Strategic infrastructure planning to enable personal vehicle electrification

by

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Abstract

The transportation sector contributes a substantial fraction of global greenhouse gas emissions. For example, in the United States (US), it contributes roughly one third of greenhouse gas emissions and is projected to remain a significant contributor several decades into the future if no further policy actions are taken. Around 40% of the US greenhouse gas emissions in the transportation sector come from personal vehicles. A transition from internal combustion engine vehicles to electric vehicles has the potential to achieve significant emission reductions from personal vehicles when combined with a decarbonized electricity system. However, electric vehicles have a limited range and charging these vehicles may stress the power grid.

To enable widespread vehicle electrification, a suitable network of electric vehicle charging stations and adequate power generation and distribution systems will be essential. Yet questions remain about the impact of different infrastructure expansion strategies.

This thesis addresses a gap in the current literature by examining infrastructure requirements in the context of varying travel patterns and technology performance. Specifically, this work evaluates infrastructure expansion strategies against spatially- and temporally-resolved vehicle and household energy-consuming behaviors, based on a physical modeling of electric vehicle energy consumption.

The central result of this thesis is that certain infrastructure expansion strategies can have significant impact on meeting travel demand to enable personal vehicle electrification. Specifically, this thesis reveals the essential role that overnight home charging can play, and the high impact of highway fast charging to meet energy requirements over time with battery electric vehicles (BEVs). This research also shows that circuit upgrades are likely needed to accommodate electricity demand peaks from BEV charging in some but not all locations. Adopting certain demand management strategies such as delaying home charging and shifting highway fast charging to adjacent highway stops may significantly reduce circuit peak loads. In the case of hydrogen fuel cell vehicles (HFCVs), this research shows that for a small fraction of personal vehicles, highway refueling can be sufficient for meeting energy requirements, though other refueling options will likely be needed for most drivers.

Insights from this thesis can inform assessments of the viability of using electric vehicles as personal vehicles to conveniently meet energy demand. These insights also help reveal effective strategies for policy-making and other investments in infrastructure expansion to support vehicle electrification. Results from this thesis also provide insight on methods for reducing the cost of BEV charging and HFCV refueling by increasing the utilization of infrastructure.

Fundamentally, this thesis contributes to an understanding of longitudinal vehicle and household energy consuming behaviors based on travel patterns and power grid electricity demand profiles. A majority of drivers can experience days with high energy requirements on a small number of days a year, leading to the high impact of occasional access to highway fast charging and supplementary long-range vehicles in meeting energy demand. Moreover, locations and times where people tend to stay for an extended period of time to allow for uninterrupted charging sessions, such as overnight at home and during the day at work, can often correspond to off-peak hours when grid electricity demand is low. In addition, the diversity in the time drivers arrive at and depart from these locations opens up opportunities for demand management to reduce electricity demand peaks from charging. These observations lay the groundwork for strategic infrastructure expansion to enable personal vehicle electrification.

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Chapter 1

Introduction

1.1 Motivation

The transportation sector is a major contributor to global greenhouse gas emissions [5]. For example, it was estimated to contribute around one third of greenhouse gas emissions in the United States (US) in 2019 [6]. Several sources have projected that transportation emissions will remain significant in the foreseeable future without further decarbonization policies [6, 7, 5]. Around 40% of the transportation emissions come from passenger vehicles in the US [8]. Decarbonization of these vehicles can be critical for reducing emissions and mitigating climate change. Electric vehicles are promising potential technology options to decarbonize personal vehicles. Electric vehicles, such as battery electric vehicles (BEVs) and hydrogen fuel cell vehicles (HFCVs), offer a lower emission intensity (even when considering the current carbon intensity of the grid in the US) at a comparable cost with gasoline-powered cars [9].

Although electric vehicles have the potential to reduce emissions, there are several possible barriers to their adoption. These barriers can be classified into three types: 1) technological barriers that are determined by the characteristics of vehicles and charging/refueling technologies, 2) infrastructural barriers that consider the availability and cost of charging/refueling infrastructure and the readiness of the power system for charging, and 3) psychological barriers where the perceived knowledge of electric vehicles prohibits their adoption. This thesis focuses on the first two types of barriers and examines how to address these barriers with strategic infrastructure planning. While the third barrier can be important to understand for enabling vehicle electrification, it is outside the scope of this thesis and further research is needed.

For BEVs, one potential barrier is that they have a limited range such that charging is needed between trips to meet travel demand [10]. For example, more than 10% of the vehicle-days (days when a vehicle is used) in the US have energy requirements that exceed the energy capacity of a BEV with a 24 kWh battery capacity [10]. It is important to address these vehicle-days with high energy requirements when planning BEV charging infrastructure since multiple charging events may be needed throughout the day. Covering drivers' needs on these vehicle-days could help determine whether or not they decide to adopt BEVs.

Another potential barrier to BEV adoption is the limited charging infrastructure. As of the end of the year 2021, there are around 100,000 public charging plugs at around 40,000 Level 2 charging stations and 5,000 fast charging stations in the US [11]. Yet more chargers are needed in order to support widespread vehicle electrification. In the US, President Biden's infrastructure plan has pledged to build 500,000 new charging plugs by year 2030 [12]. These BEV chargers need to be strategically placed in order to enable convenient and reliable access to charging.

Expansion of BEV charging infrastructure is critical for enabling BEV adoption but it can potentially pose risks of overloading the power grid. For example, BEV home charging can often occur during late afternoons and early evenings when people arrive at home and the non-charging related electricity demand is also high [13, 14, 15]. If charging is left uncoordinated, it can cause peaks in grid demand that exceed equipment limits.

While there is growing interest in BEVs, these technologies are still at an early stage of development compared to gasoline-powered vehicles. Moreover, there are other low-carbon vehicle technologies that may offer longer range and faster charging. One concern about BEVs is that the electricity supply infrastructure may not be available for all uses as different sectors, such as buildings, further electrify. Encouraging a suitably diverse portfolio of vehicle technologies may alleviate such concerns and help prevent sub-optimal technology lock-ins.

In addition to BEVs, HFCVs are alternative low-carbon vehicle technologies that have their own potential adoption barriers. Compared to BEVs, HFCVs have a longer range, but refueling infrastructure in the US is more limited and there is a higher cost per station [16, 17]. Different from BEVs that can rely on home charging, HFCVs as personal vehicles likely have to rely exclusively on refueling away from home. However, currently there are only around 40 public stations in the US, with almost all of them concentrated in California [16]. Adoption of HFCVs as personal vehicles is likely to require more refueling stations and the cost of building out these stations is still uncertain.

Considering these potential technological and infrastructure barriers to electric vehicle adoption, this thesis examines various infrastructure planning strategies to enable vehicle electrification. These strategies are built upon a modeling of human behaviors including spatial and temporal patterns of vehicle travel and electricity demand from daily activities, and a modeling of features of technologies, such as electric vehicles, batteries, charging/refueling technologies, and the power grid.

1.2 Background

With vehicle electrification, the transportation system and the energy system are becoming increasingly connected. The adoption and usage of electric vehicles in the transportation system have implications for the power generation, transmission, and distribution processes in the energy system. In turn, the characteristics and management of the energy system can affect the costs and emissions of electric vehicle charging/refueling. It is important to consider the mutual influence of the two systems, which is determined by the diverse human behaviors that affect technology adoption and usage and the characteristics of technologies and infrastructure.

There has been a great deal of research on understanding and modeling travel behavior. A body of research is devoted to study the interactions between human mobility and the built environment, focusing on community-level or regional-level metrics, such as car ownership, vehicle kilometers traveled, and access to public transit [18, 19, 20, 21]. Another body of research focuses on modeling vehicle traffic flows. For example, researchers have developed macroscopic traffic flow models to study traffic characteristics at an aggregated level, including the flow, density, and speed of a traffic stream [22, 23]. Such models have been applied to study traffic conditions on specific road segments, such as highways [24], and urban network designs [25]. Other researchers have developed microscopic traffic models that simulate the movements and decisions of individual vehicles [26, 27]. Agent-based modeling is one example of microscopic modeling, which simulates behaviors of individual agents and the interactions between the agents and the environment [28, 29]. Another type of modeling that falls between microscopic and macroscopic modeling is mesoscopic modeling. Mescoscopic models typically make some simplifications in modeling behaviors of individual vehicles to avoid the high computational requirements of microscopic models, but still capture some level of individual decision-making that is lacking in the macroscopic models [26, 29]. To be calibrated, these different types of traffic models require real-world travel data at different levels of resolutions. Various data collection methods have been developed to model travel behaviors. Some researchers have collected travel diaries through in-person, paper, or online surveys, such as the National Household Travel Survey in the US [30, 1]. Others have relied on sensors, such as cellphone Global Position System (GPS) [31, 32], vehicle on-board diagnostics [33], and traffic monitoring sensors [34]. A smaller group of researchers have relied on a combination of surveys with sensor tracking results [35]. Data have also been collected from the infrastructure directly, such as electric vehicle charging stations [36, 37].

There has also been a wealth of research on modeling technology performance and characteristics of the supporting infrastructure. A vast body of research has examined the performance of various vehicle technologies and their improvements along dimensions, such as fuel economy, emissions, and weight [38, 39, 40, 41, 42, 43]. Researchers have also constructed different types of models to further understand the levers behind technological change. Phenomenological models, such as performance curves with error models, have been used to study the rate of technology improvement with time and production [44, 45, 46, 47]. Mechanistic models, on the other hand, disentangle the contributions of individual variables to technology progress with a bottom-up approach [48, 49, 50]. Conceptual frameworks and methods have also been developed to evaluate and compare various energy supply and vehicle technologies along multiple dimensions, such as carbon intensity and cost [51, 9]. Other studies have investigated the capacity, limits, and utilization of existing infrastructure, such as the power grid [52, 53, 54] and the electric vehicle charging stations [37, 55, 56, 57, 58].

A variety of studies have subsequently modeled travel behavior and technology performance to determine how the transportation system can affect the energy system with vehicle electrification. Locations of BEV charging and HFCV refueling stations need to be designed to meet travel demand, yet they can also affect the energy generation and distribution systems. A number of studies have examined where to place BEV charging stations [59, 60, 61, 10, 62] and HFCV refueling stations [63, 64, 65, 66, 67, 68, 69, 70] to meet travel demand. However, these studies typically use some simplifications of travel patterns in such a way that they do not consider specific charging locations, such as highways. Moreover, these studies do not compare the impact of charging at different locations. In Chapters 2 and 4, we address these gaps by studying BEV charging and HFCV refueling station locations using longitudinal travel patterns over a year in Seattle and daily travel diaries from around 150,000 personal vehicles in the US. Although charging infrastructure expansion is likely required to enable BEV adoption, this expansion can potentially increase power grid demand. There are a number of studies that have examined the power grid impact of BEV charging [71, 72, 37, 73, 74, 13]. These studies often model travel patterns on a typical day and do not consider the diversity in travel patterns. Moreover, they do not consider how charging demand relates with non-charging related demand over time and space. In Chapter 3, we address these gaps by modeling the distribution grid impacts of BEV charging in a temporally- and spatially-explicit way for two substations in Connecticut over the year 2019, drawing on a range of travel patterns from around 150,000 personal vehicles in the US and hourly foot traffic data at highway rest stops over a year. We also consider the non-charging related electricity demand at hourly resolution over the year 2019 at the distribution grid circuit and substation transformer level when modeling the impacts of BEV charging.

A number of studies have also examined how the energy system can in turn affect the transportation system as vehicles become electrified. Grid operators can influence when and where people charge through demand management strategies such as time- and location-based pricing to better balance supply and demand. Specifically, drivers can be incentivized to charge at work if free work charging is available, thus reducing the need for home charging. Reducing electricity rates during off-peak hours may also encourage charging at these times. There are various studies that have looked at different strategies to manage charging [75, 76, 77, 78, 79, 80, 81]. These studies often do not consider the diversity in travel patterns. Moreover, these studies focus on the regional grid level or the transmission level but not the smaller distribution grid level. In addition, these studies do not examine how the needs of charging relate to charging availabilities at other locations. In Chapter 3, we address these gaps by proposing and examining various demand management strategies to reduce the distribution grid impacts of BEV charging. We consider various travel patterns from personal vehicles and model the availability of charging at different locations. Another way the energy system can affect the transportation system is through affecting the cost and emission of BEV charging and HFCV refueling. How power is generated and distributed can affect the life cycle cost and greenhouse gas emission of vehicles [82, 83, 84, 17, 85]. For example, different methods of hydrogen production and distribution have different cost implications on refueling HFCVs [84, 17, 85]. The regional grid carbon intensity can affect the emission reduction potential of electric vehicles [83]. However, there is limited understanding on how BEV charging and HFCV refueling stations may be utilized given travel demand, and the capacity factor of the distribution grid equipment with BEV charging. These factors can have cost implications on infrastructure expansion and upgrades. Chapters 2 and 4 address this gap by examining the potential utilization rate of BEV charging and HFCV refueling stations on highways based on longitudinal vehicle travel patterns and foot traffic data at highway rest stops. Chapter 3 also addresses this gap by studying the capacity factors of circuits and substation transformers on the distribution grid if this equipment is upgraded to accommodate BEV charging.

1.3 Contributions

This thesis contributes to studying the interactions between the transportation system and the energy system that are important for understanding the viability of vehicle electrification and the infrastructure requirements. Specifically, we consider different electric vehicle technologies and the planning of BEV charging stations, HFCV refueling stations, and the distribution grid to enable vehicle electrification.

To do this, this thesis models three factors (Figure 1-1). The first factor is travel patterns such as when and where people travel and how frequently people make highway trips. The second factor is vehicle energy requirements based on how much energy is consumed in trips. The third factor is electricity demand profiles that contain variations in demand from daily activities over time at different locations. By modeling these three factors and their interactions, this thesis informs the expansion of BEV charging stations and HFCV refueling stations and upgrades of the distribution grid to enable widespread vehicle electrification.

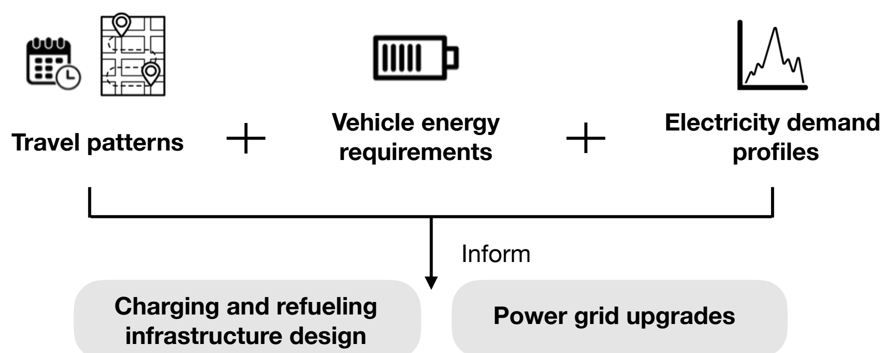

Figure 1-1: Thesis framework.

The main contributions of this thesis are three fold. The first contribution is building explanatory models using spatially- and temporally- resolved vehicle and household energy-consuming behavior for infrastructure planning. Before this work, it was unclear how travel behavior data would translate to patterns of vehicle energy consumption and patterns of vehicle charging, and how the charging demand and non-charging related electricity demand correlate temporally and spatially to affect infrastructure planning. Methodologically, Chapters 2, 3, and 4 advance a data-informed approach to evaluate various infrastructure expansion strategies, drawing on a modeling of detailed travel patterns across the population over time and space, and a physical modeling of vehicle energy consumption.

The second contribution of this thesis is proposing and evaluating specific infrastructure expansion strategies and their impacts on electrification. The thesis disentangles the various factors that are likely to determine the effectiveness of different strategies and explains why certain strategies may be more effective than others at enabling vehicle electrification. Specifically, Chapter 2 finds that home charging plays a pivotal role for BEV adoption that is unmatched by any other kinds of charging and can support the year-round energy requirements of approximately 10% of Seattle vehicles. Occasional highway fast charging is another impactful strategy and can raise this value to approximately 40%. Infrequent access to supplementary long-range vehicles as a complement to BEVs and/or other behavior modifications on a small number of days may also have an outsized impact on enabling vehicle electrification, and this is determined by the heavy-tailed energy distribution of vehicles.

Building on the findings from Chapter 2, this thesis also examines strategies to manage the distribution grid for accommodating BEV home charging and highway fast charging in Chapter 3. Chapter 3 finds that for the cases studied in Fairfield, Connecticut, BEV home charging can increase peak electricity demand on residential circuits by around 40% with 100% BEV adoption. Demand management strategies such as delaying home charging to early mornings and incentivizing work charging can reduce the increase in peak demand to around 10%. As for highway fast charging, there might be sporadic peaks occurring throughout the year and to reduce these peaks, demand in peak hours at certain highway stops may be shifted to adjacent highway stops. Enabling charging at home, work, and overnight public locations might also reduce highway charging demand significantly.

A final set of infrastructure expansion strategies this thesis examines is the refueling infrastructure expansion strategies for HFCVs in Chapter 4. Chapter 4 finds that enabling highway refueling can allow a small percentage of personal vehicles (around 5% in Seattle) to use HFCVs for meeting year-round energy requirements. The infrastructure expansion strategies proposed and examined in Chapters 2, 3, and 4 can inform policy-making and investments in infrastructure expansion for widespread vehicle electrification.

The third contribution of this thesis is a fundamental understanding of vehicle and household energy-consuming behaviors based on patterns of vehicle travel and day-to-day human activities. Specifically, we examine spatial and temporal patterns of energy consumption from vehicle trips and of electricity demand from household and commercial activities. This understanding lays the groundwork for the proposed infrastructure planning strategies. Specifically, Chapter 2 finds that although days with high energy requirements occur infrequently over time, they are observed among the majority of drivers. This phenomenon determines the potentially high impact of highway fast charging and supplementary long-range vehicles on enabling the adoption of BEVs. Chapter 3 finds that although there are individual differences in travel patterns, when aggregating vehicles at the distribution grid level, certain demand management strategies, such as shifting BEV charging time to hours before drivers leave home at the beginning of the day, might reduce the distribution grid impact of BEVs significantly. Moreover, locations and times where people stay for an extended period of time such as overnight at home and during the day at work offer natural opportunities for uninterrupted BEV charging that can potentially be beneficial for the grid. This is because these times are typically off-peak hours when non-charging related electricity demand is likely to be low. Chapter 4 finds that a small percentage of drivers pass through the highway on a regular basis such that highway refueling alone can be sufficient for meeting vehicle energy requirements if HFCVs were adopted. These insights on human behaviors can inform efficient policy-making for technology development and infrastructure planning for vehicle electrification.

The central result of this thesis is that a strategic expansion of infrastructure can enable significantly more efficient vehicle electrification. Specifically, residential charging, both for on- and off-street parking, can be foundational for BEV adoption to conveniently meet energy demand. Occasional highway fast charging and access to supplementary long-range vehicles could address some days with high energy requirements to enable vehicle electrification. These strategies are impactful because although there are only a small number of days with high energy requirements, these days are experienced by the majority of drivers. To reduce the distribution grid impact of BEV charging, certain demand management strategies, such as delaying home charging and shifting highway fast charging to adjacent stops, might be effective if adopted. This is because of the diversity in the time drivers arrive at and depart from certain locations such as home.

There are several critical assumptions of this thesis that should be highlighted and further research on these assumptions can meaningfully extend the impacts of this work. First, this work assumes that the travel behavior of electric vehicles remains the same as that of existing internal combustion engine vehicles. This assumption was made because travel data of gasoline-powered vehicles is the closest approximation to real-world travel demand. Trip patterns from existing BEVs are observed from early adopters and they may be biased representations of the majority of drivers. More research is needed to understand how travel demand might change as more people adopt BEVs. Second, this work does not explicitly consider the costs of different infrastructure expansion strategies. For example, more work is needed to understand the cost of providing supplementary long-range vehicles on the small number of days with high energy requirements. Third, this work does not consider how electrification of the transportation sector might couple with electrification of other sectors, such as buildings, to affect the power grid. For example, if heat pumps replace the conventional natural gas heating systems, there might be a different electricity grid demand profile from heating and it is unclear how BEV charging demand will correlate with non-charging related electricity demand temporally and spatially. Different adoption scenarios of heat pumps combined with electric vehicles can have different implications on the power grid expansion required to accommodate demand peaks.

1.4 Thesis overview

This thesis consists of four chapters. The following chapters address the four research questions of this thesis: Where to place BEV charging stations to meet personal vehicle energy demand over time? How can supplementary long-range vehicles complement BEV charging expansion to meet vehicle energy demand? What is the distribution grid impact of BEV charging and what are impactful strategies to manage this impact? Where to place HFCV refueling stations to meet personal vehicle energy demand over time? The first two questions are addressed in Chapter 2, the third question is addressed in Chapter 3, and the fourth question is addressed in Chapter 4. The chapters are based on a journal paper that has been published [86] and two papers that are in final preparation for submission [15, 87]. Chapter 2 is on strategies to expand BEV charging infrastructure and accessing supplementary vehicles to complement BEVs in order to meet travel demand. Chapter 3 is on the distribution grid impact of BEV charging and demand management strategies to reduce this impact. Chapter 4 is on strategies for locating HFCV refueling stations to meet vehicle travel demand.

Chapter 2 The second chapter evaluates the impacts of different kinds of BEV charging infrastructure expansion on meeting vehicle energy demand and the impacts of complementing BEV charging with accessing supplementary long-range vehicles [86]. This evaluation is based on a modeling of vehicle travel patterns and vehicle energy consumption. The longitudinal vehicle energy-consuming behavior may be used to estimate the technical potential of vehicle electrification in terms of the vehicle's ability to meet energy demand over time. This chapter considers three dimensions of infrastructure and technology design: charging availabilities, charging powers, and battery capacities. This chapter finds that home charging can be foundational for BEV mass adoption and can support the year-round energy requirements of approximately 10% of Seattle vehicles. Occasional highway fast charging is another potentially impactful strategy and can raise this value to approximately 40% when added to home charging. Infrequent access to supplementary vehicles on a small number of days per year and other behavior modifications might also be effective at supporting BEV adoption, and this is determined by the heavy-tailed energy distribution of vehicles.

Chapter 3 The third chapter examines the distribution grid impact of BEV charging and how demand management might reduce this impact [15, 14]. This chapter builds on a modeling of vehicle travel patterns and vehicle energy consumption in order to model BEV charging load profiles in different scenarios of charging availabilities. This chapter then combines hourly charging load profiles with hourly electricity demand profiles from non-

BEV related activities to quantify the distribution grid load profile in order to study the impact of BEVs. Finally, this chapter studies how various demand management strategies might reduce the impact of BEVs on the distribution grid. Specifically, this chapter focuses on reducing the impact of home charging and highway fast charging because the data allows for a deeper analysis of these two kinds of charging. The quantitative results from this chapter are based on a substation in Fairfield, Connecticut over the year 2019 because of the availability of distribution grid data. This chapter finds that for the cases examined in Fairfield, Connecticut, home charging can increase the circuit peak by approximately 40% with 100% BEV adoption. Demand management strategies, such as delaying home charging to early mornings and incentivizing work charging in middays, might reduce this increase to around 10%. As for highway fast charging, demand in peak hours may be shifted to adjacent highway stops. Enabling home, work, and overnight public charging might also reduce highway charging demand significantly.

Chapter 4 The fourth chapter studies the refueling infrastructure requirements of HFCVs to meet travel demand [87]. Similar to the methods on modeling BEV charging in Chapter 2 and Chapter 3, this chapter models vehicle travel patterns and energy consumption to understand longitudinal vehicle energy-consuming behavior if HFCVs are adopted. Using this behavior, this chapter quantifies the potential of HFCVs to meet energy demand with different refueling infrastructure availabilities. This chapter finds that a small fraction of personal vehicles makes frequent highway trips such that their year-round energy requirements can be met by HFCVs with only highway refueling. The majority of personal vehicles would require refueling at both highways and residential/work areas or behavioral changes if HFCVs are adopted.

1.5 Research applications

The specific strategies proposed in this thesis on BEV charging and HFCV refueling infrastructure expansion and power grid upgrades can inform policy-makers and service providers in preparing the infrastructure for mass vehicle electrification. For example, the high impact of BEV highway fast charging examined in Chapter 2 is informing the expansion of electric vehicle charging stations outlined in President Biden's infrastructure plan in the US. The impact of electric vehicle charging on the distribution grid and the proposed strategies to manage this impact examined in Chapter 3 are directly informing grid planning and operation in Connecticut through a collaboration with a utility company Avangrid. The strategic role of highway HFCV refueling on meeting both the needs of certain personal vehicles and medium- and heavy-duty commercial and industrial vehicles highlighted in Chapter 4 has likewise been of great interest to companies and policy planners working on hydrogen.

The infrastructure expansion strategies studied in this thesis also have implications on the cost of BEV charging infrastructure, HFCV refueling infrastructure, and power grid upgrades. Specifically, the characteristics of BEV charging and HFCV refueling requirements at different locations examined in Chapters 2 and 4 shine light on the utilization of the charging and refueling stations, which is associated with the cost of investing in such stations. The strategic role played by highway HFCV refueling to meet travel demand listed in Chapter 4 begins to suggest that some personal HFCVs may share hydrogen production and distribution infrastructure with commercial and industrial HFCVs to lower the cost of refueling, making HFCVs potentially more economically attractive as personal vehicles. In addition, the electricity demand profiles and foot traffic patterns at highway rest stops examined in Chapter 3 have implications on the utilization rate of the highway fast chargers and distribution grid equipment including circuits and substation transformers. The insights on the frequency and magnitude of peak demands from BEV charging might also inform the cost of infrastructure expansion and upgrades to accommodate these peaks.

Moreover, the viability of different electric vehicle technologies as personal vehicles under different scenarios of infrastructure expansion explored in this thesis offers valuable understanding for informing investments in technology research and development in the automobile sector. The potential of BEVs with different battery capacities to meet travel demand considering various weather conditions and driving styles examined in Chapters 2 and 3 can inform corporate and public investments in improving vehicle performance. The viability of HFCVs as personal vehicles to meet travel demand under different scenarios of refueling infrastructure expansion examined in Chapter 4 also provides valuable insights on the market size and adoption potential of HFCVs for automobile companies.

The conceptual framework and the modeling approach developed in this thesis that combine vehicle and household energy-consuming behaviors with technology performance to study electric vehicle infrastructure requirements can be adapted and applied to different locations around the world. In fact, the methodology is currently being extended to study vehicle electrification in Portugal, Indonesia, and Denmark, as countries make pledges to decarbonize the transportation and energy systems.

Overall, this research suggests that BEVs could potentially be viable at meeting travel demand with strategic expansion of chargers and power grid upgrades. In particular, ensuring reliable and predictable charging when drivers are at home is essential for electric vehicles to meet various travel demands over time. The distribution grid may need to be upgraded to accommodate the increased peak demand from residential charging and certain demand management strategies, such as last-minute delayed home charging, might reduce the upgrade needed. For densely-populated neighborhoods where on- and off-street parking can be limited to install chargers such that residential charging may not be available for all drivers, ensuring reliable public transit services could be an important piece of the puzzle in decarbonizing passenger travel. This research also suggests that highway fast charging can be impactful at addressing days with high energy requirements, and circuit upgrades are needed to accommodate the increase in peak demand. During a small number of times a year, there could be extreme peaks in highway fast charging demand, and the charging and power grid systems need to be designed to accommodate for these extreme events. However, this means that some chargers and power grid equipment might have low utilization, thereby increasing the cost of charging. Strategies to balance highway charging supply and demand, such as encouraging behavior change from drivers to delay/move forward charging activities to adjacent highway stops, might increase the utilization of infrastructure. HFCVs, on the other hand, face the challenge of a much higher cost of refueling per new station constructed. One way to reduce the refueling cost is to increase the infrastructure utilization. Enabling highway refueling that can serve both personal vehicles and heavier-duty industrial vehicles could potentially be a strategic step in expanding the

HFCV refueling infrastructure.

Chapter 2

Personal vehicle electrification and charging solutions for high-energy days

Abstract

Questions remain about the effectiveness of different proposals for battery electric vehicle (BEV) charging and other supporting infrastructure. Here we investigate options for charging BEVs and supplementing them with long-range vehicles, including on the infrequent 'high-energy days' that can otherwise impede personal vehicle electrification. We examine travel activities and their energy requirements, in Seattle and US-wide, to identify strategies that fit existing lifestyles. We find that home charging on- or off-street is pivotal in all strategies, and that highway fast charging and/or supplementary vehicles can be impactful additions. For example, home charging can support the year-round energy requirements of approx. 10% of Seattle vehicles, assuming a lower-cost BEV, but adding occasional highway fast charging or supplementary vehicles on 4 days/year raises this to nearly 40%. Infrequent supplementary vehicles may be needed even as battery technology improves. Our results outline options for nations, cities, companies, and communities seeking to support vehicle electrification despite the challenge of high-energy days.

2.1 Introduction

The transportation sector contributes an estimated 30% of US greenhouse gas emissions, more than half from gasoline-powered light-duty vehicles [88]. Despite improvements in

This chapter has been published in *Nature Energy* [86] with co-authors Sankaran Ramakrishnan, Zachary A. Needell, and Jessika E. Trancik.

vehicle fuel economy over the past decades, growing travel demand has led to rising transportation emissions [88]. Battery electric vehicles (BEVs) offer lower life cycle greenhouse gas emissions than gasoline-powered vehicles considering the power grid carbon intensity in most of the US today [9, 89, 90], and they show potential for helping to reverse the rising emissions trend [91], especially as the grid decarbonizes.

However, several barriers to vehicle electrification have been identified in research on consumer preferences [92, 93, 94]. A key impediment is an anxiety around whether the range offered is sufficient to meet personal driving needs [93, 95]. Several studies have shown that on at least some days these concerns may be justified, because vehicle travel distance on these days does exceed the range of lower-cost BEVs [10], and charging may not be conveniently available. These vehicle-days (days when a vehicle is used) with high energy requirements, though infrequent, could prevent BEVs from meeting drivers' energy needs on all days, and therefore may limit their adoption [95, 93]. In this study we focus on how to overcome this barrier to personal vehicle electrification potential, though we acknowledge that other factors will likely also influence electric vehicle adoption, including the higher upfront costs of electric vehicles, which may disproportionately limit the adoption of BEVs by lower-income households [9, 96].

Here we examine two potential solutions for meeting personal vehicle energy requirements in order to increase the vehicle electrification potential: expanded charging infrastructure and access to supplementary long-range vehicles. Expanded home, work, and public charging infrastructure may address both real and imagined range constraints by allowing drivers to charge between and during trips [97, 98]. Accessing a supplementary vehicle with a longer range than the personally-owned BEV through car-sharing services or a second vehicle in the household can also address vehicle-days with high energy requirements [60, 59], and thus support BEV adoption.

Several previous studies examine the effects of expanded charging infrastructure [60, 99, 100, 61, 101, 102, 62, 103] and supplementary vehicles [60, 59, 104, 100, 61, 105]. In a study tracking 363 vehicles in Atlanta over time, for example, it was found that on a single full charge, a 100-mile range vehicle would meet the needs of 9% of vehicles on all of their vehicle-days, while allowing supplementary long-range vehicles for at most two days a year would raise this to 17% [59]. Another study accounted for the effects of vehicle specifications, temperature, and vehicle speed profiles on fuel economy, and found that the energy consumption of 87% of vehicle-days in the US would be covered by a BEV with a below-average cost on a single full charge [10]. Another study estimated that a vehicle with a 60-mile range could satisfy 96% of vehicle-days when home, workplace, and ubiquitous public charging are available [99]. However, these studies do not consider how charging strategies and supplementary vehicle access can be matched to travel activity patterns and energy requirements (A.1).

This paper reveals how different combinations of supplementary vehicles and charging infrastructure can enable vehicle electrification, including under scenarios when battery and vehicle technology improve. To address this question, we advance a methodology to consider both detailed travel patterns and high-fidelity estimates of trip-level energy use, and we consider a wide range of battery capacities. The capacities span low-cost to higher-cost electric vehicles today, but also cover a range of possible vehicles of the future, with improved battery costs, energy densities, and management systems and automation for energy efficiency. We apply this methodology to Seattle and the U.S. as a whole. By revealing the vehicle-day energy distribution (Figure 2-1) and travel activities for individuals over time and across a population (Figure 2-2), this study design and methodology supports new fundamental understanding of the energy consumption of days with high energy requirements ('high-energy days'), and reveals the central role these play in determining the effectiveness of infrastructure strategies for electrifying personal vehicles.

2.2 Methods

2.2.1 Vehicle trip and drive cycle data

To model daily vehicle trips, we use a dataset from the 2007 Puget Sound Regional Council (PSRC)'s Traffic Choices Study obtained from National Renewable Energy Laboratory's Transportation Secure Data Center [31]. The study tracked 445 vehicles from 264 households in the Seattle metropolitan area between November 2004 and April 2006 using GPS

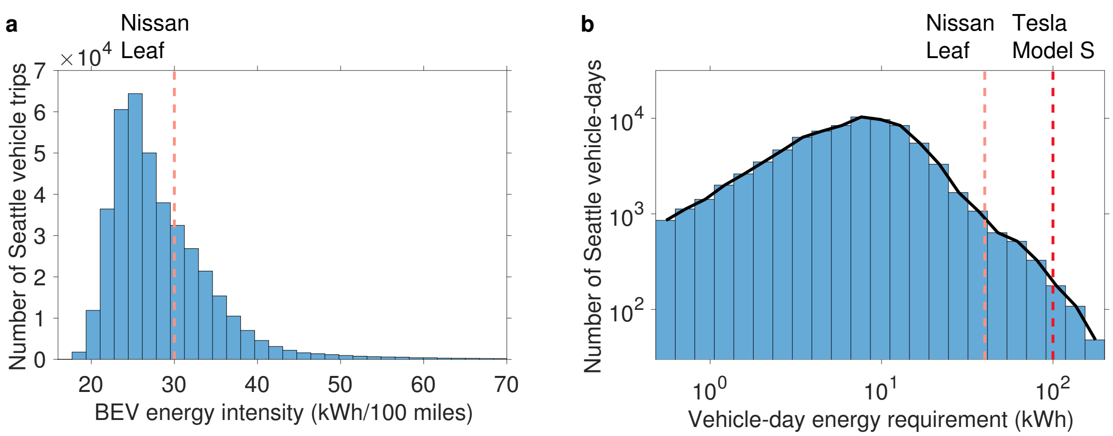

Figure 2-1: **a,** Variation in BEV energy intensity in Seattle vehicle trips calculated using the vehicle parameters of the 2019 Nissan Leaf with a 40 kWh battery capacity, as compared to this vehicle's rated energy intensity of 30 kWh/100 miles. **b,** Distribution of vehicle-day energy requirements in Seattle compared to the rated battery capacity of the Nissan Leaf and Tesla Model S shown by the dashed lines.

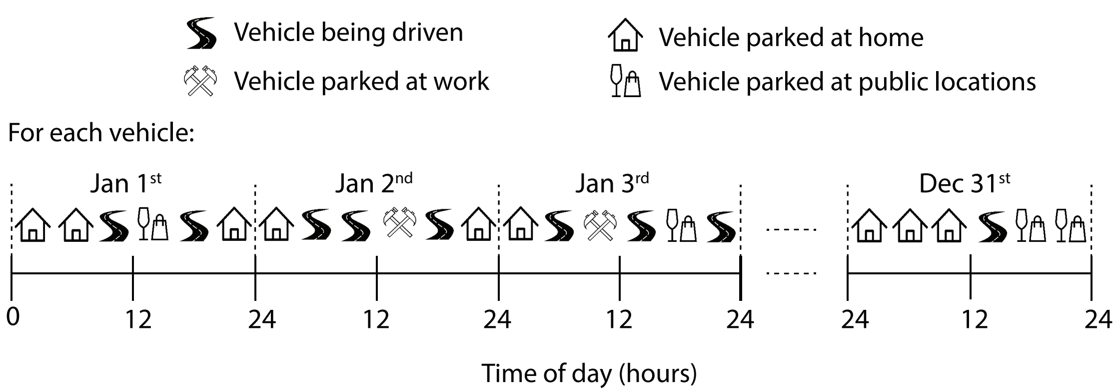

Figure 2-2: An illustration of travel activity modeling approach. Each vehicle's location is tracked through the day and year.

devices installed in their vehicles. The dataset includes trip distance, trip duration, trip date, and whether a trip starts and ends at home or work. We take into account the previous day's vehicle trip patterns and energy consumption and the period of time that a vehicle is parked overnight when analyzing consecutive vehicle-days. We examine 334 vehicles that were tracked for a year in 2005 with at least 52 vehicle trips a year (on average once a week) and whose household is located in suburban areas of Seattle with a population density of between 2,500 and 8,000 people per square mile. We remove trips with a maximum speed higher than 200 miles per hour, trip distance lower than 0.1 mile, and trip duration lower than 1 second. We also remove 64 vehicle-days made by 51 vehicles that contain single trips longer than 700 miles and assume the observed distance might be a result of GPS error. A total of 82,292 days from 334 vehicles are used in this analysis to model vehicle energy requirements over time. Possible sources of data uncertainty include GPS errors and post-processing errors, for example in the identification of trips to and from work locations. There is a need for further longitudinal data collection of this kind to expand samples and further quantify data uncertainty.

Another dataset we use to model vehicle trips is the 2017 National Household Travel Survey (NHTS) conducted by the US Department of Transportation [1], which is a comprehensive, cross-sectional dataset of trips in the US. In this survey, the trips of each household were recorded on a randomly chosen day. The data includes household demographics, vehicle ownership, trip distance, trip time, trip mode, and trip purpose. Different from the longitudinal travel data in Seattle, NHTS does not have vehicle trip data from consecutive days. Therefore, in the NHTS analysis, we make the assumption that overnight charging to a full battery is always available. In addition, we only consider driver trips to avoid double counting trips recorded for both drivers and other passengers in the same vehicle. We exclude days when a vehicle is not used. We also exclude days with single trips longer than 700 miles and trips with an average speed higher than 80 miles per hour and assume the observed trips might be a result of reporting error. A total of 157,555 vehicle-days made by 99,920 households were examined in this study. A total of 157,555 vehicle-days made by 99,920 households were examined in this study. The weakness of this dataset is that it does not capture individuals' travel over time, which is critical for understanding the electrification potential of personally-owned vehicles. However, we will use this dataset later to estimate the effect of charging and supplementary vehicles on electrification potential of vehicle-days in the US at large.

Finally, we also use a dataset of about 112,000 second-by-second drive cycles (vehicle speed profiles) from California [33], Atlanta [106], and Texas [107]. The data was collected through GPS loggers distributed to a sample of households. This set of drive cycles is used by a vehicle trip energy model, described in the next section, to estimate the energy consumption of vehicle trips in the Seattle and NHTS data.

2.2.2 Vehicle trip energy model

The energy consumption for each trip [31, 1] is estimated using the TripEnergy model [10, 108]. The TripEnergy demand model matches each trip in the Seattle data and the NHTS [31, 1] to a set of high-resolution drive cycles [33, 106, 107] that have the same trip distance and trip duration. These matched drive cycles are then used as inputs to a vehicle model that calculates the vehicle energy consumption. The TripEnergy model has a typical per-trip root median square error of 8% [108]. This error is substantially lower than that resulting from assuming a fixed fuel economy when predicting individual trip energies [108].

The vehicle model computes trip energy use E_{use} as a sum of drive energy E_{drive} used for vehicle motion and auxiliary energy E_{aux} used for other purposes (e.g., air conditioning, head-lights, etc.):

$$E_{\text{use}} = E_{\text{drive}} + E_{\text{aux}} = \frac{\varepsilon_{\text{tr}}}{\eta_{\text{drive}}} + E_{\text{aux}}. \tag{2.1}$$

Drive energy E_{drive} is determined by tractive energy ε_{tr} delivered from tank to wheels and drive efficiency η_{drive}. Tractive energy ε_{tr} of each trip is calculated based on the matched drive cycles from the demand model. A vehicle's tractive power is a function of speed v, acceleration dv/dt, a set of vehicle-specific dynamometer coefficients (a,b,c), a factor accounting for rotational inertia ε, and vehicle mass m [109].

$$P_{\mathrm{tr}}(v) = av + bv^2 + cv^3 + (1+\varepsilon)mv\frac{dv}{dt}. \tag{2.2}$$

Drive efficiency η_{drive} is estimated from the United States Environmental Protection Agency's corporate average fuel economy (CAFE) test results. For a particular CAFE drive cycle, total trip energy use and tractive energy are calculated using reported fuel economies and vehicle dynamometer coefficients. We can then calculate η_{drive} for CAFE city and highway drive cycles using Equation (1).

We use the following approach [110, 111] to account for the impact of ambient temperature on the energy consumption of a trip by adding the energy required for heating in the winter months and air-conditioning in the summer months. This additional energy requirement is calculated using vehicle-specific thermal capacity that is modeled using fuel economy data from EPA high-temperature and cold-temperature tests, trip duration (time for which heating and cooling are used during a trip), and a regional, travel-activity weighted average variation in ambient temperature.

We model cooling loads linearly as $P_{H^+}(T_{ambient} - T_{thermal\_comfort})$ and heating loads as $P_{H^-}(T_{thermal\_comfort} - T_{ambient})$. P_{H+} and P_{H-} are the electrical loads per degree of temperature difference for cooling or heating and are estimated for different vehicle makes and models using the EPA performance data for the air-conditioning test schedule (SC03 cycle) and cold-temperature schedule (FTP 75 cycle). $T_{thermal\_comfort}$ is temperature perceived to be best for thermal comfort and is usually chosen within the range 20 – 25 degrees Celsius [112]. We have chosen 20 degrees Celsius. To estimate the difference between ambient temperature and the ideal temperature for thermal comfort, for each region (a single or a collection of US zip codes), we use the "typical" hourly ambient temperature provided in the TMY3 dataset provided by NREL [113, 114].

To account for effects of relative humidity, wind speed, and direct solar radiative heat transfer to arrive at a measure of effective temperature experienced by the user of a vehicle, we take the average of three temperature measures: the dry-bulb temperature, the static ambient temperature measurement; the humidity adjusted heat index, a measure of the dry bulb temperature with adjustment for relative humidity; and the black-globe temperature that accounts for radiative heating and wind cooling. We then map the calculated temperature to regions inversely weighted by the distance of a zipcode from the nearest TMY3 weather station. Using this temperature measure, we calculate its hourly deviation from 20 degrees Celsius – the temperature considered ideal for thermal comfort – for each hour of the year. We then calculate a weighted yearly average of negative and positive temperature deviation using the number of trips occurring in the region and in the hour in the NHTS [1] and the Seattle travel dataset [31]. Weighting by the number of trips allows us to attribute more importance to temperature variations at times when most trips occur, and give less importance to those temperature variations that occur at times when most people do not drive, e.g., very cold temperatures late at night in winters. In this manner we obtain a regional, travel-activity weighted, average hot and cold temperature variation from ideal temperature for thermal comfort. We use this average cold and hot temperature difference to calculate energy load for thermal comfort for any trip. When applying these loads for trips in NHTS and Seattle datasets, we apply cooling loads in summer months (June, July, and August), heating loads in winter months (December, January, and Februrary), and neither in the remaining months.

Using the TripEnergy model, we find that in Seattle, the vehicle trip energy intensity calculated using the vehicle parameters of the 2019 Nissan Leaf can vary from 20 kWh to 70 kWh per 100 mile, compared to the rated energy intensity of 30 kWh per 100 mile (Figure 2-1a). This indicates the importance of accounting for variations in energy consumption when assessing different strategies to address days with high energy requirements, especially days with long-distance highway trips that have a higher than average energy intensity (A.3) [115]. Moreover, we find that the vehicle-day energy requirement in Seattle has a heavy tail (Figure 2-1b). This heavy tail suggests that strategies for expanding charging infrastructure or other solutions should be designed to meet the energy requirements on these days in order to support vehicle electrification.

2.2.3 Model of charging infrastructure and supplementary vehicles

We evaluate BEVs with rated battery capacities of 15 – 200 kWh. This list of battery capacities includes existing, lower-cost (relative to other BEVs) vehicles such as the 2019 Nissan Leaf (40 kWh and 62 kWh) and the high-end 2019 Tesla Model S (100 kWh). The list of battery capacities also includes the full-electric range of the 2017 Chevrolet Volt, a low-cost plug-in hybrid electric vehicle with a usable battery capacity of 15 kWh, though the results only roughly approximate the all-electric potential of this and other hybrids. We test different battery capacities but use the vehicle design parameters of the 2019 Nissan Leaf with a 40 kWh battery capacity, in order to isolate the effect of changing battery capacity rather than changing vehicle design. Results calculated using the vehicle parameters of the 2019 Tesla Model S are shown in A.13.

