Data-Driven Behavior Analysis and Implications in Plug-in Electric Vehicle Policy Studies

By

WEI JI

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Approved:

_____

Yueyue Fan, Co-Chair

_____

Gil Tal, Co-Chair

_____

Joan M. Ogden

Committee in Charge

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ABSTRACT

The adoption of plug-in electric vehicles (PEVs) is considered to be a potential solution to reduce transportation-related emissions. People's vehicle choice and driving behavior will have important implications for the realized emissions reductions from PEVs. Therefore, PEV-related policy studies require good understanding of human behavior. Traditional approaches to analyze travel behavior are mostly to build analytic models based on assumptions because of the limited accuracy and information of data. With the development of sensor technology, there are more methods than ever to collect accurate and informative behavioral data, so the crucial consideration is how to creatively use these data to better understand people's behavior. This dissertation proposed some data-driven approaches to simulate behavior and provided a discussion of the implications for three PEV-related topics.

The first study explored the potential of greenhouse gas (GHG) reductions that can be achieved with adoption of PEVs in California by simulating vehicles' emissions based on tracing data. It was found that assigning the right model of PEVs to drivers can help to reduce annual GHG emissions by 65%, compared to everyone driving a Toyota Corolla.

The second study presented a tool to evaluate the spatial distribution of fast charging demand and to assess how much a charger in a certain location would be used based on travel diary. Scenario analysis illustrated that en-route fast charging demand will shift from primarily inside metro areas to long distance corridors outside metro areas as the battery size increases.

The third study estimated the value of Clean Air Vehicle (CAV) decals by simulating the frequency of PEV owners' access to high occupancy vehicle/toll (HOV/T) lanes based on survey data. The results indicated that the CAV Decals Program is one of the most attractive incentive policies, but there is spatial heterogeneity of CAV decal value across different regions.

ACKNOWLEDGEMENTS

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1   INTRODUCTION

Transportation is one of the primary sectors of energy consumption and carbon emissions in the United States, along with residential, commercial and industrial sectors. In 2017, the transportation sector accounted for 28.8% of the total energy consumption in the U.S., and 92.2% of energy consumed by the transportation sector is in the form of petroleum (Lawrence Livermore National Laboratory, 2018). Furthermore, the transportation sector accounts for 33.8% of the total carbon emissions in the U.S. as of 2014 (Lawrence Livermore National Laboratory, 2015). Promotion and increased adoption of plug-in electric vehicle technology is expected to help reduce carbon emissions.

A plug-in electric vehicle (PEV) is defined as any motor vehicle "which is propelled to a significant extent by an electric motor which draws electricity from a battery which— (i) has a capacity of not less than 4 kilowatt hours, and (ii) is capable of being recharged from an external source of electricity" according to Internal Revenue Code Section 30D. Since the electric motor is more efficient than internal combustion engines (ICEs) (Franklin Associates, 2000) and the carbon intensity of electricity is lower than gasoline (Gagnon, Belanger, & Uchiyama, 2002), especially with increasing amounts of electricity generated from renewable sources (California Legislative Information, 2015), the adoption of PEVs is considered to be a potential solution to reduce transportation-related carbon emissions.

1.1   Motivations

Since one of the fundamental expectations of promoting PEV technology is that it will reduce carbon emissions, it is important to quantify the potential carbon emissions reductions that can be achieved by PEV adoption. There have been continuous efforts to quantify the benefit

of PEV adoption in carbon reduction (Duvall, Knipping, Alexander, Tonachel, & Clark, 2007; Kromer, Bandivadekar, & Evans, 2010; Stephan & Sullivan, 2008; Yang, McCollum, McCarthy, & Leighty, 2009). A life cycle assessment of vehicle greenhouse gas (GHG) emission usually consists of two parts: (1) the well-to-tank fuel production and transmission and (2) the tank-to-wheel fuel consumption which is also known as on-road emissions (Elgowainy, Burnham, Wang, Molburg, & Rousseau, 2009; M. Wang, Weber, & Darlington, 2005) .

PEVs can be classified into battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). A BEV uses rechargeable battery packs as its only energy source, while a PHEV has an electric motor and a gasoline engine for propulsion so that it has both rechargeable battery packs and gasoline for energy sources. The on-road emissions for a BEV are zero, but its life cycle emissions depend on the upstream emissions from electricity generation and transfer, as well as the amount of electricity consumption which is determined by the vehicle design (Bradley & Frank, 2009; Letendre & Watts, 2009) and the driving behavior (T.-K. Lee, Adornato, & Filipi, 2011; Nicholas, Tal, & Turrentine, 2016; Samaras & Meisterling, 2008b; Yuan, Li, Gou, & Dong, 2015). Estimating the GHG emissions of a PHEV is even more complex as it can be propelled by both electricity and gasoline, so charging behavior can significantly impact the on-road emissions. If a Chevrolet Volt driver charges the vehicle all the time and the trip distance is always within the range of the battery, the on-road emissions can be zero; but if the driver never charges the vehicle, it will operate like a hybrid vehicle instead. Because of the uncertainty of PHEVs' on-road emissions, there are debates about the contribution of PHEVs to carbon emissions reduction (Duvall et al., 2007; Samaras & Meisterling, 2008a).

One of the major barriers for BEV adoption is the limited driving range of the vehicle. The range of a BEV depends on the battery capacity of the vehicle, the driving behavior, external

environment, and many other factors. Most BEV models on the market before 2016 have a EPA-rated range shorter than 100 miles, such as the first-generation Nissan Leaf, Fiat 500e, and Chevrolet Spark EV. With the improvement of battery technology, batteries with higher power density and larger capacity have enabled the production of longer-range BEV models, such as Chevrolet Bolt and Tesla Model 3, which have battery ranges around 200 miles. The price of these vehicles is also more affordable compared to Tesla Model S and Model X (Lendino, 2015; Rosevear, 2015). However, because the actual range of BEVs may be shorter than the EPA-rated range when in cold environments (Dost, Spichartz, & Sourkounis, 2015) or with intensive use of heating, ventilation, and air conditioning (HVAC) systems (Yuksel & Michalek, 2015b), consumers who are not familiar with BEV technology may have "range anxiety" (Lin & Greene, 2011).

Furthermore, a previous study of Nissan Leaf owners in California indicates that these households all have extra gasoline vehicles in their households (Ji, Tal, & Nicholas, 2016). Compared to households with multiple gasoline vehicles but no electric car, the households with a Leaf use the Leaf and the other gasoline vehicles more evenly: Leaf for medium distance trips and the gasoline vehicle for short- and long-distance trips, while non-EV households primarily use one vehicle over the other. Limited range and long charging time are believed to be the key reasons that Leaf drivers prefer gasoline vehicles over the Leaf for long-distance trips. When driving a Leaf, most drivers will limit their total daily travel distance within the range of the Leaf. None drove a Leaf for long-distance travel that required more than two charging stops in one day.

Improvements to charging infrastructure accessibility can address some of the problems posed by these vehicle/battery characteristics and observed driving behavior. Optimized

distribution of DC fast charging infrastructure can enable BEVs to travel longer with limited

charging events, so as to help BEV drivers to overcome range anxiety and make BEVs a more

likely choice as a substitute gasoline vehicle for long-distance trips.

Along with the construction of EV charging stations, there are also various monetary and

non-monetary incentive policies to encourage consumers to adopt PEVs, including the up-to-

$7,500 federal tax credit, the Clean Vehicle Rebate Program (CVRP) launched by the California

Air Resources Board, local rebate programs (e.g. San Joaquin Valley Air Pollution Control

District Drive Clean! Rebate Program), subsidies for installing home chargers, utility credits to

PEV owners, workplace charging at free or reduced rates, preferred parking locations,

discounted parking, and the Clean Air Vehicle (CAV) Decals Program.

There have been many research efforts to evaluate the effects of these incentive policies

from different perspectives (Bjerkan, Nørbech, & Nordtømme, 2016; Langbroek, Franklin, &

Susilo, 2016; Sierzchula, Bakker, Maat, & van Wee, 2014). One interesting approach is to

estimate the value of non-monetary incentive policies such as the CAV decals. Effective January

1, 2018, new PEV owners in California cannot participate in both CAV Decals Program and the

CVRP unless income restriction requirements are met (California Deparment of Motor Vehicles,

2018), which means PEV owners need to make a choice between the CVRP rebate and the CAV

decal. A rational decision should be based on estimating the value of a CAV decal and

comparing it to the CVRP rebate. However, there is very limited research quantifying the value

of a CAV decal (Sheldon, DeShazo, & Carson, 2015; Shewmake & Jarvis, 2014).

The effect of range anxiety, charging infrastructure, and incentives on people's vehicle

choice and driving behavior will have important implications for the realized emissions

reductions from PEVs, thus influencing the effectiveness of PEVs as a strategy to reduce GHG

emissions from the transportation sector. It is important to explore these connections so that policy promoting PEVs can be made more effective and result in optimal GHG emission reductions. This research is motivated by the need to accurately predict and model transportation behavior so these reductions can be quantified and reflected in policy.

Questions this research aims to answer include:

- What is the potential GHG emission reductions that can be achieved in California with the adoption of PEVs?

- What is the spatial distribution of fast charging demand in California?

- What is the value of Clean Air Vehicles Decals in California?

1.2 Organization

Good understanding of human behavior is the core of transportation modeling and simulation (Goulias, 2003). During the last several decades, there have been continuing efforts to build analytic models to describe travel behavior based on assumptions (e.g.(de Dios OrtÃozar & Willumsen, 2011; Hanson & Schwab, 1995)). On the other hand, with the rapid adoption of computers and smartphones, the spread of the Internet, and the development of sensor technology, we have more methods than ever to collect detailed behavioral data with large sample size (such as tracing data obtained from Global Positioning System (GPS) trackers, on-board diagnostics (OBD) loggers, smartphones, etc.). For these new types of behavioral data, the crucial consideration is how to creatively use these data to better understand people's behavior and solve practical problems such as the topics raised in the previous section.

The paper is organized as following:

Chapter 2 assigns the most efficient plug-in hybrid or full electric vehicles to a household based on the household's travel behavior, collected by GPS tracking data of thousands of

vehicles' real trips in California. We then further explore the difference in market share when assigning optimal vehicle models by looking at vehicle-level versus household-level travel demand. We found that given currently available technology, in many cases adoption of PHEVs will not necessarily result in significantly higher GHG emissions compared to BEVs. Furthermore, PHEVs have advantages over BEVs in satisfying household's long-distance travel demand.

Chapter 3 presents a tool to estimate fast charger demand based on travel diary data and sample results for current and future BEV market scenarios. The results highlight the data and methods needed to plan for fast charger demand. To plan for existing BEVs, origin and destination data are necessary to identify which traffic is relevant to assess fast charging demand. As the battery size for BEVs increases, demand shifts from primarily inside metro areas to long distance corridors outside metro areas. The sample results show the interaction between battery size, frequency of charging, and energy needed per charge. Although energy needed per charge increases with battery size, overall electricity demand per vehicle decreases with larger batteries.

Chapter 4 estimates the value of CAV decals in California. A survey was conducted that targeted PEV owners in California to understand their attitudes towards EV-related incentive policies, as well as their commute routes and the frequency of their access to high occupancy vehicle/toll (HOV/T) lanes. The value of a CAV decal was estimated based on the toll savings and the value of travel time savings for each survey respondent respectively, and the estimated value was compared with the corresponding Clean Vehicle Rebate for which the respondent was eligible. We also examined the spatial heterogeneity of CAV decal value across different regions, and tested the impact of local HOV/T lane accessibility to the value of CAV decals.

2 MODELING THE POTENTIAL OF BEVS AND PHEVS IN GHG REDUCTION BASED ON HOUSEHOLD LEVEL GPS DATA

2.1 Introduction

Plug-in electric vehicles (PEVs), including plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs), have an important role in reducing transportation-related greenhouse gas (GHG) emissions (Duvall et al., 2007; Kromer et al., 2010; Stephan & Sullivan, 2008; Yang et al., 2009). It is a complex endeavor to quantify the benefit of PEV adoption in GHG emission reductions, especially for PHEVs, as they can be fueled by both gasoline and electricity. The amount of GHG emitted per year of traveling is a function of the vehicle characteristics and of driving and charging patterns. For some driving patterns, a short-range BEV will satisfy both travel needs and minimizing GHGs, but for other travel needs either a long-range BEV or a PHEV will produce better results. Changes in daily driving routines from one day to another or between weekdays and weekends may change the household GHG emissions for any given vehicle. This paper compares the best BEV or PHEV range (based on battery size) vehicle that will produce the lowest amount of GHGs for California households based on their GPS travel patterns. We use household level data to optimize GHG while controlling for the long and short-range vehicle mix.

A life cycle assessment (LCA) of vehicle GHG emissions usually consists of two parts: one looks at the life cycle of a vehicle (Lewis, Kelly, & Keoleian, 2014; Moon, Burnham, & Wang, 2006) including vehicle production (Samaras & Meisterling, 2008b), vehicle operation, and after-life disposal/recycling (Ma, Balthasar, Tait, Riera-Palou, & Harrison, 2012); the other looks at the life cycle of fuel (Elgowainy et al., 2009; M. Wang et al., 2005) including well-to-tank fuel production and transmission and tank-to-wheel fuel consumption, which is accounted

for in both the vehicle operation part of the vehicle life cycle and the fuel life cycle. The tank-to-wheel GHG emissions are also known as on-road emissions. There are many factors throughout the phases of a PEV's life cycle that can influence the on-road emissions of the vehicle. For example, in the vehicle production phase, the powertrain design (Bradley & Frank, 2009; Letendre & Watts, 2009), battery capacity (Shiau, Samaras, Hauffe, & Michalek, 2009), and energy-management strategies (Gonder & Markel, 2007; Wirasingha & Emadi, 2011) can all significantly influence the vehicle fuel consumption during operation, and thus influence the on-road GHG emissions. There are studies to model the performance of each power system component in order to understand the energy consumption of PHEVs (W. Lee, Choi, & Sunwoo, 2002). Although the on-road emissions of PEVs in all-electric mode is zero, the life-cycle emissions are determined by the upstream GHG emission in the electricity generation phase (Onat, Kucukvar, & Tatari, 2015; Tamayao, Michalek, Hendrickson, & Azevedo, 2015), which is subject to many uncertainties including the fluctuations in demand on the grid throughout the day and the power source used to satisfy the marginal electricity demand (Axsen, Kurani, McCarthy, & Yang, 2011; Zivin, Kotchen, & Mansur, 2014).

Beyond the vehicle design and the upstream GHG emissions from electricity generation, driving behavior is crucial for estimating the on-road GHG emissions of PEVs. There are generally two types of approaches to simulate driving behavior. One option is to use standard driving cycles to characterize the cycles (Raykin, Roorda, & MacLean, 2012; Samaras & Meisterling, 2008b; Silva, Ross, & Farias, 2009), and to create various driving cycles to represent different types of driving behavior (U.S. EPA, 2017; Yuan et al., 2015). Another common approach is to sample real-world driving behavior by either tracking vehicle performance through on-board diagnostics systems (Nicholas et al., 2016), quantifying variation

of real-world driving behavior (He et al., 2016; T.-K. Lee et al., 2011; H. Wang, Zhang, & Ouyang, 2015), or simulating vehicle performance based on speed trace data (Hamza & Laberteaux, 2016; Silva et al., 2009). Road grade (Wood, Burton, Duran, & Gonder, 2014) is another factor that impacts a vehicle's fuel economy. Charging behavior (Neubauer, Brooker, & Wood, 2013; Shiau et al., 2009; Tal, Nicholas, Davies, & Woodjack, 2014) and weather conditions (Yuksel & Michalek, 2015a) will also influence the amount of available electricity in the battery in real-world driving activities, therefore impacting the on-road GHG emissions. There are many simulators that can model an electric vehicle's energy consumption, and they all have their strengths and weaknesses in terms of the capacity to consider vehicle design, road grade, charging activities, etc. (Mahmud & Town, 2016). The Vehicle Technologies Office of the U.S. Department of Energy (U.S. DOE) supported the development of Autonomie (Kim, Rousseau, & Rask, 2012) and FASTSim (described in detail in Section 2.2) (Brooker et al., 2015).

PEV market share is another essential factor in estimating the total GHG emission reduction that can be achieved by implementing PEVs. Vehicle ownership is usually a household decision, and there are many studies that explored how household vehicle ownership is influenced by various factors including household size, age, education, income, number of workers, residential location condition, vehicle utility, operating costs, etc. (Mannering & Winston, 1985; Mannering, Winston, & Starkey, 2002; Manski & Sherman, 1980). With the introduction of PEVs, electricity become a more significant part of the vehicle's fuel so the electricity price plays an important role in the adoption of PEVs (Bhat, Sen, & Eluru, 2009; Musti & Kockelman, 2011) and the improvement in fuel economy is an important motivation for PEV adoption (Kurani, Heffner, & Turrentine, 2008; Kurani & Turrentine, 2004). On the other

hand, the limited battery range available in current technology is a primary barrier to the adoption of PEVs, especially BEVs (Egbue & Long, 2012; G. Tal & M. A. Nicholas, 2013).

This study explores the potential of reducing GHG emission by wide-scale adoption of PEVs including a mix of BEVs and PHEVs. Fuel consumption is simulated based on speed trace data using FASTSim. The rest of the paper is organized as follows: the second section introduces FASTSim and the configuration of vehicle models which are used for fuel consumption simulation; the third section introduces the speed trace data along with weights to produce representative statistics; and the fourth section shows the GHG emission reduction in different PEV adoption scenarios with and without considering household vehicle ownership limitations.

2.2 FASTSim Introduction and Configuration

The Future Automotive Systems Technology Simulator (FASTSim) is an open-source tool developed by the National Renewable Energy Laboratory (NREL) (NREL). FASTSim is capable of simulating the fuel consumption of conventional vehicles, hybrid electric vehicles, PHEVs, BEVs, compressed natural gas vehicles, and fuel cell vehicles based on speed-over-time trace data, and it accounts for "drag, acceleration, ascent, rolling resistance, each powertrain component's efficiency and power limits, and regenerative braking" (Brooker et al., 2015). Since FASTSim models vehicle performance at powertrain component level, it allows users to modify the parameters of vehicle powertrain, such as battery capacity, motor power, engine power, glider mass, etc. to examine how powertrain design impacts fuel economy.

2.2.1 Validation and Calibration of FASTSim

To validate the accuracy of FASTSim, we tracked a 2012 Chevrolet Volt performance through its on-board diagnostics (OBD) system (Nicholas et al., 2016), and compared the observed fuel consumption with the FASTSim simulation results (Figure 2.1). The second-by-

second fuel and electricity consumption (gray and orange lines in Figure 2.1-b) was calculated

by FASTSim based on the speed trace (green line in Figure 2.1-a), and then the cumulative

energy (brown and red lines in Figure 2.1-a) was calculated by assuming the energy density is

127MJ/gallon for gasoline and 3.6MJ/kWh for electricity (AFDC, 2014). The comparison shows

that the ICE was turned on much earlier in the FASTSim simulation, while in the OBD data, the

gasoline engine was not turned on until the battery state of charge (SOC) dropped below a

certain threshold. The difference between the FASTSim simulation and the OBD observation is

due to the way FASTSim models PHEVs: in the simulation, the engine will be turned on when

the motor power cannot satisfy the required power based on speed change, even if the battery

SOC is very high. This study modifies FASTSim by adding a new module to simulate PHEVs

whose engine will not turn on until the battery SOC drops below relative zero percent. The

updated version[1] was programmed by a research team from Toyota using Java to significantly

improve the execution speed, and added some extra functions to simulate the impact of charging

behavior on battery SOC. We compared the model results to the original NREL version to

validate the code and validate the PEV results with data logged from those cars.

