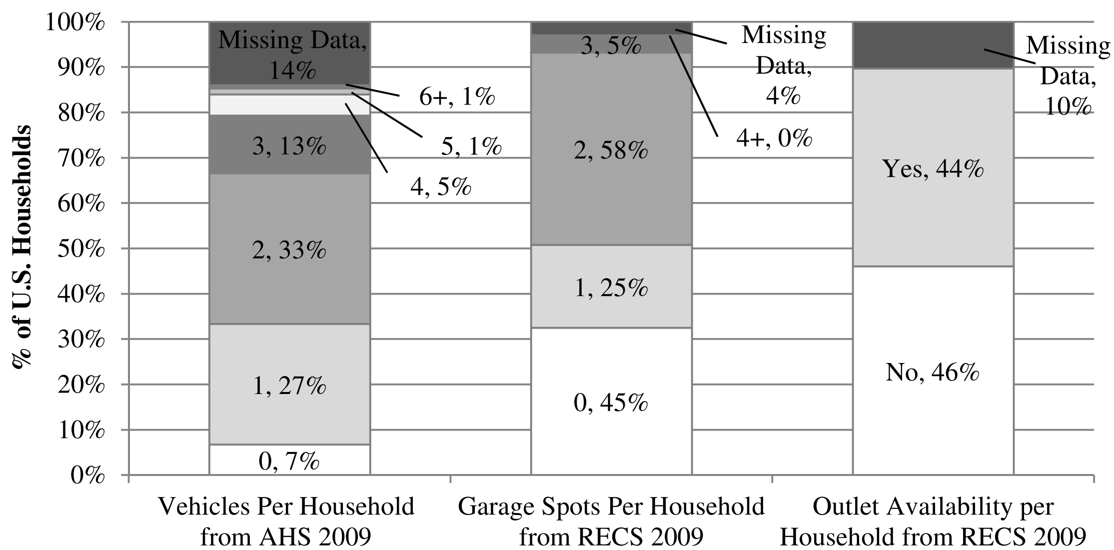

Figure 3.2 Vehicles per household, garage spots per household, and outlet availability from AHS 2009 and RECS 2009 data sets. "Missing Data" indicates uncertainty from non-responses. Zero parking spots indicates no garage.

Each of these data sets has some limitations that we took into consideration in this analysis. In AHS, households were only asked whether they have off-street parking if they stated they did not have a garage or carport. Similarly, in RECs, households were only asked whether they have a detached garage if they stated they did not have an attached garage. Therefore, we have no data on households that have multiple types of garage or that have both a garage and other off-street parking such as a driveway. Also, although RECS households were asked the size of their attached or detached garage (up to 3 spots) they were not asked the size of their carport. Aside from parking, another problematic area was the population density data. Although both data sets contain details beyond simple urban vs. rural designations, RECS uses Office of Budget and Management definitions (Metropolitan Statistical Areas versus Micropolitan Statistical Areas) and AHS uses Census definitions (Central cities, urban and rural areas inside or outside Metropolitan Statistical Areas). It should be possible to match these two types of data in more detail than only urban versus rural (US Census Bureau, Geography Division, 2012), but the numbers show that the two data sets do not appear to be consistent (see Figure 7.16). Therefore we have used only the urban versus rural designations and not the more detailed categories.

Since not all the data we would like to have for this analysis are available, we also needed to make some assumptions. We performed a sensitivity analysis to account for both the uncertainty in the data (through multiple imputation) and the uncertainty in our assumptions (through defining optimistic and pessimistic cases). Our assumptions for the base case, optimistic case, and pessimistic case are shown in Table 3.1. The major assumptions influencing charging opportunities are the size and presence of driveways (or other non-garage off-street parking), usability of outlets (such as whether the circuit would be overloaded by plugging in a vehicle), and the portion of parking spaces that are available for parking (i.e. not used for storage, boats, or other non-parking use). Some of these assumptions, such as that households have only one type of garage or that households with garages do not have driveways in the base case, are based on the structure of the data available in RECS and AHS. For example we lack data on whether any household has more than one garage or whether any household with a garage has a driveway. However, since having a driveway in front of a garage is somewhat common, we included the possibility of additional off-street parking with a garage in the optimistic case. Other assumptions are based on data that are entirely missing from these data sets. The portion of outlets that will actually support vehicle charging is not asked, probably because respondents are unlikely to know the answer. Outlets need to be on a dedicated circuit to charge a vehicle. The portion of parking that has access to outlets to charge multiple vehicles (meaning outlets on multiple dedicated circuits) is not known for the same reason. The portion of parking spaces that are actually available for parking is also not asked in these surveys. According to one study, the portion of garages that are used for storage and entirely unavailable for parking cars may be as high as 75% (Arnold and Lang, 2006). Since the sample in that study is not representative of the entire U.S. and the number seems pessimistic, we have chosen less pessimistic assumptions in our analysis.

Table 3.1 Assumptions in each sensitivity analysis case.

	Base Case	Optimistic Case	Pessimistic Case
Parking	• Carport parking spots: 1	• Carport parking spots: 1-3, drawn from distribution of garage sizes	• Carport parking spots: 1
	• Off-street parking spots: 1-3, drawn from distribution of garage sizes	• Off-street parking spots: 1-3, drawn from distribution of garage sizes	• Off-street parking spots: 1-2, drawn from distribution of 1-2 car garages
	• 10% of parking spaces are unavailable for parking (due to being used for storage or other non-parking use)	• All parking spaces are available for parking (none used for storage)	• 50% of parking spaces are unavailable for parking (used for storage or other non-parking use)
	• Each household has only one type of parking (or none)	• Homes with garages may also have driveways (off-street parking), in the same proportion as garage-less homes have them	• Each household has only one type of parking (or none)
Charging	• Only 1 vehicle can access each outlet (capacity is limited since it has only one circuit)	• 50% of outlets could be shared by two vehicles (perhaps charging at different times, and assuming household has 2 vehicles with parking) resulting in up to 1.5 vehicles per outlet on average	• Only 50% of outlets near parking can charge a vehicle (because some of the circuits are already in use and would be overloaded)

3.3 Method

We preprocess and combine the data sets and then use several equations to address the research questions. The quantities of interest are the portion of households with parking, the portion of households with vehicle charging, the portion of vehicles with parking at home, and the portion of vehicles with charging at home. It is worthwhile to compare the results on a household basis to the results on a vehicle basis, especially since fleet penetration is usually expressed as a percentage of vehicles, not households, and a large percentage of U.S. households have multiple vehicles (US Census Bureau, 2009). We expect that household-level results may be informative when discussing potential penetration of PEVs amongst primary vehicles only or when comparing to other studies that only consider primary vehicles, but that the per-vehicle results will be more informative for discussing potential penetration of PEVs in the entire personal vehicle fleet.

3.3.1 Data Preparation

We first combine RECS and AHS with our assumptions to create one data set that has no missing data and contains all the variables needed for the analysis. These include variables that will be used directly in the calculations and variables, such as demographic information, that will be used to match up the two data sets or to interpret the results. We use RECS as the base for this new data set, and we use multiple imputation with hot-deck imputation (Little and Rubin, 2008) both to fill in variables that are only available in AHS and to fill in individual values that are missing from the other variables. This method involves dividing the households into segments or bins and then using each bin as the "deck" from which to draw replacements for any missing variable values for households in that bin. By doing multiple imputations with different sets of random draws from the weighted distribution of households in the bins, we account for uncertainty in the values of the missing data using by a weighted probability distribution of the existing values. We use 10 imputations in this analysis.

Since we need to take draws from households in AHS to fill in the variables that are missing from RECS, the bin definitions need to be consistent in both data sets. Therefore we base the bins on 8 variables that both data sets have in common: housing unit type, occupancy status, population density, year the home was built, household gross annual income, number of household members age 20 or older, presence of a garage or carport, and number of rooms in the home. Where possible we use all 8 variables to segment, but where these bins result in no available data from which to take draws, we use a coarser set of bins. The coarser bins use a subset of the binning variables chosen based on their correlation with number of vehicles, since that is the variable most affected by bin definitions. Details of the levels used for bin definitions are shown in Appendix 7.2. Where there are still no data to draw from in these coarser bins (less than 6% of data) we drew missing values from all households with valid data for the variable with the missing value.

Two of our assumptions are defined as percentages or probabilities of availability: portion of parking spaces that are available for parking (not used for storage), and portion of outlets that are available to be used or shared. We implement these assumptions by creating two new variables: available parking spots and available outlets. The number of available parking spots for each household in the base case is determined by making each individual parking space available with a 90% probability, or unavailable with a 10% probability, and in the pessimistic case by making each spot available with a 50% probability. The portion of outlets available is calculated similarly: each outlet is made available with a 50% probability in the pessimistic case and made doubly available with a 50% probability in the optimistic case. These draws are taken separately for each imputation so that the multiple imputations include some uncertainty in which specific spots and outlets are available or unavailable.

3.3.2 Calculations

Once the data are prepared by having missing values filled in, all variables combined into one data set, and probabilistic assumptions accounted for, we use several equations to calculate the quantities of interest. The first quantity of interest in this chapter is how many U.S. households have dedicated parking for at least one vehicle and could therefore charge that vehicle in the future. That is, we assume any household with a designated parking space for their vehicle has the potential to charge a BEV or PHEV in the future with some additional installation of charging infrastructure at that parking spot. Households without dedicated parking we assume are not able to install charging infrastructure. The equation for portion of households with parking, P_{HP}, is

$$P_{\mathrm{HP}} = \frac{\sum_i \min(S_{\mathrm{A}i}, 1) W_i}{\sum_i W_i} \quad \forall i \tag{3.1}$$

where i is the index for each household, $S_{\mathrm{A}i}$ is the number of parking spaces available at household i, and W_i is the weighting factor for household i. The number of available parking spaces is calculated as described in Section 3.3.1 Data Preparation using S_i, the number of parking spots at household i, as the starting point. $S_i = S_{\mathrm{AG}i} + S_{\mathrm{DG}i} + S_{\mathrm{C}i} + S_{\mathrm{O}i}$ where $S_{\mathrm{AG}i}$ is the number of attached garage parking spaces at household i, $S_{\mathrm{DG}i}$ is the number of detached garage parking spaces at household i, $S_{\mathrm{C}i}$ is the number of carport parking spaces at household i, and $S_{\mathrm{O}i}$ is the number of off-street parking spaces at household i.

The second quantity of interest is how many U.S. households have Level 1 charging for at least one vehicle. We assume in the base case that a household that can park their vehicle daily at home within 20 feet of a 120V outlet has the opportunity to plug in their vehicle immediately without additional installation required. The portion of households with charging access, P_{HC}, is

$$P_{\mathrm{HC}} = \frac{\sum_i \min(O_{\mathrm{A}i}, S_{\mathrm{A}i}, 1) W_i}{\sum_i W_i} \quad \forall i \tag{3.2}$$

where $O_{\mathrm{A}i}$ is the number of outlets available at household i and is calculated as described in Section 3.3.1 Data Preparation using O_i, the number of outlets at household i, as the starting point.

The third quantity of interest is how many personal vehicles at U.S. households have dedicated parking spaces. The portion of vehicles with parking, P_{VP}, is

$$P_{\mathrm{VP}} = \frac{\sum_i \min(S_{\mathrm{A}i}, V_i) W_i}{\sum_i V_i W_i} \quad \forall i \tag{3.3}$$

where V_i is the number of vehicles at household i, and is the sum of the number of cars and the number of light trucks.

The fourth quantity of interest is how many personal vehicles have Level 1 charging access at home. The portion of vehicles with charging, PVC, is

$$P_{\mathrm{VC}} = \frac{\sum_i \min(O_{\mathrm{A}i}, V_i) W_i}{\sum_i V_i W_i} \quad \forall i \tag{3.4}$$

where all parameters have been previously defined.

3.4 Results

Table 3.2 shows results from all four calculations (Eq. (3.1)-(3.4)) for the base case, the optimistic case, and the pessimistic case. The results are averaged across 10 imputations, and as indicated by the very small standard deviations, uncertainty from missing data and from randomness in matching up the data from AHS and RECS turned out to be very small, especially compared to the range of sensitivity analysis case results.

Table 3.2 Results for each calculation in the base case, optimistic case, and pessimistic case, averaged across 10 imputations and with standard deviation shown in parentheses.

National, All Households	Base Case	Optimistic Case	Pessimistic Case
Households with Dedicated Parking	79% (0.3%)	92% (0.2%)	56% (0.3%)
Households with Charging	38% (0.3%)	41% (0.2%)	14% (0.2%)
Vehicles with Dedicated Parking	56% (0.4%)	84% (0.4%)	33% (0.5%)
Vehicles with Charging	22% (0.2%)	30% (0.4%)	8% (0.2%)

As shown, in the base case 79% of households have parking but only 56% of vehicles have parking at home. Although 38% of households have charging, it reaches only 22% of vehicles. In the optimistic case, in which we assume that households with garages also have driveways (where charging infrastructure can be installed in both locations and vehicles can routinely be shuffled into their dedicated spaces) and that all parking is available (none is unavailable due to being used for storage), at most 92% of households and 84% of vehicles have parking. However, in the pessimistic case where 50% of parking may be unavailable for vehicles, as few as 56% of households and 33% of vehicles may have parking.

Figure 3.3 displays the same base case results and further disaggregates them for urban and rural areas and by occupancy status, with error bars indicating the optimistic and pessimistic case results. As shown, all four measures of charging opportunities are lower in urban areas and higher in rural areas than the national average. If renters are ignored (due to the increased barriers to vehicle charging in that situation), the lower portions of each bar in Figure 3.3 can be read to show the results including only homeowners. In this case, only 61% of homes and only 47% of vehicles have parking. Thus, increasing PEV penetration beyond 47% of the fleet will require vehicle charging at rental units. Also, when renters are excluded from analysis the differences between

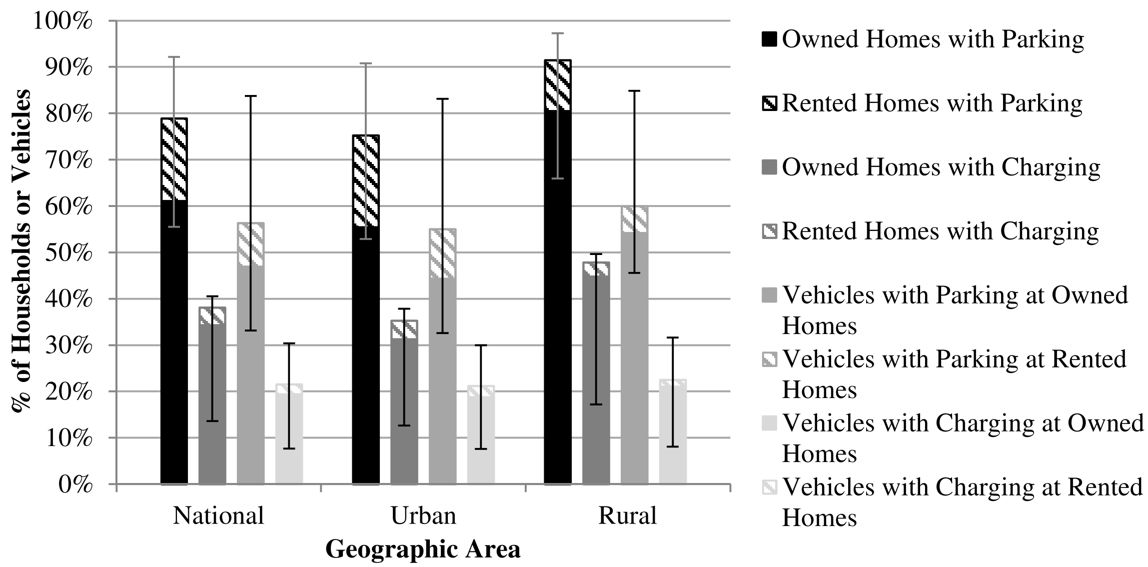

Figure 3.3 Comparison of residential parking and charging availability nationally and in urban and rural areas, disaggregated by occupancy status (rented or owned) of the home. Error bars indicate range of estimates for optimistic and pessimistic scenarios.

urban and rural areas are exacerbated. In urban areas, only 44% of vehicles have home parking. A detailed table of the data in Figure 3.3 appears in Table 7.13.

Figure 3.4 shows the one-way (changing one parameter at a time) sensitivity of the portion of vehicles with parking to two parameters that are based on assumptions due to lack of data. The portion of parking that is unavailable due to storage or other obstacles is an influential parameter. A range of parking availability from 0% to 50% results in a range of portion of vehicles with parking from 34% to 61%. Since the pessimistic case for P_{VP} is 33%, this sensitivity analysis indicates that portion of parking spaces available (not used for storage) is the major explanatory factor for the difference between the results in the base case and the pessimistic case.

In the base case, the maximum number of vehicles that could have parking per household is not explicitly limited but is effectively 3 due to the lack of data on garages larger than that or on other available parking. Limiting the maximum number of vehicles per household that are considered to 1 reduces the portion of vehicles with charging to

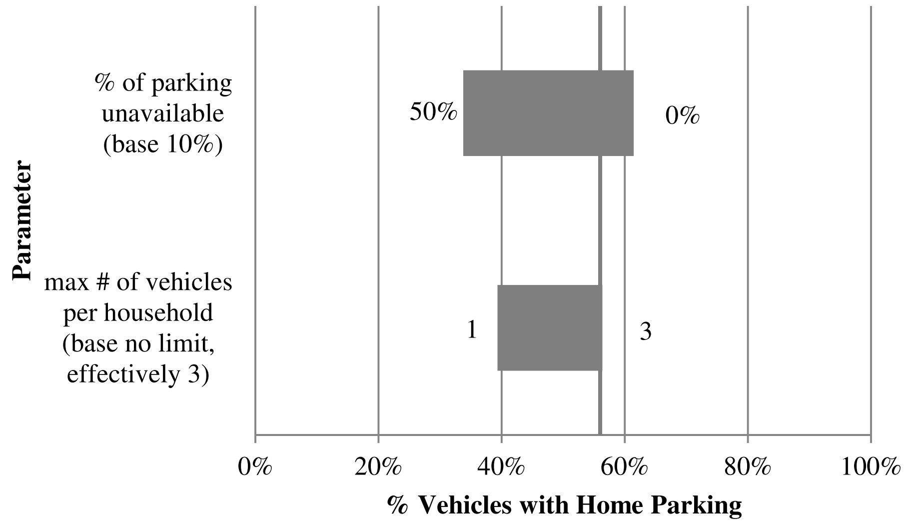

Figure 3.4 Sensitivity of portion of vehicles with home parking (P_{VP}, Eq. (3.3)) to assumptions, with all other parameters at base case values.

39%. This is an interesting case because while some households can charge one vehicle with little or no infrastructure cost, charging a second vehicle simultaneously is very likely to require an investment not only in the charger but also in circuit upgrades and possibly panel upgrades. Thus increasing PEV penetration beyond 39% of the fleet will require higher infrastructure investments. Further, if only homeowners are included and a maximum of one vehicle per household, then the portion of vehicles with residential parking that are also primary vehicles at owned homes is only 32%. Similar sensitivity analyses for the other 3 calculations appear in Appendix 7.2.

The income distribution of households with parking and charging are shown in Figure 3.5 and compared to the income distribution of all RECS 2009 households. Households with parking have a higher income profile than the sample in general, and households with charging have higher incomes still. The median income of all households is about $42,500, of households with parking is about $50,000, and of households with charging is about $60,000.

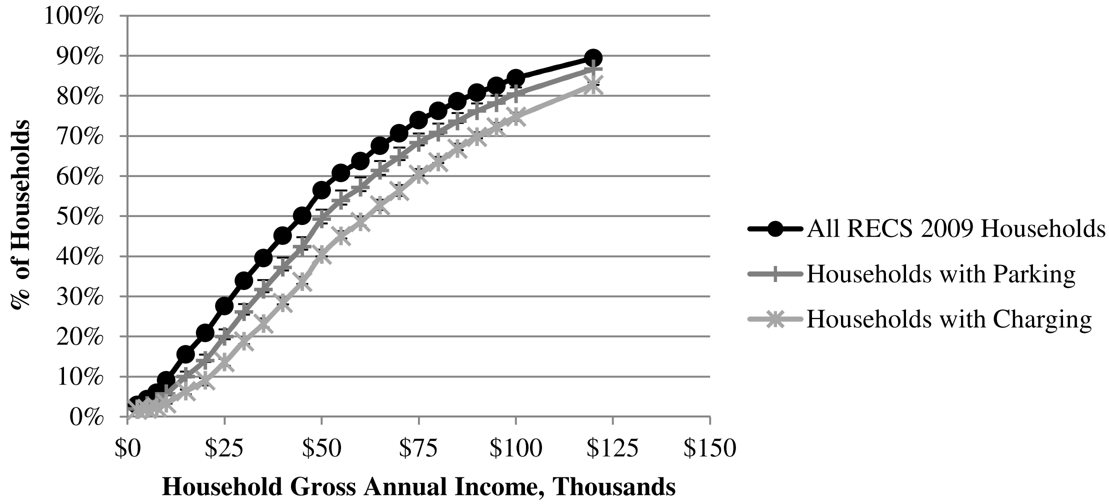

Figure 3.5 Cumulative distributions of households gross annual income for all RECS 2009 households, households with parking, and households with charging. Error bars indicate the range of incomes in the optimistic and pessimistic cases.

3.5 Discussion

Few data points exist in the literature for comparison to our results, and all of them quantify residential charging opportunities for households, not per vehicle. The EIA study, also based on RECS 2009 data, estimates that 49% of households that own a vehicle can park within 20 feet of an outlet, and that this is higher (55%) in rural areas and lower (47%) in urban areas (US EIA, 2012). Since RECS does not contain vehicle ownership information and since about 7-21% of U.S. households do not own a vehicle (based on AHS 2009 data and including uncertainty due to non-responses), the EIA estimates are consistent with our results that 38% of households overall (including those without vehicles) can park within 20 feet of an outlet, although the EIA estimates appear to be optimistic due to assuming that the portion of U.S. households without vehicles is at the high end of the uncertainty range. Another comparison point is Axsen and Kurani's survey results (2012a) that 36% of U.S. households have a Level 1 outlet within 10 feet of parking, 52% within 25 feet, and 61% within 50 feet. This is consistent with our base case result that 38% of homes have an outlet within 20 feet of parking, although we would expect their result to be slightly higher than ours since they do not require that parking spot to be available for a vehicle (i.e. not used for storage). Also their data include not only households with dedicated off-street parking but also a few households with street parking, so it is not clear whether the presence of an outlet indicates that the outlet (or the parking) would be consistently available for a PEV belonging to that household.

As mentioned in the Introduction, illustrated in Figure 3.1, and reiterated in Figure 3.6, several institutions have forecasted future market penetration of PEVs. A study from the Electric Power Research Institute (EPRI) suggests that PHEVs may have a market share of 60% by 2050 (Duvall, 2011), and a study by the Pacific Northwest National Laboratory says that PHEVs could reach as much as 70% market share by 2045 (Balducci, 2008). A study from the Center for Entrepreneurial & Technology (CET) forecasts that BEVs may have more than 80% of market share by 2030 (Becker et al., 2009). Based on our results for availability of residential charging infrastructure, without widespread addition of both residential (where residential parking exists) and public charging infrastructure, those PEV adoption rate forecasts could be too optimistic, especially in urban areas. As indicated in Figure 3.6, fleet penetration of PEVs beyond 22% will require residential infrastructure investment to increase access to outlets near home parking, and fleet penetration beyond 39% may require significant residential infrastructure investment because households will likely need to upgrade their electrical infrastructure to charge multiple vehicles. Fleet penetrations beyond 47% will require residential charging to be available for renters, and fleet penetration beyond 56% may

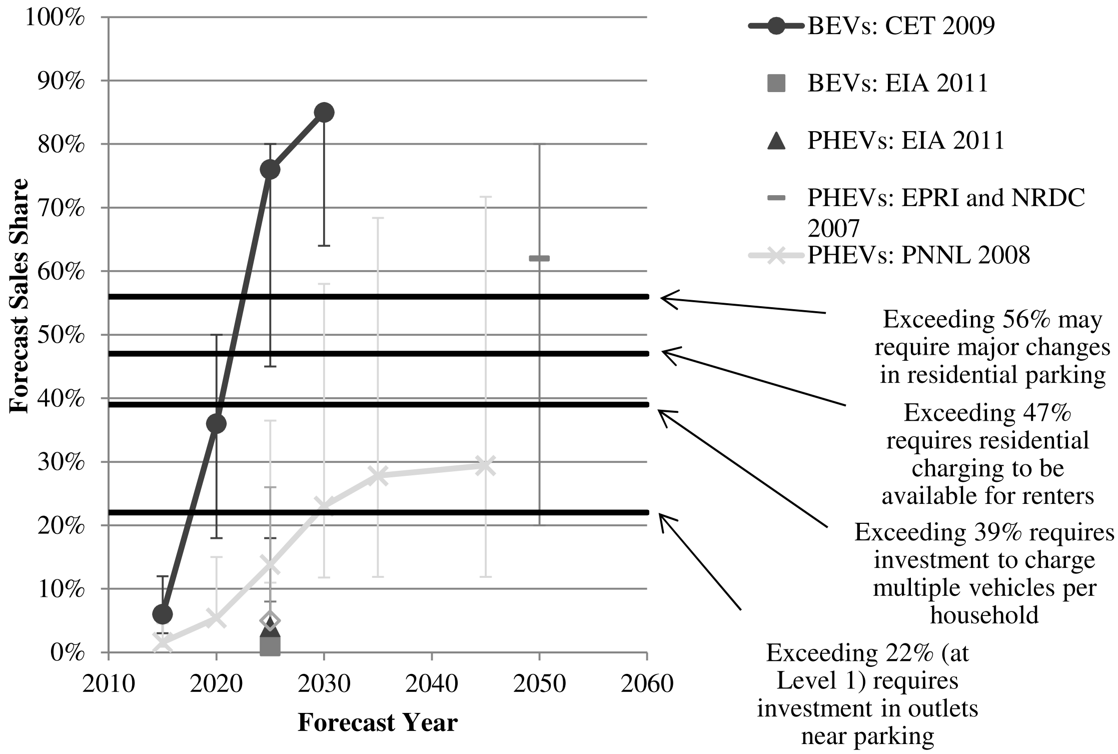

Figure 3.6 U.S. PEV sales forecasts (Heckmann et al., 2013) with barriers to fleet penetration from lack of residential charging infrastructure superimposed.

require not only chargers but also additional residential parking, with associated environmental impacts (Chester et al., 2010), to be installed. All of these limitations on PEV penetration will be more severe in urban areas, where there are fewer charging and parking opportunities. Although street parking and charging may be an option for PHEVs in residential areas since they don't need to charge every night, dedicated parking with guaranteed access to charging is necessary for BEVs and desired for PHEVs, and public charging infrastructure for street parking is likely only realistic for dense urban areas, where parking needs and charging needs will compete. Further, Peterson and Michalek (2013) note that more public charging infrastructure is needed when it is not dedicated.

The optimistic and pessimistic sensitivity case results show that the uncertainty from assumptions that were required due to lack of data could be significant. For example, the portion of vehicles with parking is 56% in the base case but could range from 33% to

84%. Table 3.1 describes the differences between these cases and Figure 3.4 shows the effect of some of the individual parameters on this calculation. The parameter with the most influence on the pessimistic case is the portion of parking spaces that are actually available for parking vehicles, as opposed to being used for storing other things (boxes, boats, etc.) or for extra living space (workshops, permanently converted offices or dens, etc.). Some of this parking could be reclaimed by clearing out unnecessarily stored clutter, but some may be permanently unavailable. In some or all cases these unavailable parking spots, especially in garages, may be offset by other available parking spaces, such as driveways outside garages. The prevalence of driveways at households that also have garages is also the most influential parameter for the optimistic case. However, available data only include the size of garages and the presence of off-street parking if a garage is not available. Data on the exact size of off-street parking and data on whether homes with garages also have driveways where additional vehicles could routinely park (with or without assuming vehicle owners will be willing to juggle vehicles daily to get them all charged) are not available. Having these data available for a representative sample of the population, as well as having more representative data on unavailable parking spaces, would help reduce the uncertainty range in our parking availability calculations.

This chapter also has implications for assumptions about PEV penetration and home charging availability in the academic literature. Availability of universal home charging is a common assumption for studies of the US (Peterson and Michalek, 2013; Traut et al., 2012), although subsequent assumptions or calculations of PEV fleet penetration vary. For example, Lemoine et al. (2008) include sensitivity analysis cases up to 100% PEV fleet penetration, Peterson et al. (2011) include sensitivity analysis from 10-50% PHEV fleet penetration, Williams (2008) includes sensitivity analysis from 2%-56% PHEV fleet penetration, and Kang and Recker (2009) assume 50% fleet penetration of PHEVs. Karplus et al. (2010) model PHEV penetration based on economic assumptions with an upper bound of 100% of the fleet, and Traut et al. (2012) model PEV penetration for minimum cost and GHG emissions with an upper bound of 100% of the fleet.

We show that universal home charging is not a valid assumption nationally, as the percentage of vehicles that even have parking at home is 56% in the base case, may be as low as 33% in the pessimistic case, and even in the most optimistic case is still only 84%. While it is reasonable for studies to include higher PEV penetration cases for sensitivity analysis purposes, using high PEV penetrations for base case analyses may be optimistic, especially where infrastructure costs are ignored since, as previously mentioned, PEV penetration beyond 39% (in the base case) will require some households to charge multiple vehicles. Even for studies that assume lower PEV penetrations, they may still be optimistic if they do not take into account potential correlations between parking availability, whatever criteria have been used to calculate which households will have one or more PEVs, and other household characteristics (such as driving patterns) that are used in the analysis.

Our analysis has some limitations. For example, we assume that households that can park their vehicle within 20 feet of a 120V outlet have Level 1 access to charge a vehicle. This assumption is based on availability of survey data, and it could be unrealistic since there could be obstacles between the vehicle and the outlet, or there could be insufficient spare electric capacity in that circuit. We also assume that households with dedicated parking could install charging equipment. This is also an optimistic assumption, especially in the near term, because although home owners can install charging infrastructure, renters will need cooperation from landlords. Also, some older homes will need significant and costly investment (such as wiring upgrades, larger electrical panels, and carpentry or concrete work) to support vehicle charging, which makes it less likely that these households would purchase a PEV. Even homes with sufficient capacity at their electric panels may need to install additional equipment such as separate meters: an online report indicates that some condo managements refuse to let owners charge their PEVs due to the lack of a way to measure the power consumed (Korzeniewski, 2012). In addition, our research focuses on Level 1 charging, which is sufficient for small PHEVs with smaller battery packs; however, most BEVs will require Level 2 charging and it currently has much lower availability than Level 1 charging (Axsen and Kurani, 2012a, 2012b).

Additional data that, if available, would decrease the uncertainty ranges of our results include data quantifying the presence of driveways at households that have garages, the portion of residential parking that is available for use by vehicles, the size of off-street parking areas other than garages (such as driveways), the correlation between residential parking availability and vehicle ownership, and the portion of households that have spare electrical capacity for charging a vehicle without a costly panel upgrade.

3.6 Conclusions

Additionally, 33% of U.S. households (38% in urban areas) are rentals, where regular tenant turnover and split incentives between landlords and tenants create additional barriers to infrastructure investment. We discuss sensitivity of results to uncertain factors.

Future scenarios of plug-in vehicle penetration that ignore the limited availability of U.S. residential charging infrastructure opportunities are likely to overestimate the potential market for plug-in vehicles.

We assess existing and potential charging infrastructure for electric vehicles in U.S. households using data from the American Housing Survey (AHS) and the Residential Energy Consumption Survey (RECS). We find that in the U.S., although 38% of households currently have Level 1 access, only 22% of vehicles currently have access to Level 1 charging sufficient to recharge a small plug-in vehicle battery pack overnight. Access to faster (Level 2, 240V) charging, required for vehicles with longer electric range, will usually require infrastructure investment (costing from several hundred dollars up to $10,000 depending on electrical panel and construction requirements). Installing multiple vehicle chargers at the same household increases the cost and the likelihood of requiring a costly breaker panel upgrade. We find that 79% of households but only 56% of vehicles have access to a dedicated home parking spot where charging infrastructure could be installed. The percentage of vehicles with access is lower than for households due to multi-vehicle households and limited garage/driveway space. Fewer homes and vehicles have charging opportunities in urban areas, where 35% of households and 21% of vehicles currently have Level 1 outlets and 75% of households and 55% of vehicles have parking. Additionally, 33% of U.S. households (38% in urban areas) are rentals, where regular tenant turnover and split incentives between landlords and tenants create additional barriers to infrastructure investment. The results are lower if renters are excluded.

