UNIVERSITY OF CALIFORNIA,
IRVINE

Charging infrastructure optimization for plug-in electric vehicles

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Mechanical and Aerospace Engineering

by

Li Zhang

Dissertation Committee:
Professor G. Scott Samuelsen, Chair
Professor Faryar Jabbari
Professor Gregory Washington

2014

DEDICATION

To mom and dad, thank you for everything during the past 27 years. To friends, I am grateful to have you around me, make me feel warm.

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Evaluated PHEV energy consumption with different ranges and charging scenarios.
Optimized Level 1 and Level 2 charging infrastructure for different location categories in California.
Optimized the allocation of the Level 3 DC fast charging stations in California.
Collaborated with government agencies (the California Energy Commission) and major automakers (Toyota and Honda) to apply research findings above to real-world settings.

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Proposed an effective control mechanism for a large amount of EVs in a region to achieve demand leveling, i.e. minimize charging impact on the grid, for the future EVs.

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First author, Paper published on Journal of Power Sources 2013

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- "*Impacts of plug-in hybrid electric vehicles on a residential transformer using stochastic and empirical analysis"*

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ABSTRACT OF THE DISSERTATION

Charging infrastructure optimization for plug-in electric vehicles

By

Li Zhang

Doctor of Philosophy in Mechanical and Aerospace Engineering

University of California, Irvine, 2014

Professor G. Scott Samuelsen, Chair

Conventional light duty vehicle fleets and petroleum are firmly bonded. It is leading to several issues, such as energy security, greenhouse gas (GHG) and criteria pollutant emissions. Plug-in electric vehicles (PEVs), including plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs), have the potential to break this bond and improve the energy and environmental landscape of personal transportation. The United States, especially the state of California is very proactive in promoting PEV adoption. Several regulations and laws have been passed to stimulate PEV growth, including the Zero Emission Vehicle (ZEV) Regulation and Assembly Bill 32 (Climate Change). However, society faces three main challenges associated with PEV deployment from the perspective of charging infrastructure. This dissertation addresses each step by step. First, a methodology is established to quantify the energy impact of PEVs. In particular, a travel behavior based PEV operating/charging model is made to characterize fleet-wide energy consumption with different PEV parameters and charging infrastructure scenarios, such as location, power level and charging time strategy. Second, PEVs face the hurdle of access to charging infrastructure. Consequently, question has to be answered as to what types,

locations, and quantities of electric vehicle supply equipment (EVSE) will be required. For this purpose, an optimal charging strategy based on 24-hour travel patterns is formulated to minimize operating cost. With that, the approximation of the Level 1 and Level 2 EVSE needed at different types of location categories is proposed. As an alternative infrastructure solution for BEVs, Level 3 DC fast charging stations are also investigated in terms of location allocation. Third, a massive population of PEVs has the potential to change the grid operation. To this end, a durable decentralized charging protocol is proposed and verified for coordinating individual PEVs with grid operation such that grid-level optimality can be achieved.

Chapter 1. INTRODUCTION

1.1. Overview

The energy flows from energy sources to energy end-use sectors. Generally, the energy sources consist of petroleum, coal, nuclear, renewables and natural gas. And the energy end-use sectors include the residential sector, commercial sector, industrial sector and transportation sector. In the United States, the total primary energy consumption was projected to be 97.7 quadrillion Btu in 2013, by the U.S. Energy Information Administration (EIA). The transportation sector is the largest part, which consumes the energy of 27.1 quadrillion Btu. More than 90% of that energy is from petroleum which also is the largest energy source supplying 36% of the total amount [1]. So the largest energy source and the largest end-use sector are firmly bounded.

In the transportation sector, light-duty vehicles (LDVs) account for 60% of the energy consumption, satisfying the personal travel demands [1]. The conventional vehicles (CVs) equipped with internal combustion engines (ICE) have dominated the LDV fleet for over 100 years [2]. The features of long range driving and rapid refueling overcame the inherent properties of low efficient operation and pollutant emission. In other words, the drawbacks of conventional vehicles have not been of concern until the growth and use of conventional vehicles have raised several issues, such as oil crises, greenhouse gas emissions, and criteria pollutant emissions.

The fact is that petroleum has served as the major energy source for motor vehicles and has not been changed since the invention of automobile in the year 1886. For the past 40 years, several oil crises have occurred, attributing to different reasons, including the

Arab oil embargo, the Iran-Iraq War, the falling value of the U.S. dollar and the concern on petroleum reserves. Those oil crises led to retail price spikes and consequently, harm to economy.

Apart from the concern of energy security, the impact on our environment from operating conventional vehicles is receiving increasing attention. For the countries in the Organization for Economic Cooperation and Development (OECD), more than 40% of energy-related greenhouse gas (GHG) emissions, e.g., the carbon dioxide (CO2), are generated from burning liquid fuels, mainly petroleum [3]. For those in the non-OECD, coal is the most significant contributor. However, in those emerging markets, energy consumption for transportation is projected to increase dramatically leading to enormous GHG emissions in the future with the condition that petroleum will remain the dominant transportation fuel.

In additional to the GHG emissions, several species from the vehicle tailpipe are well-known to be directly harmful to human health. Those pollutant emissions mainly include carbon monoxide (CO), hydrocarbons (HC) and nitrogen oxide (NO_x). Although more stringent regulations have been passed to reduce pollutant emissions for individual vehicles, it is not likely for the fleet-wide emissions to be significantly decreased given more conventional vehicles are produced, sold, and operated.

In order to resolve those issues above, breaking this firm bond between transportation and petroleum is inevitable. In particular, alternatives must be found to replace the conventional LDVs.

An electrified LDVs fleet is an alternative to conventional vehicles, consisting of battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), under the name of plug-in electric vehicles (PEVs) as one category, and fuel cell electric vehicles (FCEVs) as another category. Those vehicles have an electric motor as the main propulsion device, having the features of higher operating efficiency, and lower or zero tailpipe emissions. Those vehicles utilize electricity or hydrogen stored on board as the energy media so that the original energy sources can be diversified. The reason is that electricity and hydrogen can be generated by different feedstock, from fossil fuels to renewable sources.

Both the federal government and the state government in California are proactive in promoting electrified vehicles and relevant policies have been made. The U.S. Environment Protection Agency (EPA) and the National Highway Traffic Safety Administration (NHTSA) issued Corporate Average Fuel Economy (CAFE) standards for LDVs, model years 2017 and beyond. According to that, the fleet-wide fuel economy needs to meet 35.1 MPG, 40.3 MPG and 48.7 MPG in the year of 2017, 2021 and 2025 respectively [1]. California state governor Edmund Brown issued the executive order in 2012, which requires more than 1.5 million zero-emission and plug-in hybrid vehicles in California by 2025 [4]. Assembly Bill 32 (AB32), voted into law in 2006, requires that California reduce GHG emission to 1990 levels by 2020 [5]. In light of those legislations, all the major automakers have already introduced or planned to introduce a variety of PEVs to the market.

Compared to conventional vehicles, PEVs will shift energy consumption from gasoline stations to the electric grid, which will exhibit new problems due to the different energy production, transportation, storage and consumption characteristics.

Battery stores chemical energy on PEVs and convert it to electricity when needed. It features a low energy density so the stored capacity is limited, consequently leading to a relatively short all-electric range (AER). PHEVs can make use of the gasoline/diesel onboard after running out of electricity while BEVs will be stranded if people do not switch to other vehicles. Apparently, longer AER and more charging opportunities are more beneficial on fuel reduction. Thus, the first question that has to be answered is how much oil can be saved by massively deploying PEVs assuming different charging infrastructure availability?

New charging infrastructure needs to be built in accordance with the growth of PEV population. Charging infrastructure comprises of Level 1, Level 2, and Level 3 electric vehicle supply equipment (EVSE) [6]. Level 1 and Level 2 EVSE transfer alternating current (AC) from grid to PEVs at different charging power while Level 3 EVSE converts alternating current to direct current (DC) first and transfers to BEVs directly at a higher power level. Compared to pumping the liquid fuel to a tank, charging a car is hundreds of times slower. Given this fact and the limited AER, a large amount of EVSE will be required at different locations. In order to provide a cost effective coverage, the second question is what is the reasonable methodology for deploying charging infrastructure, in terms of power levels and allocations?

The generation and consumption of gasoline/diesel are separate while they are coupled for the electricity. When refilling the conventional vehicles does not have impact on emission generation and system cost, because these metrics are only determined by the total amount of fuel consumed. For electricity, however, a period with high system-wide demand exhibits more emission and cost than a period with a low demand. Utilizing PEVs will add more demand on the electric grid. Given the condition that PEVs have the flexibility to choose the timing to recharge, the fleet will have the capability to change the temporally resolved electric consumption/generation (demand/load) curve. This curve eventually determines emissions and cost. So the third question will be how to coordinate individual PEVs charging with the grid operation such that the optimality at the grid level can be achieved. This coordinating mechanism is also considered to be part of the charging infrastructure.

1.2. Goal

Plug-in electric vehicles have the potential to break the firm bond between LDV fleet and petroleum, along with achieving reductions in GHG and pollutant emissions. The state of California has enacted regulation that mandates growth of PEV adoption. However, PEVs present unique challenge on requiring charging infrastructures.

The goal of the dissertation research is to establish an optimized charging infrastructure and associated protocol for charging a large population of PEVs in harmony with the electric grid.

1.3. Objectives

In order to achieve the goal of this work, a set of objectives are required. Addressing those objectives will provide insights into charging infrastructure to improve the PEV deployment.

1. Establish an optimal charging strategy for allocating Level 1 and Level 2 EVSE.
2. Develop a methodology to spatially allocate the Level 3 DC fast charging stations.
3. Provide the recommendations on the deployment of PEV and EVSE.
4. Propose and evaluate a decentralized protocol for coordinating large amount of PEVs with the electric grid.
5. Explore the effect of charging PEVs under residential transformers.

Chapter 2. BACKGROUND

It is important to understand the historical development and the outlook of the vehicle-based personal transportation sector. This chapter will introduce it from the aspects of vehicle technology, infrastructure, energy consumption, and the electric grid. Related research will be reviewed to help establish a set of tasks in order to achieve the goals of this dissertation.

2.1. Transportation Overview

Transportation is the movement of people and goods from one location to another. It enables trade between people, entities and counties, serving as the foundation of the economy and civilization. Generally, the modes of transportation includes human-powered, animal-powered, road, air, marine, pipeline and rail. Since the industrial revolution, animal-powered transportation has faded and the human-power transportation has remained, but just consisting of people moving themselves for a short distance by walking, running, and/or biking. Any mode of transportation consumes energy, but at different magnitudes.

Figure 1 shows the delivered energy consumption for different transportation modes in the U.S., for the year 2011 and 2040 (projection) [1]. The road transportation is further categorized into light-duty vehicles (LDVs) and heavy-duty vehicles (HDVs). LDVs consists of passenger cars and light-duty trucks [7], which are mainly purposed to transport people in the private transportation sector. HDVs are generally used for other purposes, such as transport of goods, construction and transporting people in the public sector.

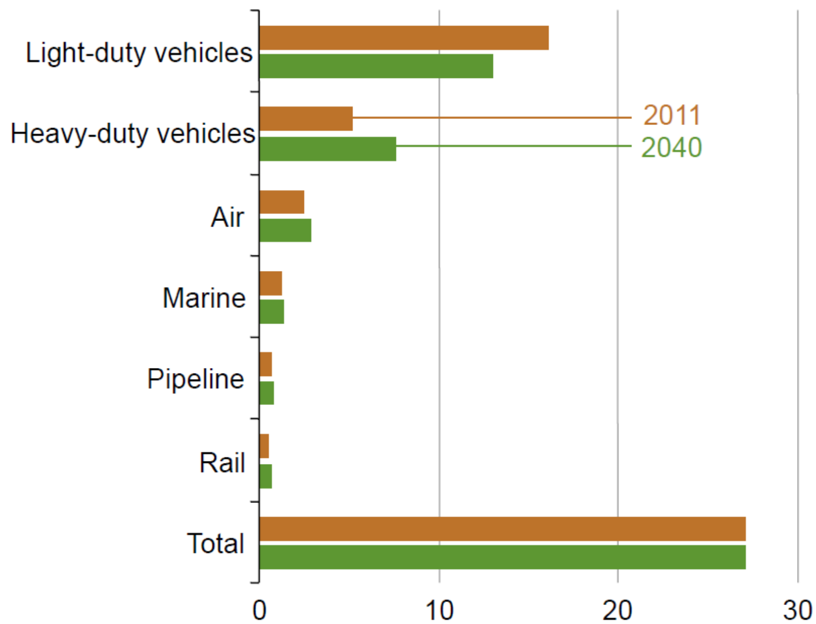


Figure 1. Delivered energy consumption for transportation by mode, 2011 and 2040 (quadrillion Btu).

LDVs consumed 16.1 quadrillion Btu in 2011, accounting for 60% of the energy consumption in the transportation sector and 16% of the total consumption in the whole U.S. In the year 2040, LDVs are projected to reduce energy consumption to 13.0 quadrillion Btu because higher fuel economy offsets modest growth in vehicle miles traveled (VMT) per driver. Nonetheless, it is still the sector that consumes the most energy. To understand the transportation sector in detail, data is required in both micro and macro scales, in particular in the micro scale.

2.1.1. National Household Travel Survey

The National Household Travel Survey (NHTS) is designed to provide information to assist transportation planners and policy makers who need comprehensive data on travel and transportation patterns in the United States. The 2009 NHTS updates information gathered in the 2001 NHTS and in prior Nationwide Personal Transportation Surveys

(NPTS) conducted in 1969, 1977, 1983, 1990, and 1995 [8]. It serves as the nation's inventory of daily travel. Data are collected by surveying individual people on daily trips taken in a 24-hour period and includes date, day of week, trip purpose, trip time, trip length and means of transportation. And, if the trip was done by personal car, vehicle information was also included, such as brand, years, the number of occupancy, etc. NHTS can represent more comprehensive travelling behaviors. For NHTS 2009, information on 961,803 vehicle trips were available nationwide.

Several processing steps were required in order to prepare the NHTS data for the use in this dissertation. In particular, data for California were selected, trips occurring without a personally owned vehicle were deleted, person-chain data were converted to vehicle-chain data, daily trips data with unlinked destinations or significant over-speed were deleted, and tours were organized into home-based daily tours (first trip from home, last trip to home). 20,295 vehicles were selected covering 83,005 single trips with an average of 7.85 miles per trip and 32.13 miles per vehicle per day.

2.1.2. VMT Distribution

In the personal transportation sector, energy is only consumed when generating VMT. So it is important to understand the VMT distribution in terms of different vehicle types and household types, as well as the aggregated travel behavior, such as the temporal VMT and trip distributions in the course of 24 hours.

Data from EMFAC shows the statistical result of the travelling information and mainly includes the time dependent vehicle miles travelled (VMT) and the amount of trips [9]. EMFAC is used to calculate the emission rates from all the motor vehicles, from the passenger cars, to the heavy-duty trucks, operating on highways, freeways and local roads in California [9]. Figure 2 and Figure 3 show them respectively of year 2013 in the state of California for the light duty vehicles.

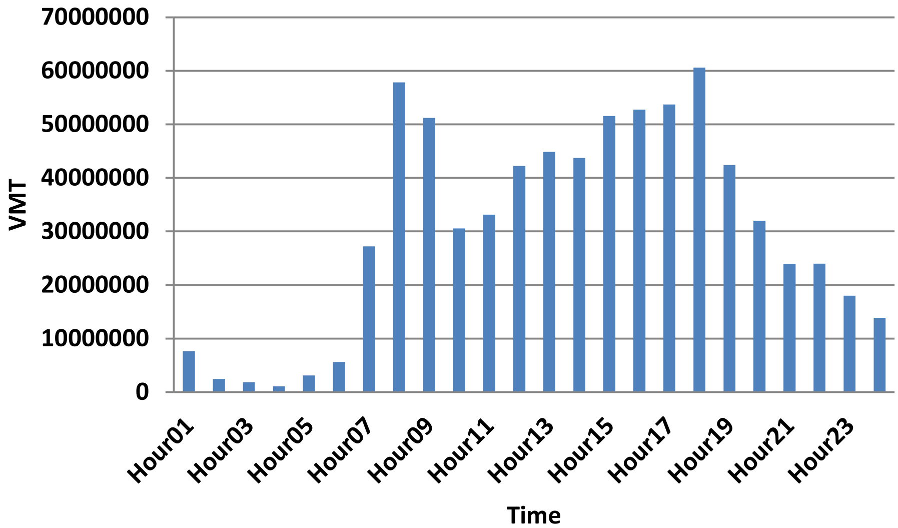


Figure 2. 24 hour VMT for LDVs in California.

As shown in Figure 2 and Figure 3, those data only show the general trend of human travelling behaviors, it does not help us look into the detailed VMT distribution in terms of vehicle types and home types. In order to do so, data associated with individual vehicles and households are needed.

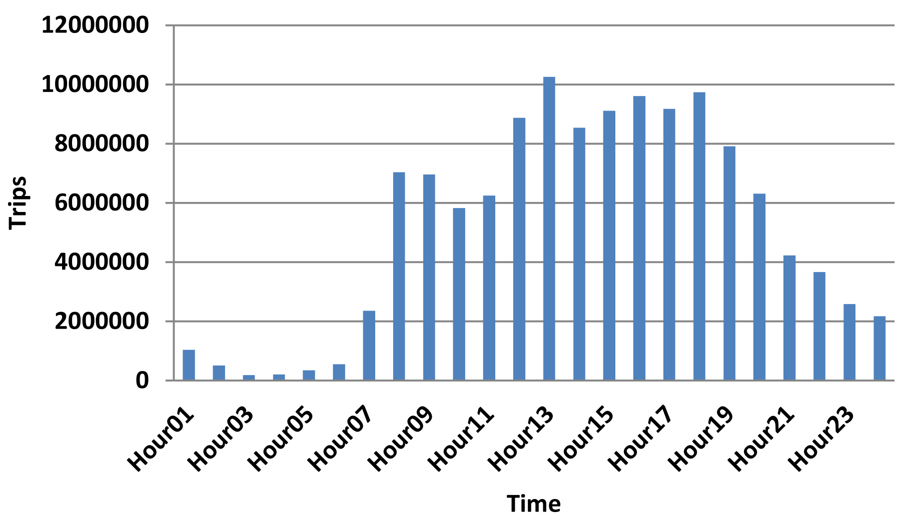
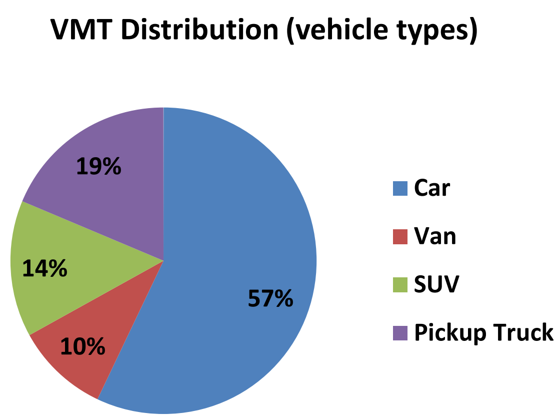


Figure 3. 24 hour trips for LDVs in California.

Derived from the 2009 NHTS data, the four main types of vehicles reported are car, van, SUV and pickup trucks. Figure 4 shows the VMT distribution for all the vehicles surveyed in California. The light duty passenger cars contribute most of the VMT, 57%, followed by the other larger types of vehicles. Light duty vehicles, especially the light duty passenger cars, are suitable to be converted to plug-in electric vehicles having smaller energy required onboard. Figure 4 shows the VMT distribution from different home types. The 74% of total are from detached single house, followed by rowhouse/townhouse, duplex and apartment/condominium. A garage is equipped for the detached single house, providing space to park vehicles. Compared to other locations, the existing circuit in the garage also provides chance to recharge PEVs though an upgrade may be required [10].



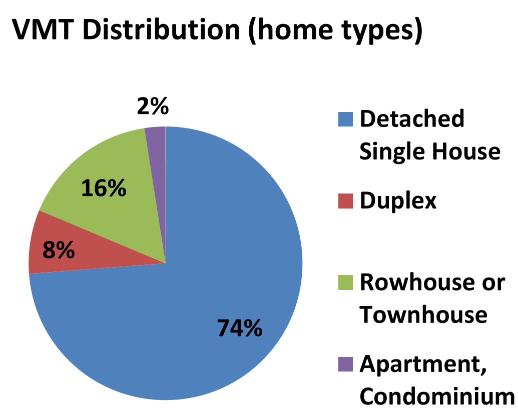


Figure 4. The VMT distribution in terms of vehicle type and home types in California.

2.1.3. Utility Factor

In addition to the VMT distributions, it is also important to understand individual vehicles' behavior in terms of daily travelled miles. So researchers have proposed a measure for this, the Utility Factor (UF) [11]. Using the NHTS, the daily VMT for each vehicle is extracted and forms a statistical curve. The daily distance UF from J2841 is shown in Figure 5 [11, 12]. It can be interpreted as follows. For a given R_{CD}, Figure 5 defines a daily distance UF, which is the fraction of miles travelled in the NHTS fleet where the vehicle has travelled a shorter distance since the start of the day than the given R_{CD} [12]. It is designed for the calculation of PHEV's fuel economy on an American average basis. Given an all-electric range, the possibility that a PHEV consumes liquid fuel can be estimated by UF, assuming battery fully recharged at the beginning of the day.

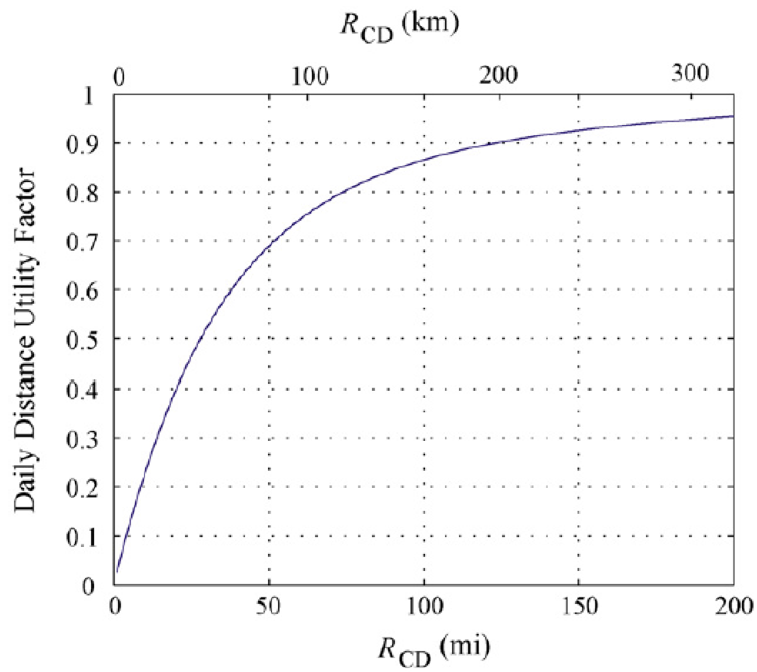


Figure 5. SAE J2841utility factor derived from 2001 NHTS.

From Figure 5, it can be observed that around 70% vehicles travel less than 50 miles in a specific day and less than 15% vehicles travel more than 100 miles in a specific day. It needs to be noted that the SAE UF utilize all vehicle travel data. If only home based travels (first trip departs from home, last trip arrives home) are used, a new curve with higher UF will be derived, as shown in Figure 6. The blue bars show how many vehicles in California out of the entire 20,295 NHTS vehicle samples lie in a VMT interval. The red curve shows the cumulative percentage. The slightly higher utility factor observed in Figure 6 is partly due to the removal of non-home based travels. It is also possible that in California people have different driving patterns. Regardless the small discrepancy, the high UF implies a high fuel reduction rate by deploying PHEV with moderate all-electric ranges and the potential to utilize BEV for numerous daily travels.

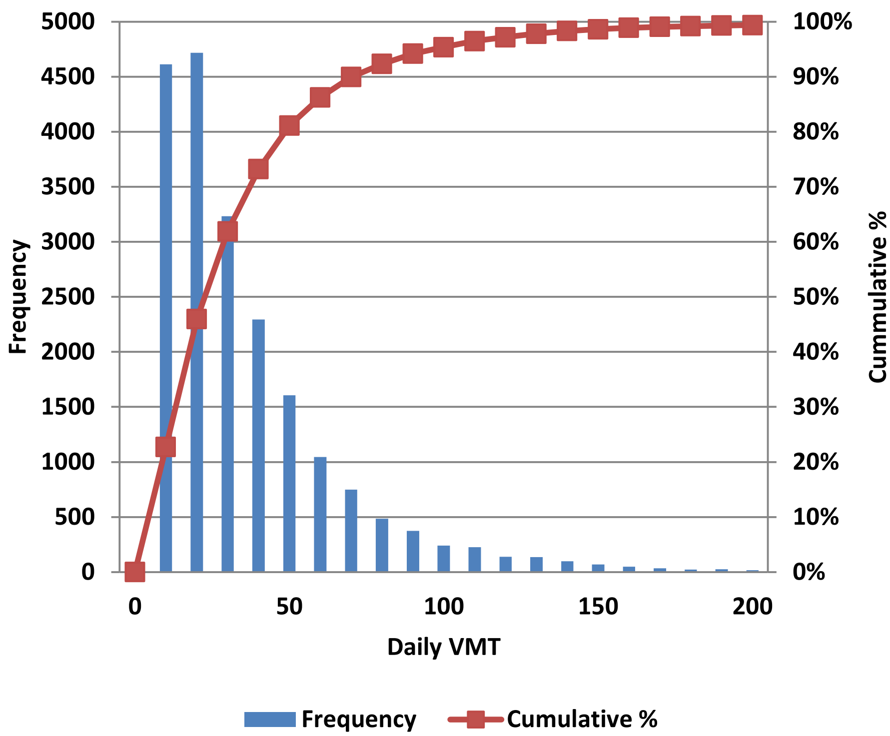


Figure 6. Utility factor derived from California home based daily travels in 2009 NHTS.

2.1.4. Dwelling Time

Figure 7 shows the normalized dwelling time for the entire personal vehicle fleet in the course of 24 hours derived from the California data in the 2009 NHTS [13]. The total dwelling time at a location category for a time interval, i.e., one hour, is divided by the total vehicle time, i.e., the vehicle number times the one hour time interval, in order to obtain the index. It indicates for a specific hour, the dwelling time distribution at different trip destinations. Daytime, particularly from 9:00 am to 5:00 pm, is when most of the non-home dwelling activities happen, while home dwelling occurs at opposite times. From midnight to 4:00 am, the normalized dwelling time at home, shown by the blue chunk, reaches almost to one, meaning almost no one drives during this time period. Those times coincide with the off-peak times of electric load for both generation and distribution.

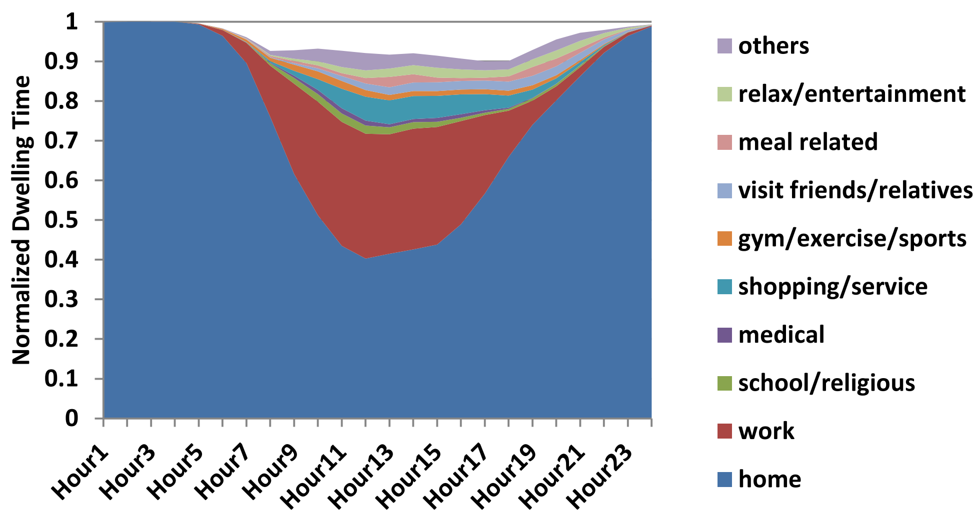


Figure 7. Spatially and temporally resolved dwelling time distribution in California.

Figure 8 shows the average dwelling time in a day for the ten location categories. Combined with Figure 7, home dwelling makes up 75% of the total dwelling time with an average of more than 12 h, while work related stops account for just 14% of the total dwelling time and an average of 6 h. As for the other non-home locations, they account for only 11% of the total dwelling time, with most averaging less than 2 h. These properties of dwelling locations and corresponding average dwelling time imply that home should be considered as the primary location for PEV charging to satisfy people's travel demand.

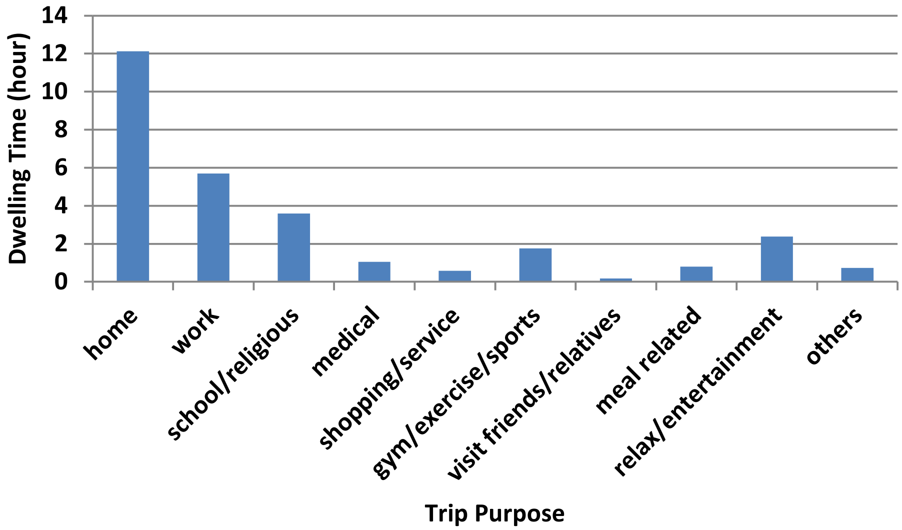


Figure 8. Average length of dwelling time by destination activity.

2.1.5. Summary

More than 70% of the VMT are from detached single homes and around 60% of the VMT are from passenger cars. The average VMT per day is less than 40 miles. Almost all personal vehicles are parked at home overnight when the electric demand is low. The average dwelling time at home is more than 12 hours per day. Those factors above indicate the potential to replace the conventional vehicles with the plug-in electric vehicles.

2.2. Vehicle Electrification

The internal combustion engine based conventional vehicles have dominated the LDV market for over 100 years. However, the inefficiency caused by the limitation of the combustion cycle and the idling and braking energy losses cannot be overcome. With more conventional LDVs produced, sold and operated, the issues of oil security, GHG emissions and pollutant emissions, the option of electrified vehicles has been brought to the agenda.

The technologies for electrifying LDV for the past 10 to 15 years will be introduced in this section.

2.2.1. Hybrid Electric Vehicle

Hybrid vehicles are featured with two or more prime movers and power sources although the net energy may come from one source. The current hybrid vehicle is usually referred to a vehicle utilizing an internal combustion engine and one or more electric motors for propulsion. A vehicle of this combination is named hybrid electric vehicle (HEV) [6]. This concept was introduced more at the early age of automobile to improve fuel economy. It ended up, however, unsuccessful due to the absence of the sophisticated computer controls available today to balance the two propelling systems. With concerns increased on the three issues for CVs, HEVs came back to the market from the year of 1997 and 1999 with the debut of Toyota Prius and Honda Insight respectively.

The motivation for the development of HEVs is to combine the advantages from both electric-motor-powered vehicles and CVs, having operating efficiency and high energy and power density, respectively. HEVs fulfill this objective through engine downsizing, the engine idle off, regenerative braking, and engine operating optimization. Three types of HEV configurations have been developed by automakers, including the series hybrid, the parallel hybrid and the series-parallel hybrid (or the combined hybrid) [14].

Although the hybrid electric vehicles developed in the recent decade have shown the enhancement on fuel economy, the majority of pollutant emission associated with the engine cold start and the consistent fuel consumption still raise concern with respect to environmental protection and oil independency [15, 16]. HEVs improve the operating efficiency but still rely on petroleum as the only energy source. Apparently, population and economic growth require more VMT particularly in the emerging markets. China itself is projected to quadruple transportation energy consumption to more than 20 quadrillion Btu in the year 2040, which will reach the same level as the U.S. [3]. Consequently, the total amount of fuel consumption is likely to increase if no further vehicle electrification is implemented.

2.2.2. Plug-in Hybrid Electric Vehicle

Plug-in hybrid electric vehicles (PHEVs) are proposed to further electrify automobiles with the ability to be connected to the grid and have the battery recharged. PHEVs have the same powertrain configurations as HEVs, but require larger electric components, mainly including the battery pack and the traction motor, to enhance the electric operation capability.

Having a battery pack fully or partially charged, PHEVs can operate in the charge depleting (CD) mode, in which the battery state of charge (SOC) may fluctuate but mainly decreases [17]; PHEVs enter into charge sustaining (CS) mode whereby the SOC is maintained in a certain window after the SOC drops to its lower bound. In the CS mode, PHEVs behave the same as HEVs except for the fact that the energy buffered by the battery can be larger than HEVs equipped with a smaller battery pack. So fuel economy in the CS mode is expected to be slightly higher than HEVs for the same vehicle mass and aerodynamic drag force.

The two equivalent-sized propulsion systems exhibit drawbacks for PHEVs, such as higher cost and more weight. The tailpipe emissions cannot be eliminated when the battery is not able to provide sufficient power or energy. This can lead to a scenario that the ICE starts multiple times to assist instantaneous power demand while most of the energy is provided by the battery pack. In this scenario, engine starts occur at a relatively low operating temperature, resulting in even worse pollutant emissions compared to a HEV or a conventional vehicle [18].

2.2.3. Battery Electric Vehicle

As a passenger car, battery electric vehicle (BEV) was introduced into the market many times. In 1894, Henry Morris and Pedro Salom designed and built the first electric automobile in Philadelphia and formed an electric car company afterward [19]. Lead acid batteries were the onboard energy storage featuring a very low energy density. With more roads built and refueling stations deployed, gasoline powered vehicles started to exhibit its advantages of more power, longer range and faster refueling for personal use. Since the early 20th century, battery electric vehicles had commonly served as delivery vehicles, such as the famous Milk Float in Britain [20].

The second try of introducing BEV as a realistic passenger car was in the late 1990s in the context that the California Air Resources Board (CARB) mandated major automakers to sell EVs. General Motor (GM) leased the EV-1 in certain U.S. areas from 1996 to 2000 [21]. Models from other makers were also introduced at the same time, including Toyota RAV4-EV, Honda EV Plus etc. Most of those BEVs utilized a nickel-metal hydride (NiMH) battery pack as the energy source [21]. This type of battery had an improvement on energy density and cycle life over the lead acid battery, but still suffered range limitations compared to gasoline-powered vehicles. Only 4017 BEVs in this time period were sold or leased to customers, followed by the mortality of this EV culmination [21]. Other than battery technology, the failure has also been attributed to 1) oil and auto industry's campaign to reduce the public acceptance of BEVs; 2) the auto industry's successful federal court challenge to CARB's zero emission vehicle (ZEV) mandate [22].

With the development of the new generation of battery technology, lithium ion (Li-ion) battery stimulated the third wave of BEV deployment. Compared to lead-acid and NiMH batteries, Li-ion batteries feature higher energy density, more cycling life small self-discharging issue, and no memory effect. All of this made it a good candidate of energy storage for the new generation of electric vehicles. In 2008, Tesla Motors launched the Roadster, its first model and the first mass production Li-ion battery based automobile. With the capability to travel more than 200 miles per charge, it can satisfy most of the daily travel demands even without any public charging infrastructure [23]. However, the feature of a sport car and the high cost of a huge battery pack resulted in only thousands sold by the year 2012, when the production stopped. Another manufacturer, Nissan, designed, produced and launched the model Leaf in 2010. It is the best-selling BEV so far, having 65,000 unit delivered by May, 2013. Rather than the Roadster, Leaf is equipped with a 24 kWh battery with 73 miles range estimated by the EPA [24], which balanced the weight, efficiency and cost of the vehicle. Since then, BEV models having a similar specification have been introduced to the market by several automakers, including Honda Fit EV, Ford Focus Electric, Mitsubishi i-MiEV, Chevrolet Spark EV, BMW i3, etc.

2.2.4. Resources Reserves

As contrast to conventional vehicles, Li-ion batteries and electric motors are the new components for PEVs. To manufacture a large number of those components, the raw materials have to be examined to see if there are sufficient reserves.

For the Li-ion battery, lithium is the crucial element of the other well-used materials, such as carbon and cobalt. As a support, the research indicates that on the order of 1 billion 40 kWh Li-based BEV batteries can be built with the currently estimated reserve base of Li [25]. This battery size doubles most of the current BEVs capacity. And 1 billion is the same order of the current vehicle population worldwide. More importantly, it is believed that lithium will be well recycled to produce new batteries as other battery types, like the lead-acid battery [26]. So its reserve does not present a hurdle on PEV deployment. Furthermore, the manufacturing cost of Li-ion battery has been reduced by more than 50% in the past 3 years and is projected to continually decrease down to $200 per kWh by the year 2020-2022 [27]. This will make the cost of PEVs more competitive to CVs.

For the electric motor, multiple types are utilized, including AC induction motor, DC permanent magnet motor, and switched reluctant motor (SRM) [2]. Among them, DC permanent magnet motor features high torque, compactness and high efficiency [28], which make it the best candidate for PEV application. However, the permanent magnet requires the rare earth elements to build, such as the Neodymium and the Dysprosium [29]. Those elements are largely scattered on the earth, resulting in mining difficulties and high cost. Thus, research has been conducted to seek alternative motors requiring less or no rare earth materials. In particularly, the SRM has been investigated to be competitive to the permanent magnet motor in terms of torque density, efficiency and torque-speed-range [30]. In this sense, it is not likely to have material shortage on manufacturing high-efficiency automotive traction motors.

2.2.5. Summary

Reducing oil dependency, GHG emissions, and pollutant emissions of the LDVs sector is a goal for automakers, government agencies and the entire society. HEVs are able to improve the tank-to-wheel efficiency to contribute to this goal. However, this effort is limited by the thermal efficiency. And with more LDVs being operated, driven by the growth of the economy, the overall fuel consumption may not decrease. To further electrify vehicles and enable vehicles to draw energy from the electric grid is the consensus to address those energy and environment issues. PHEVs combine the abilities of long range and all-electric range and are considered to be the transitioning technology before BEVs can fully function as CVs. BEVs have been introduced and failed to compete with CVs several times in the history of the automobile. However, BEVs are becoming a more promising option due to new Li-ion battery technology, large amounts of raw material reserves, and more severe energy and environmental issues becoming exposed.

2.3. Infrastructures

Along with the vehicle electrification, the energy medium transitions from gasoline/diesel fuel to the electricity stored onboard. As shown in Figure 9, to support this transition, the energy infrastructure will have to evolve from gasoline stations to charging infrastructure. This section will briefly introduce the refueling infrastructure and then describe the charging infrastructure in detail.