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[1] The java code is yet to become public, but is available upon request from Ken Laberteaux, Karim Hamza, and John Willard from the Toyota Research Institute of North America
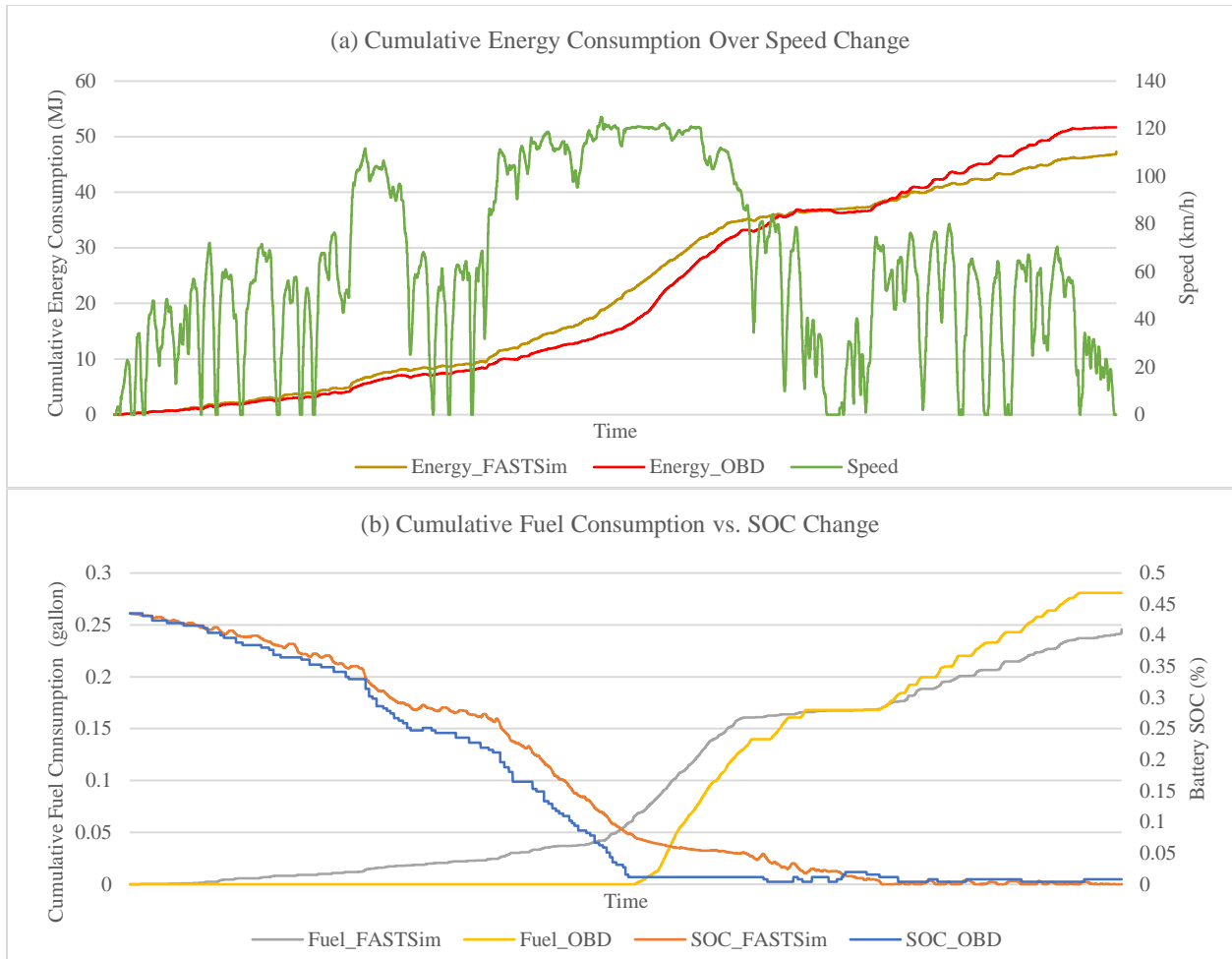
Figure 2.1 Demonstration of FASTSim simulation results

Based on the total electricity generation (CEC) and corresponding GHG emissions (CARB, 2016), the average GHG emission of the 2014 California grid is about 0.42 kg-CO2e/kWh. The well-to-wheel average GHG emission of gasoline is about 11.893 kg-CO2e/gallon, estimated by summing the U.S. average well-to-tank emission (M. Wang et al., 2005) and the carbon content of typical gasoline (U.S. EPA, 2016). We collected OBD data from 10 Nissan LEAFs and 10 Chevrolet Volts for over 300 vehicle*days, and calculated the daily total GHG emissions based on fuel and electricity consumption. The comparison (Figure 2.2) shows that FASTSim simulation results are linearly correlated with the OBD observation, but there is systematic bias between these two sets of data.
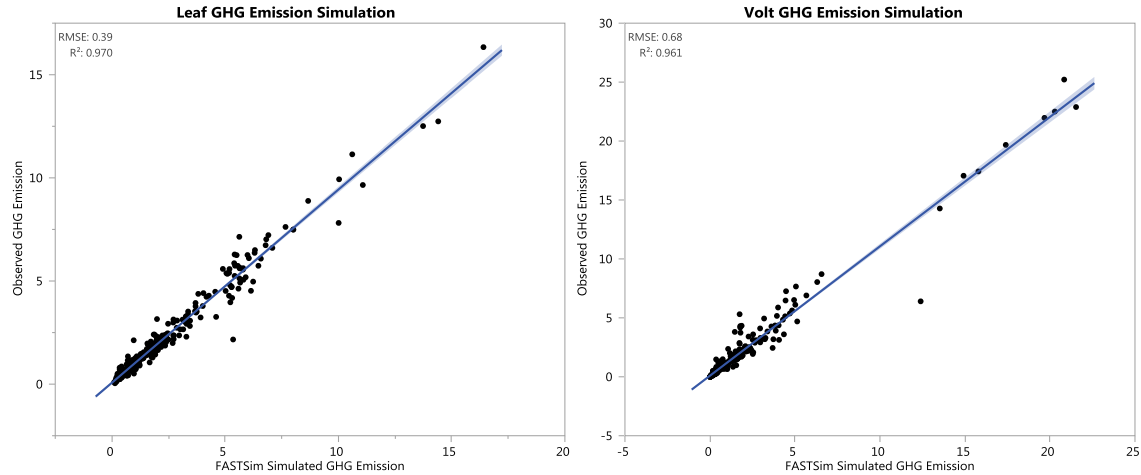
Figure 2.2 Comparison of FASTSim simulation and OBD observation

To fix the bias in the FASTSim results, we simulated the fuel consumption of a 2014
Nissan Leaf, a 2014 Chevrolet Volt (in both charge depleting (CD) and charge sustaining (CS)
mode), and a 2012 Toyota Corolla on the EPA's highway and city driving cycle (U.S. EPA,
2017), calculated the combined fuel economy based on 45% highway and 55% city driving, and
compared with the EPA rated fuel economy (U.S. DOE) to get a raking factor for each vehicle
model, which was used to calibrate FASTSim (Table 2.1).

Table 2.1 Raking factors for specific vehicle models

	FASTSim Simulated Combined Fuel Economy (MPGe)	EPA Rated Combined Fuel Economy (MPGe) (U.S. DOE)	Raking Factor
2014 Nissan Leaf	161.31	114	0.71
2014 Chevrolet Volt (CD)	153.37	98	0.64
2014 Chevrolet Volt (CS)	50.64	37	0.73
2012 Toyota Corolla	43.32	29	0.67

2.2.2 The Advantage of FASTSim

Instead of using FASTSim, a simple way to estimate fuel consumption is to multiply the
total travel distance by average fuel economy. However, since the EPA rated combined fuel
economy is calculated assuming 45% highway and 55% city driving, there will be an error when
the combined standard driving cycle cannot represent the actual driving behavior. For example,

the average fuel economy of a local trip with a lot of stop-and-go and no highway driving can be

much lower than the EPA rated combined fuel economy because the stop-and-go driving is much

less fuel efficient than the highway driving. Simulating fuel consumption based on speed trace

using FASTSim can help to improve the accuracy of estimation. For example, in a scenario

where all sample trips with GPS tracking data are completed by a 2012 Toyota Corolla, the fuel

consumption estimated based on EPA's fuel economy is 18.87% lower than the FASTSim

simulation on average (Table 2.2). The accuracy of estimating fuel consumption based on

average fuel economy is better for PEVs than for conventional vehicles. This is because internal

combustion engines have higher variance in fuel economy within different driving cycles

compared to electric motors. There is more uncertainty surrounding the actual fuel economy of

conventional vehicles, and estimating the fuel consumption of conventional vehicles using a

single number of average fuel economy can result in a larger error.

Table 2.2 The difference in fuel consumption estimated by using average fuel economy comparing to using FASTSim

2014 Nissan Leaf	2014 Chevrolet Volt	2012 Toyota Corolla
μ=1.76% σ=0.103	μ=-8.18% σ=0.215	μ=-18.87% σ=0.124
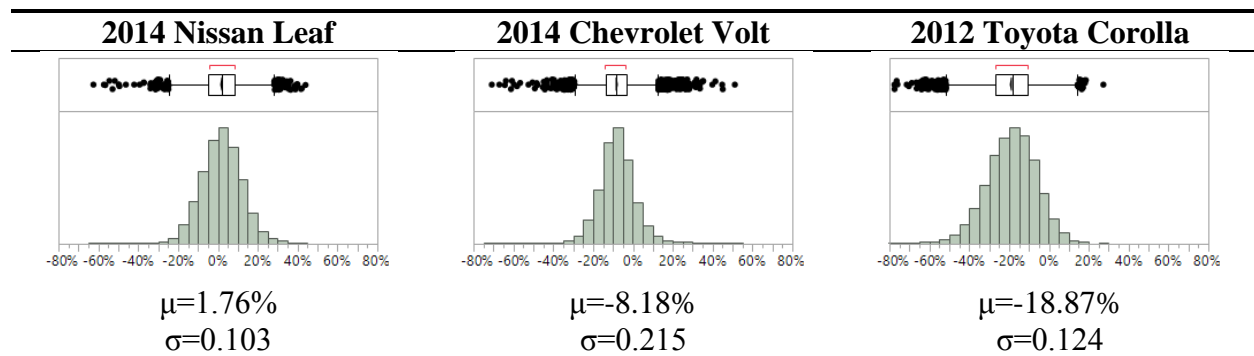
2.2.3   Approaches to Create New PEV Models in FASTSim

There are limited PEV models that are available on the market. However, for research

purposes, we want to create additional vehicle models with different battery ranges to analyze

the impact of battery range on GHG emissions. Vehicle models are specified by various

parameters in FASTSim to describe the mechanical design, and FASTSim models vehicle

performance at powertrain component level based on these parameters. For example, parameters that describe motor characteristics include motor power, peak efficiency, time to full power, mass, etc.; and parameters that describe battery include output power, energy, mass, useable minimum SOC, useable maximum SOC, etc. Therefore, by changing vehicle parameters, we can "create" new models in FASTSim to analyze how these changes influence vehicle performance.

To create a PHEV with a 25-mile range (PHEV25), there are three approaches to simulate the vehicle performance using FASTSim:

1. Change battery capacity. The 2014 Chevrolet Volt has a 16.5 kWh battery with a EPA rated range of 38 miles. By reducing the battery capacity by 35%, the range should also be reduced by approximately 35%. Since the battery density is used in calculating the vehicle weight, the impact of any the battery capacity changes to the vehicle's fuel economy is embedded in the simulation process.

2. Another approach is to simulate the fuel consumption in the first 25 miles using a Volt in CD mode and the rest of the trip using a Volt in CS mode. One drawback of this approach is that it restricts the battery range to 25 miles without any variance. However, the electrifiable range of a PHEV could be significantly different for different driving cycles.

3. One limit of the first approach is that it assumes the vehicle configuration remains the same for models of different range, excluding the battery capacity. We can use the average fuel consumption of Prius and Volt to indicate a possible average fuel consumption of a PHEV25. The motor of a PHEV with shorter range is more likely to have less power than that of a longer-range PHEV. For example, the 2014 Toyota Prius is equipped with a 36-kW motor and 4.4-kWh battery, and the EPA rated battery range is 11 miles; the 2014 Chevrolet Volt is equipped with a 111-kW motor and 16.5-kWh battery, and the EPA rated

battery range is 35 miles. Thus, the relationship between fuel economy and battery range

should be non-linear not only because of the impact of battery capacity on vehicle weight

but also because of motor power changes and many other factors.

A comparison of the total energy estimated by FASTSim using the three approaches

above shows the results of different approaches are highly linearly correlated (R2>0.998) except

for systematic bias (Table 2.3). Since the first approach is easier to implement than the other two,

we decided to use the first approach to create PHEV models with battery range from 10 miles to

80 miles and BEV models with battery range of 80, 120, and 200 miles for later scenario analysis

(Table 2.4). We used minimum and maximum levels to represent usable capacity as find in the

logger data as the OEM reports are not always consistence. BEV models are based on vehicle

design of 2014 Nissan Leaf and PHEV models are based on 2014 Chevrolet Volt by changing

only battery capacity.

Table 2.3 Comparison of Approaches to Simulate PHEV25 Energy Consumption

	X Axis: Approach 1	X Axis: Approach2
Y Axis: Approach 1		$y = 1.2619x - 0.0434$ $R^2 = 0.9981$
Y Axis: Approach 3	$y = 0.8848x + 0.0471$ $R^2 = 0.9933$	$y = 1.1185x + 0.0068$ $R^2 = 0.9949$

Table 2.4 Vehicle Model Specification for Scenario Analysis

	Average Fuel Economy in CD Mode (Mi/kWh)	Battery Capacity (kWh)	Min. Useable SOC%	Max. Useable SOC%	Electricity Range (mi)
BEV80	3.38	23.6	0%	100%	80
BEV120	3.29	36.5	0%	100%	120
BEV200	3.11	64.3	0%	100%	200
PHEV10	2.97	4.2	10%	91%	10
PHEV20	2.95	8.4	10%	91%	20
PHEV30	2.93	12.7	10%	91%	30
PHEV40	2.91	17	10%	91%	40
PHEV50	2.88	21.5	10%	91%	50
PHEV60	2.86	26	10%	91%	60
PHEV70	2.84	30.5	10%	91%	70
PHEV80	2.82	35.1	10%	91%	80

2.3   Speed Trace Data Preparation

California Department of Transportation (Caltrans) conducts the California Household Travel Survey (CHTS) every ten years to understand socioeconomic characteristics and travel behavior of households in California. The latest survey began in 2010 and concluded in 2012 (CalTrans, 2013b). Besides traditional travel diary data, the 2010-2012 CHTS also recruited 9,049 households to collect detailed information about their trips using GPS devices. There are two types of GPS data collected as part of the CHTS. The first is vehicle-based data, obtained by installing GPS devices in vehicles to collect second-by-second vehicle movement for up to seven days. This data lacks passenger and driver information. The second type of data is people-based, where all household members carried a wearable GPS device that collected their movement every three seconds for three days. Recruited households could choose either in-vehicle or wearable GPS devices; 2,808 households chose in-vehicle GPS while the other 6,241 households chose wearable GPS (Kunzmann & Daigler, 2013). For this study, only in-vehicle GPS data was used to simulate vehicle GHG emissions. A vehicle's speed may see various changes within three seconds and the temporal resolution of the wearable GPS data is too low. Since GHG

emissions are simulated based on speed trace, the second-by-second in-vehicle GPS data is preferable to get a more accurate estimation about vehicle GHG emissions. In the 2010-2012 CHTS dataset, there are in-vehicle GPS data from 1,700 households. But 360 out of the households reported in-vehicle GPS data for only one or two days. To avoid the possible randomness in reported trips, households that reported only one or two days of GPS data were excluded. In later analysis, we use 13,981 days of GPS data from 1,340 households with 2,225 vehicles in total.

2.3.1 Sample Weights

CHTS generated a poststratification weight (Holt & Smith, 1979) for each sample household to "align the weighted sample with population statistics from the latest available census data" (Kunzmann & Daigler, 2013). However, only 1,340 out of the 42,431 households in the CHTS dataset were chosen for this analysis, so the original sample weights cannot guarantee that the selected sample accurately reflects the population. Thus, a new poststratification weight was generated for the selected 1,340 households.

Originally in CHTS, the poststratification weight system was generated to reflect population statistics including household size, income, number of workers, number of vehicles, and county of residence including zero vehicles households. Thus, during the process to generate the new poststratification weights, the number of workers in the household was replaced by the number of drivers in the household, and the other four parameters remained the same.

Let $W = \{w_1, \dots, w_n\}$ denote the weight of each respondent m. Let H_k denote a set of post-stratums for variable k, $K =$

{household size, income, number of drivers, number of vehicles, county of residency}, and

P_{h_k} is the proportion of post-stratum h_k in population. The ideal weight should reflect population statistics as:

$$P_{h_k} = \Sigma_{m \in h_k} w_m / \Sigma_{m \in M} w_m \tag{2.1}$$

To calculate the ideal weight W, we first assume the weight of all respondents $w_m^{k=1,i=1} = 1$ where i represent iteration number, and generate a raking factor $r_{h_{k=1}}$ as:

$$r_{h_{k=1}}^{i=1} = E(P_{h_k})/P_{h_{k=1}}^{i=1} \tag{2.2}$$

where $E(P_{h_k})$ is the expected proportion of post-stratum h_k which is assumed known based on census data. Then, a new weight can be calculated as:

$$w_m^{k+1,i} = w_m^{k,i} * r_{h_k}^i \qquad m \in h \tag{2.3}$$

so that the new weight $w_m^{k+1,i}$ can guarantee to reflect population statistics in variable k.

In each iteration i, it needs to traverse all $k \in K$, and each step needs to repeat equation (2.2) and (2.3) to update the weight, and

$$w_m^{k=1,i+1} = w_m^{k=|K|+1,i} \tag{2.4}$$

By the end of each iteration, we can use an average raking factor to evaluate the improvement of this iteration as:

$$\bar{r}_i = 1/|K| * \Sigma_{k \in K}\{1/|H_k| * \Sigma_{h_k \in H_k}(E(P_{h_k})/P_{h_k}^i)\} \tag{2.5}$$

Over 15 iterations, the average raking factor is convergent to 1 (Figure 2.3) which means the new weights guarantee the selected sample households reflects the population statistics in terms of household size, income, number of drivers, number of vehicles, county of residency. Figure 2.4 (a, b) shows how the new sample weights influence the distribution of household vehicle ownership, and Figure 2.4 (c-e) shows the distribution of weighted number of day's data, annual vehicle miles travelled (VMT) estimation, and longest daily travel distance.
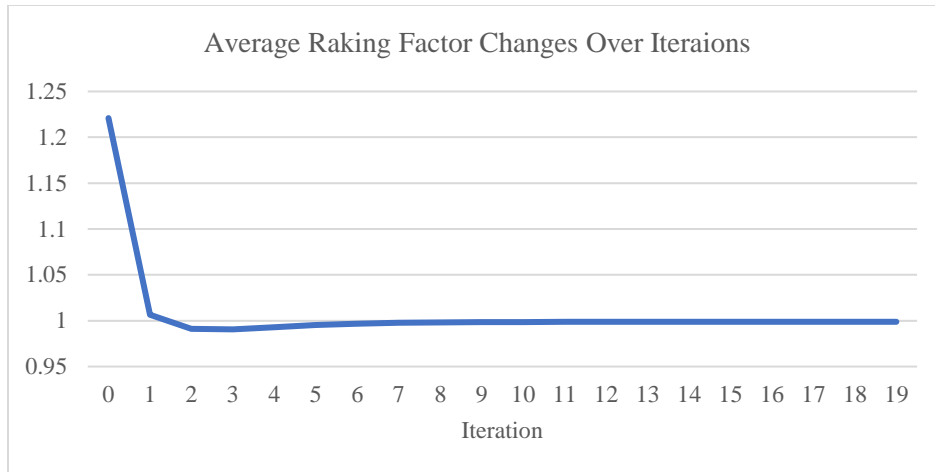
Figure 2.3 Average raking factor changes over iterations
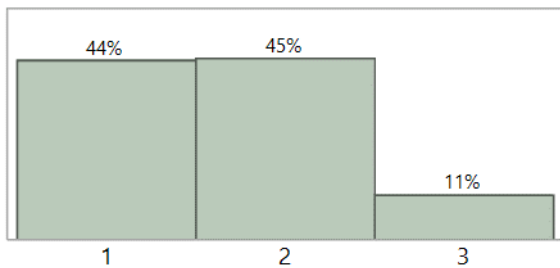
(a) Household Vehicle Ownership (w/o weight)   (b) Household Vehicle Ownership (w/ weight)
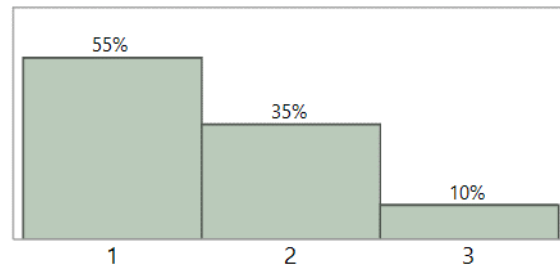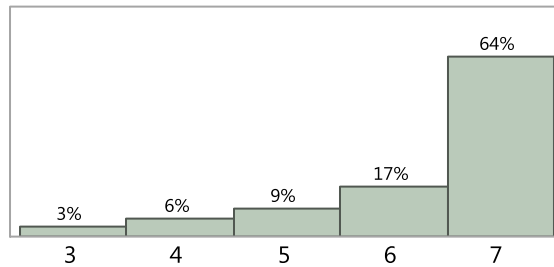
(c) Number of Day's Trip That Being Collected by GPS
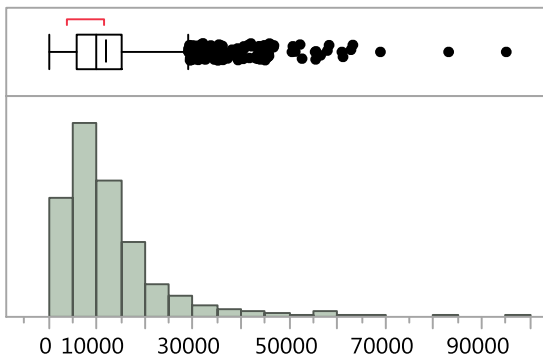
(d) Estimated Annual VMT   (e) Longest Daily Travel Distance (Mile)
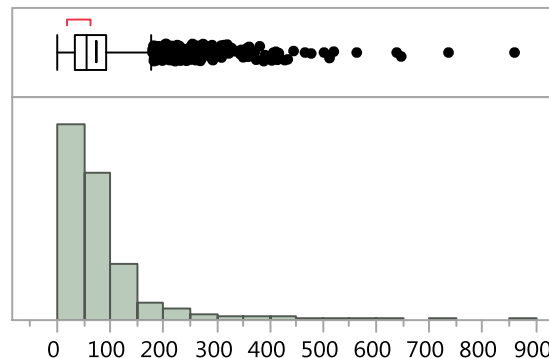
Figure 2.4 Distribution of sample data

2.3.2 The Potential Impact of Long Distance Trips

Measures of long-distance travel behavior are also important to evaluate the potential of PEVs in reducing transportation-induced GHG emissions. It requires extra charging events to complete a trip with a BEV if the trip length exceeds the BEV range. Based on previous survey, the willingness to choose a BEV for a certain trip decreases as the number of charging events necessary to complete the trip increases (Nicholas, Tal, & King, 2013). Thus, people might switch to conventional vehicles for trips that exceeds the BEV range. For PHEVs, long-distance trips mean that even a fully charged PHEV will switch to charge sustaining mode at some point during the trip, and generate significantly more emissions per mile for the rest of the trip compared to if it was operating in charge depleting mode. Furthermore, a previous study shows that 20% of respondents have one long trip account for over 5% annual VMT, and 40% respondents have one long trip that accounts for over 5% of the annual gas used (Tal & Nicholas, 2016). Therefore, long-distance trips, especially interstate trips that might happen only occasionally, can have significant impact on the annual VMT, as well as energy consumption and local emissions.

In the CHTS survey, trips over 50 miles are considered long-distance trips. There is a separate long-distance travel survey in CHTS. For this survey, respondents were asked to report all long-distance trips in the recent two months. A comparison of the annual long-distance travel mileage estimation based on the GPS data and the long-distance travel survey indicates significant difference between these two datasets (Figure 2.5). The findings were that long-distance trips under 200 miles are under-reported in the survey. The average frequency of long-distance trips under 200 miles is 0.011 trips per day in the survey, but the corresponding frequency is 0.031 trips per day based on the GPS data.