In order to achieve high adoption rates for plug-in vehicles, charging opportunities must be identified and addressed per vehicle, not just per household. Urban areas and renters may need specific attention due to limited residential charging opportunities; residential parking infrastructure changes at a much slower rate than vehicle fleet turnover. Moreover, some outstanding issues should also be addressed such as determining the availability of unused electric circuit and panel capacity (Korzeniewski, 2012). Given these limits on residential charging potential, several recent PEV penetration forecasts appear too optimistic even under optimistic cost scenarios.

4 Comparative Implications of Electric Vehicle Fast Charging and Battery Swapping Stations for Life Cycle GHG Emissions and Cost

Battery electric vehicles need some sort of rapid refueling solution for the occasional driving days that exceed the all-electric range of the vehicle. We examine potential scenarios for fast charging and battery swapping of BEVs at service stations along a highway. We construct infrastructure cost models, conduct life cycle GHG assessments, address fast charging efficiency, model vehicle queuing at stations, model inventory control and battery charging strategies for battery swapping stations, and perform sensitivity analysis on key parameters. We first use simple cost estimates, then increase model detail and accuracy by using analytical queuing models and finally numerical queuing simulations. Results suggest that a battery swapping station (with fast charging of battery inventory) costs 41% more than a fast charging station when the value of time spent waiting during service is excluded but 50% less when the $30/hour value of travel time for highway drivers is included. However, battery swapping's cost advantage due to decreased service time requires vehicles and swappable batteries to be standardized. When separate swapping stations and battery inventories are needed to serve the same number of customers driving four incompatible vehicle designs, the cost benefits disappear and battery swapping becomes 31% more expensive than fast charging. Economies of scale also matter, as very small stations, such as would be appropriate for early adopters, are much more expensive per vehicle arrival. Costs of both BEV rapid refueling technologies are in the range where depending on gasoline prices and economies of scale, they could be cost competitive with refueling a gasoline CV or HEV. A single battery swapping station (with fast charging of battery inventory) emits 1%

more GHGs than a fast charging station under today's US electricity grid mix due to battery inventory production emissions.

4.1 Introduction and Motivation

In order for BEVs to gain large-scale consumer acceptance, they will need to be practical for long-distance travel, which means some sort of solution for quickly recharging them will be needed. Options for rapid recharging of BEVs include fast-charging – which has issues with efficiency, safety, cost, and increased battery degradation, and impacts the electricity grid – or battery swapping service stations – which physically switch a depleted battery for a charged battery but have challenges in cost, battery inventory requirements, standardization, wear, location, and operations. In order to compare these options and thoroughly understand their implications for the overall lifecycle cost and environmental impacts of BEVs, models to determine the life cycle cost and GHG emissions of fast-charging and battery swapping are needed. Once available, these models can be used to evaluate policy decisions (such as purchase incentives) and design decisions (such as battery size and AER) for BEVs. This chapter poses comparable life cycle cost and GHG emissions models for fast-charging and battery swapping.

Fast-charging or battery swapping stations may offer refueling speeds of anywhere from 2 minutes to 30 minutes and are likely to be used mainly by BEVs on days when normal driving ranges are exceeded or normal overnight charging methods are unavailable. For example, as shown in Figure 4.1, the Nissan LEAF's all-electric range of 73 miles meets range requirements for 90% of vehicle driving days in the NHTS 2009 survey, but is exceeded on 10% of driving days. Eighty percent of that range, or 58.4

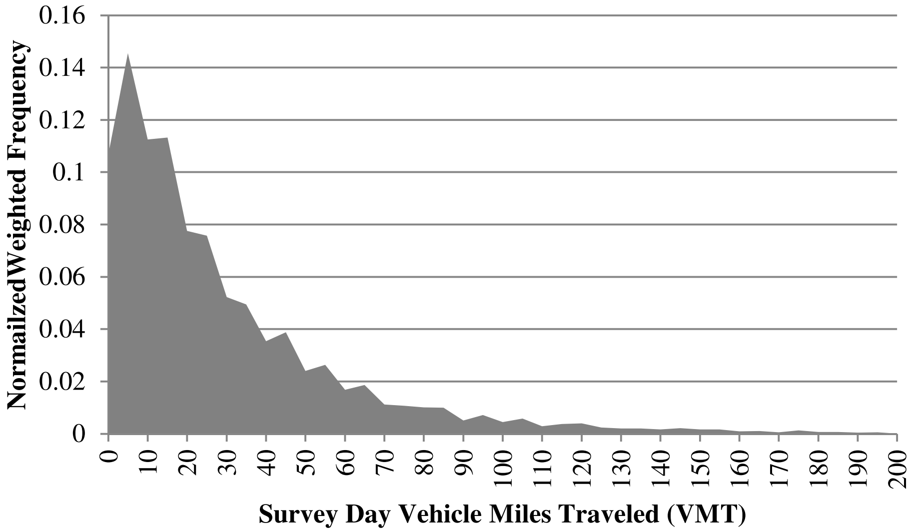

Figure 4.1 Distribution of daily driving distances from NHTS 2009 (US DOT, 2011). 90% of daily driving distances can be met with one overnight charge by the 73 mile range of the Nissan LEAF, and 85% of daily driving distances can be met with only 80% of that range.

miles, the amount that can be refueled with a 30 minute fast-charge, meets the requirements of 85% of vehicle driving days but is exceeded on 15% of driving days. Since PHEVs can achieve longer daily driving ranges using gasoline, they will not need to stop for a fast charge, although they may still choose to do so if the opportunity is available. This type of "opportunity charging" by PHEVs is out of scope for this analysis.

This chapter examines potential scenarios for sustainable personal transportation through electrified personal vehicles, with a focus on the life cycle cost and GHG emissions of different types of rapid recharging infrastructure for BEVs in the U.S., addressing several research questions:

(1) What are the life cycle costs and environmental impacts (GHGs) of fast charging (Level 3) for BEVs? What are the largest contributors to the costs? How sensitive are the costs and impacts to factors such as fast charging efficiency?

(2) What are the life cycle costs and environmental impacts (GHGs) of battery swapping? What are the largest contributors to the costs? How large does the

battery inventory need to be? How sensitive are the costs and impacts to factors such as the power level chosen to charge the battery inventory?

(3) How do the station equipment requirements and costs vary with increasing customer traffic, and what are the implications for fast charging and battery swapping as BEV penetration levels increase?

(4) Under what conditions does battery swapping make economic and environmental sense in comparison to fast charging (Level 3)? Is battery swapping significantly more expensive than fast charging even in a scenario that is optimistic about swapping costs?

4.2 Literature Review

Studies have addressed the effects of vehicle charging on the grid (Kelly et al., 2012; Parks et al., 2007; Peterson et al., 2011; Sioshansi et al., 2010; Weiller, 2011) and have studied the overall cost and emissions of PEVs (Bandivadekar et al., 2008; EPRI, 2001; Kammen et al., 2008; Michalek et al., 2011; Peterson et al., 2011; Samaras and Meisterling, 2008; Shiau et al., 2010, 2009), although most have focused on slow-charging and excluded costs and production emissions of charging infrastructure (Bandivadekar et al., 2008; Parks et al., 2007; Peterson et al., 2011; Samaras and Meisterling, 2008; Shiau et al., 2010, 2009; Sioshansi et al., 2010). Three studies do include slow charging infrastructure costs: an EPRI study includes costs for onboard vehicle chargers, household circuit upgrades, and charging cords (EPRI, 2001); and two other studies include costs of offboard chargers (Delucchi and Lipman, 2001; Michalek et al., 2011).

Fast charging has not been thoroughly treated in the literature. Some studies have focused on methods to optimally locate or utilize fast-charging or battery swapping stations, with minimal discussion of cost and environmental impacts (Capar et al., 2011; Johnson et al., 2012; Mirchandani, 2011). Schroeder and Traber (Schroeder and Traber, 2012) explore potential business models for fast charging in Germany, including some simple costs for charging equipment. They evaluate the effect on the electric grid from a combination of slow and fast charging, assuming that a fixed amount of power is needed per vehicle per day and that up to 20% of power may come from fast charging. However, they do not consider any specific driving patterns, and they assume that charging efficiencies are the same for fast and slow charging. Other studies ignore fast charging (Axsen and Kurani, 2010, 2008; Axsen et al., 2011; Bandivadekar et al., 2008; Elgowainy et al., 2010; Kang and Recker, 2009; Karplus et al., 2010; Lemoine et al., 2008; Lin et al., 2012; Michalek et al., 2011; Parks et al., 2007; Shiau et al., 2010, 2009; Simpson, 2006; Traut et al., 2012, 2011; Turker et al., 2010; Williams, 2008). Although some studies that exclude fast charging only discuss PHEVs and not BEVs (Axsen and Kurani, 2010, 2008; Axsen et al., 2011; Elgowainy et al., 2010; Kammen et al., 2008; Kang and Recker, 2009; Karplus et al., 2010; Lemoine et al., 2008; Lin et al., 2012; Parks et al., 2007; Simpson, 2006; Turker et al., 2010; Williams, 2008), some that include BEVs assume for simplicity that all charging will be slow charging, or at least do not discuss that vehicle charging may occur at varying speeds and with varying efficiencies and equipment costs (Bandivadekar et al., 2008; Michalek et al., 2011; Shiau et al., 2010, 2009; Traut et al., 2012, 2011). A complicating factor is that fast charging can be done on an as-needed basis (just enough charge to get to the next destination, which could be a full charge or not) or on an opportunity basis (charging whenever it is available, even though it is not needed).

Differences in charging efficiencies may affect how fast charging and slow charging compare in terms of GHG emissions. This difference may also affect the comparison with battery swapping because the battery swapping inventory may be charged at either Level 2 or Level 3. Level 1 charging is often cited as having a wall to battery efficiency of 87-88% (EPRI, 2001; Michalek et al., 2011; Traut et al., 2012) and Level 2 as having a wall to battery efficiency of 83% (Elgowainy et al., 2010; EPRI, 2001). Charging efficiency numbers for fast charging are less readily available, but fast charging based on high currents of 150-400A “offers relatively low charging efficiency” (Chan, 2002). Two studies cite fast-charging efficiency as 75% but with no supporting details (MacCarley, 1999; Neubauer and Pesaran, 2013). Charging efficiency also depends on C-rate, or the relationship between charging speed and battery capacity, with higher relative charging speeds leading to lower round-trip efficiencies for lithium-ion batteries (Lam, 2011). Differences in charging efficiency also may affect how fast charging and slow charging compare in terms of cost, since lower charging efficiencies will require more electricity to be purchased to drive the same distance. However, other differences between fast charging and slow charging will almost certainly have larger cost impacts. As Boulanger et al. (Boulanger et al., 2011) point out, fast chargers are more expensive than slow chargers, making vehicles and batteries compatible with fast charging more expensive, and use of fast charging may degrade batteries more than slow charging, thus reducing their lifespan. The electricity itself for fast charging may also be more expensive than for slow charging since it is more likely to be drawn at peak load times (Botsford and

Szczepanek, 2009). Fast charging batteries may also require them to have active thermal management to deal with the excess heat generated during charging, and the power used by the active thermal management system would further reduce efficiency.

Battery swapping is currently being deployed by the company Better Place ("Better Place | The Global Provider of EV Networks and Services.," n.d.; LaMonica, 2013). It is not in use by consumers yet, but prototype switching stations have been used by several Tokyo taxis (O'Dell, 2010a). Due to Better Place's aggressive plans to deploy networks of vehicles, charging stations, and battery swapping stations, studies on business models and operating models for battery swapping have appeared in the literature (Avci et al., 2012; Becker et al., 2009; Lidicker et al., 2011; MacCarley, 1999; Mak et al., 2012; Neubauer and Pesaran, 2013; Worley and Klabjan, 2011). One of these papers focuses on using dynamic programming to simulate battery inventory charging and optimally size battery inventories (Worley and Klabjan, 2011), one focuses on planning station locations and inventories given uncertain demand (Mak et al., 2012), two treat battery swapping stations as only part of a BEV battery-leasing business model and also use very simple assumptions for the number of stations and batteries needed to support the fleet (Becker et al., 2009; Lidicker et al., 2011), one uses simple estimates for battery swapping costs for small fleets (MacCarley, 1999), and one, Avci et al. 2012, addresses the GHG emissions of battery swapping by modeling it as a supply chain problem using a "classical repairable items inventory system" model (Avci et al., 2012). The conclusion from Avci et al. 2012 is that battery swapping may not always be good for the environment due to a rebound effect that will increase total miles driven, thus negating GHG savings from reduced emissions per mile. However, this conclusion is based on economic assumptions including pricing structures and consumer utilities and is driven by the battery lease vs. own assumptions. In contrast, this chapter avoids making potentially problematic assumptions about consumer utility or pricing and focuses the analysis on life cycle cost and GHG emissions of BEVs with battery swapping as compared to BEVs with fast charging. Neubauer and Pesaran (2013) also treat battery swapping stations as part of a BEV battery-leasing business model, and select the amount of equipment and batteries based on simulated demand to ensure a given maximum wait time between vehicles. However, they consider only the case where batteries in the swapping inventory are fast charged and focus on the costs seen by a battery swapping service provider. None of these studies in the literature directly compare the costs or emissions of fast charging with battery swapping. This chapter compares fast-charging to battery swapping for BEVs on life cycle cost and GHG emissions metrics by constructing models of the life cycle cost and environmental implications of fast charging and battery swapping for BEVs, taking charging efficiency and equipment and battery inventory requirements into account. This chapter uses simple cost and life cycle GHG estimates and then updates them using analytical queuing models and numerical queuing simulation to model station operation.

4.3 Methods

We address the research questions by constructing infrastructure cost models, conducting life cycle GHG assessments, modeling fast charging efficiency, modeling vehicle queuing at stations, modeling inventory control and battery charging strategies for battery swapping stations, and performing sensitivity analysis on key parameters. We first use simple cost estimates, then increase model detail and accuracy by using analytical queuing models and finally numerical queuing simulations to model station operation.

4.3.1 Model Framework

We examine potential scenarios for fast charging and battery swapping for BEVs at service stations along a highway. In both cases, the scenario is based on the assumption that these technologies will be used by BEV drivers. A consumer drives a BEV for their daily driving needs and charges the vehicle at their home overnight. Occasionally, on days with long driving distances when they are likely driving on a highway, during the day they notice that they might not have enough stored electricity in their battery. They stop at either at a fast charging station or a battery swapping station along the highway and pull into an empty parking spot or swapping bay, possibly waiting in line briefly.

The fast charging station is assumed to be similar to a current gas station or parking lot, where vehicles drive up to a charger, plug in their vehicle, wait for it to be charged to 80% of usable capacity, pay either before or after the charging period, and then leave so the next vehicle can charge. The reason it charges only to 80% is that the initial 80% charge can be achieved relatively quickly (30 minutes for the Nissan LEAF (Roper, 2013)), but the remaining 20% will be slower.

The battery swapping station operates as follows. As the vehicle drives into the swapping bay, it is automatically aligned with the battery swapping equipment. A robot removes their depleted (or partially depleted) battery and replaces it with a fully charged battery, taking about 5 minutes (2-10 in the sensitivity analysis) to complete the replacement. The consumer is now ready to drive away. In the meantime, the depleted (or partially depleted) battery is taken by forklift to an empty charging bay in an inventory charging and storage warehouse. The battery will stay in the charging bay until it is needed again, but the amount of time it will take to be charged to the 80% level that is necessary for it to be given to another customer is a function of the overall battery capacity, the battery depletion, the charging speed, and the charging efficiency. Once the battery has charged to 80%, it is available to be given to another customer. If not needed, it will continue charging, and some batteries may therefore be charged above 80%, although that situation is out of scope for this model.

We pose life cycle cost and GHG emissions models for each of these stations, as annualized cost or GHGs per station per vehicle arrival. The cost of these infrastructure types can then be compared to the cost per vehicle arrival (charge or swap) for other types of charging infrastructure. We first use simple cost estimates, then increase model detail and accuracy by using analytical queuing models and finally numerical queuing simulations. In order to compare these two technologies, we keep the model forms as similar as possible. Table 4.1 summarizes the major modeling assumptions. We assume all BEVs have the same size and type of battery and that they are standardized so that all batteries are interchangeable. We assume both types of stations have the same steady-state vehicle arrival distribution and battery depletion distribution, so that we are comparing which type of station is least costly to meet identical demand. The range of vehicle arrival rates considered is informed by highway traffic flows and the percentage of vehicles that are likely to be BEVs that would need to stop. We determine the number of individual swapping or charging points and the battery inventory size that are needed to meet that demand at minimum cost and include upfront costs of equipment (charging equipment, swapping equipment, and battery inventory including replacements), site

Table 4.1 Summary of major modeling assumptions.

Summary of Major Modeling Assumptions
• All BEVs have the same interchangeable batteries, so only one type of battery is needed in the inventory
• Vehicle arrivals are steady state and follow a Poisson distribution
• Vehicle charging times and battery swapping times are constant in the simple model and follow an exponential distribution in the analytical and numerical models o Average battery depletion corresponds to the average charging time
• In both station types, batteries charge to 80% of the usable SOC
• In the numerical model, a charged battery needs to be available at the beginning of the swapping time and a depleted battery is available at the end of the swapping time
• Batteries in the inventory have lifetimes and need occasional replacement. As a first estimate, battery lifetimes are approximated as a fixed number of years. Battery life is varied in the sensitivity analysis to account for potential effects of fast charging and swapping on battery degradation.
• Batteries in the battery charging inventory charge at a constant speed at one of the following constant power levels (SAE, 2010) o Level I slow charging: 120VAC, 15A, 1.8kW o Level II slow charging: 240VAC, 15A, 3.6kW o Level III fast charging: 480V, 50kW
• No buffer above the minimum required battery inventory size is included

preparation (including administrative and permitting costs and high voltage connection to the electric grid (Blanco, 2011)), and equipment installation. The high voltage connection is required for both types of stations, because even when the battery swapping does not fast charge the inventory, the large number of batteries that need to charge simultaneously at low voltage result in a high voltage load. Operating costs, mostly employees, are another fixed cost (does not vary with vehicle arrivals). The variable costs include electricity and value of time spent in service (charging or swapping) and waiting for a service point to be available. For the life cycle GHG model, we include production emissions from batteries in the swapping inventory and from electricity. We omit charging and swapping equipment production emissions because they are less certain and likely smaller contributors to overall GHG emissions.

Finally we perform sensitivity analysis on key model parameters to determine whether one technology is less costly in all scenarios, or if not, in which scenarios each technology is most competitive. Battery inventory size is expected to be a significant factor in battery swapping cost because the battery is the most expensive part of electric vehicles. However, there is a tradeoff between inventory size and inventory charging speed, which will be examined in the sensitivity analysis.

Batteries in the inventory have lifetimes and need occasional replacement. As a first estimate, battery lifetimes are approximated as a fixed number of years. Battery life is varied in the sensitivity analysis to account for potential effects of fast charging and swapping on battery degradation. However, the relative impacts of the two technologies on battery life are unclear. Fast charging degrades batteries faster than slow charging when used frequently. Battery swapping stations may or may not also have those degradation effects depending on whether they fast charge the batteries. Battery swapping stations also may extend battery life because more batteries will be in circulation and each battery will therefore see a lower usage rate. Finally, battery swapping may impact battery life by causing wear on battery contacts. The cumulative effect of these factors on battery life is uncertain.

Fast charging and battery swapping are compared as functional equivalents for rapidly refueling a BEV during a trip. Other alternatives are available for addressing BEV range issues, such as converting them to EREVs a small onboard gas generator or changing driving behaviors (switching to another household vehicle or renting a car for long trips), but these are less functionally equivalent from the consumer perspective.

4.3.2 Simple Cost and GHG Estimation Models

The simple model to estimate long-term annualized fast charging station cost per vehicle arrival, $A_{FC/V}$, is based on the average electricity cost per charge and is

$$A_{\mathrm{FC/V}} = \underbrace{\frac{d_{\mathrm{A}} s_C x_B p_{\mathrm{E}} \psi_{\mathrm{PDFC}}}{\eta_{FC}}}_{\text{electricity}} + \underbrace{\left(t_{\mathrm{C}} + t_{\mathrm{P}}\right) c_{\mathrm{T}}}_{\text{time}} + \underbrace{\underbrace{\frac{p_{\mathrm{GHG}} v_{\mathrm{E}} d_{\mathrm{A}} s_C x_B \psi_{\mathrm{PDFC}}}{\eta_{FC}}}_{\text{electricity}}}_{\text{carbon price}} \tag{4.1}$$

where d_A is the average depletion level of arriving vehicle batteries (0.75), s_C is the portion of the battery that will be recharged (0.8), x_B is the usable energy storage capacity of each battery in kWh (base case 19.2 kWh from approximately 80% usable portion of the 24 kWh Nissan LEAF battery (Roper, 2013)), p_E is the electricity price in \$/kWh (base case \$0.11/kWh), ψ_{PDFC} is a multiplier for electricity cost that represents peak demand charges (base case 1.2), η_{FC} is the wall-to-stored-energy efficiency of fast charging including both the charger efficiency and the battery charging efficiency (base case 78%), t_C is the time spent charging (base case 30 minutes), t_P is the time spent on paying and other related activities (base case 3 minutes), c_T is the cost of travel time for highway drivers (base case \$32/hr (Perk et al., 2011)), and pGHG is the carbon price (base case \$0.02 per kilogram carbon dioxide equivalent $kgCO_2e$). Because this is a simple long-term estimate, the upfront costs and other fixed costs drop out, and only the per-vehicle-arrival variable costs are included. Table 4.2 summarizes these parameters. This simple formulation yields a cost that is not a function of the vehicle arrival rate or

Table 4.2 Parameters in simple cost estimation models for fast charging and battery swapping.

Notation	***Description***	***Units***	***Base Case Value***	***Fast Charging Optimistic Case Value***	***Battery Swapping Optimistic Case Value***	***Source***
c_T	Value of travel time for highway drivers	\$/min	0.5333	0.3	0.6667	(Perk et al., 2011) from mean, 25th percentile, and 75th percentile of distribution of value of travel time savings
d_A	Average depletion of arriving vehicle batteries		0.75	0.75	0.75	As a percentage of the 80% of usable swing that is replenished in each charge or swap
d_O	Station operating days per year	days	365	365	365	
l_B	Battery life	years	10	8	15	Based on being slightly longer than typical warranty (Roper, 2013)
p_B	Battery price per usable kWh energy capacity	\$/kWh	600	600	200	From (Plotkin and Singh, 2009) lit review 2015 and DOE program goals 2030 cases. Converted to price per usable kWh by assuming 80% is usable. See Figure 7.1
p_E	Electricity price	\$/kWh	0.11	0.06	0.15	(Traut et al., 2012) See Chapter 2
p_{GHG}	Carbon price	\$/kgCO_2e	0.02	0.02	0.02	(Traut et al., 2012) See Chapter 2
s_C	Portion of battery usable capacity that is recharged		0.8	0.8	0.8	(Roper, 2013)
t_C	Average time spent charging	minutes	22.5	22.5	22.5	(Nguyen, 2012) Based on 30 minutes to charge to 80%, and assuming customers arrive with an average of 75% of that 80% of range depleted Level 1: 720 min Level 2: 252 min
t_P	Average time spent on paying and other activities	minutes	3	3	3	(Neubauer and Pesaran, 2013)
t_S	Average time spent swapping	minutes	5	10	2	(Neubauer and Pesaran, 2013; O'Dell, 2010b)

Notation	*Description*	*Units*	*Base Case Value*	*Fast Charging Optimistic Case Value*	*Battery Swapping Optimistic Case Value*	*Source*
x_B	Usable energy storage capacity of battery	kWh	19.2	19.2	19.2	(Nguyen, 2012; Roper, 2013) Based on 80% of the 24kWh Nissan LEAF battery
η_{BS}	Battery swapping inventory charging efficiency		0.83	0.83	0.83	See Section 4.3.4 Assumes Level 2 inventory charging
η_{FC}	Fast charging efficiency		0.78	0.83	0.75	See Section 4.3.4 Assumes Level 3 charging For Level 2 cases: 0.83 For Level 1 cases: 0.88
ν_B	Battery production emissions	$kgCO_2e$/usable kWh	150	180	120	Base value from (Samaras and Meisterling, 2008) adjusted to be per usable kWh when 80% is usable. Sensitivity analysis +/- 20%
ν_E	Electricity production emissions	$kgCO_2e$/kWh	0.752	0.066	0.9	(Traut et al., 2012) See Chapter 2
ψ_{PDBS}	Multiplier representing peak demand charges for battery swapping		1.2	1.2	1.1	This is a simplification of the wide variety of rate structures. Example: $15.70/kW/month for Southern California
ψ_{PDFC}	Multiplier representing peak demand charges for fast charging		1.2	1.1	3	Edison customers in the 200kW-500kW (4-10 fast chargers) range ("Southern California Edison Schedule TOU-GS-SOP," n.d.). See Section 4.3.6.2

the overall station size. This formulation also contains the simple model for GHGs from fast charging, which considers GHGs from electricity production and is

$$E_{\mathrm{FC/V}} = \underbrace{\frac{v_{\mathrm{E}} d_{\mathrm{A}} s_C x_B \psi_{\mathrm{PDFC}}}{\eta_{FC}}}_{\text{electricity production}} \tag{4.2}$$

where all parameters have been previously defined.

The simplest model to estimate long-term annualized cost of a battery swapping station per vehicle arrival, $A_{\mathrm{BS/V}}$, is based on the average amount of electricity needed to recharge one battery plus a portion of the battery inventory, with the size of the battery inventory estimated as the number of vehicle arrivals per day, since all the batteries will have time to fully charge overnight, and is

$$A_{\mathrm{BS/V}} = \underbrace{\frac{d_{\mathrm{A}} s_C x_B p_{\mathrm{E}} \psi_{\mathrm{PDBS}}}{\eta_{BS}}}_{\text{electricity}} + \underbrace{\frac{p_{\mathrm{B}} x_{\mathrm{B}}}{l_B d_{\mathrm{O}}}}_{\text{batteries}} + \underbrace{\left(t_{\mathrm{S}} + t_{\mathrm{P}}\right) c_{\mathrm{T}}}_{\text{time}} + \underbrace{\underbrace{\frac{p_{\mathrm{GHG}} v_{\mathrm{E}} d_{\mathrm{A}} s_C x_B \psi_{\mathrm{PDBS}}}{\eta_{BS}}}_{\text{electricity}} + \underbrace{\frac{p_{\mathrm{GHG}} v_{\mathrm{B}} x_{\mathrm{B}}}{l_B d_{\mathrm{O}}}}_{\text{batteries}}}_{\text{carbon price}} \tag{4.3}$$

where ψ_{PDBS} is a multiplier for electricity cost that represents peak demand charges (base case 1.2), η_{BS} is the wall-to-stored-energy efficiency of charging the battery inventory including both the charger efficiency and the battery charging efficiency (base case 83%), p_{B} is the cost per usable kWh energy storage capacity of the batteries (base case \$625/kWh usable), l_{B} is the battery life in years (base case 10 years), d_{O} is the number of days per year that the station operates (base case 365), t_{S} is the time spent swapping the battery (base case 5 minutes), v_{B} is the emissions from lithium ion battery production per usable kilowatt hour (base case 150 $\mathrm{kgCO_2e/kWh}$, (Samaras and Meisterling, 2008)), and all other parameters have been previously defined. Table 4.2 summarizes these parameters. This simple formulation also yields a cost that is not a function of the vehicle arrival rate or the overall station size. This formulation contains the simple model for GHGs from battery swapping, which considers GHGs from electricity production and from battery production and is

$$E_{\mathrm{BS/V}} = \underbrace{\frac{v_{\mathrm{E}} d_{\mathrm{A}} s_C x_B \psi_{\mathrm{PDBS}}}{\eta_{BS}}}_{\text{electricity production}} + \underbrace{\frac{v_{\mathrm{B}} x_{\mathrm{B}}}{l_B d_{\mathrm{O}}}}_{\text{battery production}} \tag{4.4}$$

where all parameters have been previously defined.

Simple cost models for a conventional gasoline vehicle and for a hybrid electric vehicle are used for comparison purposes to the fast charging and battery swapping costs. The cost per vehicle of filling a conventional gasoline vehicle with an amount of gasoline equivalent to the BEV's range is

$$A_{\mathrm{CV/V}} = \underbrace{\frac{p_{\mathrm{G}} d_{\mathrm{A}} r}{\eta_{\mathrm{CV}}}}_{\text{gasoline}} + \underbrace{\left(t_{\mathrm{G}} \frac{d_{\mathrm{A}} r}{\eta_{\mathrm{CV}}} + t_{\mathrm{P}}\right) c_{\mathrm{T}}}_{\text{time}} + \underbrace{\underbrace{\frac{p_{\mathrm{GHG}} v_{\mathrm{G}} d_{\mathrm{A}} r}{\eta_{\mathrm{CV}}}}_{\text{gasoline}}}_{\text{carbon price}} \tag{4.5}$$

for conventional vehicles where p_{G} is the price of gasoline in \$/gallon, r is the desired vehicle range (58.4 to be equivalent to fueling a 73 mile range BEV to 80%), η_{CV} is the CV fuel economy in miles per gallon (25 in the base case), t_{G} is the rate of gasoline refueling (0.1 minutes per gallon), v_{G} is the production and combustion emissions from gasoline (11.34 $\mathrm{kgCO_2e/gal}$ in the base case), and all other parameters have been previously defined. The cost per vehicle of filling an HEV with an amount of gasoline equivalent to the BEV's range is

$$A_{\mathrm{HEV/V}} = \underbrace{\frac{p_{\mathrm{G}} d_{\mathrm{A}} r}{\eta_{\mathrm{HEV}}}}_{\text{gasoline}} + \underbrace{\left(t_{\mathrm{G}} \frac{d_{\mathrm{A}} r}{\eta_{\mathrm{HEV}}} + t_{\mathrm{P}}\right) c_{\mathrm{T}}}_{\text{time}} + \underbrace{\underbrace{\frac{p_{\mathrm{GHG}} v_{\mathrm{G}} d_{\mathrm{A}} r}{\eta_{\mathrm{HEV}}}}_{\text{gasoline}}}_{\text{carbon price}} \tag{4.6}$$

where η_{HEV} is the HEV fuel economy in miles per gallon (43 in the base case), and all other parameters have been previously defined. The parameter values for both of these equations that have not been previously defined in Table 4.2 are shown in Table 4.3.

Table 4.3 Parameters in simple cost estimation models for refueling CVs and HEVs.

Notation	*Description*	*Units*	*Base Case Value*	*Optimistic Case Value*	*Pessimistic Case Value*	*Source*
p_G	Gasoline price	\$/gal	3.5	3	4.5	Based on the maximum and minimum costs projected in the EIA's 2013 Annual Energy Outlook reference case, with conversion factors as explained in Chapter 2 (US EIA, 2013)
r	Refuel range	miles	58.4	58.4	58.4	To be equivalent to charging a 73 mile range BEV to 80%
t_G	Rate of gasoline refueling	min/gal	0.1	0.1	0.1	(Neubauer and Pesaran, 2013)
η_{CV}	CV fuel economy	mpg	27	35	25	Base cases are GREET 2 Gasoline CV and Grid-
η_{HEV}	HEV fuel economy	mpg	38	49	35	Independent HEV default values for 2015 (ANL, 2012). Sensitivity analysis is based on the 2010 estimates and taking a slightly more optimistic value than the 2020 estimates.
v_G	Gasoline production and combustion emissions	$kgCO_2e$ /gal	11.34	11.34	11.34	See Chapter 2

These simple models are useful for a first approximation of the impact that battery price and demand charge have on which technology is least expensive. However, these simple models do not take into account the value of time spent waiting for either a charge or a swap, the upfront costs of charging and swapping equipment and high voltage grid connections, and the potential for the swapping station battery inventory size to be smaller than the number of daily vehicle arrivals since not all of the arriving batteries will be fully depleted and the batteries can also charge during the day. Therefore, models with more detail, including queuing of vehicles at the stations and queuing of batteries in the swapping inventory, are needed.

4.3.3 Detailed Cost Models

These detailed cost models extend the above simple estimates to include fixed and capital costs including site preparation, charging and swapping equipment and installation, and operating expenses (employees) and to include the time spent waiting in line for service. Two methods, analytical queuing models and queuing simulations, are used to calculate the required amount of equipment and the queuing times based on the vehicle arrival rates, but the cost equations are the same for both of those methods and are presented first.