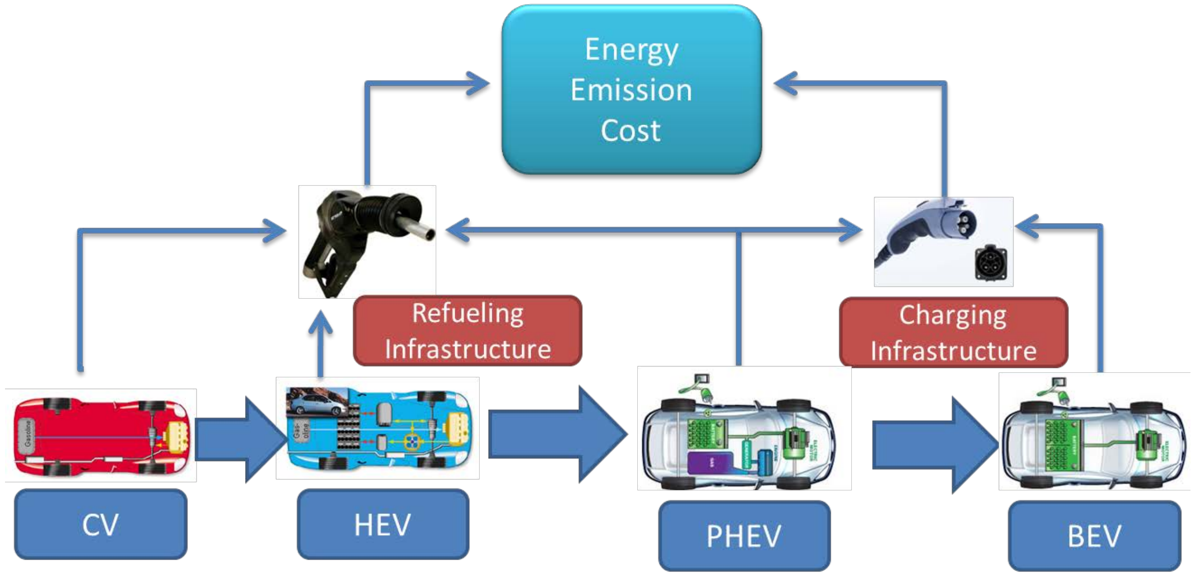


Figure 9. Energy consumption patterns for light duty vehicles.

2.3.1. Refueling Infrastructure

Oil was formed from the remains of animals and plants that lived millions of years ago. They have been covered, pressed and heated by a layer of sand and silt to become today's oil [31]. Drilling begins after measurements are taken and it will bring a steady flow of oil to the surface. This crude oil then will be transported to refineries, which mainly conduct the distillation process to produce gasoline, diesel fuel, jet fuel and other products. Finally, the gasoline and diesel fuel will be transported to numerous gas stations for LDVs.

Gas stations are the refueling infrastructure where LDVs obtain energy from. Upon the prosperity of conventional vehicles in the past hundred years, gas stations have been fully distributed in the areas where the most people's activities occur. For instance, nearly 10,000 stations are located in the state of California, mainly on the intersections of major arterial roads and close to freeway exits. It provides a decent coverage for travel activities. For instance, in the city of Irvine, California, a driver is guaranteed access to an existing gas station within 3.38 minutes assuming the road limited speed can be achieved [32].

Another feature regarding refueling is that the time consumed is negligible to pump gasoline or diesel fuel into the vehicle's tank, which is usually under 3 minutes depending on the amount refueled. Also, a full tank of fuel can support days of travel given the average VMT under 40 miles per day. Further, research found that drivers tend to refuel in areas that are detailed in their mental maps, e.g. in the vicinity of home and workplace [33]. This implies refueling is more likely to be a routine activity. Combined with abundance of the stations, refueling will not cause a significant inconvenience for drivers.

2.3.2. Charging Infrastructure

Charging infrastructure includes all of the hardware and software that ensures energy is transferred from the electric grid to the vehicle, also known as electric vehicle supply equipment, EVSE [6]. It can be specified by power level, location and charging time strategy [34]. Figure 10 is a schematic to show the PEV charging process [35]. Depending on the voltage and power transferred, Level 1, Level 2 and Level 3 charging are included. An onboard converter is required for all PEVs sold in California with a minimum 3.3 kW output power [36]. This onboard converter is used for only Level 1 and Level 2 charging while Level 3 charging relies on a designated charging station, converting AC to DC off-board. Two subsections below will introduce Level 1/Level 2 and Level 3 charging infrastructure in detail.

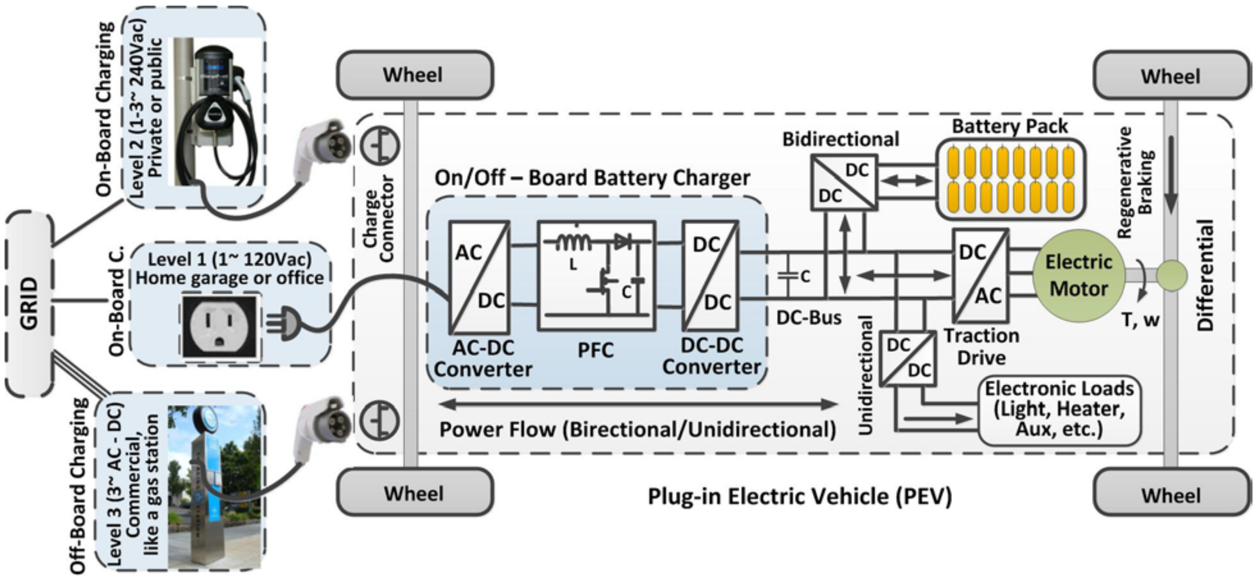


Figure 10. On/off board plug-in electric vehicle charging system and power levels.

2.3.2.1. Level 1 and Level 2 EVSE

Power Level

In the US, Level 1 uses a standard 120V/15A (or 20A) single-phase grounded outlet, such as an NEMA 5-15R [35]. The connection uses a standard J1772 connector into the PEV AC port [37], except for Tesla Motor using its own standards. For this case, the rated current is 12 A leading to a maximum 1.44 kW power input to the onboard charger. So one-hour charging can extend the electric range by about 4 miles at a normal electricity consumption rate by the current PEVs [24, 38].

Level 2 EVSE offers charging from 208V or 240V (at up to 80A, 19.2 kW) [37]. It may require a dedicated circuit and a connection installation for home or public units [10]. The connection also uses a standard J1772 connector into the PEV AC port [37] except for Tesla. Although the maximum power transferred by the EVSE is enhanced to another order, the charging power is limited by the onboard converter, which is usually 3.3 kW or 6.6 kW restricted by its cost and volume. So compared to Level 1, the charging time is reduced by 3 to 5 times assuming continuous maximum power can be utilized. However, it still takes hours to get a full charge. Thus, Level 1 or Level 2 charging cannot be the exclusive trip purpose, but the secondary trip purpose, coinciding with the primary purpose, such as home dwelling, working etc.

Location

As discussed above, Level 1 and Level 2 EVSE should be located in the primary purpose related trip destination, since those types of charging will take longer than what the driver can exclusively wait for. There are a number of trip purposes, as shown before in Figure 7, including dwelling at home, working at the work place, going to school, medical purpose, shopping, having meals, etc.

Those trip destinations can be sorted into three main categories, which are home related, work related and others. First, home is where people spend most of their time and generally all people go back home to sleep overnight. That is why for the first 4 to 5 hours in a day, almost all dwelling happens at home and it accounts for 75% of the total dwelling time. Thus, home should be considered as the primary charging location. Second, for those who are employed, going to the work place during the weekday is routine and one usually has a consistent schedule. It accounts for the second largest dwelling time. Similar to the overnight home dwelling, day-time working is predictable and should be considered as the secondary charging location. Third, for all other destinations, the related activities are not periodical and the relatively short dwelling time makes them the less effective charging locations. This is why all literatures, including this dissertation research, classify Level 1 and Level 2 charging locations into home, work and others.

Time strategy

At the long-time dwelling locations, e.g., home overnight, the dwelling time is longer than the charging time required. So decisions need to be made on when the vehicle is being charged in the course of the plugged in time. Some simple scenarios can be imagined, such as immediate charging, delay charging and smart charging. Immediate charging implies the case where no control is implemented, that charging starts at the plugged in moment, as shown in Figure 11. It will have the earliest termination time, giving most convenience for the next trip.

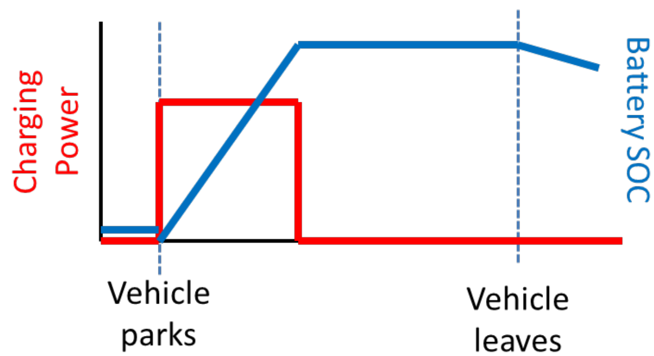


Figure 11. Diagram for immediate charging.

Figure 12 shows how delayed charging works. If the dwelling time is longer than the necessary charging time, then the charging start time is delayed to make the ending time coincide with the start of the next trip. In order to do so, the driver has to indicate the expected departure time and PEV will calculate the charging start time by considering charging power and energy needed.

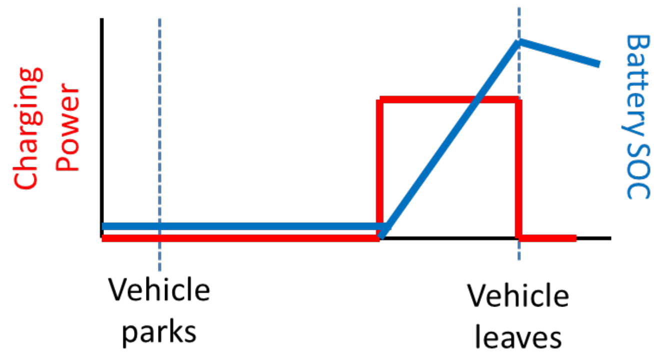


Figure 12. Diagram for delayed charging.

Smart charging in Figure 13 requires additional cost signal from utilities. The PEV will try to recharge as much as possible while minimizing the charging cost. In absence of advanced coordination between PEVs and the grid, utilities utilize the time-of-use (TOU) electricity price to guide PEVs not to charge at peak hour [34]. Using a simple, universal TOU price will work as expected at low PEV penetration, when charging will not have significant impact on the grid. However, sophisticated coordinating protocols need to be proposed with high PEV penetration in the long run.

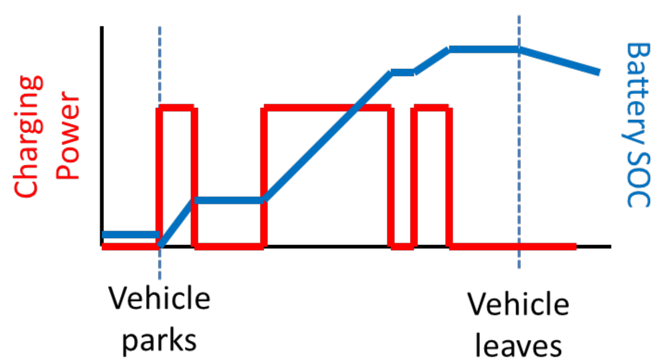


Figure 13. Diagram for smart charging.

For Level 1 and Level 2 EVSE, on one side, several studies evaluated the energy, emissions, and economic impacts of PEV adoption by considering actual travel behavior and different charging infrastructure scenarios [13, 39-45]. On the other side, several studies focused on detailed vehicle and grid operation to determine smart and optimal charging time strategies [46-51]. However, none of those research efforts have proposed a methodology on resolving the problem of the infrastructure planning, i.e., where and how many EVSE should be located. This dissertation is aimed to solve the infrastructure problem by integrating the two fields of studies together.

2.3.2.2. Level 3 DC Charging Station

Level 3 DC fast charging offers the possibility of up to 80% charge in less than 30 minutes. It typically operates with a 480V circuit [52] and requires an off-board charger to provide regulated AC-DC conversion. Having DC transferred to the PEV directly, a new charging connector is required. Two standards have been issued, including the CHAdeMO (left) and SAE J1772 Combo (right), as shown in Figure 14.

Figure 14. Level 3 DC fast charging connectors, CHAdeMO and SAE J1772 Combo.

The DC fast charging station is dedicated to BEVs, since PHEVs have ICE as the backup so they do not require fast charging. Those stations can be installed in freeway rest areas, gas stations and shopping plazas, analogous to gas stations [35]. Thus, Level 3 charging is considered to be an activity where charging BEV is the primary purpose.

Level 3 charging stations should be located on the trip routes rather than the trip destinations. A BEV driver will deviate from the original route to the charging station when realizing the vehicle does not have sufficient charge to the next destination or the final destination in a day where EVSE is available. After charging, a driver will resume travelling to the planned trip destination, so the charging activity and the time consumed should be considered as an extra cost while Level 1 and Level 2 charging does not have this drawback. But it does have some advantages. It promises fewer charging stations while satisfying a significant portion of long-distance travel demand. Additionally, the roll-out plan could be less difficult to develop compared to that for Level 2 EVSE. For example, the length of time required for sufficient charging at a Level 2 site implies that the charging needs to coincide with normal destinations. Designing an infrastructure system that meets many drivers' needs therefore requires many EVSE at many destinations. Conversely, the relative speed of Level 3 charging can enable drivers to more easily alter their behavior and make deliberate stops for charging, much like traditional gasoline refueling. Level 3 charging can supplement the insufficient Level 2 EVSE and increase travels with BEVs, although fast charging might not be profitable in the near-term [53]. There have been studies focused on fast charging station design and simulation by hybridizing batteries, supercapacitors, or flywheels with the electric grid input in order to meet the charging time requirements of DC fast chargers [54, 55]. However, no fully systematic methodology has been published on the deployment of DC fast charging stations.

2.3.3. Summary

Charging infrastructure will play a pivotal role on PEV deployment, and, in the absence of a proactive plan and schedule, is a major impediment to mass market adoption.

Infrastructure limitations are particularly pertinent to BEVs due to their sole dependency on electricity, range limits, and long recharging time. However, few research efforts have emphasized the differences in charging infrastructure requirements between PHEVs and BEVs or proposed solutions for EVSE deployment. In this dissertation, it is important to understand the requirements of power and allocation of Level 1, Level 2 and Level 3 EVSE respectively.

2.4. Potential Energy Impact of PEVs

In the process of vehicle electrification, more energy will be consumed in the form of electricity while less will be consumed in the form of gasoline/diesel fuel. Several factors will have impact on it, including the all-electric range, charging infrastructure availability, EVSE specification, fuel and electricity cost, travel behavior and people's willingness to change travel behavior. For the last one, it is definite that people will adjust their behavior when they are using PEVs and there is an entire field researching behavior changes [56-58]. However, it is not in the scope of this dissertation which is focused on the impact from the technological aspect.

Using PHEV will not impose additional inconvenience compared to driving conventional vehicles, while BEVs require drivers to plan their trip ahead. If the BEV combined with the charging infrastructure cannot meet their travel demand, it is likely people will switch to conventional vehicles for the specific travel. Thus, different methodologies are required to evaluate the energy consumption for PHEVs and BEVs, respectively.

2.4.1. PHEV

Due to the dual energy consumptions of PHEVs, fuel and electricity, it is complicated to assess each of them accurately. A PHEV can be both a HEV when never charged and an EV when the battery energy is sufficient for an entire trip before the next recharging. In general, as mentioned above, fuel and electricity consumption of a PHEV fleet depends on: 1. vehicle design parameters, such as battery capacity, electric motor size and control strategy; 2. driving behaviors, such as trip length and trip time; 3. charging scenarios, such as charging power, location and time. Several studies have analyzed PHEV adoption [44, 48, 59, 60]. However, these assessments are derived from limited analysis, based on either macroscopic trend analysis or modeling second-by-second mechanical operations of a single vehicle. These studies cannot simulate the accurate time dependent fuel and electric consumption of the vehicle fleet, nor look into the detailed impact of charging scenarios. This is addressed in this dissertation by a travel behavior based PHEV energy consumption model, incorporating a PHEV operating module and a PHEV charging module.

2.4.2. BEV

It is the general thought that BEV dose not consume any gasoline/diesel fuel and has zero tailpipe emission. This is correct after drivers decide to use BEV for their travels. However, it is important to understand the underlying fuel consumption for a BEV fleet. Given the existing travel behavior, BEV specification and the charging infrastructure availability, there will be some travel demands which cannot be met by BEV. It is anticipated that those travel activities are highly related to long distance travels, which consume more fuel than the BEV-feasible travels. Consequently, driving conventional vehicles for the small amount of travels will have a large impact on fuel consumption. The author has not found any research addressing this practical issue. Most energy-related research only looks at PHEVs.

An index needs to be introduced for BEV fleet as a measure of the range limit in terms of travel behavior. This index should reflect the percentage of BEV-feasible travels of the total travel activities. Correspondingly, the index should also reflect the percentage of electric miles travelled of the total vehicle miles traveled. A high percentage would therefore be required for mass BEV adoption. This index can be used to compare the effectiveness of different types of EVSE, e.g. Level 2 and Level 3 public charging in order to obtain the most cost effective combination of BEV design and infrastructure investment.

2.4.3. Summary

All electric range, charging infrastructure and travel behavior are the factors that influence the energy consumption of the PEV fleet. The impacts on PHEV and BEV need to be evaluated separately due to the limited range and long charging time of BEV.

2.5. Electric Grid

Introducing PEVs will shift the energy consumption from oil to electricity which can be generated by a variety of energy sources. It increases the degrees of freedom for the electricity/transportation system to utilize the cleaner energy sources. However, PEVs will impose extra demand on the grid, from power generation, transmission, to the distribution network. This is a potential challenge for the electric system.

Figure 15 shows the basic structure of the electric grid from U.S. DOE. Power flows from generating stations through high voltage transmission lines to the distribution network to feed the end users. A fundamental principle to operate the grid is that the generation has to match the demand all the time [61]. Generators can be classified by the duty cycles. The most generic ones are baseload, dispatchable, and intermittent [62]. Intermittent generation is characterized by uncontrollable and less predictable generation that is dependent largely on geographic location and meteorological conditions and includes wind, solar, wave, tidal and small-hydro. The remaining technologies are dispatchable [62].

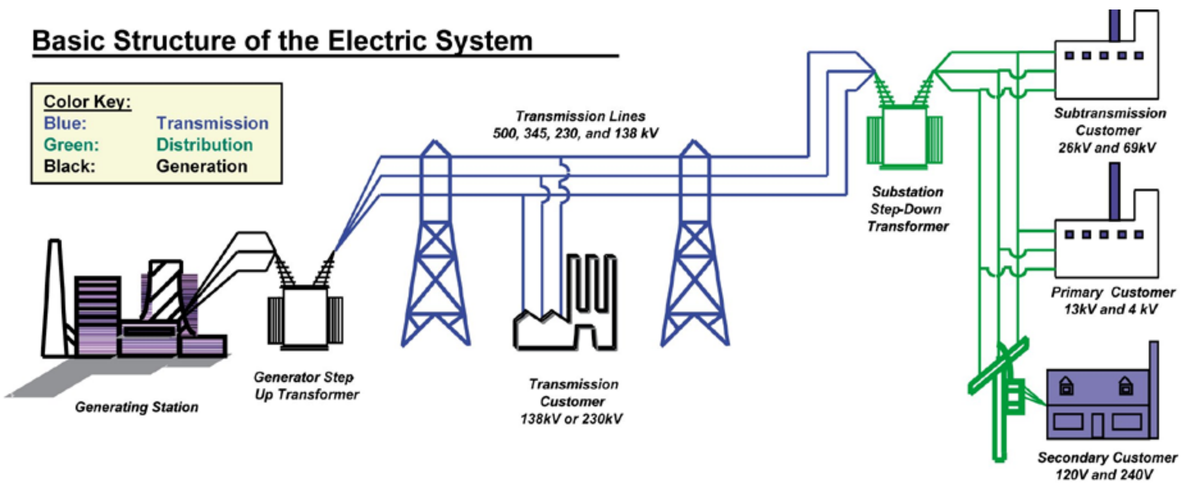


Figure 15. Basic structure of the electric system.

The demand features a diurnal pattern having a valley in the late night and a peak in the late afternoon or early evening, as shown Figure 16. In order to meet the demand and accommodate the intermittent renewable generation, the baseload and dispatchable generators need to be capable to follow the net load, which is subtracting renewable generation from the demand. A flat net load curve is generally preferred to avoid high cost and emissions. As an equivalent example shown in Figure 16, the overnight electric demand valley is filled to a completely flat level.

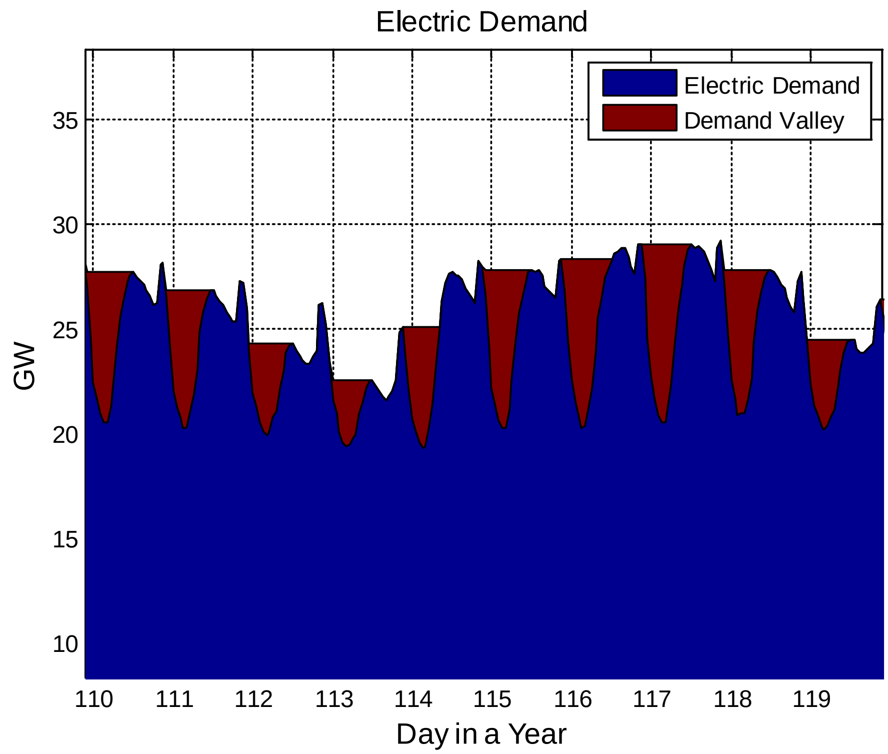


Figure 16. The diurnal pattern of the electric demand in California.

Charging PEVs will change the original net load. Depending on the PEV penetration, charging power and charging time strategy, it will have different impacts on the generation side, resulting in different emissions and costs per kWh. A lot of studies have evaluated the charging impact on the power generation and the consequent air quality [40-42, 44, 45, 63-67]. However, only the uncontrolled charging strategy (immediate charging) and the single-vehicle-based charging strategies were investigated. Other studies have proposed more advanced coordinated charging strategies among individual PEVs or just show the resulting charging profiles to achieve the grid level optimality [46, 47, 50, 68-70]. However, they are all subject to a large amount of calculation and communication, which lead to the difficulty of implementation. Thus, a more realistic coordinating protocol between individual vehicles and the grid operation needs to be investigated, such that the local charging commands and the optimality at the grid level can be met at the same time with minimal calculation and communication effort.

Most PEVs are expected to be plugged in at the secondary customer shown in Figure 15 at 120V and 240V, in particular the residential circuit. The fleet PEV penetration is not likely to exceed 10% in the year of 2025 [4], but the local penetration can reach a very high level. An extreme case can be that each household under the same residential transformer owns one PEV, which may overload the transformer during the night even when the non-charging load is very low. Several studies have looked into the charging impact on transformer degradation and shown that uncontrolled charging can speed transformer aging [71-73]. The power losses on the distribution line and voltage deviation are also among the potential issues. If not solved, the utilities have to implement network enforcement to ensure stable operation and eventually the extra cost goes to users. It is likely to jeopardize the promotion of PEVs. Consequently, a realistic protocol coordinating PEVs and the regional demand has to be proposed to deal with the potentially high PEV penetration.

2.6. Background Summary

The travel demand in the personal transportation sector, combined with the facts of most people living in garage attached houses and parking vehicles at home for a long time, implies the potential of vehicle electrification. Automakers are proactive on designing and deploying the plug-in electric vehicles to create a more sustainable transportation landscape. However, we are facing the issues that there is not a systematic methodology to assess the energy impact of PEVs beforehand, in particular for BEVs; there is not a concrete method to evaluate the requirement of charging infrastructures; and there is not a cost effective way to coordinating PEV charging with the local distribution network or the electric grid in the entire state. Those issues will be addressed in this dissertation.

Chapter 3. APPROACH

3.1. Tasks

Task-1 Establish an optimal charging strategy for allocating Level 1 and Level 2 EVSE.

This task is aimed to building a platform to evaluate the Level 1 and Level 2 charging infrastructure requirement for PEVs. To do so, an optimal charging strategy is proposed to minimize the operating cost in a 24-hour time horizon. By assuming infrastructure is unlimited, the optimal charging strategy indicates where and when the infrastructure is used. Then, the approximation of the electric vehicle supply equipment (EVSE) needed at different types of locations (e.g., home, workplace, shopping) is proposed based on the optimal charging strategy. California is selected as the research region and PEV parameters are selected based on the early deployed vehicles available in the emerging commercial market.

The BEV feasibility and VMT feasibility is defined in this task to measure how many vehicle based travels can be BEV feasible in a typical day along with the corresponding electric miles travelled. The feasibility is evaluated with all-electric range from 45 miles to 100 miles and Level 1 1.44 kW charging as well as Level 2 3.3 kW charging to represent the majority of the BEVs at present.

Task-2 Develop a methodology to spatially allocate the Level 3 DC fast charging stations for BEVs.

This task is dedicated to BEV due to its limited range and long Level 1 Level 2 charging time. Well planned Level 3 DC fast charging station network is a solution to satisfy long distance travel instead of an expansive Level 2 non-home charging infrastructure.

This task first obtains the spatially resolved travel behavior data from the 2001 California Household Travel Survey (CHTS), and assumes that BEV owners drive in the same manner. Based on the pattern of the long distance travel, a set of candidate charging locations is proposed followed by identifying potential routes for BEVs that require Level 3 DC fast charging. Then, a set covering problem is solved to minimize the number of stations needed to cover the maximum potential charging routes. This process solves the location allocation problem and provides a cost-effective station network.

The next step is to evaluate how many vehicle routes are BEV feasible (BEV feasibility) with the station network and the corresponding fuel reduction rate. Following that, the temporal utilizations of the optimized stations are investigated in terms of the 24-hour charging profile for the stations and the extra waiting time for the BEVs.

Task-3 Provide the recommendations on the deployment of PEV and EVSE.

Based on task 1 and task 2, a large variety of scenarios can be assessed in terms of feasibility, energy consumption, operating cost, and infrastructure requirement. For PHEVs, the all-electric range can vary from 10 miles to 40 miles with Level 1 1.44 kW and Level 2 3.3 kW, 6.6 kW charging. The charging location scenarios can have home charging only, home and work place charging and everywhere charging. For BEVs, the all-electric range varies from 45 miles to 200 miles with Level 1, Level 2 and Level 3 charging. The charging infrastructure requirements are approximated by satisfying as many travels as possible. More detailed analysis is conducted for Level 3 fast charging with different charging power, ranging from 25 kW to 120 kW. Level 3 charging is compared with Level 2 charging in terms of BEV feasibility and the amount and cost of infrastructure per BEV. Following these analyses, recommendations are made to roll out the charging infrastructure for PEVs.

Task-4 Propose and evaluate a decentralized protocol for coordinating a large amount of PEVs with the electric grid.

In this task, a decentralized charging protocol is proposed for PEVs with grid operators updating the command signal. Each PEV calculates its own optimal charging profile only once, after it is plugged in, and sends the result back to the grid operators. Grid operators only need to aggregate charging profiles and update the load. The existing PEV characteristics, National Household Travel Survey (NHTS), California Independent System Operator (CAISO) demand, and estimates for future renewable generation in California are used to simulate PEV operation, PEV charging profiles, grid demand, and grid net load.

With the protocol developed, the electric load is used directly as the cost signal to achieve valley filling, a flat final load overnight. Simulation runs for the entire year to assess the overnight load variation and comparisons are made with grid level valley filling results. Further, a modified protocol is developed to approach a target load in the same manner, which could be more favorable than the valley filling result. The calculation and communication effort is evaluated and compared to the existing protocols.

Task-5 Explore the effect of charging PEVs under residential transformers.

This task utilizes the decentralized protocols in task 4 with small modifications and compares results with a centralized protocol for multiple objectives in a smaller region. Electric load of the residential transformer, electricity cost from multiple utilities and representative travel behavior data are used to evaluate the proposed protocols in terms of the transformer peak demand, the power losses and the money cost. Two un-coordinating charging strategies, the immediate charging and the immediate charging with cost, are also simulated to provide references.

Chapter 4. DEVELOP OPTIMAL CHARGING STRATEGY

Part contents of this chapter have been published in the article entitled 'Evaluation of charging infrastructure requirements and operating costs for plug-in electric vehicles'. Copyright belongs to © 2013 Elsevier B.V.

This chapter investigates the Level 1 and Level 2 charging infrastructure requirements from the perspective of PEV operating cost and BEV feasibility. To minimize operating cost, an optimal charging strategy based on 24-hour travel patterns is proposed. Results indicate that charging time strategy is the most important factor in reducing PEV operating cost while greater numbers of charging locations provide diminishing benefits for PHEVs. Higher charging power capability, combined with an acceptable charging time strategy offer only slight benefits for PHEVs, but charging power is an important factor in increasing BEV functionality and decreasing public charging requirements. The approximation of the electric vehicle supply equipment (EVSE) needed at different types of locations (e.g., home, workplace, shopping) is proposed based on an optimal charging strategy.

4.1. Introduction and Literature Reviews

The charging infrastructure includes all of the hardware and software that ensures energy is transferred from the electric grid to the vehicle. It can be specified by location, power level, and charging time strategy. Several studies evaluated the energy, emissions, and economic impacts of PEV adoption [13, 39-45], while other studies [46-51] focused on detailed vehicle and grid operation to determine smart and optimal charging time strategies Specifically, a group of studies [13, 39, 42, 43, 45] used either nationwide or statewide household travel surveys to investigate PHEV energy consumption, but the infrastructure scenarios were not fully illustrated and the charging time strategies were unsophisticated. Other research [40, 41] utilized detailed electricity dispatch models and focused on the overall emission impacts of plug-in vehicles, but advanced charging time strategies were neither implemented nor explicitly explained. Two studies [44, 48] include detailed PHEV dynamic models to assess and optimize energy, economic, and environmental impacts, but include neither representative travel behavior nor detailed electricity cost considerations. A few studies [46, 47, 50] implemented optimal charging strategies and verified performance by minimizing the impact or the cost on the grid. However, these strategies were based on single daily charging events (overnight dwelling) due to the lack of realistic driving pattern data. Two final studies [49, 51] conducted optimal charging strategies over a 24 hour period to minimize vehicle operating costs with the real time price of electricity, and included real travel pattern data. Neither, however, considered ranges of charging power and charging location options.

As a next step, this chapter attempts to systematically and comprehensively address (1) the relationship between Level 1 and Level 2 charging infrastructure characteristics, PEV operating cost, and BEV feasibility, and (2) the infrastructure characteristics required to support PHEVs or BEVs, especially with regard to EVSE allocation. The goal is to evaluate the impact of realistic Level 1 and Level 2 charging infrastructure options on real travel behavior in order to delineate PEV operating cost, BEV feasibility, and optimal charging strategy designed to identify the quantity and location of EVSE and EVSE power in a given area. California was used as the focus of this study due to progressive PEV legislation and a relatively avid PEV marketplace (57% of U.S. PEVs were sold in California in 2011 [74]).

4.1.1. PEV Charging Rates

All the major investor owned utilities in California have released their specified PEV charging rates, including Pacific Gas & Electric (PE&E) [75], Southern California Edison (SCE) [76] and San Diego Gas & Electric [77]. In these service territories, customers can either combine their PEV charging with other consumption in the household, or independently with the installation of a separate meter. The latter option provides a time-of-use (TOU) rate which varies by season of the year, hour of the day, and by weekday and weekend. Figure 17 is the E-9B rate schedule for PEV charging published by PG&E in the summer of 2011 [78], where the temporal trends reflect the general behavior of the system wide electricity demand. Similar TOU rates have been developed by the other utilities, but the PG&E rate shown is used in this chapter because it has three levels: peak, partial peak, and non-peak hour.

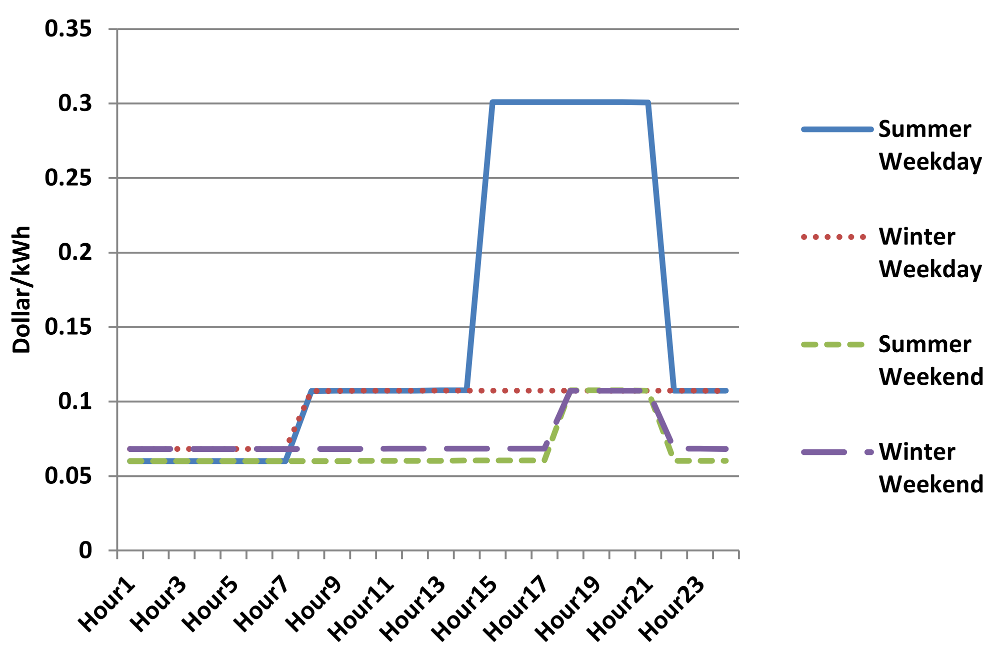


Figure 17. PG&E residential PEV charging rates.

4.1.2. Vehicle Information

Similar to other research [13, 39, 42, 43, 45], this study focuses on the macro scale of vehicle behavior where the detailed physical vehicle model was not considered; instead a parameterized vehicle operating and charging model was used. Table 1 shows vehicle parameters used in this study which were all derived from production vehicles [38]. Gasoline price is assumed to be U.S. $4.00 per gallon throughout this chapter.

Table 1. Simulation parameters for HEVs, PHEVs and BEVs.

Vehicle type	MPG	Gasoline price($/gallon)	kWh/mi(DC)	All-electric range(miles)	Efficiency from grid to battery
HEVs	40	4.00	N/A	N/A	N/A
PHEVs	40	4.00	0.34	4-40	0.85
BEVs	N/A	N/A	0.31	45-100	0.85

4.2. Model

4.2.1. Previous Work

The previous work assesses the potential energy impact of PHEVs in the South Coast Air Basin of California by considering different charging scenarios consisting of different charging powers, locations and time. Driving behaviors are derived from the National Household Travel Survey 2009 (NHTS 2009) and vehicle parameters are based on realistic assumptions consistent with projected vehicle deployments.

4.2.1.1. Model Description

A model has been developed in Matlab. As shown in Figure 18, the model consists of two components, operating and charging, circled by state-of-charge (SOC), which is simplified and defined as the proportion of instantaneous usable energy in the battery to the entire usable energy in the battery when full charged. One loop through the flow chart represents a specific trip and the consequent dwelling activity. NHTS data, which contains the trip and dwelling information, serves as the internal input. Vehicle parameters and charging strategies are the external input, which can be changed for different scenarios. Output is the time-dependent fuel and electricity consumption and other vehicle operating information such as number and times of cold starts, and time and duration of all electric operation.

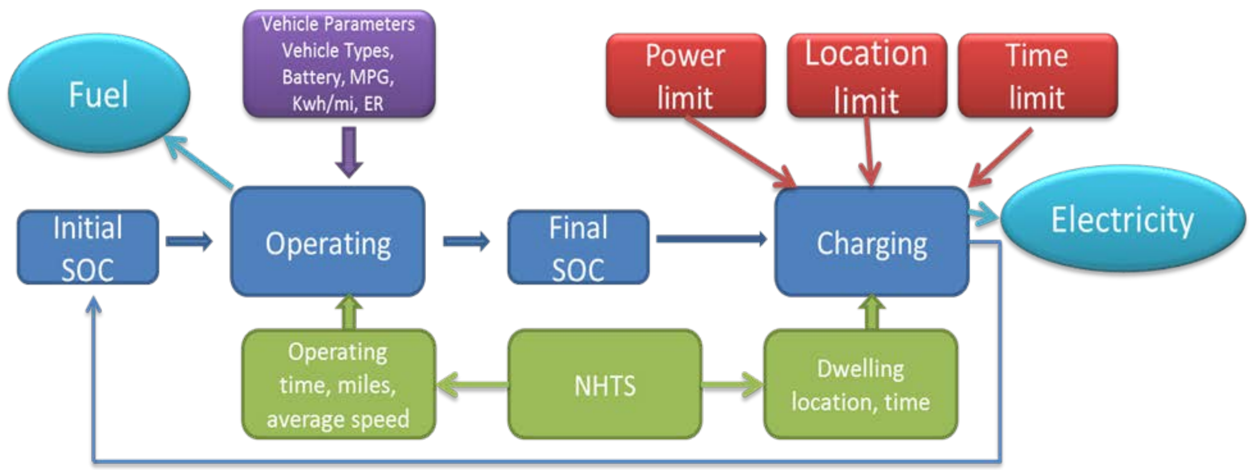


Figure 18. PHEV operating and charging model.

