Advanced Plug-in Electric Vehicle Travel and Charging Behavior Final Report

(CARB Contract 12-319 – Funding from CARB and CEC)

April 10, 2020

Prepared By:

Gil Tal, Ph.D.

Seshadri Srinivasa Raghavan

Vaishnavi Chaitanya Karanam

Matthew P. Favetti

Katrina May Sutton

Jade Motayo Ogunmayin

Jae Hyun Lee, Ph.D.

Christopher Nitta, Ph.D.

Kenneth Kurani, Ph.D.

Debapriya Chakraborty, Ph.D.

Michael Nicholas, Ph.D.

Tom Turrentine, Ph.D.

UCDAVIS

PLUG-IN HYBRID & ELECTRIC VEHICLE RESEARCH CENTER

of the Institute of Transportation Studies

Prepared For:

STATE OF CALIFORNIA ENERGY COMMISSION

California Environmental Protection Agency

Air Resources Board

Contents

Table of Figures

List of Tables

Abstract

Results from this study provide insights on the usage of plug-in electric vehicles (PEVs include both battery electric vehicles [BEVs] and plug-in hybrid electric vehicles [PHEVs]) and the environmental impacts of battery size, range, and driving and charging behavior. Project data, from the surveys, loggers, and interviews, suggest that PEVs are being used extensively. Charging behavior is important for understanding the performance of PEVs and infrastructure planning. The survey results show that more than half of the PEV owners charge only at home while 33% combine home with other locations. The 14% who do not charge at home use mostly work charging and, in some cases, fast charging opportunities. As expected, many users start charging at or around midnight to take advantages of lower electricity rates and a second peak occurs around 9 am, when charging at work. Logger data analysis results show that longer-range PHEVs have a utility factor (electric vehicle miles traveled[eVMT]/vehicle miles traveled [VMT]) that is lower but similar to the standard utility factor from SAE J2841 (SAE 2010). In contrast, short-range PHEVs as a whole have utility factors significantly lower than expected, because of driving and charging behavior and a higher share of users who drive on gas only. Among households with one PEV and one internal combustion engine vehicle (ICEV), those with a BEV have higher utility factors than those with a PHEV. When comparing greenhouse gas (GHG) emissions per household, the efficient gasoline engines of the PHEVs lead to reduced GHG emissions and environmental impact, but still BEV households present better results. The interviews show that early PEV drivers may still be learning about their PEVs performance and capabilities, even months or years after they acquired one, but they may continue to use the car based on old information. The eVMT is affected by the vehicle capabilities, as well as charging and driving behavior. HOV lane incentives, when cited as a primary purchase incentive for PHEV buyers, correlated with reduced charging frequency and higher annual mileage, leading to a lower utility factor than expected.

Overall the results suggest that longer-range PHEVs and BEVs have more electrified miles and therefore lower emissions than shorter range PEVs, but to maximize the impact of PEVs, a full set of policies is needed to address charging behavior and vehicle purchase. The results of this study point to factors that affect the environmental impact of PEVs including charging behavior, household fleet composition, vehicle usage and more. As those factors continue to change,

further research is necessary to shape policy that leads to more sustainable transportation and PEV usage. The household analysis suggests the longer-range BEVs can reduce the environmental impact of transportation, but future households may move to two PEVs; combining BEVs with PHEVs, or short- and long-range BEVs, which would significantly change the electrification of miles at the household level. The study's main limitation is the sample size of logged households. The survey results are based on a sample of more than 13,000 households, but only 264 household's data were logged through the vehicle telematic system. A second ongoing study is expected to expand and replicate the current study to more households and new vehicles that entered the market.

Preface

This report describes the findings from the Advanced Plug-in Electric Vehicle Travel and Charging Behavior Project. The purpose of this project is to understand the emissions potential of plug-in electric vehicles (PEVs) under real world conditions, highlight benefits and challenges, and present needs for improving and regulating future electric vehicles. The project and this report include results from a study on cold starts and charging behavior that was added to the initial scope of work. The project provides a platform to monitor how new PEVs are being used on a day-to-day and month-to-month basis within the household travel context, by placing data monitoring devices (loggers) in all vehicles in participant households for a period of one year. The project provides a common basis to evaluate technologies side-by-side in a consistent way.

The project began with studying three models of plug-in vehicles: the Toyota Plug-in Prius (Model Years [MY] 2012–2016), the first-generation Chevrolet Volt (MY 2010–2015) -- both plug-in hybrid electric vehicles (PHEVs) -- and the first generation Nissan Leaf (MY 2010–2016) battery electric vehicle (BEV). As the project progressed, six additional and updated models have been added: the Ford C-Max Energi PHEV (MY 2014-2016), Ford Fusion Energi PHEV (MY 2014-2016), second generation Volt (MY 2016), second generation Leaf with 30kWh pack (MY 2014–2016), BMW i3 REx range-extended BEV (BEVx) (MY 2014-2016), and Tesla Model S with battery size of 60-80kwh. The BMW i3 REx had compatibility problems with the on-board data monitoring devices resulting in bad data and are not included in the report. As part of a second study, we are continuing to collect data from second generation PEVs, including the Prius Prime, Chevrolet Bolt and Chrysler Pacifica, and the Toyota Mirai (a fuel-cell vehicle). A future report expected in 2020 will describe the findings of this complementary study.

Based on learnings from the first of four deployments of vehicles in this study, households with two PEVs have been added to the study as an important next step to understand the transition to electric vehicles. By studying households with more than one PEV, a few additional PEV models were added, including Toyota RAV4 BEVs. These households will also be included in the follow-up report on second-generation PEVs to get a larger sample size. As questions about PEV purchase and use patterns change, this project can help answer them in a timely manner.

Acknowledgements

The Authors would like to thank the California Air Resoures Board and California Energy Commission for their funding of this project. The California Air Resources Board staff were essential and thoughtful collaborators in executing this complex project. This project was made possible with the additional prelimary support of the utilities in California for pre-testing, and the data logger supplier FleetCarma. In addition to the authors, there were many staff and students who supported and contributed to this project in various ways, and without which this project would not have succeeded. Thank you to Javier De Leon, Wei Ji, Daniel Reif, Eric Racadag, Nicole Tsugawa, Andrew Ferguson, Corey Hobbs, Tommy Garcia, Marcelo Steinkemper, Alex Tang, Nicholas Magnasco, Valerie Silva, Alexa Monserret, Noh Kahsay, Melissa Ng, Gene Uehara, Devin Ciriaco, Nathaniel Kong, Jonathan Gordon, Thomas Bradas, Scott Begneski, Helen Barr, Seth Karten, Tayo Ogunmayin, and Dahlia Garas.

Executive Summary

The Advanced Plug-in Electric Vehicle (PEV) Travel and Charging Behavior Project (project) provides a platform to monitor how new plug-in electric vehicles (PEVs) are being used on a day-to-day and month-to-month basis within the household travel context by surveying owners and placing data monitoring devices in all vehicles in participant households for about a year. (PEVs include both battery electric vehicles [BEVs] and plug-in hybrid electric vehicles [PHEVs].) The long and intensive data collection answers questions on energy usage, charging behavior, type of charger used, energy use by vehicle type, and real life efficiency levels. For PEVs the study explores the differences between the standard utility factor (fraction of miles driven on electric energy) estimated based on hypothetical behavior and the actual results. The household analysis provides two advantages over simply studying individual PEVs for a long period or studying the household for a short period. First, studying only the PEV does not give a clear indication of what role it plays in the household and what travel needs are not covered by it. Second, the shorter-term household studies do not capture infrequent events, such as long trips, which may have a bearing on the purchase or lease and use of the vehicle. This project represents a crucial step in understanding these important dynamics and the potential barriers that need to be addressed in the transition to zero-emission vehicles.

The project consists of a set of over 13,000 surveys of California PEV owners and lessees, followed by intensive study of a subset of those respondents. Loggers that collect data on global positioning (i.e., GPS data), battery state of charge, speed, engine revolutions per minute (RPM), charging events, and numerous other parameters on a nearly second-by-second basis were placed in all the vehicles in the selected subset of households. The project included very limited resources for analysis of the data collected and final results—for example for causality analysis to address the impact of charging infrastructure, vehicle size, and other factors that are not included in this report. This final report includes four phases of data collection completed between June 2015 and November 2018. The data collection process involved vehicles in 264 households for up to one year. Vehicle replacements, changes in households, two PEV households, and similar considerations resulted in data collection from 300 PEVs and 199 internal combustion engine vehicles (ICEVs). Some of these households are not included in the final report, primarily due to technical problems in data collection from BMW i3 REx vehicles as well as low sample size as in the case of Kia Soul BEV(1 household) and Fiat 500e households (1 household). The report includes households who owned or leased (new or used) one of the following PEVs: Toyota Plug-in Prius, Ford C-Max Energi, Ford Fusion Energi, Chevrolet Volt, Nissan Leaf (both 24kWh and 30 kWh versions), and Telsa Model S (both 60–80kWh and 80–100kWh versions). Since both the Ford PHEVs have identical battery capacity and range, they have been combined together. A small subset of 18 of the households logged were interviewed. The results presented in this report comprise a combination of survey responses, interviews, and logger data.

Preliminary results from this study provide insights on the usage of PEVs and the impact of battery size, range, and driving and charging behavior on energy consumption, including gasoline and electric consumption at the vehicle and household fleet levels. In general, both the survey and the logged data suggest that longer-range BEVs were used more than shorter-range BEVs and for longer trips; and longer-range PHEVs yield more electric miles than shorter range vehicles. Households with longer range BEVs displace the use of their ICEVs on longer trips. By comparison households with short range BEVs must rely on a less fuel-efficient ICEV for longer trips.

Charging behavior is a focus of this research as it helps to understand how vehicle technology may be used to achieve environmental and air quality goals. Over all three years of the study, logged participants owning PHEVs with larger capacity batteries plugged in more than did participants with PHEVs with smaller capacity batteries. Presumably, PHEVs with smaller capacity batteries would need to plug-in more than those with larger capacity batteries to maximize electrification of their driving. Upon further investigation with survey data, we find that charger availability and the range recovered per charging event are significant factors in the decision to plug-in. For BEVs, the logged data shows that level 2 charging was the main source of energy and level 1 charging was used mostly in combination with level 2. Exploring the charging behavior at workplaces and with DC fast chargers (DCFCs) using the survey data, we find a variety of reasons for plugging-in, including the charging price (e.g., free DCFC and workplace charging) and travel behaviors that have an impact on the need for charging. Overall, owners of longer-range BEVs plug-in more frequently than do owners of shorter-range BEVs, but with lower kWh load at each charging event. Analysis of the distance of the charging event from home and the distance of the event from the vehicle's location at the beginning of the day suggests that the vast majority of the charging events that are not home events occur within the vehicle range (if starting the day with a fully charged battery). However, 10%-15% of the fast charging for Teslas may be correlated with trips longer than the range of the vehicles.

Our logger data results show that longer-range PHEVs have a similar household utility factor (miles from electric power/all miles driven) as short-range BEVs, based on their electric range and charging behavior. Blended PHEVs have a lower utility factor, limited both by the technology and the charging and driving behavior of the owners. While longer-range PHEVs correlate with more charging and higher battery capacity, in combination, these act to increase the average utility factor. Longer range BEVs have the highest utility factor, both on the vehicle level and the household level.

This study reveals the need for continuing studies and data collection. The interviews show that some early PEV drivers continue to learn about their PEVs and charging infrastructure, even months or years after they acquired one. Other PEV owners may use their car based on habits and routines they developed early and have remained unchanged despite changes, such as increasing infrastructure. The electric vehicle miles traveled (eVMT) are determined by a combination of vehicle capabilities, charging patterns, and driving behavior. Overall short-range PHEVs have lower eVMT than expected for drivers who charge their vehicles and a higher number of users who are not charging at all. Based on the interviews, when carpool lane incentives are cited as a primary purchase incentive, the respondents were less likely to charge their PEV yet have higher annual mileage.

Overall the project results suggest that longer-range PHEVs and BEVs have more electrified miles and therefore more emissions reductions than shorter-range PHEVs, but to maximize the impact of PEVs, a full set of policies is needed to address charging behavior and vehicle purchase. BEVs offer better greenhouse gas (GHG) reduction than PHEVs but in the household context, we find, based on the survey, that longer range BEV households studied had, in most cases, lower efficiency ICEVs. The household analysis suggests the longer-range BEVs can improve environmental performance (by decreasing GHG emissions and cold starts) and future households may move to own or lease multiple PEVs, combining BEVs and PHEVs, or short- and long-range BEVs, as well as fuel cell electric vehicles (FCEVs). We expect higher utility factors as the second generation of PEVs, including longer-range and larger vehicle platforms, are adopted by households in California. The longer range vehicle model logged in this study is the high end Tesla model S; the usage of these vehicles may not reflect the usage of the new generation of affordable BEVs with a 150-250 mile range that started entering the market in 2017. The follow-up project using the same methods will focus on the second generation of PEVs and users as well FCEVs.

1. Introduction

Road transportation accounted for 21% of global energy consumption (Contestabile, Alajaji et al. 2017) and it will increase unless and until the share of carbon intensive transportation fuels are substituted by cleaner sources. Plug-in electric vehicles (PEVs)– which include full battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) – are promising alternative to conventional internal combustion engine vehicles (CVs/ICEVs) because of their energy conversion efficiency and reduced tail-pipe emissions compared to CVs(McLaren, Miller et al. 2016, DOE/AFDC 2017) . Globally, PEVs saw a record sales in 2017 with over 3 million sold annually, an increase of 50% from the 2016 sales (International Energy Agency 2018). In the U.S. , May 2018 marked the 32nd month of consecutive year-over-year monthly sales gain for PEVs(Loveday 2018). Even as the uptake of PEVs is expected to continue on an upward trend, they are not rising at a level that could fully realize the benefits of electrified transportation from an energy security and environmental impacts perspectives. Plug-in electric vehicles (PEVs) have characteristics that will limit, expand, and alter how they are driven and refueled compared to conventional household vehicles, as well as other prospective replacements for the current fleet. Many variables confound the assumption of simple substitution for a previous conventionally fueled vehicle, including limited electric driving range, household access to charging locations with various capabilities, costs, and charger access rights as well as behavioral variables such as the habits and desires of households for using these new types of vehicles. Depending on travel needs, desires, fuel costs, charging opportunities, and how much drivers like or dislike their PEV, they may end up using their new PEV for more or less vehicle miles traveled (VMT) than they had for a previous vehicle, and with PHEVs, may charge more or less frequently resulting in higher or lower percentage of electric powered VMT (eVMT)—where the proper denominator for calculating the percentage is the household's total VMT, not merely the total VMT of the PHEV. Such complexity can complicate attempts to predict and calculate the impact of new technologies on emissions in coming decades. This study identifies and begin to measure these new patterns.

Consumer's perceptions on PEVs ability in meeting daily mobility needs compared to CVs, higher upfront capital cost compared to CVs, range anxiety, and reliable access to charging infrastructure continue to be major barriers to large-scale PEV adoption(Dimitropoulos, Rietveld et al. 2013, Liao, Molin et al. 2017, Lutsey, Meszler et al. 2017, Hardman, Jenn et al. 2018). These barriers create uncertainties in the evolution of PEV market. Heterogeneities in daily driving patterns and needs across various sociodemographic indicators and geographical locations, further compound these uncertainties. Since PEVs are uniquely positioned to interact with the energy and the transportation sector, uncertainties in the evolution of the PEV market poses many problems for policy makers, auto manufacturers, electric utility companies, and charging infrastructure developers (Wietschel, Plötz et al. 2013). Policy makers have to continually fine tune existing incentives (financial and/or non-financial) or introduce new incentives to encourage the adoption of PEVs. Understanding daily driving needs is crucial for auto manufactures for optimal PEV design and model choice offerings. Charging infrastructure developers have to ensure that electric vehicle supply equipment (EVSE) are efficiently located and managed to alleviate concerns about range anxiety and accessibility to EVSE. Utility companies are particularly concerned about PEV charging patterns as it has the potential to create localized hot spots when not managed properly, necessitating network upgrade or expansion(Muratori 2018). Utility companies also would have to design their PEV specific rates keeping in mind when and where PEVs are charged.

The decision to own a PEV will have long-term will have long-term consequences on the user from a total cost of ownership (TCO), value proposition, and life-time GHG reduction potential perspectives, whereas its daily driving and charging behavior will have near to short-term impacts on planning charging infrastructure roll out and effectively managing the incremental demand imposed by PEV charging. In order to better understand the impacts of PEVs across varying timescales given the negligible global share of PEVs (1-1.5%)(International Energy Agency 2018) and the scarcity of PEV usage data compared to CVs, studies have relied on existing data to model their behavior. Modeling PEV driving behavior will offer qualitative and quantitative insights into the feasibility of PEV in replacing a CV or even a regular HEV. The daily and long-term energy, emissions and economics of PEV is directly related to the extent to which prospective and current PEV owners perceive the daily driving utility of PEV when compared to a CV or HEV. The charging demand imposed by PEVs is affected by their daily driving distance and depending on the trip start/end times and dwelling times by location; opportunities for charging could be uncovered.

Given the relative scarcity of actual PEV usage data, researchers and policymakers create scenarios by combining various sources of travel data and superimposing a set of preconceived expectations about PEV driving and charging needs. There has been an increase in efforts to analyze data from the real world operation of PEVs to estimate eVMT, since it is the most widely adopted metric to determine the potential of electricity as a transportation fuel. The scope of such efforts have expanded recently to estimate the zero emission VMT or zVMT, which is the miles traveled on electricity only. For BEVs, VMT, eVMT and zVMT are the same. However for the PHEVs, due to their blended mode of operation, zVMT is lower than eVMT. Information about PEV usage based either on assumptions or from real-world operations have direct consequences on not only their VMT, eVMT, zVMT, energy consumption (electricity and gasoline), and emissions (from driving and charging), but also on specific policies that rely on them such as credit allocation under the ZEV mandate (CARB 2017) and PEV infrastructure projections and investments(Wood, Rames et al. 2018, Brecht and Orenberg 2019).

Plug-in electric vehicles (PEVs) have characteristics that will limit, expand, and alter how they are driven and refueled compared to conventional household vehicles, as well as other prospective replacements for the current fleet. Many variables confound the assumption of simple substitution for a previous conventionally fueled vehicle, including limited electric driving range, household access to charging locations with various capabilities, costs, and charger access rights as well as behavioral variables such as the habits and desires of households for using these new types of vehicles. Depending on travel needs, desires, fuel costs, charging opportunities, and how much drivers like or dislike their PEV, they may end up using their new PEV for more or less vehicle miles traveled (VMT) than they had for a previous vehicle, and with PHEVs, may charge more or less frequently resulting in higher or lower percentage of electric powered VMT (eVMT)—where the proper denominator for calculating the percentage is the household’s total VMT, not merely the total VMT of the PHEV. Such complexity can complicate attempts to predict and calculate the impact of new technologies on emissions in coming decades. This study identifies and begins to measure these new patterns.

Travel behavior researchers have known that the household is the critical unit to study, because activities are often allocated among a fleet of household vehicles on a trip-by-trip basis. Previous studies of household vehicle travel have been for short periods or have not used data loggers.

However, this project planned to study the use of vehicles by the household as a whole, instrumenting all of their vehicles with GPS enabled logging devices, to measure accurately the trip allocation and activity space formation of the whole household across a whole year.

This research is designed to investigate these alternative travel patterns and lifestyle activity space in response to PEVs across a large set of households.

The overarching objective of this research project is to collect and analyze longitudinal, spatial, in-use vehicle data, including electric vehicle miles traveled (eVMT), from a variety of plug-in electric vehicles (PEVs). PEVs are central to achieving California's long-term air quality and climate stabilization goals. This means measuring the travel and fueling of all vehicles within a PEV-owning household. Usage and charging habits of PEV owners remain ambiguous due to the diversity of PEV designs, technologies, and electric ranges, and the prior failure to account for other travel within households. However, these behaviors will have significant implications for statewide emissions, energy consumption, and electrical grid management based on the miles these vehicles travel using off-board electricity sources. Objectives include:

1. Determining the share of a PEV's miles traveled powered exclusively by off-board electricity (eVMT) and therefore how emissions profiles might differ between the various types of PEVs.

2. Learning the allocation patterns between household vehicles for daily, weekly, seasonal and infrequent trips. Knowing these reasons will assist ARB and others in creating policies to increase eVMT in the future and better estimate current eVMT;

3. Learning recharging patterns of PEVs in a household context. These patterns can assist ARB and other State partners to develop the charging network in ways that will help households maximize their eVMT. Additionally, knowing the locations and times of charging events will help ARB and partners to assess the time of day emissions impacts, and perhaps influence the recharging of PEVs in a way to reduce emissions and optimize the use of the grid across time and seasons. These same data will also assist utilities and their regulators to understand grid impacts from PEV charging, rate impacts on charging behavior, and the need for public infrastructure. Temporal and spatial data will provide a better picture of when and where PEVs are charging, which informs upstream emissions estimates;

4. Understanding how any measure of eVMT develops within the overall travel of households because of systematic variation caused by, for example, household self-selection into different types of PEVs. Within a household that owns either a BEV or a PHEV, the percent of the household's total VMT that is eVMT is hypothetically just as variable (except in single vehicle, BEV households). Further, while an individual PEV may have a high share of own-eVMT, total transportation-related emissions from the household will also depend on the activity and usage of all other vehicles in the household fleet.

5. An additional objective of this research project are to characterize the engine start activity profiles of blended PHEVs. In the 2017 market, many PHEVs are "blended" in that an internal combustion engine (ICE) can start to help power the vehicle before the battery is depleted. These ICE starts occur when the electric drivetrain is not sufficient to meet immediate high torque demand, regardless of the battery state of charge. These ICE starts occur under high power demand scenarios and are distinct from cold starts for conventional vehicles, which typically occur with the vehicle stopped, in park/neutral, and with a very low immediate torque demand. PHEVs likely have a different distribution of engine-on events compared to conventional vehicles and these can occur due to battery depletion in addition to high-torque demand events. The result of this study will be used to improve the emission inventory model (EMFAC) in estimating PHEV start emissions. The result will also be used to guide the development of future clean car standards.

2. Background and Research Methods

2.1. Recruitment and Background Survey

This project seeks to collect the data that can answer essential questions about future travel and charging behavior of PEV owners in California households and the benefits that are likely to result. What are the environmental benefits of these vehicles? How much travel can and will be shifted to PEVs, and specifically to BEVs and to PHEVs, per vehicle and for the household fleet? What kind of charging network is needed?

The funds for this project cover **collection**, cleaning, and basic analysis of the data, but not the analysis aimed to understand the interaction between the data factors collected or potential causalities. This study uses data from three main sources: 1) survey data of more than 13,000 PEV households, 2) vehicle-level data collected from 264 households through loggers connected to the vehicle telematic system, and 3) interviews of 18 PEV users that participated in the logging component. This research helps identify ways to facilitate increased use of zero-emission vehicles (ZEVs) by Californians. Also, longitudinal, temporal, and spatial data provide a picture of when and where PEVs are charging, as well as the electric- and gasoline-vehicle miles traveled by PEVs and other vehicles in the household.

A detailed, approximately 30-minute recruitment survey of PEV owners/lessees (hereafter referred to as owners for simplicity) was conducted to determine how many participants would be needed for each region and sociodemographic group so that the results would be representative of statewide PEV owning households—i.e., so the results could be generalized to the wider population. The survey included eight categories of questions: travel behavior, driving behavior, vehicle performance (MPG), vehicle characteristics, response to PEV related incentives, vehicle purchase history, current household vehicle fleet, PEV charging behavior, and sociodemographic characteristics. The survey targeted owners of all PEV models in the market at the time of the survey. The initial survey also was the first step in recruitment, asking whether respondents would be willing to participate in the second part of the study by having a logger installed in their vehicle. The information also helped determine whether household vehicles were suitable for participation based on logger limitations and vehicle usage (appropriate mileage, accessible OBD port, household with vehicles newer than 1996). In addition, the surveys allowed us to capture information about the households such as commute location, charger access, sensitivity to price, demographics, etc. We invited participants to take the internet-based survey three different ways. First, CARB sent email invitations to PEV owners who had applied for the California Vehicle Rebate Project (CVRP); second, CARB sent postcards to a random selection of persons who had a PEV registered based on the DMV records but did not apply for CVRP; and third, CARB sent postcards to a random selection of owners of used PEVs based on DMV records.

18,782 new PEV owners and lessees started our survey between May 2015 and August 2017 in addition to 680 used PEV owners. Of those surveyed, 12,396 households had enough information and answer all parts of the survey and indicated that we could contact them for the logging phase, but this number included surveys with missing information for some survey part based on our skip logic or households that owned a vehicle that was incompatible with the loggers. The overall response rate to the surveys was 18%, and 82% of these respondents completed the survey. However, this 82% included persons who were not eligible for the logging study because they utilized their PEV for business purposes, no longer owned a PEV, and similar cases.

2.2. Logger Installation Process

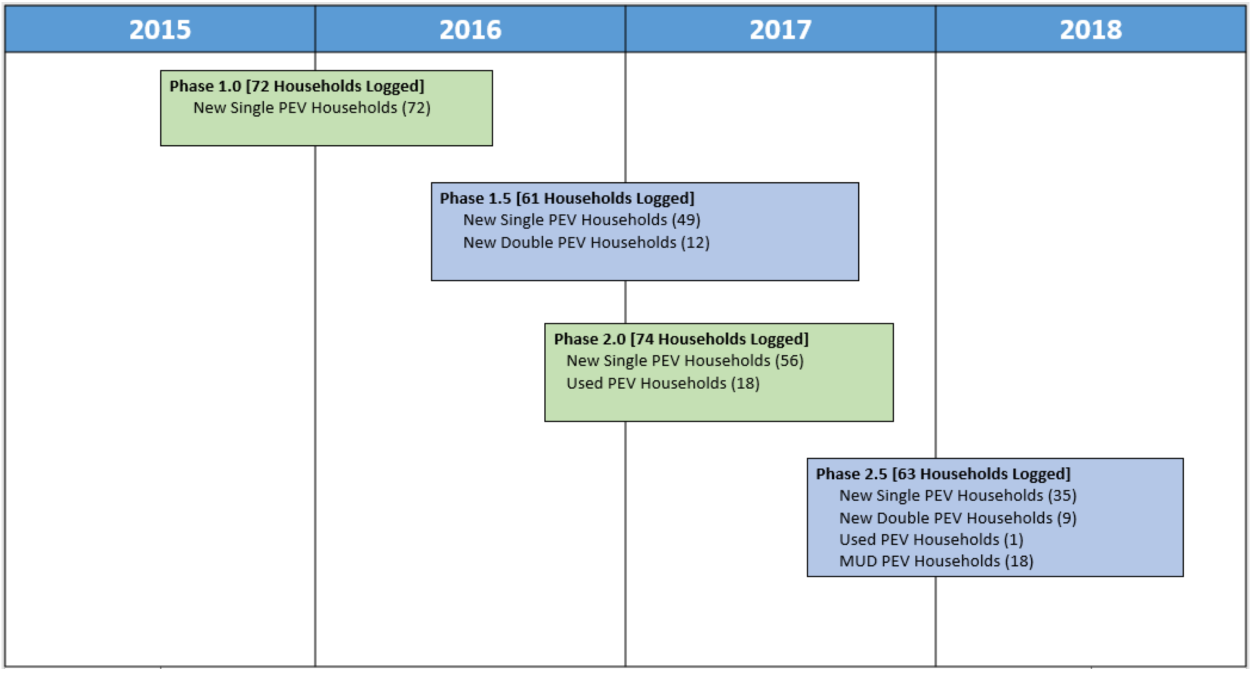
The project design called for a simple process. After identifying potential households for the logging part of the study, we emailed those households to reaffirm their interest, that they still had the PEV, and that they planned on having it for the next 12 months. Of the households we invited, 15–25% agreed to participate and moved to the next phase. The overall rate of recruitment was 1 logger installation for every 300 households that received the initial survey.

The project was budgeted to allow two visits to each household, one to install loggers on all household vehicles and another to remove them. The initial plan also called for the project team to make one trip per region to do all installations in that region and a second trip to do all the removals. The regions included areas from San Diego in the south to Crescent City in the north, and the project team was based in Davis. The installation-removal team included the project researchers, a full-time project manager, and 16 undergraduate students.

The loggers for this project were obtained from a vendor selected by a bid conducted by UC Davis. Each logger had to be programed to a specific PEV model, a process that was done manually at the beginning of the project and through the logger internet connection later. The data collected by the loggers was analyzed and then sent by cellular connection to the vendor servers and from there to UC Davis servers.

By the end of the project we had to make many more trips to each region than what was originally planned for and budgeted. The main reason for this difference between the planned and actual execution was the difficulty of scheduling installations during weekdays, when people had their vehicle or vehicles away from home (e.g., at work). As a result, evenings and weekends were often the only times when we could install, and later remove, loggers in all the household vehicles at once. Other than these limitations on workable time windows, we underestimated the number of additional visits that would be necessary beyond the initial installation and final removal of the loggers. Over the project period we had to replace more than 30 faulty loggers or data cables, we had to remove loggers from vehicles owned by households who chose to leave the study, sold the vehicle, had an accident, moved out of the state, etc. In many cases we recruited an additional household to maintain the total sample size. We had to make approximately 25 trips to Los Angeles, 20 to the San Diego area, 200 to the Bay Area, 50 to the Sacramento area, and 25 to the regions north and east of Davis.

The participation incentive was $350 split between the installation ($150) and completion of the data collection and return of the data logger ($250). Overall, we had to pay incentives to about 1.8 households more than the number used in this final report and to visit each household 4–6 times instead of the 2 times planned. We installed loggers at 264 households, in 300 PEVs and about 200 ICEVs.



presents the number of installations along the study timeline, with installations classified according to the number and type (new or used) of PEVs per household. **Figure 2** shows greater detail, including information on the model of PEVs that had loggers installed. To reduce the project cost we reinstalled the loggers from phase 1.0 in phase 2.0 vehicles and those from phase 1.5 in phase 2.5 vehicles. Therefore, this final project report includes data collected between June 2015 and October 2018.

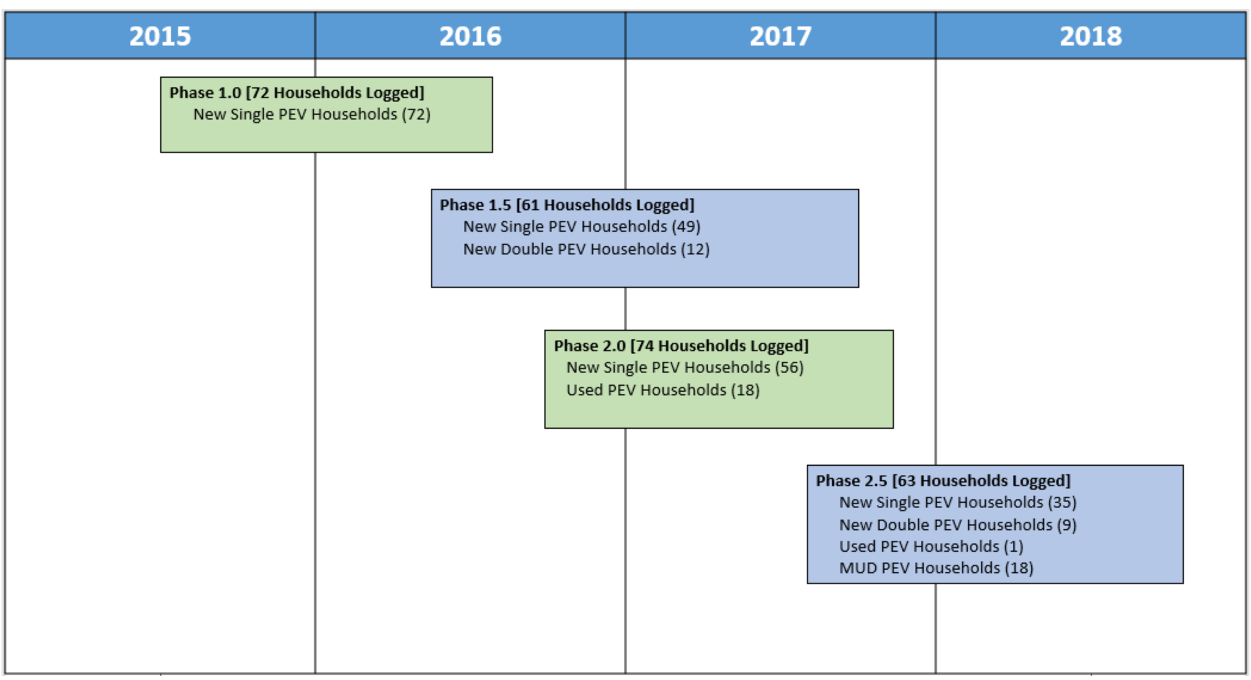


Figure 1. Overview of Number of Logger Installations During Each Phase of the Project, Classified by Number and Type (New or Used) of Vehicles per Household. MUD= multi-unit dwelling

We planned the recruitment to cover the main vehicle models at the time of each phase and to cover the shift from buyers of new PEVs to buyers of used PEVs and households with two PEVs. We also covered all main electric utilities in California. However, the long period of data collection 2015–2018 and the relatively small sample prevented us from having statistically significant results in all categories needed to fully represent the changing PEV owner population.

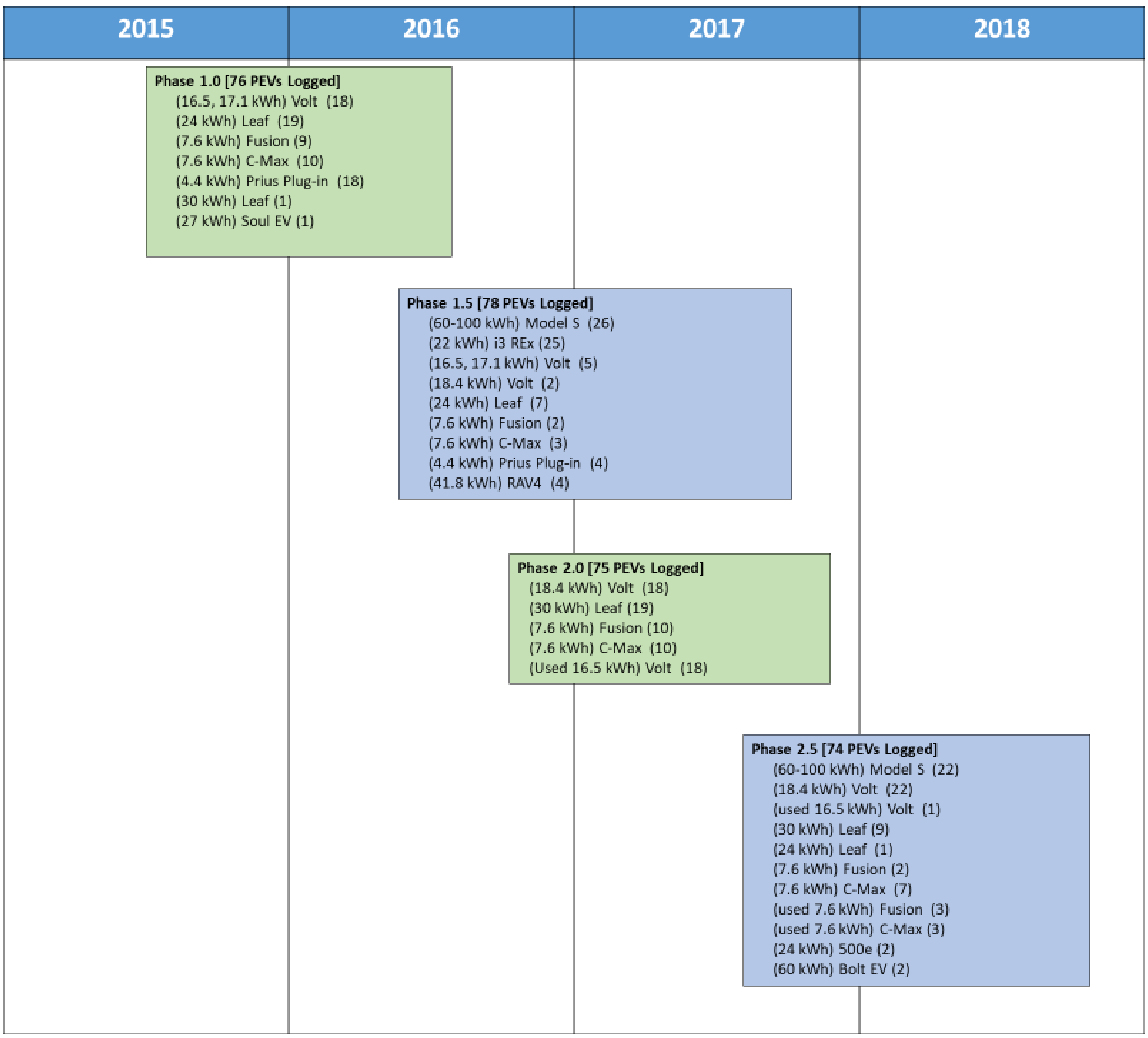


Figure 2. Specific Numbers of Logger Installations in Different PEV Models (new vs. used), Shown Along the Study Timeline

Figure 3 represents the home location (with added random error for privacy) and charging location of each PEV in the sample. The figure also includes total kWh charged during the daytime by the vehicles in the sample. Additional ICE usage metrics are provided in Section 6.1 for the subsample of households used in the household analysis for consistency.

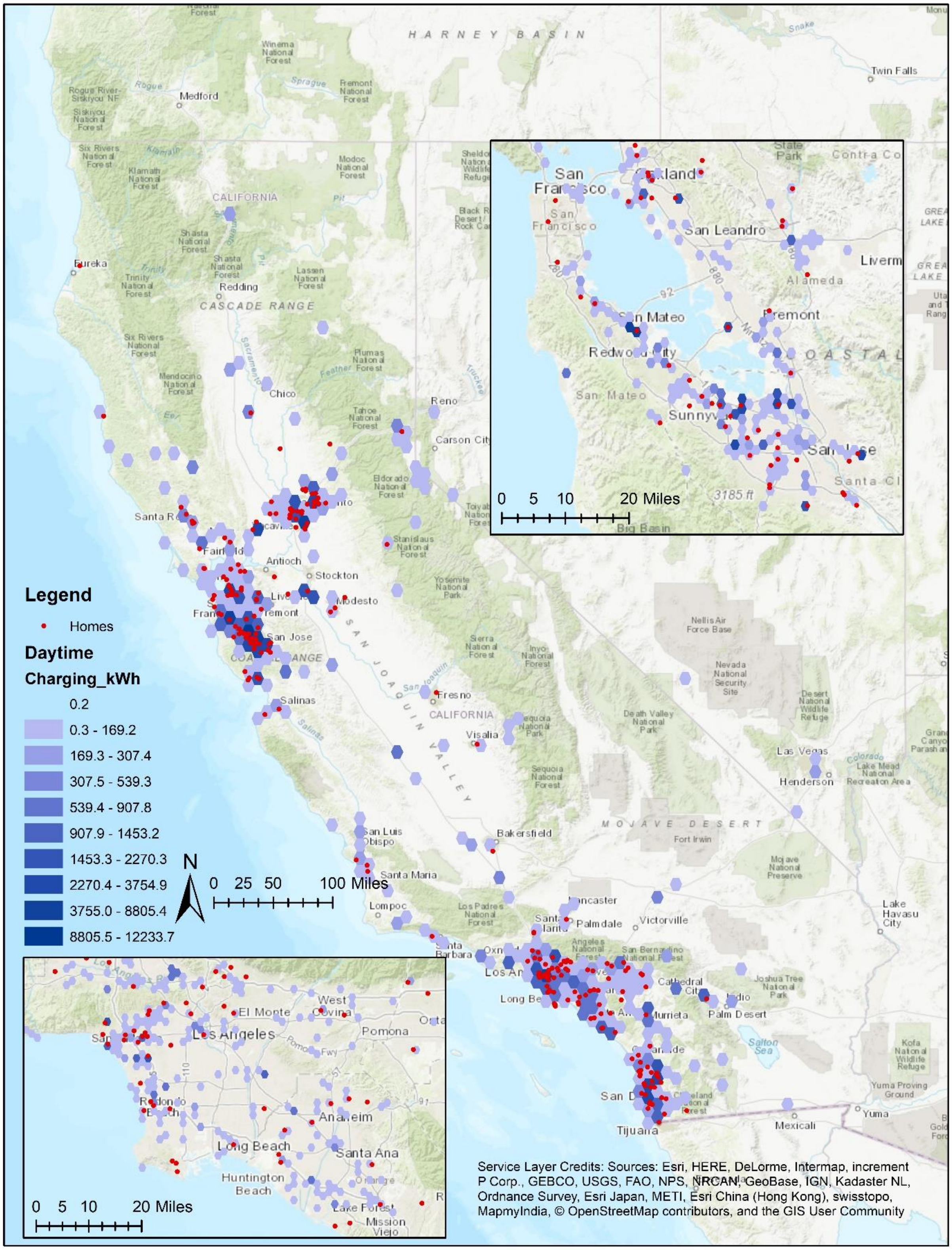


Figure 3. Home and Daytime Charging Locations 2015-2018

2.3. Data Collection and Limitations

A very important bias in the household selection and the results presented is the fact that no participants were chosen who did not plug in their PEV on a regular basis. Not all logger parameters were available on all vehicle models and the parameters collected changed over time with changes made by the logger vendor to the dataset design, the logger hardware, and the vehicle software. The data transferred from the logger includes raw data from the vehicles and calculated data based on algorithms programmed in the loggers. Some parameters, such as miles per gallon (MPG), are derived from multiple parameters such as revolutions per minute (RPM), engine load, mass air flow, and intake air temperature. Other parameters, such as distance, were derived from speed and time. Most parameters were collected approximately every second but others, such as GPS and State of Charge (SOC), were collected every 10 seconds.

One of the most important limitations of the data is that if one of the paramaters being recorded changed, a new row would be generated in the dataset/spreadsheet and values for all of the parameters would be populated in that row. However, because different parameters were recorded at different rates, a parameter that had the same value between adjacent rows may have been updated and had truly stayed the same over two collection times, or it may not yet have been updated and the program had populated the cell with the last recorded value from the previous row. In summary, it was impossible to distinguish whether an unchanged parameter was copied from the last collection time or recollected but had the same value.

Another limitation in the data collection was that data from ICEVs within a given household that were estimated to be driven less than 1000 miles per year did not have loggers installed. Thus, logger data was not collected from these vehicles. However, the VMT on these ICEVs was recorded manually from odometer readings with only one vehcile ecced 1000 miles.

We developed four different methods to estimate energy consumption from PHEVs (and ICEVs) based on the data reported for each vehicle, as described in section 2.2.

2.4. Sampling of the Logged Participant Households

The distribution of households was selected by electric utility and generally follows the market for electric vehicles with most participants being in one of the four largest metropolitan regions in California, as shown in **Figure 3**: San Francisco, Sacramento, Los Angeles, and San Diego.

Some participants were in exceptional locations, such as in the mountains or along the coast, where isolation or temperature may have had an impact on how they used their vehicles compared to those in major metropolitan regions. Although the sample size is small in those cases, interacting with them and observing their behavior presents the possibility for additional learning from the project.

This survey participants—PEV households who purchased or leased their vehicle in the last 4 years—differs from average Californian households. For the general population, less than one-third of households buy a new car every 3-5 years, according to the 2012 California Household Travel Survey (CHTS) (CalTrans 2013). To compare PEV buyers to the general population (based on the CHTS 2012), we combined the income distribution by vehicle type and purchase year.

Considering the market penetration of alternative fuel vehicles, many of the current PEV owners are early adopters of the technology. As observed in cases of other technologies, early adopters may have unique characteristics compared to other new car buyers—age group, education level, and technology awareness, among others.

Table 1 presents the statistics on sociodemographics and vehicle models among the survey participants. The sample was stratified by income to represent the income of the larger survey sample. More than 80% of households had an income higher than the median income in California ($67,739 according to the Census American Community Survey 1-year survey) and the percentage of people with graduate or professional degrees was 48.7% (California statewide 12.3%). In our dataset, males tended to drive the PEV more than females in a household, and slightly more BEVs were driven than PHEVs. More than 80% of respondents owned their houses, and more than 80% lived in detached units. About 50% of respondents had the Chevrolet Volt, Tesla, or the Nissan Leaf, and a significant number of the rest used the Prius plug-in hybrid or the Bolt.

Table 1. Sociodemographics and Vehicle Types Among the Usable Surveyed Participants

Income		Age		Education	
<50K	208	10-19 years old	10	High school	992
50-99K	1,024	20-29 years old	321	College	3,089
100-149K	1,616	30-39 years old	1,718	Post-graduate	3,867
150-199K	1,469	40-49 years old	2,067	Gender	
200-249K	973	50-59 years old	1,842	Male	5,920
250-299K	637	60-69 years old	1,344	Female	1,982
300-350K	348	70-79 years old	533	Decline to state	77
350-399K	196	> 80 years old	71	Household size	
400-449K	148	Missing	73	1 person	829
450-499K	100			2 persons	3,090
> 500K	341			3 persons	1,454
				4 persons	1,930
				5+	675
Number of Vehicles		Types of PEV		Model	
1	961	Battery	4,230	500e	160
2	4,131	Plug-in Hybrid	3,749	Bolt EV	748
3	1,961	Purchase or Lease		C-Max Energi	480
4	652	Purchased	3,812	e-Golf	472
5+	274	Leased	4,167	Fusion Energi	377
Number of drivers		Housing types		i3	590
1	1,047	Own houses	6,707	Leaf	1,175
2	5,472	Rent or others	1,272	Prius Plug-in	792
3	922	Detached housing		Tesla	1,384
4	457	Detached	6,479	Volt	1,442
5+	80	Others	1,500	Others	359

We tried to select households for logging that would reflect the geographic distribution and sociodemographic distribution of PEV households as reflected in the initial survey.

Figure 4

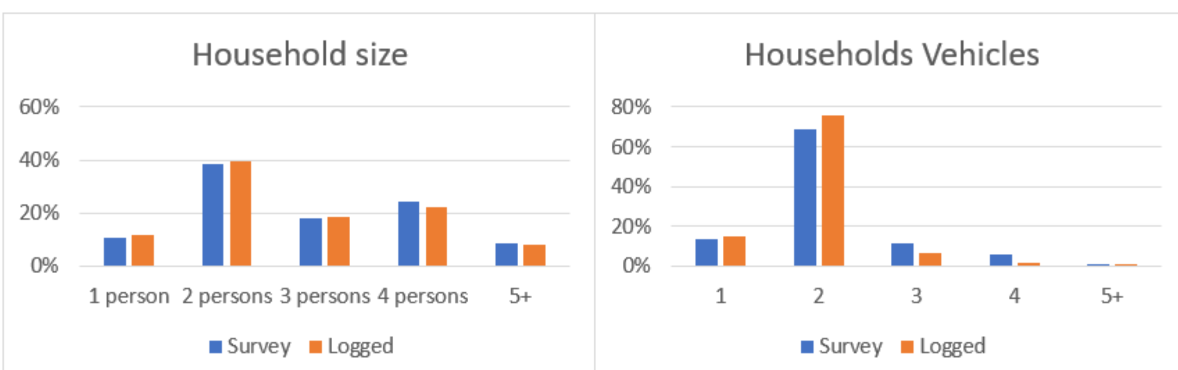


Figure 5 present the distributions of income, household size, and number of vehicles per household among the survey population with suitable vehicles and willingness to participate (N=~8,000) and the logged population (N=282). All the results presented in the reports are based on the relevant sample and are not weighted, as we focused on the impact of different technology types and did not estimated total impact.

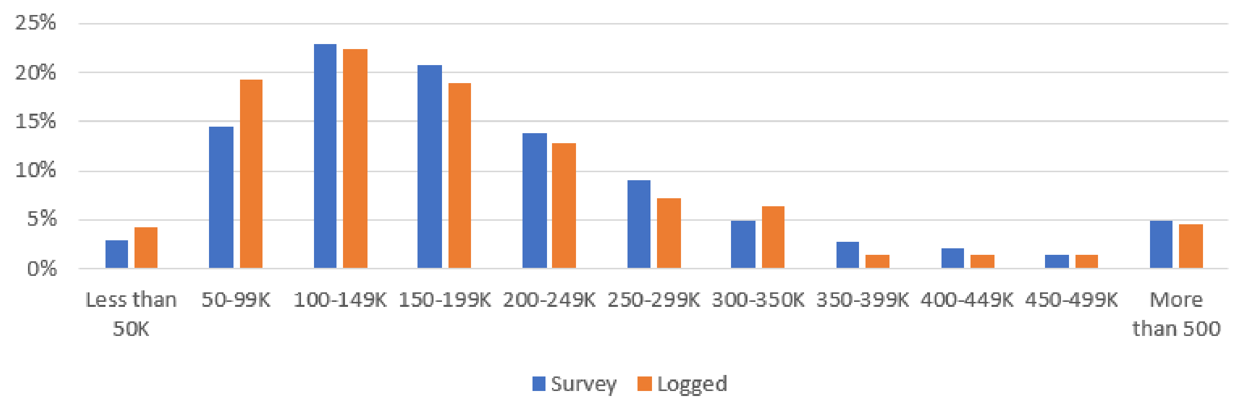


Figure 4. Distribution of Household Income Among Survey Respondents and Logged Households

Overall, the logged households are very similar to the surveyed households, other than having a minor oversampling of households with incomes of $50k-$100k and households with two vehicles.

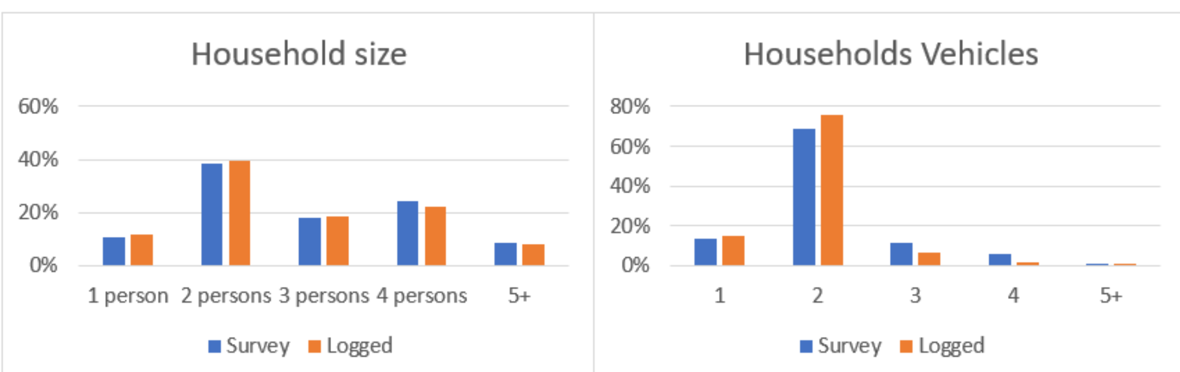


Figure 5. Distrubution of Household Size and Number of Vehicles Among Survey Respondents and Logged Households

The main difference between the logged households and the survey and general populations that is not reflected in the sampling methods is the exclusion of PHEV users who are not plugging in their vehicles. Our 2014 research article suggests that short-range PHEVs are more likely to be used as conventional hybrids.(Tal et al. 2014) A more recent study suggests that about a third of the short-range secondary PHEV owners who finished the survey are using the vehicle as a hybrid only without pluging in. (Turrentine, Tal, and Rapson 2018)

2.5.PHEV eVMT Calculation

Attributing vehicle miles travelled (VMT) to either electricity (eVMT) or gasoline (gVMT) in an ICEV or BEV is trivial, all the VMT fall into either one or the other category; however, PHEVs have two energy sources and correctly tracking the energy can be rather challenging when both sources are used during a trip. The following sections describe the methodology used to calculate eVMT for PHEVs.

2.5.1. Need for Energy Efficiency Ratio

One obvious way of calculating the portion of VMT that should be attributed to eVMT would be to calculate the ratio of total electrical energy consumed to the total energy consumed for both gasoline and electric, and multiply this ratio by the total VMT. The problem with this approach is that energy consumption for the two sources does not yield the same number of miles. For example, the 2011 Chevy Volt has an EPA rated 37 MPG on gasoline and a 93 MPGe when running purely electric. That means that for every kWh of electricity the Volt can travel over 2.5 times as far as with the equivalent energy in gasoline.

To correct for this, an Energy Efficiency Ratio (EER) needed to be calculated for comparing the electrical and gasoline usage of energy. Ideally the EER would be calculated for every operating condition of the vehicle (i.e., every combination of vehicle speed, engine speed, engine torque, motor speed, motor torque, battery SOC, etc.). However, since this approach is not practical, a single EER was calculated based upon the vehicle type. The combined fuel economy numbers from fueleconomy.gov was used for calculating the EER. The EER was calculated by dividing the all-electric fuel economy in MPGe by the gasoline-only fuel economy in MPG. For example, the 2011 Chevy Volt described previously would have an EER of 2.5 (93 MPGe / 37MPG). The calculated EER was used to adjust the electrical energy consumed by the vehicle before calculating the ratio of electrical energy consumed to total (gas and electric).

Equation 1 shows the calculation of the EER; Equation 2, the calculation of the gasoline equivalent electrical energy consumption; and Equation 3, the calculation of eVMT.

Equation 1. EER Equation

$$EER = \frac{MPGe_{EPA}}{MPG_{EPA}},$$

where $MPGe_{EPA}$ is the EPA electric only fuel economy and MPG_{EPA} is the EPA combined highway and city fuel economy for the vehicle using gasoline only.

Equation 2. Electrical Energy Consumption to Gasoline Equivalent

$$E_{ElecGE} = EER \cdot E_{Elec},$$

where E_{Elec} is the measured electric energy consumption and E_{ElecGE} is the gasoline equivalent electrical energy consumption.

Equation 3. eVMT Calculation

$$eVMT = VMT\frac{E_{ElecGE}}{E_{ElecGE}+E_{Gas}},$$

where E_{ElecGE} is the value calculated from Equation 2 and E_{Gas} is the measured gasoline energy consumption.

2.5.2. Adjusting for Battery Efficiency

The eVMT calculated using Equation 3 is dependent upon the calculation of E_{ElecGE}, which in turn is dependent upon the measurement (or calculation) of E_{Elec}. One may intuitively think that the E_{Elec} value should not be calculated, but rather directly measured by integrating the power in and out of the battery. However, this approach would not be correct because batteries are not 100% efficient. Energy is lost when it is either put into or taken out of the battery. To correct for this, the energy consumed (energy taken from the battery) and energy produced (energy put into the battery) are maintained separately and an efficiency factor is applied to the energy produced.

Equation 4 is the equation for calculating the electrical energy consumed. Ideally the battery efficiency should be determined by testing each individual vehicle, and will vary with temperature, rate of power draw, age of the battery, etc. Since this approach would not be practical, a 90% battery efficiency was used for all vehicles. The 90% efficiency was based on a linear fit of data analyzed for energy consumed, energy produced, and delta SOC.

Equation 4. Electrical energy consumption calculation

$$E_{Elec} = E_{BattCon} - Eff_{Batt} \cdot E_{BattProd} \text{ ,}$$

where $E_{BattCon}$ and $E_{BattProd}$ are the energy consumed and produced measured at the battery, and Eff_{Batt} is the battery efficiency.

2.5.3. eVMT Before Engine On

The eVMT calculation for the equations provided thus far apply a fraction of the VMT to eVMT on a trip basis. While this approach is valid, further improvements can be made to increase the accuracy of the calculations by addressing other variables that could influence eVMT. For example, one such variable is that during a single trip the driving conditions (as well as vehicle efficiency) may vary dramatically and therefore the use of energy consumption alone may not accurately attribute VMT to gasoline or electric. It was observed that all of the miles traveled prior to the first engine-on event were actually eVMT, where the miles travelled after the first engine-on were a blend of gVMT and eVMT. It was this observation that prompted the change to Equation 3. Equation 5 is the updated eVMT equation (Equation 3) that attributes 100% of miles traveled to eVMT prior to the first engine-on event, and the fraction of the miles after to eVMT based upon the fraction of energy.

Equation 5. Updated eVMT calculation

$$eVMT = VMT_{EngOn} + \left(VMT - VMT_{EngOn}\right)\frac{E_{ElecGEAEO}}{E_{ElecGEAEO}+E_{Gas}} \text{ ,}$$

where VMT_{EngOn} is the VMT at the first engine-on, and $E_{ElecGEAEO}$ is the gasoline equivalent electrical energy consumption after the engine is first turned on.

2.5.4. Adjusting for Kinetic Energy

The initial eVMT equation provided assumed that it was on a trip basis, so the vehicle both starts and ends at rest. However, the starting point of the hybrid mode may not be at rest, therefore, in the updated eVMT equation (Equation 5), the $E_{ElecGEAEO}$ accounts for the kinetic energy of the vehicle. The kinetic energy of the vehicle, when it is moving and the engine is on, will carry the vehicle some further distance. One may wonder if this energy is significant or not. Consider a 2011 Chevy Volt with a curb weight of 3,781 lbs carrying 200 lbs (passenger and cargo) at 80 mph, the kinetic energy in the vehicle would be 1.15MJ or 0.32kWh which is equivalent to approximately 3% of the 10.9kWh of usable battery capacity. This amount of energy would propel the vehicle 0.89 mi according to the EPA all-electric fuel economy for the Volt (before any adjustments for battery and motor efficiencies). PHEVs with smaller battery packs will potentially have a higher percentage of the usable battery capacity converted into kinetic energy. This is due to the fact that the kinetic energy of a vehicle is related to the mass of the vehicle, and there is not a 1:1 scaling of vehicle mass to battery capacity. A doubling in battery capacity will roughly double the mass of the battery pack, but this will not double the mass of the vehicle.

Equation 6 is the equation for kinetic energy.

Equation 7 is the calculation for the gasoline equivalent electric energy at engine-on. The kinetic energy is divided by Eff_{Motor} which is the assumed motor efficiency of 90%. The 90% motor effieciency was chosen as it provided a simple round number that was in line with published motor efficiencies and also fit the data that had been collected. The energy consumed at the battery would be higher than the output of the electric motor and must be accounted for.

Equation 6. Kinetic Energy Calculation

$$E_{Kin} = \frac{1}{2} m v_{AEO}^2 ,$$

where m is the mass of the vehicle (assumed to be curb weight plus 200lbs), and v_{AEO} is the velocity of the vehicle at engine-on.

Equation 7. Electric Energy Gasoline Equivalent at Engine-On

$$E_{ElecGEAEO} = EER \cdot \left(E_{Elec} + \frac{E_{Kin}}{Eff_{Motor}} \right) ,$$

where Eff_{Motor} is the motor efficiency, which was assumed to be 90%.

3. Charging Behavior Based on Survey Data

Travel patterns and vehicle driving ranges primarily impact PEV owners' charging needs. Past studies have identified four main locations at which charging occurs - overnight charging at or near home, at workplaces, at publicly accessible locations like those near grocery stores, shopping malls, and in parking lots; and on travel corridors where drivers stop between their trip origin and destination points (Idaho National Laboratory, 2015; Ji et al., 2015; M. Nicholas et al., 2017; Nicholas and Tal, 2015; Hardman et al.,2018). Consumers can charge at only one of these locations, some combination of two locations, or all three locations. Though, multiple studies have tried to identify the optimal location for building infrastructure for PEVs, depending on the source and nature of data (stated or revealed) results can vary substantially (Dong et al., 2014; Ji et al., 2015; Santini et al., 2014; Tal and Dunckley, 2016; Weiller, 2011). To accurately model the effect of statewide or nationwide PEV charging demands on future infrastructure needs and on the power grid, it is important to understand the usage pattern of L1, L2, and DC Fast chargers along with choice of charging location. It is also critical to understand the factors driving this charging behavior and choice of charging location. The literature related to charging behavior and use of chargers have often considered the importance of public, workplace, and home infrastructure in isolation. However, in reality the infrastructure is often used in an integrated way with PEV owners plugging in at multiple locations to satisfy their charging needs. We were unable to identify any studies that investigate the combined choice of charging locations. Better understanding of how the charging infrastructure is used by PEV owners and the factors characterizing this behavior will be particularly important when we develop policies for future PEV buyers. It will be possible to forecast better their usage of charging infrastructure based on the charging environment, their demographic characteristics, and travel behavior

The data used in this section is a sub-sample of PEV owners drawn from the recruitment survey discussed in Section 0. Since, phase 1 of the survey did not have questions on charging behavior the sub-sample includes respondents from phase 1.5, phase 2, phase 2.5, and phase 3 of the survey. Also, only PEV owners who charge at least once during the period for which we collect their charging history are included here. The final sample size is 7,979 households, including 4,230 BEV owners and 3,749 PHEV owners. The survey included eight categories of questions: travel behavior, driving behavior, vehicle performance (MPG), vehicle characteristics, response to PEV related incentives, vehicle purchase history, current household vehicle fleet, PEV charging behavior, and sociodemographic characteristics. For charging behavior, we asked the respondents to provide 7 days of charging history and answer, for each day, which of the following combinations of chargers and charging locations were used: Level 1 (L1) home, Level 2 (L2) home, L1 work, L2 work, DC Fast charger (DCFC) work, L1 public, L2 public, DCFC public. An L1 charger adds approximately 4.5 miles of range per hour of charging, an L2 charger adds an average 26 miles of range per hour of charging, and a DCFC provides up to 40 miles of range for every 10 minutes of charging. Also note, here “work” includes vehicle charging events while at work and “public” implies charging events at public locations other than home and when not at work. For each day, a respondent was asked to indicate “yes” or “no” for each of these combinations of charger and location types. In addition, we also asked them to record the price they paid for charging and the availability of charging stations at work and other locations—factors that are potentially related to charging behavior.

Figure 6 shows the difference in charging behavior between BEV users and PHEV users. Overall, more BEV owners use L2 chargers at home than do PHEV owners (more than 40% vs. less than 30%), whereas significantly more PHEV owners use L1 chargers at home than do BEV owners (about 50% vs. about 15%). Home charging is marginally higher during weekends, as expected. L2 chargers at work are used at similar rates among BEV and PHEV owners, with both user groups showing significantly reduced work charging during the weekend. BEV owners reported more DCFC use on the weekends at non-work locations than at work during the weekdays. As PHEVs cannot be charged at DCFC stations, the use of public chargers is low among PHEV owners. The percentage of “no-charging days” for BEV users was twice that of the PHEV users.