However, trips over 200 miles are reported more in the long-distance survey. The average frequency of trips over 200 miles in the GPS data is 0.00072 trips per day. But in the survey, the corresponding frequency is greater at 0.0036 trips per day. The GPS data also fails to represent some long-distance one-way trips such as moving, or one-way flights and one-way drives. All trips recorded by GPS are under 300 miles. But there are some extreme long-distance trips over 1,000 miles reported in the survey, such as coast-to-coast driving trips. Because the in-vehicle GPS devices only collected up to one week of trips, it is understandable that some occasional long-distance trips are less likely to be collected by GPS.
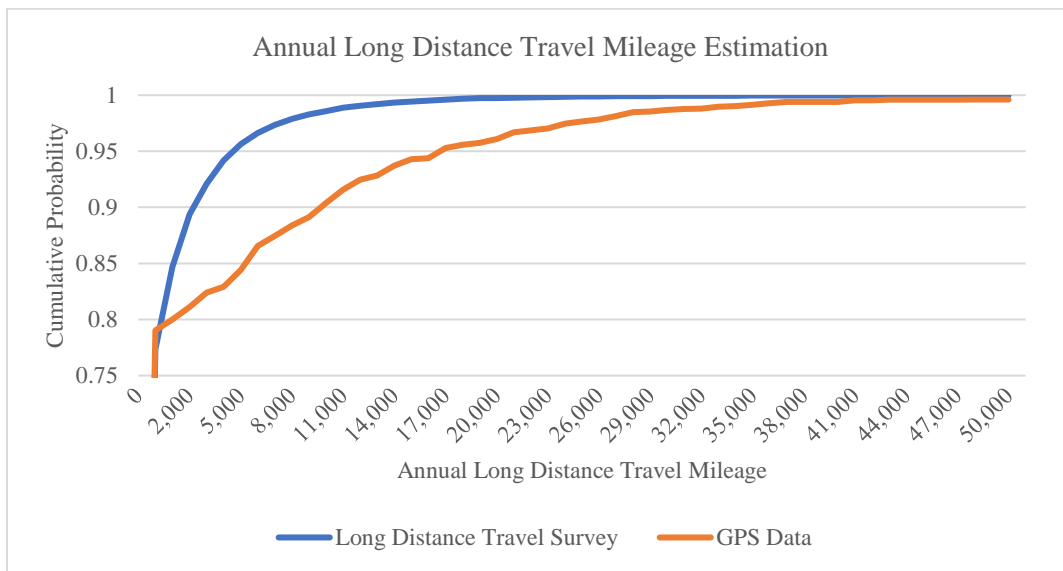
Figure 2.5 Comparison of long distance travel survey and GPS data

2.4 Scenario Analysis of GHG Emissions Reduction by PEVs

To explore the potential of reducing transportation-induced GHG emissions by implementing PEVs, we selected speed trace data from the 2010-2012 CHTS (as mentioned in Section 2.3), simulated the GHG emissions of these ICE trips if they had been completed by the PEV models listed in Table 2.4 (using FASTSim), and calculated the GHG emissions reduction achieved by each PEV model compared to a 2012 Toyota Corolla. As mentioned in Section 2.1, charging behavior could have significant impact on a PEV's GHG emissions, so it was assumed

22

that (1) drivers only charge vehicles overnight after completing all trips in a day; (2) vehicles are always fully charged before the first trip in a day; and (3) there are no extra charging events during the day. Vehicles that have one or more days with travel longer than the range of a BEV are marked as PHEV only. For example, if one vehicle has six days' speed trace and the longest daily travel distance is 150 miles, then this vehicle is marked as not suitable for BEV80 and BEV120 because the longest daily travel distance exceeds the range of these two models and vehicles are assumed to only be charged overnight, but this vehicle is still suitable for BEV200. For each vehicle, the model that can reduce GHG emissions the most is the best choice.

As Table 2.5 shows, given BEV120, BEV200 and PHEV10-80 as candidate models, for 86.5% vehicles the BEV120 was the best choice, for 8.5% of vehicles the BEV200 was the best choice, and for the remaining 5% of vehicles the PHEV80 was the best choice. If all trips are completed by each vehicle's best choice model, it can reduce annual GHG emission by 65% using a 2012 Toyota Corolla for comparison. The major factor that determines a vehicle's best choice is the longest daily miles traveled. Because it is assumed that no extra charging events will happen during the day, the PHEV80 presented the best results for all vehicles with longest daily miles over 200, and the BEV120 was the best model for most vehicles with longest daily miles within 120 miles (Figure 2.6).
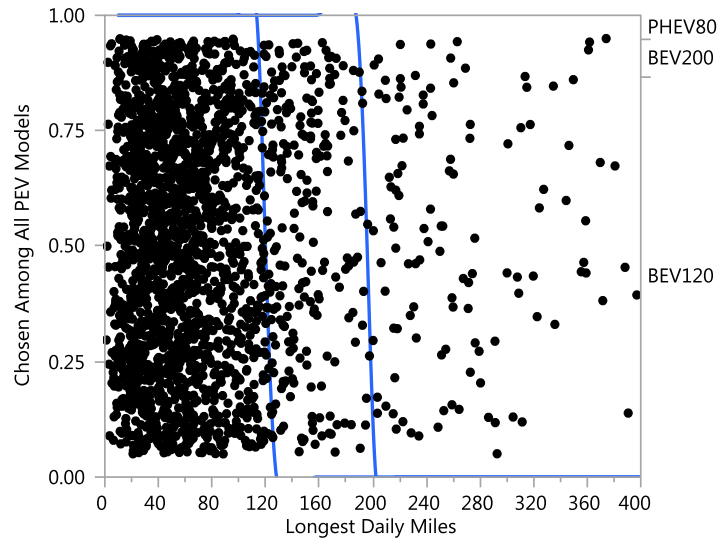
Figure 2.6 The impact of the longest daily miles to the model choice among all PEV models

In other words, when the travel distance is within the BEV range, BEVs offer a

significant advantage in GHG reduction over PHEVs. For example, if BEV120 is not available

and only BEV200 and PHEV10-80 are candidate models, the market share of PHEVs will not

increase while all vehicles that originally modeled as BEV120 will shift to BEV 200. If the

BEV200 is not available but the BEV120 is, the limit of BEV range will lead some vehicles to

switch to PHEVs, but the annual GHG reduction decreases by 1.4%.

To satisfy the travel demand for longer distances, there are more BEV models with

bigger battery capacity available in the market: for example, the 2016 Nissan Leaf provides an

option of a 30 kWh battery while the older model year has only 24 kWh (Nissan, 2017), and the

Chevrolet Bolt with a 60 kWh battery has been available since November 2016 (Chevrolet,

2017). However, a bigger battery also increases the total vehicle weight and reduces the fuel

economy. As Table 2.5 shows, if BEV120 is not available (Scenario 3), most vehicles will have

modeled to BEV200. At the same time, the annual GHG reduction achieved is also 1.4% lower

than the scenario with BEV120. If BEV 120 is replaced by BEV80, 25.1% vehicles will be

BEV200 as their best choice because of range limit. For the remaining 69.9% vehicles, they

achieve better fuel economy from BEV80 compared to BEV120. Therefore, the total annual GHG reduction achieved by BEV80, BEV200, and PHEV10-80 is only 0.4% lower than the scenario with BEV120, BEV200, and PHEV10-80 (Table 2.6). However, if there is only one range of BEV in the market, then the range should sufficient for travel distance needs. The scenario with BEV200 and PHEVs achieved the greatest GHG reduction compared to the other two scenarios with BEV80 and BEV120 respectively.

When comparing PHEVs with BEVs, the advantage of PHEVs is that there is no range limit, so only vehicles with the longest daily miles exceeding BEV range will choose PHEV80 as their best choice. However, if PHEVs are the only available models in the market, they can still achieve 60.9% of annual GHG reduction compared to the Toyota Corolla scenario, only 4.1% lower than with BEV120 and BEV200 (Table 2.5). However, if drivers forget to charge PHEVs, the vehicle will operate as a hybrid car, and it can only achieve 22% GHG reduction, as the "All PHEV Models (never charger)" scenario shows in Table 2.5.

The choice among different PHEV models mainly depends on the average daily miles, and the mean of the average daily miles of the vehicles who choose each PHEV model increases almost linearly with the battery range of PHEV models, except PHEV80 which catches all the outliers (Figure 2.7).
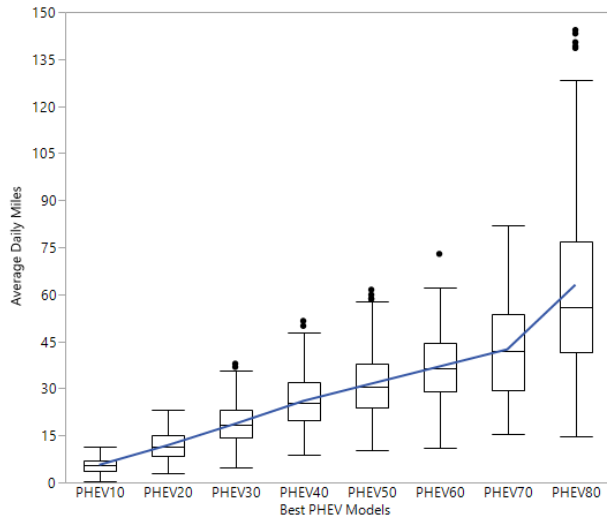
Figure 2.7 The impact of average daily miles to the model choice among all PHEV models

Increasing battery capacity can result in significantly higher benefit for PHEVs compare to BEVs in GHG reduction. As Figure 2.8 shows, the unavailability of small-range PHEV models has a slight impact on the annual GHG reduction of the whole fleet. If there are only PHEV80s available, the annual GHG reduction is reduced by 0.5% compared to if all PHEV10-80s are available. But the unviability of mid-range PHEV (20-80) models can cause increase GHG by up to 21% comparing to PHEV 10s only.
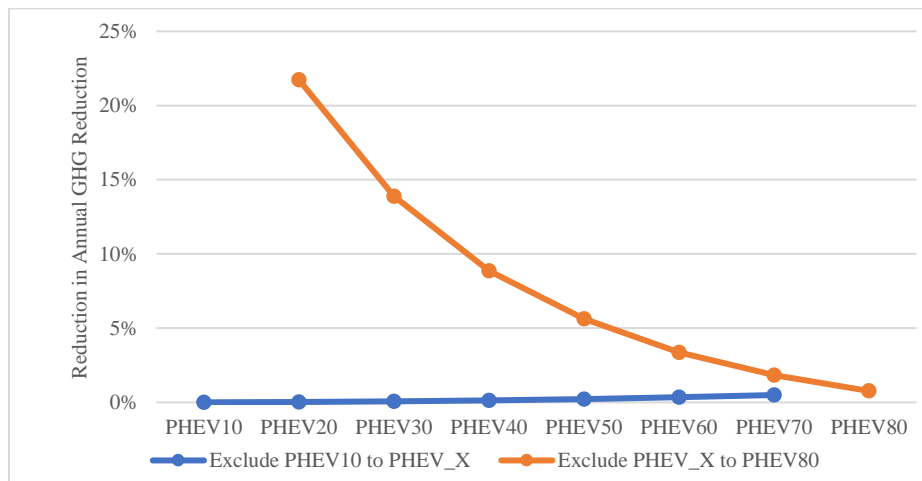
Figure 2.8 Percent decrease in Annual GHG Reduction

Table 2.5 Scenario analysis about PEV model choice at vehicle level

Candidate PEV Models	BEV84	BEV120	BEV200	PHEV10	PHEV20	PHEV30	PHEV40	PHEV50	PHEV60	PHEV70	PHEV80	Annual GHG Reductio
BEV120, BEV200, and All PHEV Models	NA	86.5%	8.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	5.0%	65
BEV120 and All PHEV Models	NA	86.5%	NA	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	13.5%	63
BEV200 and All PHEV Models	NA	NA	94.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	5.0%	62
BEV84, BEV200, and All PHEV Models	69.9%	NA	25.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	5.0%	64
BEV84 and All PHEV Models	69.9%	NA	NA	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	30.1%	62
All PHEV Models	NA	NA	NA	5.1%	16.7%	14.6%	14.4%	10.8%	9.7%	6.3%	22.4%	60
HEV Models (never charge)	NA	NA	NA	5.1%	16.7%	14.6%	14.4%	10.8%	9.7%	6.3%	22.4%	22

Table 2.6 Scenario analysis about PEV model choice at household level

Candidate PEV Models	One Vehicle Per HH		Two Vehicles Per HH			Three Vehicles Per HH		
	PHEVs Only	BEVs Only	PHEVs Only	Mix	BEVs Only	PHEVs Only	Mix	BEVs Only
BEV120, BEV200, and All PHEV Models	2.7%	52.5%	0.2%	3.9%	30.7%	0.0%	0.8%	9.3%
BEV120 and All PHEV Models	7.5%	47.6%	1.1%	7.4%	26.2%	0.1%	3.3%	6.7%
BEV200 and All PHEV Models	2.7%	52.5%	0.2%	3.9%	30.7%	0.0%	0.9%	9.2%
BEV84, BEV200, and All PHEV Models	2.7%	52.5%	0.2%	3.9%	30.7%	0.0%	0.8%	9.3%
BEV84 and All PHEV Models	18.5%	36.7%	3.5%	12.0%	19.2%	0.6%	5.8%	3.7%

Table 2.7 Scenario analysis about PEV model choice at household level with household vehicle ownership limits

Candidate PEV Models	BEV120	BEV200	PHEV10	PHEV20	PHEV30	PHEV40	PHEV50	PHEV60	PHEV70	PHEV80	Annual GHG Reducti
BEV120, BEV200, and All PHEV Models	86.5%	8.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	5.0%	65
No more than one BEV120, allow no PHEV	28.2%	32.9%	2.0%	6.4%	3.4%	5.6%	3.9%	3.3%	2.1%	12.1%	63
At least one PHEV per HH	30.3%	5.0%	4.7%	13.4%	9.8%	9.2%	6.5%	5.0%	2.9%	13.3%	62
No more than one BEV per HH	24.0%	4.8%	4.7%	14.1%	11.3%	10.4%	7.1%	6.0%	3.5%	14.0%	62
No more than one BEV120 and at least one PHEV per HH	28.2%	7.1%	3.5%	11.5%	8.8%	8.7%	6.0%	5.6%	3.0%	17.6%	62

As mentioned in Section 2.1, vehicle purchase is usually a household decision - whether a PEV can satisfy the household travel demand is an important factor that impacts adoption. Table 2.6 summarizes the scenarios being discussed in Table 2.5 at household level, and it shows that significant proportion of households have BEVs as the best model for all the vehicles in their households. Since the GPS data used in this analysis fails to represent occasional long-distance trips, it is reasonable to assume PEV model choice in Table 2.5 overestimates BEV ownership, especially the dominant market share of BEV120. Our study about the current PEV market indicates that most households who bought a Nissan Leaf also have at least one conventional vehicle as a secondary choice for long-distance trips (Tal, Nicholas, Woodjack, & Scrivano, 2013).

We further examined how household vehicle ownership could influence the PEV model choice. For households with only one vehicle, we assumed they will only consider a PHEV because it has no range limit. For households with two or more vehicles, we built five scenarios:

1. No limit on vehicle model choice

2. Each household can have up to one BEV120, and not allowed to have a PHEV

3. Each household should have at least one PHEV

4. Each household can have up to one BEV

5. Each household can have up to one BEV120 and at least one PHEV

As Table 2.7 shows, the household vehicle ownership limitations significantly change the market composition of PEV models: if it only limits the ownership of BEV120 while allowing BEV200 to satisfy the long-distance travel demand ("up to one BEV120, allows no PHEV" scenario), the market share of BEV200 will increase by over 20%; but if we assume that extra charging events are a barrier for people to use BEVs for long-distance trips, then around 70% of

the market will be composed of PHEVs. Although the market share of PHEVs increases

significantly by considering the household vehicle ownership limits, it only has a slight impact

on GHG reduction, as the annual GHG reduction decreases by no more than 2.8% among all

scenarios. Furthermore, PHEV20 and PHEV80 become the two most popular PHEV models.

Considering the impact of the longest travel distance as discussed above, PHEV80 are believed

to satisfy all the long-distance travel demand. PHEV20 becomes popular because the average

daily travel distance that characterizes most day travel is between 10 and 20 miles (Figure 2.9).

This explains why PHEV20 is the second most popular PHEV model except PHEV80 in the "All

PHEV Models" scenario in the Table 2.5.
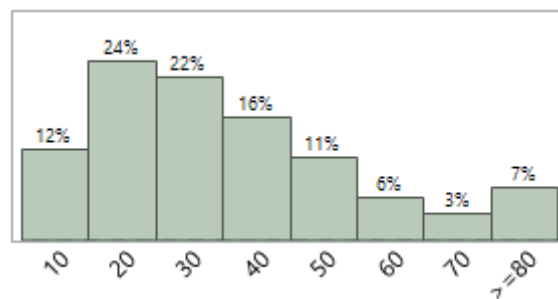
Figure 2.9 Distribution of Average Daily Miles

Additionally, vehicles with more annual VMT are more likely to choose BEVs, while

those with less annual VMT are more likely to choose PHEVs. As Table 2.8 shows, in the

scenario which allows only one BEV in the household, 94.3% of BEVs are the most used vehicle

in households with multiple vehicles; while in the scenario which requires at least one PHEV,

94.3% of PHEVs are the least used vehicle in the household. This finding is consistent with

previous results that BEVs can always achieve more GHG reduction than PHEVs, it is

reasonable to choose a BEV to replace the vehicle with higher annual VMT. Our survey about

PEV drivers also shows that BEVs have higher annual VMT than other conventional vehicles in

the same household (Ji et al., 2016). It should be noted that annual VMT has no clear relationship

with model year. Thus, choosing the newest vehicle in the households as the only BEV has

higher probability to achieve the optimal household GHG reduction than choosing the oldest one

as the only BEV, but determining BEV replacement strategy based on model year doesn't

guarantee to achieve the optimal household GHG reduction.

Table 2.8 Performance of different BEV replacement strategies comparing to the optimal strategy

	As the only BEV in the HH	As the only PHEV in the HH
Choose the most used vehicle	94.3%	4.3%
Choose the least used vehicle	4.3%	94.3%
Choose the newest vehicle	51.4%	39.9%
Choose the oldest vehicle	39.7%	52.3%

2.5 Conclusions

This paper explored the potential of PEVs in GHG reduction. Nearly one week's GPS

trace data from over two thousand California vehicles were used, and we used FASTSim to

simulate the local emission of these trips if they are completed by different vehicle models and to

find out the best vehicle model for each sample vehicle that can achieve the most GHG

reduction. It was found that when the travel demand is within the battery range, BEVs with

shorter range can always achieve better local emission reduction than BEVs with extra longer

range or PHEVs. For long distance trips exceeding the battery range of BEVs, PHEVs with

longer battery range can achieve more local emission reduction. By assigning the right vehicle

model for each sample vehicle, it can help to reduce annual GHG emission by 65% compared to

if all sample vehicles are 2012 Toyota Corolla, and BEV120 dominates the market in this

scenario with 86.5 percent.

Another contribution of this study is that we analyzed the impact of household vehicle

ownership limitations to the adoption of PEVs. If households are limited to have at least one

PHEV to overcome range anxiety, it was found that the market share of PHEVs increase by 59.7

percent. There are two segments of market for PHEVs: one is short-distance trips which can benefit from short-range PHEVs such as PHEV20, the other is long-distance trips which can benefit from long-range PHEVs such as PHEV80. In this scenario, it helps to overcome range anxiety by increasing the market share of PHEVs with limited sacrifice in local emission reduction. One potential risk of promoting PHEVs is that if people never charge their vehicle, they can only achieve about one third of the GHG reduction compared to overnight charge PHEVs.

For future studies, we suggest relaxing some of the assumptions and use real-world data as it becomes available. We assumed one full overnight charging event per day. However, as there are increasing number of public chargers available, more and more people use public chargers as a supplement/substitution of home charger on an occasional or even a regular basis. Public chargers can significantly extend the travel radius of BEVs, but the reliability of public chargers and the willingness to use public chargers are also important factors to determine whether BEVs will be used for long-distance trips. However, drivers may occasionally forget to charge overnight. Will a BEV at 50% SOC be capable to satisfy the daily travel demand, or maybe a PHEV can compete a BEV in that case? One potential focus for future studies is to explore the impact of different charging behaviors on GHG reduction using the FASTSim model and the California waited travel data.

2.6 Acknowledgements

3 ELECTRIC VEHICLE FAST CHARGER PLANNING FOR METROPOLITAN PLANNING ORGANIZATIONS: ADAPTING TO CHANGING MARKETS AND VEHICLE TECHNOLOGY

3.1 Introduction

To achieve the 2025 CAFE standard of 54.5 mpg average fuel economy, there is growing interest in battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). PHEVs have a significant advantage over BEVs in terms of long-distance travel since PHEVs have gasoline as an energy source whereas a BEV's range is restricted by the battery capacity. Improving charging infrastructure is crucial to support BEVs for long-distance trips and to give range confidence. In recognition of this, U.S. Department of Energy (DOE) announced 16 electric vehicle planning grants totaling $8.5 million in 2011 to help prepare for plug-in electric vehicles (PEVs) and charging infrastructure in 24 states (U.S. DOE, 2011). These plans were very successful in engaging stakeholders, but the science of fast charger placement was not well developed in many cases. Many plans either did not focus on this aspect or dealt with it in generalities. Building on this stakeholder engagement, these plans should be revisited to produce better guidance regarding fast charger needs. More recent behavior data, vehicle growth projections, and battery size projections make better planning possible.

There are three common charging levels: AC level 1 uses a standard 120 volt alternating current to provide slow charging (typically of 1.4 kW – 1.9kW); AC level 2 uses a 208/240 volt alternating current to provide charge power from about 1.5 kW – 19.2kW; "Fast Charging" typically refers to DC level 2 and uses a high voltage direct current to provide power from 36 to 90 kW, although DC level 1 which is less than 36kW could be considered fast charging as well

(SAE Hybrid Committee, 2011). To provide EV drivers access to longer range trips, more fast charging stations will be needed.

3.2   Background

There are various DC fast charger siting strategies planners have used to site fast charging stations. (M. A. Nicholas, G. Tal, & J. Woodjack, 2013; Tanimoto, 2013; U.S. DOE, 2013). For example, the Metropolitan Transportation Commission in the San Francisco Bay Area (MTC) derived trips by potential PEV adopters based on their own regional transportation demand model, and used it to choose sites for fast charging stations(ICF, 2012). San Diego's Association of Governments (SANDAG) identified sites based on location of existing level 2 chargers and a list of siting requirements (ECOtality, 2010; ETEC, 2010). The Sacramento Area of Council of Government (SACOG) assessed locations by analyzing existing and forecasted PEV owner demographics, corresponding driving patterns, and land uses (SACOG, 2014). California's North Coast Region built an agent-based model to identify PEV infrastructure sites (SERC, 2013; Sheppard, 2013). The West Coast Electric Highway Project proposed by the State of Washington and the Oregon Department of Transportation (DOT) is an extensive charging network with fast charging stations located every 25 to 50 miles along interstate 5 and other major roadways (Washington State Department of Transportation, 2013). However, lack of consistency among these strategies, makes comparing results difficult. Further, the data used to create these scenarios use regional travel data or simple traffic counts and do not have long distance travel, causing two issues. First, demand from outside a metropolitan area is not well represented. Many times, there is an aggregate inflow of traffic from outside an area, but not how far they traveled before drivers arrive at in a metro area boundary. This makes assessing demand difficult in both the likelihood of this traffic will be a BEV, and in what energy might be

needed. Some corridors such as highways away from cities have primarily long-distance trips while other highways have a mix of long and short distance trips. Knowing in detail the origin gives modelers the opportunity to identify trips originating in areas with a high PEV density. Knowing the destination shows how far the vehicle traveled and where along the journey they would need to charge.

This paper presents a model that uses long distance data and addresses demand coming from outside a metro region in the context of any battery size. The model will be free for any modeler to use, providing consistency in modeling fast charging given sufficient travel data. The model incorporates the latest behavior data, can assess the potential usage of current stations and assess proposed sites based on future growth and increase in battery size. A detailed explanation of the model is below followed by two scenarios showing the ability to model any distribution of demand and battery size and what effects those parameters may have on any analysis.