It is assumed at the beginning of a day, a PHEV is fully charged, having 100% SOC. In the operating component of the model, the vehicle consumes electricity in the battery first during charge depleting mode and then starts the engine converting to charge sustaining mode if the battery is depleted. In the charge depleting mode, the vehicle can consume both electric energy in the battery and fuel when the engine is operating to assist extra power demand. The extent of engine operation in this mode depends on vehicle design parameters, such as battery and traction motor's power limit and vehicle operating parameters such as velocity and acceleration. These complicated parameters are simplified by one parameter, the electrification ratio (ER), which defines the ratio of the amount of energy drawn out of the battery if driven on battery and engine, to the energy drawn out of the battery if driven on battery only. For example, a vehicle having 0.7 ER means that for a given operating distance, on average, the battery provides 70% of the energy and the engine provides 30%. In the California Air Resources Board's (CARB) PHEV test procedure, 'Test Procedures for 2012 and Subsequent Model Off-Vehicle Charge Capable Hybrid Electric Vehicles'', a closely related ratio is called the all-electric fraction, while other studies define similar ratios as charge decreasing electric energy fraction [45].

The final SOC from the operating component of the model is passed to the charging component in which the vehicle can be charged with a given power, location and time strategy. Based on the NHTS data, the vehicle may then embark on a second trip with a new initial SOC and go back to the operating component to circulate again until the vehicle activities terminate at the end of a day.

4.2.1.2. Results

Figure 19 shows the total fuel consumption per 100 miles for CVs, HEVs and PHEVs having all-electric range of 4 to 40 miles. Fuel consumption can be reduced 45% by simply switching from 25 MPG CVs to 45 MPG HEVs. Furthermore, PHEVs with 16 and 40 miles all electric range can reduce fuel consumption an additional 46% and 74% respectively, compared to HEVs by only using 1.44 kW (SAE J1772 Level 1) home recharging. This result number is very similar to that in the reference [43, 45, 79]. Figure 19 shows that the benefits in fuel reduction diminish with increasing all-electric range. It is also observed that increasing charging power from 1.44 kW to 3.3 kW does not substantially benefit fuel reduction for any charging scenario. Having more charging locations can future reduce the fuel consumption while the extra reduction is limited.

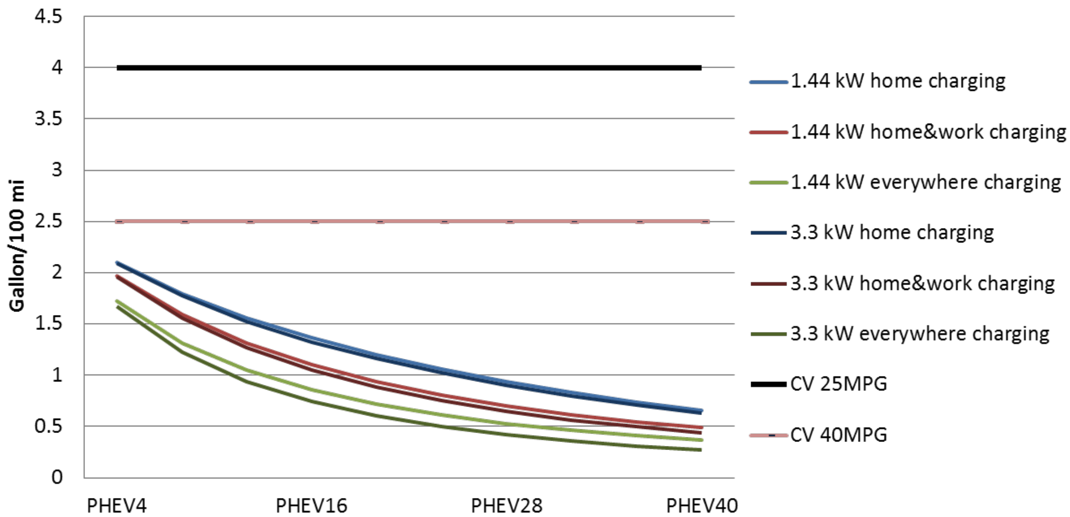


Figure 19. Fuel savings as a function of vehicle type, PHEV all-electric range, and different charging scenarios.

The previous work indicates the huge fuel reduction potentials with modest all-electric range. However, the detailed infrastructure requirements and operating costs have not been evaluated, in particularly for BEVs. Moreover, the charging time strategies investigated are immediate charging, delayed charging and average charging, which are the uncontrolled or lightly controlled strategies. More work needs to be done based on the previous model with regard to those aspects mentioned above. Thus, in the rest of this chapter, the smart charging for PHEVs and the 24-hour operating cost based optimal charging for BEVs and PHEVs are proposed. The BEV and VMT feasibility are defined to measure the percentage of BEV-feasible travels and the electric miles travelled. Results are shown in terms of PEV operating cost, charging profile, infrastructure distribution and BEV/VMT feasibility.

4.2.2. Non-Optimal Charging

The non-optimal PHEV charging model is based on previous work [13], with the addition of two scenarios: 1) smart charging, and 2) smart charging with fuel price. The uncontrolled and lightly controlled charging strategies, i.e., the immediate charging, delayed charging, and average charging, are carried over from the previous study for comparison. For the smart charging and smart charging with fuel price strategies, a cost signal, e.g., the one in Figure 17, is incorporated into the model such that the driver is able to minimize charging cost during a specific dwelling activity, such as an overnight stay at home. The smart charging with fuel price strategy is designed specifically for PHEVs and compares operating costs for gasoline and electricity such that charging is not undertaken if electricity is more expensive than gasoline during that dwelling period. Charging power scenarios are chosen based on current charger specifications, standards, regulations, and future projections [37, 80]. All charging infrastructure options are listed in Table 2.

Table 2. Charging infrastructure options.

Vehicle types	Charging power (kW)	Charging location	Charging strategy
PHEVs	1.44, 3.3, 6.0	Home, Home & work, Anywhere	Immediate, Delayed, Average, Smart, Smart with fuel price, Optimal
BEVs	1.44, 3.3, 6.0	Home, Home & Work Anywhere	Optimal

4.2.3. Optimal Charging

The optimal charging strategy considers an entire day's travel pattern and determines the optimal charging behavior based on a specific charging rate schedule. This differs from the above "non-optimal" methodology because it assumes complete knowledge of an entire day's travel and electricity price. This is not unreasonable in most cases as daily commutes are generally repetitive and electricity rates are currently published in advance.

The fundamental hypothesis is that drivers will adjust their charging behavior such that some objective can be achieved. In this case, the objective is the operating cost of PEVs, which mainly includes the electricity cost for BEVs and additional gasoline cost for PHEVs. This concept can prescribe the infrastructure required for PEVs which is particularly important for BEVs that require a non-home charging infrastructure. The methodology assumes that electric vehicle supply equipment (EVSE) is already available in prescribed locations. The optimal charging algorithm then outputs the locations that will be used during daily trips while minimizing charging costs. These locations then constitute the locations where EVSE should actually be installed. Although optimal charging has been implemented in previous studies [46-51], it has not been utilized to determine the locations for PEV infrastructure deployment. The method also serves as a baseline for the operating costs of non-optimal charging strategies.

Figure 20 shows a schematic diagram of the model. Optimization requires knowledge of the whole day's vehicle travel pattern and the charging cost during each dwelling activity, which can be provided by the NHTS data and PG&E E-9B rate schedule, respectively. Given particular charging power limits, EVSE locations, battery capacity constraints, and energy conservation, the cost function can be minimized. The model outputs the location and duration of daily charging activity for each individual vehicle captured in the NHTS data. With the large and representative data set of NHTS, the summation of individual results is used to provide fleet-wide characteristics.

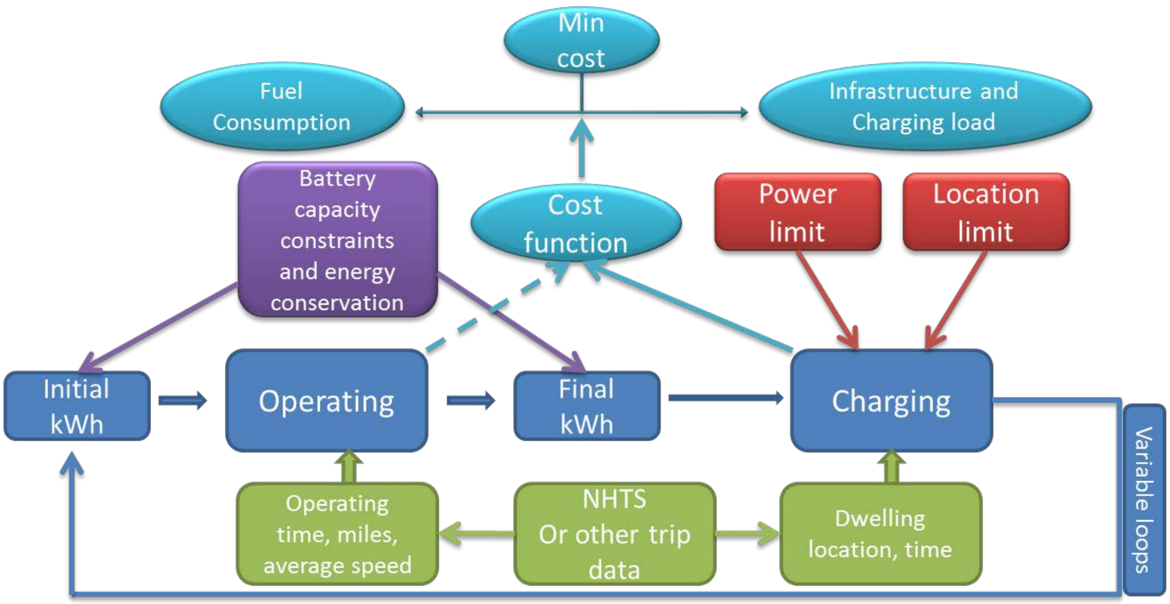


Figure 20. PEV optimal operating and charging model.

Figure 21 shows an example of BEV battery charging and discharging energy throughout the course of one day. Solid red circles represent trip starting points while checkered black circles signify ending locations. For example, a vehicle may make m trips during the course of 24 hours (3 trips in the figure). The periods of battery state-of-charge (SOC) decrease (i.e., electricity consumption) are shown as $y_1, y_2, \dots \dots\ y_m$. Following each trip, a dwelling activity takes up a set of dwelling hours, indicated by $x_{m1}, x_{m2}, \dots \dots, x_{m\ seg(m)}$. The optimization problem solves for the accumulated stored battery energy in each hour during each dwelling activity, represented by x_{ij} , required to fulfill a day's driving at the lowest cost. The formulation of the optimization is given below.

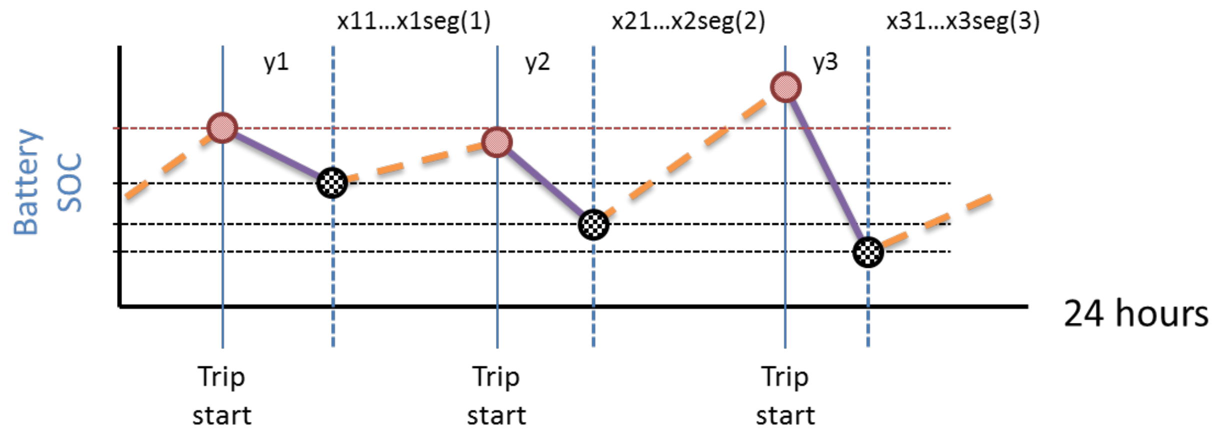


Figure 21. Example of BEV optimal charging model.

4.2.3.1. Variables:

The SOC increase (or electricity recharged) during the j[th] hour in the i[th] dwelling activity is given by:

x_{ij}

4.2.3.2. Cost Function:

The summation of the total charging cost is given by:

$$\sum_{i=1}^{m} \sum_{j=1}^{seg(i)} f_{ij} \times x_{ij} \tag{1}$$

where, f_{ij} is the charging cost per kWh (DC) during the j[th] hour in the i[th] dwelling activity.

4.2.3.3. Constraints:

1) The charged and discharged energy are assumed to be equal for 24 hours. So the energy conservation equality constraint is given by:

$$\sum_{i=1}^{m} \sum_{j=1}^{seg(i)} x_{ij} + \sum_{i=1}^{m} y_i = 0 \tag{2}$$

2) Inequality constraint: battery size. The window between the highest and lowest SOC points is not allowed to violate the battery size. In other words, as shown in Figure 21, between any red circle (local maxima) and any black circle (local minima), the window has to be less than the battery capacity, (kwh). From each red circle, there are m inequality constraints, as shown in the equations below. Consequently, there are m^2 total constraints.

$$y_1 > -kwh \tag{3}$$

$$y_1 + \sum_{j=1}^{seg(1)} x_{1j} + y_2 > -kwh \tag{4}$$

$$y_1 + \sum_{j=1}^{seg(1)} x_{1j} + y_2 + \sum_{j=1}^{seg(2)} x_{2j} + y_3 > -kwh \tag{5}$$

……

$$y_1 + \sum_{j=1}^{seg(1)} x_{1j} + y_2 + \cdots + \sum_{j=1}^{seg(m-1)} x_{(m-1)j} + y_m > -kwh \tag{6}$$

4.2.3.4. Bounds on the Variables:

The lower bound of x_{ij} is zero and the upper bound is a function of the following parameters, as shown in equation (7):

1) The charging power level at the specific location which is derived from the charging location and power limits.
2) The time span of available charging, fixed by the NTHS data. For instance, if the first hour in the first dwelling activity starts at 30 minutes past the hour, then the x_{11} equals 0.5.
3) The AC to DC efficiency which is assumed to be a constant value in this dissertation.

$$0 \leq x_{ij} \leq power_{ij} \times \overline{\Delta t_{ij}} \times \eta \tag{7}$$

4.2.3.5. Applied to PHEVs

The same concept can be applied to PHEVs with the objective to minimize total electricity and gasoline cost. As shown in Figure 22, the light blue hashed circles indicate the final SOC if there were no engine assist.

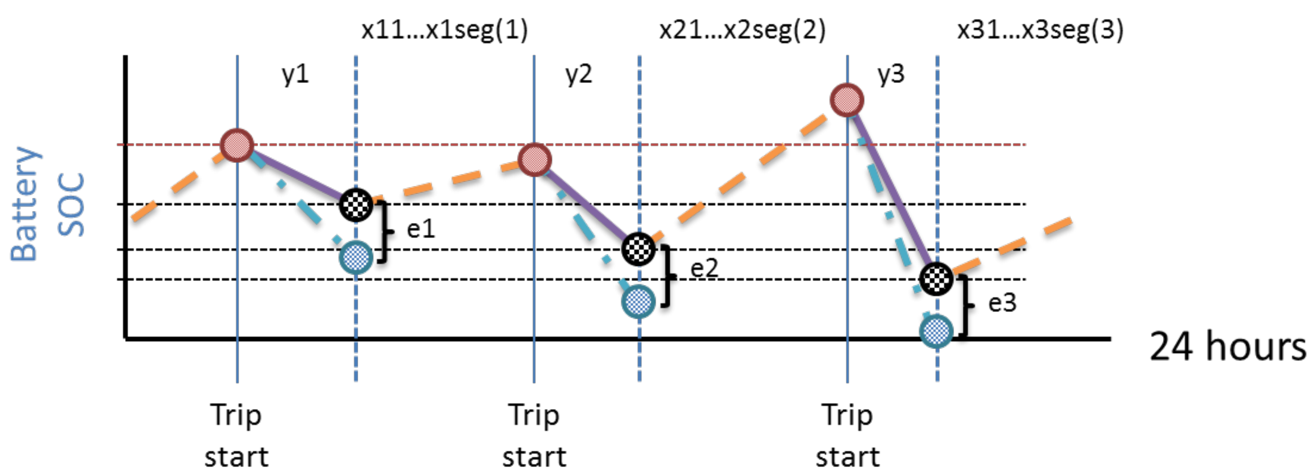


Figure 22. Example of PHEV operating and charging model.

As before, $y_1, y_2, \dots \dots y_m$ are known from the survey data. The values of $x_1, x_2 \dots \dots x_m$ represent the actual SOC decrease when considering engine assist. So the equivalent battery work, $e_2, \ldots \ldots\ e_m$ with positive values are added to account for the SOC difference:

$$y_i + e_i = x_i \tag{8}$$

A cost function is developed to minimize total operating cost:

$$\sum_{i=1}^{m} \sum_{j=1}^{seg(i)} f_{ij} \times x_{ij} + \sum_{i=1}^{m} Dollar\ per\ Gallon \times g_i \tag{9}$$

where, the extra term g_i is the gasoline consumption in the i^{th} trip. With the equation below, the equivalent energy consumption e_i from the battery can be derived with the efficiencies of hybrid drive and BEV drive.

$$g_i \times MPG = e_i \times \frac{1}{kWh\ per\ Mile} \tag{10}$$

So equation (9) becomes:

$$\sum_{i=1}^{m} \sum_{j=1}^{seg(i)} f_{ij} \times x_{ij} + \sum_{i=1}^{m} f_i \times e_i = \sum_{i=1}^{m} \sum_{j=1}^{seg(i)} f_{ij} \times x_{ij} + \sum_{i=1}^{m} f_i \times (x_i - y_i) \tag{11}$$

where,

$$f_i = Dollar\ per\ Gallon\ \times \frac{1}{MPG} \times \frac{1}{kWh\ per\ Mile} \tag{12}$$

The equality and inequality constraints are the same as for BEV optimal charging. The optimization can solve x_{ij}, when and where to recharge the battery, as well as the amount of energy, x_i, g_i, provided by the battery and engine during vehicle operation.

4.3. Results

4.3.1. PHEVs

4.3.1.1. Operating Cost

Figure 23 shows the operating cost for PHEVs having 35 mile all-electric range with different charging infrastructure options. A HEV with a 40 MPG fuel economy is used as a comparative baseline. All the PHEV scenarios show significant operating cost reductions compared to the baseline. The results can be divided into six clusters based on charging time options; different charging locations show variation within each of the six clusters. As shown, charging time strategies reduce operating cost more significantly than charging availability (location). However, within each charging time strategy cluster, more charger locations reduce cost because driving on electricity is usually less expensive than driving on gasoline. More charging locations implies more gasoline reduction [13], and hence lower cost.

From a PHEV cost perspective, a higher charging power is not necessarily good. Firstly, an EVSE upgrade is required, which, though not considered in this chapter, is a significant overall cost penalty. Secondly, if a PHEV is charged inappropriately, for example immediate or delayed charging as shown in Figure 24, high power leads to higher operating cost, even if slightly more gasoline reduction can be achieved [13]. Thirdly, a benefit of higher power charging occurs only during smart and optimal charging when non-home charging locations are used. However, this further reduction in cost from 1.44 kW Level1 to 6 kW Level2 charging is limited to just 50 cents/100 miles.

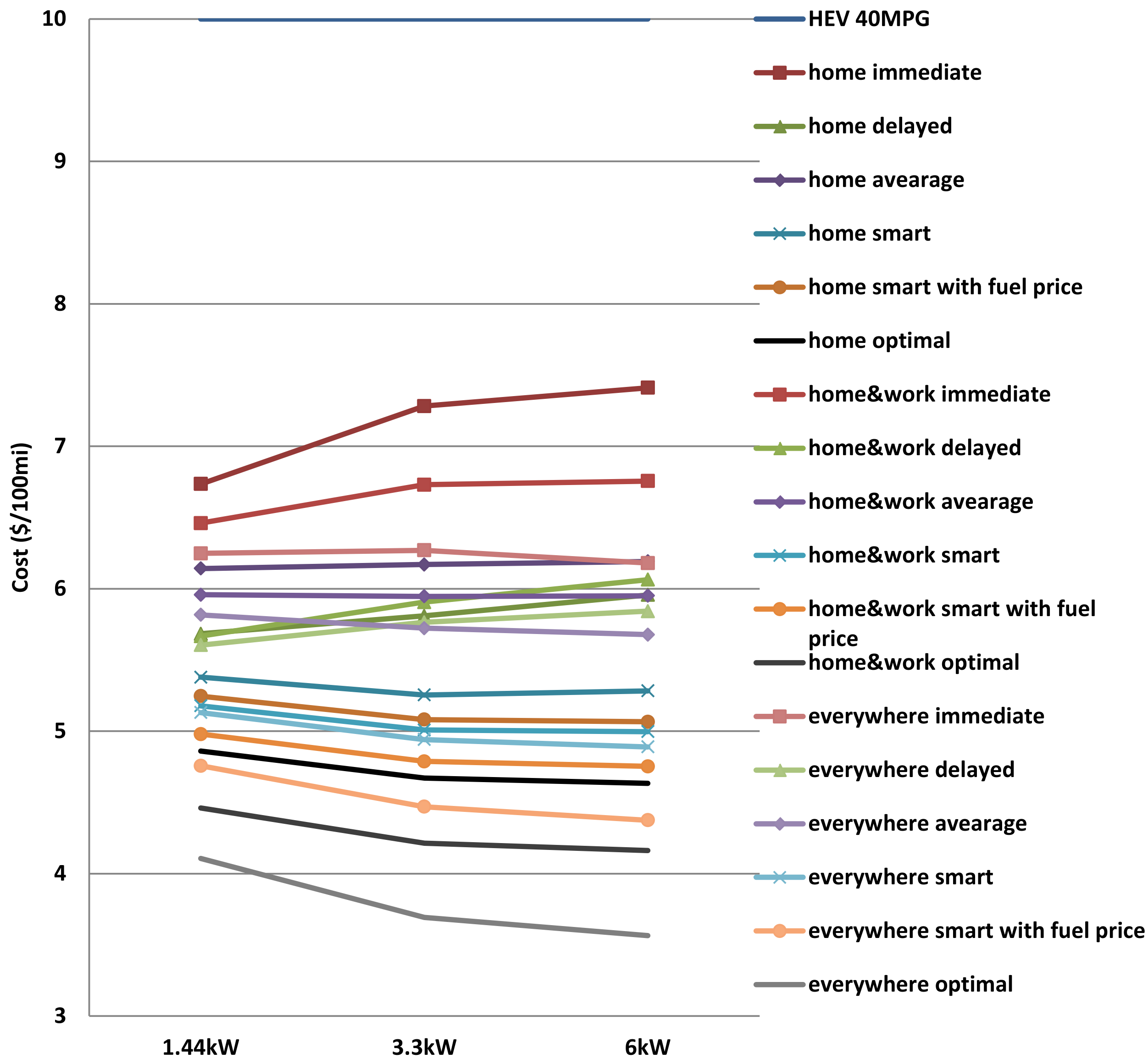


Figure 23. PHEV35 operating cost.

4.3.1.2. Charging Profile

The charging profile from “non-smart” charging strategies was fully demonstrated in previous work and is shown in Figure 24 [13]. The U.S. Department of Energy EV project provides real world data that verify these previous model results. Compared to the immediate charging shown in Figure 24, the real charging profile in Nashville [81] shows the same diurnal trend with a peak in the early evening. The immediate charging strategy is essentially optimal for that region since no time-of-use pricing has been established there. Charging as soon as possible is consequently more convenient while posing no financial impact.

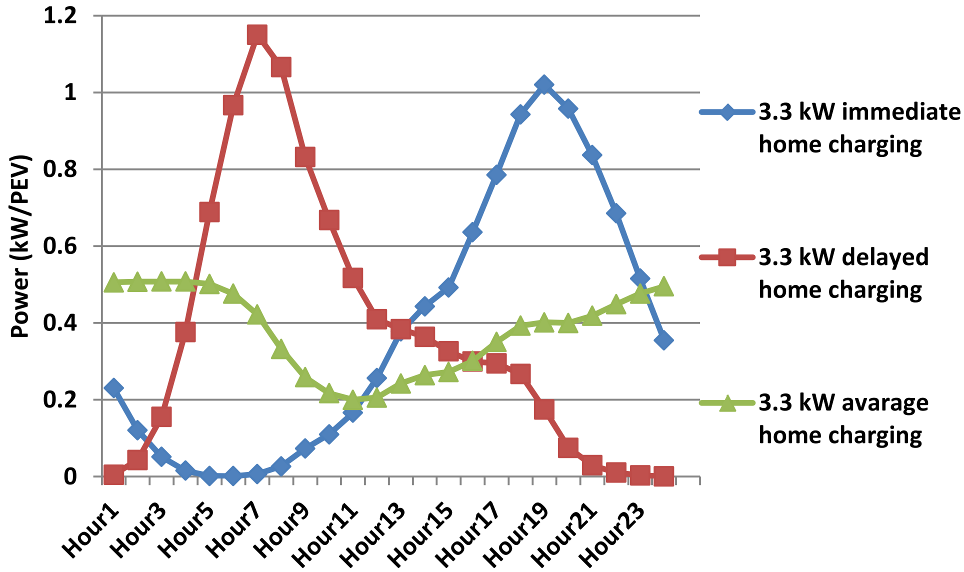


Figure 24. PHEV35 diurnal charging profile for home immediate, delayed and average charging.

Figure 25 shows the annual average charging power over the course of 24 hours with no restrictions on charging locations (i.e., EVSE located at all dwelling locations) for an advanced charging time strategy. In Figure 25, the charging profile at home for smart charging with fuel price shows the same trend as the real charging profile recorded in San Diego [81] during the course of 24 hours with a peak at midnight. The main reason is that both PG&E's rates used in the model, and SDG&E's rates in the San Diego area EV project, have minimum electricity prices starting from midnight.

These results demonstrate that the model predicts well the charging profile trend when the key conditions are the same; e.g., charging location and electricity rates. Similarly, the hypothesis is verified that drivers' charging behavior follow the objectives of reducing cost and being convenient.

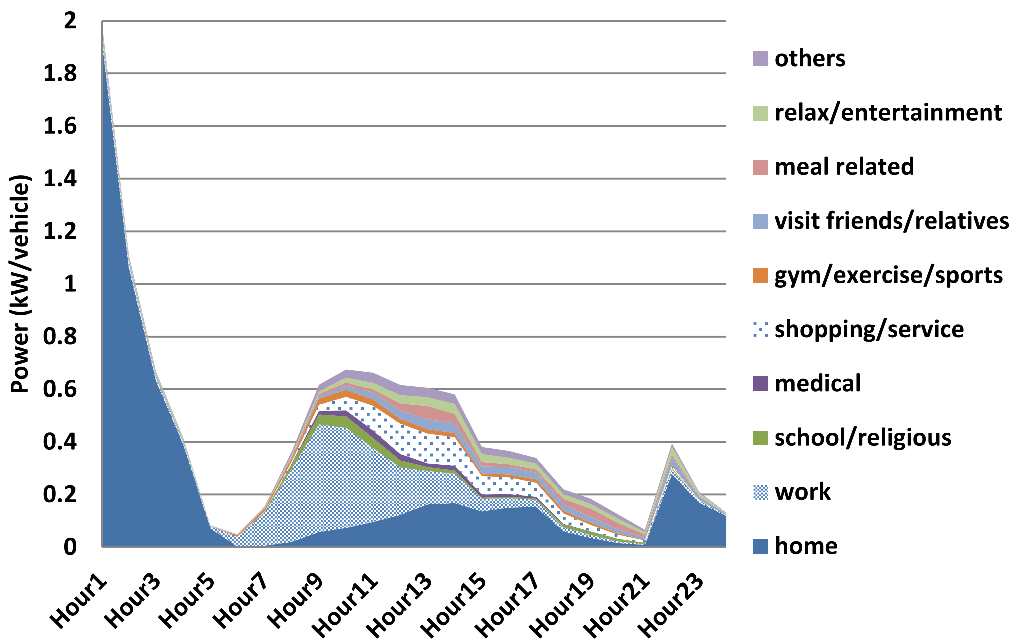


Figure 25. PHEV35 annual charging power distribution for smart charging with fuel price.

4.3.1.3. Case Analysis

By using the model, results from numerous scenarios can be generated in terms of fuel consumption, charging profile, operating cost, and EVSE allocations. Two cases are shown below focusing on EVSE allocation.

Lowest cost, least gasoline consumption

With a goal to minimize charging cost while also reducing gasoline consumption, and the assumption that charging is available at all locations, the smart charging with fuel price strategy demonstrates a general view of the charging profile at different locations. For the scenario shown in Figure 25, charging activities at non-home locations account for 56% of the total charging events, while the additional gasoline and cost reduction compared to home-only charging is relatively small. Compared with HEVs, around 70% gasoline reduction can already be accomplished by PHEV35s with home charging only [13].

As a result, it appears that relatively little additional energy or environmental benefit can be obtained from PHEVs, regardless of the breadth and expense directed towards non-home charging locations.

Lowest cost, regardless of gasoline consumption

A similar scenario can be examined whereby operating cost is minimized, but in this case, there is no particular goal to reduce gasoline consumption. It should be noted that a slight slope was added into the original cost function from the electricity rate structure according the basic electric demand in California, in order for the optimization algorithm to find a solution for this scenario. Figure 26 shows that for optimal cost reduction, most energy will be drawn from home charging (79%). However, the charging activity distribution (number of charging events) is 67%, 12% and 21% for home, work and other locations, respectively. This serves as an indicator for EVSE allocation. In other words, many EVSE installations would be needed at non-home locations to provide the lowest cost operation, even though most are rarely used. Table 3 details the distribution of charging activity and energy distribution by location.

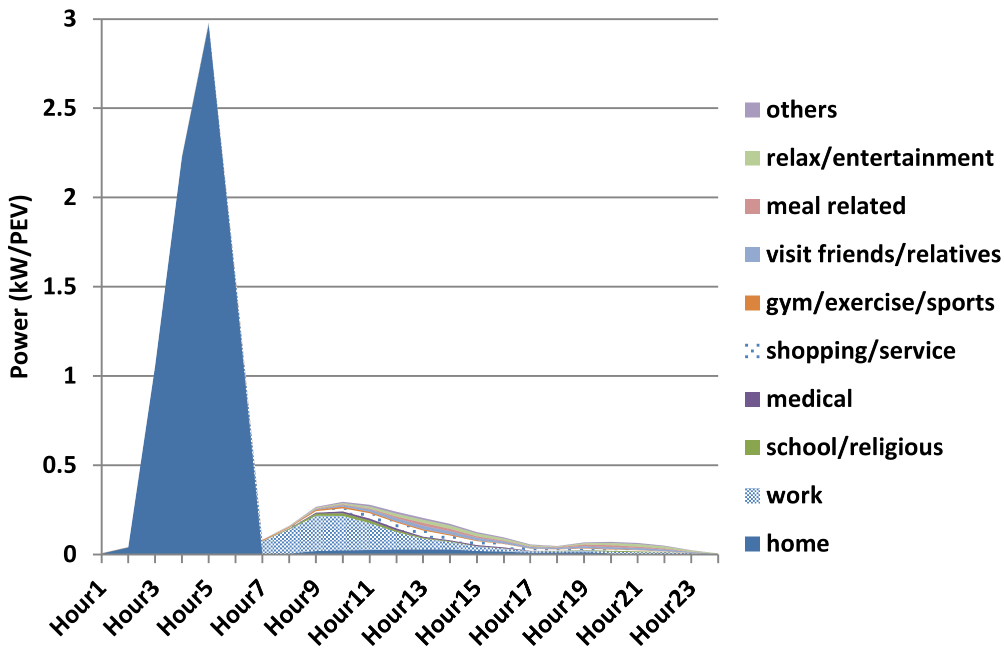


Figure 26. PHEV35 annual charging power distribution for optimal operating and charging.

As shown in Table 3, shopping and meal related activities represent the most used public charging locations; however, the average charged energy is only around 2 kWh, amounting to only about 5 miles of additional range per vehicle per day. As mentioned in the previous section, more charging locations lead to more operating cost reductions, but infrastructure cost and EVSE capacity factors (not considered herein) should be taken into account when assessing the deployment of non-home EVSE. More economic analysis needs to be conducted to fully understand the feasibility of installing public charging infrastructure for PHEVs to accomplish a relatively small amount of operating cost reduction.

Table 3. Distribution of charging activities and energy for PHEV35 optimal charging

Locations	Dwelling Count (%)	Charging Count (%)	kWh/Charging Event	Total Energy Delivered (%)
Home	36%	67%	7.26	79%
Work	13%	12%	5.26	11%
School/religious	2%	2%	3.56	1%
Medical	2%	2%	2.70	1%
Shopping/service	21%	7%	1.97	2%
Gym/exercise/sports	3%	2%	2.98	1%
Visit friends/relatives	3%	2%	4.49	2%
Meal related	6%	3%	2.28	1%
Relax/entertainment	3%	2%	5.02	2%
Other	12%	2%	3.50	1%

4.3.2. BEVs

4.3.2.1. Feasibility

Limited range is the most important operational barrier faced by BEVs. As a result, an index is introduced as a measure of the range limit in terms of driving behavior. Feasibility is defined as the ratio of the number of vehicles that could meet normal daily operating behavior as BEVs to the total number of vehicles. A high feasibility ratio would therefore be required for mass BEV adoption. BEV range and availability of charging infrastructure influence feasibility, as shown in Figure 27. It should be noted that behavior changes can also affect BEV feasibility, as assumed in other studies [23]. The methodology herein assumes that drivers make no changes to their normal vehicle usage habits. This represents a "worst case" scenario for BEVs and charging infrastructure. As a result, the high feasibility shown here is a testament to the potential of current BEV technology to dramatically shift petroleum transportation paradigm, if appropriate market forces occur.

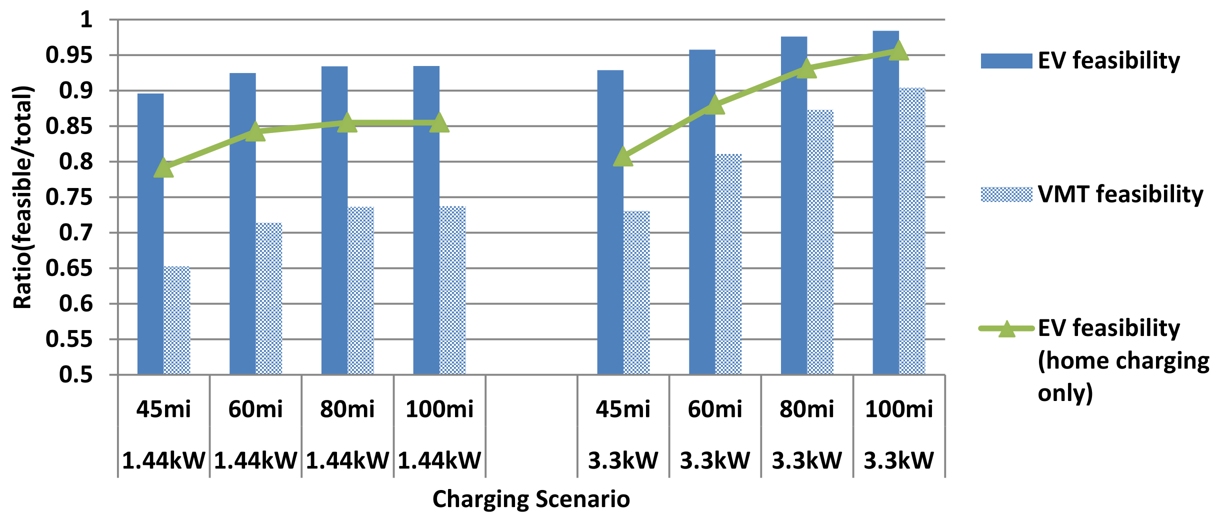


Figure 27. BEV feasibility with different ranges and charging power options.

BEVs with ranges from 45 miles to 100 miles are shown in Figure 27, for scenarios with Level 1 (1.44 kW) and Level 2 (3.3 kW) infrastructure located at all dwelling locations. Both the BEV feasibility, defined above, and the VMT feasibility, defined by the vehicle miles traveled ratio, are illustrated. Figure 27 results demonstrate the maximum feasibility with only the limits imposed by vehicle range and charging power; by assuming EVSE is located at all dwelling locations, the results remove the issue of charger availability. As a baseline, the BEV feasibility with charging locations limited only to home is shown.

For Level 1 charging, feasibility increases with vehicle range from 45 miles to 80 miles, but becomes saturated beyond 80 mile vehicle range. Level 2 charging exhibits continuously increasing feasibility with longer range BEVs. These results demonstrate the importance of higher power charging for BEVs, in particular for BEVs with longer range capability. Either larger capacity batteries or higher power charging is necessary to increase feasibility. Additionally, Figure 27 shows that home charging alone can meet the most of the daily travels.

Figure 28 provides results of charging cost and infrastructure requirements, defined to be the ratio of charging events to the total dwelling events. For instance, all scenarios point out that all vehicles would charge at home, so the charging events at home equal the total dwelling events at home. Contrarily, even if Level 1 EVSE were located at all workplaces, a scenario with 60 mile BEVs would only utilize 48% of those chargers. The optimization leads to a 100% home charging requirement, which is an intuitive conclusion since home is the location where vehicles have the longest dwelling time and the period coincides with low charging cost and low electricity demand. As for work place and public charging locations, Level 2 charging shows a significant potential for reducing the infrastructure requirements. With Level 2 charging and a 60 mile range, work place charging decreases from 48% to 20% while public location charging drops from 17% to 6%. The charging cost tends to be fairly constant with different BEV ranges, but a 10% reduction can be achieved by upgrading from Level 1 to Level 2 infrastructure.

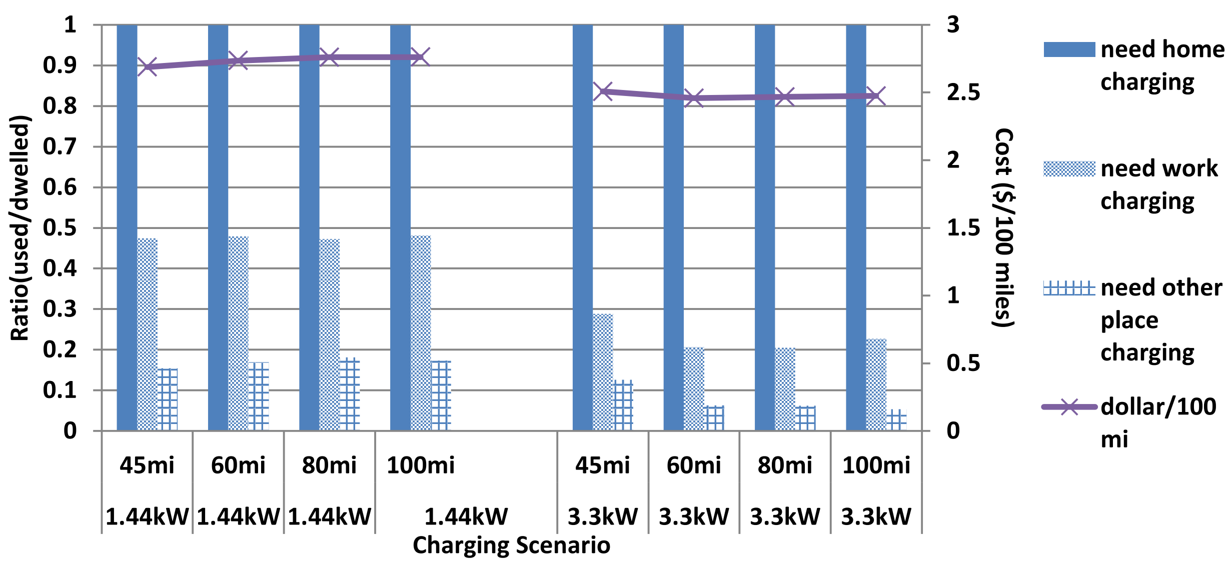


Figure 28. Infrastructure requirements for different BEV ranges and charging power options.