We develop a model to keep track of a BEV's battery state of charge (SoC) throughout a day under different charging scenarios. On each vehicle-day k made by vehicle i, for each trip, we use the TripEnergy model and calculate trip energy consumption of a given vehicle model [10, 108] (A.2). At the end of each vehicle trip, we calculate the battery SoC after the trip by subtracting the trip energy requirement E_{trip} from the battery SoC before the trip:

$$\text{SoC}_j^{k,i} = \text{SoC}_{j-1}^{k,i} - E_{\text{trip}} \tag{2.3}$$

At the end of each stop, we determine if charging is available at the stop based on the stop location and dwelling time. If charging is available at the stop, we update battery SoC by adding the amount of charge taken by the vehicle that is calculated as the multiplication of charging power p, charging efficiency η, and charging duration t:

$$\text{SoC}_j^{k,i} = \min(E_{battery}, \text{SoC}_{j-1}^{k,i} + p\eta t) \tag{2.4}$$

When the battery is full, we assume charging automatically stops. Charging efficiency

η is defined as the percentage of power drawn from the electrical grid that is actually taken up by the vehicle battery, which can vary with factors including charging power, battery SoC, and ambient temperature [116, 117, 118]. In this study, we assume a charging efficiency of 89%. This is a reasonable assumption as the small fluctuations in charging efficiency does not change the overall conclusions (A.4).

For home and workplace charging, we examine 6.6 kW charging, a typical charging power for a Nissan Leaf. Home charging can take place at a public location near home such as offstreet parking. For public charging, we examine 6.6 kW charging and 120 kW fast charging. We assume that the vehicle is plugged in for the entire stop duration if charging is available. In addition, we assume that BEVs are not charged when they are parked at a location for less than 30 minutes.

We keep track of battery SoC after each stop and trip for an entire year and assume the battery capacity is full at the beginning of the year. An example of vehicle-day trip patterns over a year is illustrated in Figure 2-2. For consecutive vehicle-days, we take into account the battery SoC at the end of the previous day and the effects of overnight charging. Depending on where the vehicle is parked overnight and for how long, as well as the charging availability scenario, the increase in battery SoC from overnight charging can vary. For non-consecutive vehicle-days, if the vehicle is parked at a location where charging is available, we assume that the vehicle starts with a full battery at the beginning of the next vehicle-day. If charging is not available at the location, we assume the battery SoC at the beginning of the next vehicle-day is the same as the SoC at the end of the last vehicle trip.

For each vehicle's travel, we model access to long-range vehicles for N_{supp} days a year, so that a BEV can be used to meet the energy requirements on the remaining days. We estimate the effect of using supplementary vehicles on days when the BEV cannot meet the energy requirements of a home-based tour (a chain of trips that start from home and end at home). We consider home-based tours because of the convenience to leave personal vehicles at home while traveling with a supplementary vehicle for multiple days. We consider the use of supplementary vehicles on a range of 1 to 365 days a year and how this impacts the number of vehicles that can be substituted by BEVs to meet the remaining days' energy requirements.

Here we summarize the list of charging and supplementary vehicle model assumptions. We assume that the BEV starts with a full battery at the beginning of the year. For home charging, work charging, overnight public charging, and ubiquitous public charging scenarios, the vehicle is plugged in for the entire stop duration if charging is available and the vehicle is parked for at least 30 minutes, and charging automatically stops when the battery is full. For the highway fast charging scenarios, we assume highway fast charging is only used as needed for as little time as possible to charge the battery to full. For example, in the scenario where home and work charging and fast charging on all highway trips are available, fast charging is only used on days that are un-electrified with home and work charging. Moreover, we assume that trips longer than 20 miles pass through the highway based on an analysis of the 2009 National Household Travel Survey [30], where we find that only 5% of the personal vehicle trips that do not pass interstate highway have a trip distance longer than 20 miles. In addition, when a vehicle is parked at a location overnight or for multiple days where charging is not available, we assume that the battery SoC does not change. With the above assumptions, we model battery SoC throughout each vehicle-day and consider the day to be electrified if battery SoC does not drop below 20% of the rated battery capacity at any time during the day. Finally, we assume supplementary vehicles are used for home-based tours (instead of individual days) whose energy requirements cannot be covered by the BEV under each charging scenario.

2.2.4 Metrics for quantifying vehicle electrification potential

The electrification potential of a personal vehicle may depend on the daily vehicle energy requirements over an extensive period of time, the availability of different charging infrastructures, and the availability and use of supplementary vehicles (private or commercial car sharing or an additional car at home) on some days. We define a metric called the vehicle electrification potential (VEP) to measure the fraction of vehicles whose energy requirements can be met by a BEV with a given battery capacity on all of their vehicle-days.

On a particular vehicle-day k, made by vehicle i, if the battery SoC after every trip calculated using Equation (1) does not drop below 20% of the rated battery capacity, this day is considered electrified. We account for limits on depth of discharge (DoD) relative to the rated capacity, and that this also allows for the expected degradation of the battery with time. The 80% DoD limit we place also means that our linear charging rate (constant with each charging power) assumption is reasonable, as we do not enter into much slower charging regimes.

In this way, we calculate the number of electrified days for each vehicle i. If the number of electrified days N^i is equal to the total number of vehicle-days observed N^i_{total}, the vehicle i can be replaced by a BEV to cover all of its energy needs as represented by an indicator function δ^i:

$$\delta^i = \begin{cases} 1, & \text{if } N^i = N^i_{\text{total}} \\ 0, & \text{otherwise} \end{cases} \quad \forall i \tag{2.5}$$

Finally, VEP is calculated as fraction of vehicles I that can be replaced by a BEV with a certain battery capacity to cover all of their energy needs on all days:

$$\text{VEP} = \frac{\sum_{i=1}^{I} \delta^i (N^i = N^i_{\text{total}})}{I}. \tag{2.6}$$

To account for the effect of using supplementary vehicles, we introduce another metric called the vehicle electrification potential with flexibility (VEP+) that measures the fraction of personal vehicles that requires supplementary vehicles for at most N_{flex} days a year in order to be replaced by BEVs with a certain battery capacity to meet energy requirements on the rest of the days. To calculate VEP+, we follow the same steps as in calculating VEP except we replace the indicator function in Equation (3) with $\delta^i (N^i \geqslant N^i_{\text{total}} - N_{\text{flex}})$:

$$\text{VEP+} = \frac{\sum_{i=1}^{I} \delta^i (N^i \geqslant N^i_{\text{total}} - N_{\text{flex}})}{I}. \tag{2.7}$$

We also apply the daily adoption potential (DAP) metric, defined as the percentage of vehicle-days in a population in which the energy requirements are met by a BEV [10].

This metric does not consider the variation of vehicle-day energy requirement of a given vehicle over time but aggregates all vehicle-days across vehicles and provides the technical adoption potential of a BEV on a given day.

2.3 Results

2.3.1 Electrification potential with expanded charging stations

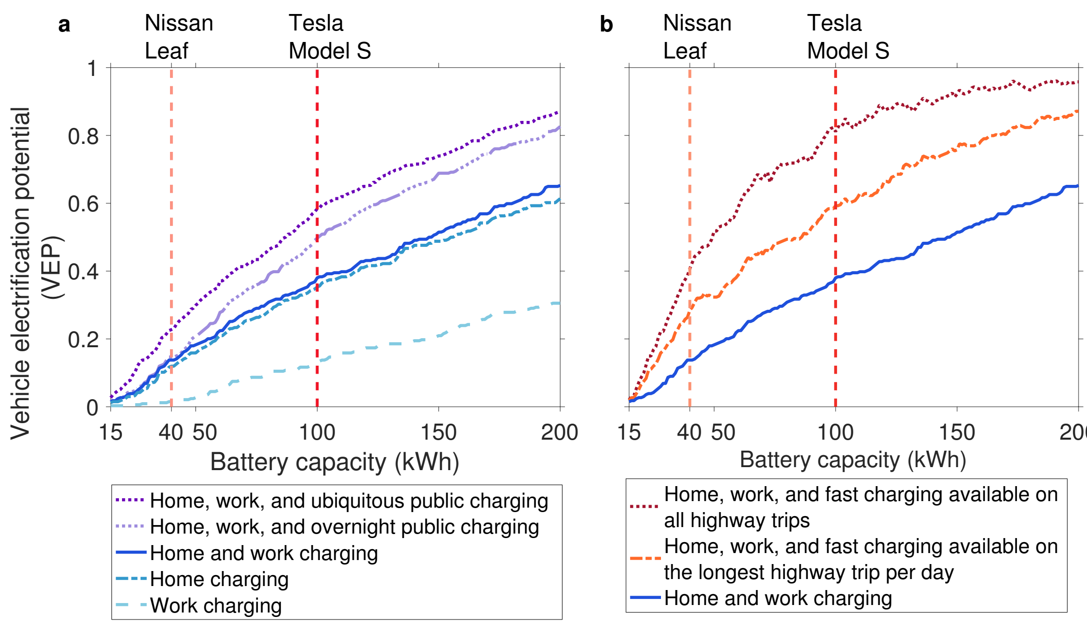

Figure 2-3: **a,** Fraction of vehicles in Seattle whose energy requirements on all days can be covered by a BEV with a given battery capacity (VEP) in Seattle under the following scenarios: home charging; work charging; home and work charging; home, work, and overnight public charging; and home, work, and ubiquitous public charging with 6.6 kW charging power. **b,** VEP in Seattle under home and work charging with 6.6 kW charging power and adding additional 120 kW fast charging stops to charge the BEV to full battery capacity on all highway trips and on the longest highway trip per day when needed.

We examine the effect of different combinations of home, work, and various types of public charging on the vehicle electrification potential (VEP), defined as the fraction of vehicles for which the daily energy requirements can be met by a given BEV on all days of the year (Methods). Overall we find that home charging plays a pivotal role (Figure 2-3a) that is unmatched by workplace charging or any other strategy alone. This home charging could occur on- or off-street, infrastructure allowing. When added to home charging, workplace charging adds little to VEP, though can play an important role in benefitting the power grid [14]. Ubiquitous public charging nearly doubles VEP when added to home and work charging, though installing a charger at every public parking spot could be expensive and difficult to achieve in practice (A.5). Fast charging on only a small number of days shows potential for greatly increasing VEP when added to home and work charging, requiring only short interruptions in travel activities. The quantitative results for Seattle are discussed below.

We find that 12% of Seattle vehicles can be replaced with a 40 kWh Nissan Leaf for all of their days' energy requirements where only 6.6 kW home charging is available (Figure 2-3a). The availability of work charging in addition to home charging increases VEP to 14% (Figure 2-3a).

Due to the difficulties of accessing chargers at home in some cases, for example in locations with less off-street, private parking and where charging is not available for public overnight parking, we consider scenarios where home charging is not available (Figure 2-3a and Figure A-12, A-16, A-17). We find that the VEP of the 40 kWh BEV with work charging alone is 2% (Figure 2-3a). Increasing battery capacity to 100 kWh increases VEP with work charging to 13% (Figure 2-3a). The addition of ubiquitous public charging in addition to work charging further increases the VEP of a 40 kWh BEV to 14% for a 40 kWh BEV (Figure A-16). In this scenario, public charging is available and used in any public location where a vehicle is parked for 30 minutes or longer. Ubiquitous public charging alone supports a VEP of only 5% for a 40 kWh BEV (Figure A-17).

Making fast charging available for all highway trips can measurably increase VEP when compared to home and work charging alone. In this scenario we assume vehicles will only stop at fast chargers when needed, for as little time as needed. This scenario departs from the others considered here in that there is a small behavioral modification in the form of a short interruption to travel activities. Among the 269 (out of 334) Seattle vehicles that make use of highway fast charging in this scenario, 81% of these vehicles use fast charging on 10 days a year or less, and the stops at fast chargers last for 30 minutes or less on 68% of these vehicle-days (the ones with fast charging) (Figure 2-4). The impacts on VEP are significant. When fast charging is added to home and work charging, VEP increases from

14% to 41% for a 40 kWh BEV. (When added to work charging, VEP increases from 2% to 4% (Figure A-12a).) These results suggest that if drivers have the flexibility to adjust trip schedules by a small amount of time on a few days a year, adding highway fast charging to home and work charging could have an outsized effect on VEP (A.7).

An alternative to fast charging could be to supply overnight parking infrastructure in public places (away from drivers' residences, though this could include visitor, overnight parking in residential neighborhoods). We consider this in our overnight public charging scenario and find that it can increase VEP but that it is not a replacement for fast charging. Adding overnight public charging to an infrastructure strategy of home and work charging increases VEP from 14% to 15% for a 40 kWh BEV, and from 38% to 50% for a 100 kWh BEV. Thus the effects are greater for a larger battery capacity, and closer to the effects of fast charging (Figure 2-3a), likely because drivers are able to reach their destinations on high-energy days with these vehicles and then plug in overnight. Thus as batteries improve and greater battery capacities become more available, overnight charging away from home could begin to replace the need for fast chargers, though this will likely not happen quickly enough to address equity considerations (since less-wealthy households cannot currently afford the higher-capacity BEVs) and meet near-term climate targets [96].

2.3.2 Electrification potential with supplementary vehicles

Considering that not all vehicle-days' energy requirements can be met with home, work, and public charging, even as batteries improve, access to a supplementary long-range vehicle for a given number of days a year might allow more drivers to use a BEV for the remaining days. Here we examine the effect that access to supplementary vehicles might have on increasing VEP+ (defined as VEP aided by supplementary vehicles) alongside charging infrastructure. To begin to understand whether and how such supplementary vehicles could be made practical beyond multi-vehicle households, we also examine the characteristics of the un-electrified vehicle-days that require supplementary vehicles and their distribution over the year.

Providing access to supplementary vehicles on only a few days a year leads to large

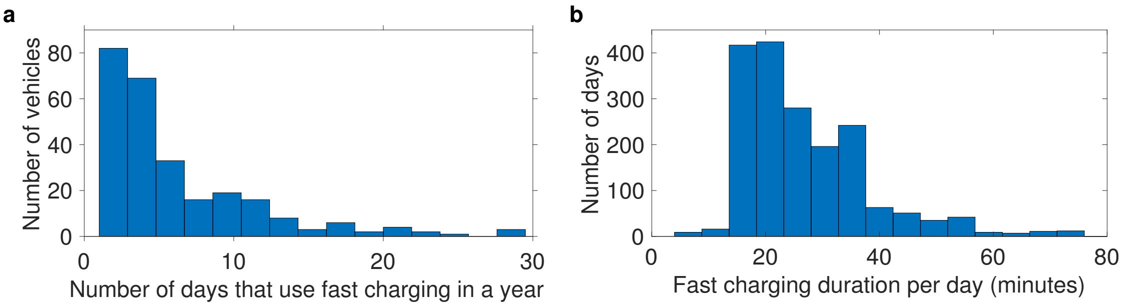

Figure 2-4: **a,** Histogram of number of days in a year in Seattle that would require 120 kW fast charging to charge a 40 kWh BEV to full during highway trips, so that the vehicle-day's energy requirement is covered with the BEV. In this scenario, home and work charging are available and used when the car is parked in those locations. **b,** Histogram of fast charging duration per day to charge a 40 kWh BEV to full while en route on highway trips when needed, thereby delaying future trips by this amount of time when home and work charging are available, such that the vehicle-day's energy requirement is covered with the BEV.

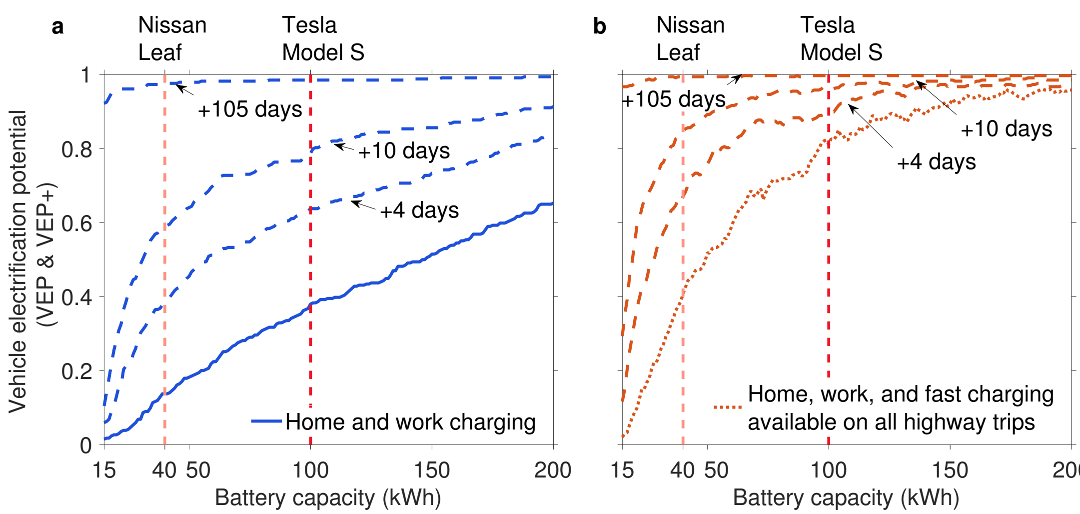

Figure 2-5: **a,** VEP and VEP+ in Seattle with BEVs with a given battery capacity when supplementary vehicles are used on 4, 10, and 105 (calculated as 2 out of 7 days over 365 days to approximate using supplementary vehicles every weekend) days a year so that the energy requirements on the remaining days are covered by the BEV when 6.6 kW home and work charging are available. The solid line represents VEP and the dashed lines represent VEP+. **b,** when 6.6 kW home and work charging are available and adding additional 120 kW fast charging stops to charge the BEV to full battery capacity on all highway trips when needed. The dotted line represents VEP and the dashed lines represent VEP+.

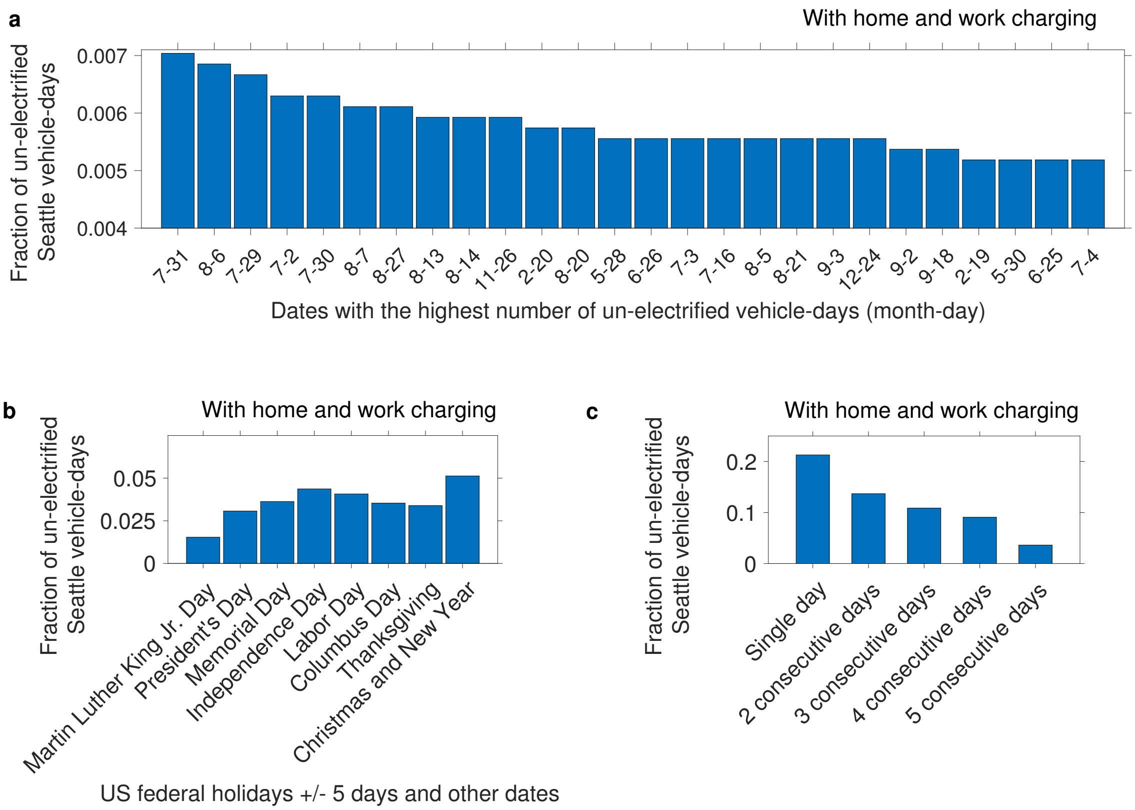

Figure 2-6: **a,** Histogram of dates with the highest number of un-electrified vehicle-days covering 15% of all un-electrified vehicle-days, sorted from the highest fraction of un-electrified vehicle-days to the lowest fraction. **b,** Histogram of un-electrified vehicle-days that fall on federal holidays in the US and the five days before and after each holiday compared to other dates of the year. A total of 11 days are covered in each holiday period except for the combined Christmas and New Year which covers 18 days. **c,** Histogram of the number of un-electrified Seattle vehicle-days that require single day and 2-5 consecutive days' of supplementary vehicles.

increases in VEP. For example, access to supplementary vehicles on only 4 days a year increases the electrification potential with home and work charging available from VEP=14% (for a 40 kWh BEV) to VEP+=38% (Figure 2-5a). This is similar to the increase seen from adding fast charging possibilities on all highway trips. This increase is also equivalent to that seen in VEP when increasing the battery capacity from 40 kWh to 100 kWh (Figure 2-5a). For a 100 kWh BEV, adding access to supplementary vehicles on 10 days a year has a similar effect on the electrification potential to adding highway fast charging to home and work charging (Figure 2-5a and Figure 2-5b). We also approximate a case where BEVs are used as commuting vehicles only, by considering the use of supplementary vehicles on two out of every seven days or 105 days per year. In this case, VEP+ reaches close to 100% with only home and work charging (as well as with only home charging). This scenario could be problematic from both equity and climate change perspectives, however. Accessing multiple cars may not be possible for less wealthy households (unless new, affordable, shared vehicle models are realized). Even if access can be improved, using long-range vehicles run on fossil fuels would limit the emissions-savings offered by the BEVs.

Taken together, these results suggest that accessing supplementary vehicles on a small number of days a year could be as effective in terms of increasing VEP as installing highway fast charging or increasing battery capacity to increase the fraction of vehicles electrified (A.8). However, the most effective strategies will likely combine expanded charging infrastructure with access to supplementary vehicles, though many questions remain about how to conveniently supply supplementary vehicles beyond multi-car households.

To begin to answer questions about the practicality of commercial or community supplementary vehicles, we consider how the high-energy days on which they are required are distributed throughout the year. We find that no single day accounts for more than 0.7% of the days per year that remain un-electrified with home and work charging (Figure 2-6a). 21% of the vehicle-days that are not electrified with home and work charging are single, non-consecutive vehicle-days, and 79% are part of home-based tours that span multiple days (Figure 2-6c). 29% of the un-electrified vehicle-days occur on US federal holidays or the five days before and after each holiday (Figure 2-6b). However, no single holiday period (10 or more days around a holiday) accounts for more than 5% of the high-energy days. Friday, Saturday, and Sunday are the three days of the week with the highest number of un-electrified days and they account for a total of 59% of high-energy days (Figure A-27). This is a result of longer trips and not having access to full charging between trips. We also find that there are un-electrified vehicle-days in each month, though January, February, and March are the three months with the lowest number of un-electrified vehicle-days (Figure A-28).

These results suggest that the un-electrified vehicle-days with high energy requirements are distributed throughout the year and thus that supplementary vehicles such as rental and shared cars can be used fairly regularly throughout the year (instead of sitting idle), thus achieving a higher capacity factor (percentage of time a machine is used) and lower cost (A.9 and A.10). Moreover, these high-energy days may be inversely correlated with the use of ride-hailing services such as Uber and Lyft, the drivers of which often use rental cars or other commercially shared vehicles when working (A.14). In this way the capacity factor of the vehicles could be increased. However, we note that these questions require further investigation.

As battery capacities increase and costs decline, allowing more of the population to afford and adopt BEVs with higher battery capacities, the need for supplementary vehicles may decline (Figure 2-5). However, the need for supplementary vehicles will likely persist far into these battery improvement trajectories. This observation combined with a recognition that supporting electric vehicle adoption only in multi-vehicle households would amount to a focus on higher-income households, and that electric vehicles can offer local air quality improvements needed in all neighborhoods, and sometimes especially in less wealthy ones, suggests that providing easy-access supplementary rental or otherwise commercially-shared vehicles deserves further attention [119, 120].

2.3.3 Vehicle electrification potential in the US

Here we extend the previous analysis of trip data from Seattle, which tracks vehicles over time, to examine data on a daily snapshot of driving across the US. While this larger cross-sectional US data cannot be directly compared to the longitudinal Seattle data, certain similarities are important to note, as they suggest that the qualitative conclusions from this analysis apply more broadly. In the analysis of US data, we use the daily adoption potential (DAP), defined as the daily percentage of vehicle-days in a population whose energy requirements are met by a BEV [10].

We find that DAP equals 98% in the US for a 40 kWh Nissan Leaf with 6.6 kW home charging (Figure 2-7a), which is a similar percentage to that for Seattle with home charging (92%) that is calculated by aggregating Seattle vehicle-days across all vehicles (Table A.3). Adding work charging and additional fast charging stops to charge the battery to full during all highway trips when needed electrifies an additional 1% of US vehicle-days, increasing DAP to 99%. The remaining 1% are un-electrified days, which is a similarly low percentage to that for Seattle (3%), when aggregated across the set of Seattle vehicles (A.6). In both datasets, even with home, work, and public charging, a small fraction of vehicle-days cannot be electrified at this battery capacity. If BEVs are to be used on all days, this small number of days can limit VEP.

This result is explained by a distribution of vehicle-day energy requirements, which like the Seattle energy distribution is heavy-tailed (Figure 2-7b). The exponent of a fitted power law distribution of the vehicle-day energy requirement for the NHTS data is 2.54 and that for the Seattle data is 2.49 (A.15). A higher battery capacity of 100 kWh, comparable to that of a Tesla Model S, would still leave less than 1 percent of days un-electrified based on the US data, and 1 percent in the Seattle data (with a VEP=81%) when home, work, and highway fast charging are available.

We further compare the vehicle-day activity patterns in Seattle and the US datasets, which adds insight on the generalizability of the Seattle results to other regions. The Seattle data contains a higher percentage of mixed-use days that have both work and leisure activities and a lower percentage of days with only work activities compared to the US data (A.11). Moreover, the average energy requirements of mixed-use days and days with only work activities in Seattle are 10 kWh and 6 kWh, which are lower than the US average of 12 kWh and 9 kWh (Table A.6). These differences could be due to the dense urban setting in the Seattle metropolitan area that results in shorter travel and better access to retail services, where leisure activities can be added before or after work with less detour. This suggests that work charging might be more effective at electrifying vehicle-days in less-dense urban areas or rural areas, though further research is required.

2.3.4 Strategic packages for enabling vehicle electrification

We highlight a few combinations of expanded charging infrastructure and supplementary vehicle access that can inform policymakers or companies working to support vehicle electrification (Figure 2-8). Each of these combinations may serve different segments of the population within and across geographical regions. Below we highlight quantitative results for the case of Seattle and a lower-cost BEV with a 40 kWh battery capacity (Figure 2-8), and we discuss more general findings to motivate strategies in other locations and further in-depth case studies of particular locations.

Package 1 includes home and work charging, and access to long-range supplementary vehicles. For sub-populations where it is possible to install and access home charging, for both on- and off-street parking, this is a central component of an effective strategy for increasing VEP. Moreover, work charging when added to home charging can offer grid benefits such as limiting peak power demand and storing solar energy [14], while also increasing VEP by a small amount (from 12% to 14% in the case of Seattle). Incentivizing business models that allow for easy access to long-range supplementary vehicles is a third component of this package, where easy access to supplementary vehicles on at most 10 days per year raises VEP to 59%.

Package 2 augments home charging with overnight public charging and fast charging capabilities on highways to further increase VEP, raising it from 12% to 46% in Seattle for a lower-cost BEV, even without the use of supplementary vehicles. If supplementary vehicles are accessible and used on up to 10 days per year per person, VEP rises to 88%.

Package 3 addresses areas where home charging is difficult to implement by instead focusing on work charging augmented by supplementary vehicle access and fast charging. This package can allow for a portion of personal vehicles to be electrified. For example, the VEP for Seattle reaches 15% with this strategy and a lower-cost BEV when supplementary vehicles are used on at most 10 days per year. Higher VEPs are possible with greater bat-

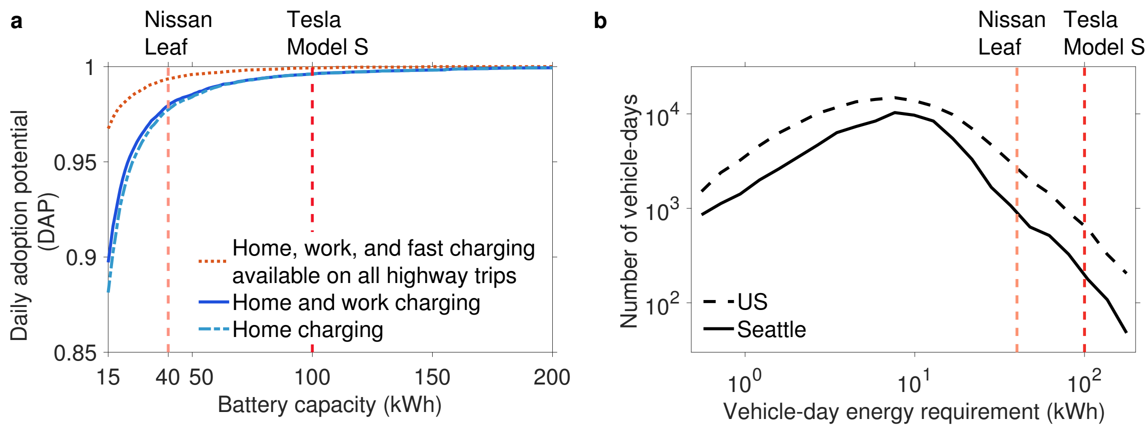

Figure 2-7: **a**, Fraction of vehicle-days in the NHTS whose energy requirements can be covered by a BEV with a given battery capacity (DAP) with 6.6 kW home charging, home and work charging, and home, work, and adding additional 120 kW fast charging stops to charge the BEV to full battery capacity on all highway trips when needed. **b**, Distribution of vehicle-day energy requirements in the NHTS representing the US and Seattle.

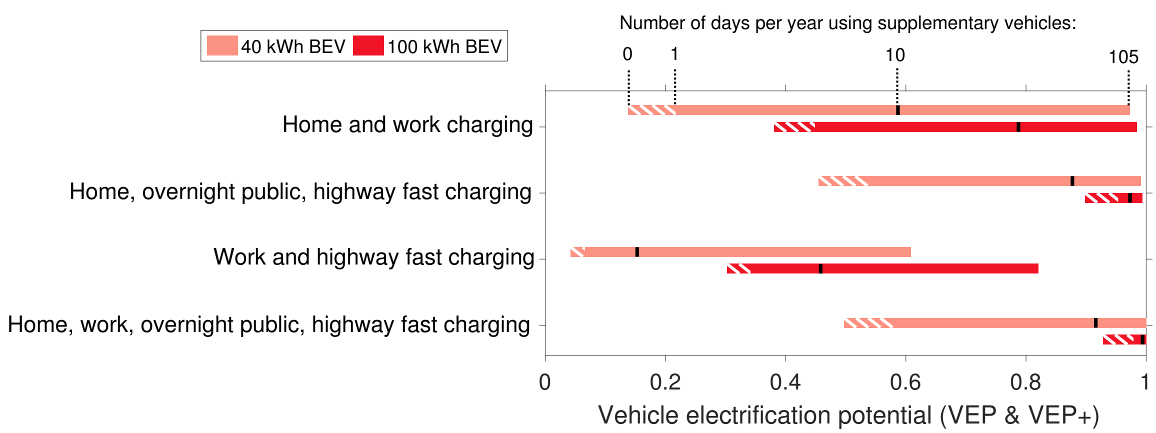

Figure 2-8: VEP and VEP+ in Seattle with BEVs with a battery capacity of 40 kWh and 100 kWh with different combinations of home charging, work charging, overnight public charging, additional fast charging stops on all highway trips, and accessing supplementary vehicles on 0 to 105 days (calculated as 2 out of 7 days over 365 days to approximate using supplementary vehicles every weekend) a year so that the remaining days' energy requirements are covered by the BEV. The left end of each hatched box represents VEP without supplementary vehicles. Each solid box represents VEP+ with supplementary vehicles ranging from 1 to 105 days per year, and the bold black line on the box represents VEP+ with supplementary vehicles on 10 days per year. Charging availabilities in strategic packages 1-4 are listed from top to bottom in the above plot.

tery capacity, but these are currently more costly and therefore unlikely to be immediately accessible to a large portion of the population. Access to supplementary vehicles on more days could also increase VEP, but would be accompanied by greater carbon dioxide and other emissions if these vehicles are powered by fossil fuels. This strategy may be less effective than Packages 1 and 2, and demonstrates the importance of finding ways to support charging near homes.

Finally, for maximum impact, larger regions can focus on Package 4, which includes home, work, and highway fast charging, along with overnight public charging ~~(Package 4)~~. Here decision-makers would likely need to work in regional partnerships or at the national level, since the overnight charging needed to cover high-energy days for a given local population would likely be located far from that local jurisdiction, in order to allow vehicles leaving from one city or town and traveling far afield to recharge after the trip.

These strategies remain useful for increasing personal vehicle electrification potential even as batteries improve to allow higher battery capacities at lower vehicle costs (through less expensive and more energy-dense batteries). Moreover, these strategies should be pursued with equity and climate change mitigation considerations in mind, to enable an equitable access to BEVs and their air quality benefits, and to support immediate emissions reductions. These strategies can also be designed explicitly to create co-benefits such as sustained, high-quality jobs and community economic development and innovation opportunities [121].

2.4 Discussion and conclusions

In this research, we consider various potential solutions to meeting personal vehicle energy requirements with BEVs. We examine the potential of expanded home, work, and public charging infrastructure, as well as a supply of supplementary vehicles when needed. Using driving data from 334 vehicles that were each tracked for a year in the Seattle metropolitan area, we find that home charging alone allows 12% of the vehicles to meet all of their energy requirements with a 40 kWh lower-cost electric vehicle. Adding work charging enables an additional 2% of vehicles to become fully electrified, by electrifying additional vehicle-days with both work and leisure activities. Adding additional fast charging to home and work charging, in order to allow the vehicle to charge on highway trips when needed, thereby introducing short delays on a small number of days per year, further raises VEP to 41%.

However, even in the scenario where home charging, work charging, and highway fast charging are available, the energy requirements over the year of over half of the vehicles cannot be met with a low-cost BEV. We find that supplementing BEVs with access to additional, long-range vehicles for at most 4 days a year allows 38% of the Seattle vehicles to be replaced by a 40 kWh Nissan Leaf to meet the energy requirements with home and work charging alone. This electrification potential is comparable to that of a 100 kWh Tesla Model S that costs more than twice as much as a 40 kWh Nissan Leaf or other similar vehicle.

The high-energy vehicle-days are distributed across different dates over the year, with no more than 1% of these vehicle-days occurring on any single calendar date. This suggests that supplementary vehicles might be offered at a reasonable cost, though further research is needed to understand this potential.

As batteries improve to offer higher capacity at lower cost, mass, and volume, the need for supplementary vehicles will likely diminish. However, because of the heavy tail of high-energy days in the vehicle-day energy distribution, a small number of supplementary vehicles will be needed far into the future. This conclusion may also apply to many other regions that also experience high-energy days [122]. Carbon dioxide emitting long-range supplementary vehicles could strategically be phased out and replaced by options without carbon emissions as batteries and other low-carbon vehicle technologies improve.

Recognizing that different populations will have varied constraints in the charging infrastructure that can be adopted, we outline four strategic packages that can be pursued, and mixed and matched to suit different contexts. The benefits of home charging, either on- or off-street, are clear across all packages (Packages 1, 2, 4 in Figure 2-8), as is access to supplementary vehicles on a small number of vehicle-days. However, the strategic use of work charging and fast charging can serve to electrify at least a portion of vehicles (Package 3), even when home charging is not available, and particularly if supplementary vehicles are easy to access. Greater use of fossil fuel powered supplementary vehicles could increase carbon dioxide and other emissions, but would likely still offer savings on electrified vehicle-days served by a BEV. Fast charging access on highways also emerges as a high-impact infrastructure component across all packages, with only short interruptions in travel activities on a small number of days per year (less than 10 days for majority of the population in Seattle).

Several areas of future work can meaningfully extend these results. First, personalizing forecasts for car owners within particular regions or neighborhoods, considering current or planned charging infrastructure and shared supplementary vehicle development, might help overcome range anxiety as a barrier to electric vehicle adoption (A.12). Collecting publicly-available longitudinal data on the travel activity patterns of cities and rural areas over a year or, ideally, even longer would help enable further detailed place-specific studies of the infrastructure requirements and the development of personalized forecasts. Further research is needed to understand how to make infrastructure development plans more equitable. Moreover, these infrastructure developments offer the opportunity to create co-benefits in terms of high-quality and sustained jobs, air pollution improvements, and community innovation and economic development opportunities [123].

The four strategic packages outlined (Figure 2-8) could help guide efforts to understand the preferences of drivers and car-owners, which are as important in determining outcomes as the technical potentials estimated here. Other barriers to BEV adoption, such as the higher upfront costs of BEVs [9] and the lower diversity of vehicle choices, should also be considered. Moreover, any policies should consider the objective of emissions reductions and equity in setting climate policy, rather than supporting electric vehicles per se.

It is also important to recognize that travel activities may change with time. The diurnal cycle and the seasons provide some constraints, but automation and more flexibility to work remotely could induce changes. However, to meet climate policy goals, the support infrastructure for electrification will likely need to be accelerated, and these developments could in turn help shape other trends, for example toward automation and resulting behavioral changes, so as to enable emissions reductions alongside other changes to mobility.

Chapter 3

Strategies for managing the distribution grid impact of BEV charging

Abstract

Vehicle electrification requires charging infrastructure expansion to meet travel demand. However, this expansion can cause increases in power grid demands that exceed the power generation capacity and distribution grid equipment limits. Here we examine the impact of electric vehicle charging on the distribution grid and how to manage this impact by developing a temporally- and spatially- explicit model that builds on longitudinal vehicle and household energy-consuming behaviors. Specifically, we quantify this impact in Fairfield, Connecticut over the year 2019 under different scenarios of charging infrastructure availability and charging patterns. We then investigate hypothetical scenarios for demand management to mitigate charging-induced peaks through temporal and spatial shifts of charging demand, taking into account local travel patterns and non-charging related electricity demand patterns. We find that certain simple demand management strategies, if adopted, can potentially have a significant impact on reducing peaks on circuits and substation transformers. For example, with delayed home charging and incentivized work charging, a simulation of electricity demand shows that 100% BEV adoption only increases the circuit peak by approximately 10%, much lower than the 40% increase if home charging is left uncontrolled. Moreover, our results begin to suggest that highway fast charging peaks that occur on a small number of days in a year may also be mitigated by shifting charging activities to adjacent highway rest stops. This is because peaks at some adjacent highway rest stops are not coincident in time. Enabling charging at home, work, and overnight public locations can reduce the percentage of days that require highway fast charging from

This chapter is a working paper that is in final preparation with co-author Jessika E. Trancik [15].

19% to only 2%. Insights from this analysis can inform utility companies and planners on strategies to manage peak loads on the distribution grid and provide cost implications on charging and power infrastructure upgrades as vehicles become electrified.

3.1 Introduction

The transportation sector is currently the largest carbon dioxide emitting sector in the US [6]. Around 40% of the transportation-related emissions come from passenger vehicles in 2015 [109]. Decarbonization of the transportation system to curb greenhouse gas emissions has become increasingly urgent to mitigate climate change [8].

Vehicle electrification, while a promising path to achieve deep decarbonization [9], still requires expanded charging infrastructure to ensure that charging is available when needed [10, 86]. The electricity demand increase from battery electric vehicle (BEV) charging further poses a challenge to existing power generation and distribution systems [53, 124, 125]. The added electricity demand from electric vehicle charging could lead to increase in peak loads that exceed the distribution grid limits at the circuit and transformer level, and generation capacity at the larger regional grid level [14, 124, 71]. To accommodate for this increase and reduce the risks of overloading that may cause blackouts, distribution grids need to be upgraded and generation capacity needs to be expanded, but these would incur additional costs for the utility companies [126]. In particular, the required distribution grid upgrades are closely linked with electric vehicle adoption levels and strategies of charging infrastructure expansion that affect the spatial and temporal distribution of electricity demand. Therefore it is critical to place the charging stations strategically and plan charging station expansion and distribution grid upgrades simultaneously to mitigate the impact of charging.

Here we examine the distribution grid impact of electric vehicle charging and strategies to manage this imapct. By modeling the spatial and temporal patterns of BEV charging demand and non-charging related electricity demand from day-to-day activities, we investigate occurrence of peak demands and the effectiveness of various demand management strategies that allow temporal and spatial shifts of charging loads to address these peaks. We also examine a range of BEV adoption scenarios to study near-term and longer-term solutions for grid upgrades and expansion.

Several previous studies examine strategies for charging infrastructure expansion [127, 128, 62, 86, 60] and power grid upgrades [14, 71, 72, 37, 73, 74] to support vehicle electrification. In particular, previous work has shown that home, work, and highway fast charging would suffice to meet most travel demand [86], and that certain demand management strategies can be impactful on reducing peaks at the regional grid level [14]. For example, in a study tracking 334 vehicles in Seattle over one year, it was found that overnight home charging plays a pivotal role at meeting longitudinal travel demand that is unmatched by any other kinds of charging infrastructure [86]. Highway fast charging is an impactful addition because it addresses the occasional days with high energy requirements [86]. Among studies that estimate the grid impact of BEV charging, one study simulates charging profile on a typical workday and a typical holiday and examines the grid impact under different EV penetration levels [71]. The National Renewable Energy Laboratory has also developed an electric vehicle infrastructure-projection (EVI-Pro) tool to estimate daily charging load profiles for different regions in the US [13]. However, these studies do not capture the variations in vehicle energy consumption and electricity demand over time (such as different seasons over a year) that could cause different patterns of peak loads that exceed the grid limits. Moreover, none of these studies consider how charging infrastructure expansion and distribution grid upgrades can be designed together to meet travel demand over time while minimizing grid upgrades. In addition, these studies focus on the regional grid level instead of the smaller distribution grid level.

To address these gaps, this work examines the impact of electric vehicle charging at the distribution grid level and proposes and evaluates various strategies to manage this impact. We develop a spatially-explicit model with high temporal resolution that combines a diverse set of vehicle travel patterns with vehicle energy consumption to estimate longitudinal charging load profiles. We then model the interaction of electricity demands from charging and non-charging related activities to quantify peaks on circuits and substation transformers in Fairfield, Connecticut over year 2019. We also quantify how the needs of charging relates to charging availabilities at other locations. We consider a range of BEV adoption levels. By revealing the distribution grid electricity demand profiles under different BEV adoption levels, charging infrastructure expansion scenarios, and demand management strategies, this study uncovers strategies for distribution grid upgrades and charging infrastructure expansion to manage peaks from BEVs.

3.2 Methods

To model the distribution grid impact of BEV charging, we first model BEV adoption scenarios and vehicle travel patterns. Using these patterns, we then model vehicle energy consumption and subsequently the BEV charging load profiles. Finally we combine the charging load profiles with non-charging related load profiles to quantify the impact of BEV charging on circuits and substation transformers on the distribution grid. We also propose and examine various demand management strategies to reduce impact of BEV charging on the grid. An overview of the modeling approach is shown in Figure 3-1.

3.2.1 Data

To model travel patterns and subsequently time of day and duration where people are at different locations to charge BEVs, we use data from the 2017 National Household Travel Survey (NHTS) conducted by the US Department of Transportation [1]. The dataset records cross-sectional trip patterns of vehicles across the US. The variables we use include trip distance, trip time of the day, trip duration, trip purpose, and household demographics. A diverse set of vehicle travel patterns can be modeled with the NHTS data. For example, 100 observations of vehicle travel patterns over 24 hours beginning from 4 AM on Mondays are shown in Figure 3-2.

To estimate trip-level energy consumption and capture the effect of different driving conditions on fuel economy, we used a dataset of 112,000 second-by-second drive cycles (vehicle speed profiles) from California [33], Atlanta [106] and Texas [107]. The drive cycles are matched to vehicle trips in the NHTS and used in the TripEnergy model [**?**, 10] to estimate energy consumption of trips recorded in the NHTS data and subsequently charging loads.