3.3   Model

A model was built to evaluate BEV charging demand and to assess the usage of current and proposed charger locations based on that demand. Use of this model is predicated on having access to long-distance travel data and can be used for two analysis purposes: to evaluate charging demand based on current and proposed chargers and to propose new locations based on unmet gaps in demand. The demand is presented in charge events per day or "utility" of proposed charger locations. Data on California statewide travel in gasoline vehicles is provided by a statewide survey done by the California Department of Transportation (CalTrans) in 2012 (CalTrans, 2013a).

3.3.1   Charge Windows

There are two main concepts used to evaluate fast charger utility: tours and charge windows. A tour is made up of all the travel from the time a vehicle leaves home to the time it returns home. This done because charging is likely to be available at home making it easier to assess which travel might require public charging. The concept of a "charge window" is proposed which refers to a section of a long-distance tour such that if a charger were placed anywhere in the window, the vehicle could make it to its destination. The inputs that define the charge window are chosen by the modeler. For our scenario, we assume a safety buffer of 20% state of charge (SOC) such that a vehicle will need a charge if it will fall below that level. Batteries are assumed to charge only to 80% SOC matching the point where charge rate begins to taper on most BEVs. This means that at any fast charger, only 60% of a battery can be recovered (48 miles in the BEV 80 case). For large batteries the safety buffer can be lowered so that more than 60% can be recovered.

Charge windows are shown in Figure 3.1. Assuming a BEV driver wants to travel from Elk Grove to Livermore, the distance is 85 miles, as Route D in Figure 3.1 shows. The BEV has a range of 80 miles, so one fast charge is needed to reach the destination. With a safety buffer of 20% the vehicle can only go 64 miles before needing to charge, creating an upper limit to the charge window. The maximum number of miles that can be traveled from a fast charger is 48 miles (from 80% to 20% SOC) so the lower limit of the charge window is 85-48 or at mile 37. Thus, the charge window for this trip is from mile 37 to mile 64.
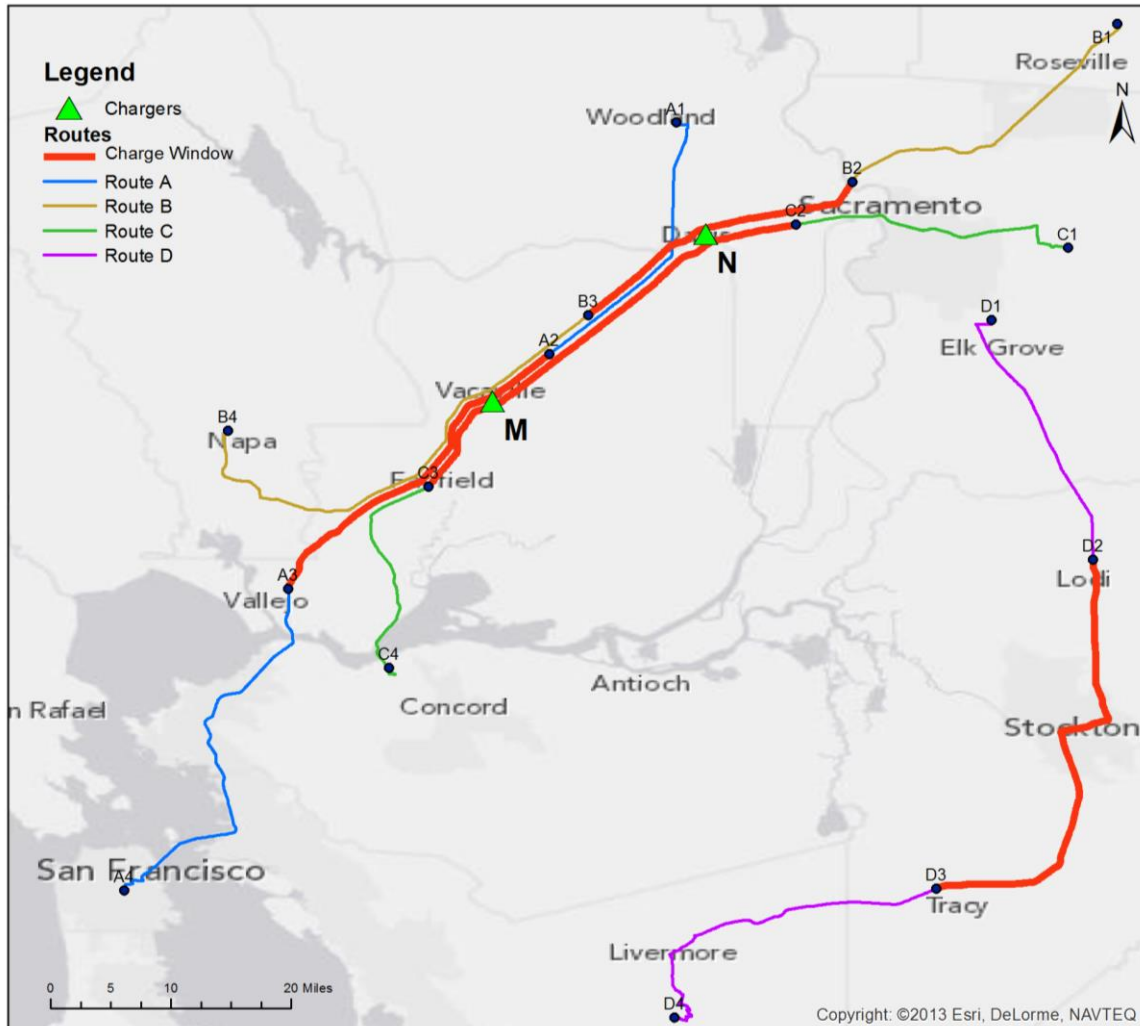
Figure 3.1 Charge window illustration

Although the trips shown in Figure 3.1 are single trips, most travel in the model is round

trip to home creating a tour. For an 85-mile tour, the same principles apply with a slight

modification if work charging is incorporated in the middle of a charge window. Routes A, B,

and C are important for evaluating utility of multiple tours and are explained later.

3.3.2   Input Parameters

Travel diary or other origin destination data are necessary to support this model. A travel

diary consists of respondents' trip information on an assigned survey date, including the location

of origin and destination, departure and arrival time, travel mode, trip purpose, etc. It is widely

used to analyze travel behavior. The ultimate goal of building a charging infrastructure is to enable travel to consumers' chosen destinations. Therefore, the model uses travel in the Caltrans Survey from trips that are currently taken in gasoline vehicles. However, alternate data sets which include origin and destination data can be used.

To prepare the data, the origin and destination trip data must be converted to tour based data, which, as previously defined, is travel done between the time the vehicle leaves home and returns home. AC level 1 and level 2 charging can also be incorporated as travel diary data include dwell times at locations as well as trip purpose. Different level 1 and level 2 scenarios can be used to test the effect on DC fast charging demand or can be used as analysis outputs themselves.

Currently, there are various models of BEVs with different ranges available in the market, e.g. the 2013 Nissan Leaf has an Environmental Protection Agency (EPA) range of 75 miles (DOE, 2014), the 2012 Mitsubishi i-MiEV has EPA range of 62 miles (DOE, 2014), and Tesla Model S has a 208 mile and 265 mile EPA range for the 60-kWh and 85-kWh battery respectively (DOE, 2014). The mo can evaluate the charging demand of a mix of BEV models by allowing users to define county-level ownership of different ranges of BEVs.

In this study, constant BEV range and vehicle efficiency are used to calculate charging demand. However, BEVs could have different vehicle efficiency on highway and local street, e.g. the 2013 Nissan Leaf has a miles per gallon gasoline equivalent (MPGe) of 129 in city and 102 on highway (DOE, 2014). Further analysis will focus on improving this evaluation.

3.3.3 Scaling

The scaling factor for each BEV model is calculated as the ratio of the number of corresponding BEVs to the number of households in each county, so that the product of this scaling factor and the household weight is the number of BEVs that each sample household

represents. For example, if there are 1000 county respondents in the survey and the county has 100 vehicles in existence then each household would represent about 1/10th of a vehicle. This of course varies since each household's scaling factor is a little different to account for underrepresented or overrepresented groups.

BEV charging is time-consuming compared with refueling a conventional vehicle, so consumers' willingness to choose a BEV for a certain trip decreases as the number of charging events necessary to complete the trip increases (Figure 3.2) (Michael A. Nicholas et al., 2013). Thus, the model has another scaling factor to account for BEV drivers choosing other modes as the number of fast charging events increases per tour.
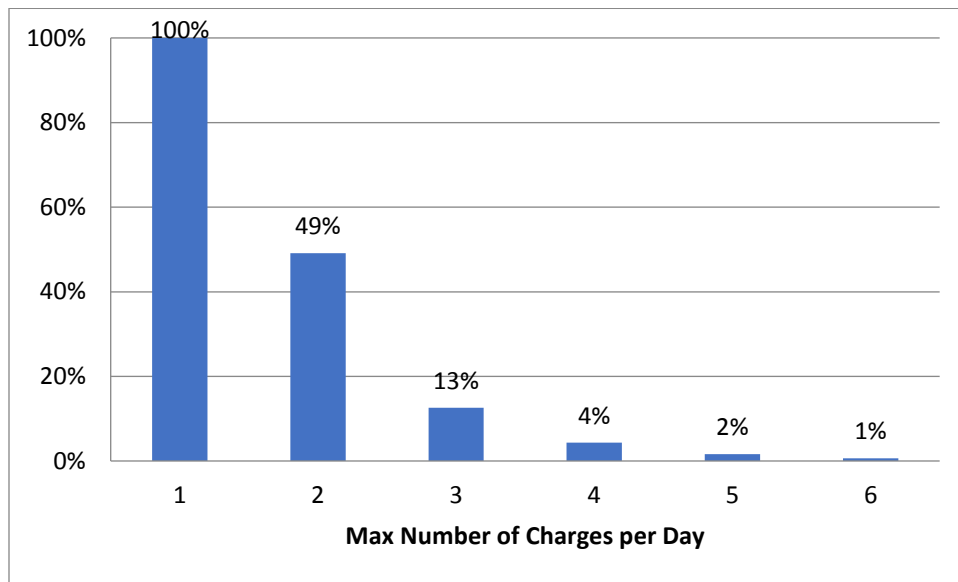
Figure 3.2 Max number of times per day subjects are willing to fast charge

As a result, the weight of each tour is:

$$W_{kx} = C_{ij} \frac{B_{ix}}{\sum_{j=1}^{N_i} C_{ij}} R_k \qquad (3.1)$$

where

W_{kx} is the final weight of $Tour_k$ for BEV with a range of x miles;

C_{ij} is the household weight of corresponding household from $County_i$ and each household

from $County_i$ has a unique identification marked as j;

N_i is the total number of sample households from $County_i$ B_{ix} is the number of BEV_x in

$County_i$;

R_k is the scaling factor of the number of required charging events within $Tour_k$.

Two further scaling factors are applied for each tour. Based on the travel survey data, not

all vehicles were used on the assigned day which could be influenced by many factors e.g.

vehicle type, travel day, residential location, etc. (Zhou, Vyas, & Santini, 2013). However, for a

state-wide model, one constant vehicle usage rate is acceptable and the idle factor consisting of

the households that drive on a certain day are divided by the total households in the survey (78%

of respondents did not travel by car in the California sample). Also a factor is applied to

decrease the demand from any one household since there may be two or more drivers and

vehicles in the household. Only one of which may be a PEV. This factor is the number of

households who drive divided by the number of total tours (48%). This results in a combined

scaling factor of 36.5% for this analysis. This last scaling factor will be updated as it is a slightly

imprecise method of reducing BEV tour probability. Using only one vehicle in a household is

also an option, but since there are so few tours, keeping the variety of tours, but reducing their

value was preferred.

3.3.4   Charging Demand Evaluation

Charging demand can be represented as a heat map created with charge windows. For

each tour, charge windows are generated for each BEV range respectively. The final weight of

each charge window is the same as the tour it belongs to. A total charging demand density can be

calculated as the line density of charge windows multiplied by the scaling factor, divided by the

length of the charge window to normalize long and short charge windows. The value of each cell represents the number of charging events per unit area.

3.3.5 Charger Utility Assessment
The utility of each charger is the combined weights of all charge windows within a user-defined search radius from the charger. However, the tool takes two different assignment strategies when assessing the utility of existing/proposed chargers versus predicting potential chargers. Different from existing chargers, the proposed ones have been approved to build but not been used yet.

3.3.6 Existing/proposed chargers
When assessing the utility of existing/proposed chargers, charging demand will be assigned evenly to all chargers within the charge window. For instance, there are two existing chargers M and N that can serve the charge windows of route A, B, and C (Figure 3.1). The charge window of route A has a weight of 4, charge window of route B has a weight of 3, and charge window of route C has a weight of 6. Charge window A and C are within the search radius from charger M, and charge window B and C are within the search radius from charger N. Thus, the utility of charger M is $4 + 6/2 = 7$ and the utility of charger N is $6/2 + 3 = 6$.

3.3.7 Potential chargers
At times modelers want to find which potential sites are the best choices. When predicting the utility of potential chargers, all unserved charge windows are assigned to all potential chargers, then the charger with the highest utility will get all charge windows assigned to it, and the two steps will repeat to assign charge windows to the next highest-utility charger until no more charge windows can be assigned. Assuming both chargers M and N in Figure 3.1 are potential chargers after the first round assignment, the utility of charger M is $4 + 6 = 10$ and the utility of charger N is $6 + 3 = 9$. Charger M has higher utility so both charger window A and

C are assigned to charger M, and the final utility of charger M is 10. In the next round assignment, only charge window B is assigned to charger N (since charger window C has been assigned to charger M), so the final utility of charger N is 3. After the desired number of chargers is chosen by the tool, the final assignment of demand is again distributed among nearby chargers as described in the existing/proposed chargers.

3.4 Data

3.4.1 2012 CHTS Dataset

Scenario analysis in this paper uses the dataset of 2010-2012 California Household Travel Survey (CalTrans, 2013a) conducted by CalTrans including 42,431 households from all of California's 58 counties. Since the travel diary doesn't have detailed information about route choice of each trip, the route with the fastest network distance between origin and destination is used to analyze respondents' travel patterns. Each trip is represented by a line, and the line density is the traffic density. The highest traffic density is located in the Bay Area and Sacramento in Northern California, and Los Angeles and San Diego in Southern California (Figure 3.3).
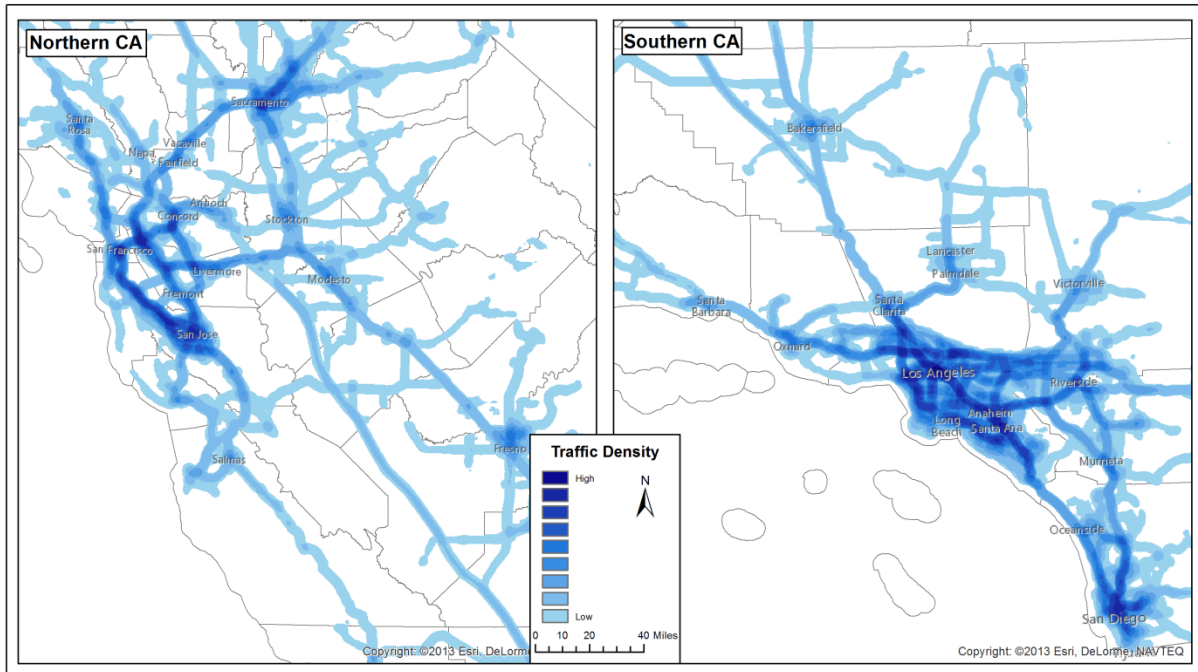
Figure 3.3 Traffic density of non-work purpose tours in California

A potential limitation of the "fastest path" method is that it might not reflect the true traffic demand when there are parallel paths. Considering traffic congestion, user equilibrium traffic assignment can be a better approximation to real traffic. For example, there are three parallel paths from the Bay Area to Los Angeles including Interstate 5, California State Route 99, and U.S. Route 101. According to the "fastest path" method, all traffic will be assigned to Interstate 5 because it is the fastest path assuming normal speeds. But such assignment could cause heavy congestion on Interstate 5 and make U.S. Route 101 a quicker path than Interstate 5. A user equilibrium algorithm can assign traffic more evenly and better simulate the travel pattern. However, the travel could be completed with the assigned paths and if a modeler has access to actual paths the tool can reflect this demand.

By converting the travel diary into home-based tours, there are a total of 70,917 tours which can be put into two categories: one has at least one trip for work purpose and is called "work tour", and the other has no trip for work purpose so it is called "non-work tour". There are

42

47,288 non-work tours which is twice more than work tours. Another study about Atlanta commute trips has similar conclusion about the share of work and non-work tours (Santini, Zhou, Elango, Xu, & Guensler, 2014). Only very few work tours are longer than 160 miles which requires more than one extra charge within a day for a BEV with a range of 80 miles or less (which accounts for most of popular BEV models expect Tesla). Because users are not expected to fast charge every day, work tours are treated separately in the tool. They can be included, included with workplace charging available or excluded. The scenarios below mostly show the demand from non-work tours to reflect the non-habitual use of fast chargers.

3.4.2   BEV Ownership

According to the Clean Vehicle Rebate Project (CVRP) from the California Air Resources Board (CARB), there are 22 BEV models available in California. The Nissan Leaf and the Tesla Model S are the two most popular models as the Nissan Leaf accounts for nearly half of the BEV market share and Tesla Model S accounts for around a quarter of the BEV market share. Currently most BEV models have a range of around 60 to 80 miles save the Tesla Model S. Further, most current fast chargers only support the Nissan Leaf and Mitsubishi i-MiEV. Therefore, the present scenario considered only the Mitsubishi i-MiEV and Nissan Leaf. There are a total of 16,961 Leafs and iMiEVs combined in the analysis representing those who received a rebate from the CVRP. As battery and powertrain technology improve, more long-range BEV models are expected to be available in the future (Offer, Howey, Contestabile, Clague, & Brandon, 2010), so the future scenario with 500,000 BEVs is interpolated using a combination of buying patterns from the Leaf and Tesla.

PEV households have higher income than the general population. According to a previous study about the PEV market in California, there is a significant difference in household income between ICE and PEV buyers. 51% of new ICE car buyers (or leasers) reported an

annual income lower than $100,000 while only 11% of PEV owners reported similar income(G.

Tal & M. Nicholas, 2013). Detailed explanation about the BEV types used in the will be given

later in the description of each sample scenario.

3.5 Sample Scenarios and Results

3.5.1 Present Scenario

The present scenario highlights the ability of the tool to perform gaps analysis to show

where chargers may be needed in the context of existing chargers. Connecting the origins with

the destinations allows the tours originating in areas with more BEVs to be weighted accordingly

and reflects where people in those regions would like to travel. This important, because getting

spatially resolved demand by road segment any other way is difficult. In the present scenario,

actual BEV ownership is sourced from CVRP rebates and used together with travel diaries from

2012 CHTS to analyze the demand of fast charging.

According to the U.S. DOE, there are 148 existing CHAdeMO fast charging stations in

California(United States Department of Energy, 2014). Additionally, at least 53 more fast

charging stations have been proposed to be built in the near future. Locations of these chargers

are used to assess potential use of these stations. Using these inputs, statewide fast charging

demand was generated by the tool (Figure 3.4). For the current scenario, a range of 80 and 60

were used with a 20% buffer. The range of vehicles decrease with highway speed, but the buffer

gives the model some margin for error when computing actual vehicle range. Based on the

tool's assessment, the average utilization of fast chargers in San Francisco is 3.9 events per

charger per day which conforms to the real utilization which is about 4.2 charging events per day

per charger (ECOtality, 2013). The modeled usage is expected to fluctuate up or down depending

on a host of factors including price, nearby services, level 2 availability, nearby homes of PEV customers, and season.
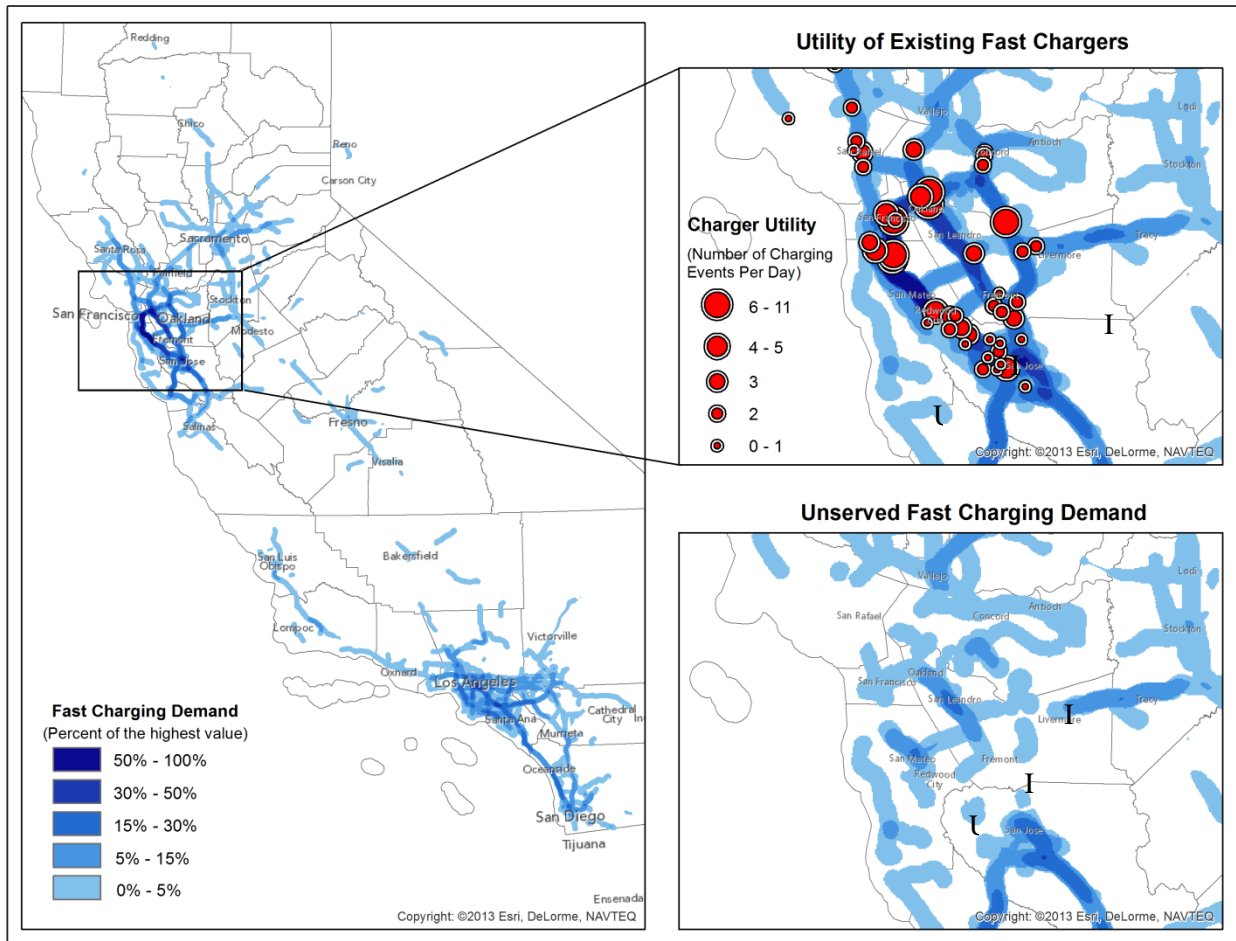
Figure 3.4 Result of present scenario with existing fast chargers

Based on the present scenario's result, the highest fast charging demand density (indicated by the colors on the map) is 0.27 charging events per square mile. Most fast charging demand is in the San Francisco Bay Area, Los Angeles and San Diego. A close-up view of fast charging demand in the Bay Area indicates that most demand is on the north-south corridors of U.S. Route 101, Interstate 880, and Interstate 680. Based on the travel survey, these are the routes most likely to be used by BEV owners. However, the demand on these three freeways are not equal. I680 in the center right has less demand than the parallel route on I880 in the center. It

could be the real charging demand, or it could represent the "parallel route" problem caused by the "fastest path" method as mentioned in section 3.1. The model indicates the most popular charger locations have a potential demand of up to 10 charging events per day.