4.3.3.1 Fast Charging Cost Model

Annualized fast charging station cost per vehicle that arrives to charge is

$$\begin{aligned} A_{\mathrm{FC/V}} = & \underbrace{\frac{1}{t_{\mathrm{O}}\lambda}\left(\underbrace{\left(c_{\mathrm{A}} + c_{\mathrm{I}} + c_{\mathrm{HV}}\right) r}_{\text{site preparation}} + \underbrace{p_{\mathrm{CP}} n_{\mathrm{CP}} f_{\mathrm{A/P}}\left(r, l_{\mathrm{C}}\right)}_{\substack{\text{charging equipment} \\ \text{with installation}}} + \underbrace{c_{\mathrm{OFC}}}_{\substack{\text{station operation} \\ \text{(employee)}}} \right)}_{\text{fixed cost, annualized, per vehicle arrival}} + \\ & \underbrace{\underbrace{\frac{d_{\mathrm{A}} s_{\mathrm{C}} x_{\mathrm{B}} p_{\mathrm{E}}}{\eta_{\mathrm{FC}}} + p_{\mathrm{EB}} + p_{\mathrm{ED}}\left(n_{\mathrm{CP}}\right)}_{\text{electricity}} + \underbrace{\underbrace{t_{\mathrm{C}} c_{\mathrm{T}}}_{\text{charging}} + \underbrace{W_q c_{\mathrm{T}}}_{\text{queuing}}}_{\text{cost of time}}}_{\text{variable operating cost, per vehicle arrival}} \end{aligned} \tag{4.7}$$

where all parameters that have not been previously defined appear in Table 4.4. Some parameters are calculated from analytical or numerical queuing models, which are described in Sections 4.3.4 and 4.3.5. Although Level 1 and Level 2 are not fast charging and are not likely to be deployed in this station format, their costs are calculated using the same equation for comparison purposes, so their relevant parameter values are also shown in Table 4.4.

Table 4.4 Additional cost parameters for fast charging.

Notation	***Description***	***Units***	***Base Case Value***	***Source***
c_A	Administrative/legal/permitting fees per site	$	20000	(Morrow et al., 2008) based on a Level 2 station
c_{HV}	High voltage access point	$	15000	WDOT (Parsons Brinckerhoff, 2009) Assuming station close to high voltage transmission line
c_I	Site installation	$	25000	(Morrow et al., 2008) Includes meters, panel upgrades, concrete work, etc.
c_{OFC}	Operating cost per year	$	80000	Based on one employee, WDOT (Parsons Brinckerhoff, 2009)
l_C	Charging equipment life	years	25	For chargers and battery swapping equipment
n_{CP}	Number of charge points/bays at the station			Value selected for minimum cost at each value of lambda (so far by exhaustive search since only integers are valid and there are derivative discontinuities)
p_{CP}	Charging equipment price	$	Level 3: 50000 Level 2: 2000 Level 1: 1000	Includes installation of the individual charge points, estimates for Level 3 range from 10000-90000+ (McKinsey & Company, 2009; Motavalli, 2011; Parsons Brinckerhoff, 2009) Level 1 and Level 2 costs from (Morrow et al., 2008)
p_E	Electricity price per kWh	$/kWh	0.075	("Southern California Edison Schedule TOU-GS-SOP," n.d.) Averaging over the year and assuming constant demand
p_{EB}	Base electricity price per customer	$/yr	5050	("Southern California Edison Schedule TOU-GS-SOP," n.d.)

Notation	*Description*	*Units*	*Base Case Value*	*Source*
$p_{ED}(n_{CP})$	Electricity demand charge	$/yr	Level 1: 370 n_{CP} Level 2: 940 n_{CP} Level 3: 13000n_{CP}	("Southern California Edison Schedule TOU-GS-SOP," n.d.) Based on peak power demand which is a function of the number of chargers, averaging over the year and assuming constant demand. Cost is $21.60/kW/month. Each Level 1 charger is 1.44 kW, Level 2 charger is 3.6 kW, and Level 3 charger is 50 kW
r	Discount rate		0.1	
t_O	Station operating time per year	minutes	525,600	Equivalent to 365 days
η_{FC}	Fast charging efficiency		Level 1: 0.88 Level 2: 0.83 Level 3: 0.78	Depends on charging speed. See Section 4.3.4
λ	Mean vehicle arrival rate	veh/min	0-2.5	Based on highway traffic volumes of 20-40 veh/min with up to 12.5% of vehicles stopping to charge or swap

4.3.3.2 Battery Swapping Cost Model

Annualize battery swapping station cost per vehicle that arrives to swap is

$$
\begin{aligned}
A_{\mathrm{BS/V}} = & \underbrace{\frac{1}{t_{\mathrm{O}}\lambda}\left(\begin{array}{l}\underbrace{\left(c_{\mathrm{A}}+c_{\mathrm{I}}+c_{\mathrm{HV}}+c_{\mathrm{W}}\left(L_{B}\right)\right)r}_{\text{site preparation}}+\underbrace{p_{\mathrm{S}}n_{\mathrm{S}}f_{\mathrm{A/P}}\left(r,l_{\mathrm{S}}\right)}_{\text{swapping equipment installation}}+ \\ \underbrace{p_{\mathrm{ICP}}n_{\mathrm{ICP}}f_{\mathrm{A/P}}\left(r,l_{\mathrm{C}}\right)}_{\substack{\text{inventory charging equipment}\\ \text{with installation}}}+\underbrace{c_{\mathrm{OBC}}n_{\mathrm{S}}}_{\substack{\text{station operation}\\ \text{(employees)}}}+\underbrace{L_{\mathrm{B}}p_{\mathrm{B}}x_{\mathrm{B}}f_{\mathrm{A/P}}\left(r,l_{\mathrm{B}}\right)}_{\text{batteries}}\end{array}\right)}_{\text{fixed cost, annualized, per vehicle arrival}}+ \\
& \underbrace{\underbrace{\frac{d_{\mathrm{A}}s_{\mathrm{C}}x_{\mathrm{B}}p_{\mathrm{E}}}{\eta_{\mathrm{BS}}}+p_{\mathrm{EB}}+p_{\mathrm{EDI}}\left(n_{\mathrm{ICP}}\right)}_{\text{electricity}}+\underbrace{\underbrace{t_{\mathrm{S}}c_{\mathrm{T}}}_{\text{swapping}}+\underbrace{W_{q}c_{\mathrm{T}}}_{\text{queuing}}}_{\text{cost of time}}}_{\text{variable operating cost, per vehicle arrival}}
\end{aligned}
\tag{4.8}
$$

where

$$
c_{\mathrm{W}}\left(L_{\mathrm{B}}\right)=\begin{cases}1.1\dfrac{p_{\mathrm{W}}a_{\mathrm{B}}L_{\mathrm{B}}}{b_{\mathrm{B}}} & \dfrac{a_{\mathrm{B}}L_{\mathrm{B}}}{25000b_{\mathrm{B}}}\leq 0.5 \\ \left(\dfrac{a_{\mathrm{B}}L_{\mathrm{B}}}{25000b_{\mathrm{B}}}\right)^{-0.1375}\dfrac{p_{\mathrm{W}}a_{\mathrm{B}}L_{\mathrm{B}}}{b_{\mathrm{B}}} & 0.5\leq\dfrac{a_{\mathrm{B}}L_{\mathrm{B}}}{25000b_{\mathrm{B}}}\leq 1 \\ \left(\dfrac{a_{\mathrm{B}}L_{\mathrm{B}}}{25000b_{\mathrm{B}}}\right)^{-0.0841}\dfrac{p_{\mathrm{W}}a_{\mathrm{B}}L_{\mathrm{B}}}{b_{\mathrm{B}}} & 1\leq\dfrac{a_{\mathrm{B}}L_{\mathrm{B}}}{25000b_{\mathrm{B}}}\leq 3.5 \\ 0.9\dfrac{p_{\mathrm{W}}a_{\mathrm{B}}L_{\mathrm{B}}}{b_{\mathrm{B}}} & \dfrac{a_{\mathrm{B}}L_{\mathrm{B}}}{25000b_{\mathrm{B}}}\leq 3.5\end{cases}
\tag{4.9}
$$

and where all other parameters that have not been previously defined are defined in Table 4.5. Operating cost is higher than for fast charging because employees need to use forklifts to move the batteries to and from charging bays. The swapping equipment only moves batteries in and out of the vehicles. Some parameters are calculated from analytical or numerical queuing models, which are described in Sections 4.3.4 and 4.3.5.

Table 4.5 Additional cost parameters for battery swapping.

Notation	***Description***	***Units***	***Base Case Value***	***Source***
a_B	Warehouse area per battery charging stack	ft.^{2}	36	Based on 2 times the footprint of a battery (from (Nguyen, 2012)), to allow for aisle space
b_B	Number of batteries per battery charging stack	batteries	4	Number of batteries that can be stacked vertically in the charging warehouse
$c_W(L_B)$	Warehouse cost as a function of battery inventory size	$	Eq. (4.9)	Cost of warehouse to protect charging bays, based on size factor for warehouses (adjusts price per square foot based on the price at the typical square footage of 25,000 square feet) (Balboni, 2007) (equation fit to graph using Eureqa Formulize software, (Schmidt and Lipson, 2009))
L_B	Inventory queuing system size	batteries		Number of batteries needed in inventory
l_C	Charging equipment life	years	25	For chargers
l_S	Swapping equipment life	years	10	For battery swapping equipment, based on usable life of industrial robots (Bard, 1986; Fryman, 2002; Nof, 1999; Yusuf and Nabeshima, 2006)
n_{ICP}	Number of charge bays at the warehouse			Value selected for minimum cost at each value of lambda (so far by exhaustive search since only integers are valid and there are derivative discontinuities)
n_S	Number of swapping bays			Values for both calculated as the maximum of the number of charge points and the number of batteries assigned by the queuing model, so that batteries can stay in a single bay and not need to be moved between separate queues
c_{OBC}	Operating cost per swapping point per year	$	80000	Based on one employee, WDOT (Parsons Brinckerhoff, 2009)
p_B	Battery price per usable kWh energy capacity	$/kWh	600	From (Plotkin and Singh, 2009) lit review 2015 case. Converted to price per usable kWh by assuming 80% is usable. See Figure 7.1

Notation	*Description*	*Units*	*Base Case Value*	*Source*
$p_{EDI}(n_{ICP})$	Electricity demand charge for charging the inventory	\$/yr	Level 1: 370 n_{ICP} Level 2: 940n_{ICP} Level 3: 13000n_{ICP}	("Southern California Edison Schedule TOU-GS-SOP," n.d.) Based on peak power demand which is a function of the number of chargers, averaging over the year and assuming constant demand. Cost is \$21.60/kW/month. Each Level 1 charger is 1.44 kW, Level 2 charger is 3.6 kW, and Level 3 charger is 50 kW
p_{ICP}	Price per inventory charging bay	\$	Level 3: 50000 Level 2: 2000 Level 1: 1000	Includes installation of the individual charge points, estimates for Level 3 range from 10000-90000+ (McKinsey & Company, 2009; Motavalli, 2011; Parsons Brinckerhoff, 2009) Level 1 and Level 2 costs from (Morrow et al., 2008)
p_S	Price per swapping bay equipment	\$	500,000	Preliminary cost ranges for battery swapping stations are very rough point estimates and range from \$40,000 (McKinsey & Company, 2009) to \$500,000 (O'Dell, 2010a)
p_W	Warehouse price per square foot	\$/ft.^{2}	56	(Balboni, 2007) Median cost of warehouses is \$56 per square foot at typical size of 25,000 sq. feet
t_O	Station operating time per year	minutes	525,600	Based on 365 days per year
η_{BS}	Battery inventory charging efficiency		Level 1: 0.88 Level 2: 0.83 Level 3: 0.78	Depends on inventory charging speed. See Section 4.3.4

4.3.4 Analytical Queuing Models

Analytical queuing models are used for a first approximation of the amount of equipment (charging, swapping, and battery inventory) needed and the wait times involved in the two station types. By calculating wait times and battery inventory needs as closed form functions of amount of swapping and charging equipment, they allow the stations to be designed for minimum cost with much less computational effort than the more complex numerical simulations that are needed for the highest level of detail. To obtain closed form solutions, we use M/M/c queuing models (also sometimes called M/M/m) (Kleinrock, 1975). In M/M/c (or M/M/m) queuing models, vehicle arrivals are steady state Poisson distributions, charging or swapping times are exponentially distributed, there is a fixed number of service (charging or swapping) points, and there is infinite space for lines to form (Kleinrock, 1975). (We find that the infinite waiting space assumption is reasonable, because in the minimum-cost station designs the waits are short and the lines are not very long.)

As illustrated in Figure 4.2, we model the vehicles arriving at the fast charging station, charging, and then leaving as one M/M/c model. We model vehicles arriving at the swapping station, swapping, and then leaving as another M/M/c model and batteries arriving, being charged in the inventory, and then leaving as a third M/M/c model. This method ensures that the battery inventory is large enough that batteries will be ready to swap at the same rate as vehicles need them (Gross et al., 2008), but it underestimates battery inventory size because some additional batteries will be needed to ensure that batteries are ready not only at the same rate, but at the same times. Thus, the numerical simulations are used later to quantify this portion of the battery inventory that is missing from the analytical models. The parameters and equations for the M/M/c queuing models are presented in Table 4.6 (Baron, 2007; Gross et al., 2008; Kleinrock, 1975). Code for the numerical simulations is included in Appendix 7.3.

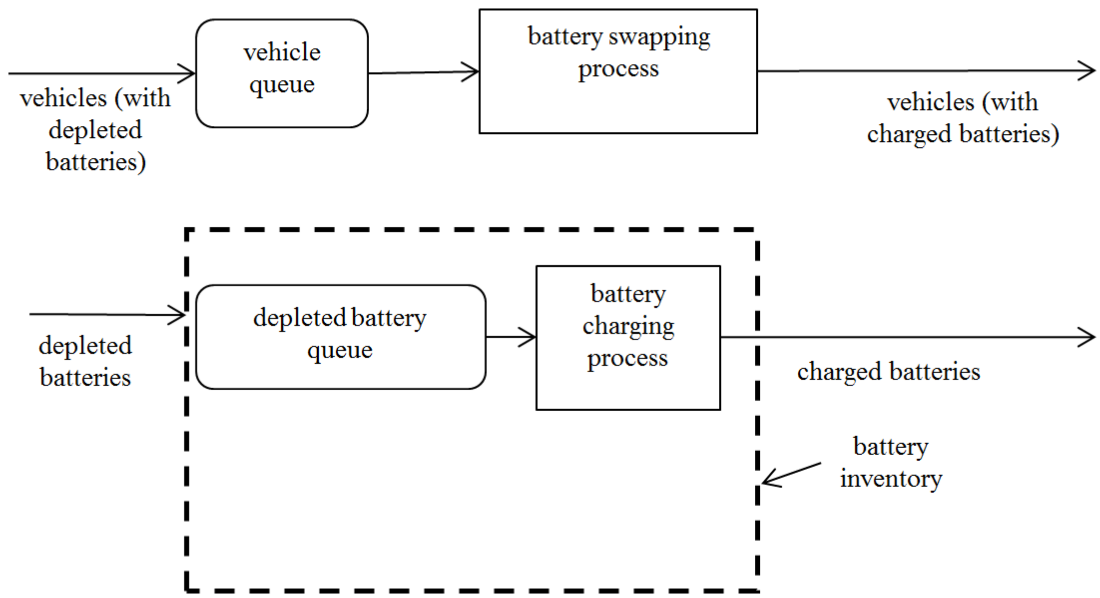

Figure 4.2 Diagram of M/M/c analytical queuing simulation of battery swapping station. The vehicle queue with swapping process and the battery queue with charging process are modeled separately but have the same arrival and departure rates.

Table 4.6 Parameters and calculations for M/M/c (also known as M/M/m) queuing models (Baron, 2007; Gross et al., 2008; Kleinrock, 1975).

Parameter or Variable	***Description***	***Value and Units***	***Formula***	***Notes***
c	Number of service bays			For fast swapping, the number of charging points n_{CP}. For swapping, the number of swapping bays n_S. For battery inventory, the number of charging bays, n_{ICP}.
μ	Mean service rate	0.0444 veh/min for fast charging 0.2 veh/min for swapping	$1/t_C$	Equivalent to 22.5 min/veh mean fast charging time, 5 min/veh mean swapping time, etc.
ρ	Traffic intensity of charging station		$\dfrac{\lambda}{c\mu}$	
p_O	probability of zero vehicles in system, or portion of time it is idle		$\left(\dfrac{r^c}{c!(1-\rho)}+\sum_{n=0}^{c-1}\dfrac{r^n}{n!}\right)^{-1}$	
L_q	expected (mean) queue size	vehicles or batteries	$\dfrac{p_0 r^c \rho}{c!(1-\rho)^2}$	
W_q	expected (mean) waiting time in	minutes	Lq/λ	

	queue			
W	expected waiting time in system (queue time + charging time)	minutes	Wq+1/μ	
L	expected system size (queue length + number charging)	vehicles or batteries	$W\lambda$	For the battery inventory queue, this gives the number of batteries required
W_{q0}	probability that an arriving customer does not have to wait in the queue		$1-\frac{r^c p_0}{c!(1-\rho)}$	
λ	Mean vehicle arrival rate	veh/min	0-2.5	Based on highway traffic volumes of 20-40 veh/min with up to 12.5% of vehicles stopping to charge or swap

4.3.5 Numerical Queuing Simulations

The most detailed models we consider are numerical queuing simulations for determining station equipment and inventory requirements and waiting times. The numerical simulations are developed based on an approach presented in Baron 2007 that calculates the times of each event in the queuing system. For fast charging, the numerical simulation is a basic G/G/c queue, allowing the arrival times and the arrival battery depletions to follow any distribution but still with a fixed number of charging points and infinite waiting space. We perform sensitivity analysis on the arrival battery depletion distribution, since the exponentially distributed charging times were the least realistic aspect of the M/M/c queuing model for fast charging. We compare the exponentially distributed battery depletions to uniformly distributed battery depletion levels where batteries arrive with between 50% and 100% of their 80% (of useable SOC) charge depleted.

For battery swapping, the numerical model allows arrival times and battery depletions to follow any distribution. As shown in Figure 4.3, the battery inventory queue and the vehicle inventory queue are combined into one numerical simulation model. It connects the vehicle queue with the battery inventory charging queue by requiring a charged battery to be available before each vehicle can start swapping. Extra time is added to the vehicle's queue wait when a charged battery is not yet available. Instead of modeling separate queues for depleted and charged batteries, the inventory is modeled with an equal number of charging points and batteries. This assumption makes sense because not having separate queues for depleted and charged batteries means the batteries will need to be moved around the warehouse less frequently, and moving the batteries around the warehouse more than necessary could cause delays. The code used for numerical simulation is presented in Appendix 7.3.

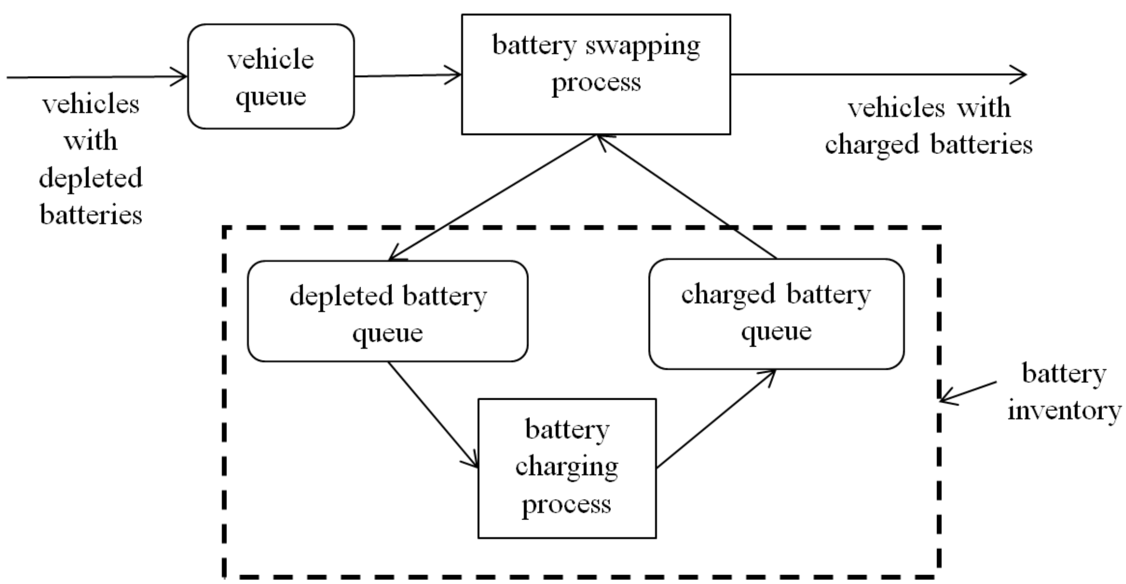

Figure 4.3 Diagram of numerical queuing simulation of battery swapping station.

4.3.6 Parameter Values and Sensitivity Analysis

Further details for some parameter values are provided here.

4.3.6.1 Fast Charging Efficiency

Level 1 charging is often cited as having a wall to battery efficiency of 87-88% (EPRI, 2001; Michalek et al., 2011; Traut et al., 2012). This accounts for a charger efficiency of 90% and a charging efficiency in the battery itself of 97% (Elgowainy et al., 2010). Similarly, Level 2 charging has an overall wall to battery efficiency of 83%, with a charger efficiency of 87% and battery charging efficiency of 95% (Elgowainy et al., 2010; EPRI, 2001). Charging efficiency numbers for fast charging are less readily available, but fast charging based on high currents of 150-400A "offers relatively low charging efficiency" (Chan, 2002) and two studies use 75% for fast-charging efficiency (MacCarley, 1999; Neubauer and Pesaran, 2013).

We calculate fast-charging efficiency as a combination of charger efficiency and battery charging efficiency, based on manufacturer specs and points in the literature (MacCarley, 1999; Neubauer and Pesaran, 2013). We find that fast charging can achieve a wall to battery efficiency of 75% to 83% and that the efficiency from "well" to wall is the same for fast and slow charging. The wall to battery efficiency of 83% is calculated from an assumed charger efficiency of 92% and battery charging efficiency of 90%, and the 75% is calculated from a charger efficiency of 83% and a battery charging efficiency of 90%. A charger efficiency of 87% and a battery charging efficiency of 90% result in a wall to battery efficiency of 78%, which is the base case for this analysis. Based on the limited information available on fast charging efficiency ("E-station - CHAdeMO Fast

Charge E-Bowsers," n.d.; St. John, 2012), these numbers are plausible, but may be reduced by up to 20% if the ambient temperature is not ideal (Pesaran, 2011).

4.3.6.2 Electricity Rate Structures

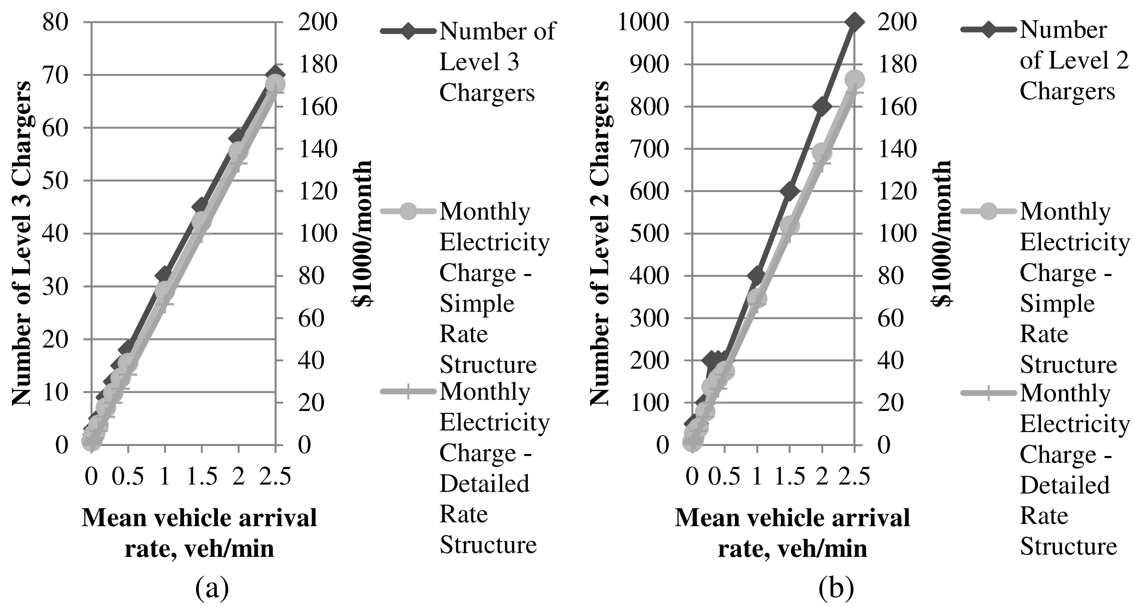

Figure 4.4 Comparison of detailed and simple electricity rate structures for Level 2 charging (a) and Level 3 charging (b).

The detailed rate structure is based on Southern California Edison's 200kW-500kW schedule: $420/month + $0.07/kWh + $22/kW/month. The simple rate structure is $0.11/kWh plus 20% extra to account for demand charges. As shown in Figure 4.4, for the cases relevant to these charging technologies, these two rate structures end up being approximately equivalent. Since this rate structure is only for 200kW-500kW it actually only applies to a subset of the points on this graph (4-10 fast chargers or 55-138 Level 2 chargers), and I have extrapolated in both directions. Since real electricity rates and rate structures vary widely, these rate structures are used as an approximation for the base case (simple rate structure for the simple estimate models, detailed rate structure for the detailed cost models) and sensitivity analysis is conducted. The impact of changing the rate structure is expected to be less significant than the impact of changing the magnitude of the rate. This is especially the case since the high value of time spent waiting in line means that the electricity peak demand charge would need to be extremely high to justify reducing the number of charge points and thereby increasing wait time.

4.3.6.3 Sensitivity Analysis

The sensitivity analysis approach is to define an optimistic case for fast charging and an optimistic case for battery swapping. This approach allows us to determine whether it is clear which of the two technologies is less expensive or whether the uncertainty means that we are unsure which is least expensive. Sensitivity analysis values for the simple estimate models are given in Table 4.2 and Table 4.3. Further sensitivity analysis values for the more detailed models are given in Table 4.7. Sensitivity analysis values used in the one-way sensitivity analysis but not included in the optimistic/pessimistic cases are shown in Table 4.8. Additional sensitivity analysis, such as battery size/vehicle range, is left for future work.

Table 4.7 Parameter values for optimistic sensitivity analysis case for each station type. Each station type's optimistic case is also the pessimistic case for the other station type.

Description	*Units*	*Base Case Value*	*Fast Charging Optimistic Case Value*	*Battery Swapping Optimistic Case Value*	*Source*
Charging equipment life	years	25	15	25	For chargers including battery inventory charging equipment
Swapping equipment life	years	10	10	8	For battery swapping equipment, based on usable life of industrial robots (Bard, 1986; Fryman, 2002; Nof, 1999; Yusuf and Nabeshima, 2006)
Charging equipment	$	Level 3: 50000	Level 3: 10000	Level 3: 90000	Also battery inventory charging price per bay. Includes installation of the

Description	*Units*	*Base Case Value*	*Fast Charging Optimistic Case Value*	*Battery Swapping Optimistic Case Value*	*Source*
price		Level 2: 2000 Level 1: 1000			individual charge points, estimates for Level 3 range from 10000-90000+ (McKinsey & Company, 2009; Motavalli, 2011; Parsons Brinckerhoff, 2009). Level 1 and Level 2 costs from (Morrow et al., 2008)
Electricity price per kWh	$/kWh	0.075	-20%	+20%	("Southern California Edison Schedule TOU-GS-SOP," n.d.) Averaging over the year and assuming constant demand
Base electricity price per customer	$/yr	5050	-20%	+20%	("Southern California Edison Schedule TOU-GS-SOP," n.d.)
Electricity demand charge	$/yr	Level 1: 370 n_{CP} Level 2: 940 n_{CP} Level 3: 13000n_{CP}	-20%	+20%	("Southern California Edison Schedule TOU-GS-SOP," n.d.) Based on peak power demand which is a function of the number of chargers, averaging over the year and assuming constant demand. Cost is $21.60/kW/month. Each Level 1 charger is 1.44 kW, Level 2 charger is 3.6 kW, and Level 3 charger is 50 kW
Fast charging or battery inventory charging efficiency		Level 1: 0.88 Level 2: 0.83 Level 3: 0.78	Level 3: 83%	Level 3: 75%	Depends on charging speed. See Section 4.3.4
Battery price per usable kWh energy capacity	$/kWh	600	600	200	From (Plotkin and Singh, 2009) lit review 2015 and DOE program goals 2030 cases. Converted to price per usable kWh by assuming 80% is usable. See Figure 7.1
Battery life	years	10	15	8	Based on being slightly longer than typical warranty (Roper, 2013)

Description	*Units*	*Base Case Value*	*Fast Charging Optimistic Case Value*	*Battery Swapping Optimistic Case Value*	*Source*
Price per swapping bay equipment	$	500,000	750,000	40,000	Preliminary cost ranges for battery swapping stations are very rough and range from $40,000 (McKinsey & Company, 2009) to $500,000 (O'Dell, 2010a).
Value of travel time for highway drivers	$.min	0.5333	0.3	0.6667	(Perk et al., 2011) from mean, 25th percentile, and 75th percentile of distribution of value of travel time savings

Table 4.8 Parameter values used in one-way sensitivity analysis

Description	*Units*	*Base Case Value*	*Sensitivity Values*	*Source*
Operating cost per year	$	80000	+/-20%	Also per swapping point. Based on one employee, WDOT (Parsons Brinckerhoff, 2009)
Charging equipment life	years	25	15	For chargers including battery inventory charging equipment
Swapping equipment life	years	10	8	For battery swapping equipment, based on usable life of industrial robots (Bard, 1986; Fryman, 2002; Nof, 1999; Yusuf and Nabeshima, 2006)
Charging equipment price	$	Level 3: 50000 Level 2: 2000 Level 1: 1000	Level 3: 10000, 90000	Also battery inventory charging price per bay. Includes installation of the individual charge points, estimates for Level 3 range from 10000-90000+ (McKinsey & Company, 2009; Motavalli, 2011; Parsons Brinckerhoff, 2009). Level 1 and Level 2 costs from (Morrow et al., 2008)
Electricity price per kWh	$/kWh	0.075	+/-20%	("Southern California Edison Schedule TOU-GS-SOP," n.d.) Averaging over the year and assuming constant demand
Base electricity price per customer	$/yr	5050	+/-20%	("Southern California Edison Schedule TOU-GS-SOP," n.d.)