Another two datasets we use to analyze potential peaks of highway fast charging loads

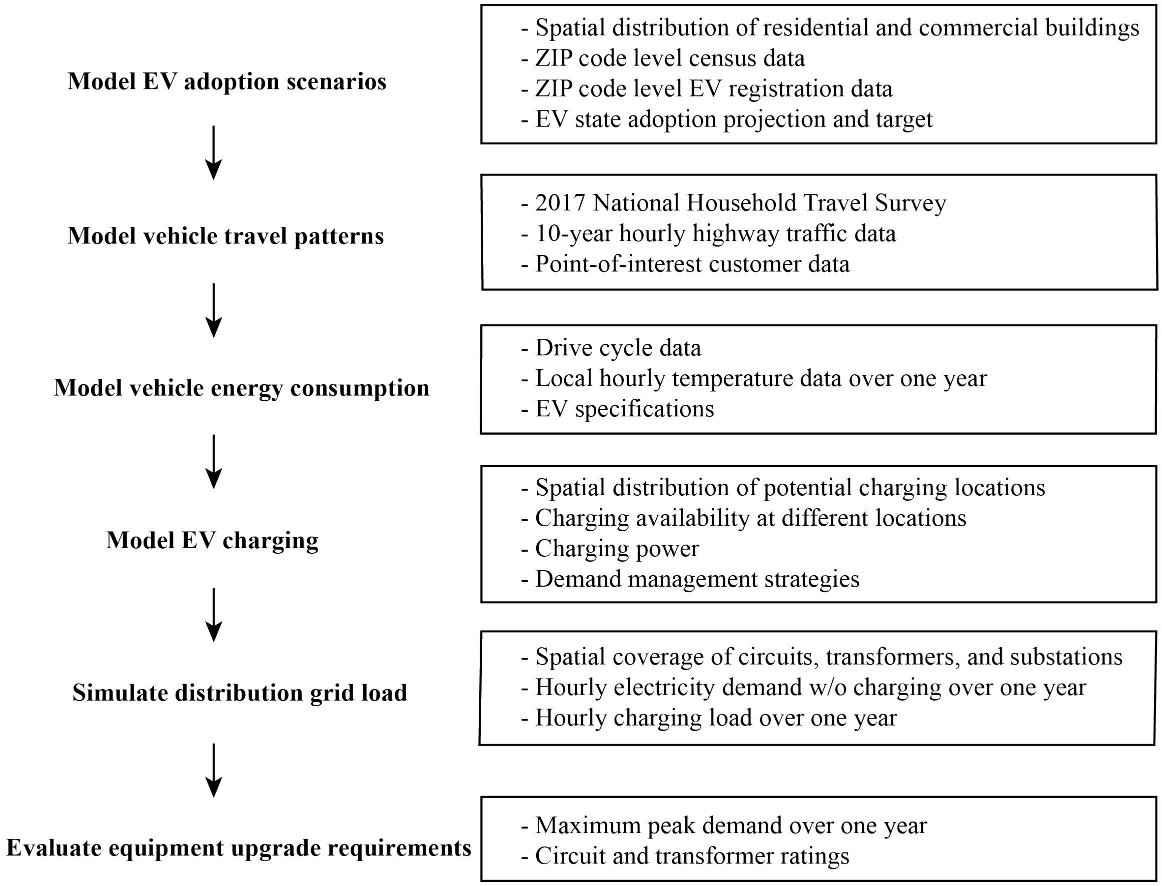

Figure 3-1: An overview of the modeling approach.

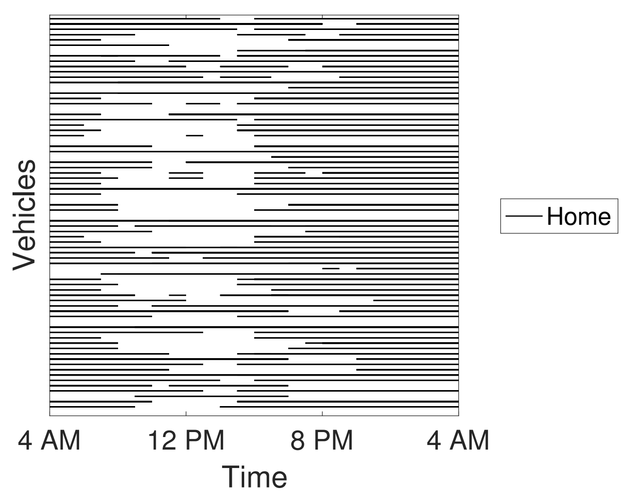

Figure 3-2: Patterns of times when vehicles are parked at home on Mondays from 100 randomly selected vehicles from the National Household Survey [1], where the vehicles are owned by households residing in an area with a similar demographics with Fairfield, Connecticut. Each row represents an individual vehicle.

are the highway traffic volume monitoring data from the Department of Transportation [34] and data on visitor patterns to highway rest stops from SafeGraph [32]. The Safegraph dataset is based on cellphone data and includes the number of visitors at a given point-of-interest at an hourly resolution. The Safegraph data has been validated against company reported data of customer volume [129]. We extract the data for one year 2019 for multiple I-95 highway rest stops and highway gas stations in Connecticut, including the rest stop served by the Ashcreek substation in Fairfield.

Finally, we use the electricity demand data at the circuit, transformer, and substation level for two substations: Ashcreek and North Haven substations in Connecticut [2]. The Ashcreek substation covers the southern half of Fairfield and a western part of Bridgeport. The North Haven substation covers the southern half of North Haven town.The data is provided by utility company Avangrid. The electricity demand is at an hourly resolution over one year 2019. The data also includes information on how many customers are served by each circuit and maps of where the circuits are located at. We combine this data with commercial business data extracted from Safegraph [32] to identify the number of residential and commercial customers served by each circuit.

3.2.2 BEV adoption scenarios

We model different levels of BEV adoption in a spatially explicit way in order to estimate the impact of BEV charging on the distribution grid. We first estimate the number of households served by each circuit and substation transformer based on the spatial distribution of residential and commercial buildings. We then assume there are 2 vehicles per household, which is the average for Fairfield, CT in year 2019 [130]. We examine a range of BEV adoption level from 0 to 100%, where 100% BEV adoption means that all household vehicles are BEVs.

3.2.3 Vehicle trip energy model

To estimate charging loads, we calculate trip energy consumption using the TripEnergy model [108, 10]. The TripEnergy model includes a demand model that matches vehicle trips to drive cycles based on trip distance and average speed, and a vehicle model that calculates energy consumption using the matched drive cycle and estimates auxiliary energy consumption based on hourly ambient temperature over a year [114]. The quantitative results presented in this analysis are based on the vehicle parameters of the 2019 Nissan Leaf with a 62 kWh battery capacity, which is a lower-cost vehicle (relative to other BEVs) that has a comparable life cycle cost with internal combustion engine vehicles [9].

3.2.4 Vehicle charging model

Using vehicle trip patterns and energy requirements, we examine different scenarios of charging availability and demand management strategies to shift loads such as delayed home charging and incentivized work charging. We formulate an optimization problem building upon previous work [14] as follows. For each vehicle-day, at the end of each 30-minute time bin, the energy stored in the battery is E_b and energy drawn from the grid is E_g. The optimization constraints are as follows. The energy stored in the battery should never exceeds 80% of the battery capacity E_{batt} or goes below zero:

$$0 \leq E_b \leq 0.8 \times E_{batt} \tag{3.1}$$

The energy drawn from the grid is greater than or equal to zero and less than or equal to the maximum amount of charge the vehicle can draw while parking at a particular location where charging is available This amount is equal to the multiplication of stop duration T_{stop}, charging power P_{charge}, and charging efficiency η_{charge}:

$$0 \leq E_g \leq T_{stop} \times P_{charge} \times \eta_{charge} \tag{3.2}$$

For each 30-minute time bin out of the total 48 time bins in one day, the difference in the amount of energy stored in the battery at time t and previous time step $t-1$ is equal to the amount of energy drawn from the grid at time t minus vehicle trip energy consumption

E_{trip} from time $t-1$ to t:

$$E_b(t) - E_b(t-1) = E_g(t) - E_{trip}(t), \forall t = 2, ...48 \tag{3.3}$$

The objective function varies for different demand management scenarios. In the uncontrolled charging scenario, charging starts immediately after the vehicle arrives at locations where charging is available and the vehicle is plugged in for the entire stop duration. The objective function is:

$$\min - \sum_{t=1}^{48} E_b(t) \tag{3.4}$$

In the delayed home charging scenario, charging is preferred in early mornings after 4AM when electricity demand without charging is low. The objective function is:

$$\min \sum_{t=\text{early morning at home}} E_b(t) \times 0.01 + \sum_{t=\text{rest of the day}} E_b(t) \tag{3.5}$$

In the incentivized work charging scenario, charging is preferred when the vehicle is parked at work so that charging is shifted to midday when electricity demand without charging is low. The objective function is:

$$\min - \sum_{t=1}^{48} E_b(t) + \sum_{t=\text{not at work}} E_g(t) \times 1000 \tag{3.6}$$

In the scenario where delayed home charging and incentivized work charging are combined, charging is preferred at work and if charging is still needed at home, charging in early mornings is preferred. The objective function is:

$$\min \sum_{t=\text{early morning at home}} E_b(t) \times 0.01 - \sum_{t=\text{at work}} E_b(t) + \tag{3.7}$$

$$\sum_{t=\text{rest of the day}} E_b(t) + \sum_{t=\text{not at work}} E_g(t) \times 100000 \tag{3.8}$$

This optimization formulation assumes a perfect foresight of a vehicle-day's travel patterns and energy consumption. We also assume a charging power of 6.6 kW for both home and work charging and a charging efficiency of 89%.

3.2.5 Distribution grid load simulation

We simulate hourly electricity demand on the distribution grid equipments including circuits and substation transformers. We take two approaches to model load profile depending on the charging location. The first approach models charging loads at home and work using sampled vehicle travel patterns from the National Household Travel Survey [1]. To simulate travel patterns made by households in the Fairfield and North Haven area, we sample vehicle-days from the NHTS that are made by households residing in urban areas with a census block group population density between 750 and 17000 people per square mile. For each date of the year, we only sample vehicle-days made on the same day of the week to account for differences in travel patterns over a week.

We then perform a Monte Carlo simulation to simulate hourly BEV charging loads over an entire year for each circuit and substation transformer. For each date of the day, we sample N vehicle-days with replacement, where N is equal to the number of BEVs owned by households residing in the area covered by the circuit/transformer. For each sampled vehicle-day, we calculate vehicle trip energy requirements and run the vehicle charging model to calculate the hourly charging load for the charging availability and demand management scenario considered. This simulation for the entire year is repeated for K times so that we obtain a range of hourly charging loads over an entire year. The quantitative results shown in this paper are based on K=100. Finally we combine hourly BEV charging load with hourly electricity demand without charging over one year using data from a utility company Avangrid to estimate the impact of charging on circuits and substation transformers.

The second approach models charging load using foot traffic data at public locations such as highway rest stops with cellphone data from Safegraph [32]. The foot traffic data at highway rest stops are normalized based on cellphone sampling rate in each month at Connecticut and surrounding states, where drivers residing at these locations might use the Interstate-95 rest stop at Fairfield, Connecticut. To translate foot traffic to charging demand, we assume vehicles are always charging when parked at the rest stop to estimate the maximum impact of charging. We also assume a vehicle occupancy of 1.7 passengers per vehicle, which is the reported US average [131].

3.3 Results

3.3.1 Magnitude of distribution grid load increase from BEV home charging

We first examine the increase in electricity demand from electric vehicle home charging on circuits and substation transformers.We model the impact of charging in a spatially explicit way by accounting for the number of residential customers on each circuit and substation transformer (Figure 3-3). We estimate hourly home charging load throughout the year 2019 from detailed travel patterns and energy-consuming patterns and perform a Monte Carlo simulation to obtain a range of possible charging load (Figure 3-1).

We model the variations in hourly electricity demand on the circuit when coupling non-BEV related electricity demand and BEV home charging demand on weekdays and weekends over one year 2019 (Figure 3-4). The circuit shown is the largest residential circuit in Ashcreek substation that serves 2515 households and 210 commercial customers in Fairfield, Connecticut. The quantitative results of circuits shown in this paper are based on this circuit. We find that the maximum hourly electricity demand without BEVs varies from 1.5 (1^{st} percentile) to 5.3 MW (99^{th} percentile) on weekdays and from 1.5 to 5.6 MW on weekends (Figure 3-4). After adding BEV home charging, the maximum hourly electricity demand increases to 1.6 – 7.5 MW on weekdays and to 1.7 – 7.1 MW on weekends (Figure 3-4). This variation demonstrates the diversity in electricity demand patterns with and without BEVs on different days over the year that cannot be captured by modeling a “typical" day.

We measure distribution grid impacts in terms of maximum peak load on circuits and substation transformers. Maximum peak load is defined as the maximum hourly peak load over one year that includes both baseline non-charging related electricity demand and BEV charging demand.

We examine hourly electricity demand over one year 2019 with and without BEVs on the largest residential circuit in Ashcreek substation. (Figure 3-5a). We examine other circuits in Appendix B. Here we assume a 100% BEV adoption level where every household served by the circuit owns two BEVs (the average number of vehicles per household in Fairfield). We assume charging starts immediately when the vehicle arrives at home and the vehicle is plugged in for the entire stop duration. Here we only show electricity demand from BEV charging for vehicle-days whose energy requirements can be covered by the BEV with the considered charging availability. For example, 92% of the vehicle-days can be covered with 6.6 kW home charging.

We find that even at 100% BEV adoption level, adding immediate home charging on the residential circuit only results in a maximum peak load of 7.5 – 8.1 MW with 100 runs of Monte Carlo simulation (Figure 3-5). The maximum peak load occurs on Monday, July 29th in 2019 at 7 PM and its value is close to the circuit limit of 7.9 MW (Figure 3-5c). The circuit limit is defined as 90% of the circuit rating based on the industry rule-of-thumb to leave sufficient spare capacity for unanticipated events. This result suggests that this circuit might only require a minimal upgrade to meet BEV home charging demand even with widespread BEV adoption and no external interventions such as demand management. Moreover, the small variation in maximum peak load across Monte Carlo simulations suggests that when aggregating different vehicle travel patterns at the circuit level, the total BEV home charging load becomes stable and predictable despite the diversity in individual travel patterns.

We also find that the maximum peak load with BEV home charging on the residential

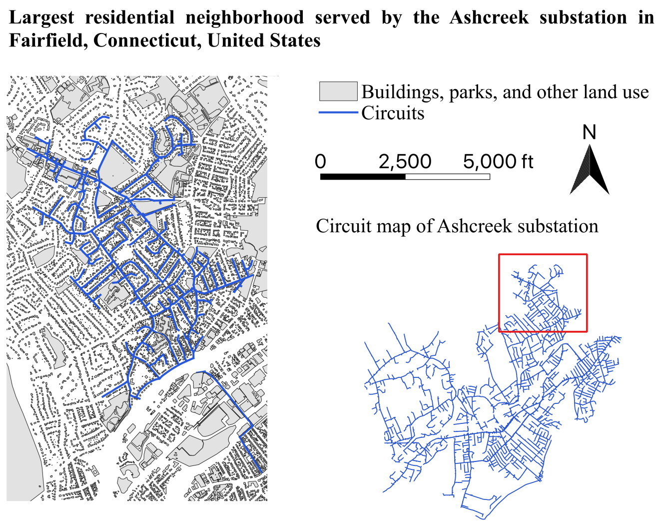

Figure 3-3: A map of land use and circuits in the largest residential neighborhood served by the Ashcreek substation in Fairfield, Connecticut. The circuit data is provided by a utility company Avangrid [2] and the land use data is obtained from OpenStreetMap [3].

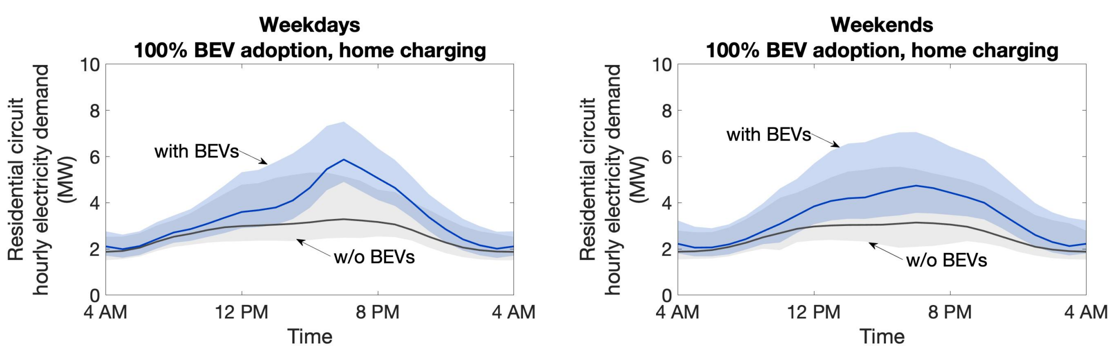

Figure 3-4: Hourly electricity demand on **a.** weekdays and **b.** weekends in year 2019 of the circuit serving the largest residential neighborhood in Ashcreek substation in Fairfield, Connecticut assuming 100% BEV adoption level and immediate home charging. The shaded blue area shows the 1^{st} – 99^{th} percentile of hourly electricity demand with BEV charging using results from 100 runs of a Monte Carlo simulation of the year. The blue line represents the hourly average electricity demand with BEV home charging across 100 runs of the Monte Carlo simulation. The shaded grey area shows the 1^{st} – 99^{th} percentile of hourly baseline electricity demand without BEV charging. The baseline data is provided by a utility company Avangrid [2]. The grey line represents the hourly average electricity demand without BEV home charging. The figure demonstrates the variation in weekday and weekend electricity demand that cannot be captured by a “typical" day. The variation in BEV charging demand comes from travel patterns, driving conditions, and ambient temperature when the trips are made.

circuit is largely determined by the peak load from non-BEV related activities. Although we observe more charging-induced electricity demand during winter when the temperature is low and vehicle energy consumption is high, this is not the dominant factor that determines the maximum peak load and the maximum peak load occurs in the summer months when non-charging related electricity demand is high (Figure 3-5a).

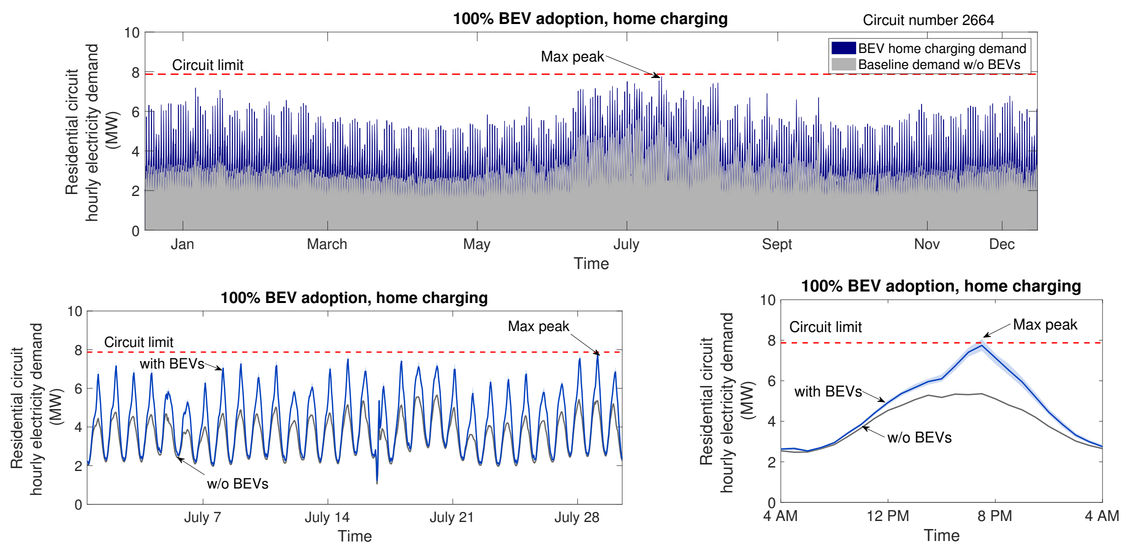

Figure 3-5: Hourly electricity demand of the circuit serving the largest residential neighborhood in Ashcreek substation in Fairfield, Connecticut assuming 100% BEV adoption level and immediate home charging over **a.** year 2019; **b.** the month of July when the maximum peak demand (the sum of baseline demand without BEVs and BEV home charging demand) occurs; **c.** the day when the maximum peak demand with charging occurs (July 29th). The shaded blue area shows the variation in BEV home charging demand from 100 runs of Monte Carlo simulation of the entire year. The blue line shows the hourly average electricity demand with BEVs, calculated as the average electricity demand across all NHTS vehicle-days made on the same day of the week multiplied by the number of vehicles served by the circuit. The red dashed line shows the circuit limit, which is 90% of the circuit rating used as an industry rule-of-thumb to allow for a buffer.

At the level of substation transformers, we find that even at 100% BEV adoption level, immediate BEV home charging does not cause a transformer overload (Figure 3-6). This is partly because current substation transformers are typically oversized so that one substation transformer can meet the electricity demand of the entire substation in case the other transformer fails. Similar to the residential circuit, we find that the maximum peak load on the substation transformer occurs in the summer months when non-BEV related electricity demand is high (Figure 3-6).

3.3.2 Demand management strategies to shift home charging loads on distribution grids

We examine the effectiveness of demand management strategies that allow temporal and spatial shifts of BEV home charging loads to reduce maximum peak loads on circuits and substation transformers. The strategies we investigate include delaying home charging to hours when electricity demand from non-BEV related activities is low, adding access to work charging, incentivizing charging at work, and their combinations.

We examine the hourly electricity demand with BEVs on the circuit with different demand management strategies considering a 100% BEV adoption level (Figure 3-7 and 3-8). We show the hourly electricity demand with and without BEVs under four demand management strategies on the day when the maximum peak load with immediate home charging occurs (Figure 3-7). The demand management strategies we show are adding un-incentivized work charging to home charging, adding incentivized work charging to home charging, delaying home charging to early mornings when non-BEV related electricity demand is low, and combining delayed home charging with incentivized work charging. We find that all demand management strategies have a significant impact on shifting the maximum peak load that appears with uncontrolled immediate home charging (Figure 3-7). For example, after enabling delayed home charging and incentivized work charging, the electricity demand with BEVs at the hour when the maximum peak load occurs with immediate home charging reduces from 7.5 – 8.1 MW (Figure 3-5c) to 5.5 – 5.6 MW (Figure 3-7d).

We quantify the reduction in circuit and transformer maximum peak load with different demand management strategies for a range of BEV adoption levels from 0 to 100% (Figure 3-9). We find that adding access to work charging and incentivizing work charging becomes more useful at reducing circuit and substation transformer maximum peak load when BEV adoption level is above 20%, while delaying home charging has a more prominent impact on reducing maximum peak load at low BEV adoption levels (Figure 3-9). Moreover, delaying home charging continues to be more effective than enabling and incentivizing work charging at reducing circuit and substation transformer maximum peak load at almost all BEV adoption levels as BEV adoption level increases (Figure 3-9). For example, delaying

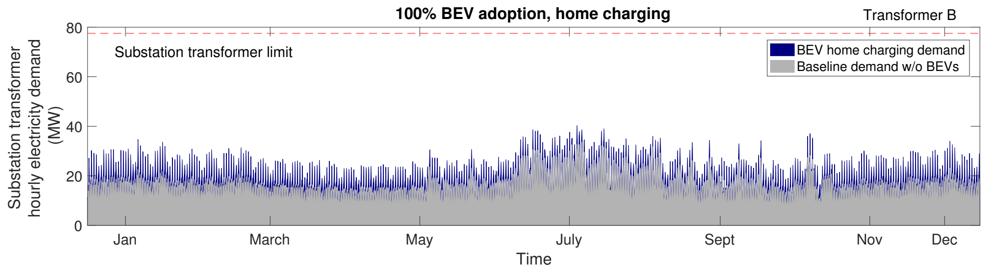

Figure 3-6: Hourly electricity demand of the substation transformer serving the largest residential neighborhood in Ashcreek substation in Fairfield, Connecticut over year 2019, assuming 100% BEV adoption level and immediate BEV home charging.

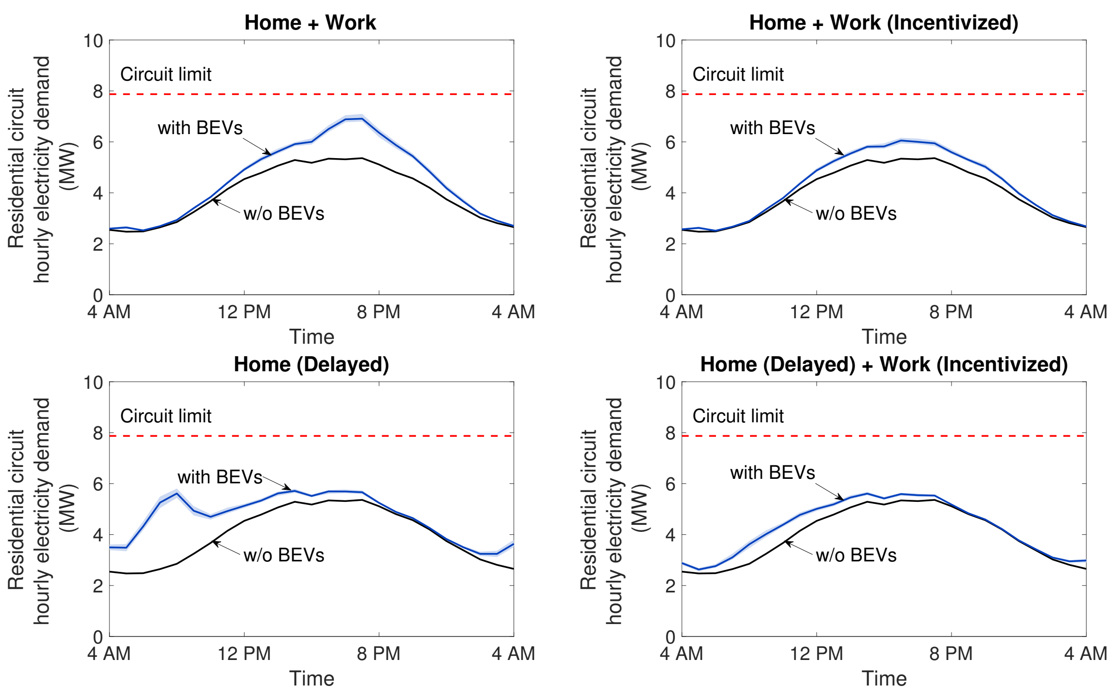

Figure 3-7: Hourly electricity demand with different demand management strategies on the day when the maximum peak load with 100% BEV adoption occurs with immediate home charging on the circuit that serves the largest residential neighborhood in Ashcreek substation in Fairfield, Connecticut. The shaded blue area shows the variation in BEV home charging demand from 100 runs of Monte Carlo simulation of the year. The red dashed line shows the circuit limit, which is 90% of the circuit rating.

home charging can reduce circuit maximum peak load by 11% from 6.6 MW to 5.9 MW at 50% BEV adoption level, and by 10% from 7.7 MW to 6.9 MW at 100% BEV adoption level. The results suggest that smart grid management technologies that can delay home charging has the potential to effectively reduce circuit and substation transformer upgrades required to accommodate BEV home charging loads.

3.3.3 Impact of highway fast charging on distribution grid loads

The impact of BEV highway fast charging on the distribution grid is more uncertain than home charging due to less predictability and more variability in travel patterns on highways. In this analysis, we quantify hourly highway fast charging demand and examine its impact on the circuit and substation transformer. We also investigate strategies to shift highway charging demand to mitigate the peaks loads on these equipments.

To understand if and when vehicles may cluster together at a certain location along the highway to use fast chargers and thereby causing surges in distribution grid loads, we examine hourly highway traffic volume over 10 years from year 2007 to 2016 at an Interstate 95 (I-95) traffic monitoring station in Norwalk, Connecticut (Figure 3-10). We find that some highway traffic peaks occur. We also examine the hourly highway traffic around Thanksgiving from year 2007 to 2016, as congestions at highway fast chargers was reported in California in 2019 during the Thanksgiving period [132]. We find that for days that fall on Thanksgiving and the five days before and after the holiday, the daily peak traffic exceeds the average traffic and occurs around morning rush hours and noon (Figure 3-10b). This result suggests that we may observe a high volume of vehicles at this location during these times and the highway fast chargers need to be prepared for accommodating this situation.

We then use point-of-interest data from Safegraph [32] that records the temporal distribution of number of customers at highway rest stops to understand potential electricity demand patterns from highway fast charging. Using hourly customer count data at the Fairfield I-95 highway rest stop, where fast chargers are likely to be installed to minimize the interruptions of charging activities to existing travel schedules, we examine the impact of

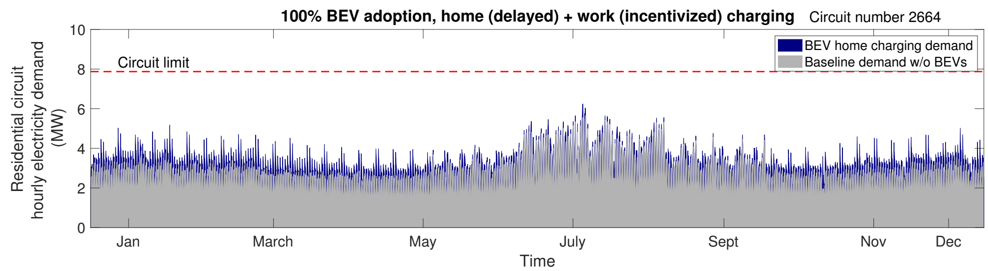

Figure 3-8: Hourly electricity demand of the circuit serving the largest residential neighborhood in Ashcreek substation in Fairfield, Connecticut assuming 100% BEV adoption level if delayed home charging and incentivized work charging are adopted over year 2019.

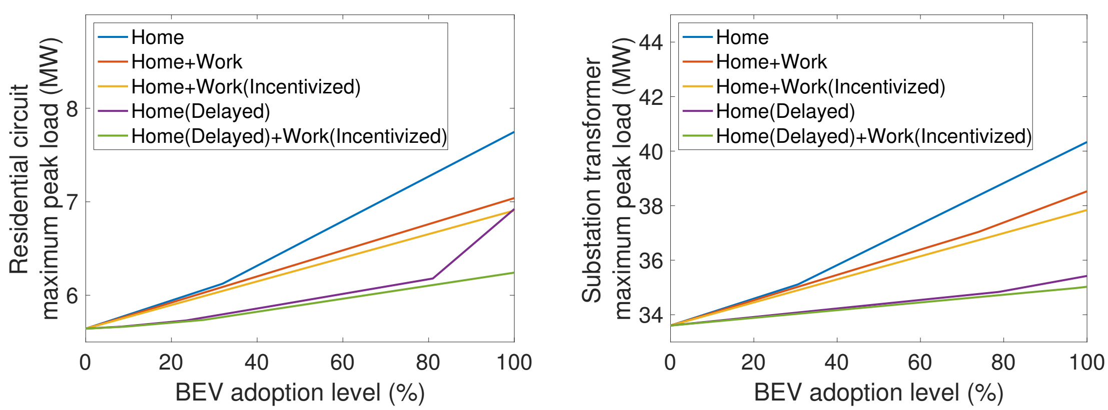

Figure 3-9: Maximum peak loads over year 2019 at a residential circuit and a substation transformer that covers this circuit for a range of BEV adoption levels from 0 to 100% before and after adopting demand management strategies in Ashcreek substation in Fairfield, Connecticut. The circuit serves the largest residential neighborhood covered by the substation where the examined demand management strategies can have the largest impact on reducing peaks.

charging demand on the circuit over one year (Figure 3-11). As the Safegraph data only records a fraction of the population [133], we normalize the raw data by the sampling rate to obtain an estimate of the actual number of customers at the rest stop. To calculate highway charging demand, we assume a vehicle occupancy of 1.7 [131] and divide the hourly customer number with vehicle occupancy to estimate the number of vehicles parked at the rest stop at each hour. We assume all vehicles parked at the rest stop are electric vehicles and they are plugged in when parked. We then assume that there are 150 fast chargers, which is equal to the parking capacity of passenger cars at the rest stop [134], and that the fast charging power is 150 kW. For the small number of residential customers served by the circuit that also serves the highway rest stop, we assume a 100% BEV adoption level and immediate home charging.

We find that after adding highway fast charging and home charging, hourly electricity demand on the circuit exceeds the circuit limit on a number of days throughout the year (Figure 3-11). The calculation suggests that upgrading the circuit from the current limit of 8 MW to 24 MW, three times of the existing circuit limit, is required to accommodate highway charging. At the substation transformer level, adding home charging and highway fast charging does not cause electricity demand to exceed the transformer limit (Figure 3-11).

We further examine demand management strategies that shift highway fast charging loads to nearby rest stops in order to mitigate peaks in circuit electricity demand. We investigate visitor patterns at highway rest stops that are adjacent to the Fairfield highway rest stop along I-95. We find that for the top 1% peak hours, there is no positive correlation between hourly visitor counts at the Fairfield rest stop and its adjacent highway rest stops along I-95 at Darien and Milford (Figure 3-12). The adjacent highway rest stops are around 15 miles apart. We also observe a similar trend for adjacent highway rest stops at Milford and Branford along I-95. This suggests that shifting highway charging demand to adjacent highway rest stops, thereby delaying or moving forward highway charging sessions, may mitigate the peak charging demand that only occur on a small number of days a year. For the remaining non-peak hours, we find that there is a statistically significant positive correlation between hourly visitor counts at adjacent highway rest stops (Figure 3-13). This

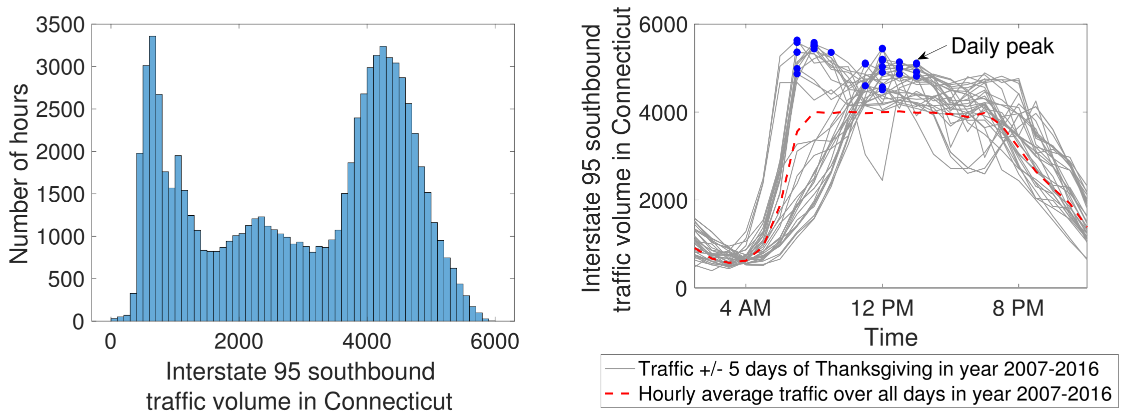

Figure 3-10: **a:** Histogram of hourly traffic volume measured by the Interstate 95 southbound monitoring station in Norwalk, Connecticut from year 2007 to 2016. **b:** Hourly traffic volume measured by the Norwalk traffic monitoring station on days that fall on Thanksgiving and the five days before and after the holiday in year 2007 – 2016. The blue dots represent the peak traffic on these days. The dashed line represents the hourly traffic volume averaged over all days in the same 10-year period.

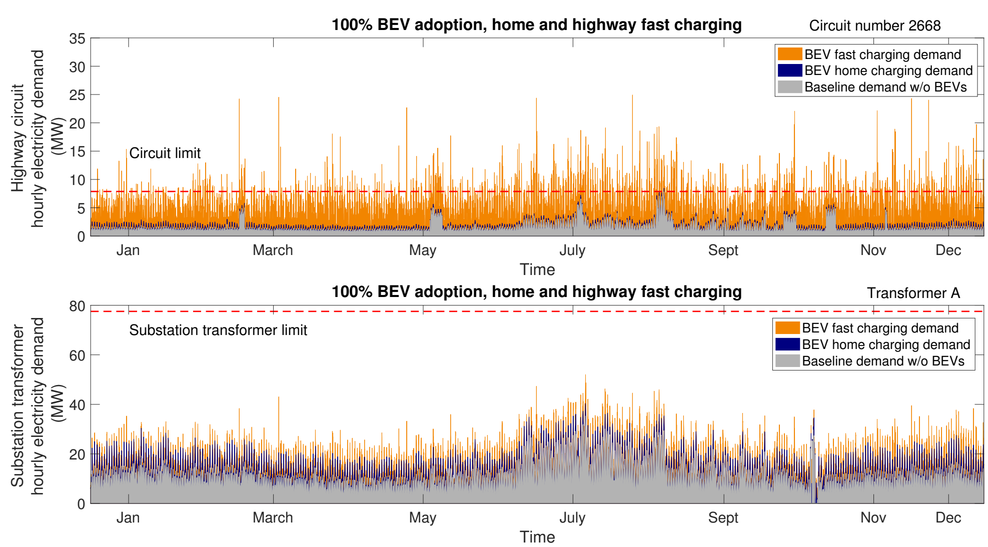

Figure 3-11: Hourly electricity demand of the circuit and the substation transformer that serve the interstate highway rest stop and the surrounding neighborhood in Ashcreek substation in Fairfield, Connecticut assuming 100% BEV adoption level and immediate home charging and highway fast charging over year 2019.

is reasonable as during non-peak hours, the visitor counts at adjacent highway stops should be coherent with traffic in the area.

There are also cost implications of the observed patterns of BEV highway charging as the extreme peaks affect the capacity factor of the highway fast chargers and the circuit and substation transformer that serve these chargers. The proposed approach of encouraging drivers to shift charging locations appears to be a potentially effective way to deal with these extreme peaks. There can be rare cases when adjacent stops experience high volume of vehicles at the same time, and the charging infrastructure and distribution grid need to be built to accommodate these rare events. Alternatively, drivers may need to be flexible with their schedules and wait at the stops to charge. As more data becomes available, we can examine these extreme events at more locations where drivers cluster together at a certain time to validate the effectiveness of the proposed solution.

In addition to shifting highway charging demand to adjacent stops, we examine the effectiveness on reducing the need for highway fast charging by enabling charging at home, workplaces, and overnight public locations using vehicle travel patterns from the NHTS data (Figure 3-14 and 3-15). We find that 19% of the vehicle-days in NHTS pass through highway and would require highway charging when none of home, work, or overnight public charging is available. When home charging is available, only 4% of the vehicle-days would require highway charging to meet the day's energy requirements for a Nissan Leaf with a 62 kWh battery capacity (Figure 3-14). When overnight public charging is available, this percentage is 18% (Figure 3-14). When work charging is available, this percentage is 11% (Figure 3-14). When home, overnight public, and work charging are available, this percentage further decreases to 2% (Figure 3-14). These results suggest that charging at home, work, and overnight public locations can play a critical role in reducing highway fast charging loads to meet vehicle energy requirements.

We also quantify the percentage reduction in highway charging hours when enabling charging at home, workplaces, and overnight public locations for different combinations of BEV battery capacity and highway charging power (Figure 3-15). The number of highway charging hours is calculated as the minimum required charging hours to meet a vehicle-day's energy requirements under different scenarios of charging availability, charg-

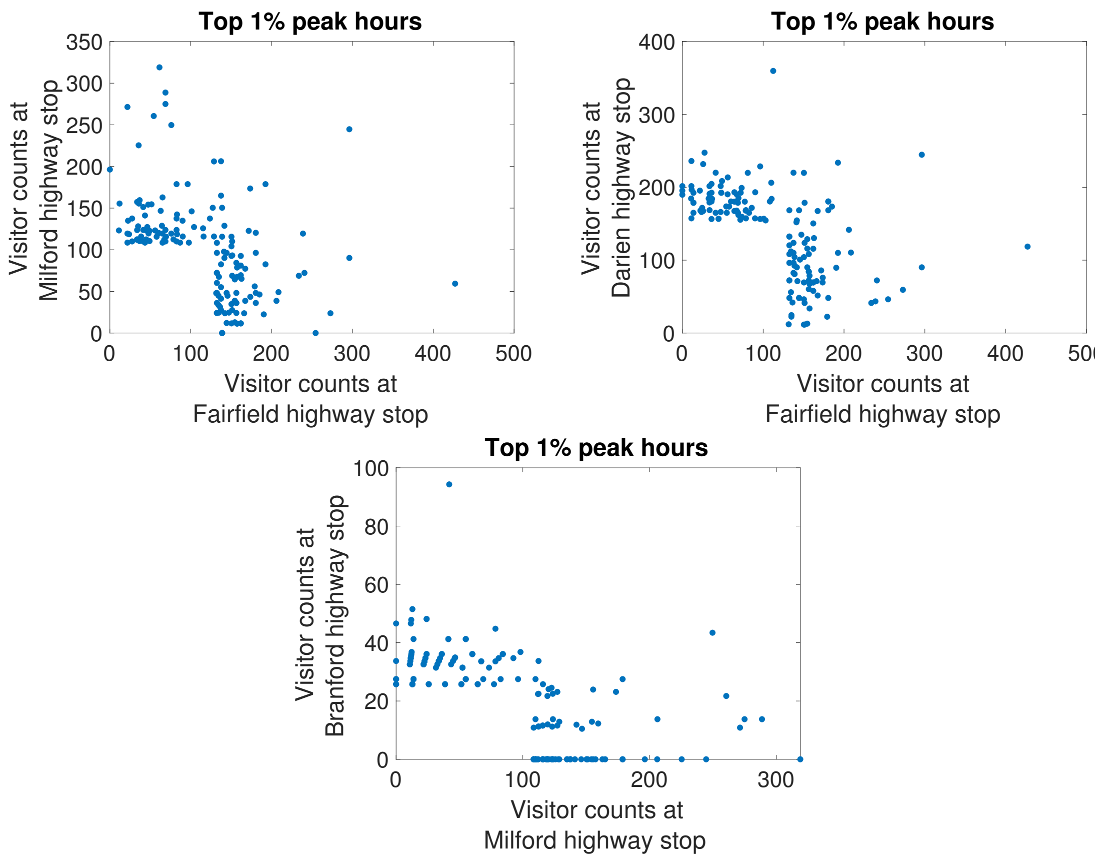

Figure 3-12: Correlations of visitor counts at adjacent highway stops during peak hours along Interstate 95 in Connecticut. The x- and y- axis show the top 1% hourly visitor counts at Fairfield, Darien, Milford, and Branford highway service plaza along Interstate-95 in Connecticut. We find that there is no positive correlation between hourly visitor counts at adjacent highway stops when hourly visitor counts are at the highest (top 1%).

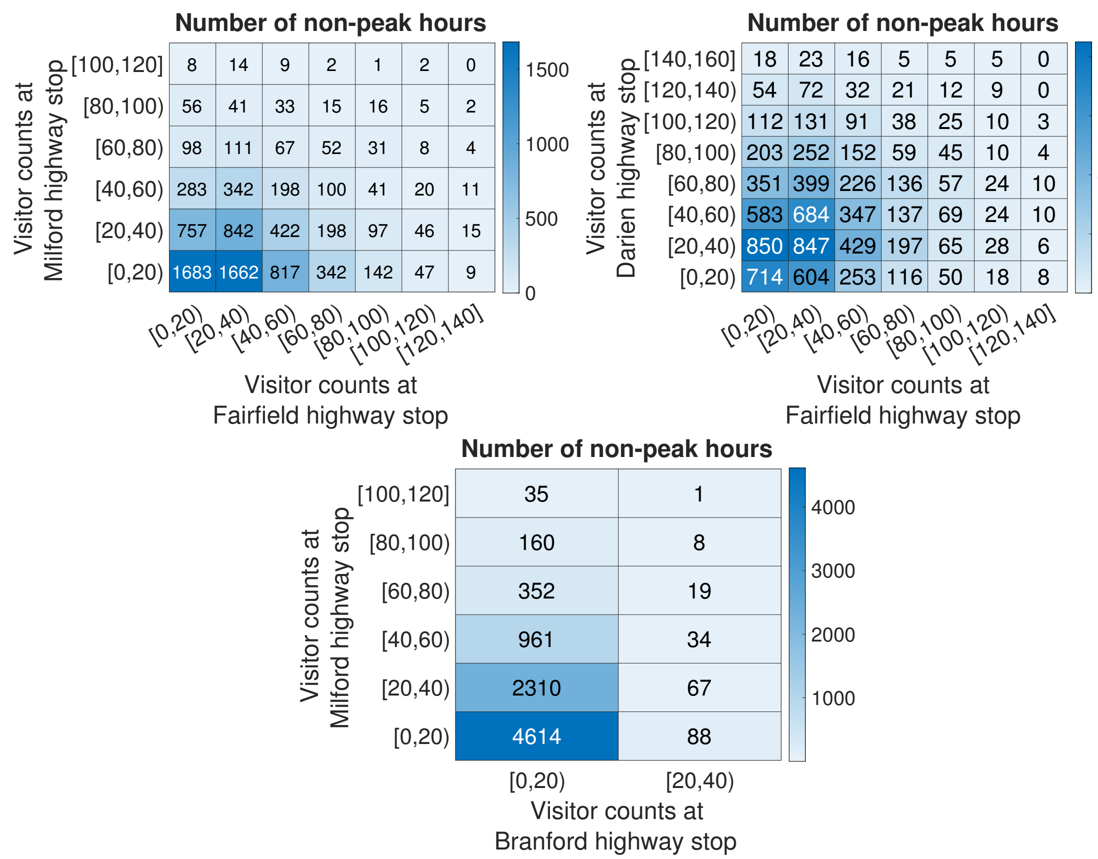

Figure 3-13: Heatmaps of number of non-peak hours (defined as hours with visitor counts below the 99^{th} percentile) at adjacent highway stops along Interstate 95. The x- and y- axis show the hourly visitor counts at Fairfield, Darien, Milford, and Branford highway service plazas in Connecticut during non-peak hours. We find that there is a positive correlation in visitor counts at adjacent highway stops during non-peak hours. The correlation coefficient is 0.35 between Fairfield and Milford, 0.32 between Fairfield and Darien, and 0.16 between Milford and Branford. All of the correlations are statistically significant with a p-value close to 0.