After demand is served by existing chargers in the model, the tool reports the unserved fast charging demand for which there is no fast charger within one mile of the charge windows. The unserved demand in Figure 3.5 shows that there is a need for chargers south from San Jose connecting to Santa Cruz and Gilroy and east from Livermore to Tracy.
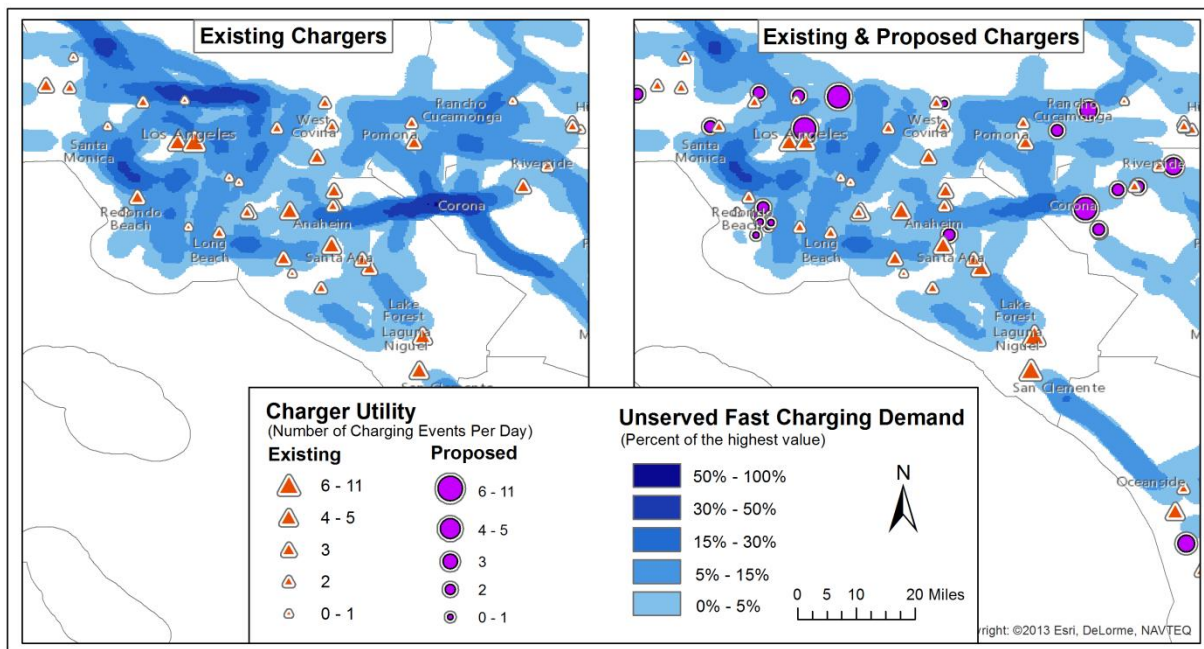
Figure 3.5 Results of present scenario with existing VS. existing & proposed chargers in Los Angeles with utility in charging events per day

The tool can also evaluate proposed chargers in the context of existing chargers. A comparison of unserved fast charging demand before and after the installation of the 53 proposed chargers taking Los Angeles as an example is given in Figure 3.5. The highest unserved demand density is 0.082 charging events per square mile which is around 1/3 of the highest served demand density. With only the existing chargers, most unserved fast charging demand is in

46

Northwest Los Angeles and Corona. But both areas have proposed chargers to be installed, and these proposed chargers can relieve charging demand to a great extent according to the results.

3.5.2 Future Scenario

The tool also helps inform policy surrounding future growth in the market with larger battery BEVs and helps answer the question of what sort of infrastructure may be needed and where. The scenario presented here provides insights into what may come. With the improvement of battery and powertrain technology, more long-range BEV models are expected to be available in the future (Offer et al., 2010), so BEVs with range of not only 80 miles, but also 150 miles and 300 miles were considered in the future scenario. Our scenario assumes that there are a total of 500,000 BEVs in California among which 50% of them are BEV 80s, 25% of them are BEV 150s and 25% of them are BEV 300s. The distribution of the 250,000 BEV 80s among California's 58 counties is assumed to be the similar to today's Nissan Leaf customer characteristics, whereas the characteristics of Tesla Model S owners were used to predict the distribution of BEV300s. The distribution of BEV 150s was a combination of Leaf and Tesla owner demographics. These distributions were created with the model by Fitch et al(Fitch, Tal, & Nicholas, 2015 Forthcoming). In general, the distribution of vehicles was much more widespread than in the present scenario because there was not geographic filter in the model. If the household fit the model in terms of income, commute, garage etc., that household would be equally likely to buy as any other household with similar characteristics.

A prediction of future fast charging demand is given in Figure 3.6. The highest fast charging demand density in the future scenario is 4.67 charging events per square mile, which is about 18 times the maximum in the present scenario.
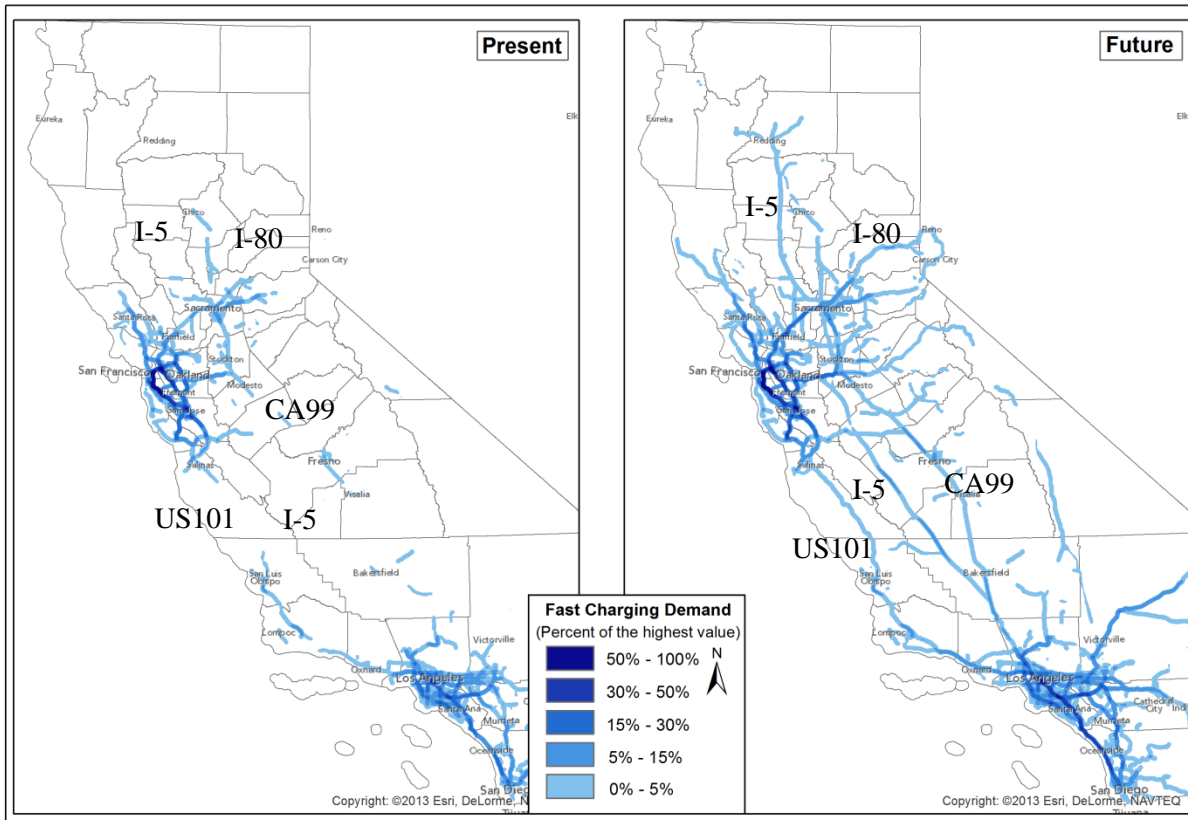
Figure 3.6 Results of fast charging demand in present scenario vs. future scenario

To highlight the change in demand location between the present and future scenario, the colors were normalized so that the highest demand in each scenario is represented by red. In the future scenario there is relatively more charging demand on long distance corridors such as Interstate 80 and Interstate 5 reflecting large battery BEVs used for longer-distance trips such as from the Bay Area to Los Angeles or from Sacramento to Oregon. Such trips can be made by a BEV 300 with one or two fast charges. Conversely, in the present scenario only CA99 shows up with any significant demand signaling that for a near term north-south corridor in California, CA99 is the clear choice.

Table 3.1 Future Scenario Results

Tour Purpose	BEV Range (Mi.)	# Cars	Total Charge Events	Total Cons. (kWh)	Average Cons. (kWh/Car/Day)	Average Cons. (kWh/Charge)	Average Charge Events/Car
Non-Work Purpose	80	250k	6731	83562.6	0.33	12.42	2.70E-02
	150	125k	1244	28906.6	0.23	23.25	9.90E-03
	300	125k	296	13167	0.11	44.41	2.40E-03
Work Purpose	80	250k	8040	117487	0.47	14.61	3.20E-02
	150	125k	474	12176.5	0.1	25.71	3.80E-03
	300	125k	73	3411	0.03	46.31	6.00E-04
All Purposes	80	250k	14770	201049	0.8	13.61	5.90E-02
	150	125k	1717	41083	0.33	23.92	1.40E-02
	300	125k	369	16578	0.13	44.93	3.00E-03

To examine the interaction between battery size and number of charging events we show scenario results in Table 3.1. As we hypothesize that non-work tours are more likely to incorporate fast charging, we separate them from non-work tours. 67% of statewide tours are non-work tours. Out of 250,000 BEV 80s, they would generate 6731 charging events on any given day on non-work tours assuming there were no public level 2. However, comparing the BEV 80 to the BEV 150 there are some important interactions.

1. Events per vehicle per day decrease by 63%

2. Electricity dispensed per charge increases by 87%

3. Energy needed per event in the state decreases by 31%

Even though the battery size of the BEV 150 is nearly double that of the BEV 80, the consumption per day per car reduces only by about 31%. This is not only due to the fact that batteries are bigger, but also because trips that are too long for BEV 80s are more palatable to BEV 150 customers since they have to stop fewer times as shown in other studies(M. Nicholas, G. Tal, & J. Woodjack, 2013).

Looking at work trips in Table 3.1we see a large apparent potential for fast charging based on distance, but we hypothesize that this demand will not materialize to this degree if

workplace charging is available as an alternative to fast charging. Due to this large potential

demand some work based fast charging could be expected in lieu of level 2 on an occasional

basis.

In the future scenario, a fast charger location might have over 170 charging events per

day (Figure 3.7), so multiple chargers are needed for certain areas. Although this demand is

represented at one point, most likely, the demand will be spread over several locations nearby the

point. Charging likewise is not expected to happen evenly throughout the day, and charging a

Nissan Leaf battery to 80% is up to 25 minutes long (ECOtality, 2013) assuming a 50kW

charger. We assume higher capacity chargers corresponding to larger battery vehicles preserving

the 20-30 minute charge times, so each charger is expected to serve an average of 15 charging

events per day(M. Nicholas et al., 2013). Therefore, a location with 170 charging events needs

about 12 chargers to satisfy all charging demand.
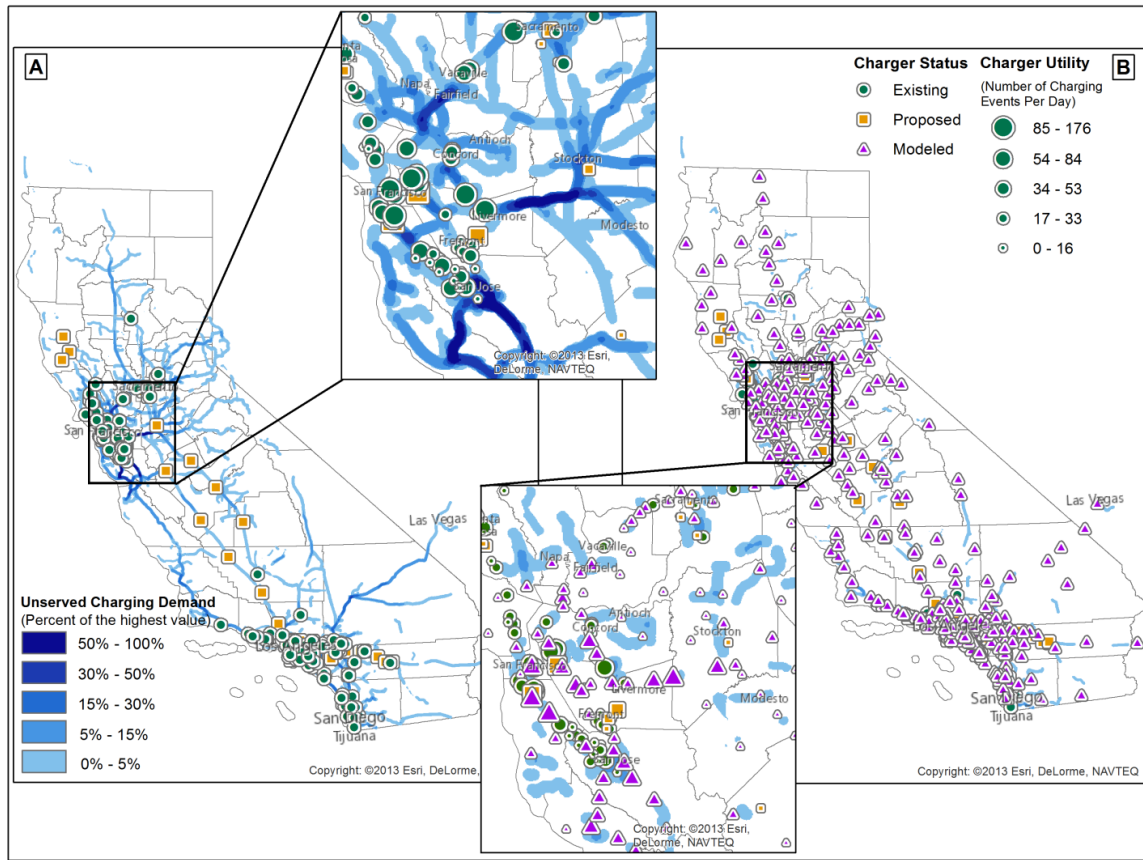
Figure 3.7 Future scenario select 300 additional sites based on potential usage

Another feature of the model is to select the best sites from possibilities input by the user.

Our analysis used 800 possible locations beyond the planned and existing sites. The model

assessed their potential utility based on the method outlined in charger utility assessment section.

The top 300 locations with the most utility are presented in Figure 3.7 as "Modeled". With the

300 modeled locations, there will be little significant fast charging demand in California based

on the input data. This compares well with previous studies(M. Nicholas et al., 2013).

3.5.3   Work Charging

Many Californians will have workplace charging in the future. Since people are not as

likely to fast charge regularly to or from work, work tours were taken out of the analysis above.

They can be included however with or without work charging. Fast charging demand reduces as

the highest level of demand in the case of "without work charging" doesn't appear in the case of "with work charging" (Figure 3.8). Including work charging allows the possibility that drivers may have non-habitual trips starting from work that may require fast charging in combination with level 2 work charging.
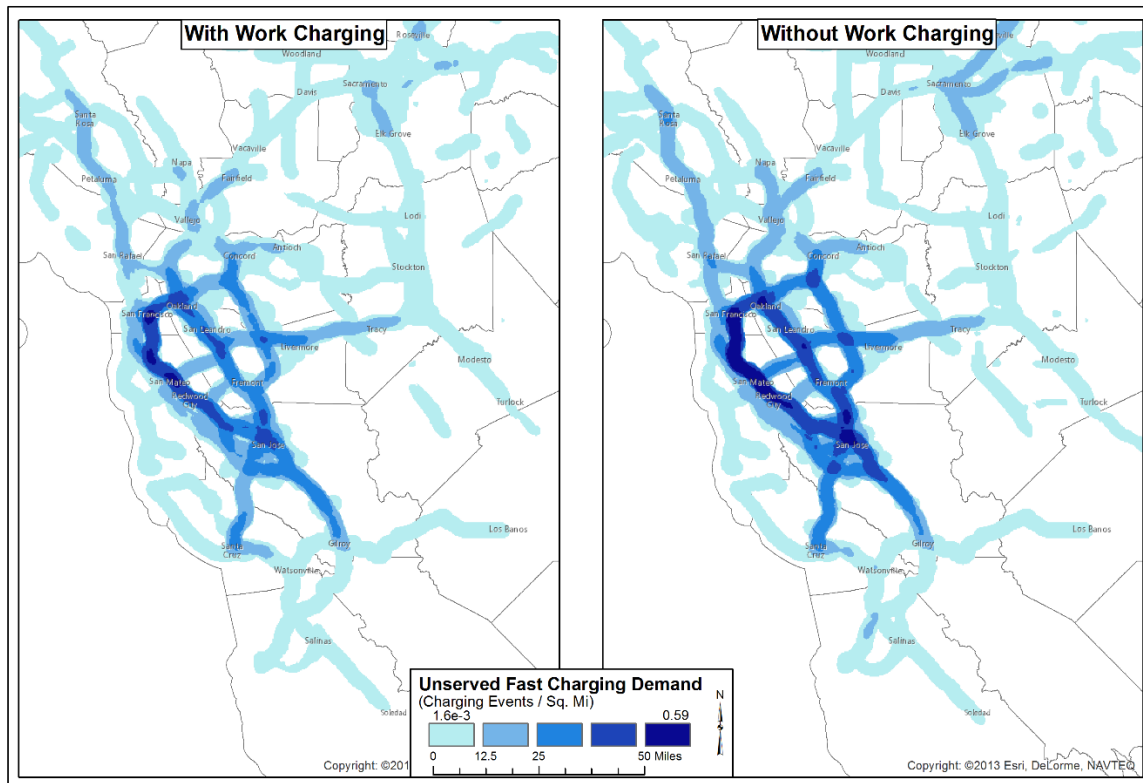
Figure 3.8 Influence of work charging on fast charging demand

The number of charge windows can give a rough estimation of fast charging demand. For the present scenario, the number of charge windows for work tours reduced by 39.8% after implementing work charging. In the future scenario, work charging can reduce fast charging demand by 25.8%. Since in the future scenario, there are more long-range BEVs, it is reasonable that work charging has less influence on fast charging demand.

3.5.4   Limitations of Regional Data

As mentioned before, fast charging demand analysis benefits from travel data beyond a regional context. To illustrate this, the results from the future scenario were separated as either

coming from those living inside a region and those coming from outside a region. The regions were identified by the census urbanized area(United States Census Bureau, 2013) and four regions were analyzed: the Sacramento Area, the San Francisco Bay Area, the Los Angeles Area and the San Diego Area. The percent of fast charger demand coming from inside the region varies with battery size (Figure 3.9).
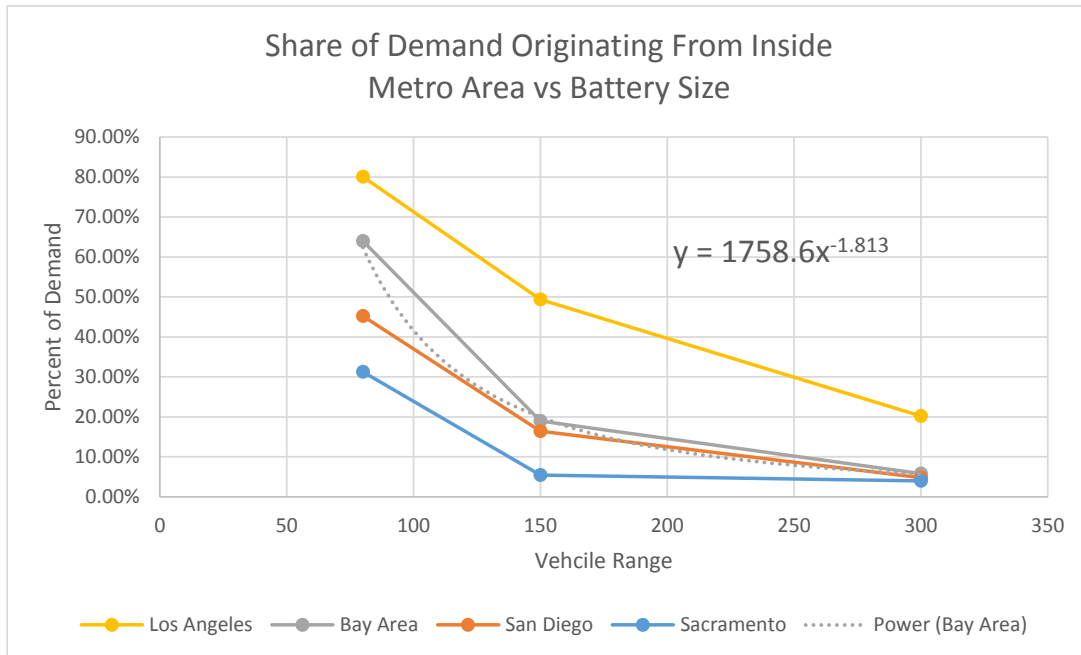
Figure 3.9 Fewer trips originate from within a metro area as battery size grows

For larger regions such as Los Angeles the "inside" demand reaches nearly 80% in the BEV 80 case meaning that a reasonably good estimation should be possible with only regional data. As the regions get smaller and as the battery size gets bigger, predicting demand becomes more difficult. For example, in Sacramento for BEV 80s, only 32% of demand is from local traffic showing the value of Statewide or greater region data.