Description	*Units*	*Base Case Value*	*Sensitivity Values*	*Source*
Electricity demand charge	\$/yr	Level 1: 370 n_{CP} Level 2: 940 n_{CP} Level 3: 13000n_{CP}	+/-20%	("Southern California Edison Schedule TOU-GS-SOP," n.d.) Based on peak power demand which is a function of the number of chargers, averaging over the year and assuming constant demand. Cost is \$21.60/kW/month. Each Level 1 charger is 1.44 kW, Level 2 charger is 3.6 kW, and Level 3 charger is 50 kW
Fast charging or battery inventory charging efficiency		Level 1: 0.88 Level 2: 0.83 Level 3: 0.78	Level 3: 75%, 83%	Depends on charging speed. See Section 4.3.4
Battery price per usable kWh energy capacity	\$/kWh	600	200	From (Plotkin and Singh, 2009) lit review 2015 and DOE program goals 2030 cases. Converted to price per usable kWh by assuming 80% is usable. See Figure 7.1
Battery life	years	10	8, 15	Based on being slightly longer than typical warranty (Roper, 2013)
Price per swapping bay equipment	\$	500,000	40000, 750000	Preliminary cost ranges for battery swapping stations are very rough and range from \$40,000 (McKinsey & Company, 2009) to \$500,000 (O'Dell, 2010a).
Value of travel time for highway drivers	\$.min	0.5333	0.3, 0.6667	(Perk et al., 2011) from mean, 25th percentile, and 75th percentile of distribution of value of travel time savings
Average depletion of arriving vehicle batteries		0.75	0.6, 0.9	As a percentage of the 80% of usable swing that is replenished in each charge or swap

4.4 Results

4.4.1 Simple Estimation Models

Figure 4.5 shows results from the simple estimate models for annual station cost per vehicle arrival for 8 types of stations: Level 1 charging, Level 2 charging, Level 3 fast charging, battery swapping where the inventory is charged at Level 1, battery swapping where the inventory is charged at Level 2, battery swapping where the inventory is charged at Level 3, a gasoline station serving CVs, and a gasoline station serving HEVs. The cost is broken down by contributions from electricity; gasoline; batteries in the swapping inventory; service time, including swapping, charging, or gas pumping time plus some time to get in and out of the station and pay; and a carbon cost on GHG emissions from electricity and battery production. Error bars indicate optimistic and pessimistic sensitivity analysis cases for each technology, and parameter values for the base case and sensitivity analysis cases are given in Table 4.2 and Table 4.3. As shown, the major cost contributor for all of the BEV refueling stations is service time. The majority of this time is spent actively charging the vehicle or swapping the battery. When the cost of service time is considered, battery swapping costs less than charging, and battery

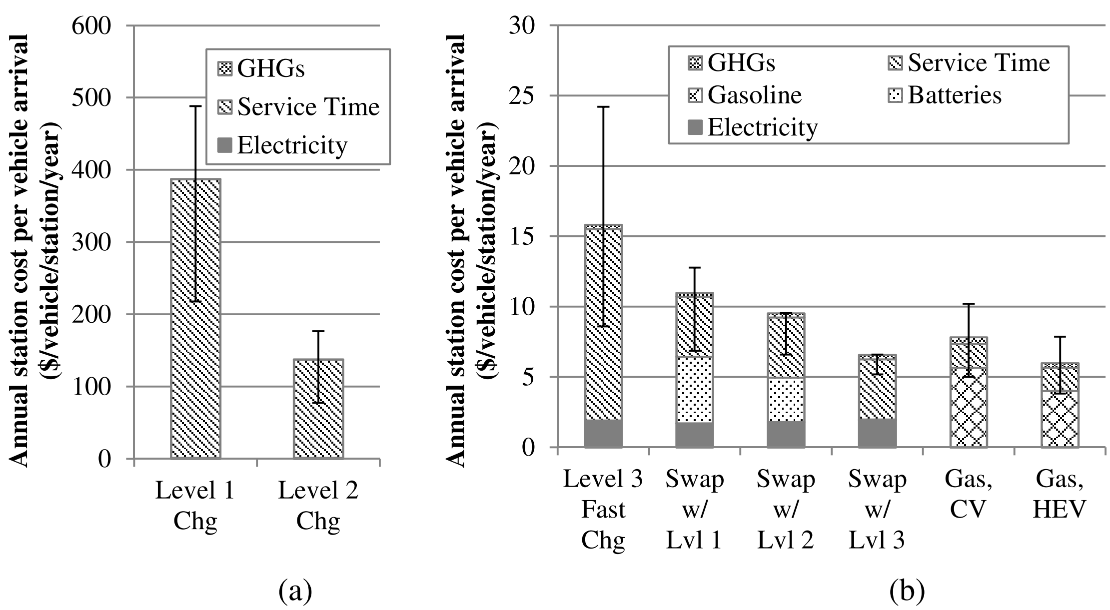

Figure 4.5 Annual station cost per vehicle arrival calculated from simple cost estimate models. Results are shown on two sets of axes (a) and (b) due to order of magnitude. Error bars indicate the range of optimistic and pessimistic cost scenarios for each technology. Chg=Charging, Lvl=Level. Swap w/ Lvl 1 indicates that the battery inventory at the swapping station is charged at Level 1.

swapping while fast-charging the inventory is least expensive due to the combination of low service time and a small battery inventory. However, when service time is ignored, the charging stations are competitive with the swapping station that charged inventory at Level 3 and less expensive than the swapping stations that charge batteries more slowly. To determine what effect capital equipment costs and waiting (in line) times will have on these costs, more detailed cost models including queuing models are needed. These are presented in Section 4.4.2.

The GHG emissions results that were used to calculate the carbon costs are shown in Figure 4.6. The carbon cost turns out to be a small contributor to the overall station cost, and also turns out to be similar for each BEV refueling technology because the GHG emissions levels are similar for all of the charging and swapping scenarios. The slight differences are due to the differences in charging efficiency and number of batteries

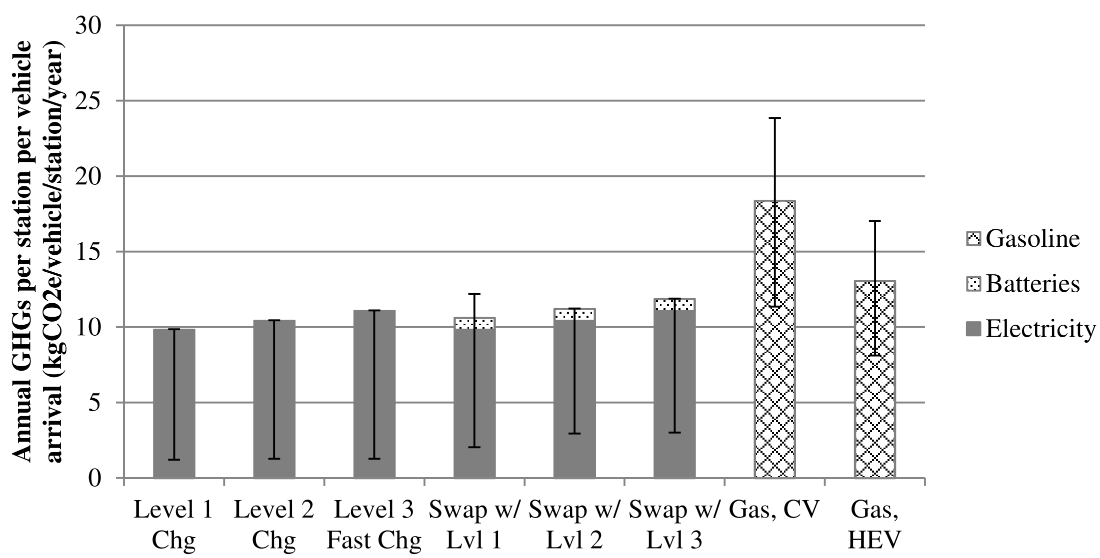

Figure 4.6 Annual station GHG emissions per vehicle arrival calculated from simple estimate models. Error bars indicate the range of optimistic and pessimistic cost scenarios for each technology. Chg=Charging, Lvl=Level. Swap w/ Lvl 1 indicates that the battery inventory at the swapping station is charged at Level 1.

required in inventory. Since this cost is a so small it has been left out of subsequent modeling for simplicity.

4.4.2 Detailed Cost Models

Figure 4.7 compares detailed cost results from analytical queuing models for the least costly type of charging station (Level 3) and the 2 least costly battery swapping stations (Level 2 and 3 inventory charging) to serve a customer arrival rate of one vehicle arrival per minute. This vehicle arrival rate is equivalent to about 2% of vehicles stopping on a busy highway. As shown, the annual station costs per vehicle as calculated from the detailed cost models with analytical queuing are somewhat higher for fast charging and lower for battery swapping than those found from the simple models. These detailed results include all of the costs from the simple model except carbon costs, for simplicity since the carbon costs turned out to be very small. In addition, the detailed cost models include waiting time (in line waiting for service), a more detailed calculation of the number of batteries in the inventory (which turns out to be lower than the initial estimates), operating costs (employees), capital equipment costs (charging and swapping equipment), and site preparation costs (including battery storage warehouses). Waiting time has a very small impact on overall cost. However, it is important to note that this is a result of the stations having been designed for minimum cost and therefore for short wait times due to the high cost of waiting. If stations are not designed for short wait times, wait times could become a significant cost. These results suggest that if vehicles and batteries are standardized for swapping, it may be worthwhile to fast charge the batteries used for swapping instead of slow charging them. This would combine the benefits of fast charging (no battery inventory) with the benefits of battery swapping (less time).

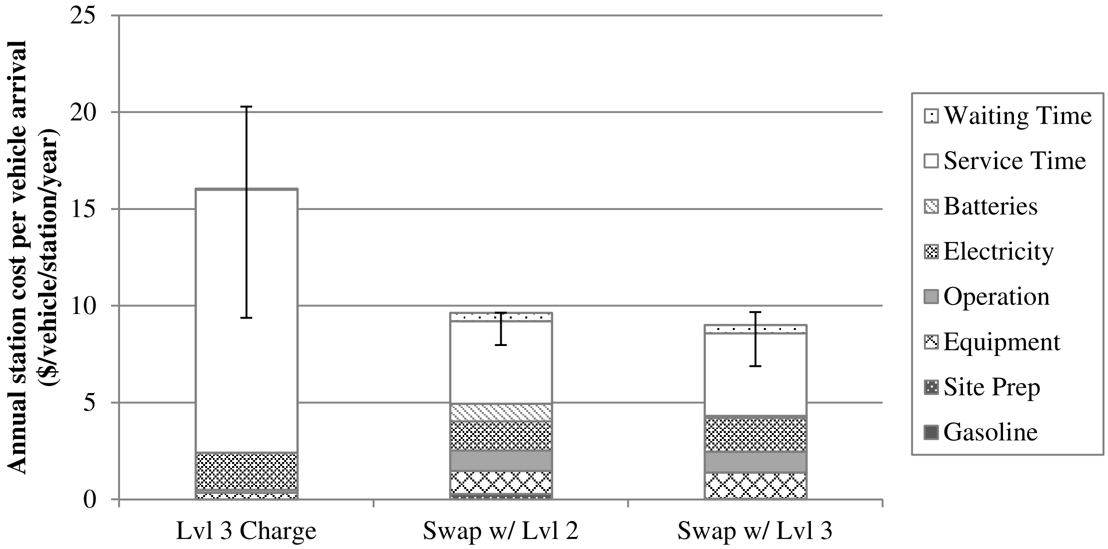

Figure 4.7 Annual station cost per vehicle arrival calculated from detailed cost models with analytical queuing, comparing Level 3 fast charging, battery swapping with the battery inventory charged at Level 2, and battery swapping with the battery inventory charged at Level 3. Error bars indicate optimistic and pessimistic sensitivity analysis cases results. Lvl=Level, Swap w/ Lvl 2 indicates that the battery inventory at the swapping station is charged at Level 2.

Drawbacks would include the combined effects of fast charging and swapping on battery life, as well as the other drawbacks of battery swapping, mainly needing to have large numbers of vehicles with compatible swappable batteries. The Level 3 charging station shown has 32 charging points. The swapping station with Level 2 inventory charging has 8 swapping points, 253 charging points, and 253 batteries. The swapping station with Level 3 inventory charging has 7 swapping points, 26 charging points, and 26 batteries. Details of the results presented in Figure 4.7 are given in Table 7.15.

Figure 4.8 shows the same results as Figure 4.7, with the addition of three station scenarios representing battery swapping with less vehicle and battery standardization and CV and HEV refueling stations for comparison. Details of the results presented in Figure 4.8 are given in Table 7.15. The fourth and fifth bars in Figure 4.8 represent cases 3 smaller stations are built, each serving one third of the traffic. This represents a situation in which there are three vehicle designs with swappable batteries, but they have not been

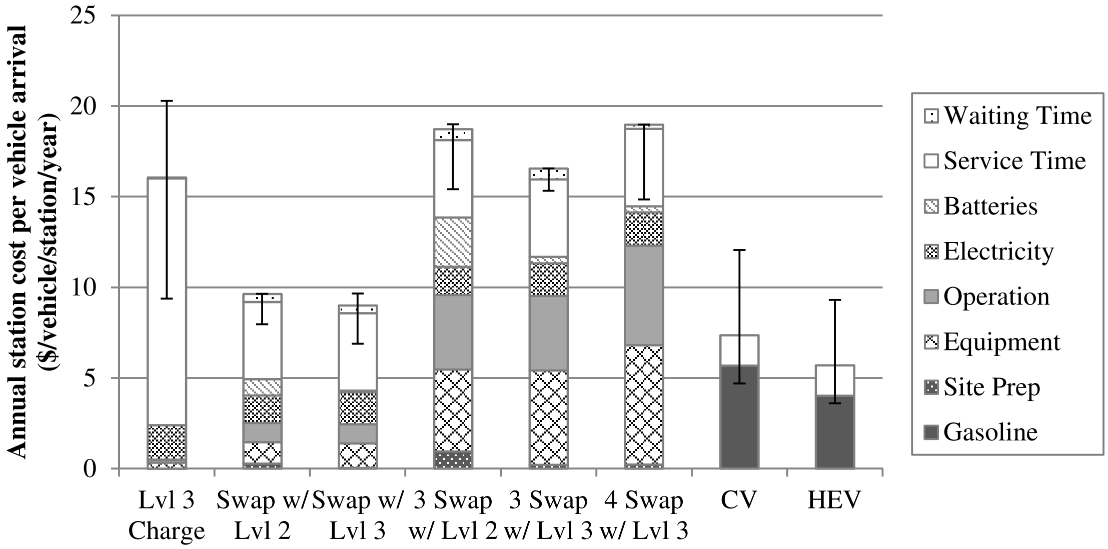

Figure 4.8 Annual station cost per vehicle arrival for a station serving an arrival rate of 1 vehicle per minute calculated from detailed cost models with analytical queuing and comparing Level 3 fast charging; battery swapping with the battery inventory charged at Level 2 or Level 3; and battery swapping with the battery inventory charged at Level 2 or 3 but with demand divided between 3 or 4 smaller swapping stations each serving an equal portion of the customers due to non-standardized battery and vehicle designs. Error bars indicate optimistic and pessimistic sensitivity analysis cases results. Lvl=Level, Swap w/ Lvl 2 indicates that the battery inventory at the swapping station is charged at Level 2.

standardized to use the same batteries or swapping equipment. In this situation, each battery swapping station can have fewer swapping points (3) and a smaller battery inventory (90 for Level 2 inventory charging, 11 for Level 3 inventory charging), but the 3 stations considered together have more equipment and a larger battery inventory than the single station serving all vehicles. (The fixed costs for the smaller stations are multiplied by 3 and the variable costs per vehicle (electricity, service time, and waiting time) are not.) The battery swapping cost savings seen in Figure 4.7 due to lower service time than Level 3 charging are lost due to the additional equipment and battery costs. Considering more than 3 incompatible vehicle types, as shown in the sixth bar in Figure 4.8, exacerbates these issues, since the smaller the stations are the more the upfront and capital costs are per vehicle. This scale issue is shown in Figure 4.9, and may be a particular issue early adopter scenarios and other situation with low traffic volumes. The cost decreases as the station size increases due to economies of scale for the equipment and other fixed costs. Discontinuities in the slopes of the cost curves in Figure 4.9 indicate increases in the number of swapping or charging points, as in process-based cost modeling. The results shown in Figure 4.8 for cases without vehicle standardization indicate that battery swapping may be cost competitive with fast charging only when vehicles and batteries are standardized. The cost of standardizing vehicles and batteries is out of scope for this analysis, but the investment cost and other challenges of vehicle and swappable battery standardization should be considered in any policy decisions regarding battery swapping.

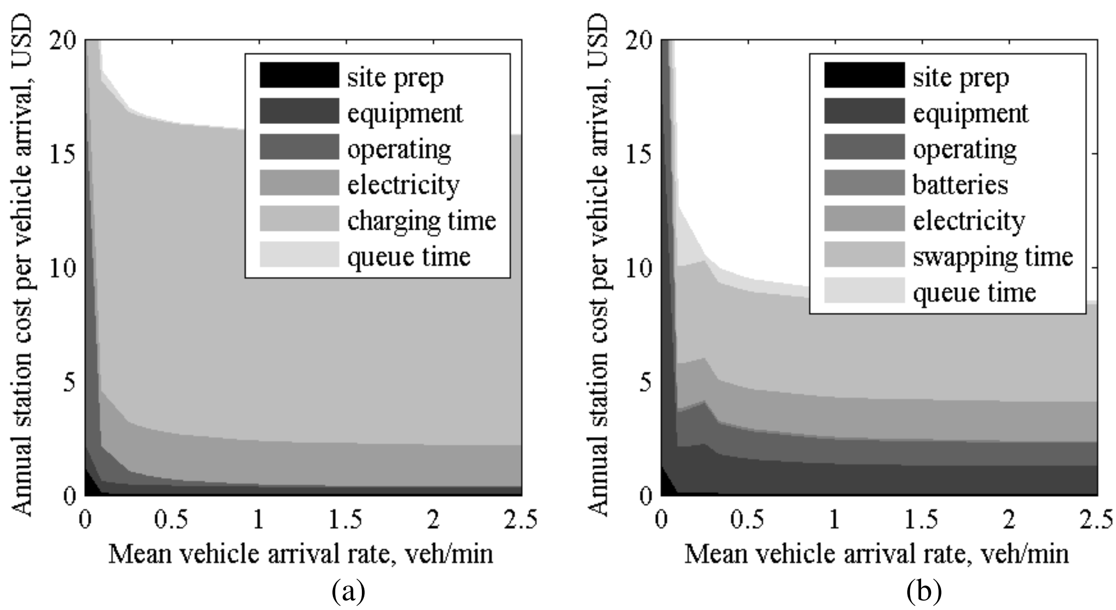

Figure 4.9 Annual station costs for fast charging (left) and battery swapping (right) as a function of vehicle arrival rate.

Updating the GHG emission estimates from Section 4.4.1 using the number of batteries calculated for each case from the analytical models results in GHG emissions for battery swapping that are only 1% higher than for fast charging.

To find the incremental cost that fast charging or battery swapping adds to BEV cost each time it is used, the direct cost (excluding service time and waiting time) for a Level 1 or Level 2 charging station can be subtracted from the results shown in Figure 4.8. Direct cost is appropriate for this calculation because we assume that the default charging method is home-based overnight charging, when cost of time is not relevant. (These results are not shown in Figure 4.8 due to the order of magnitude when time is included.) The direct cost of Level 1 charging is found to be $1.8 per charge and the total cost including time is $390 per charge. For Level 2 charging the direct cost is $1.77 per charge and the total cost is $140 per charge. (Level 2 costs are lower than for Level 1 because less equipment is required to operate a station at the assumed capacities; costs for home charging will likely vary slightly from these station charging cost estimates.) The incremental cost of Level 3 charging compared to Level 2 charging is $0.64 per charge when value of time is not included but $14 per charge when value of time is included. The incremental cost of battery swapping compared to Level 2 charging is $2.50 when value of time is not included and $7.25 when value of time is included. Thus the added cost per vehicle for Level 3 charging or battery swapping can be estimated based on how often each refueling method will be utilized.

Results from numerical queuing simulations indicate that the battery inventory size for battery swapping is about 10% larger than found from the analytical models when the inventory is charged at Level 2 and about 50% larger than found from the analytical models when the inventory is charged at Level 3. The updated base case results are shown in Figure 4.10. Because the battery cost is the main difference, the cases most

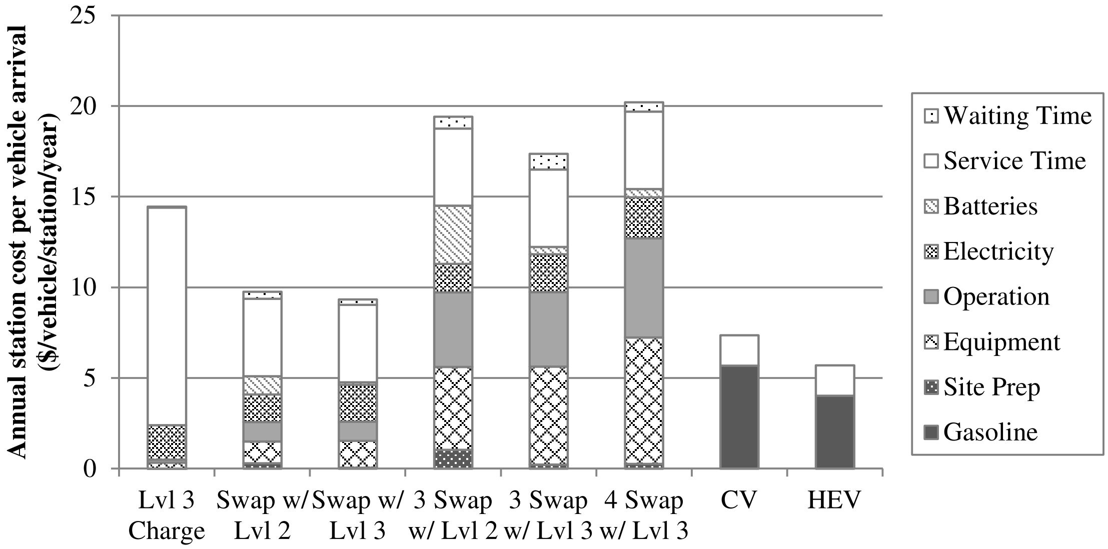

Figure 4.10 Annual station cost per vehicle arrival for a station serving an arrival rate of 1 vehicle per minute calculated from detailed cost models with numerical queuing simulations and comparing Level 3 fast charging; battery swapping with the battery inventory charged at Level 2 or Level 3; and battery swapping with the battery inventory charged at Level 2 or 3 but with demand divided between 3 or 4 smaller swapping stations each serving an equal portion of the customers due to non-standardized battery and vehicle designs. Lvl=Level, Swap w/ Lvl 2 indicates that the battery inventory at the swapping station is charged at Level 2.

affected are the cases with the most batteries, which are the cases where the swapping inventory is charged at Level 2.

The sensitivity analysis results in the previous figures included only an optimistic case for fast charging and an optimistic case for battery swapping (equivalent to also a pessimistic case for each technology). We also performed a one-way sensitivity analysis by varying individual parameters to determine which have the largest effect. These results are shown for fast charging in Figure 4.11 and for battery swapping in Figure 4.12. As shown the most sensitive parameter for both models is value of time. Since the value of time varies widely across the population, this indicates that the choice of which type of refueling is least costly would also vary across the population. Fast charging cost is somewhat sensitive to electricity cost, charger cost, and average depletion of arriving batteries. Battery swapping is sensitive to those parameters as well as swapping

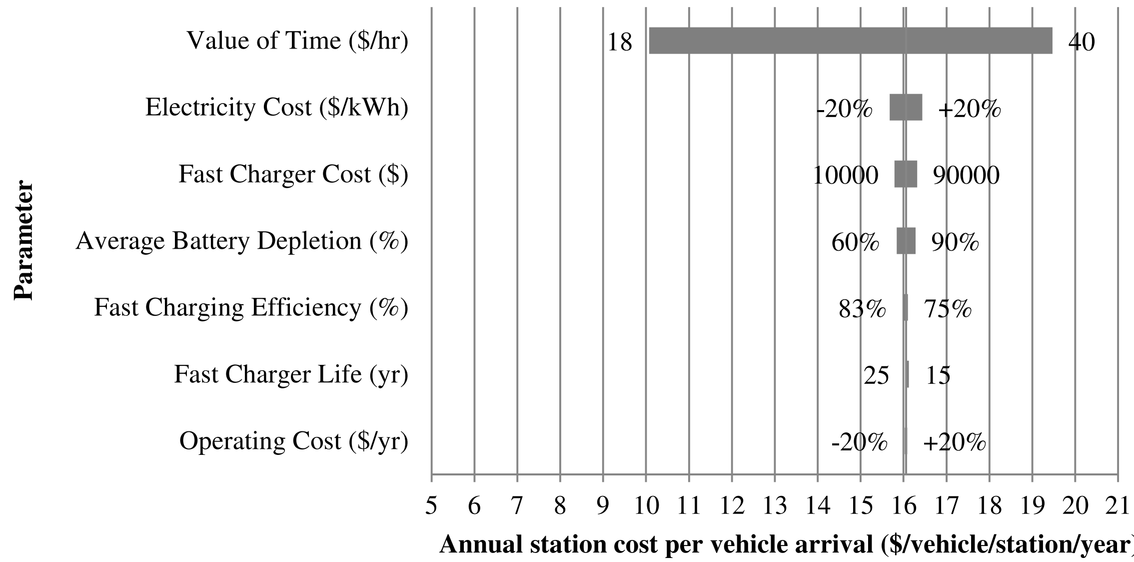

Figure 4.11 Sensitivity of fast charging station cost to individual parameters. Parameter input values are shown next to their resulting costs.

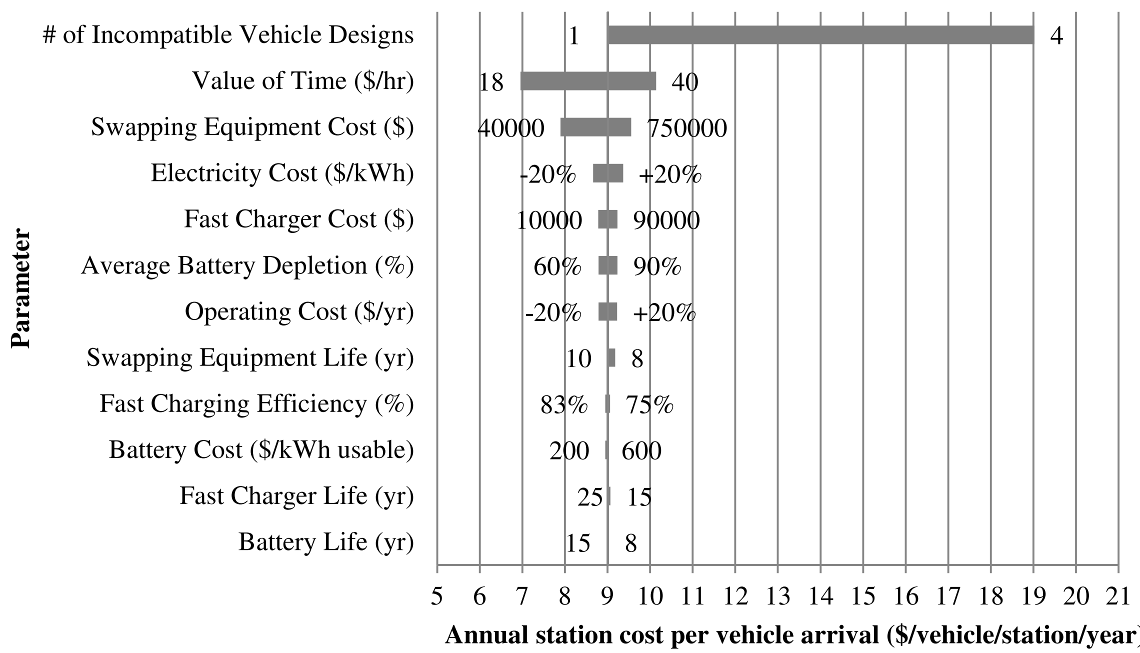

Figure 4.12 Sensitivity of battery swapping (with Level 3 inventory charging) station cost to individual parameters. Parameter input values are shown next to their resulting costs.

equipment cost and operating costs. Both of these costs are very uncertain for swapping stations and improved information about them could reduce the uncertainty in decisions about which technology is less costly.

4.5 Discussion and Limitations

We find that the conclusion as to whether fast charging or battery swapping is less costly depends on whether the value of waiting time during service is included and whether vehicles are standardized to use interchangeable swappable batteries. If the value of time is not included, fast charging is less expensive. If the value of time is included and vehicles and batteries are standardized, battery swapping with Level 2 or Level 3 inventory is less expensive, and battery swapping with Level 3 charging is least expensive. However, if vehicles and batteries are not standardized, depending on how many different battery types and swapping equipment types need to be available, battery swapping costs can exceed fast charging costs even with value of waiting time included. This indicates that the barriers to standardizing vehicles and swappable batteries and the costs of doing so merit further investigation. Battery swapping may deliver significant value to consumers by way of eliminating costly waiting time, but this may or may not offset the required investment in and challenges of standardization. Policies aimed at subsidizing fast charging, battery swapping, or vehicle standardization should be based on an understanding of the tradeoffs involving the direct costs of these technologies but also involving consumers' travel time.

The largest contributor to uncertainty in the analysis is the value of travel time. Value of time spent charging or swapping batteries is a major contributor to which station type is less expensive, and the main reason that the uncertainty ranges overlap. Thus it will be important to consider when and how this cost should be considered in comparing these technologies. From the perspective of service providers, the value of the customers' time is not a direct cost. However, it may indicate a significant difference in customers; willingness to pay for these different types of refueling services. Also, customers' value of time varies widely by customer (Perk et al., 2011) and may also vary widely for the same customer depending on other circumstances, such as the overall length of the trip, whether they are in a hurry, whether they need to stop for lunch anyway, etc. Therefore there may be significant heterogeneity in the market for these refueling technologies, with some customers who are willing to pay a significant premium for the faster refueling technology, but others who are not. This may have implications for where and when customers would be willing to pay higher prices for battery swapping than for fast charging due to the time savings. Another uncertain factor that we have not addressed is the arrival pattern. We assume steady state and look at traffic flows that may represent peak times. Running the numerical simulations using an appropriate daily arrival pattern may change the results, but care must be taken in identifying the distribution since it will likely be very different from gasoline station arrivals.

We also find that the overall costs per station arrival for both fast charging and battery swapping are lower than gasoline refueling costs, even for HEVs, when value of service time is excluded, but higher when value of service time is included. The major contributors to whether gasoline refueling or BEV rapid refueling is less expensive are value of time and gasoline prices. This indicates that for some consumers (with low value of travel time) BEV rapid refueling is already less expensive, and that BEV rapid refueling may be less expensive for many more consumers if gasoline prices rise.

Station cost per vehicle arrival for both fast charging and battery swapping is much higher at small station sizes, drops off quickly, and then remains flat. These models become less accurate as station size increases due to requiring increasingly large amounts of equipment that may become impractical, due to omitting certain costs such as land cost and upgrades to regional power systems, and due to neglecting some potential economies of scale at larger sizes such as in warehouse costs, operating expenses, and electricity rate structures. However, the shape of the cost curve at low and moderate arrival rates indicate that there are significant economies of scale from ensuring that stations receive at least some minimum level of traffic. This point is about 0.5 veh/min in the base case. Achieving this traffic rate will be a function of station location, but perhaps more importantly a function of BEV penetration in the fleet and an accurate understanding of when individual BEV drivers will use these services. These results indicate that although rapid refueling may be prohibitively expensive for very small stations while BEV fleet penetrations remain low and usage is mostly for shorter trips, once some sufficient level of fleet penetration is reached and consumers become comfortable using BEVs for longer trips and recharging on the way, the costs per station arrival drop significantly and the refueling cost becomes potentially competitive with CVs or HEVs, depending on gasoline prices, as shown in the sensitivity analysis. This also indicates that PHEV opportunity fast charging, if it occurs, may be of benefit to fast charging by allowing further economies of scale in station design, as long as the demand has been accurately predicted so that stations are large enough not to have long wait times.

Limitations of this work include the assumption that vehicles and batteries are standardized, and the lack of any cost estimates for achieving this standardization. Since battery swapping requires standardization and fast charging does not, this cost could change the technology comparison results. We also assume that batteries consist of a single large swappable pack that must be swapped by a robot (it weighs about 700 pounds). We do not consider cases where smaller battery modules can be swapped by a human, which may reduce cost by not requiring swapping equipment, by allowing a smaller number of modules to be swapped (enough to get to your next destination with charging), and by reducing barriers to standardization.

4.6 Conclusions

Results suggest that a battery swapping station (with fast charging of battery inventory) costs 40% more than a fast charging station when the value of time spent waiting during service is excluded, but 50% less when the $30/hour value of travel time for highway drivers is included. However, battery swapping's cost advantage due to decreased service time requires vehicles and swappable batteries to be standardized. When four separate swapping stations and battery inventories are needed to serve the same number of customers driving four incompatible vehicle designs, the cost benefits disappear and battery swapping becomes 30% more expensive than fast charging. A single battery swapping station (with fast charging of battery inventory) emits only 1% more GHGs than a fast charging station under today's US electricity grid mix due to battery production. This indicates that the barriers to standardizing vehicles and swappable batteries and the costs of doing so merit further investigation. Battery swapping may deliver significant value to consumers by way of eliminating costly waiting time, but this may or may not offset the required investment in standardization and the slightly higher GHG emissions.

Aside from standardization costs, the major contributors to cost uncertainty are value of travel time, which also varies widely among consumers, and station size. Very small stations such as those appropriate for early adoption scenarios are much more expensive per vehicle arrival. The combination of wide ranging values of travel time and uncertainty in gas prices indicates that BEV rapid refueling by either fast charging or battery swapping could already be cost effective for some consumers compared to gasoline refueling of a CV or HEV if sufficient economies of scale are achieved, and rising gas prices would make BEV rapid refueling cost effective for even more consumers.

Important limitations include that we are looking at life cycle station cost, which is equivalent to refueling cost, not cost of ownership. Also, we assume steady state arrival patterns. More research is needed to determine actual demand patterns and their effect on these results. Finally, we include only one vehicle design. Determining impact of vehicle range on the relative attractiveness of these two refueling technologies is also left for future work.

5 Summary, Conclusions, and Policy Implications

This thesis examines life cycle cost, greenhouse gas (GHG) emissions, petroleum use, and policy implications of scenarios for electrified vehicles and charging infrastructure in the U.S., addressing several questions: What mix of vehicles minimizes life cycle cost? GHG emissions? What are the implications of workplace charging in addition to home charging? How much current and potential U.S. residential charging exists? What are the costs and GHG emissions of fast-charging and battery swapping service stations? How sensitive are these results to uncertain parameters? What factors are most critical? and What are the policy implications?