The two figures above demonstrate that Level 2 charging will play an important role to increase BEV feasibility and decrease infrastructure requirements at non-home locations, as well as to decrease the charging cost. However, the infrastructure upgrade costs required to install Level 2 charging differ substantially from Level 1 due to not only the EVSE unit costs, but also the secondary distribution system upgrades. These factors need to be evaluated thoroughly in future work.

An additional important aspect for future work is residential locations that do not have easily accessible Level 1 (or Level 2) charging such as most apartment buildings. California survey results show that 20% of residents live in apartments or condominiums that likely do not have access to readily available home charging.

4.3.2.2. Charging Profile

Figure 29 shows the average 24 hour optimal charging profile for a fleet of 60 mile range BEVs having access to Level 2 charging at all locations and using the PG&E PEV rate structure. Sixty mile range BEVs were chosen by adding a range safety factor to current commercial BEV performance [38]. Comparison to the results from the PHEV35 above (Figure 26) show that home charging still dominates the electricity consumption with a wider charging time from 12 am to 8 am due to the increased battery capacity. The energy consumption from home charging accounts for 93%, as shown in Figure 30. A small portion of charging at the work place still appears in the early morning, before the peak pricing hour, but amounts to just 5% of the total energy. Other locations account for only 2% of the total energy. As the vehicle's all-electric range increases, the optimal charging profile shows that home charging plays an even greater role.

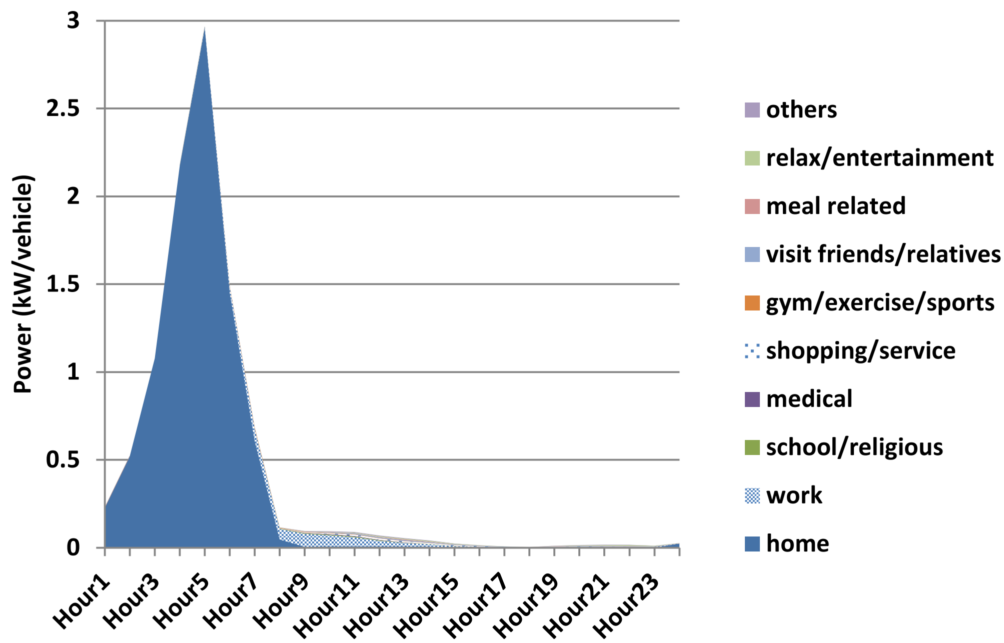


Figure 29. BEV60 diurnal charging profile for optimal 3.3 kW charging.

Figure 30 shows the distribution of charging energy and charging events by location. As shown, a greater portion of charging events occur at non-home locations in comparison to the amount of energy delivered at non-home locations. The difference is due to charging characteristics as stated in Table 3 which show a lower charging utilization factor at non-home locations. In contrast to PHEVs which have the ability to operate on gasoline power if the battery SOC is low, the EVSE requirement reflected by the charging events for BEVs must be met such that the historical travel pattern can be fulfilled. In this sense, the charging event chart for BEVs can be a blueprint to allocate EVSE.

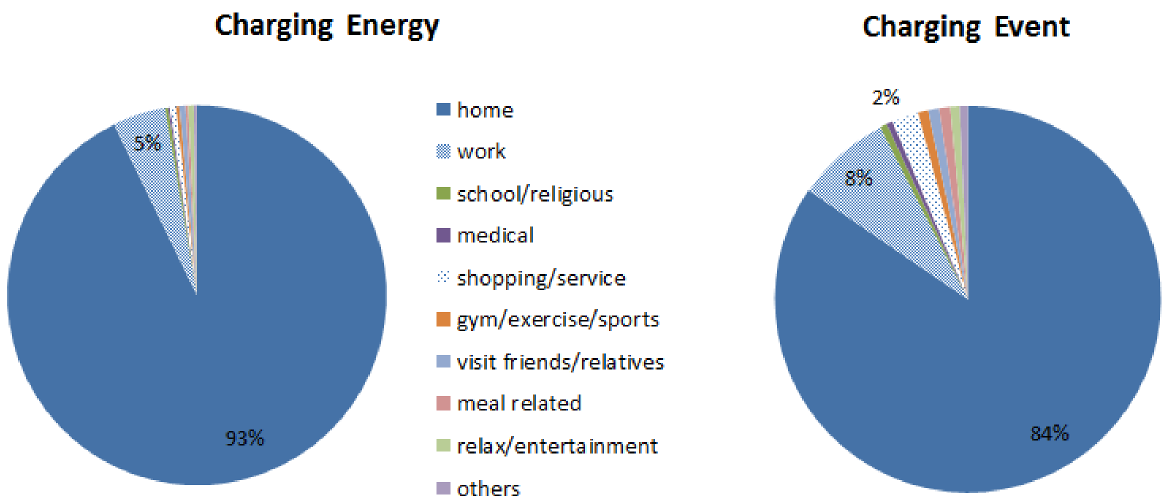


Figure 30. BEV60 charging energy and event distribution for optimal 3.3 kW charging.

4.3.2.3. Approximation of EVSE Allocation

To promote PEV deployment, both policymakers and automakers are highly interested in the allocation of EVSE. However, research has not previously been conducted that addresses EVSE allocation quantitatively from the cost perspective. This study uses the charging activities distribution to approximate EVSE with a focus on BEVs only, since non-home charging is determined to be not necessary for PHEVs.

As the details of Figure 30 and Figure 31 show, the charging event counts for both weekday and weekend have different patterns. The weekend has more charging activity at home, 87%, but work place charging shrinks to just 2% as the counts at other locations increase.

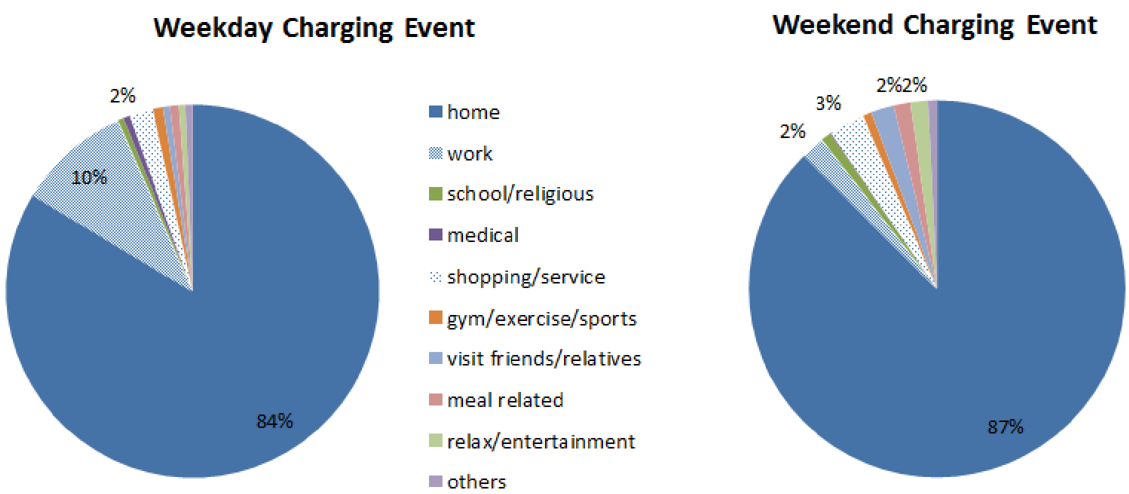


Figure 31. Comparison of the charging event distribution for weekday and weekend.

The two independent dwelling patterns of weekday and weekend require EVSE to fulfill BEV requirements for both cases. The proposed methodology is:

1. Take the total BEVs number in the interested area, e.g. N_{BEVs}.
2. Use the charging activity at home, P_{home}, as a baseline, since it is assumed that 100% of BEVs require home charging.
3. Approximate the amount of EVSE at other locations by the charging activity $P_{location}$ for both weekday and weekend, as expressed below.

$$N_{EVSE,Location,weekday} = N_{BEVs} \times \frac{P_{location,weekday}}{P_{home,weekday}} \tag{13}$$

$$N_{EVSE,Location,weekend} = N_{BEVs} \times \frac{P_{location,weekend}}{P_{home,weekend}} \tag{14}$$

4. Take the maximum number of EVSE for each location.

$$N_{EVSE,location} = max\{N_{EVSE,Location,weekday}, N_{EVSE,Location,weekend}\} \tag{15}$$

The results are shown in Figure 32. Approximately 80% of EVSE should be allocated to home locations and 9.6% should be placed at work places. The next locations that have most EVSE are shopping/services and visit friends/relatives.

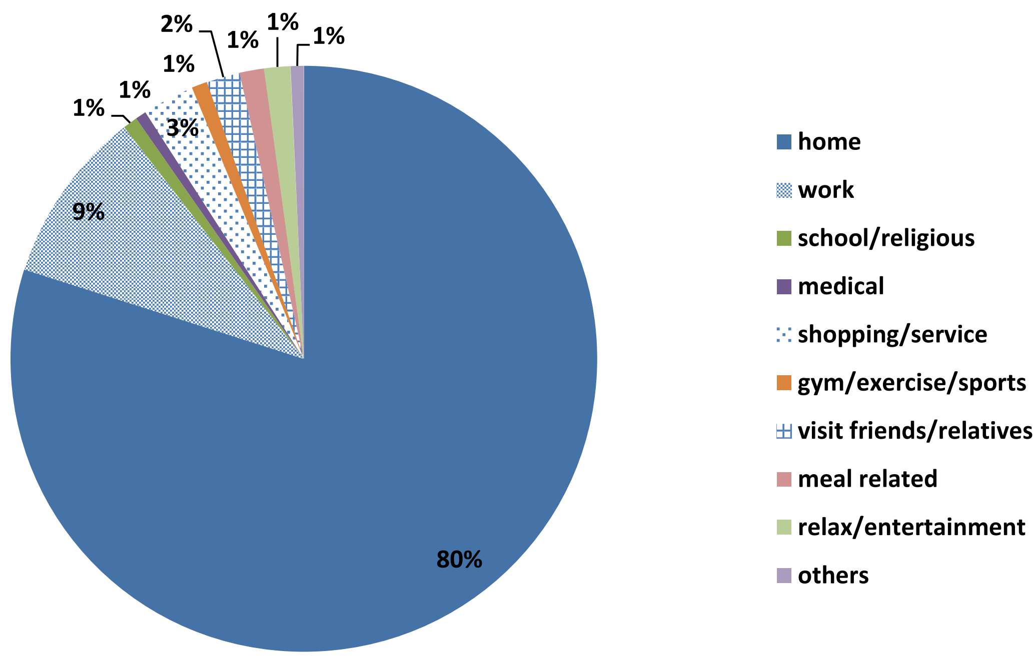


Figure 32. 3.3 kW EVSE allocation approximation for BEV60.

4.3.2.4. Discussion

The EVSE allocation results do not include multiple vehicles using one EVSE during the same day, nor multi-unit dwellings where home charging may not be readily available. It can be predicted that with a large number of BEVs, some BEVs may share the same EVSE at the same location in the same day if their dwelling schedules are not overlapped. In this sense, the result above is an upper bound for the quantity of non-home EVSE.

The EVSE allocation results are valid when the number of electric vehicles becomes considerable. In other words, when the deployment of BEVs is small, more non-home EVSE is required than the results show. For instance, if there is only one BEV on the road, the infrastructure has to cover all of that vehicle's travel patterns, so multiple EVSE are required at different locations. With increased BEVs, a specific public charging location can be used by different users in different days and times. The ratio of number of non-home EVSE per vehicle drops as more BEVs are deployed.

While the results provide key insights into EVSE allocation, it is difficult to use the results as a detailed rollout plan. First, the NHTS does not show the geographic coordinates for the trip destinations, so the model cannot allocate EVSE spatially. Therefore, more geographically specific travel pattern data will be beneficial. Secondly, the small percentage of EVSE at public locations or workplaces and the large amount of potential candidate charging locations lead to a discrepancy. This will be analyzed in detail in Chapter 6. The analysis herein provides a statistical approach to allocating infrastructure between location types, but does not determine the exact locations for the charging infrastructure.

DC fast charging should also be considered within the context of a whole charging infrastructure system. DC fast charging can increase BEV feasibility when Level 2 charging cannot satisfy the demand; for example, during trips greater than 60 miles for a BEV60. The number and allocation of fats charging stations have the potential to be exactly optimized [82]. In the next chapter, a new methodology is proposed to optimize the location allocation of the DC charging stations.

4.4. Conclusions

A model with smart charging, smart charging with fuel price, optimal charging and operating for PHEVs, and optimal charging for BEVs, has been developed and applied. Most charging infrastructure options have been included in the model. From the results, analysis, and discussion above, the following conclusions can be drawn:

1. The model results and real EV project charging data show high correlation for a case with flat electricity rates and for a case with time-of-use rates, such that the model is verified to capture the real charging behavior as well as the hypothesis that people's charging behavior tends to minimize their costs. The study adopts California as an example by using the NHTS, but the methodology can be used for other geographic areas and vehicle travel pattern data.
2. The model results demonstrate a different infrastructure strategy for PHEVs and BEVs.

   For PHEVs:

   - All charging infrastructure options show substantial operating cost reduction for PHEVs compared to traditional hybrid vehicles, while the magnitude has significant variation, from 3.5 to 7.5 dollars/100miles.
   - The advanced charging time strategy results in the largest reduction in operating cost.
   - The benefit of high charging power can be effective with the right time strategy.
   - Although the use of more non-home charging locations can further reduce the fuel reduction and operating cost for PHEVs, the activity distribution from smart charging with fuel price and optimal charging indicate that more than 30% of charging will take place at non-home locations to garner a meager 1 dollar/100mile operating cost reduction. Consequently, society should carefully consider the overall benefit of non-home EVSE investment for PHEVs.

For BEVs:

- Unlike PHEVs, sufficient EVSE must be installed to satisfy BEVs.
- Level 2 charging plays an important role in increasing BEV feasibility defined in this chapter, as well as decreasing EVSE at non-home locations dramatically, and cutting the charging cost by 10%.
- BEV60 shows a feasibility of 88% and 96% with 3.3kW home charging only and non-restrictive charging, respectively.
- An optimal charging activity based EVSE allocation methodology was exercised to determine that for BEV60, 96% BEV feasibility requires 80%, 9% and 11% EVSE allocated for home, work and other places, respectively. This result can be used as a guide for EVSE investment. More work needs to be done in terms of the detailed rollout plan, such as using geographic enabled travel pattern data, considering parking capacity for a specific dwelling location, and integrating Level 3 DC fast charging into the model.

Chapter 5. OPTIMIZE LEVEL 3 FAST CHARGING STATION

Battery electric vehicles (BEVs) are important for reducing fuel consumption and vehicle operating cost, and have the potential to reduce GHG and pollutant emissions. However, the range limits and long recharging times serve as obstacles to mass deployment. Well planned Level 3 DC fast charging stations may be a solution to satisfy long distance travel demand instead of an expansive Level 2 non-home charging infrastructure. This chapter identifies candidate charging routes and uses freeway exits and highway intersections as approximate candidate charging locations, and consequently solves a set covering problem to minimize the number of charging stations. Results show that 290 charging locations are required for the State of California for the initial coverage based on the 2000 California Travel Survey. With this optimized station network, electric light duty vehicle miles travelled (VMT) can reach 92% and 98% of travels can be BEV-feasible. This study also assesses the temporal utilization of charging stations. Congestion at several stations suggests extra chargers are required. A reservation system can benefit both the BEV drivers and station operators by reducing the wait times, decreasing the extra chargers needed, and more evenly utilizing all the stations. Related policies are also discussed to better deploy fast charging stations.

5.1. Introduction and Literature Reviews

Plug-in electric vehicles (PEVs) include plug-in hybrid electric vehicles (PHEVs) having internal combustion engines onboard to extend vehicle range, and battery electric vehicles (BEVs) which solely rely on the on-board electric storage. By partially or fully shifting vehicle energy usage from petroleum to electricity, PEVs can provide benefits for energy security, greenhouse gas (GHG) reduction, and urban air quality.

As with other alternative fueled vehicles, the infrastructure required for mass commercial adoption poses a significant obstacle for BEVs. However, with the existing infrastructure of gasoline stations and Level 1 (120 volt) [83] home charging the market hurdle for PHEVs is relatively small. Previous studies suggest that for PHEVs, home charging alone can significantly reduce gasoline consumption [13, 43]. Additionally, several studies have shown the potential energy, emissions, and economic benefits of PHEVs with different scenarios of Level 1 and Level 2 charging [34, 41, 42, 45, 64, 84]. Unfortunately, the purchase price for PHEVs can be high, in part due to the requirement of two full powertrains. Additionally tailpipe emissions still exist, and can possibly be worse than equivalent hybrid electric vehicle (HEV) emissions, depending on the vehicle design [15, 85]. Alternatively, BEVs having just one powertrain offer the opportunity to lower purchase prices and guarantee zero tailpipe emissions [24]. However, a critical issue for widespread BEV adoption is charging infrastructure that can satisfy personal travel demand while mitigating the characteristics of limited range and long recharging time.

If non-home charging infrastructure is unavailable, BEVs can still meet some driving needs with the condition that drivers cannot travel long distances [23]. For example, only 9% of drivers in the study reported that they never travelled more than 100 miles on any given day. As a result, to use BEVs, most drivers must make changes to their driving habits. The Level 1 and Level 2 charging infrastructure research in Chapter 4 showed that if Level 2 charging is accessible at all destinations, then BEV60s (BEVs with 60 mile range) could meet the need of 96% of travels for any given day; this represents a BEV "feasibility" of

96%. However, it is not likely that this level of infrastructure could be funded or constructed in the near-term. Furthermore, the exact locations for Level 2 electric vehicle supply equipment (EVSE) are not likely to be optimized, ultimately increasing costs and redundancy. Consequently, it appears that compromising long distance travel demands or deploying numerous non-home EVSE to facilitate widespread BEV adoption is not an optimal option, especially in the near future.

Alternatively, Level 3 DC fast charging [83] promises fewer charging stations while satisfying a significant portion of long-distance travel demand. Additionally, the development of a deployment roadmap is more straightforward compared to that for Level 2 EVSE. For example, the length of time required for sufficient charging at a Level 2 site implies that the charging needs to coincide with normal destinations. Therefore, designing an infrastructure system that meets many drivers' needs requires many EVSE at many destinations. Conversely, the relative speed of Level 3 charging can enable drivers to more easily alter their behavior and make deliberate stops for charging, more like traditional gasoline refueling. Level 3 charging can supplement the insufficient Level 2 EVSE and increase BEV feasibility, although fast charging might not be profitable in the near-term [53]. Several studies have focused on fast charging station design and simulation to meet the charging time requirements of DC fast chargers [54, 55]. However, no study on the deployment of DC fast charging stations using a fully systematic methodology has been published.

Some studies address DC fast charging station allocation indirectly. Nicholas, Tal, Davies and Woodjack [82] used GPS recorded vehicle routes from 48 households during one month to simulate the scenario of BEV driving and evaluate fast charging requirements in the Sacramento, California area. Furthermore, the Nicholas, Tal, Woodjack and Terrentine [86] work presented at the Electric Vehicle Symposium 26 used CHTS data to investigate Level 3 station allocation in California. However, it was not clear in those models when the charge demand was determined, thus the station locations appear to not be optimized. Liu [87] assessed battery swapping and fast charging stations in the city of Beijing by considering gasoline station candidate sites and the distance from electrical substations. The work focused more on land coverage than BEV travel patterns. Hiwatari et al. proposed an algorithm to move charging stations close to where many BEVs would run out of electricity [88-90]. A similar concept can be seen from Simpson and Markel [91], which also assumed fast charging will occur when the battery energy drops to a low level. However, these studies rely on the assumption that BEVs will use fast chargers only when running low on energy. Other work [32, 92] optimizes hydrogen station locations for fuel cell vehicles (FCVs) in a specific area with the criteria that all the demand points (home addresses) are able to reach a candidate hydrogen station location (gasoline station) within a certain time; this is essentially a set covering problem [93]. But this method cannot be applied to fast charging stations directly since home addresses cannot be used as demand points, and gasoline stations cannot be treated as the only candidate charging stations. The locations where BEVs require fast charging are likely to be far away from drivers' homes and not only at existing gasoline stations, but also locations like grocery stores, shopping malls, and large department stores.

The dissertation herein optimizes Level 3 charging station deployment by considering actual vehicle routes and potential candidate charging locations, as well as evaluating the temporal utilization of charging stations.

5.2. Material and Methods

The study's methodology can be summarized as:

1. Obtain petroleum fueled light-duty vehicle long-distance travel pattern data and assume that BEV owners drive in the same manner.
2. Identify approximate candidate charging locations.
3. Identify potential routes for BEVs that require Level 3 charging.
4. Minimize the number of stations needed to cover the maximum potential charging routes (set covering problem).
5. Model the operation of each BEV under the optimized station network with different charging strategies to determine temporal charging characteristics.

5.2.1. California Household Travel Survey

The vehicle travel pattern data used in this chapter are derived from the 2000 California Household Travel Survey (CHTS) [94]. Several processing steps were required in order to prepare the data for input to the model. Trips occurring without a personally owned vehicle and/or without geographic destination information were deleted. Person-chain data were converted to vehicle-chain data. Vehicle routes and vehicle miles travelled (VMT) were determined using ArcGIS [95] software by calculating the fastest path between the known geographic positions. Daily trip data with unlinked destinations or significant over-speed were deleted, and tours were organized into home based daily tours (first trip from home, last trip to home). After these data processing steps, the resulting travel survey data included 15,703 vehicles covering 64,084 single trips with an average of 7.8 miles per trip and 31.8 miles travelled per vehicle per day.

5.2.2. Model

Figure 33 illustrates the model used in this work with a flow chart. The processed CHTS vehicle travel pattern data are input into a sub-model that determines the optimal charging strategy for Level 1 and Level 2 charging infrastructure allocation, which was described in a previous study [34]. This sub-model obtains the optimal pattern to charge a BEV during the 24-hour time period, and further evaluates the charging infrastructure requirements in different location categories (e.g., home or work). This allocation sub-model can also determine "feasible" and "non-feasible" daily tours based on different Level 1 and Level 2 charging infrastructure scenarios. Feasible tours can be accomplished with the given BEV characteristics and specified Level 1 and Level 2 charging infrastructure; non-feasible tours would result in stranded drivers with depleted batteries. The non-feasible tours are then used to investigate the fast charging station allocation. According to the vehicle and charging parameters, tours can be divided into those requiring one fast charge, and those requiring multiple fast charges. Tours requiring just one fast charge are input into ArcGIS to identify the candidate charging routes on which the fast charging can take place. The next step uses the candidate locations along the candidate charging routes to form a set covering problem to solve for the minimal required locations. Once the optimized fast charging station network for tours requiring one fast charge is determined, tours requiring multiple charging events are examined to assess whether they can be fulfilled. Since it is possible that drivers have multiple fast charging locations available along the charging route, temporal utilization and capacity issues can be evaluated for different station selection strategies. Finally, it should be noted that several Level 1 and Level 2 charging infrastructure scenarios can be combined to evaluate the public Level 3 charging station requirements, e.g., home charging plus public Level 3 charging or home and work charging plus public Level 3 charging. However, as a conservative estimate, this chapter will only address a scenario with home charging after the last trip and no Level 1 or Level 2 non-home charging. This will result in the largest requirement of Level 3 chargers.

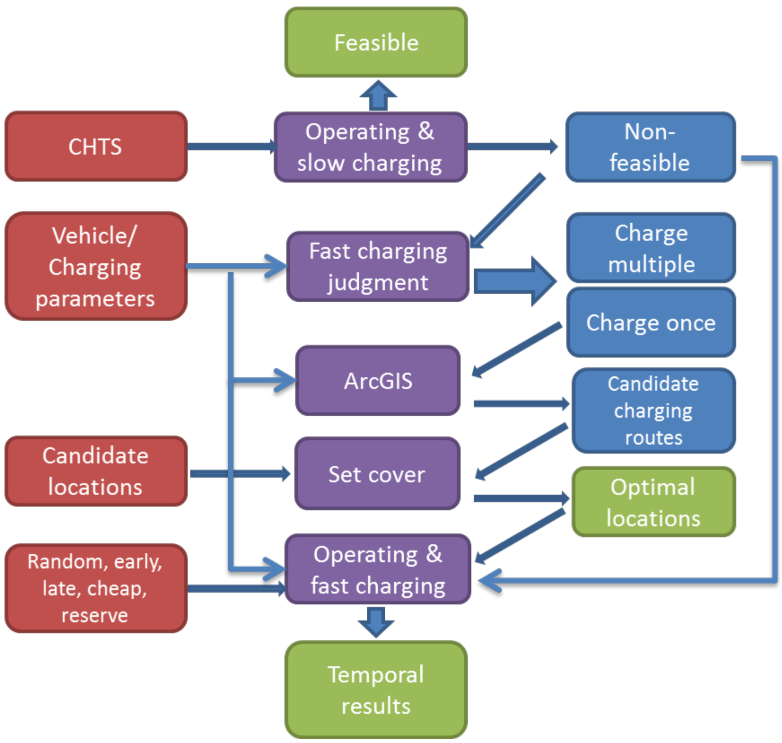


Figure 33. BEV Level 3 fast charging station allocation optimization model.

5.2.3. Long Distance Driving and Candidate Charging Locations

This dissertation assumes that each BEV is fully recharged at the beginning of the day and that the Level 3 charging stations are the only charging opportunities during the day before finally returning home. Consequently, based on conservative commercial BEV performance, any daily VMT beyond 60 miles will require at least one charging event. There are 2,204 vehicles surveyed in the CHTS with daily VMT longer than 60 miles, accounting for 14% of the total surveyed vehicles. In Chapter 6, the total vehicle routes will be slightly different due to the consideration of the toll road.

A high correlation between long distance driving and highway use seems intuitive. To verify this assumption, ArcGIS was used to calculate the freeway/highway portion of each individual long distance tour. The histogram in Figure 34 shows that more than 80% of long distance vehicles have at least 50% of their routes on a freeway/highway and that on average 73% of the long distance driving occurs on a freeway/highway. This result implies that it is reasonable to locate fast charging sites near freeways/highways.

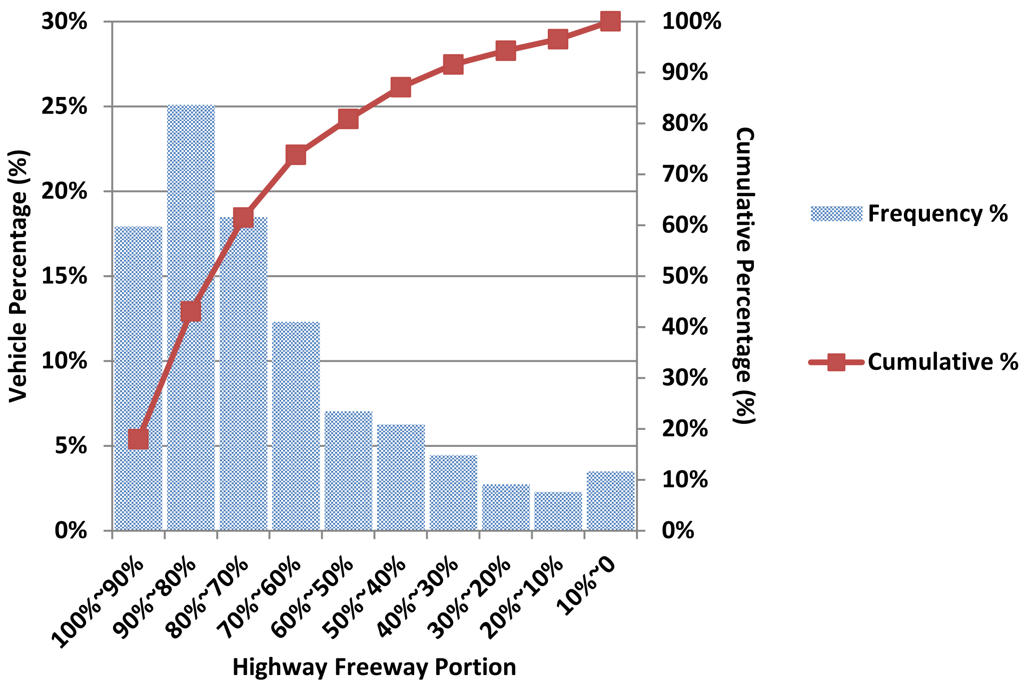


Figure 34. Highway/freeway portion of driving for vehicle routes greater than 60 miles.

The determination of exact candidate locations for charging stations is difficult since multiple real factors need to be considered, such as land use, electric circuit availability, and eligible and interested businesses. Thus, in this chapter, it is preferred to use approximate candidate locations assuming the actual station could be installed nearby with the consideration of the factors above and without much loss in the robustness of the fast charging network. Freeway exits and highway intersections are selected as approximate candidate locations for several reasons: proximity to freeways and highways and easy ingress and egress. Table 4 lists the number of approximate freeway exit and highway intersection candidate charging locations in California based on a network database from StreetMap North America [96]. If specific, actual charger locations are available, they can be used as an alternative or supplement to the approximate candidate locations.

Table 4. The approximate candidate charging locations used in the model.

Freeway exits	Intersections (between major highway and major highway)	Intersections (between major highway and secondary roads)	Total (Aggregated locations)
6244	137	337	2929

As shown in Figure 35, most freeway exits exist in pairs. Thus, the freeway exit pairs were aggregated such that all readily accessible roadway near the freeway would be included as one candidate location, as shown in Figure 35. This process reduces the approximate candidate locations to 2929, and potentially increases the service area.

Figure 35. Aggregated polygon encompassing two freeway ramps and associated cross street.

5.2.4. Candidate Charging Opportunities

Charging opportunities must be identified during the daily tour for each individual vehicle. Figure 36 shows a histogram of the daily VMT for long distance tours, in which the frequency generally decreases with the daily travel distance. The vertical line in Figure 36 delineates those trips greater or less than 110 miles (72% of long distance daily tours accumulate less than 110 miles and 28% accumulate greater than 110 miles).

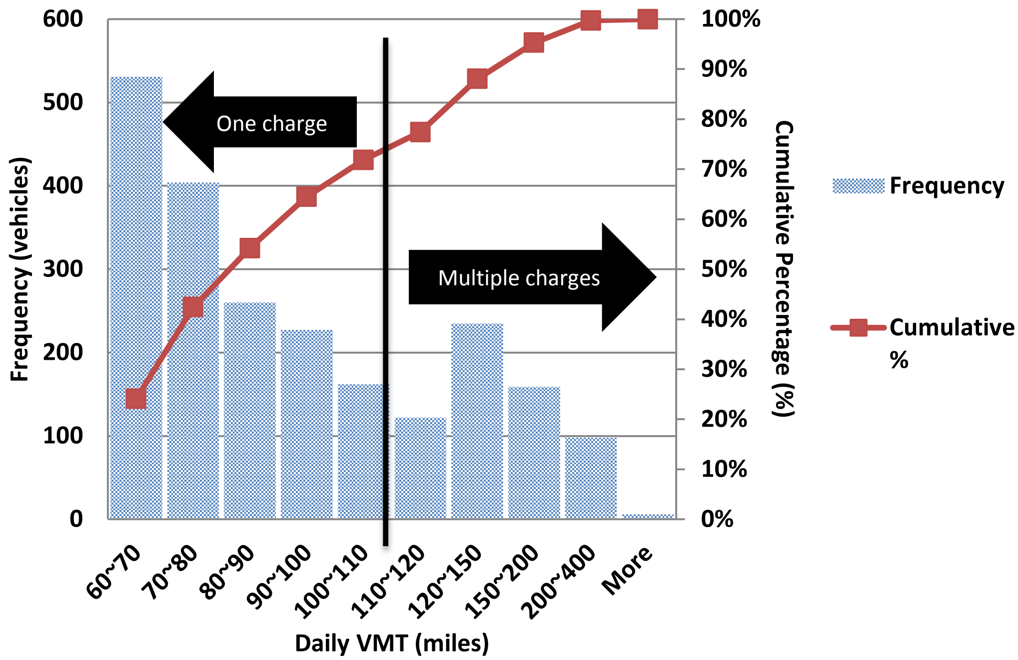


Figure 36. VMT histogram for vehicle tours greater than 60 miles.

Based on commercially available BEVs and fast charging station characteristics [97, 98], it is assumed that BEVs have a 60 mile range when fully recharged and that fast charging can be performed anytime, as long as the vehicle has at least 5 miles of battery energy remaining. Thus, any daily tours with VMT below 60 miles do not require fast charging. Tours greater than 60 miles need recharging, and the VMT between two consecutive charging events must be within 55 miles. For 60-110 mile tours, a minimum one time charge is needed, and multiple charges are required for the higher VMT tours. More scenarios of longer BEV ranges are examined in Chapter 6. Table 5 classifies tours by VMT and indicates the number of vehicles in the CHTS falling within each category.

Table 5. Tour characteristics and associated charging assumptions for BEV60.

	No Charge	Charge once	More than once
Maximum range between charge	60	55	55
Daily tour VMT	<60	60-110	>110
Number of instances in CHTS	13,499	1,584	620

5.2.4.1. One Time Charging

Figure 37 illustrates the candidate charging locations and candidate charging routes for vehicles requiring one charge. The total daily VMT is represented by X, and there are several approximate candidate charging locations on the route symbolized by the orange and purple dots. From the origin O, the BEV has to be recharged once before reaching the position marked by Y, which is the range between charges (55 miles in this case). Similarly, from the position marked by X-Y to the final destination X(O), a charging event has to take place. Thus, the charging event must occur in the overlapped region, from X-Y to Y, which is the candidate charging route with potential charger locations indicated by purple circles. The existing studies all assume that drivers will take the last charging opportunity when battery energy is the lowest [88-91].

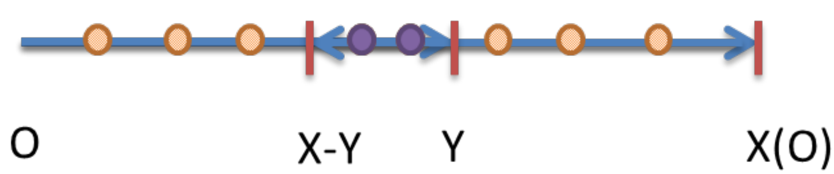


Figure 37. Diagram of the candidate charging route for BEVs requiring at least one fast charging.

5.2.4.2. Tours Requiring More than One Charge

Figure 38 illustrates the case in which 2 charging events are required. Using the same method as above, two regions can be determined to be the sets of candidate charging routes. However, it becomes a combinatorial problem since the selection of a charging station in one region can determine which stations are eligible in another region. For example, if the first point (blue) is chosen in the first charging region, then the second point (green) cannot be chosen because the distance between the two will violate the criteria that the distance has to be within Y (55) miles. It is also considered that charging more than once may not be practical from the perspective of changing drivers' behavior because it will require more detouring to the stations and more charging time at charging stations during a single day. Consequently, charging more than once is not considered in the station optimization. Vehicles that require more than one charge are instead checked against the optimized stations determined by one time charging in order to determine BEV feasibility for these tours requiring more than one charge.

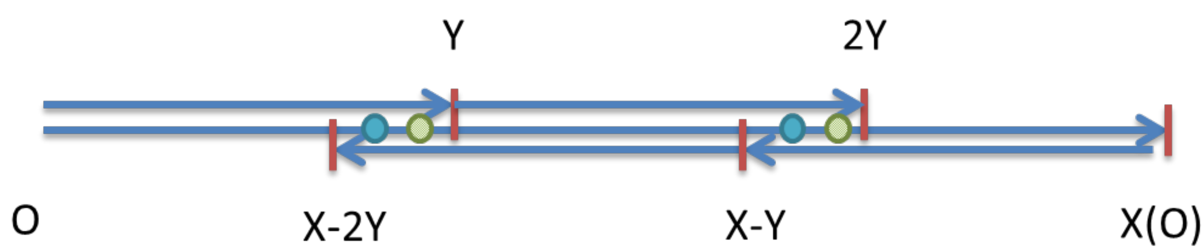


Figure 38. Diagram of candidate charging routes for BEV required at least two times fast charging.

5.2.5. Set Covering Problem

With the basis of the candidate charging routes and the approximate candidate locations, a set covering problem is formed. The objective is to choose the minimum set of the approximate candidate charging locations to cover all those candidate charging routes which have intersections with any of the approximate candidate charging locations. Binary integer programming functions in Matlab [99] and CPLEX [100] are used to solve this problem.

5.3. Results

5.3.1. Station Number and Allocation

Figure 39 is an overview of the optimized charging station allocation in California. By using aggregated exits as the approximate candidate charging locations, just 290 sites are required. Also, most locations are distributed in the most populated areas (i.e., greater Los Angeles, San Diego, San Francisco Bay area, and Sacramento). From the detailed map for the Los Angeles region in Figure 39, it is clear that most locations appear to be close to freeway intersections. This can be an intuitive result that those locations may have more candidate charging routes intersected than other locations. In order to verify the result, different sets of candidate charging locations is also used to perform the optimization in Chapter 6, including a set containing all the gasoline stations and shopping centers in California. Similar results are obtained having around 260 locations required and most stations sited in the populated areas.