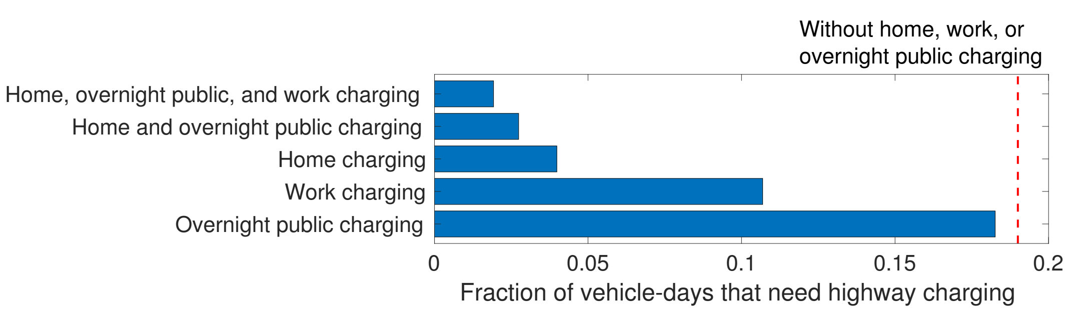

Figure 3-14: Fraction of vehicle-days that need highway charging when charging is available at different locations such as home, overnight public locations, and workplaces with a BEV that has a 62 kWh battery capacity. The dashed line indicates the fraction of vehicle-days that need highway charging when none of home, overnight public, or work charging is available.

ing power, and battery capacity. We find that for a BEV with a battery capacity of 150 kWh, providing 6.6 kW home charging can cause a 95% reduction in highway charging hours with a highway charging power of 200 kW (Figure 3-15). When charging is available at home, overnight public locations, and workplaces, the percentage reduction in highway charging hours further increases to 98% (Figure 3-15).

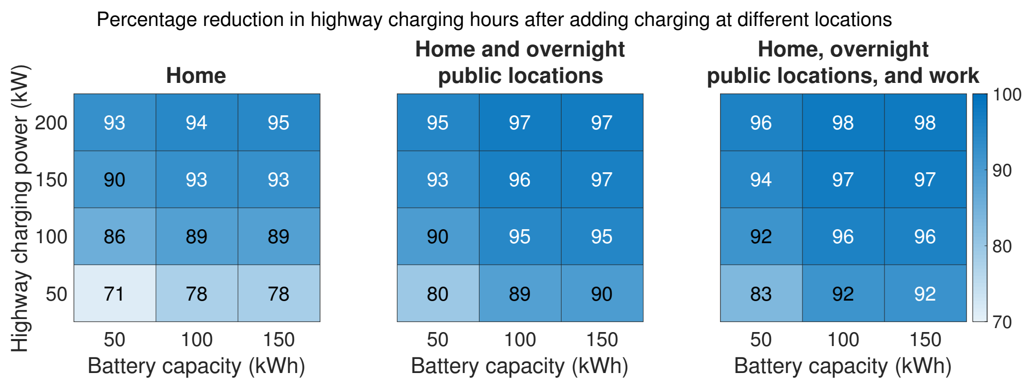

Figure 3-15: Percentage reductions in highway charging hours after adding charging availabilities at different locations including home, overnight public locations, and workplaces, compared to when only highway charging is available. Percentage reductions are shown for different combinations of vehicle battery capacity and highway fast charging power. The number of highway charging hours is calculated such that it is the minimum amount of charging required to cover vehicle-days' energy requirements.

3.4 Discussion and conclusions

In this research we examine the impact of BEV charging on the distribution grid. Specifically, we quantify the impact of BEV home charging and highway fast charging on circuits and substation transformers with a spatially- and temporally-resolved modeling of vehicle travel patterns and electricity demand from household and commercial activities. Using hourly electricity demand over year 2019 at the Ashcreek substation in Fairfield, Connecticut and simulated vehicle travel patterns, we find that at an 100% BEV adoption level, uncontrolled immediate home charging can cause an approximately 40% increase in the circuit maximum peak load when compared to the existing electricity demand without BEVs. Highway fast charging can cause an approximately 300% increase in the circuit maximum peak load at an 100% BEV adoption level. At the level of substation transformers, we observe an increase by approximately 20% from home charging and by approximately 40% from home charging combined with highway fast charging.

Certain demand management strategies, if adopted, can significantly reduce maximum peak loads caused by BEV home charging. For example, at the circuit level, if delayed home charging and incentivized work charging are adopted, home charging only increases maximum peak load by around 10% at a 100% BEV adoption level. At the substation transformer level, this percentage is around 5%.

To address the occasional peak demands from highway fast charging, encouraging spatial and temporal shifts of charging activities appears to be a potentially effective solution. For example, enabling charging at home, work, and overnight public locations can effectively reduce fast charging demand, allowing an up to 98% reduction in fast charging time required to meet travel demand. The percentage of days that require highway charging with a low-cost BEV also reduces from 19% to 2% when home, work, and overnight public charging are available on top of highway charging. We also observe a small number of hours where circuit electricity demand is at the highest after adding highway fast charging. To address these peak hours and reduce circuit upgrades needed, shifting fast charging activities to adjacent highway rest stops, if charging is available, may be an effective solution. This is because most peaks at adjacent highway stops are not coincident in time. In rare cases where peaks occur at adjacent highway stops simultaneously, the charging system needs to be designed to accommodate these extreme events. For example, on-site battery storage may be needed to serve as a back up power. Alternatively, drivers need to adjust their schedules to allow a longer waiting time at highway stops to charge.

The methodology developed in this research that combines real-world travel and electricity demand data with simulations of charging behaviors can be extended to study various locations. The numeric results from this analysis are based on distribution grid electricity demand data and foot traffic data in Fairfield, Connecticut where these data are available. Further research is needed to understand the distribution grid impact of BEV charging at other locations, where patterns of peak demands may vary.

Further research is needed to examine longitudinal foot traffic patterns over a year or longer at public locations where chargers may be installed. Publicly-available data on this topic is currently limited and this data is critical for understanding peak charging demands from drivers clustering at certain locations and the nature and frequency of these extreme events.

More work is also needed to understand real-world behaviors and preferences of electric vehicle charging and infrastructure constraints that can affect the practicality of the proposed demand management strategies. Community- and regional-specific incentive programs may be designed for different population segments to encourage the adoption of these strategies.

Finally, electrification of buildings and other sectors apart from transportation, will likely result in different grid electricity demand profiles and can affect the results in this analysis on distribution grid peak demands. However, this impact is difficult to quantify as there are still many uncertainties about the adoption and usage of the various electricity-powered technologies, such as heat pumps, that can affect the electricity demand. Further research is needed to understand the implications of electrification of various technologies and services, beyond vehicles, on the power generation and distribution systems.

Chapter 4

Strategic refueling infrastructure expansion for personal vehicle electrification with hydrogen fuel cell vehicles

Abstract

Questions remain on the refueling infrastructure requirements of hydrogen fuel cell vehicles (HFCVs) to meet the energy demand of personal vehicle travel. One major challenge of HFCV adoption is the high cost of refueling and one way to reduce the cost is to increase the utilization of refueling infrastructure. In order to do that, we need to examine vehicle activity patterns and HFCV technology features. Here, we examine HFCV refueling requirements to meet personal vehicle energy demand. We use a year-long vehicle travel dataset in Seattle and daily vehicle trip diaries in the Northeastern US to estimate refueling needs. We also construct a synthetic year-long vehicle travel dataset for the Northeastern US using the daily trip diaries to account for the lack of longitudinal data in the region. We focus initially on highway refueling because this might naturally lends itself to higher utilization as it may serve both personal vehicles and heavier-duty industrial vehicles. We find that only a small percentage of personal vehicles make frequent highway trips such that year-round energy requirements can be met by HFCVs with highway refueling alone.

This chapter is a working paper that is in final preparation with co-authors Sankaran Ramakrishnan and Jessika E. Trancik [87].

For example, if only highway refueling is available, around 5% of Seattle vehicles and 10% of vehicles in the Northeastern US can use an existing HFCV model, the Toyota Mirai with a 5 kg hydrogen tank capacity, to meet energy demand over a year. These percentages can increase if detours to highway refueling stations are allowed. For example, with 7 days of detour a year, around 30% of Seattle vehicles and 15% of Northeastern US vehicles can use the Mirai for their energy demand. Alternatively, refueling might be needed at other locations on top of highways such as near home, workplaces, and grocery stores to meet energy demand. If HFCVs were used only as weekday commuting vehicles, 85% of the personal vehicles in the Northeastern US require less than 1 kg of hydrogen per commuting day, suggesting that their needs may be covered by the Mirai if refueling once a week near home/workplaces. This study provides insights on the technical potential of HFCVs to be adopted as personal vehicles to meet travel demand and the refueling infrastructure requirements to make this feasible.

4.1 Introduction

Hydrogen fuel cell vehicles (HFCVs) are among a set of promising vehicle technology options for decarbonizing the transportation sector [135, 136, 137]. The life-cycle greenhouse gas emissions of HFCVs are lower than those of internal-combustion engine vehicles (ICEVs), considering an average US power grid carbon intensity today and a hydrogen production method of steam methane reforming [9]. HFCVs offer a refueling time that is comparable to that of ICEVs and shorter than the current charging time of other low-carbon vehicle technologies such as battery electric vehicles (BEVs). The time needed to refuel a full tank of hydrogen/gasoline is around 5 minutes. While for BEVs, it takes around 60 minutes to supply the amount of charge needed to achieve a similar range as an HFCV when using a 150 kW fast charger [138]. HFCVs also have a longer range between refueling compared to most BEV models on the market today [9].

However, the current lack of hydrogen refueling infrastructure is a significant barrier to the adoption of HFCVs as personal vehicles [139, 140, 141, 139, 142, 143, 144, 145]. A number of surveys and behavioral studies of drivers have shown that convenient and reliable access to hydrogen refueling stations is one of the most important factors to consider when adopting HFCVs [141, 139, 142, 143, 144, 145]. Yet the current number of HFCV refueling stations in the US is limited, and the cost of expanding HFCV refueling infrastructure can be high [146, 147, 148]. Most HFCV refueling stations in the US today are concentrated in California, with around 40 stations in operation in California by mid 2019 [149, 150]. Fewer than 10 refueling stations have been built in the Northeastern US, but there are plans to further expand this refueling network [149].

Currently, questions remain on the feasibility of HFCVs as personal vehicles and the most cost-efficient strategy to roll out and expand HFCV refueling stations, and we may approach these questions by considering it in the context of gasoline refueling and BEV charging. The expansion of gasoline refueling stations started out from filling stations outside refineries in the 1910s, and gradually expanded to curbside stations on urban streets (concentrating around residential areas, especially wealthy neighborhoods, and central business market districts), and then to a distribution system along interstate highways [151, 152]. While for BEV fast charging stations, they have typically been installed in high-density urban areas with limited access to home charging (such as high-rise apartments), and along high-traffic corridors (such as freeway intersections) to cover intercity travel [153, 124, 154]. It has been found that occasional highway charging with fast chargers can have a significant impact on meeting longitudinal travel demand to support BEV adoption [155]. The values of these past experiences with siting gasoline refueling stations and BEV charging stations deserve further attention when we consider the placement of HFCV refueling stations in the context of today.

The features of hydrogen refueling might, at a first glance, suggest that hydrogen refueling stations should follow a similar roll-out strategy with gasoline refueling stations. However, during the early stage of ICEV adoption, the US highway system was not well-developed, which limited the siting of gasoline refueling stations near highways. With the current more extensive road network, we need to examine if there is a more efficient way to build out hydrogen refueling stations to meet travel demand to make HFCVs economically feasible, considering the high cost of installing such stations [146, 147].

Several previous studies have come up with strategies to identify optimal locations for a limited set of hydrogen refueling stations [63, 64, 65, 66, 67, 68, 69, 70]. One group of studies use flow-based models to maximize the number of origin-destination flows that pass by a set of candidate stations and these models typically choose intersection of highways that have a high traffic volume as the optimal solution [63, 64]. Another group of studies designs roll-out strategies based on spatial clustering of early adopters and choose to locate most stations around residential areas to cover routine travel, complemented by a few highway stations to cover long-distance intercity travel [65, 66, 67, 68, 69]. This group of study typically uses spatially-explicit models and aggregated statistics such as population distribution and average vehicle miles traveled originating from the early adopters' cluster to determine the number and location of refueling stations that can minimize travel time to refuel. However, none of these studies models drivers' activity patterns explicitly, especially from a longitudinal perspective, to determine the optimal refueling locations to meet different kinds of travel demand over time. Moreover, these studies do not consider variations in vehicle fuel economy due to factors such as ambient temperature and driving conditions when evaluating the refueling infrastructure requirements.

In particular, highway refueling can serve both the long distance travel needs of personal vehicles and routine travel needs of medium- and heavy-duty commercial and industrial vehicles [156, 17]. Therefore, enabling highway refueling may be a strategic first-step in building out HFCV refueling stations and the ability of highway refueling to meet personal vehicle travel demand deserves further study.

In this study, we evaluate the refueling needs of HFCVs to meet personal vehicle energy requirements given existing travel patterns, with a particular focus on the impact of highway refueling on meeting travel demand. The quantitative results presented in this analysis are based on vehicle travel patterns in Seattle where longitudinal vehicle travel data is available and daily vehicle travel patterns in the Northeastern US where hydrogen refueling infrastructure is yet to be built in most cities. We combine trip patterns with energy requirements while taking into account driving conditions and ambient temperature. We adapt the TripEnergy model [10, 108] and construct a vehicle model and a temperature model for HFCVs. We match vehicle trips in the 2017 National Household Travel Survey (NHTS) [1] with a larger set of real-world high-resolution drive cycles [33, 106, 107] based on trip distance and average speed. Using the matched drive cycles, we then estimate trip energy consumption. We also model activity patterns throughout a day to determine whether a cold start is needed for each trip. By combining trip-level energy use and trip patterns, we examine the daily energy requirements of HFCVs and the impact of different refueling station deployment strategies to meet travel demand. In addition, to address the lack of longitudinal travel data in the Northeastern US when determining the optimal siting of hydrogen refueling stations, we construct a synthetic year-long travel dataset based on driver demographics and vehicle trip patterns to evaluate the impact of refueling stations at certain locations to meet drivers' travel demand on different kinds of days over time.

The paper is organized as follows. In the methods section, we discuss the data used to model vehicle trips and drive cycles, and then describe the vehicle model and temperature model developed to estimate HFCV energy consumption. We also describe the modeling of longitudinal vehicle travel patterns, hydrogen refueling needs, and drivers' behavior change to accommodate refueling. In the results section, we examine the refueling needs in Seattle and the Northeastern US and discuss strategies to build out refueling stations to meet vehicle energy requirements over time.

4.2 Methods

To study the feasibility of HFCVs to meet vehicle energy demand and refueling needs, we first model vehicle travel patterns and vehicle energy consumption. We then model HFCV refueling needs to meet travel demand and driver behavior change to allow detours to refueling stations. An overview of the modeling approach is shown in Figure 4-1.

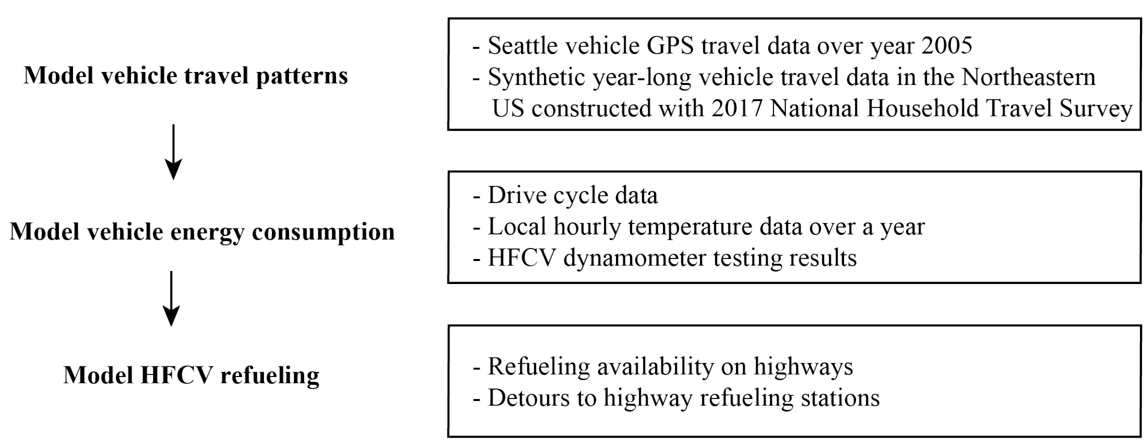

Figure 4-1: An overview of the model framework.

4.2.1 Vehicle trip and drive cycle data

To model vehicle trip patterns, we used two datasets. The first dataset is GPS data of 334 personal vehicles in Seattle over year 2005 [31]. This longitudinal dataset includes information on vehicle trip distance, duration, start and end time, and purpose. The second dataset is the 2017 National Household Travel Survey (NHTS) conducted by the US Department of Transportation [1]. This is a cross-sectional dataset that contains daily snapshots of vehicle trips in the US. The dataset includes household demographics such as the employment status of the drivers and trip characteristics such as trip distance, trip duration, trip start time, trip mode, and trip purpose. We focused this analysis on trips made by households residing in the 12 states in the Northeastern US where hydrogen refueling stations have yet to be built and planners need to start from scratch when designing a station roll-out strategy. In addition, we only considered driver trips to avoid double counting trips recorded for both drivers and other passengers in the same vehicle. We excluded days when a vehicle is not used. A total of 26,740 vehicle-days (days when a vehicle is used) that contain 117,772 vehicle trips were used in this study.

We also used a dataset of around 111,000 second-by-second drive cycles (vehicle speed profiles) that were collected from California [33], Atlanta [106], and Texas [107]. The data was collected through GPS loggers distributed to a sample of households. This set of drive cycles was used by the vehicle trip energy model to estimate the energy consumption of vehicle trips in the Seattle data and the NHTS data in order to account for variations in fuel economy due to driving conditions.

4.2.2 HFCV trip energy model

To estimate trip energy consumption and model its variations with trip patterns, driving condition, and ambient temperature, we adapted the TripEnergy model [108, 10] and developed a vehicle model and a temperature model for HFCVs. For a given trip with unknown drive cycles, we matched this trip with a number of drive cycles with a similar trip distance and average speed, and estimated fuel economy with the vehicle model and temperature model using these matched drive cycles. We also modeled the auxiliary power required for heating and air-conditioning depending on the hour when the trip starts, month of the year when the trip is made, and household location. In addition, we modeled the effect of a cold start on fuel economy. The vehicle model and temperature model were calibrated and validated using the vehicle dynamometer testing results of the 2017 Toyota Mirai, a commercially available HFCV that has a hydrogen tank capacity of 5 kg. We can apply this trip energy model to study other HFCVs when vehicle testing data becomes available.

HFCV vehicle model

To develop the vehicle model, we studied the powertrain control of the Toyota Mirai using dynamometer load traces [157]. We summarize the power-split between the battery and the fuel-cell stack, and the charging and discharging modes of the battery under different speed and acceleration conditions in Table 4.1.

	Cruising	**Accelerating**	**Decelerating**
Low speed ($0-20$ mph)	Battery powered	Fuel cell powered. Battery assist	Regenerative braking charges battery. Fuel cell inoperative
Medium speed ($20-40$ mph)	Fuel cell powered. Battery charged		
High speed (>40 mph)	Fuel cell powered		

Table 4.1: Battery and fuel cell operation modes under different driving conditions of a Toyota Mirai.

Based on these modes of operation and the typical current-voltage profiles for fuel cells, we modeled tractive and braking power using three parameters: η_{constant}, $\eta_{\text{accelerate}}$, and η_{brake}. The efficiency of the fuel cell was modeled as a constant when tractive power is below 10 kW and the efficiency linearly decreases with acceleration a when tractive power is above 10 kW (Equation 4.1). The decrease in fuel cell efficiency at high loads is consistent with the increase in kinetic losses due to electrochemical reactions and transport within the fuel cell. The efficiency of energy recuperation during braking was modeled using η_{brake}.

$$
\eta_{\text{fuel cell}} = \begin{cases} \eta_{\text{constant}} & P_{\text{tractive}} < 10 \text{ kW} \\ \eta_{\text{constant}} - a\eta_{\text{accelerate}} & P_{\text{tractive}} \geq 10 \text{ kW} \end{cases} \tag{4.1}
$$

We also assumed that when battery assists fuel cell in providing power when the vehicle accelerates, the power split between the battery and the fuel cell stack is 1 : 2, and that the maximum power provided by the battery is 10 kW. We assumed a battery charging and discharging efficiency of 95%.

HFCV temperature model

We developed a temperature model to estimate the auxiliary power required for climate control and the effect of a cold start on vehicle efficiency. When ambient temperature is above 22 degrees celsius, air conditioning load $P_{aux,AC}$ was modeled as a linear function (Equation 4.2) of the temperature difference between the ambient temperature $T_{ambient}$ and the reference temperature T_{ref}. We assumed T_{ref} to be 22 degrees celsius based on EPA testing procedures.

$$
P_{aux,AC} = p_{AC}(T_{ambient} - T_{ref}) \tag{4.2}
$$

When ambient temperature is below 22 degrees celsius, instantaneous heating load was modeled as a non-linear function of time t (starting from 0) and the difference between ambient temperature and reference temperature (Equation 4.3). At time 0 when the vehicle is started, heating load is a high-order polynomial of the temperature difference because electrical heating is needed to warm up the cabin. As the vehicle warms up and t increases, the heating load decreases but we still accounted for the added load from the blower to circulate warm air through the cabin.

$$
P_{aux,heating} = p_{heating}\left(1 + (T_{ref} - T_{ambient})^{\alpha_{heating}} \frac{1}{0.01 + t}\right)(T_{ref} - T_{ambient}) \tag{4.3}
$$

We also modeled the reduction in powertrain efficiency during a cold start (Equation 4.4) as a function of time t (starting from 0), where efficiency increases at a slower rate as time increases.

$$\eta_{cold\_start} = 0.4 + 0.6\left(\frac{t}{t+\alpha_{cold\_start}}\right) \tag{4.4}$$

We calibrated the parameters in the temperature model: α_{cold_start}, p_{AC}, $p_{heating}$, and $\alpha_{heating}$, and the vehicle efficiency parameters in the vehicle model using vehicle dynamometer testing results of the 2017 Toyota Mirai [157]. The test drive cycles and conditions used for the calibration are listed in Table 4.2.

Test drive cycle	**Test temperature ()**	**Cold start (on/off)**	**Reported MPGe**
US06	22	off	56
UDDS	22	off	95
HWFET	22	off	94
UDDS	22	on	92
UDDS	-7	on	36
UDDS	-7	off	59
UDDS	35	off	75
UDDS	-7	on	36

Table 4.2: Test cycles and conditions to calibrate vehicle model and temperature model [157].

The calibrated model was validated using the following dynamometer testing results as shown in Table 4.3 and has a less than 5% prediction error in fuel economy. The final set of parameters used in the vehicle model and temperature model to estimate HFCV trip energy use is shown in Table 4.4.

We illustrate the variation of fuel economy with ambient temperature and whether a cold start is needed using the UDDS drive cycle (an EPA test cycle to approximate urban driving) (Figure 4-2). When ambient temperature is at or above 22 degrees celsius and thus no heating is used, we observe a smaller reduction in vehicle fuel economy due to a cold start, compared to when ambient temperature is below 22 degrees celsius and heating is used. This is because of the need for electrical heating in cold weather.

Test drive cycle	Test temperature ()	Cold start (on/off)	Reported MPGe	Predicted MPGe
US06	-7	off	51	49
US06	35	off	50	52
HWFET	35	off	88	85
HWFET	-7	off	80	76
UDDS	-18	on	28	27

Table 4.3: Test cycles and conditions used for validation of calibrated parameters in the vehicle model and the temperature model [157].

	Parameters	Values	Units	Parameters	Values	Units
Vehicle model	a	143.79	N	P_{idle}	100	Watts
	b	1.99	N/(m/s)	$\eta_{constant}$	0.50	-
	c	0.41	$N/(m/s)^2$	$\eta_{accelerate}$	0.10	-
	Mass	1928	kg	η_{brake}	0.69	-
Temperature model	P_{aux_base}	150	Watts	$p_{heating}$	60	Watts/°C
	α_{cold_start}	17	-	p_{AC}	59	Watts/°C
	$\alpha_{heating}$	0.63	-			

Table 4.4: Final set of Mirai parameters used in the vehicle model and temperature model to calculate trip energy consumption. The a,b,c coefficients and vehicle mass are from the EPA dynamometer testing results.

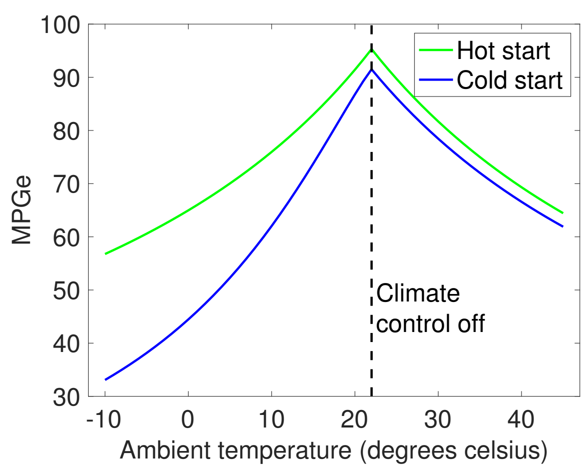

Figure 4-2: The effect of ambient temperature and a cold start on fuel economy evaluated using the EPA Urban Dynamometer Driving Schedule (UDDS). Heating is used when ambient temperature is below 22 degrees celsius, air-conditioning is used when ambient temperature is above 22 degrees celsius, and no heating or air-conditioning is used when ambient temperature is at 22 degrees celsius.

4.2.3 Variations in HFCV fuel economy

We modeled the impact of ambient temperature on Seattle and NHTS trips' energy consumption as follows. For each vehicle trip, we matched hourly ambient temperature to the trip based on the hour when the trip starts, month of the year when the trip is made, and location of the household using temperature reported in the Typical Meteorological Year (TMY3) dataset [114, 113]. We assumed heating is used when ambient temperature is below 22 degrees celsius and air-conditioning is used when ambient temperature is above 22 degrees celsius. We also assumed that cold start is needed when the vehicle is parked for more than 2 hours before the trip starts.

Using this method, we show the variation of energy intensity in Seattle trips (Figure 4-3) and in NHTS trips made by households that reside in the Northeastern US (Figure 4-4), taking into account trip patterns, driving conditions, and ambient temperature. Trips that use air conditioning have a smaller variation in fuel economy compared to trips that use heating. This is because air conditioning loads are primarily dependent on temperature reduction needed in the cabin, and do not vary significantly with trip speed and acceleration. While for heating loads, the drag increase due to cold air, the amount of waste heat produced by the fuel cell, and the fuel cell efficiency can vary depending on how the vehicle is driven. Adding heating loads also has a higher impact on reducing fuel economy than air-conditioning loads, especially when a cold start is needed. A cold start requires electric heating that is energy intensive, and the amount of electric heating needed is dependent on how soon the fuel cell stacks can provide waste heat.

We examine variations in trip fuel economy in the 12 states in the Northeastern US taking into driving conditions, trip patterns, and ambient temperature at hourly resolutions. We find that states with higher average ambient temperature when vehicle trips are made (averaged over trips that originate from each state in the NHTS depending on the hour when the trip starts and month of the year) tend to have a higher fuel economy (Figure 4-5). States with a lower average ambient temperature, such as Maine, Vermont, Connecticut, New Hampshire, Massachusetts, and Rhode Island, have a lower fuel economy than the mean across all trips made in the northeastern states. Washington DC has a lower fuel

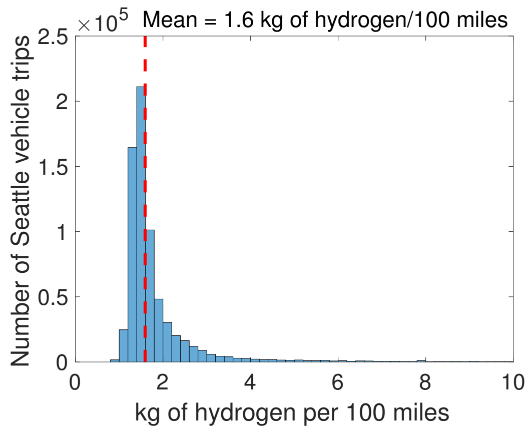

Figure 4-3: Histogram of energy intensity across Seattle vehicle trips. The red line indicates the mean energy intensity, calculated as the sum of all trips' energy consumption divided by the sum of all trips' distance.

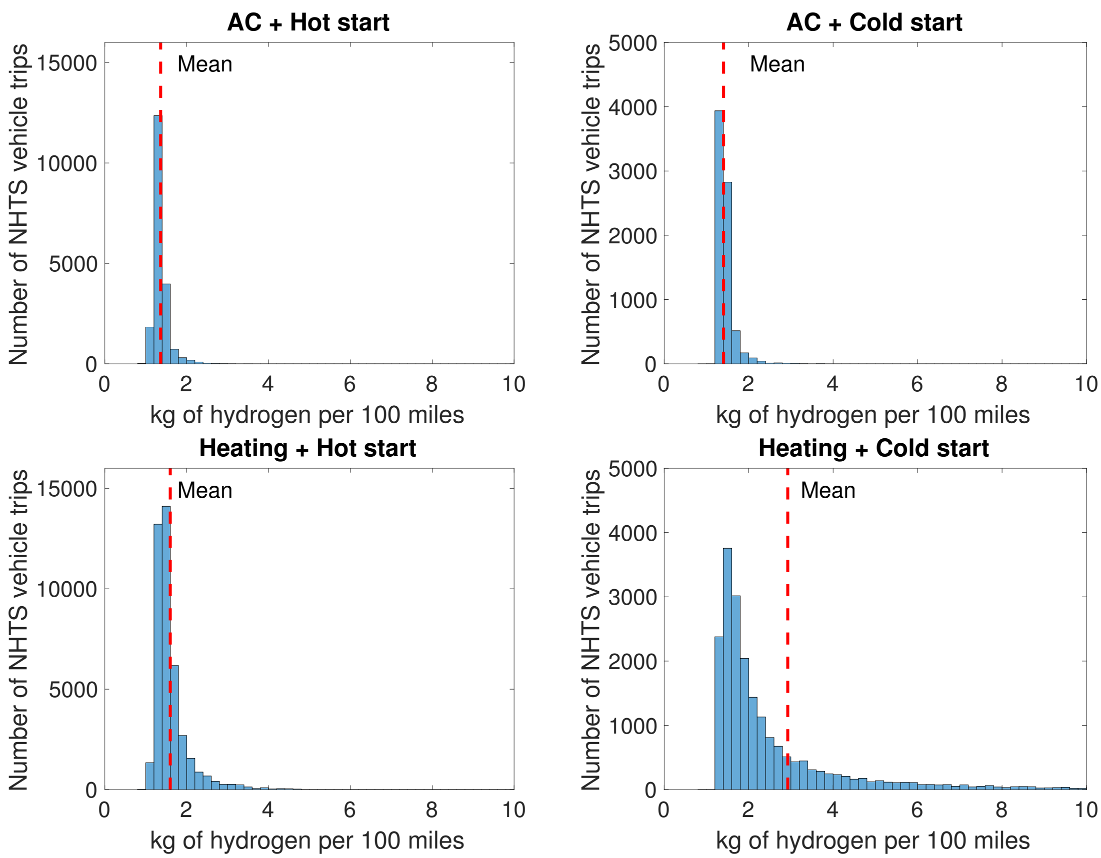

Figure 4-4: Histogram of energy intensity across NHTS vehicle trips made by households in the Northeastern US for different combinations of heating/air-conditioning (AC) and a hot start/cold start, estimated using the trip energy model. A cold start is needed when the vehicle is parked for more than 2 hours before the trip starts. Heating is used when the ambient temperature at the hour when the trip starts is below 22 degrees celsius, and air-conditioning is used when the ambient temperature is above 22 degrees celsius.

economy compared to other states with a similar average ambient temperature. This is because vehicle trips made in DC have a lower average speed (15 miles per hour) compared to other states (21 – 24 miles per hour), which is likely due to the dense urban setting in DC compared to the mix of urban and rural areas in other states. This decrease in fuel economy for trips with low average speed is consistent with what has been found in field studies of HFCV fuel economy performance [158].

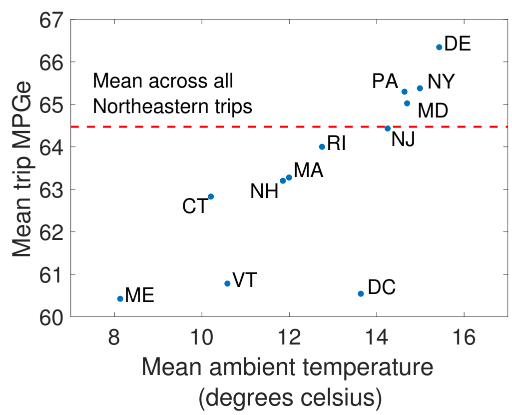

Figure 4-5: The y axis shows the mean fuel economy for vehicle trips made in each north-eastern state in the NHTS, taking into account driving conditions, ambient temperature at hourly resolutions, trip patterns, and whether a cold start is needed (we assume a cold start is needed when the vehicle is parked for more than 2 hours before the trip starts). The x axis shows the average ambient temperature over vehicle trips made in each state, taking into account the hour when the trip starts, month of the trip, and location of the household that are used to calculate auxiliary power needed for the HVAC system. The dashed line represents the mean fuel economy across all trips made in the 12 northeastern states. To adjust for the different sample size of trips recorded in each state, we calculate mean fuel economy as the weighted mean, where the weights are the trip weights provided in the NHTS that adjusts for over/under-counting of certain trips to have a representative sample.

4.2.4 Modeling HFCV refueling and longitudinal vehicle travel patterns

We developed a model to keep track of a HFCV's hydrogen tank level throughout a day under different refueling scenarios. On each vehicle-day (day when a vehicle is driven), for each trip, we used the HFCV TripEnergy model and calculated trip energy consumption of the Toyota Mirai. At the end of each vehicle trip, we calculated the hydrogen tank level after the trip by subtracting the trip energy requirement from the hydrogen tank level before the trip. At the end of each trip, we determined whether refueling en route was available based on the location of the trip. If refueling was available en route a trip, we updated hydrogen tank level by adding the amount of hydrogen taken by the vehicle. We assumed the HFCV was always refueled to a full tank due to the short refueling time required.

To model vehicle travel demand over time, we constructed a synthetic year-long vehicle travel dataset by sampling from the cross-sectional NHTS that only records one day of travel data per vehicle. For a given vehicle, we assumed that the trip patterns and driving conditions on the commuting vehicle-day recorded in the NHTS remains the same throughout a year (around 5 days a week, 20 days a month, and 240 days a year). This is a reasonable assumption because vehicle commuting trip patterns for a given driver is unlikely to change significantly with season. For each month in a year, we estimated trip-specific energy consumption on the commuting days by matching ambient temperature to the month considered, the hour when the trip starts, and the location of the trip to account for the effect of temperature on trip fuel economy for the same trip patterns on commuting days. For the remaining days of the year that are not commuting days, for each month, we sampled non-commuting vehicle-days from NHTS (vehicle-days with no commuting trips that are made in the same season and by households residing in the same state and population density group), so that we accounted for the variations in both trip patterns on non-commuting days and in trip fuel economy (a function of trip pattern, driving condition, and ambient temperature) across different months in a year. We modeled a larger variation in non-commuting days because different from commuting days, the trip patterns on non-commuting days are likely to vary with season.

To model detours to highway refueling stations so that HFCVs can meet year-round energy demand with only highway refueling, we kept track of HFCV hydrogen tank level after each trip and if the hydrogen tank level drops below zero after a trip that does not pass highway, we assumed the driver made a detour to the highway refueling station and filled the tank full. The hydrogen tank level at the beginning of the next trip is equal to the hydrogen tank capacity minus the energy required to make a round trip to and from the nearest highway refueling station.

4.3 Results

We combine trip patterns with HFCV energy requirements to estimate the refueling needs in Seattle and the Northeastern US. In the first subsection, we discuss the HFCV refueling requirements in Seattle by examining longitudinal vehicle travel patterns and energy demand. In the second subsection, we examine the distribution of HFCV daily energy requirements in the Northeastern US and discuss the refueling needs. In the third subsection, we construct a synthetic year-long travel dataset for the Northeastern US to quantify the impact of highway refueling stations on meeting travel demand.

4.3.1 HFCV refueling requirements in Seattle

We first examine the refueling requirements of Seattle vehicles based on longitudinal travel patterns over year 2005 [31]. Specifically, we study where refueling is needed to meet year-round travel demand with HFCVs. Because of the lack of hydrogen refueling infrastructure in the US and the high cost of building such infrastructure, HFCVs as personal vehicles may only become viable in the US after medium- and heavy-duty vehicles adopt the technology so that they can share the hydrogen production and refueling infrastructure and lower the cost. Highway refueling is essential for day-to-day use of medium- and heavy-duty vehicles and for long-distance travel of personal vehicles. Therefore, in analyzing the location of refueling stations, we focus on the impact of highway refueling stations on meeting personal vehicle travel demand.

We categorize Seattle vehicles into two types based on whether highway refueling alone is sufficient for meeting year-round travel demand. The first type of vehicle makes frequent and regular highway long trips (trips longer than 20 miles) so that highway refueling during long trips is sufficient for meeting year-round travel demand with an existing HFCV model, the Toyota Mirai with 5 kg of hydrogen tank capacity. Their highway trip patterns over the year 2005 and over the month of November when the number of highway trips is high are shown in Figure 4-6. Around 5% of Seattle vehicles fall into this category (Figure 4-8). This type of personal vehicle can best utilize the highway refueling infrastructure installed for medium- and heavy-duty vehicles and might not require residential/work refueling to use HFCVs.

The second type of vehicle makes sporadic long trips over the year so that if only highway refueling is available, HFCVs have limited use and the lack of refueling infrastructure is a real constraint. Their highway trip patterns over the month of November in year 2005 is shown in Figure 4-7. A more expansive network of refueling infrastructure near residential and work areas is needed in addition to highway refueling. The majority of Seattle vehicles (95%) belongs to this type.

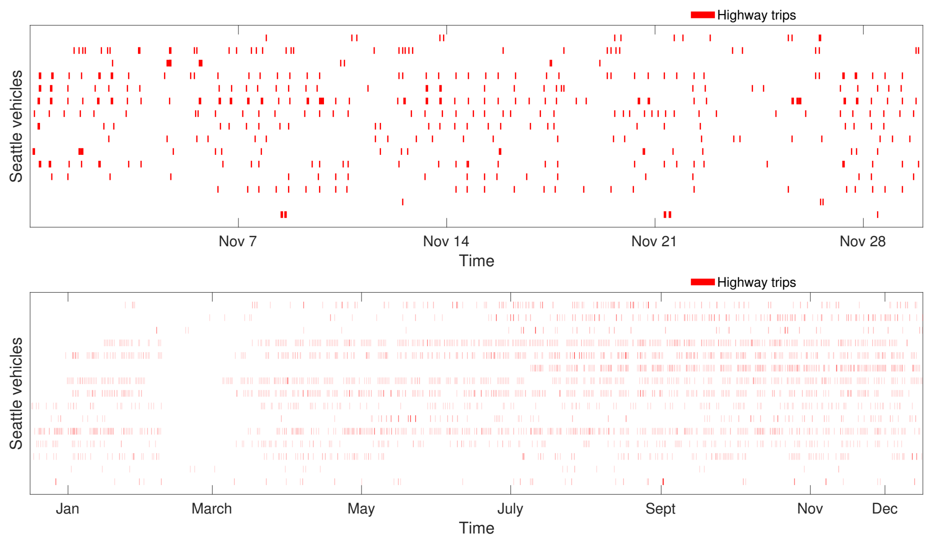

Figure 4-6: Patterns of highway trips over the month of November in year 2005 and over year 2005 for Seattle vehicles whose year-round energy requirements can be met with an HFCV with a 5 kg hydrogen tank capacity when only highway refueling is available. Each row represents highway trips patterns of an individual vehicle. The left and right end of each line segment represents the beginning and end of each highway trip.

We examine the feasibility of the Toyota Mirai with a 5 kg hydrogen tank capacity to meet longitudinal travel demand in Seattle when only highway refueling is available but detours to refuel on highway are allowed (Figure 4-8). We use a metric called vehicle electrification potential (VEP) that measures the fraction of vehicles examined whose energy requirements over a year can be covered with a given vehicle for the refueling scenario considered [155]. To account for the added travel demand due to detours, we assume 10 miles of extra travel for each detour (one way is 5 miles, around 10 minutes of driving) [159, 160]. We find that VEP in Seattle reaches around 30% when allowing detours on 7 days a year, and VEP reaches 1 when allowing detours on 35 days a year. This suggests that

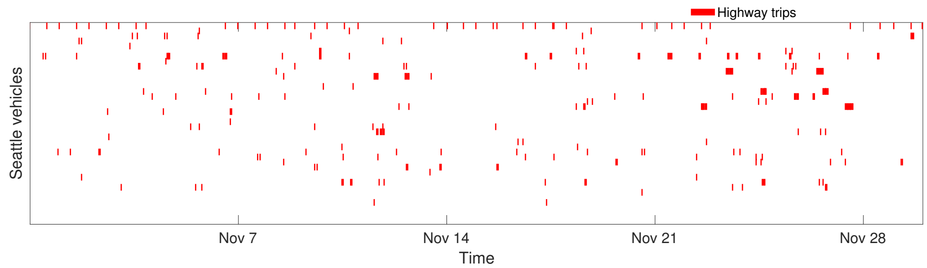

Figure 4-7: Patterns of highway trips over the month of November in year 2005 for 50 randomly selected Seattle vehicles whose year-round energy requirements cannot be met with an HFCV with a 5 kg hydrogen tank capacity when only highway refueling is available. Each row represents highway trips patterns of an individual vehicle. The left and right end of each line segment represents the beginning and end of each highway trip.

for certain drivers, if they can allow flexibilities in their travel schedules to make detours to highway refueling stations on a small number of days a year, they may be able to use HFCVs to meet year-round travel demand.

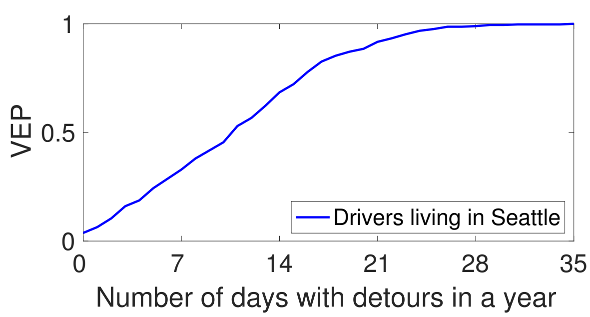

Figure 4-8: Vehicle electrification potential (VEP) in Seattle with the Toyota Mirai that has a 5 kg hydrogen tank capacity if detours to highway refueling stations are allowed on 0 to 35 days a year.