We identify gas prices ($6/gal) as a price lever to make PEVs cost competitive, and we find that relatively high gas prices ($4.5/gal) combined with low vehicle and battery prices (DOE 2030 program goals) create a price lever that can make PEVs dominate HEVs for minimum cost. PEV adoption reduces petroleum consumption, but grid decarbonization is also needed for GHG emissions reductions. With cleaner electricity, GHG emissions benefits of PEVs can be substantial.

Lack of residential charging potential could curb adoption if not addressed, since parking and housing infrastructure turn over more slowly than the vehicle fleet, and several key home charging infrastructure barriers are identified. Excluding renters, who face additional barriers to charging infrastructure installation, we find that less than half of U.S. vehicles have reliable access to off-street parking where charging could be installed. To achieve even that much PEV adoption, some of the households who do have parking will need to charge multiple vehicles, requiring electrical upgrades. Thus a policy encouraging the installation of vehicle charging circuits in residential garage new construction (and renovation) may be a relatively inexpensive way to mitigate a barrier to

PEV adoption. Further, incentivizing the installation of multiple vehicle charging circuits, or at least of household electricity panels that have space for additional vehicle charging circuits, will be more costly but will also mitigate the more expensive (and therefore larger) barrier to charging multiple vehicles per household, which is needed to achieve PEV penetration above 40%. To achieve PEV penetration above 56%, additional dedicated home parking is needed, but policymakers should consider whether the benefits of PEVs in comparison to grid-independent HEVs or other alternative vehicle technologies are worth the potential negative impacts of adding parking, which include land cost and production/construction emissions as well as other impacts (Chester et al., 2010; Shoup, 2005). Since housing and parking infrastructure turn over more slowly than the vehicle fleet, these policies should be considered proactively in advance of desired future PEV adoption.

For drivers who do have home charging and a PEV, additional dedicated workplace charging increases the effective AER of the vehicle on commuting days but has little GHG emissions benefit under the current U.S. grid mix. Workplace charging could have substantial additional GHG emissions benefits in combination with cleaner electricity.

BEV adoption is restricted by limited range. Range requirements to meet 95% of driving day distances mean that for some drivers a BEV with a long enough range does not exist, and for other drivers a BEV with a long enough range has such a large battery that it is more expensive and emits more life cycle GHGs (from battery production and reduced vehicle efficiency) than an appropriately sized PHEV. BEVs only appear in the minimum cost solution for the 6% of drivers with the shortest driving distances, and only in the case with high gas prices ($4.5/gal) and low vehicle and battery prices (DOE 2030 program goals).

The issue of what BEV owners should do on the 5% of days when range is exceeded also needs to be addressed. Although some BEV drivers have the option of using another household vehicle, that would mean at most one vehicle per household could be a BEV, and only in multi-vehicle households. Renting a car on those days is also an option, but inventory would be strained major holidays. Both of those options also require advance planning.

To allow BEVs to meet driving requirements on long driving days, including unexpected ones, rapid BEV refueling options include fast charging, which incurs costly waiting times during service, or battery swapping, which is potentially faster and less costly but requires vehicle and battery standardization. Since there are many challenges to vehicle and battery standardization, policymakers should consider whether it would be worthwhile to incentivize standardization in order to reduce BEV rapid refueling time and make it a more attractive option for customers. It is possible that the costs and design tradeoffs necessary for vehicle and swappable battery standardization may outweigh the time savings, or the increased attractiveness to consumers of BEVs with wide availability of very fast refueling may be the dominant factor. This also needs to be considered in combination with BEV adoption goals since a sufficiently high traffic level, and therefore a sufficiently high BEV adoption level, is needed for battery swapping stations to reach economies of scale for utilizing expensive swapping equipment. Economies of scale mean that both types of rapid refueling stations are very costly (on a per refuel event basis) for early adopters due to low utilization rates.

All of these results are discussed for the entire U.S. Since several of the factors affecting PEV scenario outcomes vary by region, including electricity generation mix, home parking availability, vehicle efficiency and performance (especially due to temperature effects and terrain), and driving patterns, all of these policy implications can be considered on smaller geographic scales as well.

5.1 Contributions

5.1.1 Methodological contributions

Methodological contributions from the optimization study described in Chapter 2 include an MINLP optimization formulation to minimize life cycle cost or greenhouse gas emissions over the midsize 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 to vehicles in the fleet based on annual VMT; and (3) the optimal allocation of home and workplace charging infrastructure to xEVs vehicles in the fleet. A model for estimating driving patterns was also constructed for use in the optimization model, taking variability in driving distances across days and across vehicles into account.

Methodological contributions from the home charging study presented in Chapter 3 include applying multiple imputation with hot deck imputation, a Monte Carlo method, to combine two parking availability datasets and some assumptions to estimate vehicle-level parking availability.

Methodological contributions from the fast charging and battery swapping study presented in Chapter 4 include life cycle cost and GHG emissions models of fast charging stations and battery swapping stations as a function of demand (vehicle arrival patterns).

Detailed cost estimates are developed that can be solved analytically with simple queuing models or can be solved in more detail using the developed numerical queuing simulations. The models enable comparison of the two rapid refueling technologies, including in cases where multiple smaller battery swapping stations supporting incompatible vehicle designs are to be compared to a larger fast charging station.

5.1.2 Applicative contributions

Applicative contributions from the optimization study described in Chapter 2 include identifying scenarios in which PEVs may become optimal for life cycle cost or GHG emissions of the U.S. midsize personal vehicle fleet, as well as an analysis of the impact workplace charging availability has on optimal vehicle designs and allocations.

The applicative contribution of the study on home charging opportunities, presented in Chapter 3, is quantification of the current and future availability of home charging in the U.S. on a per vehicle basis and in urban and rural areas, including disaggregation by rented or owned status of the home, and quantification of how many vehicles would gain access to home charging if all homeowners with dedicated parking installed charging, or if all homes (rented and owned) with residential parking installed charging. Implications of these results on some PEV market share forecasts are also identified.

Applicative contributions from the fast charging and battery swapping study presented in Chapter 4 include a comparison of fast charging to battery swapping to determine which method of managing limited BEV range is best for cost or GHG emissions objectives, and under what scenarios. Results show that battery swapping stations are least expensive when the battery inventory is fast charged. Battery swapping stations cost 41% more than fast charging stations when the value of time spent waiting during service is excluded, but 50% less when the $30/hour value of travel time for highway drivers is included. However, battery swapping's cost advantage due to decreased service time requires vehicles and swappable batteries to be standardized. When separate swapping stations and battery inventories are needed to serve the same number of customers driving four incompatible vehicle designs, the cost benefits disappear and battery swapping becomes 31% more expensive than fast charging. Economies of scale also matter, as very small stations, such as would be appropriate for early adopters, are much more expensive per vehicle arrival. Costs of both BEV rapid refueling technologies are in the range where, depending on gasoline prices and economies of scale, they could be cost competitive with refueling a gasoline CV or HEV. A single battery swapping station (with fast charging of battery inventory) emits 8% more GHGs than a fast charging station under today's US electricity grid mix.

5.2 Recommendations for Future Work

Future work for the study presented in Chapter 2 includes incorporating the home charging infrastructure limitations found in Chapter 3 into the model as constraints on PEV adoption and determining effects, especially on the mix of vehicle designs in the fleet.

Future work for the home charging study in Chapter 3 includes determining cost of infrastructure improvements by gaining information on the electrical capacity of home wiring. Although a survey of consumers is unlikely to obtain information such as electrical circuit panel capacity, an expert elicitation from electricians across the country could approximate existing home electrical infrastructure. Other opportunities for future work include disaggregating the results by region or into smaller geographic areas to determine where PEVs will face more or fewer barriers to penetration and which geographic areas might need more investment in home charging infrastructure. Finally, the uncertainty ranges can be further reduced by conducting surveys of parking availability, especially driveway presence and the number of cars that can comfortably be parked in each driveway but also the amount of parking space that is available for cars as opposed to being used as living space or for storage.

Future work suggested by the fast charging and battery swapping study presented in Chapter 4 includes extending the sensitivity analysis to the detailed cost model and to include additional vehicle designs (battery size and vehicle range). The presented single-station models can also be scaled to define scenarios of infrastructure needed to support a regional fleet. This would involve defining station locations and calculating the arrival patterns of depleted BEVs at each station. The analytical models developed can be used for arrival patterns that are steady-state or close to steady-state, and the numerical simulations developed in this chapter can be used in cases where the arrival pattern is not steady state, so determining a better model for expected BEV refueling arrival patterns in a high adoption scenario is also an area for future work. The scope of the life cycle GHG assessment presented can be expanded to include additional sources of GHG emissions, such as equipment manufacturing and end-of-life considerations. The scope can also be expanded to include other environmental impacts besides GHG emissions, for example toxic releases from battery production.

In addition to future work directly indicated by each study, some overall areas for future work include further investigation of driver behavior, such as impact of electrified vehicle adoption on driving patterns and VMT. Some studies have theorized that a rebound effect will exist from the reduced cost per mile of driving when powered by electricity, but further investigation of this and other impacts on driving behavior are needed, especially to determine how the average driver would respond, not just early adopters.

Interactions between driver behavior with PEVs and price structure for public vehicle charging also merits attention. This work has focused on cost, not price structure. In particular, pricing structures may wish to incentivize the use of public charging early on to encourage adoption and provide economies of scale, but then deter use of public charging later on as it reaches capacity. There may be interesting implications for the attractiveness to consumers of PEVs versus other vehicle technologies. Pricing may also affect whether there is a rebound effect from electrifying travel (Avci et al., 2012). Owning versus leasing batteries is another key feature of PEV pricing structures that merits further attention. Leasing batteries makes vehicles more attractive to consumers by lowering the upfront cost, but it also will most likely lock them in to a service provider for battery swapping and maybe also for charging (such as with prices that are structured per mile and include all driving) which may make this model less attractive to consumers.

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7 Appendices

7.1 Appendix A: Supplemental Information for Optimal Design and Allocation of Electrified Vehicles and Dedicated Charging Infrastructure for Minimum Life Cycle GHG Emissions and Cost

This supporting information document provides additional details including a description of the adjusted growth rates used for future fuel prices; tables of variables, functions, and parameters; parameter values for the base case and sensitivity analysis; details of the vehicle performance simulations and metamodels; AER calculations; and additional results.

7.1.1 Approach

7.1.1.1 Description of adjusted growth rates for future fuel prices

To compute the equivalent annualized cost of future fuel purchases when the discount rate and the rate of increase of fuel prices are not equal, one must account for increases in the nominal price of fuel and discounting of those prices paid in future years. To make the formula compact, we introduce adjusted growth rates for gasoline r_{AG} and electricity r_{AE}. The formulas are given in the main body of the paper, and a brief explanation of their origin is shown below for the example of gasoline prices.

Price of gas in year n: $p_G\left(1+r_{NG}\right)^n$

Present value of gas purchases: $P=\sum_{n=1}^{N}\frac{S_G}{\eta_{\mathrm{G}}}\frac{p_G\left(1+r_{NG}\right)^n}{\left(1+r_N\right)^n}=p_G\frac{S_G}{\eta_{\mathrm{G}}}\sum_{n=1}^{N}\left(\frac{1+r_N}{1+r_{NG}}\right)^{-n}$

Define $r_{AG}=\left(\frac{1+r_N}{1+r_{NG}}-1\right)$

Then $\left(\frac{1+r_N}{1+r_{NG}}\right)=1+\left(\frac{1+r_N}{1+r_{NG}}-1\right)=1+r_{AG}$

$$P=p_G\frac{S_G}{\eta_{\mathrm{G}}}\sum_{n=1}^{N}\frac{1}{\left(1+r_{AG}\right)^n}=\frac{p_G S_G}{\eta_{\mathrm{G}}}\frac{1}{f_{\mathrm{A|P}}\left(r_{AG},N\right)}$$

$$EAC = Pf_{\mathrm{A|P}}\left(r_N, N\right) = p_G \frac{S_G}{\eta_{\mathrm{G}}} \frac{f_{\mathrm{A|P}}\left(r_N, N\right)}{f_{\mathrm{A|P}}\left(r_{AG}, N\right)}$$

7.1.1.2 Model Notation and Parameter Values

Model notation with descriptions, units, and ranges are shown in Table 7.1 for design variables, in Table 7.2 for functions, and in Table 7.3 for parameters. Table 7.4 provides further details for the distribution of annual vehicle miles traveled (VMT) and Table 7.5 and Table 7.6 provide further details for the vehicle performance metamodels.

Table 7.1 Model notation, descriptions, units, and ranges for decision variables.

Notation	Description	Units	Range of Values
x_{B}	Number of battery cells	-	CV: 0; HEV: 168; PHEV: 200–1000; BEV: 200–9000
x_{E}	Peak engine power	kW	CV: 126; HEV: 57; PHEV: 30–60; BEV: 0
x_{M}	Peak motor power	kW	CV: 0; HEV: 52; PHEV: 50–110; BEV: 70–250
x_{SW}	Battery swing window	-	CV & HEV: 0; PHEV & BEV: 0.1–0.8
α_{ij}	Binary selection variable for each bin i and vehicle alternative j		{0,1}

The cost, $c_{\mathrm{V}j}$, of producing the base vehicle excluding engine, motor, and batteries in the base case is \$12,970 for a CV, \$13,860 for an HEV, \$14,140 for a PHEV, and \$13,010 for a BEV. The cost of engine production as a function of peak engine power is $c_{\mathrm{E}}(x_{\mathrm{E}j}) = a_{c\mathrm{E1}}x_{\mathrm{E}j}+a_{c\mathrm{E2}}$ where $a_{c\mathrm{E1}}$ = \$2.785/kW and $a_{c\mathrm{E2}}$ = \$1626. The cost of motor production as a function of peak motor power is $c_{\mathrm{M}}(x_{\mathrm{M}j}) = a_{c\mathrm{M}}x_{\mathrm{M}j}$ where $a_{c\mathrm{M}}$ = \$8.102/kW. The cost per kWh (rated energy capacity) of battery production is constructed as a least-squares fit to the data reported by Plotkin and Singh (2009), as a function of the number of battery cells (equivalent to a scaled function of kWh): $c_{\mathrm{B}}(x_{\mathrm{B}j}) = a_{c\mathrm{B1}}\ln(x_{\mathrm{B}j}) + a_{c\mathrm{B2}}$, where $a_{c\mathrm{B1}}$ = -\$50.17 and $a_{c\mathrm{B2}}$ = \$832.5. This function results in a range of costs from\$376/kWh for

Table 7.2 Model notation, descriptions, units, and ranges for functions. Dollars are 2010 dollars.

Notation	Description	Units	Function	Range	Ref	Notes
$c_B(x_{Bj})$	Battery production cost for li-ion batteries	$/ kWh rated energy capacity	$a_{cB1}\ln(x_{Bj}) + a_{cB2}$	PHEV: 486 – 567; BEV: 376 – 567	(Plotkin and Singh, 2009)	Functional form chosen for its fit through battery price data for several different energy capacities (see Figure 7.1)
$c_E(x_{Ej})$	Engine production cost	$	$a_{cE1}x_{Ej}+a_{cE2}$	CV: 1977; HEV: 1785; PHEV: 1710 – 1793	(Plotkin and Singh, 2009)	Functional form from the literature
$c_M(x_{Mj})$	Motor production cost	$	$a_{cM}x_{Mj}$	HEV: 421.3; PHEV: 405.1 – 891.2; BEV: 567.1 – 2026	(Plotkin and Singh, 2009)	Functional form from the literature
$f_{A\vert P}(r,n)$	Capital recovery factor		$\frac{r(1+r)^n}{(1+r)^n-1}$			
$F_S(S)$	CDF of annual VMT over the fleet		data table lookup; see Table 7.4		§2.4	
$F_\sigma^V(\sigma,S)$	family of exponential distributions describing variation in daily driving distance		$1 - \exp(-\sigma/\mu(S))$		§2.4	
$l_V(S)$	Vehicle (and battery) life given annual VMT S	years	S_{LIFE}/S		§2.1.1	Based only on miles driven; not capped in terms of years
r_{AE}	Real discount rate		$\frac{1+r_N}{1+r_{NE}}-1$	-0.019 – 0.079	§2.1.1	
r_{AG}			$\frac{1+r_N}{1+r_{NG}}-1$	-0.049 – 0.046	§2.1.1	
$s_{AER}(\mathbf{x}_j)$	All-electric range of vehicle alternative j	mi.	$\frac{\eta_E(\mathbf{x}_j)\kappa_{Bj}x_{Bj}x_{SWj}}{\eta_C}$	PHEV: 12 – 88; BEV 11 – 354		

Notation	Description	Units	Function	Range	Ref	Notes
$S_E(\mathbf{x}_j,S)$	Annual distance powered by electricity for vehicle j given annual VMT S	mi.	§2.4		§2.4	
$S_G(\mathbf{x}_j,S)$	Annual distance powered by gasoline for vehicle j given annual VMT S	mi.	§2.4		§2.4	
$s_\phi(S)$	Driving distance of ϕ^{th} percentile day for a vehicle given annual VMT S	mi.	§2.4	$s_{99\%}(S) = 3.61(S/d) + 108$ $s_{95\%}(S) = 2.62(S/d) + 40.3$ $s_{MEAN}(S) = 1.11(S/d) + 13.3$	§2.4 (Sierra Research, 2005)	
$t_E(\mathbf{x}_j)$	0-60 mph acceleration time on electric power for vehicle j	sec.	§2.2	PHEV: 6.5 – 14.7; BEV: 6 – 36.5	§2.2	
$t_G(\mathbf{x}_j)$	0-60 mph acceleration time on gasoline power for vehicle j	sec.	§2.2	PHEV: 6.0 – 34.8	§2.2	
$v_E(x_{Ej})$	Engine production GHGs for vehicle alternative j	$kgCO_2e$	$a_{vE}c_E(x_{Ej})$	CV: 2620; HEV 1510; PHEV: 1070 – 1560		Based on engine production cost equation and tCO_2e/USD2002 multiplier from EIO-LCA Sector #336300: Motor vehicle parts manufacturing (Carnegie Mellon University Green Design Institute, 2008)

Notation	Descrip-tion	Units	Function	Range	Ref	Notes
$v_M(x_{Mj})$	Motor production GHGs for vehicle *j*	$kgCO_2e$	$a_{vM}c_M(x_M)$	CV: 0; HEV: 1500; PHEV: 1460 – 2720; BEV: 1880 – 5660		Based on motor production cost equation and tCO_2e/USD2002 multiplier from EIO-LCA Sector #335312: Motor and generator manufacturing (Carnegie Mellon University Green Design Institute, 2008)
Δ	Integration step size	mi.	S_{MAX}/mK		§2	
$\eta_E(\mathbf{x}_j)$	5-cycle combined electrical efficiency of vehicle *j*	mi./kWh	§2.2	PHEV: 3.02 – 3.23; BEV 1.54 – 2.88	§2.2	
$\eta_G(\mathbf{x}_j)$	5-cycle combined gasoline efficiency of vehicle *j*	mpge	§2.2	CV: 25; HEV: 43; PHEV: 40.3 – 75.7	§2.2	
$\mu(S)$	Mean driving-day distance	mi./day	$1.110(S/d) + 13.33$		§2.4 (Sierra Research, 2005)	Functional form chosen for its fit through data (see Figure 2.)

Table 7.3 Model notation, descriptions, units, and parameter values for the base case and the sensitivity analysis.

Nota-tion	Description	Units	Base Value	Range	Ref.	Notes
a_{cB1}	First coefficient of battery cost function		LR2015: -50.17	LR2030: -42.07 LR2045: -42.91 PG2030: -10.94	(Plotkin and Singh, 2009)	Coefficients from natural log function fit to values in the literature, scaled to USD2010 using the CPI (US DOL, 2010) (see Figure 7.1)
a_{cB2}	Second coefficient of battery cost function		LR2015: 832.5	LR2030: 647.8 LR2045: 577.9 PG2030: 233.8	(Plotkin and Singh, 2009)	
a_{cE1}	First coefficient of engine cost function	\$/kW	LR2015: 2.785	LR2030, LR2045, & PG2030: 2.735	(Plotkin and Singh, 2009)	From function in the literature for 4-cylinder engine, scaled to USD2010 using the CPI (US DOL, 2010)
a_{cE2}	Second coefficient of engine cost function	\$	LR2015: 1626	LR2030 & LR2045: 1777 PG2030: 1701	(Plotkin and Singh, 2009)	

Notation	Description	Units	Base Value	Range	Ref.	Notes
a_{cM}	Coefficient of motor cost function	$/kW	LR2015: 8.102	LR2030 & LR2045: 7.090 PG2030: 3.342	(Plotkin and Singh, 2009)	Scaled to USD2010 using the CPI (US DOL, 2010)
a_{vE}	Coefficient of engine GHG function		0.6245			Based on tCO_2e/USD2002 multiplier from EIO-LCA Sector #336300: Motor vehicle parts manufacturing (Carnegie Mellon University Green Design Institute, 2008) and USD2010 to USD 2002 conversion factor from the CPI (US DOL, 2010)
a_{vM}	Coefficient of motor GHG function		0.5445			Based on tCO_2e/USD2002 multiplier from EIO-LCA Sector #335312: Motor and generator manufacturing (Carnegie Mellon University Green Design Institute, 2008) and USD2010 to USD2002 conversion factor from the CPI (US DOL, 2010)
a_{vV}	Coefficient of base vehicle GHG function		0.4645			Based on tCO_2e/USD2002 multiplier from EIO-LCA Sector #336111: Automobile Manufacturing (Carnegie Mellon University Green Design Institute, 2008) and USD2010 to USD2002 conversion factor from CPI (US DOL, 2010)

Notation	Description	Units	Base Value	Range	Ref.	Notes
b_B	Scaling factor for number of battery cells	-	1/1000		(Shiau et al., 2010)	
b_E	Scaling factor for peak engine power	-	1/57		(Shiau et al., 2010)	
b_M	Scaling factor for peak motor power	-	1/52		(Shiau et al., 2010)	
c_{Bj}	Battery cost for NiMH battery $\forall j \in J_{HEV}$	$	LR2015: 1438	LR2030: 1093 LR2045: 1007 PG2030: 517.7	(Plotkin and Singh, 2009)	Scaled to USD2010 using the CPI (US DOL, 2010)
c_C	Charger cost	$	1500	0, 1500, 2500	(Morrow et al., 2008)	Including installation, excluding home wiring upgrade
c_{Vj}	Base vehicle cost	$	LR2015: CV 12970; HEV 13860; PHEV 14140; BEV 13010	LR2030: CV 12970; HEV 14440; PHEV 14670; BEV 13410 LR2045: CV 12970; HEV 14280; PHEV 14510; BEV 13320 PG2030: CV 12970; HEV 14220; PHEV 14380; BEV 13120	(Plotkin and Singh, 2009)	Scaled to USD2010 using the CPI (US DOL, 2010)
d	Days per year	days/year	365			
D	Driving days per year	days/year	243.8		(Sierra Research, 2005)	
i	Index of bins					
j	Index of vehicle designs					
k	Index of numerical integration segments within each bin					

Notation	Description	Units	Base Value	Range	Ref.	Notes
K	Number of integration segments per bin	-	1			
m	Number of bins for vehicle allocation	-	20			
n	Size of set J (number of vehicles in choice set)	-	10	1 – 10		
p_{ELEC}	Electricity price	\$/kWh	0.12	0.06 – 0.30	(US EIA, 2011e)	2009 average U.S. residential electricity cost
p_{G}	Gasoline price	\$/gal	2.26	1.5 – 8	(US EIA, 2011f)	2009 average U.S. gasoline price, all grades
$q_{\mathrm{C}j}$	Number of chargers allocated to vehicle j	chargers	{1,2}			
r_{NE}	Nominal gasoline price growth rate		1.9%		(US EIA, 2011c)	Projected growth rate from 2009 to 2035
r_{NG}	Inflation rate		5.2%		(US EIA, 2011c)	Projected growth rate from 2009 to 2035
r_{N}	Nominal discount rate		0.05	0.0 – 0.1		
S_{LIFE}	Vehicle life	mi.	150,000			
S_{MAX}	Maximum annual VMT considered in the model	mi.	73,000			
t_{MAX}	Maximum allowed 0-60mph acceleration time	sec.	11			
$v_{\mathrm{B}j}$	GHG emissions from li-ion battery production $\forall\ j \in J_{\mathrm{PHEV}} \cup J_{\mathrm{BEV}}$	$kgCO_2e$ / kWh	120		(Samaras and Meisterling, 2008)	

Notation	Description	Units	Base Value	Range	Ref.	Notes
	GHG emissions from NiMH battery production $\forall j \in J_{HEV}$	$kgCO_2e$ / kWh	230		(Samaras and Meisterling, 2008)	
v_C	GHG emissions from producing a charger	$kgCO_2e$	753.6	$0.5024c_C$		Based on charger production cost values, tCO_2e/USD2002 multiplier from EIO-LCA Sector #33441A: Electronic capacitor, resistor, coil, transformer, and other inductor manufacturing (Carnegie Mellon University Green Design Institute, 2008), and USD2010 to USD2002 conversion factor from the CPI (US DOL, 2010)
v_{ELEC}	GHG emissions from electricity generation	$kgCO_2e$ / kWh	0.752	0.066 – 0.9	(Shiau et al., 2010)	U.S. average electric grid emissions in 2005
v_G	GHG emissions from gasoline	$kgCO_2e$/ gal	11.34		(Shiau et al., 2010)	

Notation	Description	Units	Base Value	Range	Ref.	Notes
ν_{Vj}	GHG emissions from vehicle production excluding batteries	$kgCO_2e$	CV: 6026; HEV: 6437; PHEV: 6566; BEV 6044	$0.4645c_{\mathrm{V}}$		Based on vehicle production cost values, tCO_2e/USD2002 multiplier from EIO-LCA Sector #336111: Automobile Manufacturing (Carnegie Mellon University Green Design Institute, 2008), and USD2010 to USD2002 conversion factor from the CPI (US DOL, 2010)
β_{abc}	PSAT metamodel coefficients	-	See Table 7.5		(ANL, 2008)	Coefficients fit to PSAT data points
η_{C}	Vehicle charging efficiency	%	88%		(Shiau et al., 2010)	
$\kappa_{\mathrm{B}j}$	Energy capacity of one li-ion battery cell $\forall\ j \in J_{\mathrm{PHEV}} \cup J_{\mathrm{BEV}}$	kWh/cell	0.0216		(Shiau et al., 2010)	
	Energy capacity of one NiMH battery cell $\forall\ j \in J_{\mathrm{HEV}}$	kWh/cell	0.00774		(Shiau et al., 2010)	
ρ	Carbon tax	$/ $kgCO_2e$	0	0, 0.02 ($20/$tCO_2e$), 0.1 ($100/tCO_2e)	(Interagency Working Group on Social Cost of Carbon, United States Government, 2010; IPCC, 2007)	
σ	Random variable representing driving distance on a particular day	mi./day				

Table 7.4 Probability distribution of annual VMT over the fleet, from lookup table for $F_S(S)$.

Bin	Annual VMT Range (mi./yr)	% of Vehicles	Cumulative % of Vehicles
1	0 – 3,650	6.29	6.29
2	3,650 – 7,300	15.5	21.8
3	7,300 – 10,950	19.1	40.9
4	10,950 – 14,600	18.5	59.4
5	14,600 – 18,250	14.4	73.8
6	18,250 – 21,900	9.48	83.3
7	21,900 – 25,550	5.85	89.1
8	25,550 – 29,200	3.62	92.8
9	29,200 – 32,850	2.25	95.0
10	32,850 – 36,500	1.45	96.5
11	36,500 – 40,150	0.98	97.4
12	40,150 – 43,800	0.70	98.1
13	43,800 – 47,450	0.50	98.6
14	47,450 – 51,100	0.36	99.0
15	51,100 – 54,750	0.27	99.3
16	54,750 – 58,400	0.20	99.5
17	58,400 – 62,050	0.17	99.6
18	62,050 – 65,700	0.14	99.8
19	65,700 – 69,350	0.12	99.9
20	69,350 – 73,000	0.09	100

larger battery packs to \$567/kWh for smaller battery packs. The natural log form of this function was chosen for its fit through individual battery prices provided in the Argonne report for batteries of several different energy capacities, as illustrated in Figure 7.1.

The electricity price p_{ELEC} is \$0.12 per kWh, the 2009 average U.S. electricity cost to the transportation and residential sectors. The nominal electricity price growth rate, r_{NE}, including inflation and other factors, is 1.9%. For simplicity, we ignore differences in electricity price between nighttime, residential charging and daytime, workplace charging. We use a nominal discount rate of $r_{\text{N}} = 5\%$ in the base case. Although the cost function includes a carbon tax ρ, the base case value is \$0 per metric ton CO_2 equivalent (tCO_2e). Other values are considered in the sensitivity analysis.

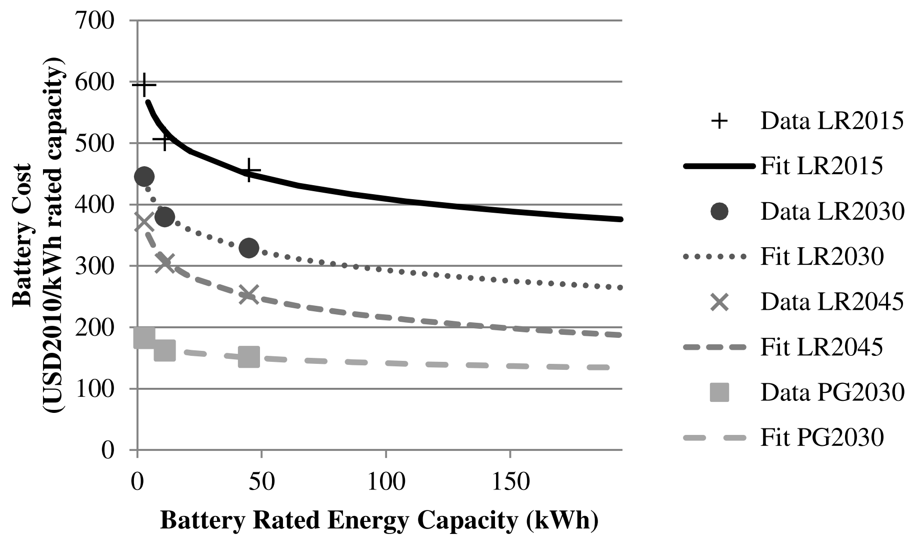

Figure 7.1 Battery cost functions for base case (LR2015) and sensitivity analysis cases, constructed to fit data reported by Plotkin and Singh (2009)

Vehicle production GHGs v_{Vj} excluding engine, motor, and batteries are 6026 kgCO_2e for a CV, 6437 kgCO_2e for an HEV, 6566 kgCO_2e for a PHEV, and 6044 kgCO_2e for an EV. These values are based on the vehicles production cost values $c_{\mathrm{V}j}$ for each vehicle type, adjusted to 2002 dollars using the Consumer Price Index (CPI) (US DOL, 2010), and then converted to GHG emissions (including supply chain) using a metric tons CO_2 equivalent (tCO_2e) per USD2002 multiplier from the EIO-LCA 2002 U.S. producer price model, Sector #336111: Automobile Manufacturing (Carnegie Mellon University Green Design Institute, 2008). GHG emissions from production of the engine, $v_{\mathrm{E}}(x_{\mathrm{E}j}) = a_{v\mathrm{E}}c_{\mathrm{E}}(x_{\mathrm{E}j})$ where $a_{v\mathrm{E}} = 0.6245$, are calculated in the same manner from the engine cost equation, using Sector #336300: Motor vehicle parts manufacturing, which includes NAICS sector 33631: Motor Vehicle Gasoline Engine and Engine Parts Manufacturing. GHG emissions from production of the motor, $v_{\mathrm{M}}(x_{\mathrm{M}j}) = a_{v\mathrm{M}}c_{\mathrm{M}}(x_{\mathrm{M}})$ where $a_{v\mathrm{M}} = 0.5445$, are calculated in the same manner from the motor cost equation, using Sector #335312: Motor and generator manufacturing. Charger production GHG emissions v_C = 753.6 $kgCO_2e$ per charger are calculated in the same manner from the base case charger production cost and Sector #33441A: Electronic capacitor, resistor, coil, transformer, and other inductor manufacturing.