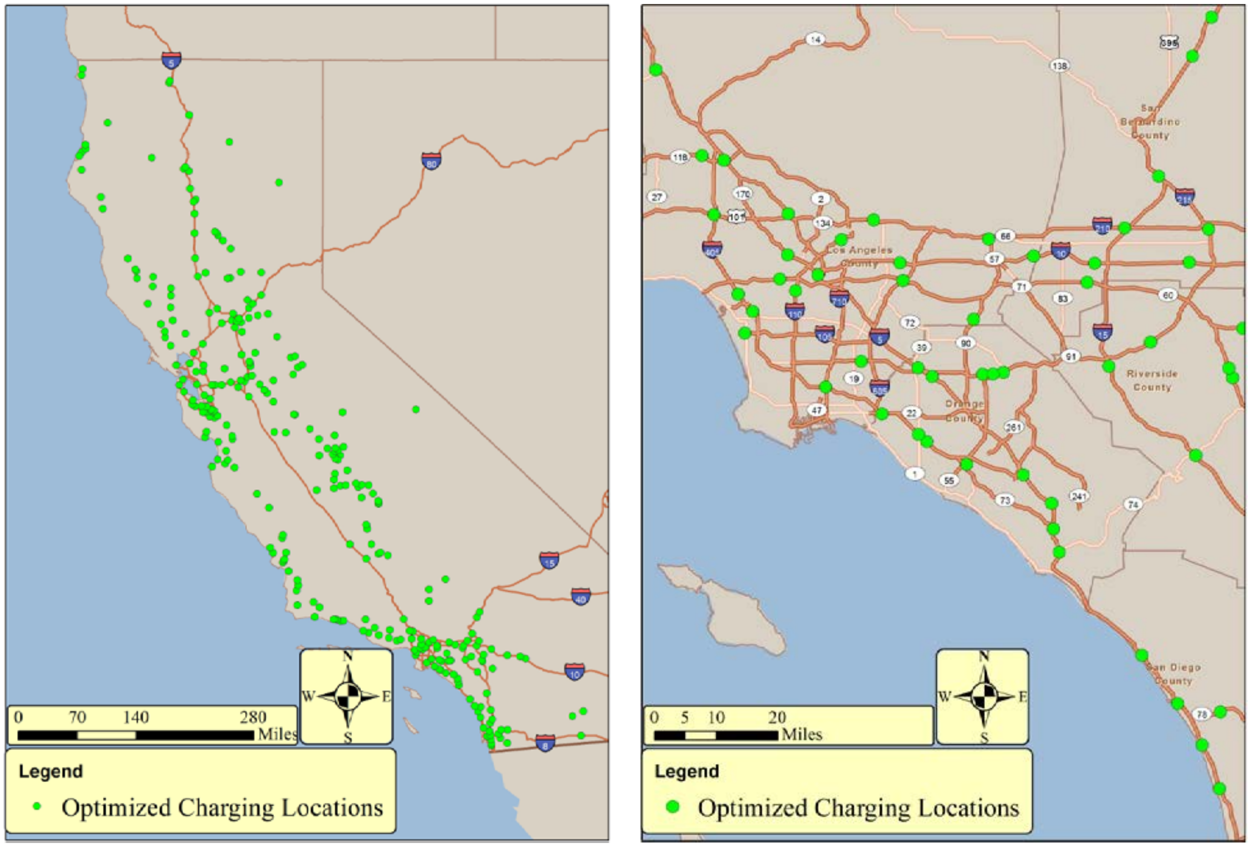


Figure 39. Optimized charging locations for California (left) and the Los Angeles region (right).

5.3.2. BEV Feasibility

Given the optimized charging location network of 290 sites within California, it is important to understand how many BEVs could fulfill daily travel needs. The corresponding BEV feasibility was defined in Chapter 4 to be the ratio of the number of BEVs that could meet daily operating behavior to the total number of vehicles [34]. A high feasibility ratio is therefore required for mass BEV adoption.

By design, all of the vehicle tours used in the optimization can be fulfilled by BEVs with one time fast charging, and all vehicles with daily tours less than 60 miles need no public charging. However, a portion of vehicles require more than one daily recharge (daily tour greater than 110 miles), which needs more investigation. Figure 40 shows the charging station locations along with one specific vehicle route with a length over 110 miles. Visual inspection indicates that the optimization method performed on one-time charging tours produced sufficient charging sites to meet the needs of this multiple-charging vehicle. Quantitative analysis using ArcGIS and Matlab confirms the visual analysis by breaking the route into segments shorter than Y (55) miles. The same analysis is performed for all the daily tours over 110 miles.

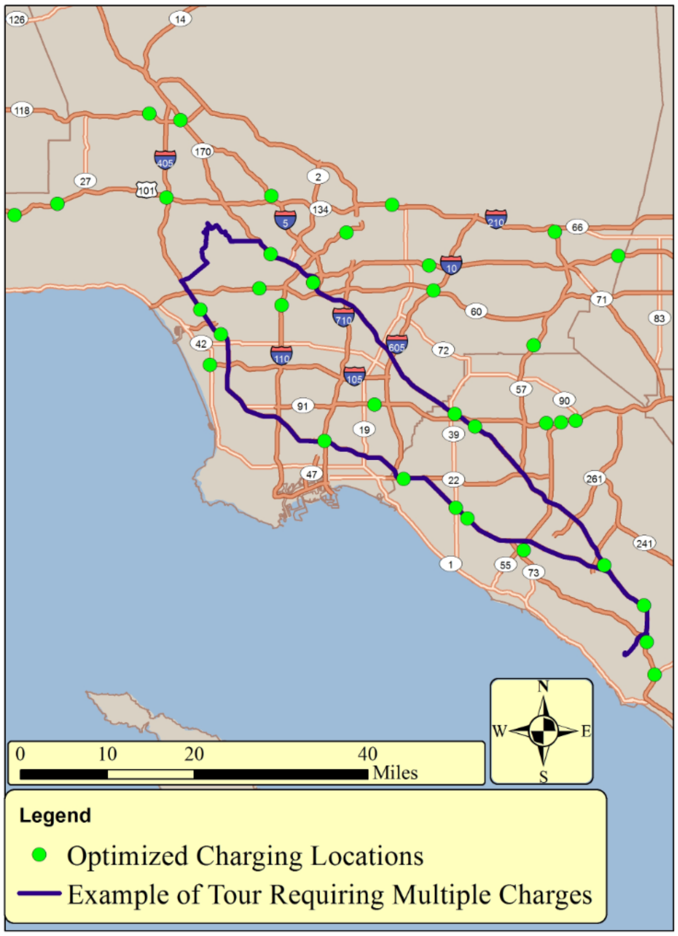


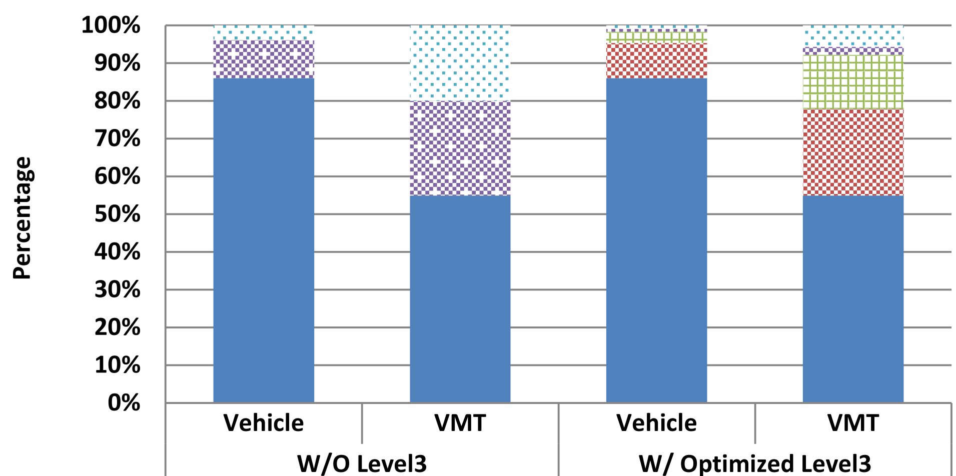
Figure 40. An example tour for a vehicle requiring multiple fast charging events.

Table 6 and Figure 41 show BEV and VMT feasibility. Eighty-six percent (13,499) of daily tours in the CHTS are shorter than 60 miles, so they are considered feasible routes. The optimized station network satisfies 93% of daily tours in the 60-110 mile range. The station network can also satisfy 75% of daily tours over 110 miles. Consequently, with just

290 charger locations, BEV feasibility is 88% and 98% for long distance driving and all driving, respectively. This is a stunning result compared to Chapter 4 on Level 2 charging infrastructure which showed BEV feasibility is 96% only when 3.3 kW Level 2 charging is available everywhere.

Table 6. BEV and VMT feasibility for different charging requirement categories.

	Total	No L3 Charging Required	Need L3	Need L3 once	Need more than once
Total # of Vehicles	15,703	13,499	2,204	1,584	620
BEV Feasible	15,434	13,499	1,935	1,467	466
Percentage	98%	100%	88%	93%	75%
Total VMT	498,692	273,842	224,849	124,856	99,993
BEV Feasible	458,653	273,842	184,810	113,480	71,330
Percentage	92%	100%	82%	91%	71%



	W/O Level3 Vehicle	W/O Level3 VMT	W/ Optimized Level3 Vehicle	W/ Optimized Level3 VMT
Infeasible (Charge More)	3.95%	20.05%	0.98%	5.75%
Infeasible (Charge Once)	10.09%	25.04%	0.75%	2.12%
Charge More	0.00%	0.00%	2.97%	14.30%
Charge Once	0.00%	0.00%	9.34%	22.91%
No Need	85.96%	54.91%	85.96%	54.91%

Figure 41. BEV and VMT feasibility with and without the optimized fast charging station network.

With regard to VMT feasibility, the impact of fast charging stations is different. For example, the VMT that can be fulfilled by 60 mile BEVs with no public charging is only 55%, which indicates that long distance driving accounts for significant VMT and fuel consumption. More specifically, the long distance tours which account for 14% of the total tours, contribute 45% of the total VMT or fuel consumption which is considered not feasible without the optimized station network. The optimized Level 3 charging station network increases the feasible VMT to 92% by capturing 91% VMT of the 60-110 mile tours and 71% VMT of the tours longer than 110 miles.

An increase of BEV feasibility to almost 100% will seemingly make BEVs more acceptable to consumers in terms of the range limit, and the increase of VMT feasibility to 92% would dramatically increase BEV benefits related to petroleum use reduction and tailpipe pollutant emissions.

5.3.3. Temporal Distribution of Charging Events

Even with a sufficient Level 3 charging station network installed, BEV drivers may have to choose between multiple stations along the candidate charging route. Table 7 shows the number of charging stations along the candidate charging routes derived from the 1,469 feasible vehicles having 60-110 mile tours as shown in Table 6. Approximately 58% of the BEVs have only one available station. The remaining 42% can select from multiple stations on their tours. The selection of charging sites will impact electricity consumption, as well as charging station capacity. Thus, five charging station selection strategies were evaluated: *random*, *as early as possible*, *as late as possible*, *as cheaply as possible*, and with a *reservation system*. For the first four strategies, BEV drivers would only consider the geographic information of the charging stations and predict the arrival time at each station along their charging routes. The drivers could then decide where to recharge their vehicles according to the criteria of each strategy. These four strategies represent methods similar to those used by drivers to select gasoline stations; the approach is simple for the driver and does not require communication with charging stations or any other vehicle. The fifth strategy (reservation system) provides BEV drivers the opportunity to reserve a charger for a time period at a specific station prior to arrival such that schedule conflict can be avoided. With ever-increasing "smart" electronic capabilities available in phones, cars, and other devices, the mechanics of such a reservation system are easy to imagine.

Table 7. Number of vehicles versus available stations on the candidate charging route.

Available Stations	Frequency (vehicle)	Cumulative %
1	848	57.81%
2	397	84.87%
3	176	96.86%
4	42	99.73%
5	3	99.93%
6-10	1	100.00%

Figure 42 shows the distribution of charging events over 24 hours for the *random* and *as late as possible* station selection strategies. The vehicle arrival time represents when vehicles enter a charging station. It is important to note that the model accounts for the delay of actual charging events due to limited station capacity. The estimated charging profile is determined by assuming that BEVs would be only *sufficiently* recharged (i.e., enough to finish the rest of the tour). This assumption stems from the likelihood that Level 3 charging will be significantly more expensive than home charging and will, therefore, persuade drivers to use Level 3 as little as possible. Additional assumptions are listed in Table 8.

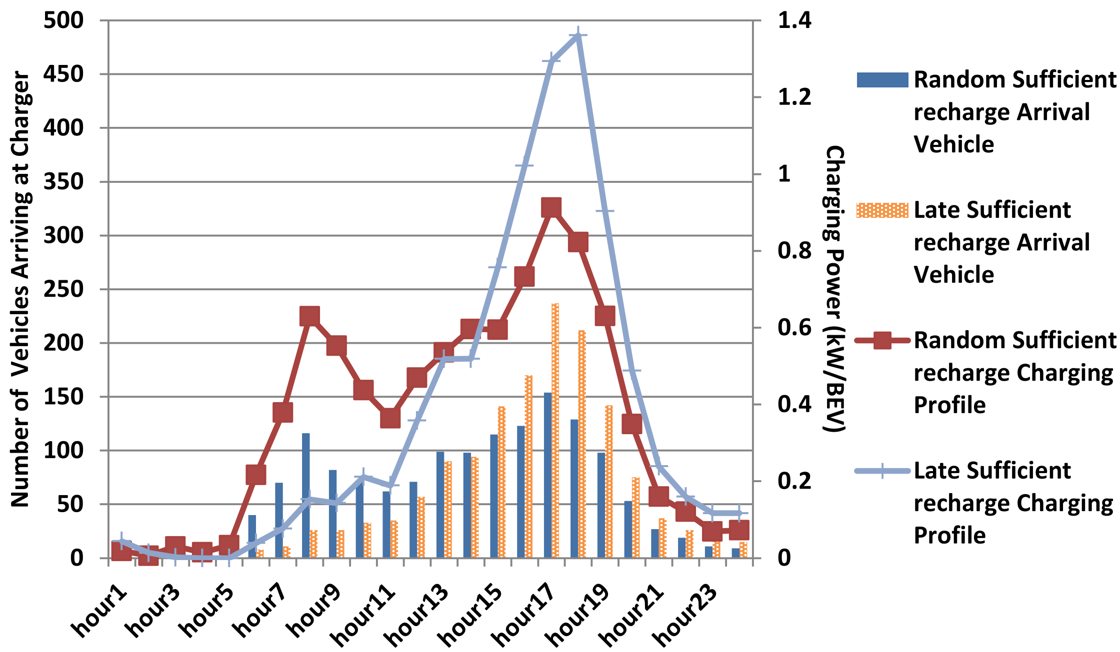


Figure 42. BEV arrival time and charging load distribution for random and late charging.

Table 8. BEV operating and charging parameters.

Electricity Consumption Rate (DC)	Charging Efficiency	Charging Rate	Station Selection	Charging Strategy
0.31 kWh/mi	0.85	2 miles / min	random, late, early, cheap, reserve	Sufficient recharge

The charging profile of the *random* charging station selection strategy shows peaks in the morning and afternoon. The afternoon peak is longer and slightly larger than the morning peak. Interestingly, this trend is nearly identical to the daily VMT distribution during weekdays [7]. Also, the peak charging demand time overlaps with typical diurnal electricity demand peaks. The consequences of this overlap with typical electric demand peaks would be increased peak electric load, higher time-of-use electricity costs, and increases in GHG and pollutant emission compared to other charging strategies [41].

The *as late as possible* station selection strategy requires no planning for the driver and has the potential to most extend the range of BEVs. However, from the grid perspective, the *as late as possible* strategy appears to be the worst case, as shown by the charging profile that exhibits a single large peak from 4pm to 7pm.

The *as early as possible* strategy results are shown in Figure 43. This strategy demonstrates a large peak at 8 am. Although this strategy shifted the BEV charging profile peak, substantial charging events occur during the day for the three scenarios examined thus far. This implies that different Level 3 charging strategies cannot substantially shift BEV elctrical loads from the day to the night.

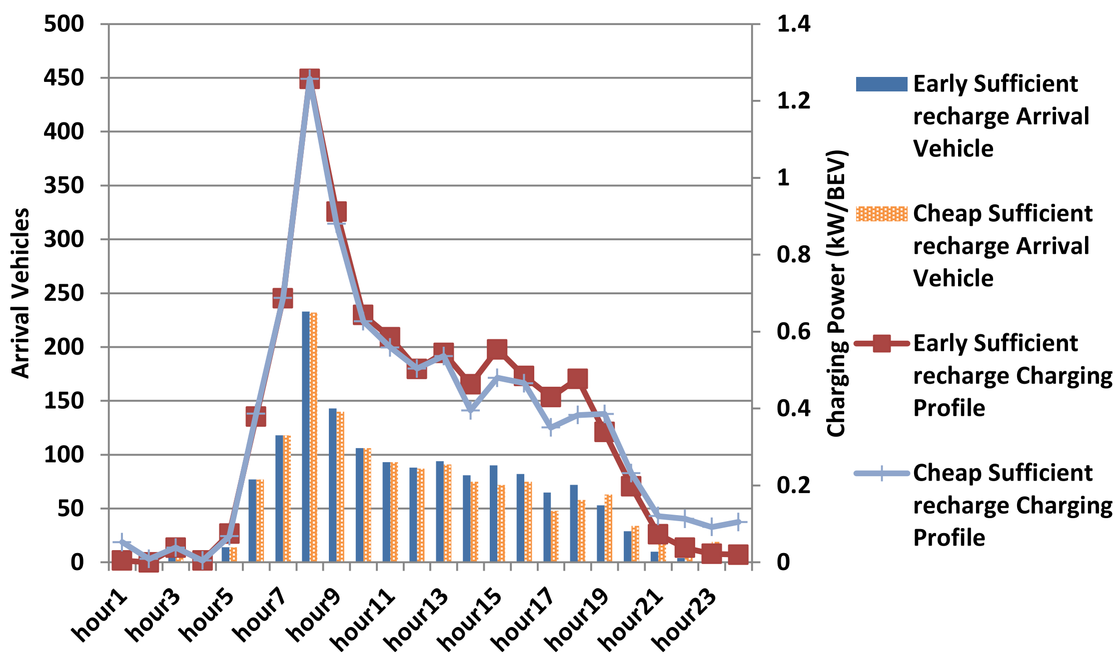


Figure 43. BEV arrival time and charging load distribution for early and cheap charging.

Interestingly, the *as cheaply as possible* strategy shown in Figure 43 is nearly identical to the *as early as possible* strategy. The electricity pricing for this strategy was based on the PG&E summer weekday PEV charging rates and previous work [34, 78]. The small differences when compared to the *as early as possible* strategy are the slightly reduced charging events in the late afternoon and the slightly increased charging events late at night.

The *reservation system* strategy shown in Figure 44 provides more evenly distributed charging events throughout the day. The *reservation* strategy has similar trends as the previous two strategies, however, the *reservation* strategy has a lower peak in the morning and more charging events in the afternoon.

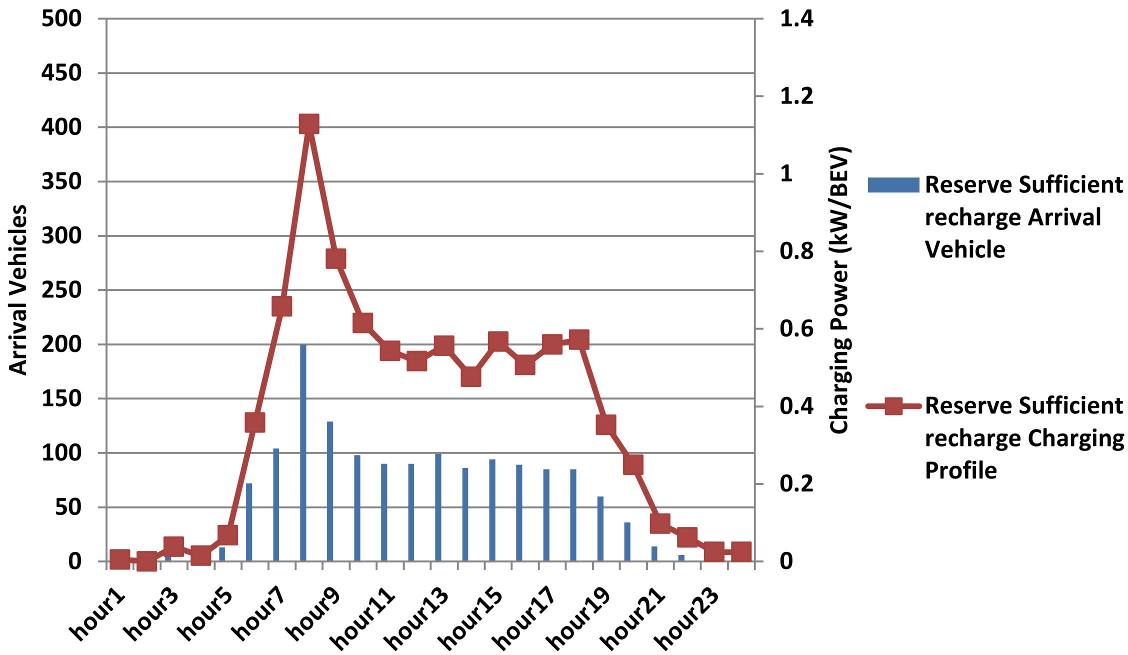


Figure 44. BEV arrival time and charging load distribution for reserve charging.

From these results, it can be summarized that: (1) most of the Level 3 charging events and charging load will occur in the daytime no matter what station selection strategies are used; (2) both random charging and late charging would increase the grid demand in the afternoon; (3) early, cheap and reserve strategies have similar trends with a short peak from 8am to 9am and would be preferred given current electricity demand profiles.

It should also be noted from these results that the owners of these charging stations will have electricity demand profiles that have large peaks regardless of the station selection strategy and will impact their cost of electricity that they pay to the electric utility. This will primarily occur because the charging peaks will incur higher demand charges on the station owner than if the charging profile was nearly flat. Electric utility rate structures are typically classified into energy and demand charges. Energy charges are those paid for each kWh used. Demand charges are collected in different ways, but a typical way is to charge the customer based on their peak demand in a month. Therefore, the higher the peak demand the higher the cost of electricity. This situation will be exacerbated for those owners that already have electric loads in addition to the newly installed Level 3 chargers. Additionally, since these peaks typically occur during the day, if the owner's station or property is on a time-of-use rate structure then the owner could experience even higher demand charges. This results from time-of-use demand charges being higher during peak load periods of the day. This issue warrants further investigation by policymakers to ensure that electric rate structures are not hindering fast charger deployment or cause fast charger stations to be abandoned after the cost of electricity becomes too high.

5.3.4. Wait Time and Station Usage

Charging event distribution, potential wait time capacity issues, and charging cost (energy charges only) have also been assessed. These factors have been estimated based on the five charging station selection strategies. It is assumed that the actual charging event will take a time proportional to the extended miles required to finish the whole tour. Also, if there is any schedule conflict, it is assumed that the next driver's charging event begins immediately when the previous one finishes, otherwise it begins upon arrival at the station incurring a zero wait time. The waiting events and wait times are calculated and accumulated at each station. The electricity cost is the product of the charging load and the PG&E summer weekday PEV charging rates for the given time of day when charging occurs [78]. The results shown here are for the 1,467 vehicle tours in Table 6 and analyze coverage versus capacity requirements for vehicle fueling infrastructure.

5.3.4.1. One Charger per Station

Table 9 shows the results for all the five scenarios with only one charger at each station. Comparisons are made from two perspectives: 1) the convenience and electricity cost for BEV drivers and 2) the benefit for station operators. It should be noted that the results for the *random* station selection strategy are different for each model run and the results here depict the average value for a total 10 runs.

Table 9. Wait time, wait event, electricity cost, and station operating status for different station selection strategies.

	Total Wait Time (minutes)	Total Wait Events	Average Wait Time for 1,467 Vehicles (minutes)	Average Wait Time for Wait Events (minutes)	Maximum Wait Events at any Station
Random	**1189**	**129.9**	**0.81**	**9.15**	**9.7**
Late	**2216**	**200**	**1.51**	**11.08**	**15**
Early	**1679**	**175**	**1.14**	**9.59**	**12**
Cheap	**1471**	**169**	**1.00**	**8.71**	**12**
Reserve	**313**	**46**	**0.21**	**6.81**	**3**

	Maximum Accumulated Wait Time at any Station (minutes)	Electricity Cost per Charge (dollar)	Average Charges / Station	Standard Deviation of Charging Distribution
Random	**184.28**	**1.75**	**5.06**	**0.91**
Late	**415.17**	**2.10**	**5.06**	**1.48**
Early	**150.54**	**1.38**	**5.06**	**1.27**
Cheap	**150.54**	**1.35**	**5.06**	**1.24**
Reserve	**47.49**	**1.45**	**5.06**	**0.47**

Wait events exist for all of the strategies with *late* charging having the most, followed by *early*, *cheap*, and *random* charging. A *reservation system* decreases the number of wait events from 200 to less than 50. A *reservation system* would also make the average wait time at least 70% shorter than any other scenario. Although the average wait times per vehicle are all below 1.5 minutes which appears very low and acceptable, the average wait time per wait event is always greater than 8.5 minutes for non-reservation charging. Consequently, if the wait events occur, drivers would have to spend a relatively long time waiting. The maximum accumulated wait time is the maximum of the accumulated wait times of all 290 stations. In the worst case, the maximum accumulated wait time is nearly 7 hours for the *late* charging strategy. For the other non-reservation charging strategies, the maximum wait time is around two and half hours, but the *reservation system* can decrease this value dramatically to less than 1 hour. The same trend can be seen for the maximum wait events. As for the electricity cost, results range from \$1.35 to \$2.10 per charge. The *cheap* charging strategy provides the lowest electricity cost, but is only slightly better than *early* charging and *reserve* charging.

From the perspective of the station owner or operator, all charging strategies result in 5 charging events per station on average since the total station and vehicle numbers are fixed. However, the *reserve* charging strategy provides a much lower standard deviation for the charging events because charging events are more evenly distributed at all the stations. Consequently, charger operators may prefer a *reservation system* strategy.

5.3.4.2. More Chargers to Decrease Wait Time

In order to better understand the inconvenience caused by the station capacity limitations, additional chargers are assigned within the model to the stations with the longest accumulated wait times. Therefore, the relationship can be seen between extra chargers, wait events, and wait time. Figure 45 shows the results for *cheap* and *reserve* station selection strategies, respectively. Just three to four additional chargers for the *cheap* charging strategy could bring the maximum accumulated wait time and number of wait events to the same level as the original *reserve* charging strategy. More chargers do little to further improve the results. As for the total wait time and total wait events, the *reserve* charging continuously shows a substantial improvement compared to *cheap* charging, regardless of additional charger installations. Consequently, the additional chargers for cheap charging might effectively mitigate the extreme conditions at specific stations, but the system-wide benefit is limited. Similar results were observed with the other non-reservation station selection strategies.

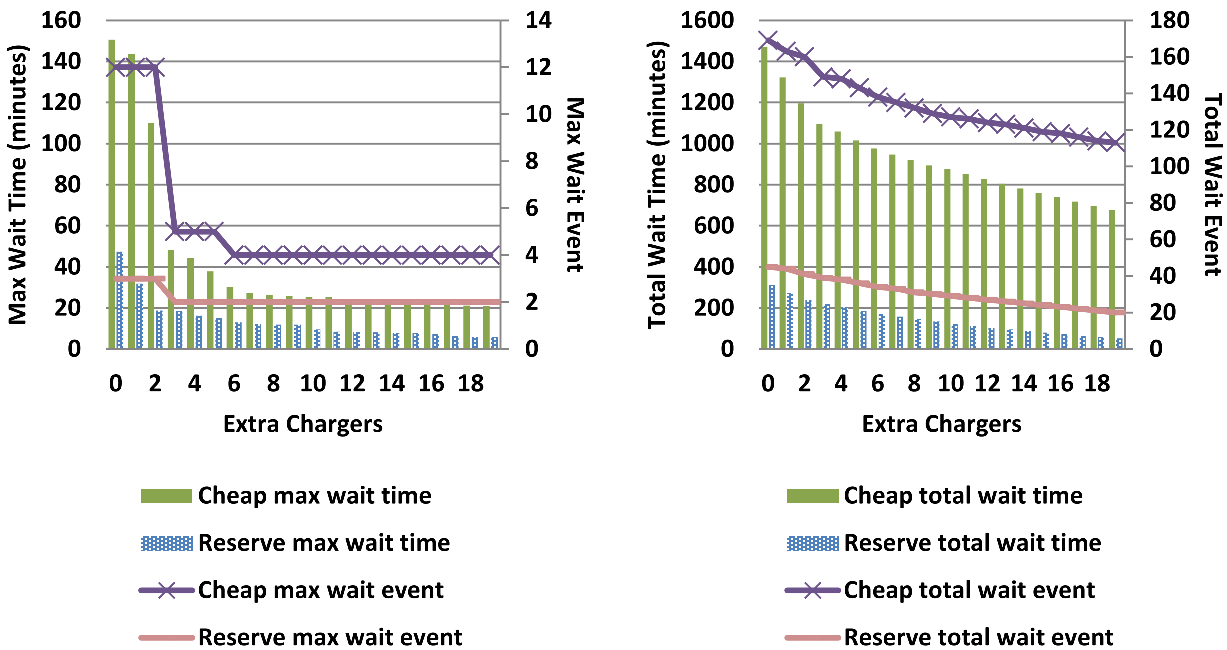


Figure 45. Extra chargers vs. maximum wait time and event (left), extra chargers vs. total wait time and event (right).

5.4. Discussion

The methodology and the optimal solution discussed in this chapter require that two main conditions be satisfied such that the analysis is accurate. The first condition involves candidate locations and the assumption that all land owners are willing to install chargers (i.e., the real candidate locations are not difficult to find). The second condition is that the optimization can be implemented at one time for a relatively large area. Existing policies and regulations obstruct using land for charging stations, which impacts satisfying the first condition. Some cities view the marking of stalls for EV charging as a loss of stalls.

Policy could be designed to encourage the conversion of parking stalls to EV charging stalls. Additionally, most cities' zoning codes do not address EV charging stations further complicating installations. Commercial and residential zoning codes should include language stating whether a charging station is allowed as well as some details on guidance for approval, so station planning can be more efficient. With regard to the second condition, multiple entities in the same area are always involved in station allocation. For instance, in southern California, utilities, automakers, governments and some fast charging oriented companies are all planning station installations, but may not communicate with each other. This gives rise to decisions based on inadequate information leading to redundant plans and/or waste. An agency such as the California Energy Commission could provide a platform where stakeholders can exchange information, and a third party, such as universities or other agencies, can provide un-biased information and optimized solutions. Better information effectively supports a better station network roll out.

The parameters for BEV range used in this study are conservative and provide a "worst case" scenario. Longer BEV range will result in a decreased need for charging stations, as shown in Chapter 6, but the optimized station allocations in this study will satisfy any longer range BEVs with at least the same BEV feasibility. The reason is that the candidate charging route generated by a shorter range BEV is also a portion of the longer range BEV candidate charging route. Future research can be focused on combinations of different BEV ranges and the corresponding requirements of the fast charging stations. It will be valuable to investigate more cost effective ways to deploy BEVs (e.g., shorter BEV range with more charging stations or longer BEV range with fewer charging stations).

The arrival times at the fast charging stations are estimated values because linear referencing is used assuming BEVs are driven at constant speeds for any specific trip. The wait times and waiting events are also estimated values because the actual charging time is generally non-linear and depends on the state of the vehicle battery. The time to setup the charging equipment should be much shorter compared to the real charging time, thus it is not considered in the model to accumulate extra charging time.

Compared to non-home Level 2 EVSE, the number of fast charging stations is significantly lower. Approximately 25 Level 2 EVSE (plus home charging at all residences) are required per 100 BEVs to achieve a 96% BEV feasibility, as described in Chapter 4. However, the quantity of Level 3 chargers required to achieve 98% BEV feasibility is just 2 chargers per 100 vehicles (plus home charging at all residences). Furthermore, it is less difficult to optimize the exact Level 3 station allocations compared to the statistical EVSE distributions at different location categories for Level 2 charging.

For a BEV with 60 mile range, the 98% BEV feasibility and the 92% VMT feasibility shown in the results imply the upper bound. It is also possible that drivers will switch back to conventional vehicles for long distance tours rather than use fast charging BEVs since it would require behavioral changes and upwards of 30 minute charging times. This is an especially important concern for those drivers needing more than one fast charge in a day. Technology to further increase the charging rate, and BEVs with longer range will mitigate this concern.

The methodology proposed in this study can be applied to other areas using travel pattern data other than CHTS as well as different BEV parameters. The model presented solves for approximate charging station allocation. The analysis can also be performed with existing or proposed Level 3 charging locations included in the network. In this case, the tours served by the existing or proposed charging locations will be ignored in the optimization. This would be highly advantageous for government agencies deploying many of the fast charging stations.

Although the CHTS includes data covering the whole state of California, actual BEV deployment will likely concentrate in certain areas. Consequently, the rollout plan for station allocation must consider real BEV deployment. Due to the limited data available, the amount of chargers required at each station to serve a specific number of BEVs in the future (e.g., 1 million BEVs) cannot be fully addressed. However, by scaling the current results, an upper bound can be established that not more than 1 Level 3 charger will be required per 50 vehicles.

5.5. Conclusions and Policy Implications

A model that optimizes Level 3 charging station allocation and the temporal utilization of charging stations has been developed and applied. The CHTS provides travel pattern data in California, and vehicle parameters are based on commercial BEVs. The candidate charging route was defined for vehicles that require one fast charge per daily tour, and aggregated freeway exits and highway intersections were used as approximate candidate charging locations. This formulated a classic set covering problem. In addition, several charging station selection strategies were investigated to understand the utilization of the charging stations. From the methodology, data, results, and discussion above, the following conclusions can be drawn:

1. By using around 3,000 aggregated freeway exits and highway intersections as the approximate candidate charging locations, 290 locations are determined to be the minimum number required to meet CHTS driver needs. This network is shown to provide good coverage with 98% BEV feasibility and 92% VMT feasibility. The near 100% BEV feasibility can facilitate BEV consumer acceptance by mitigating range anxiety, and the high VMT feasibility can lead to significant reductions in petroleum consumption and tailpipe emissions. Compared to non-home Level 2 EVSE, the Level 3 station allocation can be more precisely prescribed and provides a higher BEV feasibility. A maximum of two Level 3 chargers will be required per 100 BEVs to enable 98% of travels BEV feasible and to replace 92% of current petroleum miles travelled with electric miles travelled.
2. The temporal distribution of charging events and charging load profiles are evaluated with five charging station selection strategies. Most of the events and load will occur in the daytime regardless of strategy. Both *random* and *late* charging will increase the grid demand in the afternoon. The *early*, *cheap* and *reserve* strategies have similar trends of evenly distributed charging during the day with a short peak from 8 am to 9 am. These strategies are preferable since they do not contribute to the peak loads on the electric grid.
3. A *reservation* system can dramatically reduce the wait time and number of wait events as well as utilize all the stations more evenly. With only one charger per station the congestion and wait time at some locations would be unacceptable for the 1,467 drivers considered in this study. A *reservation* system or the installation of extra chargers would reduce congestion. More travel pattern data are required to

fully understand the required chargers at a specific station for a specific future BEV penetration.

4. Policies should be designed to encourage the conversion of parking stalls to EV charging stalls. Policymakers should encourage rate structures that support fast charging by altering or removing the demand charge for those customers with fast chargers installed. A state level government agency should provide a platform where stakeholders can exchange information so that a cost effective station network can be built. Fast charger operators should collaborate on implementing a *reservation* system.

Chapter 6. RECOMMENDATIONS FOR EVSE DEPLOYMENT

This chapter analyzes different types of PEVs and EVSE scenarios more comprehensively and provides recommendations on the deployment.

Based on task 1 (Chapter 4) and task 2 (Chapter 5), a large variety of scenarios can be assessed on feasibility, energy consumption, operating cost, and infrastructure requirement. For PHEVs, the all-electric range can vary from 10 miles to 40 miles with Level 1 1.44 kW and Level 2 3.3 kW, 6.6 kW charging. The charging location scenarios can be home charging only, home and work place charging and everywhere charging. For BEVs, the all-electric range varies from 45 miles to 200 miles with Level 1, Level 2 and Level 3 charging. The charging infrastructure requirements are approximated by satisfying as many travels as possible. More detailed analysis is conducted for Level 3 fast charging with different charging power, ranged from 25 kW to 120 kW. Level 3 charging is compared with Level 2 non-home charging in terms of BEV feasibility and the amount and the cost of infrastructure per BEV.

6.1. PHEVs

PHEVs have the same or longer ranges compared to the conventional vehicles or the hybrid electric vehicles. Additionally, fast refueling of the gasoline tank enables PHEVs to have the same function to travel long distance continuous as the CVs and HEVs. Thus, the feasibility of using PHEVs should not be lower than any CVs or HEVs and considered to be 100%. From the feasibility perspective, charging infrastructure is not necessarily required to make PHEVs better than other types of vehicles.

In Chapter 4, it is shown that PHEV16 and PHEV40 can reduce fuel consumption by 46% and 74% respectively, compared to the corresponding HEV by only charging at home with Level 1 charging at a maximum of 1.44 kW. The cold start criteria pollutant emission reductions are estimated to be 65% and 88%, respectively [13]. Increasing charging locations to anywhere at 1.44 kW can save more fuel (about 0.5 gallon/100miles) compared to only home charging. Increasing charging power to 6 kW at home, home and work related locations, and anywhere can benefit less than 5%, 10% and 20% on fuel reduction compared to 1.44 kW charging at these three locations [13]. Thus, having more charging locations and higher charging power can increase the fuel reduction rate. However, considering the limited fuel reduction benefit and the massive installation of infrastructure that would be required for high power, non-home charging locations, large batteries with home 1.44 kW charging show the potential for considerable fuel reduction with minimal infrastructure investment.

In Chapter 4, it is shown that immediate home charging results in an electricity demand peak from 6:00 pm to 9:00 pm, averaging less than 1 kW per vehicle. Increasing immediate home charging power from 1.44 kW to 7.2 kW would undesirably shift the peak hour closer to the existing grid peak [13]. Further, charging at non-home locations adds to the existing peak grid load during day time, between 9:00 am and 5:00 pm. Immediate, delayed, and average charging show similar results in this period. In Chapter 4, it is also shown that with non-home charging locations available, more charging power is required in the day time even considering the smart and optimal charging strategies. It is not likely to eliminate this drawback if more fuel reduction is required by increasing non-home charging events.

It is the advanced charging time strategies rather than more charging locations and higher charging power that dramatically reduce the operating cost for PHEVs. The benefit of higher charging power than Level 1 can only be effective with the right time strategy. Although the use of more non-home charging locations can further reduce the fuel reduction and operating cost for PHEVs, the activity distribution from smart charging and optimal charging indicate that more than 30% of charging will take place at non-home locations to garner a meager 1 dollar/100mile operating cost reduction.

Non-home charging locations and high charging power would not increase the feasibility of PHEVs, would have very limited benefit for more fuel reduction and operating cost reduction, would increase the power demand during the day time and would require a large individual and public investment on charging infrastructure. Consequently, it is recommended that Level 1 home charging with smart or optimal charging strategy is a cost-effective infrastructure solution for PHEVs in the state of California.

6.2. BEVs

As introduced in Chapter 4 and Chapter 5, the EVSE is crucial to BEV deployment, which determines the BEV feasibility, the VMT feasibility, i.e., the electric miles travelled or the fuel reduction rate, and also the operating cost. There is tradeoff between EVSE and the BEV range. Longer range leads to higher feasibility but higher initial cost on the vehicle while reduce the EVSE. This section is aimed to evaluate all the possible BEV and EVSE scenarios and provide a recommendation on what relatively favorable scenarios should be.

6.2.1. Model Parameters

6.2.1.1. Vehicle and EVSE

In Chapter 5, a worst case scenario is investigated by assuming 60 miles range for BEVs. In pursuant to the objective of this section, several different BEVs are incorporated. Below in Table 10 are the characteristics of those BEVs from 60 to 200 miles provided by Honda R&D. To have a longer range, a BEV has to have larger battery onboard. Consequently, the energy consumption per unit length is increased. The maximum charging rate for the battery is determined by the C rate, here 2C is used. So the shortest time to fully charge a BEV will be the same with different all-electric ranges, assuming sufficient power can be supplied.