3.6   Conclusions

This paper presents a tool which uses travel survey data to evaluate fast charging demand and to assess the utility of proposed charger locations. Compared with other existing regional

planning processes, this model can provide a statewide assessment with great consistency, and results are comparable among regions. The analysis also shows the importance of data on long distance trips in order to analyze fast charging. Even for small battery BEVs, a significant portion of demand originates outside of a region making analysis with regional data incomplete.

The scenario analysis highlights several aspects important for planners. First, planning for today's vehicles is different from planning for tomorrow's vehicles. If the distributions of vehicles shift from today's concentrations to a more even distribution, and battery size grows, the demand shifts to more areas and some demand appears on long distance corridors where before there was little. The demand in kWh from fast charging per vehicle reduces as the battery size grows due to the lower number of events although per session energy grows. Work-based demand shows an apparent high potential, but this demand may not materialize with reliable workplace charging. If the number of chargers needed at work is insufficient, fast charging may provide an important bridge to ubiquitous level 2 in the case of BEV 80s.

The analysis focusses mostly on corridor charging. Although the tool incorporates survey data on willingness to stop, there are still many further factors that may affect demand that are not reflected. This analysis does not consider level 2 demand outside of work, but this can be included in future scenarios. Likewise, some demand for fast charging will come from nearby homes or apartment dwellers who have poor access to charging. However, the tool and analysis should help identify where fast chargers are needed to enable longer trips in battery electric vehicles.

3.7   Acknowledgements

4 THE VALUE OF CLEAN AIR VEHICLES HIGH OCCOPANCY LANE ACCESS IN CALIFORNIA

4.1 Introduction

To prompt the adoption of energy-efficient, low-emission vehicles, the State of California launched the Clean Air Vehicle (CAV) Decals Program (California Air Resources Board, 2018), which grants eligible vehicles the right to use High Occupancy Vehicle (HOV) lanes without meeting the minimum passenger occupancy requirement and to use High-Occupancy Toll (HOT) lanes and some toll bridges for free or at a reduced rate. Eligible vehicle buyers need to file an application to the California Department of Motor Vehicles (DMV), and if approved they will receive CAV decals[2] to place on their vehicle. Vehicles without the CAV decals cannot take advantage of the HOV/T policy even if the vehicle model is eligible for CAV decals. This paper will explore the value of the 2019 -2022 CAV Decals Program to electric vehicle adopters, assess the accessibility of HOV/T lanes, and estimate the value of CAV decals.

The decals have two main benefits. First, users pay reduce tolls which results in direct monetary saving; and second, the use of HOV/T lane results in shorter and more reliable travel time compared to other single occupancy drivers on general purpose lanes which is important especially for commute trips (Chowdhury, Ceder, & Schwalger, 2015). This paper will explore the value of both benefits to current PEV drivers in California.

Besides the CAV Decals Program, there are also many other incentive policies to encourage purchasing PEVs. These policies can be categorized into two types: monetary purchase incentives and non-monetary recurring incentives. PEVs are currently more expensive

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[2] CAV decals are also known as HOV stickers

than conventional gasoline vehicles, so monetary purchase incentives are used to make PEVs more affordable. Monetary purchase incentives can be in the form of (1) a government grants that reduce the upfront purchase price, e.g. the plug-in car grant in the U.K. offers £4,500 off the purchase price of a BEV and £2,500 off a PHEV; (2) exemption from value-added tax (VAT) and/or purchase tax, e.g. BEV buyers are exempted from 25% VAT and 100% purchase tax in Norway (3) post purchase rebate, e.g. the Clean Vehicle Rebate Project (CVRP) in California, and (4) income tax reduction, e.g. the up-to-$7,500 federal income tax credit in U.S.. Unlike monetary incentives which occurs only one time for each purchase activity, non-monetary incentives are usually reoccurring and can be received at any increment during certain timeframe, such as public charging infrastructure, access to HOV lanes or bus lanes, parking incentives, toll waivers, etc. Studies have found close relationship between the number of incentives in place and the PEV market growth (Hardman, Chandan, Tal, & Turrentine, 2017; Hardman, Turrentine, et al., 2017) as these policies help to reduce the operating cost or increase the convenience of owning a PEV in comparison to a conventional gasoline vehicle.

California is using CAV access to HOV/T lanes as an incentive for many years. Hybrid vehicles received Yellow CAV decals starting from 2005 under Assembly Bill (AB) 2628. Yellow CAV decals were limited to the first 85,000 applicants, and they expired on July 1, 2011. White CAV decals are issued to an unlimited number of qualifying zero emission vehicles which are typically battery electric vehicles (BEVs) and hydrogen fuel cell electric vehicles (FCEVs). Green CAV decals are issued to transitional zero emission vehicles (TZEVs) or enhanced advanced technology partial zero emission vehicles (Enhanced AT PZEVs) which are typically plug-in hybrid electric vehicles (PHEVs). Green CAV decals were originally limited to the first 40,000 applicants, but the limit was increased several times and eventually removed pursuant to

Senate Bill (SB) 838. Both white and green CAV decals will expire on January 1, 2019 according to AB 266. The new-generation red CAV decals started to be issued in March 2018 and will be valid from January 1, 2019 to January 1, 2022 according to AB 544. Vehicles issued green or white CAV decals in 2017 or 2018 are eligible to reapply for the red CAV decals.

Previous studies about EV policies found that the yellow CAV decals were an important incentive to prompt the early adoption of hybrid vehicles (Diamond, 2009; Sangkapichai & Saphores, 2009). Similarly, the white and green CAV decals were important incentives for PEV adoption – in some cases the decal itself was the reason for some consumers' choice of a PEV over a conventional vehicle (Tal & Nicholas, 2014). There were significant differences in consumer's response to the CAV decals across regions in California as HOV/T accessibility varies by region (Sheldon & DeShazo, 2017).

However, there are a limited number of studies that estimate the value of the CAV decals. Shewmake and Jarvis (Shewmake & Jarvis, 2014) compared the difference in the sale price of used hybrid vehicles with and without a CAV decal, and they found that the average willingness to pay for four-year access to the HOV lanes is $3500-$4000. Sheldon et al (Sheldon et al., 2015) built a vehicle choice model based on consumer survey data, and the study indicates that the average value of one-year HOV access is about $900. Bento et al (Bento, Kaffine, Roth, & Zaragoza-Watkins, 2014) estimated the average benefit of a CAV decal in southern California is $743 per year by employing a regression model to describe the interaction between CAV decals and unpriced congestion in Los Angeles. This paper provides a new approach to estimate the value of CAV decals by calculating the toll reduction and the value of travel time saved with CAV decals based on a PEV travel activity simulation developed with survey data.

Studies about current PEV buyers show that the PEV purchase behavior have some effect of self-selection as the people with commute distance shorter than the battery range are more likely to adopt a PEV (G. Tal & M. A. Nicholas, 2013), and households with multiple vehicles are more likely to use PEVs for their daily commute trips while using the conventional gasoline vehicle for occasional long-distance trips (Khan & Kockelman, 2012; Tamor & Milačić, 2015). The impact of the CAV decals is also highly correlated with commute time both from the cost reduction perspective and the time saving. Therefore, this paper will focus on commute trips and estimate the value of CAV decals based on commute trips.

Current policy adopted in California allow PEV buyers to choose between CVRP rebate or HOV access. This paper will explore the value of the decals to current drivers and will help policy makers in estimating the total dollar value of the policy. Furthermore, this paper will allow estimating the preferred choice by region and vehicle type and will help refine this type of future policies.

In this paper, we first describe the survey that was conducted to understand PEV travel activities and PEV owners' attitude toward the CAV Decals Program. Following that is an explanation of how the value of CAV decals is estimated in this paper, analysis of the importance and value of CAV decals, and a concluding discussion about what our results imply for future analysis and policy making.

4.2 Methodology

4.2.1 Data description

A web-based cross-sectional survey was designed to better understand PEV owners in California. This survey was first implemented in April 2015, targeting all CVRP applicants as of that time. Two additional phases of survey were implemented in August 2016 and June 2017, each one targeting new CVRP applicants not covered in the previous survey phase. The sample

in each phase was generated randomly based on the list of CVRP applicants. Over all three phases of the survey, in total 18,782 households started the survey and 73% of them completed the survey with a median completion time of 33 minutes. The data collected includes their home location, household vehicle ownership, commute trips, attitude towards different incentive policies, etc. Table 4.1 presents descriptive statistics of the sample.

Since the survey was sent to CVRP applicants, all the sample households were eligible for the CAV Decals Program. However, only 79.5% of respondents have CAV decals (Table 4.1). For those who don't have a CAV decal, 44% say they think CAV decals are not useful to them and 25% say it is because DMV ran out of stickers when they applied or their application is pending. Some other popular reasons include that they don't know of the incentive, don't know how to apply, or are concerned about the aesthetics and don't want to place the CAV decals on their vehicles.

We also asked in the survey how many times the respondent used HOV/T lanes, whether the CAV decals helped to reduce toll costs, and if so how much do they save. These answers will help to validate our simulation about PEV driver's driving activity and HOV/T lane access in the later analysis.

Table 4.1 Sample Descriptive Statistics

Characteristics (sample size)	N (%)	Characteristics (sample size)	N (%)
Gender (13637)		**Annual Household Pre-tax Income (12625)**	
Female	3613 (26.5%)	Less than $50,000	382 (3.0%)
Male	9903 (72.6%)	$100,000 to $149,999	2625 (20.8%)
Decline to state	121 (0.9%)	$150,000 to $199,999	2263 (17.9%)
		$200,000 to $249,999	1486 (11.8%)
Age (13637)		$250,000 to $299,999	973 (7.7%)
18 to 29	574 (4.2%)	$300,000 to $349,999	555 (4.4%)
30 to 39	2780 (20.4%)	$350,000 to $399,999	308 (2.4%)
40 to 49	3589 (26.3%)	$400,000 to $449,999	232 (1.8%)
50 to 59	3411 (25.0%)	$450,000 to $499,999	155 (1.2%)
60 to 69	2237 (16.4%)	$50,000 to $99,999	1679 (13.3%)
70 to 79	817 (6.0%)	$500,000 or more	594 (4.7%)

80 or older	112 (0.8%)	Prefer not to answer	1373 (10.9%)
Decline to state	117 (0.9%)		
		Number of HOV/T Lane Access Monthly (13637)	
Home Belonging MPO (13637)		Less than 1	2416 (17.7%)
MTC	5241 (38.4%)	1-5	3173 (23.3%)
SACOG	824 (6.0%)	5-10	1731 (12.7%)
SANDAG	1128 (8.3%)	10-20	1817 (13.3%)
SCAG	5405 (39.6%)	20-30	2163 (15.9%)
Others	1039 (7.6%)	30-40	1268 (9.3%)
		Over 40	1069 (7.8%)
Vehicle Type (13637)			
BEVs	6948 (51.0%)	**CAV Decals Ownership (13637)**	
PHEVs	6684 (49.0%)	No	2800 (20.5%)
		Yes	10837 (79.5%)
Education Level (12627)			
Grade 8 or less	9 (0.1%)	**CAV Decals Reduce Toll Costs (10453)**	
Some High School	22 (0.2%)	No	7810 (74.7%)
High School Graduate or GED	173 (1.4%)	Yes	2643 (25.3%)
Some College	1422 (11.3%)		

Continuous Variables	**Mean**	**SD**
Commute Distance (miles)	17.41	19.67
Household Size	2.86	1.25

(Education Level continued):

College Graduate	4022 (31.9%)
Some Graduate School	899 (7.1%)
Masters, Doctorate, or Professional Degree	6045 (47.9%)
Prefer not to answer	35 (0.3%)

CAV decals allow vehicles to use HOV lanes without meeting the minimum passenger occupancy requirement. There were nearly 1,500 mile HOV lanes that existed as of 2016 and over 750 mile HOV lanes under construction or that have been planned/proposed (Caltrans, 2016). In Northern California, HOV lanes are only operational on Monday through Friday during posted peak hours; in Southern California, HOV lanes are generally operating 24-hours a day, 7-days a week.

According to AB 1721, vehicles with CAV decals can also use toll bridges under the jurisdiction of the Metropolitan Transportation Commission (MTC) at a reduced rate and HOT/express lanes for free. Existing HOT/express lanes in California that vehicles with CAV decals can use for free include:

- Interstate 10/110 Metro ExpressLanes, Los Angeles County
- Interstate 15 Express Lanes, San Diego County
- 91 Freeway ExpressLanes, Orange County

- State Route 125 South Bay Expressway, San Diego County
- State Route 237 Express Lanes, Santa Clara Valley
- Interstate 580 Express Lanes, Alameda County
- Interstate 680 Southbound Express Lane, Alameda County
- Interstate 680 Express Lanes, Contra Costa

As Figure 4.1 shows, most existing HOV/T lanes and all the toll bridges on which CAV decals are applicable are within the jurisdiction of the Metropolitan Transportation Commission (MTC), Southern California Association of Governments (SCAG), San Diego Association of Governments (SANDAG), and Sacramento Area Council of Governments (SACOG). Survey respondents from these four Metropolitan Planning Organizations (MPOs) account for 92.4% of the total sample (Table 4.1). Thus, later analysis will focus on these four MPOs only.
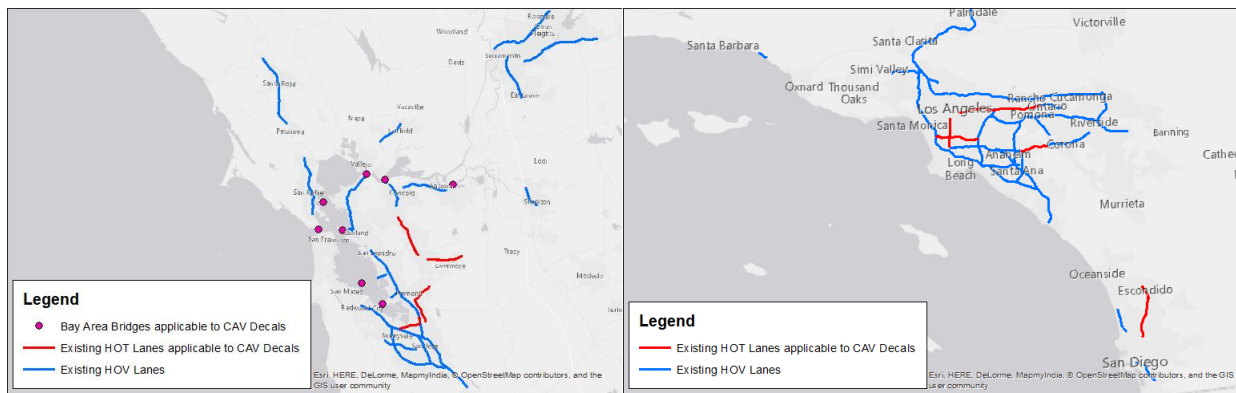
Figure 4.1 HOV/T Lanes in California

To correct the unequal probabilities of selection in the sample which might lead to bias, sample weights were developed according to CVRP statistics considering PEV types and associated MPOs (Table 4.2), and the weighted sample is expected to better represent the spatial distribution of California's current PEV market.

Table 4.2 Survey Sample Weight Construction

Vehicle Type	MPO	CVRP Statistics	Survey Sample	Weights
BEV	MTC	54309	3097	17.54
BEV	SACOG	4283	379	11.30
BEV	SANDAG	11300	604	18.71
BEV	SCAG	51581	2343	22.01

PHEV	MTC	27232	2144	12.70
PHEV	SACOG	2972	445	6.68
PHEV	SANDAG	6252	524	11.93
PHEV	SCAG	45328	3058	14.82

4.2.2 CAV decals value estimation

CAV decals grant vehicles ability to drive on HOV lanes without meeting the minimum passenger occupancy requirements and to use HOT lanes for free or at reduced rate. As mentioned above, nearly half of the survey respondents who don't have a CAV decal said CAV decals are not useful to them, which might because they rarely use HOV/T lanes in their daily driving activities. From a driver's perspective, the value of CAV decals consists of (1) the reduced toll costs and (2) the value of travel time saved. Therefore, the value of CAV decals can vary a lot depending on specific driving patterns and the corresponding HOV/T lane accessibility. For each driver i, the corresponding value of CAV decal c_i is:

$$c_i = m_i + v_i * h_i \qquad (4.1)$$

where m_i is the toll cost reduction, v_i is the value of time and h_i is the travel time saved on HOV/T lanes. What's more, assuming that a CAV decal in each time period, t, is valued as c_t, the net present value of a CAV decal at time t is:

$$NPV(t) = \int_t^T c_s e^{-r(s-t)} \, ds \qquad (4.2)$$

where T is the time when the CAV Decals Program will end and r is the rate of time preference.

4.2.2.1 Toll cost reduction with CAV decals

In our survey, respondents were asked to report their home and work locations. Based on this information, the shortest path was generated for each home and work location pairing. The commute route was matched to the layout of existing HOV/T lanes in California and toll bridges under the jurisdiction of MTC to simulate the total length of HOV/T lanes that the corresponding respondent could use in a commute trip, and then the corresponding toll cost reduction and the value of travel time savings to be calculated.

The toll of HOT lanes may change over time based on real-time traffic conditions (Alameda County Transportation Commission; Caltrans, 2017; Metro Express). Prior to the entrance of each HOT lane segment, there will be electronic signs to display the current toll. Single-occupied vehicle drivers can compare the toll price with their willingness to pay (Abulibdeh & Zaidan, 2018) to determine if they will take the HOT lane. Toll rate increases when congestion is getting worse to reduce the number of vehicles entering HOT lanes, thus maintaining the flow speed. Once a vehicle enters a HOT lane, the toll rate for this vehicle will be locked until the vehicle exits the HOT lane. There are usually upper and lower bounds for the toll rate. For example, the minimum toll rate of I-10/110 HOT lanes is $0.10/mile during off-peak hours and $0.35/mile during peak hours, and the maximum toll rate is $1.50/mile (Metro Express, 2016). In later analysis, we will conduct scenario analysis, and set the toll rate of HOT lanes to be $0.10/mile, $0.35/mile and $1.50/mile respectively in each scenario, considering round-way commute trips on each work day, assuming 5 work days per week and 52 weeks per year to calculate the annual total toll cost reduction for each survey respondent. The toll rates of Bay Area bridges for regular vehicles and carpool vehicles are fixed (Table 4.3) and will also be used to calculate the total toll cost reduction with CAV decals.

Table 4.3 Toll Costs of Bay Area Bridges (FasTrak)

Bridge	Regular	Carpool	Toll Cost Reduction with CAV Decals
Golden Gate Regular Toll with FasTrak	$7.50 $6.50	$4.50	$3.00 $2.00
San Francisco - Oakland Bay	$6.00	$2.50	$3.50
Antioch Benicia - Martinez Carquinez Dumbarton Richmond - San Rafael	$5.00	$2.50	$2.50

San Mateo - Hayward			

4.2.2.2 *The value of travel time saved with CAV decals*

There are many studies about the value of travel time savings (VTTS). Small (Small, 2012) reviewed the empirical literature and concluded that the average value of time for commute trips is typically around one-half of the gross wage rate; values rise with wage rate but less than proportionally, and drivers value time by 25% to 55% higher under congested conditions than under free flow conditions. Brownstone and Small (Brownstone & Small, 2005) analyzed the State Route 91 and I-15 toll facilities and found the value of travel time is between $20-$40 per hour, which is typically 50%-90% of the wage rate of the sample. For simplification purposes, the value of travel time savings for each respondent was calculated as one-half of their corresponding wage rate in this paper.

The travel time saving of each respondent was simulated using an Monte Carlo approach (Mooney, 1997). Flow speed on HOV/T lanes and adjacent general purpose lanes during peak hours[3] were achieved from the Caltrans Performance Measurement System (PeMS) (Caltrans) to generate a probability distribution of travel time saved per mile on HOV/T lanes compared to general purpose lanes (shown in Figure 4.2). The total travel time saved for one commute trip will be the total distance of HOV/T lanes along the commute trip multiplied by the simulated travel time saved per mile on HOV/T lanes.

People are expected to use HOT lanes when their VTTS is equal or higher than the toll rate. For example, the average flow speed of I-10E from 2/26/18 to 3/2/18 is 50mph on HOT lanes and 35mph on the adjacent general-purpose lanes based on PeMS data, so a driver can save about 0.5 minutes for each mile on HOT lanes. Assuming the VTTS of a driver is $40/hour, the

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[3] In this paper, peak hours refer to 5:00 a.m. – 10:00 a.m. and 3:00 p.m. to 7:00 p.m. from Monday to Friday.

driver will be willing to pay $0.33/mile on HOT lanes, which is close to the minimum toll rate of

I-10 during peak hours.
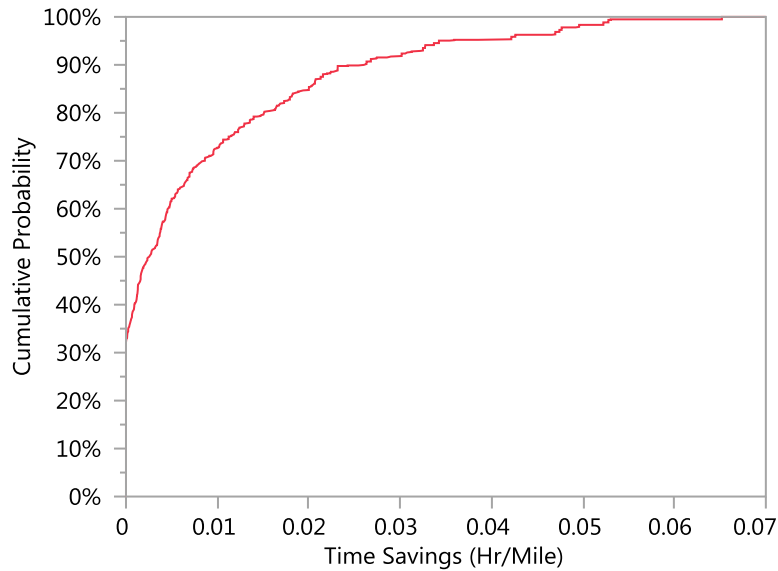
Figure 4.2 Cumulative Distribution Function of Travel Time Saved on HOT Lanes on I-10/110 During Peak Hours on Weekdays Based on PeMS Data

4.3   Results

4.3.1   The importance of CAV Decals Program

There are various monetary and non-monetary incentive policies to encourage consumers

to adopt PEVs. These include the up-to-$7,500 federal tax credit, the CVRP rebate, and other

local rebate programs (e.g. San Joaquin Valley Air Pollution Control District Drive Clean!