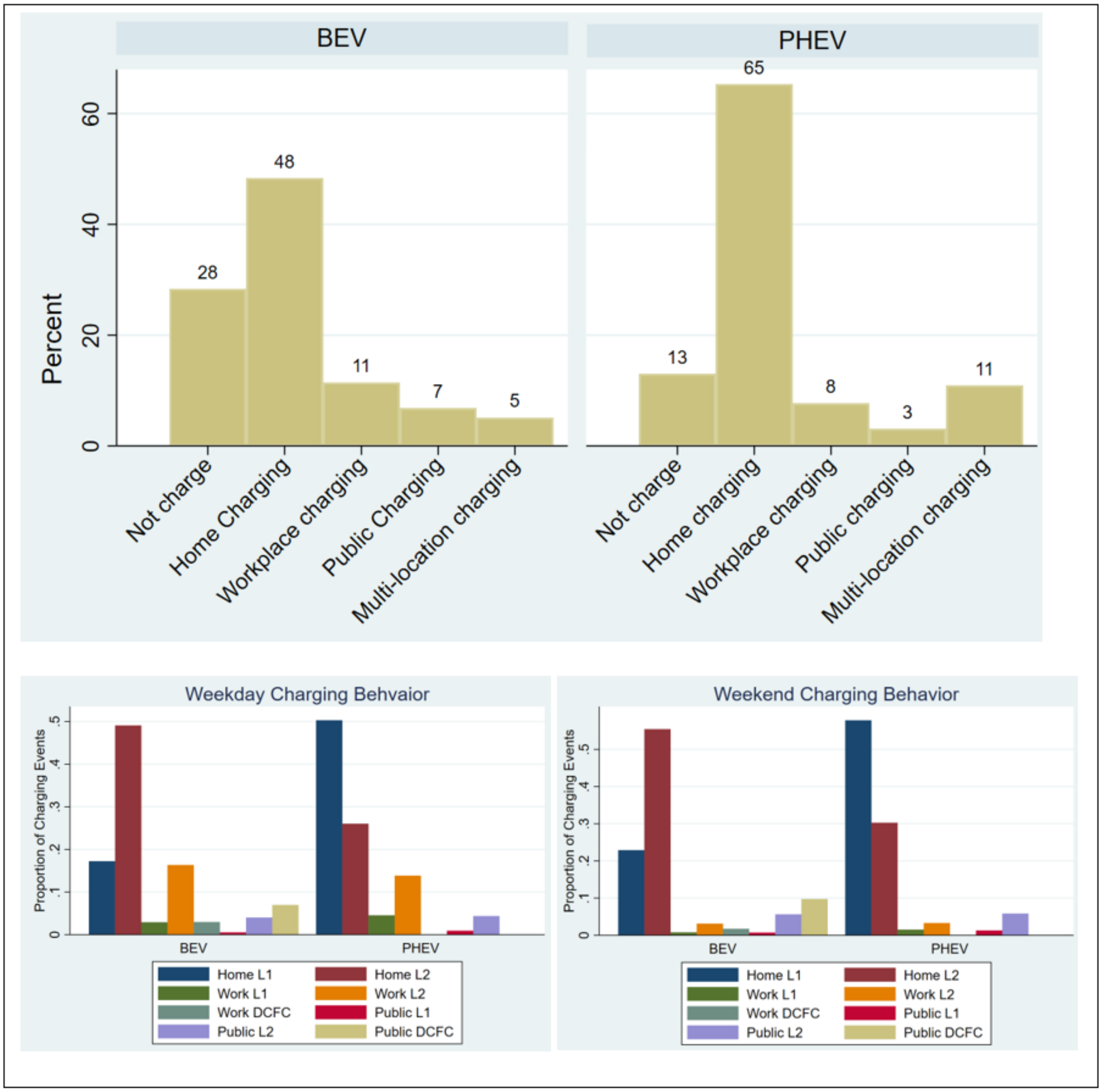


Figure 6. Charging Behavior of BEV and PHEV Users Who Responded to the Initial Survey (N=7,979)

3.1. Distribution of Charging Behavior Among Survey Respondents

Exploratory analysis of the charging behavior of PEV owners reveals that their choice of charging location and charger type is influenced by socio-demographic characteristics like dwelling type and home ownership. The dwelling type of a PEV owner often dictates their access to charging infrastructure and, as **Figure 7** indicates, apartment dwellers and PEV owners residing in condominiums and apartments with limited access to chargers at home are heavily dependent on non-home locations.

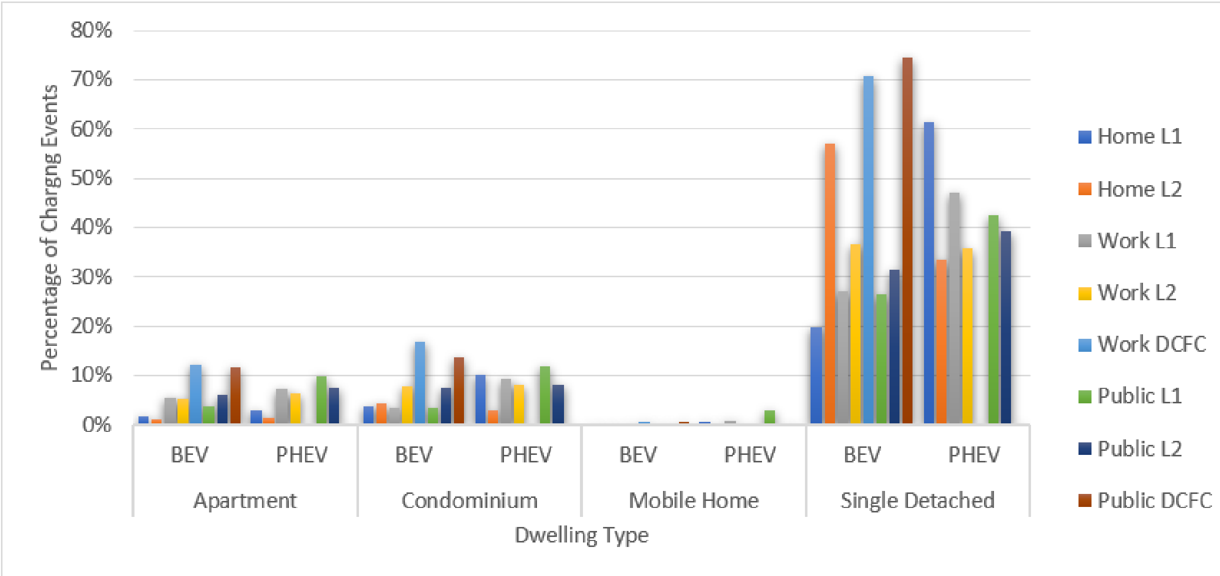


Figure 7. Distribution of Charging Location and Type of Charger by Dwelling Type

To investigate heterogeneous charging behavior, we first classified respondents into different groups based on their mixed usage of charging locations. Using the three types of charging locations (Home, Work, and Public) reported in the survey, we designated seven groups defined by use of one or more of these locations: *Home-only*, *Work-only*, *Public-only*, *Home-work*, *Home-public*, *Work-public*, *All*.

Figure 8 shows the relative share of each charging behavior group in the overall sample according to fuel type and PEV model. Overall, more than half (53%) of the respondents rely only on home charging (**Figure 8,** pie chart**)**. The second and third largest groups, respectively, are those who used workplace charging and public charging facilities together with home charging. These groups account for 16% and 13% of total PEV owners, respectively.

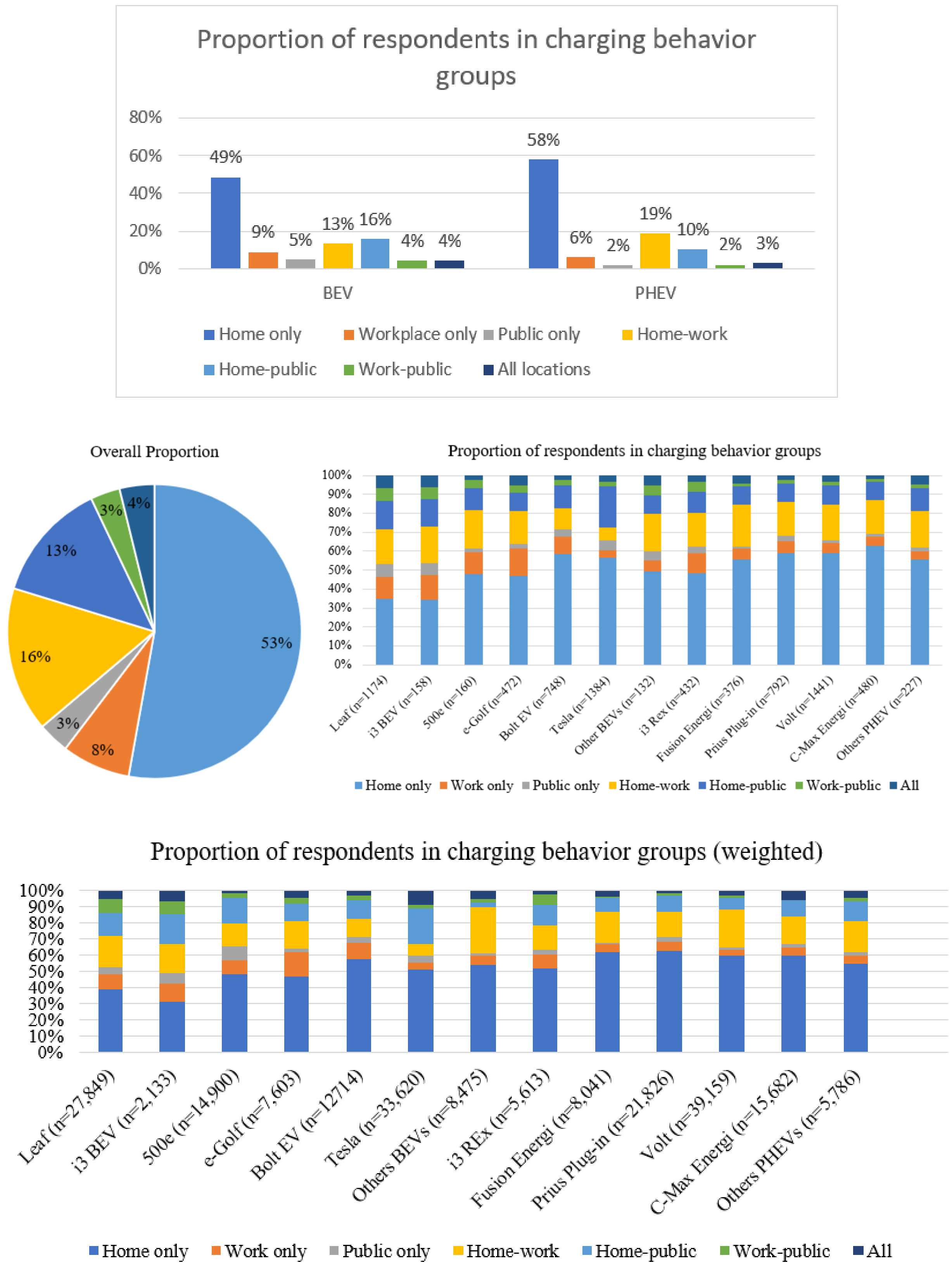


Figure 8. Proportion of Charging Behavior Groups by Fuel type and PEV Models

In total, 86% of respondents used their home charging infrastructure to charge their vehicles (i.e., were in the *Home-only, Home-work*, *Home-public*, or *All* group), indicating that home was the most important charging location for most PEV users during this study. Also, about half of the respondents rely only on home charging regardless of the PEV model, except for Leaf and i3 BEV owners. As shown in Figure 8, these people tend to use other charging facilities, like workplace and public charging locations, more than do owners of other short-range BEVs like the 500e or the e-Golf. The proportion of *Work-only* and *Home-work* chargers are almost the same across other short-range (<100 miles) BEV owners, but there were more Leaf and i3 BEV users in the *Home-public* and *All* groups. In terms of workplace charging, about 30–40% of BEV owners use these charging facilities, and a large proportion of them (48–63%) use this charging with home charging. On the other hand, less than 30% of PHEV owners use workplace charging, and most of them (68–77%) belonged to the *Home-work* group, suggesting they do not use public or corridor chargers frequently. The most unique charging behavior was found in Tesla users. More than half of Tesla users charged their BEVs only at home. Moreover, the proportion of Tesla owners in *Home-public* group was the largest in comparison to all other models of BEVs and PHEVs, perhaps due to the free supercharger network they have access to.

As the survey may have over-sampled certain groups of vehicle owners, we re-calculated the proportions using weighted data (**Figure 8**, bottom panel). The weights are calculated using data from the California Clean Vehicle Rebate Project (CVRP) records. The CVRP dataset contains information on about 200,000 PEVs that have been sold between 2010 and 2017 in California. The purchase year and make of PEVs were used to calculate weights because model information is not available from the CVRP dataset. As **Figure 8** shows, the relative size of each charging behavior group is not markedly different in the weighted analysis (bottom panel) than in the unweighted analysis (middle panel). The relative size of the *Home-only* group for short-range BEVs (Leaf and i3) is slightly different: among Leaf users, this group is larger in the weighted than in the unweighted analysis, while among i3 BEV users, this group is larger in the unweighted analysis. The difference in the weighted vs. unweighted analysis for the i3 BEV users can be related to the incentives and no-cost charging provided by BMW in North America.

It is important to understand not only the choice PEV owners make in terms of charging location, but also in terms of the type of charger—L1, L2, or DCFC. **Figure 9** illustrates the average number of PEV charging days using different levels of chargers in different locations during the weekdays and weekends, according to different charging behavior groups. Home charging is indicated by different shades of blue; workplace charging, red; and charging in all public locations, green.

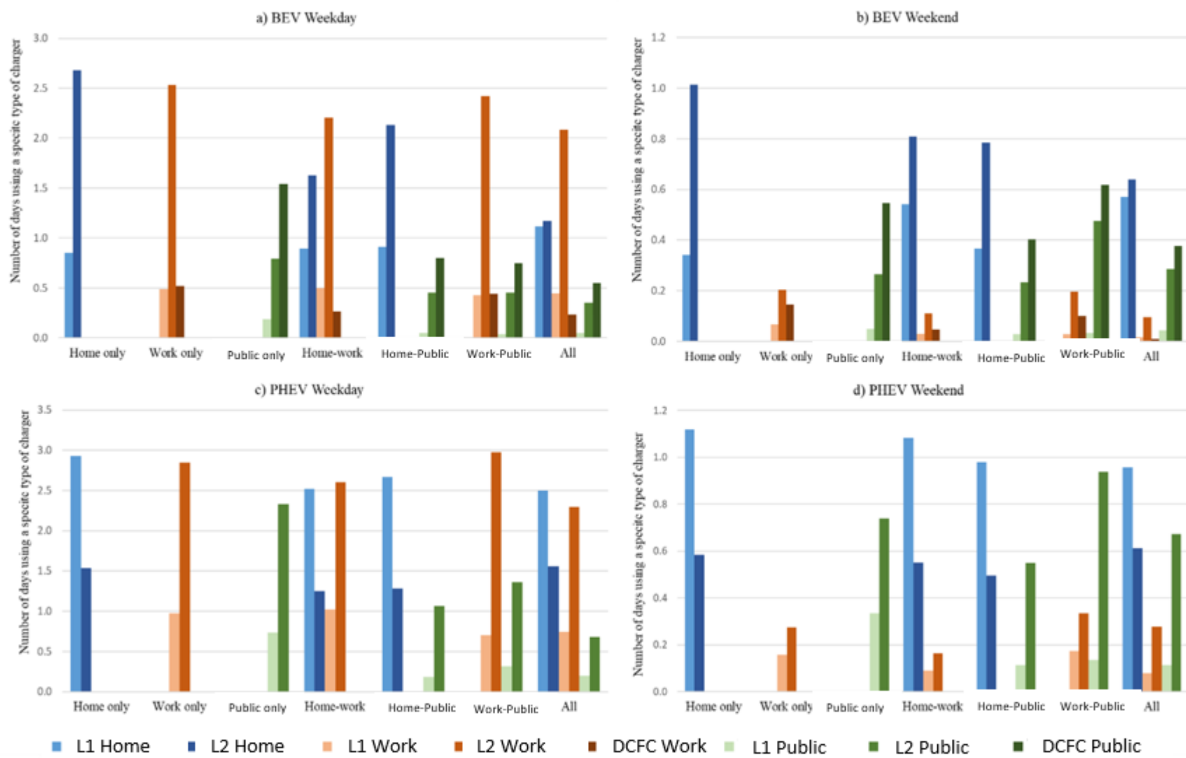


FIGURE 3. Proportion of usage of different level of chargers in within charging behavior group

Figure 9. Average Weekly Usage of Different Level of Chargers within Charging Behavior Groups

BEV owners (**Figure 9**a-b): Regardless of BEV owners' charging behavior group, an L1 charger was not the preferred option. An L2 charger was the most frequently used charger at home and the workplace, with BEV owners in the *Home-only* group using L2 chargers at home more than 2.5 days per week during weekdays, on average. Average usage of L2 chargers is similar in the case of *Work-only* group. Similar trends are observed for the *Home-work*, *Home-public*, *Work-public*, and *All* groups when charging at home or work. DCFC was the most frequently used charger type among groups that charge in public locations. Note that although the BEV users' average number of charging days per week at home using an L1 charger is 0.8 and an L2 charger is 2.7 (Figure 9a), this does not reflect the use of different types of chargers by a particular household, but rather the average usage of L1 and L2 chargers by BEV owners. Though most BEV owners used an L2 charger, a considerable number used an L1 charger at home. Similarly, most of the BEV owners in the *Work-only* group used an L2 charger at work, but they also used L1 chargers and DCFCs. People who rely on charging only in locations other than home used DCFCs (about 1.5 days per week) or L2 chargers (about 0.8). In terms of the BEV owners using chargers in more than one location, the *Home-work* group seemed to use both charging locations in equal proportion. On the other hand, the *Home-public* and *Work-public* groups seemed to be more dependent on home and workplace chargers (more than 2 days at these chargers), respectively. The *All* group primarily used home and workplace chargers and were less dependent on other types of chargers. **Figure 9**b shows weekend charging behavior of BEV owners, which are very similar to the BEV weekday pattern with the exception of workplace charging.

PHEV owners (**Error! Reference source not found.**9c-d). PHEV owners tended to charge more often than BEV owners. More than 60% of PHEV owners used L1 chargers at home, although their main chargers at the workplace or other locations were L2 chargers. Unlike BEV users, PHEV owners in the *Home-only* and *Home-work* groups use L1 chargers more frequently at home. However, they use L2 chargers at work equally.Those in the *Home-public*, *Work-public*, and *All* groups tend to mainly use their L1 chargers at home or L2 chargers at work and use other chargers as a supplement. As with BEV owners, PHEV owners do not have marked differences between weekdays and weekend charging patterns, again with the exception of workplace charging.

3.2. Potential Factors Related to Charging Behavior: Logistic Regression Model

To understand and identify factors related to charging behaviors, we used the multinomial logit model. We divided the sample into two groups (BEV and PHEV), and estimated the structural choice model separately for the two groups using the statistical software package LatentGold 5.1 (also called Step 3 model with Modal option). The dependent variable was the charging behavior group, as described in Section 3.1: *Home-only*, *Work-only, Public-only, Home-work*, *Home-public, Work-opublic,* or *All*. We used effect coding for the dependent variable so that we could estimate parameters in terms of differences from the average and not from the reference category. In this way, it is possible to identify correlated factors for all types of charging behavior.

We examined the effect of 27 independent variables on the probability of a PEV owner belonging to a charging behavior group. They are as follows:

1. Income of houshold
2. Education
3. Age
4. Gender (Female: 1)
5. usage of PEV within household (multiple drivers:1)
6. Homeownership (Owner:1)
7. Housing type (Detached: 1, other: 0)
8. Number of vehicles in household (NVeh)
9. Household size (HHsize)
10. Number of drivers in household (NDriver)
11. PEV purchase year (BuyYear)
12. Purchase or lease (Purchased: 1, Leased: 0)
13. Vehicle holding decisions (i.e., purchasing an additional PEV or replacing a PEV; Replace: 1, Add:0),
14. Workplace charger availability (AvailCharger, Yes 1, No: 0),
15. Electric range of PEV (Range), electric range used for PHEV model,
16. Free workplace charging (FreeWorkChar_1, Yes: 1, No: 0),
17. Having limitation in workplace charging (WorkCharLimit, Yes: 1, No: 0),
18. Number of workplace chargers (N_WorkChrgers),
19. Frequency of change in parking spots for charging in a month (Swap_Parking,Yes:1,No: 0),
20. Whether or not the owner changed the home electricity plan (ChangeRate_1, Yes:1, No: 0),
21. Ownership of solar panels (Solar_1, Yes: 1, No: 0),
22. Charging network membership (ChargeMembership_1,Yes=1,No),
23. Commute distance (CmtDist),
24. Availability of L1 public chargers within 300 meters of residence (EV_L1_0_3m) for PHEV owners,
25. Availability of L2 public chargers within 300 meters of residence (EV_L2_0_3m) for both samples,
26. Availability of DC Fast public chargers within 300 meters of residence (EV_DC_0_3m) for BEV owners sample, and

27. Tesla ownership (Yes: 1, No: 0),
    only used for the BEV model.

The final model specification was developed based on intuitive reasoning, previous literature on charging behavior, and parsimony in the representation of variable effects.

3.2.1. BEV Regression Model

Table 2 shows the estimated parameters from the multinomial logit model of BEV owners. The group charging at *Home-only* was more likely than other groups to be high-income, older, and owners of detached houses. Their BEVs are more likely to have a longer electric range than other groups, and they do not have access to workplace chargers. They are more likely than other groups to change their electricity plans, mostly because they heavily rely on home charging. The apartment renters with higher education are more likely to belong to the *Work-only* group than to other groups. BEV users in the *Work-only* group tend to have a greater number of vehicles in the household, but mostly use leased non-Tesla BEVs. This group was more likely than other groups to have unlimited free or paid workplace charging, but have to swap parking spots for workplace charging. This group is less likely to change their electricity plan, as may be expected since they rely exclusively on workplace charging. The *Public-only* group tended to be relatively “lower-income” renters using a Tesla with a higher number of drivers in the household. Although this group tends to have “lower income” than BEV users in other groups, this is just in relation to the average income in our sample (see Table 1). It is not a low-income group as is defined by standards external to this study (for example, with an income 100-400% of the poverty line, or less than $60,000 per year for a 4-person household). Compared to the BEV users in other groups, those in the *Home-work* group were more likely to be younger, residents of single-detached homes, and have relatively older non-Tesla BEVs. They tended to use both home chargers with a revised rate plan as well as free workplace chargers. The older BEV owners of Teslas with single-detached homes were more likely to use chargers at home and other locations (*Home-public*). Workplace charging was not available to this group and therefore they tended to use other types of chargers. People in the *Work-public* group are almost the same as the *Work-only* group, except that that the following independent variables (parameters) did not significantly correlate with their being in this *Work-public* group: education level, number/limit of workplace chargers, and Tesla ownership. Lastly, people who used all types of charging facilities (the *All* group) were more likely than members of other groups to be young BEVs owners with access to free chargers at their workplace.

Table 2. Potential Factors Associated with BEV Charging Behavior - Multinomial Logistical Regression Analysis

BEV Model	Covariates	Home-Only	z-value		Work-only	z-value		Public-only	z-value		Home-Work	z-value		Home-public	z-value		Work-public	z-value		All	z-value		Wald	p-value
Socio-demo	Income	0.00	3.30	*	0.00	0.81		0.00	-2.97	*	0.00	1.80		0.00	0.11		0.00	0.37		0.00	-0.63		21.11	0.00
	Education	-0.04	-0.82		0.24	2.77	*	-0.05	-0.57		-0.05	-0.75		-0.11	-1.69		0.03	0.24		0.00	-0.02		9.34	0.16
	PrimaryAge	0.02	5.12	*	0.00	0.00		0.00	0.27		-0.01	-1.80		0.01	2.24	*	0.00	-0.18		-0.02	-2.88	*	34.88	0.00
	Female_1	0.28	3.39	*	0.13	1.00		-0.23	-1.48		-0.27	-2.42	*	0.11	1.12		-0.19	-1.02		0.17	1.08		23.94	0.00
	Mixed_1	0.40	2.44	*	-0.41	-1.34		-0.24	-0.73		-0.08	-0.36		0.15	0.74		-0.26	-0.74		0.44	1.63		10.06	0.12
	HouseOwner	0.59	5.14	*	-0.20	-1.40		-0.48	-2.71	*	0.40	2.67	*	0.16	1.13		-0.68	-4.31	*	0.22	0.98		60.43	0.00
	Detached_1	0.45	2.97	*	-0.37	-2.05	*	-0.34	-1.53		0.55	2.60	*	0.31	1.68		-0.40	-1.74		-0.20	-0.79		24.85	0.00
	NVeh	-0.08	-1.67		0.15	1.85		0.01	0.14		0.00	0.04		-0.17	-2.75	*	0.05	0.47		0.04	0.51		9.58	0.14
	HHsize	-0.06	-1.53		0.05	0.93		-0.14	-1.75		0.05	1.12		-0.02	-0.54		0.04	0.54		0.08	1.25		6.56	0.36
	NDriver	-0.02	-0.34		-0.16	-1.57		0.26	1.99	*	0.04	0.54		0.10	1.13		-0.08	-0.55		-0.13	-1.03		8.35	0.21
PEV characteristics	ReplaceAddPrev	0.04	0.50		-0.22	-1.53		0.06	0.37		0.19	1.79		0.05	0.48		-0.21	-1.14		0.08	0.49		6.32	0.39
	Tesla_1	-0.05	-0.49		-0.65	-3.50	*	0.76	3.72	*	-0.91	-6.46	*	0.67	5.22	*	0.27	1.12		-0.08	-0.38		88.06	0.00
	BuyYear	0.00	0.07		0.13	2.16	*	0.08	0.97		-0.21	-4.14	*	0.06	1.11		0.14	1.62		-0.21	-2.83	*	31.20	0.00
	Purchased_1	0.06	0.76		-0.17	-1.28		0.20	1.25		-0.07	-0.70		0.24	2.30	*	-0.46	-2.32	*	0.20	1.29		12.65	0.05
Workplace charging	AvailCharger	-0.80	-6.91	*	0.88	4.12	*	-1.35	-6.01	*	0.63	3.57	*	-1.13	-7.85	*	0.78	2.61	*	0.99	3.26	*	136.13	0.00
	FreeWorkChar_1	-1.03	-8.98	*	0.76	5.66	*	-0.40	-1.64		0.55	4.95	*	-0.88	-5.42	*	0.68	3.88	*	0.32	2.02	*	167.60	0.00
	WorkCharLimit_1	0.13	1.19		-0.32	-2.51	*	0.11	0.44		-0.08	-0.72		0.30	2.05	*	-0.13	-0.76		-0.01	-0.07		10.17	0.12
	N_WorkChargers	-0.01	-1.16		0.01	3.77	*	-0.01	-1.00		0.01	1.78		-0.01	-1.18		0.00	0.20		0.00	1.20		17.01	0.01
	Swap_Parking	-0.14	-5.31	*	0.06	5.82	*	-0.03	-1.07		0.04	4.62	*	-0.07	-3.78	*	0.08	6.44	*	0.06	5.29	*	70.94	0.00
Home charging env.	Solar_1	0.47	5.64	*	-0.57	-3.86	*	-0.30	-1.72		0.04	0.40		0.39	3.76	*	-0.21	-1.01		0.17	1.07		48.23	0.00
	ChangeRate_1	0.63	8.39	*	-0.57	-4.28	*	-0.58	-3.71	*	0.29	3.09	*	0.48	5.17	*	-0.43	-2.52	*	0.18	1.24		101.68	0.00
Other charging env.	ChargMembership_	-0.78	-8.10	*	-0.33	-2.57	*	0.52	3.20	*	-0.37	-3.49	*	0.27	2.34	*	0.47	2.90	*	0.23	1.47		113.75	0.00
	EV_L2_0_3m_APT	0.00	0.83		0.00	-0.78		0.00	-0.94		0.00	-0.24		0.00	1.21		0.00	1.32		0.00	-0.85		5.75	0.45
	EV_DC_0_3m_APT	0.02	1.61		0.00	0.18		-0.01	-0.68		-0.01	-0.33		0.00	-0.06		0.00	-0.24		0.00	0.11		2.95	0.82
Commute Nature	CmtDist	0.00	0.13		-0.01	-0.76		0.00	-0.24		0.00	1.35		0.00	-0.18		0.00	1.65		0.00	1.53		8.81	0.18

Note: Variables marked with a * are factors that are significant at 5% level of significance. (N=4,230)

3.2.2. PHEV Regression Model

Table 3 shows the estimated parameters from the multinomial logit model of PHEV owners. Overall, fewer parameters estimated in this model were significant than in the BEV model, but the significant ones were similar to those in the BEV model. Compared to PHEV owners in other groups, those in the *Home-only* group was more likely to be older, live in detached houses, use relatively older PHEVs, and have no access to chargers at work. The PHEV owners in the *Work-only* group are also similar to the corresponding group among BEV owners: they tend to be apartment renters with access to free or paid workplace charging. Interestingly, while we do not observe any effect of commute distance on charging behavior for BEV users, PHEV owners in the *Work-only* group tend to commute shorter distances than other PHEV groups. Among PHEV owners, people in the *Public-only* group are more likely to be renters and have no access to free workplace charging. Compared to the BEV owners in the *Public-only* group, the PHEV owners in the *Public-only* group tends to have fewer household vehicles. The PHEV *Home-public* group is more likely than the other PHEV charging behavior groups to own detached homes and not have access to workplace charging. In comparing the corresponding charging behavior groups between BEV and PHEV owners, the *Home-public* group differed more than any other charging behavior group. The BEV owners in this group tended to be new Tesla owners, while the PHEV owners in this group tended to be home owners with a smaller number of vehicles in households and no access to chargers at workplace. In comparison to the corresponding BEV *Home-public* group, PHEV owners in the *Home-public* group were more likely to use their vehicles for long distance commutes. The *Work-public* group of PHEV owners are similar to the corresponding group of BEV owners, but the latter use relatively longer-range electric vehicles. Lastly, compared to the equivalent BEV group, the PHEV *All* group is more likely to have young, long distance commuters with more vehicles and fewer drivers per household.

3.2.3. BEV and PHEV Model Results Comparison

Overall, the results of the two multinomial logit models of BEV and PHEV owners show charging behavior correlates with many different factors including socio-demographics, household vehicle characteristics, commute travel behavior, and workplace charging availability and limits. The model does not account for the cost of charging in public locations and the cost of charging at work is captured using a dummy variable. However, most charging locations other than home usually have free-to-the-user charging. Even home-charging is inexpensive, particularly if the household subscribes to the special rate plans offered to PEV owners by most utiltity companies in California. Therefore, at present, more than price, the factors we considered in the model may drive charging behavior.

Among all of the factors, workplace charging availability and free charging are the most important factors characterizing charging behavior. Home ownership, type of house, and age of the primary driver are also important factors that correlate with charging behavior. Interestingly, commute distance is a significant factor only for PHEV owners and not for BEV owners. As shown in **Table 3**, among PHEV owners, longer commute distance was positively correlated with being in the *Home-Work* and *Work-public* groups and negatively correlated with being in the *Work only* charging group. Assuming that PHEV owners want to reduce their carbon footprint as well as the vehicle operating cost, they may want to maximize the use of their electric driving capacity. Consequently, if the commute distance is longer it is unlikely that the household would want to rely only on home or workplace charging to achieve the purpose.

Multiple case studies have discussed the importance of public infrastructure for residents of multi-unit dwellings. To control for this effect, we interacted the dwelling type of respondents, namely if the respondent resides in an apartment complex with availability of L1 and L2 public chargers within 300 meters of residence for PHEV owners. For BEV owners, we explore the interaction between dwelling type of respondents and availability of public L2 chargers and DCFCs within 300 meters of residence. We observe that the presence of this factor has no significant effect on the choice of charging location for BEV owners. For PHEV owners, the availability of L2 chargers within 300 meters of their residence correlates positively with being in the *Public-only* group. BEV and PHEV owners who reside in multi-unit dwellings can self-select into apartment complexes where charging infrastructure is available and, as noted before, they are usually renters with no access to free workplace charging. The model also controls for the effect of having solar panels at home and membership in charging networks like Blink and EVgo. While the presence of solar panels increases the probability of BEV owners charging at home (i.e., being in any group that includes home charging), it has a negative effect on workplace charging. In the case of PHEV owners, similar results are observed. Membership in charging networks has a positive impact on the probability of charging at public infrastructure for BEV owners—i.e., being in a group that includes “Public” charging—and a negative effect on being in charging behavior groups that use only home, work, or a combination of work and home charging. For PHEV owners, while membership in a charging network has a negative effect on being in the *Home-only* charging group, it has no significant effect on any other charging group.

Table 3. Potential Factors Associated with PHEV Charging Behavior - Multinomial Logistical Regression Analysis

PHEV Model	Covariates	Home-Only	z-value		Work-only	z-value		Public-only	z-value		Home-Work	z-value		Home-public	z-value		Work-public	z-value		All	z-value		Wald	p-value
Socio-demo	Income	0.00	-0.42		0.00	0.66		0.00	-0.76		0.00	1.51		0.00	-0.96		0.00	-0.31		0.00	1.17		4.93	0.55
	Education	0.04	0.71		0.18	1.69		-0.16	-0.93		-0.01	-0.12		0.07	0.79		-0.09	-0.58		-0.03	-0.22		4.16	0.66
	PrimaryAge	0.01	3.82	*	-0.01	-0.90		0.01	1.77		0.00	-0.41		0.01	1.78		-0.01	-1.52		-0.02	-2.20	*	22.71	0.00
	Female_1	0.32	3.34	*	0.04	0.25		0.09	0.33		-0.10	-0.81		-0.02	-0.19		-0.26	-1.02		-0.07	-0.33		17.23	0.01
	Mixed_1	0.22	1.01		-0.25	-0.63		0.50	1.05		0.06	0.22		-0.32	-0.98		-0.17	-0.26		-0.04	-0.09		4.25	0.64
	HouseOwner	0.49	4.41	*	-0.31	-1.90		-0.55	-2.16	*	0.26	1.98	*	0.51	3.16	*	-0.47	-2.16	*	0.06	0.26		33.98	0.00
	Detached_1	0.26	1.72		-0.37	-1.64		0.17	0.48		0.09	0.48		0.03	0.13		-0.43	-1.59		0.26	0.77		8.32	0.22
	NVeh	-0.01	-0.16		0.07	0.58		-0.40	-1.97	*	0.11	1.47		-0.21	-2.40	*	0.16	1.01		0.28	2.14	*	15.54	0.02
	HHsize	-0.04	-0.98		0.06	0.80		-0.07	-0.59		0.06	1.05		-0.03	-0.49		-0.12	-1.03		0.14	1.74		6.53	0.37
	NDriver	0.00	0.00		0.03	0.21		0.13	0.66		-0.10	-1.02		0.21	1.82		0.11	0.57		-0.38	-2.29	*	8.89	0.18
PEV characteristics	ReplaceAddPrev	-0.03	-0.21		-0.13	-0.50		0.26	0.73		-0.06	-0.37		0.02	0.12		-0.24	-0.59		0.18	0.70		1.51	0.96
	Range	0.00	-0.42		0.00	-0.12		0.01	1.13		-0.01	-3.36	*	0.00	0.27		0.01	2.17	*	0.00	-1.02		16.81	0.01
	BuyYear	-0.10	-2.20	*	0.03	0.34		-0.08	-0.68		0.07	1.34		-0.04	-0.66		0.07	0.61		0.06	0.72		10.09	0.12
	Purchased_1	0.00	-0.05		-0.24	-1.71		-0.09	-0.40		0.04	0.40		0.08	0.66		-0.11	-0.52		0.33	1.80		6.34	0.39
Workplace charging	AvailCharger	-1.18	-8.17	*	0.70	2.32	*	-0.79	-2.06	*	1.74	8.71	*	-1.47	-7.55	*	0.35	0.87		0.64	2.01	*	221.03	0.00
	FreeWorkChar_1	-1.10	-7.10	*	1.03	5.37	*	-1.37	-2.69	*	0.70	5.18	*	-0.12	-0.58		0.65	2.56	*	0.21	0.95		150.67	0.00
	WorkCharLimit_1	0.31	2.17	*	-0.36	-1.99	*	-0.13	-0.29		-0.13	-1.00		0.15	0.67		0.09	0.37		0.07	0.31		12.14	0.06
	N_WorkChargers	-0.02	-2.41	*	0.02	3.27	*	-0.01	-0.63		0.01	2.63	*	-0.01	-0.62		0.01	1.08		-0.01	-0.60		17.29	0.01
	Swap_Parking	-0.09	-6.00	*	0.04	4.24	*	-0.02	-0.82		0.03	3.36	*	-0.04	-1.99	*	0.05	3.36	*	0.04	3.29	*	59.62	0.00
Home charging	Solar_1	0.32	2.75	*	-0.48	-2.08	*	-0.05	-0.16		0.35	2.56	*	0.24	1.58		-0.75	-1.79		0.38	1.72		16.43	0.01
	ChangeRate_1	0.33	3.35	*	-0.66	-3.53	*	-0.56	-1.93		0.37	3.29	*	0.24	1.83		-0.25	-0.97		0.54	2.94	*	34.30	0.00
Other charging env.	ChargMembership_1	-0.56	-4.15	*	0.24	1.13		0.11	0.36		0.03	0.16		-0.28	-1.55		0.43	1.57		0.04	0.14		19.34	0.00
	EV_L1_0_3m_APT	-0.01	-0.42		-0.01	-0.42		0.10	2.10	*	-0.02	-0.60		0.00	-0.06		-0.05	-1.33		0.01	0.09		5.76	0.45
	EV_L2_0_3m_APT	0.00	-0.29		0.00	1.59		0.00	-0.32		0.00	-1.47		0.00	0.02		0.00	0.67		0.00	-0.18		6.01	0.42
Commute Nature	CmtDist	0.00	0.06		-0.02	-2.67	*	0.01	1.04		0.01	3.42	*	-0.01	-1.74		-0.01	-0.66		0.01	3.26	*	22.10	0.00

Note: Variables marked with a * are factors that are significant at 5% level of significance. (N=3,749)

4. Comparative VMT Analysis of PEVs Based on Survey Data

Estimating actual usage of current PEVs is a difficult task, given their relatively short time on the market and the fast pace of technological change. For example, only 5 years ago the range of first-generation BEVs on the market (Tesla excluded) was about 70–80 miles. Today, there are many more models available, and many (non-Tesla) BEVs with much higher ranges, e.g., 150-250 miles. The market for PEVs is evolving in terms of both technology and users. This evolution should be taken into account when analyzing the VMT of PEVs and the associated impact on GHG emissions. Recent estimates of how far PEVs are driven using the 2017 National Household Travel Survey (NHTS) data are based on a limited sample of early adopters who were using those first-generation cars, primarily short-range BEVs (McGuckin and Fucci 2017, Davis 2019). While 46% of the 325 BEV owners (37% of 257 PHEV owners) bought a vehicle less than 2 years old, the remaining adopters had BEVs and PHEVs that were more than three years old, with an average age of 3.5 years[1]. The annual VMT estimates from these vehicles can present a biased picture that underestimates vehicle usage and may result in incorrect policy recommendations.

We explore PEV usage based on our project survey, which included a large sample of owners who reported their current odometer readings and the month and year of purchase. We compare the results to the recent 2017 NHTS survey that includes a small sample of first-generation PEVs and the 2017 California's Advanced Clean Cars Midterm Review. The comparative analysis demonstrates the challenges of using large-scale travel behavior surveys like the NHTS that may not be able to capture the changes in vehicle use in response to technological changes. Targeted studies of PEV owners are required to get reliable estimates of PEV usage and driving patters.

To date, there have been a limited number of studies on PEV use patterns, due to a lack of reliable data (Nicholas, Tal, and Turrentine 2017). The 2017 NHTS, a nationally representative database for travel behavior studies, offers researchers the opportunity to fill this gap in the literature—and undoubtedly researchers would use the data to analyze VMT patterns of PEV and non-PEV vehicles. The problem is that the 2017 NHTS data have certain limitations explained below that may not give an accurate picture of the driving patterns of households, particularly VMT.

[1] In the NHTS survey age of a vehicle is measured on the basis of the model year since purchase information is not available

Consider the distribution of annual VMT for different fuel types calculated from the NHTS California Add-On Survey of 26,112 households.[2,3]

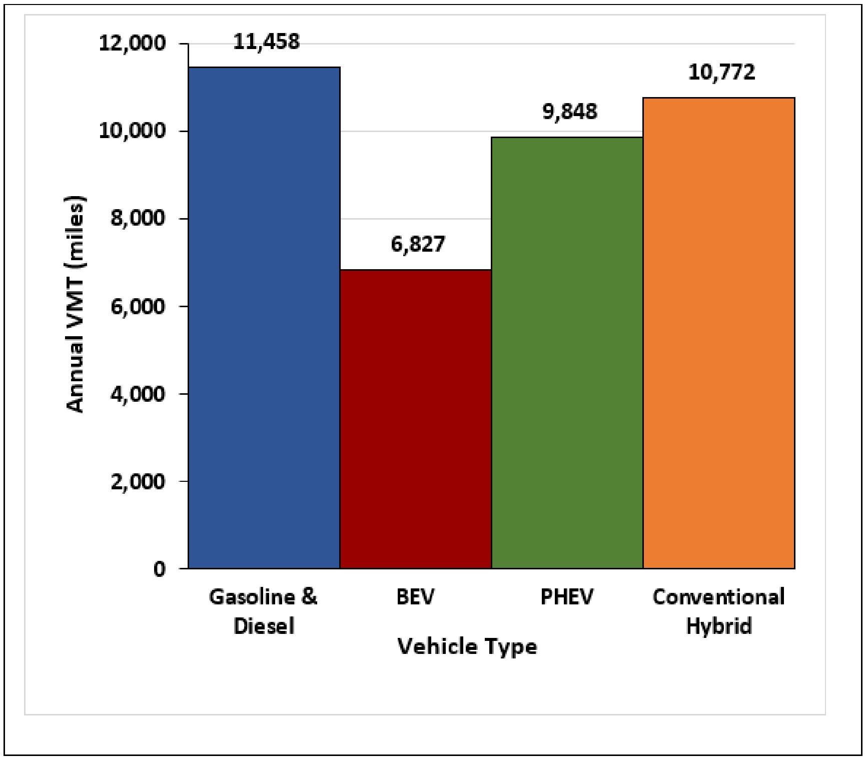


Figure 10. Annual VMT Distribution (weighted) by Fuel Type Using NHTS 2017 California Add-On Data (N=10,447 including: 9,391 gasoline and diesel vehicles, 207 BEVs, 196 PHEVs, and 653 conventional hybrids)

Focusing only on vehicles that are less than 4 years old, as shown in **Figure 10**, BEVs (including all makes and models) drive an average 6,827 miles, approximately 40% less than conventional gasoline and diesel vehicles. Among non-ICEVs, conventional hybrids have the highest annual

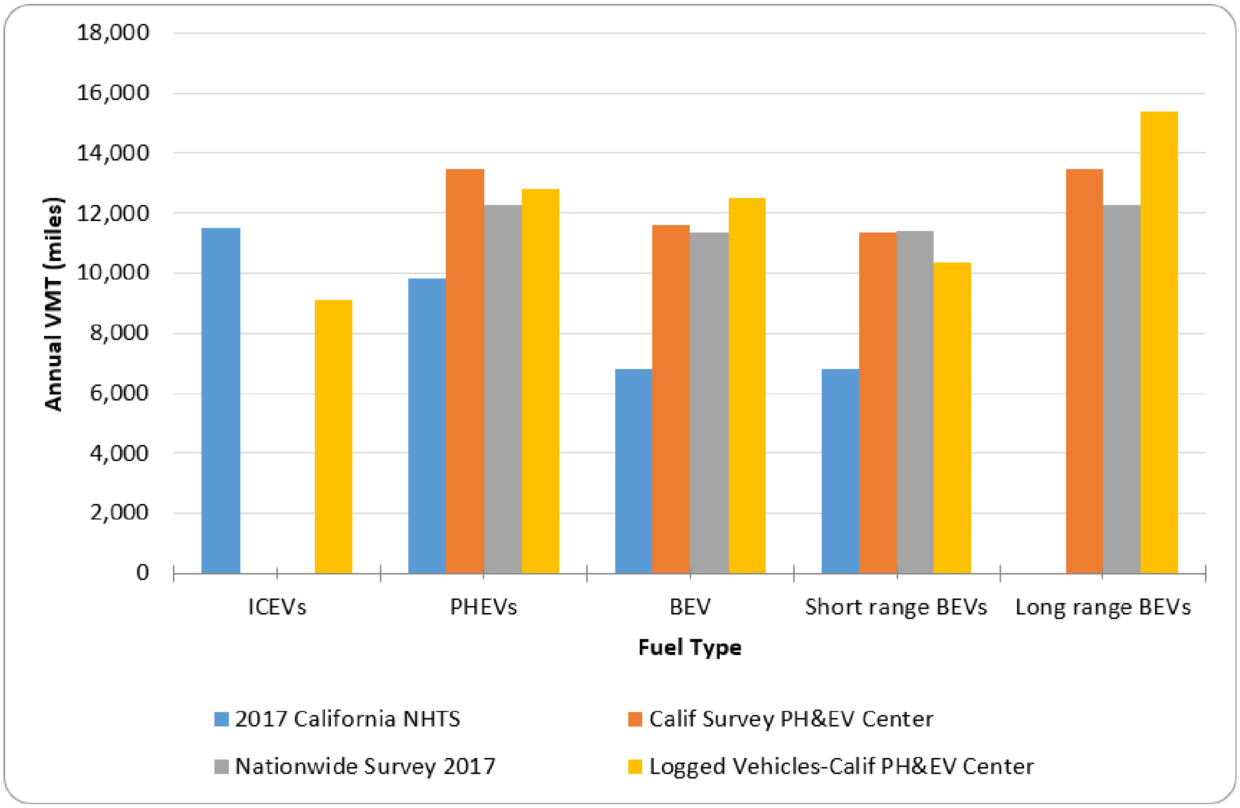
[2] The estimates are weighted using the 7-day household raked weights provided in the NHTS survey.
[3] 95% of vehicles owned by the surveyed households were gasoline or diesel vehicles. Out of the 2,526 alternative fuel vehicles, 1,866 vehicles were conventional hybrid cars and the remaining were PEVs. Among the plug-in hybrids (PHEVs), the Chevrolet Volt was the most commonly owned vehicle, among BEVs it was the Nissan Leaf.

VMT followed by PHEVs. The weights used to generate the VMT estimates are the 7-day ranked weights reported in the 2017 NHTS California add-on data.

Undoubtedly, these numbers seem to paint a grim picture about the environmental benefits of BEVs in terms of reducing greenhouse gas emissions from the tailpipe. They raise questions about the benefit of incentives for these vehicles, and they challenge the VMT assumptions of some popularly used forecast models like the GREET model.

Are BEV adopters not driving their vehicles?

Contrary to the NHTS estimates, our recruitment survey indicates that in California BEV owners drive an average of 11,352 miles annually, and PHEV owners, 13,028 miles annually. We also recently completed a similar survey in 38 states. Annual VMT estimates from this nationwide survey also show that BEV owners drive on average more than 10,000 miles annually (Figure 10). Data from the logged vehicles in the California study reveal VMT estimates in the same range as the recruitment and nationwide surveys. Here, the VMT estimates are not weighted. Due to a lack of reliable data on the total sales of BEVs and PHEVs by vehicle model and year for California or the other states included in the nation-wide survey, it is not possible to calculate valid weights.



Fuel Type	2017 California NHTS N=10,447	California Survey by PH&EV Research Center N=11,269	Nationwide Survey 2017 N=2,102	Logged Vehicles - Calif PH&EV Research Center* N=427
ICEVs	11,485 ± 25,695.7			9,104 ± 5,616
PHEVs	9,848 ± 9,007.1	13,472 ± 7,407.9	12,287 ± 6,932.5	12,802 ± 5,657
BEV	6,827 ± 6,644.2	11,604 ± 6,447.8	11,374 ± 7,096.1	12,522 ± 7,180
Short range BEVs	6,827 ± 6,644.2	11,366 ± 6,591.7	11,436 ± 7,235.5	10,364 ± 4,682
Long range BEVs		13,456 ± 7,277.5	12,251 ± 7,113.5	15,369 ± 8,798
Values expressed as mean ± standard deviation.				

Figure 11. Average Annual VMT by Data Collection and Vehicle Type.
The Annual VMT Numbers Derived from Our Surveys and Logged Vehicles are Similar to the Estimates Reported in the 2017 California's Advanced Clean Car Midterm Review, where the Mean VMT was 10,294 Miles for Leaf Owners, 13,494 Miles for Tesla Owners, and 15,283 Miles (2,304 miles eVMT) for Prius Plug-in Owners (*For additional details, please see **Table 8**)

4.1. Why this difference in estimates?

The potential reasons for the difference in annual VMT estimates (NHTS compared to the rest) are limitations in the NHTS data related to vehicle-level information. First, vehicle age in the NHTS data was estimated as the difference between the model year and 2017. Since new vehicle models can be released at the end of the previous calendar year, using the model year to calculate vehicle age is not always reliable. Second, the single reported odometer reading can be noisy, especially when the survey respondent is not the primary driver of the vehicle (Lloro and Brownstone 2018). Also, being early adopters, PEV owners are generally different from ICEV owners in terms of demographic characteristics, income distribution, and environmental attitudes, all of which can impact their travel patterns. Standard survey methods and sampling techniques used for large-scale surveys like the NHTS may not be able to capture a representative sample of PEV owners.

Unlike the NHTS survey, the PH&EV Research Center’s survey focus only on PEV owners and have more details on PEV ownership, such as purchase month and year, whether the vehicle was purchased or leased, and whether new or used. The focus on PEV owners allows us to obtain more accurate data on their travel behavior. The survey that was part of this project is representative of the PEV owners in California. It tracks the purchase and usage of PEVs every year, allowing analysis of evolving vehicle technology and purchasers. Consequently, the PH&EV Research Center’s California and nationwide surveys have information on short-range and long-range BEVs. Purchase month information allows us to estimate the accurate number of months of ownership and subsequently the annualized VMT. Also, our survey specifically asks for the odometer reading of the PEV owned by the household, usually the newest vehicle. This should reduce the chances of erroneous reporting.[4] The results of this study are based on the most recent sample of “on the road” owners, unlike most of the literature published that is based on short term assignment of PEVs to households (Davies and Kurani 2013, Crain, Gorgia et al. 2016, Björnsson and Karlsson 2017) or on very early adopters over the first year of two of the vehicles’ introduction (Smart and Schey 2012, Smart, Powell et al. 2013, Smart, Bradley et al. 2014).

[4] When asked the odometer reading plus or minus a possible error value (in case they did not actually check the odometer), 80% of the respondents indicated an error value of 500 miles or less.

Nevertheless, the difference in estimates of average annual VMT between the surveys cannot be solely driven by the difference in the method of vehicle age calculation. Compared to the NHTS, the PH&EV Research Center’s California and nationwide surveys have a higher fraction of new long-range BEVs, like the Tesla or Chevrolet Bolt, and newer first-generation BEVs with larger batteries and longer range (such as the Nissan Leaf with the 30kWh battery). The majority of the BEVs in the NHTS sample were Nissan Leafs with an average age of 3.5 years. In other words, these were shorter-range Nissan Leafs (with the 24kWh battery), with an average range of 84 miles. The age of these vehicles indicates they are owned by early adopters. Comparing the long-range and short-range BEVs in the PH&EV Research Center’s California survey, we find that the former have an average annual VMT of 3% more . Since range anxiety does impact BEV usage, the difference in model and age of the vehicles sampled in the surveys may explain the difference in VMT estimates.

5. Logger Data: Vehicle Level Analysis

In this section, we present our results and observations on PEV usage at the vehicle level using data collected from the loggers. In total, **109 BEVs and 166 PHEVs** . Out of the 300 PEVs, 23 BMW i3 REX had trouble acquiring data and were dropped from our analysis. There was one Kia Soul (111 mile range) and one Fiat 500e (84 mile range), which were also dropped for our analysis due to very low sample size. Vehicles have a reliable data for most parameters and for longer than 120 days and can be consider for the analysis. are considered in the vehicle level analysis presented in **Section** Error! Reference source not found.. In order to take advantage of the wealth of vehicle-usage information, all the remaining PEVs were considered in the vehicle-level analysis. The sample size of vehicles and households used in the household level analysis is provided in Section 6

All the descriptive analyses and related summary statistics summarized in **Table 4** to **Error! Reference source not found.** are from the loggers. Likewise, the descriptive analyses and related summary statistics depicted in **Figure 12** to **Figure 84** are from the loggers.

5.1.Data Description

Descriptive summaries and analyses summarized in **Table 4-Table 8** and depicted in **Figure 12-Figure 16** are based on the data collected from the loggers.

Table 4

Table 7 summarize, respectively, the data collected on BEV driving, BEV charging, PHEV driving, and PHEV charging from the loggers. From the raw data, which includes very short trip events of zero to a few hundred yards, we used a filtering criteria of 1 km to denote a valid trip for both PHEVs and BEVs. The filtering criteria of 1 km is based on filtering out GPS noise and very short trips registered at the loggers with no energy use and the rule of thumb values for acceptable walking distances (Smith and Butcher 2008; Yang and Diez-Roux 2012). For the charging sessions, a cutoff of 1 kWh for the BEVs and 0.25 kWh for the PHEVs were used. In addition, we filtered out trips and charging sessions that did not report variables that are usually included for this type of vehicle such as battery SOC, distance traveled, energy charged, and driving energy (electrical and gasoline) consumed. Overall, 99.8% of charging energy (PHEVs and BEVs), 99.7% of BEV VMT, and 96% of PHEV VMT were still retained after filtering. We further classified the 109 BEVs into 5 types based on the battery capacity: Leaf-24 kWh (L24, Leaf-24); Leaf-30 kWh (L30, Leaf-30); RAV-40kWh (R40, RAV4-40); Tesla ModelS_60-80kWh (T60, ModelS_60-80); and Tesla Models_80-100kWh (T80, ModelS_80-100). For the PHEVs, we adopted a similar approach and classified the PHEVs into 4 types: Plug-in Prius 4 kWh (PluginPrius-4); C-Max Energi and Fusion Energi 8 kWh (CMaxFusion-8); Volt 16 kWh (Volt-16); Volt 18 kWh (Volt-18). Since both the Ford C-Max Energi and Fusion Energi have the same battery capacity, we combined them together as CmaxFusion. Chevy Volts model year (MY) 2016 or later have bigger batteries than do earlier model years and they are classified as Volt-18kWh; the rest of the Volts were classified as Volt-16kWh.

Table 4. BEV Driving Data Overview

		Raw Data		**Filtered Data**		
BEV Type	**Number of Vehicles**	**Trips**	**Total VMT**	**Trips**	**VMT**	**Average Driving Days/Vehicle**
Leaf-24	29	40,714	263,645	34,061	262,209	264
Leaf-30	28	38,326	267,303	33,292	266,059	264
RAV4-40	5	8,775	60,161	7,715	60,004	344
ModelS_60-80	22	21,229	31,6671	18,465	316,129	257
ModelS_80-100	25	23,540	326,387	21,378	325,956	255
All BEVs	***109***	***132,584***	***1,234,167***	***114,911***	***1,230,313***	***264***

Table 5. BEV Charging Data Overview

		Raw Data		Filtered Data		
BEV Type	**Number of Vehicles**	**Charging Sessions**	**Total kWh**	**Charging Sessions**	**Total kWh**	**Average Charging Days/Vehicle**
Leaf-24	29	9,191	64,127	8,481	63,832	219
Leaf-30	28	6,765	70,920	6,604	70,844	183
RAV4-40	5	1,513	20,053	1,468	20,027	251
ModelS_60-80	22	5,783	115,283	5,483	115,160	188
ModelS_80-100	25	5,886	125,313	5,584	125,192	173
All BEVs	***109***	***29,138***	***395,696***	***27,620***	***395,055***	***194***

Table 6. PHEV Driving Data Overview

		Raw Data		Filtered Data		
PHEV Type	**Number of Vehicles**	**Trips**	**Total VMT**	**Trips**	**Total VMT**	**Average Driving Days/Vehicle**
PlugInPrius-4	**22**	36,915	315,465	31,424	313,182	312
CMaxFusion-8	**60**	88,381	727,173	74,119	710,862	271
Volt-16	**44**	60,830	568,379	50,201	511,158	287
Volt-18	**40**	56,386	454,496	49,371	445,055	296
All PHEVs	***166***	***242,512***	***2,065,513***	***205,115***	***1,980,258***	***287***

Table 7. PHEV Charging Data Overview

		Raw Data		Filtered Data		
PHEV Type	**Number of Vehicles**	**Charging Sessions**	**Total kWh**	**Charging Sessions**	**Total kWh**	**Average Charging Days/Vehicle**
PlugInPrius-4	**22**	8,043	10,925	7,929	10,923	236
CMaxFusion-8	**60**	25,200	77,624	21,685	77,309	217
Volt-16	**44**	17,694	100,311	15,942	100,224	252
Volt-18	**40**	12,494	83,482	10,959	83,424	211
All PHEVs	***166***	***63,431***	***272,341***	***56,515***	***271,879***	***226***

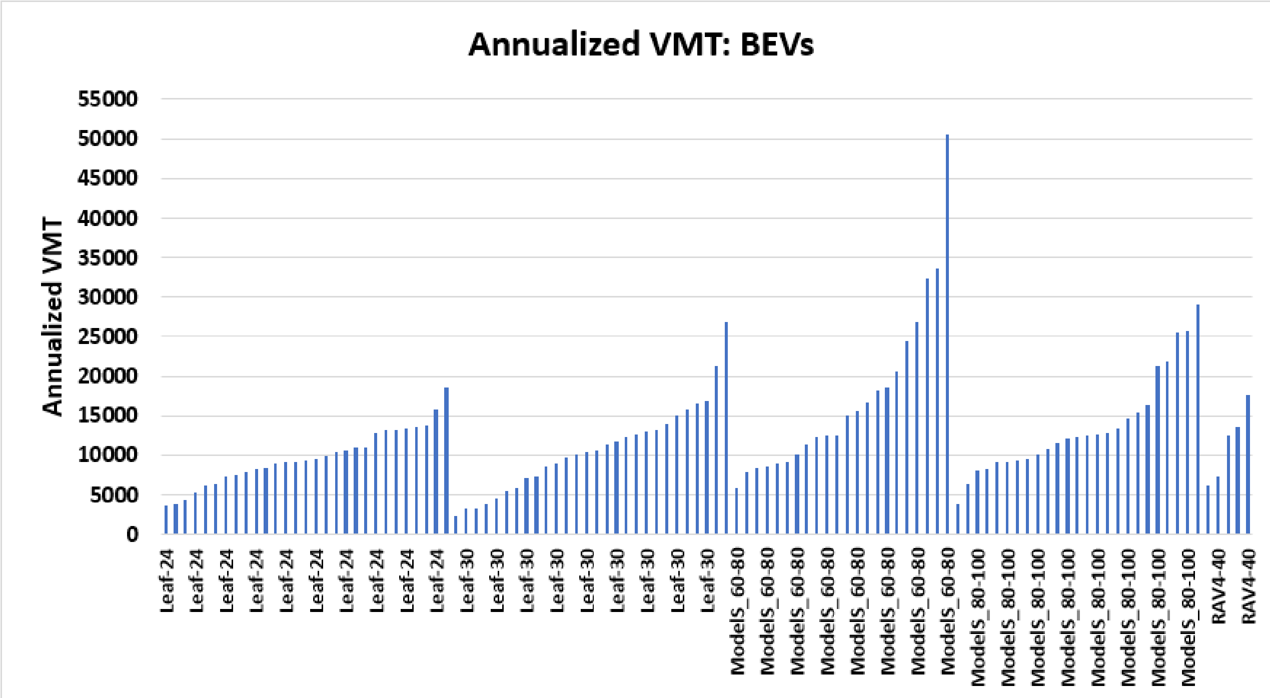


Figure 12. Annualized VMT of BEVs

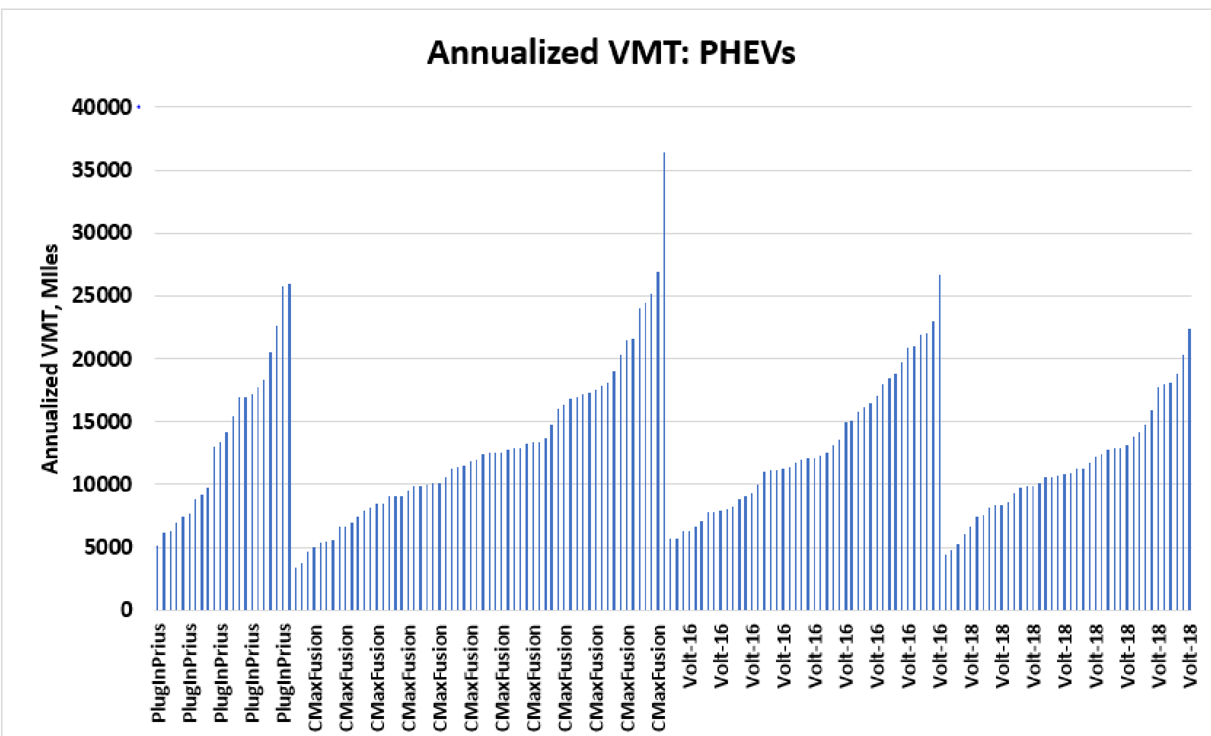


Figure 13. Annualized VMT of PHEVs

Figure 12Figure 13 depict the annualized VMT of the BEV and PHEVs based on data collected from the loggers. **Figure 14** shows the average annualized VMT by PEV type. The fleet average annualized VMT for the BEVs and PHEVs were 12,522 miles and 12,802 miles, respectively. The ModelS_60-80 BEVs have the highest average annualized VMT, whereas the ModelS_80-100 average annualized VMT was comparable to that of the Prius Plug-in PHEV. The average annualized VMT of the the Leafs (24 kWh and 30 kWh versions) and RAV4 were lower than that of all the PHEV types as well as the fleet PHEV average.