4.3.2 HFCV daily energy requirements and refueling needs in the Northeastern US

We examine the daily energy requirements of HFCVs in the Northeastern US when they are used to meet travel demand of personal vehicles. Different from Seattle, longitudinal vehicle travel data for the Northeastern US is not available so that we first rely on a cross-sectional dataset (NHTS) where only one day's travel data is available for each vehicle. We find that 99% of all vehicle-days require less than 5 kg of hydrogen per day, which is the tank capacity of an existing HFCV model – Toyota Mirai (Figure 4-9). 84% of all vehicle-days require less than 1/5 of the tank capacity of the Toyota Mirai per day and 35% of all vehicle-days require less than 1/20 of tank per day (Figure 4-9). This suggests that an existing HFCV model can meet the energy requirements of most vehicle-days with recharging once every few days, while a small percentage of vehicle-days (1%) would require refueling between trips during the day to meet travel demand. Moreover, we find that all of the vehicle-days that require refueling during the day contain trips longer than 20 miles. These trips likely pass through the highway based on our analysis of the earlier 2009 NHTS data, where we find that only 5% of the trips that do not pass through the highway are longer than 20 miles. The observation that all vehicle-days that require refueling during the day contain trips longer than 20 miles suggests that refueling stations on the highway might meet the needs of these less frequent vehicle-days with high energy requirements.

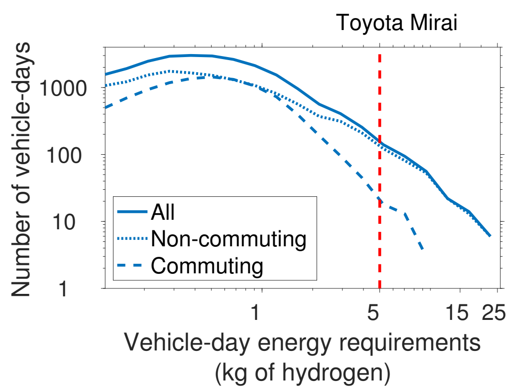

Figure 4-9: Distribution of HFCV energy requirements on all vehicle-days, non-commuting vehicle-days (days that do not contain commuting trips), and commuting vehicle-days made by drivers residing in the Northeastern US. The red dashed line shows the hydrogen tank capacity of the Toyota Mirai.

To examine the potential impacts of installing refueling stations near home or work locations, we examine trip patterns in combination with energy requirements. We find that among all vehicle-days we examine in the Northeastern US, 41% are commuting days (days that go to work) and the remaining 59% are non-commuting days. In particular, almost all of the commuting vehicle-days require less than 5 kg of hydrogen per day, where only 0.2% would require refueling during the day on the way to or from work (Figure 4-9). 85% of the commuting vehicle-days require less than 1 kg of hydrogen per day (Figure 4-9), thereby can be covered by the Toyota Mirai if refueled once a week on the way to or from work, assuming working five days a week and a fixed work location.

Moreover, we find that 26% of the commuting vehicle-days contain single trips longer than 20 miles that likely pass through the highway. This suggests that installing refueling stations on the highway might allow some workers to refuel on commuting days so that a HFCV is used as a commuting vehicle. For the remaining commuting vehicle-days that might not pass through the highway and use highway refueling stations without a detour, we examine their activities before and after work to explore the refueling opportunities at other locations that drivers may visit on a regular basis such as grocery stores. We find that for the trips made on commuting vehicle-days, trips between home/work and stores are among the most frequent trips made on commuting vehicle-days (Figure 4-10a) and these trips account for 17% of all trips made on commuting vehicle-days. In addition, 26% of the commuting vehicle-days visit stores to buy goods at least once during the day before or after work. This suggests that refueling stations at locations such as grocery stores that workers might visit on a regular basis can also address the refueling needs on the commuting days.

We also examine the characteristics of the non-commuting vehicle-days and find that 98% of the non-commuting vehicle-days require less than 5 kg of hydrogen per day when made with the Toyota Mirai (Figure 4-9). Moreover, 95% of the non-commuting vehicle-days require less than 2.5 kg of hydrogen per day, thereby requiring refueling once every two days or less frequently (Figure 4-9). We find that 19% of the non-commuting vehicle-days contain highway trips that could utilize highway refueling stations without a detour. The most frequently observed trip origin-destination pairs on non-commuting days are trips between home and stores to buy goods, restaurants to buy meals, home of friends/relatives, and places to drop off/pick up someone (Figure 4-10b). In addition, 56% of the non-commuting vehicle-days contain trips to stores to buy goods, suggesting that refueling stations near grocery/clothing stores could be convenient. We also find that for drivers that are employed and thus have commuting days, 93% of the employed drivers' non-commuting vehicle-days require less than half of the tank capacity of the Toyota Mirai. This suggests that for most employed drivers with commuting days, if there is an opportunity to refuel near work locations or en route on work trips, the HFCV can be used to meet most of the non-commuting vehicle-days' energy requirements (such as over the weekends).

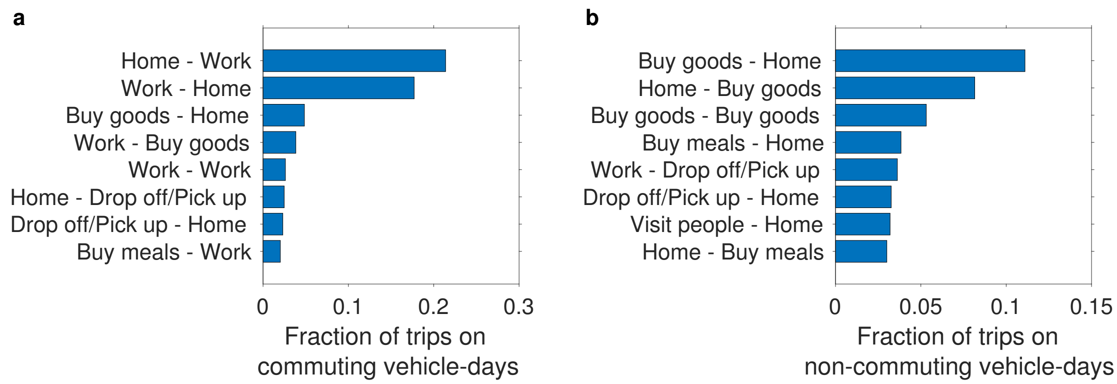

Figure 4-10: **a:** Fraction of trips on commuting vehicle-days with the top 8 most frequent trip origin-destination pairs. **b:** Fraction of trips on non-commuting vehicle-days with the top 8 most frequent trip origin-destination pairs.

Considering HFCVs have a similar range with internal combustion engine vehicles (ICEVs), we consider a few studies that have examined the relationship between travel activity patterns and location of gasoline refueling for ICEVs [161, 162] and discuss the implications for HFCV refueling stations. Using a driver survey of 1,521 participants conducted in northern California, it has been found that the location of refueling is largely determined by and linked to the location of home and out-of-home activities, especially work [161]. In particular, three quarters of the drivers refuel during a trip to or from home, and less than 10% of the drivers make a refueling trip that is not part of any other out-of-home activities [161]. The study also found that the refueling stop is not randomly distributed along the length of a trip, but rather clustered at the beginning or end; in particular, close to home and work locations. For long-distance commuters, freeway refueling stations are used. These observations of ICEVs suggest that the convenience of refueling near home and work locations or en route on work trips might be important for HFCV drivers as well. However, we still need to consider the feasibility and cost of installing hydrogen refueling stations that are as accessible as gasoline refueling stations.

4.3.3 Role of highway refueling in the Northeastern US

We further examine the role of highway refueling stations on meeting vehicle-day energy requirements in the Northeastern US by combining trip patterns with energy requirements and discuss the utilization rate of highway refueling stations. We find that the highway refueling stations can be useful for not only the occasional vehicle-days with high energy requirements that require refueling during the day, they may also be used en route on routine trips that occur on a regular basis. To account for the lack of longitudinal travel data in the Northeastern US, we also construct a synthetic year-long vehicle travel dataset to quantify the impact of highway refueling stations on meeting longitudinal travel demand.

The 2009 National Household Travel Survey (NHTS) records trip characteristics and whether part of a vehicle trip is made on the interstate highway [30]. For the 121,455 personal vehicle trips made by households residing in the Northeastern US (excluding taxis and trucks), 14% of the trips go through interstate, 16% of the trips do not go through interstate, and the rest 70% of the trips are unknown. Out of the 26,444 vehicle-days recorded, 26% of the vehicle-days contain at least one vehicle trip that goes through the interstate highway. We find that for the 17,300 interstate trips made on 6,924 interstate vehicle-days (days that pass through interstate), 29% of the interstate trips and 44% of the interstate vehicle-days are work commute-related. Moreover, 2% of the interstate trips and 3% of the interstate vehicle-days are school commute-related. The most frequently observed origin-destination pairs for trips that pass through interstate are: home to work (11%), work to home (8%), stores (groceries/clothing/hardware) to home (4%), home to stores (3%), stores to stores (3%), home to visit friends/relatives (2%), and visit friends/relatives to home (2%).

The 2017 NHTS has removed the question on interstate highway so we assume that trips longer than 20 miles pass through the highway based on our analysis of the 2009 NHTS. Using the 2017 NHTS, we find that 89% of the highway trips visit routine destinations such as home, work, school, stores, and child care services. These findings suggest that a significant fraction of the interstate vehicle trips are predictable and likely to occur on a regular basis. Although we only have one day's of travel data for each vehicle here, the regularity of the interstate vehicle trips suggests that installing refueling stations on the interstate can likely cover a significant fraction of the vehicle-days made by each vehicle over time.

To quantify the capability of highway refueling stations to meet travel demand over time and the required refueling frequency, we construct a synthetic year-long vehicle travel dataset by sampling from the cross-sectional NHTS that only records one day of travel data per vehicle. For the purpose of this analysis on the impact of interstate refueling stations, sampling vehicle-days made by other vehicles is a reasonable approximation because we did not find significant differences in the distribution of interstate vehicle trips across locations and times of the year.

We examine the synthetic year-long vehicle travel data of 10,777 vehicles that have a recorded commuting vehicle-day in the NHTS whose households reside in the Northeastern US. Over a year, we assume the HFCV starts with a full tank of hydrogen at the beginning of the year and keep track of the hydrogen tank capacity throughout a day after each trip and each stop, where trip energy is estimated using the TripEnergy model (see methods for details) that accounts for variations in fuel economy due to driving condition, trip patterns, and ambient temperature. We assume that the vehicle is refueled to a full tank en route on trips longer than 20 miles (for these trips, we assume they pass through the interstate based on our analysis of the 2009 NHTS data). If there are multiple highway trips on a day, we examine two scenarios: 1) refuel on all highway trips and 2) refuel on the longest highway trip that day.

We find that 26% of these vehicles that have regular commutes on weekdays can cover their year-long energy requirements with the Toyota Mirai with a tank capacity of 5 kg of hydrogen if highway refueling is available (Figure 4-11). After adjusting for vehicles that do not make regular commutes, around 10% of all Northeastern US vehicles can meet year-round energy requirements with only highway refueling.

We also examine vehicle electrification potential (VEP) when allowing for detours to highway refueling stations in the Northeastern US (Figure 4-11). To account for the added travel demand due to detours, we assume 10 miles of extra travel for each detour (one way is 5 miles, around 10 minutes of driving) for drivers living in urban areas and 100 miles of extra travel for each detour (one way is 50 miles, around 1.5 hours of driving) for drivers living in rural areas. These assumptions are based on the spatial distribution of national highway system in the northeastern US states [159, 160] and are calculated as the maximum distance the driver needs to travel to the nearest highway entrance. Rural areas in Maine, northern New York, and northern Pennsylvania have the most sparse highway network that requires the longest detour as assumed above. Other rural areas may require a much shorter detour such as a maximum of 30 miles in Massachusetts (excluding Cape Cod). For urban areas, all urbanized areas across the US (areas with a population of more than 50,000) can reach a highway within 5 miles (including other parts of the US with a much sparser highway system than the east coast) [159].

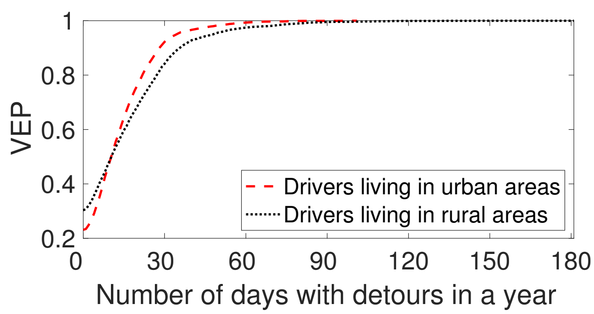

Figure 4-11: Vehicle electrification potential (VEP) in urban and rural areas of the Northeastern US with the Toyota Mirai that has a 5 kg hydrogen tank capacity if detours to highway refueling stations are allowed on 0 to 181 days a year.

Compared to results from Seattle, we observe that when not allowing detours, VEP in Seattle is lower than that in urban and rural areas of the northeastern US (Figure 4-8 and 4-11). This is because drivers pass by highways as part of their existing trips less frequently, subsequently missing opportunities to refuel if no detours are made. When allowing detours, we find that VEP increases faster and reaches 1 faster in Seattle than the northeastern US (35 days in Seattle and 181 days in the northeastern US) (Figure 4-8 and 4-11). This is due to the shorter work trips observed in Seattle, where in the northeastern US, drivers with long-distance work trips require more frequent detours to highways during weekdays.

The high capital cost of hydrogen refueling stations might prohibit the establishment of a hydrogen refueling network that is as extensive as the current gasoline refueling and BEV charging network in the near future, which makes strategic placement of hydrogen refueling stations particularly important [146, 163]. Installing hydrogen refueling stations near interstate highway can not only, as we have found, meet travel demand. This centralized approach to concentrate refueling stations near highways (in contrast to a decentralized approach where a higher number of refueling stations with a lower per-station capacity are spread across different locations in urban residential and business areas) might also minimize station deployment cost by lowering hydrogen transportation cost while still maximizing the station utilization rate to meet demand.

4.4 Discussion and conclusions

In this research, we examine HFCV refueling infrastructure requirements of personal vehicles in Seattle based on travel patterns and energy demand over a year. In particular, we quantify the impact of highway refueling on meeting energy demand considering the high costs of the hydrogen infrastructure and the potential of personal vehicles sharing highway refueling with heavier-duty commercial and industrial vehicles to lower the cost. We find that when only highway refueling is available, 5% of Seattle vehicles can meet their year-round energy requirements with an existing commercially available HFCV – the Toyota Mirai with a hydrogen tank capacity of 5 kg. This percentage increases to around 30% if detours to highway refueling stations are allowed on 7 days a year and to around 100% if detours are allowed on 30 days a year. The majority of Seattle vehicles still likely requires refueling near residential neighborhoods/workplaces/grocery stores on top of highway refueling to meet energy demand.

We also examine HFCV refueling needs in the Northeastern US based on daily vehicle trip diaries and trip energy consumption. For the Northeastern US where longitudinal travel data is not readily available, we find that 99% of all vehicle-days require less than 5 kg of hydrogen per day if HFCVs are adopted. 85% of the commuting vehicle-days require less than 1 kg of hydrogen per day if HFCVs are adopted. For drivers with these commuting days, a Mirai might potentially be used as a commuting vehicle if there are refueling opportunities once a week between/near home and work locations. We also find that about a quarter of vehicle-days in the Northeastern US go through the interstate highways. These vehicle-days include almost all of the observed days with high energy requirements that exceed the energy capacity of the Toyota Mirai. Almost half of the vehicle-days that pass highways include commuting trips, suggesting regularities in travel going through highways.

To further quantify the impact of highway refueling stations in the Northeastern US, we construct a synthetic year-long travel data using driver demographics and trip patterns to explicitly model longitudinal travel demand and the impact of highway refueling stations on meeting refueling needs on different kinds of days over a year. We find that around 10% of Northeastern US vehicles' year-round energy requirements can be met by the Toyota Mirai if only highway refueling is available. If detours to highway refueling stations are allowed on 7 days a year, this percentage increases to around 15%.

Put together, these observations imply that installing refueling stations on or near major interstate highways could potentially meet demands of not only commercial and industrial vehicles such as long-haul trucks, but also routine travel of personal vehicles such as daily commutes on weekdays and occasional long-distance trips such as intercity travel for leisure activities. This makes siting refueling stations at highways an efficient first step in building out HFCV refueling stations. This insight is especially relevant for companies, cities, regions, and countries who are at the beginning stage of deploying HFCV refueling stations and are looking to minimize infrastructure costs while meeting as many travel demands as possible.

Moreover, installing hydrogen refueling stations near highways could potentially lower the transportation cost of hydrogen via tank trailers for stations with off-site hydrogen generation. Highway refueling can make use of the larger land space available for on-site hydrogen generation and storage (compared to denser urban areas) while also easing public safety concerns for storing hydrogen at high pressure in urban communities.

Many other considerations might also affect the siting of hydrogen refueling stations, such as land availability, choices of hydrogen production and delivery methods, locations of existing gasoline refueling stations, and financing options to offset the high capital cost of refueling stations. These factors can be important to consider in evaluating the optimal placement of HFCV refueling stations given the specific context of each community.

Appendix A

Charging solutions for personal vehicle electrification

A.1 Literature review

We discuss in detail the previous studies that examine the effects of expanded charging infrastructure [60, 99, 100, 61, 101, 102, 62, 103] and the studies that examine the effects of accessing long-range vehicles as supplementary vehicles [60, 59, 104, 100, 61, 105] on meeting the range requirements of personal vehicle travel with BEVs. We also discuss the differences between these previous studies and our analysis, and highlight the novelties in our paper.

In Table A.1, we summarize the studies that examine the effects of charging in terms of travel data used for the analysis, charging scenarios considered, and vehicle range. All of these studies devise various charging scenarios to quantify the effect of home, work, and public charging. However, for public charging, these studies do not distinguish charging at different public locations and do not characterize the kind of public charging that is effective at extending the BEV range. In contrast, our analysis detangles the trip patterns on vehicle-days that can be electrified with different charging availabilities and provides insights on the kind of public charging that is required to electrify more vehicle-days. In addition, these studies assume days always start from home with a full charge and consecutive vehicle-days are independent. They do not account for energy requirements and trip patterns on consecutive vehicle-days, where one day's energy use and trip patterns can affect the battery state-of-charge available at the beginning of the next day depending on location of the overnight stop, stop duration, and charging availability. In the Seattle data examined, 12% of the vehicle-days do not end at home, suggesting that these assumptions underestimate the effect of work and public charging.

A number of studies have analyzed the effect of accessing supplementary vehicles on a limited number of days in order to electrify the remaining days [60, 59, 104, 100, 61, 105]. These studies quantify the number of days that cannot be electrified with BEVs based on vehicle daily travel distance and the rated range of BEVs in terms of distance. Some of these studies assume a constant cost per day for the long-distance travel days that require supplementary vehicles, such as $15 per day [60] and $50 per day [104]. However, these studies do not discuss the implications for the availability of supplementary vehicles, such as when supplementary vehicles are needed. In contrast, we provide an analysis of characteristics of days that require supplementary vehicles in Section 4 of the manuscript. Moreover, none of these studies compare the effect of charging and supplementary vehicles to support vehicle electrification.

We also note that the definition of supplementary vehicles is different in our analysis compared with papers in the literature. In our analysis, supplementary vehicles are defined as vehicles used on days when battery electric vehicles cannot meet the energy requirements of a home-based tour (a chain of trips that start from home and end at home that might span across multiple days). We consider home-based tours because of the convenience of parking a personal vehicle at home while traveling with an alternative supplementary vehicle for several days. Previous analysis defines supplementary vehicles as vehicles that are used on days that exceed the BEV range (in miles) and consider each vehicle-day as single individual days without taking into account the detailed activity patterns. For example, in our analysis, for some of the un-electrified home-based tour that spans across multiple vehicle-days, not all vehicle-days in the home-based tour have high energy requirements. These vehicle-days would be considered as electrifiable in the previous paper's models because they do not consider travel patterns. However, in our model, when we take into account stop locations and trip patterns, the same vehicle-days are not electrifiable and would still

Table A.1: A summary of previous papers that examine the effect of expanded charging infrastructure on meeting the range requirements of personal vehicle travel with battery electric vehicles.

Paper	Travel data	Charging scenarios	Vehicle range
Lin and Greene 2011 [60]	NHTS (2001)	Home, work, public everywhere, home + work + public everywhere; Charging power: 1.1, 6, 90 kW	100 miles, 150 miles, 200 miles
Zhang et al. 2013 [99]	NHTS (2009)	Home, home + work, home+ work +public everywhere; Charging power: 1.44, 3.3, 6 kW	45–100 miles
Dong et al. 2014 [100]	Seattle GPS	Home, home + public everywhere; Charging power: 1.44, 6, 90 kW	100 miles
Dong and Lin 2014 [61]	Seattle GPS	Home, once between trips anywhere, between trips everywhere Charging power: N/A	0–150 miles
Greaves et al. 2014 [101]	Sydney GPS	Home; Charging power: 2.4–7.2 kW	8–36 kWh
Kontou et al. 2017 [102]	Seattle, Atlanta, LA-Long beach-Anaheim GPS	Public at selected locations; Charging power: N/A	80 miles, 95 miles, 100 miles
Wu 2018 [62]	Seattle GPS	Home, home + work; Charging power: 1.2, 3.3, 6.6 kW	107 miles, 238 miles
Zhou et al. 2020 [103]	Beijing stated-preference survey	Charging stops selected in the survey; Charging power: 7 kW	0–600 miles

require supplementary vehicles.

To summarize, the key novelties in our analysis compared to the previous papers are:

- Combine travel activity patterns with trip energy modeling to determine how different charging strategies and supplementary vehicles can be combined to meet energy requirements.

- Compare the effect of expanded charging infrastructure and accessing supplementary vehicles on electrifying more vehicles.

Modeling detailed trip patterns allows us to analyze different kinds of charging such as work charging, overnight public charging and highway fast charging. Using the trip patterns, we also show the kind of vehicle-days that are addressed or not addressed with different kinds of charging infrastructure. This is critical for guiding a strategic expansion of charging infrastructure considering charging everywhere might not be available in the near term and can incur a substantial cost. Moreover, different from the previous studies that assume battery always starts with a full charge every morning, we take into account trip patterns and energy requirements on consecutive days where the battery state of charge at the end of the previous day is equal to the battery state of charge at the start of the next day. We also take into account dwelling time overnight and the location of the overnight stop (whether at the end of day, the vehicle is parked at home, work, or a public location that is not home or work) when evaluating the impact of different charging availabilities on electrifying vehicle-days.

A.2 Details of TripEnergy model application

We apply the TripEnergy model [10, 108] to estimate the energy consumption of each trip in the National Household Travel Survey (NHTS) and the Seattle dataset. We calibrate the vehicle efficiency parameters for the Nissan Leaf using the dynamometer parameters of the 2019 Nissan Leaf with a 40 kWh battery capacity, where coefficients a = 116.988 N, b = 2.854 Ns/m, c = 0.446 Ns^2/m^2, and we assume a vehicle mass of 1810 kg. We use a drive efficiency of 0.87, braking efficiency of 0.92, and idling power of 100 Watts. We match

GPS drive cycles to NHTS and Seattle trips using distance and average speed bins, where we sample one random drive cycle from the corresponding bin of the trip and use this drive cycle to estimate fuel economy of the trip using the vehicle model of TripEnergy. The distance bin edges we use are 0, 1, 2, 3, 4, 6, 8, 10, 12, 14, 16, 18, 20, 25, 30, 40, 50, 80, 100, 150, 200, 300, 500, and 10000 kilometers. The average speed bin edges are 0, 2, 4, 6, 8, 10, 12, 14, 16, 18, 20, 25, 99 meters per second. For the auxiliary power model, we use a base auxiliary load of 737 Watts that is assumed to be on for all trips. For heating, we add an additional heating load assuming 160 Watts per degree of temperature difference. For cooling, we add an additional cooling load assuming 80 Watts per degree of temperature difference [110, 111].

We compare this method with another approach where for each NHTS and Seattle trip, we sample multiple drive cycles for the corresponding distance and average speed bin (number of drive cycles in each bin can vary from 10 to 500 depending on the bin), average over the drive cycles to obtain an average moment for each bin, and then use this average moment to calculate trip energy. We find that the vehicle electrification potential (VEP) results of Nissan Leaf for different charging scenarios examined in the paper change by around 0–2 percentage points. Considering a 40 kWh BEV, VEP with home charging changes from 12% to 11%, VEP with home, work, and ubiquitous public charging changes from 23% to 24%, VEP with home, work, overnight public charging changes from 15% to 14%, VEP with home, work, and fast charging on all highway stops changes from 41% to 43%, VEP with work and ubiquitous public charging changes from 14% to 15%, and VEP for all other scenarios remain the same. The difference between the two approaches' results is small because of the large number of trips we examine, so that the small variations among drive cycle fuel economy in the same distance and average speed bin avearge out when we consider a large number of trips.

A.3 Comparison of VEP with a fixed and variable fuel economy

In this paper, we model the variations in fuel economy across driving styles and routes, due to differences in vehicle speed profiles (drive cycles) and ambient temperatures affecting auxiliary energy consumption by adapting the TripEnergy model [10, 108]. Variations in fuel economy has an impact of the modeled effects of charging and supplementary vehicles as shown in Figure A-1. This is because, for example, BEV fuel economy is lower than average for long-distance highway trips [115], and therefore the energy requirements of these trips are underestimated when using a fixed-fuel-economy assumption.

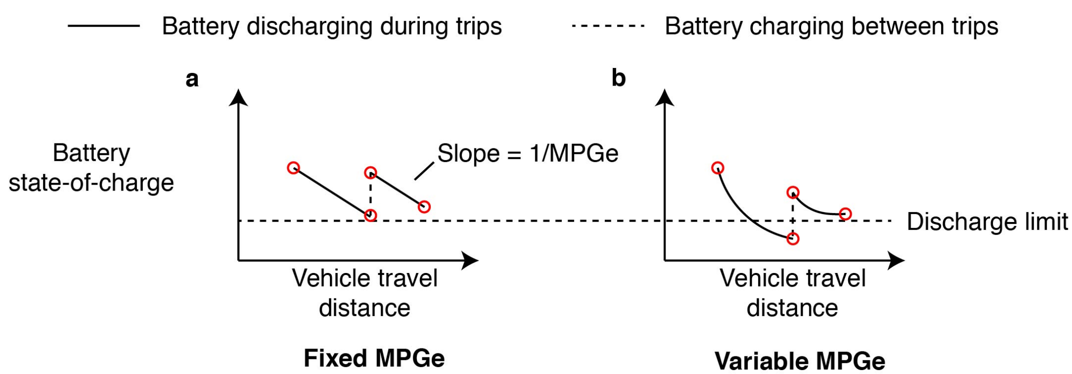

Figure A-1: Schematic diagrams showing variations in battery state-of-charge with trip patterns and trip energy consumption when **a**: using a fixed fuel economy and **b**: using a variable fuel economy that is estimated with a vehicle trip energy model. The slopes shown are for illustration but the convexity is based on experimental observations of battery discharging [4]. The first trip in panel **b** exceeds the battery discharge limit (a modeled lower bound on battery state-of-charge to optimize battery life) so that the trip is not feasible, while the same trip may not exceed the discharge limit and become feasible in panel **a** due to a different fuel economy.

When we compare these results on the effect of charging with previous studies that use a fixed fuel economy, we find that using a fixed fuel economy can overestimate the effect of workplace and public chargers on the adoption potential of battery electric vehicles. Using a fixed fuel economy such as the rated fuel economy of the 2019 Nissan Leaf (112 MPGe), compared to a variable fuel economy that captures the effect of driving behaviors on vehicle energy consumption, leads to an overestimation of VEP by about 2 percentage points in the city of Seattle for workplace chargers (Figure A-2). When ubiquitous 6.6 kW public chargers are added to workplace chargers, this overestimation of VEP increases to about 4 percentage points. The overestimation increases because among the vehicle-days electrified by adding public charging on top of home and work charging, there are more vehicle-days that constitute trips that are longer than 20 miles. These trips are very likely to pass through the interstate highway based on our analysis of the 2009 National Household Travel Survey, where we find that 5% of the personal vehicle trips that do not pass interstate highway have a trip distance longer than 20 miles. For BEVs, urban driving with more stop and gos have a lower energy intensity than highway driving with more cruising. Therefore, for the vehicle-days electrified with public charging, the vehicle energy intensity is underestimated to a larger extent compared to the vehicle-days electrified with home and work charging.

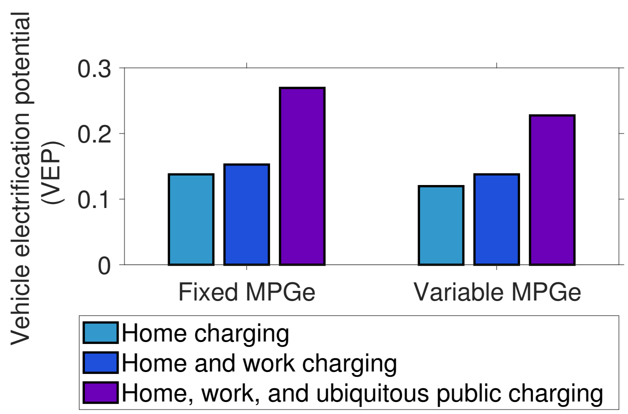

Figure A-2: Comparison of the effect of 6.6 kW home, work, and public charging on VEP of a 40 kWh Nissan Leaf in Seattle when using a fixed fuel economy (rated 112 MPGe) versus a variable fuel economy that changes across trips with different driving styles and routes.

A.4 Sensitivity analysis of charging efficiency

Electric vehicle charging efficiency affects the amount of charge taken up by the vehicle for a given charging time period, and subsequently affects our evaluation of VEP and VEP+ under different charging scenarios. In the paper, we assume a 89% charging efficiency for the range of charging powers we examine. In this section, we present results of VEP and VEP+ using different charging efficiencies from the range of reported values in the literature [116, 118].

A study collected data on charging efficiency of Level 1 and Level 2 charging of Nissan Leaf and Chevrolet Volt in the US state of Vermont from June to November in 2013 [116]. The study finds that Level 1 chargers have an average charging efficiency of 84% and Level 2 chargers have an average charging efficiency of 89%, when averaging across observations made under different charging instances (e.g., ambient temperature, amount of charge being drawn etc.) [116]. When less than 4 kWh of charge is taken up by the vehicle, Level 1 chargers have an average charging efficiency of 74% and Level 2 chargers have an average efficiency of 87% [116]. Another study that tests the charging efficiency of fast chargers (with a charging power of up to 50 kW) under different ambient temepeatures observes a minimum efficiency of 39% and a maximum efficiency of 93%, these efficiencies were each observed at -25 °C and 25 °C [118].

Table A.2 shows VEP calculated using a range of charging efficiencies for a 40 kWh Nissan Leaf using the Seattle data, under different charging powers and charging availabilities at home, work, and public locations. For the cases we have tested, we find that the effect of different charging efficiencies on VEP is nearly negligible for level 2 charging. For fast charging, the drop in charging efficiency from 89% to 39% due to low ambient temperature decreases VEP from 28% to 23% in the scenario of home, work, and 30-minute highway fast charging on the longest highway trip per day. This suggests that for regions with a cold climate, the effect of fast charging on increasing VEP might be lower than estimated in this analysis.

A.5 Public charging with varying charging power

Increasing public charging power impacts VEP (Figure A-3). For example, adding ubiquitous 120 kW public charging to home and work charging increases VEP of a BEV with a 40 kWh battery capacity to 24 percentage points, which is an increase of 1 percentage point compared to adding ubiquitous 6.6 kW public charging (Figure A-3). However, this increase in VEP from a higher charging power is relatively small compared to the increase in VEP from a higher battery capacity. Considering the availability of 6.6 kW home, work, and ubiquitous public charging, increasing BEV battery capacity from 40 kWh to 100 kWh results in an increase in VEP from 23 percentage points to 58 percentage points (Figure A-3).

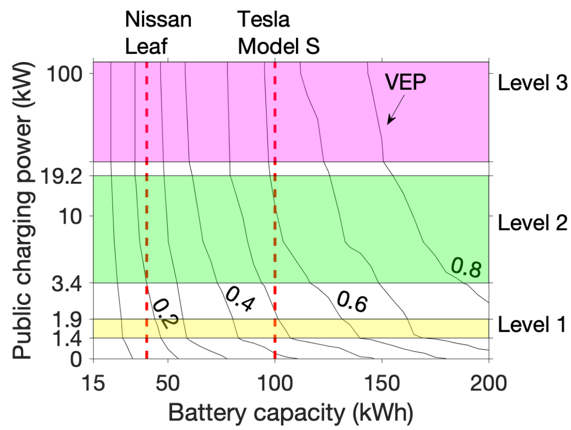

Figure A-3: VEP of BEVs with a given battery capacity when adding ubiquitous 1.4–120 kW public charging (covering Level 1, Level 2, and Level 3 charging standards) on top of 6.6 kW home and work charging. A public charging power of zero means that only home and work charging are available. The commercial battery capacities of the 2019 Nissan Leaf and the Tesla Model S are indicated with red vertical lines.

In the scenario where overnight public charging is added on top of home and work charging, we compare VEP when charging power of overnight public charging is 6.6 kW and 120 kW (Figure A-4). We find that adding overnight public charging with a charging power of 6.6 kW can increase VEP of a 40 kWh BEV from 14% to 15% when home and work charging are available. Increasing overnight public charging power to 120 kW does not increase the VEP of a 40 kWh BEV. When battery capacity increases to 100 kWh, increasing overnight public charging power from 6.6 kW to 120 kW can increase VEP by less than 1 percentage point. This is because overnight public charging stops have a long duration (at least 2 hours) and the amount of charge taken by the BEV is limited by the battery capacity. These results show that regular level 2 charging could be as effective as fast charging at overnight public locations such as hotels where charging takes place overnight.

In the scenario where an extra charging stop is added en route on highway trips on top of home and work charging, we compare VEP when charging power of the highway charging

Table A.2: VEP of the 40 kWh Nissan Leaf under different combinations of charging availability, charging power, and charging efficiency.

Charging availability	Charging power (kW)	Charging efficiency	VEP
Home	6.6	87%	12%
		89%	12%
Work	6.6	87%	2%
		89%	2%
Home + work	6.6	87%	14%
		89%	14%
Home + work + ubiquitous public	6.6	87%	23%
		89%	23%
Home + work + overnight public	6.6	87%	15%
		89%	15%
Home + work + 30-minute fast charging on the longest highway trip per day	6.6 (Home+work), 120 (Highway)	89% (Home + work), 39% (Highway)	23%
		89% (Home + work + highway)	28%
		89% (Home + work), 93% (Highway)	28%

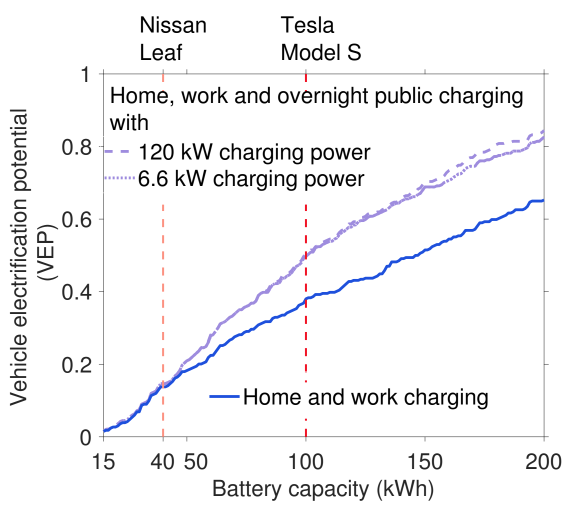

Figure A-4: VEP of BEVs with a given battery capacity when home and work charging are available, and when adding overnight public charging with a charging power of 6.6 kW and 120 kW.

stop is 6.6 kW and 120 kW (Figure A-5). We find that adding 60-minute highway charging stops with a charging power of 6.6 kW en route on the longest highway trip on the days that are not electrified with home and work charging can increase VEP of a 40 kWh BEV from 14% to 15% when home and work charging are available. When highway charging power increases to 120 kW, VEP increases to 28%. These results show that interventions in travel behaviors to allow more time for charging such as adding highway charging stops need to be combined with fast charging to have a significant impact on increasing VEP.

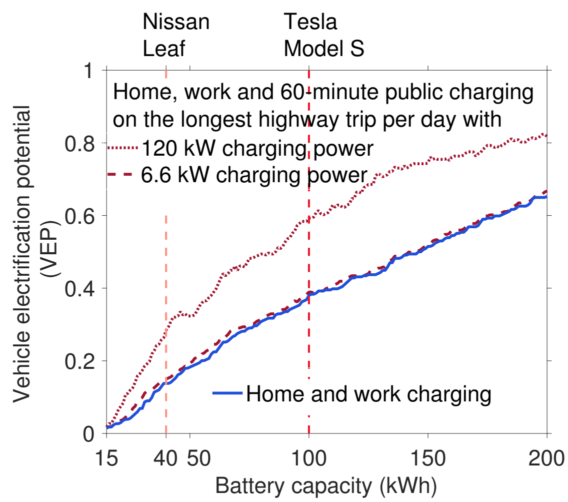

Figure A-5: VEP of BEVs with a given battery capacity when home and work charging are available, and when adding 60-minute highway charging on the longest highway trip per day with a charging power of 6.6 kW and 120 kW. Fast charging is only used on days that are not electrified with home and work charging and pass through highway.

A.6 Type of electrified vehicle-days under different charging scenarios

We examine the kinds of vehicle-days that are electrified with different charging availabilities at home, work, and different public locations. The vehicle-days aggregated across all Seattle vehicles are split into three categories based on the type of activities performed during the day: mixed-use days (days with both work and leisure activities), work-only days (days with only work activities), leisure-only days (days with only leisure activities). Across all vehicle-days, 37% are mixed-use days, 9% are work-only days, and 54% are leisure-only days. Table A.3 shows the percentage of all Seattle vehicle-days aggregated across vehicles that are electrified with different combinations of home charging, work charging, overnight public charging, ubiquitous public charging, and highway fast charging.

We find that home charging alone is able to electrify a significant fraction of all three kinds of vehicle-days. Work charging alone can electrify 31% of vehicle-days aggregated across all Seattle vehicles, where 16% are mixed-use days, 5% are work-only days, 10% are leisure-only days. This suggests that even when home and public charging are not available, work charging might still be effective in electrifying mixed-use days and leisure-only days. Adding fast charging stops en route on highway trips in addition to home and work charging can electrify almost all mixed-use days. However, a small percentage of mixed-use days and leisure-only days remain un-electrified with home, work, and public charging. This is a result of either single long trips that exceed the battery capacity, or multiple shorter trips without charging opportunity.

A.7 Discussion on the effect of Highway fast charging

We examine the duration and frequency of highway fast charging in the scenario where 120 kW fast charging is available on all highway trips (trips with a distance longer than 20 miles) and the BEV is charged to full during the fast charging stop when needed. If the amount of battery capacity that is available for use at the beginning of the highway trip is higher than the trip energy requirement, we assume the battery is charged to full at the end of the highway trip so that the battery is full at the beginning of the following trip. Otherwise, it means the battery will be depleted (to the 20% limit) during the trip. In this case, we assume the fast charging takes place when the battery is depleted during the trip and charges the battery to full. These assumptions allow us to maximize the effect of fast charging on increasing the electrification potential of vehicle-days.

In Figure A-6, we show the maximum, mean, and minimum fast charging duration per day for each Seattle vehicle that uses fast charging and can have some or all of their vehicle-days' energy requirements covered by a 40 kWh BEV because of the added fast

Table A.3: Percentage of Seattle vehicle-days that are electrified with a 40 kWh Nissan Leaf under different availabilities of 6.6 kW home charging, work charging, overnight public charging, ubiquitous public charging, and 120 kW fast public charging en route on highway trips.

	Charging availability scenarios	Mixed-use days	Work-only days	Leisure-only days	All days
% of Seattle vehicle-days that are electrified	Home charging	34%	9%	49%	92%
	Work charging	16%	5%	10%	31%
	Home and work charging	35%	9%	49%	93%
	Home, work, and overnight 6.6 kW public charging	36%	9%	50%	95%
	Home, work, and ubiquitous 6.6 kW public charging	36%	9%	51%	96%
	Home, work, and 120 kW fast charging on the longest highway trip per day	36%	9%	51%	96%
	Home, work, and 120 kW fast charging on all highway trips	36%	9%	52%	97%

charging. We find that despite the heterogeneity across vehicles, the mean fast charging duration for most vehicles is around 20–50 minutes per day. When we consider a BEV with a larger battery capacity of 100 kWh, the charging time required to charge the battery to full during the added fast charging stop increases and fewer vehicles use fast charging because there are fewer un-electrified days with home and work charging (Figure A-7). Despite the increase, the mean fast charging duration for most vehicles is around 60–90 minutes per day.

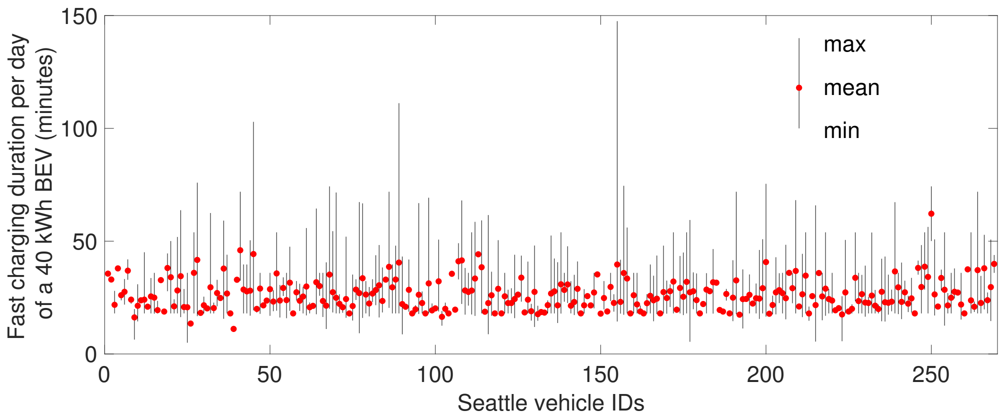

Figure A-6: For each Seattle vehicle that uses highway fast charging, the maximum, mean, and minimum fast charging duration per day to charge a 40 kWh BEV to full on all highway trips using 120 kW fast charging when home and work charging are available. The vehicle days' energy requirements in this case are covered by BEVs.

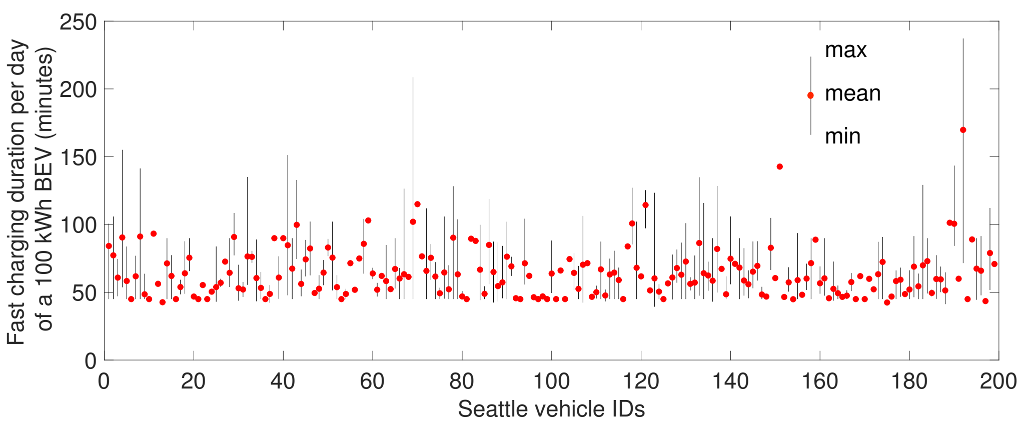

Figure A-7: For each Seattle vehicle that uses highway fast charging, the maximum, mean, and minimum fast charging duration per day to charge a 100 kWh BEV to full on all highway trips using 120 kW fast charging when home and work charging are available. The vehicle days' energy requirements in this case are covered by BEVs.

In Figure A-8, we show the number of times that vehicles use fast charging per day to charge a 40 kWh BEV to full on all highway trips, so that the vehicle-days become electrified because of adding fast charging to home and work charging. We find that 63% of the vehicle-days use fast charging at most 2 times a day, and 95% of the vehicle-days use fast charing at most 3 times a day. When battery capacity increases to 100 kWh, we find that the fraction of vehicle-days that use fast charging at least 3 times a day increases from 37% to 52% (Figure A-9).

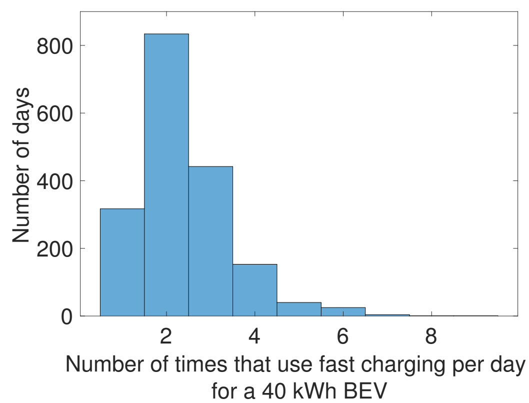

Figure A-8: Histogram of the fast charging frequency per day to charge a 40 kWh BEV to full on all highway trips using 120 kW fast charging when home and work charging are available. The vehicle-day's energy requirement is covered by the BEV in this case.