Table 10. BEV specifications from Honda R&D America.

	kWh/100miles City	kWh/100miles HWY	kWh/100miles	Battery Size kWh	Max Charge Rate kW
BEV60	**26**	**33**	**29**	**17**	**35**
BEV80	**26**	**33**	**29**	**23**	**46**
BEV100	**26**	**33**	**29**	**30**	**60**
BEV125	**29**	**33**	**31**	**40**	**80**
BEV150	**32**	**34**	**33**	**50**	**100**
BEV175	**34**	**34**	**34**	**60**	**120**
BEV200	**36**	**35**	**35**	**70**	**140**

The Level 1 and Level 2 charging utilize an onboard converter, for converting AC current to DC current. The EVSE for Level 1 and Level 2 charging has the function to provide power, safety and communication. Depending on the EVSE and the onboard converter, the charging power can range from 1.44 kW to 19.2 kW. Table 11 shows the power of Level 1 and Level 2 charging. The real charging rate is also determined by the battery capacity. From Table 10, it can be seen that any charging power listed in Table 11 does not exceed the maximum power acceptable by the battery. Thus, battery capacity does not have limit on charging power for Level 1 and Level 2 charging.

Table 11. Level 1 and Level 2 charging power.

Charging Power (kW)	1.44	1.92	3.3	6.6	9.6	19.2

The Level 3 DC fast charging utilizes an off board EVSE, a charging station, for converting AC current to DC current. Depending on the types of the EVSE, the output power can range from 25 kW to 120 kW. Table 12 shows the power output of the DC fast charging stations provided by Honda R&D. The real charging rate is determined by both the EVSE power and the battery capacity. In this dissertation, it is assumed that battery is able to take 2C charging rate all the time. Thus, if EVSE power is smaller than the 2C charging rate, the real charging rate is equal to the EVSE power.

Table 12. Level 3 EVSE output power.

Level 3 EVSE Power (kW)	25	36	50	90	120

6.2.1.2. NHTS and CHTS

The 2009 NHTS are used to evaluate the Level 1 and Level 2 EVSE, which are exactly the same as described in section 2.1.1. The 2000 CHTS are used to evaluate the Level 3 DC fast charging EVSE. It is the same as described in section 5.2.1, except for accounting for the usage of toll road. Table 13 classifies the routes by daily VMT and indicates the number of vehicles in the CHTS falling within each category. In this chapter, all BEVs are assumed to have 60 miles or more all-electric range, so only the routes with daily VMT greater than 60 miles will be utilized in the location optimization, which accounts for 15% of all the daily routes.

Table 13. Daily VMT distribution of the CHTS.

	No Fast Charging	Need Fast Charging	Total
Daily tour VMT	**<= 60 miles**	**> 60 miles**	
Number of instances in CHTS	**13631**	**2469**	**16100**

6.2.1.3. Level 3 Candidate Charging Locations

In Chapter 5, freeway exits and highway intersections are selected to be the approximated candidate charging locations. In this chapter, the actual locations, including the gasoline stations, the shopping centers and the Target shops serve as the candidate locations for the fast charging stations. They are derived from the DOE data base, the USGS data base and the Target website. Table 14 is a summary of those candidate locations.

Table 14. Number of candidate charging locations.

Gas Station	Shopping Center	Target Shop	Total (aggregated locations)
9816	**2292**	**250**	**12358**

Figure 46 shows all the candidate locations in the state of California. The shopping centers are located in the populated areas while the gasoline stations are more evenly spread out the entire state. Compared to freeway exits and highway intersections, the new candidate location set appears to provide a more comprehensive coverage and is expected to reduce the minimum number of stations for the set covering problem.

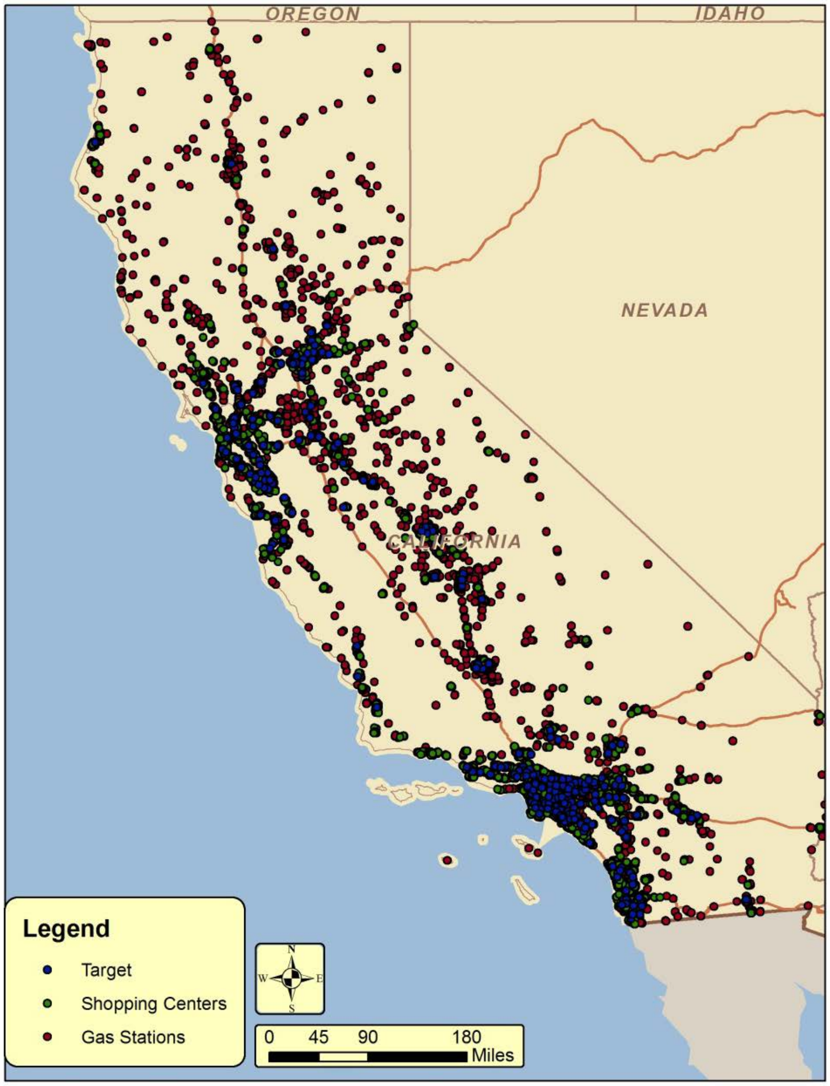


Figure 46. Candidate locations for Level 3 DC fast charging stations.

6.2.2. Level 1 and Level 2 EVSE Results

In this section, BEV feasibility, fuel reduction, EVSE distribution and cost per BEV are investigated regarding different all-electric ranges for battery electric vehicles.

6.2.2.1. BEV and VMT Feasibility

BEVs with ranges from 60 miles to 200 miles are shown in Figure 47, for scenarios with Level 1 (1.44 and 1.92 kW) and Level 2 (3.3 – 19.2 kW) infrastructure located at all dwelling locations. The results demonstrate the maximum feasibility with only the limits imposed by the all-electric range and charging power; by assuming EVSE is located at all dwelling locations, the results remove the issue of charger availability. As a baseline, the BEV feasibility and VMT feasibility with charging locations limited only to home is shown by the green line and purple line.

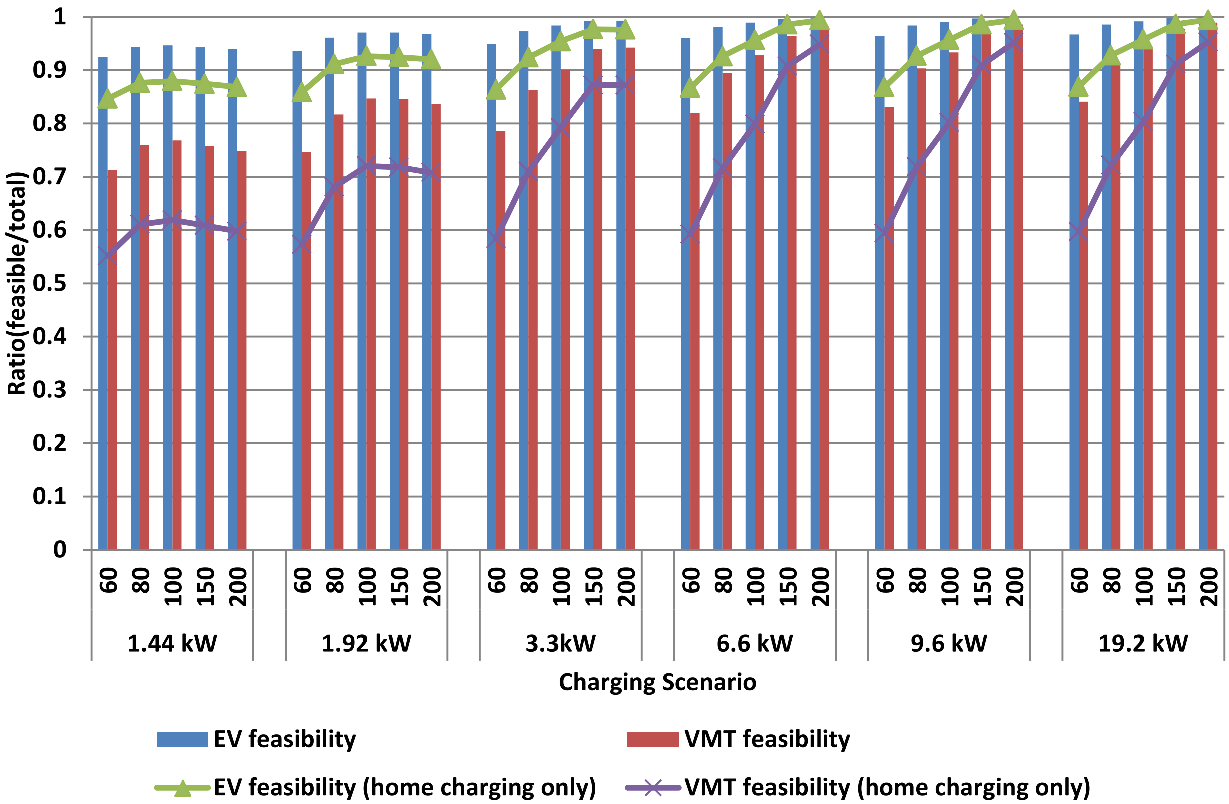


Figure 47. EV feasibility and VMT feasibility for different ranges of BEVs with different charging scenarios.

For Level 1 1.44 kW charging, feasibility increases with vehicle range from 60 miles to 80 miles, but becomes saturated even decreases beyond 80 mile range. The highest BEV feasibility is around 95%. The reason for this pattern is with such a low power for charging, long distance ranged BEV cannot get enough charge during the dwelling time, especially overnight at home. Also, the energy consumed per mile is increasing with increased ranges (heavier vehicle body), requiring more charging time compared to BEVs with shorter all-electric ranges. Level 1 1.92 kW charging exhibits the same trend compared to 1.44 kW with a little higher peak feasibility, which is around 97%. The 33% charging power increase from 1.44 to 1.92 kW can enable some extra users to fully charge their BEV after the night.

Level 2 charging (3.3 – 19.2 kW) exhibits continuously increased feasibility for BEVs with longer ranges. These results indicate the importance of higher power charging for BEVs, in particular for BEVs with longer range capability. Either larger capacity batteries or higher power charging is necessary to increase feasibility. However, the impact of charging power is diminished significantly when the power is beyond 6.6 kW, even not observable. It is also interesting that although longer ranges can continuously increase the feasibility for Level 2 charging, the same increasing trend of feasibility can only sustain to BEVs with 150 miles. From 150 to 200 miles, the slop of feasibility becomes more flattened.

The above analysis is based on the scenarios with unlimited EVSE access. In Figure 47, the results are also shown when charging is only available at home. The same trends can be observed for all scenarios compared to unlimited EVSE case, only having lower BEV feasibility and VMT feasibility. From 1.44 kW, 1.92 kW Level 1 charging to 3.3 kW Level 2 charging, the power impact on increasing feasibility is significant. BEVs with longer ranges need high power EVSE to satisfy more travel demands. However, above 3.3 kW, especially over 6.6 kW, the feasibility almost maintains the same for the BEVs with the same all-electric range. Thus, under the current condition that non-home charging EVSE is not sufficient, the EVSE with power higher than 6.6 kW does not have extra benefit. This is the same finding observed before in the unlimited EVSE cases. Moreover, high power charging at home may cause transformer overloading, power losses increasing and other issues associated with the distribution circuits. The charging power impact on the distribution transformer is investigated in Chapter 8.

Figure 48 provides results of charging cost and infrastructure requirements, defined to be the ratio of charging events to the total dwelling events. For instance, all scenarios point out that all vehicles would charge at home, so the charging events at home equal the total dwelling events at home. Contrarily, even if Level 1 1.44 kW EVSE were located at all workplaces, a scenario with 60 mile BEVs would only utilize 40% of those chargers. The optimization leads to a 100% home charging requirement, which is an intuitive conclusion since home is the location where vehicles have the longest dwelling time and the period coincides with low charging cost and low electricity demand. As for work place and public charging locations, Level 1 1.92 kW charging and all Level 2 charging show a significant potential for reducing the infrastructure requirements. With Level 1 1.92 kW and Level 2 3.3 kW charging and 60 mile ranged BEVs, work place charging decreases from 40% to 30% and 23% while public location charging drops from 17% to 9% and 8%.

Similarly like the feasibility graph, for 1.44 and 1.92 kW Level 1 charging, increased ranges cannot have impact to reduce the amount of EVSE at non-home locations. When the 3.3 kW and 6.6 kW Level 2 EVES is selected, especially 6.6 kW, the impact of long ranged BEV can be observed. However, beyond 6.6 kW, power is not very sensitive to the results. Also very similar like the feasibility graph, when the all-electric range is beyond 150 miles, it will not reduce the EVSE at non-home locations. The charging cost tends to be fairly constant with different BEV ranges, but a 10% reduction can be achieved by upgrading from Level 1 to Level 2 infrastructure, which is the same as observed in section 4.3.2.1. It needs to be noted that the TOU price for EV charging used in this chapter is different than the one in Chapter 4. They are both from PG&E but released in different years. The TOU price in this section is an updated one and is higher than before for all three levels, i.e., peak, partial peak, and non-peak time. That is why all the operating costs are higher than the previous results in Chapter 4.

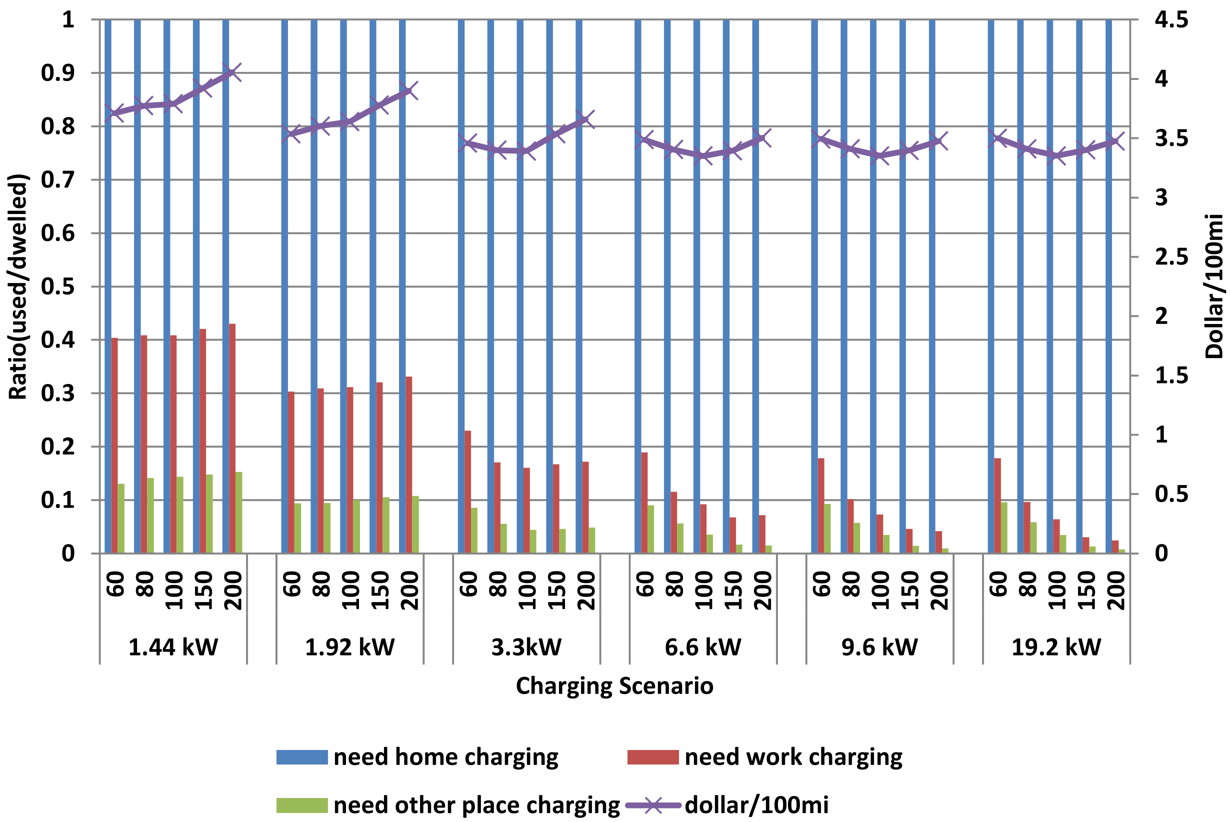


Figure 48. Infrastructure requirements for different BEV ranges and charging power options.

6.2.2.2. EVSE Allocation

In Chapter 4, a methodology is proposed to approximate the number of EVSE at different location categories and results are showed based on BEV60 with 3.3 kW Level 2 charging. In this section, the EVSE is approximated for all different all-electric ranges with charging power from 1.44 kW to 19.2 kW.

With the EVSE distribution for the ten location categories and the total BEV population, the exact number of EVSE can be shown. The cumulative PEV sales in California reached 60,000 in December 2013 and around half belongs to BEV sales. Assuming the same trend of sales, around 15,000 per year, the cumulative BEV sales can reach up to 100,000 by 2020. Figure 49 shows the number of EVSE for 100,000 BEVs. The same as the Figure 48 for the infrastructure requirements, the number of EVSE decreases with higher charging power and longer BEV range. Exception occurs only at 1.44 kW and 1.92 kW charging, where longer BEV range increases the amount of EVSE. The reason is the same as before that BEV with longer range consumes more energy per mile only to require more time for charging. The dwelling time at home is not sufficient at such a low power to charge some of the BEVs. Thus, extra charging opportunities are required at work and other locations.

As discussed before, Level 1 charging exhibits limitation on increasing BEV feasibility and the amount EVSE required is very large, which can be observed in Figure 49 as well. More than 40,000 EVSE needs to be installed at non-home locations for 1.44 kW charging and the number is as high as 30,000 for 1.92 kW charging. For Level 2 charging, EVSE at non-home locations are all below 20,000 except for the case of BEV60. For BEV60 with Level 2 charging, the non-home EVSE is around 25,000, consistently with different charging power. 60 miles for a BEV appears the shortest range that automakers will deploy, so 25 EVSE per 100 BEVs should be an upper bound for non-home locations when the BEV population reaches a certain level. When BEV population is relatively small, the EVSE at non-home locations might be more than what has been shown. The analysis is conducted in the following.

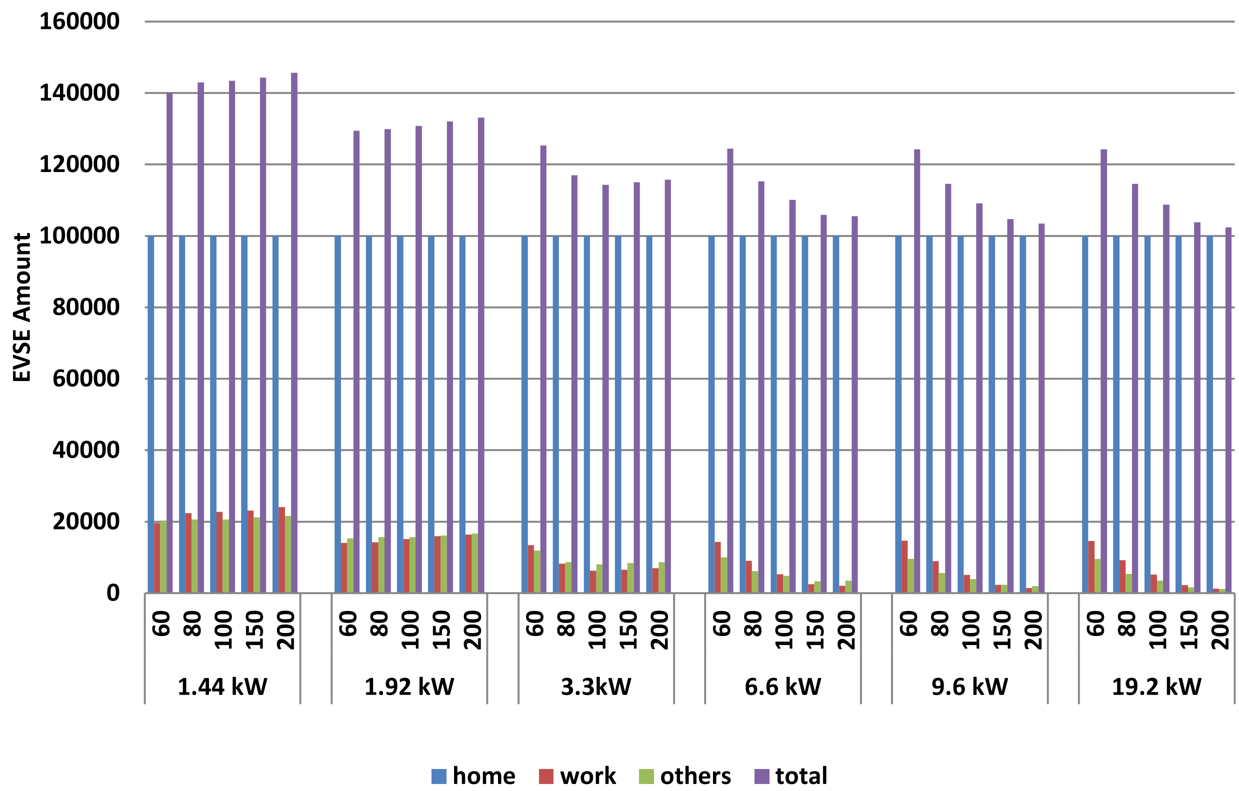


Figure 49. EVSE amount at home, work, other locations and total number for 100,000 BEV.

Figure 50 shows the detailed EVSE distribution with 100,000 BEVs assuming 60 miles range and 6.6 kW charging power. As discussed before, with such a small amount of total BEV population, some location categories require very few EVSE. In Figure 50, three of the ten categories require no more than one thousand EVSE. It needs to be noted that the results apply for the entire state of California. Thus, it becomes very difficult to allocate such a small amount of EVSE accurately to a large candidate sets.

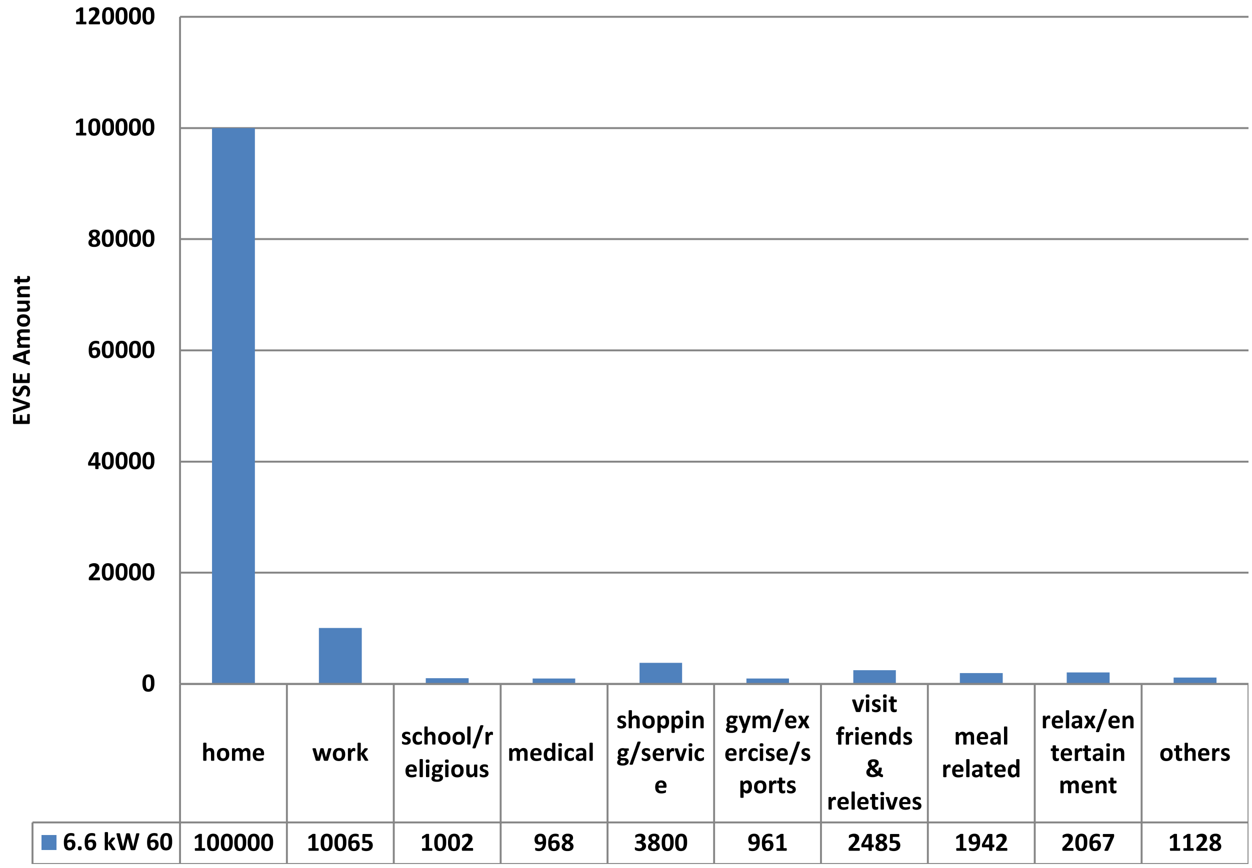


Figure 50. Amount of EVSE at the ten location categories for 100,000 BEV100 with 6.6 kW charging.

Figure 51 shows the results for the 100 miles case. Compared to BEV60, The non-home EVSE shrinks to only half of the quantity, which makes the same problem more obvious as discussed before. For instance, it is around 1,000 EVSE required at shopping and service locations while the number of the large shopping centers is already higher than 2,000 in the entire state.

Based on the results and analysis, it is likely that more EVSE might be required than shown at non-home locations for the short term since the volume of BEVs is still relatively small. For example, 100,000 BEVs is less than 0.5% penetration compared to the whole light duty vehicle fleet in California [7]. However, the methodology and results exhibited in this work can still be utilized to distribute a given funding for EVSE at different location categories.

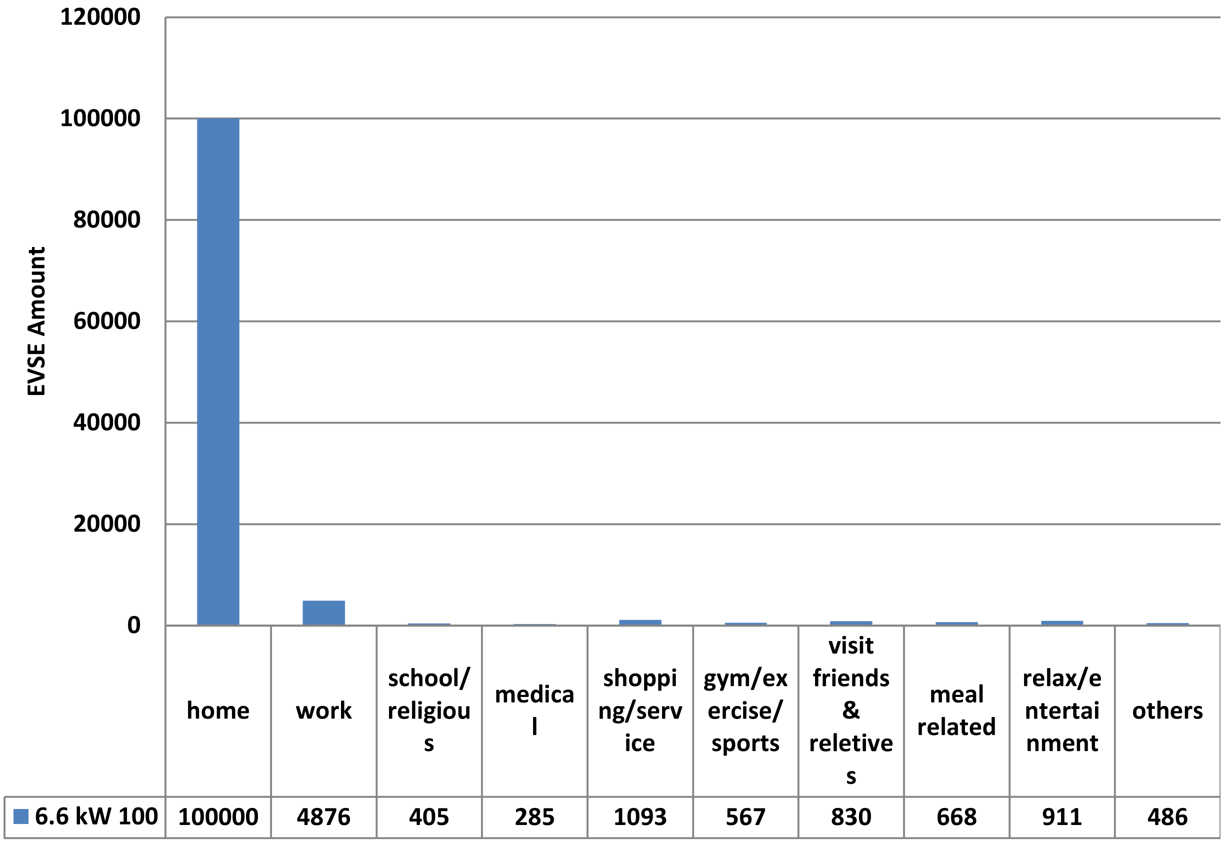


Figure 51. Amount of EVSE at the ten location categories for 100,000 BEV100 with 6.6 kW charging.

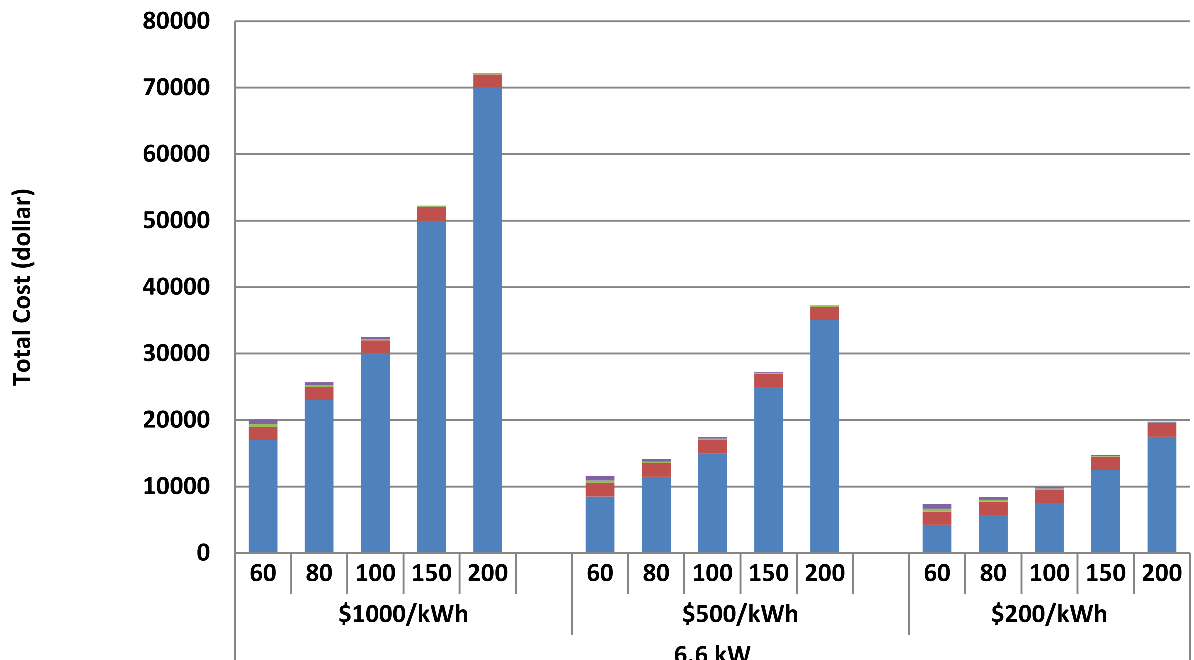
6.2.2.3. Battery Cost and EVSE Cost

This section evaluates the cost associated with battery and the EVSE, aiming to provide a general idea on the distribution of non-operating cost per BEV. Table 15 shows the cost assumption of EVSE at different locations with 6.6 kW charging capability [10].

Table 15. Assumption of EVSE cost at different locations.

	Home EVSE Cost ($)	Work EVSE Cost ($)	Other EVSE Cost ($)
6.6 kW	2000	4000	5000

Figure 52 shows the accumulated cost per BEV ranged from 60 miles to 200 miles. Three battery costs are evaluated, including \$1000/kWh, \$500/kWh and \$200/kWh. For the first two battery cases, the batteries completely dominate the total costs. For the \$200/kWh case, EVSE constitutes a more important part, in particular for the range less than 100 miles. However, with such a low cost on battery, more ranges will be expected for BEVs. Moreover, components other than battery on the BEV also contribute the total vehicle cost. Thus, EVSE cost should be a relatively small portion of the non-operating cost for BEVs.



	\$1000/kWh					\$500/kWh					\$200/kWh				
	60	80	100	150	200	60	80	100	150	200	60	80	100	150	200
Other EVSE Cost	718	454	262	126	102	718	454	262	126	102	718	454	262	126	102
Work EVSE Cost	403	248	195	134	140	403	248	195	134	140	403	248	195	134	140
Home EVSE Cost	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Battery Cost	1700	2300	3000	5000	7000	8500	1150	1500	2500	3500	4250	5750	7500	1250	1750

Figure 52. Cost estimation of battery and Level 2 EVSE per BEV.

The EVSE at work places and other locations are considered more than twice as costly as those at home per unit. However, cost distribution per BEV clearly shows that

EVSE at home is the dominant portion and its share increases with the increased BEV range. Although the cost of the non-home EVSE is the minimal part in this per-BEV cost analysis, those locations, in particular the public location, are relatively difficult to be funded. It has been only the state government that invests in this area. More parties and more forms of investment are suggested in the future.

6.2.2.4. Summary

From the results and analysis above, summary can be made below:

1. 25 Level 2 EVSE per 100 BEVs at non-home locations is considered an upper bound.
2. It is difficult to allocate Level 1 and Level 2 EVSE at non-home locations when the volume of BEV is low.
3. Currently, battery cost is significantly higher than the EVSE cost on a per-BEV basis. Public EVSE requires small amount of investment but needs to have a clear funding source.

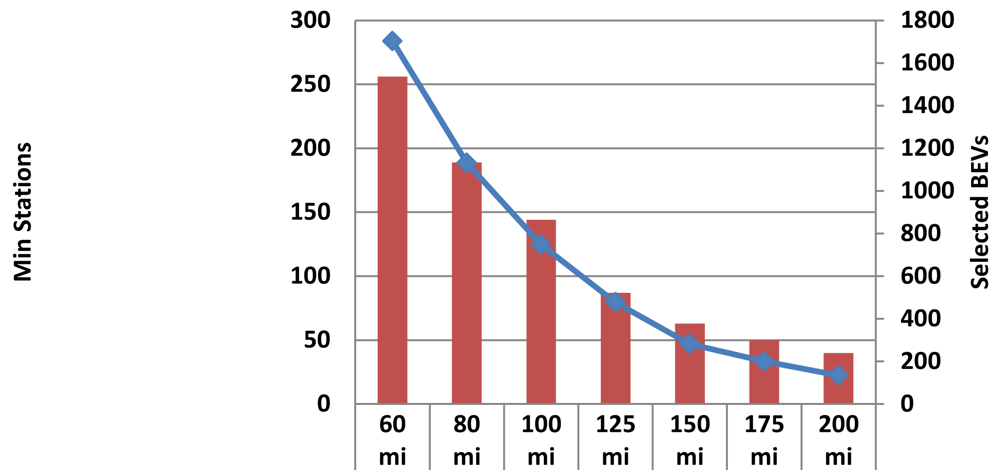
6.2.3. Level 3 EVSE Results

In this section, optimized Level 3 DC fast charging locations, BEV feasibility, fuel reduction rate, charging time, extra waiting time and cost of EVSE per BEV are investigated regarding different all-electric ranges and fast charging power.

6.2.3.1. Optimized Locations

The optimization formulated in Chapter 5 is to find the minimum number of charging stations and the corresponding locations to serve as many charging events as possible. Thus, only the BEV range has impact on the result, which determines which vehicle routes in CHTS are used in the optimization and what portion of a specific route is considered to be the candidate charging route.

In Figure 53, the number of vehicle routes selected from CHTS and the minimal number of required fast charging stations is shown based on seven different BEV ranges. Longer range leads to fewer BEVs requiring fast charging and fewer stations. From BEV60 to BEV200, the minimal number of stations decreases from 256 to 40.



	60 mi	80 mi	100 mi	125 mi	150 mi	175 mi	200 mi
Min Number of Stations	256	189	144	87	63	50	40
Number of Vehicle Routes Selected	1702	1131	748	477	282	200	135

BEV Ranges

Figure 53. Number of vehicle routes selected in CHTS and minimal number of stations for different BEV ranges.

Figure 54 shows the layout of the optimized station network for BEV60. A total number of 256 locations are required to cover the most candidate routes. Compared to the results in Chapter 5, the number of stations is decreased by around 10% from 290. One reason is that the new candidate location set provides a more comprehensive coverage than the old one, which is the set of freeway exits and major highway intersections. Another reason is the way to calculate candidate charging routes is improved. In this chapter, the shortest length of a candidate charging route is 10 miles while this is not required in Chapter 5. If the candidate charging route is too short, it is likely that only one candidate station is available, which might not serve other candidate charging routes. Thus, more locations can be required.