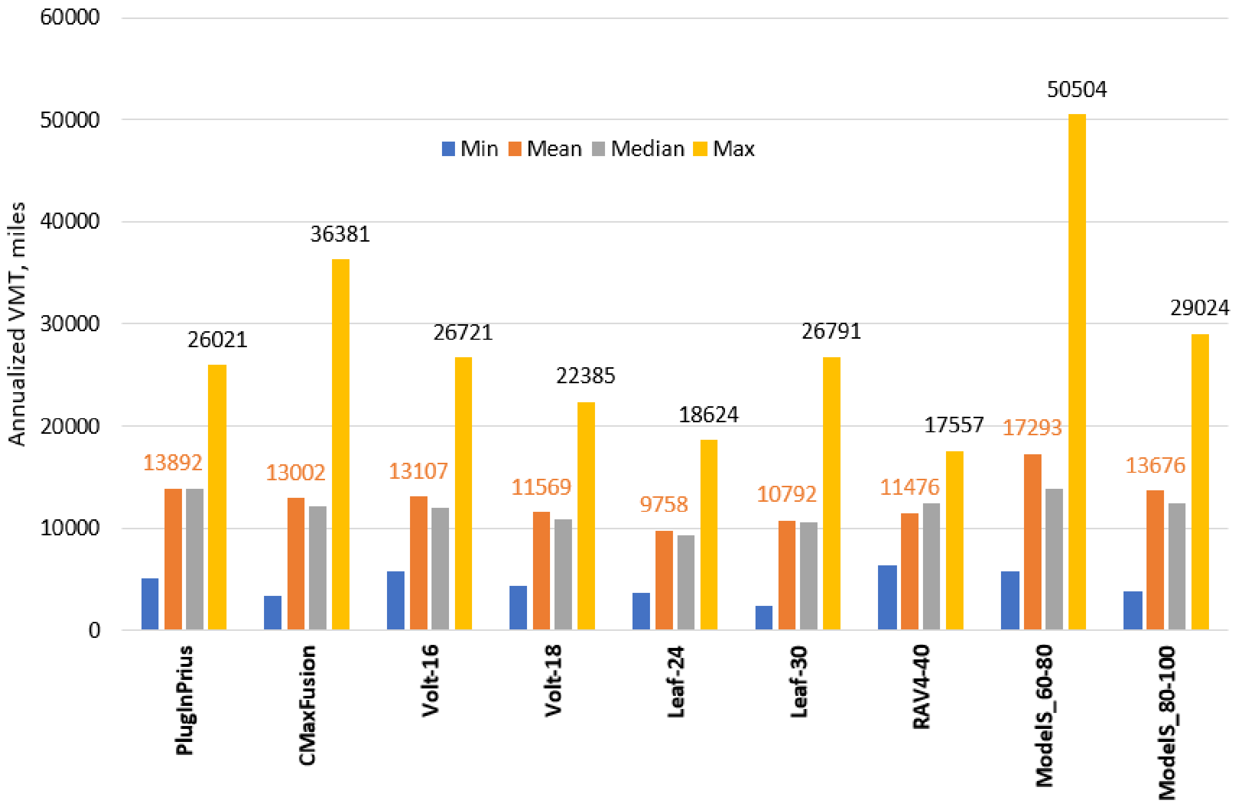


Figure 14. Average Annualized VMT by PEV Model

Table 8. Annualized VMT by Vehicle Types

Veh Type	Average	Std Err	Median	Std. Dev	Max
ICE	9,104	355	8,106	5,616	37,890
PHEV	12,802	439	11,873	5,657	36,380
BEV	12,522	688	11,032	7,180	50,504
SRBEV	10,364	595	10,044	4,682	26,791
LRBEV	15,369	1,283	12,541	8,798	50,504

Figure 14 and **Table 8** summarize descriptive statistics of annual VMT for all types of logged vehicles. On average, the PHEVs had a slightly higher annualized VMT than the BEVs. LRBEVs (ModelS BEVs) had the highest average and median annual VMT of all vehicle technologies logged, even compared to the ICE.

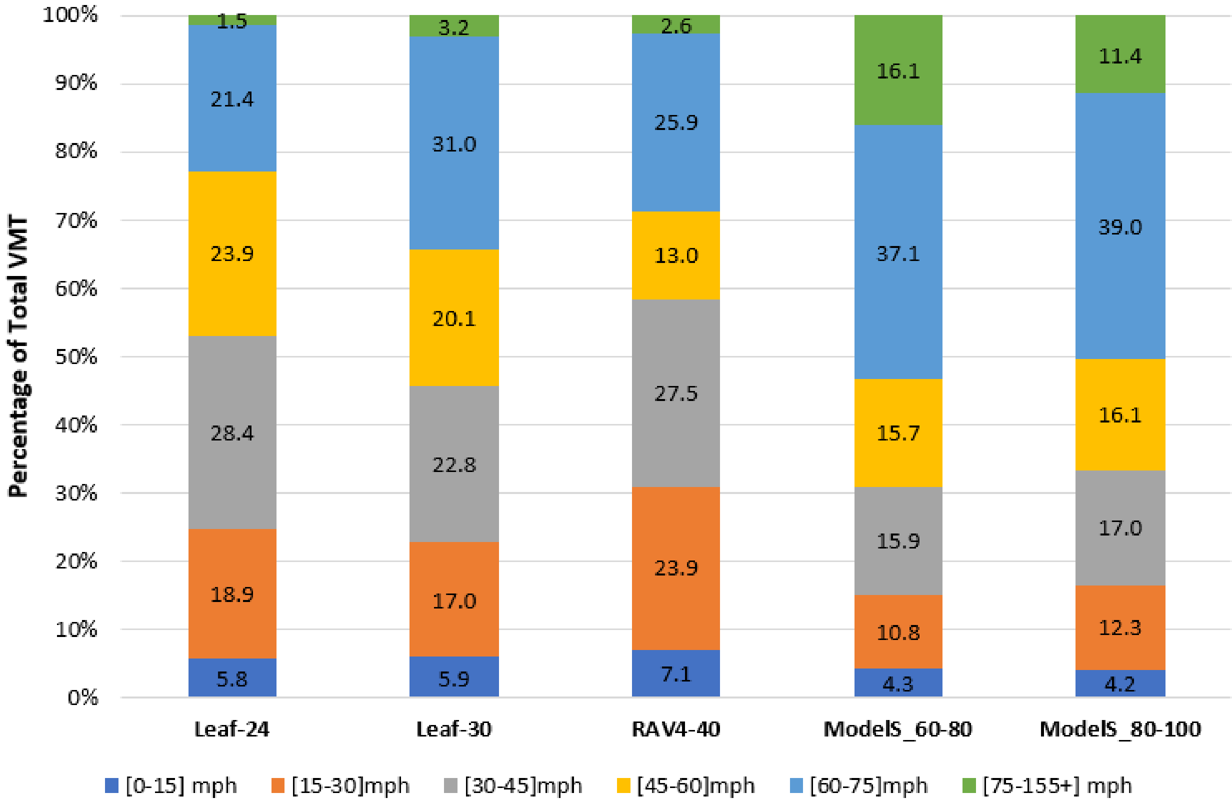


Figure 15. BEVs: Percentage Share of Total VMT by Trip Speed (in mph)

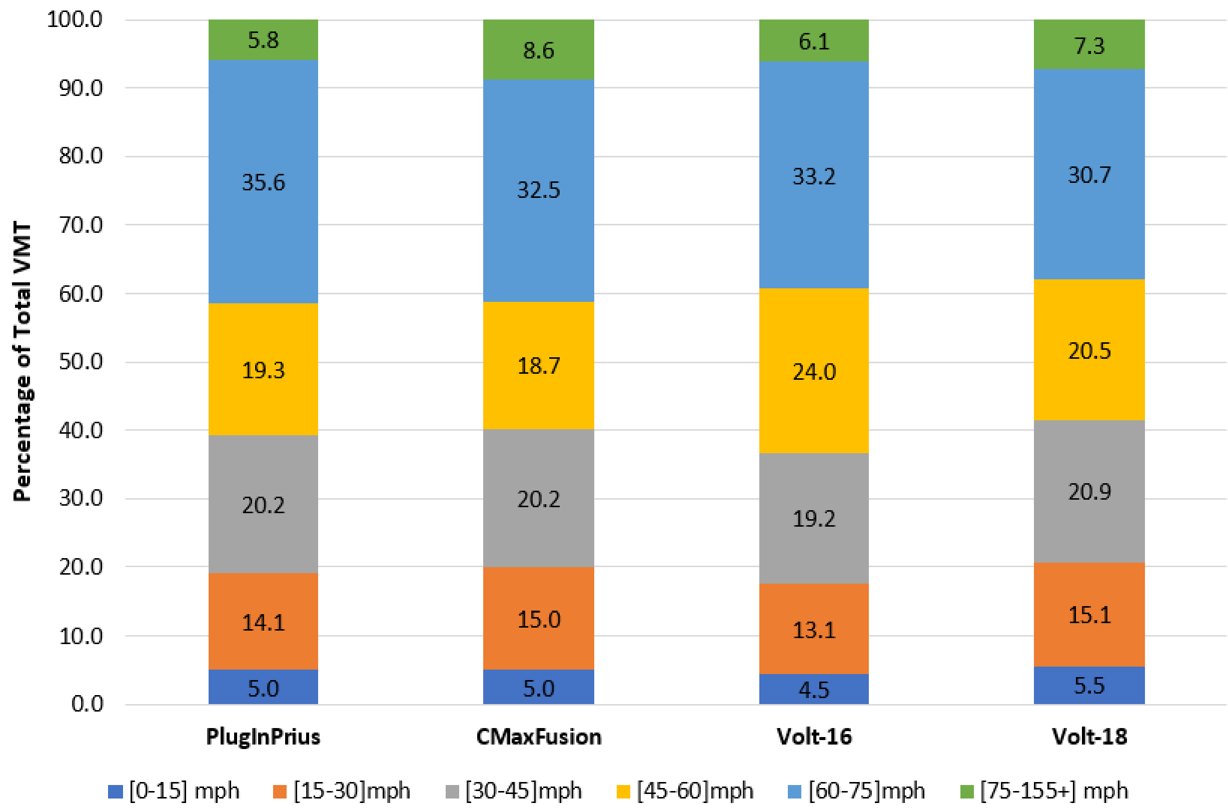


Figure 16. PHEVs: Percentage Share of Total VMT by Trip Speed (in mph)

Figure 15 and **Figure 16** show the share of total VMT by trip speed bin for BEVs and PHEVs, respectively. Compared to all other PEVs (Leafs, RAV4, and all PHEV types), the Model S BEVs have a higher share of VMT at trip speeds 60 mph or faster. In fact, almost 50% of Model S total VMT was from trips at speeds of 60 mph or faster, whereas only 15% of its VMT was from trips with speeds less than 30 mph. Furthermore, the high all-electric range (AER)/battery capacity could have contributed to the Model S having the highest share of VMT at very high speeds (75 mph or more) compared to all other PEVs. Among the PHEVs, short range PHEVs (Prius and CmaxFusion) and Volts have a comparable share of VMT from trips driven at speeds of 60 mph or faster (~40%) and from trips driven at speeds less than 45 mph. At very high speeds (75 mph or more), Prius has the lowest share of total VMT, followed by Volt-16, Volt - 18, and CmaxFusion.

5.2.Battery Electric Vehicles Driving

Descriptive summaries and analyses summarized in **Table 9**-**Table 14** and depicted in **Figure 17**-**Figure 25** are based on the data collected from the loggers. As shown in **Table 9**, on average the Leaf (L24 and L30) drivers make fewer trips and drive shorter trip distances than do T60 and T80 BEV drivers. The average trip distance of the R40 is comparable to that of the Leafs (24 kWh and 30 kWh versions). The average trip distance of the Model S BEVs (60-80kWh and 80-kWh versions) was almost twice that of the Leafs and RAV4. The average trip distance of the Leafs did not vary much between weekdays and weekends. Except for the L30, the weekday maximum trip distance of L24, R40, T60, and T80 were higher than their respective weekend maximum trip distance (**Figure 17**). Almost half of the L24, L30, and R40 trips were less than 5 miles. At least 15% of T60 and T80 trips were more than 30 miles, whereas at least 95% of the L24, L30 and R40 trips were less than 30 miles (**Figure 18Error! Reference source not found.**). R40 had the highest kWh/mile consumption for average trip speeds ranging from 15 mph to 75 mph. L30 and T80 had slightly higher average kWh/mile consumption than their respective lower range versions (**Figure 19Error! Reference source not found.**).

Table 9. BEV Driving Trip Level Summaries (on days when the BEV was driven)

BEV.TYPE	Average Trips/Day	Average Trip Distance(miles)	Average kWh /Trip	Average kWh/Mile
Leaf-24	4.45	7.70	1.82	0.236
Leaf-30	4.50	7.99	2.06	0.257
RAV4-40	3.27	7.77	2.86	0.368
ModelS_60-80	3.27	17.12	5.71	0.337
ModelS_80-100	3.35	15.24	5.29	0.347
ALL BEVs	***3.99***	***10.7***	***3.23***	***0.302***

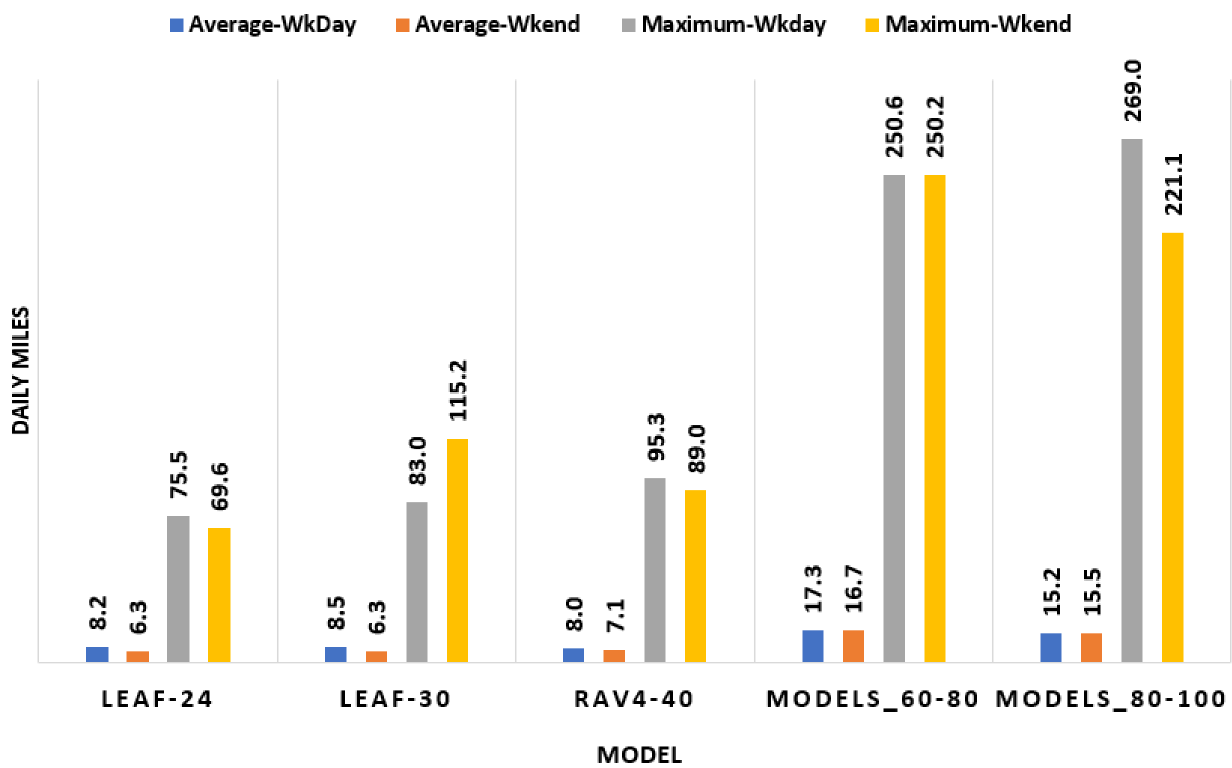


Figure 17. Average and Maximum Trip Distance on Weekdays (Wkday) and Weekends (Wkend) by BEV Type

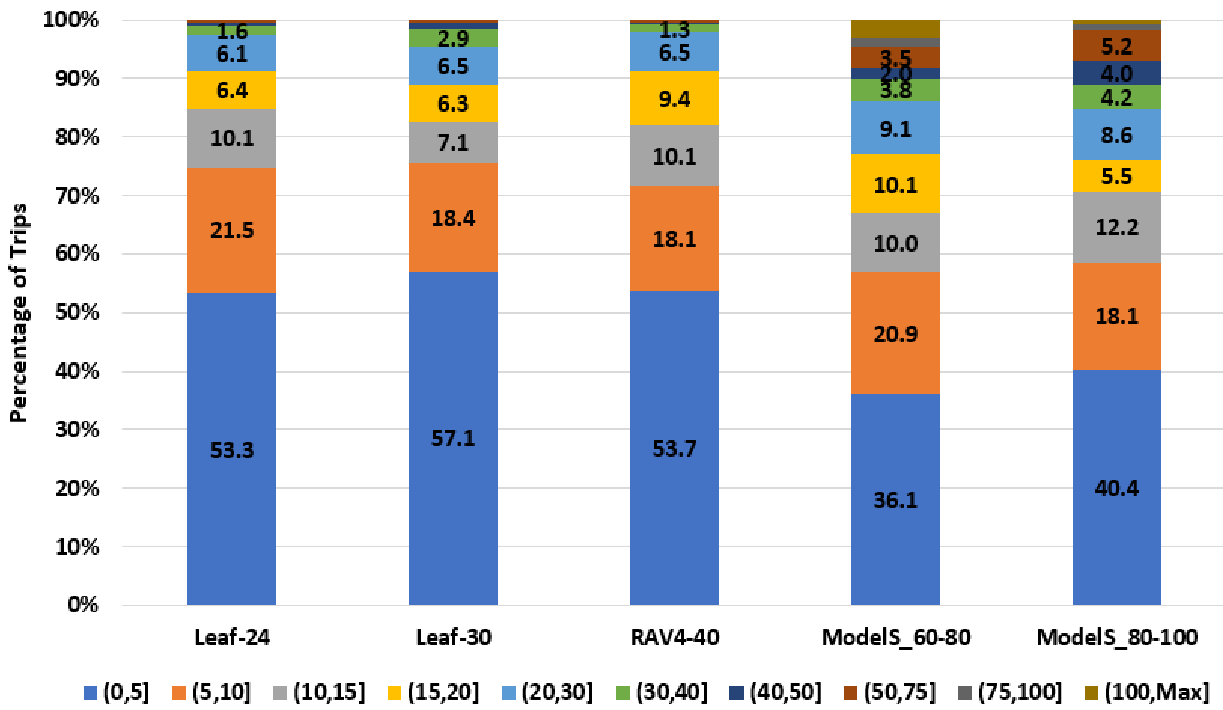


Figure 18. Percentage of Trips by Trip Distance Bins (miles) and by BEV Type

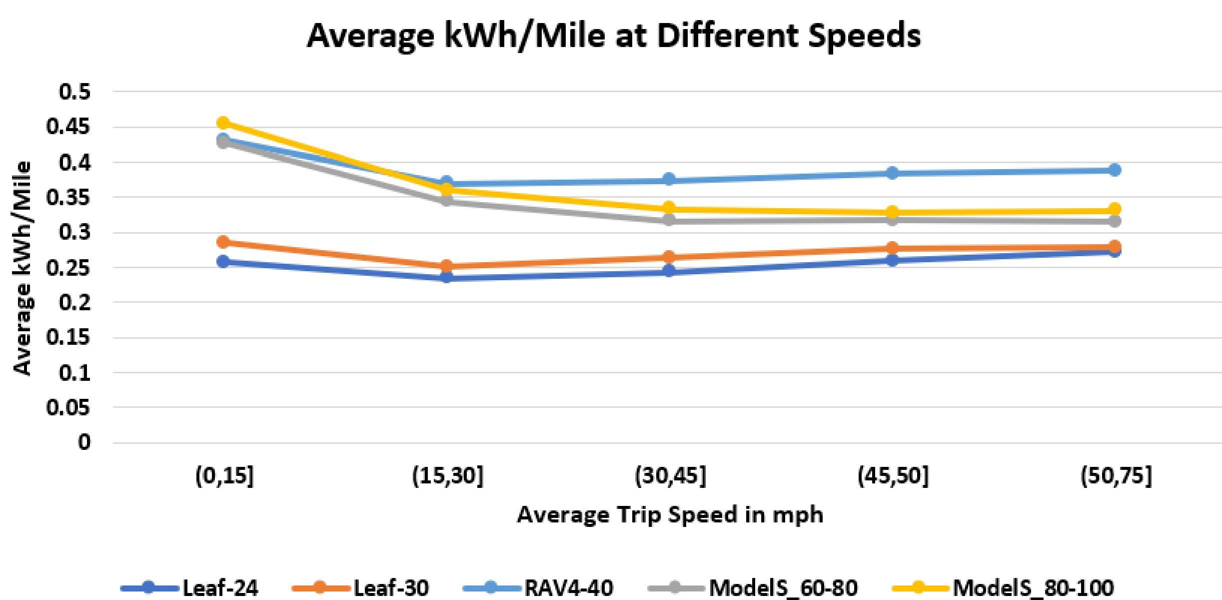


Figure 19. Effect of Speed on Energy Consumption per Mile

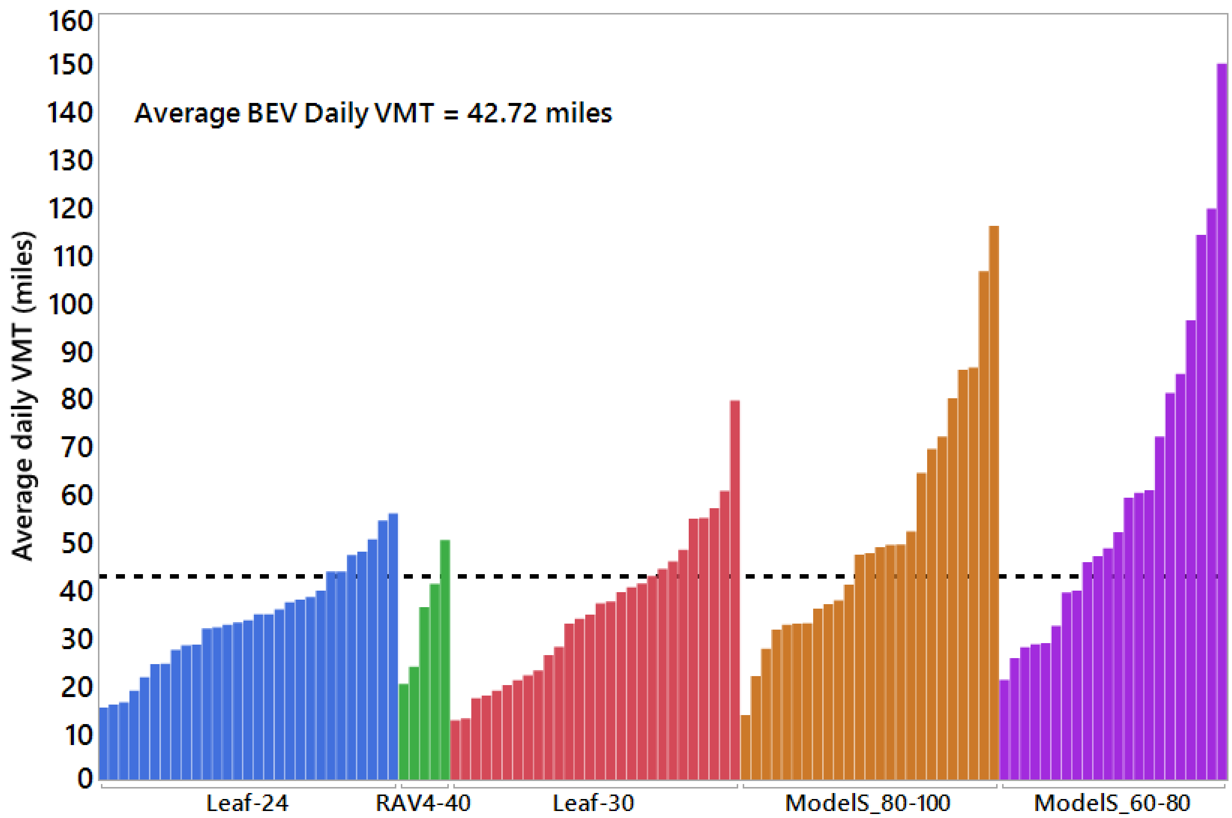


Figure 20. Average Daily VMT of the Individual BEVs by BEV Model

Figure 20 shows the average daily VMT of the individual BEVs. Only 5 of 29 L24s and 8 of 28 L30s had a daily average VMT higher than the overall BEV fleet average daily VMT of 42.72 miles. For the majority of the T60 and T80 BEVs, the average daily VMT was higher than 42.72 miles. Though the average daily VMT could be a useful and straightforward metric to compare how different BEVs utilize their AER, it could be quite misleading as we illustrate in the following subsection.

5.2.1. Habitual Driving Distances

To quantify the impact of the battery capacity and AER utilization, it is not sufficient to look only at the average daily VMT for four main reasons. First, the average values do not capture similarities or dissimilarities between different BEV types from the perspective of AER utilization. Second, average daily VMT does not account for the impact of type of day (weekday or weekend) on the daily VMT. Third, one cannot infer any information about the daily VMT distribution. Finally, average values present an aggregate picture without considering the differences or similarities between different BEV drivers (within same BEV type or between different BEV types). To address these, we use an additional daily VMT related metric called the Habitual Driving Distance (HDD). HDD is the distance the BEV most frequently repeats, and it represents the mode of the daily VMT distribution. There are two methods to extract the HDD. The first method uses the histogram of daily VMT, where the peak of the histogram is the HDD. In the second method, empirical right skewed distributions such as Weibull, LogNormal, Normal and Gamma distributions are fitted to the daily.(Plötz, Jakobsson, and Sprei 2017; Plötz, Funke, and Jochem 2018; Lin et al. 2012) Using suitable goodness of fit metrics such as the Akaike Information Criterion (Glatting et al. 2007), the distribution that best fits the daily VMT pattern is selected and then the distance corresponding to the peak of the probability density function of the fitted distribution is the HDD.

Figure 21 depicts the daily VMT distribution of all Leaf-24kWh on weekdays and weekends. The histograms are binned in 1-mile intervals. Normal, LogNormal and Weibull distributions were fitted to both these distributions and the parameters of the fitted distribution are shown alongside the distribution. Using the Akaike Information Criterion, we determined that the Weibull distribution had the best fit for the Leaf-24kWh, the goodness of fit values are presented in **Table 10**. **Table 11** summarizes the HDD extracted after distribution fitting and from the peak of the histogram. Since the latter method is highly sensitive to the width of the distance bin, the daily VMT values corresponding to the first 3 peaks of the histogram are shown in **Table 11**.

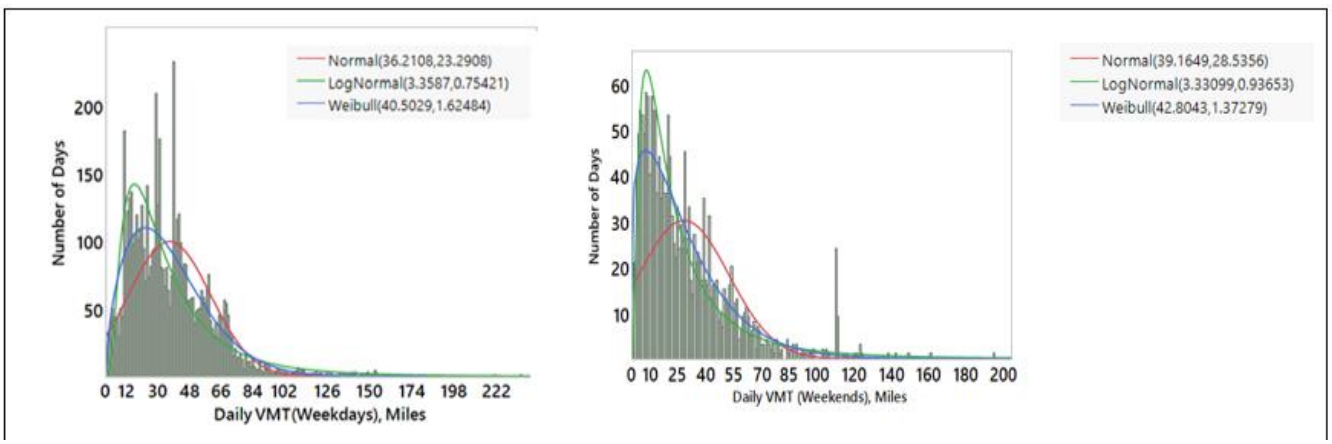


Figure 21. Leaf-24 Daily VMT (Left-Weekdays ; Right –Weekends) Fitted With Normal, LogNormal and Weibull Distributions

Table 10. BEVs: Daily VMT Goodness of Fit Metrics

BEV.TYPE	Type of Day	LogNormal AICc	Normal AICc	Weibull AICc
Leaf-24	Weekday	52,359	53,190	***51,597***
Leaf-24	Weekend	15,807	16,865	***15,758***
Leaf-30	Weekday	51,860	52,808	***50,909***
Leaf-30	Weekend	***15,813***	17,360	15,880
RAV4-40	Weekday	11,366	11,578	***11,193***
RAV4-40	Weekend	4,163	4,272	***4,098***
ModelS_60-80	Weekday	***41,967***	46,382	42,207
ModelS_60-80	Weekend	***14,496***	16,141	14,511
ModelS_80-100	Weekday	46,792	50,373	***46,712***
ModelS_80-100	Weekend	16,234	17,683	***16,163***

Table 11. Illustrative Comparison of HDD: Fitting Weibull Distribution on Daily VMT vs. Peaks Of Daily VMT Histogram

Average (miles)		**Weibull Fitted (miles)**		**Peaks of Histogram (miles)**					
Weekdays	*Weekends*	*Weekdays*	*Weekends*	*Weekdays*			*Weekends*		
				1st	2nd	3rd	1st	2nd	3rd
36.2	28	15.34	4.6	38.5	28.5	11.5	7.5	10.5	19.5

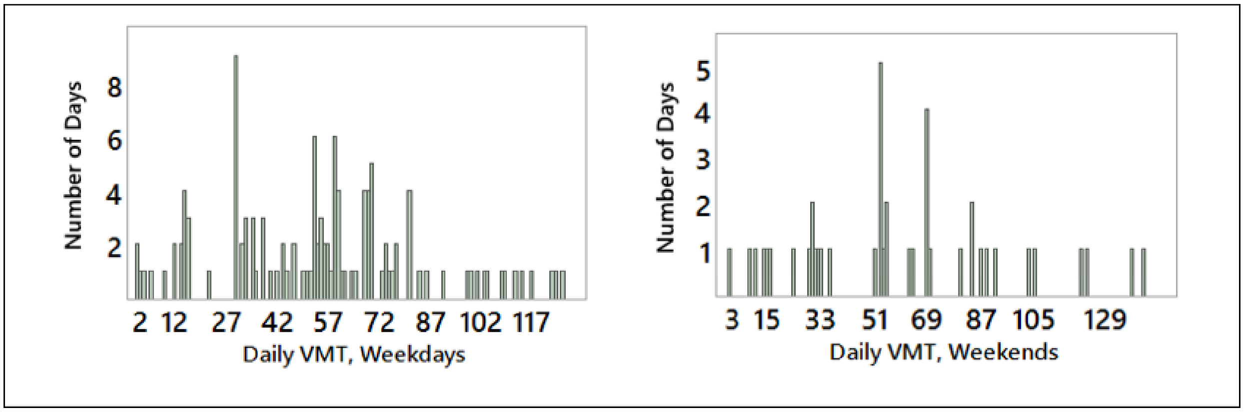


Figure 22. A Leaf-24 Sparsely Driven on Weekends

In two publications by Tamor et al. (Tamor, Gearhart, and Soto 2013; Tamor et al. 2015), the daily driving distance is modeled as (i) the sum of standard emprirical distributions (Normal, Weibull, or Lognormal) to denote habitual driving distances; and (ii) an exponentially decaying distribution to denote the occasional driving distances. More recently, there have been efforts directed towards standardizing driving distance metrics.(Hinds 2017) To replicate the methodologies outlined in these publications (Tamor, Gearhart, and Soto 2013; Tamor et al. 2015; Hinds 2017), one would require a relatively higher number of vehicles (at least 2 orders of magnitude higher than the sample size used in our analysis). In our study, we noted that the distribution that best fit the daily VMT was not necessarily the same for all the BEV types and, even within a given BEV type, the same distribution did not always have the best fit for both weekday and weekend VMT. At an individual vehicle level, for the BEVs that had a disproportionately lower number of weekend driving days compared to weekdays, were driven sparsely, or did not have a well-defined distribution of daily VMT (**Figure 22** and **Table 11**), distribution fitting may not be the best approach to find the HDD. Due to the reasons outlined above, when looking at the occasional driving distances, we used the maximum driving distance and the Bureau of Transportation Statistics (BTS 2017) reference value of 50 miles to denote long-distance travel.

To understand the BEV usage at a vehicle level that captures HDDs and the needs of a particular BEV owner, we used the peak of histogram approach for every BEV. This method was found to be a reasonable tradeoff that accounts for individual driver level HDD while also capturing the effect of AER/battery capacity on the HDD. After extracting the average, HDD, and the maximum (Max) daily VMT on weekdays and weekends for every BEV, we performed ANOVA and non-parametric pairwise group means comparison tests. The results of these tests are shown in **Table 12** and **Table 13**, respectively. The ANOVA tests indicated that there were not statistically significant differences among the BEV types in either their weekday HDDs or weekend HDDs. However, the ANOVA tests indicated that the maximum and the average distances traveled on weekdays and weekends were statistically significant across 5 BEV types. This demonstrates that the distances that BEV owners most often drive on weekdays as well as on weekends are not significantly different from each other. **Figure 23** shows the HDDs on weekdays and weekends for the 109 BEVs categorized by BEV type. These data show that the weekday HDDs of L24, L30, R40, but not for T60 and T80, are relatively similar. This crucial observation cannot be gathered by just looking at the average daily VMT values. Relying on just average daily VMT would not offer insights into whether the BEV is more suited for regular weekday commuting or for weekend recreational/other non-commute purposes, because range utilization is affected by both the AER and the BEV usage purpose (weekday commute or weekend driving). Another way to intepret the results of ANOVA and the pairwise comparison results is the fact that average values can over/underestimate range utilization. From a market adoption and policy perspecitve, conventional wisdom would indicate that the long-range BEVs alleviate, to an extent, range anxiety, enabling them to be driven farther on average than their short-range counterparts. However, in reality, such conclusions cannot be assumed by default.

Table 12. ANOVA Results of HDD, Average and Maximum Daily VMT Across all BEV Types on Weekdays and Weekends

Daily VMT	Sum of Squares	Mean Square	F Ratio	P-value*
HDD Weekday	2,590.206	647.552	0.6979	0.5951
HDD Weekend	3,550.391	887.598	1.8469	0.1254
Max Weekday	68,1292.5	1,70323	23.4147	<.0001
Max Weekend	62,3987.5	155,997	19.7786	<.0001
Mean Weekday	11,827.6	2,957	4.2742	0.003
Mean Weekend	16,384.8	4,096	11.2325	<.0001

**p-value < 0.05 : statistically significant differences at 0.95 confidence levels*

Table 13. P-values from Non-Parametric Wilcoxon RankSum Pairwise Comparison of HDD, and Mean and Maximum Daily VMT on Weekdays and Weekends

Vehicles Compared		P-values					
		Weekday			Weekend		
BEV.Type	**BEV.Type**	**Max**	**Mean**	**HDD**	**Max**	**Mean**	**HDD**
Leaf-30	Leaf-24	**0.0131**	0.8046	0.7495	**0.022**	0.8669	**0.0347**
RAV4-40	Leaf-24	0.1086	0.884	0.4221	**0.015**	**0.0462**	0.284
RAV4-40	Leaf-30	0.94	0.8605	0.6333	0.3275	0.1027	0.1732
ModelS_60-80	Leaf-24	**<.0001**	**0.0105**	0.894	**<.0001**	**<.0001**	0.8044
ModelS_60-80	Leaf-30	**<.0001**	**0.0252**	0.6181	**<.0001**	**<.0001**	0.0881
ModelS_60-80	RAV4-40	**0.0045**	0.0981	0.3819	0.0313	0.1796	0.3648
ModelS_80-100	Leaf-24	**<.0001**	0.0685	0.722	**<.0001**	**<.0001**	0.2176
ModelS_80-100	Leaf-30	**<.0001**	0.1277	0.6559	**<.0001**	**<.0001**	**0.0074**
ModelS_80-100	RAV4-40	**0.0064**	0.2657	0.7807	**0.0064**	0.0585	0.8021
ModelS_80-100	ModelS_60-80	0.9745	0.4884	0.798	0.4365	0.6776	0.2004
p-value < 0.05 : statistically significant differences at 0.95 confidence levels							

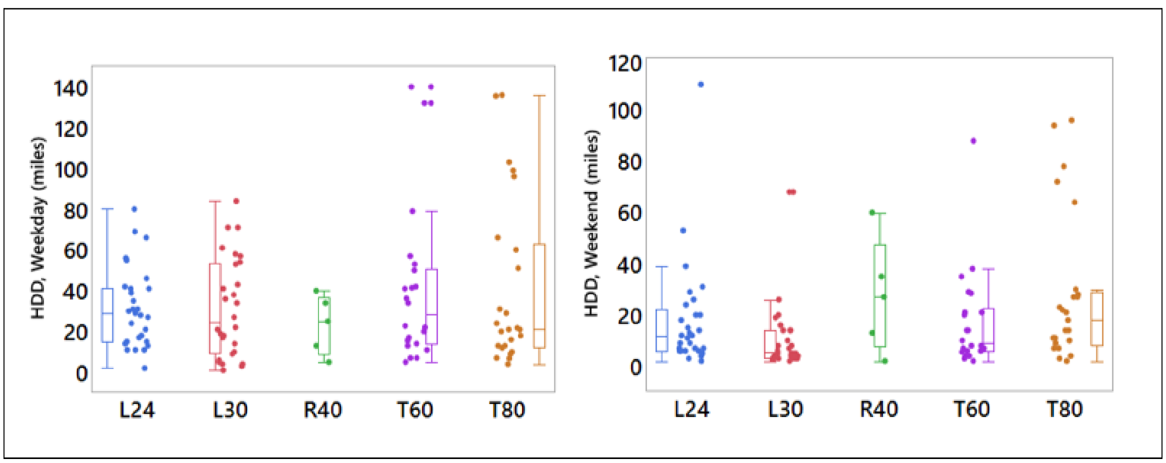


Figure 23. BEV Habitual Driving Distances on (Left) Weekdays and (Right) Weekends

To further investigate which groups (i.e., BEV types) had statistically significant differences, pairwise comparison tests were performed. The results of these tests depend on the method used. The most commonly used methods are t-tests and Tukey's HSD test, which assumes a normal distrubtution, whereas the Wilcoxon method does not require a certain type of distribution. Thus, we used the Wilcoxon method to analyze daily VMT. Non-parametric pairwise group means comparisons further reinforced the above observations (**Table 13**), where p-values less than 0.05 indicate statistically significant differences.

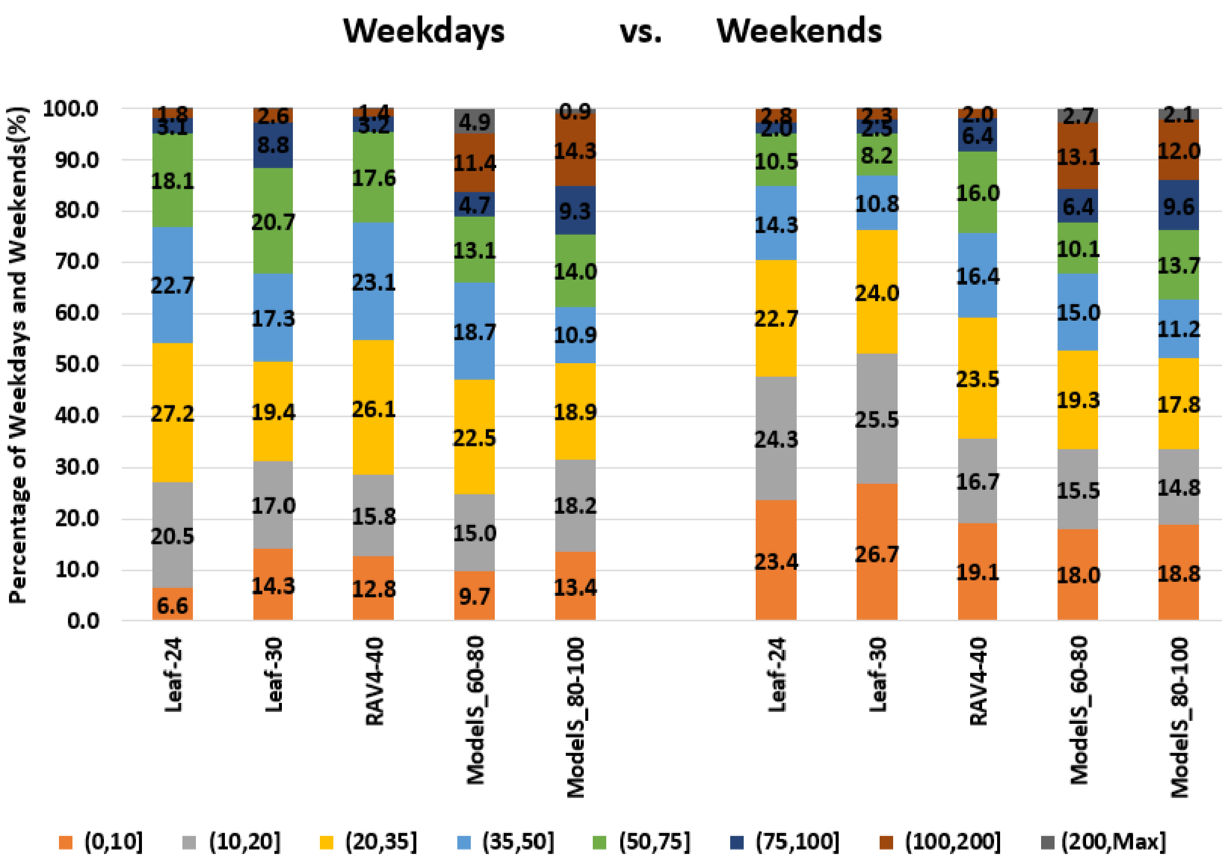


Figure 24. Percentage of Daily VMT by Distance Bins: Weekdays vs. Weekends (Range in MPH)

Figure 24Error! Reference source not found. shows the share of weekdays/weekends when the BEV was driven, binned by daily VMT. For all BEV models, the percentage of days with trips that were 10 miles or less was higher on the weekends than on weekdays. Both the T60 and T80 had a higher share of weekdays than weekends when they drove between 100-200 miles. Using the criteria for 50 miles or more to define Long Distance Travel (LDT)(BTS 2017) days, **Figure 25** shows the share of VMT accomplished on these days as a percentage of the total VMT. VMT on LDT days accounted for an average of 51% of the total VMT for all BEVs, and 36%, 40%, and 44.7% for the L24, R40, and L30, respectively. Both the T60 (63.7%) and T80 (67.4%) have almost two-thirds of their VMT accomplished on LDT days, perhaps indicating that long-range BEVs are more often used for long-distance travel rather than regular weekday commuting.

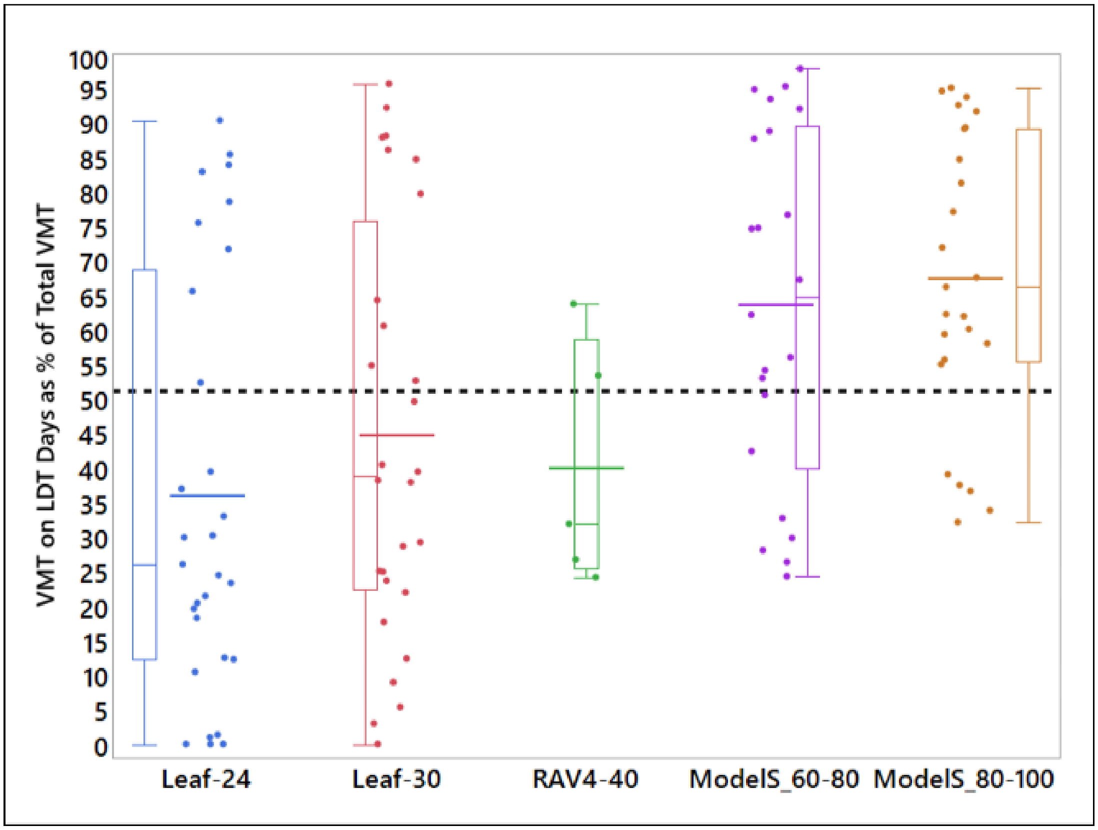


Figure 25. Share of VMT on LDT (50 miles or more) as Percentage of Total VMT by BEV Type

Table 14 summarizes the key charging related information of the BEVs. When we consider only the days when the BEV charged, the Leaf-24 and ModelS_60-80 had a comparable number of charging sessions per day, as did the Leaf-30 and ModelS_80-100. However, when we include the days on which the BEV did not charge, as may be expected, the ModelS_60-80 and ModelS_80-100 had fewer charging sessions per day than the Leaf-24 and Leaf-30, respectively. The Leaf-24 had the longest average charging duration per day, whereas the RAV4 had the lowest.

Table 14. Charging Summaries on by BEV Type

	Within the Logging Window Including Days When BEV Did not Charge				
BEV	**Average Sessions/Day**	**Average DCFC Sessions/Day**	**Average L1/L2 Sessions/Day**	**Average kWh/Day**	**Average Duration/Day (minutes)**
Leaf-24	0.885	0.048	0.837	6.66	203.23
Leaf-30	0.725	0.140	0.585	7.77	139.27
RAV4-40	0.780	0.001[5]	0.779	10.65	108.24
ModelS_60-80	0.783	0.125	0.657	16.44	141.22
ModelS_80-100	0.663	0.067	0.596	14.87	130.23
	On Days When the BEV Charged				
BEV	**Average Sessions/Day**	**Average DCFC Sessions/Day**	**Average L1/L2 Sessions/Day**	**Average kWh/Day**	**Average Duration/Day (minutes)**
Leaf-24	1.334	0.072	1.262	10.04	306.52
Leaf-30	1.290	0.249	1.041	13.84	247.98
RAV4-40	1.169	0.002[13]	1.167	15.95	162.10
ModelS_60-80	1.326	0.212	1.114	27.84	239.21
ModelS_80-100	1.291	0.131	1.160	28.95	253.51

5.3.Battery Electric Vehicle Charging

Descriptive summaries and analyses depicted **Figure 17-Figure 39** are based on the data collected from the loggers. BEV charging summary statistics are presented in **Table 14**; **Figure 26** shows the probability that the BEV charges on a given day within the duration for which it was logged, called the logging window. **Figure 27** and **Error! Reference source not found.**, respectively, depict the percent share of charging sessions and charged kWh by charging level.

[5] RAV 4 EV is technically not DCFC capable but may be converted. In this case, we suspect that the logger erroneously reported a higher charging rate (kW).

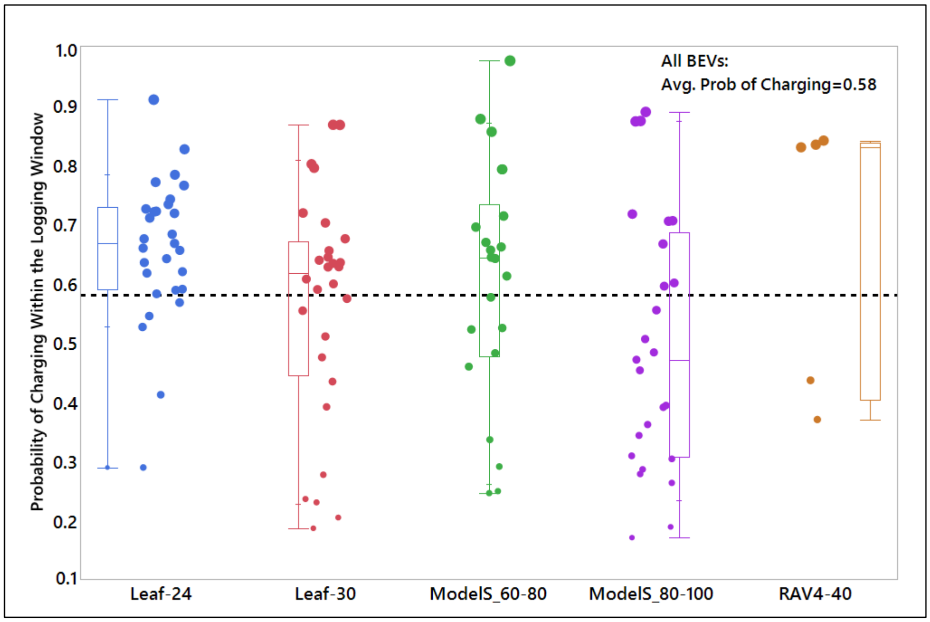


Figure 26. Probability of Charging Within the Logging Window of Individual BEVs by BEV Type

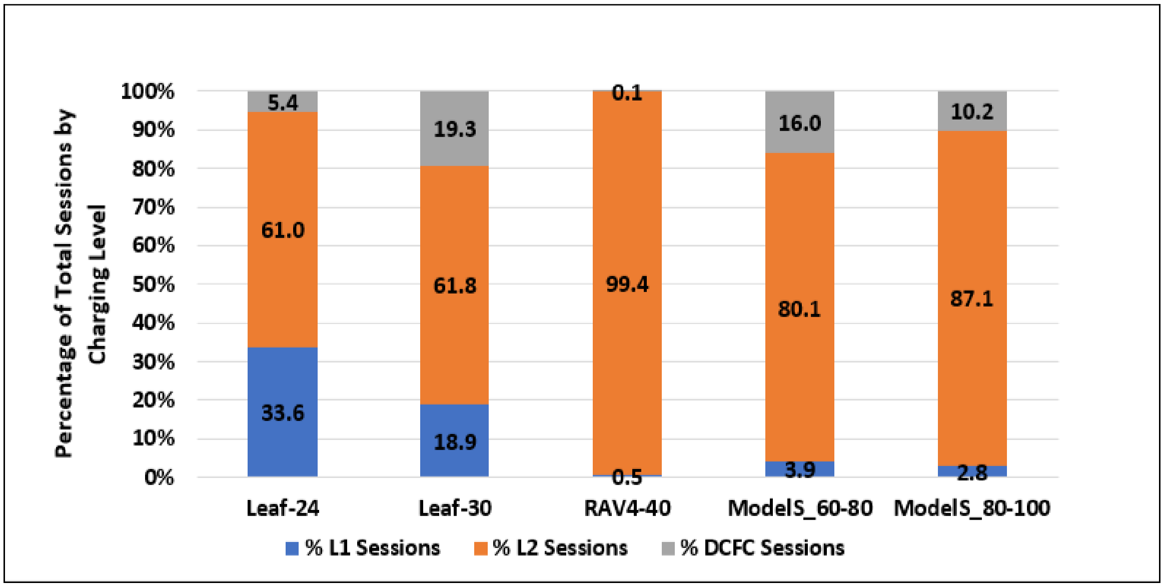


Figure 27. Share of Charging Sessions by Charging Level and BEV Type

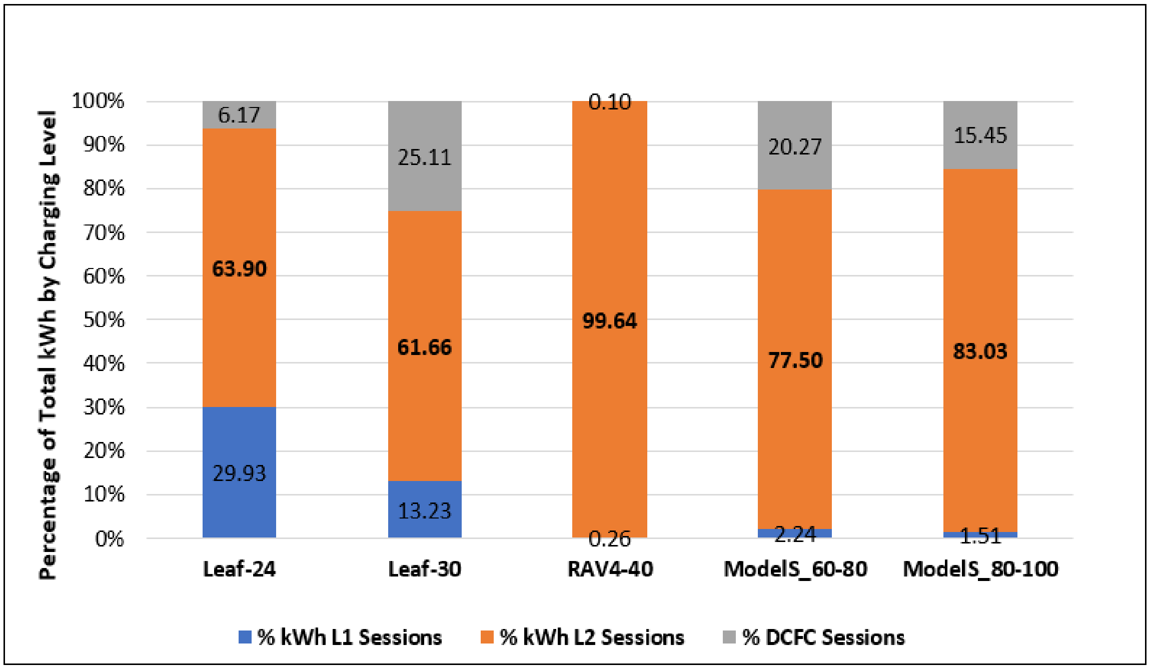


Figure 28. Share of Charging kWh by Charging Level and BEV Type

Out of the 28,000 charging sessions in total, 11% were at L1, 72% were at L2, and the rest were DCFC sessions. L2 charging accounted for the majority of charging sessions and charged kWh for all the BEV types. Leaf-30 had the highest share of DCFC sessions and the highest share of charged kWh from DCFC charging. DCFC charging sessions by Leaf-30 accounted for close to 40% of all the DCFC charging sessions, followed by ModelS_60-80 and ModelS_80-100, which respectively accounted for 28% and 17% of all the DCFC charging sessions. **Figure 29** shows the percent of charging sessions (all charging levels combined) by start time (hourly intervals) on weekdays and weekends. There was a noticeable peak around 8 am, which can be attributed to charging at work, and the 11 pm-1am window on weekdays, which is typical of home charging. On the weekends, highest percentage of charging sessions occur during the 11pm-1am window, followed by 9 pm and 7 pm.

Since the R40 had only a few L1 sessions and is not DCFC compatible, it has been omitted from the charging session starting time, charger utilization, and charging session starting and charged SOC plots (**Figure 30**, **Figure 32**, **Figure 33**, **Figure 35**, **Figure 36**, **Figure 38**).

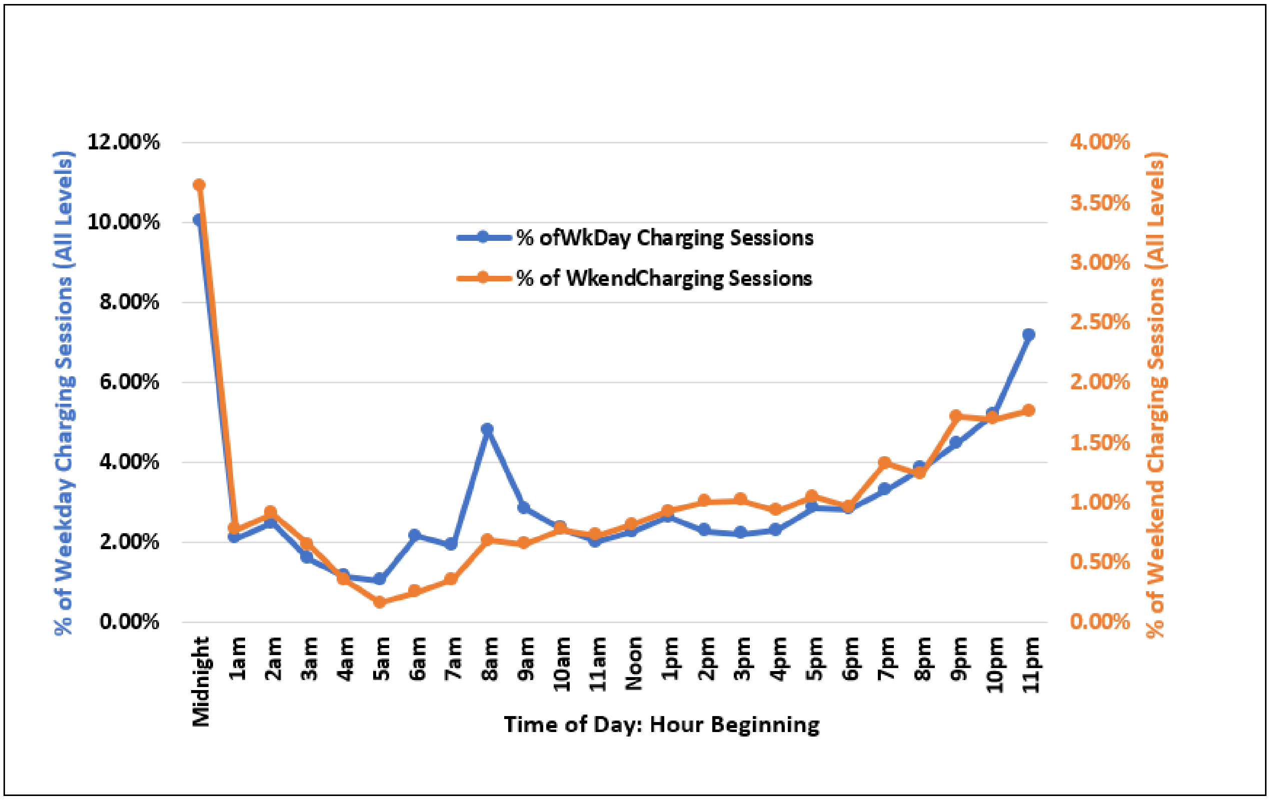


Figure 29. Charging Session Starting Time: Weekdays vs. Weekends (all BEVs and all charging levels)

Figure 30Figure 32 show the results of a closer inspection of the charging session start time by charging level (L1, L2, and DCFC). The highest percent of L2 sessions started around or after 11pm, across all BEV types, whereas the peak in L1 charging session start time was around 9pm for Leaf-30. For the Leaf-24, 11pm was still the preferred charging session start time, when the highest share of its L1 sessions began. There was a noticeable spike in the share of L2 charging sessions starting around 8am, perhaps indicative of access to L2 charging away from home. One of the more interesting observations with respect to DCFC charging was the noticeable peak in DCFC charging session start times of Leaf-30 at 5am. This time window could potentially reflect the preference of Leaf-30 owners to stop and use DCFC charging on their commutes. The peak DCFC session starting time for ModelS_60-80 and ModelS_80-100 was around 8am, whereas for the Leaf-24 it was around 10am.