Rebate Program, subsidies for installing home chargers, utilities credit to PEV owners, free or

reduced rate workplace charging, preferred parking location, discounted parking, and the CAV

Decals Program). However, some incentive programs have specific eligibility criteria; for

instance, PEV lessees are not eligible for the federal tax credit which is usually $7,500 for BEV

purchasers and around $4,000 for PHEV purchasers depending on the specific battery range; and

consumers with gross annual income above the income cap[4] are not eligible for the CVRP rebate, which is $2,500 for BEV drivers and $1,500 for PHEV drivers.

In the survey, we asked respondents to rate the importance of each incentive policy on a -3 to +3 scale where -3 means *not important* and 3 means *very important*. Respondents were also asked to rank the relative importance of all applicable incentive policies. As Table 4.4 shows, the CAV Decals Program is recognized as one of the three most important incentive policies by over 60% of respondents across the four respondent groups. PEV lessees gave the CAV Decals Program relatively higher ranking compared to PEV purchasers. This is because PEV lessees are not eligible for the federal tax credit, which is generally the most important incentive policy for PEV purchasers. The CVRP rebate is generally the most important policy for PEV lessees and the second most important policy for PEV purchasers. Another interesting finding is that PHEV drivers gave the CAV Decals Program relatively higher ranking compared to BEV drivers, as the sum of monetary incentives available for PHEVs is lower than for BEVs. These findings indicate that the CAV Decals Program is one of the most important incentive policies, and CAV decals are on par with the federal electric vehicle tax credit and CVRP rebate in importance.

Table 4.4 The importance of CAV Decals Program in PEV purchase decision

Ranking	BEV Lease	BEV Purchase	PHEV Lease	PHEV Purchase
1st	27.77%	22.87%	36.95%	29.12%
2nd	25.39%	9.97%	23.09%	10.23%
3rd	17.53%	27.82%	12.59%	21.78%
4th+	14.61%	21.15%	10.75%	18.03%
Not Applicable	14.71%	18.19%	16.62%	20.84%
Total Respondents	3868	2908	2828	3733

[4] CVRP income cap is $150,000 for single filers, $204,000 for head-of-household filers, and $300,000 for joint filers

On the other hand, there is also a significant number of respondents who gave the CAV Decals Program a fourth or even lower ranking while some others didn't even apply for the CAV Decals Program. We further asked respondents about how frequently they used HOV/T lanes and whether CAV decals help to reduce the cost of tolls. By comparing the self-reported monthly number of uses of HOV/T lanes with their rating of the importance of the CAV Decals Program, we find that the more people use HOV/T lanes, the more travel time is saved, which corresponds to their valuation of the importance of CAV decals (Figure 4.3). Similarly, we found that if a CAV decal helps to reduce the cost of tolls, it becomes more important (Figure 4.4). The opposite case is that CAV decals are useless for people who don't have access to HOV/T lanes in their daily travel activities, and this is the primary reason why some people do not have a CAV decal. These findings also support the equation (4.1) proposed in section 4.2.2 that the value of CAV decals consists of the toll cost reduction and the value of travel time savings.
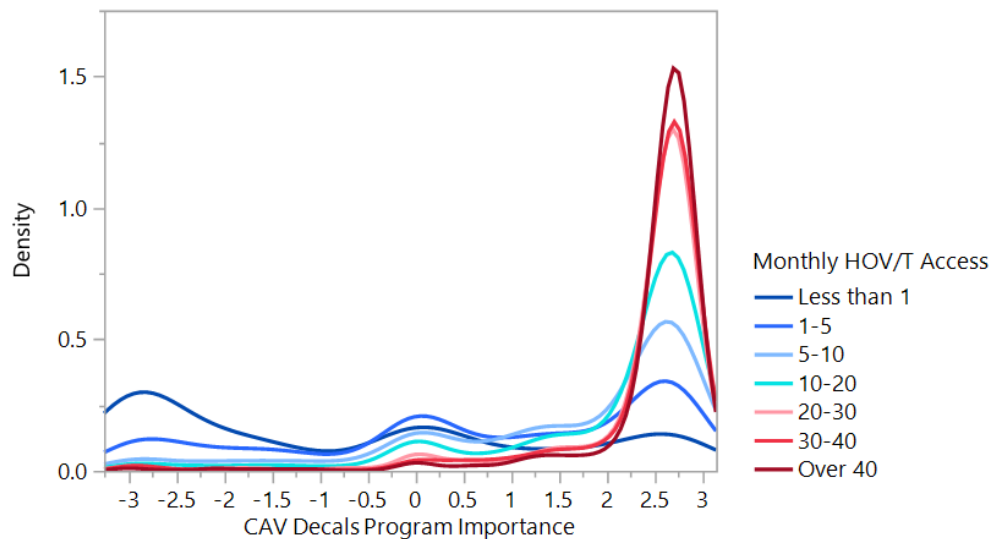
Figure 4.3 CAV Decals Program Importance VS. Monthly HOV Access
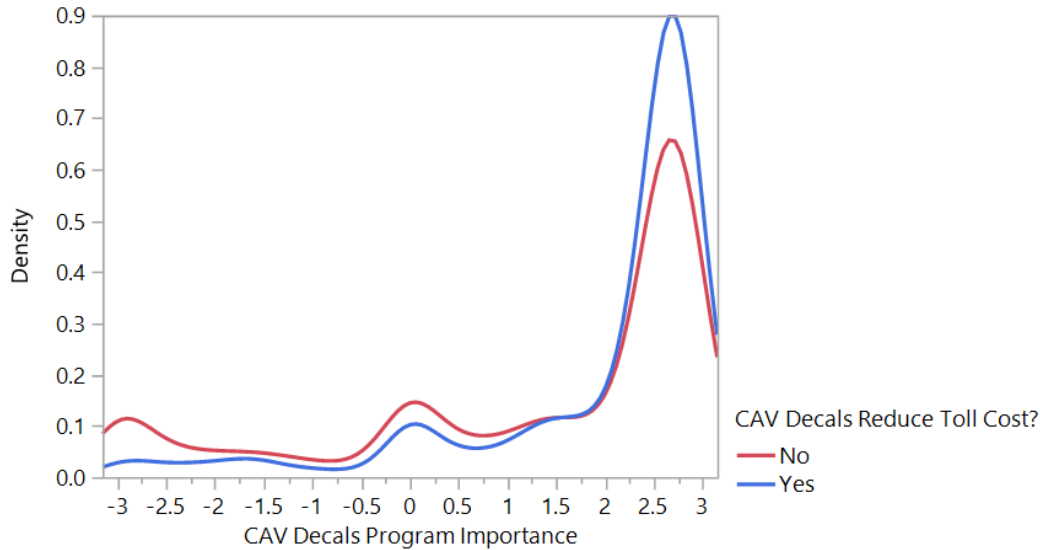
Figure 4.4 CAV Decals Program Importance VS. Toll Cost Reduction

4.3.2 The accessibility of HOV/T lanes

As discussed in the last section, the importance of CAV decals depends on the frequency people use HOV/T lanes: according to the survey results, as the frequency of a person's HOV/T access increases the CAV Decals Program also increases in importance. We further explored factors that impact HOV/T lane access frequency, and we found that it is positively correlated with the HOV/T lane density near home, as Table 4.5 shows.

Another interesting finding is that a significant proportion of respondents only use HOV/T lanes a few times per month (see Table 4.5). If the normal traffic condition on one person's commute route during peak hours is light congestion or worse and the traffic flow speed on HOV/T lanes is reliably higher than general-purpose lanes, we expect the person to use HOV/T lanes very often, such as 20 times per month. One possible reason for low HOV/T access frequency is that the trip is being done at time were traffic flow speed is similar across different lanes (maybe there is no traffic in general or maybe the HOV/T lanes have similar congestion condition), so drivers with CAV decals won't choose HOV/T lanes on purpose or they don't think they take advantage of HOV/T lanes even if they drive on them. Additionally, some people

might only have HOV/T lane access on some non-commute trips, in which case the access

frequency is expected to be lower.

Table 4.5 Monthly HOV/T Access VS. HOV/T Lane Density Near Home

Monthly HOV/T Access	Number of Respondents	HOV/T Lane Density Near Home			
		Mean	Std. Error	Mean of Lower 95%	Mean of Upper 95%
Less than 1	1792	1.12E-04	5.02E-06	1.00E-04	1.20E-04
1-5	2924	1.32E-04	3.93E-06	1.20E-04	1.40E-04
5-10	1679	1.65E-04	5.19E-06	1.50E-04	1.70E-04
10-20	1771	1.80E-04	5.05E-06	1.70E-04	1.90E-04
20-30	2134	2.01E-04	4.60E-06	1.90E-04	2.10E-04
30-40	1241	2.13E-04	6.04E-06	2.00E-04	2.20E-04
Over 40	1047	2.19E-04	6.57E-06	2.10E-04	2.30E-04

As Figure 4.1 shows, the density of HOV/T lanes is significantly different across

different regions. Generally, people who live in MTC's jurisdiction have the shortest distance to

the nearest HOV/T lanes from their home (Figure 4.5), followed by SCAG and SANDAG.

SACOG has the longest distance from home to the nearest HOV/T lanes among these four

MPOs. Correspondingly, respondents from MTC and SCAG rate the CAV Decals Program

relatively more important than those from SANDAG and SACOG.
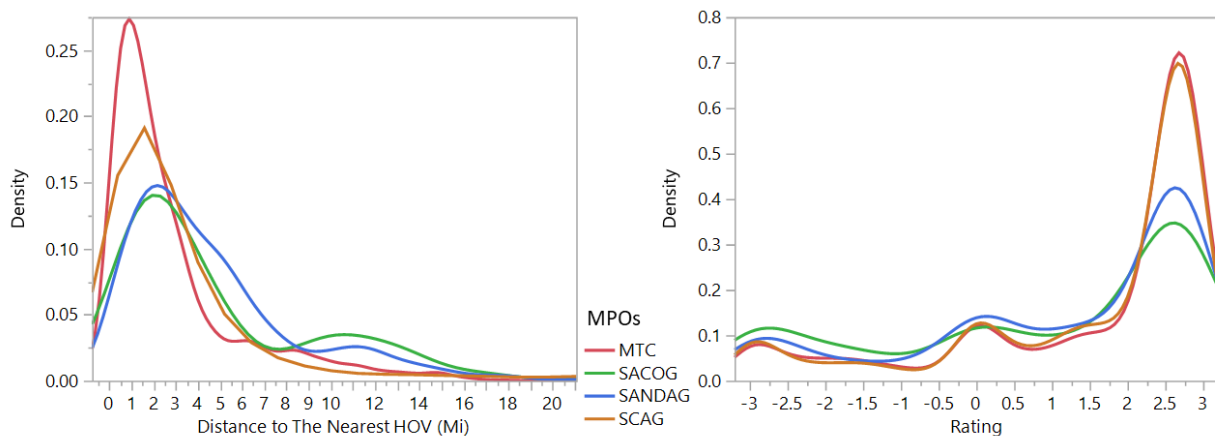
Figure 4.5 Distance from Home to The Nearest HOV/T Lanes VS. CAV Decals Program Rating

If we focus on commute trips only, there is also significant difference in terms of the

accessibility of HOV/T lanes along the commute route among different regions (Figure 4.6). As

Table 4.6 shows, the average commute distance of respondents from different MPOs is similar. However, 53.5% of respondents from MTC have access to HOV/T lanes, and the total length of HOV/T along their commute route is on average 40.4% of the commute distance. Furthermore, 15.4% of respondents from MTC use Bay Area bridges along their commute routes, and they enjoy reduced toll rates because of the CAV decals. Similarly, 48.7% of respondents from SCAG have access to HOV/T lanes on their way to work, and the shared length of HOV/T accounts for 43.9% of the commute distance on average, which is even higher than MTC. In contrast, fewer than 40% of respondents from SANDAG and SACOG have access to HOV/T lanes, and the shared length of HOV/T is around 30% of the commute distance on average, much lower than MTC and SCAG.
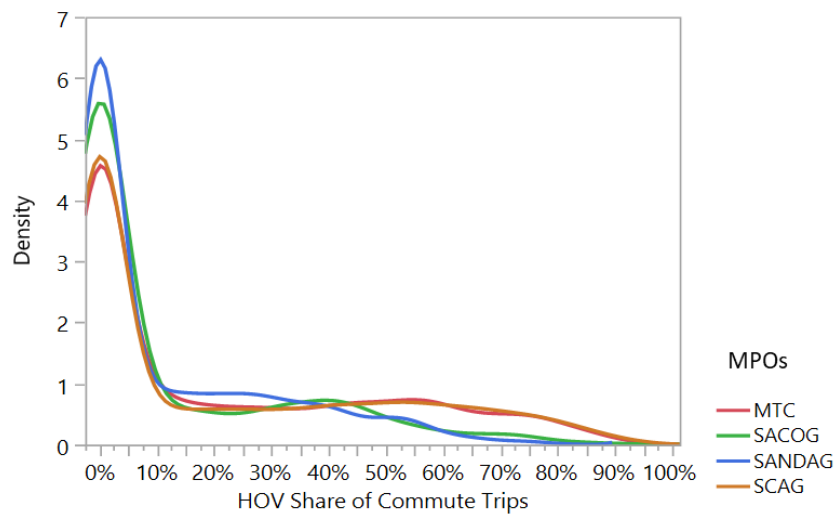
Figure 4.6 Commute Distance and HOV Share Length

Table 4.6 Statistics Summary of Commute Trips

	Number of Respondents	Commute Distance (mi)		% of Respondents Have Access Along Commute Trip	
		Mean	Std. Dev.	HOV/T Lanes	Bay Area Bridges
MTC	5240	16.59	59.63	53.52%	15.40%
SACOG	824	17.73	73.84	37.53%	4.00%
SANDAG	1127	16.05	66.09	39.68%	0.00%
SCAG	5396	17.66	84.11	48.74%	0.00%

We focus only on HOT lanes and Bay Area bridges where people with CAV decals can get toll cost reduction, and we find that 15.4% of respondents from MTC have access to Bay Area bridges along their commute routes and 13.7% of them have access to HOT lanes (Table 4.7). In terms of the length of accessible HOT lanes along commute routes, respondents from SCAG and SANDAG have longer HOT lanes than those from MTC. Since only a few respondents from SACOG have access to HOT lane, the corresponding length of HOT lanes is less meaningful.

Table 4.7 Simulated HOT lanes and Bay Area bridges access on commute trips

	MTC	SACOG	SANDAG	SCAG
Number (Percent) of sample with access to HOT lanes	714 (13.7%)	9 (1.1%)	199 (17.6%)	554 (10%)
Median HOT lanes length along commute route (excl.0)	4.62	26.40	7.29	7.39
Mean HOT lanes length along commute route (excl. 0)	6.70	22.80	7.67	8.37
Std. Dev. HOT lanes length along commute route (excl. 0)	25.08	18.82	22.95	27.93
Percent of sample with access to Bay Area bridges	15.4%	4.0%	0.0%	0.0%
Percent of sample with toll cost reduction	28.3%	4.1%	17.6%	10.0%

4.3.3   The value of CAV decals

4.3.3.1   *Toll cost reduction*

In the survey we ask a direct question to estimate the toll cost reduction because of the CAV decals. The question asked for the dollar value saving per selected timeframe, for example "I save $12 per week" or "$40 per month" etc. As Table 4.8 shows, between 12.15% and 31.71% of respondents from the four MPOs reported that CAV decals help to reduce the toll cost of either HOT lanes or bridges in the jurisdiction of MTC. It is interesting to find that although MTC has the highest percent of respondents who enjoy toll cost reduction with CAV decals, SCAG and SANDAG have higher median annual toll cost reduction and even higher mean annual toll cost reduction. One possible explanation is that a large proportion of respondents from MTC enjoy toll reduction at bridges only. By comparing Table 4.8 with Table 4.7, it can be found the percent of sample with toll cost reduction along commute route simulated in Table 4.7

is roughly close to the reported number in Table 4.8. The median and mean toll cost reduction in MTC is lower than SANDAG and SCAG, since 15.25% of sampled commuters in MTC have access to Bay Area bridges which provide a fixed cost reduction, while the toll cost reduction of respondents from SCAG and SANDAG is from HOT lane toll reduction which increases along with the travel distance on HOT lanes.

The comparison between Table 4.7 and Table 4.8 also indicates that there is a higher percentage of respondents from SACOG and SCAG who reported toll cost reduction than results simulated based on reported commute trips. We believe those toll cost reductions are from non-commute trips. For example, there are no HOT lanes in SACOG's jurisdiction, so respondents can only enjoy toll cost reductions from trips to MTC or even the SCAG and SANDAG regions, which would not be regular commute trips for most of the population. Unfortunately, due to the lack of knowledge about people's non-commute trips, we are unable to simulate those trips in this study.

Table 4.8 Self-reported annual toll cost reduction with CAV Decals

	MTC	SACOG	SANDAG	SCAG
Percent of sample with toll cost reduction	31.71%	12.15%	17.66%	20.50%
Median annual toll cost reduction (excl. 0)	300	100	480	360
Mean annual toll cost reduction (excl. 0)	541.36	292.34	959.83	1039.23
Std. Dev. of monthly toll cost reduction	3478.81	1220.95	4354.54	6740.42

A comparison of the overall distribution of simulated and self-reported toll cost reduction (Figure 4.7) finds that the percent of the sample with toll cost reduction is higher based on self-reported data than commute based simulation. But in general, the Empirical Cumulative Distribution Function (ECDF) curve of self-reported toll reduction is close to the ECDF curves of 35 cents/mile simulation scenarios which is the minimum toll rate during peak hours, and about 5% respondents report higher toll reduction but still lower than the $1.5/mile peak hours

toll rate upper limit. This indicates that the commute trips can explain most of the toll cost

reduction.
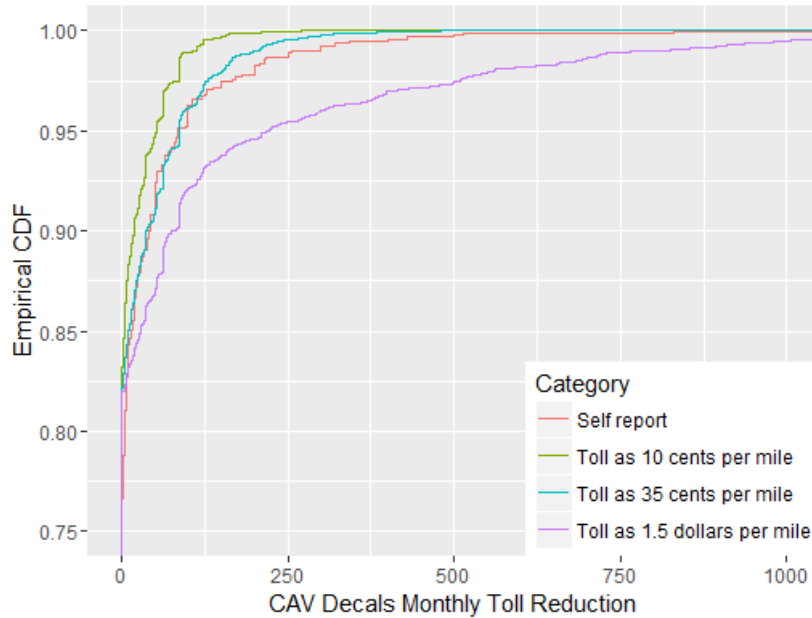
Figure 4.7 Comparison of Simulation Approaches

4.3.3.2 *Value of travel time savings*

Travel time saved on HOV/T lanes compared to adjacent general-purpose lanes is

simulated using a Monte Carlo approach based on PeMS traffic flow speed data, and the value of

per travel time savings is simplified as half of the gross wage rate, as described in section 4.2.2.2.

Around 30% of the sample will save travel time by driving on HOV/T lanes. Samples from

SCAG have the highest mean length of accessible HOV/T lane along commute trips, and the

median and mean annual value of travel time savings (VTTS) on HOV/T lanes are also higher

than the other three regions. Although the mean HOV/T length along commute trips (excluding

0) is higher in SACOG than MTC, the median and mean annual VTTS of SACOG is lower than

MTC which is likely because the wage rate of respondents in MTC is higher than in SACOG.

The percentage of the sample that save time using the HOV/T lanes (Table 4.9) is lower

than the corresponding percentage of sample who have access to HOV/T lanes along commute

trips (Table 4.6). This indicates that having HOV/T lane access does not necessarily mean saving travel time. When there is no traffic congestion on general-purpose lanes, the traffic flow speed should be similar across different road lanes. This also helps to explain the lower-than-expectation HOV/T access frequency in Table 4.5.

Table 4.9 Simulated annual value of travel time savings

	MTC	SACOG	SANDAG	SCAG
Percent of sample with travel time savings	35.74%	23.97%	25.46%	31.76%
Mean HOV/T Length Along Commute Trips (excl. 0)	9.22	10.34	7.76	11.56
Std. Dev. HOV/T Length Along Commute Trips (excl. 0)	30.25	33.92	30.41	42.10
Median annual VTTS (excl. 0)	436.33	366.76	294.01	436.43
Mean annual VTTS (excl. 0)	1392.32	1064.88	835.37	1513.4
Std. Dev. of monthly VTTS	9905.9	6370.5	7847.3	12675.9

4.3.3.3 *Total value of the CAV decals*

The total value of a CAV decal for each respondent is calculated as the sum of the self-reported toll cost reduction on HOT lanes and Bay Area bridges and the value of travel time saved on HOV/T lanes. As Table 4.10 shows, 52.08% of the sample from MTC will find CAV decals useful to them, which means the CAV decals help to reduce toll cost, to save travel time, or both. SCAG has the second highest percentage of sample to whom CAV decals are useful, and the median and mean annual value of CAV decals (excluding samples to whom CAV decals are not useful) of samples from SCAG is the highest among all four MPOs. As discussed in the previous section, it is because people from SCAG drive longer on HOV/T lanes. Although a higher percent of the sample from MTC will find CAV decals useful, many of them only enjoy fixed toll cost reduction at Bay Area bridges and travel time saved on HOV lanes but will not use HOT lanes in their daily commute trips, so the median and mean value of CAV decals in MTC is lower than SCAG. It is as expected that samples from SANDAG and SACOG value CAV decals lower than SCAG and MTC, especially for SACOG where there is no HOT lane or bridge where CAV decals can help to reduce toll cost.