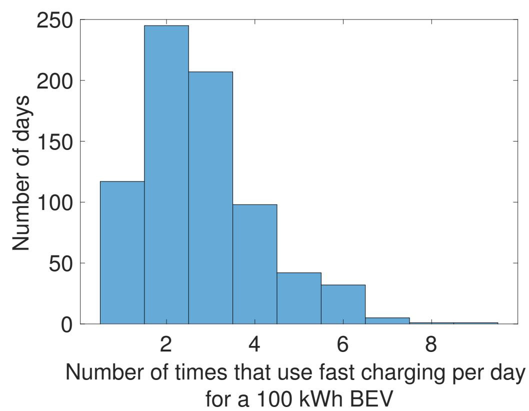

Figure A-9: Histogram of the fast charging frequency per day to charge a 100 kWh BEV to full on all highway trips using 120 kW fast charging when home and work charging are available. The vehicle-day's energy requirement is covered by the BEV in this case.

In addition to the two highway fast charging scenarios in the manuscript where we assume the BEV is charged to full during the fast charging stop, we also examine scenarios where the added fast charging stop has a fixed duration and the battery may not charge to full. In Figure A-10, we show the VEP with BEVs of different battery capacities when adding highway fast charging with a duration of 60 minutes, 30 minutes, and 15 minutes on the vehicle-days that are electrified with home and work charging. For a BEV with a battery capacity of 40 kWh, VEP increases from 25% to 28% when the duration of the highway fast charging stop increases from 15 minutes to 30 minutes, and VEP stays constant at 28% when the duration increases from 30 minutes to 60 minutes. This is because the maximum amount of charge the battery can take during fast charging is limited by the battery capacity. When battery capacity increases to 100 kWh, VEP increases from 41% to 51% when the duration of the highway fast charging stop increases from 15 minutes to 30 minutes, and to 59% when the duration increases to 60 minutes.

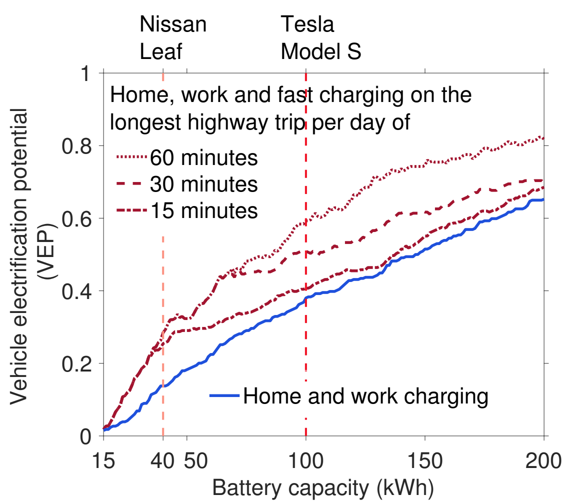

Figure A-10: VEP in Seattle when 6.6 kW home and work charging and 120 kW fast charging on the longest highway trip per day are available. We examine fast charging stops with a duration of 15 minutes, 30 minutes, and 60 minutes.

We examine the scenario when home charging is available, and fast charging is added to home charging (Figure A-11). For a BEV with a 40 kWh battery capacity, adding fast charging stops on the longest highway trip on days that cannot be electrified with home charging can increase VEP from 12% to 25% when home charging is available. Adding fast charging on all highway trips on days that cannot be electrified with home charging further increases VEP of the same BEV to 36%. When battery capacity increases to 100 kWh, adding fast charging on the longest highway trip on days that cannot be electrified with home charging can increase VEP from 35% to 56% when home charging is available. Adding fast charging on all highway trips on days that cannot be electrified with home charging further increases VEP of the 100 kWh BEV to 77%. These results show that when work charging is not available, home charging combined with fast charging can still have a significant impact on increasing VEP.

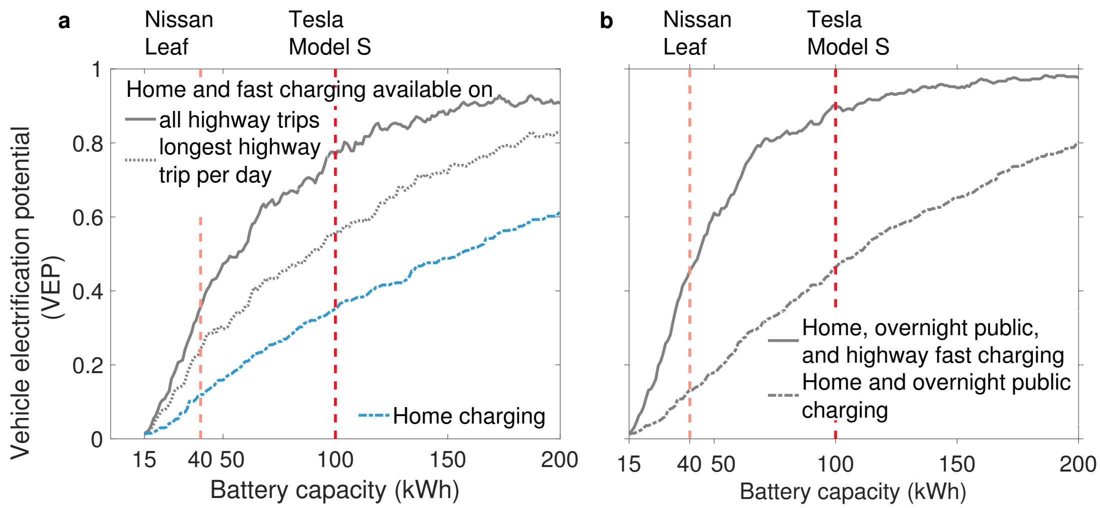

Figure A-11: **a:** VEP in Seattle under home charging with 6.6 kW charging power and adding 120 kW fast charging on the longest highway trip per day, and 120 kW fast charging on all highway trips per day. **b:** VEP under home and overnight public charging with 6.6 kW charging power and adding 120 kW fast charging on all highway trips. Fast charging is only used on days that are not electrified with home charging and pass through highway.

We also examine the scenario when home charging is not available, and fast charging is added to work charging (Figure A-12). For a BEV with a 40 kWh battery capacity, adding fast charging on the longest highway trip on days that cannot be electrified with work charging can increase VEP from 2% to 3% when work charging is available. Adding fast charging on all highway trips on days that cannot be electrified with work charging further increases VEP of the same BEV to 4%. When battery capacity increases to 100 kWh, adding fast charging on the longest highway trip on days that cannot be electrified with work charging can increase VEP from 13% to 22% when work charging is available. Adding fast charging on all highway trips on days that cannot be electrified with work charging further increases VEP of the 100 kWh BEV to 30%. These results suggest that when home charging is not available, highway fast charging combined with work charging has a small effect on increasing VEP. However, this effect becomes more prominent as battery capacity increases.

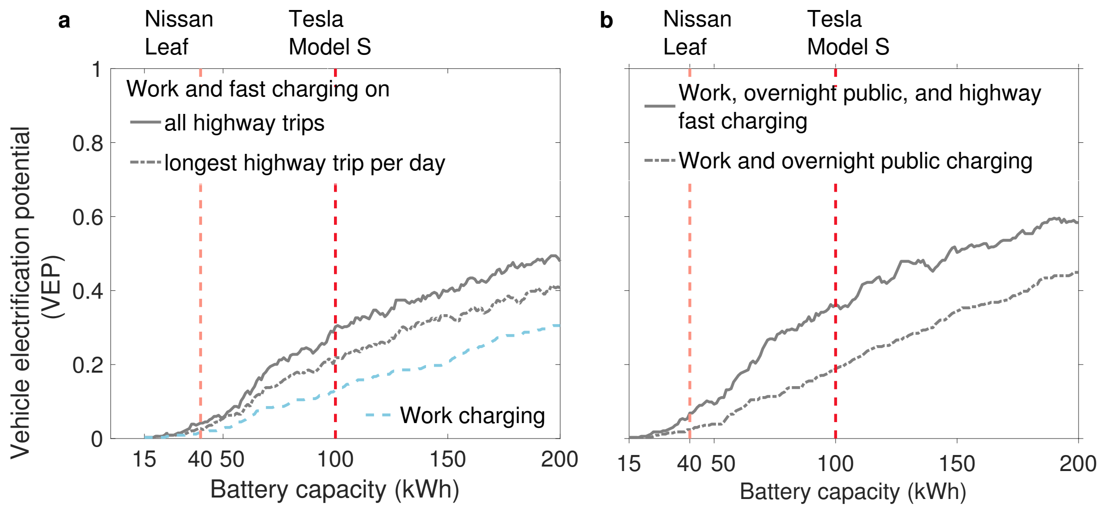

Figure A-12: **a:** VEP in Seattle when work charging with 6.6 kW charging power is available, and adding 120 kW fast charging stops on the longest highway trip per day and on all highway trips per day. **b:** VEP when work and overnight public charging with 6.6 kW charging power are available and adding 120 kW fast charging stops on all highway trips. Fast charging is only used on days that are not electrified with work charging and pass through highway.

We also examine the scenario when fast charging is added to ubiquitous public charging under different combinations of home and work charging (Figure A-14, A-15, A-16, A-17). We find that for a 40 kWh BEV, VEP is 23% when 6.6 kW home, work, and ubiquitous public charging are available. When adding additional fast charging stops to charge the battery to full on the longest highway trip per day on days that are un-electrified with home, work, and ubiquitous public charging, we find that VEP increases to 40%. This percentage further increases to 46% when adding fast charging on all highway trips. When work charging is not available, adding fast charging on all highway trips to home and ubiquitous public charging can still increase VEP from 20% to 53%. When home charging is not available, adding fast charging on all highway trips to work and ubiquitous public charging can also increase VEP from 14% to 35%.

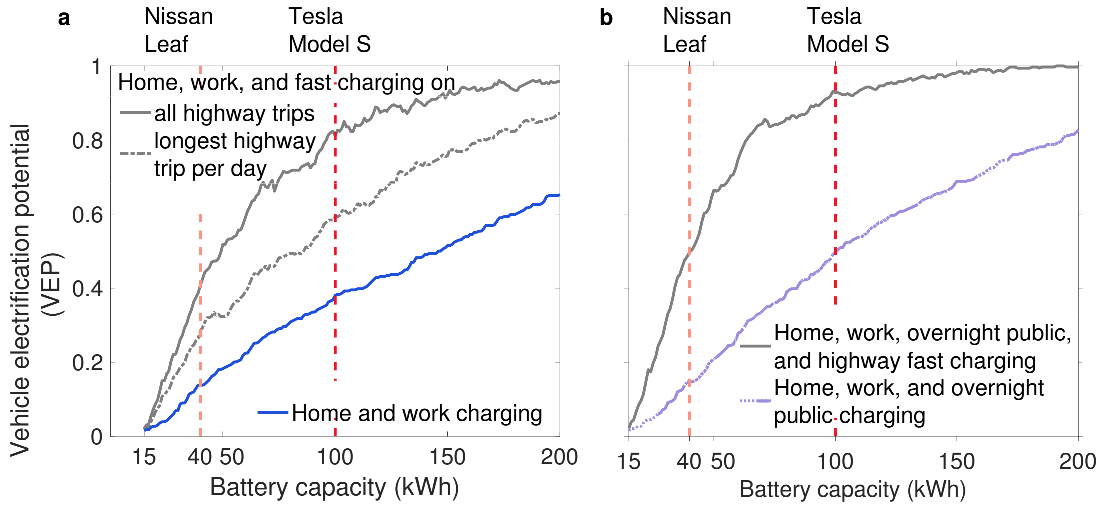

Figure A-13: **a:** VEP in Seattle under home and work charging with 6.6 kW charging power and adding 120 kW fast charging on the longest highway trip per day, and 120 kW fast charging on all highway trips per day. **b:** VEP under home, work and overnight public charging with 6.6 kW charging power and adding 120 kW fast charging on all highway trips. Fast charging is only used on days that are not electrified with home and work charging and pass through highway.

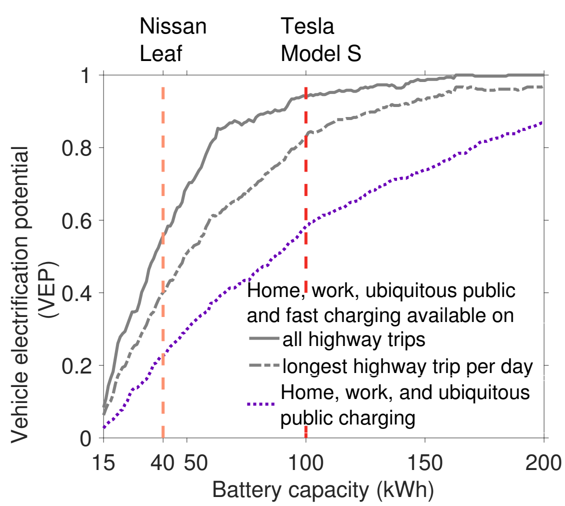

Figure A-14: VEP in Seattle when home, work, and ubiquitous public charging with 6.6 kW charging power are available, and adding 120 kW fast charging stops on the longest highway trip per day and on all highway trips per day.

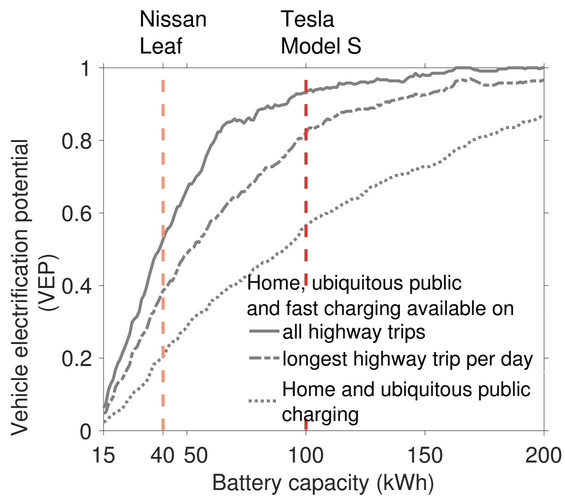

Figure A-15: VEP in Seattle when home and ubiquitous public charging with 6.6 kW charging power are available, and adding 120 kW fast charging stops on the longest highway trip per day and on all highway trips per day.

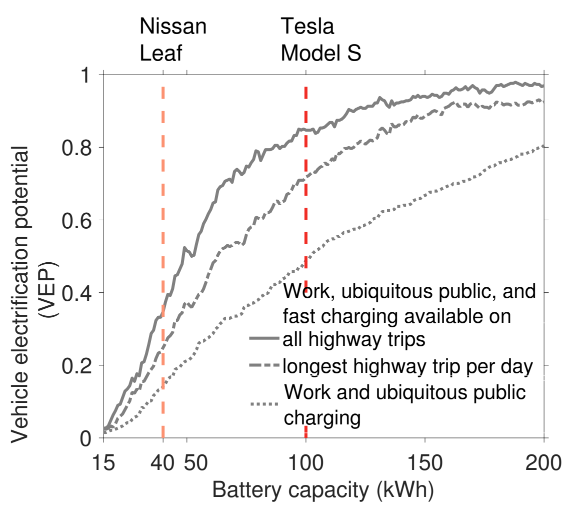

Figure A-16: VEP in Seattle when work and ubiquitous public charging with 6.6 kW charging power are available, and adding 120 kW fast charging stops on the longest highway trip per day and on all highway trips per day.

A.8 VEP+ in different charging scenarios

We examine VEP+ (VEP when aided by supplementary vehicles) of BEVs with a battery capacity ranging from 15 to 200 kWh when home and work charging are available and supplementary vehicles are available on 1 to 30 days a year (Figure A-18). We find that adding access to supplementary vehicles on 2 days a year on top of home and work charging increases VEP+ of the 40 kWh BEV to 28%, compared to the VEP of 14% when home and work charging are available. Adding access to supplementary vehicles on 7 days a year on top of home and work charging increases VEP+ to 52%. Adding access to supplementary vehicles on 30 days a year on top of home and work charging increases VEP+ to 97%.

We also examine VEP+ in different charging scenarios with different combinations of home, work, and public charging. Figure A-19 shows VEP when home charging is available and VEP+ when adding 4, 10, and 105 (calculated as 2 out of 7 days over 365 days in a year) days of supplementary vehicles. We find that with home charging, VEP+ is 36% when adding access to 4 days of supplementary vehicles, compared to the VEP of 12% with home charging. VEP+ increases to 97% when supplementary vehicles can be accessed on 105 days a year. Considering 70% of the Seattle vehicles examined are owned by multi-vehicle households, this result suggests that if a longer-range ICEV is owned by the household and may be used on days with higher travel demand such as weekends, BEVs can be used as a second vehicle in the household to meet the energy requirements on the remaining days.

Figure A-20 shows VEP when only work charging is available and VEP+ when adding 4, 10, and 105 days of supplementary vehicles on top of work charging. We find that with work charging, VEP+ of a 40 kWh BEV is 6% when adding access to 4 days of supplementary vehicles, compared to the VEP of 2% with work charging. VEP+ of the same BEV increases to 28% when supplementary vehicles can be accessed on 105 days a year. When battery capacity increases to 100 kWh, VEP+ increases to 53% when supplementary vehicles can be accessed on 105 days a year. This suggests that around half of the Seattle vehicles might be able to use a BEV with work charging if a long-range vehicle is also available in the household as a supplementary vehicle on two days a week to cover days

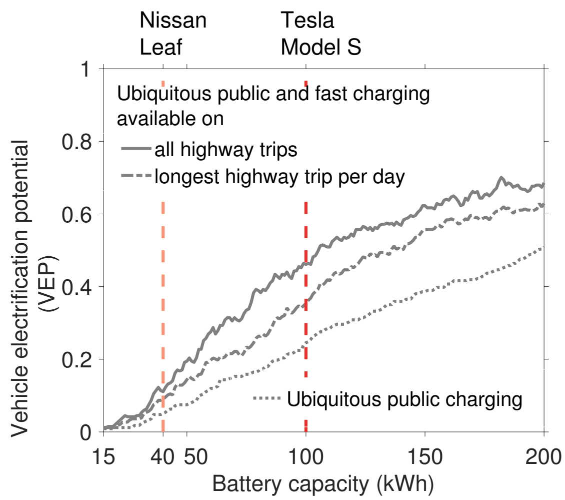

Figure A-17: VEP in Seattle when ubiquitous public charging with 6.6 kW charging power is available, and adding 120 kW fast charging stops on the longest highway trip per day and on all highway trips per day.

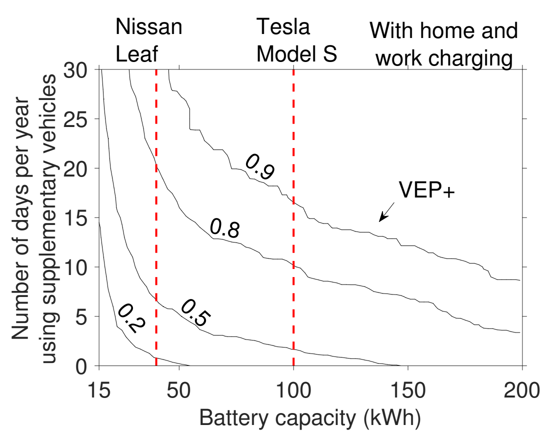

Figure A-18: VEP+ of BEVs with a given battery capacity when supplementary vehicles are used on 0 to 30 days a year when 6.6 kW home and work charging are available.

with high travel demand such as weekends.

We note that there are some fluctuations in VEP+ with a given number of days of supplementary vehicle and it does not always increase as battery capacity increases. This is because we consider consecutive vehicle-days' energy requirements where the previous days' energy requirements determine the battery state-of-charge at the start of the current day. When battery capacity increases, days with high energy requirements that were previously not covered by the BEV with a lower battery capacity might now be covered, which lowers the battery state-of-charge. This might lead to some future vehicle-days with low energy requirements un-electrified, where these vehicle-days were previously covered by the BEV with a low battery capacity. However, the general trend remains that VEP+ with a given number of days of supplementary vehicles increases as battery capacity increases.

Figure A-21 shows VEP when home, work, and ubiquitous public charging are available and VEP+ when adding 4, 10, and 105 days of supplementary vehicles. We find that with home, work, and ubiquitous public charging, VEP+ is 55% when adding access to 4 days of supplementary vehicles, compared to the VEP of 23% without supplementary vehicles. VEP+ of the 40 kWh BEV increases to 99% when supplementary vehicles can be accessed on 105 days a year. When battery capacity increases to 100 kWh, VEP+ with home, work, ubiquitous public charging and 105 days' of supplementary vehicles reaches 100%.

Figure A-22 shows VEP when home, work, and overnight public charging are available and VEP+ when adding 4, 10, and 105 days of supplementary vehicles. We find that with home, work, and overnight public charging, VEP+ is 43% when adding access to 4 days of supplementary vehicles, compared to the VEP of 15% without supplementary vehicles. VEP+ of the 40 kWh BEV increases to 98% when supplementary vehicles can be accessed on 105 days a year. When battery capacity increases to 100 kWh, VEP+ with home, work, and overnight public charging and 105 days' of supplementary vehicles reaches 100%.

Figure A-23 shows VEP when home, work, and fast charging on the longest highway trip are available and VEP+ when adding 4, 10, and 105 days of supplementary vehicles. Fast charging is only used on days that are not electrified with home and work charging and pass the highway. We find that with home, work, and highway fast charging on the

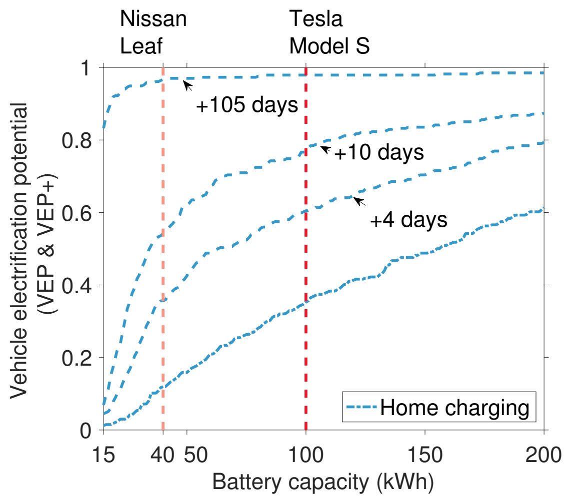

Figure A-19: VEP and VEP+ of BEVs with a given battery capacity when supplementary vehicles are used on 4, 10, and 105 (calculated as 2 out of 7 days over 365 days to approximate using supplementary vehicles every weekend) days a year when 6.6 kW home charging is available.

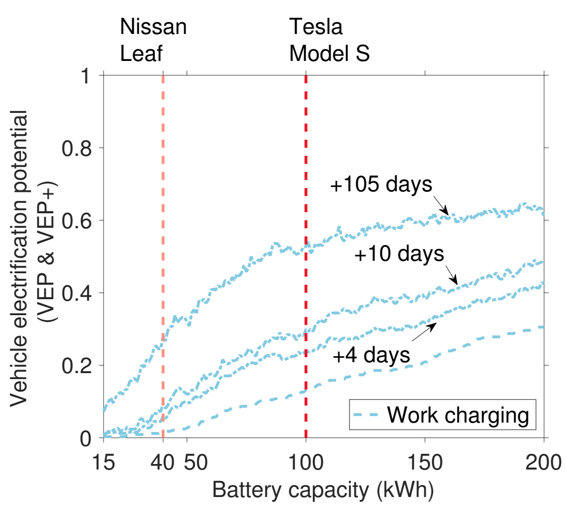

Figure A-20: VEP and VEP+ of BEVs with a given battery capacity when supplementary vehicles are used on 4, 10, and 105 (calculated as 2 out of 7 days over 365 days to approximate using supplementary vehicles every weekend) days a year when 6.6 kW work charging is available.

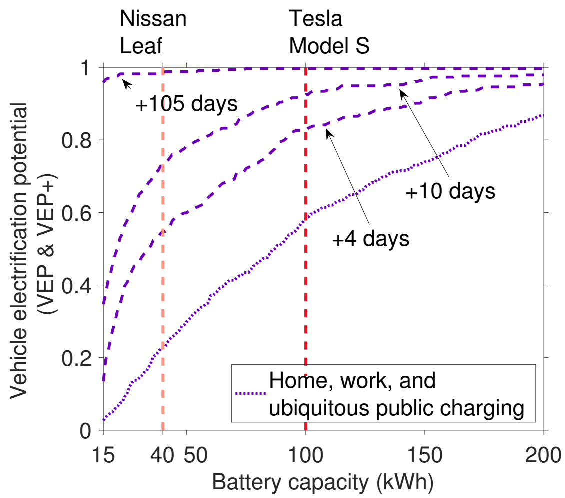

Figure A-21: VEP and VEP+ of BEVs with a given battery capacity when supplementary vehicles are used on 4, 10, and 105 (calculated as 2 out of 7 days over 365 days to approximate using supplementary vehicles every weekend) days a year when 6.6 kW home, work, and ubiquitous public charging are available.

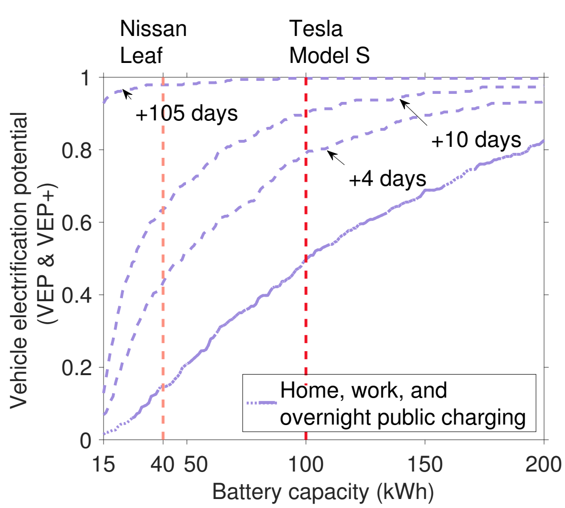

Figure A-22: VEP and VEP+ of BEVs with a given battery capacity when supplementary vehicles are used on 4, 10, and 105 (calculated as 2 out of 7 days over 365 days to approximate using supplementary vehicles every weekend) days a year when 6.6 kW home, work, and overnight public charging are available.

longest highway trip per day, VEP+ is 54% when adding access to 4 days of supplementary vehicles, compared to the VEP of 28% without supplementary vehicles. VEP+ of the 40 kWh BEV increases to 99% when supplementary vehicles can be accessed on 105 days a year. When battery capacity increases to 100 kWh, VEP+ with home, work, and highway fast charging on the longest highway trip per day and 105 days' of supplementary vehicles reaches 100%.

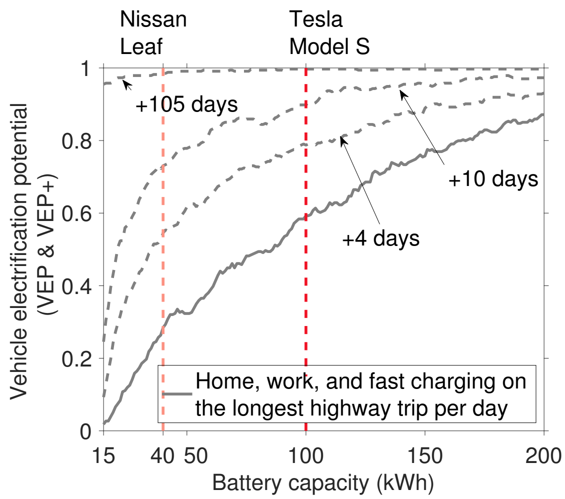

Figure A-23: VEP and VEP+ of BEVs with a given battery capacity when supplementary vehicles are used on 4, 10, and 105 (calculated as 2 out of 7 days over 365 days to approximate using supplementary vehicles every weekend) days a year when 6.6 kW home and work charging and 120 kW fast charging on the longest highway trip per day are available. Fast charging is only used on days that are not electrified with home and work charging and pass highway.

A.9 Characteristics of un-electrified vehicle-days

We examine the characteristics of the un-electrified vehicle-days that require supplementary vehicles when home and work charging are available in order for all Seattle vehicles to be replaced by a 40 kWh BEV. In Figure A-24 and A-25, we show the distribution of the un-electrified vehicle-days among Seattle vehicles. The distribution shows that a significant number of Seattle vehicles has a small number of un-electrified vehicle-days per year, which explains the significant impact of a small number of days with access to supplementary vehicles. In Figure A-26, we show the 365 calendar dates in the year 2005 that has the highest to lowest fraction of un-electrified vehicle-days. We find that a total of 348 calendar dates in the year 2005 have un-electrified days. 109 dates make up a total of 50% of unnelectrified days, 213 dates make up 80% of un-electrified days, and 293 dates make up 95% of un-electrified days. In Figure A-27, we show the distribution of un-electrified vehicle-days over different days of the week. We find that Friday, Saturday, and Sunday experience the highest number of un-electrified vehicle-days, and the rest vehicle-days are evenly spread across Monday, Tuesday, Wednesday, and Thursday. In Figure A-28, we show the distribution of un-electrified vehicle-days over different months of a year. We find that January, Februrary, and March have the least number of un-electrified vehicle-days, and July and August have the highest number of un-electrified vehicle-days.

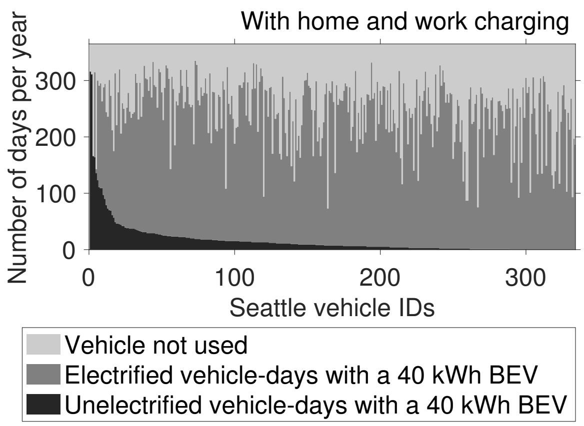

Figure A-24: Number of days per year that a personal vehicle is not driven and number of electrified and un-electrified vehicle-days whose energy requirements can and cannot be covered by a 40 kWh Nissan Leaf for each Seattle vehicle when home and work charging are available. The vehicles are sorted from ones with the highest number of un-electrified vehicle-days per year to the lowest.

For the un-electrified vehicle-days, we further categorize them into consecutive and non-consecutive vehicle-days. The non-consecutive vehicle-days are days that start and end at home on the same day, thus requiring supplementary vehicles on individual days. The consecutive vehicle-days consist of home-based tours that span across multiple days, and therefore require supplementary vehicles on multiple, consecutive days.

In Figure A-29 and Figure A-30, we show the distribution of vehicle-day energy requirements on non-consecutive and consecutive un-electrified vehicle-days with a 40 kWh

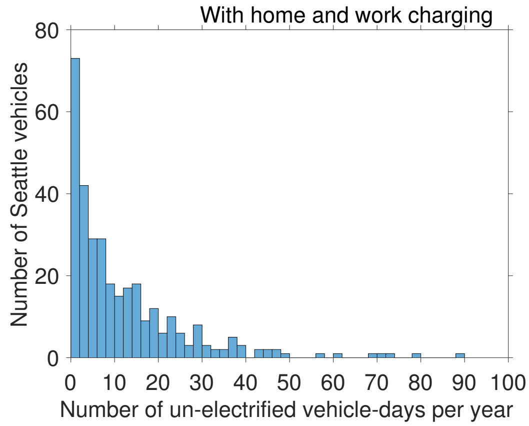

Figure A-25: Histogram of un-electrified vehicle-days per year per Seattle vehicle with a 40 kWh Nissan leaf when 6.6 kW home and work charging are available.

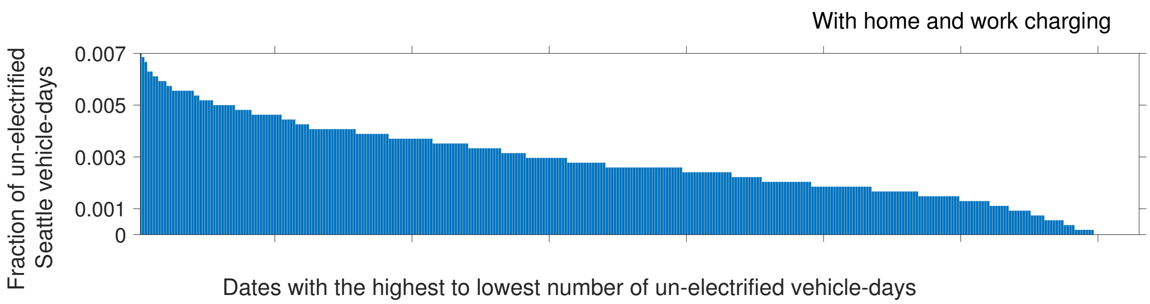

Figure A-26: Histogram of 365 calendar dates in the year 2005, sorted from the highest fraction of un-electrified vehicle-days to the lowest fraction aggregated over Seattle vehicles considering a 40 kWh Nissan Leaf with 6.6 kW home and work charging

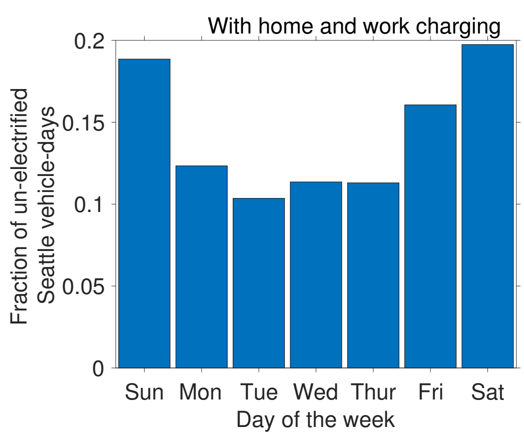

Figure A-27: Histogram of day of the week for un-electrified vehicle-days aggregated over Seattle vehicles considering a 40 kWh Nissan Leaf with 6.6 kW home and work charging.

BEV respectively. The non-consecutive un-electrified vehicle-days have an average energy requirement of 87 kWh (Figure A-29), while the consecutive un-electrified vehicle-days have an average energy requirement of 34 kWh (Figure A-30). For non-consecutive vehicle-days, the days are un-electrified due to either long trips with high energy requirements or low battery state-of-charge because of travel patterns on previous days. For consecutive vehicle-days that are un-electrified, there are more vehicle-days with relatively low energy requirements because these vehicle-days are part of multi-day, home-based tours with high energy requirements that are un-electrified.

A.10 Cost comparison

We estimate the per mile cost of BEVs when adding access to supplementary vehicles and when using fast charging based on vehicle travel distance and energy consumption. The purchase cost of the 2020 Nissan Leaf with a 40 kWh battery capacity is around $32,000, and of the 2020 Tesla Model S P100D with a 100 kWh battery capacity is around $75,000 [164, 165] (Table A.4). We assume a vehicle annual driving distance of 12,000 miles and 6 years of vehicle lifetime. The added cost of renting supplementary vehicles using services such as Zipcar or other car rental services is around $0.3–0.5 per mile in the case of full-day rental [166, 167] (Table A.4). We assume a gasoline price of $0.2/gallon and an ICEV is used as the supplementary vehicle. We also assume the cost of fast charging and home and work charging is $0.15/mile [168].

By multiplying BEV purchase cost per lifetime driving distance with trip distance on days that can be replaced by a BEV in the Seattle data, and per distance cost of car sharing or rental services with trip distance on days that require supplementary vehicles, we find that the cost of a Tesla Model S without using any supplementary vehicle is 120 – 140% higher than the cost of a Nissan Leaf plus a 4 day-cost of a supplementary vehicle. These rough estimates, combined with observations around the distribution of high-energy days across different calendar dates, begin to suggest that supplementing low-cost BEVs with commercial supplementary vehicles, for those that do not have access to a long-range second car, may be a cost-effective option for increasing the vehicle electrification potential.

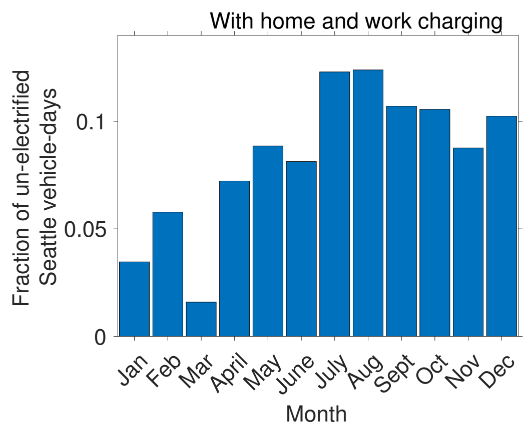

Figure A-28: Histogram of month of the year for un-electrified vehicle-days aggregated over Seattle vehicles considering a 40 kWh Nissan Leaf with 6.6 kW home and work charging.

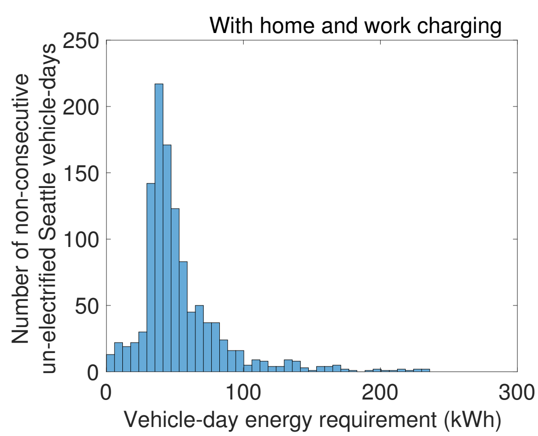

Figure A-29: Histogram of vehicle-day energy requirements on non-consecutive un-electrified vehicle-days aggregated over Seattle vehicles considering a 40 kWh Nissan Leaf with 6.6 kW home and work charging.

However, further analyses are needed to estimate the costs of supplementary vehicle supply and the convenience for consumers.

Table A.4: Cost comparison of renting supplementary vehicles (through services such as Zipcar and Avis car-rental) with the purchase costs without federal tax credit per lifetime distance of two BEVs with different battery capacities: the 2020 Nissan Leaf with a 40 kWh battery capacity and the Tesla Model S P100D with a 100 kWh battery capacity [166, 167].

Supplementary vehicle cost (US$/mile)	Purchase cost per lifetime distance (US$/mile)	
Zipcar/Car rental	Nissan leaf (40 kWh)	Tesla Model S (100 kWh)
0.30 - 0.50 [166, 167]	0.44 [164]	1.04 [165]

Per mile cost of a BEV with supplementary vehicles is calculated as the sum of four parts: 1) purchase cost per lifetime distance traveled, 2) per kWh cost of home and work charging times the vehicle-day energy consumption for vehicles that can be replaced by a BEV in the Seattle data, 3) per distance cost of car sharing or rental services with vehicle-day travel distance on days that require supplementary vehicles, and 4) gasoline cost of using supplementary vehicles, divided by the sum of distance traveled with the BEV and the supplementary vehicle. Per mile cost of a BEV with fast charging is calculated as the sum of three parts: 1) purchase cost per lifetime distance traveled, 2) per kWh cost of fast charging times the amount of charge output by the fast chargers for vehicles that can be replaced by a BEV in the Seattle data, 3) per kWh cost of home and work charging times the total vehicle-day energy requirements subtracting the energy provided by fast charging, divided by the sum of distance traveled with the BEV.

We find that the total cost per mile of the 40 kWh Nissan Leaf with access to 4 days of supplementary vehicle is around 0.47 – 0.49 $/mile when home and work charging are available. This is similar to adding fast charging on all highway trips on top of home and work charging that has a cost of 0.49$/mile (Table A.5). More analysis is needed to account for the inconvenience associated with renting and using a vehicle that is not regularly used by the driver, and the inconvenience associated with delaying some trips to allow time for fast charging.

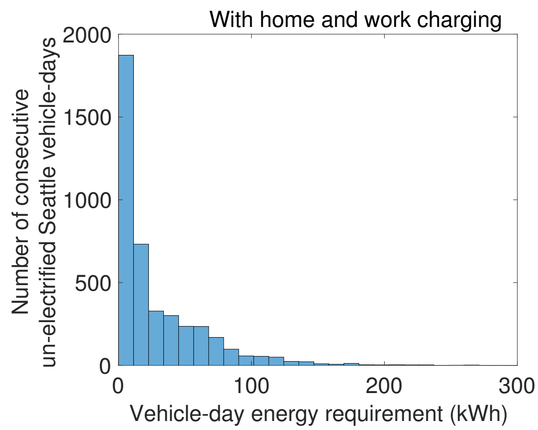

Figure A-30: Histogram of vehicle-day energy requirements on consecutive un-electrified vehicle-days aggregated over Seattle vehicles considering a 40 kWh Nissan Leaf with 6.6 kW home and work charging.

Table A.5: Cost comparison of renting supplementary vehicles (through car sharing or rental services on 4 days a year and using fast charging en route on all highway trips for the 40 kWh Nissan Leaf and the 100 kWh Tesla Model S. For both scenarios, we assume home and work charging are available.

	Total cost per distance (US$/mile)	
	Nissan Leaf (40 kWh)	Tesla Model S (100 kWh)
Access supplementary vehicles on 4 days a year	0.47-0.49	1.05-1.06
Use fast charging en route on all highway trips	0.49	1.09

A.11 Comparison of US and Seattle vehicle-days and households

We compare vehicle-day and household characteristics in the Seattle data and the National Household Travel survey (NHTS) that represents the US. The Seattle data and the US data have a similar percentage of leisure-only days (days with only leisure activities), while the Seattle data has more mixed-use days (days with both work and leisure activities) and fewer work-only days (days with only work activities). This could be due to the dense urban setting of the Seattle metropolitan area that leads to better retail accessibility, which makes it convenient to perform leisure activities after work. The three kinds of vehicle-days in Seattle also have a lower energy requirements than those observed in the US for similar reasons. The two datasets have a similar percentage of multi-vehicle households, suggesting that the Seattle-based results on using a second household vehicle as supplementary vehicles to supplement BEVs might be feasible for the US at large.

Table A.6: Vehicle-day and household characteristics of those examined in this analysis in Seattle and the US.

		Seattle		US	
		% of all vehicle-days	Mean energy use	% of all vehicle-days	Mean energy use
Vehicle-day characteristics	Mixed-use days	37%	10 kWh	27%	12 kWh
	Work-only days	9%	6 kWh	17%	9 kWh
	Leisure-only days	54%	10 kWh	56%	11 kWh
Household characteristics	% of multi-vehicle households	70%		66%	

A.12 NHTS BEV driving characteristics

The National Household Travel Survey includes vehicle-day trip data of 607 BEVs. We examine the energy requirements of these actual BEVs driven today. In Figure A-31, we show the distribution of vehicle-day energy requirements of the BEVs. We find that the mean vehicle-day energy requirement is 9 kWh, which is lower than the average energy requirement of vehicle-days made by ICEVs (11 kWh). Moreover, all of the vehicle-days have an energy requirement below 100 kWh. These driving behaviors are likely behaviors of early adopters. We also find that the BEVs are used for both work and leisure activities. 32% of the vehicle-days are days with both work and leisure activities, 17% are days with only work activities, and 51% are days with only leisure activities. Moreover, 95% of the BEVs are owned by multi-vehicle households. These observations are likely behaviors of early adopters and further studies are needed to examine changes in EV driving behaviors as more EVs are adopted and charging infrastructure is expanded.

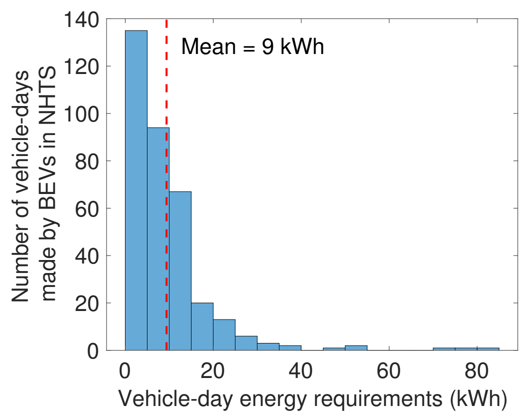

Figure A-31: Histogram of vehicle-day energy requirements made by BEVs in real-life in the NHTS.