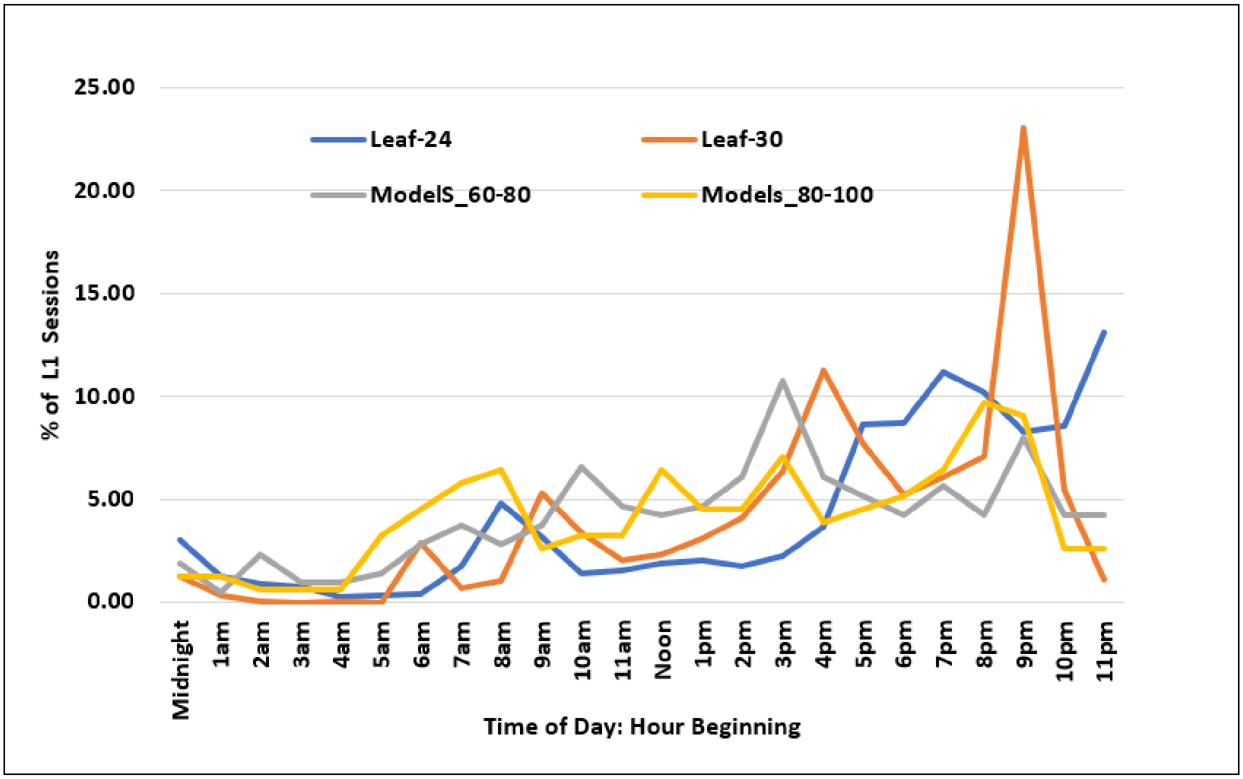


Figure 30. Percentage of L1 Charging Start Times by Time of Day and BEV Type (RAV4 is excluded from this dataset, as it was very rarely charged on an L1 charger)

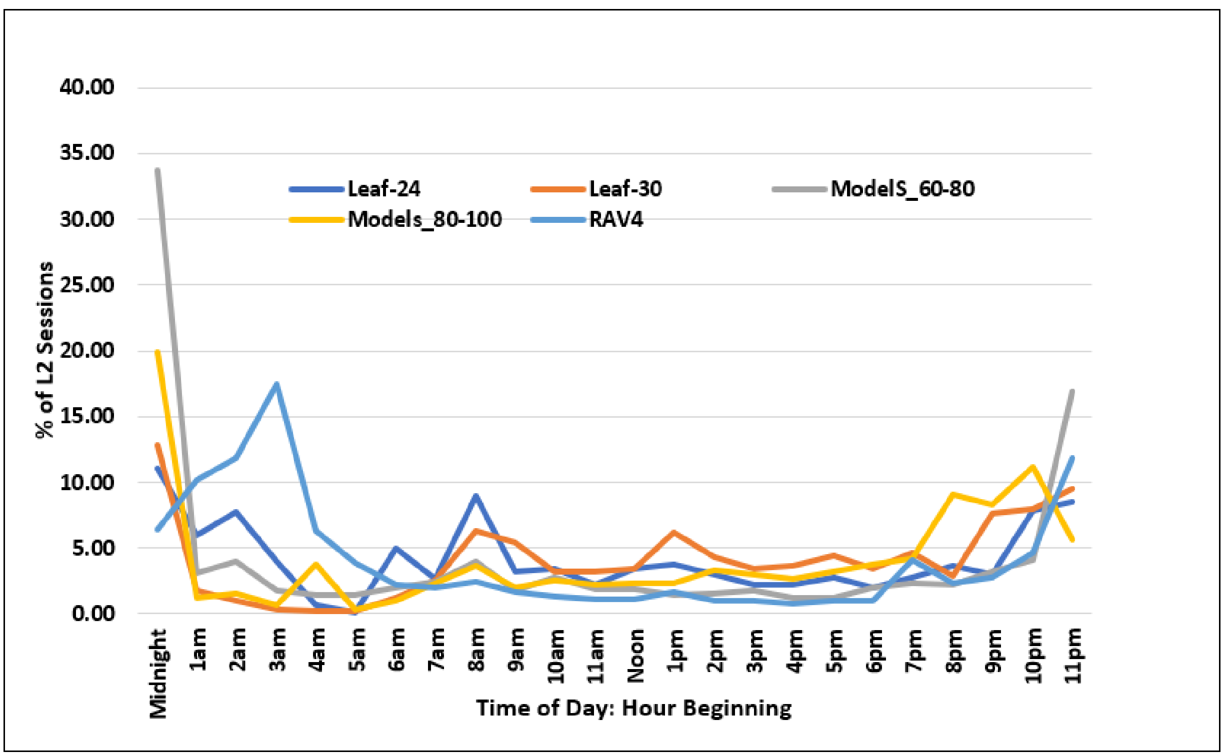


Figure 31. Percentage of L2 Charging Start Times by Time of Day and BEV Type

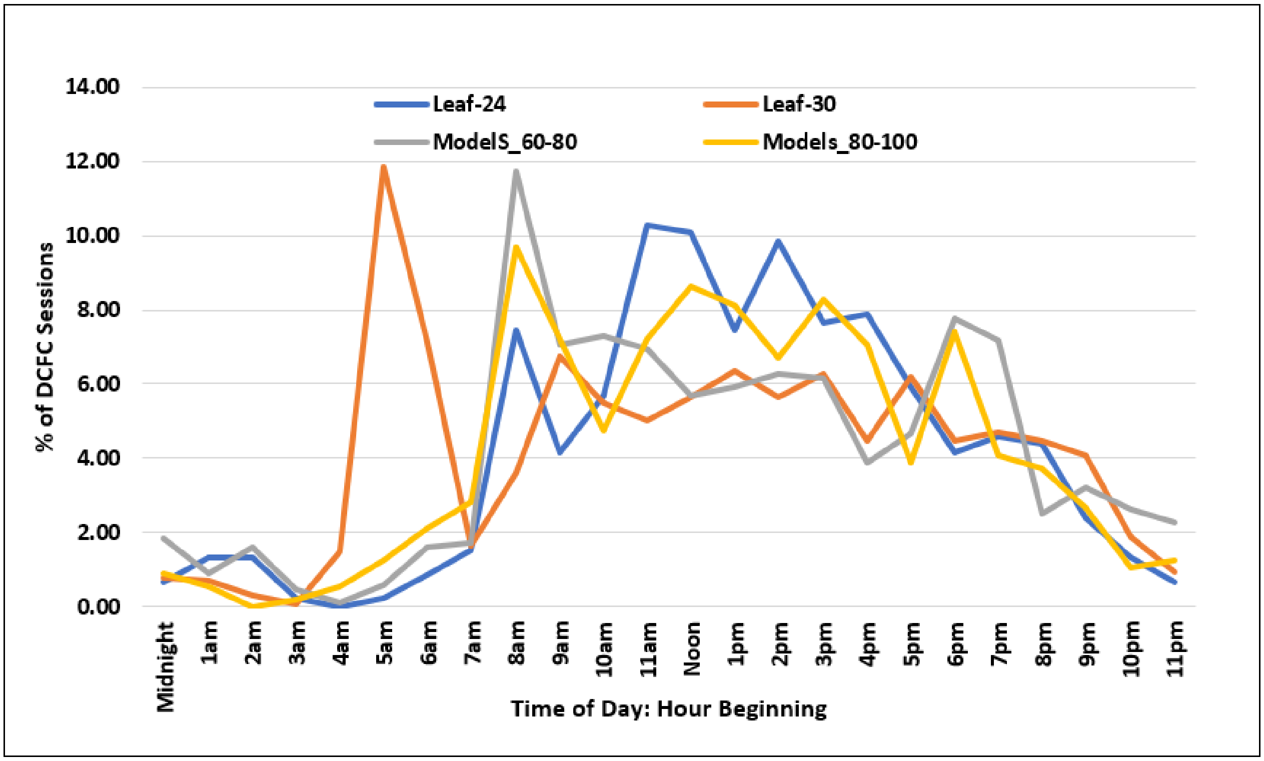


Figure 32. Percentage of DCFC Charging Start Times by Time of Day and BEV Type (RAV4 is excluded from this dataset, as it cannot be charged on a DCFC)

Figure 33Figure 35 show the average charging session duration and kWh charged by charger level. For L1 charging, the L30 and T60, on average, had higher charging energy per session and longer charging sessions on weekends than on weekdays. In contrast, for L1 charging, the L24 and T80 had lower charging energy per session and shorter sessions on weekends than on weekdays. When using L2 charging, all BEV models except the L24, on average, had lower charging energy per session and shorter charging sessions on weekends than on weekdays. The L24 had similar average charging energy per session and charging session duration on weekdays and weekends when using L2 charging.

The average charging session duration and amount of charge per session on DCFCs were similar between the weekdays and weekends for the L30, but greater on the weekends than weekdays for the T60 (**Figure 35**). On the other hand, the two vehicles with extreme battery sizes, the L24 and T80, both had shorter charging sessions and less charge per session on weekends than on weekdays.

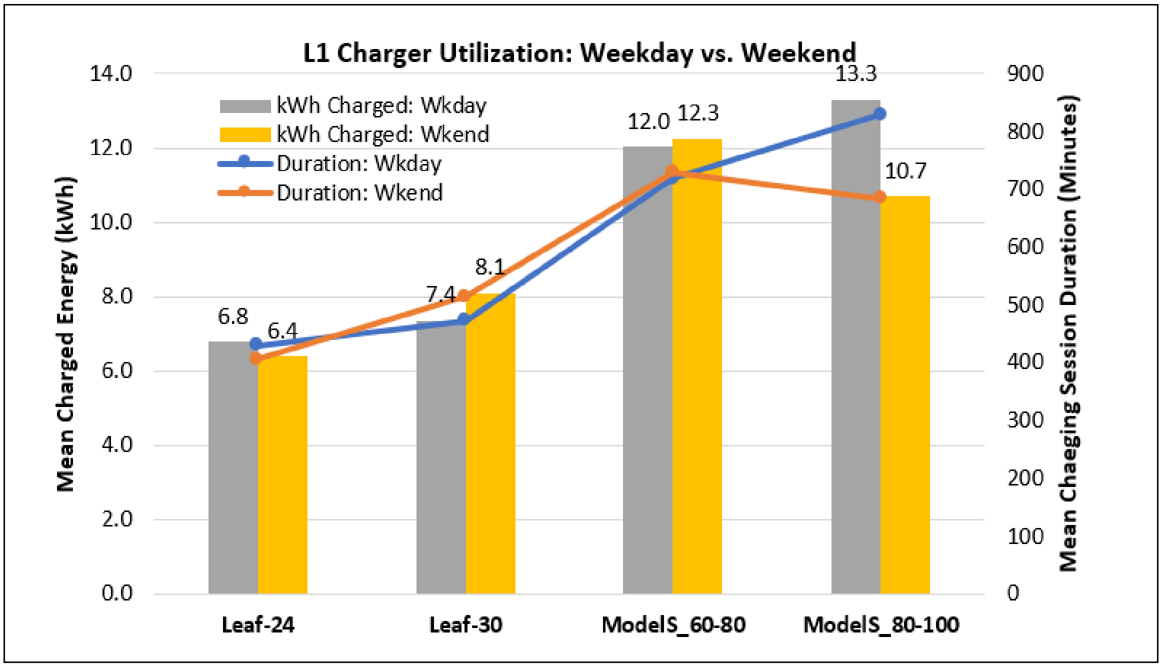


Figure 33. Average L1 Charging kWh Charged and Charging Duration: Weekdays vs Weekends (RAV4 is excluded from this dataset, as it was very rarely charged on an L1 charger)

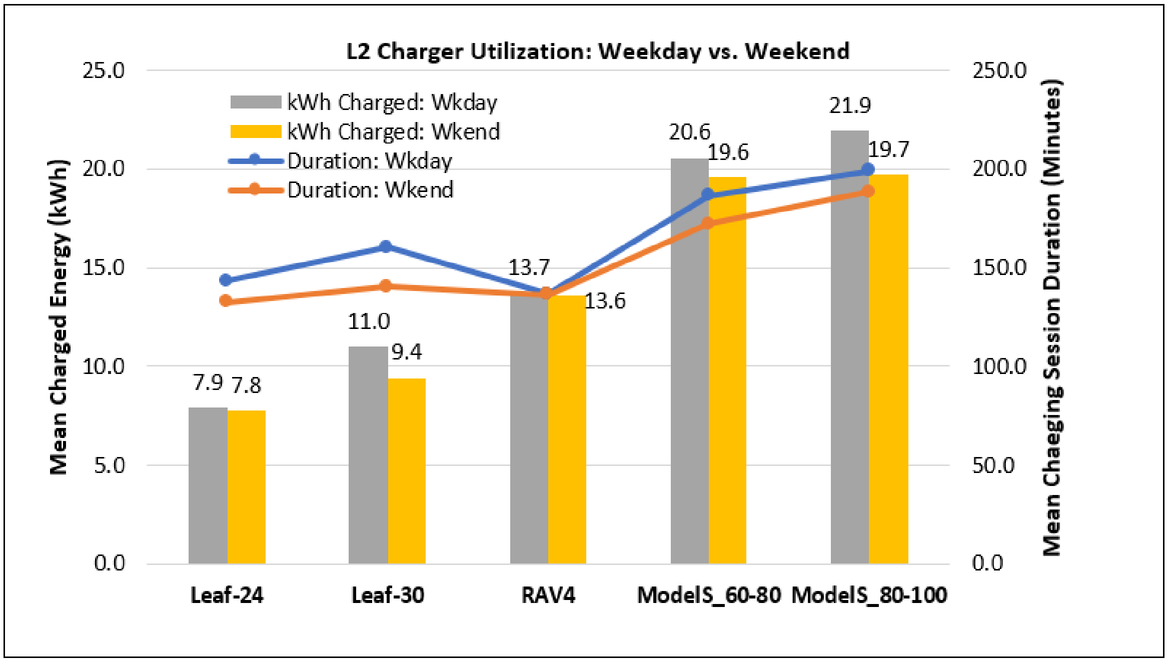


Figure 34. Average L2 Charging kWh Charged and Charging Duration: Weekdays vs Weekends

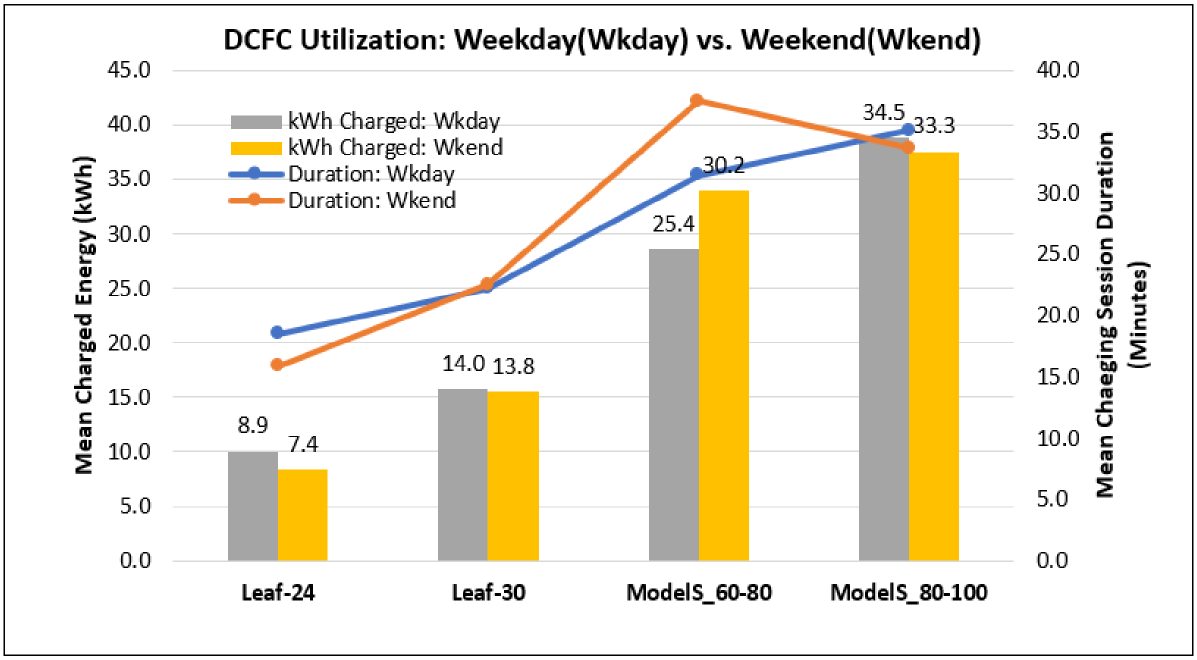


Figure 35. Average DCFC Charging kWh Charged and Charging Duration: Weekdays vs Weekends (RAV4 is excluded from this dataset)

Figure 36Figure 38 show the average charging session starting and ending battery SOC by charger level on weekdays and weekends. When using L2 charging, the L30 compared to the other BEV types had the lowest average starting SOC on weekdays and weekends, but when using L1 charging, it had the highest average starting SOC on weekdays. The T60 and T80, compared to all other BEV types, had the lowest average charged SOC when using L1 or L2 charging on weekdays and weekends. When using DCFCs, the L30 average starting SOC on weekdays was the lowest and its charged SOC on weekdays and weekends was the highest. Overall, for short-range BEVs (L24 and L30), the charging session ending SOC was 90% or more on weekdays and weekends when using L1 or L2 charging. In addition, the L30 average charging session ending SOC was highest (90% or more) when using DCFCs on weekdays and weekends. The T60 and T80 started their L2 charging sessions on weekdays and weekends at higher SOCs compared to other BEVs.

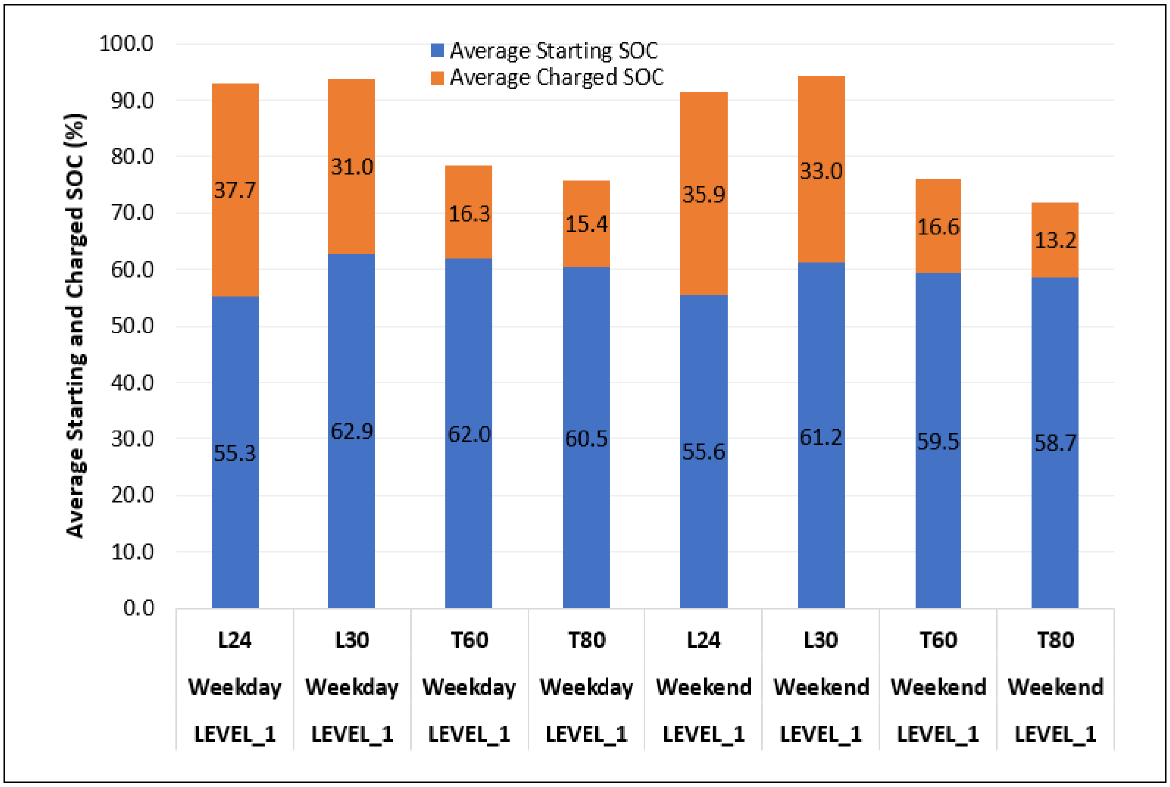


Figure 36. L1 Charging: Average Starting and Charged SOC (RAV4-40 excluded from this dataset)

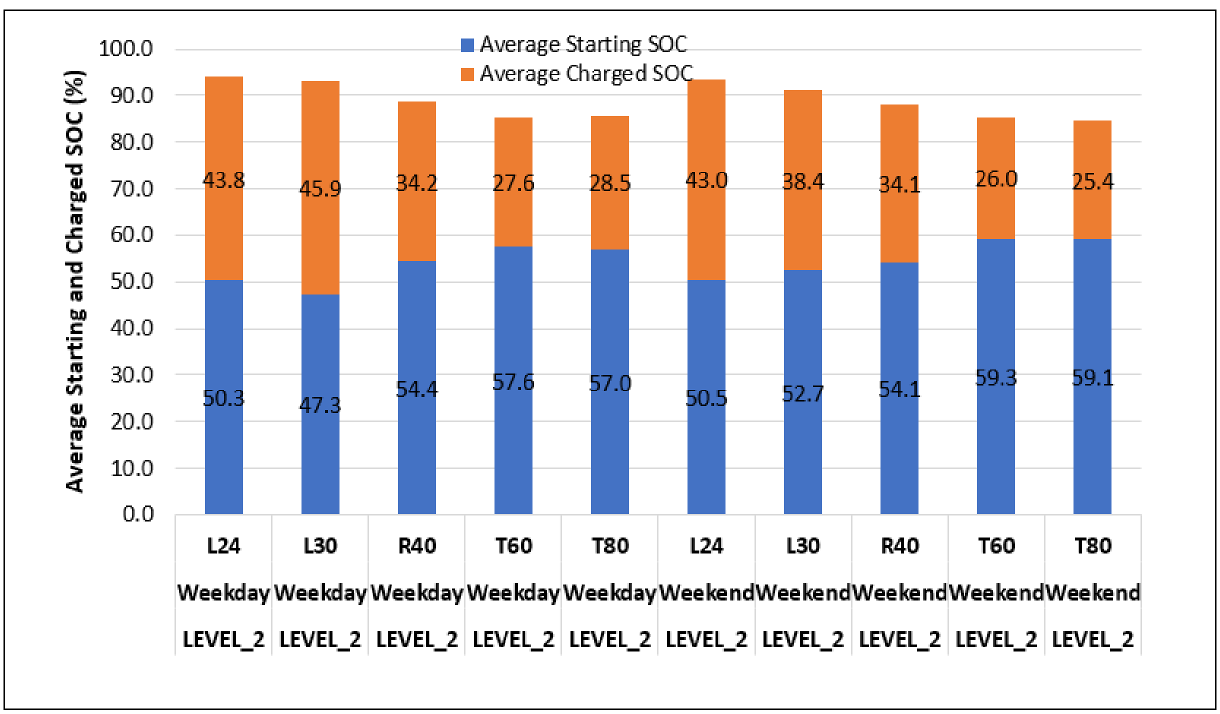


Figure 37. L2 Charging: Average Starting and Charged SOC

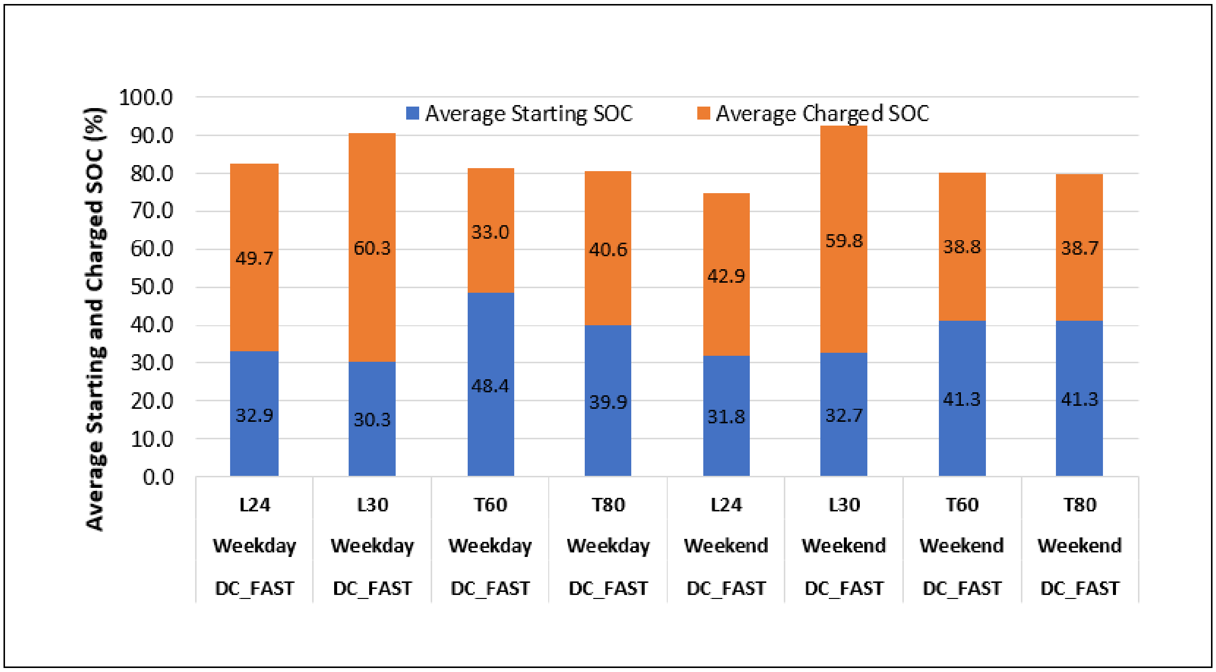


Figure 38. DCFC: Average Starting and Charged SOC (RAV4 excluded from this dataset)

5.3.1. Habitual Charging Energy

Similar to the process outlined in Section 5.2.1 for the Habitual Driving Distances, we extend the methodology used for identifying the HDD to find the Habitual Charging Energy (HCE) by charging level. HCE denotes the kWh per session that the BEV repeatedly or most often charged. **Figure 39** depicts the distribution of daily charging energy per session for all Leaf-24s on weekdays and weekends. In contrast to the daily VMT, we noticed that the distribution of charging energy per session was well suited for the distribution fitting methodology for two main reasons. First, there is an upper limit to the amount of energy that could be charged per session and this is a vehicle-specific parameter and not a driver-specific parameter, and it does not depend on the rated kW of the charger. Second, the distribution of charging energy by charger level had well defined peaks, with far fewer charging sessions falling in the lowest (5% or less) or the highest percentile (95% or more). Intuitively we can understand that from the perspective of the BEV owner, there is not much incentive in charging an empty battery to just 5% SOC or charging a relatively fully charged battery from 95% to 100%.

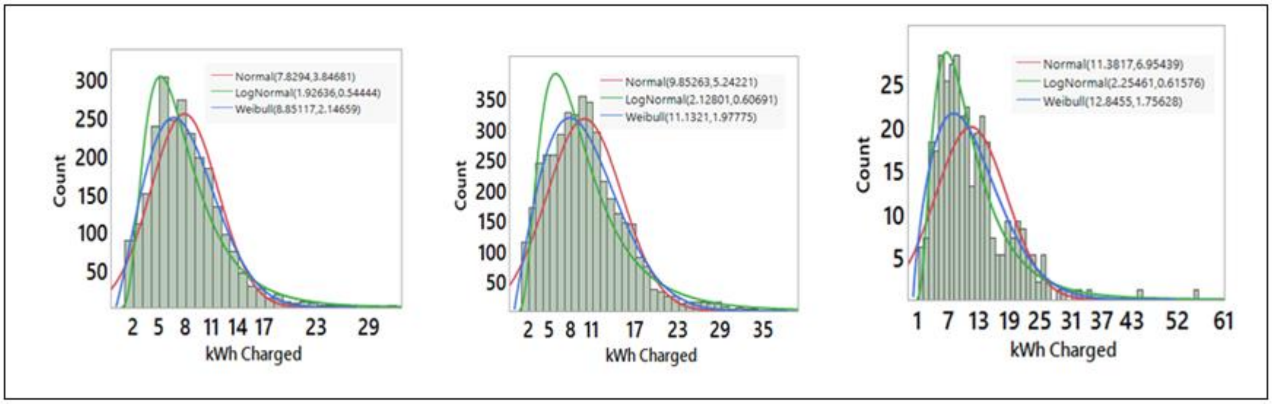


Figure 39. Distribution Fitting on Charging Energy (kWh) per Session for Leaf-24 by Charging Level (Left: L1, Center: L2, Right: DCFC)

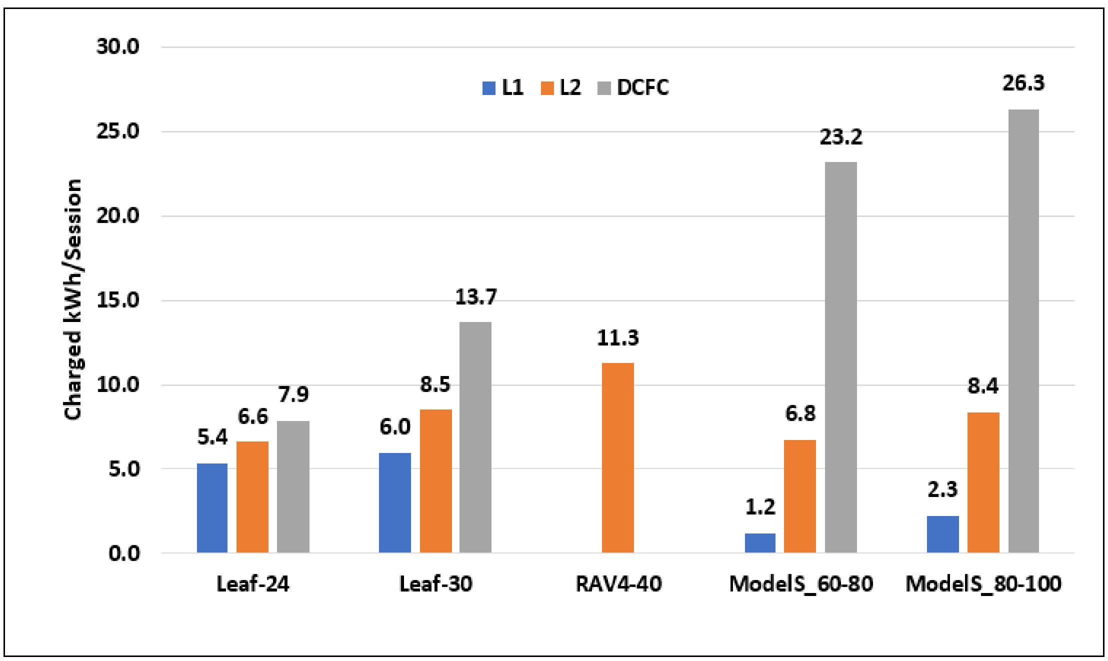


Figure 40. Habitual Charging Energy per Session by Charging Level

Figure 40 shows the HCE by charger level and BEV type. For each vehicle type, comparing the HCEs per charger level (**Error! Reference source not found.**) with the share of charging sessions per charger level (**Figure 27**) demonstrates how these two parameters can differ. For example, for the Leaf-30, 19% of charging sessions used L1 chargers and an equal percentage used DCFCs; however, the HCE when using DCFC was more than twice that when using L1 chargers. Though current DCFCs are rated up to 50 kW, T60 and T80 BEVs do not use DCFCs to charge their empty battery nor to fully charge their battery. In fact only 1.1% of all DCFC sessions started with an SOC less than 20% and ended with an SOC of 50% or more. We can also notice that eventhough current DCFCs are rated up to 50 kW, BEV owners, especially Tesla owners, do not fully take advantage of the rated kW capabilities.

The HCE is a useful metric to derive the time BEV owners most often spend from the kWh most often charged when using a L1, L2, or a DCFC charger. Information about the habitual charging behavior will be valuable for charging infrastructure planning and sizing and electricity pricing studies. Based on when the highest percentage of L1, L2, or DCFC charging sessions occur by BEV type and location (home or away), combined with the HCE (duration and energy), suitable modifications can be made to current pricing strategies toa: (i) incentivize charging during times coinciding with peak renewable energy production; and (ii) mitigate charger accessbility concerns by penalizing longer dwelling times compared to the actual charging duration.

5.4.Plug-in Hybrid Electric Vehicles (PHEVs) Driving

Results presented in **Table 15-Table 17** and depicted in **Figure 41-Figure 53** in this section are based on the data collected from the loggers. In this section, we present the vehicle level analysis of the PHEVs. We used the methods presented in Section 2.5 to estimate the trip level distribution of electric vehicle miles travelled (eVMT), gasoline vehicle miles travelled (gVMT), and the total energy consumption per trip, reported in gallons of gas and kWh of electricity used. We also compare the different PHEVs in terms of their utility factor (UF), which is the ratio of the charge depleting range to the distance travelled (SAE 2010). Compared to BEVs, which have only one source of propulsive power, estimating the eVMT of PHEVs is not as straightforward since the PHEVs have three driving modes: Charge Sustaining (CS), Charge Depleting Blended (CDB), and All Electric (AE) or Zero Emission (ZE) modes. In the CS mode, a PHEV is driven like a regular hybrid electric vehicle using only gasoline. When the PHEV is driven in ZE mode, the engine is never turned on and only electricity is consumed, whereas in the CDB mode, both gasoline and electricity are consumed.

Table 15. PHEV VMT, eVMT, gVMT, Fuel and Energy Consumption by PHEV Type

PHEV Type	Total eVMT (miles)	Total gVMT (miles)	Total VMT (miles)	Total Gasoline Consumed (Gallons)	Total Charging Energy(kWh)
Plugin Prius	45576	267607	313182	5520	77309
CmaxFusion	238137	472706	710862	11717	10923
Volt-16	314451	196707	511159	5731	83424
Volt-18	304055	141000	445055	3765	100224
All PHEVs	***902,220***	***1,078,020***	***1,980,259***	***26,733***	***271,879***

Table 15 provides an overview of the PHEV driving and charging data considered in the vehicle level analysis. **Figure 41** shows the total eVMT, total miles travelled on gasoline (gVMT), and total PHEV VMT for the individual PHEVs by type.

Figure 42 shows the average utility factor UF by PHEV type. On average, the Volt-18 had the highest UF, followed by the Volt-16. The UF of the CmaxFusion PHEV was half that of the Volt-18. The UF measured in our project is different than that used for current policies and regulations. Current regulation are based on a UF standardized in the SAE J2841 (SAE 2010) that is based on daily miles from travel surveys and the assumption that each vehicle starts the travel day fully charged. Our sample suggests that not all PHEVs are charged every day and that different PHEVs charge differently. Furthermore, we did not install loggers in vehicles that were used as hybrids or charged less than 4 times per month. Based on the project survey, 5.9% of Volt owners, 16.5% of the Ford Energi owners, and 18.5% of the Prius owners drove mostly on gas and were not accumulating eVMT. We believe that these figures underestimate the phenomena, because of a selection bias, where users who do not plug in their cars are less likely to take and finish a survey on the topic. **Figure 43** shows the UF for each of the vehicles based on the SAE2841 standard, the actual eVMT and VMT measured, and the utility factor adjusted to the survey results, including the vehicles with utility factor of zero. For all vehicles, we measured lower UFs than the SAE standard as the logged Prius PHEVs achieve only 52% of the expected UF or 41% when taking into account users who are not plugging in. For the longer-range Volts, we measured UFs that were closer to the values determined by the SAE2841.

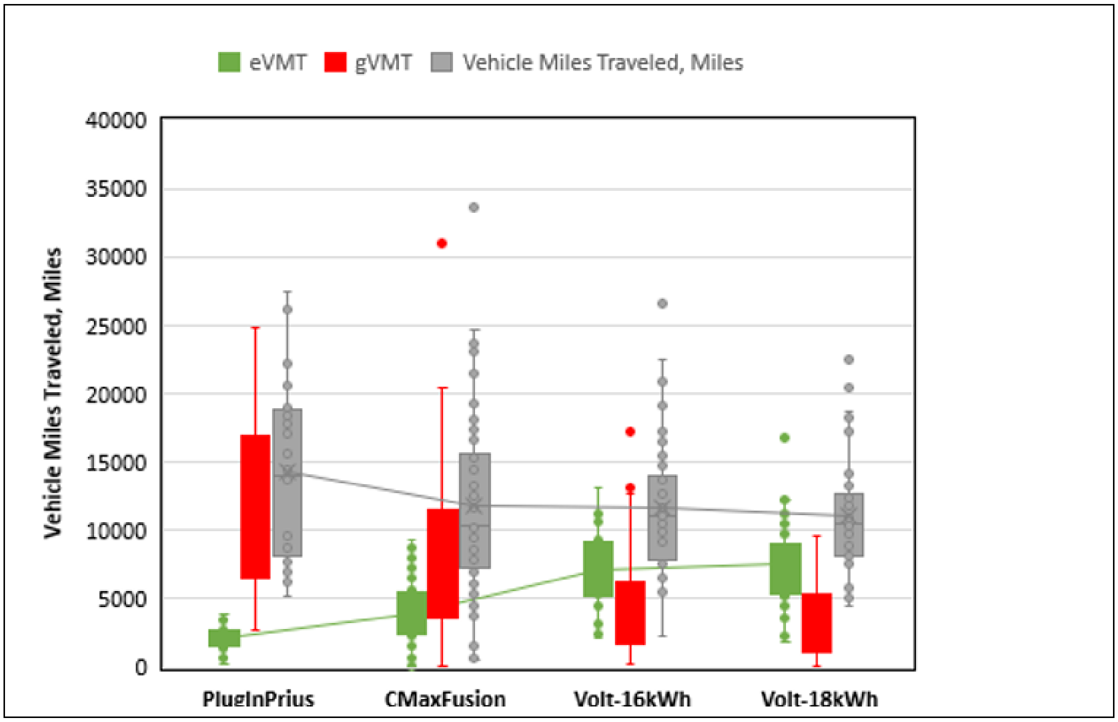


Figure 41. PHEV eVMT, gVMT, and VMT of Individual PHEVs by PHEV Type

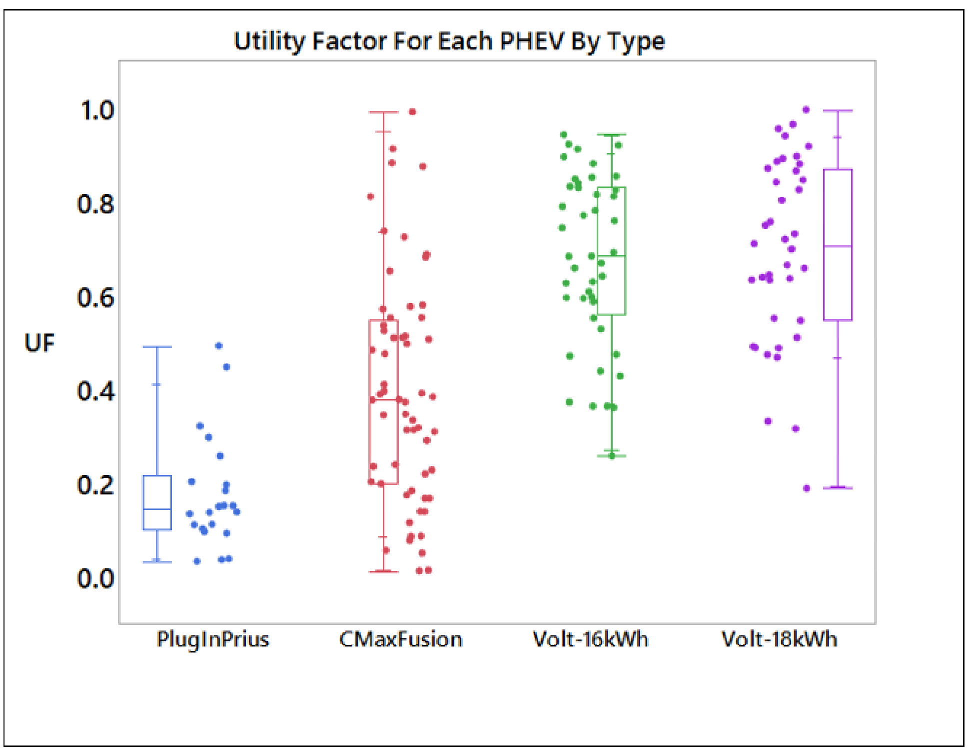


Figure 42. Utility Factor (UF) for Each PHEV by Type

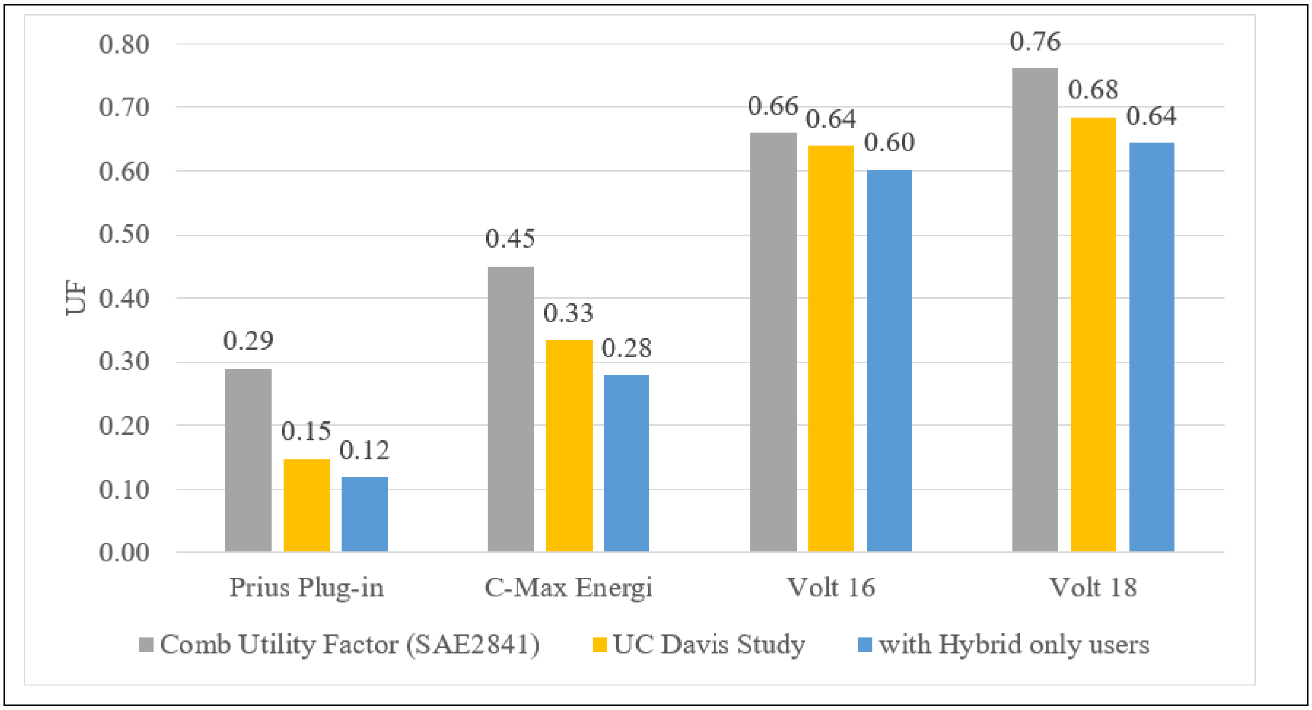


Figure 43. Average UF by PHEV Type

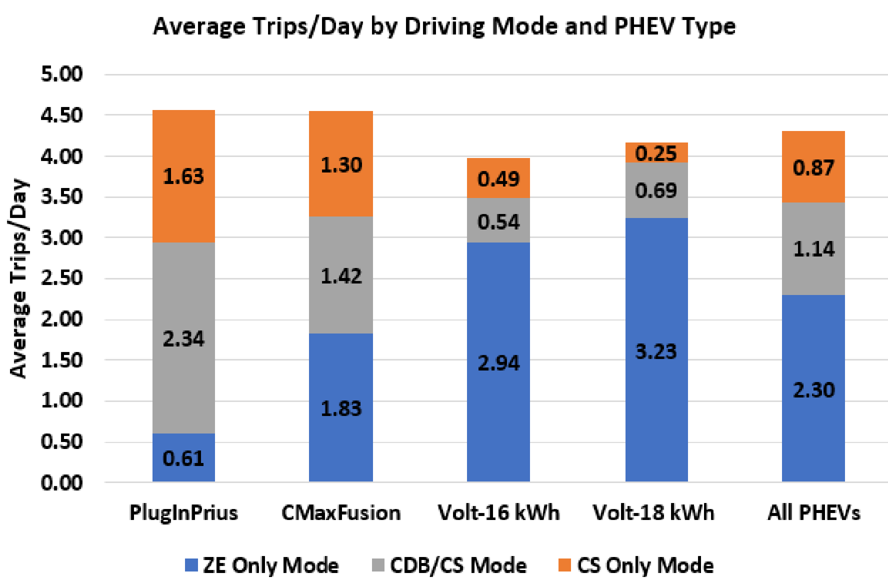


Figure 44 Average Trips per Day by Driving Mode

At the day level, on average, the PluginPrius and the CmaxFusion PHEV were driven approximately 4.5 trips/day, whereas the Volt-16, 3.97 trips/day. Both the Volt-16 and Volt-18 had fewer average daily trips than the PHEV fleet (4.31 trips/day). On average, when compared to other PHEVs, the Volt-18 had the greatest share of trips accomplished on electricity alone (ZE only mode), also referred to as zero emission trips. The Volt-18 also had the lowest share of trips that were accomplished on gasoline alone in the charge sustaining mode (CS only mode). Referring to **Figure 45**, we can see that, compared to the other PHEVs, the Volt-18 by far had the lowest percentage of CS only trips and the highest percentage of ZE only trips. In contrast, the PluginPrius had the highest percentage of CDB/CS trips. At the PHEV fleet level, there was a relatively even split between ZE only trips and CS only or CDB/CS trips.

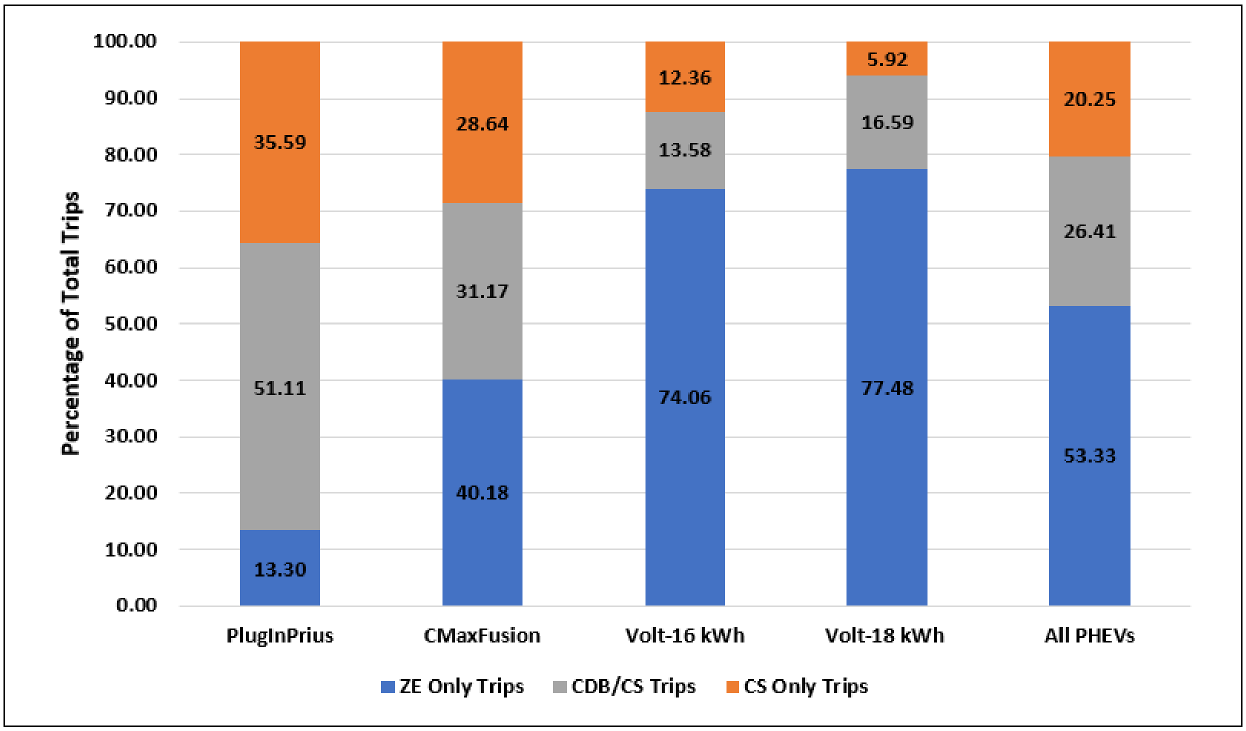


Figure 45. Percentage of Total PHEV Trips by PHEV Driving Mode

As shown in **Figure 45**, the Volt-18 had a higher share of ZE trips and lower share of CS only trips than did the Volt-16. Referring back to **Figure 16**, which showed the total share of VMT by trip speed bins and PHEV type, we see that the Volt-16 had a slightly higher share of VMT accomplished at low trip speeds (30 mph or less) and at high speeds (60 mph or more). The incremental battery capacity of Volt-18 compared to Volt-16 is enabling the Volt-18 to do a higher share of blended trips. The share of CDB and CS trips for the PlugInPrius is higher than for other PHEVs, simply due to its smaller battery.

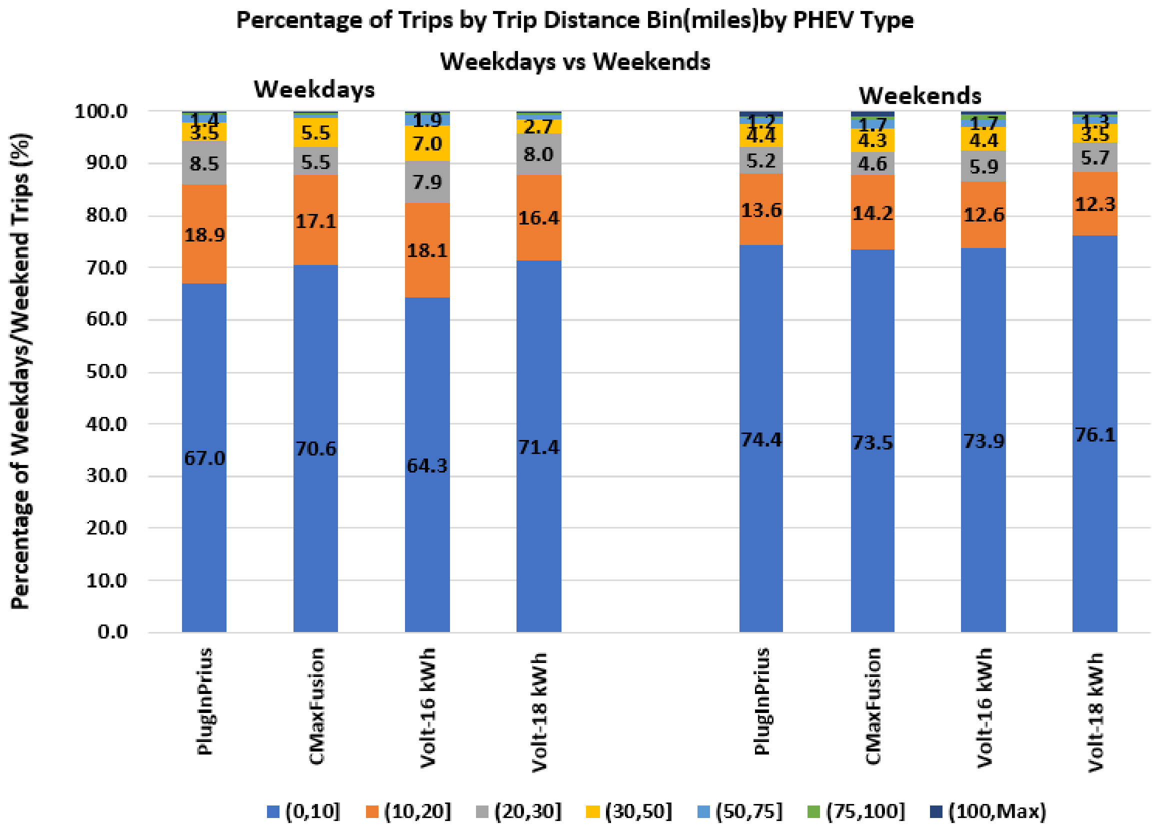


Figure 46 Share of Trips by Trip Distance Bins: Weekdays vs Weekends

Figure 46 shows the percent share of trip distance by trip distance bin on weekdays and weekends. At least 90% of the trips were less than 30 miles for all the PHEV types on weekdays and weekends. During weekends as compared to weekdays, PHEVs are driven on a higher share of trips less than 10 miles and a lower share of trips of 10–20 miles. The Volt-18 has a higher share of trips between 30–50 miles on weekends (3.5%) than it does on the weekdays (2.7%); this contrasts with the Volt-16, which has a lower share of 30–50 mile trips on weekends(4.4%) than it does on weekends (7.0%).

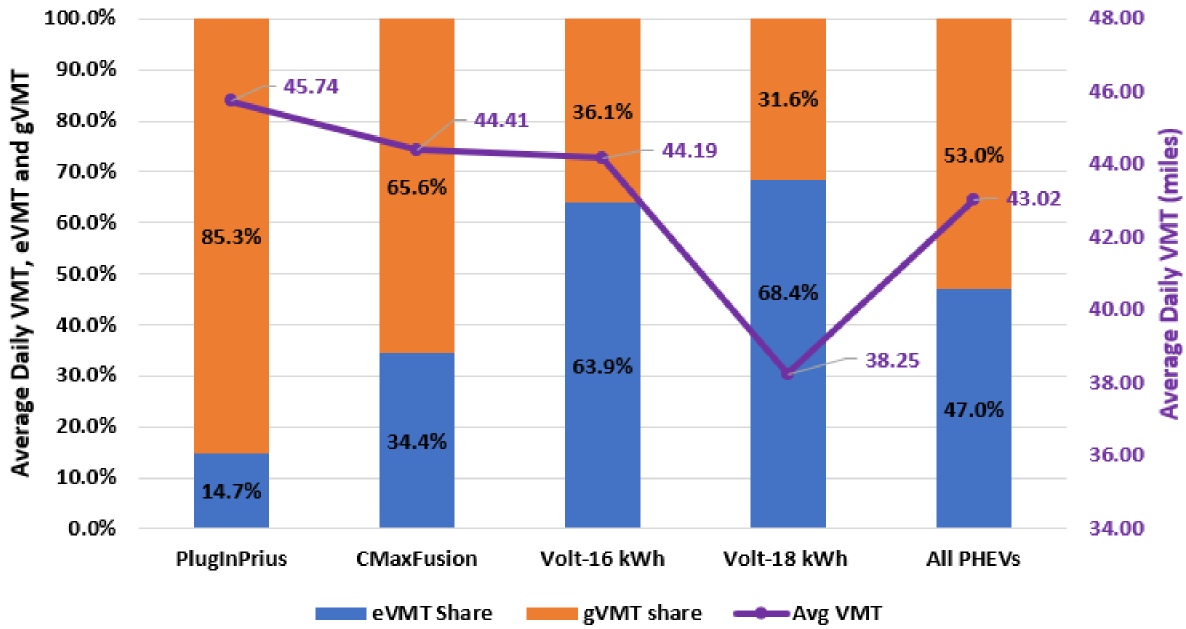


Figure 47 Daily Average VMT, eVMT, and gVMT Share by PHEV Type

Figure 47 shows the average daily VMT, eVMT and gVMT along with the percentage share of eVMT and gVMT. The PlugInPrius had the highest daily average VMT, and the Volt-18kWh had the lowest daily average VMT. Compared to the Volt-18kWh, the Volt-16kWh had a higher daily average VMT, higher share of gVMT, and lower share of eVMT. The average daily VMT of CmaxFusion and the Volt-16kWh were approximately equal but their split between eVMT and gVMT were opposite, with the Volt-16kWh eVMT share being 64% and the CmaxFusion's gVMT share being 66%.

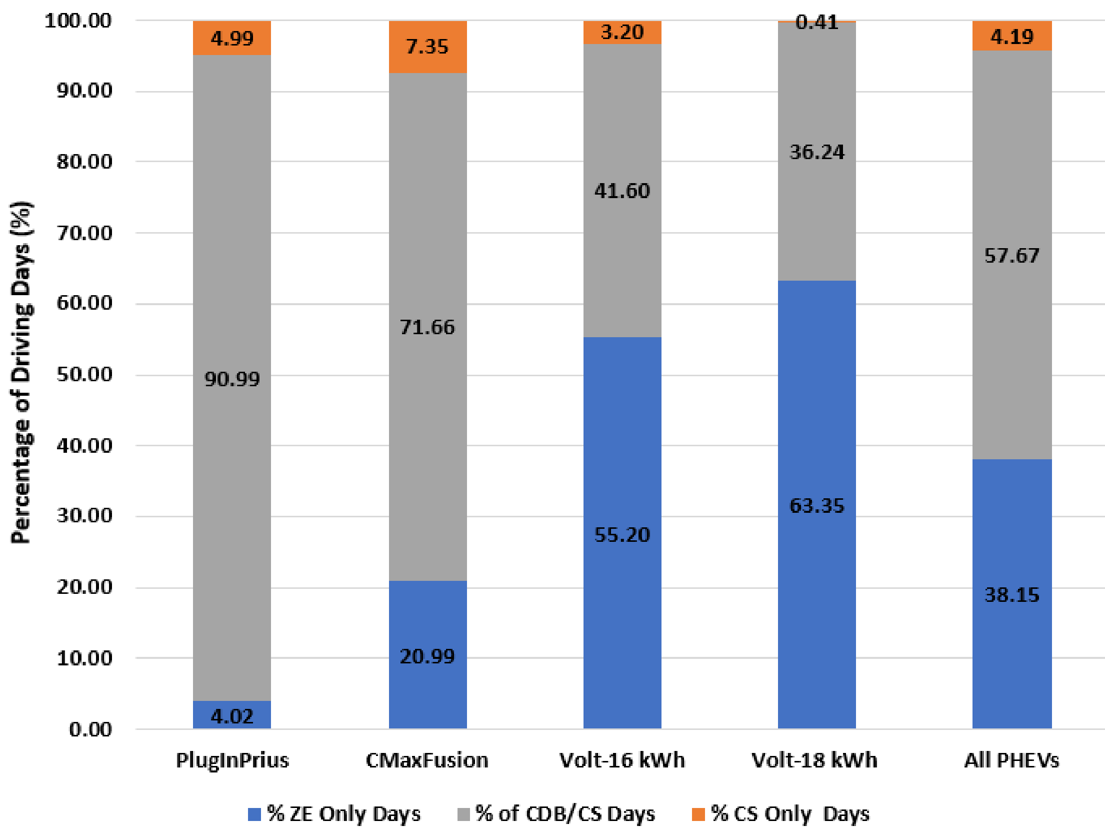


Figure 48 Share of ZE Days, CS Days and CDB/CS Days

Figure 48 shows the share of days the travel was accomplished on electricity alone (ZE only days), gasoline alone (CS only days), and gasoline and electricity (CDB/CS days). It also shows that even among households that charged the vehicle regularly, for all PHEVs, 4.2% of days start with zero SOC, and this is more common for the CmaxFusion than other vehicle types. The Volt-18 had an almost negligible percentage of days when it was driven on gasoline only, with two-thirds of its driving days being ZE only days. Even though the CmaxFusion has a bigger battery than the PluginPrius has, it had a higher percentage of CS only days.

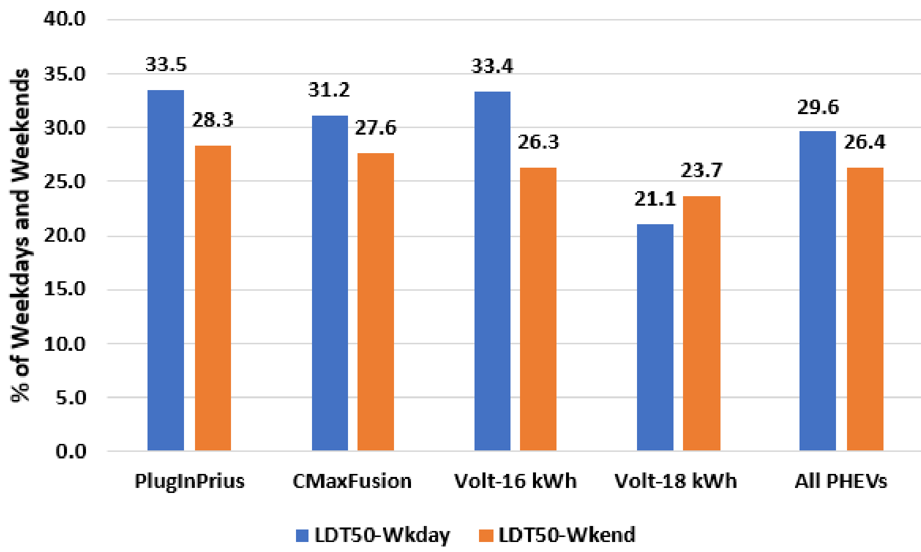


Figure 49 Share of Long-Distance Travel (LDT; 50 miles or more) Days: Weekdays vs Weekends

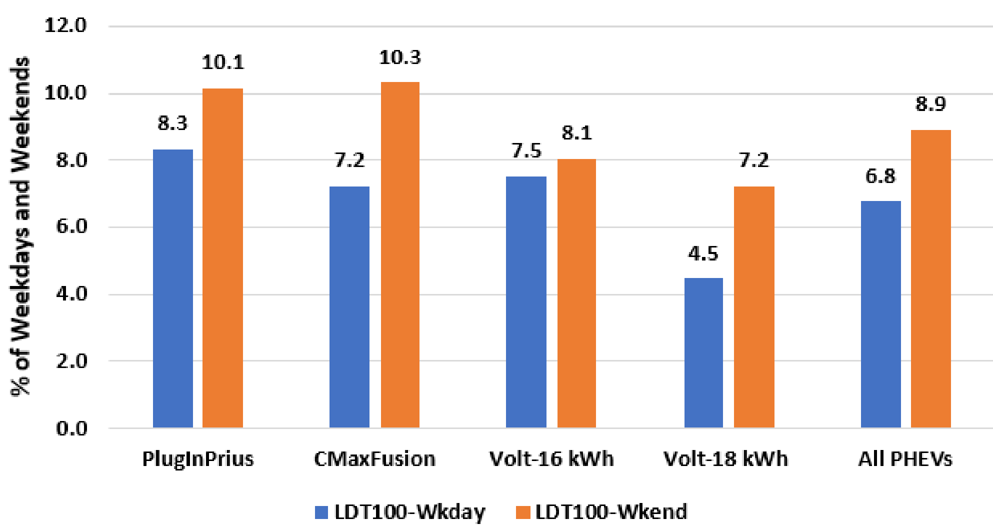


Figure 50 Share of Long-Distance Travel (LDT; 100 miles or more) Days: Weekdays vs Weekends

Figure 49 and **Figure 50** show the share of days on weekdays and weekends, out of the total logged days, that the PHEV was driven 50 miles or more and 100 miles or more, respectively. PluginPrius, CmaxFusion, and Volt-16kWh had a higher percent of weekends than weekdays when the vehicle was driven 50 miles or more. The Volt-18kWh had a slightly higher percent of weekends than weekdays when it was driven 50 miles or more. All the PHEVs had a higher percent of weekends than weekdays when they were driven 100 miles or more.