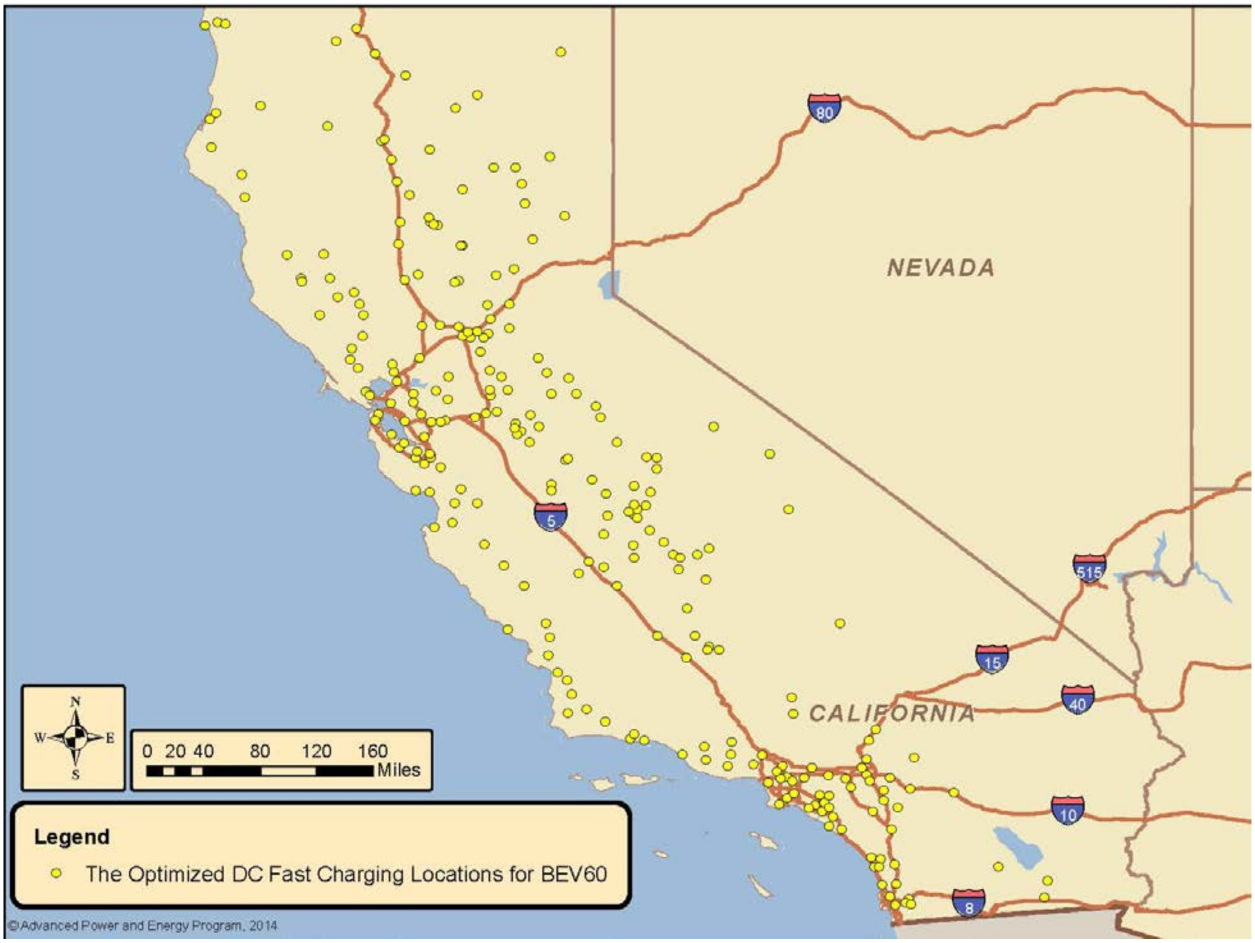


Figure 54. Optimized charging stations for BEV60.

Figure 55 is the spacial distribution of the optimized stations for BEV80. It appears very simliar like the one for BEV60 with fewer stations concentrated everywhere. An interesting finding is along the I-5 from southern California to the Bay Area, there are fewer stations than the US-110 and US-99. The first reason for that is there are more travel activities along the 110 and 99 highway. So there are more candidate charging routes which have to be covered. The second reason is for the I-5, most travel length is beyound the capability of BEVs with 80 miles range. Since the model assumes that one fast charging in a day is typical, those long distance travel (longer than 170 miles in one day) will be ignored.

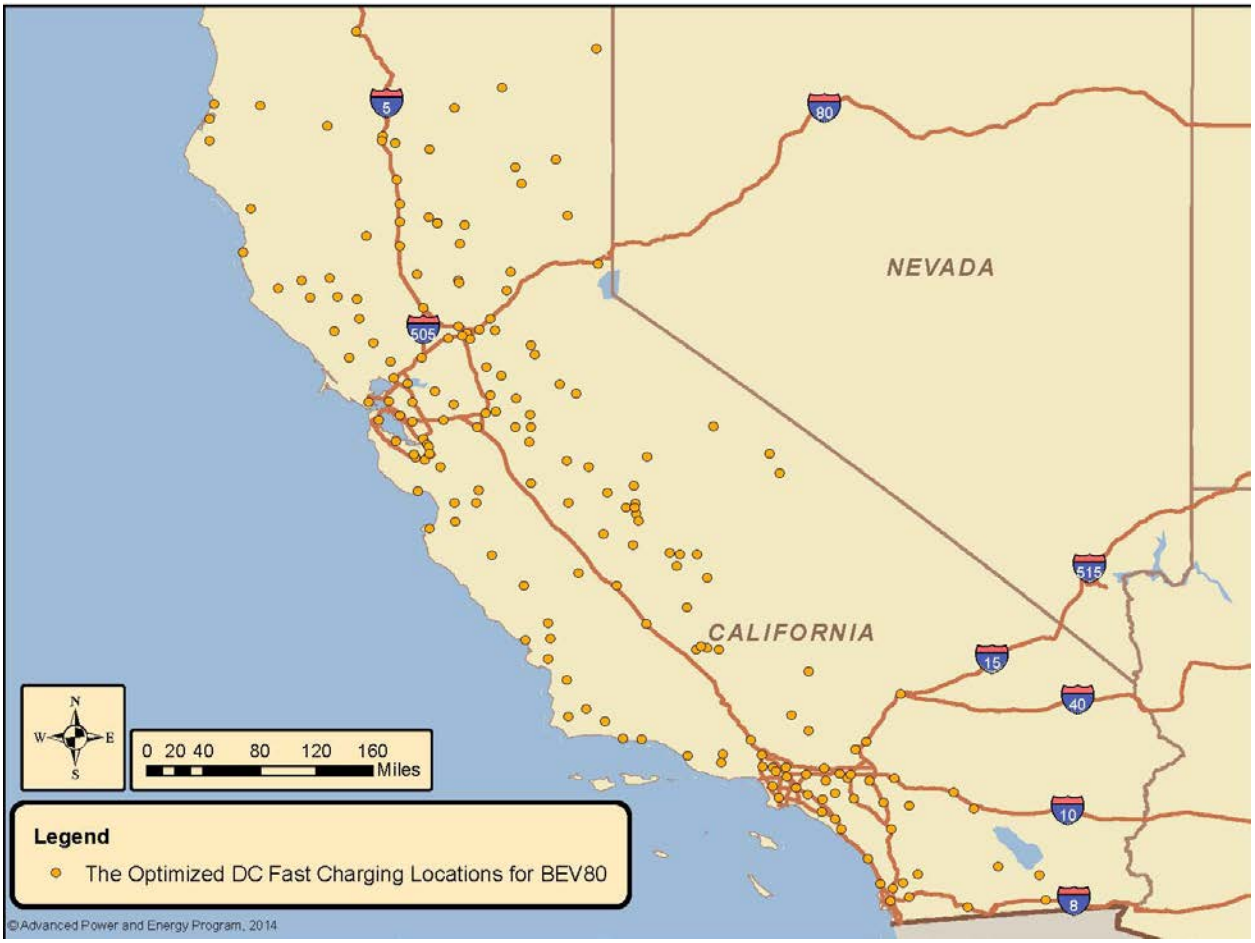


Figure 55. Optimized charging stations for BEV80.

The optimization result indicates that the minimum number of the stations is 144 for BEV100 and Figure 56 shows the layout of this optimized station network. With 40 miles increment on the range of the BEVs from 60 miles, the required stations are reduced by almost 50%. Although not using the freeway exits as the candidate locations, most optimized stations are along the freeways and major highways.

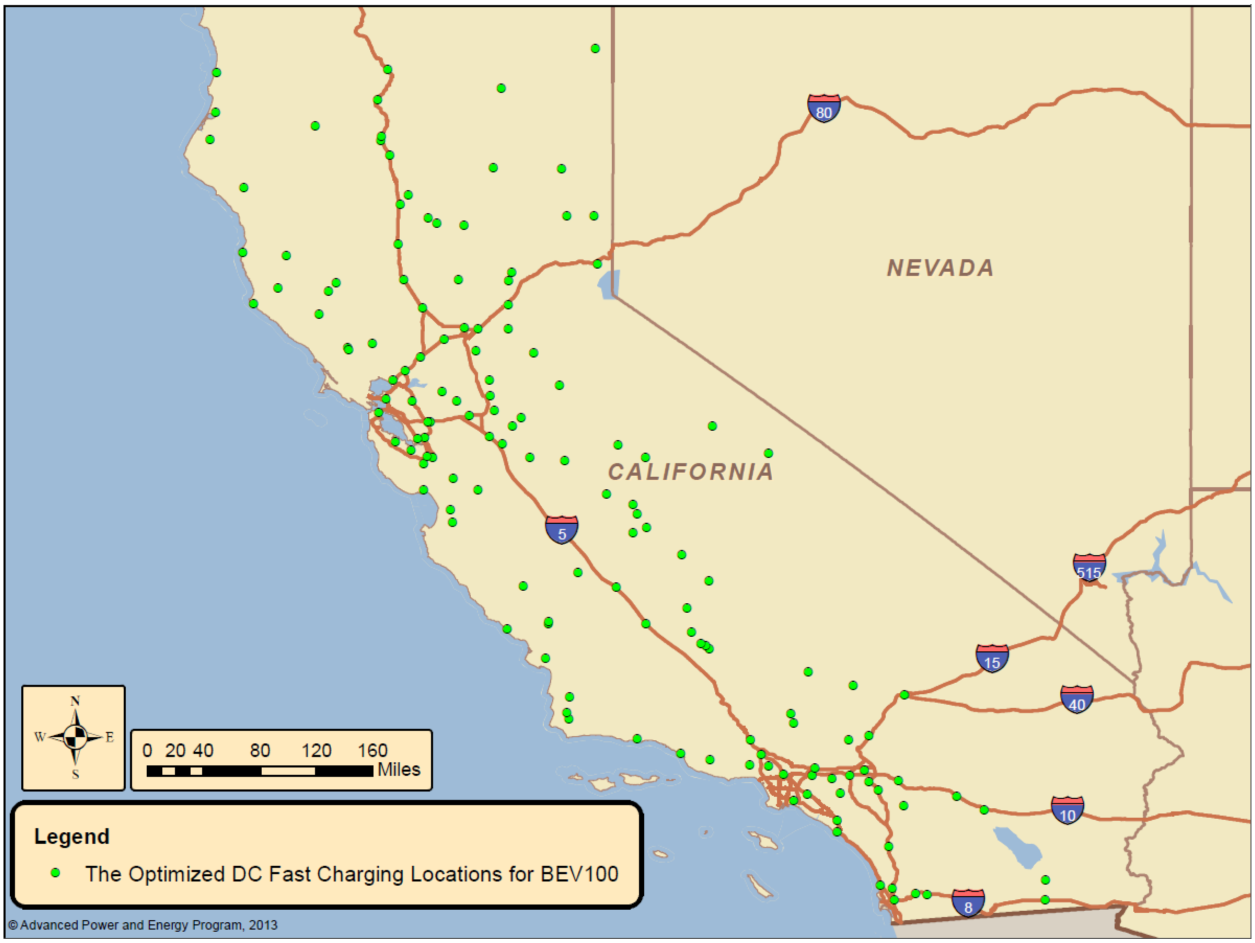


Figure 56. Optimized charging stations for BEV100.

Figure 57 is the case for BEV125 and only 87 stations are required. From BEV60 to BEV125, the range is doubled while the number of stations is decreased significantly to one thirds. This trend can be clearly observed in Figure 53 from 60 miles range to 125 miles range.

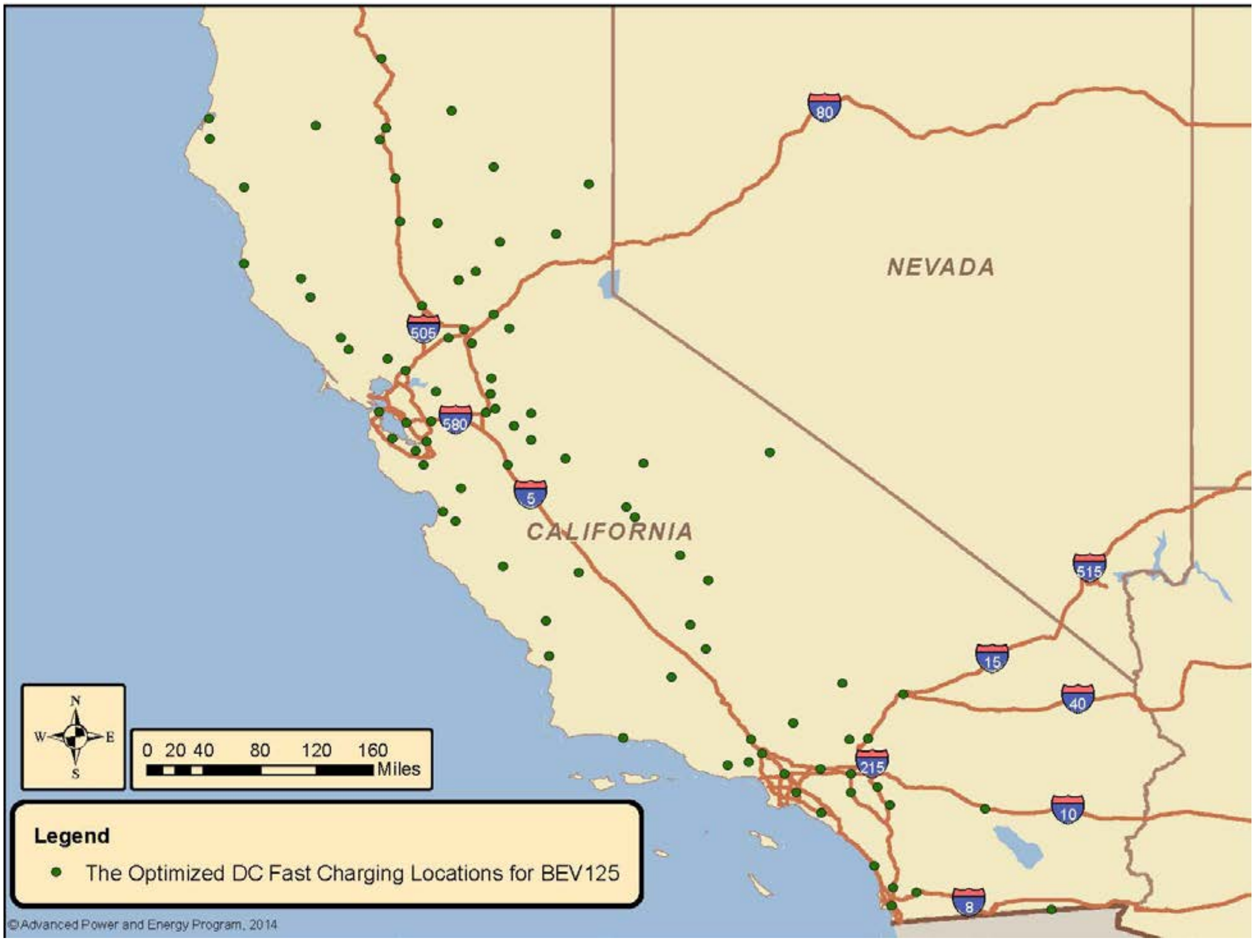


Figure 57. Optimized charging stations for BEV125.

Figure 58, Figure 59 and Figure 60 are the stations layouts for 150 miles, 175 miles and 200 miles all-electric ranges. The total number of stations is still decreasing while the slope is getting more flat. It implies that beyond 150 miles, the benefit of increasing all electric range on reducing fast charging activities and fast charging stations becomes smaller and smaller. Thus, deploying long ranged BEV (greater than 150 miles) might not be cost effective from the system perspective.

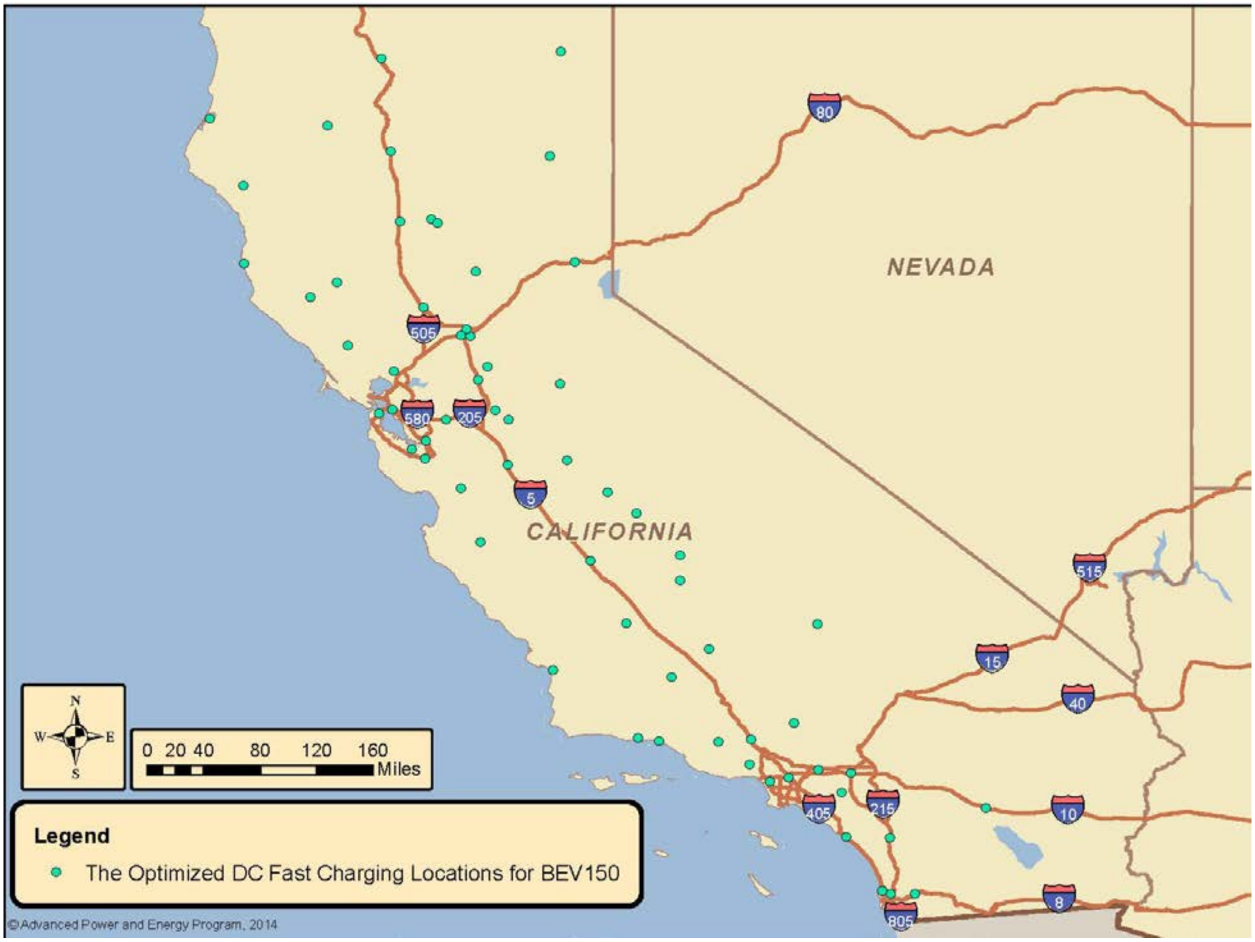


Figure 58. Optimized charging stations for BEV150.

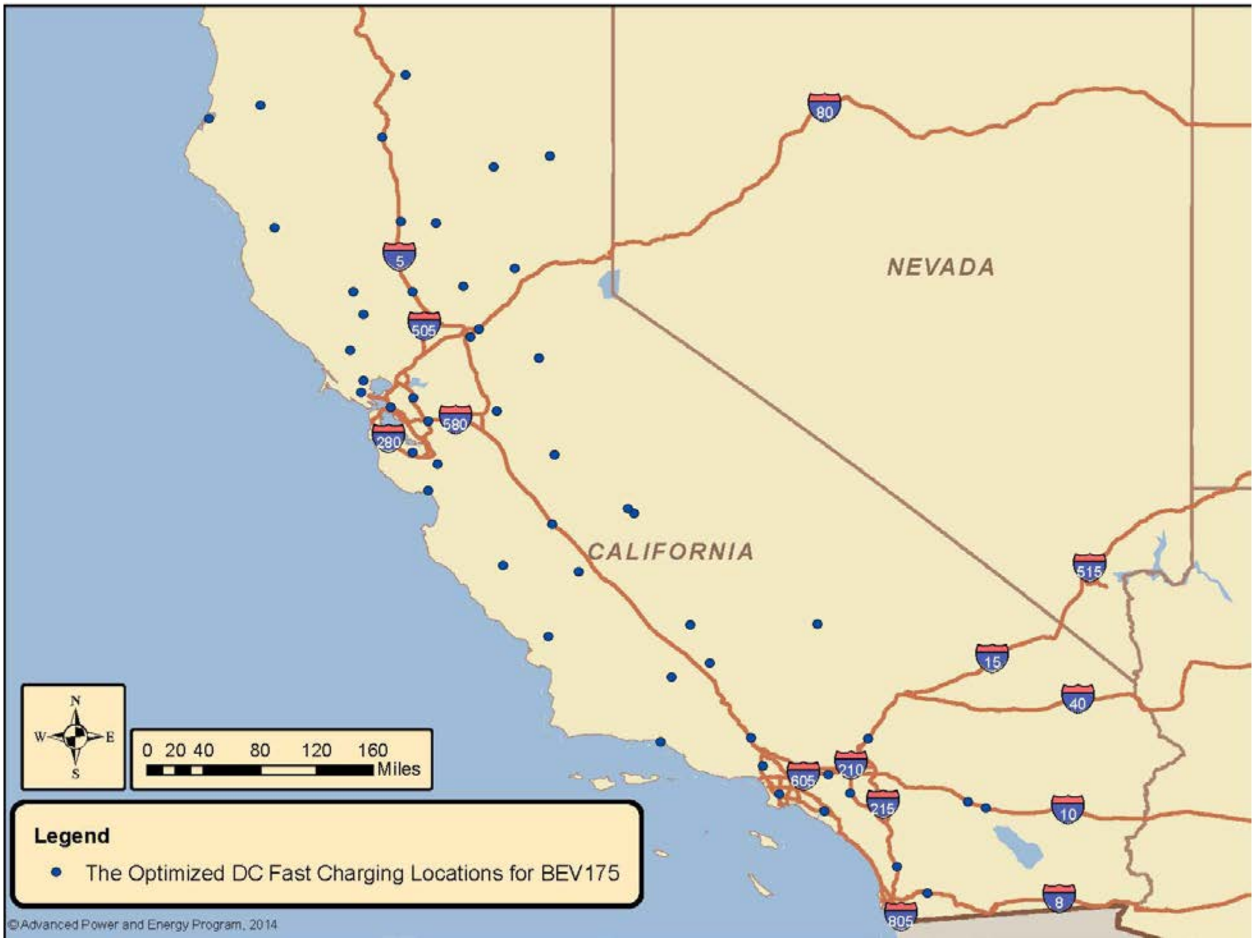


Figure 59. Optimized charging stations for BEV175.

Figure 60 shows 40 stations are needed to meet the travel demands with BEV200. Compared to a shorter ranged BEV, the station distribution below is quite different. Most of the optimized stations are located on the long-distance freeway, such as I-5 and US-110, rather than in the areas with dense population.

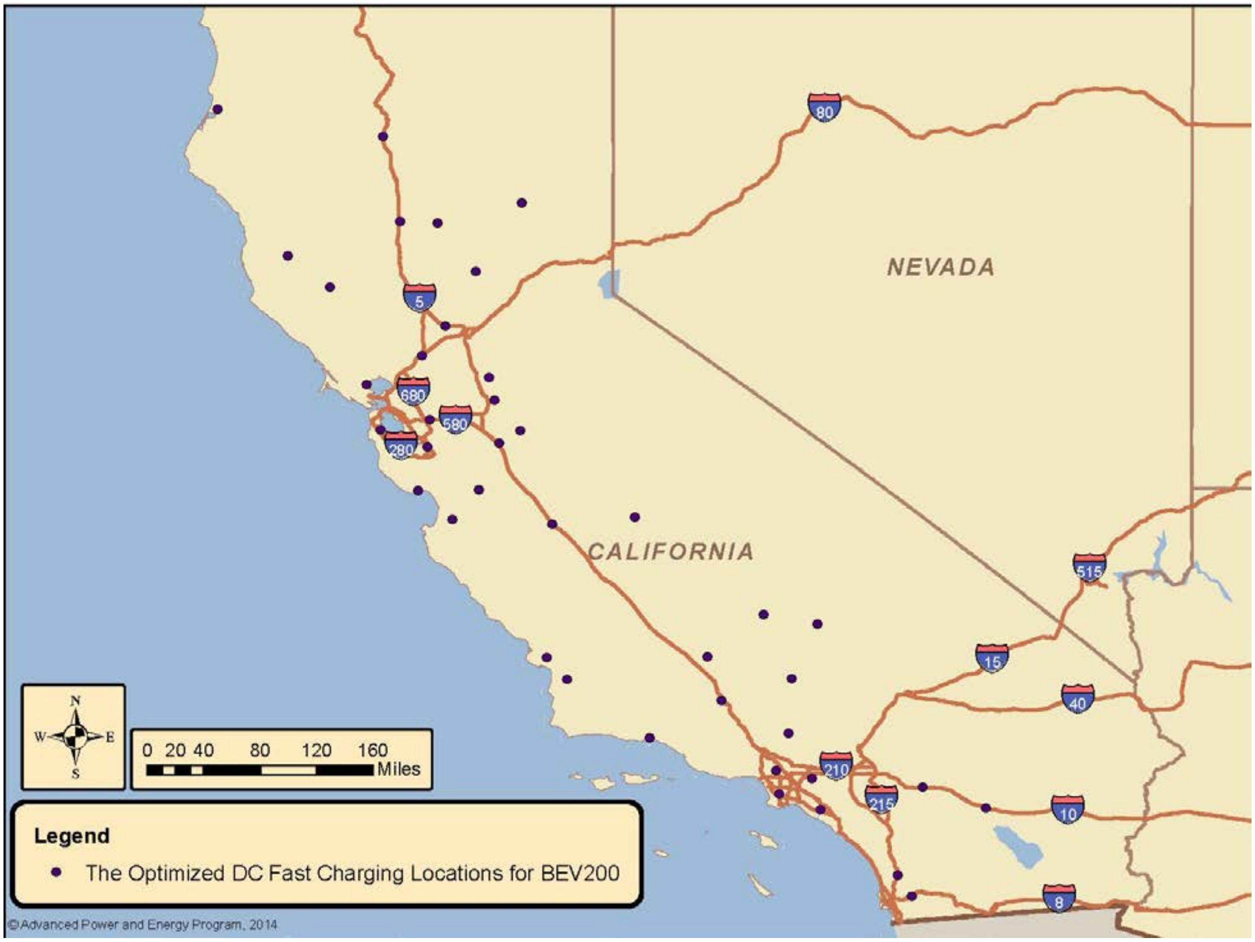
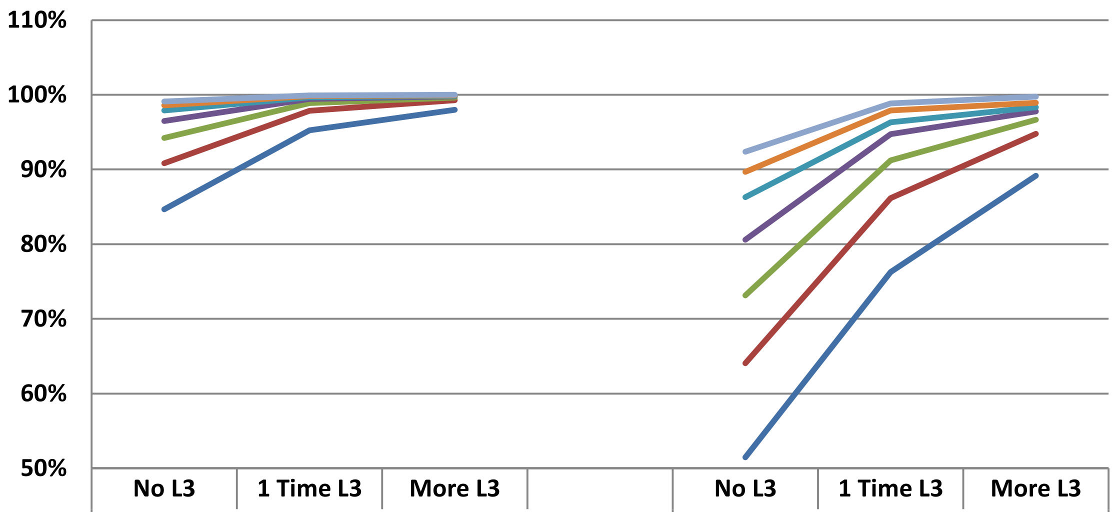


Figure 60. Optimized charging stations for BEV200.

6.2.3.2. BEV and VMT Feasibility

Figure 61 shows the BEV and VMT feasibility for all BEV types with and without fast charging. The feasibility of BEV60 is 85%, 95% and 98% respectively for no fast charging, one time fast charging in one day and multiple fast charging in one day. This result is very close to the one shown in section 5.3.2, using freeway exits and highway intersections as the candidate locations. The corresponding VMT feasibility is much lower. For instance, without fast charging, VMT feasibility is only 51%, meaning only half of the fuel consumption can be reduced. Allowing one time fast charging in one day can increase the fuel reduction rate to 76%, which is 2% higher than using PHEV40 with only home charging at 1.44 kW. Without a good coverage of public EVSE, BEV60 is expected to have lower electric miles travelled compared to PHEV40, which is confirmed by the collected data [101].

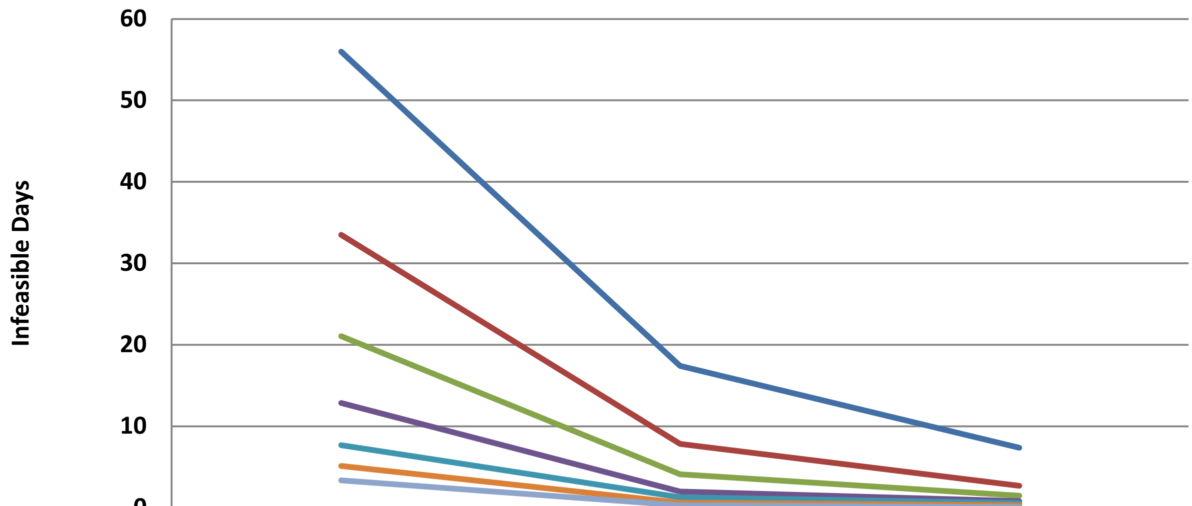


	BEV Feasibility			VMT Feasibility		
	No L3	1 Time L3	More L3	No L3	1 Time L3	More L3
BEV60	84.66%	95.23%	97.99%	51.44%	76.28%	89.16%
BEV80	90.83%	97.85%	99.26%	64.07%	86.16%	94.78%
BEV100	94.24%	98.88%	99.60%	73.14%	91.24%	96.67%
BEV125	96.48%	99.45%	99.78%	80.58%	94.74%	97.75%
BEV150	97.89%	99.65%	99.84%	86.30%	96.30%	98.35%
BEV175	98.60%	99.84%	99.93%	89.65%	97.91%	98.91%
BEV200	99.09%	99.93%	99.98%	92.36%	98.84%	99.73%

Figure 61. BEV and VMT feasibility without and with fast charging.

Similarly like the Level 1 and Level 2 EVSE, longer BEV range will not only reduce the requirement for EVSE but also increase the feasibility. It can be seen from Figure 61, with BEV125 or longer ranges, the feasibility can reach up to 99% and the electric miles travelled can increase to 95%. Those numbers look more acceptable for BEV deployment and more beneficial for fuel reduction. However, the cost on larger batteries will be a big barrier. Both the battery cost and EVSE cost are taken into account in section 6.2.3.4 for a more comprehensive analysis on the non-operating cost.

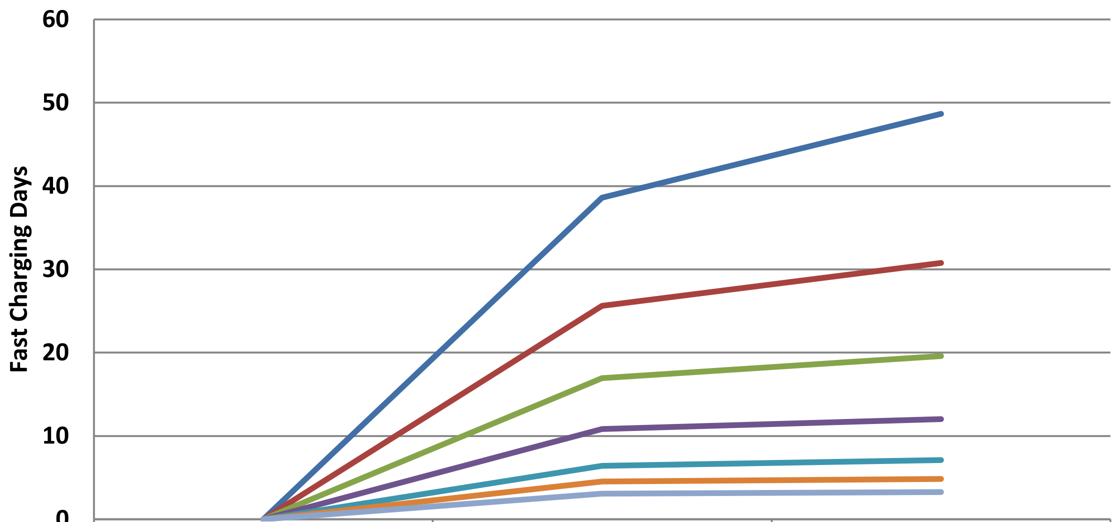
In Figure 62, the BEV feasibility is converted to the average infeasible days in a whole year by multiplying 365 days per year and subtracting from 365 days. It shows the fleet-wide possibility that a daily travel cannot be met by a curtain ranged BEV. Even with fast charging network, BEV60 indicates more than 17 infeasible days in a year which is one day for every three weeks. This is considered to be a large amount of behavior changes. If the range can be doubled to 125 miles, only two days out of the entire year is infeasible, which might not be noticeable. For BEV200, the infeasible day is less than one, meaning, for every four years there can be one infeasible day.



	No L3	1 Time L3	1 Time + More L3
BEV60	55.99	17.41	7.34
BEV80	33.48	7.84	2.70
BEV100	21.04	4.08	1.45
BEV125	12.83	1.99	0.82
BEV150	7.69	1.27	0.57
BEV175	5.12	0.59	0.27
BEV200	3.33	0.27	0.07

Figure 62. Estimation of infeasible days for a whole year for BEVs with and without fast charging.

The average number of days in a whole year when fast charging is required is also evaluated. Results are shown in Figure 63. The relationship between the fast charging days below and the infeasible days above is that the summation of them is equal to the total infeasible days if no fast charging is available, which is listed in the first column in Figure 62. For instance, BEV60 needs about 39 days for one time fast charging in a whole year while still has around 17 infeasible days, which leads to 56 days in total that behavior changes are required. It is almost two months in a year or equivalently 1 day in a week. From 2009 NHTS, the frequency of refueling gasoline tank is 15 days, which is as half frequent as the behavior changes for BEV60.



	No L3	1 Time L3	1 Time + More L3
BEV60	0.00	38.58	48.65
BEV80	0.00	25.64	30.78
BEV100	0.00	16.96	19.59
BEV125	0.00	10.84	12.01
BEV150	0.00	6.42	7.12
BEV175	0.00	4.53	4.85
BEV200	0.00	3.06	3.26

Figure 63. Number of days in a whole year requiring fast charging.

The only way to reduce behavior changes is to increase the all-electric range. BEV125 requests 11 days for one time fast charging and the infeasible days is about 2. This case appears to be more competitive compared to the conventional vehicles, having fast charging activities half frequent as the refueling activities.

6.2.3.3. Charging Time and Extra Waiting Time

This section investigates the time spent at a fast charging activity and the extra time cost by waiting for a fast charger, given one fast charger per station.

As introduced in Chapter 5, there are two options to fast charge BEVs. One is full charge, the others is sufficient charge. Figure 64 and Figure 65 shows the average fast charging time regarding different all-electric ranges and EVSE power for the two fast charging options respectively.

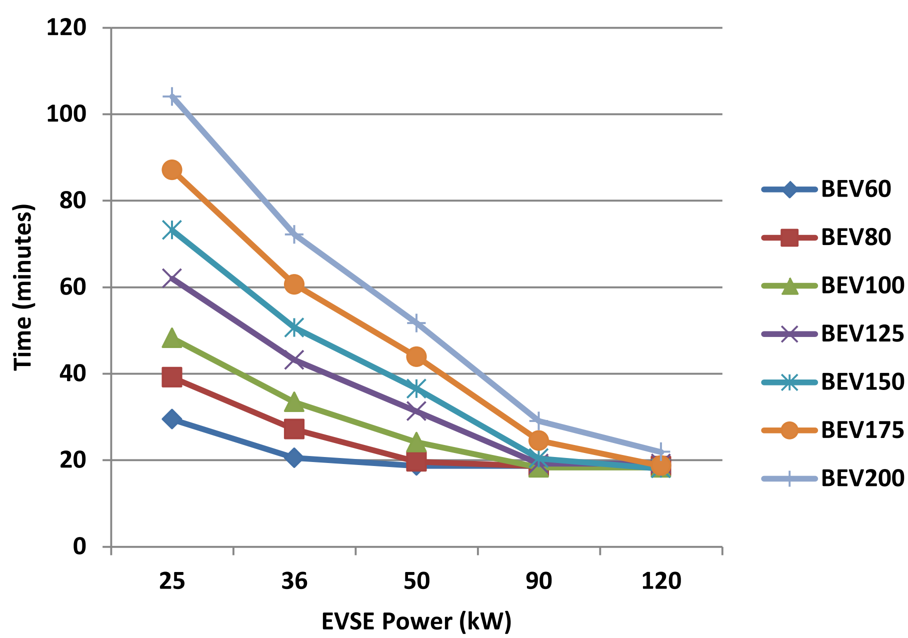


Figure 64. Average fast charging time for full charge with different BEV ranges and EVSE power.

With 25 kW charging power, BEV60 requests 30 minutes on average for full charge while BEV200 request more than 100 minutes. With increased charging power, intuitively, charging time for all BEV types are reduced, in particularly for long ranged BEVs. However, they are all converged to 20 minutes. The reason is that the maximum charging rate is limited to 2C in order to protect the batteries. In this sense, it is not meaningful to deploy fast chargers with a power higher than 120 kW since it would not future decrease the charging time. A very similar pattern can be observed for the sufficient charge option, as shown in Figure 65. It is very interesting that the only difference is that the charging time is all converged to 10 minutes, which is half of the full charge option. Reducing half of the charging time can be significantly valuable for BEV users. However, it relies on the accurate estimation of the rest travels back to home and people tend to have some charge reserved to be safe. Those factors implies that the sufficient charging can only provide a lower bound for charging time and a more realistic time span should be between Figure 64 and Figure 65.

It is well known that battery cannot be charged with high current at high SOC conditions [102, 103], which means time for full charge is likely to be higher than the one shown in Figure 64. It is strongly suggested that more investigation should be conducted on the fast charging at high SOC. Another solution can be installing extra battery so that battery does not have to be fully charged to achieve the same all electric range. In this sense, high power charging can sustain when the SOC reaches a certain level.