A.13 Results using Tesla Model S vehicle parameters

In this manuscript, we use the energy requirements calculated using the vehicle parameters of the 2019 Nissan Leaf with a 40 kWh battery capacity to estimate VEP. To account for changes in vehicle design and weight when increasing battery capacity, we also calculate VEP using the vehicle parameters of the Tesla Model S P100D with a larger battery capacity of 100 kWh. In Table A.7, we show the VEP of a BEV with a 100 kWh battery capacity when using the vehicle parameters of the Tesla Model S P100D and the Nissan Leaf. We find that using the vehicle parameters of the 40 kWh Nissan Leaf to estimate the VEP of a 100 kWh BEV can lead to a difference of around 1 – 2% compared to using the vehicle parameters of the 100 kWh Tesla Model S P100D when considering charging availability with a charging power of 6.6 kW. This difference increases to up to 7% when considering fast charging with a charging power of 120 kW.

Table A.7: VEP of a 100 kWh BEV in Seattle under different charging availabilities calculated using the vehicle parameters of the Tesla Model S P100D with a 100 kWh battery capacity and the Nissan leaf with a 40 kWh battery capacity.

	VEP of a 100 kWh BEV	
Charging availability	Tesla Model S vehicle parameters	Nissan Leaf vehicle parameters
Home	34%	35%
Work	11%	13%
Home + work	37%	38%
Home + work + ubiquitous public	60%	58%
Home + overnight public	47%	46%
Work + overnight public	17%	19%
Home + work + overnight public	49%	50%
Home + fast charging on all highway trips	74%	77%
Work + fast charging on all highway trips	23%	30%
Home + work + fast charging on all highway trips	78%	81%
Home + overnight public + fast charging on all highway trips	87%	90%
Work + overnight public + fast charging on all highway trips	31%	36%
Home + work + overnight public + fast charging on all highway trips	90%	93%

In Figure A-32, we show the VEP and VEP+ of a 40 kWh BEV calculated using the vehicle parameters of the Nissan Leaf and a 100 kWh BEV calculated using the vehicle parameters of the Tesla Model S P100D for four different combinations of charging and supplementary vehicles. This figure corresponds to Figure 8 in the manuscript where the manuscript shows the VEP and VEP+ of a 40 kWh BEV and a 100 kWh BEV that are both calculated using the vehicle parameters of the Nissan Leaf.

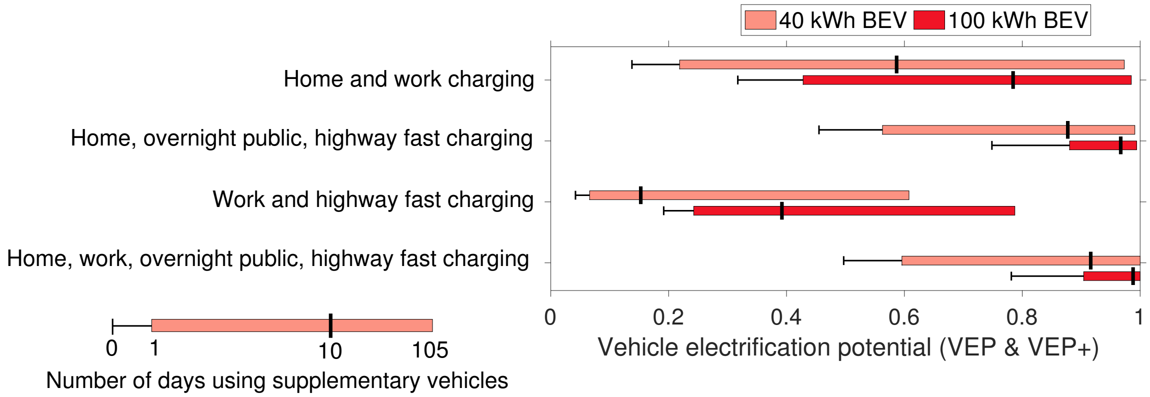

Figure A-32: VEP and VEP+ of BEVs with a battery capacity of 40 kWh and 100 kWh that are each calculated with the vehicle parameters of the Nissan Leaf and Tesla Model S P100D with different combinations of home charging, work charging, overnight public charging, fast charging on all highway trips, and accessing supplementary vehicles on 0 to 105 days (calculated as 2 out of 7 days over 365 days to approximate using supplementary vehicles every weekend) a year.

A.14 NHTS vehicle occupancy

To assess the opportunity of right-sizing supplementary vehicles and BEVs, we examine the vehicle occupany in the NHTS data and find that for trips that are shorter than 20 miles, 62% of the trips are made with one person in the vehicle. While for trips that are longer than 20 miles that likely pass through highway, 58% of the trips are made with one person in the vehicle. This suggests that although more trips are made with a single occupant, there are still a quite significant number of trips (both long and short) that have more than one occupant.

We also examine the vehicle occupancy on days that are electrified and not electrified with different combinations of charging availability. Figure A-33 and A-34 show vehicle occupancy on un-electrified vehicle-days and electrified vehicle-days with a 40 kWh BEV and 6.6 kW home charging. We find that the electrified vehicle-days have a higher percentage of single-occupant vehicle-days (58%) compared to un-electrified vehicle-days (30%). Moreover, the electrified vehicle-days have a lower percentage of vehicle-days that have more than 5 occupants (less than 1%) compared to un-electrified vehicle-days (2%).

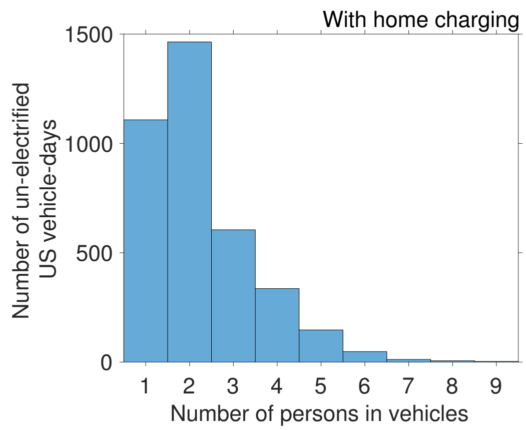

Figure A-33: Number of persons in vehicles on un-electrified vehicle-days whose energy requirements are not met by a 40 kWh BEV with 6.6 kW home charging.

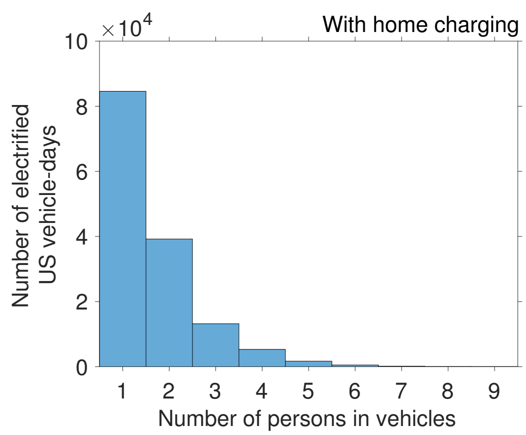

Figure A-34: Number of persons in vehicles on electrified vehicle-days whose energy requirements are met by a 40 kWh BEV with 6.6 kW home charging.

Figure A-35 and A-36 show vehicle occupancy on un-electrified vehicle-days and electrified vehicle-days with a 40 kWh BEV and 6.6 kW home and work charging. We find that similar to the home charging scenario, the electrified vehicle-days have a higher percentage of single-occupant vehicle-days (58%) compared to un-electrified vehicle-days (28%). Moreover, the electrified vehicle-days have a lower percentage of vehicle-days that have more than 5 occupants (less than 1%) compared to un-electrified vehicle-days (2%).

Figure A-37 and A-38 show vehicle occupancy on un-electrified vehicle-days and electrified vehicle-days with a 40 kWh BEV and 6.6 kW home and work charging and additional 120 kW highway fast charging stops to charge the battery to full on all highway trips

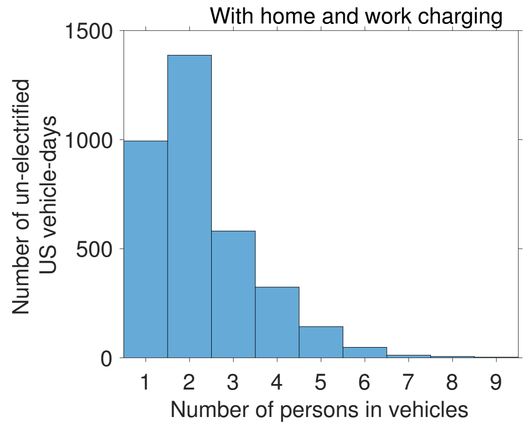

Figure A-35: Number of persons in vehicles on un-electrified vehicle-days whose energy requirements are not met by a 40 kWh BEV with 6.6 kW home and work charging.

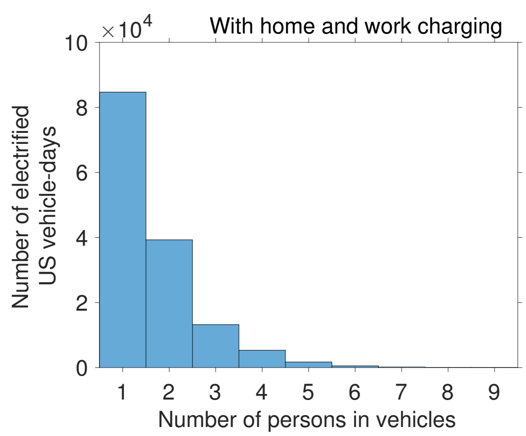

Figure A-36: Number of persons in vehicles on electrified vehicle-days whose energy requirements are met by a 40 kWh BEV with 6.6 kW home and work charging.

(thereby delaying future trips). We find that similar to the home charging scenario and home and work charging scenario, the electrified vehicle-days have a higher percentage of single-occupant vehicle-days (58%) compared to un-electrified vehicle-days (27%). Moreover, the electrified vehicle-days have a lower percentage of vehicle-days that have more than 5 occupants (less than 1%) compared to un-electrified vehicle-days (3%).

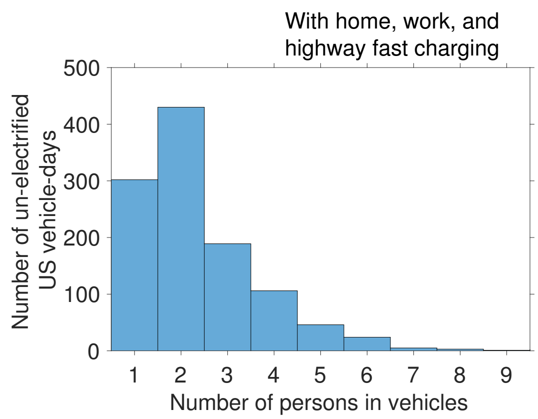

Figure A-37: Number of persons in vehicles on electrified vehicle-days whose energy requirements are met by a 40 kWh BEV with 6.6 kW home and work charging and 120 kW highway fast charging.

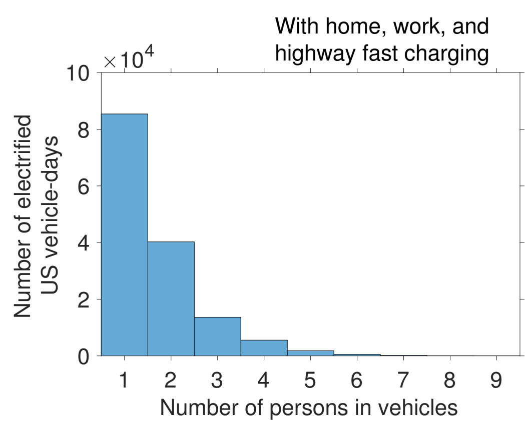

Figure A-38: Number of persons in vehicles on electrified vehicle-days whose energy requirements are met by a 40 kWh BEV with 6.6 kW home and work charging and 120 kW highway fast charging.

A.15 Heavy tail fitting of the vehicle-day energy requirements

We observe that there is heavy tail in the vehicle-day energy requirements as shown in Figure 1b and Figure 7b in the paper. To quantify this heavy tail and make comparisons between the Seattle and the US data, we take the vehicle-days that have an energy requirement higher than 40 kWh (the rated battery capacity of the Nissan Leaf) and fit a power law distribution. We fit a function $y = a * x^{-b}$, where x is the empirical frequency of vehicle-days and y is the vehicle-day energy requirements, in order to estimate the exponent b. Based on this approach, we find that the Seattle vehicle-days at the tail (vehicle-day aggregated across all vehicles) have a fitted exponent of 2.49 and the NHTS data has a fitted exponent of 2.54. The fitting of the Seattle data has an adjusted R-squared of 0.972 and that of the NHTS data has an adjusted R-squared of 0.995.

Appendix B

Grid impacts of BEV charging

B.1 Impacts on different kinds of circuits

We examine the impacts of BEV home charging on two other circuits in Fairfield, Connecticut (Figure B-1). The impacts are examined for a 100% BEV adoption level. We find that the electricity demand profile over the year and the magnitude of the peak demand can vary depending on characteristics of the neighborhood covered by the circuit, such as the mix of residential and commercial customers on the circuit. More work is needed to understand the generalizability of the results.

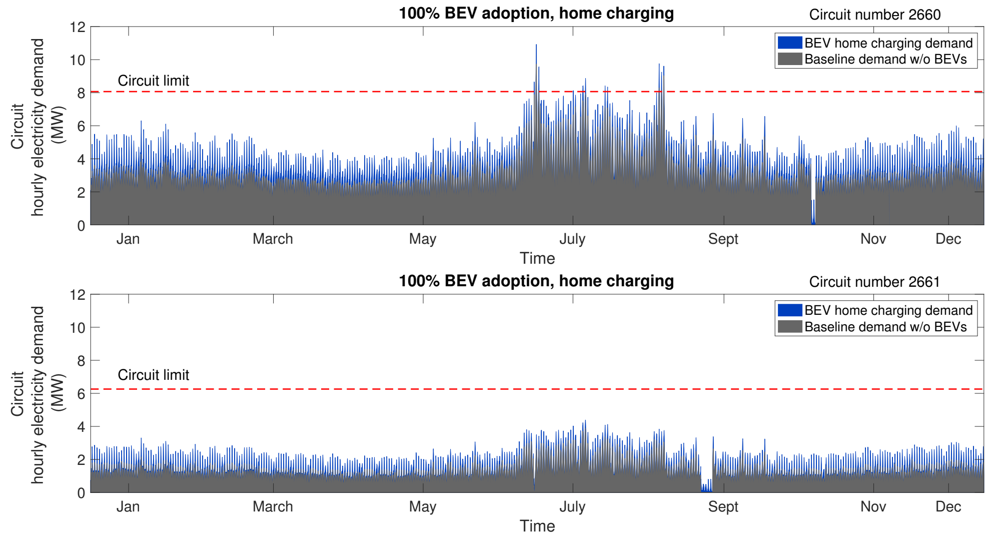

Figure B-1: Hourly electricity demand of different circuits in Ashcreek substation in Fairfield, Connecticut assuming 100% BEV adoption level and immediate home charging over one year 2019.

B.2 Patterns of hourly number of visitors at highway rest stops over one year

We examine hourly foot traffic at several highway rest stops along Interstate 95 in Connecticut (Figure B-2) and in other parts of the northeastern US (Figure B-3). The data is extracted from cellphone data provided by Safegraph [32] and the figures here show the data before normalization. We find that there can be occasional extreme peaks in foot traffic over the year at the examined locations. This suggests that there might be occasional extreme peaks in highway fast charging demand and the charging system needs to be designed to accommodate for these peaks.

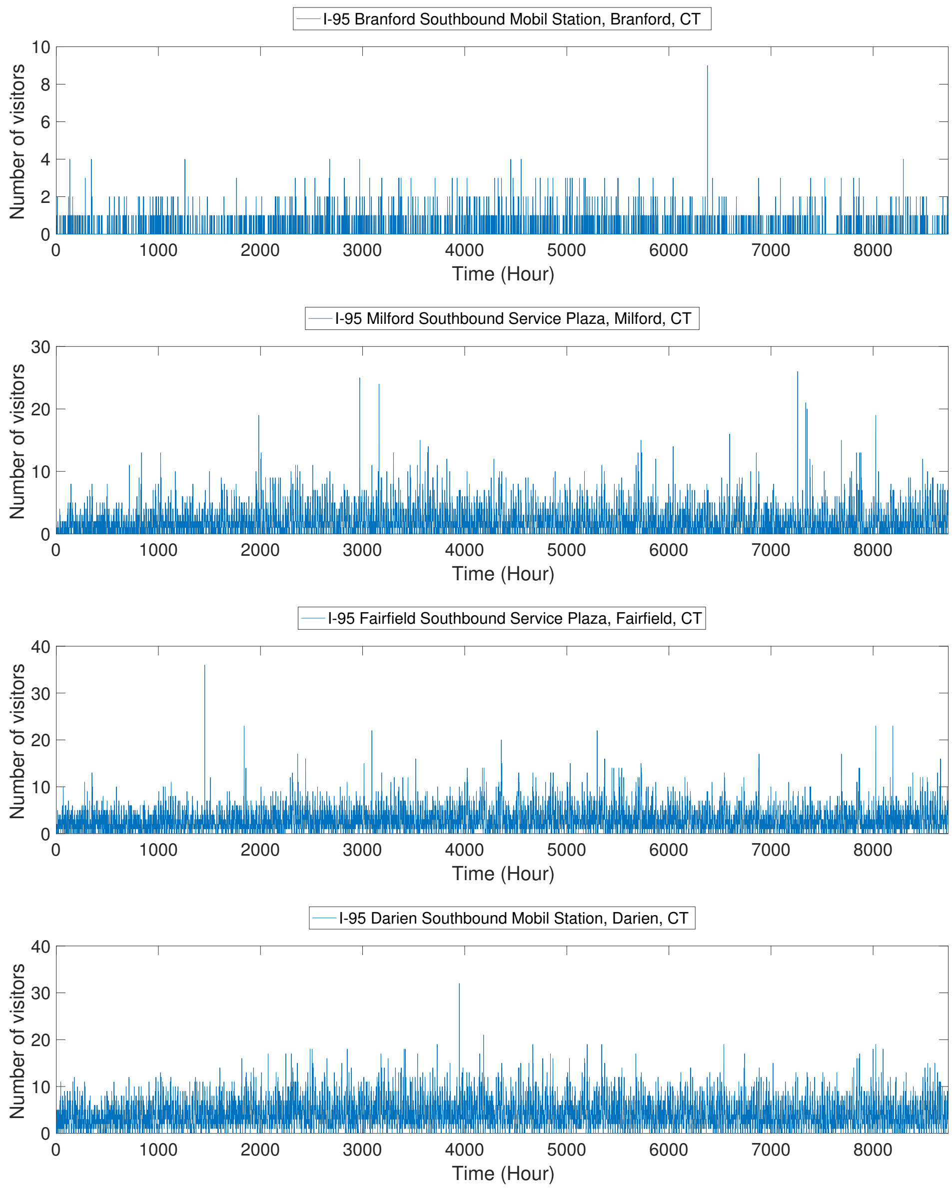

Figure B-2: Number of visitors at each hour at nearby I-95 highway rest stops over one year, ordered from top to bottom as stops from north to south on the southbound I-95.

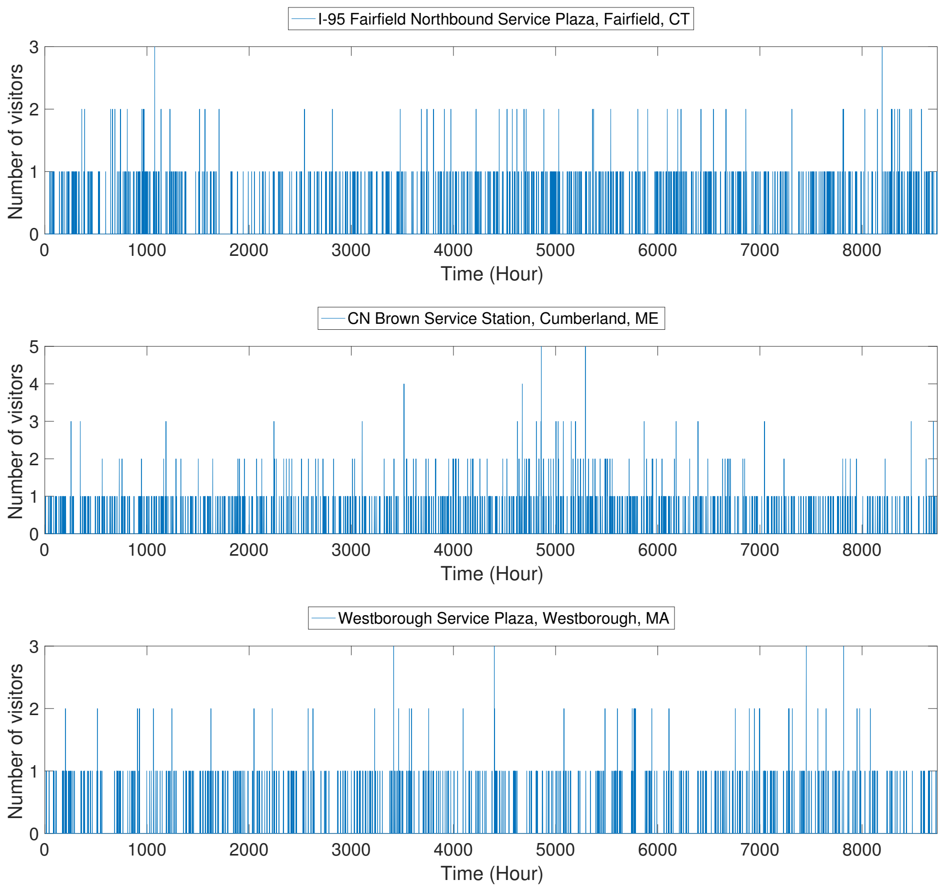

Figure B-3: Number of visitors at each hour at other different highway rest stops over one year.

B.3 Patterns of highway trips in NHTS

We show the temporal patterns of highway trips in all states in the US using the National Household Travel Survey [1]. Different from the northeastern states, we observe peaks around 5-6 pm when looking at the entire US. This suggests that in the northeast, travelers might plan their highway trips to occur earlier during the day so that they arrive at their destinations before dinner time. This might be due to earlier sunsets and colder climate in the northeast.

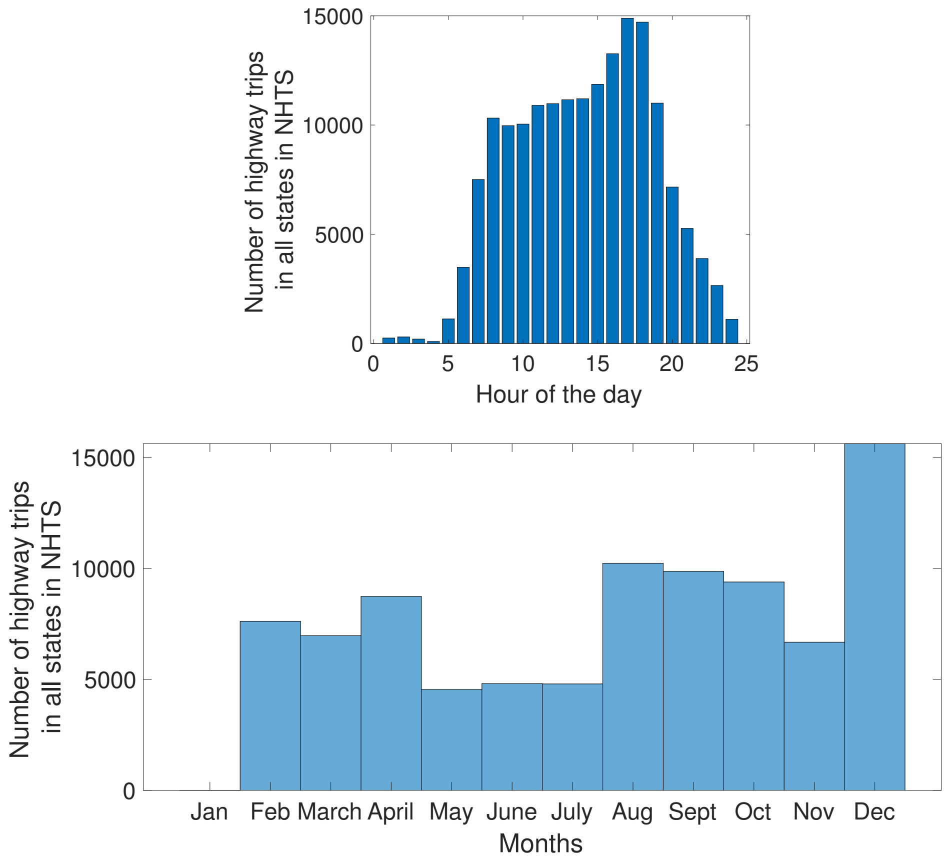

Figure B-4: Distribution of highway trips in all states using NHTS data.

B.4 Distribution grid impact analysis for North Haven substation

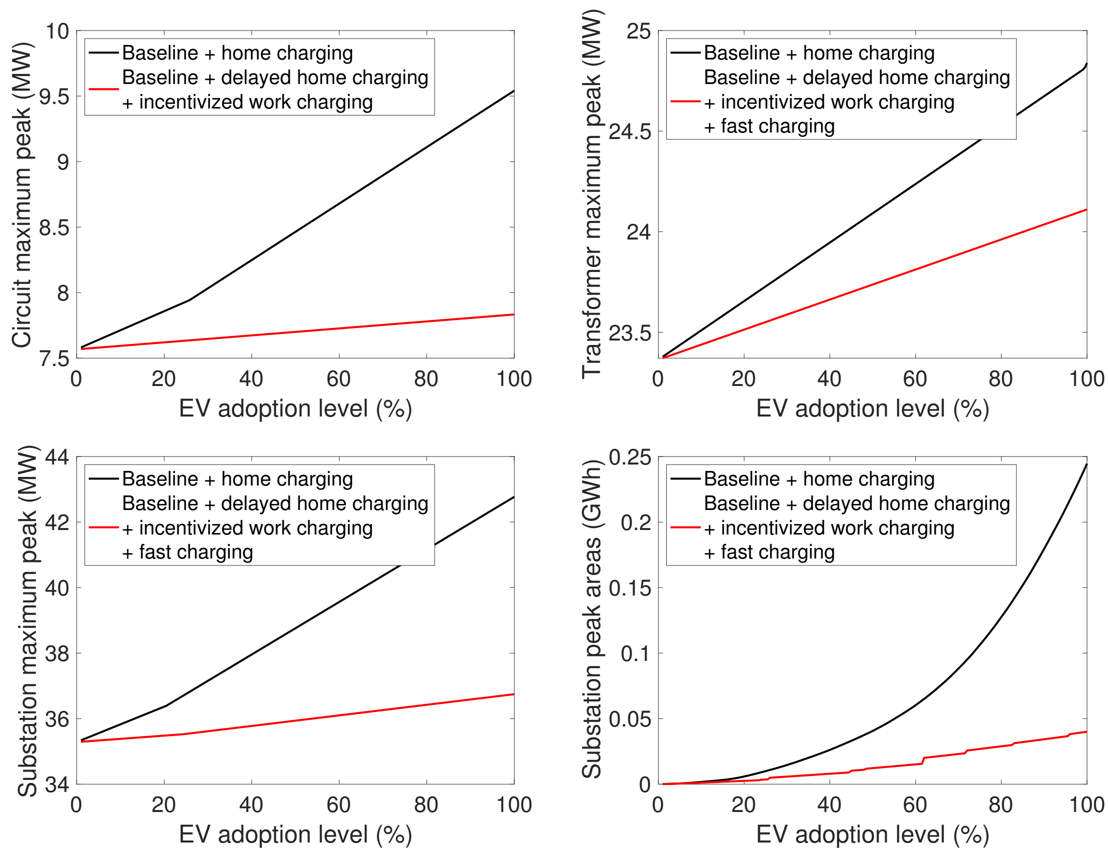

Figure B-5: Maximum peak load over one year at the circuit, transformer, and substation level and peak areas at the substation level under North Haven substation for a range of BEV adoption levels before and after demand management to shave peaks. The circuit shown is the circuit that serves the largest residential neighborhood in the area where demand management has the largest impact on shaving peaks.

B.5 Fast charging patterns at other highway stops served by the New England ISO

In addition to the highway stop examined in the manuscript that is located at I-95 Fairfield Southbound Service plaza in Fairfield, Connecticut, we examine the patterns of highway stops at three other locations in the Northeastern US that belong to the New England ISO region using the Safegraph data [?]. We show the temporal distribution of highway stops over different hours in a day and different months in a year, whereby the y axis shows the number of hours that have at least one customer at the stop over one year 2019. We show this distribution for CN Brown Service Station, Cumberland, Maine (Figure B-6), Westborough Service Plaza, Westborough, Massachusetts (Figure B-7), and I-95 Fairfield Northbound Service Plaza, Fairfield, Connecticut (Figure B-8).

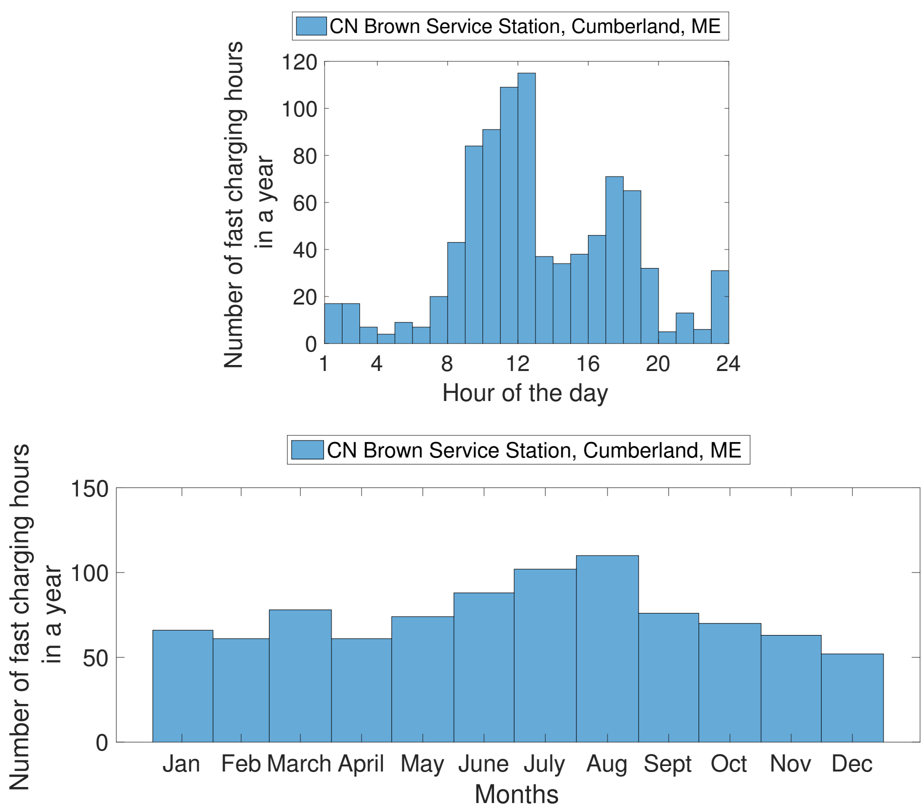

Figure B-6: Distribution of highway stops (with at least one customer at the stop) over different hours in the day and different months in a year.

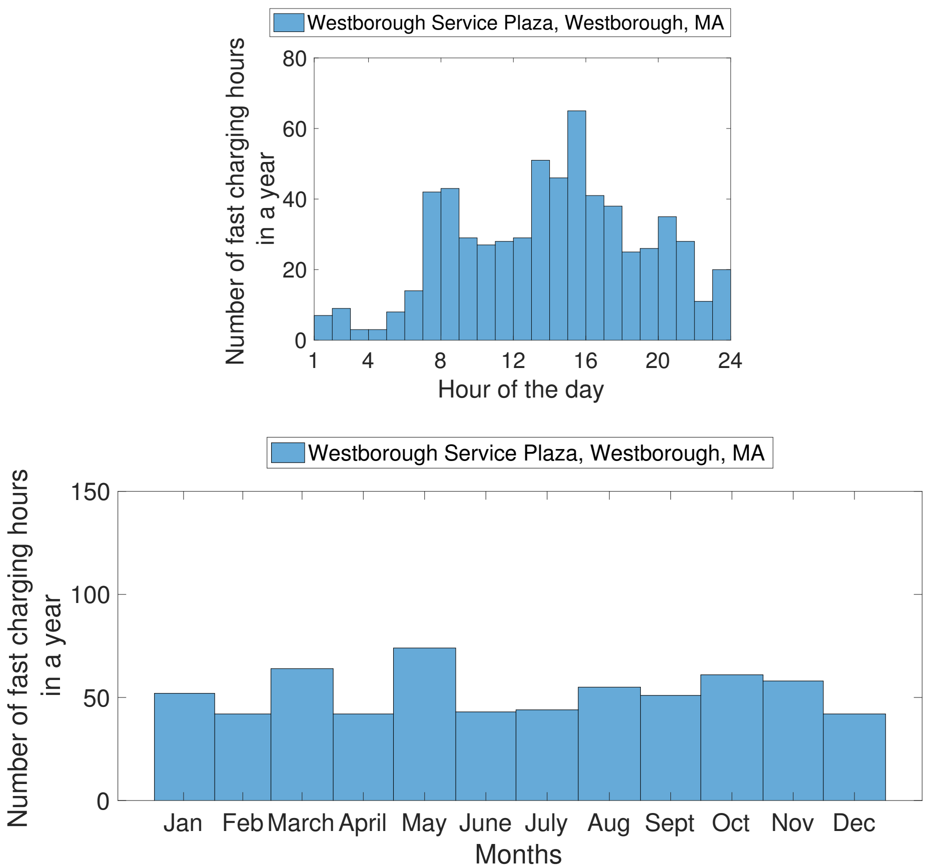

Figure B-7: Distribution of highway stops over different hours in the day and different months in a year.

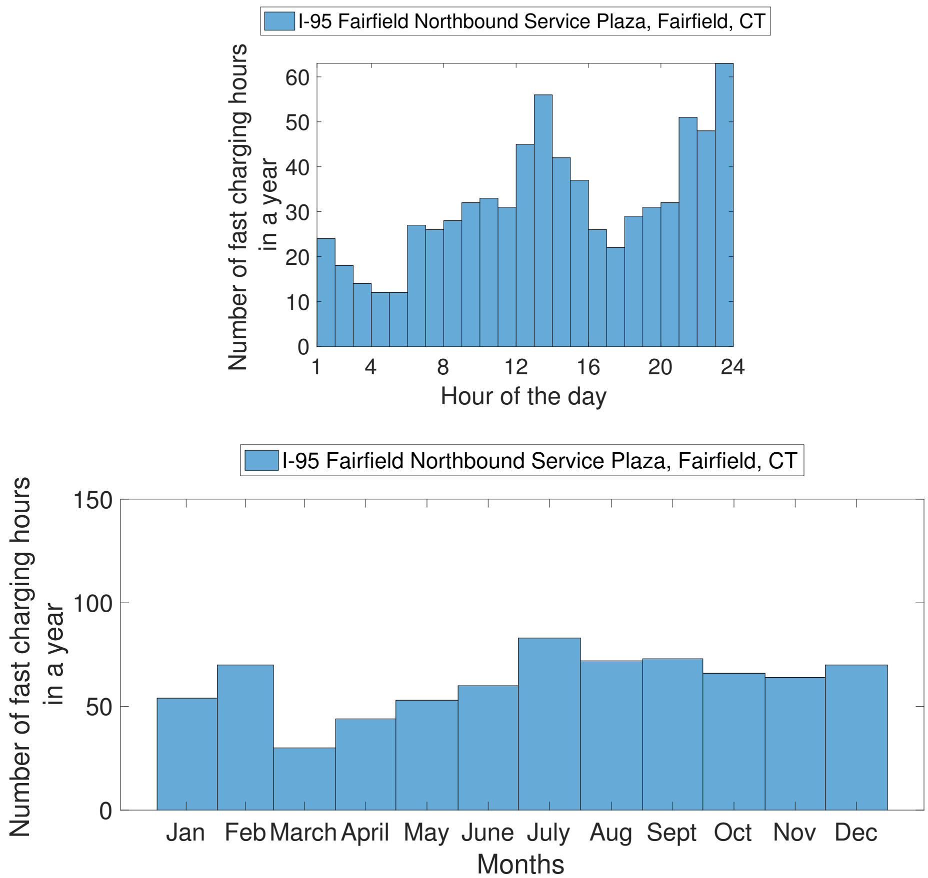

Figure B-8: Distribution of highway stops over different hours in the day and different months in a year.

B.6 Impact of fast charging on grid generation capacity at the ISO level

We quantify the potential impact of fast charging at the spatial level of ISO grid region to estimate the implications on grid generation capacity. For the New England ISO, if we assume there are 2 million EVs (using state forecasts for year 2030 based on EV registration numbers and growth rate) [169] and one plug per 1000 EVs [13] in the regions covered by the New England ISO, there would be 2000 public fast chargers. Assuming the 2000 fast chargers are used at the same time and a charging power of 150 kW, the total maximum power required is then 300 MW. This is around 1% of the existing generation capacity of the New England ISO [170]. As EV adoption level increases, a 100% EV adoption level would roughly translate to around 20 million EVs in the ISO New England region, which is around 10% of the existing generation capacity.

Appendix C

HFCV refueling requirements

C.1 Variations in HFCV fuel economy and daily energy requirements in the Northeastern US

We show the variation of fuel economy in NHTS trips made by households that reside in the Northeastern US (Figure C-1), taking into account trip patterns, driving conditions, and ambient temperature. We also examine the vehicle-day energy requirements of HFCVs in different states in the Northeastern US. We find that Delaware, New Hampshire, Maine, New Jersey, Connecticut, Maryland, and Vermont have a mean vehicle-day energy requirement that is above the average across northeastern states, after taking into account trip patterns, driving conditions, and ambient temperature (Figure C-2). Most of these states (except for DC) have a vehicle-day energy requirement that is close to the average of the northeastern region (Figure C-2). This is because of the dense urban setting in the DC that results in a lower vehicle-day travel distance compared to the mix of urban and rural areas in other states (Figure C-3a). Moreover, the average daily energy requirement in Delaware is 1.3 times of that in Philadelphia. Although Delaware has the highest mean trip fuel economy, the state also has the highest mean vehicle-day travel distance (Figure C-3a), resulting in the combined effect of a high vehicle-day energy requirement. New Hampshire, New Jersey, and Maryland have a similar average vehicle-day travel distance, but New Hampshire has a slightly higher vehicle-day energy requirement than the other two states because of the lower fuel economy due to a colder climate (Figure C-3b). For New York and Philadelphia that have a similar vehicle-day travel distance and vehicle fuel economy (Figure C-3), travel distance has a slightly larger effect on vehicle-day energy requirements so that New York has a slightly higher average vehicle-day energy requirement.

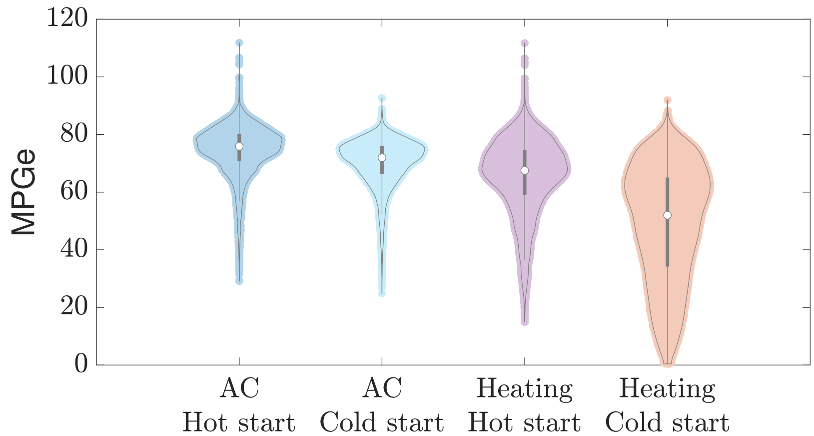

Figure C-1: Variation of fuel economy across NHTS trips in the Northeastern US for different combinations of heating/air-conditioning (AC) and a hot start/cold start, estimated using the trip energy model. A cold start is needed when the vehicle is parked for more than 2 hours before the trip starts. Heating is used when the ambient temperature at the hour when the trip starts is below 22 degrees celsius, and air-conditioning is used when the ambient temperature is above 22 degrees celsius.

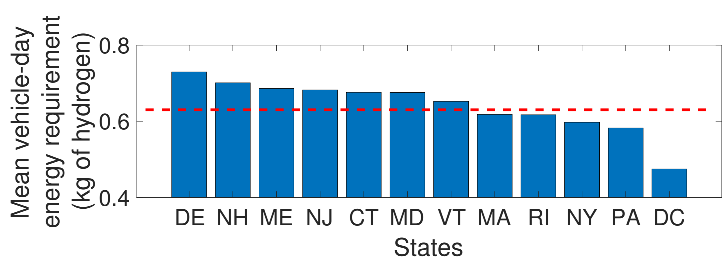

Figure C-2: Mean vehicle-day energy requirements of an HFCV for trips made by households residing in the northeastern states taking into account trip patterns, driving conditions, and hourly ambient temperature. The states are sorted from the state with the highest mean vehicle-day energy requirement to the lowest. The dashed line shows the energy requirements averaged across all vehicle-days in the northeastern states. To adjust for different sample sizes of vehicle-days in different states, we calculate the weighted mean by weighting vehicle-days with the vehicle weight provided in the NHTS to obtain a representative sample of vehicles for each state.

We find that the vehicle-days made by drivers living in areas with a low population density (less than 500 persons per square mile) have a higher average daily energy requirement (0.8 kg of hydrogen) compared to those with a higher population density (0.6 kg of hydrogen per day on average for drivers living in areas with a population density between 500 and 5,000 persons per square mile, and 0.5 kg of hydrogen per day for drivers living in areas with a population density above 5,000 persons per square mile), after taking into account the effect of ambient temperature, trip patterns, and driving conditions (Figure C-4). Trips made by households living in low population density areas have a higher fuel economy on average compared to those living in higher population density areas because of a higher trip average speed (66 MPGe on average for population density less than 500 persons per square mile compared to 63 – 64 MPGe for higher population density areas). However, the average vehicle-day travel distance is also higher in areas with a lower population density. The lowest population density group has an average vehicle-day travel distance that is 1.4 times higher than that of the highest population density group. The difference in travel distance and fuel economy result in the combined effect we observe on energy requirement, where the lowest population density group has an average vehicle-day energy requirement that is 1.3 times higher than that of the highest population density group.

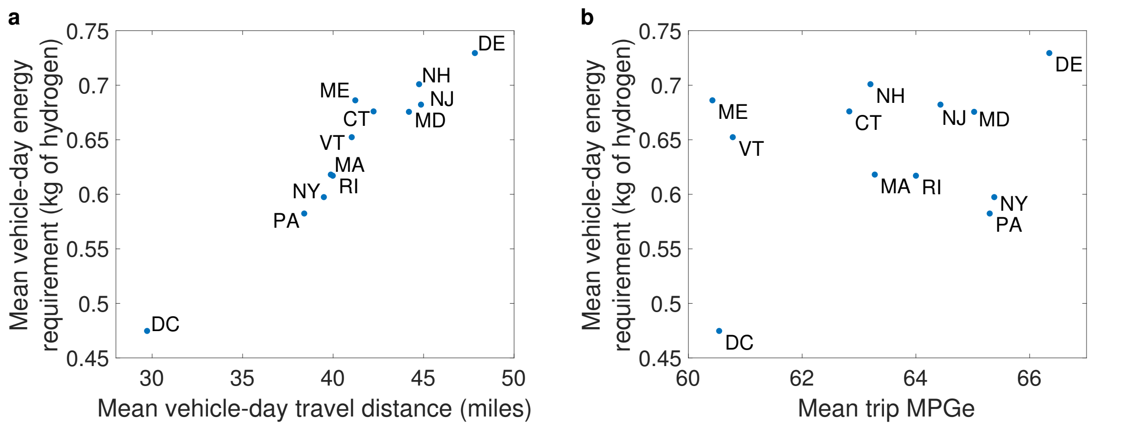

Figure C-3: The y axis shows the weighted mean vehicle-day energy requirements for trips made by households residing in each state in the Northeastern US in the NHTS. The x axis shows **a:** the weighted mean vehicle-day travel distance in each state; **b:** the weighted mean trip fuel economy in each state. This figure highlights the relative impact of trip distance and fuel economy on energy requirements for different states.

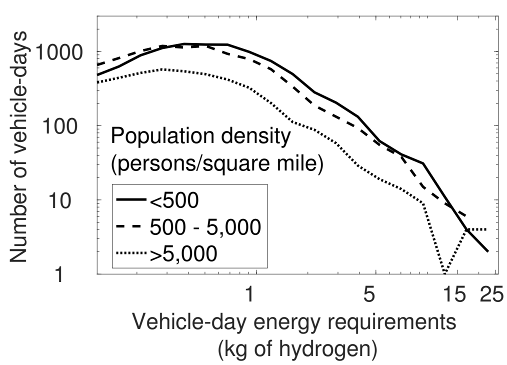

Figure C-4: Distribution of HFCV vehicle-day energy requirements for vehicles owned by households living in areas with different population density in the Northeastern US.