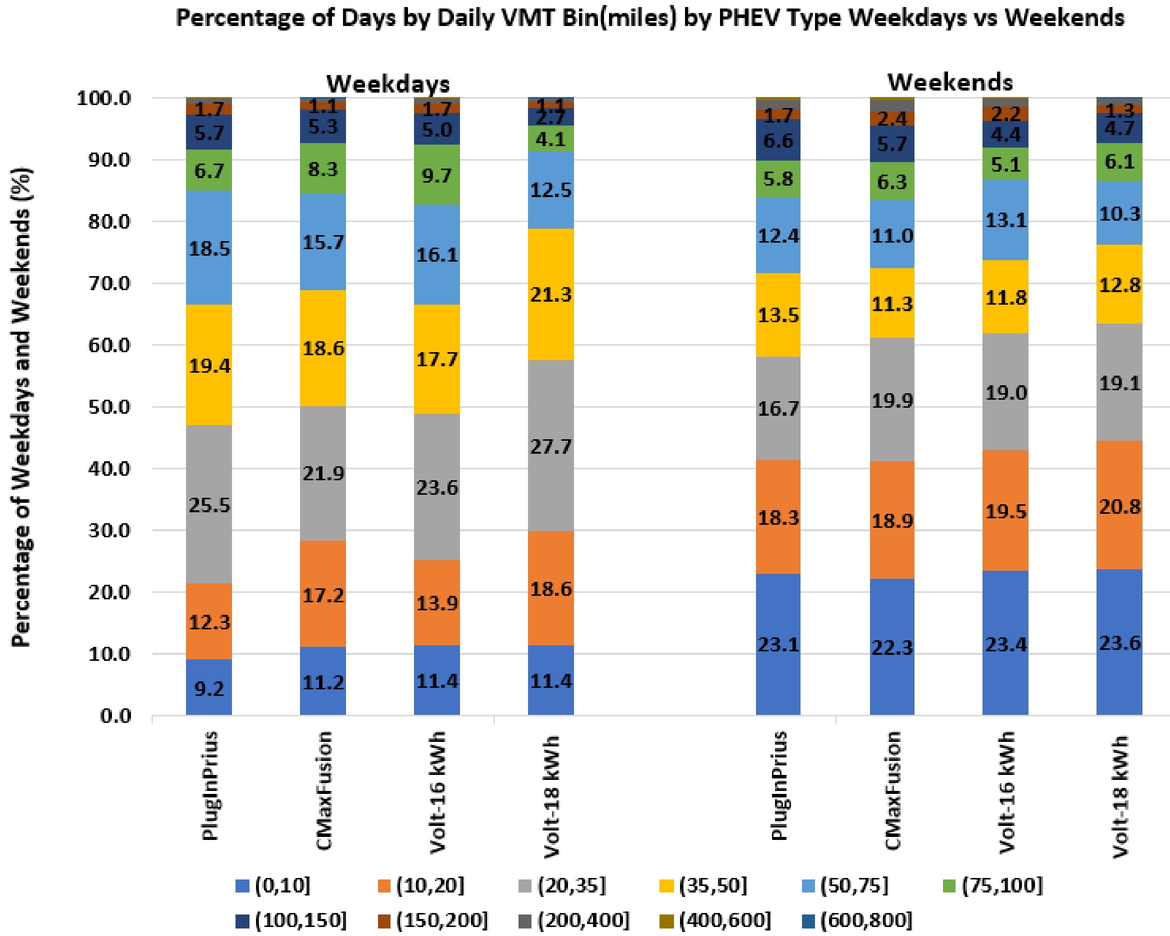


Figure 51 Share of Daily VMT by Distance Bin: Weekdays vs Weekends

Figure 51 shows the percentage of weekdays and weekends by daily VMT bin. Approximately 50% of all the PHEV distances (except for the Volt-18) on weekdays were less than 50 miles. Almost 58% of the Volt-18 VMT on weekdays were less than 50 miles. During the weekends, for all the PHEVs, 60% of the distances were less than 35 miles. The Volt-18k had the highest percentage of weekdays when it was driven 35–50 miles or 20–35 miles. The percentage of days when VMT was less than 10 miles was almost double on weekends compared to weekdays, for all PHEV types. The percentage of days when the VMT was 75–100 miles was lower on weekends than on weekdays for all PHEVs.

5.4.1. Habitual Driving Distances (HDD)

The methodology outlined for estimating the HDD of the BEVs (Section 5.2.1) was adopted to find the HDD of PHEVs. Similar to the HDD for BEVs, we performed ANOVA and non-parametric group means comparison tests and the results are summarized in **Table 16** and **Table 17**.

Table 16. ANOVA Summary of PHEV HDD, Mean and Maximum Daily VMT

Daily VMT	Sum of Squares	Mean Square	F Ratio	P-value*
HDD Weekday	393.35	131.116	0.1966	0.8986
HDD Weekend	1954.11	651.371	1.9911	0.1174
Max Weekday	81317.93	27105.978	1.3844	0.2495
Max Weekend	50823.21	16941.071	0.8283	0.4801
Mean Weekday	1418.58	472.859	1.2481	0.2942
Mean Weekend	1024.29	341.428	1.0476	0.3732

**p-value < 0.05: statistically significant differences at 0.95 confidence levels*

Table 17. Non-Parametric Wilcoxon Pairwise Comparison of HDD, Mean and Maximum Daily VMT

Vehicles Compared		P-values					
		Weekday			Weekend		
PHEV.Type	PHEV.Type	Max	Mean	HDD	Max	Mean	HDD
PlugInPrius	CMaxFusion	0.2562	0.5266	0.7297	0.3653	0.822	**0.0313**
Volt-18 kWh	CMaxFusion	0.5381	0.3368	0.8603	0.3229	0.2896	0.0604
Volt-18kWh	PlugInPrius	0.1171	0.1242	0.9355	0.1171	0.5222	0.3926
Volt-16kWh	CMaxFusion	0.9685	0.624	0.8332	0.9921	0.4512	0.3329
Volt-16kWh	PlugInPrius	0.234	0.9187	0.9133	0.2083	0.6389	0.1884
Volt-16kWh	Volt-18kWh	0.5018	0.161	0.8367	0.2425	0.8614	0.5657
p-value < 0.05: statistically significant differences at 0.95 confidence levels							

ANOVA tests indicated that for all comparisons between paired PHEV types, on both weekdays and weekends, the HDD and mean and maximum daily VMT did not differ significantly. Wilcoxon's non-parametric tests simiarly showed no signficant differences in paired comparisons of PHEV types for HDD and mean and maximum VMT, with the exception of HDD on weekends differing significantly between the PluginPrius and CmaxFusion.

The fleet average HDDs on weekdays for the BEVs and PHEVs were 31.8 miles and 32.8 miles, respectively. On weekends, the fleet average HDDs for the BEVs and PHEVs were 16.6 miles and 20.1 miles, respectively. **Figure 52** and **Figure 53** show the average weekday and weekend HDD by PEV type on weekdays and weekends, respectively. Overall, the PEV average weekday HDD was 33 miles and the PEV average weekend HDD was 17.5 miles.

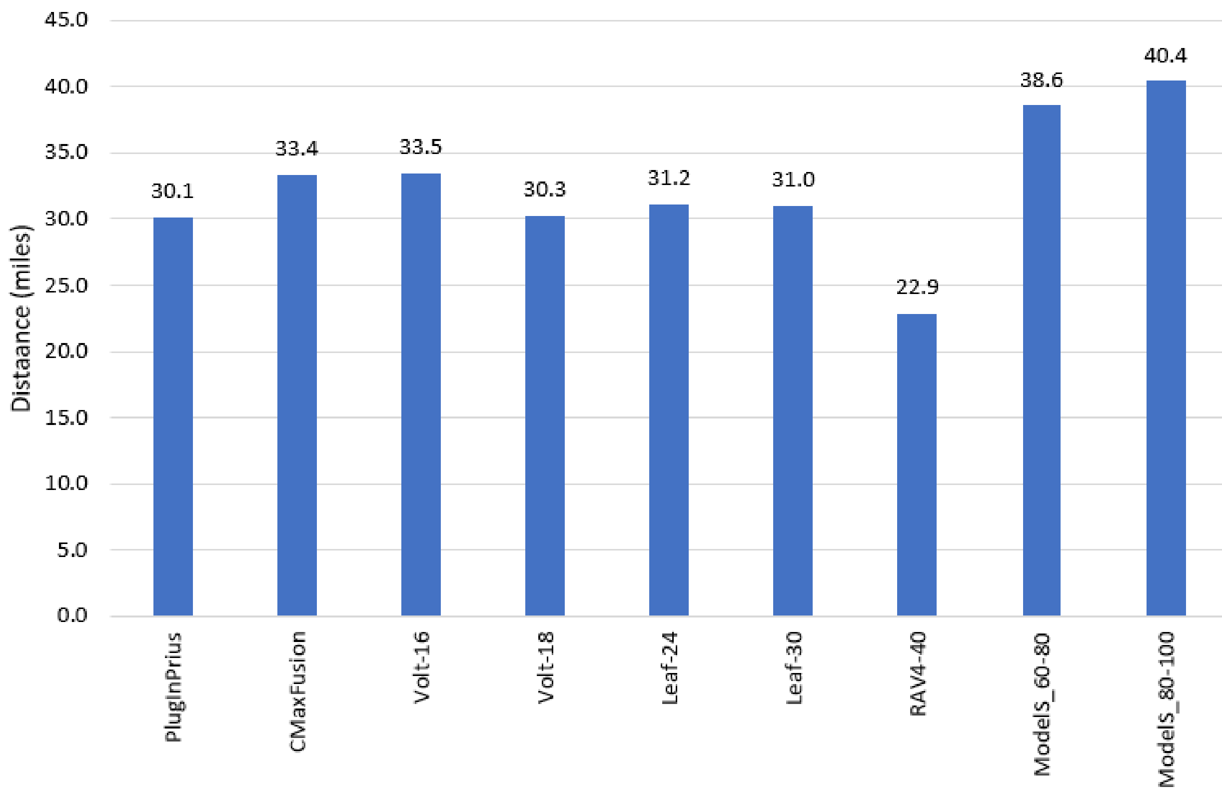


Figure 52. Average weekday HDD by PEV Type

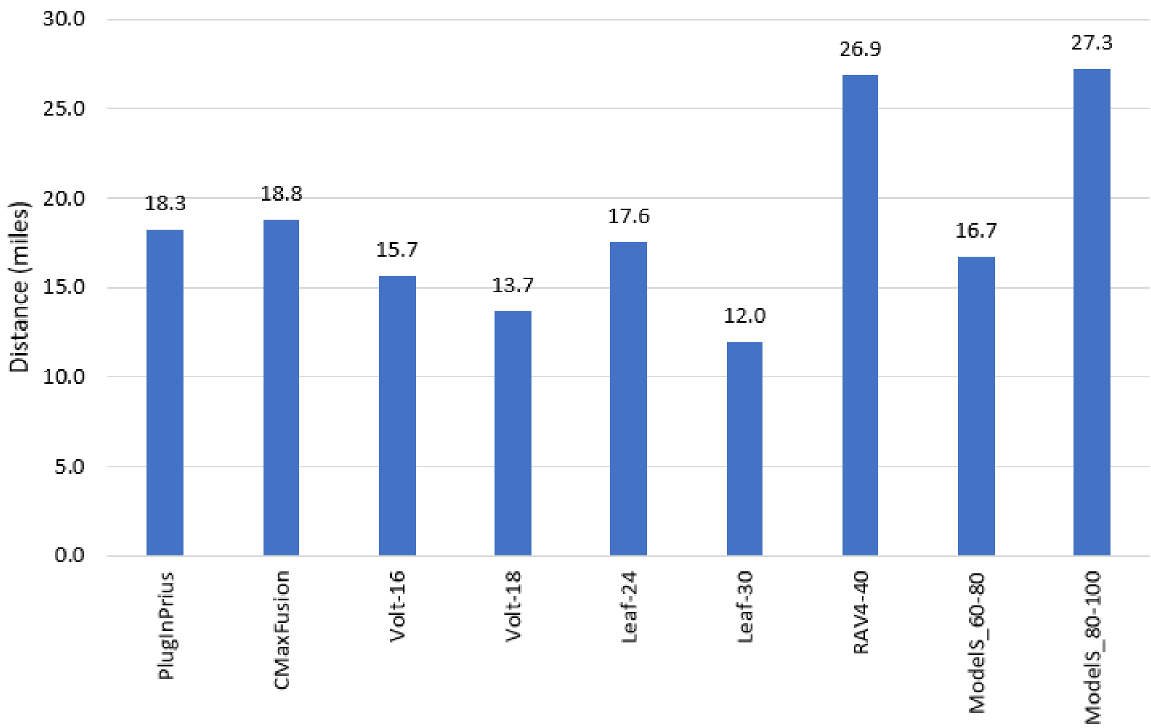


Figure 53. Average Weekend HDD by PEV Type

5.5.Plug-in Hybrid Electric Vehicle Charging

Results presented in **Table 18** and depicted in **Figure 54** – **Figure 59** are based on the logger data. **Table 18** summarizes the average number of PHEV charging sessions, kWh charged, and the duration of charging per day by charging level.

Table 18 PHEV Charging Summary Statistics

	On Days When the PHEV Charged				
PHEV	**Average Sessions/Day**	**Average L1 Sessions/Day**	**Average L2 Sessions/Day**	**Average kWh/Day**	**Average Duration/Day**
PlugInPrius	1.52	1.40	0.12	2.10	150.20
CMaxFusion	1.66	0.90	0.76	5.92	249.52
Volt-16kWh	1.44	0.66	0.78	9.04	375.23
Volt-18kWh	1.30	0.53	0.78	9.90	384.57
	Within the Logging Window Including Days When PHEV Did not Charge				
PHEV	**Average Sessions/Day**	**Average L1 Sessions/Day**	**Average L2 Sessions/Day**	**Average kWh/Day**	**Average Duration/Day**
PlugInPrius	0.99	0.91	0.08	1.36	97.33
CMaxFusion	1.11	0.60	0.50	3.95	166.39
Volt-16kWh	1.02	0.47	0.55	6.43	266.96
Volt-18kWh	0.77	0.31	0.46	5.87	227.83

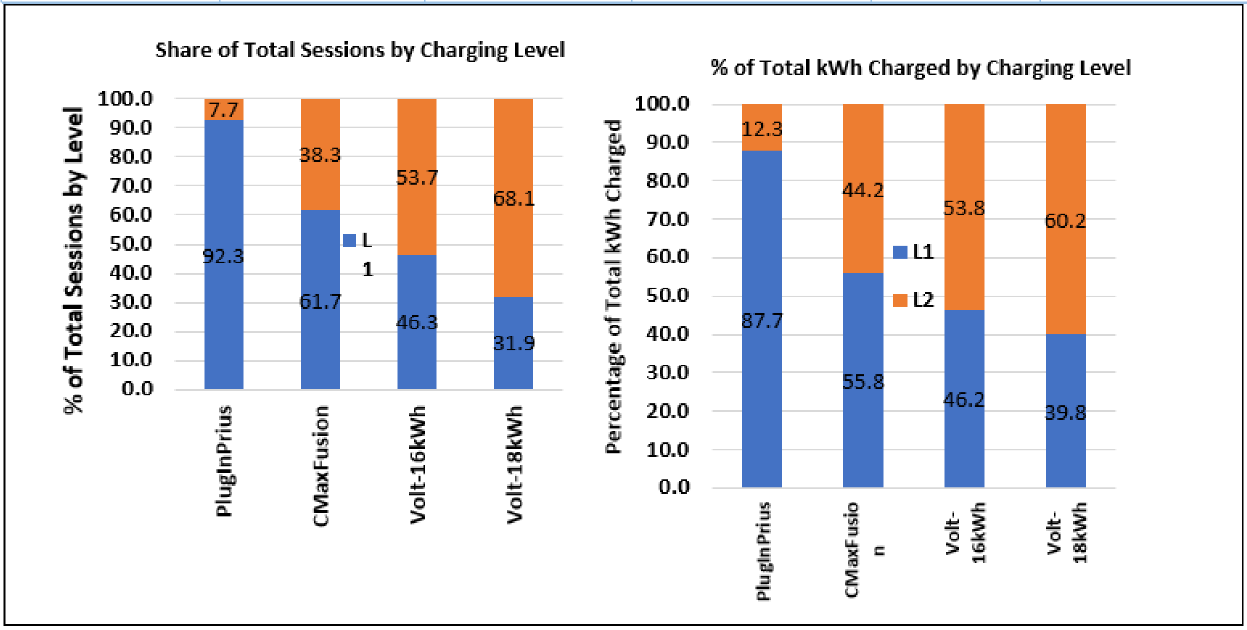


Figure 54. Share of Charging Sessions Charged Energy by Charging Level

Referring to **Figure 54**, L1 charging accounted for a majority of the PluginPrius and CmaxFusion charging sessions and charging energy. The Volt 16-kWh had almost an even split between L1 and L2 charging sessions and charged energy. For the Volt-18kWh roughly 30% of its charging sessions and 40% of charged energy were using L1 charging.

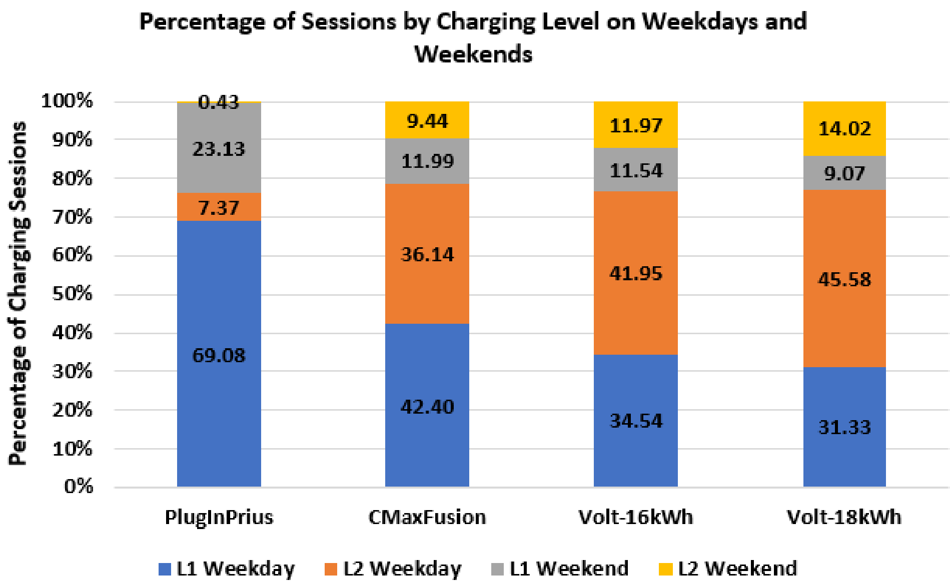


Figure 55. Share of Total Number of Sessions by Charging Level

Referring to **Figure 55**, CmaxFusion and Volt-16 had a comparable number of L1 and L2 charging sessions on weekdays. Compared to the Volt-16, the Volt-18 had a slightly lower percentage of L1 charging sessions on weekends and a relatively higher percentage of L2 charging sessions on weekends and weekdays.

Figure 56Figure 58 show the average kWh charged per charging session and the average charging session duration by charging level on weekdays and weekends. Except for the PlugInPrius, on average, all PHEVs were plugged in for relatively longer times (irrespective of the charger level) on weekdays than on weekends and subsequently the average charging energy/session was also higher on weekdays than on weekends. Compared to other PHEVs, the Volt-18kWh had relatively longer charging sessions and higher charged energy/session (irrespective of the charger level) on weekdays and weekends.

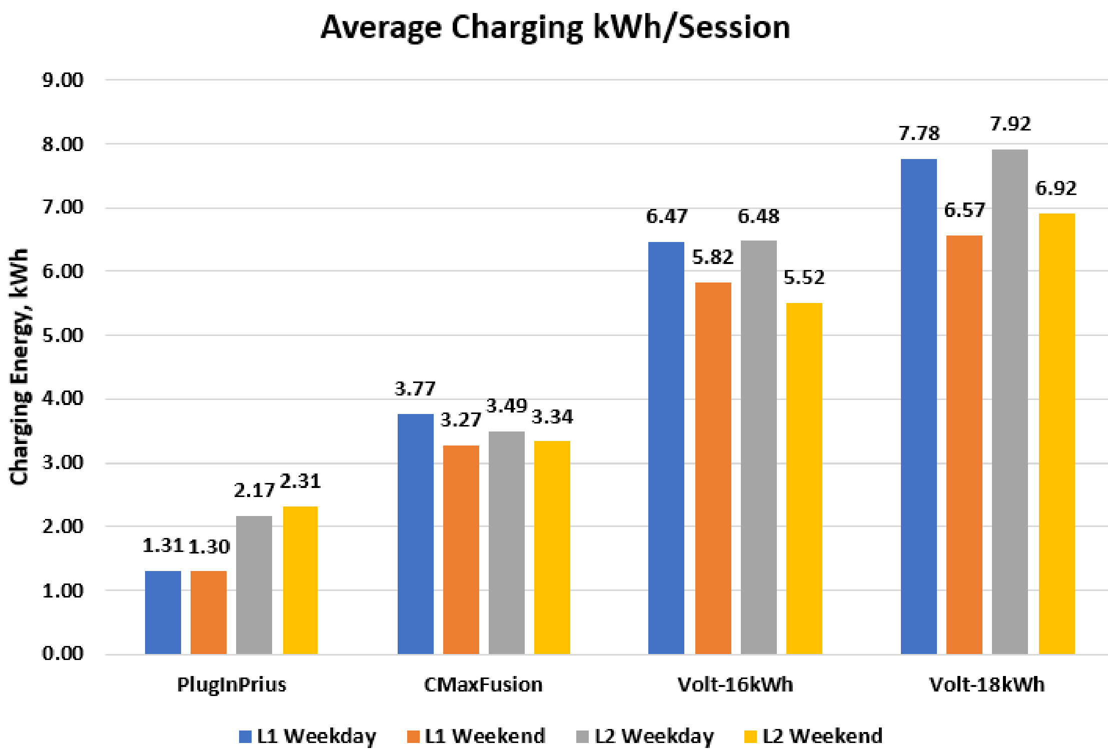


Figure 56. Average L1 and L2 Charging kWh/Session: Weekdays vs Weekends

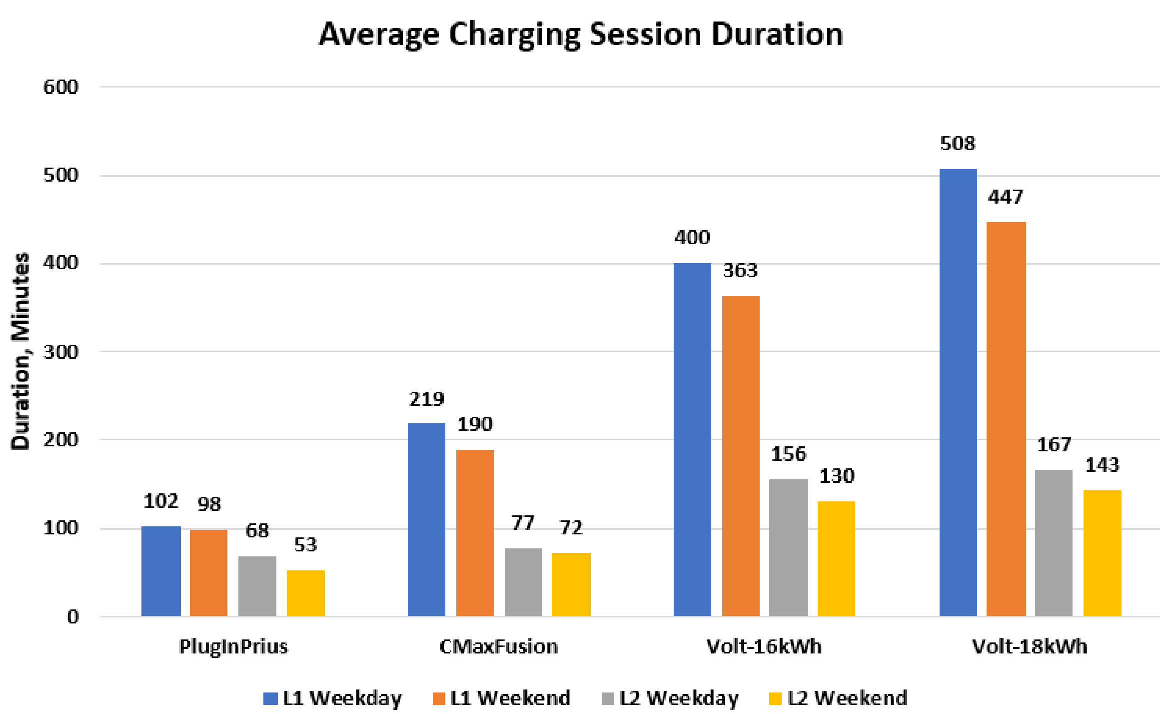


Figure 57. Average L1 and L2 Charging Session Duration : Weekdays vs Weekends

Figure 58 and **Figure 59** show the percentage of charging sessions for each starting time on weekdays and weekends. The percentage of charging sessions noticably spike on weekdays at around 8 am, around noon-1pm, and between 5-7pm; and on weekendsat around noon, 5pm-7pm and after 11 pm.

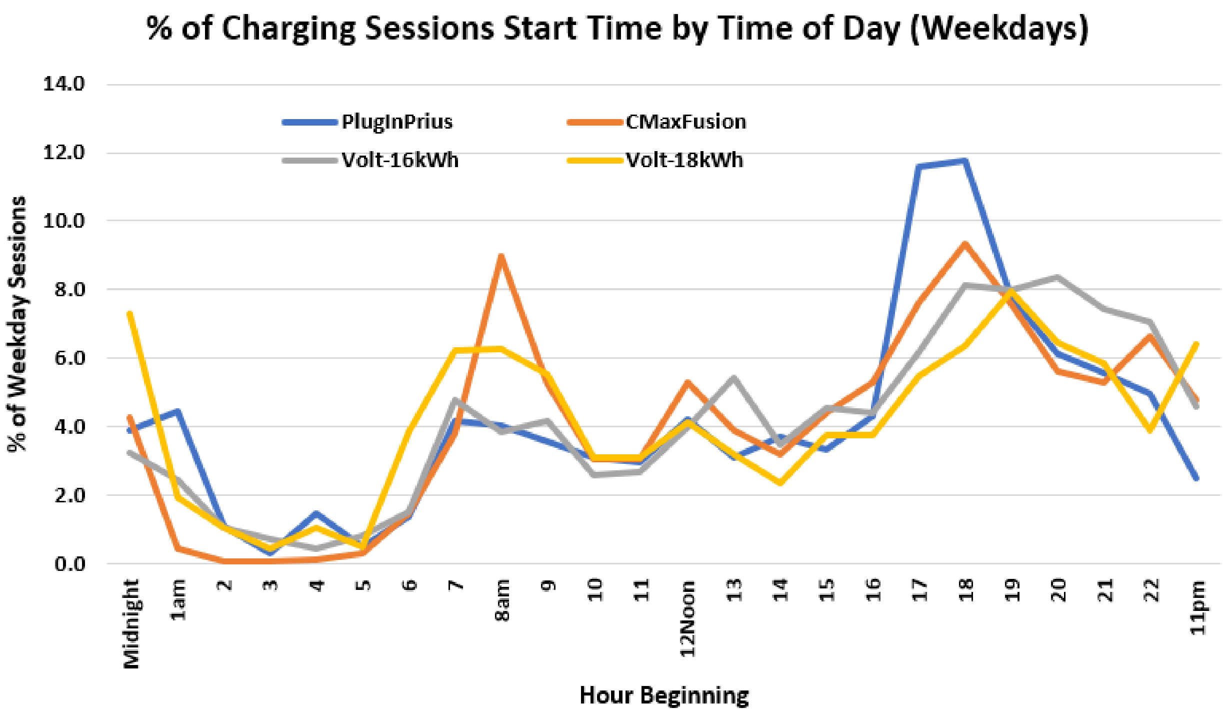


Figure 58. Percentage of Charging Sessions Starting Time (L1 and L2): Weekdays

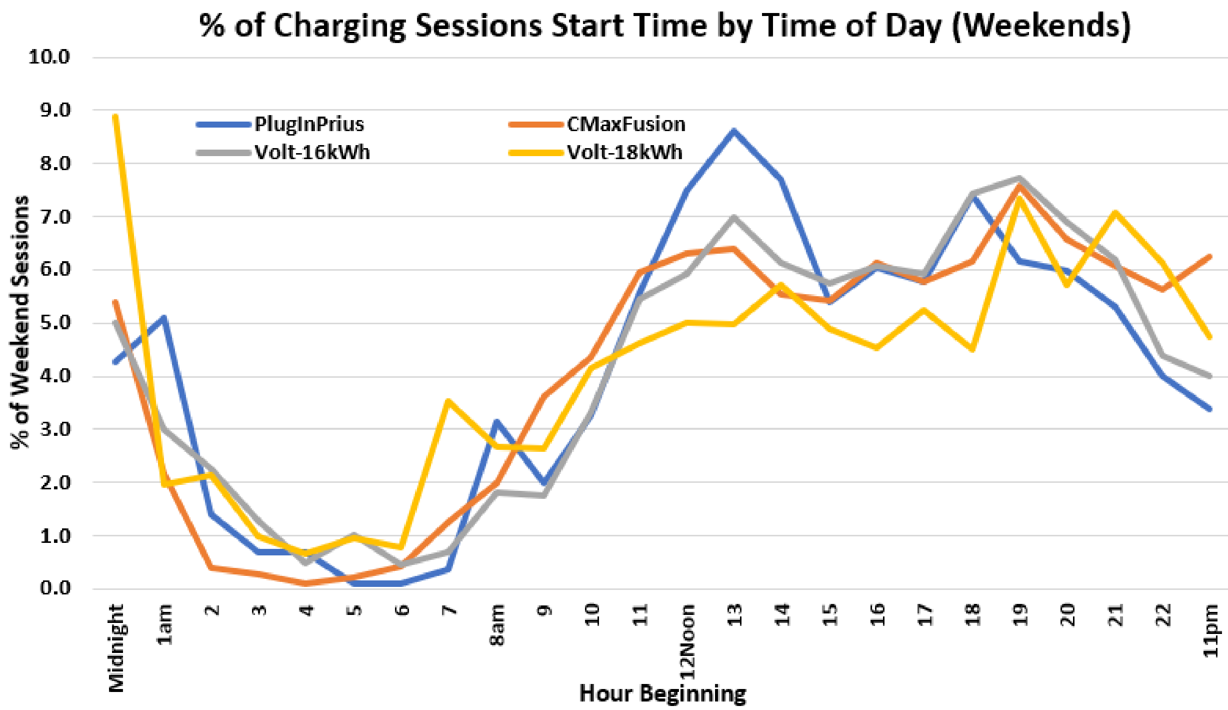


Figure 59. Percentage of Charging Sessions Starting Time (L1 and L2): Weekends

5.6. Charging Distance Based on GPS Location

We use the survey data to analyze charging location based on self-reported information about home, work, or public charging events. We use the logger GPS location to estimate charging location based on a "crow's flight" distance from the most common vehicle location at 3am while collecting data (designated as "home" in this section), and from the over-night location before the charging. The total number of charging events used in this section is 165,659; of those, 19,993 are out of home events logged from 166 vehicles. Overall, 87.3% of the recorded level 1 charging events happened at the highest frequency over-night location, meaning that other level 1 charging events may have happened in the household's other "home", or in public locations. Similarly, 71% of the level 2 charging events occured at the same location, and even 2% of the DC fast charging events happened within a one mile distance from home.

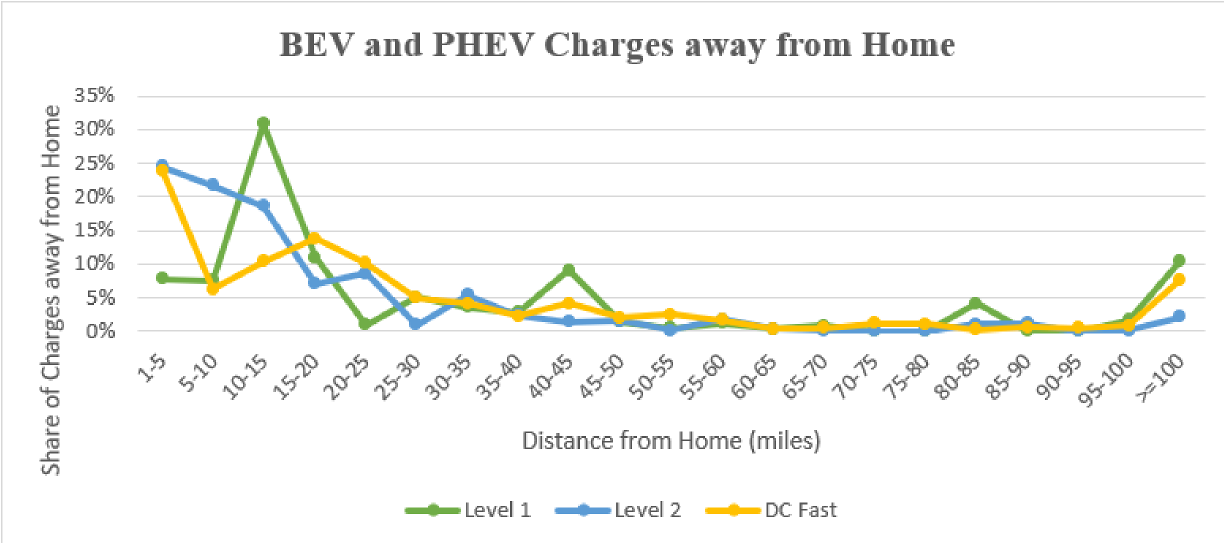


Figure 60. Percentage of Charging Sessions More Than 1 Mile From Home (includes 13% of the L1 events, 29% of L2 events and 97% of DCFC events)

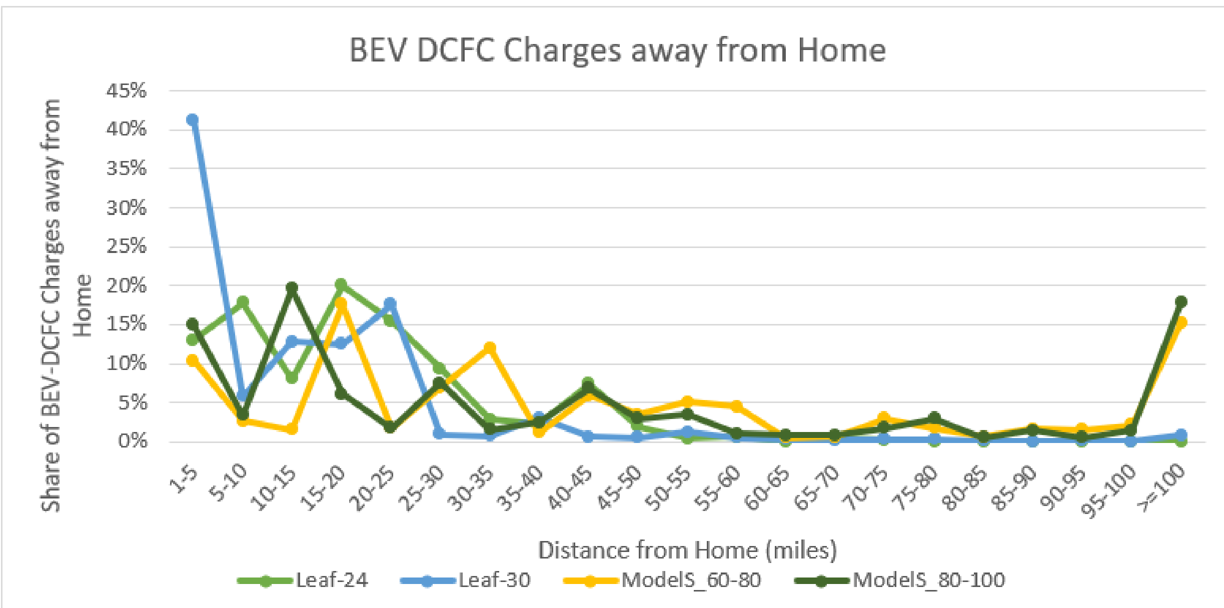


Figure 61. Percentage of DCFC Charging Sessions by BEV Type and Distance from Home

As presented in **Figure 60**, 25% of the level 2 and DCFC events are within 5 miles from home, while level 1 peaked at 15 miles from home, most likely at the commute location. 65% of the DCFC events are within 25 miles from home and only 7% are more than 100 miles from the main home. When exploring the distance from the location at the start of the day we find a similar picture, but charging events for level 2 over 100 miles from home dropped to 1.6% and for DCFC dropped to 5.8%. **Figure 61** shows that most of the DCFC charging events happen within 35 miles from home for all vehicles. When exploring the number of charging events based on one way trips (using two thirds of the BEV travel range to reflect the difference between straight lines and the road network) we conclude that 75% of the Leaf-24, 90% of the Leaf-30, and more than 84% of the Tesla charging events are within range for a round trip from home, if starting the day with a full battery.

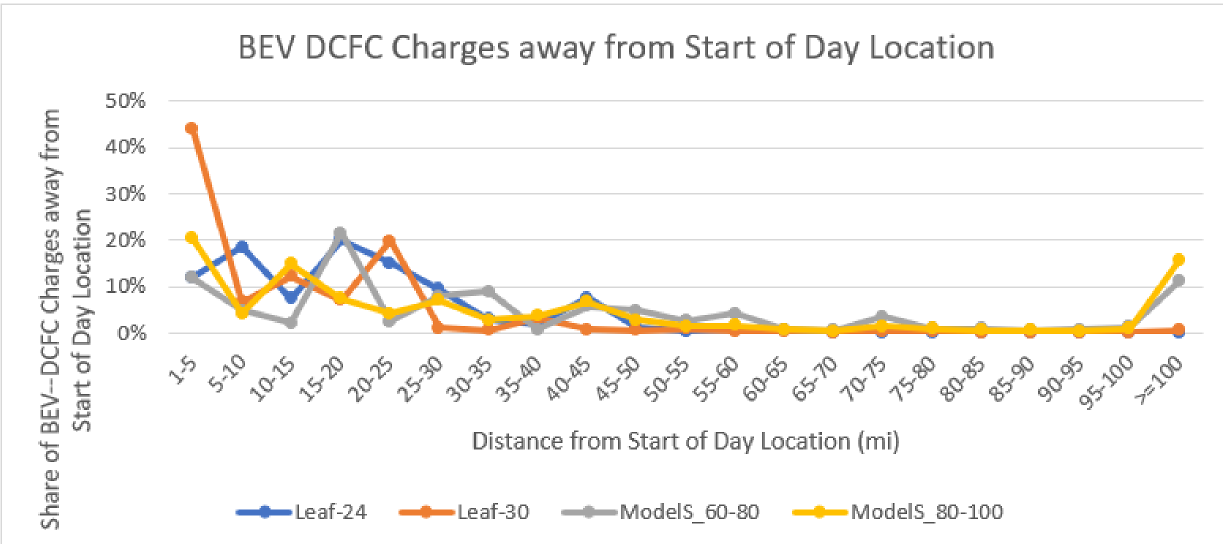


Figure 62. Percentage of DCFC Charging Sessions by BEV Type and Distance from Last Night Location

Using the "last night's" location rather than the "home" location reduces the distance even more, especially for the longest trips. The Tesla 60-80 charging events over 100 miles from home drops from 15% to 11%, most likely as a result of multi-day trip that end and start on the road. This method also accounts for long vacations, summer homes, etc. that result in short trips every day but many charging events far from home.

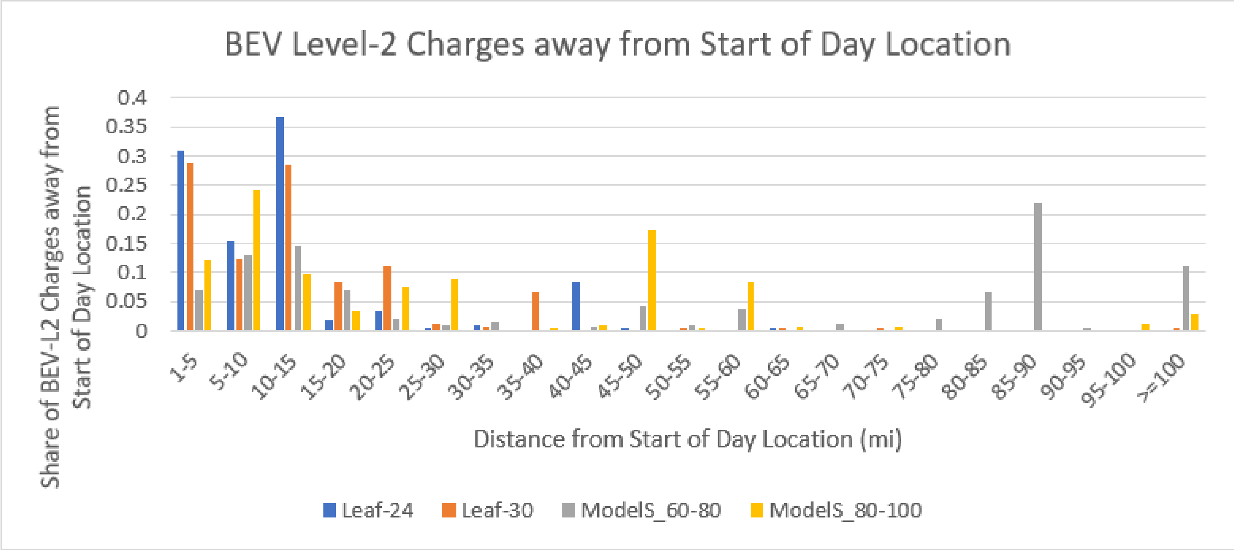


Figure 63. Percentage of Level 2 Charging Sessions by BEV Type and Distance from Start of Day Location

As expected, most of the L2 events are within 1-25 miles from home, with additional spikes for Tesla 80 and 100 who travel longer trip distances. Overall, level 2 is being used at the destination, and therefore most events are at work and within the vehicle range.

6. Logger Data: Household Level Analysis

Self-reported trip diaries of travel behavior surveys (PSRC TCS 2006, Kunzmann and Masterman 2013, TxDOT 2015, FHWA 2017) are often used as the starting point for generating the set of assumptions about PEV driving and charging behavior. Instrumented ICE data has better spatio-temporal resolution compared to trip diaries(Aviquzzaman 2014). This still cannot characterize PEV travel patterns because of the implicit assumption that ICEs and PEVs are operated the same manner. It dilutes the risk perception associated with new technology adoption, especially in the case of range anxiety associated with BEVs. Stated and revealed preferences of current PEV owners are increasingly being used to obtain information about how current PEV owners drive and charge(Nicholas, Tal et al. 2017). Instrumented PEVs by far are the best source of data compared to cross sectional or longitudinal survey data of ICEs and stated or revealed preferences of existing PEV users(Nicholas, Tal et al. 2017, Raghavan and Tal 2019). Prior research advocates the need to have realistic representation of PEV usage in order to increase their usefulness to policymakers. Assuming homogenous usage of a specific PEV model across diverse strata of demographics and travel needs, and subsequently their emission reduction potential presents an inaccurate picture of the day-to-day substitution patterns between an ICE and PEV. Even if high-resolution data from actual PEV usage is available, it is necessary to observe them over a considerably longer duration of time in order to capture rare and infrequent long-distance travel, which may have a bearing on the purchase or lease and use of the vehicle.

A crucial aspect, which is often overlooked in majority of PEV usage studies in literature as well as in the policy realm, is the household (HH) context. While evaluating travel behavior and emissions implications of PEV adoption, household context is pivotal because day-to-day activities are allocated between PEVs and the other vehicles in the household on a per-trip basis at disaggregate temporal levels. Furthermore, survey of 15,000 PEV owners in California, roughly 45% of BEVs and 42% of PHEVs belong to two-car households(Turrentine and Tal 2015, Nicholas, Tal et al. 2017). PEVs have unique features that will alter how they are driven and charged compared to ICEs. Depending on travel needs, individual driver preferences, fuel and electricity costs, charging access and opportunities, VMT by the PEV has cascading effects on VMT of other household vehicles. Apart from the quantity of miles, it is also important to account for the derived impact of miles (GHG/mile) PEVs substituted at the household level. Therefore, studying PEV usage in isolation may lead to inaccurate estimates of their net environmental impacts, since it is based on partial information.

To ensure parity when comparing different PEV households, we excluded households that have more than 1 PEV of the same type, irrespective of the number of ICEs in the household (for example a 3-car household with 2-Leaf and 1 ICE or a 2-car household with 2 Volts were dropped). Furthremore, To understand substituion and emission profile at the household, the sample size of the household was limited to single PEV(BEV or PHEV), single ICE-PEV(ICE-BEV or ICE-PHEV), double ICE and single PEV (ICE-ICE-BEV or ICE-ICE-PHEV), and household with both BEV and PHEV (BEV-PHEV or ICE-BEV-PHEV). The above selection criteria was deemed fit based on the fact that 65% of California households have 2 or less vehicles ; 16% of California households have 3 vehicles(McGuckin and Fucci 2017). Since only 9% of California households have 4 or more vehicles (McGuckin and Fucci 2017), we excluded households and the respective vehicles with 4 or more vehicles from our analysis. In addition, as outlined in Section 5 , the BMW i3 REX and the households were excluded because the data logger could not acquire any data from them. Out of the 264 Households that were logged, 23 households that accounted for 25 BMW i3 ; 1 household with Fiat 500e BEV; and 1 household with Kia Soul BEV were dropped. The sample size of PEVs used in the household level analysis differs from the sample size referred in Table 4-Table 7 simply because of excluding the households and their vehicle holdings due to household car ownership patterns exceeding the 3 and/or the type of vehicles belonging to the household (double BEV or PHEV of the same type). In our household (HH) level analysis, there are 90 BEVs (21 Leaf 24 kWh, 26 Leaf-30 kWh, 20 ModelS_60-80 kWh, 20 ModelS_80-100 kWh, and 3 RAV4-40kWh) and 145 PHEVs (21 PluginPrius, 49 CmaxFusion, 41 Volt-16 kWh, and 34 Volt-18kWh). The total household level sample size is 226. **Table 19** summarizes the HHs by the PEV type. Approximately 60% of the HHs in our study had two-vehicles, 30% had one vehicle, and 10% had three vehicles. Out of the 66 single-vehicle HHs, 47 had a PHEV and 16 had a BEV. Of the 133 two-vehicle HHs, 77 have an ICEV and a PHEV, 51 have an ICEV and a BEV, and 5 had a BEV and PHEV. Among the 27 HHs with three-vehicles, 12 had two ICEVs and a PHEV, 11 had two ICEVs and a BEV, and 4 had an ICE, a BEV, and a PHEV. Overall, 95% (215 out of 226) of the HHs had only one PEV (BEV or PHEV). There were 66 single-vehicle HHs with only a BEV or a PHEV, 128 two-vehicle HHs with an ICEV and a PHEV or BEV, 23 three-vehicle HHs with a PEV and two ICEVs, and 9 multi-PEV HHs (with and without an ICEV). Summary statistics and results presented in **Table 19** – **Table 31** and depicted in **Figure 64** – **Figure 84** are based on the logger data.

Compared to the vehicle level analysis, where we focused mainly on the days when the PEV was driven or charged, in the HH context, it was important to have parity in terms of the number of days each vehicle was logged within each HH as well as across different HHs. When comparing two HHs with the same number of vehicles and vehicle types—for example two-vehicle HHs with one ICEV and one Leaf-24 kWh—if the first HH was logged for 350 days and the second household was logged for 400 days, at an aggregate level, comparing the VMT and energy consumption (gasoline and electricity) between these two HHs would be inaccurate and could potentially lead to false conclusions about PEV usage and the HH level eVMT. It was crucial to classify the days on which we had no data (no trips or charging sessions) as unobserved or unused in order to avoid over- or underestimating HH level eVMT, which depends on the VMT of not just the PEVs but also the ICEVs.

Unobserved days typically denoted days when we knew the data logger had a problem, and the unused days denoted days when we had no issues with the data logger and the vehicle was simply not used. Reasons for the vehicle not being used could be that the study participant was out of town/traveling/taking a vacation, the car was temporarily unavailable because of service/maintenance, or there was no demand for travel on that day. Consider the same example of 2 HHs each having an ICEV and a Leaf-24. If the ICEV in one HH had data logger issues for a few weeks, and we had data from the BEVs during the period, if we incorrectly assume the ICEV was not used, then eVMT will be overestimated.

We used the days the individual vehicles (ICEV, BEV, PHEV) were logged (used and unused days) to annualize all the key metrics (trips, charging sessions, VMT, driving/charging energy, gasoline consumed).

The HH level analysis section is organized as follows: we present first the results from BEV HHs (only a BEV; an ICEV and BEV; and two ICEVs and a BEV) and then the results from PHEV HHs (only a PHEV; an ICEV and PHEV; and two ICEV and a PHEV). Finally, since only 5% of the HHs (9 HHs in total) in our study had both a BEV and PHEV (with or without an ICEV), and

7 of these 9 HHs did not have any the same types of BEVs and PEVs, their results are presented separately. **Error! Reference source not found.** shows the breakdown of double PEV HHs.

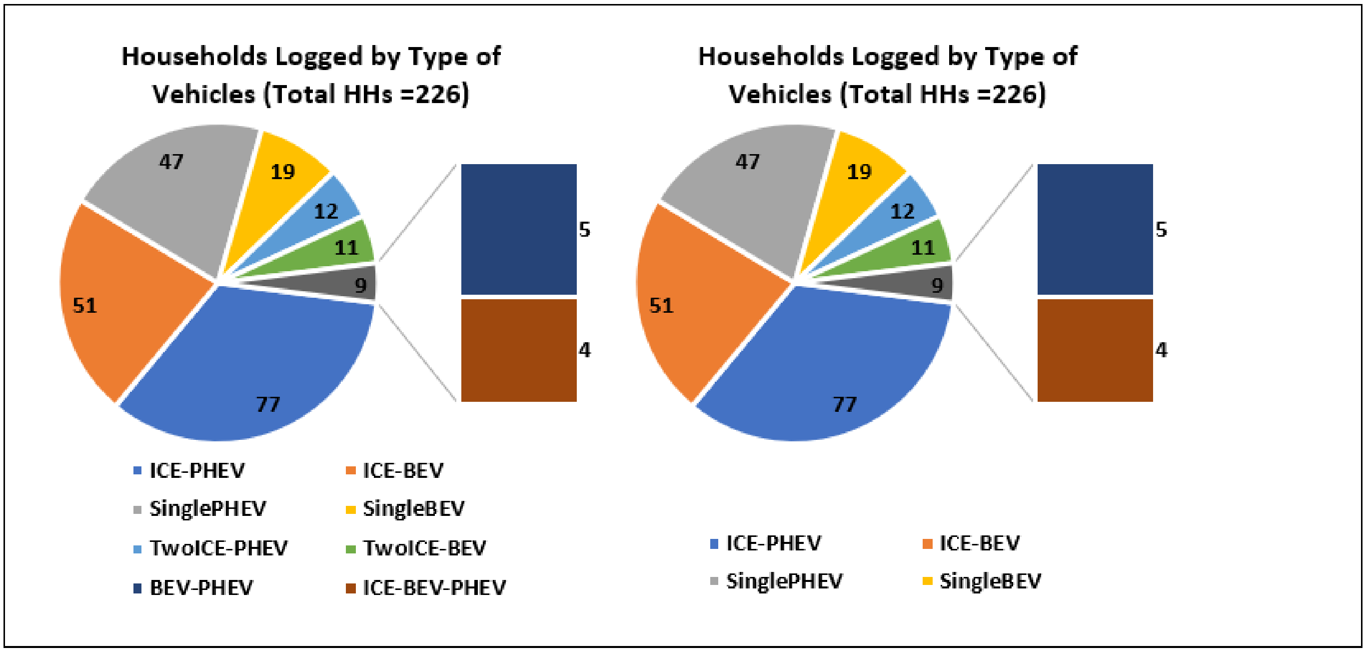
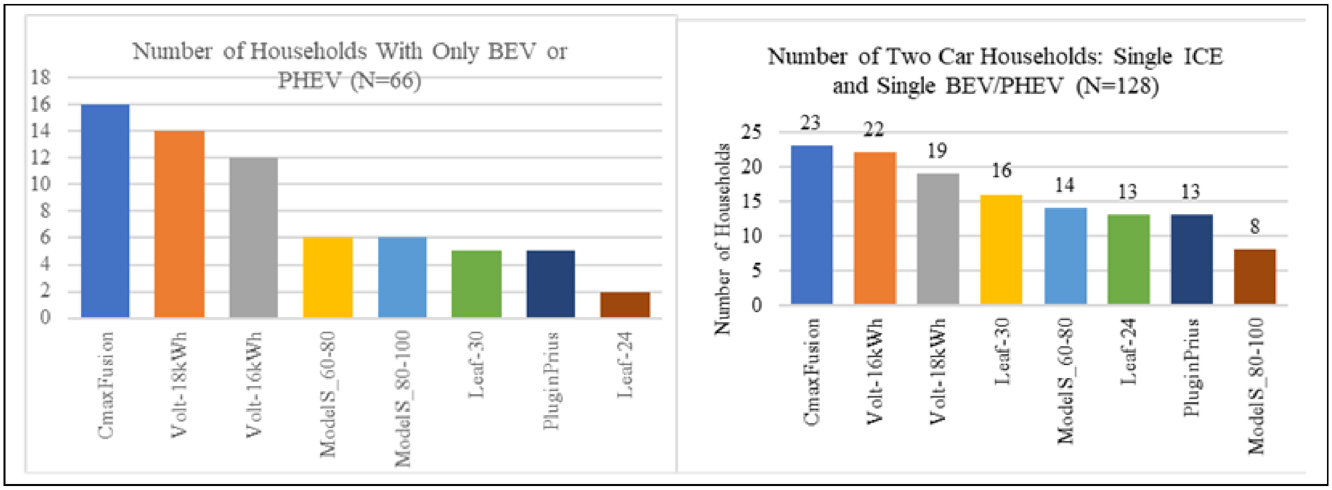


Figure 64. Composition of Households Included in the Analysis



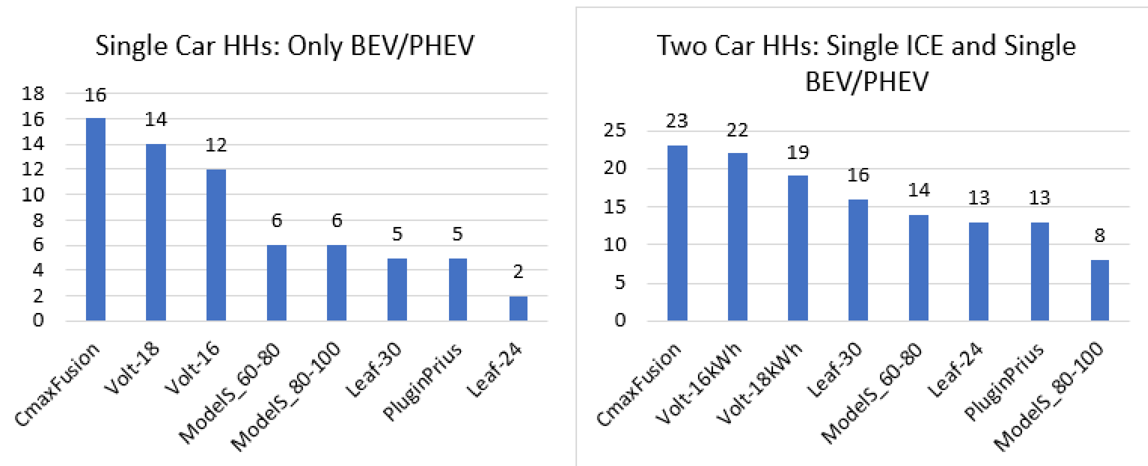


Figure 65. Number of Households with only Single BEV or PHEV Logged in the Study (Left) and Number of Two Car Households with single ICEV and One BEV or PHEV Logged (Right)

Table 19. Double-PEV (1 BEV and 1 PHEV) With or Without an ICEV (N=9)

Type of HH	BEV, PHEV in the HH	Number of HHs
ICE-BEV-PHEV	L24,CMaxFusion	2
ICE-BEV-PHEV	R40-Volt16	1
ICE-BEV-PHEV	R40-CMaxFusion	1
BEV-PHEV	T60,Volt16	1
BEV-PHEV	L30,Volt16	1
BEV-PHEV	L24,CMaxFusion	1
BEV-PHEV	L24,Volt16	1
BEV-PHEV	R40,PluginPrius	1

6.1. Households with a BEV Only or BEV and ICEV

Table 20 (Average) Annualized Estimates of VMT and Energy Consumption in BEV HHs

		BEV Driving				ICEV		HH	HH
	Num. HHs	BEV	Trips	eVMT	kWh Driving	gVMT	Fuel (gallons)	VMT	UF
2-ICEV-BEV	2	L24	1262	12355	-3025	18,164	721	30519	0.404
	4	L30	1659	12881	-3383	20,477	738	33359	0.386
	2	T60	1056	18805	-5790	9,034	410	27838	0.675
	3	T80	446	10385	-3391	20,418	892	30802	0.337
ICEV-BEV	13	L24	1679	9984	-2337	10,406	379	20390	0.489
	16	L30	1649	11890	-3079	9,012	352	20901	0.568
	14	T60	1057	16551	-5654	7,819	359	24369	0.679
	8	T80	1003	15249	-5265	5,577	261	20826	0.732
BEV	2	L24	1510	8098	-1845	0	0	8098	1
	5	L30	1315	7122	-1883	0	0	7122	1
	3	T60	1131	9759	-3167	0	0	9759	1
	9	T80	1336	14710	-5314	0	0	14710	1

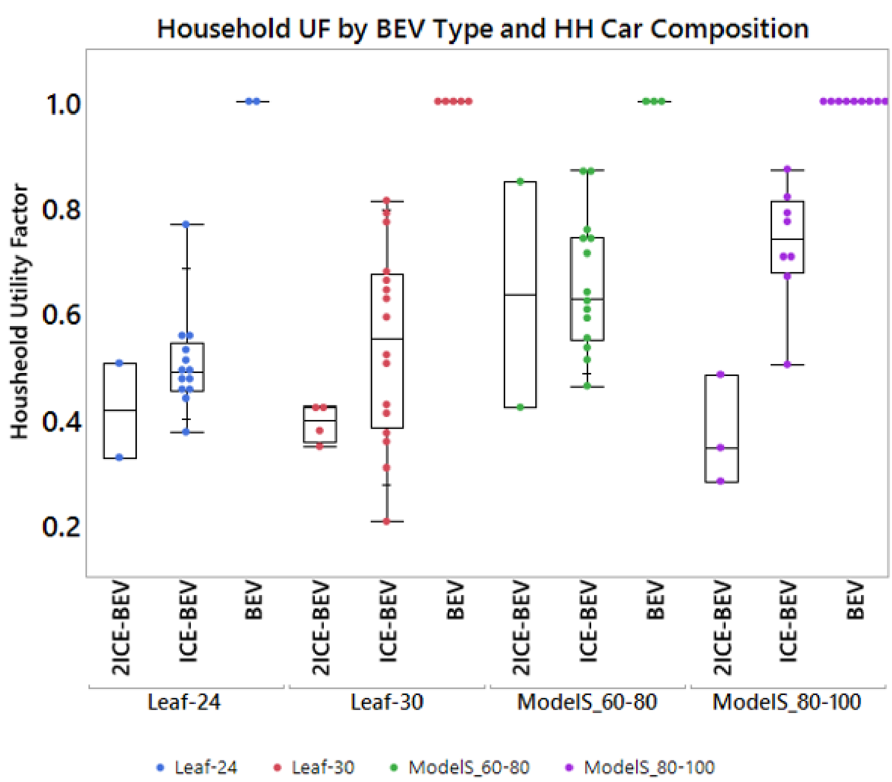


Figure 66 BEV HH UF by Number of Cars and BEV Type

Table 20 summarizes the (average) annualized estimates of key metrics such as eVMT, gVMT, HH VMT, UF, and energy consumption (driving and charging). **Figure 66** depicts the HH UF in BEV HHs by number of vehicles in the HH and the type of BEV in the HH.

Some of the key insights regarding the HH level UF of HHs with ICEVs and BEVs are as follows:

- The average UF of HHs with a ModelS_60-80kWh with either 1 or 2 ICEVs were relatively similar (0.679 vs. 0.675)
- On average, HHs with a ModelS_80-100kWh and one ICEV have the highest UF, whereas HHs with a ModelS_80-100kWh and two ICEVs, have the lowest UF
- The UF in two-BEV HHs increased with the battery capacity
- HHs with a ModelS_80-100kWh tend to have a lower average daily HH VMT relative to other BEV types in HHs with either one ICE or two ICEs.
- Long-range BEVs, namely the ModelS_60-80 and ModelS_80-100kWh, were predominantly used for long-distance travel (100 miles or more) in both two- and three-car HHs.

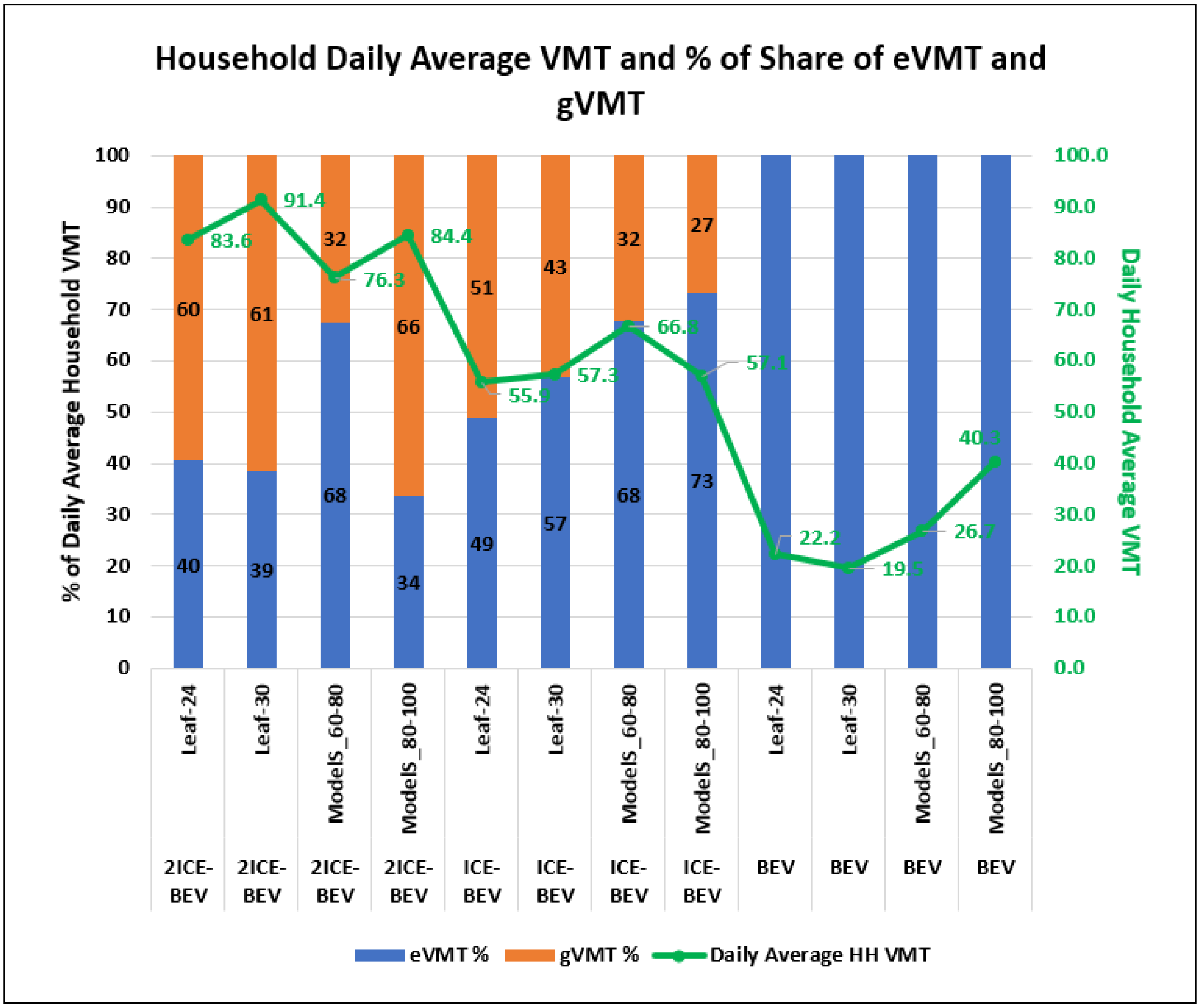


Figure 67. HH Average Daily VMT in HHs with BEVs, Showing the eVMT and gVMT Percentages

Figure 67 shows the average daily HH VMT and the share of eVMT and gVMT in BEV HHs. Three-car HHs with two ICEVs and one Leaf had higher average daily HH VMT than did three-car HHs with one ModelS_60-80 BEV. However, probably due to range constraints, these HHs with Leafs had nearly two-thirds of their VMT attributable to gasoline-power (gVMT) share of VMT that was gasoline-powered (gVMT). In two-car HHs, there is a clear trend pointing to more ICEV miles being replaced by PEV miles when the PEV is a Tesla rather than a Leaf.