Battery production GHG emissions v_{Bj} are 120 $kgCO_2e$/kWh for li-ion battery production $\forall j \in J_{PHEV} \cup J_{BEV}$ and 230 $kgCO_2e$/kWh from NiMH battery production $\forall j \in J_{HEV}$ (Samaras and Meisterling, 2008; Shiau et al., 2010). Gasoline production and combustion GHG emissions v_G are 11.34 $kgCO_2e$/gal (Shiau et al., 2010) and GHG emissions from electricity production in the base case are 0.752 $kgCO_2e$/kWh, representing the average U.S. grid mix in the year 2005 and including transmission and distribution losses (Shiau et al., 2010).

Charger production emissions, v_C = 753.6 $kgCO_2e$, are found by using the EIO-LCA 2002 U.S. producer price model (Carnegie Mellon University Green Design Institute, 2008) and assuming that a charger is reasonably represented by \$1500 (2010 dollars, adjust to 2002 dollars for use in the 2002 EIO-LCA model using the CPI (US DOL, 2010)) of purchases from Sector #33441A: Electronic capacitor, resistor, coil, transformer, and other inductor manufacturing.

7.1.1.3 Vehicle Performance Models

To estimate the electrical and gasoline efficiencies and the acceleration performances and 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 U.S. 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. This configuration file is available as “gui_split_compact_MY04_US_prius_HEV_in” in PSAT V6.2.

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). The powertrain configuration used in PSAT is based on the “gui_conv_compact_civic_85kW_in.m” configuration file available in PSAT V6.2. To make this vehicle more comparable to the HEV model, the wheel model was changed to wh_0291_P175_65_R14, the lead-acid battery model was changed to match the one in the HEV model, and the electrical accessory load was changed to 800 kW. Finally, the engine size was optimized for best 5-cycle combined fuel economy, resulting in engine peak power of 126 kW. One kilogram of structural weight is added to the vehicle per kilogram of additional engine weight (Shiau et al., 2009).

We construct our PHEV model based on the HEV model by substituting Li-ion batteries (ess_li_6_75_saft) 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). Finally, since the battery size range includes batteries significantly larger than the HEV battery, we adjust the control strategy to take better advantage of these larger batteries by increasing the regenerative braking on-off points to 100% of the battery SOC. We also turn on the EV mode flag in PSAT for the CD mode efficiency runs. 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. For this reason, the vehicles that we refer to here as PHEVs might sometimes be referred to as extended range electric vehicles (EREVs) (although that term can also have powertrain implications).

Our BEV model is based on a generic BEV drive train (gui_elec_midsize_in.m in PSAT V6.2) modified to use the same body (veh_824_225_026_US04prius), final drive (fd_4113_prius), motor (the same by default), electrical accessory load (800 kw), and batteries (lithium ion, ess_li_6_75_saft; also same lead acid battery) as the PHEV, and also with one kilogram of structural weight added to the vehicle per kilogram of battery, engine, and motor to support the weight of those components. We ignore the possibility of using different battery designs on BEVs vs. PHEVs.

Since PSAT does not directly simulate the effects of cold starts, ambient temperature, or AC loads, the 5-cycle test cannot be simulated directly in PSAT, but only approximated. Instead of using PSAT's built-in approximations for the 5-cycle test, we used the EPA's MPG-based estimation approach (US EPA, 2006) to calculate the 5-cycle efficiency from the results of running 2 cycles that PSAT can simulate directly: the Urban Dynamometer Driving Schedule (UDDS) driving cycle and the Highway Fuel Economy Driving Schedule (HWFET) driving cycle (US EPA, 1996). The 5-cycle testing procedures have been developed for CVs, HEVs, PHEVs, and BEVs, but the MPG-based approximations have been developed only for CVs and HEVs. This is because they are calculated from production vehicles, and no production PHEVs or BEVs were available for testing at the time of development. We assume for now that the same approximations developed to estimate 5-cycle gasoline efficiency for CVs and HEVs can also be used to estimate 5-cycle gasoline and electrical efficiency for PHEVs and BEVs.

Following EPA procedures, all gasoline and electricity (measured at the wall) consumed during each simulated cycle is accounted for, using a conversion factor of 33.705 kWh of electricity per gallon of gasoline to calculate the equivalent miles per gallon (mpge) (US EPA, 2006). We then use the MPG-based conversions from the EPA procedures (US EPA, 2006): 5-cycle city fuel economy = 1 / (0.003259 + 1.18053 / UDDS fuel economy) and 5-cycle highway fuel economy = 1 / (0.001376 + 1.3466 / HWFET fuel economy). Finally we weight these city and highway fuel economies together to find the 5-cycle combined fuel economy (US EPA, 2006): combined fuel economy = 1 / ((0.45/ city fuel economy) + (0.55 / highway fuel economy)).

Because the performance of CVs and HEVs are independent of variations in driving patterns (represented by annual VMT S), we identify the optimal designs for these vehicles *a priori* (Shiau et al., 2010). For the CV, $\mathbf{x}_j$ = [126 kW, 0 kW, 0 cells, 0], $\eta_G(\mathbf{x}_j)$ = 25.0 mpg and $t_G(\mathbf{x}_j)$ = 11 seconds. For the HEV, $\mathbf{x}_j$ = [57 kW, 52 kW, 168 cells, 0.8] with $\eta_G(\mathbf{x}_j)$ = 43.0 mpg, and $t_G(\mathbf{x}_j)$ = 11 seconds.

For the PHEV and BEV cases, we construct metamodels fit to an array of points tested within the bounds of the design space to calculate PHEV CS-mode 0-60 mph acceleration time, PHEV CD-mode 0-60 mph acceleration time (sec), PHEV CS-mode 5-cycle combined efficiency (mpge), PHEV CD-mode 5-cycle efficiency (mi./kWh), BEV 0-60 mph acceleration time (sec) and BEV 5-cycle efficiency (mi./kWh). We require PHEVs to use strict all-electric mode for the efficiency tests, but not for the acceleration tests: since the PHEVs are able to meet the acceleration requirements of the UDDS and HWFET cycles in all-electric mode, we do not require them to meet the extreme test of hitting 0-60 mph in 11 seconds without using the engine. (The only difference between the CS mode and CD mode acceleration time tests for the PHEV is the initial battery SOC.)

Most of the metamodels are cubic, of the form $\Sigma_{a,b,c\in\{0,1,2,3\}|a+b+c\leq 3}\, \beta_{abc}\, (b_{\mathrm{E}}x_{\mathrm{E}})^{a}\, (b_{\mathrm{M}}x_{\mathrm{M}})^{b}\, (b_{\mathrm{B}}x_{\mathrm{B}})^{c}$, where $b_{\mathrm{E}} = 1/57$, $b_{\mathrm{M}} = 1/52$, and $b_{\mathrm{B}} = 1/1000$ are scaling factors. The coefficients are fit using least squares regression and are listed in Table 7.5 (for BEVs, the terms involving x_{E} drop out). The exceptions to the cubic form are the BEV acceleration time metamodel and the PHEV CS mode acceleration metamodel, for which the cubic form did not fit well. For these two models, Cornell's Eureqa Formulize software was used to find appropriate functional forms (Schmidt and Lipson, 2012, 2009). These two resulting metamodels are, for the PHEV CD mode acceleration time

$$\begin{aligned} t_{\mathrm{G}}\left(\mathbf{x}_j\right) = \quad & 1.188 + x_{\mathrm{E}j}x_{\mathrm{M}j} + \frac{1.659x_{\mathrm{M}j}}{0.2667x_{\mathrm{B}j} + x_{\mathrm{E}j}x_{\mathrm{M}j}x_{\mathrm{B}j}} + \\ & \frac{10.26x_{\mathrm{M}j}x_{\mathrm{B}j} - 0.4512}{0.2667x_{\mathrm{B}j} + x_{\mathrm{M}j}^{3} + 0.2667x_{\mathrm{E}j}x_{\mathrm{B}j}^{2} - 0.4512x_{\mathrm{M}j}^{2}}, \quad \forall \in J_{\mathrm{PHEV}} \end{aligned} \tag{7.1}$$

and for the BEV acceleration time

$$t_{\mathrm{E}}\left(\mathbf{x}_j\right) = \frac{0.3983x_{\mathrm{M}j}}{x_{\mathrm{B}j}} + \frac{12.2 + 4.734x_{\mathrm{B}j}}{x_{\mathrm{M}j} - 0.1421}, \quad \forall \in J_{\mathrm{BEV}} \tag{7.2}$$

The error for all metamodels is within 0.5 seconds, 0.03 mpge, and 0.06 mi./kWh over the set of data points used for fitting. To avoid optimization algorithm failures caused by function calls to the metamodels returning infinity or negative infinity when the design variables were out of range, we modified the functions to avoid extrapolation by returning the metamodel value at the nearest valid design variable values.

Table 7.5 Metamodel coefficients for PSAT models of PHEV and BEV designs. Coefficient for $t_E(x_j)$ $\forall j \in J_{PHEV}$ and for $t_E(x_j)$ $\forall j \in J_{BEV}$ are instead provided as part of Eq. (7.1) and Eq. (7.2), respectively.

	$\eta_E(x_j)$ $\forall j \in J_{PHEV}$	$\eta_G(x_j)$ $\forall j \in J_{PHEV}$	$t_E(x_j)$ $\forall j \in J_{PHEV}$	$\eta_E(x_j)$ $\forall j \in J_{BEV}$
β_{300}	4.487	5.30	8.54	
β_{030}	1.02	0.274	-1.54	0.0435
β_{003}	19.3	1.21	-4.60	0.0387
β_{210}	0.0137	-1.44	-2.52	
β_{120}	-0.189	0.588	-1.99	
β_{201}	-0.0300	-0.312	0.181	
β_{102}	-0.0578	0.599	-2.37	
β_{021}	-1.02	-0.339	-1.04	-0.0465
β_{012}	-0.0726	-0.0209	4.25	-0.0242
β_{111}	-0.00816	0.0168	2.17	
β_{200}	-10.7	-11.6	-14.9	
β_{020}	-4.50	-1.65	12.8	-0.299
β_{002}	-48.1	-3.46	5.26	-0.298
β_{110}	0.736	0.0855	10.5	
β_{101}	0.482	1.42	-0.589	
β_{011}	4.25	1.35	-6.40	0.870
β_{100}	5.88	-0.0891	-0.501	
β_{010}	3.77	1.92	-31.6	-2.98
β_{001}	34.8	-1.07	5.51	-6.53
β_{000}	97.9	48.3	31.2	105

Figure 7.2 shows the vehicle design metamodel for PHEVs graphically, illustrating that it is highly nonlinear. Figure 7.3 similarly shows the vehicle design metamodel for BEVs. Although both the PHEV metamodel plots and the BEV metamodel plots show fits extrapolated beyond the range of the PSAT data points, in practice this caused issues with the optimization formulation because some metamodel function calls with design variables outside the permitted range resulted in infinity or negative infinity. As previously mentioned, to fix this issue the metamodels were changed to return the result at the nearest valid boundary value of any invalid design variable. In Figure 7.2 and

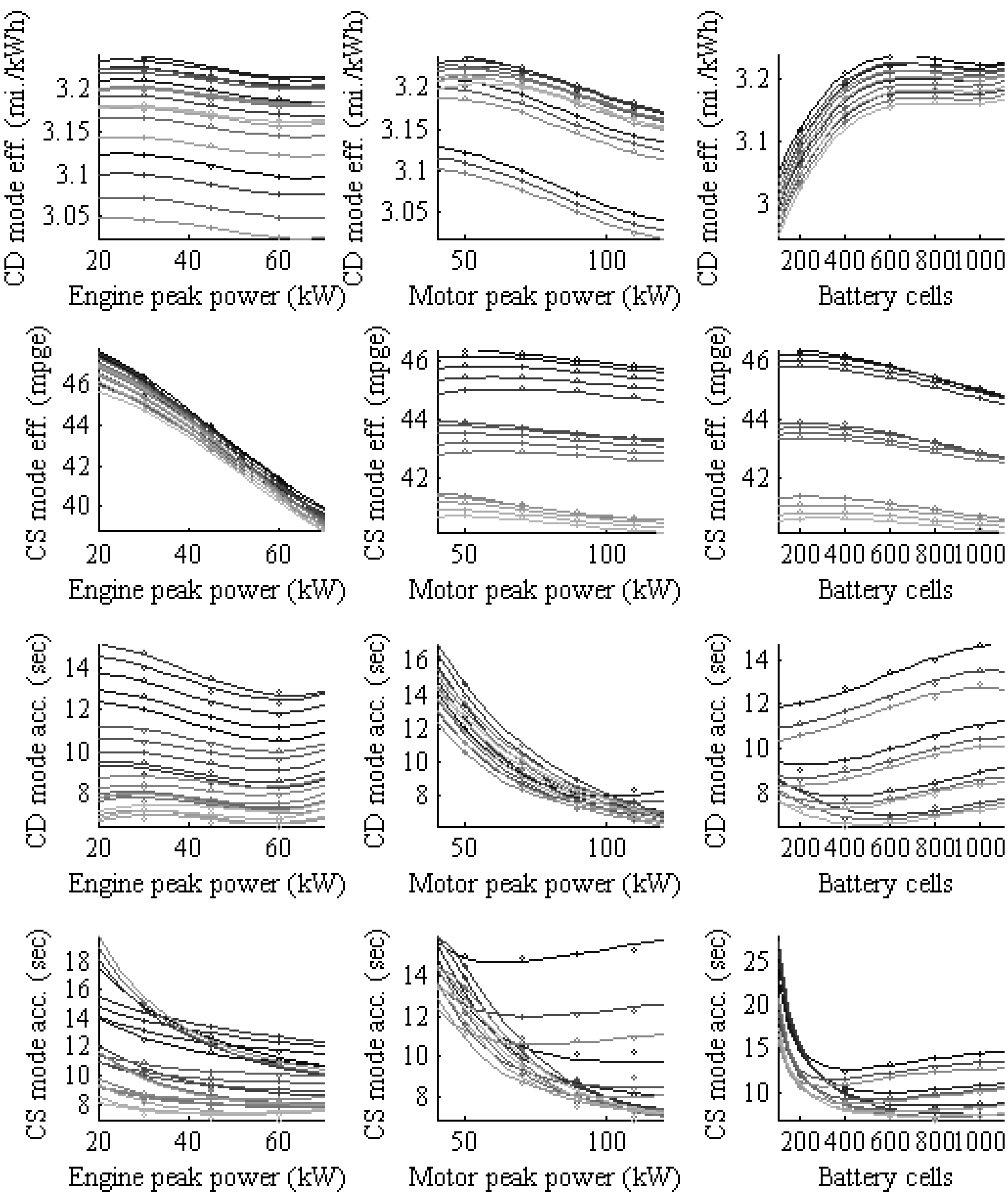

Figure 7.2 PHEV design metamodel. Dots indicate PSAT runs and lines indicate metamodel fits.

Figure 7.3 as shown, this would have the effect of making all lines flat and horizontal outside the range of the PSAT data points.

Based on the metamodel for electrical efficiency $\eta_E(\mathbf{x}_j)$ for PHEVs and BEVs, we calculate the AER $s_{AER}(\mathbf{x}_j) = \eta_E(\mathbf{x}_j)\kappa_{Bj}x_{Bj}x_{SWj} / \eta_C$, where $\eta_C = 88\%$ is the charging

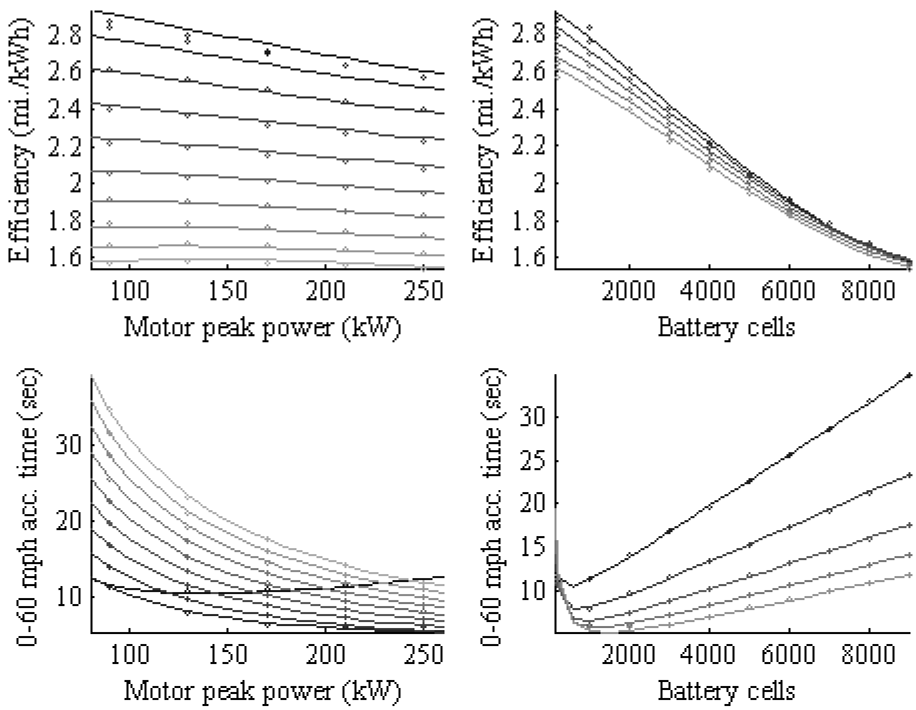

Figure 7.3 BEV design metamodel. Dots indicate PSAT runs and lines indicate metamodel fits.

efficiency. The AER calculation involves dividing by charging efficiency because the 5-cycle combined electrical efficiency includes electrical losses in battery charging, which should not be included when calculating how many miles the vehicle can drive using the energy stored in the battery. The effective AER is the AER multiplied by the number of chargers, q_{Cj} (i.e. number of charges per day), assuming optimistically that (1) a second charge takes place at half of the daily distance traveled, and (2) the battery is always charged fully when it is parked either at home (for nighttime charge) or at work (for daytime charge). Results of the metamodels for each vehicle type are summarized in Table 7.6.

Table 7.6 Metamodel results for PHEV and BEV designs (including only PSAT data points, not interpolated designs, and including only designs with valid acceleration times)

Property	CV	HEV	PHEV	BEV
Efficiency	25 mpg	43 mpg	CD mode: 102-109 mpge (3.03-3.22 mi./kWh, 0.31-0.33 kWh/mi.) CS mode: 40.3-46.1 mpge	55-94 mpge (1.6-2.8 mi./kWh, 0.36-0.61 kWh/mi.)
0-60 mph Acceleration Time (sec)	11	11	CD mode: 6.5-11 CS mode: 6.9-11	6-11
AER (mi.)			3.1-62.8	1.4-256

7.1.1.3.1 BEV and PHEV Metamodels with Improved Efficiency for Sensitivity Analysis

As shown in Table 7.6, our BEV metamodels is less efficient than our PHEV metamodels. In the sensitivity analysis we also consider a case where the BEV efficiency is comparable to PHEV efficiency. We find this metamodels by using the PSAT PHEV model in CD mode to model the BEV. This way the efficiency is comparable for vehicles with the same battery size and range. For this version of the metamodels we also cap the 5-cycle adjustments at a 30% efficiency reduction, because that corresponds to the level for the most efficient vehicle that was tested when the equations were developed and the EPA uses that calculation method. As a result both the PHEV CD mode metamodels and the BEV metamodels are more efficient than the previous PHEV CD mode metamodels. The new range of PHEV efficiency becomes 3.5-3.8 mi/kWh (instead of 3.03-3.22 mi/kWh as shown in Table 7.6) and the new range of BEV efficiency becomes 2.6-3.8 mi/kWh (instead of 1.6-2.8 mi/kWh as shown in Table 7.6). The updated efficiency metamodels coefficients are shown in Table 7.7. Figure 7.4 and Figure 7.5 show the metamodels graphically.

Table 7.7 Updated efficiency metamodel coefficients for PSAT models of PHEV and BEV designs

	$\eta_E(x_j)$ $\forall j \in J_{PHEV}$	$\eta_G(x_j)$ $\forall j \in J_{PHEV}$	$\eta_E(x_j)$ $\forall j \in J_{BEV}$
β_{300}	4.487	5.30	
β_{030}	1.02	0.274	0.0435
β_{003}	19.3	1.21	0.0387
β_{210}	0.0137	-1.44	
β_{120}	-0.189	0.588	
β_{201}	-0.0300	-0.312	
β_{102}	-0.0578	0.599	
β_{021}	-1.02	-0.339	-0.0465
β_{012}	-0.0726	-0.0209	-0.0242
β_{111}	-0.00816	0.0168	
β_{200}	-10.7	-11.6	
β_{020}	-4.50	-1.65	-0.299
β_{002}	-48.1	-3.46	-0.298
β_{110}	0.736	0.0855	
β_{101}	0.482	1.42	
β_{011}	4.25	1.35	0.870
β_{100}	5.88	-0.0891	
β_{010}	3.77	1.92	-2.98
β_{001}	34.8	-1.07	-6.53
β_{000}	97.9	48.3	105

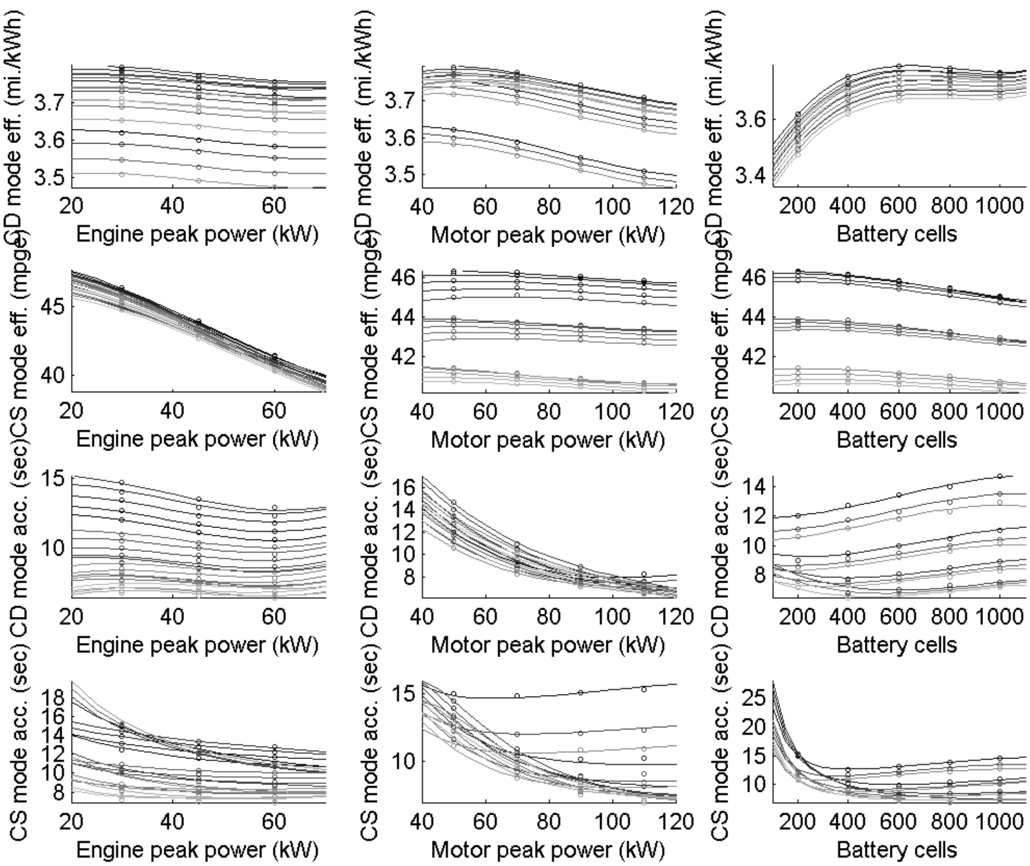

Figure 7.4 PHEV design metamodels with improved efficiency from capping 5-cycle adjustment at 30% reduction. Dots indicate PSAT runs and lines indicate metamodel fits.

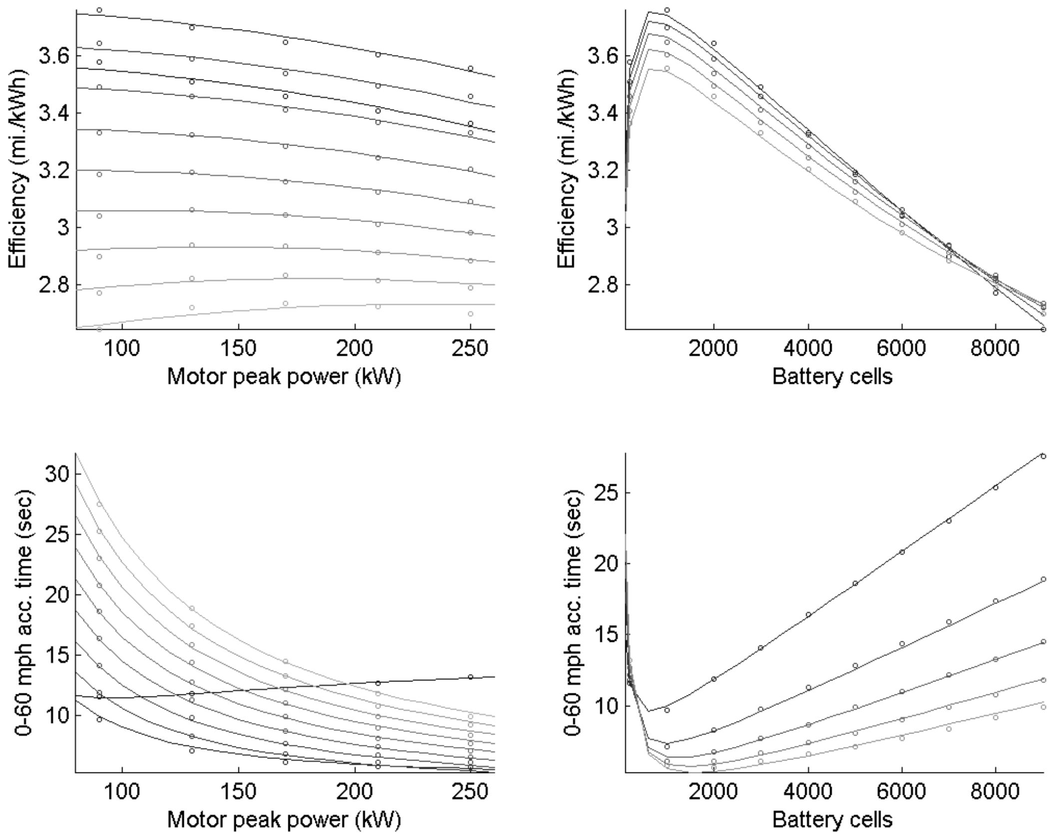

Figure 7.5 BEV design metamodels with improved efficiency from capping 5-cycle adjustment at 30% reduction and from using the PSAT PHEV model in CD mode to represent the BEV. Dots indicate PSAT runs and lines indicate metamodel fits.

7.1.1.4 Driving Patterns

Based in part on the summary statistics shown in Table 7.8, we determined that the Minnesota data (Sierra Research, 2005) is a sufficiently representative source of driving distance variability across days.

Table 7.8 Comparison of summary statistics for NHTS (US DOT, 2003) and Minnesota (Sierra Research, 2005) driving data. Zeros refer to days on which a vehicle did not drive (i.e. drove zero miles).

Data Source for Daily VMT	Mean Daily VMT (excl. zeros)	Median Daily VMT (excl. zeros)	Std. Dev. VMT (excl. zeros)	% Zeros	Annual VMT per Vehicle (calculated from mean and % of zeros)
NHTS 2001 total survey day VMT	33.0	22.0	33.4	31.8%	8,200
NHTS 2001 average daily odometer VMT	33.3	27.8	27.1	3.0%	11,800
Minnesota total VMT for each driving day	47.0	35.8	49.3	34.5%	11,300
Minnesota average daily VMT for each vehicle	32.5	30.5	14.2	0%	11,900

7.1.1.5 Sensitivity Analysis

As discussed in Section 2.2.1.1, base case cost estimates for vehicles and components, including batteries, are taken from Plotkin and Singh (2009) literature review estimates of costs in the year 2015. Sensitivity analysis vehicle and battery cost values are the literature review estimates for 2045 (LR2045) and Department of Energy program goals for 2030 (PG2030) (Plotkin and Singh, 2009). For each of these cases, the report provides functions for engine and motor costs as a function of peak power. To estimate battery costs as a smooth function of battery pack size in each sensitivity case, we fit a natural log function to the $/kWh estimates cited in the report, as presented in Section 2.2.1.1. The battery cost function for the LR2045 case results in a range of costs from $187/kWh for larger battery packs to $351/kWh for smaller battery packs, and the PG2030 case has costs from $134/kWh for larger battery packs to $176/kWh for smaller battery packs. Detailed coefficient values for the sensitivity analysis cost cases are provided in the Supplemental Information. In cases where GHG emissions are calculated based on cost using EIO-LCA factors, we used the base case cost to calculate GHG emissions. This means that the EIO-LCA-based GHG emissions remain constant when the cost parameters change, though they are still a function of component size. Charger costs are assumed \$1500 for Level 2 charging equipment and installation, with sensitivity cases ranging from \$0 to \$2500. The \$0 charger cost case was chosen to represent an analysis in which charger costs are disregarded. Electricity prices are \$0.12 (\$0.06 – \$0.30) and gasoline prices are \$2.22 (\$1.50 – \$8.00), with the base case representing average prices in 2009. Greenhouse gas emissions from electricity production for vehicle charging are 0.752 (0.066 – 0.9) $kgCO_2e/kWh$, with the base case representing an average U.S. electricity mix in 2005. Sensitivity analysis cases are chosen to represent mid-range numbers from the literature for current-technology plants of four types (nuclear, natural gas, IGCC-CCS, and coal). Although IGCC-CCS may not be viable in the near future due to costs and nuclear may not be used for vehicles due to not being dispatchable, these plants are chosen as examples that bound the likely range of GHG emissions levels from the power grid. For example, the nuclear case could also represent power from hydro, wind, or other low-emissions sources. Electricity used in the rest of the supply chain does not vary in the sensitivity analysis. Nominal discount rate is 5% (0% – 5% – 10%) and inflation is included in nominal price growth rates for electricity and gasoline.

In addition to cases with one-way and multi-way sensitivity analysis on the above parameters, we also ran cases that combine the two objectives (cost and GHGs) by including a carbon tax. Carbon price is \$0 (\$0 – \$20 – \$100)/tCO_2e. The \$20/tCO_2e and \$100/tCO_2e levels are chosen based on the IPCC fourth assessment on social cost of carbon (Interagency Working Group on Social Cost of Carbon, United States

Government, 2010; IPCC, 2007). The effects of the carbon tax on the electric grid and other parts of the economy besides vehicle design, vehicle allocation, and charging infrastructure allocation are exogenous to this model.

The reference scenario representing the current U.S. car fleet most closely is the case in which CVs are allocated universally, with all parameters at their base case values. However, it is worth noting that the CV was designed to be comparable in performance and design to the reference HEV, the 2004 Toyota Prius, and not to represent the range of cars, trucks, and SUVs in today's market. We have also included a sensitivity analysis case in which the CV achieves better fuel economy.

7.1.2 Results

For each scenario, Table 7.9 and Table 7.10 report equivalent annual life cycle cost per vehicle, annual life cycle GHG emissions per vehicle, annual gasoline consumption per vehicle, annual electricity consumption per vehicle, and the percentage of vehicle miles traveled that are powered by electricity at the optimal solution for that scenario. Finally the composition of the fleet is reported as percentage of the fleet that are CVs, HEVs, PHEVs with home charging only, PHEVs with home and work charging, BEVs with home charging only, and BEVs with home and workplace charging.