C.2 Characteristics of highway refueling required for HFCVs in the Northeastern US

We find that 15% of these vehicles' year-long energy requirements can be covered by the Toyota Mirai with a tank capacity of 5 kg of hydrogen if the vehicle refuels on the longest highway trip per day, and 26% if the vehicle refuels on all highway trips (Figure C-5). In fact, for almost all vehicles whose energy requirements throughout the year is covered by the Toyota Mirai, the hydrogen tank capacity never drops below 1 kg (1/5 of the tank capacity) throughout the year, suggesting that even if a detour is needed for refueling, these vehicles might still be able to meet the energy requirements (Figure C-6). We also find that for vehicles that do not pass highway during commuting days, and therefore rely on refueling on highway trips on non-commuting days over the weekend, the number of refueling opportunities can vary from 2 to 49 days a year (Figure C-7). These results begin to suggest that refueling stations on the interstate could be a critical first step to meet HFCV energy demand and thereby support HFCV adoption.

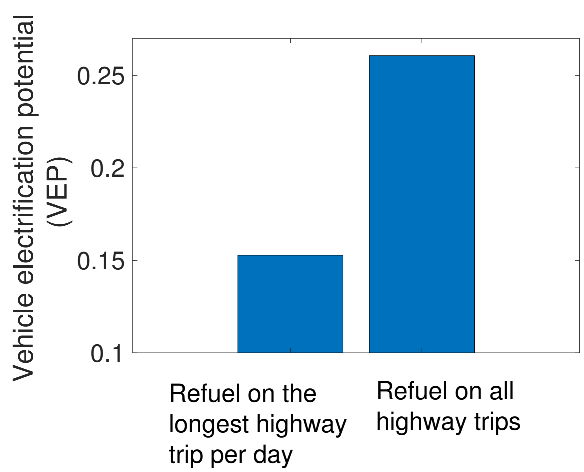

Figure C-5: Vehicle electrification potential (VEP) with the Toyota Mirai that has a 5 kg hydrogen tank capacity under two refueling scenarios, estimated for vehicles residing in the northeastern states using synthetic year-long travel data.

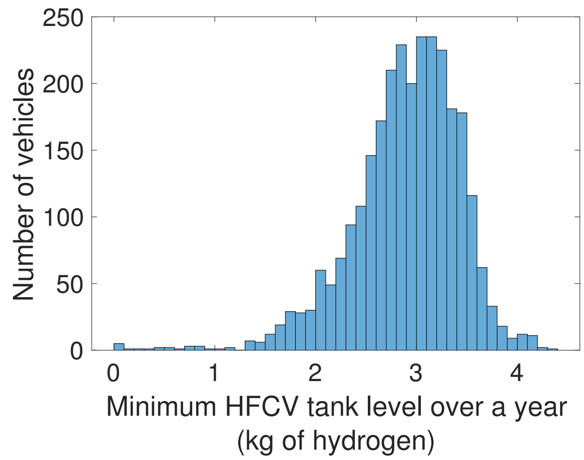

Figure C-6: Histogram of minimum HFCV tank level over a year for vehicles whose year-long energy requirements are met by the Toyota Mirai with a 5 kg hydrogen tank capacity and refueling on all highway trips. This is estimated by taking synthetic year-long travel data and tracking hydrogen tank level throughout a year.

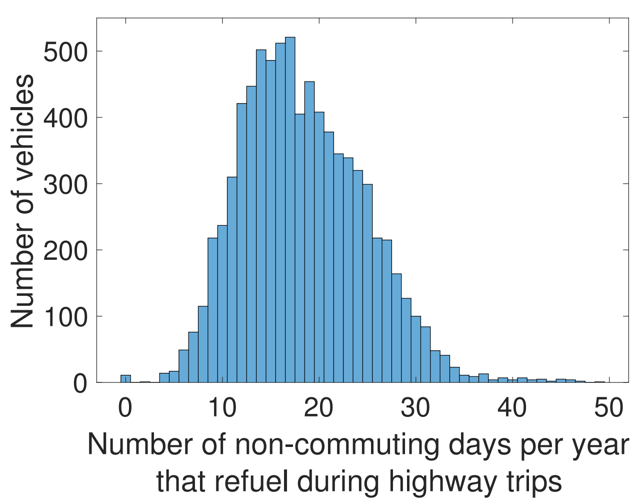

Figure C-7: Histogram of number of non-commuting days per year during which the vehicle is refueled along the highway (for vehicles that do not pass highway during commuting days) using the synthetic year-long travel data.

C.3 Battery electric vehicle and hydrogen fuel cell vehicle comparison

Compared to hydrogen fuel cell vehicles (HFCVs), battery electric vehicles (BEVs) have a shorter range and a longer charging time. BEVs and HFCVs also have a different fuel economy performance in cold climate with low ambient temperature. However, the advantages of BEVs are their convenient access to at-home charging and lower cost of fuel. HFCV refueling stations are also more expensive to build and require more land space for hydrogen storage, whereas BEV charging stations are available at a much lower cost and do not require as much land space for installation. For HFCVs, due to the lack of home refueling and being completely reliant on public refueling, strategic placement of HFCV refueling stations is particularly important for HFCV adoption and detours to HFCV refueling stations might be necessary given the limited number of HFCV refueling stations due to cost.

We first compare the fuel economy performance of HFCVs and BEVs under different ambient temperatures. For BEVs, we calibrate the vehicle model parameters using reported values for the 2018 Nissan Leaf with a 40 kWh battery capacity under different drive cycles and ambient temperatures [171]. The drive cycles and conditions that were used to calibrate the vehicle model and temperature model are shown in Table C.1. The calibrated vehicle parameters are shown in Table C.2. The model has a validation error of less than 5% (Table C.3). To compare with HFCVs, we show the variation of fuel economy in Figure C-8, which corresponds to Figure 1 for HFCVs in the manuscript. For BEVs' cold start effect, different from HFCVs where the cold start efficiency increases over time as the vehicle warms up, we found that a constant cold start efficiency is a natural fit when calibrating the model.

Moreover, we often observe multiple highway trips clustered on the same day. For BEVs, charging multiple times a day could then be very helpful for the shorter range BEVs. While for HFCVs, this clustering effect does not really help HFCV refueling because ideally we need the highway trips to spread over the year instead of being concentrated around a few days a year so that there are more highway refueling opportunities.

Test drive cycle	**Test temperature ()**	**Cold start (on/off)**	**Reported MPGe**
UDDS	24	off	119
HWFET	24	off	97
UDDS	24	on	109
UDDS	-7	on	77
UDDS	35	off	101

Table C.1: Test cycles and conditions to calibrate vehicle model and temperature model [171].

	Parameters	**Values**	**Units**	**Parameters**	**Values**	**Units**
Vehicle model	a	115.16	N	P_{idle}	400	Watts
	b	3.43	N/(m/s)	η_{max}	0.72	-
	c	0.43	$N/(m/s)^2$	η_{brake}	0.78	-
	Mass	1758	kg	-	-	-
Temperature model	P_{aux_base}	300	Watts	$p_{heating}$	54	Watts/$^{\circ}C$
	η_{cold_start}	0.92	-	p_{AC}	65	Watts/$^{\circ}C$

Table C.2: Final set of Nissan Leaf parameters used in the vehicle model and temperature model to calculate trip energy consumption. The a,b,c coefficients and vehicle mass are from the EPA dynamometer testing results.

Test drive cycle	**Test temperature ()**	**Cold start (on/off)**	**Reported MPGe**	**Predicted MPGe**
US06	24	off	69	71
US06	24	on	67	65
US06	-7	on	62	59
US06	35	off	66	68
HWFET	-7	on	80	78
HWFET	35	off	91	92

Table C.3: Test cycles and conditions used for validation of calibrated parameters in the vehicle model and the temperature model [171].

The purchase cost of the 2021 Toyota Mirai is around $50,000 (around 400 mile range), for the 2021 Tesla Model S with a similar range costs around $70,000. As a comparison, a lower-cost BEV such as the 2021 Nissan Leaf with the longest range (226 miles) is around $40,000. The cost of hydrogen at pump in California is around $16 per kg. The toyota Mirai has a 5 kg tank capacity, assuming refueling once a week. The total fuel cost over 10 years is around $40,000. The cost of electricity for charging BEVs, assuming 4 cents per mile and 13 cents per kWh, it takes around $9 to get a 200 mile range, so that is around $20 to get a 400 mile range. Assuming once a week recharge with this range, the total fuel cost over 10 years is around $10,000. Future projection of hydrogen cost at pump may drop to $4 per kg due to economies of scale, so that the hydrogen fuel cost becomes similar with the electricity cost. For battery electric vehicles, there are longer-term concerns on running out of precious metals to produce batteries in larger quantities such as cobalt, nickel, lithium, and manganese. Extraction of these metals might lead to cost increase in the future.

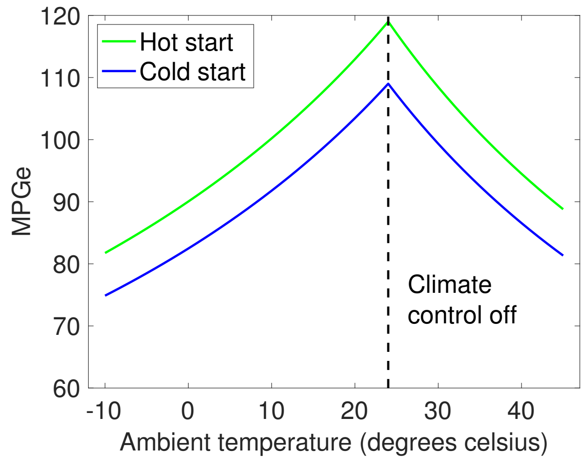

Figure C-8: The effect of ambient temperature and a cold start on Nissan Leaf fuel economy evaluated using the EPA Urban Dynamometer Driving Schedule (UDDS). Heating is used when ambient temperature is below 24 degrees celsius, air-conditioning is used when ambient temperature is above 24 degrees celsius, and no heating or air-conditioning is used when ambient temperature is at 24 degrees celsius.

Bibliography

[1] Federal Highway Administration. 2017 National Household Travel Survey. Technical report, U.S. Department of Transportation, Washington, DC, 2018.

[2] Avangrid. Distribution grid hourly electricity demand data over one year 2019 in Connecticut. Technical report, Avangrid, 2021.

[3] OpenStreetMap Contributors. Planet dump. Technical report, 2021.

[4] Chokkalingam Bharatiraja, Sanjeevikumar Padmanaban, Pierluigi Siano, Ramesh Krishnamoorthy, and Raghu Selvaraj. Real-time forecasting of EV charging station scheduling for smart energy systems. *Energies*, 10(3):1–16, 2017.

[5] International Council on Clean Transportation. Vision 2050: A strategy to decarbonize the global transport sector by mid-century. Technical report, International Council on Clean Transportation, 2020.

[6] US Energy Information Administration. Annual Energy Outlook. Technical report, US Energy Information Administration, 2021.

[7] International Energy Agency. Net Zero by 2050: A Roadmap for the Global Energy Sector. Technical report, International Energy Agency, 2021.

[8] Ashley Lawson and Fatima Maria Ahmad. Decarbonizing US transportation. Technical report, Center for Climate and Energy Solutions, 2018.

[9] Marco Miotti, Geoffrey J Supran, Ella J Kim, and Jessika E Trancik. Personal Vehicles Evaluated against Climate Change Mitigation Targets. *Environmental Science and Technology*, 50(20):10795–10804, 2016.

[10] Zachary A Needell, James McNerney, Michael T Chang, and Jessika E Trancik. Potential for widespread electrification of personal vehicle travel in the United States. *Nature Energy*, 1(August):1–7, 2016.

[11] US Department of Energy. Electric Vehicle Charging Station Locations, 2021.

[12] The White House. President Biden's Bipartisan Infrastructure Law. Technical report, Washington, D.C., 2021.

[13] Eric Wood, Dong-Yeon (D-Y) Lee, Nicholas Reinicke, Yanbo Ge, and Erin Burrell. Electric Vehicle Infrastructure Projection Tool. In *California Energy Commission (CEC) Integrated Energy Policy Report (IEPR) Workshop*, 2020.

[14] Zach Needell, Wei Wei, and Jessika E. Trancik. Strategies for beneficial electric vehicle charging to reduce peak electricity demand and store solar energy. *In review*, 2021.

[15] Wei Wei and Jessika E Trancik. Strategies for managing the distribution grid impact of BEV charging. *In preparation*.

[16] US Department of Energy. Hydrogen Fueling Station Locations, 2021.

[17] Hall Dale and Nic Lutsey. Estimating the infrastructure needs and costs for the launch of zero-emission trucks | International Council on Clean Transportation. Technical Report August, International Council on Clean Transportation, 2019.

[18] Christopher Zegras. The built environment and motor vehicle ownership and use: Evidence from Santiago de Chile. *Urban Studies*, 47(8):1793–1817, 2010.

[19] Yang Jiang, P. Christopher Zegras, and Shomik Mehndiratta. Walk the line: Station context, corridor type and bus rapid transit walk access in Jinan, China. *Journal of Transport Geography*, 20(1):1–14, 2012.

[20] Jinhyun Hong, Qing Shen, and Lei Zhang. How do built-environment factors affect travel behavior? A spatial analysis at different geographic scales. *Transportation*, 41(3):419–440, 2014.

[21] Susan Handy, Xinyu Cao, and Patricia Mokhtarian. Correlation or causality between the built environment and travel behavior? Evidence from Northern California. *Transportation Research Part D: Transport and Environment*, 10(6):427–444, 2005.

[22] Dirk Helbing, Ansgar Hennecke, Vladimir Shvetsov, and Martin Treiber. MASTER: Macroscopic traffic simulation based on a gas-kinetic, non-local traffic model. *Transportation Research Part B: Methodological*, 35(2):183–211, 2001.

[23] Martin Treiber and Arne Kesting. *Traffic Flow Dynamics: Data, Models and Simulation*. Springer, 2013.

[24] Gang Len Chang and Zuojin Zhu. A macroscopic traffic model for highway work zones: Formulations and numerical results. *Journal of Advanced Transportation*, 40(3):265–287, 2006.

[25] Elvira Thonhofer, Toni Palau, Andreas Kuhn, Stefan Jakubek, and Martin Kozek. Macroscopic traffic model for large scale urban traffic network design. *Simulation Modelling Practice and Theory*, 80:32–49, 2018.

[26] A. Ferrara, S. Sacone, and S. Siri. *Microscopic and Mesoscopic Traffic Models*. Springer, 2018.

[27] Carlos Lima Azevedo, Neeraj Milind Deshmukh, Balakumar Marimuthu, Simon Oh, Katarzyna Marczuk, Harold Soh, Kakali Basak, Tomer Toledo, Li Shiuan Peh, and Moshe E. Ben-Akiva. Simmobility short-term: An integrated microscopic mobility simulator. *Transportation Research Record*, 2622(1):13–23, 2017.

[28] Charles M. Macal and Michael J. North. Tutorial on agent-based modeling and simulation. *Proceedings - Winter Simulation Conference*, 2005:2–15, 2005.

[29] Muhammad Adnan, Corresponding Author, Francisco C Pereira, Carlos Miguel, Lima Azevedo, Kakali Basak, Milan Lovric, Sebastian Raveau Feliu, Yi Zhu, Joseph Ferreira, Christopher Zegras, and Moshe E Ben-akiva. SimMobility : A Multi-Scale Integrated Agent-based Simulation Platform. *Transportation Research Board (TRB) 95th Annual Meeting*, pages 1–18, 2015.

[30] Federal Highway Administration. 2009 National Household Travel Survey. Technical Report October, U.S. Department of Transportation, Washington, DC, 2011.

[31] National Renewable Energy Laboratory. Puget Sound Traffic Choices Study. Technical report, Available online: www.nrel.gov/tsdc, 2019.

[32] SafeGraph. Weekly patterns, 2021.

[33] National Renewable Energy Laboratory. California Household Transportation Survey. Technical report, National Renewable Energy Laboratory, 2012.

[34] Connecticut Department of Transportation. Traffic monitoring count data: Volume and classification information. Technical report, Connecticut Department of Transportation, 2021.

[35] Caitlin D Cottrill, Francisco Câmara Pereira, Fang Zhao, Inês Ferreira Dias, Hock Lim, Moshe E Ben-akiva, and Christopher Zegras. Future Mobility Survey Experience in Developing a Smartphone-Based Travel Survey in Singapore. pages 12–17, 1996.

[36] Zachary J. Lee, Tongxin Li, and Steven H. Low. ACN-Data: Analysis and applications of an open EV charging dataset. *e-Energy 2019 - Proceedings of the 10th ACM International Conference on Future Energy Systems*, pages 139–149, 2019.

[37] Stephen Schey, Don Scoffield, and John Smart. A first look at the impact of electric vehicle charging on the electric grid in the EV project. *World Electric Vehicle Journal*, 5(3):667–678, 2012.

[38] John Heywood, Don MacKenzie, Ingrid Bonde Akerlind, Parisa Bastani, Irene Berry, Kandarp Bhatt, Alice Chao, Eric Chow, Valerie Karplus, David Keith, Michael Khusid, Eriko Nishimura, and Stephen Zoepf. On the Road toward 2050:

Potential for Substantial Reductions in Light-Duty Vehicle Energy Use and Greenhouse Gas Emissions. Technical report, Massachusetts Institute of Technology, 2015.

[39] Don MacKenzie and John B. Heywood. Quantifying efficiency technology improvements in U.S. cars from 1975-2009. *Applied Energy*, 157(2015):918–928, 2015.

[40] Donald MacKenzie, Stephen Zoepf, and John Heywood. Determinants of US passenger car weight. *International Journal of Vehicle Design*, 65(1):73–93, 2014.

[41] Lynette Cheah and John Heywood. Meeting U.S. passenger vehicle fuel economy standards in 2016 and beyond. *Energy Policy*, 39(1):454–466, 2011.

[42] Lynette Cheah. *Cars on a Diet : The Material and Energy Impacts of Passenger Vehicle Weight Reduction in the U.S.* PhD thesis, Massachusetts Institute of Technology, 2010.

[43] Lynette Cheah, Christopher Evans, Anup Bandivadekar, and John Heywood. *Factor of Two: Halving the Fuel Consumption of New U.S. Automobiles by 2035*, pages 49–71. Springer Netherlands, Dordrecht, 2009.

[44] Alan McDonald and Leo Schrattenholzer. Learning rates for energy technologies. *Energy Policy*, 29(4):255–261, 2001.

[45] Béla Nagy, J Doyne Farmer, Quan M Bui, and Jessika E Trancik. Statistical Basis for Predicting Technological Progress. *PLOS ONE*, 8(2):1–7, 2013.

[46] William D. Nordhaus. The Perils of the Learning Model for Modeling Endogenous Technological Change. *The Energy Journal*, 35(1):1–13, 2014.

[47] Micah S. Ziegler and Jessika E. Trancik. Re-examining rates of lithium-ion battery technology improvement and cost decline. *Energy and Environmental Science*, 14(4):1635–1651, 2021.

[48] James McNerney, J. Doyne Farmer, and Jessika E. Trancik. Historical costs of coal-fired electricity and implications for the future. *Energy Policy*, 39(6):3042–3054, 2011.

[49] Goksin Kavlak, James Mcnerney, and Jessika E Trancik. Evaluating the causes of cost reduction in photovoltaic modules. *Energy Policy*, 123(August 2017):700–710, 2018.

[50] Micah S Ziegler and Jessika E Trancik. Determinants of lithium-ion battery technology cost decline. *Energy & Environmental Science*, 14:6074–6098, 2021.

[51] Jessika E. Trancik and Daniel Cross-Call. Energy technologies evaluated against climate targets using a cost and carbon trade-off curve. *Environmental Science and Technology*, 47(12):6673–6680, 2013.

[52] Hassan ZAHEER and Saqib SAEED. Power transformer âĂŞ global market analysis Capacity additions and aging infrastructure driving the growth. *Transformer Magazine*, 5(1):62–68, 2018.

[53] David Hurlbut, Joyce McLaren, Sam Koebrich, Juliana Williams, and Emily Chen. Electric Vehicle Charging Implications for Utility Ratemaking in Colorado. Technical report, 2019.

[54] Caitlin Murphy, Trieu Mai, Yinong Sun, Paige Jadun, Matteo Muratori, Brent Nelson, and Ryan Jones. Electrification Futures Study: Scenarios of Power System Evolution and Infrastructure Development for the United States. Technical report, National Renewable Energy Laboratory, 2021.

[55] Carlos Madina, Inmaculada Zamora, and Eduardo Zabala. Methodology for assessing electric vehicle charging infrastructure business models. *Energy Policy*, 89:284–293, 2016.

[56] Afoma Ihekwaba and Charles Kim. Analysis of electric vehicle charging impact on grid voltage regulation. *2017 North American Power Symposium, NAPS 2017*, 2017.

[57] Se Hoon Baik, Young Gyu Jin, and Yong Tae Yoon. Determining equipment capacity of electric vehicle charging station operator for profit maximization. *Energies*, 11(9):1–15, 2018.

[58] Matteo Muratori, Emma Elgqvist, Dylan Cutler, Joshua Eichman, Shawn Salisbury, Zachary Fuller, and John Smart. Technology solutions to mitigate electricity cost for electric vehicle DC fast charging. *Applied Energy*, 242(March):415–423, 2019.

[59] Nathaniel S Pearre, Willett Kempton, Randall L Guensler, and Vetri V Elango. Electric vehicles: How much range is required for a day's driving? *Transportation Research Part C: Emerging Technologies*, 19(6):1171–1184, 2011.

[60] Zhenhong Lin and David L. Greene. Promoting the market for plug-in hybrid and battery electric vehicles. *Transportation Research Record*, 2252(1):49–56, 2011.

[61] Jing Dong and Zhenhong Lin. Stochastic Modeling of Battery Electric Vehicle Driver Behavior. *Transportation Research Record: Journal of the Transportation Research Board*, 2454:61–67, 2014.

[62] Xing Wu. Role of workplace charging opportunities on adoption of plug-in electric vehicles - Analysis based on GPS-based longitudinal travel data. *Energy Policy*, 114(December 2017):367–379, 2018.

[63] Aviral Shukla, Joseph Pekny, and Venkat Venkatasubramanian. An optimization framework for cost effective design of refueling station infrastructure for alternative fuel vehicles. *Computers and Chemical Engineering*, 35(8):1431–1438, 2011.

[64] Michael Kuby, Lee Lines, Ronald Schultz, Zhixiao Xie, Jong Geun Kim, and Seow Lim. Optimization of hydrogen stations in Florida using the Flow-Refueling Location Model. *International Journal of Hydrogen Energy*, 34(15):6045–6064, 2009.

[65] Ying Wei Wang and Chuan Ren Wang. Locating passenger vehicle refueling stations. *Transportation Research Part E: Logistics and Transportation Review*, 46(5):791–801, 2010.

[66] Shane D. Stephens-Romero, Tim M. Brown, Jee E. Kang, Wilfred W. Recker, and G. Scott Samuelsen. Systematic planning to optimize investments in hydrogen infrastructure deployment. *International Journal of Hydrogen Energy*, 35(10):4652–4667, 2010.

[67] Joan Ogden and Michael Nicholas. Analysis of a "cluster" strategy for introducing hydrogen vehicles in Southern California. *Energy Policy*, 39(4):1923–1938, 2011.

[68] Baris YIldIz, Okan Arslan, and Oya Ekin Karasan. A branch and price approach for routing and refueling station location model. *European Journal of Operational Research*, 248(3):815–826, 2016.

[69] Scott Kelley and Michael Kuby. On the way or around the corner? Observed refueling choices of alternative-fuel drivers in Southern California. *Journal of Transport Geography*, 33:258–267, 2013.

[70] Matteo Muratori, Brian Bush, Chad Hunter, and Marc W. Melaina. Modeling hydrogen refueling infrastructure to support passenger vehicles. *Energies*, 11(5), 2018.

[71] Yue Xiang, Zhuozhen Jiang, Chenghong Gu, Fei Teng, Xiangyu Wei, and Yang Wang. Electric vehicle charging in smart grid: A spatial-temporal simulation method. *Energy*, 189:116221, 2019.

[72] Yanyan Xu, Serdar Çolak, Emre C. Kara, Scott J. Moura, and Marta C. González. Planning for electric vehicle needs by coupling charging profiles with urban mobility. *Nature Energy*, 3(6):484–493, 2018.

[73] G. Celli, G. G. Soma, F. Pilo, F. Lacu, S. Mocci, and N. Natale. Aggregated electric vehicles load profiles with fast charging stations. *Proceedings - 2014 Power Systems Computation Conference, PSCC 2014*, 2014.

[74] Semen Uimonen and Matti Lehtonen. Simulation of Electric Vehicle Charging Stations Load Profiles in Office Buildings Based on Occupancy Data. *Energies*, 13(21):5700, 2020.

[75] Fakeha Sehar, Manisa Pipattanasomporn, and Saifur Rahman. Demand management to mitigate impacts of plug-in electric vehicle fast charge in buildings with renewables. *Energy*, 120:642–651, 2017.

[76] James Druitt and Wolf Gerrit Früh. Simulation of demand management and grid balancing with electric vehicles. *Journal of Power Sources*, 216:104–116, 2012.

[77] Zhanle Wang and Raman Paranjape. An evaluation of electric vehicle penetration under demand response in a multi-agent based simulation. *Proceedings - 2014 Electrical Power and Energy Conference, EPEC 2014*, pages 220–225, 2014.

[78] Fanxin Kong and Xue Liu. Distributed Deadline and Renewable Aware Electric Vehicle Demand Response in the Smart Grid. *Proceedings - Real-Time Systems Symposium*, 2016-Janua:23–32, 2016.

[79] Andrew M. Mowry and Dharik S. Mallapragada. Grid impacts of highway electric vehicle charging and role for mitigation via energy storage. *Energy Policy*, 157(August), 2021.

[80] Elham Akhavan-Rezai, Mostafa F. Shaaban, E. F. El-Saadany, and Fakhri Karray. Online intelligent demand management of plug-in electric vehicles in future smart parking lots. *IEEE Systems Journal*, 10(2):483–494, 2016.

[81] Christoph M. Flath, Jens P. Ilg, Sebastian Gottwalt, Hartmut Schmeck, and Christof Weinhardt. Improving electric vehicle charging coordination through area pricing. *Transportation Science*, 48(4):619–634, 2014.

[82] Orkun Karabasoglu and Jeremy Michalek. Influence of driving patterns on life cycle cost and emissions of hybrid and plug-in electric vehicle powertrains. *Energy Policy*, 60:445–461, 2013.

[83] Mili Ann M Tamayao, Jeremy J. Michalek, Chris Hendrickson, and Ine??s M L Azevedo. Regional variability and uncertainty of electric vehicle life cycle CO2 emissions across the United States. *Environmental Science and Technology*, 49(14):8844–8855, 2015.

[84] J. J. Brey, A. F. Carazo, and R. Brey. Exploring the marketability of fuel cell electric vehicles in terms of infrastructure and hydrogen costs in Spain. *Renewable and Sustainable Energy Reviews*, 82(July 2017):2893–2899, 2018.

[85] Guannan He, Dharik S. Mallapragada, Abhishek Bose, Clara F. Heuberger, and Emre Gencer. Hydrogen supply chain planning with flexible transmission and storage scheduling. *IEEE Transactions on Sustainable Energy*, 12(3):1730–1740, 2021.

[86] Wei Wei, Sankaran Ramakrishnan, Zachary A. Needell, and Jessika E. Trancik. Personal vehicle electrification and charging solutions for high-energy days. *Nature Energy*, 6(1):105–114, 2021.

[87] Wei Wei, Sankaran Ramakrishnan, and Jessika E Trancik. Strategic refueling infrastructure expansion for personal vehicle electrification with hydrogen fuel cell vehicles. *In preparation*.

[88] United States Environmental Protection Agency. Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2015. Technical report, United States Environmental Protection Agency, Washington, DC, 2017.

[89] Arash Noshadravan, Lynette Cheah, Richard Roth, Luis Dias, and Jeremy Gregory. Stochastic comparative assessment of life-cycle greenhouse gas emissions from conventional and electric vehicles. *The International Journal of Life Cycle Assessment*, 20(6):854–864, 2015.

[90] Hongrui Ma, Felix Balthasar, Nigel Tait, Xavier Riera-Palou, and Andrew Harrison. A new comparison between the life cycle greenhouse gas emissions of battery electric vehicles and internal combustion vehicles. *Energy Policy*, 44:160–173, 2012.

[91] Jonathan Coignard, Samveg Saxena, Jeffery Greenblatt, and Dai Wang. Clean vehicles as an enabler for a clean electricity grid. *Environmental Research Letters*, 13(5):54031, may 2018.

[92] Thomas S Turrentine. Lifestyles and Life Politics: Towards a Green Car Market. Technical report, University of California, Davis, 1994.

[93] Ona Egbue and Suzanna Long. Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions. *Energy Policy*, 48(2012):717–729, 2012.

[94] Joseph Bailey, Amy Miele, and Jonn Axsen. Is awareness of public charging associated with consumer interest in plug-in electric vehicles? *Transportation Research Part D: Transport and Environment*, 36:1–9, 2015.

[95] Lance Noel and Benjamin K Sovacool. Why Did Better Place Fail?: Range anxiety, interpretive flexibility, and electric vehicle promotion in Denmark and Israel. *Energy Policy*, 94:377–386, 2016.

[96] Hanna L. Breetz and Deborah Salon. Do electric vehicles need subsidies? Ownership costs for conventional, hybrid, and electric vehicles in 14 U.S. cities. *Energy Policy*, 120(May):238–249, 2018.

[97] Jeremy Neubauer and Eric Wood. The impact of range anxiety and home, workplace, and public charging infrastructure on simulated battery electric vehicle lifetime utility. *Journal of Power Sources*, 257:12–20, 2014.

[98] Myriam Neaimeh, Shawn D. Salisbury, Graeme A. Hill, Philip T. Blythe, Don R. Scoffield, and James E. Francfort. Analysing the usage and evidencing the importance of fast chargers for the adoption of battery electric vehicles. *Energy Policy*, 108(December 2016):474–486, 2017.

[99] Li Zhang, Tim Brown, and Scott Samuelsen. Evaluation of charging infrastructure requirements and operating costs for plug-in electric vehicles. *Journal of Power Sources*, 240:515–524, 2013.

[100] Jing Dong, Changzheng Liu, and Zhenhong Lin. Charging infrastructure planning for promoting battery electric vehicles: An activity-based approach using multiday travel data. *Transportation Research Part C: Emerging Technologies*, 38:44–55, 2014.

[101] Stephen Greaves, Henry Backman, and Adrian B. Ellison. An empirical assessment of the feasibility of battery electric vehicles for day-to-day driving. *Transportation Research Part A: Policy and Practice*, 66(1):226–237, 2014.

[102] Eleftheria Kontou, Yafeng Yin, Zhenhong Lin, and Fang He. Socially optimal replacement of conventional with electric vehicles for the US household fleet. *International Journal of Sustainable Transportation*, 11(10):749–763, 2017.

[103] Yue Zhou, Ruoxi Wen, Hewu Wang, and Hua Cai. Optimal battery electric vehicles range: A study considering heterogeneous travel patterns, charging behaviors, and access to charging infrastructure. *Energy*, 197:116945, 2020.

[104] Mobashwir Khan and Kara M. Kockelman. Predicting the market potential of plug-in electric vehicles using multiday GPS data. *Energy Policy*, 46:225–233, 2012.

[105] Zhenhong Lin. Optimizing and diversifying electric vehicle driving range for U.S. drivers. *Transportation Science*, 48(4):635–650, 2014.

[106] Atlanta Regional Commission. Regional travel survey: Final report. Technical report, Atlanta Regional Commission, 2011.

[107] Texas Department of Transportation. 2002 - 2011 Regional Travel Surveys with GPS data for Abilene, Austin, El Paso, Houston Galveston, Laredo, Rio Grande Valley, San Antonio, Tyler Longview, and Wichita Falls. Technical report, Texas Department of Transportation, 2014.

[108] James McNerney, Zachary A Needell, Michael T Chang, Marco Miotti, and Jessika E Trancik. TripEnergy: Estimating Personal Vehicle Energy Consumption Given Limited Travel Survey Data. *Transportation Research Record: Journal of the Transportation Research Board*, 2628(1):58–66, 2017.

[109] United States Environmental Protection Agency. Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2015. Technical report, U.S. Environmental Protection Agency, Washington, D.C., 2017.

[110] Marco Miotti. *Variability in the emissions savings potential of battery electric vehicles across regions and individuals*. PhD thesis, Massachusetts Institute of Technology, 2020.

[111] Marco Miotti, Sankaran Ramakrishnan, and Jessika E. Trancik. Determinants of emissions savings from vehicle electrification. *In review*, 2020.

[112] Fergus Nicol. Adaptive thermal comfort standards in the hot-humid tropics. *Energy and Buildings*, 36(7):628–637, 2004.

[113] Wilcox S and Marion W. Users Manual for TMY3 Data Sets. Technical report, National Renewable Energy Laboratory, 2008.

[114] NREL. TMY | National Solar Radiation Database (NSRDB). Technical report, National Renewable Energy Laboratory, 2019.

[115] Irene M Berry. The effects of driving style and vehicle performance on the real-world fuel consumption of US light-duty vehicles. Master thesis, Massachusetts Institute of Technology, Cambridge, 2010.

[116] Justine Sears, David Roberts, and Karen Glitman. A comparison of electric vehicle Level 1 and Level 2 charging efficiency. *2014 IEEE Conference on Technologies for Sustainability, SusTech 2014*, pages 255–258, 2014.

[117] Antonino Genovese, Fernando Ortenzi, and Carlo Villante. On the energy efficiency of quick DC vehicle battery charging. *World Electric Vehicle Journal*, 7(4):570–576, 2015.

[118] Germana Trentadue, Alexandre Lucas, Marcos Otura, Konstantinos Pliakostathis, Marco Zanni, and Harald Scholz. Evaluation of fast charging efficiency under extreme temperatures. *Energies*, 11(8):1–13, 2018.

[119] Weeberb J. Requia, Moataz Mohamed, Christopher D. Higgins, Altaf Arain, and Mark Ferguson. How clean are electric vehicles? Evidence-based review of the effects of electric mobility on air pollutants, greenhouse gas emissions and human health. *Atmospheric Environment*, 185(April):64–77, 2018.

[120] Anjum Hajat, Charlene Hsia, and Marie S. O'Neill. Socioeconomic Disparities and Air Pollution Exposure: A Global Review. *Curr Environ Health Rep.*, 2(4):440–450, 2015.

[121] Magdalena M Klemun, Morgan R Edwards, and Jessika E Trancik. Research priorities for supporting subnational climate policies. *WIREs Clim Change*, page e646, 2020.

[122] Niklas Jakobsson, Till Gnann, Patrick Plötz, Frances Sprei, and Sten Karlsson. Are multi-car households better suited for battery electric vehicles? - Driving patterns and economics in Sweden and Germany. *Transportation Research Part C: Emerging Technologies*, 65:1–15, 2016.

[123] Fan Tong and Inês M L Azevedo. What are the best combinations of fuel-vehicle technologies to mitigate climate change and air pollution effects across the United States? *Environmental Research Letters*, 15(7):074046, 2020.

[124] Michael Nicholas and Dale Hall. Lessons Learned on Early Fast Electric Vehicle Charging Systems. Technical Report July, 2018.

[125] Shanti Pless, Amy Allen, Lissa Myers, David Goldwasser, Andrew Meintz, and Ben Polly. Integrating Electric Vehicle Charging Infrastructure into Commercial Buildings and Mixed-Use Communities : Design , Modeling , and Control Optimization Opportunities. In *2020 ACEEE Summer Study on Energy Efficiency in Buildings*, number C40, pages 1–16, 2020.

[126] US Drive. Summary Report on EVs at Scale and the U. S. Electric Power System. Technical Report November 2019, US Drive, 2019.

[127] Jing Dong, Changzheng Liu, and Zhenhong Lin. Charging infrastructure planning for promoting battery electric vehicles : An activity-based approach using multiday travel data. *Transportation Research Part C*, 38:44–55, 2014.

[128] Jing Dong and Zhenhong Lin. Stochastic modeling of battery electric vehicle driver behavior: Impact of charging infrastructure deployment on the feasibility of battery electric vehicles. *Transportation Research Record*, 2454(December 2014):61–67, 2014.

[129] Safegraph. Validating Store Counts for Brands Against Company Reporting. Technical report, Safegraph, 2021.

[130] Data USA. Data USA: Fairfield county, CT. Technical report, 2021.

[131] Federal Highway Administration. Average Vehicle Occupancy Factors for Computing Travel Time Reliability Measures and Total Peak Hour Excessive Delay Metrics. Technical report, Department of Transportation, 2018.

[132] YouTube. Tesla Supercharger station overwhelmed. Technical report, 2019.

[133] Ryan Fox Squire. What about bias in the SafeGraph dataset? *SafeGraph*, pages Available at: https://www.safegraph.com/blog/what–, 2019.

[134] Google. Google Maps Street View. Technical report, 2021.

[135] Mark Z Jacobson, Mark A Delucchi, Zack A F Bauer, Jingfan Wang, Eric Weiner, Alexander S Yachanin, Savannah C Goodman, William E Chapman, Mary A Cameron, Cedric Bozonnat, Liat Chobadi, Hailey A Clonts, Peter Enevoldsen, Jenny R Erwin, Simone N Fobi, Owen K Goldstrom, Eleanor M Hennessy, Jingyi Liu, Jonathan Lo, Clayton B Meyer, Sean B Morris, Kevin R Moy, Patrick L O'neill, Ivalin Petkov, Stephanie Redfern, Robin Schucker, and Michael A Sontag. 100% Clean and Renewable Wind, Water, and Sunlight All-Sector Energy Roadmaps for 139 Countries of the World 100% Clean and Renewable Wind, Water, and Sunlight All-Sector Energy Roadmaps for 139 Countries of the World. *Joule*, page 202, 2019.

[136] Iain Staffell, Daniel Scamman, Anthony Velazquez Abad, Paul Balcombe, Paul E. Dodds, Paul Ekins, Nilay Shah, and Kate R. Ward. The role of hydrogen and fuel cells in the global energy system. *Energy and Environmental Science*, 12(2):463–491, 2019.

[137] Sonal Singh, Shikha Jain, Venkateswaran Ps, Avanish K. Tiwari, Mansa R. Nouni, Jitendra K. Pandey, and Sanket Goel. Hydrogen: A sustainable fuel for future of the transport sector. *Renewable and Sustainable Energy Reviews*, 51:623–633, 2015.

[138] Martin Robinius, Jochen Linßen, Thomas Grube, Markus Reuß, Peter Stenzel, Konstantinos Syranidis, Patrick Kuckertz, and Detlef Stolten. Comparative Analysis of Infrastructures: Hydrogen Fueling and Electric Charging of Vehicles. Technical Report January, 2018.

[139] Scott Hardman, Eric Shiu, Robert Steinberger-Wilckens, and Thomas Turrentine. Barriers to the adoption of fuel cell vehicles: A qualitative investigation into early adopters attitudes. *Transportation Research Part A: Policy and Practice*, 95:166–182, 2017.

[140] David Browne, Margaret O'Mahony, and Brian Caulfield. How should barriers to alternative fuels and vehicles be classified and potential policies to promote innovative technologies be evaluated? *Journal of Cleaner Production*, 35:140–151, 2012.

[141] María Yetano Roche, Susana Mourato, Manfred Fischedick, Katja Pietzner, and Peter Viebahn. Public attitudes towards and demand for hydrogen and fuel cell vehicles: A review of the evidence and methodological implications. *Energy Policy*, 38(10):5301–5310, 2010.

[142] J. Javier Brey, R. Brey, and Ana F. Carazo. Eliciting preferences on the design of hydrogen refueling infrastructure. *International Journal of Hydrogen Energy*, 42(19):13382–13388, 2017.

[143] Oscar Lopez Jaramillo, Rhian Stotts, Scott Kelley, and Michael Kuby. Content Analysis of Interviews with Hydrogen Fuel Cell Vehicle Drivers in Los Angeles. *Transportation Research Record*, 2019.

[144] Aimee Krafft, Scott Kelley, Michael Kuby, Oscar G. Lopez Jaramillo, and Rhian Stotts. Hydrogen Refueling Station Consideration and Driver Experience in California. *Transportation Research Record*, 2675(1):280–293, 2020.

[145] Gregory Trencher and Achmed Edianto. Drivers and barriers to the adoption of fuel cell passenger vehicles and buses in Germany. *Energies*, 14(4), 2021.

[146] M Melaina and M Penev Nrel. Hydrogen Station Cost Estimates. Technical Report September, 2013.

[147] Jean Baronas, Gerhard Achtelik, and Et al. Joint Agency Staff Report on Assembly Bill 8: 2019 Annual Assessment of Time and Cost Needed to Attain 100 Hydrogen Refueling Stations in California. Technical report, California Energy Commission and California Air Resources Board, 2019.

[148] California Fuel Cell Partnership. Costs and financing. Technical report, California Fuel Cell Partnership, 2021.

[149] Genevieve Saur, Sam Sprik, Jennifer Kurtz, Chris Ainscough, and Mike Peters. Hydrogen Station Data Collection and Analysis. Technical report, National Renewable Energy Laboratory, 2019.

[150] Sandra Curtin and Jennifer Gangi. Fuel Cell Technologies Market Report 2016. Technical report, US Department of Energy, 2017.

[151] W. Dwayne Jones. A field guide to gas stations in Texas. Technical report, Texas Department of Transportation, 2003.

[152] Marc W. Melaina. Turn of the century refueling: A review of innovations in early gasoline refueling methods and analogies for hydrogen. *Energy Policy*, 35(10):4919–4934, 2007.

[153] Ben Rubin and Michelle Chester. Zero-Emission Vehicles in California : Community Readiness Guidebook. Technical report, 2013.

[154] Abdulkadir Bedir, Noel Crisostomo, Jennifer Allen, Eric Wood, and Clement Rames. California Plug-In Electric Vehicle Infrastructure Projections: 2017-2025. Future Infrastructure Needs for Reaching the State's Zero- Emission-Vehicle Emission-Vehicle Deployment Goals. Technical report, 2018.

[155] Wei Wei, Sankaran Ramakrishnan, Zachary A. Needell, and Jessika E. Trancik. Personal vehicle electrification and charging solutions for high-energy days. *Nature Energy In Press*, 2020.

[156] CAFCP-California Fuel Cell Partnership. Medium- and Heavy-Duty Fuel Cell Electric Truck Action Plan for California. Technical Report October, 2016.

[157] Argonne National Laboratory. Technology Assessment of a Fuel Cell Vehicle: 2017 Toyota Mirai. Technical report, Argonne National Laboratory, 2018.

[158] Jennifer Kurtz, Sam Sprik, Genevieve Saur, and Shaun Onorato. Fuel Cell Electric Vehicle Driving and Fueling Behavior Fuel Cell Electric Vehicle Driving and Fueling Behavior. Technical Report March, NREL, 2019.

[159] Rodney E. Slater. The National Highway System: A Commitment to America's Future. *Public Roads*, 1996.

[160] Federal Highway Administration. National Highway System, 2021.

[161] Ryuichi Kitamura and Daniel Sperling. Refueling Behavior of automobile drivers. *Transportation Research Part A: General*, 21(3):235–245, 1987.

[162] Dennis Dingemans, Daniel Sperling, and Ryuichi Kitamura. Mental maps and the refueling behavior of vehicle drivers. *Transportation Research Record*, pages 1–10, 1986.

[163] Michael Nicholas. Estimating electric vehicle charging infrastructure costs across major U.S. metropolitan areas. Technical report, 2019.

[164] Nissan. 2020 Nissan LEAF. Accessed online at https://www.nissanusa.com/vehicles/electric-cars/leaf.html, 2020.

[165] Tesla. Model S Tesla. Accessed online at https://www.tesla.com/models, 2020.

[166] Zipcar. Miles included. Accessed online at https://support.zipcar.com/hc/en-us/articles/220623207-Miles-Included, 2018.

[167] Avis. Best car rental deals in the US. Accessed online at https://www.avis.com/en/offers/us-offers, 2018.

[168] Brennan Borlaug, Shawn Salisbury, Mindy Gerdes, and Matteo Muratori. Levelized Cost of Charging Electric Vehicles in the United States. *Joule*, pages 1–16, 2020.

[169] Victoria Rojo. 2021 Final Transportation Electrification Forecast. Technical report, ISO New England, 2021.

[170] ISO New England. Resource mix. Technical report, ISO New England, 2021.

[171] American Automobile Association. Electric Vehicle Range Testing. (February):66, 2019.