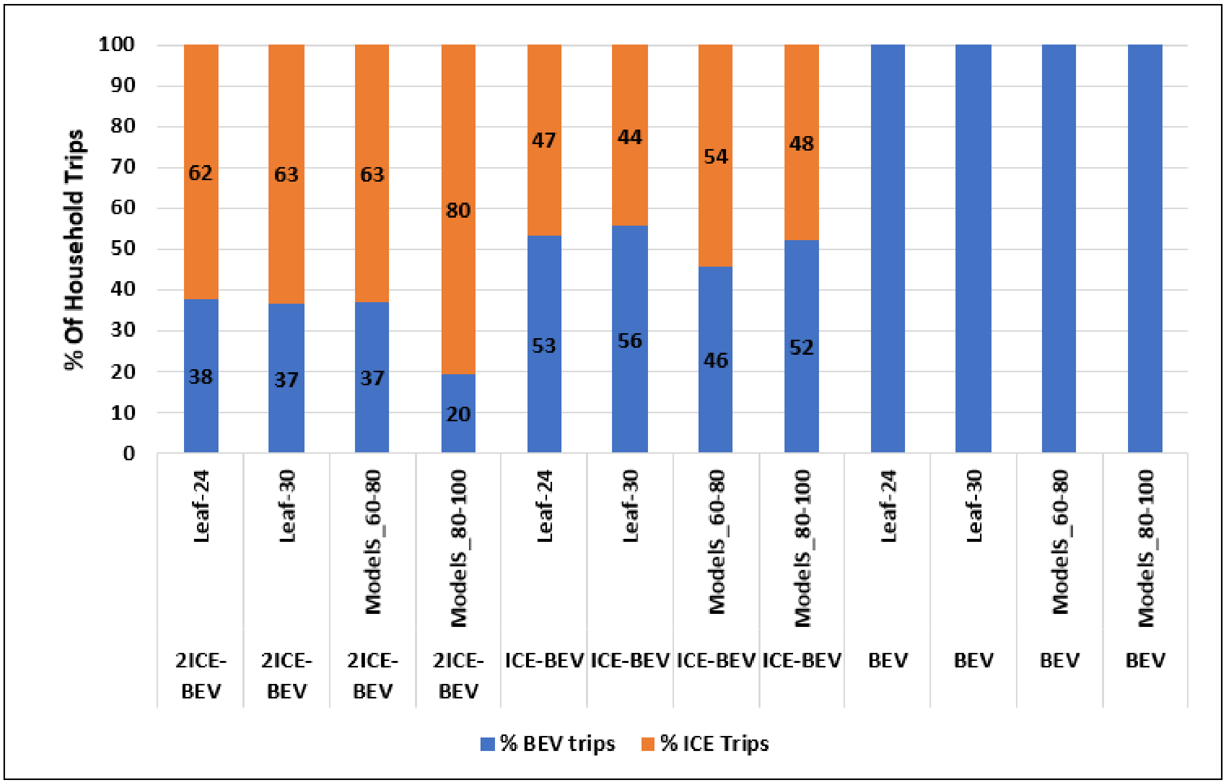


Figure 68. Percentage of BEV and ICEV trips in HHs with BEVs

Figure 68 summarizes the percentage of HH trips taken using the BEV and the ICEVs. On average, except for HHs with the ModelS_80-100, the BEV share of HH trips was approximately 40% in three-vehicle HHs and 50% in two-vehicle HHs. **Figure 67** and **Table 20** together show that, in two car BEV HHs, roughly 50% of HH trips were taken using the ICEV, but the share of miles replaced by the BEV is noticably different between HHs with Leafs and ModelSs. The percentage of total HH VMT driven using the ICEV in two-car BEV HHs was 51%, 43%, 32%, and 27% in Leaf-24, Leaf-30, ModelS_60-80 and Models_80-100 HHs.

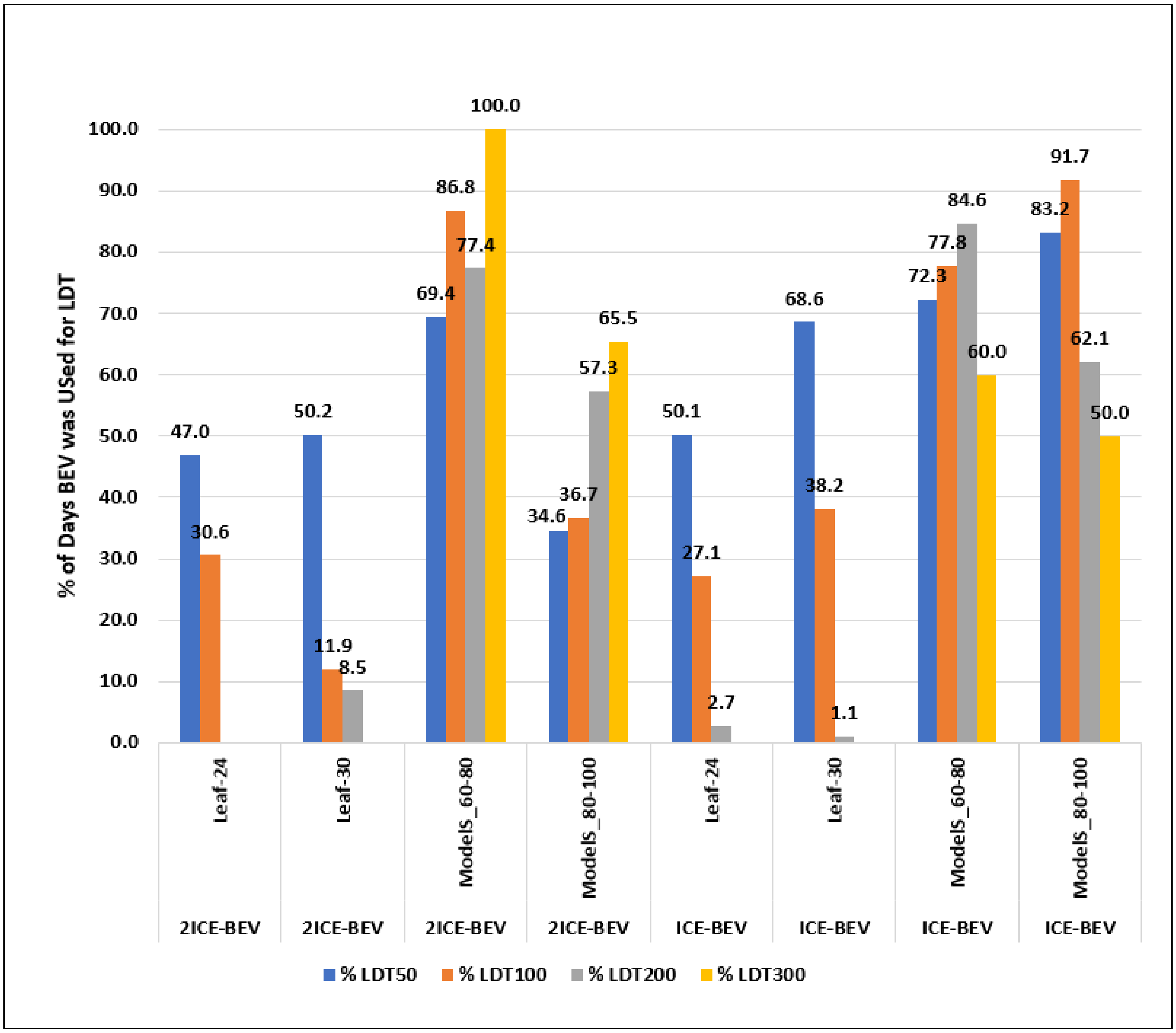


Figure 69. Share of Days When BEV was Used for Long Distance Travel (LDT; 50 miles or more). LDTx: x or more miles/day

Figure 69 shows the percentage of days the BEV was used for long distance travel (LDT) in HHs with ICEVs and BEVs. The Leaf-24, on average, is used about 50% of the days to travel 50 miles or more and about 30% of the days to travel 100 miles or more in both three- and two-vehicle HHs. The Leaf-30 shows a similar trend in three-vehicle HHs, but in two-vehicle HHs it is used on 69% of the days with travel distances of 50 miles or more. There is also a divergence in the usage of the Leaf-30 for days with travel distances of 100 miles or more. In three-vehicle households the Leaf-30 was only used about 12% of these days, while in two-vehicle households it was used 38% of these days. The ModelS_80-100kWh was used on the majority of days to travel 50/100/200/300 miles or more in two- and three-vehicle HHs.

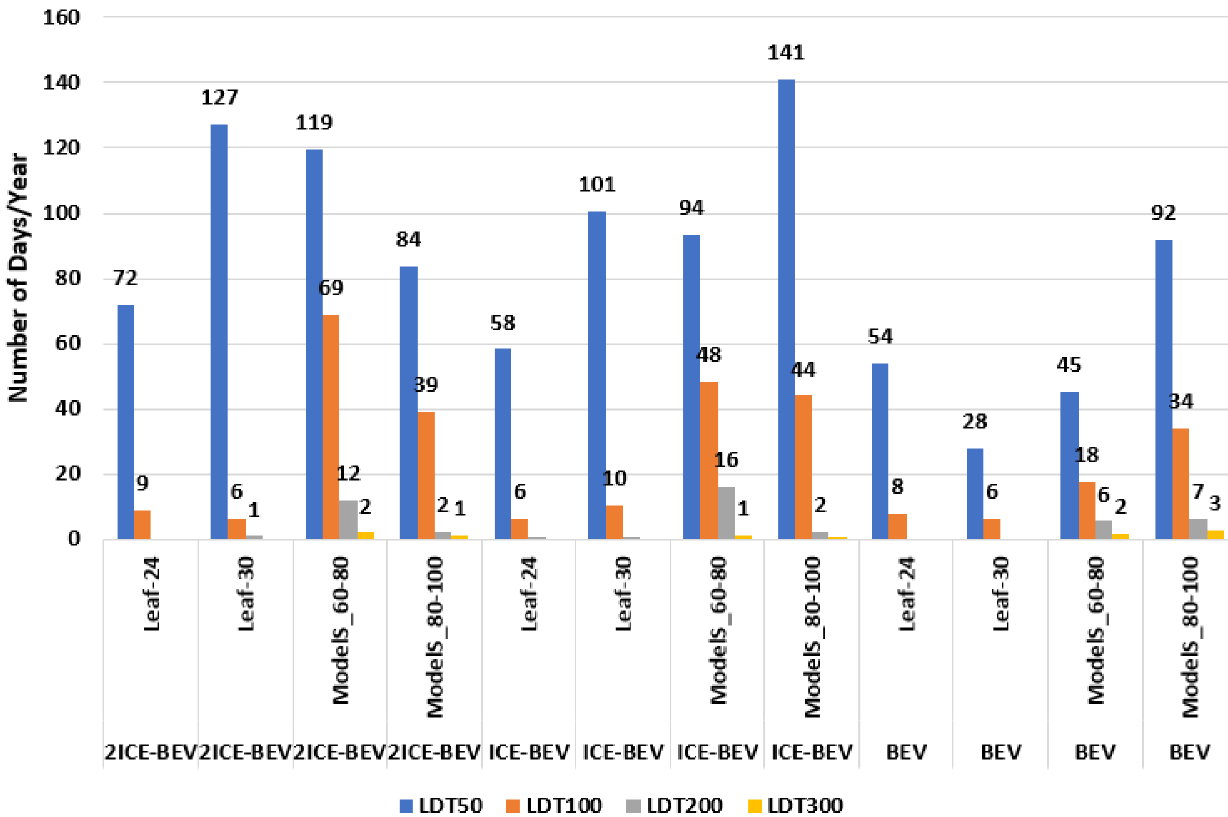


Figure 70. Number of Days/Year BEV was Used for Long Distance Travel (LDT). LDTx: x or More Miles/Day

Figure 70 shows the absolute number of days BEV was used for LDT. Overall, the ModelS_80-100 was used on the highest number of LDT50 days (i.e., days with travel of 50 or more miles), followed by Leaf-30. In the three-vehicle households, the Leaf-30 was the most used BEV for LDT50, while for the two-vehicle households and single-BEV households it was the ModelS_80-100. However, the ModelS_60-80 was the most used BEV for three- and two-vehicle households for trips greater than 100 and 200 miles. LDT50 days for Leaf-30 were higher than for Leaf-24 and ModelS_60-80 in three- and two-car HHs, but the contrary was observed in HHs with just a BEV.

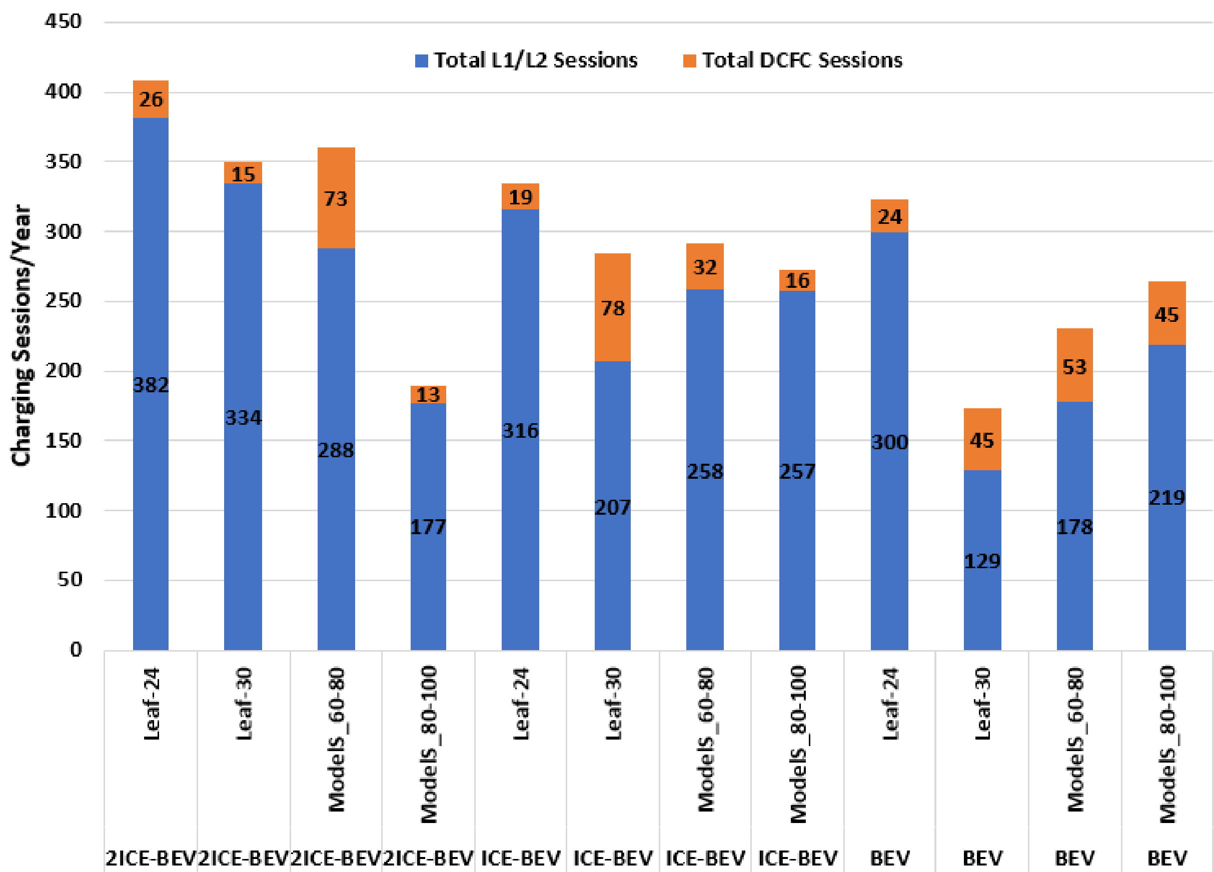


Figure 71 (Average) Annualized Number of L1 or L2 charger (L1/L2), and DCFC Sessions in BEV HHs

Figure 71 shows the average annualized number of L1 or L2 charger and DCFC sessions by BEV type and number of cars in the HH. The Leaf-30 in two-vehicle HHs used DCFCs the most (78 times per year) followed by ModelS_60-80 in 3 car HHs (73 times per year).

In two car ICE-BEV(Tesla) households, the BEV was used for commuting in 10 out of the 14 Model S 60-80 cases, and 7 out of the 18 Model S 80-100s cases. The average number of licensed drivers and the total HH size was similar in the two categories of Tesla HHs at 2 drivers per HH and 3 members per HH. Overall, the BEVs in 11 of the 17 Model S 60-80 and 14 of the 17 Model S 80-100 HHs were used by HH members working full-time for commuting purposes.

6.2.Households with a PHEV Only or PHEV and ICEV

Analyses and results summarized in **Error! Reference source not found.-Error! Reference source not found.** and shown in **Figure 66** – **Figure 76** are based on the logged data.

Households with a PHEV only or a PHEV and ICEV have no range limitation on their trips, but have lower potential for eVMT. **Table 21**–**Table 24** summarize the average annualized estimates of VMT and energy consumption by number of vehicles in the HH and the PHEV type. As a reminder, we recruited only PHEV households that plugged-in their vehicle, which complicates the interpretation of our results in this section.

Table 21 (Average) Annualized Estimates of VMT and Energy Consumption in PHEV HH by Number of Cars and PHEV Type

		PHEV Driving									**ICEV**		
		Trips				***VMT***			**Driving Energy**				
		Total	***ZE Only***	***CDB/ CS***	***CS Only***	**Total**	***e***	***g***	**Fuel Gal.**	**kWh**	**Trips**	**VMT**	**Fuel**
2ICEV-PHEV	Prius	1384	78	683	623	7,305	1,360	5,945	128	-399	2383	29,338	1074
	Cmax	1434	555	319	560	12,724	3,389	9,335	227	-1035	3014	16,381	587
	Volt16	993	811	87	95	8,257	6,456	1,801	51	-1844	2064	16,312	473
ICEV-PHEV	Prius	1542	175	802	565	15,069	1,849	13,21	276	-1589	1607	7,079	279
	Cmax	1612	623	498	490	14,227	4,570	9,656	244	-2649	1455	9,928	426
	Volt16	1410	1041	211	158	14,728	9,427	5,301	155	-3986	1243	9,358	386
	Volt18	1281	1029	189	63	10,746	7,478	3,268	88	-3249	1217	8,656	325
PHEV	Prius	1491	445	713	334	10,779	2,260	8,518	168	-1359	0	0	0
	Cmax	1578	732	446	400	12,086	4,071	8,015	197	-2488	0	0	0
	Volt16	1452	1133	118	201	10,933	6,384	4,549	133	-2970	0	0	0
	Volt18	1534	1094	321	119	12,348	7,359	4,989	133	-3207	0	0	0

In three-car HHs with two ICEVs and one PHEV, the total HH VMT decreased and HH UF increased with an increase in the AER of the PHEV. The percentage of HH miles driven in ICEVs was the highest in Prius HHs (80%), followed by Volt-16 HHs (66%), and CmaxFusion HHs (56%). Annual mileage of ICEVs in CmaxFusion and Volt-16 HHs was almost the same (16,381 and 16,312 miles), but the number of trips and the VMT of the CmaxFusion was higher than those of the Volt-16.

In two-car HHs, the percentage of total HH VMT driven using the PHEV was roughly the same in CmaxFusion and Volt-16 HHs (60%). The HH UF was only slightly higher in Volt-16 than in

Volt-18 HHs (0.391 vs. 0.385), but the Volt-16 was driven 4000 miles more than the Volt-18 (14,728 miles vs. 10,746 miles), had a higher share of ZE trips (1,041 vs. 1,029), and charged more often (430 sessions vs. 336 sessions). Even though the Volt-18 has a slightly bigger battery than the Volt-16, its eVMT was lower than that of the Volt-16 (7,478 miles vs. 9,427 miles). The average daily PHEV VMT in Volt-16 HHs (40 miles) was closer to its AER capabilities (38 miles), but for the Volt-18 HHs, the average daily PHEV VMT (30 miles) was noticeably lower than its AER capabilities (53 miles). UF and eVMT (vehicle and household level) did not improve by upgrading from a Volt-16 to a Volt-18. In 2 car HHs, as compared to 1-car single PHEV HHs, the Volt-18 had a slightly higher UF compared to the Volt-16. To better understand these contrasting aspects, we looked at certain key HH level attributes reported by the respondent in the survey; our observations are summarized below for the 2 car (ICE-PHEV) and 1 car (single PHEV) HHs separately.

Volt-16 and Volt-18 in 2-car HHs:

Out of the 22 Volt-16 HHs (ICE-Volt16 HHs) only 1 was leased, whereas out of the 19 Volt-18 HHs (ICE-Volt18 HHs) 13 of them were leased. 21 of the 22 Volt-16 HHs reported that they either charged at home only, or home and away in the past 30 days. Out of the 19 Volt-18 HHs, 15 of them reported that they either charged at home only, or home and away in the past 30 days. Only 1 of the Volt-16 HHs reported that they charged away only, whereas this number was slightly higher in the case of Volt-18 HHs, where 4 of them reported that they charged away only. The average number of drivers in both the Volt-16 and Volt-18 HHs was comparable (2.1 vs. 2), the average HH size of Volt-18 HHs was slightly higher (3) compared to Volt-16 HHs average HH size (2.36). 70% of the Volt-16 (16 of the 22) and 90% of the Volt-18 (17 of the 19) were used by HH members working full-time for commuting purposes.

In spite of the longer range of Volt-18 compared to Volt-16, the ICE was probably used more often due to the HH size. Since the Volt-16 was the first ever mass produced series type PHEV, higher annual VMT of Volt16 in two car HHs could also be due to the fact that these were driven by early adopter technology enthusiasts who were also innovators. Furthermore, the smaller HH size and lower share of Volt16 being leased and charging exclusively away as compared to Volt-18 are the other reasons for the difference in usage between Volt-16 and Volt-18 in 2 car HHs (ICE-PHEV)

Volt-16 and Volt-18 in 1-car HHs:

9 out of 12 Volt-16 were purchased whereas only 5 of out of 14 Volt-18 were purchased. The higher annual VMT of Volt-18 compared to Volt-16 can be primarily attributed to the higher share of drivers in Volt-18 HHs who used it for commute purposes. 60% of the Volt-16 (7 of the 12) and 90% of the Volt-18 (13 of the 14) were used by HH members working full-time for commuting purposes.

Table 22. (Average) Annualized Estimates of PHEV VMT, HH VMT, and HH UF

	Number of HHs	PHEV Type	*PHEV eVMT*	*HH VMT*	*HH UF*
2ICE-PHEV	2	PluginPrius	1,360	36,642	0.037
	6	CmaxFusion	3,389	29,106	0.116
	4	Volt16	6,456	24,568	0.263
ICE-PHEV	13	PluginPrius	1,849	22,148	0.083
	23	CmaxFusion	4,570	24,155	0.189
	22	Volt16	9,427	24,086	0.391
	19	Volt18	7,478	19,402	0.385
PHEV	5	PluginPrius	2,260	10,779	0.210
	16	CmaxFusion	4,071	12,086	0.337
	12	Volt16	6,384	10,933	0.584
	4	Volt18	7,359	12,348	0.596

Table 23 summarizes the average annualized and daily estimates of PHEV charging needs by number of cars in the HH and the PHEV type and **Table 24** summarizes the average daily estimates of PHEV charging by PHEV type.

Table 23 (Average) Annualized Estimates of Number of Charging Sessions and kWh Charged in PHEV HHs by Number of Vehicles and PHEV Type

		Annualized		Average/Session	
		Charging Sessions	**Charging kWh**	**Charging Session Duration (minutes)**	**kWh/Session**
2ICE-PHEV	Prius	231	373	179	1.62
	Cmax	266	1082	332	4.06
	Volt16	315	1850	233	5.88
ICE-PHEV	Prius	350	476	191	1.36
	Cmax	385	1400	235	3.63
	Volt16	395	2612	356	6.61
	Volt18	282	2157	361	7.65
PHEV	Prius	427	587	144	1.38
	Cmax	383	1328	196	3.47
	Volt16	330	1803	358	5.46
	Volt18	248	2001	406	8.06

Table 24. (Average) Annualized Estimates of Charging Sessions by PHEV Type in PHEV HHs

	Average Annual	
PHEV	**Charging Sessions/Year**	**Charging Energy kWh/Year**
PluginPrius	336	479
Cmax/Fusion	345	1270
Volt-16	347	2088
Volt-18	265	1545
	Average Daily	
PHEV	**Charging Sessions/Day**	**kWh /Day**
PluginPrius	0.920	1.31
Cmax/Fusion	0.944	3.48
Volt-16	0.949	5.72
Volt-18	0.726	4.23

Figure 72–Figure 74 depict the HH UF from four different perspectives calculated using the logged data, individual HH level UF by number of vehicles in the HH and PHEV type; average HH UF by PHEV type; average HH UF by number of vehicles in the HH; and average HH UF by number of vehicles in the HH and PHEV type.

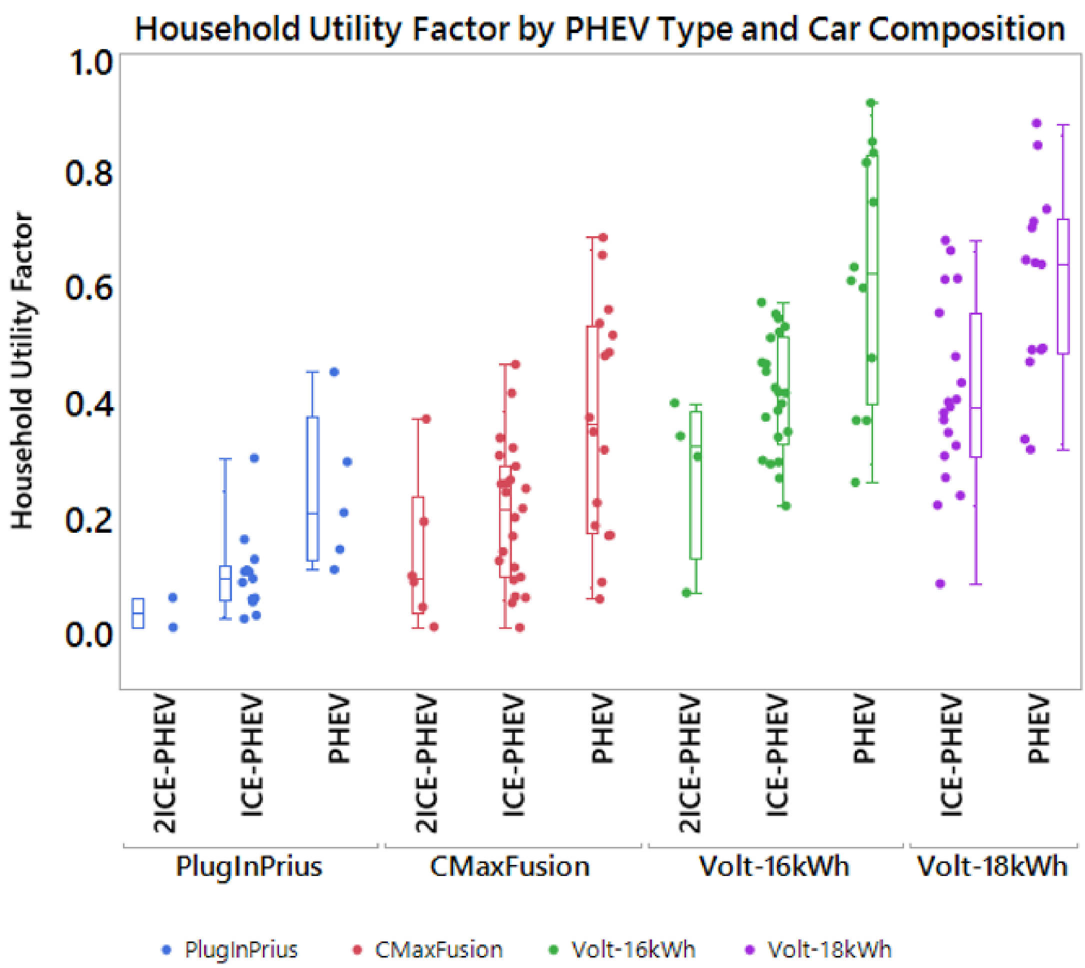


Figure 72. Individual HH UF by PHEV Type in PHEV HH

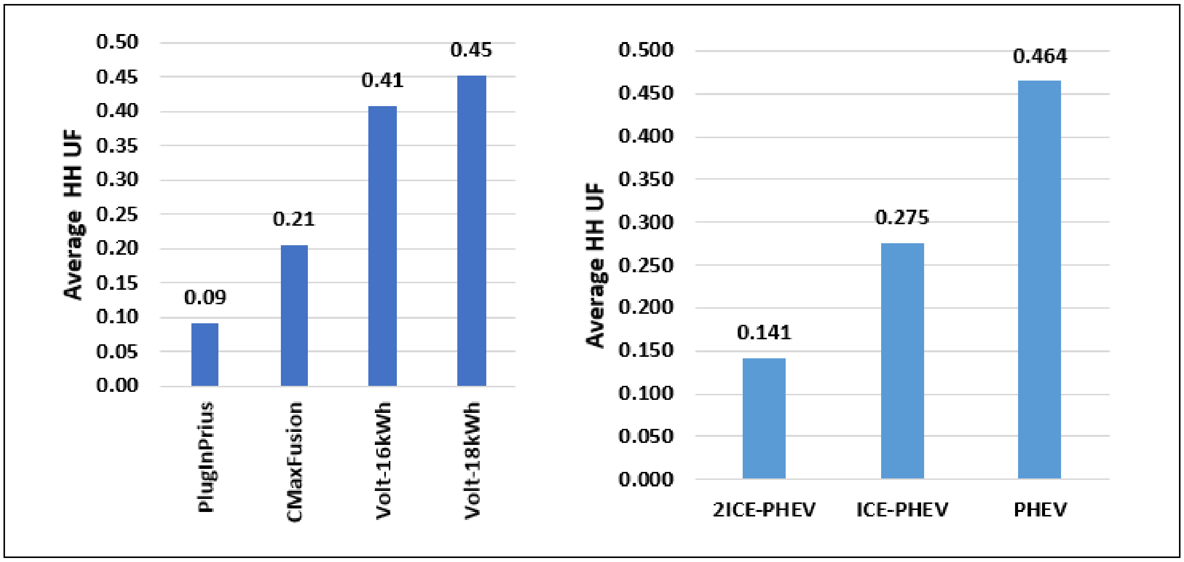


Figure 73. Average HH UF by PHEV Type (Left: all HHs); and Average HH UF by Number of Cars in the HH (Right: All PHEVs)

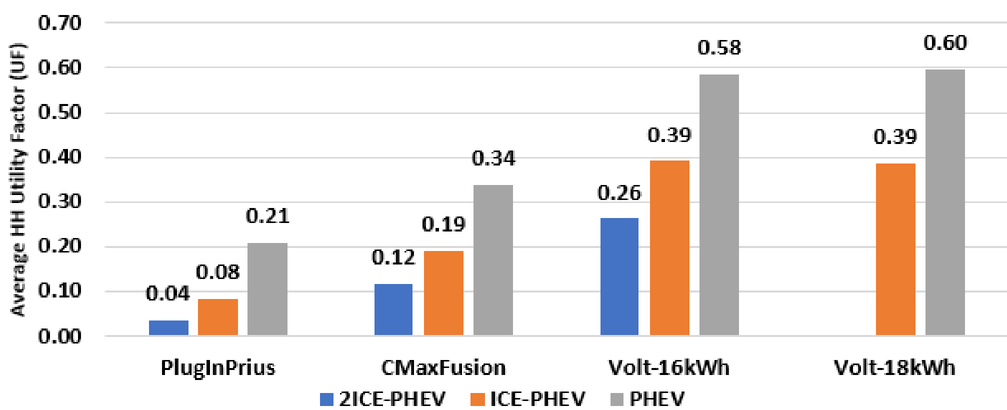


Figure 74. Aveage HH UF by Number of Cars per HH and PHEV Type

Table 25. Average Utility Factor (UF) of PHEVs by Model Year (MY) According to the EPA Dataset.

	MY	EPA Fuel Economy			CARB Midterm Report
		City	**Highway**	**Combined**	
Prius Plug-in	2012-2014	0.320	0.250	0.290	0.15
C-Max Energi	2013-2017	0.481	0.421	0.455	0.32
Volt	2011-2015	0.664	0.642	0.652	0.6
Volt	2016-2017	0.778	0.737	0.761	0.6

Table 25 shows the average UF of PHEVs by different model years that are in the logged vehicle dataset from EPA. The UF based on the CARB ACC Midterm Review (CARB 2017b, 2017a) is also added to **Table 25** for comparison purposes. Overall, the EPA UFs are higher than the CARB Midterm Review (MTR) UFs and the UC Davis values calculated from the logger data. UFs of logged PHEVs from single PHEV HHs are closer to the CARB MTR UFs except in the case of the Prius UF.

The interpretation of UFs varies noticeably by level of aggregation (vehicle or household level) and the number of vehicles in the household. In addition, the marginal improvements in upgrading from Volt-16 to Volt-18 were negligible in one- and two-car HHs. If we ignore the context of the HH (**Figure 73**, left), we find that the fleet average UFs of PHEVs in our study were lower than the CARB MTR UFs by 0.06-0.19, depending on the PHEV type.

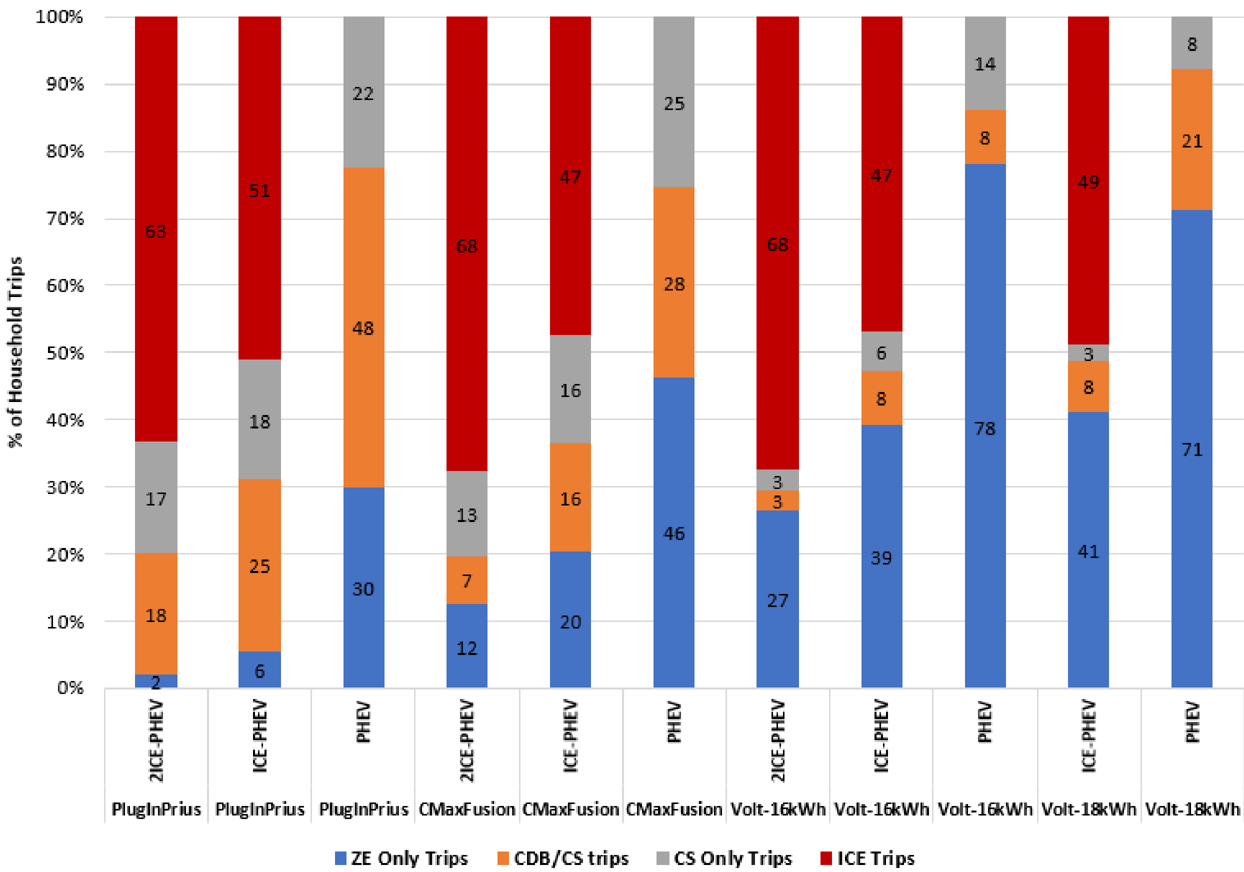


Figure 75. Percentage of Household Trips Powered by Different PHEV Driving Modes or ICEVs

Figure 75 depicts the share of HH trips accomplished by the PHEV in ZE only, CDB/CS, CS only modes and ICEV trips by number of cars in the HH and PHEV type.

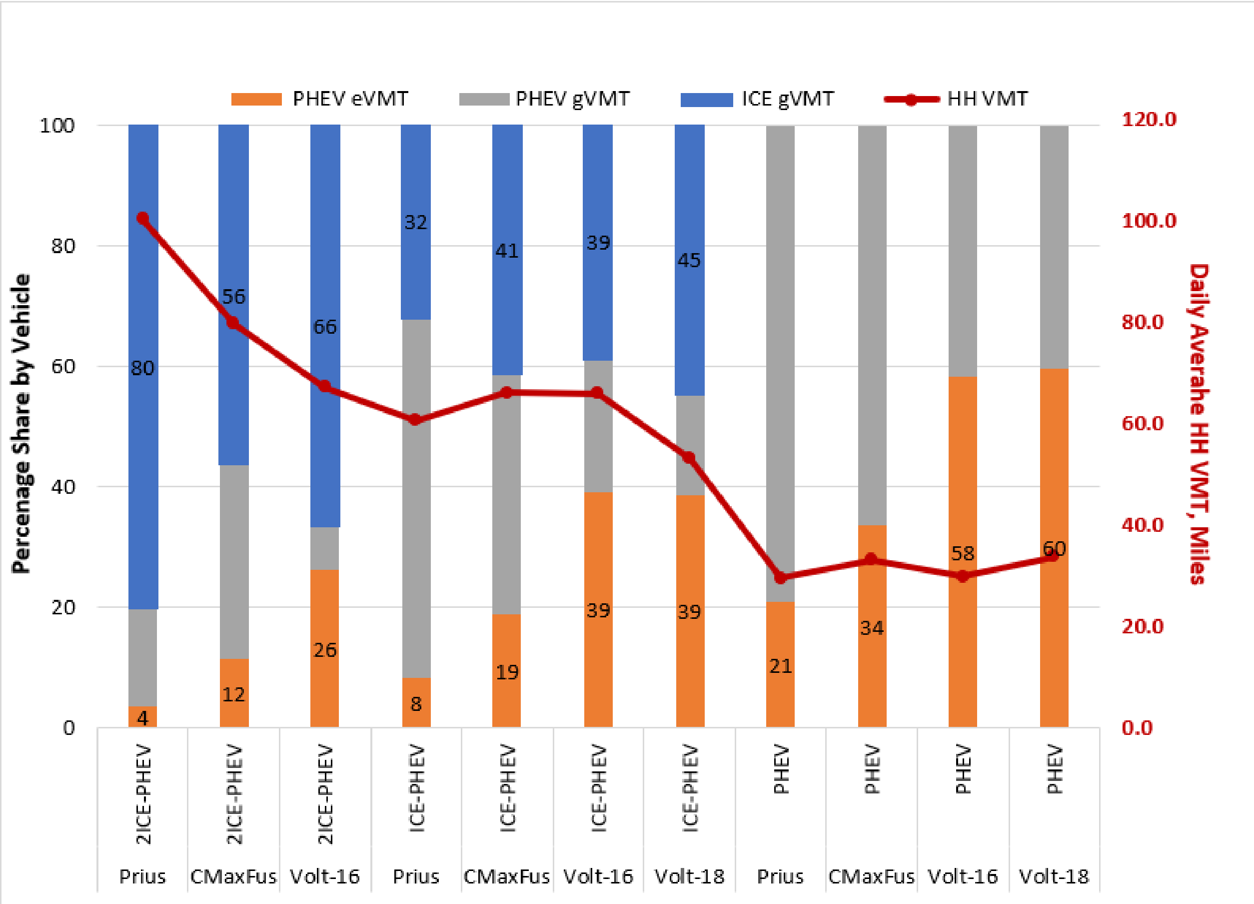


Figure 76. Daily Average HH VMT and Percentage Share of PHEV eVMT, PHEV gVMT and ICE gVMT

Figure 76 shows the average daily HH VMT and percentage share of eVMT and gVMT. This figure demonstrates that the average daily HH VMT of Volt-16 HHs did not change much between three car HHs and two car HHs. Daily eVMT of Volt-18 was similar in two car and single car HHs (20 miles). On average, the daily HH VMT of Volt HHs was lower than that of Prius and CmaxFusion HHs in two car and three car HHs.

6.3. Two-PEV Households: BEV and PHEV Mix

In the following section we present data from households with two PEVs. The sample size is only 9 households and, even though the total number of days and miles is high, the analysis cannot be generalized to the population of PEV users. Analyses and results presented in **Table 26- Table 31** and depicted in **Figure 77– Figure 81** are based on the logger data.

Table 26. Double-PEV (1 BEV and 1 PHEV) HHs With or Without ICEV(s) (N=9)

Type of HH	BEV,PHEV in the HH	Number of HHs
ICE-BEV-PHEV	L24,CMaxFusion	2
ICE-BEV-PHEV	R40-Volt16	1
ICE-BEV-PHEV	R40-CMaxFusion	1
BEV-PHEV	T60,Volt16	1
BEV-PHEV	L30,Volt16	1
BEV-PHEV	L24,CMaxFusion	1

6.3.1. Households with a BEV and a PHEV

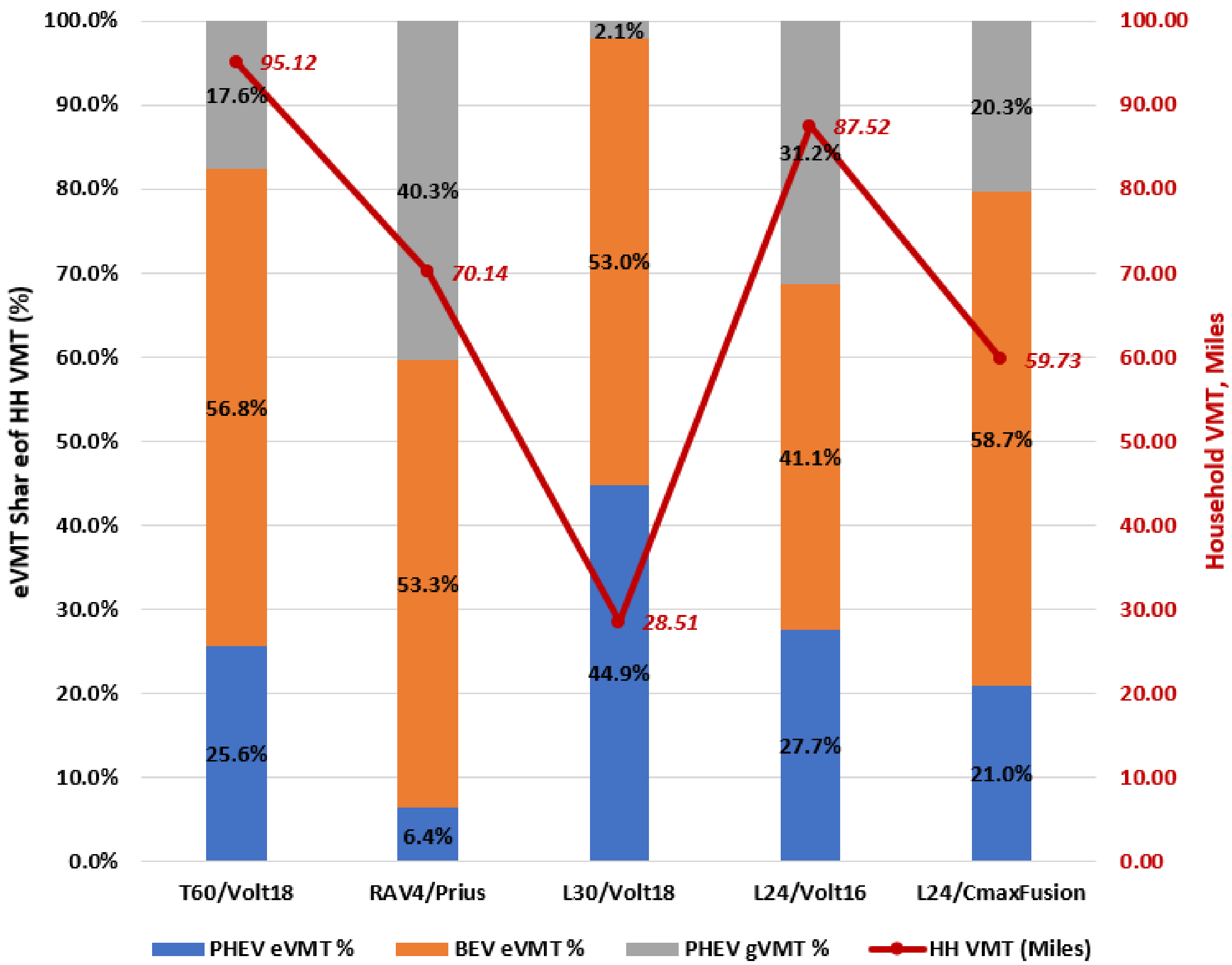


Figure 77. Daily Average HH VMT, and Percentage of eVMT and gVMT BEV-PHEV Households

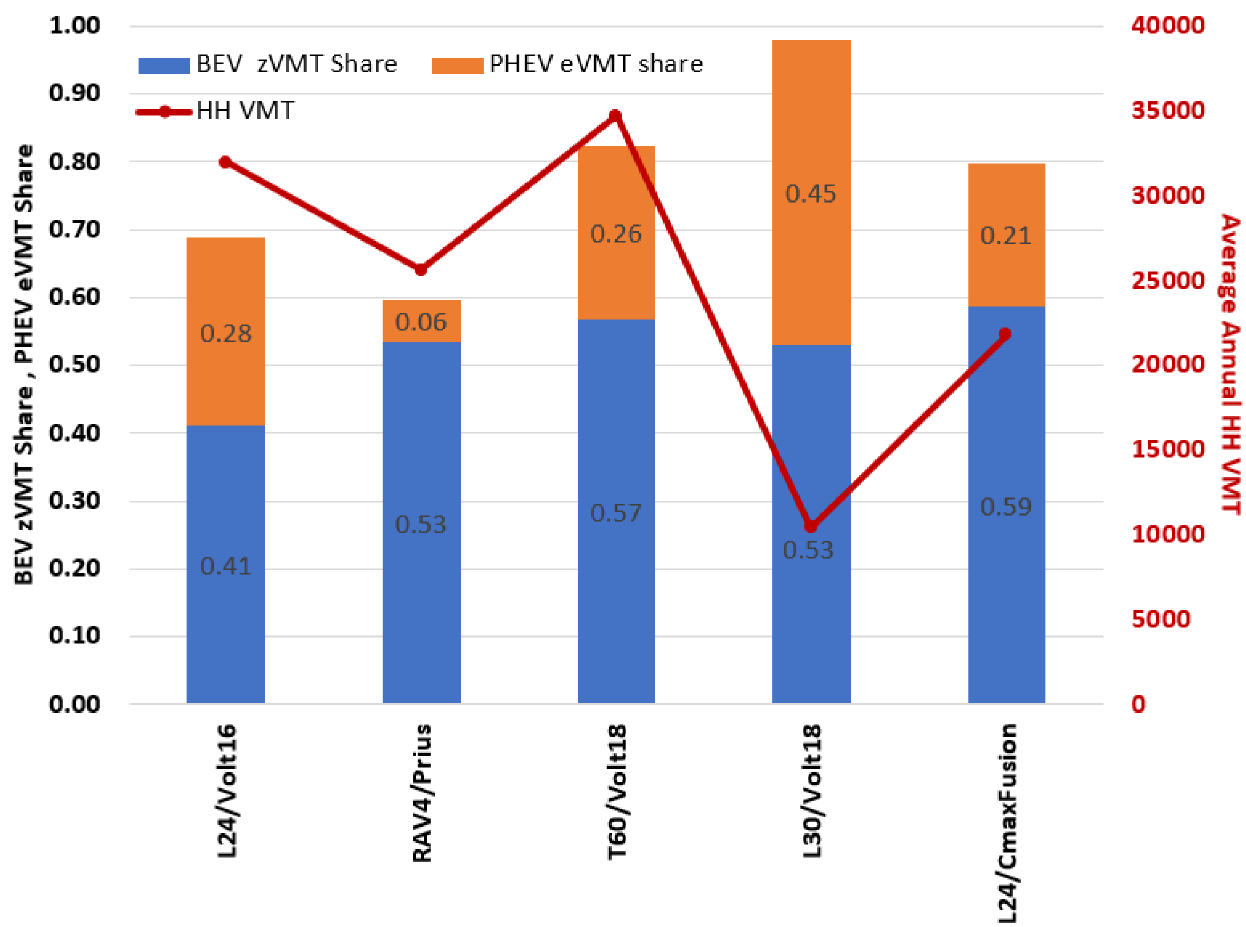


Figure 78. Average Annual HH VMT and Proportion of BEV zVMT and PHEV eVMT in BEV-PHEV HHs

As shown in **Figure 77** and **Figure 78**, the average daily VMT of Leaf30/Volt18 HH was lowest but had the highest UF compared to all other BEV/PHEV HHs.

The average annualized estimates of other metrics in BEV-PHEV HHs are summarized below in **Table 27** and **Table 28**.

Table 27. Annualized Driving Metrics in BEV/PHEV HHs

BEV/PHEV	PHEV eVMT	BEV eVMT	PHEV gVMT	HH VMT	HH UF	PHEV Fuel (gal)	PHEV Driving Energy (kWh)	BEV Driving Energy (kWh)
L24/Volt16	8,840	13,124	9,980	31,945	0.688	262.80	-2611	-3257
RAV4/Prius	1,630	13,657	10,314	25,601	0.597	226.35	-516	-5219
T60/Volt18	8,892	19,708	6,121	34,720	0.824	190.74	-2780	-6101
L30/Volt18	4,669	5,515	223	10,407	0.979	6.34	-1480	-1625
L24/CmaxFusion	4,577	12,796	4431	21,803	0.797	119.94	-1537	-3385

Table 28. Annualized Charging Metrics in BEV/PHEV HHs

BEV/PHEV	PHEV Total Sessions	PHEV Total Charging kWh	BEV Total Sessions	BEV Total Charging kWh	BEV DCFC Sessions
L24/Volt16	424	2804	365	3352	3.8
RAV4/Prius	296	382	342	4893	0.0
T60/Volt18	371	2930	259	6565	32.7
L30/Volt18	243	1465	180	1596	0.0
L24/CmaxFusion	460	1592	450	3101	0.0

6.3.2. Households with an ICEV, BEV, and PHEV

In this section we focus on households with two PEVs and one or more ICEVs. The sample size is only 9 households and therefore the analysis has no statistical power and can be used to explore potential behaviors rather than generalize to the population.

Table 29–Table 31 summarize the annualized estimates of driving, energy consumption, and charging in ICEV-BEV/PHEV three-car HHs. **Figure 79** shows the contribution of BEV zVMT and PHEV eVMT to the HH UF and the annual HH VMT. **Figure 80** shows the daily average HH VMT and the share from each of the car in the HH by type of fuel consumption.

Table 29. (Average) Annualized Estimates of VMT in ICE-BEV/PHEV Households

	PHEV eVMT	PHEV gVMT	PHEV VMT	BEV eVMT	ICE VMT	HH VMT	HH UF
Leaf24-CmaxFusion	3879	9307	13187	4213	4943	22343	0.35
RAV4-Volt16	5052	1359	6411	16390	10814	33615	0.64
RAV4-CmaxFusion	3531	3207	6739	4931	4272	15941	0.53

Table 30. (Average) Annualized Energy Consumption Estimates of Energy Consumption in ICE-BEV/PHEV Households

	PHEV Fuel Gallons	PHEV Driving kWh	BEV Driving kWh	ICEV Fuel Gallons
Leaf24- CmaxFusion	217.18	-1246.06	-1014.45	246.20
RAV4-Volt16	37.98	-1291.09	-5718.43	561.33
RAV4-CmaxFusion	73.63	-967.17	-1775.44	140.53

Table 31. (Average) Annualized Charging Estimates in ICE-BEV/PHEV Households

	PHEV Charging Sessions	PHEV Charging kWh	BEV Charging Sessions	BEV DCFC Sessions	BEV Charging Energy
Leaf24-Energi	330	1396	165	3.3	1167
RAV4-Volt16	262	1407	369	0	5043
RAV4-CmaxFusion	360	1243	142	0	1434

Table 29Error! Reference source not found. and **Error! Reference source not found.-Error! Reference source not found.** indicate that the HH UF in ICEV-BEV/PHEV HH were positively correlated with the total AER capabilities of the HH (AER of BEV and PHEV combined). The UF, total and daily average HH VMT, and ICE gVMT of the RAV4-Volt-16 HH was the highest.

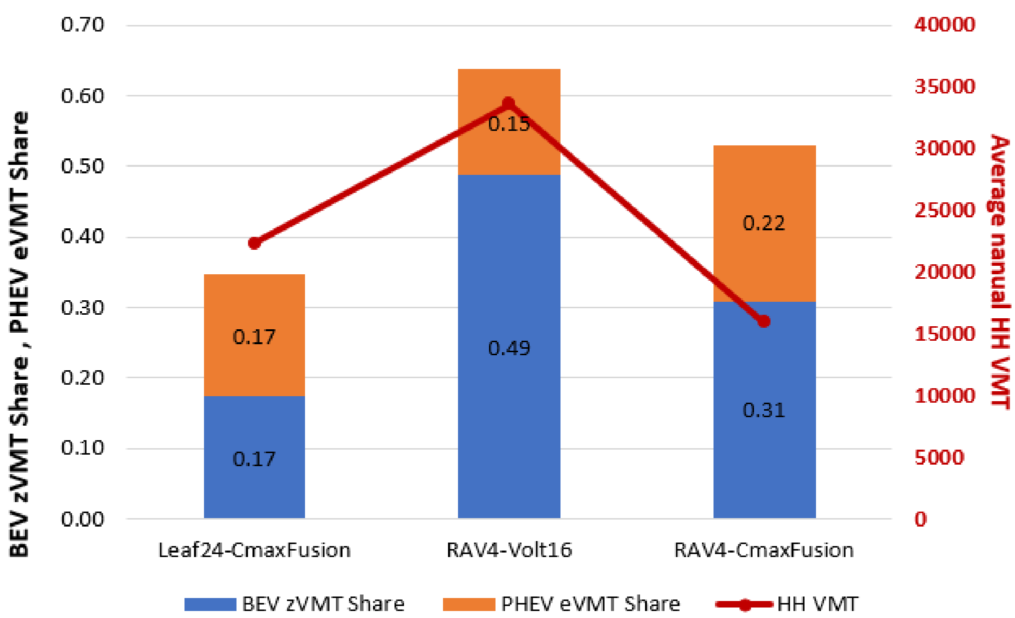


Figure 79. Average Annual HH VMT, BEV zVMT ,PHEV eVMT share in ICEV-BEV/PHEV HH

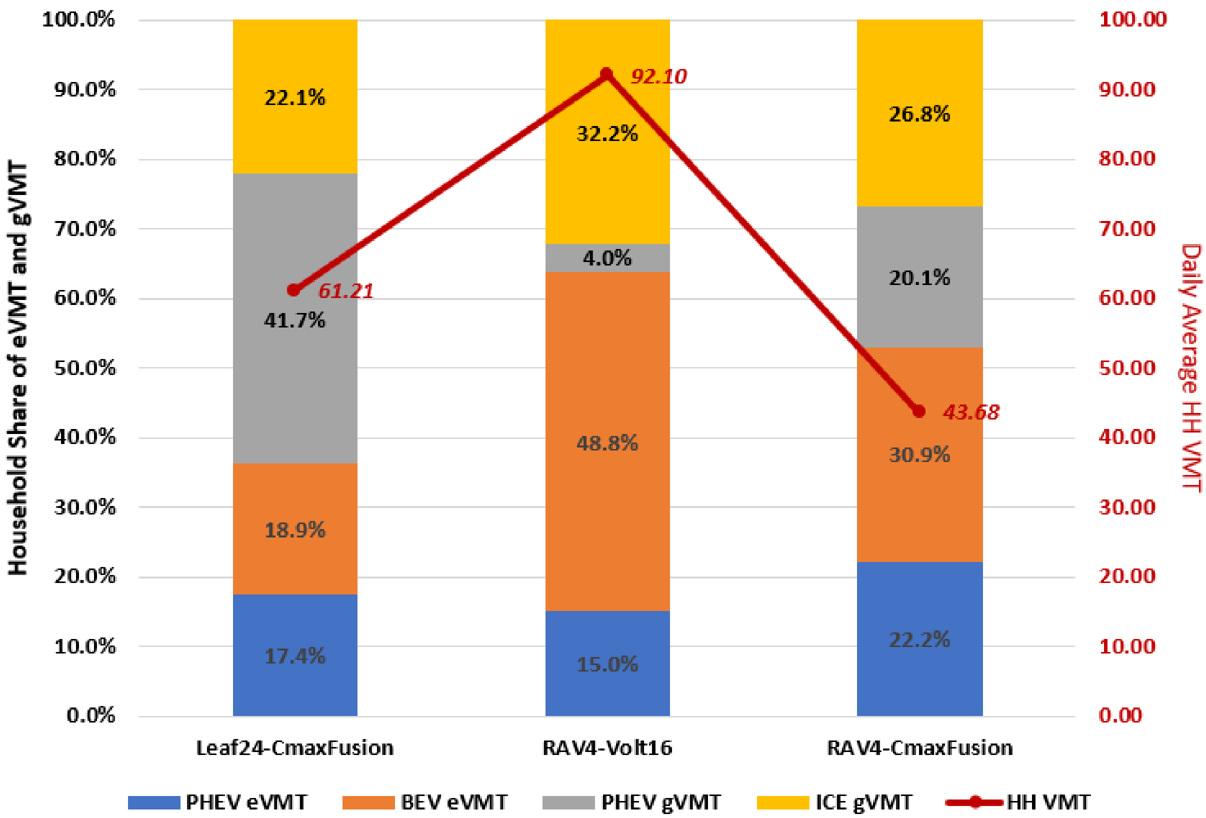


Figure 80. eVMT and gVMT Share of Daily Average HH VMT in ICE-BEV-PHEV Households

6.4. UF and GHG Profile

In this section, we focus on the utility factors and GHG emissions of the PEVs and the household fleets of which they are a part using the logger data. We use a subset of the 226 HHs with one PEV and one ICE and exclude one and more than two vehicles households and analyze the disparities in vehicle and household level UF and GHG emissions. The UF and GHG profile of the 128 two car households (51 HHs with ICE-BEV and 77 HHs with ICE-PHEV) is analyzed using the average annualized estimates of the relevant PEV usage metrics by PEV type covered in Sections **Error! Reference source not found.-Error! Reference source not found.**. For parity purposes, we restrict this analysis to only two car HHs with single ICE and single PHEV or BEV. Since the logged HH are PEV early adopter HHs, the ICEs in these HHs are not representative of general population of ICE owners. The PEVs in these early adopter HHs typically replace or supplement older, bigger, and less fuel-efficient ICEs. The well to wheel emissions factors for gasoline and electricity are 378.54 gCO2e/kWh and 11405.85 gCO2e/Gallon of gasoline.(CARB 2017c)

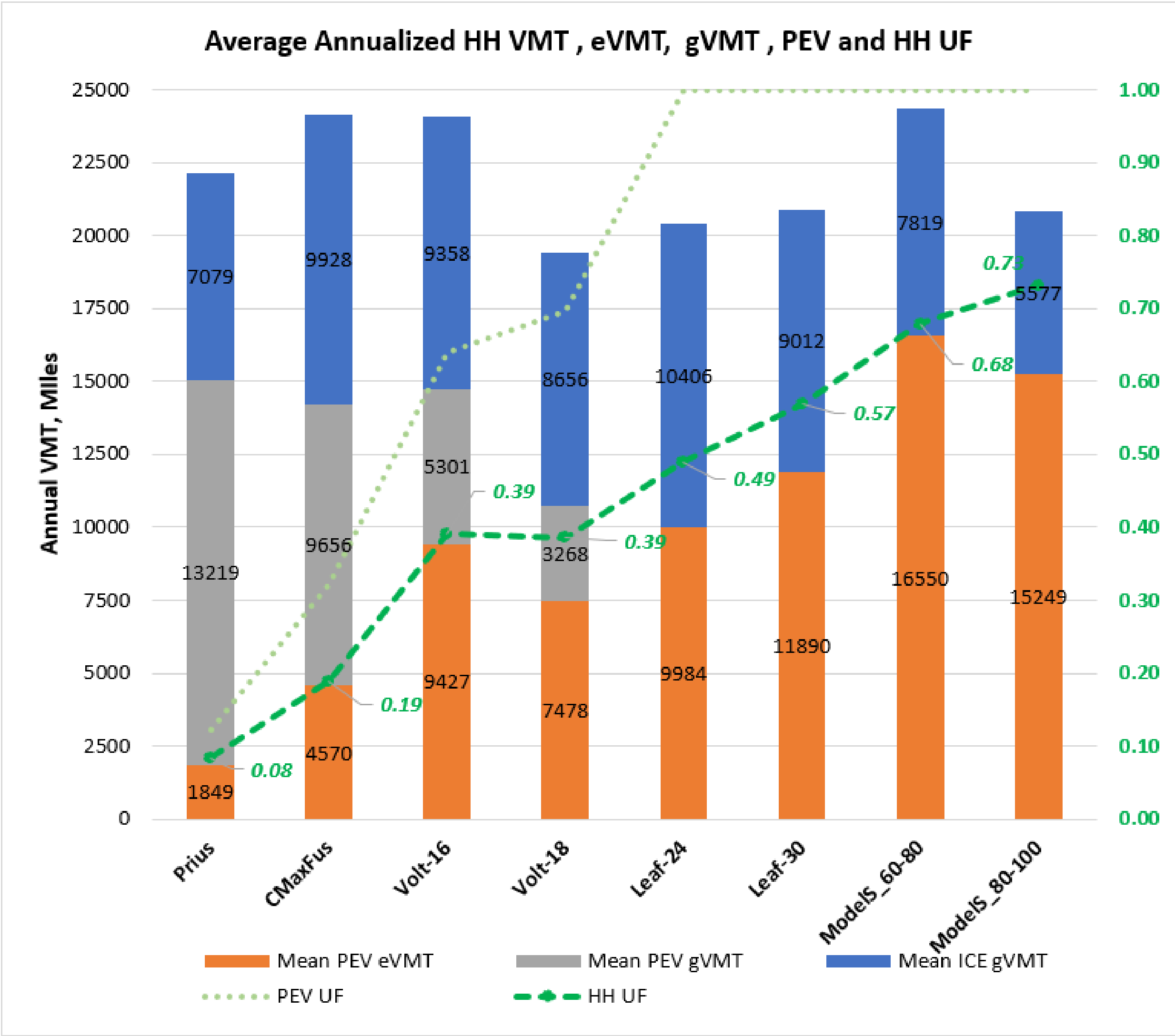


Figure 81. Two car HHs VMT by Vehicle Type, PEV UF and HH UF

Figure 81 presents the VMT by vehicle and fuel source, vehicle and HH UF of two car HHs by PEV type. The total annual miles of these households change between 19,400 for the Volt 18 and 24,000 for the Tesla 60-80, but the HH utility factor is always growing with the PEV range. For short range PHEV the household utility factor is just over half of the PEV utility factor. For the Volts the PHEV electrify about half of the household miles, like the 24kWh Leaf. The longer range BEVs electrify 57% to 75% of the household VMT partly because of lower miles for the ICEV in long-range Tesla HH.