The GHG-minimized results in Table 7.9 and Figure 7.6 have implications for the impact of grid decarbonization and workplace charging availability on the GHG-optimal fleet. Scenarios 3, 1, and 4-6 as well as scenarios 28, 24, and 29-31 can be compared in increasing order of grid decarbonization. The first set includes both home and workplace charging availability, and the second set has only home charging available. It turns out that under the current U.S. average grid mix (Scenarios 1 and 24), workplace charging is

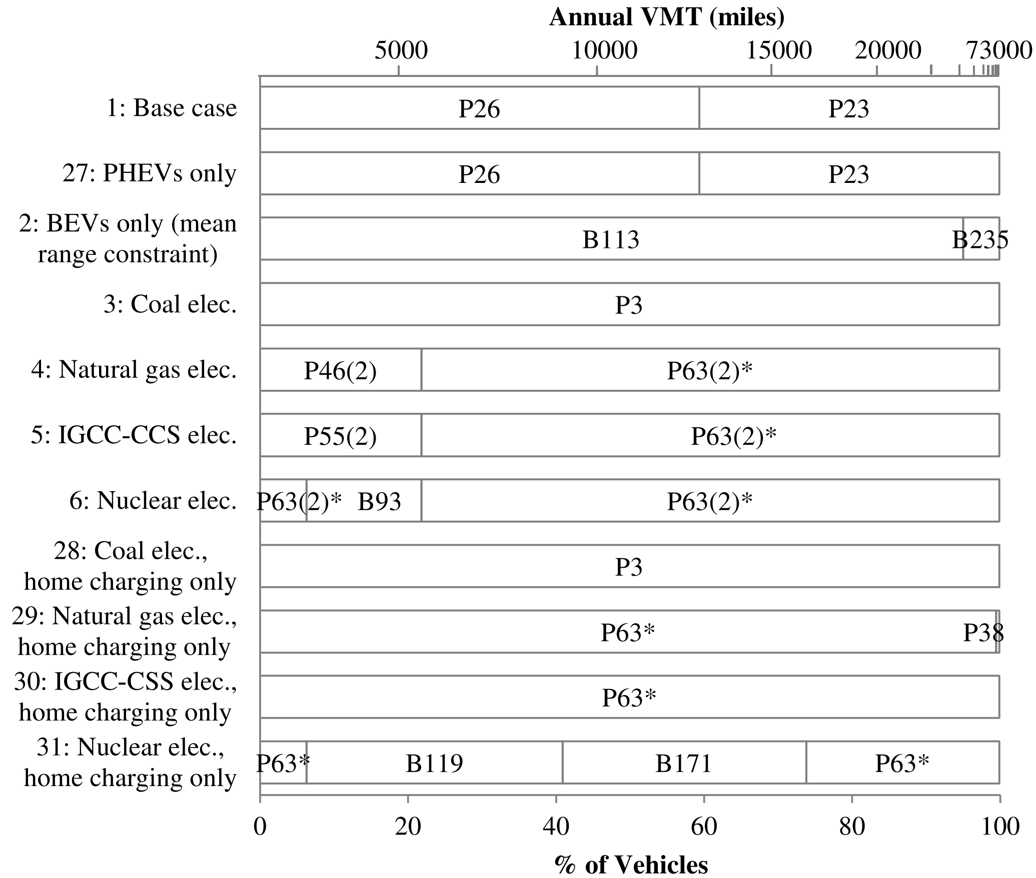

Figure 7.6 Optimal vehicle allocations for scenarios with the objective of minimizing annualized life cycle GHG emissions. "P" indicates PHEV and "B" indicates BEV. Numbers after vehicle abbreviations indicate the AER in miles, and "(2)" indicates with workplace charging in addition to home charging. Asterisks indicate vehicle designs with battery sizes (and AERs) at the bounds of our model.

not allocated even when it is available. Under decarbonized grid scenarios, greater penetration of vehicles with larger battery packs are observed, including BEVs, and GHG emissions are reduced substantially; however, costs increase. In these cases, all PHEVs utilize workplace charging, providing (optimistically) up to 21% additional GHG reductions compared to having only home charging, as shown in Table 7.9. Availability of workplace charging in the decarbonized grid scenarios 4-6 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.

Table 7.9 GHG-minimized results. Dollars are 2010 dollars.

					Allocations in Fleet of Each Vehicle and Charging Type					
Scenario	**Cost (\$/veh-yr)**	**GHGs (tCO_2e/veh-yr)**	**Fuel (gal/veh-yr, kWh/veh-yr)**	**% of VMT Electrified**	CV	HEV	PHEV, home	PHEV, home & work	BEV, home	BEV, home & work
1: Base case, U.S. average grid mix *0.752 $kgCO_2e$/kWh*	3350	3.95	186, 1310	33%			100%			
23: Home charging only	3350	3.95	186, 1310	33%			100%			
24: CVs only	3310	6.44	511, 0	0%	100%					
25: HEVs only	2960	4.08	297, 0	0%		100%				
26: PHEVs only	3350	3.95	186, 1310	33%			100%			
2: BEVs only, *mean range constraint*	5600	5.36	0, 5410	100%					100%	
3: Coal electricity *0.9 $kgCO_2e$/kWh*	3400	4.01	265, 180	4%			100%			
4: Natural gas electricity *0.47 $kgCO_2e$/kWh*	4030	3.15	51, 3260	82%				100%		
5: IGCC-CCS electricity *0.252 $kgCO_2e$/kWh*	4050	2.44	50, 3270	82%				100%		
27: Nuclear electricity *0.066 $kgCO_2e$/kWh*	4130	1.83	49, 3350	83%				84%	16%	
28: Coal electricity, home charging only *0.9 $kgCO_2e$/kWh*	3400	4.01	265, 180	4%			100%			
29: Natural gas electricity, home charging only *0.47 $kgCO_2e$/kWh*	3960	3.38	110, 2430	61%			100%			
30: IGCC-CCS electricity, home charging only *0.252 $kgCO_2e$/kWh*	3970	2.84	110, 2440	61%			100%			
31: Nuclear electricity, home charging only *0.066 $kgCO_2e$/kWh*	5180	2.22	67, 3890	76%			32%		68%	

Table 7.10 Cost-minimized results. Dollars are 2010 dollars.

					Allocations in Fleet of Each Vehicle and Charging Type					
Scenario	**Cost ($/veh-yr)**	**GHGs (tCO_2e/veh-yr)**	**Fuel (gal/veh-yr, kWh/veh-yr)**	**% of VMT Electrified**	CV	HEV	PHEV, home	PHEV, home & work	BEV, home	BEV, home & work
6: Base case	2960	4.08	297, 0	0%		100%				
32: Home charging only	2960	4.08	297, 0	0%		100%				
7: PHEVs only	3240	4.19	246, 780	19%			100%			
33: One PHEV only, home charging only or home & work charging	3240	4.19	246, 770	19%			100%			
8: BEVs only, *mean range constraint*	5520	5.36	0, 5420	100%					100%	
34: One BEV only, home charging only or home & work charging, *mean range constraint*	9690	7.75	0, 7370	100%					100%	
35:Gas price $3/gal+5.2%/yr	3260	4.08	297, 0	0%		100%				
9. Gas price $3.25/gal+5.2%/yr	3350	4.08	280, 220	6%		84%		16%		
36: Gas price $4/gal+5.2%/yr	3610	4.06	250, 620	15%		65%		35%		
37: Gas price $5/gal+5.2%/yr	3870	4.01	163, 1740	44%		17%		83%		
10: Gas price $6/gal+5.2%/yr	4040	3.99	123, 2250	57%		5%		95%		
11: Gas price $7/gal+5.2%/yr	4180	4.00	99, 2570	65%		1%		99%		
38: Gas price $8/gal+5.2%/yr	4290	4.01	84, 2780	70%				100%		
39: Low vehicle and battery costs (LR2045)	2970	4.08	297, 0	0%		100%				
12: Low vehicle and battery costs (PG2030)	2870	4.07	283, 190	5%		84%	16%			
13: Low charger cost ($500)	2960	4.08	297, 0	0%		100%				
14: Lower charger cost ($475)	2960	4.08	283, 190	5%		84%		16%		
15: Charger cost disregarded	2940	4.09	260, 510	12%		59%		41%		

					Allocations in Fleet of Each Vehicle and Charging Type					
Scenario	**Cost ($/veh-yr)**	**GHGs (tCO_2e/veh-yr)**	**Fuel (gal/veh-yr, kWh/veh-yr)**	**% of VMT Electrified**	CV	HEV	PHEV, home	PHEV, home & work	BEV, home	BEV, home & work
40: High electricity cost	2960	4.08	297, 0	0%		100%				
41: Low electricity cost	2960	4.08	297, 0	0%		100%				
16: High discount rate r_N = *10%*	3550	4.12	301, 0	0%	6%	94%				
17: No discount rate r_N = *0%*	2420	4.07	274, 310	8%		78%		22%		
18: High CV efficiency *32 mpg*	2950	4.10	299, 0	0%	6%	94%				
42: HEV only with \$3.25/gal+5.2%/yr gas	3360	4.08	297, 0	0%		100%				
43: HEV only with \$6/gal+5.2%/yr gas	4460	4.08	297, 0	0%		100%				
44: Gas price \$6/gal+5.2%/yr, home charging only	4230	3.98	194, 1270	32%		11%	89%			
19: Low vehicle & battery costs (PG2030), gas price \$4.5/gal+5.2%/yr	3340	4.05	68, 3030	76%		1%		92%	6%	
45: Low vehicle & battery costs (PG2030), gas price \$6/gal+5.2%/yr	3460	4.07	53, 3230	81%			6%	94%		
46: Gas price \$6/gal+5.2%/yr, Nuclear electricity *0.066* $kgCO_2e/kWh$	4040	2.45	123, 2250	57%		5%		95%		
47: Low veh. & batt. costs (PG2030), gas \$4/gal+5.2%/yr, charger cost disregarded (\$0)	3100	4.08	52, 3250	82%				94%	6%	
20: CO_2 tax of \$100/tCO_2e	3510	4.08	297, 0	0%		100%				
48: CO_2 tax of \$20/tCO_2e, gas price \$6/gal+5.2%/yr	4050 (4140 w/ tax)	3.99	122, 2260	57%		5%		95%		
49: CO_2 tax of \$100/tCO_2e, gas \$6/gal+5.2%/yr	4090 (4530 w/ tax)	3.99	117, 2320	59%		4%		96%		

					Allocations in Fleet of Each Vehicle and Charging Type					
Scenario	**Cost ($/veh-yr)**	**GHGs (tCO_2e/veh-yr)**	**Fuel (gal/veh-yr, kWh/veh-yr)**	**% of VMT Electrified**	CV	HEV	PHEV, home	PHEV, home & work	BEV, home	BEV, home & work
21: CO2 tax of $20/tCO2e, Nuclear electricity 0.066 kgCO2e/kWh	3070	4.08	297, 0	0%		100%				
22: CO_2 tax of $100/t$CO_2$e, Nuclear electricity *0.066 kgCO_2e/kWh*	3480 (3510 w/ tax)	3.92	280, 220	6%		84%		16%		
50: CO_2 tax of $20/t$CO_2$e, gas price $6/gal+5.2%/yr, Nuclear electricity *0.066 kgCO_2e/kWh*	4050 (4100 w/ tax)	2.39	116, 2340	59%		4%		96%		
51: CO_2 tax of $100/t$CO_2$e, gas $6/gal+5.2%/yr, Nuclear electricity *0.066 kgCO_2e/kWh*	4080 (4340 w/ tax)	2.27	102, 2520	64%		2%		98%		
52: CO_2 tax of $100/t$CO_2$e, gas $6/gal+5.2%/yr, Nuclear electricity, PG2045 veh. & batt. costs	3460 (3700 w/ tax)	1.84	51, 3250	82%			6%	94%		

These results are calculated under the optimistic assumption that workplace charging occurs at the halfway point of daily distance for each vehicle. Under more realistic assumptions, 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.

In the GHG-minimized nuclear electricity cases (27 and 31 in Table 7.9), we might expect BEVs to dominate the solutions. However, there are still a significant number of PHEVs appearing. No BEVs are allocated for vehicles exceeding 18,250 miles per year, except when BEVs are required. In order to show a case for comparison purposes that has all BEVs, we had to relax the range constraint to the mean daily driving distance. The base case range constraint of 95th percentile longest daily driving distances means that for vehicles exceeding about 27,000 miles per year, none of the BEV design in scope are sufficient. Even for vehicle below that annual AER, the range constraint is always active and the large battery packs required to meet the range constraint make the BEVs emit more life cycle GHGs than PHEVs for many drivers. Note that all PHEVs and BEVs except the PHEV3s in cases 3 and 28 have the maximum allowed battery swing window of 80%.

Table 7.11 shows the results for the sensitivity analysis cases with improved PHEV and BEV efficiency, shown in the same style as Table 7.9 and Table 7.10. Allocations for each case may not sum to exactly 100% due to rounding.

Table 7.11 Results for cases with improved PHEV and BEV efficiency. Allocation percentages may not add to 100% due to rounding.

			Allocations in Fleet of Each Vehicle and Charging Type					
Scenario	**Cost ($/veh-yr)**	**GHGs (tCO_2e/ veh-yr)**	CV	HEV	PHEV, home	PHEV, home & work	BEV, home	BEV, home & work
Min GHGs, improved PHEV and BEV efficiency, U.S. average grid mix *0.752 $kgCO_2e$/ kWh*	3670	3.66				PHEV 51: 78%	BEV 67: 6% BEV 93: 16%	
Min cost, improved PHEV and BEV efficiency	2960	4.08		100%				

From the cost-minimization results shown in Figure 7.7 and Table 7.10, especially scenarios 7, 10, 13-15, 17, 19, 21-23, 32, 35, and 39-41, we see that 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. PHEVs appear in the no discount rate case (18) and the no charger cost case (16), but neither of these is a real-world case. A discount rate of 5% and a charger cost of at least $500 remove PHEVs from the cost-optimal solution.

The cost-minimization results in Figure 7.7 indicate that there are several sensitivity analysis cases that cause plug-in vehicles (PEVs, including PHEVs and BEVs) to enter the cost-optimal fleet. The sensitivity analysis cases where PHEVs enter the cost-optimal fleet include scenario 13, in which vehicle and battery costs are at DOE program goal 2030 level. Battery costs in this scenario are $134-176/kWh. Another scenario in which PEVs enter the cost-optimized fleet is scenario 10, when gas prices reach $3.25/gal (with 5.2% growth rate) ($3/gal is not sufficient). At this gas price, Table 7.10 shows that 16% of vehicles are PHEVs with home and workplace charging, and Figure 7.7 shows that they are PHEV19s allocated to the range of 3650-7300 miles per year. At this point when PHEVs are just entering the cost-optimal fleet, they are very similar in cost to allocating an HEV to the entire fleet. The cost benefits of PHEVs increase as the gas price moves further from this critical point, as shown by comparing scenarios 10 to 42 and 11 to 43 in Table 7.10. PHEVs appear in the cost-minimized solution when charger costs drop below $500, as previously mentioned, and when the nominal discount rate is 0%.

Figure 7.7 also reports several sensitivity analysis cases in which PEVs dominate the cost-optimized fleet. These include when gas prices reach $7/gal (with 5.2% growth rate) (scenario

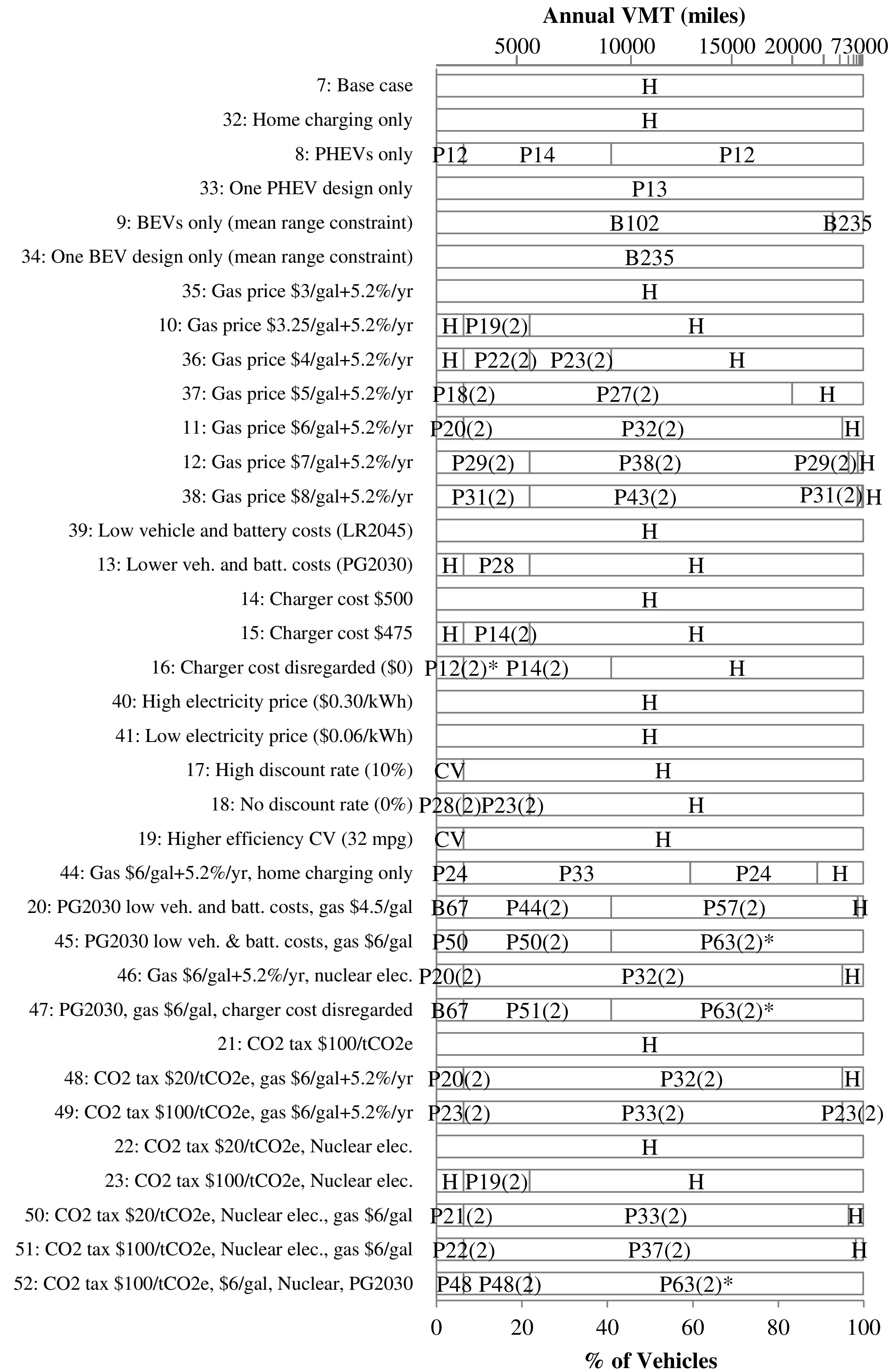

Figure 7.7 Optimal vehicle allocations for scenarios with the objective of minimizing equivalent annualized life cycle cost. "C" indicated CV, "H" indicated HEV, "P" indicates PHEV, and "B" indicates BEV. Numbers after vehicle abbreviations indicate the AER in miles, and "(2)" indicates with workplace

charging in addition to home charging. Asterisks indicate vehicle designs with battery sizes (and AERs) at the bounds of our model.

12, in which PHEVs comprise 99% of the fleet), when low vehicle and battery costs (PG2030 levels) are combined with gas at $4.50/gal (with 5.2% growth rate) (scenario 20, in which PHEVs comprise 92% of the fleet and BEVs 6%), and when CO_2 taxes of $100/t$CO_2$e are combined with $6/gal gas (with 5.2% growth rate) (scenario 49, in which PEVs comprise 96% of the fleet). In scenarios 49-52, although the CO_2 tax is present, the gas price is a more significant factor, since the $6/gal gas price without the CO_2 tax already causes 95% of the fleet to shift to PHEVs, as shown in scenario 11. The decarbonized grid in scenario 51 has very little impact compared to scenario 49, since its only impact on cost is through the CO_2 tax. Thus we can conclude that high gas prices and low vehicle and battery costs are the main drivers for PHEVs to enter and dominate the cost-optimized fleet.

Figure 7.8 and Figure 7.9 display the results for the GHG-minimized base case and the cost-minimized base case, respectively, with all vehicle types shown, in the style of Figure 2.. Note that since only some of the vehicles were allocated, the ones not allocated may not meet the design and allocation constraints.

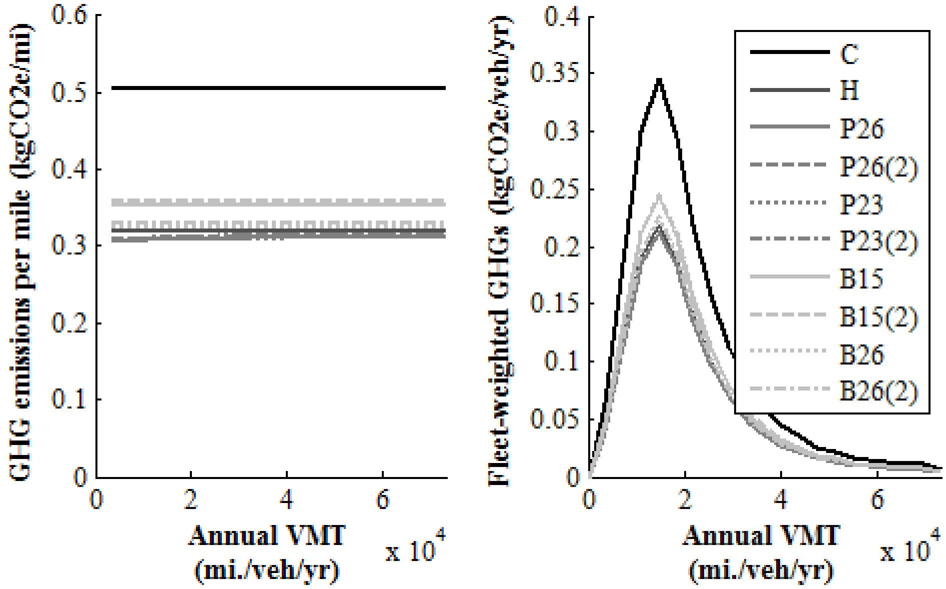

Figure 7.8 Vehicle objective function curves for all 10 combinations of vehicle and charging infrastructure for the base case for minimum GHG emissions. "C" indicated CV, "H" indicated HEV, "P" indicates PHEV, and "B" indicates BEV. Numbers after vehicle abbreviations indicate the AER in miles, and "(2)" indicates with workplace charging in addition to home charging. Note that since BEVs were not allocated in the optimal solution, these BEV designs may not be feasible for allocation to any VMT bin.

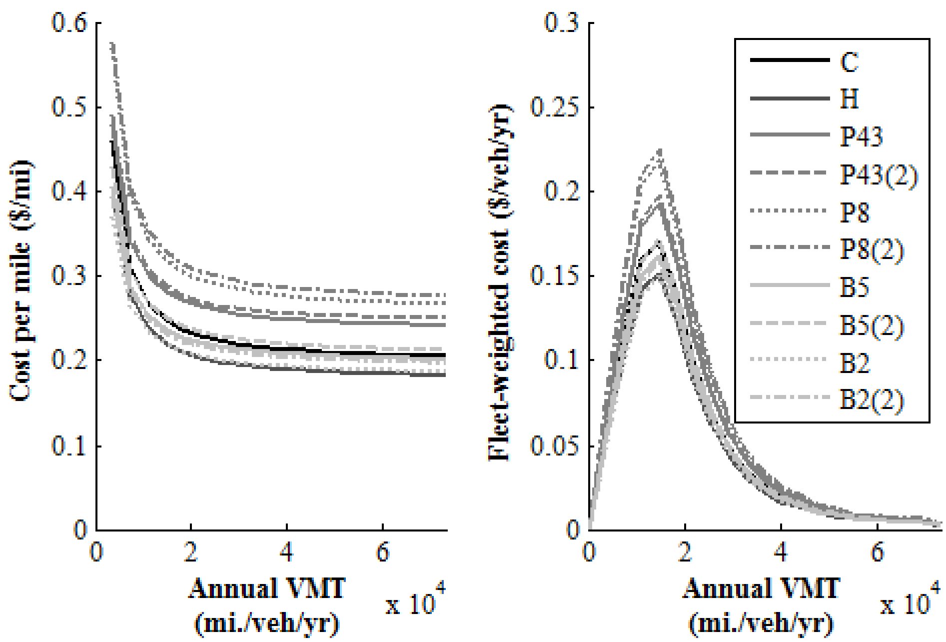

Figure 7.9 Vehicle objective function curves for all 10 combinations of vehicle and charging infrastructure for the base case for minimum cost. "C" indicated CV, "H" indicated HEV, "P" indicates PHEV, and "B" indicates BEV. Numbers after vehicle abbreviations indicate the AER in miles, and "(2)" indicates with workplace charging in addition to home charging. Note that since BEVs were not allocated in the optimal solution, these BEV designs may not be feasible for allocation to any VMT bin.

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7.2 Appendix B: Supplemental Information for U.S. Residential Charging Potential for PEVs

7.2.1 Details of Major Variables

Table 7.12 lists the major variables we take from RECS 2009 (US EIA, 2011d) and AHS 2009 (US Census Bureau, 2009) along with details on how the analysis is divided into bins for each variable and what sensitivity analysis is performed on each variable.

Table 7.12 Variables with their sources, binning method details, and sensitivity analysis details. "No" for binning method indicates that this variable was not used to match up the two data sets, in some cases because it appeared in only one of the data sets.

Variable	Source	Bins	Sensitivity Analysis	Notes
Housing type	AHS 2009, RECS 2009	Yes, 4 bins: Detached home, attached home, apartment, and mobile home	MI (multiple imputation) accounts for the (very small) uncertainty from missing data in AHS (see Figure 7.14)	
Density (urban vs. rural)	AHS 2009, RECS 2009	Yes, 2 bins: Urban and rural	MI accounts for the (very small) uncertainty from missing data in AHS (see Figure 7.16)	The urban/rural split in AHS and RECS is not the same, and uncertainty does not explain the difference. We are not sure of the reason for this inconsistency (see Figure 7.17). Additional density breakdowns are available in each data set but the definitions do not match up enough for more detailed bin designations. When coarser bins are used, density is disregarded.
Occupancy status (owned vs. rented)	AHS 2009, RECS 2009	Yes, 2 bins: owned, or rented or occupied without rent	MI accounts for uncertainty from missing data (see Figure 7.15)	Occupied without rent has been combined with rented because it is such a small category

Variable	Source	Bins	Sensitivity Analysis	Notes
Parking type	AHS 2009, RECS 2009	Yes, 2 bins: Garage and no garage	MI accounts for uncertainty from missing data Sensitivity analysis accounts for further assumptions (whether households with garages also have additional off-street parking)	Since RECS and AHS provide different types of parking data, the only parking data that could be matched between the two data sets was garage or no garage.
Number of parking spaces	Garage: RECS 2009 Off-street: assumption Portion that are usable: assumption	No	MI accounts for uncertainty in RECS data and in matching RECS households to AHS households Sensitivity analysis accounts for assumptions (number of off-street spots, portion of spots that are usable)	
Number of vehicles per household	AHS 2009	No	MI accounts for uncertainty in AHS data and in matching AHS households to RECS households	
Household gross income	AHS 2009, RECS 2009	Yes, 4 bins: Less than $20,000, $20,000 to $45,000, $45,00 to $75,000, $75,000 or more	MI accounts for uncertainty in data	When coarser bins are used, the 2 income bins are above or below $45,000
Number of adults age 20 and older per household	AHS 2009, RECS 2009	Yes, 2 bins: 0-1, 2 or more	MI accounts for uncertainty in data	We use adults 20 years and older instead of total number of people or total number of adults 18 and older because this is the most inclusive set that can be determined for both AHS and RECS.

Variable	Source	Bins	Sensitivity Analysis	Notes
Household weighting factor	AHS 2009, RECS 2009	No	No	
Number of rooms in unit	AHS 2009, RECS 2009	Yes, 2 bins: 1-5, 6 or more	MI accounts for uncertainty in data	When coarser bins are used, number of rooms is disregarded
Year unit built		Yes: 2 bins, before or after 1970	MI accounts for uncertainty in data	When coarser bins are used, year built is disregarded
Outlet near parking	RECS	No	MI accounts for uncertainty in RECS data	

7.2.2 Details of Results

Table 7.13 provides details of the results shown in Figure 3.3 of the paper.

Table 7.13 Results for each calculation in the base case, optimistic case, and pessimistic case, averaged across 10 imputations and with standard deviation shown in parentheses.

National, All Households	**Base Case**	**Optimistic Case**	**Pessimistic Case**
Households with Dedicated Parking	79% (0.3%)	92% (0.2%)	56% (0.3%)
Households with Charging	38% (0.3%)	41% (0.2%)	14% (0.2%)
Vehicles with Dedicated Parking	56% (0.4%)	84% (0.4%)	33% (0.5%)
Vehicles with Charging	22% (0.2%)	30% (0.4%)	8% (0.2%)

National, Homeowners Only	**Base Case**	**Optimistic Case**	**Pessimistic Case**
Households with Dedicated Parking	61% (0.2%)	65% (0.2%)	44% (0.3%)
Households with Charging	34% (0.4%)	36% (0.3%)	12% (0.2%)
Vehicles with Dedicated Parking	32% (0.2%)	34% (0.2%)	23% (0.2%)
Vehicles with Charging	19% (0.2%)	20% (0.2%)	7% (0.1%)

Urban, All Households	**Base Case**	**Optimistic Case**	**Pessimistic Case**
Households with Dedicated Parking	75% (0.3%)	91% (0.2%)	53% (0.5%)
Households with Charging	35% (0.4%)	38% (0.2%)	13% (0.3%)
Vehicles with Dedicated Parking	39% (0.4%)	46% (0.3%)	28% (0.4%)
Vehicles with Charging	21% (0.3%)	23% (0.2%)	8% (0.2%)

Urban, Homeowners Only	**Base Case**	**Optimistic Case**	**Pessimistic Case**
Households with Dedicated Parking	55% (0.2%)	59% (0.1%)	39% (0.4%)
Households with Charging	31% (0.4%)	33% (0.3%)	11% (0.2%)
Vehicles with Dedicated Parking	31% (0.3%)	33% (0.3%)	22% (0.2%)
Vehicles with Charging	19% (0.3%)	20% (0.2%)	7% (0.2%)

Rural, All Households	**Base Case**	**Optimistic Case**	**Pessimistic Case**
Households with Dedicated Parking	91% (0.4%)	97% (0.3%)	66% (0.9%)
Households with Charging	48% (0.8%)	50% (0.5%)	17% (0.8%)
Vehicles with Dedicated Parking	40% (0.3%)	42% (0.5%)	29% (0.6%)
Vehicles with Charging	23% (0.3%)	24% (0.2%)	8% (0.4%)

Rural, Homeowners Only	**Base Case**	**Optimistic Case**	**Pessimistic Case**
Households with Dedicated Parking	80% (0.4%)	83% (0.3%)	58% (1.1%)
Households with Charging	45% (0.6%)	46% (0.4%)	16% (0.7%)
Vehicles with Dedicated Parking	35% (0.3%)	37% (0.3%)	26% (0.6%)
Vehicles with Charging	21% (0.2%)	22% (0.2%)	8% (0.4%)

7.2.3 Comparison with Literature Results

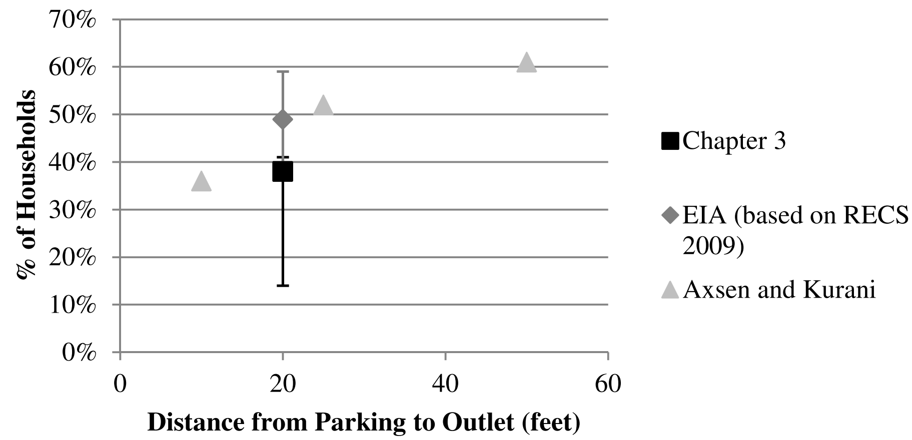

Figure 7.10 Comparison of estimates of percentage of U.S. households with an outlet near parking. Error bars for Chapter 3 represent range of optimistic and pessimistic cases. Error bars for EIA study (US EIA, 2012) are based on nonresponses to outlet question in RECS (US EIA, 2011d); error range will be larger when uncertainty in vehicle ownership (not available in RECS) is taken into account. Error ranges for Axsen and Kurani's results are not given (Axsen and Kurani, 2012b).

7.2.4 Comparison of Demographics in AHS and RECS

Unless otherwise stated, all data have been weighted using the weighting factors available in AHS 2009 or RECS 2009 as appropriate.