Table 4.10 Value of CAV Decals

	MTC	SACOG	SANDAG	SCAG
Percent of sample to whom CAV decals are useful	52.08%	30.27%	35.34%	42.36%
Median annual value of CAV decals (excl. 0)	496.23	285.05	368.78	500.00
Mean annual value of CAV decals (excl. 0)	1236.74	939.31	991.42	1566.42
Std. Dev. of annual CAV decals value	8952.30	5859.80	7402.20	12182.60
NPV of median 3-yr. CAV decals value (r=5%, excl. 0)	1418.93	815.08	1054.48	1429.71
Percent BEVs value CAV decals higher than CVRP rebate	17.40%	7.81%	11.33%	15.24%
Percent PHEVs value CAV decals higher than CVRP rebate	25.16%	13.64%	14.75%	22.14%

Figure 4.8 shows the median NPV of 3-year CAV decals of samples in each census tract.

Due to the limited sample size and considering we are still in early market stages of the PEV

adoption process, over 95% of census tracts have sample sizes of 5 or smaller. However, the

spatial distribution of CAV decals value does appear to be higher closer to HOV/T lanes or at

locations with higher density of HOV/T lanes, which is consistent as discussed in section 4.3.2.

However, it is evident that the spatial distribution of CAV decal value is also related to

the PEV market. Considering the relatively high price of PEVs and limited size of the used PEV

market, it has been found that PEV drivers have higher income levels in general compared to the

general population (Diamond, 2009; Hidrue, Parsons, Kempton, & Gardner, 2011). A significant

proportion of higher income people live in suburban areas and commute to downtown areas for

work. Thus, we find that there are some census tracts which are relatively farther away from

HOV/T lanes but the median value of CAV decals in those census tracts is even higher than

some census tracts nearer to the HOV/T lanes. Furthermore, most census tracts near the I-10/110

HOT lanes in downtown Los Angeles are lacking CAV decals value estimation, which means no

survey respondents live in those areas. Considering the actual income level and vehicle

ownership of residents in those areas, we believe that in those areas contain very few PEV

owners.
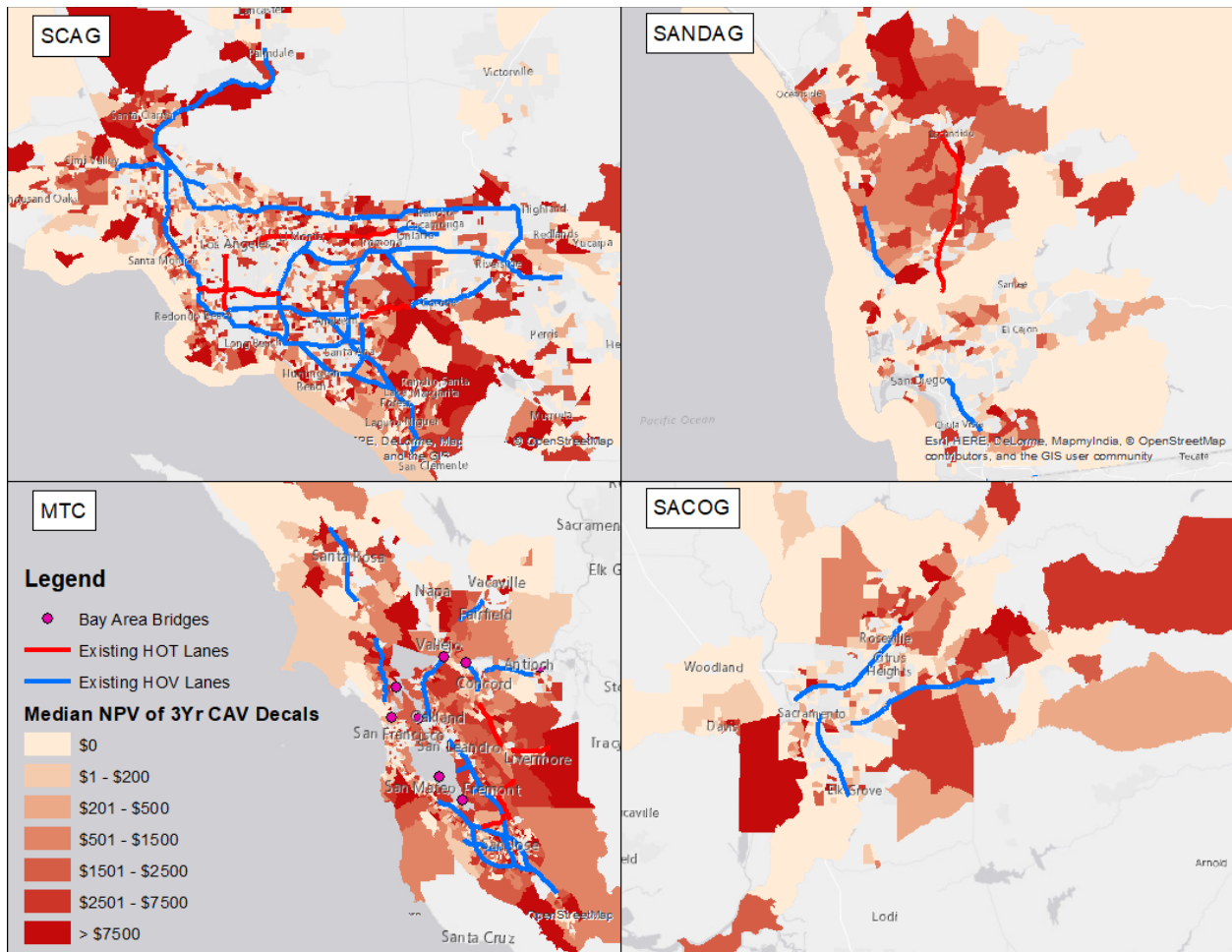
**Figure 4.8 Spatial Distribution of CAV Decals Value**

4.4 Discussion

Effective on January 1, 2018, applicants cannot participate in both the CAV Decals

Program and the CVRP unless income restriction requirements are met (California Deparment of

Motor Vehicles, 2018), which means EV buyers need to make a choice between the two

incentives. The CVRP rebate is a simple one-time monetary incentive: the standard rebate is

$1,500 for a PHEV and $2,500 for a BEV, consumers with gross annual incomes above a certain

threshold are not eligible to apply, and low-income consumers can receive extra rebate dollars

(California Clean Vehicle Rebate Project, 2018). But the value of a CAV decal consists of the

time savings on HOV lanes and the toll reduction on HOT lanes which could be variable for

different people depending on their daily HOV/T access. Therefore, it is expected that extensive

HOV/T lanes and Bay Area bridges users will find the NPV of a 3-year CAV decal is higher for them compared to the CVRP rebate, especially for PHEV owners whose CVRP rebate rate is lower.

The NPV of 3-year CAV decals was compared with the corresponding CVRP rebate rate of each sample to see how many people are likely to get CAV decals with value higher than the CVRP rebate (Table 4.10). For samples from MTC, 17.4% of sampled BEV owners and 25.16% of sampled PHEV owners will find the NPV of 3-year CAV decals exceeds the corresponding CVRP rebate, so a rational decision for them is to choose the CAV Decals Program instead of the CVRP rebate. A similar percentage of the sample from SCAG will prefer the CAV Decals Program over the CVRP, while in SACOG a much lower percentage of sample will choose the CAV Decals Program. We find that in all four MPOS, a higher percetage of PHEV owners (compared to BEV owners) value CAV decals higher than CVRP, which is consistent with the ranking results in Table 4.4.

If we don't consider the actual type of PEV each sample respondent purchased, and assuming there is no significant difference between PHEV and BEV drivers in terms of the accessibility of HOV/T lanes, then comparing the NPV of 3-year CAV decals with the PHEV and BEV CVRP general rebate rate finds that for 25% of the MTC sample the NPV of a 3-year CAV decal exceeds the PHEV CVRP rebate rate and for 17% of the sample it exceeds the BEV CVRP rebate rate (Figure 4.9). This is similar to the results in Table 4.10. By comparing the distribution of the NPV of 3-year CAV decals across different MPOs, it is evident that SCAG has a longer tail than MTC, indicating that more people in SCAG value CAV decals extremely high compared to MTC. The high standard deviation of the annual CAV decal value in SCAG in Table 4.10 supports the same story.
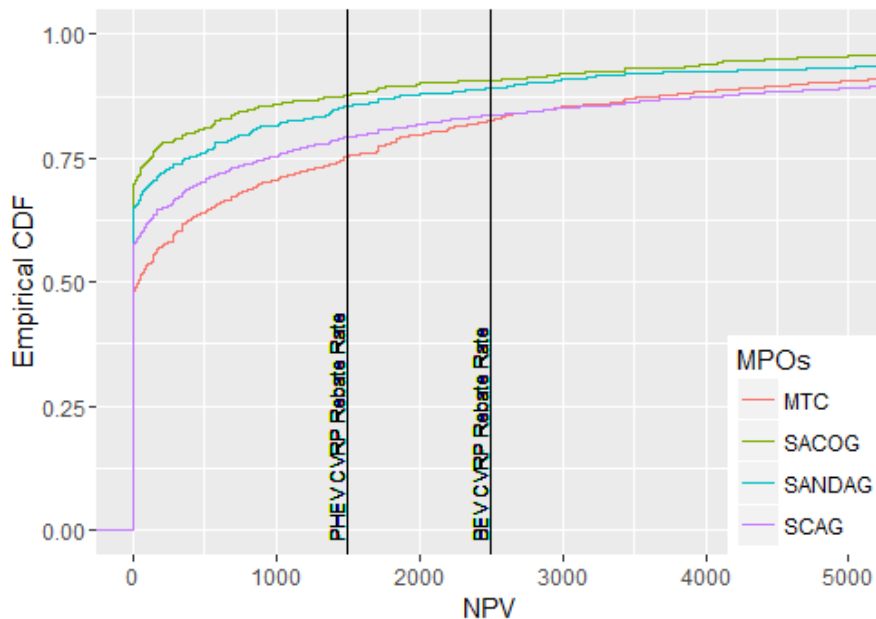
Figure 4.9 Net Present Value of 3-Year CAV Decals (discount rate = 5%)

One advantage of the CAV Decal Program over CVRP is that the mechanism of CAV Decal Program encourage applicants to drive their PEVs more so that they can gain more value from the decals. CVRP is a one-time financial incentive with fixed amount of rebate, and the driving activity will not impact the CVRP eligibility. However, the CAV Decal Program is a reoccurring incentive that can be received at any increment, and the value of CAV decals depends on the frequency people use HOV/T lanes. Results above show that the value of a CAV decal can be higher than the CVRP rebate if a PEV owner use HOV/T lanes frequently. Purchasing a PEV doesn't necessarily result in environmental benefits, but choosing a PEV over a conventional gasoline vehicle does. Thus, CAV Decal Program can more effective than CVRP in terms of achieving environmental benefits.

It requires public education to let consumers realize that they can gain higher value from a CAV decal compared to the CVRP rebate. But the CVRP is not substitutable from the point of view throughout California because the HOV/T lanes are not distributed evenly, and there is a

social equity issue in terms of the achievable CAV decal value for people from different regions as the local accessibility to HOV/T lanes is different.

4.5 Conclusions

This paper conducted a survey of existing PEV owners in California. A central finding was that the CAV Decals Program is one of the most important incentive policies to prompt the adoption of PEVs, along with the federal tax credit and the CVRP rebate. Depending on the specific travel pattern, CAV decals can (1) help to reduce toll rates on HOT lanes and bridges in the Bay Area, (2) grant vehicles access to HOV lanes without meeting the minimum occupancy requirement, resulting in saved travel time, or (3) be useless to people without HOV/T lanes available along the route. Therefore, this paper examined the accessibility of HOV/T lanes and toll bridges along people's commute route and estimated the value of CAV decals for each respondent based on toll cost reduction and the value of travel time savings on their commute routes. The mechanism of the CAV Decals Program encourages people to drive PEV more often so that the decals can achieve higher value of travel time savings and toll reductions. However, the unequal accessibility of HOV/T lanes in different regions could have significant impact on the achievable value of CAV decals. Thus, the CAV Decals Program has potential social equity issues and cannot substitute the CVRP.

CAV decals are also expected to increase the residual value of PEVs in the secondary market. The yellow CAV decals for hybrid vehicles are found to have a significant impact on the sales price in the used car market, and a similar impact is expected in the used PEV market. Vehicles issued green or white CAV decals in 2017 or 2018 are eligible to reapply for the red CAV decals which will grant them at least three more years access to HOV/T lanes. If a vehicle

with a red CAV decal is sold in the used market, e.g. a leased vehicle in SACOG sold in MTC after a 2-year lease, the red CAV decal is expected to add extra value to the vehicle.

However, the impact of CAV Decals Program on vehicle emission is a worthy topic for further study. Currently, PEVs are relatively higher priced than conventional vehicles, so the income level of current PEV owners is higher than the general population. Considering commonalities in the lifestyle of the middle class, a significant proportion of potential PEV buyers live in suburban areas and have longer commute distances. If range anxiety is a barrier for BEV adoption, PHEVs have no range issue and are eligible for CAV decals. Longer commute distance increases the likelihood that longer lengths of HOV/T lanes will be accessible along the commute route, which will make the value of CAV decals even higher. However, given the limited battery range of PHEVs, the achievable emission reduction is uncertain, and requires further analysis.

5 CONCLUSIONS

5.1 Contributions

In terms of methodology, traditional approaches to analyze travel behavior are mostly to build analytic models based on assumptions because of the limited size and information of survey data. However, with the development of technology, we are able to collect behavioral data that is more accurate and informative than ever, such as second-by-second vehicle OBD data with information including real-time position, fuel consumption, weather, pedal position and etc. We don't need to make a lot of assumptions about how people travel, but it requires more efforts to understand the tracing data and let the data to tell us about people's behavior. Therefore, this dissertation used several new approaches to analyze behavioral data and provided a discussion of the implications for three PEV-related topics.

Chapter 2 explored the potential of PEVs to result in GHG emissions reduction based on household level GPS tracing data. There are some existing studies about this topic, but many of them simplify the methodology by using standard driving cycles to represent driving behavior. As discussed in Chapter 2, driving behavior can significantly impact a vehicle's energy consumption, so using standard driving cycles disregards the variation in the real world. This chapter also analyzed the impact of household vehicle ownership limitations on the adoption of PEVs. Most existing studies look at driving behavior on the trip level or vehicle level, which means they focus on trips or the travel demand of a vehicle to analyze how PEV technology can help to reduce GHG emissions. But one key limitation of those studies is that they are not able to consider the vehicle swap behavior in households with multiple vehicles. Based on our survey about BEV owners in California, all of them have at least one extra PHEV or a gasoline vehicle for long-distance trips. Analyzing travel behavior at the household level enabled us to explore

the impact of vehicle assignment decisions in multi-vehicle households on PEV adoption and usage.

Chapter 3 presented a tool developed on the ArcGIS platform to evaluate the spatial distribution of fast charging demand based on travel survey data and to assess how much a charger in a certain location would be used. Existing fast charger siting strategies are mostly based on indirect measures of fast charging demand, e.g. assuming the spatial distribution of fast charging demand is consistent to the distribution of regional transportation demand, basing it on the spatial distribution of the PEV market, or simply allocating chargers to maximize coverage. This chapter proposed a new approach to directly measure fast charging demand based on PEV drivers' travel patterns and charging behavior. Compared to other existing regional planning processes, this approach can provide a statewide assessment of charging demand with consistency. This approach is also able to measure the charging demand of through traffic for small regions, which is important for regional planning authorities, especially as longer-range BEV models become available which will result in a larger portion of charging demand originating outside regions. If regional planning authorities analyze charging demand based only on regional traffic data and lack of origin-destination information about through traffic, the analysis won't be able to accurately measure the charging demand of through traffic.

Chapter 4 estimated the value of CAV decals in California based on a survey of PEV owners. Although applicants do not need to pay for the CAV decals and the decals are not transferable to another vehicle, meaning people cannot directly make money with them, the CAV decals help drivers to save toll costs and travel time. Thus, the CAV decals are an attractive incentive to PEV owners. Two previous studies have tried to estimate the value of CAV decals, but they did so by measuring customers' willingness to pay for CAV decals. This chapter

proposed a new approach to directly calculate the toll cost savings and the value of travel time savings with CAV decals based on simulated commute trips of PEV owners in California. The results also illustrated how varying accessibility of HOV/T lanes across regions drives geographic differences in the valuation of CAV decals.

Since electric vehicles are an emerging technology and the State of California holds a leading position in developing EV-related policy, this dissertation also tries to derive policy implications based on the findings.

Chapter 2 showed that assigning the right model of PEVs to drivers can help to reduce annual GHG emissions by 65%, compared to everyone driving a Toyota Corolla – a gasoline vehicle which is already efficient. It illustrates the great benefit of reducing transportation-induced GHG emissions that can be achieved by promoting PEV adoption. Even if everyone drives a PHEV with appropriate battery range (with no BEVs at all), it can still achieve 60.9% of GHG reduction. However, if everyone drives a PHEV but never charges the vehicle, only 22.8% of GHG reduction can be achieved rather than 60.9%. Therefore, one key task is to encourage PHEV drivers to charge their vehicles. Based on our survey about PEV drivers, respondents with a longer-range PHEV are more likely to frequently charge their vehicle, so we think it is reasonable to encourage longer-range PHEVs over shorter-range ones to achieve more electric vehicle miles traveled.

The scenario analysis in Chapter 3 indicated that planning fast charging stations for today's PEV fleet could be different from planning for tomorrow's PEV fleet. There are more longer-range BEV models available in the market, which enables people to travel longer with the same number of en-route charging events. For example, people can only drive from Sacramento to Lake Tahoe with a first-generation Nissan Leaf (84 miles range) and one en-route charge; but

a second-generation Nissan Leaf (151 miles range) is able to go from San Jose to Santa Barbara with one en-route charge. It means interregional long-distance travel demand will get a larger proportion of en-route fast charging demand in the future. Most of the en-route fast charging demand is still within the same metropolitan area that EV owners reside in, but there will be increasing demand appearing in inter-region areas. For example, very few BEVs with shorter than a 100-mile range will appear on I-5 in the Central Valley section even if fast charging stations are available, because it requires too many charging events to drive from San Francisco to Los Angeles through I-5 and there are very limited attractive stops in between. They might choose CA-99 over I-5 if they decide to drive a BEV100 for such a trip. However, if a driver had a BEV such as the Chevrolet Bolt with over 200 miles of range, drivers are more likely to choose I-5 over CA-99 because one en-route fast charging event in rural area is still tolerable, and they can save some travel time.

Chapter 4 explored the value of CAV decals in California. We found that the CAV Decals Program is one of the most attractive incentive policies, especially to PEV lessees who are not eligible for the federal tax credit. The value of CAV decals is correlated to the daily use of HOV/T lanes. The more often a driver uses HOV/T lanes, the more valuable the CAV decal is to him/her. Based on the simulation results, 45% of respondents enjoy toll savings or travel time savings without meeting the minimum occupancy requirement because of the CAV decals. The new-generation red CAV decals will be valid from January 1, 2019 to January 1, 2022, and the median simulated net present value of 3-year CAV decals of those respondents is $1,372, which is very close to the CVRP rebate for a PHEV. If the effective period of the red CAV decals gets extended, the value of the decals will increase proportionally. Additionally, a used PEV with CAV decals is expected to be more attractive than the same one without CAV decals since the

used car buyer can still enjoy the benefit of the CAV decals as long as the policy is not expired. Therefore, beyond inducing new car buyers to choose PEVs, CAV decals might also help to promote the used market of PEVs compared to other monetary incentive policies which only target new car buyers.

5.2 Future Research

One limitation of behavior simulation based solely on tracing data is lack of capacity to simulate uncertainty in travel behavior. For example, people might make an extra stop at a grocery store on their way home which results in a detour, an EV driver might forget to charge overnight at home and need an unscheduled fast charge the next day, or a public charging station with a long waiting line might cause a driver to choose another charging station. There is great uncertainty about travel behavior in the real world. However, tracing data represents trips that have happened, so they are fixed with no uncertainty. Therefore, one important question is how to simulate the uncertainty inherent in behavior based on tracing data. Depending on the specific dataset, there could be many different approaches. If we have a large sample size or a long time period of data about the same sample, we might be able to compare and find out the routine trips versus the variance in behavior. Even with limited data available, we can conduct scenario analysis about potential irregular behavior to test the impact. When there is so much data that traditional simulation approaches would take too long in computing time, cluster analysis and other statistical tools can help to recognize routine behavior. It is always a primary goal in transportation research to better understand travel behavior based on tracing data.

From the policy perspective, electric vehicle miles traveled (eVMT) is another important topic. Most current incentive policies aim to encourage the adoption of PEVs, such as the federal tax credit and the CVRP which help to cover the price difference between EVs and gasoline

vehicles in the same class. As EV technology develops, the price difference is expected to get smaller. But EV adoption doesn't necessarily result in reducing transportation-induced carbon emissions. Our survey of EV owners in California showed that all of the Nissan Leaf households had at least one gasoline vehicle in their households in addition to the Leaf. If they never drive the Nissan Leaf but keep using their gasoline vehicles, it will not achieve any carbon emission reduction. Furthermore, Chapter 2 showed that if a PHEV is never recharged from an external source of electricity, it operates as a normal hybrid vehicle and can only achieve one-third of the potential carbon reduction of an always-charged PHEV. It follows that there are several key areas of research that require further exploration. What is the mechanism by which PEV households assign multiple vehicles to different household members, and how does this behavior impact overall eVMT? Shall we solely encourage longer-range PEVs to achieve better eVMT or mid-range PEVs can help customers with occasional long-distance travel demand to achieve better balance between range anxiety and efficiency loss caused by redundant battery capacity? What's the current percentage of eVMT for PHEVs and the impact of charging behavior on that proportion? What are feasible policies to encourage PHEV drivers to charge more? All these questions are very important and require further analysis.

Furthermore, electrification, automation, and shared mobility are believed to be three transformative trends in the transportation field (Sperling, 2018) that are closely related. It is easier to realize autonomous vehicles as electric vehicles over conventional gasoline vehicles since EVs are controlled electronically instead of mechanically. A fully automated vehicle doesn't need a driver, which makes shared mobility service more economically competitive compared to owning a personal vehicle. If shared mobility is widely adopted and most people don't have a personal vehicle anymore, then their travel mode choice would be different from

today, where mode choice is dominated by driving. Shared mobility also means we don't need so many parking spaces for vehicles as we do today. Fully automated vehicles would help to achieve better traffic conditions through vehicle-to-vehicle communication, and the gap between vehicles on the road can become smaller meaning fewer lanes will be needed. However, these three transformation trends might also result in a lot of zero-occupant vehicles running on the road without a destination but wasting energy if the technologies are not implemented properly. Therefore, the three revolutions in transportation are also interesting topics for future study.

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