Figure 82 presents the average GHG per mile for the PEVs in the studied fleet. As expected, the short-range BEVs have the best performance followed by the larger battery capacity BEVs and the PHEVs. We see that the relatively gas-efficient engine on PHEVs results in GHG emissions not much higher than larger battery vehicles. The results are based on the assumption on average electricity derived GHG described above and the logged travel behavior.

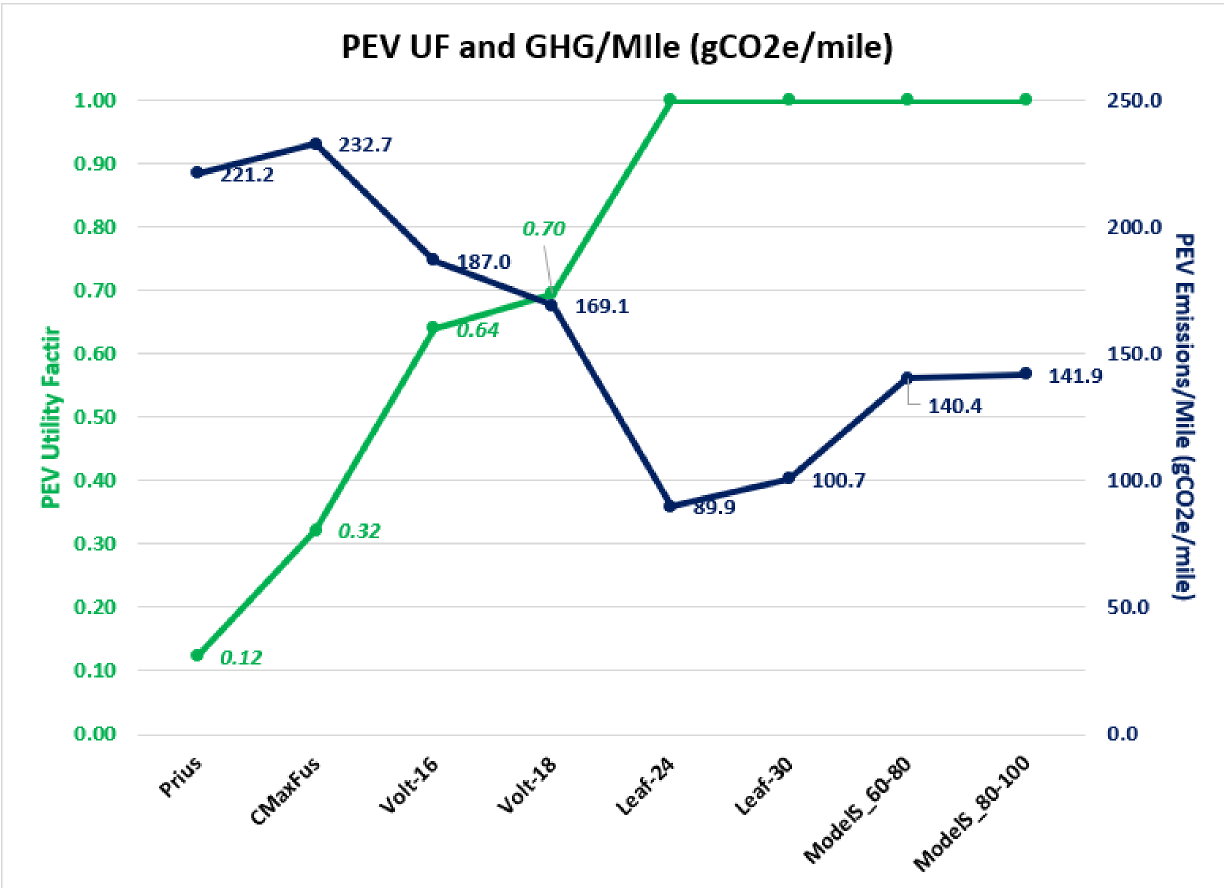


Figure 82. Average GHG per Mile and Utility Factor

Figure 83 adds the household level (PEV+ICEV households) GHG sources comparing GHG per mile from electricity, gasoline consumed by the PHEVs, and gasoline consumed by the ICEV of two vehicle households. We also include the household utility factor (HH eVMT/VMT).

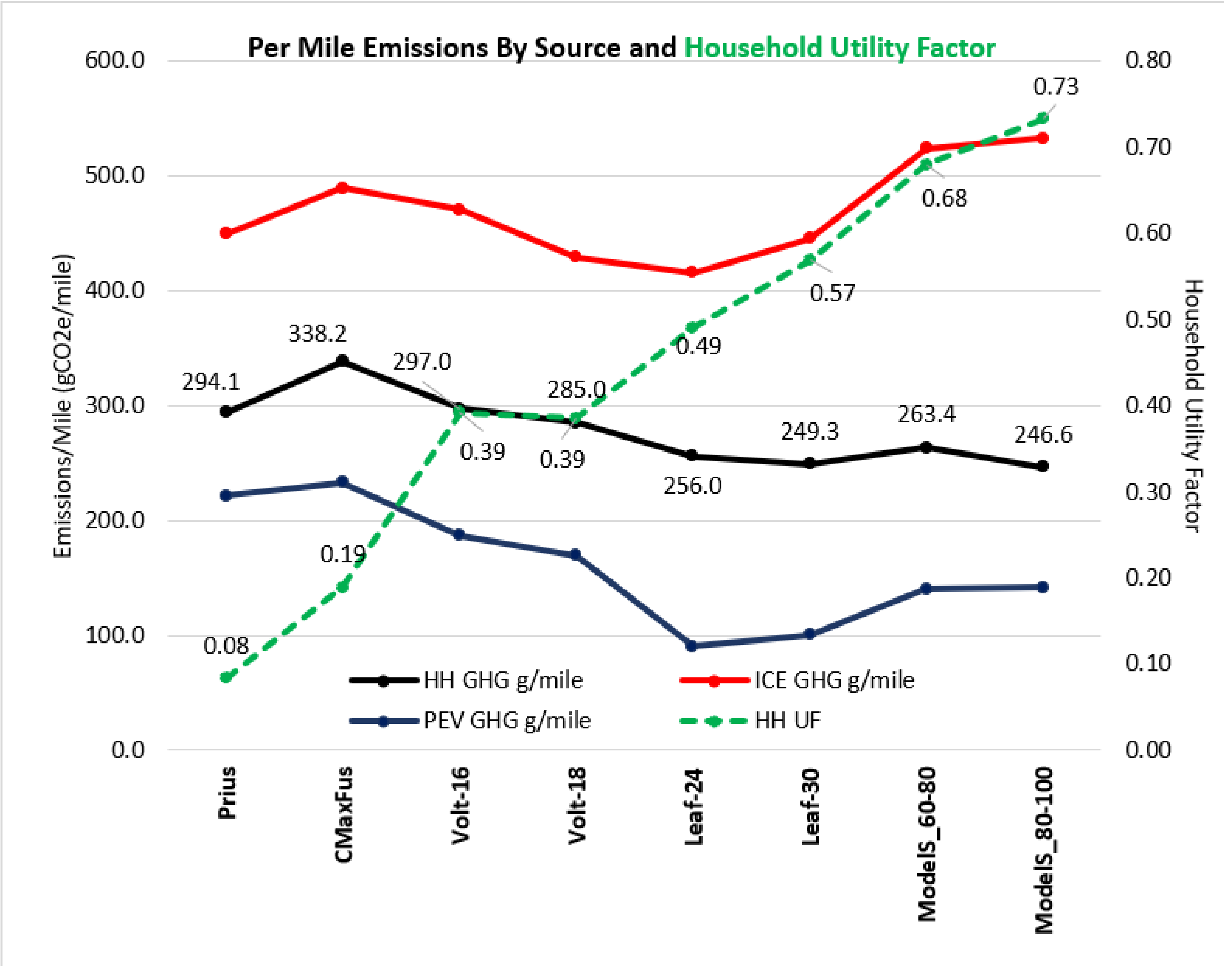


Figure 83. Household Level GHG and Utility Factor per Mile

The actual performance of each household depends on the metric considered. At the household level, the total VMT and ICE VMT substituted with PEV eVMT are the major determinants of the HH UF. From emissions perspective, in addition to the aforementioned factors, it is also important to account for not just the quantity of ICE VMT substituted but also the quality. The disparities in HH GHG/mile between HHs with different PEVs is therefore influenced by (1) energy and carbon intensity of ICE; (2) usage intensity of the ICE (absolute VMT); (3) energy intensity (kWh/mile) of the PEV and its charging related emissions; (4) battery capacity of the PEV which directly impacts the eVMT; (5) CDB or CS mode miles and gasoline consumption in PHEV HHs. **Figure 81**, **Figure 83**, and **Figure 84**, when analyzed together, present a complete picture of HH level emission impacts of PEVs.

The ICE VMT in Tesla HHs is approximately between 8000-9000 miles, whereas in the Leaf HHs, it is between 9000-10000 miles. Leaf-30 HHs have lower HH GHG/mile compared to Leaf-24 HHs because of its bigger battery. The incremental eVMT enabled due to the bigger battery of Leaf-30 overcompensates for the fact that ICEs in Leaf-30 HHs are less efficient compared to Leaf-24 HHs (445 gCO2e/mile compared to 415 gCO2e/mile).

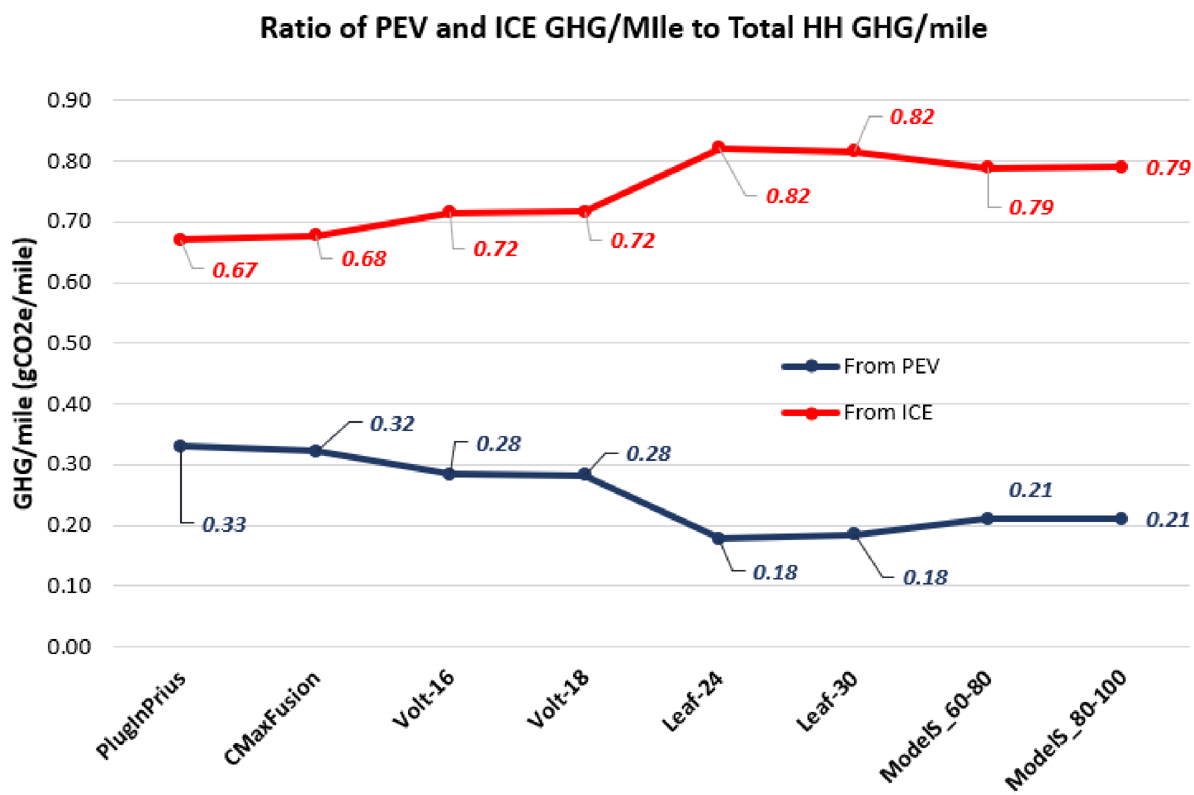


Figure 84. Ratio of PEV and ICE GHG/Mile to Total HH GHG/Mile

The ICEs in Model S_80-100 HHs are the most inefficient (533 gCO2e/mile) but have the lowest ICE usage intensity on an absolute VMT basis, and thereby the highest HH UF. However, on a per mile HH GHG/mile it performs best among the rest of PEV types simply because of its lowest ICE usage intensity. In contrast, the ICE in ModelS_60-80 has a higher usage intensity relative to the carbon intensity when compared to the ICE in ModelS_80-100 HHs. The ICE GHG/mile in ModelS_60-80 HHs was only 2% lower (524 gCO2e/mile vs. 533 gCO2e/mile) when compared to ICE in ModelS_80-100 HHs, but the usage intensity of ICE was 40% higher (7819 miles vs 5577 miles).

The Leaf HHs on the other hand have a higher ICE usage intensity compared to the Model S HHs on an absolute VMT basis, which is the reason for Leaf HHs having lower UF compared to the UF of Model S HHs. However, on average the ICEs in Leaf 24 HHs are 20% more efficient than the ICEs in the ModelS HHs (both 60-80 and 80-100 kWh) on a gCO2e/mile basis and this causes the overall HH GHG/mile in Leaf 24 HHs to be lower than that of the Model S HHs.

Three factors cumulatively work in favor of the Leaf-30 HH to have the lowest HH GHG/mile compared to other BEV HHs: lower ICE usage intensity compared to Leaf-24 HH, lower energy intensity of the PEV and carbon intensity of the ICE compared to Model S HH. When we look at the PHEV HHs, Volt-18 HHs have the lowest HH GHG/mile. Though the UF of Volt-16 HH was similar to that of the Volt-18 HH, the Volt-16 HH GHG/mile is higher. This is because the ICEs in Volt-16 HHs have higher usage intensity, higher share of PHEV gVMT, and higher total HH VMT compared to the Volt-18 HHs. Referring to Fig. xx, we can clearly see on that on a GHG/mile basis, the only distinguishing aspect between Volt-16 and Volt-18 HHs is the ICE usage intensity. CmaxFusion HHs have the highest ICE usage intensity among PHEV HHs and the highest HH GHG/mile across all PEV HHs. Prius HHs have lower GHG/mile when compared to Volt-16 HHs because their ICE usage intensity and carbon intensity are lower. This difference is sufficient to overcome the eVMT deficit due to smaller battery capacity of the Prius from an emissions perspective at the HH level.

The HH GHG/mile (blackline in the middle of **Figure 83**) shifts upwards if the ICE usage intensity and ICE carbon intensity increases. As far as determining how the curve would shift, we have to consider the carbon, energy and usage intensity of the ICE and PEVs. If we ignore the specific ICE class/segment (compact, SUV, sedan etc.), ICE carbon intensity increases with the AER in BEV HHs. The reverse of this trend can be observed as we move (left to right) from CmaxFusion HHs up to Volt-18 HHs. Long-range BEV HHs (ModelS HHs) on average have higher emissions from the ICE on a per-mile basis compared to all other PEVs.

6.5. Additional ICE Usage Metrics

We briefly summarize usage metrics of the ICE in PEV HHs using the average annualized estimates summarized in **Table 20** - **Table 28** based on the logger data. For the purpose of clarity, the ICE usage summaries of 2 car HHs and 3 car HHs are presented separately. In the case of 3 car HHs (2 ICEs and 1 BEV or PHEV), the total ICE VMT is considered. Due to a low sample size of HHs with single ICE and more than 1 PEV (4 HHs), we have excluded them, therefore the sub-sample of HHs considered is 151. The breakdown is as follows: 77 ICE-BEV HHs, 51 ICE-PHEV HHs, 11 HHs with a BEV and 2 ICEs, and 12 HHs with a PHEV and 2 ICEs. Among the ICEs logged there were 35 different OEMs. Toyota, Honda, Ford, Chevrolet and Subaru were the top 5 OEMs among the ICEs logged. Toyota accounted for a maximum of 19 different models, followed by Ford (11), Chevrolet (9), Honda and Lexus (6 each) and Nissan and Subaru (5 each). Toyota Prius (14) ; Honda Odyssey and Toyota Senna (6 each) ; and Honda Civic, Subaru Outback, Toyota Highlander (5 each) were the top 5 make and models respectively. Overall among the logged households, the average fuel economy of the ICE was 25.18 mpg

6.5.1. Average Annual ICE VMT

Figure 81 and Figure 82 depict the average annualized ICE VMT in 2 car and 3 car HHs respectively.

Referring to **Figure 85,** we notice a steady decline in the annual ICE VMT in BEV HHs with increase in range/battery capacity in 2 car HHs. In the case of PHEV HHs, the annual ICE VMT exhibited a similar trend but only after a certain range threshold (20 miles corresponding to the Ford CMaxFusion PHEVs). ICEs in Prius HH drove the least among the 2 car PHEV HHs and was even lower than the ICE VMT in 2 car ModelS_60-80 HHs.

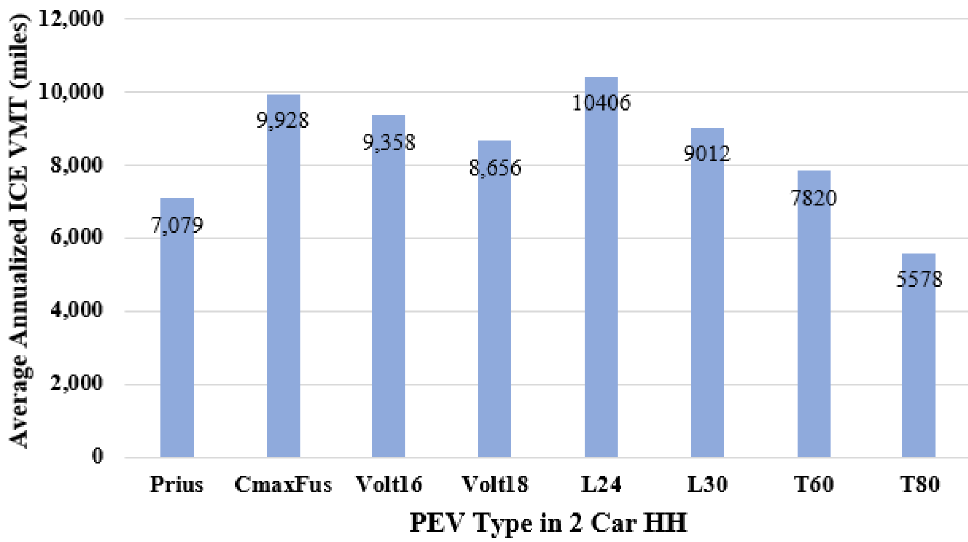


Figure 85. Average Annualized ICE VMT in 2 Car HHs (Single ICE and Single PHEV or BEV) by PEV Type. N=128 HHs

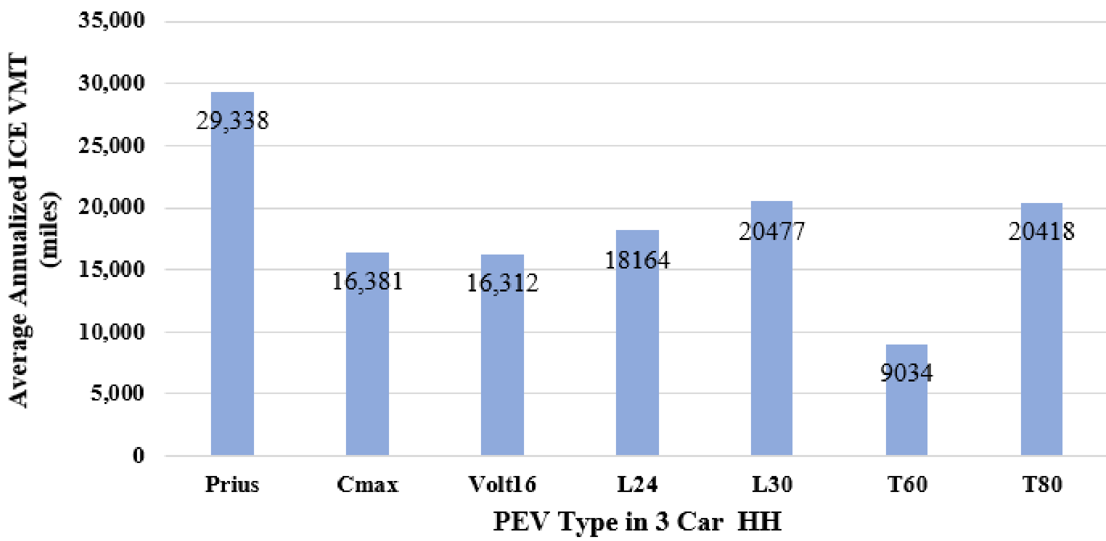


Figure 86. Average Annualized ICE VMT in 3 Car HHs (Two ICEs and Single PHEV or BEV) by PEV Type. N=51 HHs.

There was considerable variation in annual ICE VMT of 3 car HHs within across all PEV types, **Figure 86**. The ICEs in 3 car Prius HHs had the highest annual ICE VMT followed by Leaf30 HHs and the ICE VMT in Model S 80-100 HHs.

6.5.2. ICE Usage for Long Distance Travel (LDT)

We characterized long distance travel (LDT) using two daily VMT thresholds, 50 miles and 100 miles (LDT50 and LDT100). **Figure 87** and **Figure 88** depict the average annualized number of days/year the PEV and ICE was used for LDT50 and LDT100 in 2 car PHEV and BEV HHs respectively. The ICE share (%) of total HH LDT50/100 days is shown using the secondary Y axis in **Figure 87** and **Figure 88.**

Referring to **Figure 87,** in 2 car ICE-PHEV HHs, on an absolute days/year and on a percentage share of the total number of HH LDT50/100 days/year, the ICE in Prius HHs are used the least followed by the ICE in Volt-16 HHs. The ICE usage for LDT50 and LDT100 in CMaxFusion HH were comparable on a percentage share of the HH LDT50(100) days/year and a similar trend was observed in Volt-18 HHs. The ICE in 2 car Volt-16 HHs was used roughly on 10% more days for LDT100(44%) compared to LDT50(33%).

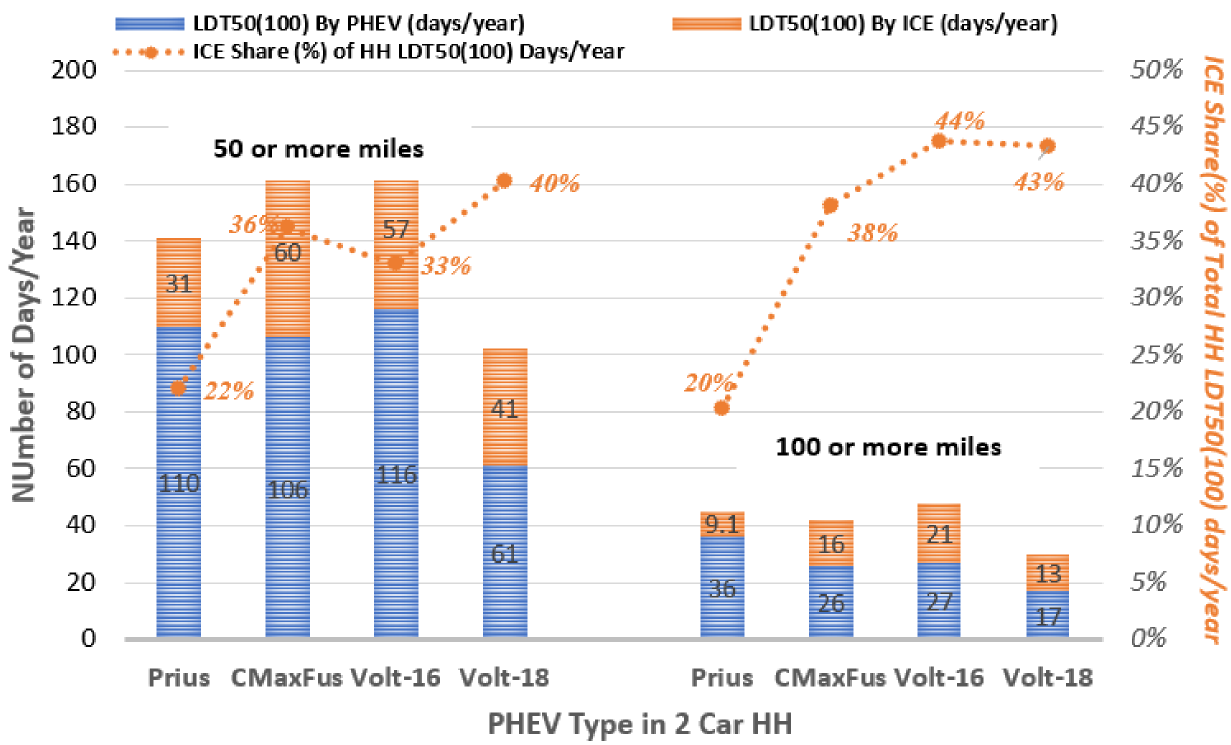


Figure 87. PHEV and ICE Use (Days/Year) for Long Distance Travel 50(100) Miles or More in 2 Car HHs (Single ICE and Single PHEV) ; ICE Share(%) Total HH LDT50(100) days/year shown on the secondary Y axis . N=77 HHs.

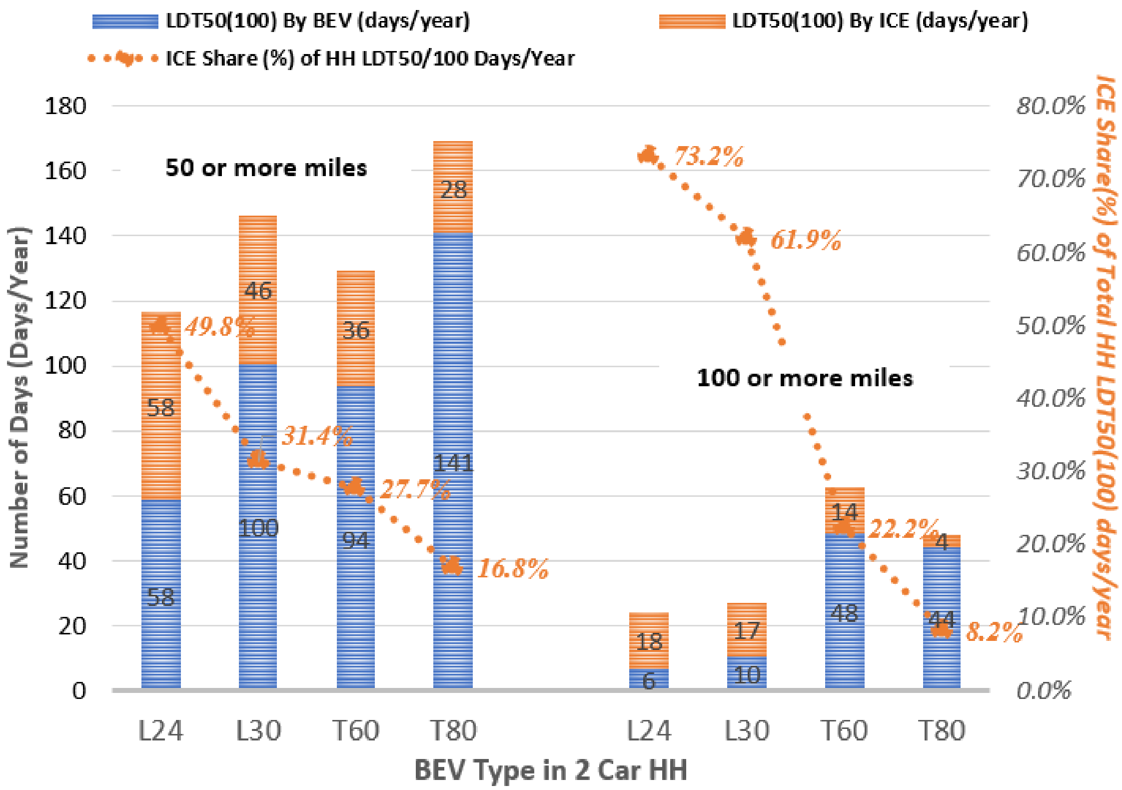


Figure 88. BEV and ICE Use (Days/Year) for Long Distance Travel 50(100) in 2 Car HHs (Single ICE and Single BEV) ; ICE Share(%) of Total HH LDT(50/100) days/year shown on the secondary Y axis. N=51 HHs.

Referring to **Figure 88**, in 2 car ICE-BEV HHs, we notice a clear trend in decreasing ICE usage for LDT with an increase in the range of the BEV, and this effect is more pronounced in the case of LDT100. In terms of number of days, there was only a 4% reduction in ICE usage for LDT50 in T60 HHs compared to Leaf30 HHs. However, the reduction in ICE usage for LDT100 was more prominent in T60 and T80 HHs compared to Leaf HHs. Overall, on an absolute days/year basis, Leaf24 HHs had the least number of LDT50 and LDT100 days compared to the all other BEVs.

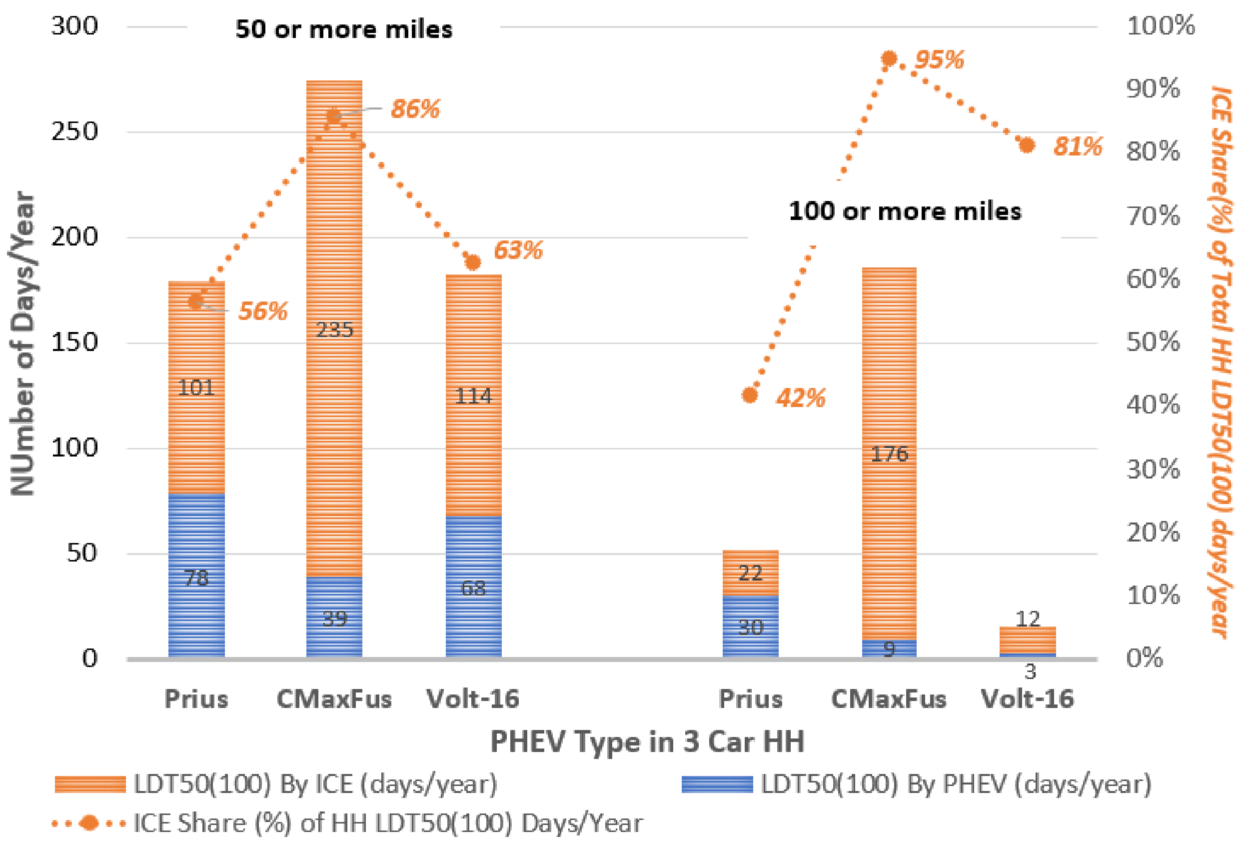


Figure 89. PHEV and ICE Use (Days/Year) for Long Distance Travel 50(100) Miles or More in 3 Car HHs (Two ICEs and Single PHEV) ; ICE Share(%) of Total HH LDT50(100) days/year shown on the secondary Y axis . N=12 HHs.

Figure 89 and **Figure 90** depict the average annualized number of days/year the PEV and ICE was used for LDT50 and LDT100 in 3 car PHEV and BEV HHs respectively. The ICE share (%) of total HH LDT50/100 days is shown using the secondary Y axis in **Figure 89** and **Figure 90.**

Referring to **Figure 89,** in 3 car HHs**,** we can observe that that the ICEs in CMaxFusion HHs were used the maximum for LDT50 and LDT100 followed by the ICEs in Volt-16 and Prius HHs.

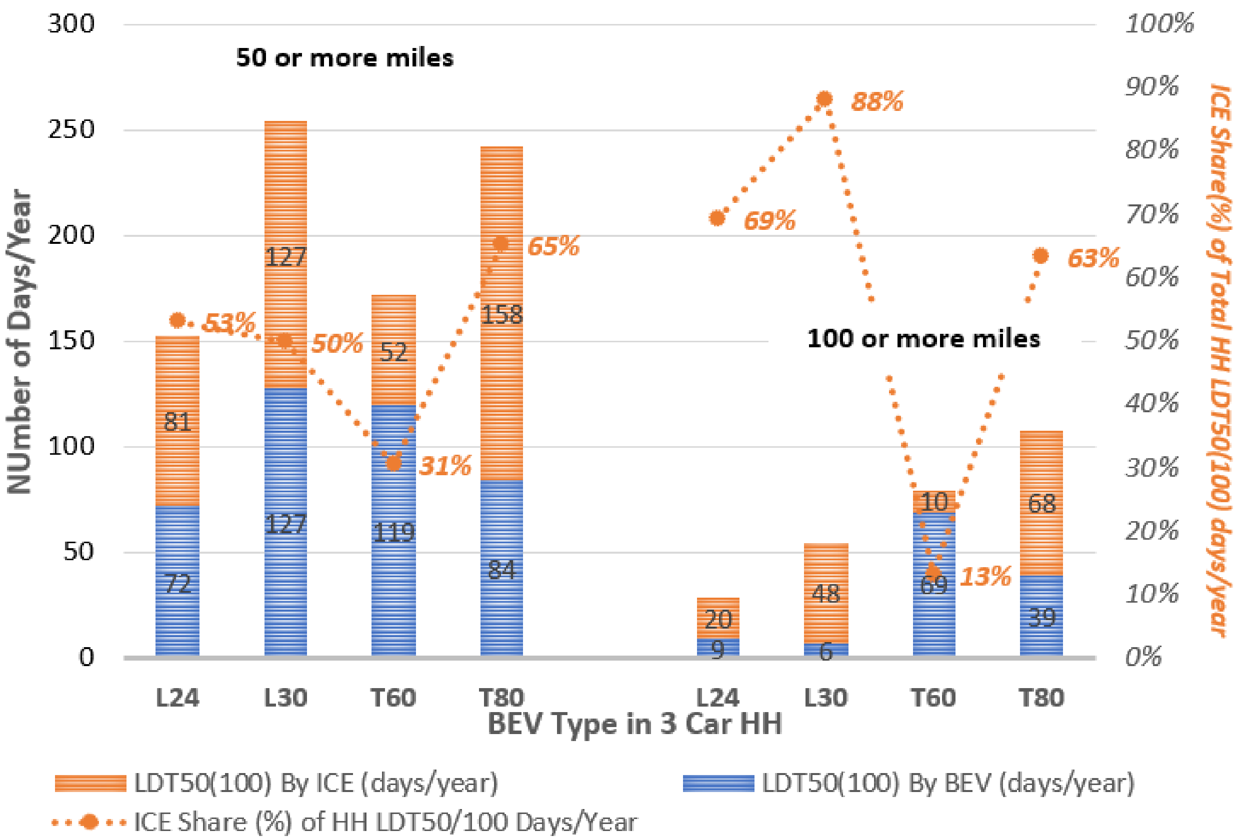


Figure 90. BEV and ICE Use (Days/Year) for Long Distance Travel 50(100) Miles or More in 3 Car HHs (Two ICEs and Single BEV) ; ICE Share(%) of Total HH LDT50(100) days/year shown on the secondary Y axis . N=11 HHs.

Referring to **Figure 90,** in 3 car HHs**,** we can observe that that the ICEs in T80 HHs were used the maximum for LDT100, whereas the ICEs in Leaf30 HHs were used the maximum for LDT100. The ICE usage in Leaf24 and Leaf30 HHs for LDT50 was almost similar. It can also be noticed that that ICE usage for LDT100 in T80 HHs reduced only by 4% compared to the Leaf24 HHs, whereas the reduction in ICE usage is more prominently reflected in T60 HHs compared to Leaf24 HHs.

6.6.PEV Used for Commuting

Figure 91 below shows the number of PEVs by type that were used by HH members working fulltime for commuting purposes and non-commuting purposes across all the HHs for which logger data was used (N=226 HHs). Percentage share of use for commuting is also displayed in italics. Overall, if we ignore the RAV4 because of small sample size, at least 70% of the PEVs were used for commuting purposes. The percentage share is especially noticeable in the case of Volt-18 and Leaf-24, followed by CMaxFusion, ModelS_80-100 and Prius respectively.

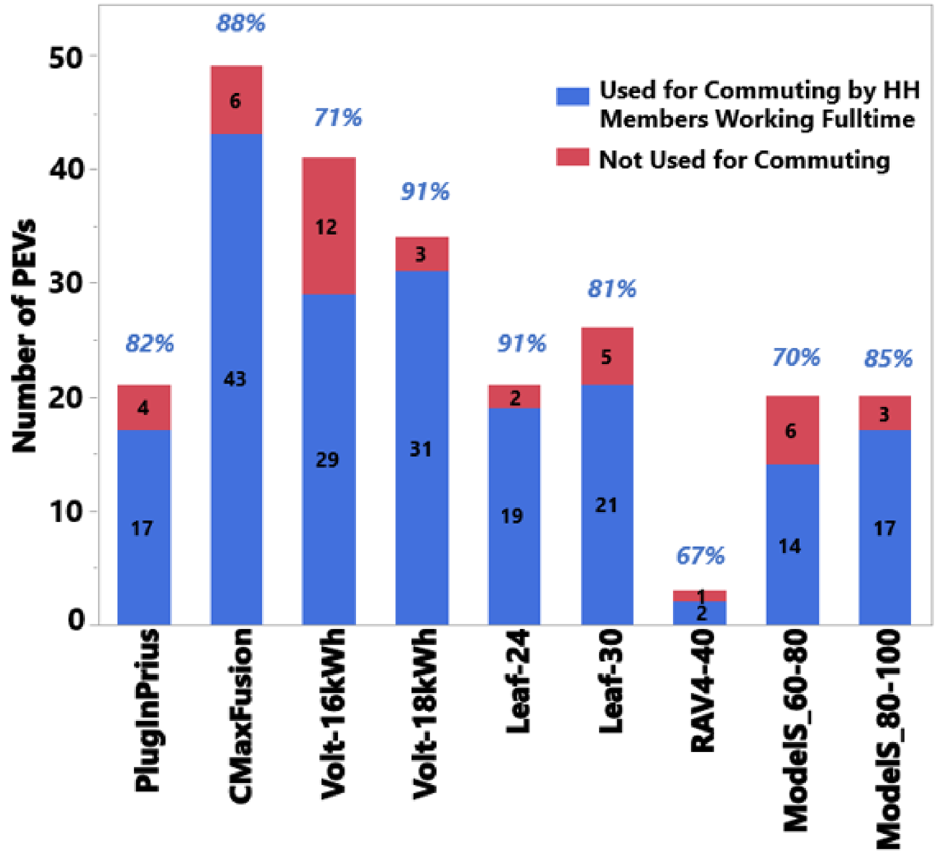


Figure 91. Number of PEVs Used for Commute Purposes by Type. The share (%) of commute purpose use is indicated in % on top of the bar

7. Regional Level Analysis

To perform a regional level analysis, we divided California into 5 areas defined by coverage from major electric utility companies: Pacific Gas and Electric (PG&E), San Diego Gas and Electric, Southern California Edison, Los Angeles Department of Water and Power (LADWP), and "Other" (**Figure 92**).

Figure 92. Map of California Showing the Areas Used in the Regional Analysis, as Defined by Electric Utility Companies

As shown on the map, these regions defined by utility companies roughly correspond to northern California, San Diego, southern California, Los Angeles, and other regions. Despite our best efforts to recruit households that were as representative as possible by utility district, the results were not representative of every region. Nonetheless, there is value in this analysis to identify the effect of the region-specific emissions. The regional distribution of eVMT and charging demand is a factor of the vehicle type and driving behavior. As presented in **Figure 93** the sample from the PG&E region had lower eVMT per BEV than the other regions, this is because, based on the survey and CVRP data the fleet in that region includes a larger share of short-range Leafs.

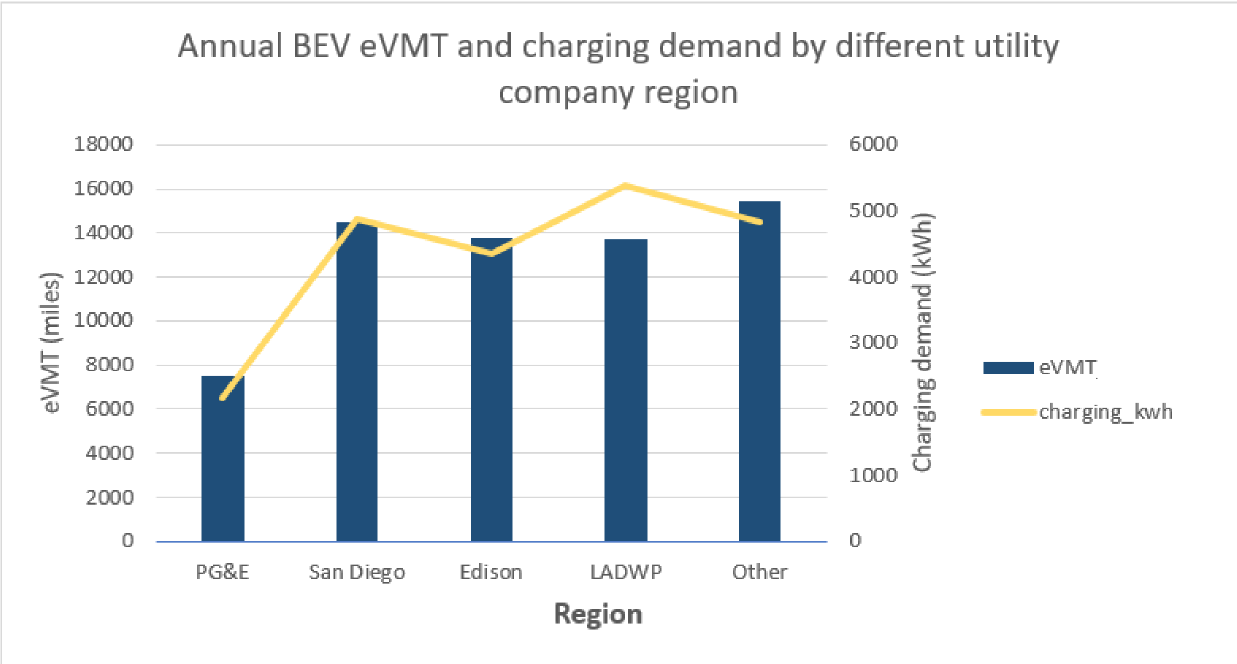


Figure 93. Annual BEV eVMT and Charging Demand for Each Region Defined by a Major Utility Company. PG&E = Pacific Gas and Electric; San Diego = San Diego Gas and Electric; Edison = Southern California Edison; LADWP, Los Angeles Department of Water and Power; Other = all other utility company regions

Similar to the BEV, PHEV eVMT is also a function of the fleet composition and travel behavior. Households in PG&E region, as compared to other regions, have more short-range PHEVs that travel relatively long trips per day.

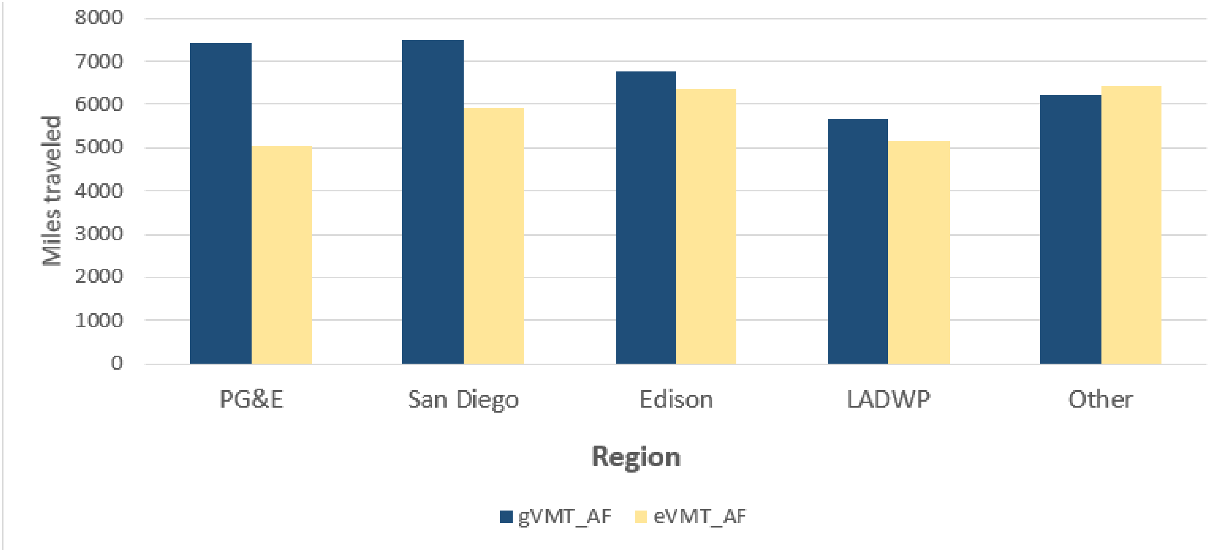


Figure 94. Annual Average PHEV eVMT for Each Region Defined by a Major Utility Company. PG&E = Pacific Gas and Electric; San Diego = San Diego Gas and Electric; Edison = Southern California Edison; LADWP, Los Angeles Department of Water and Power; Other = all other utility company regions

Unlike other estimations of energy demand of PEVs the data presented here is based on actual demand as measured by the logged PEVs. Similarly, the gasoline consumption is calculated based on the logged vehicle data.

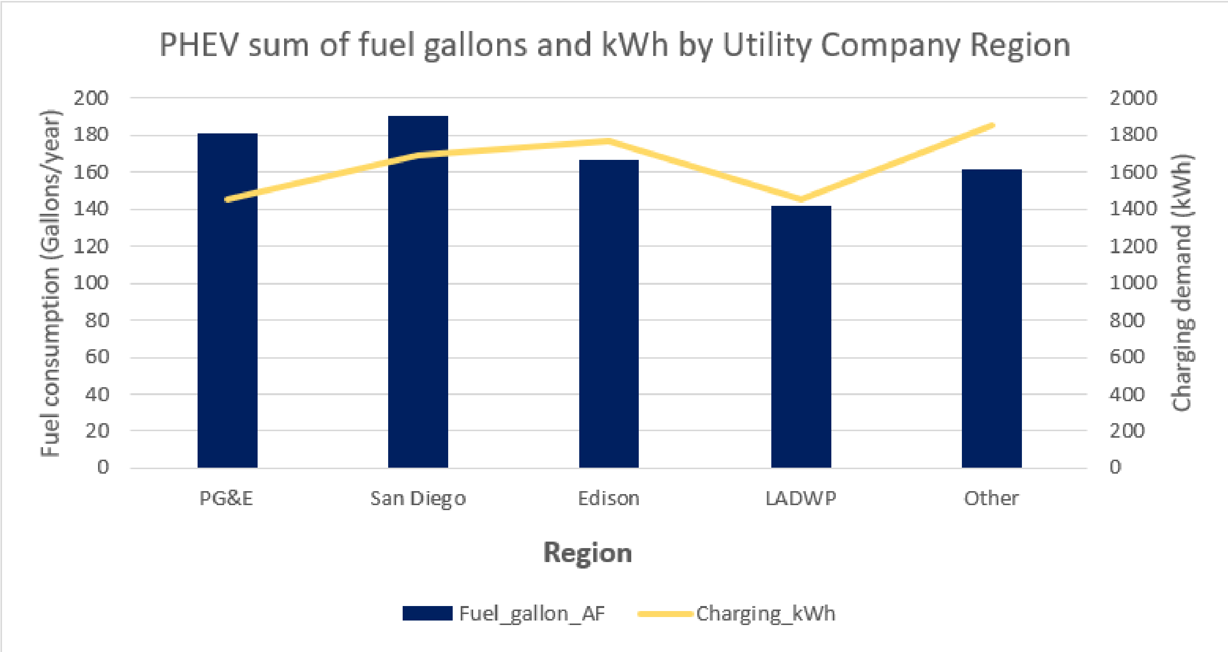


Figure 95. PHEV Sum of Fuel Consumption and Charging Demand for each Region Defined by a Major Utility Company. PG&E = Pacific Gas and Electric; San Diego = San Diego Gas and Electric; Edison = Southern California Edison; LADWP, Los Angeles Department of Water and Power; Other = all other utility company regions

8. Interview summary

Interviews were conducted with drivers of the PHEVs and BEVs in the first logged wave of this study. The variety of vehicle types represented in these interviews is shown in **Table 32**. As may be inferred from the different generations of the Chevrolet Volt and battery sizes of Nissan Leafs, the presence of later market entrants such as the Ford and Toyota PEVs, and the presence of a few vehicles purchased as used by the households, the interviewees' experience with PEVs prior to their enrollment in this study spans from a few months to a few years. The PHEVs span the electric-only driving range capabilities of PHEVs available in the early market: 11 miles (Toyota Prius Plug-in) to 35 miles (Chevrolet Volt, gen. 1), and then to 53 miles (Chevrolet Volt, gen. 2) (All distances based on manufacturer estimates based on USEPA emissions test cycles, not on driver reports.)

Table 32. Plug-in Electric Vehicles in the Interview Sub-Sample

Plug-in type		
PHEVs	**Purchased new or used**	**Number of interviews**
Chevrolet Volt (Generation 1)	New	3
Chevrolet Volt (Generation 1)	Used	2
Chevrolet Volt (Generation 2)	New	4
Ford C-max	New	2
Ford Fusion	New	3
Prius Plug-in	New	3
BEVs		
24 kWh Leaf	New	2
30 kWh Leaf	New	3

Houseohlds were selected randomly to observe a wide variety of conditions that might plausibly affect their choice of PEV(s) and subsequent use. Drivers live in the service areas of six different electricity supplier service areas, three investor-owned utilities (PG&E, Southern California Edison (SCE), and San Diego Gas & Electric (SDG&E)) and two municipal utilities (Sacramento Municipal Utility District (SMUD) and Roseville Electric), and one community choice aggregator (Sonoma Clean Power). The vehicles represented in these interviews are most of those from the first wave of data collection and starting the second wave; notably, there are no interviews of Tesla or BMW i3 owners as they had yet to be logged. In addition to hearing from drivers of PEVs across the available electric driving range of PHEVs, other criteria included households who had purchased more than one PEV, i.e., their "study" vehicle represents a difference from a PEV they had previously owned, households who own more than one PEV, and whether or not people had installed an EVSE at their home. Interviews were conducted only after households vehicles had been logged for several months; a few had completed the vehicle logging phase. An additional incentive was paid to households who participated in interviews.

Two researchers conducted the interviewers either in-person or via Skype. Interviews typically lasted one hour or longer. All interviews were audio-recorded. The results reported here are drawn from these recordings and the interviewers' notes.

Summary observations are presented in the following discussion; longer summaries of individual interviews exemplifying these observations are included in the subsequent sections.

8.1. Interviews Discussion

We make these overall observations from these interviews:

1. Learning and not learning about PEVs
    a. Early PEV drivers may still be learning about their PEVs, even months or years after they acquired one;
    b. Conversely, early PEV drivers may still be operating with old ideas/information, that is, they are not learning, even months or years after they acquired a PEV;
    c. Across drivers interviewed here, their knowledge of PEVs ranges from shallow to deep knowledge of their particular vehicle; few display broad knowledge of different types of PEVs.

2. Many goals for owning and driving PEVs are simplified to "use less gasoline": reduce costs, national petroleum use or imports, or emissions (the latter more often associated with air quality than climate change).
3. Vehicle (and EVSE) purchase and use incentives shape outcomes
    a. Vehicle purchase incentives are described as essential by some PEV owners;
    b. Incentive for home chargers may produce home chargers, but their subsequent effect on eVMT is not straightforward
    c. If people value carpool lane access, they really value carpool lane access, allowing them to accumulate many miles but again with effects on eVMT that are not straightforward.
4. PHEVs allow for a much wider range of behaviors affecting eVMT—at any given electric range capability—than do BEVs
    a. PHEVs may allow for a shorter electric range to produce as many or more eVMT as a BEV with a longer electric range;
    b. PHEVs may allow for zero eVMT, too.

8.2. Learning and Non-Learning

Early PEV drivers routinely go through extended periods of figuring out how their PEV works and what charging is like in their personal context. This period often involved confronting expectations they had prior to acquiring their PEV; these people brought one set of expectations, then figured out how their PEV really works for them. For example, BEV buyers will buy and install an EVSE at home expecting that is where they will charge the vehicle only to subsequently do much or even all charging away from home. A PHEV buyer will eschew charging—anywhere—because of (in)convenience, charging etiquette, and fuel economy ("It's still a hybrid.") while remaining so committed to the idea of PEVs they see themselves as a household who will one day own two BEVs. Another PHEV owner will actively engage in the project of using only electricity in their vehicle to the extent possible by investing in a home EVSE, learning the location of away-from-home charging opportunities throughout their daily lives, and planning longer trips around the possibilities to charge their vehicle.

Differences in charge time duration, driving range on a "full" charge between level 2 and quick charging, and the effect of quick charging on battery life are all subject to changing evaluations over time. Though not immediately relevant to one respondent (she drives a PEV without the capability to quick charge), her question reflects a typical amount of confusion and frustration with multiple charging speeds and different charging networks: “Why would you invent a car and a battery that [is damaged by charging fast]?”

Some interviewees started their interviews asking the interviewers about details of the interviewee’s PEV, other PEVs, and charging—including how to find and use public charging. More typically, PEV owners were familiar with their specific vehicle, but remain uninformed about PEVs generally. They imagined what they would do with more (electric) driving range (see #2 below), but without considering the possible cost implications of using more electricity. For example, if they have not switched to a time-of-use electricity program using more electricity for a longer range PEV might shift more of their charging to a higher price tier.

Even if PEV buyers compared different PEVs when they purchased or leased theirs, this does not mean they have accurate and up-to-date information on other PEVs. We heard also instances of incidental PEV purchase, in which we hear an example of how an informed and motivated automobile sales person can be an effective advocate for PEV sales.

One of the topics mentioned by several PEV drivers was declining driving range over time. None of these people indicated they anticipated this would happen over time. Knowledge of other PEVs might be no deeper than widely shared beliefs, e.g., “Teslas are too expensive,” or reactions to styling (the styling of Nissan’s Leaf can be polarizing) or size (four seats only in Chevrolet’s Volt). Declining driving range has prompted increased frequency of charging and moderating of driving styles in order to continue achieving the goal to “use less gasoline,” the topic to which we turn next.

8.3. “Use Less Gasoline”

If these PEV drivers express a generalized heuristic or shortcut to valuing electric-drive it is “use less gasoline.” This heuristic stands in place of goals to reduce private costs by substituting electricity for gasoline and to (real or perceived) social benefits from reducing the nation’s consumption of (generally, imported) petroleum and emissions. If emissions reductions are stated as a goal, those emissions are more often tied to local air quality than global warming.

Few PEV drivers routinely measure or track progress toward this goal. Even those who track electricity expenditures for their PEV generally lack other information required to know whether they are reducing gasoline use at all across all household travel. In short, from the perspective of almost every driver interviewed, achieving their goals for driving electric is more a matter of hope than measurement, desire than knowledge. Based on these interviews, state policies that support expanded ZEV market offerings (e.g., the ZEV mandate pushing manufacturers to bring PEVs to market and incentivizing consumers to buy PEVs) and making them easier to use (e.g., PEV charging infrastructure deployment) are likely to increase their appeal among consumers. But consumer adoption, and eVMT, is likely to remain limited by the lack of consumer awareness and understanding of ZEV technologies, and these interviews suggest that state efforts to increase consumer awareness of ZEV technologies, incentives, and charging infrastructure availability would be likely to increase consumer adoption as well.

8.4. Incentives

Purchase and use incentives are “producing” some PEV sales that would not have otherwise occurred; carpool lane access and the resulting time savings can be especially important within the specific context of individual households. Charging incentives such as Nissan’s “no charge to charge” program were described as entirely substituting for home charging—until concerns about the effect of fast charging on the vehicle’s battery life and the shorter driving range per charge from quick charging vs. overnight level 2 charging at home caused a wholesale swing to home charging only.

8.5. Behavioral Outcomes by Vehicle Types

This fourth point runs through the previous three as a sort of sub-text; each of the first three points sounds different for BEV drivers than for PHEV drivers. One of the differences is the greater possible variability among PHEV drivers because PHEVs allow for more variable behaviors and outcomes.

For PEVs, achieving the goal to use less gasoline is, in general, achieved by driving as many miles as possible on electricity—accomplished through a match between a driver’s driving distance, electric range of their PHEV, and charging behavior. The behavior of PHEV drivers ranges from such a close match between daily travel distances, electric range and charging behavior that buying gasoline happens rarely and then typically only for infrequent longer trips to people who faced with seemingly solvable problems with charging simply stop or nearly stop doing so altogether, turning their PHEV into effectively an HEV.

BEVs—as a purely (with connotations of purity) electric vehicle—can allow a more “purist” pursuit of goals. Some BEV drivers disavow a cost-savings motivation for purchase or cost effects on charging behavior. These may be acting out of strong moral motivations, evidenced by other lifestyle sectors in which they enact those same values. Notably, this does not forbid private benefits such as time savings (conferred in part by HOV access) and convenience. These may guide charging behavior toward the most convenient rather than the least cost times and locations to charge.

9. Engine Starts Analysis

9.1. Cold Starts

According to CARB's vehicle emission inventory model (EMFAC), for typical ICE vehicles, a cold start is defined as an engine ignition event after the engine has been off and the vehicle is stationary for 12 hours(CARB 2018). PHEVs have both a battery and an ICE engine and under certain circumstances, the ICE engine may go through an ignition event while the vehicle is already on the road after it was initially started by the battery. Under this circumstance the ICE engine in a PHEV may be going through both a cold start under the usual ICE vehicle definition while also being high power because it is already on the road and operating at an elevated speed or at high torque. In some PHEVs, the first time an engine starts may be when higher power is required at some point during a trip, negating some of the environmental benefits of reducing total number of cold engines starts results from completing trips and travel days on electric mode only and the benefit of the low total gas consumption. High-power engine starts have been associated with high local emissions of NOx and organic gases. Estimates based on dynamometer measurements demonstrate that during such events, blended PHEVs emit at rates higher than they do during the lower power start events that occur during emission certification tests(CARB 2017, Pham and Jeftic 2018).

The objectives of this section are to characterize the engine start activity profiles of PHEVs, including: 1) to define characteristics associated with all PHEV engine start events; 2) to identify conditions including driving behavior, battery level, and other factors that trigger high SOC start engine events; and 3) to determine the frequency of various types of starts. Further, more information is needed on total number of engine-starts and how these compare with conventional vehicles. The analysis of this activity data will be combined by CARB with previous emissions test results to better characterize real-world emissions levels and to improve a future version of CARB's EMFAC vehicle emission inventory model. Based on results of this project, regulators may want to work with car manufacturers to devise emission control strategies that mitigate high emission events during high power cold starts.

This study logged blended PHEV models (i.e., Plugin Prius and the CMax/Fusion Energi) and the non-blended PHEV model (i.e., Volt). The second-by-second logger activity data from the logged PHEV models were analyzed to better understand ICE-engine high power cold starts in the PHEVs described in this report. Because the data on some parameters was collected at high frequency (approximately once every 1 to 10 seconds), we can monitor the existing conditions in the few seconds before the engine starts in a PHEV. Our analysis was able to classify all engine starts by state of charge (SOC), soak time, travel distance, and speed. However, due to technical limitations inherit in the loggers in the second-by-second activity logging, we were unable to pinpoint the reason for engine starts, such as high-power requirement resulting from acceleration or a change in road grade.

The data collection was not synchronized for all parameters, and even though some parameters update every 1-10 second. Furthermore, any parameter update generates a new timestamp and update of all the old values of the other parameters that were not updates. We cannot distinguish between parameters that have been updated but remained constant over several seconds versus those that have not been updated and are simply duplicated from the previous measurement. A quick split-second change in pedal position from 0% to 100% and back to 0%, for example, can be missed all together or alternatively "stuck" for a few seconds on 100%. In order to overcome this limitation, we used the maximum value recorded five and ten seconds before the engine start (RPM>500) to explore reasons for engine starts. For vehicle models older than 2019, the SOC On-Board Diagnostic (OBD) Parameter Identification (PID) value is not reported in a standardized way. Note that results for SOC reported here are shown as reported by the CAN bus, but may not reflect absolute battery SOC. Our logger reported modeled catalyst temperature only for the Volt and Energi. The data shows that cold starts happened only for the first engine start of a trip and even for the longer range Volt we did not record even one cold start that is not the first in the trip. Our analysis, therefore is focused on the first engine start in each trip.