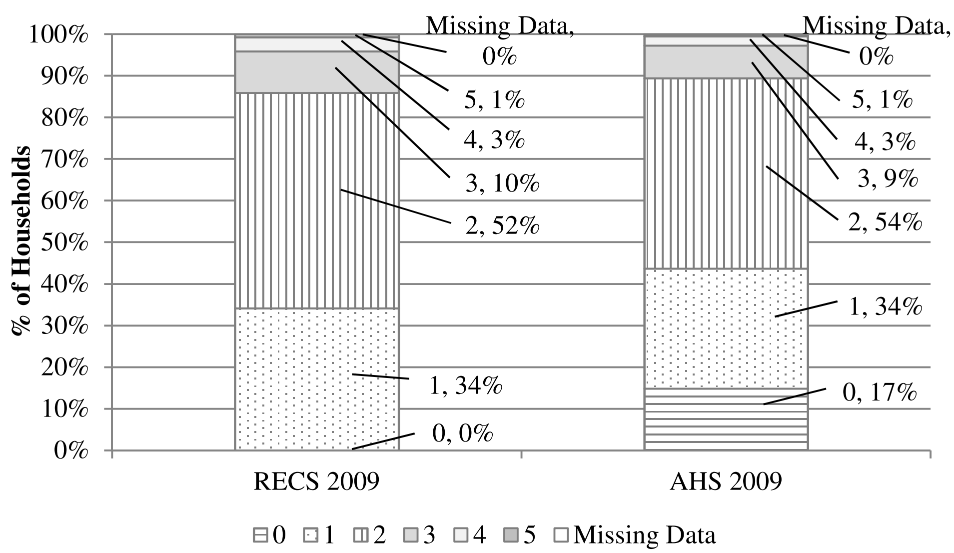

Figure 7.11 Comparison of number of adults age 20 and older per household in RECS 2009 and AHS 2009. Occupants aged 18-19 are aggregated with teenagers aged 15-17 in RECS 2009 and so are not be included here.

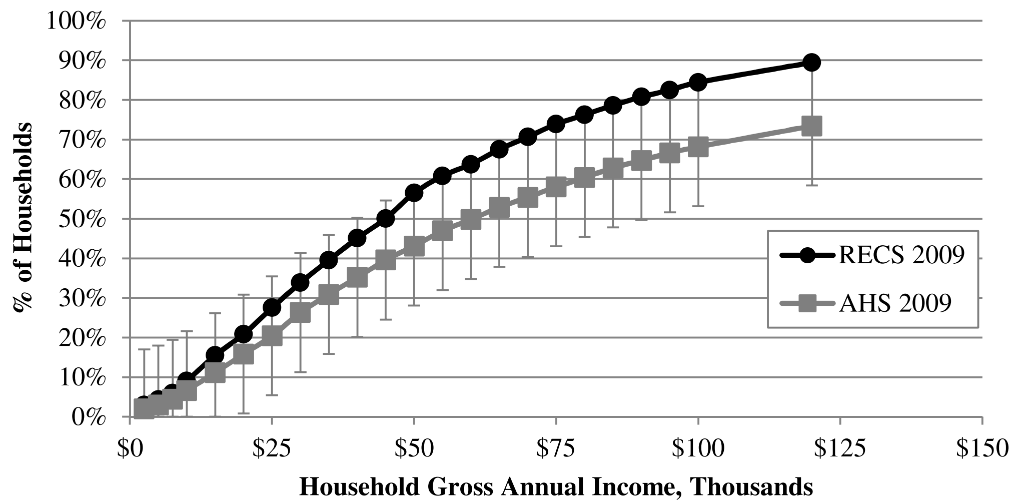

Figure 7.12 Income distributions in RECS 2009 and AHS 2009.

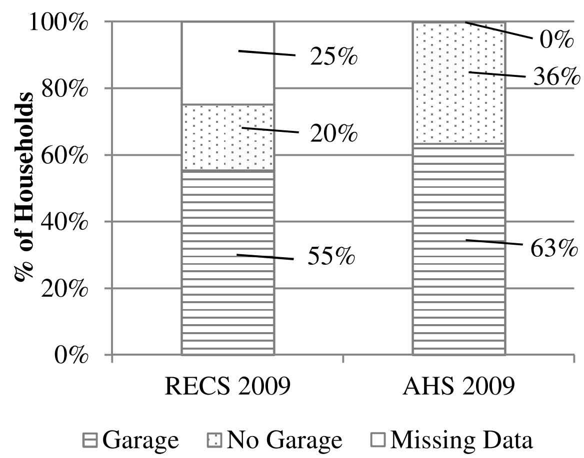

Figure 7.13 Comparison of parking type data from RECS 2009 and AHS 2009.

7.2.5 Occupancy Analysis

In our analysis, we mention that the owner/renter status of a housing unit can affect future PEV charging opportunities due to the principal-agent problem of renters having to cooperate with landlords to have charging infrastructure installed (Murtishaw and Sathaye, 2006). Here we analyze RECS and AHS data on percentage of owners and renters nationally and in urban and rural areas.

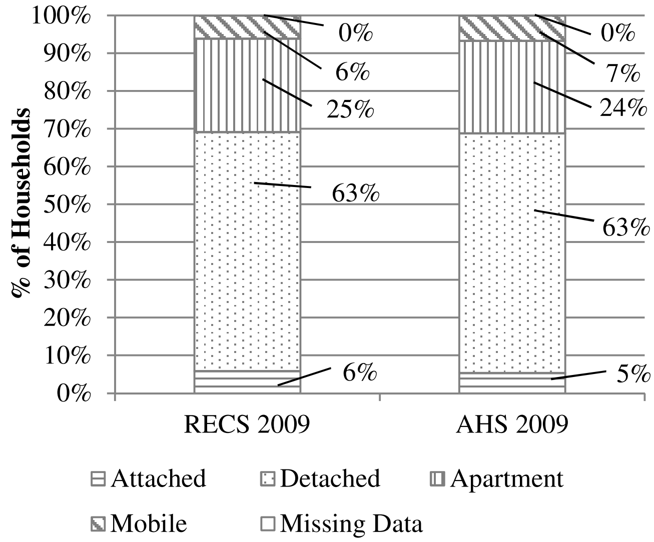

Figure 7.14 Comparison of housing type in RECS 2009 and AHS 2009.

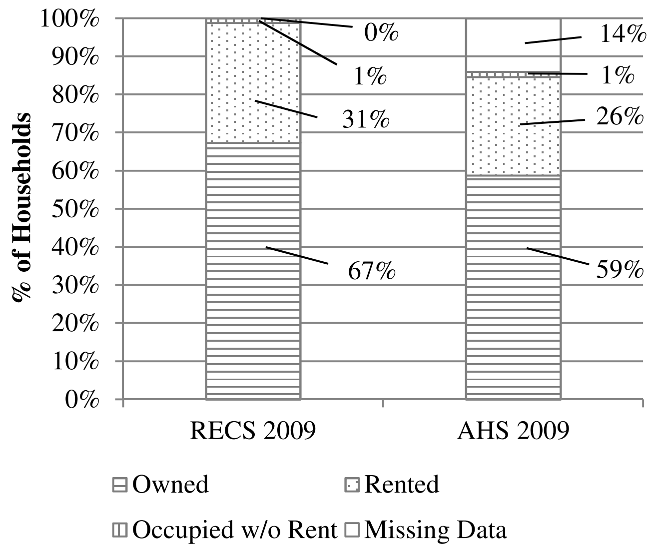

Figure 7.15 Comparison of occupancy status in RECS 2009 and AHS 2009.

Figure 7.16 indicates that the urban and rural designations in RECS and AHS may not be entirely consistent, since the uncertainty from missing data (0%) is less than the difference between the results from the two data sets (9%).

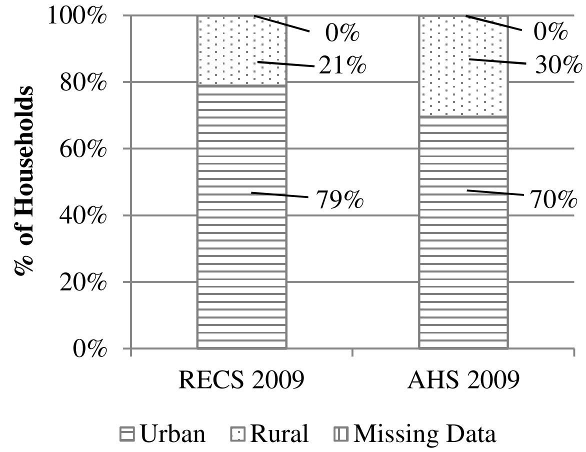

Figure 7.16 Comparison of density in RECS 2009 and AHS 2009.

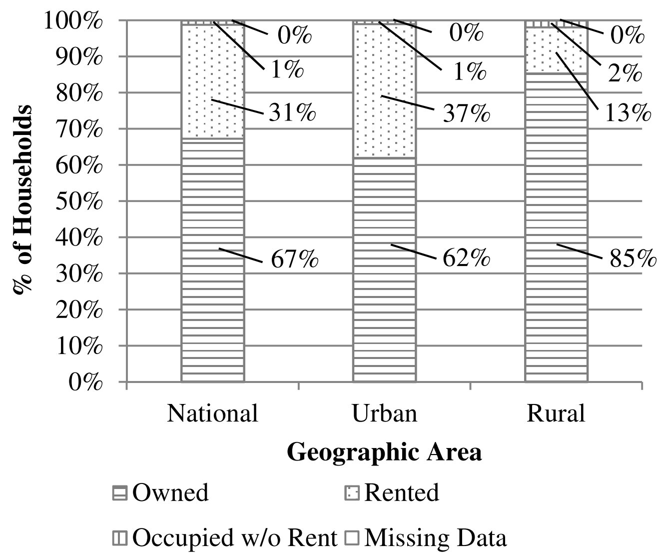

Figure 7.17 Comparison of occupancy status by density.

7.2.6 Additional Sensitivity Analysis Results

Figure 7.18, Figure 7.19, and Figure 7.20 show the sensitivity of Equations (3.1), (3.2), and (3.4), respectively, to some of the model parameters that are based on assumptions. These are one-way sensitivity analysis cases, with only one parameter varied at a time and all other parameters remaining at base case values. The portion of parking that is unavailable (due to being used for storage or other purposes) is 10% in the base case and varies from 0% to 50% here, resulting in a range of 56% to 82% of households having parking. Since the pessimistic case also has a result of 56% for P_{HP}, this one-way sensitivity analysis demonstrates that the portion of parking unavailable accounts for almost all of that reduction from the base case result. For both of the charging cases, the availability of outlets is a more influential parameter than the availability of parking. In Figure 7.20, the reason the maximum number of vehicles considered does not affect P_{VC} is because in the base case each household has only one outlet that can be used by only one vehicle, so it does not matter whether a household has multiple vehicles.

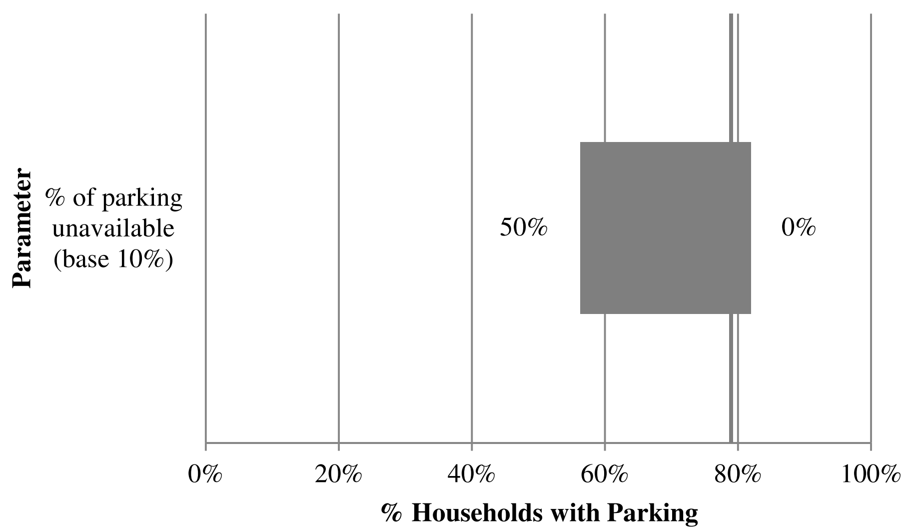

Figure 7.18 Sensitivity of portion of households with parking (P_{HP}, Eq. (3.1)) to the assumed portion of parking that is unavailable due to being used for storage, with all other parameters at base case values.

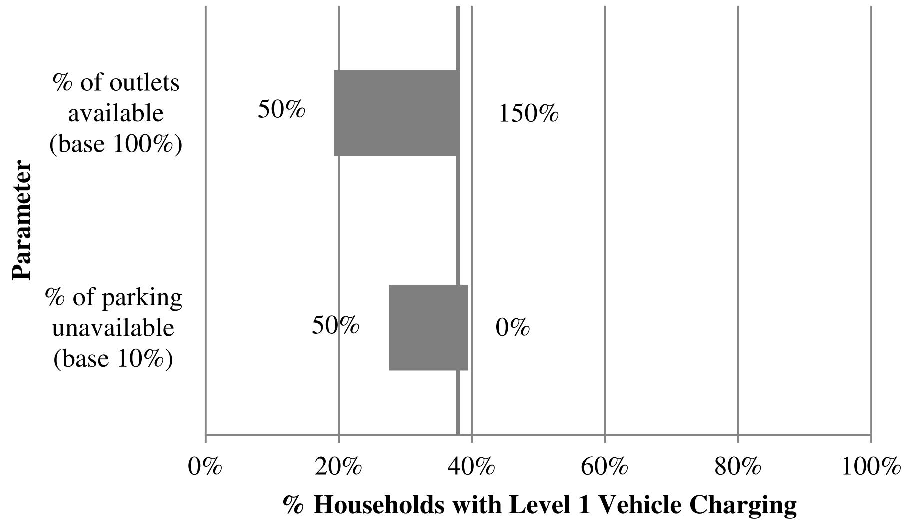

Figure 7.19 Sensitivity of portion of households with Level 1 vehicle charging (P_{HC}, Eq. (3.2)) to assumptions, with all other parameters at base case values.

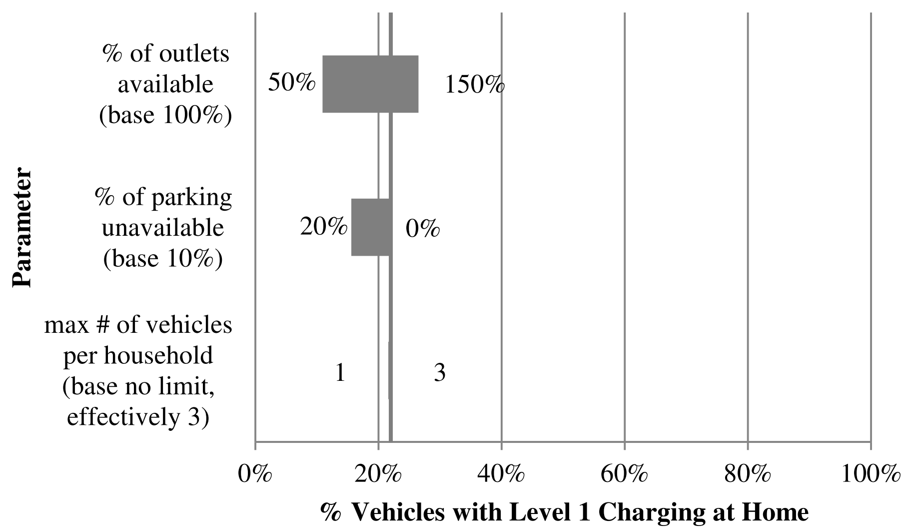

Figure 7.20 Sensitivity of portion of vehicles with Level 1 charging at home (P_{VC} Eq. (3.4)) to assumptions, with all other parameters at base case values.

7.2.7 Comparison of Level 1 and Level 2 Charging Opportunities from the Literature

We have briefly discussed Level 2 charging in the paper, saying that although Level 2 charging is preferable to Level 1 charging due to the shorter charging time and ability to charge a larger battery overnight, residential Level 1 charging is more available now than Level 2 charging due to infrastructure cost barrier. Also, limited data is available on existing Level 2 residential charging opportunities. Axsen and Kurani (Axsen and Kurani, 2012a, 2012b) conducted a survey asking about Level 2 outlets available within 25 feet of vehicle parking, for respondents in the San Diego area only. They found that 72% of respondents in the San Diego area had Level 1 charging and 35% had Level 2. It is not clear whether these outlets are actually available to charge a vehicle in all cases or whether in some cases other household appliances might already be using the circuits. Since this data set is only for the San Diego area it is likely not representative of the U.S. as a whole.

7.2.8 References

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7.3 Appendix C: Supplemental Information for Comparative Implications of Electric Vehicle Fast Charging and Battery Swapping Stations for Life Cycle GHG Emissions and Cost

7.3.1 Numerical Simulation Code

MATLAB code for the numerical simulations. Algorithm partly based on examples in Baron (2007) and Gross *et al.* (2008).

7.3.1.1 Fast Charging

```
function [mu,r,rho,L_q,W_q,W,L,W_q_0,d_A] =
   func_numerical_queue_fast_charge(lambda, charging_bays,charge_time)

n_runs=1; % for multiple Monte Carlo runs
number_of_vehicles=5000;
mu=1/charge_time;
r=lambda/mu;
rho = lambda/(c*mu); % traffic intensity
if rho>=1
   disp('Rho must be less than 1 for a steady state solution to
   exist');
   L_q=Inf; W_q=Inf; W=Inf; L=Inf; W_q_0=0; d_A=0; return
end

max_in_charging_bays=zeros([1,n_runs]);
max_queue_wait=zeros(1,n_runs);
mean_queue_wait=zeros(1,n_runs);
mean_charging_time=zeros(1,n_runs);
median_nonzero_queue_wait=zeros(1,n_runs);
mean_queue_size=zeros(1,n_runs);
max_queue_size=zeros(1,n_runs);

for r=1:n_runs
   veh_id=[1:number_of_vehicles]';
   uniform_random_draws_for_interarrival_times=rand(number_of_vehicles,
   1);
   interarrival_times=-log(uniform_random_draws_for_interarrival_times)
   / lambda; % minutes, random draws from an exponential distributions
   uniform_random_draws_for_charging_times=rand(number_of_vehicles,1);
   charging_times=-log(uniform_random_draws_for_charging_times)/mu;
   arrival_times=zeros(size(veh_id));
   queue_wait=zeros(size(veh_id));
   start_times=zeros(size(veh_id));
   departure_times=zeros(size(veh_id));
   bay_available_times=zeros(1,charging_bays);
   bay_assigned=zeros(size(veh_id));
   number_charging_just_before_arrival=zeros(size(veh_id));
   number_charging_just_after_arrival=zeros(size(veh_id));
   number_in_queue_just_before_arrival=zeros(size(veh_id));
   number_in_queue_just_after_arrival=zeros(size(veh_id));
   for i=1:number_of_vehicles
      if i==1
```

```
            arrival_times(i)=0;
        else
            arrival_times(i)=arrival_times(i-1)+interarrival_times(i);
        end
        bays_available=sum(bay_available_times<=arrival_times(i));
        if bays_available==0
            [time,bay_index]=min(bay_available_times);
            bay_assigned(i)=bay_index;
            start_times(i)=time;
            queue_wait(i)=start_times(i)-arrival_times(i);
            departure_times(i)=start_times(i)+charging_times(i);
            bay_available_times(bay_index)=departure_times(i);
        else
            [time,bay_index]=min(bay_available_times); % will return an
    available bay but the time will be either equal to the arrival time
    or in the past
            bay_assigned(i)=bay_index;
            start_times(i)=arrival_times(i);
            queue_wait(i)=0;
            departure_times(i)=start_times(i)+charging_times(i);
            bay_available_times(bay_index)=departure_times(i);
        end
        number_charging_just_before_arrival(i)=sum(start_times(1:i-
    1)<arrival_times(i))-sum(departure_times(1:i-1)<arrival_times(i));
        number_charging_just_after_arrival(i) =
    sum(start_times(1:i)<=arrival_times(i))-sum(departure_times(1:i-
    1)<=arrival_times(i));
        number_in_queue_just_before_arrival(i) = veh_id(i)-1-
    sum(start_times(1:i-1)<arrival_times(i));
    end
    mean_queue_wait(r)=mean(queue_wait);
    mean_charging_time(r)=mean(charging_times);
    median_nonzero_queue_wait(r)=median(queue_wait(queue_wait>0));
    max_queue_wait(r)=max(queue_wait);
    mean_queue_size(r)=mean_queue_wait(r)*number_of_vehicles/start_times
    (number_of_vehicles);
    max_queue_size(r)=max(max(number_in_queue_just_before_arrival),max(n
    umber_in_queue_just_after_arrival));
    max_in_charging_bays(r)=max(max(number_charging_just_before_arrival)
    ,max(number_charging_just_after_arrival));
end
L_q=mean(mean_queue_size);
W_q=mean(mean_queue_wait);
W=W_q+charge_time;
L=L_q+charging_bays;
W_q_0=sum(queue_wait==0)/(sum(queue_wait~=0)+sum(queue_wait==0));
d_A=mean(charging_times)/(charge_time/.75); % note: because charge_time
    is based on 75% of the max
```

7.3.1.2 Battery Swapping

```
function
    [mu_V,r_V,rho_V,L_q_V,W_q_V,W_V,L_V,W_q_0_V,mu_B,r_B,rho_B,L_q_B,W_q
    _B,W_B,L_B,W_q_0_B,d_A] =
    func_numerical_queue_swap(lambda,c_V,c_B,swap_time,charge_time)
```

```
n_runs=1; % for multiple Monte Carlo runs
number_of_vehicles=5000;
mu_V=1/swap_time; % mean swapping rate, veh/min
r_V=lambda/mu_V;
rho_V=lambda/(c_V*mu_V);
if rho_V>=1
   disp('Rho_V must be less than 1 for a steady state solution to
   exist');
   L_q_V=Inf; W_q_V=Inf; W_V=Inf; L_V=Inf; W_q_0_V=0; mu_B=0; r_B=0;
   rho_B=0; L_q_B=Inf; W_q_B=Inf; W_B=Inf; L_B=Inf; W_q_0_B=0; d_A=0;
   return
end
mu_B=1/charge_time; % mean charging rate, veh/min
r_B=lambda/mu_B;
rho_B=lambda/(c_B*mu_B);
if rho_B>=1
   disp('Rho_B must be less than 1 for a steady state solution to
   exist');
   L_q_V=Inf; W_q_V=Inf; W_V=Inf; L_V=Inf; W_q_0_V=0; L_q_B=Inf;
   W_q_B=Inf; W_B=Inf; L_B=Inf; W_q_0_B=0; d_A=0; return
end

swapping_bays=c_V;
charging_bays=c_B;
max_in_swapping_bays=zeros([1,n_runs]);
max_veh_queue_wait=zeros(1,n_runs);
mean_veh_queue_wait=zeros(1,n_runs);
mean_veh_queue_size=zeros(1,n_runs);
max_veh_queue_size=zeros(1,n_runs);

for r=1:n_runs
   veh_id=[1:number_of_vehicles]';
   uniform_random_draws_for_interarrival_times=rand(number_of_vehicles,
   1);
   interarrival_times=-
   log(uniform_random_draws_for_interarrival_times)/lambda; % minutes,
   random draws from an exponential distributions
   uniform_random_draws_for_swapping_times=rand(number_of_vehicles,1);
   swapping_times=-
   log(uniform_random_draws_for_swapping_times)/mu_swap;
   uniform_random_draws_for_charging_times=rand(number_of_vehicles,1);
   charging_times=-
   log(uniform_random_draws_for_charging_times)/mu_charge;
   arrival_times=zeros(size(veh_id)); % initializations
   veh_queue_wait=zeros(size(veh_id));
   swap_start_times=zeros(size(veh_id));
   veh_departure_times=zeros(size(veh_id));
   swap_bay_available_times=zeros(1,swapping_bays);
   swap_bay_assigned=zeros(size(veh_id));
   charge_start_times=zeros(size(veh_id));
   charge_departure_times=zeros(size(veh_id));
   charge_bay_available_times=zeros(1,charging_bays);
   charge_bay_assigned=zeros(size(veh_id));
   number_swapping_just_before_arrival=zeros(size(veh_id));
   number_swapping_just_after_arrival=zeros(size(veh_id));
   number_in_veh_queue_just_before_arrival=zeros(size(veh_id));
   number_in_veh_queue_just_after_arrival=zeros(size(veh_id));
```

```
    for i=1:number_of_vehicles
       if i==1
             arrival_times(i)=0;
       else
             arrival_times(i)=arrival_times(i-1)+interarrival_times(i);
       end
       [time_s,swap_bay_index]=min(swap_bay_available_times); % time may
    be in the past
       [time_c,charge_bay_index]=min(charge_bay_available_times); % time
    may be in the past
       swap_bay_assigned(i)=swap_bay_index;
       charge_bay_assigned(i)=charge_bay_index;
       swap_start_times(i)=max([time_s,time_c,arrival_times(i)]);
       veh_queue_wait(i)=swap_start_times(i)-arrival_times(i);
       veh_departure_times(i)=swap_start_times(i)+swapping_times(i);
       swap_bay_available_times(swap_bay_index)=veh_departure_times(i);
       charge_bay_available_times(charge_bay_index) =
    veh_departure_times(i)+charging_times(i);
       number_swapping_just_before_arrival(i)=sum(swap_start_times(1:i-
    1)<arrival_times(i))-sum(veh_departure_times(1:i-
    1)<arrival_times(i));

       number_swapping_just_after_arrival(i)=sum(swap_start_times(1:i)<=
    arrival_times(i))-sum(veh_departure_times(1:i-1)<=arrival_times(i));
       number_in_veh_queue_just_before_arrival(i)=veh_id(i)-1-
    sum(swap_start_times(1:i-1)<arrival_times(i));
    end
    mean_veh_queue_wait(r)=mean(veh_queue_wait);
    max_veh_queue_wait(r)=max(veh_queue_wait);
    mean_veh_queue_size(r)=mean_veh_queue_wait(r)*number_of_vehicles/swa
    p_start_times(number_of_vehicles);
       max_veh_queue_size(r)=max(max(number_in_veh_queue_just_before_arr
    ival),max(number_in_veh_queue_just_after_arrival));
    max_in_swapping_bays(r)=max(max(number_swapping_just_before_arrival)
    ,max(number_swapping_just_after_arrival));

end
L_q_V=mean(mean_veh_queue_size);
W_q_V=mean(mean_veh_queue_wait);
W_V=W_q_V+swap_time;
L_V=L_q_V+swapping_bays;
W_q_0_V=sum(veh_queue_wait==0)/(sum(veh_queue_wait~=0)+sum(veh_queue_wa
   it==0));
L_q_B=0; % there is no battery queue because the number of batteries
   equals the number of charging bays and the vehicles just wait extra
   time for one to be available
W_q_B=0; W_q_0_B=0;
W_B=W_q_B+charge_time;
L_B=L_q_B+charging_bays;
d_A=mean(charging_times)/(charge_time/.75); % note: because charge_time
   is based on 75% of the max
```

7.3.2 Fast Charge Results Details

Details of the intermediate analytical queuing model calculations for fast charging, using base case parameter values. As shown, number of charging bays needed increases fairly linearly with vehicle arrival rate, and average vehicle queue wait time for the minimum cost cases is short, less than 3.5 minutes.

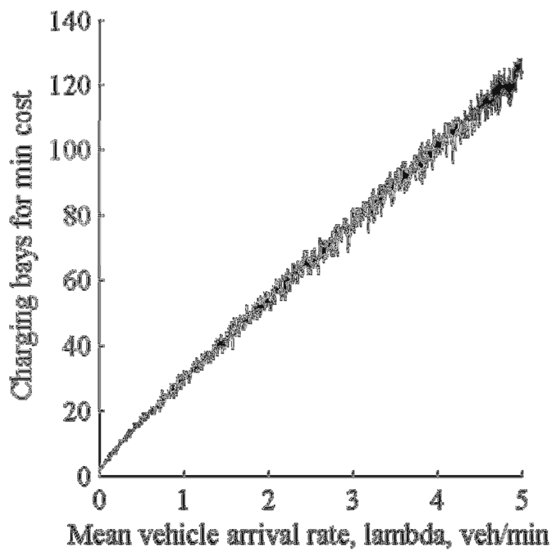

Figure 7.21 Number of charging points

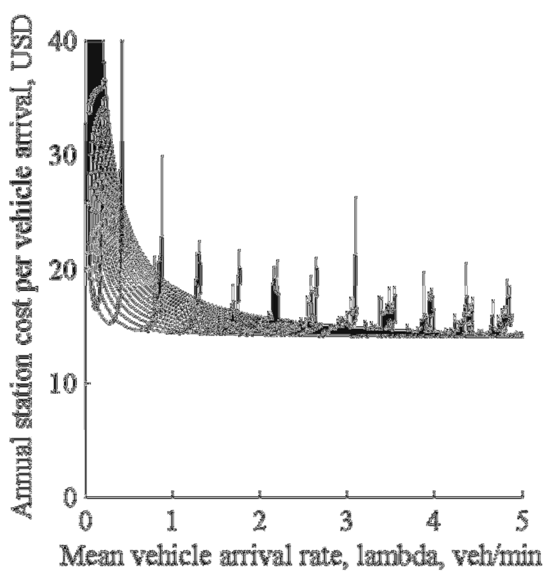

Figure 7.22 Cost per vehicle arrival

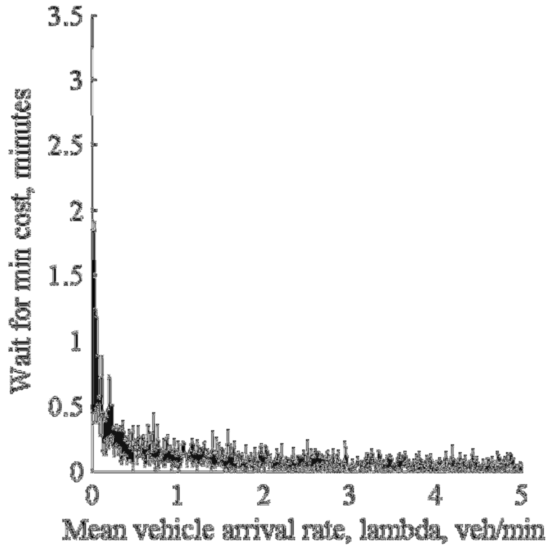

Figure 7.23 Wait time in queue

7.3.3 Agreement of Numerical Queuing Simulation with Analytical Model

Results for M/M/c numerical queuing simulation have good agreement with the analytical solution, and agreement improves with number of vehicle arrivals simulated and number of Monte Carlo runs. The results shown in Table 7.14 are based on 4000 vehicle arrivals and 20000 Monte Carlo runs.

Table 7.14 Comparison of analytical and numerical queuing results.

Parameter	***Analytical Model***	***Numerical Simulation***	***% Error***
λ	1.02 veh/min		
μ	0.05 veh/min		
r	20.4		
ρ	0.85		
n	24		
W_q	1.92 min	1.87 min	3%
L_q	1.96 vehicles	1.91 vehicles	3%

7.3.4 Results Details

Table 7.15 Results table for Figure 4.7 and Figure 4.8

Case	***Gasoline***	***Site Prep***	***Equipment***	***Operation***	***Electricity***	***Batteries***	***Service Time***	***Waiting Time***	***Total***
Level 1 Chg *(721 chargers)*	-	0.01	0.15	0.15	1.50	-	385.60	0	390
Level 2 Chg *(253 chargers)*	-	0.01	0.11	0.15	1.50	-	136.00	0	140
Lvl 3 Charge *(32 chargers)*	-	0.01	0.34	0.15	1.91	-	13.60	0.05	16
Swap w/ Lvl 2 *(8 swapping points, 253 chargers and batteries)*	-	0.28	1.19	1.07	1.50	0.90	4.27	0.43	10
Swap w/ Lvl 3 *(7 swapping points, 26 chargers and batteries)*	-	0.04	1.36	1.07	1.76	0.09	4.27	0.43	9
3 Swap w/ Lvl 2 *(9 swapping points, 270 chargers and batteries)*	-	0.96	4.52	4.11	1.55	2.72	4.27	0.60	19
3 Swap w/ Lvl 3 *(9 swapping points, 33 chargers and batteries)*	-	0.21	5.22	4.11	1.80	0.35	4.27	0.60	17
4 Swap w/ Lvl 3 *(12 swapping points, 32 chargers and batteries)*	-	0.24	6.58	5.48	1.84	0.34	4.27	0.24	19
CV	5.68	-	-	-	-	-	1.69	0	7.4
HEV	4.03	-	-	-	-	-	1.66	0	5.7

7.3.5 References

Baron, M., 2007. Probability and Statistics for Computer Scientists. Chapman & Hall/CRC, New York.

Gross, D., Shortle, J.F., Thompson, J.M., Harris, C.M., 2008. Fundamentals of Queueing Theory, 4th ed. Wiley-Interscience, Hoboken, NJ.