9.2. Proportion of Days with Engine Starts

For PHEVs, engine starts are a function of many parameters, including SOC and power requirement, among others. **Figure 96** suggests a high correlation between battery size and days with no engine starts that is similar to the zero emission trips and zero emission miles described in Section 5.4. For example, the percentage of travel days that end without engine starts is 4% for the short-range Plug-in Prius compared to 21% for the Energi. The Volt has such a high percentage of zero-emission driving days (63%) because it is a non-blended PHEV. These percentages may be lower when including PHEV users who drive their vehicle primarily as a conventional non-plug-in hybrid (charge less than 4 times per month).

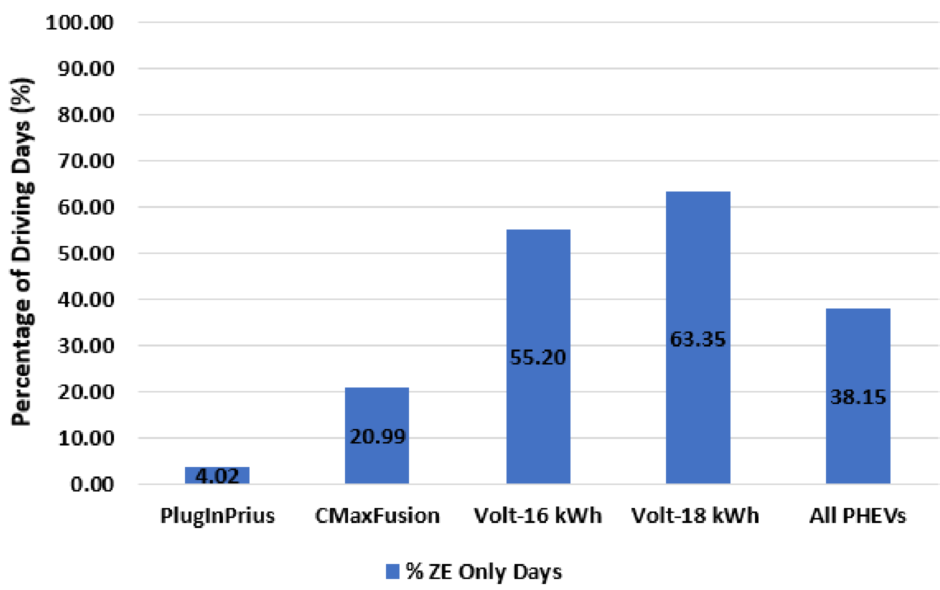


Figure 96 Share of Drive Days with No Engine Starts

9.3.Engine Start Event Description

The data collected per trip was chronologically ordered in a time series database to extract valid engine start events. An engine start event captures key metrics such as travel time and SOC within or around a timeframe in a trip wherein the RPM is greater than zero for more than 10 seconds. **Figure 97** provides a snapshot of the raw, time trace of a valid engine-on event. The total number of engine start events shared with CARB and used for this anlysis is 2,252,785 events, generated using data collected from 166 PHEVs, for up to one year per vehicle.

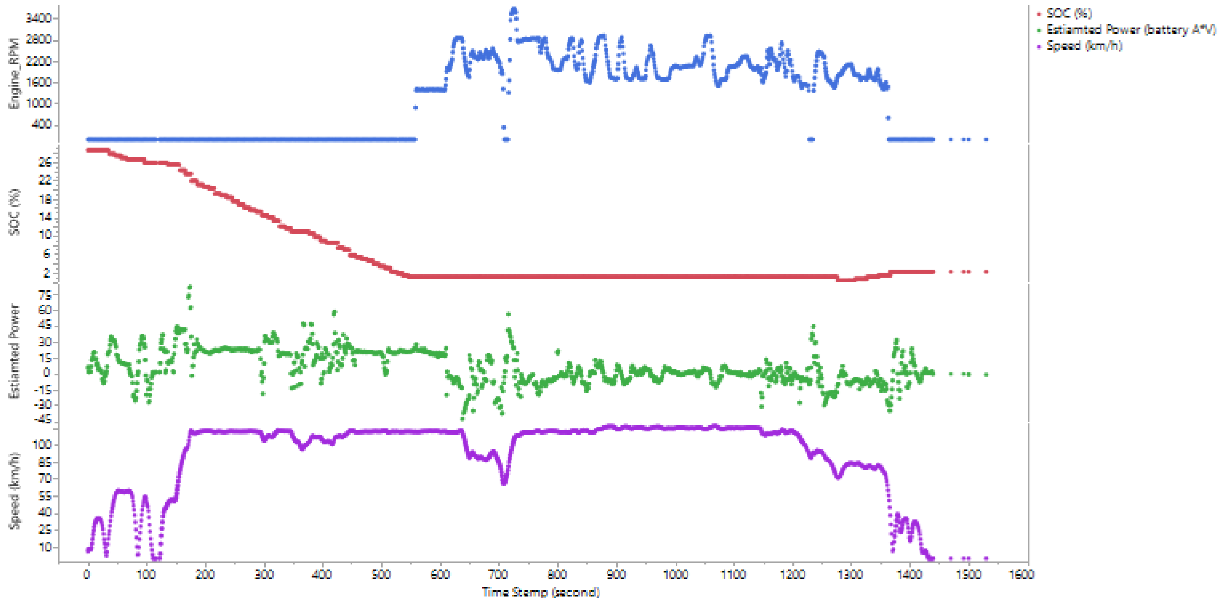


Figure 97 Engine-on Time Trace

It is critical to note that the sample frequencies of the collected data attributes aren't always consistent. For instance, some attributes are collected every few seconds while other parameters are recorded only when a change in value is detected; in such cases, a distinction cannot be made between parameters that have been updated but remained constant over several seconds versus those that have not been updated and are simply duplicated from the previous measurement. This lack of synchronicity makes is extremely challenging to analyze the relationship between certain attributes. In **Figure 97** for example we have a consistent speed trace for 10 seconds with one change in pedal position 3 seconds in. We don't know if the speed change and pedal position change actually happened within 3 seconds as both events could have happened within 5-10 seconds from reporting.

9.4. **Travel Conditions at Engine Start**

We first isolated and analyzed the following metrics, recorded at or prior to engine start events: SOC, maximum power requirement (calculated based on battery current and voltage), and catalytic converter temperature when available. We then analyzed the engine soak time (i.e., time elapsed between two consecutive engine start events). Although we aimed to explore the relationship of vehicle power requirements with road grade, we couldn't do so due to the differing data sample rates and imprecise data values. The relationship with accelerator pedal position is based on max pedal position recorded 10 seconds before the engine start to cover for the data limitations.

9.4.1. SOC at Engine Start

One of the major causes for engine starts is the inability of the electric motor to adequately propel the vehicle due to a low battery SOC (state of charge). We, therefore, explored the distribution of battery SOC when the engine is first turned-on within trips for all three PHEV models in the study. **Figure 98** illustrates this SOC distribution and highlights the fact that, for all vehicle models, most engine starts are invoked at a near-zero usable SOC (reported by the vehicle) as expected. Around 80% of Energi and Volt engine starts occur at SOCs below 1% while around 30% of Prius engine starts occur at SOCs under 1%. Moreover, roughly 90% of Energi, Volt and Prius engine starts occurred at SOCs below 5%, 2% and 12% respectively. As presented in previous sections, the Prius engine is more likely than the other models to start at high SOCs due to its relatively low battery capacity while the Volt engine is least likely to start at high SOCs due to being a non-blended PHEV and having a significantly higher battery capacity.

This analysis led to the development of three SOC classifications for engine starts with the range for each classification being dependent on the vehicle model. Low or Empty (E) SOC for all models is between 0% to 1%. Medium (M) SOC ranges for the Energi, Volt, and Prius is 1-5%, 1-2%, and 1-12% respectively. High (H) SOC for all vehicle models is any SOC above their medium range.

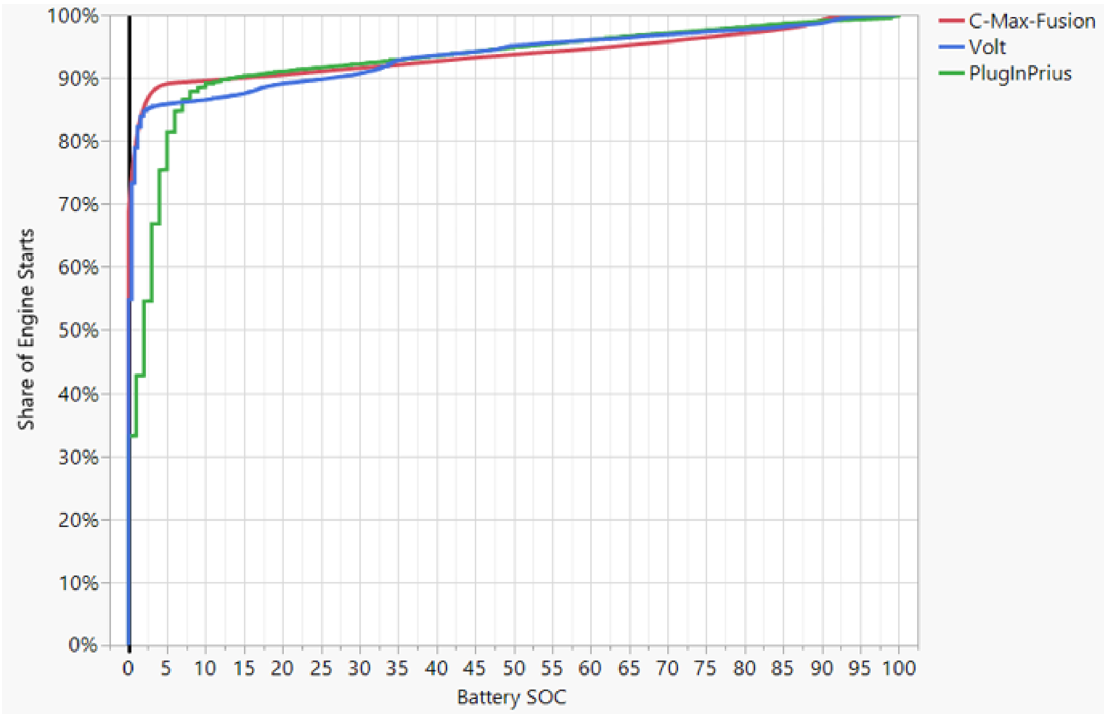


Figure 98 SOC at Engine Start

9.4.2. Maximum Estimated Power Requirement before Engine Start

In certain driving situations such as traveling at high speeds or climbing a steep incline, a PHEV's power requirement may exceed the power that can effectively be provided by its electric motor, regardless of the vehicle's battery SOC; these situations can force the internal combustion engine to start up in order to provide the additional power required to propel the vehicle at an appropriate speed. We explored the distribution of the maximum power requirement 10 seconds before the first engine start within trips, acknowledging the potential error due to time reporting gaps between the parameters, broken down by the SOC classifications determined in section 9.4.1, for each vehicle model (**Figure 99**). For the Prius, most low and medium SOC engine starts correlate with lower power requirements (0-12 kW) while majority of high SOC engine starts correlate with relatively higher power requirements (25-42 kW). The Energi engine starts follow a similar trend to that of the Prius starts for low and high SOC starts as low SOC is correlated with engine start at low power recruitment and high SOC is correlated with high power requirement. The medium SOC for the Energi is correlated with a wide range of power requirements (5-70 kW) as the engine starts before the battery is fully empty. On the other hand, there does not seem to be a strong correlation between SOC level and power requirements for

Volt engine starts; Most low, medium and high SOC engine starts correlate with approximately the same range of power requirements. Overall, the Prius and Energi vehicles, having relatively smaller battery capacities, are more likely to turn on their engine to meet high power requirements while the Volts, being non-blended PHEVs and having a larger battery capacity, are least likely to start their engine in the presence of high-power requirements.

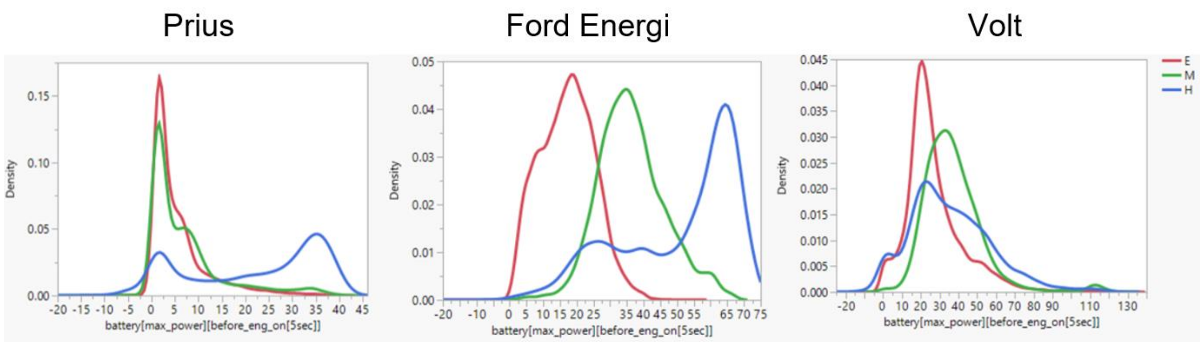


Figure 99 Maximum Power Requirement 5 Seconds before Engine Start (E-empty, M – medium SOC, H-high SOC)

9.4.3. Catalyst Temperature before Engine Start

Our loggers captured modeled catalyst temperature data for only the Energi and Volt vehicles. For all engine start trips of these two PHEV models, we analyzed the distribution of catalyst temperature for the first engine starts and all subsequent engine starts separately, assuming that the first starts would include a mixture of cold and hot starts and that subsequent starts would predominantly include hot starts. **Figure 100** depicts the distribution of catalyst temperature of first engine starts in blue and all subsequent engine starts in red. For both vehicle models, around half of the first engine starts occurring at temperatures above ambient temperatures. We didn't observe any cold starts after the first start for all trips even though 0.4% of the starts may not be fully warmed up to 425ºC. The lack of cold restarts could be because the vehicles are keeping the engine on for enough time to ensure that the first engine start adequately warms up the catalyst for any potential subsequent starts within the same trip. In addition, the time elapsed between consecutive engine starts is fairly small; among all the PHEV trips, the longest time elapsed between the first engine start and its successive start was 245 seconds which isn't enough time for the catalyst to completely cool off.

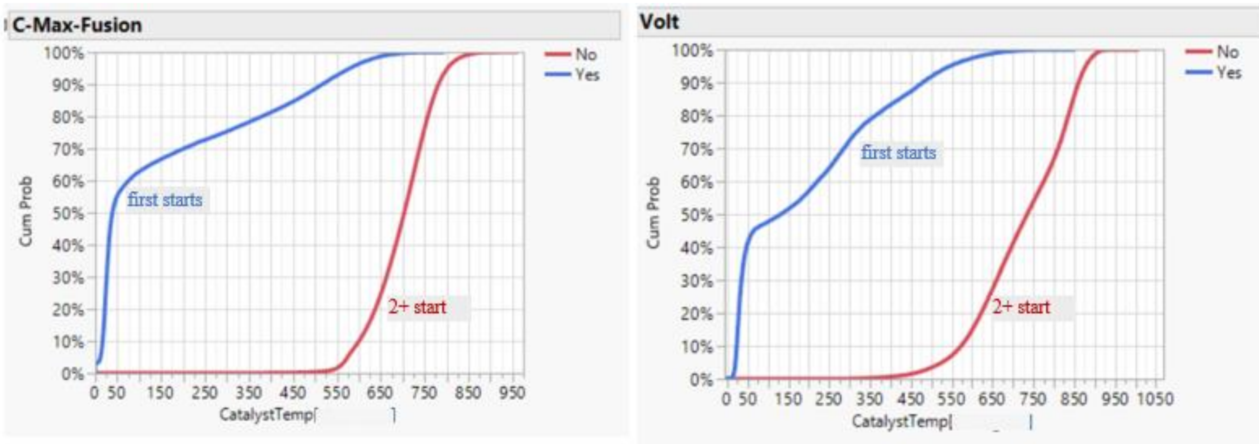


Figure 100 Catalyst Temperature at Engine Start

9.4.4. Engine Soak Time

For all engine start trips, we analyzed the time elapsed between two consecutive engine starts (soak time). This analysis includes any engine start regardless of travel distance and is based only on time and RPM. Engine starts that weren't the first engine start of trips were filtered out; we solely studied the soak time of the first engine start of every trip. Cold starts were defined, as starts after 720 minutes (i.e., 12 hours), which is consistent with EMFAC, with variation of warm starts depending on the minutes the engine is at idle. The soak time of each engine start was calculated by measuring the duration between it and the engine start preceding it. The SOC classification criteria derived in Section 9.4.1 was again used to categorize the engine starts.

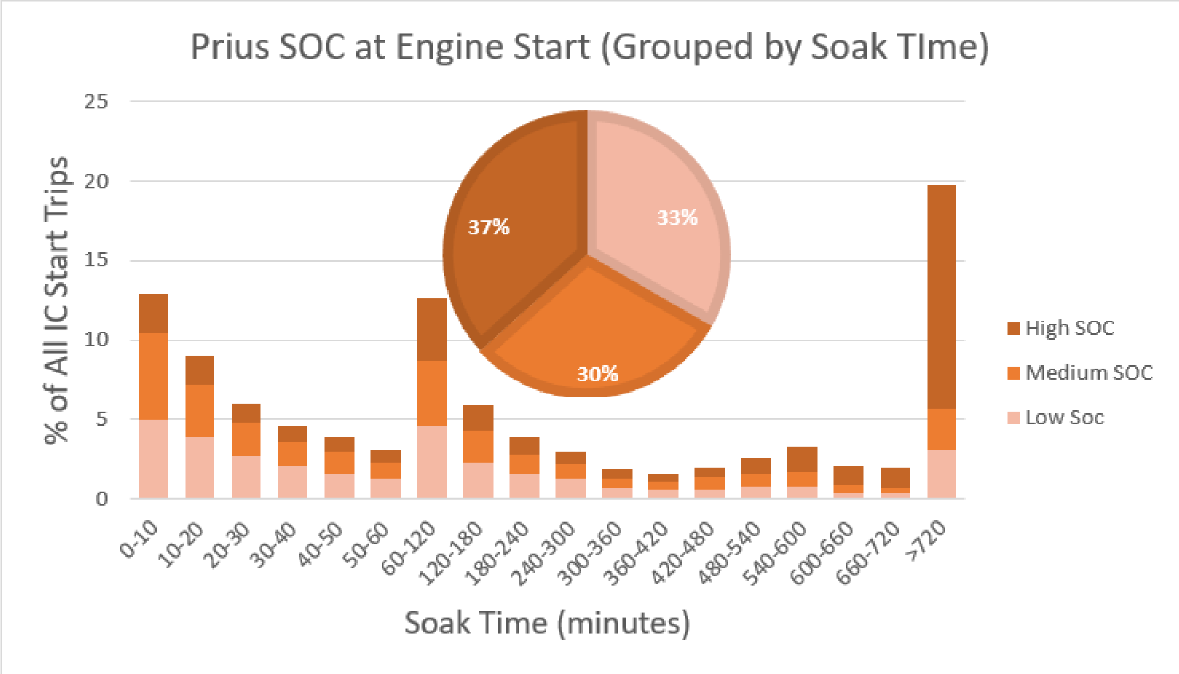


Figure 101 to **Figure 103** present the soak time distribution of Prius, Energi and Volt engine starts, respectively.

For all vehicles, there seems to be an inverse relationship between soak times and engine start shares; the proportion of engine start events decay as soak time increases. For all PHEV starts, high SOC starts seems to be more prevalent with greater soak times; engine starts with higher soak times may be more likely to have higher SOCs than engine starts with lower soak times because the vehicles higher SOC time reflect higher probability for charging events between the trips. For comparison to the PHEVs, **Figure 104** presents the soak time distribution of ICE vehicles starts from the conventional gasoline vehicles from the households participating in this study. The soak distribution from these conventional vehicles seems to be similar to that of the PHEVs.

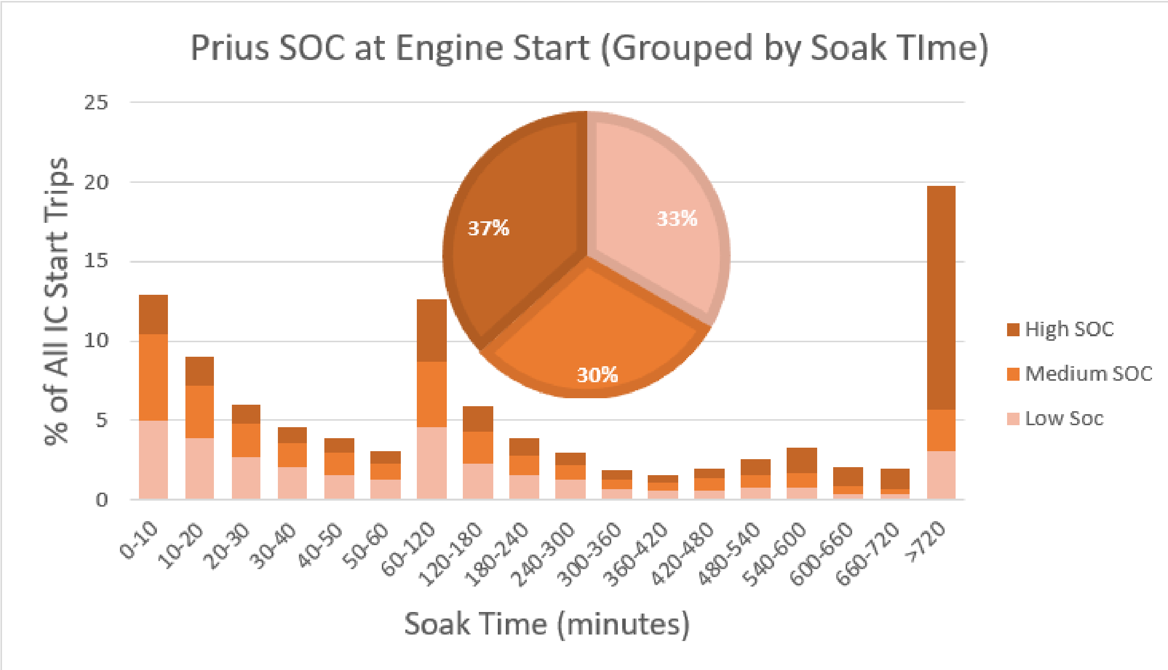


Figure 101 Prius Soak Time by SOC at Engine Start

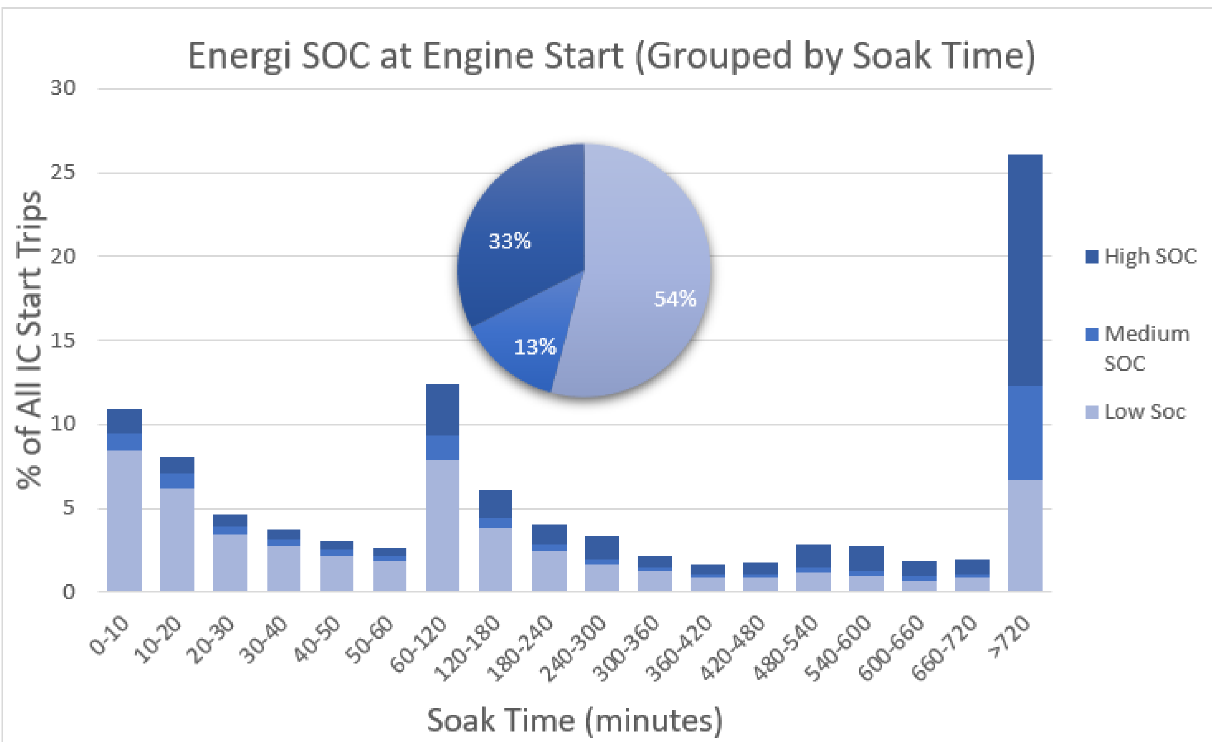


Figure 102 Energi Soak Time by SOC at Engine Start

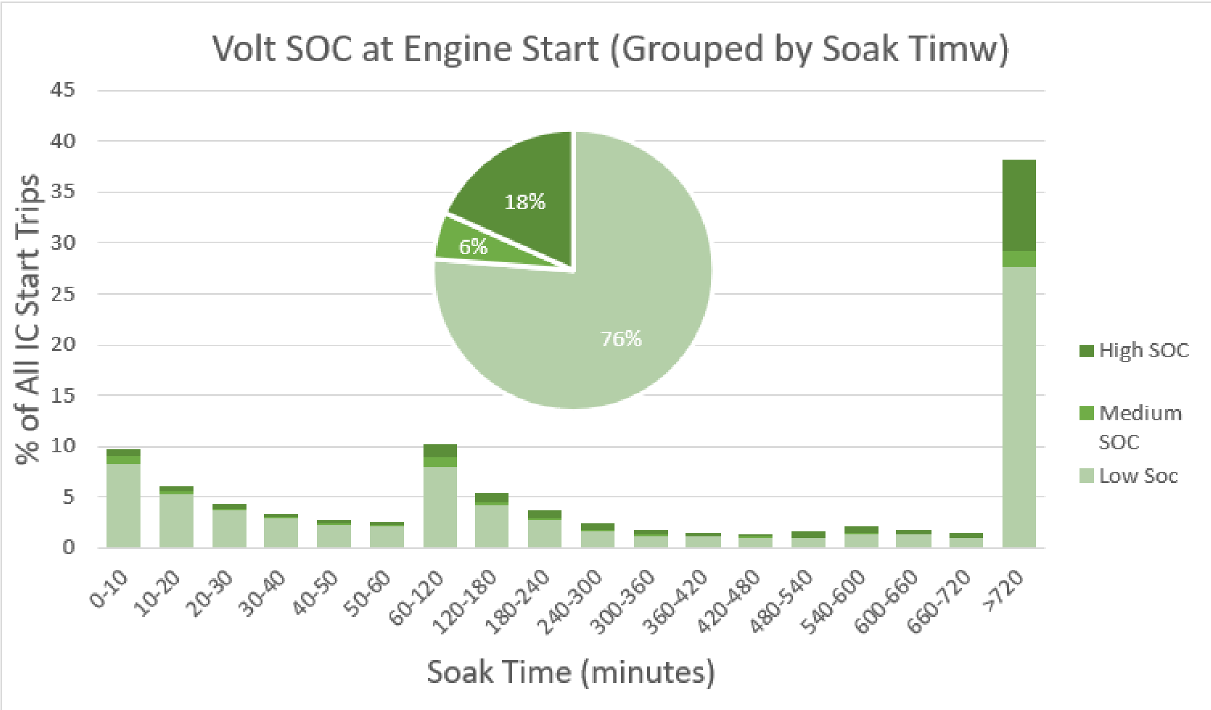


Figure 103 Volt Soak Time by SOC at Engine Start

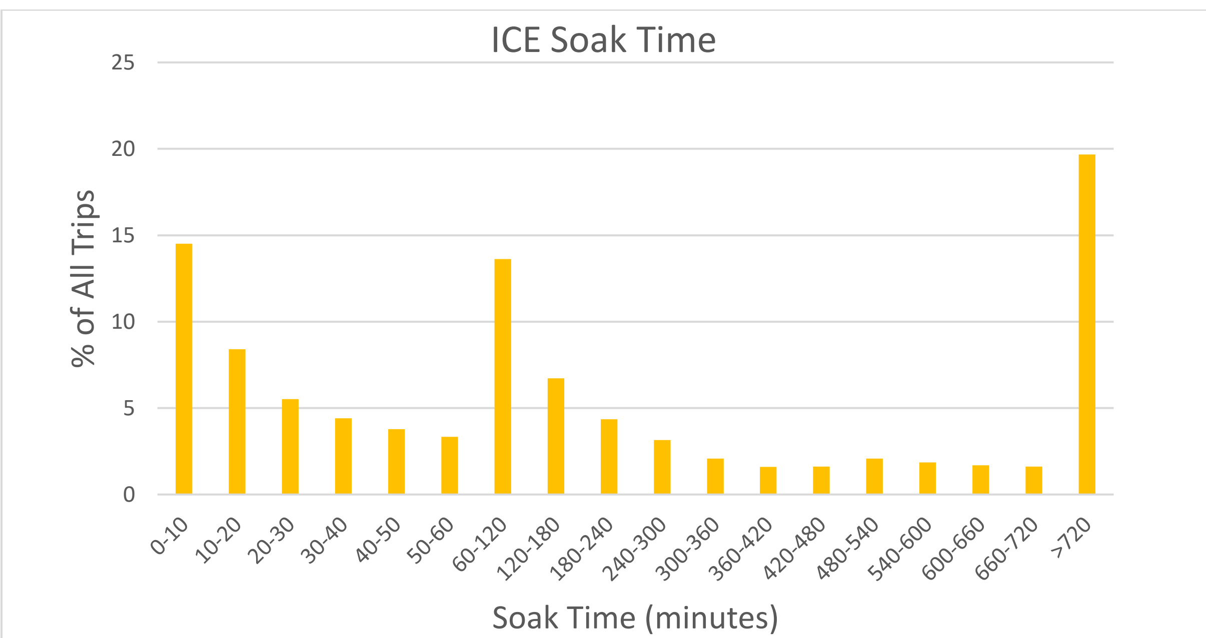


Figure 104 ICE Soak Time for the Conventional Gasoline Vehicles in Households

For each engine start trip, we analyzed two key distance metrics: the distance traveled from the beginning of a day to the first engine start of the day and the distance traveled from the beginning of a trip to the first engine start of the trip. To derive the first distance metric, we first grouped trips into days with a 3AM cutoff rather than the standard 12AM cutoff and then aggregated the distance of all trips that took place between the start of a day and the first engine start of the day for all days with an engine start. We chose a 3AM cutoff as it is the hour with the lowest trip frequency for all vehicle trips in our dataset. For the second distance metric, we simply calculated the distance from the start of a trip to the point at which the engine is first initiated for all engine start trips. For the first metric, we're only considering the first engine start of each day with an engine start while for the second metric, we are considering the first engine start of every trip. **Figure 105** and **Figure 106** depict the distribution of these two distance metrics for all PHEV vehicles.

Over 90% of the Prius' first engine starts occurring after less than 5 miles of travel from the beginning of the day; most of these starts happen at medium to high SOCs. On the other hand, only a little over 30% of the Volts' first engine starts occur after less than 5 miles of travel from the beginning of the day, most of which happen at low SOCs; the Volts are also more likely to have engine starts after longer distances of travel from the start of the day than other PHEVs. The Energi vehicles have a lower proportion of engine starts than the Prius and a greater proportion of engine starts than the Volts after less than 5 miles of travel from the beginning of the day. These observations are in line with section 9.4.2 which found that PHEVs with relatively small battery capacities such as the Prius' and the Energi vehicles are more susceptible to engine starts at medium and high SOCs than PHEVs with larger battery capacities such as the Volts, to meet high power demands. Overall, the occurrence of engine starts is more correlated to power demand for small battery PHEVs and with SOC (vehicle range) for large battery PHEVs. For all PHEVs, over 70% of engine starts occurring after less than 5 miles of travel from the start of the trip; most of these starts happen at low to medium SOCs, suggesting that most engine start trips start with low SOCs.

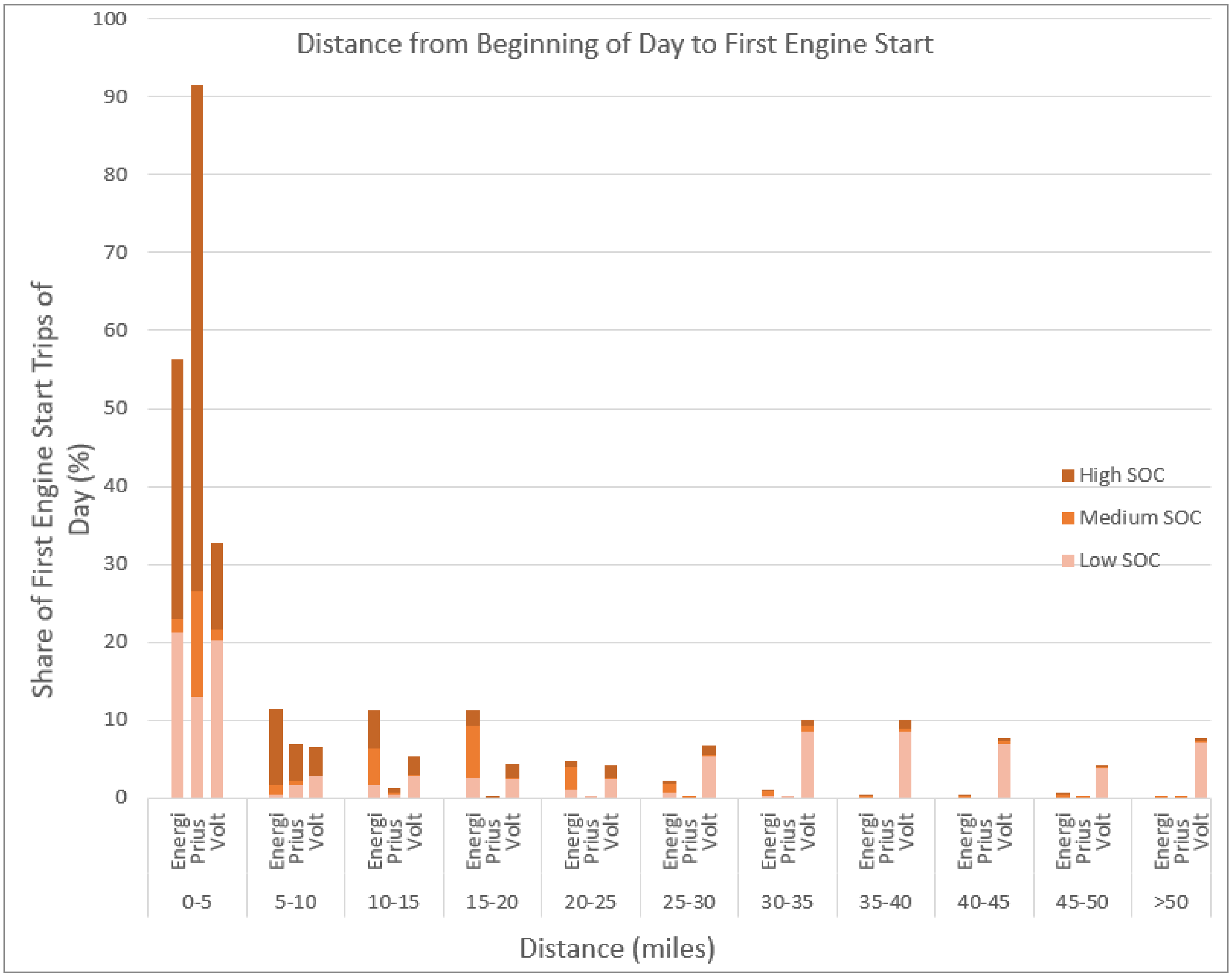


Figure 105 Distance from Start of Day to First Engine Start of Day for all PHEVs

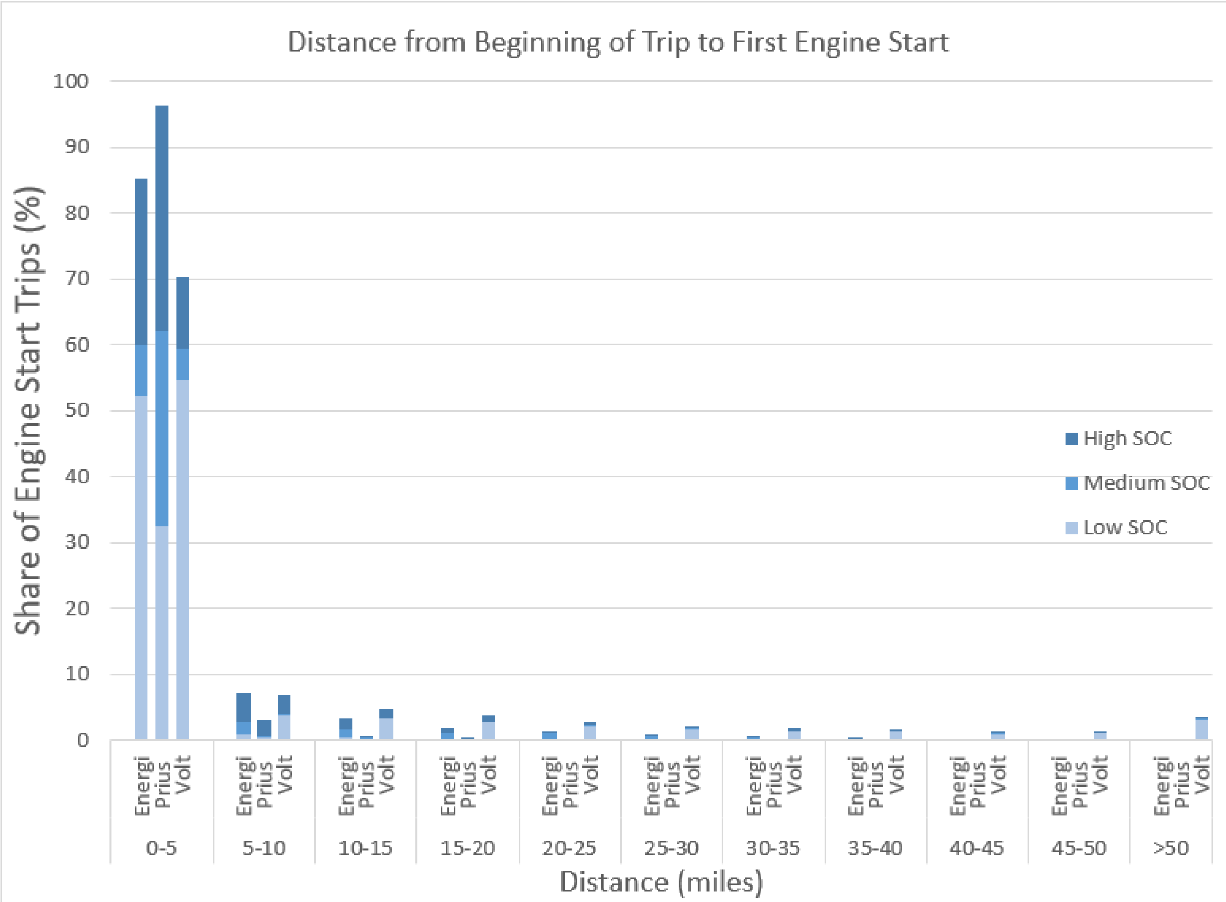


Figure 106 Distance from Start of Trip to First Engine Start of Trip for all PHEVs

9.5. Engine Starts Discussion

This section includes only the initial analysis of the data collected. The main task of this project was to provide to CARB the full dataset of engine starts including the events before and after the engine starts for further analysis. The data preparation included quality control and cleaning missing and bad data results from problems in logger configurations. We also tested the GPS elevation data using GIS models and conclude that the accuracy level was not sufficient for energy and power analysis. Overall, the data collected, and the sample times are not sufficient for calculating their power requirement and other factors for engine starts. Nevertheless, data analysis shows that long-range plug-in hybrids can finish many days and trips without any engine starts. We also conclude that long-range plug-in hybrids engine starts are mostly correlated with battery state of charge, while short range PHEVs' engine starts may be correlated with other factors. For all vehicles, there seems to be an inverse relationship between soak times and engine start shares; the proportion of engine start events decay as soak time increases. For all

PHEV Starts, high SOC starts seeming to be more prevalent with greater soak times; engine starts with higher soak times may be more likely to have higher SOCs than engine starts with lower soak times because the vehicles had more time to potentially recharge their batteries.

10. Conclusions

Results from this study provide insights on the usage of first generation PEVs and the environmental impacts of battery size, range, and driving and charging behavior.

Our data, from the survey, loggers, and interviews suggest that PEVs are being used extensively. Both long-range BEVs and PHEVs reported odometer readings corresponding to more than 13,000 miles/year on the survey and about 12,000 miles/year in the logged sample; and short-range BEVs, such as the Nissan Leaf, traveled more than 11,000 miles/year based on the survey and 9,800 miles/year for the logged vehicle sample. The logged household miles on PEVs and ICEVs were similar to the average California household fleet miles reported in the 2017 NHTS. While short-range BEVs had habitual daily driving distances similar to most of the PHEVs and long-range BEVs, the main difference is the total VMT resulted from fewer long trips.

Plug-in behavior was a focus of this research, as it helps us to understand how vehicle technology and configurations may be used to achieve environmental and air quality goals. Our survey shows that more than half of the PEV owners charge only at home while 33% combine home with other locations. The 14% who are not charging at home use mostly workplace charging and, in some cases, fast charging opportunities. We find that charging power is correlated with battery size as short-range PHEVs and BEVs have more L1 charging events, but on average most of their energy comes from L2 chargers. DCFC events provide almost 25% of the energy for Nissan Leafs with 30kwh battery but only 6% for the older 24kwh Leaf. This difference is most likely a result of new LEAF owners having access to free charging for the first two years of ownership. Over the 3 years of the study so far, PHEV participants with larger batteries plugged-in more frequently than those with smaller batteries. Presumably, PHEVs with smaller batteries would benefit from plugging-in more than those with larger batteries. Upon further investigation through surveys and interviews, we found that charger availability combined with the range recovered per charging event is a significant factor in the decision to plug-in or not. For BEVs, we find a variety of reasons for plugging-in, including the price of charging (e.g., free DCFC, free workplace charging) and travel behavior, which have a strong impact on the need for charging. Overall, longer-range BEVs plug-in at the same frequency as shorter range BEVs but with a higher kWh load at each charging event. As expected, many users started charging at or around midnight at home to enjoy lower electricity rates and a second peak occurred around 9am, when charging at work. Our data do not show a peak that correlated with the afternoon commute but, rather, a slow growth of charging demand between 2pm and the midnight peak.

Our results show that longer-range PHEVs have a utility factors (eVMT/VMT) that are lower but similar to the standard utility factor, while short range PHEVs have utility factors that are significantly lower than expected, because of driving and charging behavior different than assumed by the standard and because users who drive on gasoline only.

In the context of a household with one PEV and one ICEV, BEV/ICEV households have higher utility factors compared with the PHEV/ICEV households. When comparing GHG emissions per households, the efficient gasoline engines of the PHEVs lead to reduced GHG emissions and environmental impact but still BEV households present better results. Some households with Plug-in Priuses had lower gasoline consumption than households with longer-range PHEVs. However, based on their electric range and the drivers' charging and driving behavior, households with longer-range PHEVs and longer-range BEVs typically have less gasoline consumption than households with short-range BEVs (such as the 24kWh LEAF). Blended (or short-range) PHEVs have a lower utility factor than do long-range PHEVs, because they are limited by both the electric range and the drivers' behaviors. Longer-range PHEVs tend to have more frequent charging and higher battery capacity than do short-range PHEVs, and these acts to increase the average utility factor. Longer-range BEVs had the highest utility factor, as did the entire household fleet to which they belonged.

Longer-range BEVs had more electrified miles than did shorter-range BEVs and all-range PHEVs, as did the household fleet to which they belonged. Households with longer-range BEVs displace the use of their ICEVs on longer trips, whereas households with short-range BEVs must rely on a less efficient ICEV for longer trips.

The interviews showed that early PEV drivers may still be learning about their PEVs, even months or years after they acquired one, but they may continue to use the car based on old information. The eVMT is affected by the vehicle capabilities, as well as charging and driving behavior. HOV lane incentives, when cited as a primary purchase incentive, correlated with reduced charging frequency and higher annual mileage, leading to a lower utility factor than expected.

For the engine starts, we see that longer-range Volts have fewer cold starts by finishing more trips and days without starting the ICE. We didn't identify a second cold start in a single trip even though we see engine start results from power requirements for the Ford Energi and Prius.

Overall the results suggest that longer-range PHEVs and BEVs have more electrified miles and that results in low GHG footprint, but to maximize the impact of PEVs, a full set of policies is needed to address charging behavior and vehicle purchase. The results of this study point to factors that affect the environmental impact of PEVs. As those factors continue to change, on-going research is necessary to shape policy that leads to more sustainable transportation and PEV usage. The household analysis suggests the longer-range BEVs can reduce the environmental impact of transportation, but future households may move to multiple PEVs or fuel cell electric vehicles. Combining BEVs with PHEVs, or short- and long-range BEVs, and fuel cell electric vehicles would significantly change the electrification of miles at the household level. The second generation of PEVs and fuel cell electric vehicles will likely have a higher utility factor, due to the availability of longer electric ranges and larger vehicle platforms. The follow-up project currently underway using the same methods as presented in this report will focus on the second generation of PEVs and fuel cell electric vehicles and their users.

11. Glossary

AE	all electric (a mode of PHEVs)
AER	all-electric range
BEV	battery electric vehicle
CDB	charge depleting blend
CS	charge sustaining
DCFC	DC fast charger
eVMT	electric vehicle miles traveled
GHG	greenhouse gas
gVMT	gasoline vehicle miles traveled
HDD	habitual driving distance
HH	household
HOV	high occupancy vehicle
ICEV	internal combustion engine vehicle
L1	Level 1 (refers to type of charger)
L2	Level 2 (refers to type of charger)
LDT	long distance travel
MPG	miles per gallon
MPGe	miles per gallon equivalent
MY	model year
PEV	plug-in electric vehicle
PHEV	plug-in hybrid electric vehicle
SOC	state of charge
UF	utility factor
VMT	vehicle miles travelled
ZE	zero emission
zVMT	zero tailpipe emission trip

12. Research Papers Based on the Collected Data

Published

Nicholas, M. A., Tal, G., & Turrentine, T. S. (2016). Advanced Plug-in Electric Vehicle Travel and Charging Behavior Interim Report. Institute of Transportation Studies, University of California. Davis, Research Report UCD-ITS-RR-16-10.

Tal, G., Lee, J. H., & Nicholas, M. A. (2018). Observed Charging Rates in California.

Tal, G., & Xing, Y. (2017). Modeling the choice of plug-in electric vehicles in California: a nested logit approach (No. 17-02193).

Hardman, S., & Tal, G. (2018). Who are the early adopters of fuel cell vehicles?. International Journal of Hydrogen Energy, 43(37), 17857-17866.

Berliner, R. M., Hardman, S., & Tal, G. (2019). Uncovering early adopter's perceptions and purchase intentions of automated vehicles: Insights from early adopters of electric vehicles in California. Transportation research part F: traffic psychology and behaviour, 60, 712-722.

Lee, J. H., Hardman, S. J., & Tal, G. (2019). Who is buying electric vehicles in California? Characterizing early adopter heterogeneity and forecasting market diffusion. Energy Research & Social Science, 55, 218-226.

Publications under review (September 2019):

Jae Hyun Lee, Alan Jenn, Scott Hardman, Gil Tal (2019). An in-depth examination of electric vehicle incentives: consumer heterogeneity and changing response over time. Under Review at Transportation Research Part A: Policy and Practice (First submission: October 2018)

Debapriya Chakraborty, Jae Hyun Lee, David Bunch, Gil Tal (2019) Demand Drivers for Plug-In Vehicle Charging Infrastructure-An Analysis of Plug-In Electric Vehicle Commuters. Under review at Transportation Research Part D: Transport and Environment (First submission: January 2019)

Jae Hyun Lee, Debapriya Chakraborty, Scott Hardman, Gil Tal (2019). Exploring Heterogeneous Electric Vehicle Charging Behavior: Mixed Usage of Charging Infrastructure. Under review at Transportation Research Part D: Transport and Environment (First submission: November 2018)

Ahmet Mandev, Frances Sprei, Gil Tal, (2019). Electrification of vehicle miles travelled within the household context. Under review at Transportation Research Part D: Transport and Environment (First submission: August 2019)

Seshadri Srinivasa Raghavan and Gil Tal. (2019). Plug-in Hybrid Electric Vehicle Observed Utility Factor: Why the Observed Electrification Performance Differ from Expectations? Under Review at the International Journal of Sustainable Transportation (First submission: August 2019)

13. References

Aviquzzaman, M. (2014). Analysis of Plug-In hybrid Electric Vehicles' utility factors using GPS-based longitudinal travel data, Lamar University-Beaumont.

Björnsson, L.-H. and S. Karlsson (2017). "Electrification of the two-car household: PHEV or BEV?" Transportation Research Part C: Emerging Technologies 85: 363-376.

Brecht, P. and J. Orenberg (2019). 2019-2020 Investment Plan Update for the Alternative and Renewable Fuel and Vehicle Technology Program. California Energy Commission. Technical Report CEC-600-2018-005-SD.

BTS. 2017. "National Household Travel Survey Long Distance Travel Quick Facts." https://www.bts.gov/statistical-products/surveys/national-household-travel-survey-long-distance-travel-quick-facts.

———. 2018. "Long Distance Transportation Patterns: Mode Choice." https://www.bts.gov/statistical-products/surveys/national-household-travel-survey-summer-travel-quick-facts.

CalTrans. 2013. "2010-2012 California Household Travel Survey." https://www.nrel.gov/transportation/secure-transportation-data/tsdc-california-travel-survey.html.

CARB (2017). California's Advanced Clean Cars Midterm Review , Appendix I: Alternative Credits for Zero Emission Vehicles and Plug-in Hybrid Electric Vehicles.

CARB (2017). California's Advanced Clean Cars Midterm Review Appendix H: Plug-in Hybrid Electric Vehicle Emissions Testing

CARB. 2017a. "California's Advanced Clean Cars Midterm Review."

———. 2017b. "California's Advanced Clean Cars Midterm Review , Appendix I: Alternative Credits for Zero Emission Vehicles and Plug-in Hybrid Electric Vehicles."

———. 2017c. "California Climate Investments Quantification Methodology Emission Factor Database." https://www.arb.ca.gov/cc/capandtrade/auctionproceeds/cci_emissionfactordatabase.xlsx?_ga=2.192111850.1503633160.1549935127-1695908195.1547853262.

CARB (2018). EMFAC2017 Volume III - Technical Documentation, V1.0.2.

Contestabile, M., M. Alajaji and B. Almubarak (2017). "Will current electric vehicle policy lead to cost-effective electrification of passenger car transport?" Energy Policy 110: 20-30.

Crain, T., T. Gorgia and R. J. Alley (2016). Application of PHEV Fractional Utility Factor Weighting to EcoCAR On-Road Emissions and Energy Consumption Testing, SAE Technical Paper.

Crain, T., T. Gorgia, and R. J. Alley. 2016. Application of PHEV Fractional Utility Factor Weighting to EcoCAR On-Road Emissions and Energy Consumption Testing.In, SAE Technical Paper, Davies, J. and K. S. Kurani (2013). "Moving from assumption to observation: Implications for energy and emissions impacts of plug-in hybrid electric vehicles." Energy Policy 62: 550-560.

Davies, J., and K. Kurani. 2010. Recharging Behavior of Households' Plug-In Hybrid Electric Vehicles: Observed Variation in Use of Conversions of 5-kW-h Blended Plug-In Hybrid Electric Vehicle. Transportation Research Record: Journal of the Transportation Research Board, No. 2191 pp. 75-83.

Davis, L. W. (2019). "How much are electric vehicles driven?" Applied Economics Letters 26(18): 1497-1502.

Davis, L.W., 2019. How much are electric vehicles driven?. Applied Economics Letters, pp.1-6.

Dimitropoulos, A., P. Rietveld and J. N. Van Ommeren (2013). "Consumer valuation of changes in driving range: A meta-analysis." Transportation Research Part A: Policy and Practice 55: 27-45.

DOE/AFDC. (2017). "Electric Vehicle Benefits and Considerations." Retrieved July 17, 2018, from https://www.afdc.energy.gov/fuels/electricity_benefits.html.

Dong, J., Liu, C., Lin, Z., 2014. Charging infrastructure planning for promoting battery electric vehicles: An activity-based approach using multiday travel data. Transp. Res. Part C Emerg. Technol. 38, 44–55. https://doi.org/10.1016/j.trc.2013.11.001

Federal Highway Administration. (2017). 2017 National Household Travel Survey, U.S. Department of Transportation, Washington, DC. Available online: https://nhts.ornl.gov.

FHWA (2017). Summary of Travel Trends: 2017 National Household Travel Survey.

Glatting, Gerhard, Peter Kletting, Sven N Reske, Kathrin Hohl, and Christina Ring. 2007. “Choosing the Optimal Fit Function: Comparison of the Akaike Information Criterion and the F-test.” Medical Physics 34 (11): 4285–92.

Hardman, S., A. Jenn, G. Tal, J. Axsen, G. Beard, N. Daina, E. Figenbaum, N. Jakobsson, P. Jochem and N. Kinnear (2018). "A review of consumer preferences of and interactions with electric vehicle charging infrastructure." Transportation Research Part D: Transport and Environment 62: 508-523.

Hardman, S., Jenn, A., Tal, G., Axsen, J., Beard, G., Daina, N., Figenbaum, E., Jakobsson, N., Jochem, P., Kinnear, N., Plötz, P., Pontes, J., Refa, N., Sprei, F., Turrentine, T., Witkamp, B., 2018. A review of consumer preferences of and interactions with electric vehicle charging infrastructure. Transp. Res. Part D Transp. Environ. 62, 508–523. https://doi.org/10.1016/j.trd.2018.04.002

Hinds, Brett. 2017. “Ford Pushing for Common Industry Metrics to Understand Customer Daily Electric Driving Requirements.” https://www.greencarcongress.com/2017/02/20170213-ford.html.

Idaho National Laboratory, 2015. How Americans Charge Their Electric Vehicles Findings from the largest plug-in electric vehicle infrastructure demonstration in the world.

International Energy Agency. (2018). "Global EV Outlook 2018-Towards Cross-Modal Electrification." Retrieved July 17, 2018, from https://www.iea.org/gevo2018/.

Ji, W., Nicholas, M., Tal, G., 2015. Electric vehicle fast charger planning for metropolitan planning organizations: Adapting to changing markets and vehicle technology. Transp. Res. Rec. 2502, 134–143. https://doi.org/10.3141/2502-16

Kunzmann, M. and V. Masterman (2013). California Household Travel Survey (CHTS)

Liao, F., E. Molin and B. van Wee (2017). "Consumer preferences for electric vehicles: a literature review." Transport Reviews 37(3): 252-275.

Lin, Zhenhong, Dong, Changzheng Liu, and David Greene. 2012. "Estimation of Energy Use by Plug-in Hybrid Electric Vehicles - Validating Gamma Distribution for Representing Random Daily Driving Distance." Transportation Research Record. https://doi.org/10.3141/2287-05.

Lloro, Alicia, and David Brownstone. 2018. "Vehicle Choice and Utilization: Improving Estimation with Partially Observed Choices and Hybrid Pairs." Journal of Choice Modelling. https://doi.org/10.1016/j.jocm.2018.05.005.

Loveday, S. (2018). "May 2018 Plug-In Electric Vehicle Sales Report Card." Retrieved July 17, 2018, from https://insideevs.com/may-2018-plug-in-electric-vehicle-sales-report-card/.

Lutsey, N., D. Meszler, A. Isenstadt, J. German and J. Miller (2017). "Efficiency Technology and Cost Assessment for US 2025–2030 Light-Duty Vehicles." International Council on Clean Transportation (ICCT), Washington, USA, White Paper, 22nd March.

McGuckin, N. and A. Fucci (2017). Summary of Travel Trends: 2017 National Household Travel Survey, Federal Highway Administration.

McLaren, J., J. Miller, E. O'Shaughnessy, E. Wood and E. Shapiro (2016). "Emissions associated with electric vehicle charging: Impact of electricity generation mix, charging infrastructure availability, and vehicle type." NREL (National Renewable Energy Laboratory (NREL), Golden, CO (United States)), Tech. Rep.

Muratori, M. (2018). "Impact of uncoordinated plug-in electric vehicle charging on residential power demand." Nature Energy 3(3): 193.

Nicholas, M., G. Tal and T. Turrentine (2017). Advanced Plug-in Electric Vehicle Travel and Charging Behavior Interim Report, Research Report–UCD-ITS-RR-16.

Nicholas, M., Tal, G., 2015. Charging for Charging at Work: Increasing the Availability of Charging Through Pricing.

Nicholas, Michael, Gil Tal, and Thomas S Turrentine. 2017. "Advanced Plug-in Electric Vehicle Travel and Charging Behavior Interim Report Advanced Plug in Electric Vehicle Travel and Charging Behavior Interim Report." International Energy Agency (IEA). https://www.iea.org/topics/transport/subtopics/mobilitymodelpartnership/.

Pham, A. and M. Jeftic (2018). Characterization of Gaseous Emissions from Blended Plug-In Hybrid Electric Vehicles during High-Power Cold-Starts, SAE Technical Paper.

Plötz, Patrick, Niklas Jakobsson, and Frances Sprei. 2017. “On the Distribution of Individual Daily Driving Distances.” Transportation Research Part B: Methodological 101: 213–27. internal-pdf://68.234.155.95/On the distribution of individual daily drivin.pdf.

Plötz, Patrick, Simon Árpád Funke, and Patrick Jochem. 2018. “The Impact of Daily and Annual Driving on Fuel Economy and CO2 Emissions of Plug-in Hybrid Electric Vehicles.” Transportation Research Part A: Policy and Practice 118: 331–40.

PSRC TCS (2006). 2004–2006 Puget Sound Traffic Choices Study.

Raghavan, S. S. and G. Tal (2019). Characterizing Plug-In Electric Vehicle Driving and Charging Behavior: Observations from a Year Long Data Collection Study.

SAE. 2010. “J2481_201009 : Utility Factor Definitions for Plug-In Hybrid Electric Vehicles Using Travel Survey Data.” https://www.sae.org/standards/content/j2841_201009/.

Santini, D.J., Zhou, Y.F., Elango, V., Xu, Y., Guensler, R., 2014. Daytime Charging: What Is the Hierarchy of Opportunities and Customer Needs? Case Study Based on Atlanta Commute Data.

Smart, J. and S. Schey (2012). "Battery electric vehicle driving and charging behavior observed early in the EV project." SAE International Journal of Alternative Powertrains 1(2012-01-0199): 27-33.

Smart, J., T. Bradley and S. Salisbury (2014). "Actual versus estimated utility factor of a large set of privately owned Chevrolet Volts." SAE International Journal of Alternative Powertrains 3(1): 30-35.

Smart, J., T. Bradley, and S. Salisbury. 2014. Actual versus estimated utility factor of a large set of privately owned Chevrolet Volts. SAE International Journal of Alternative Powertrains, Vol. 3, No. 1, pp. 30-35.

Smart, J., W. Powell and S. Schey (2013). Extended range electric vehicle driving and charging behavior observed early in the EV project, SAE Technical Paper.

Smart, J., W. Powell, and S. Schey. 2013 Extended range electric vehicle driving and charging behavior observed early in the EV project.In, SAE Technical Paper.

Smith, Mary S, and Thomas A Butcher. 2008. “How Far Should Parkers Have to Walk?” Parking 47 (4).

Tal, Gil., Dunckley, J., 2016. Plug-In Electric Vehicle Multi-State Market and Charging Survey, in: EVS29.

Tal, Gil, Michael A Nicholas, Jamie Davies, and Justin Woodjack. 2014. “Charging Behavior Impacts on Electric Vehicle Miles Traveled: Who Is Not Plugging In?” Transportation Research Record 2454 (1): 53–60. internal-pdf://0678763843/Charging Behavior Impacts on Electric Vehicle.pdf.

Tamor, Michael A, Chris Gearhart, and Ciro Soto. 2013. “A Statistical Approach to Estimating Acceptance of Electric Vehicles and Electrification of Personal Transportation.” Transportation Research Part C: Emerging Technologies 26: 125–34. internal-pdf://61.229.123.13/A statistical approach to estimating acceptanc.pdf.

Tamor, Michael A, Paul E Moraal, Briana Reprogle, and Miloš Milačić. 2015. “Rapid Estimation of Electric Vehicle Acceptance Using a General Description of Driving Patterns.” Transportation Research Part C: Emerging Technologies 51: 136–48. internal-pdf://210.174.249.38/Rapid estimation of electric vehicle acceptanc.pdf.

Turrentine, T. and G. Tal (2015). Advanced Plug-In Electric Vehicle Usage and Charging Behavior. Contract #12-319. California, CARB and CEC.

Turrentine, Thomas, Gil Tal, and David Rapson. 2018. “The Dynamics of Plug- in Electric Vehicles in the Secondary Market and Their Implications for Vehicle Demand, Durability , and Emissions.” Institute of Transportation Studies. https://doi.org/10.3141/2454-07.

TxDOT (2015). 2002-2015 Texas Regional Travel Surveys.

Weiller, C., 2011. Plug-in hybrid electric vehicle impacts on hourly electricity demand in the United States. Energy Policy 39, 3766–3778. https://doi.org/10.1016/j.enpol.2011.04.005

Wietschel, M., P. Plötz, A. Kühn and T. Gnann (2013). "Market evolution scenarios for electric vehicles." Summary report. Fraunhofer Institute for Systems and Innovation Research ISI: Karlsruhe. Retrieved April 11: 2014.

Wood, E. W., C. L. Rames, A. Bedir, N. Crisostomo and J. Allen (2018). California Plug-In Electric Vehicle Infrastructure Projections: 2017-2025-Future Infrastructure Needs for Reaching the State's Zero Emission-Vehicle Deployment Goals, National Renewable Energy Lab.(NREL), Golden, CO (United States).

Yang, Yong, and Ana V. Diez-Roux. 2012. “Walking Distance by Trip Purpose and Population Subgroups.” American Journal of Preventive Medicine. https://doi.org/10.1016/j.amepre.2012.03.015.

Appendix A: Survey Questionnaire