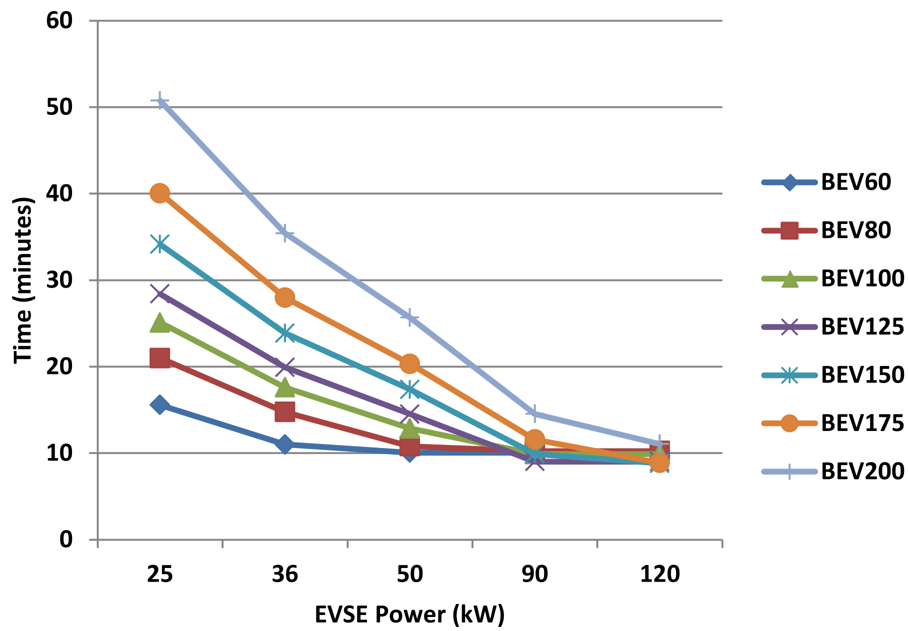


Figure 65. Average fast charging time for sufficient charge with different BEV ranges and EVSE power.

From the analysis above, high charging power can significantly reduce the charging time, which can affect the extra waiting time as well. Figure 66 shows the average extra waiting time per waiting event for BEV100 with the option of sufficient charge. Four station selection strategies are included, as introduced in section 5.3.4. The cheap, early and late strategies exhibit a very similar result while the reserve strategy shows the advantage. As expected, high charging power can also mitigate the extra waiting time. From 25 kW to 66 kW, the waiting time can be reduced below 10 minutes from more than 35 minutes.

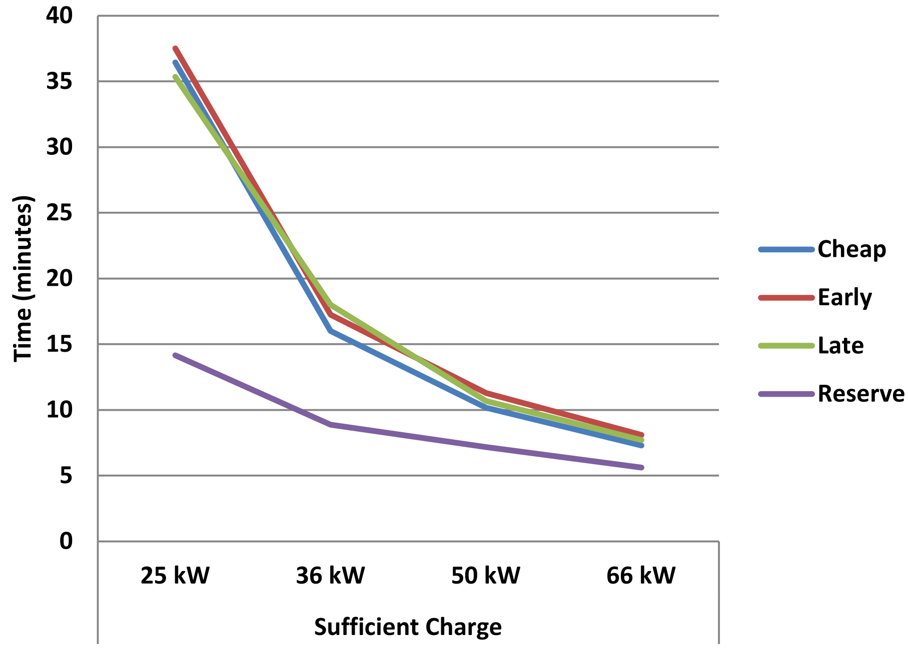


Figure 66. Average extra waiting time per waiting event for BEV100 with optimized station network.

The impact of reserve charging on reducing the maximum accumulative waiting time at one fast charging station is more significant. Figure 67 shows the details. A 25 kW EVSE with reserve charging can achieve the same level of the accumulative waiting time compared to a 50 kW EVSE with any other station selection strategies. In section 5.3.4.2, it is shown that additional chargers at one station can also reduce the average waiting time and the maximum accumulative waiting time. Thus, high power charging, reservation system and additional chargers are the solutions for the extra waiting time.

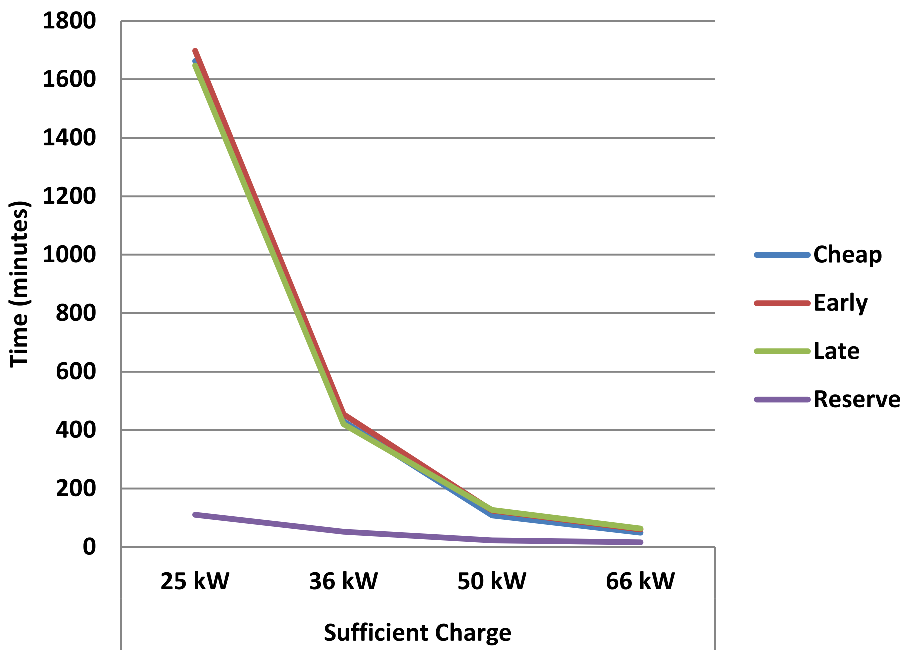


Figure 67. Maximum accumulative waiting time at one station for BEV100 with the optimized station network.

6.2.3.4. Battery Cost and EVSE Cost

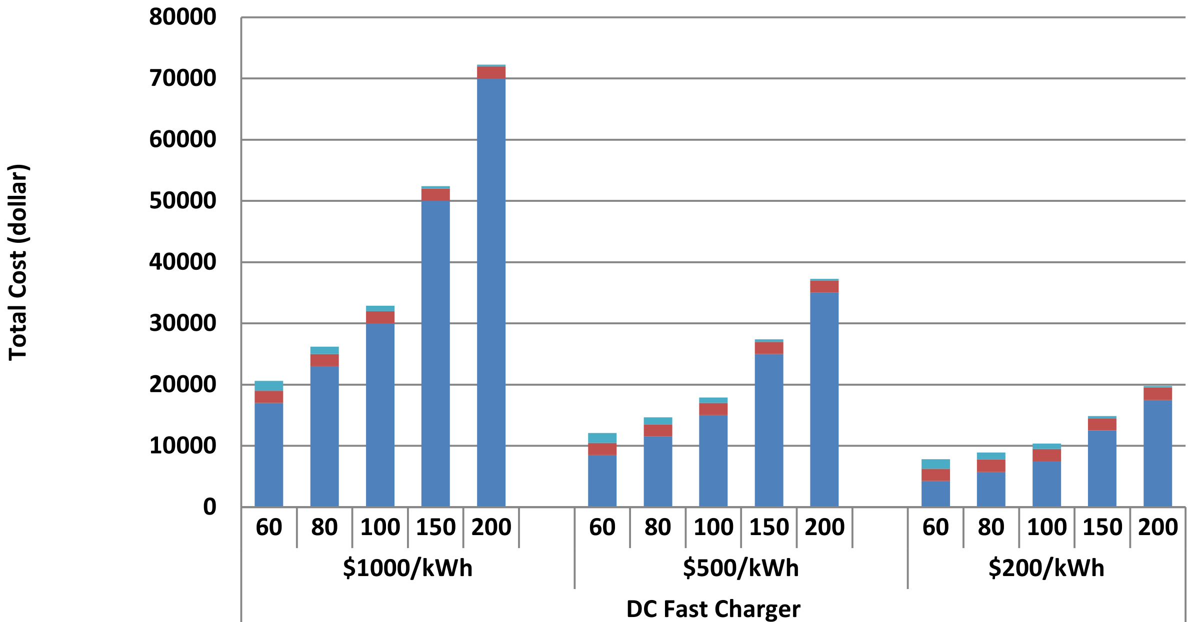
In parallel to section 6.2.2.3, this section evaluates the cost associated with battery and the fast charging stations, providing the distribution of non-operating cost per BEV with the setting of home charging plus public fast charging. Table 16 shows the cost assumption of home Level 2 EVSE and public fast charging stations [104].

Table 16. Cost assumption of home EVSE and fast charging station.

Home Level 2 EVSE Cost ($)	Level 3 EVSE Cost ($)
2,000	100,000

Figure 68 shows the accumulated cost per BEV ranged from 60 miles to 200 miles. The same as the Level 2 EVSE cases, three battery costs are evaluated, including $1000/kWh, $500/kWh and $200/kWh. The general results are very similar like the Level

2 cases that the EVSE cost including home charging and fast charging is much smaller compared to the battery cost on the vehicles.



	60	80	100	150	200	60	80	100	150	200	60	80	100	150	200
Level 3 EVSE Cost	1590	1174	894	391	248	1590	1174	894	391	248	1590	1174	894	391	248
Other EVSE Cost	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Work EVSE Cost	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Home EVSE Cost	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Battery Cost	1700	2300	3000	5000	7000	8500	1150	1500	2500	3500	4250	5750	7500	1250	1750

Figure 68. Cost estimation of battery and Level 3 EVSE per BEV.

Level 3 DC fast charger is the most expensive EVSE but the small amount required makes the cost per BEV very low. In Figure 68, the cost of Level 3 EVSE per BEV is lower than the home EVSE for all BEV range scenarios. Although the Level 3 EVSE cost is a very small portion, it is relatively difficult to be funded. It is suggested that all the stakeholders should cooperate and make a good plan for the entire state so that the limited funding can be spent at good locations.

Compared to the cost analysis in section 6.2.2.3, the Level 3 EVSE cost in the fast charging case is close to the Level 2 EVSE cost at non-home locations for the Level 2 charging case. Thus, from the infrastructure cost perspective, a similar amount of funding needs to be invested for either Level 2 or Level 3 EVSE.

6.2.3.5. Summary

From the results and analysis above, summary can be made below.

1. The all-electric range of BEV plays an important role to reduce the number of fast charging stations required. From BEV60 to BEV200, the minimal number of stations decreases from 256 to 40.
2. The all-electric range of BEV also has significant impact on reducing the number of days when people need to make behavior changes, including conducting fast charging and changing travel plans.
3. Beyond 150 miles, the impact of all electric range on reducing station number and behavior changes becomes smaller and smaller. It is not cost effective to deploy BEVs with such a long range in a large scale.
4. The capacity issue of the fast charging stations has been observed. Increasing charging power, having a reservation system and installing extra chargers can mitigate it. It is suggested that a reservation system and higher power charging should be given higher priority rather than extra chargers, since their impacts are more significant on reducing wait time.
5. Currently, battery cost is significantly higher than the cost of EVSE at home and fast charging stations on a per-BEV basis. Level 3 EVSE requires small amount of investment but requires the stakeholders to have a cooperative plan.

6.3. Recommendations

PHEVs have an equivalent or longer range and the same refueling time as the conventional vehicles. Consequently, PHEVs do not require non-home EVSE to increase feasibility. The fuel reduction analysis indicates that 1.44 kW home charging can decrease fuel consumption significantly. The extra benefit from non-home charging and higher charging power is limited. The charging profiles implies that high charging power can cause higher demand in the peak hour when charging is not well controlled, and more non-home charging locations can increase the demand during the day time. The operating cost analysis also shows charging time strategy is most important compared to high charging power and more non-home locations for cost reduction. Considering all those facts above, it is recommended that home Level 1 1.44 kW charging is all that needed for PHEVs and funding should be allocated on the investigation of advanced charging strategies.

BEVs require Level 2 EVSE at home and a well-designed plan for non-home EVSE. In the short term, a low BEV volume will require more non-home Level 2 EVSE per BEV and the accurate locations are difficult to be determined. In contrast, an optimized Level 3 fast charging station network can be designed to provide the initial coverage for most BEVs to dramatically decrease the infeasible days. Thus, it is recommended that in the near future, fast charging stations should be considered with higher priority than the public Level 2 EVSE. With an optimized fast charging station network, it is believed that the acceptance of BEV will be increased dramatically as indicated by the feasibility analysis. However, the feasibility analysis also shows that the scenario of home charging plus fast charging stations results in a large amount of behavior changes for most BEVs on the market. It may cause that the users switch to conventional vehicles when having long travels even though it is feasible to use BEV with fast charging station. To resolve this issue, it is recommended that high power fast charging and a reservation system should be deployed such that the charging time and extra waiting time can be reduced significantly to mitigate the issue of behavior changes. At the same time, more public Level 2 EVSE need to be installed according to the EVSE distribution plan proposed in this dissertation. If an initial BEV market can be formed to decrease the cost of batteries, longer ranged BEVs are recommended. However, it is not suggested to deploy BEVs with range longer than 150 miles in a large scale given the current battery technology and the fact that it will not increase the feasibility to a higher level.

Chapter 7. COORDINATE PEV CHARGING WITH GRID

Part contents of this chapter have been published in the article entitled 'Coordinating plug-in electric vehicle charging with electric grid: valley filling and target load following'. Copyright belongs to © 2014 Elsevier B.V.

This chapter proposes a decentralized charging protocol for PEVs with grid operators updating the command signal. Each PEV calculates its own optimal charging profile only once, after it is plugged in, and sends the result back to the grid operators. Grid operators only need to aggregate charging profiles and update the load. The existing PEV characteristics, national household travel survey (NHTS), California Independent System Operator (CAISO) demand, and estimates for future renewable generation in California are used to simulate PEV operation, PEV charging profiles, grid demand, and grid net load. Results show the proposed protocol has good performance for overnight net load valley filling by using the load directly as the cost signal. Annual results are shown in terms of overnight load variation and comparisons are made with grid level valley filling results. Further, a target load can be approached in the same manner by using the gap between current load and the target load as the cost. The communication effort involved is quite modest.

7.1. Notation

Some of the symbols in this chapter are listed as follows.

t_i	Time slot i in the 48-hour window, e.g., 12am-1am, 1am-2am,…,11pm-12am
i	Time slot number, e.g., 1,2,…,48
Δt	Time slot duration, e.g. 60 minutes (1 hour)
$\overline{\Delta t_n(t_i)}$	Plugged in time in time slot i for vehicle n, known
n	PEV number
ta_n	Home arrival time after the last trip for PEV n
$E(t_i)$	Electric demand
$D(t_i)$	Electric net load
$x_n(t_i)$	Charging energy at each time slot for vehicle n, decision variable
$r_n(t_i)$	Maximum charging energy at each time slot for vehicle n, known
$L(t_i)$	Final load with PEVs charging
T_k	Time when cost is updated
V_k	Vehicle number when cost updated
T_{step}	Time interval for cost function updating
V_{step}	Vehicle number interval for cost function updating
k	k^{th} step to update cost function
$s_k(t_i)$	Aggregated charging profile for step k

$C_k(t_i)$	Cost function for charging at step k
$R(t_i)$	Maximum overall charging power at each time slot, known
$X(t_i)$	Overall charging load at each time slot, decision variable
$TL(t_i)$	Target load
$TC_k(t_i)$	Cost function for charging at step k with target load

7.2. Introduction and Literature Reviews

Plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) are typically classified under the category of plug-in electric vehicles (PEVs) [6]. PEVs have drawn interest from government, automakers, and the public due to the potential to reduce fossil fuel consumption, tailpipe emissions, overall greenhouse gas emissions, and operating cost [105]. A variety of research papers have evaluated PEV benefits quantitatively [13, 41, 44, 45]. However, a consensus has been reached that one of the hurdles for large deployment (or acceptance) of PEVs is the shortage of charging infrastructure or electric vehicle supply equipment (EVSE) [34, 98]. The state and local governments, as well as automakers, have shown interest in building a sufficient charging network. Previous chapters have presented analysis of the allocation of charging infrastructure. There, it is shown that with large PEV penetration, even with a reliable charging network, the majority of the charging activities occur at home with the current PEV characteristics and charging rates, due to the cheap night time residential electricity and the long dwelling time needed. Furthermore, charging time strategy has been showed to have the most significant impact on charging cost reduction and overall grid operation.

Thus, here focuses on the details of coordinating PEV charging, at home, with the electric grid.

The electricity demand and generation of the grid have to be balanced at all times to assure operational stability. Charging PEVs increases the electric demand and has the potential to change the demand curve, if PEV penetration becomes significant. The time needed to charge PEVs, for most travel demands, is less than the dwelling time overnight. Unlike daytime charging, overnight charging can be flexible and can be managed so that, aggregated with overall demand, it results in lower generation cost and emissions. Generally, constant (or flat) demand curves are considered beneficial for cost and environmental consideration [61]. Typically, wind and solar generation are treated as negative demand since the power cannot be controlled in the same way as other forms of generation. So the net load, total demand minus renewable generation, is targeted to be flat or at least slowly varying. The problem can be simply stated as obtaining a charging pattern so that the final net load curve has the least variation over an extended time horizon, given an original net load curve from the grid and the total charging demand for numerous PEVs.

It has become clear that if there is a significant penetration of PEVs, some form of scheduled charging protocol will be needed. The power requirement of a large number of PEVs at peak or near peak times can lead to significant challenges in cost, delivery through grid, and even in generation and ramping capacities. This has led to several approaches to address this problem. Generally, the main goal is to schedule and shift the charging demand of the PEVs to the late evening and very early morning when the overall demand is the lowest. These are often called `valley filling' approaches since they are aimed at leveling the overall demand to reduce the need for shutting down and restarting of large power plants.

Of course, depending on specific, and relatively uncertain, costs associated with ramping and other considerations, it is possible that valley filling is not the optimal solution. For example, results in [106] show that under certain combinations of level 2 charging, station penetration, and costs assigned to ramp rates, etc., one can design a more desirable (e.g., less costly) charging profile, though how such a global plan can be realized is unclear. Here focuses on the decentralized approach to address this challenge, as centralized approaches are difficult to implement and unlikely to be accepted.

Among the decentralized approaches that have appeared recently, paper [47] first solves a centralized optimization problem that takes into account costs associated with CO2 generation and/or other economic and environmental costs. Based on the obtained average charging power, it then develops an algorithm that yields a decentralized implementation. Papers [68, 69] use non-cooperative game concepts to develop a global valley filling protocol, under the assumption that all BEVs have similar state of charge (SOC) and other properties, and are plugged in at the same time. Paper [46] removes the homogeneity assumption and allows varied SOC, max charge rate, etc. The approaches in [13-15] are aimed at solving the global valley filling problem through a decentralized, and iterative, approach. In each iteration, a `price' structure is communicated to the fleet of PEVs, so that each vehicle can develop an optimal (with respect to the broadcasted cost) charging profile. These profiles are sent back to the central communication node or the grid operator (e.g., the ISO – Independent System Operator), who will aggregate the total demand, based on the individual profiles, and broadcast a new price. Under relatively minor assumptions, the algorithms have convergence proofs. While the results are quite impressive, there are some challenges. Both techniques require the total number of PEVs be available for participation in the iterations needed in the optimization ([46] has results for the asynchronous case as well). Such an iterative approach might require significant communication if the number of vehicles is large. More crucially, these techniques do not ensure each PEV is charging at the maximum charging rate, which is how PEVs are currently charged. Reference [107] attempts to address the last concern by relying on a stochastic approach in which the start of the charging period is the decision variable in the optimization problem, given the charging rate and SOC – which yields the charging duration. Under mild assumptions, the proposed iterative algorithm converges with probability one.

In this dissertation, it is focused on the similar problem with somewhat a different tack. Two approaches are proposed that ensure charging occurs at the maximum power, as is required with the current charging technology (1.44 kW for level 1 and 3.3 kW for level 2 EVSE), and the partial charging rate will lead to efficiency drop of the converter [108]. As a key contribution, it is attempted to minimize the amount of communication needed between the large fleet of PEVs and grid operator and do not require availability of all PEVs for initiating the charging time assignments. Similar to other approaches, it can be modified to address excessive ramp rates or possible intermittent renewable sources (with some reasonable prediction window).

The basic approach can be summarized as follows. This dissertation uses a cost schedule that reflects the desirable `valley' or `valleys' for the PEVs to charge (by assigning low costs to such periods). This is shared with individual vehicles, each solving a simple linear program to identify the periods for charging (at peak power), which will be the lowest `cost' - and overall demand - periods. The solution is then sent back to grid operator for updating the charge structure. Note that this is not an iterative technique - there is only one set of data transmitted each way, once. The approach uses the natural flow of PEVs in and out of the overnight (or valley) period, plus an enforced queue, and lets each vehicle sign up for a specific time period for charging. By controlling the queue (and thus the rate of communication), one can ensure the lowest cost periods (grid level valleys) are filled without solving the global valley filling problem directly.

7.2.1. Plug-In Pattern

The vehicle travel behavior data used in this chapter are derived from the 2009 National Household Travel Survey (NHTS) [8]. The NHTS data and data process are the same as described in section 2.1.1. In particular, data for California were selected, trips occurring without a personally owned vehicle were deleted, person-chain data were converted to vehicle-chain data, daily trips data with unlinked destinations or significant over-speed were deleted, and tours were organized into home based daily tours (first trip from home, last trip to home) [34]. A total of 20,295 vehicles were selected covering 83,005 single trips, with an average of 7.85 miles per trip and 32.13 miles per vehicle, per day.

Figure 69 shows the histogram of the last home arrival time of the day, with 15 minutes (0.25 hour) intervals for all those 20,295 vehicles. The peak arrivals occur in the late afternoon with almost 800 vehicles for the data set, which is around 4% of the total vehicles for this interval (around 17:00). The accumulation curve shows by 20:00, 80% vehicles have arrived and will stay until the next morning.

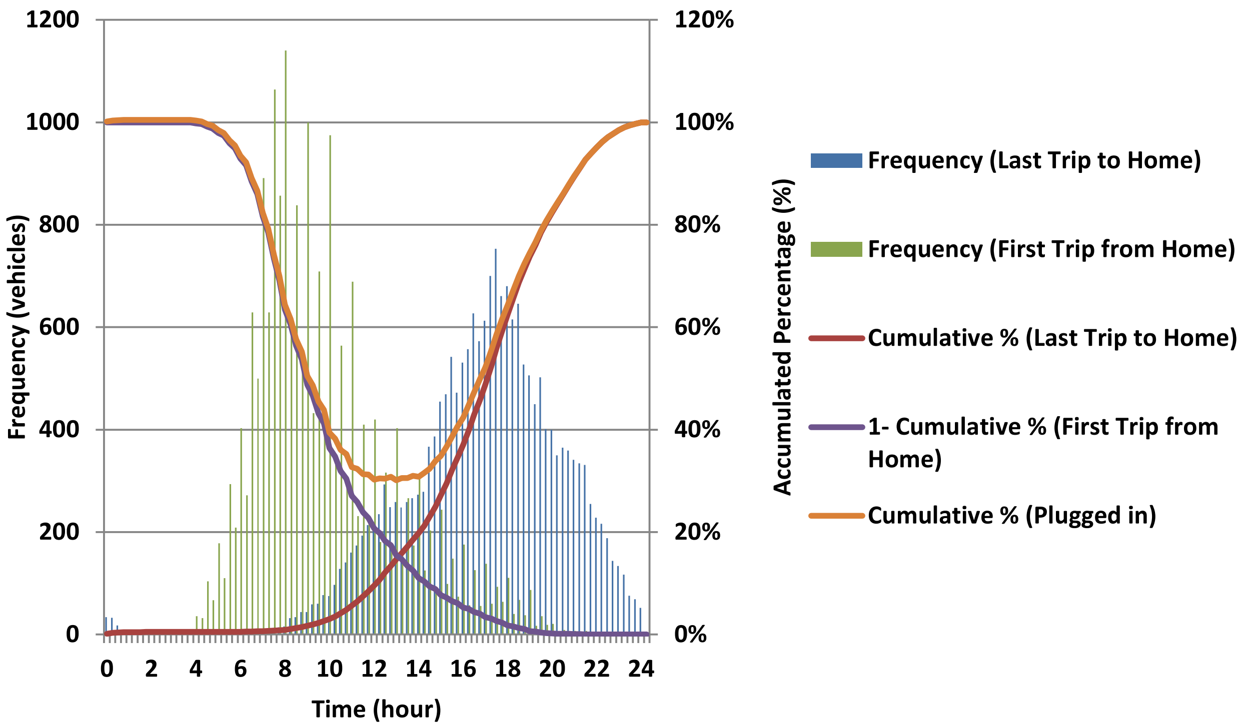


Figure 69. Vehicles home departure and arrivial time distribution and charging availability.

Figure 69 also shows when vehicles leave home for the first trip of the day and the peak occurs in the early morning at around 7:00, by which time, 80% of vehicles have not left. Combined with the arrival time, shown in the` Plugged in' curve, 80% of vehicles can be coordinated with the grid at home for almost half of the day, from 20:00 to 7:00 in the next day. So this time period is considered to be the most effective coordinating window between PEVs and grid.

7.2.2. Vehicle Information

Similar to other research [46, 47, 68, 69, 106, 107], this study focuses on the gird impact of macro scale of vehicle behavior where the detailed physical vehicle model was not considered; instead a parameterized vehicle operation and charging model was used. Table 1 shows vehicle parameters used in this study which were all derived from current production vehicles [38]. Gasoline price is assumed to be high enough throughout this chapter in order to ensure PHEVs use electricity first rather than gasoline. To simulate the future scenario, this chapter uses a 10% penetration of all passenger cars (PC) and light duty trucks (around 2.1 million PEVs in California) [7]. So the scaling factor from NHTS data to more than 2 million PEVs will be around 100.

Table 17. Simulation parameters for PHEVs and BEVs.

Vehicle type	MPG	kWh/mi(DC)	All-electric range(miles)	Efficiency from grid to battery	AC Charging power (kW)
PHEVs	40	0.34	40	0.85	3.3
BEVs	N/A	0.31	60	0.85	3.3

7.2.3. Renewables and Net Load

The electricity sector in many countries and states have targets for meeting increasing fractions of their load demand with renewable resources to promote a shift towards a low-carbon, low-pollutant emission grid mix [61]. In California, the target is to provide 33% of all retail sales of electricity from renewable resources by the year 2020. Other states in the U.S. also aim to reach similar goals to some extent.

Figure 70 shows the electric demand $E(t_i)$ and net load $D(t_i)$ based on wind and solar installed capacities at around 30% renewable penetration in terms of hourly resolved and monthly averaged signals. Those capacities were specified by California Public Utilities Commission (CPUC) [109]. It is well known that the demand has a diurnal pattern with a valley hours after midnight. The same pattern also can be observed for the net load for most of the days. However, as shown from day 98 to 99 and day 108 to 109, additional large peaks and valleys may also exist, in particular the relatively large valley in the afternoon. Ideally, the aggregated PEV charging profile can be used to smooth this curve as much as possible so the final load is met with lower cost and/or emissions.

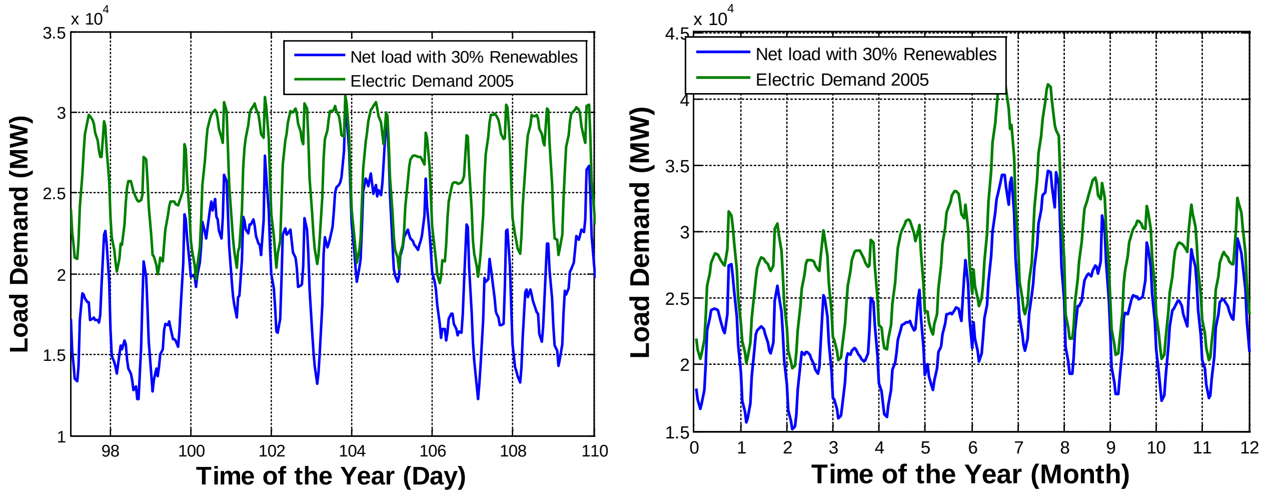


Figure 70. Hourly resolved electric demand and net load for ten days (left) and on a monthly average basis (right).

To fulfill this goal, in the rest of this chapter, the optimization of valley filling from the grid perspective will be first introduced to provide a reference solution. And it will introduce the mechanism of optimal charging from the perspective of each individual PEV as well as the protocol to update the cost function broadcast by the grid operator to achieve the optimality at the grid scale. Additionally, the year-long results will be shown and compared to the original net load and the results from grid level valley filling. Finally, a modified protocol will be introduced for the final load to approach a pre-defined target load which may not only be the solution of grid level valley filling.

7.3. Grid Level Valley Filling

As mentioned earlier, the grid favors certain types of load curves, independent of the behavior of individual PEVs. Valley filling is thus a strong preference, in which ideal valley filling is to solve a convex optimization problem with the constraints on total energy consumption of PEVs. The optimization details can be formatted as follows.

$$min \sum_{i} (D(t_i) + X(t_i))^2 \tag{16}$$

Subject to

$$\Delta t \times \sum_{i} X(t_i) = B = \sum_{n} b_n \tag{17}$$

Where $X(t_i)$ is the overall charging power at each time slot t_i, and B is the total charging energy of all PEVs for a whole day, which is considered to be known, which the summation of the charging energy b_n for individual PEV. This problem format or the corresponding result has been seen in papers [46, 68, 70, 106]. And the well-known solution is

$$X(t_i) = (\lambda - D(t_i))^+ = \max\{(\lambda - D(t_i)), 0\}$$

$$\sum_{i} (\lambda - D(t_i))^+ = B \tag{18}$$

However, unless all vehicles are plugged in for the whole time horizon, this solution ignores an important constraint associated with the overall charging power: the ideal valley filling result is not feasible if there are not enough PEVs plugged-in for a specific time slot according to the PEV charging availability shown in Figure 69. Similarly, In reference [106], a Charge Flexibility Constraint (CFC), is added to consider the overall charging power constraint, as well. However, the Charge Flexibility Constraint indicates a sharp decrease on the maximum charging power (plugged in PEVs) from 1:00 to 6:00, which is quite different than Figure 69. In this time period, most PEVs are at home, thus the maximum charging power should be relatively flat. Here, Figure 69 is used to derive an additional constraint shown in Equation (19) to provide an upper bound on the overall charging power, depicted by the black line in Figure 71. Essentially, $R(t_i)$ is the product of the amount of plugged in PEVs and the individual charging power (3.3 kW in this study). This constraint is independent from the electric load curve and in reality can be derived from historical plug-in and plug-out data. As contrast to the ideal valley filling without a power limit, the combination of (16)(17)(19) can be defined as *constrained* valley filling.

$$X(t_i) \leq R(t_i) \tag{19}$$

Figure 71 shows an example of the optimal solutions for both cases on the net loads from day 97 to day 99 (hour 0 to hour 72). It is assumed that only the PEVs that arrive in Day 97 and 98 count. Day 98 is not a typical day since the largest valley does not occur overnight but in the early afternoon (at hour 39 on the graph). The ideal valley filling result, the red dashed line, requires more vehicles than are actually plugged in between hours 36-40 (i.e. arrived and plugged in). For another period from hour 1 to hour 4on the graph, when there is not a single PEV since no vehicle has arrived, the ideal valley filling draws power from the grid as well. When the inequality constraint in Equation (19) which is represented by the black curve at the bottom of the figure is used, no power flows to PEVs before hour 6. And, the deepest valley from hour 36 to 42 ends up being filled only partially, as shown by the solid red line. Although the situation of having the biggest valley in the afternoon may not happen often, it underlines the point that the ability of PEVs to alter electric load significantly may be somewhat limited to the overnight period. Although constraint (19) considers PEV availability, it is most restrictive in the early afternoon periods. During late night periods, with some of the PEVs fully charged, the real available

PEV number becomes smaller than that of plugged in PEVs. Thus, during these periods, (4) overestimates the limit and is not a restrictive constraint.

Naturally, a perfect valley filling solution from (16)(17)(19) may not be achievable depending on the specific shape of the net load, the availability of the PEVs, and the individual level charge needs. A complete global valley filling solution would require a problem with decision variables on the order of the PEV population, while the ideal valley filling requires a number that is on the order of time slots (as it solves the aggregate charge at each time slot). As a compromise, in this chapter, the optimal solution of the constrained valley filling, i.e., (16)(17)(19), is considered the reference profile. For simplicity, the constrained valley filling will be called valley filing in the rest of this chapter.

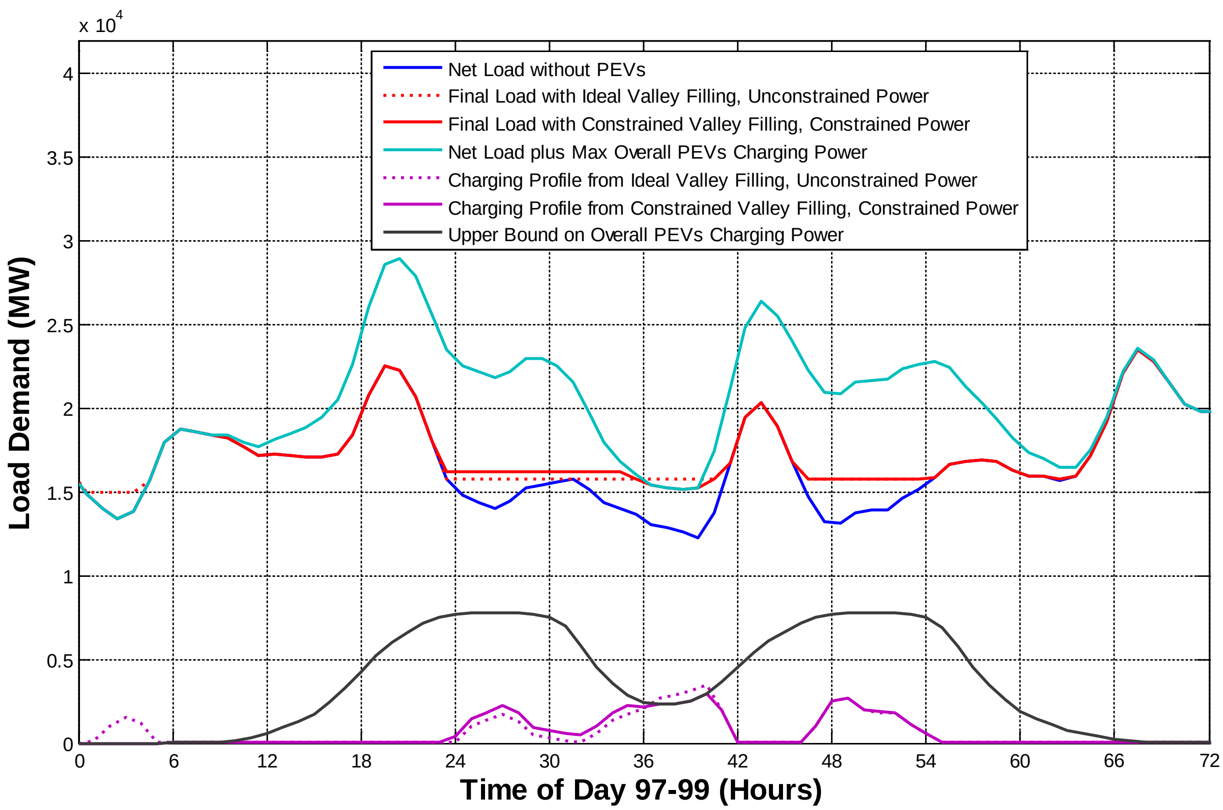


Figure 71. Comparison of ideal valley filling results without power constraint and constrained valley filling results with power constraint.

7.4. Protocol of Individual PEV Charging and Cost Updating

The charging profile of individual PEVs is trivial compared to the grid load and only the aggregated profile has to be considered. In a decentralized scheme, every vehicle makes the best decision for its own, in terms of the overall electricity cost available to it. This section will introduce the mechanism of optimal charging for single PEVs as well as the protocol to update the cost function broadcast by the grid operator to achieve the optimality at the grid scale, to the extent possible (given the constraint on PEV availability). After that, a one-day result will be shown at different updating frequencies. Then, the communication effort will be evaluated to verify the feasibility of the proposed protocol. Finally, the year-long results will be demonstrated and compared to the original net load and the results from valley filling formatted in the previous section.

7.4.1. Individual PEV Charging

The initial charging strategy used for individual PEVs is similar to that in [34], except that here it is focused on overnight (at home) period. In summary, given charging vehicle demand (i.e. energy), charging constraints (i.e. plugged in time window and charging power limits), charging cost (i.e. price of electricity, as provided by grid operator), each PEV finds the optimal way to charge such that its individual cost can be minimized, as shown below.

Problem formulation

1. Decision Variables:

The SOC increase (or electricity recharged) of the PEV n for each time slot t_i given by

$x_n(t_i)$.

2. Cost function:

The summation of the total charging cost is given by:

$$\sum_i C(t_i) \times x_n(t_i) \tag{20}$$

where $C(t_i)$ is the cost per kWh (DC) during the time t_i, derived from the electricity cost provided by grid operator.

3. Constraints:

   1) The total energy charges during the home dwelling period should match the consumed energy during the day (known and fixed):

$$\sum_i x_n(t_i) = b_n \tag{21}$$

   2) The lower bound on $x_n(t_i)$ is zero and for the upper bound, it is the product of the charging power at home $p_n(t_i)$ (3.3 kW), plugged in time for charging in each time slot $\overline{\Delta t_n(t_\iota)}$, and charging efficiency η (0.85).

$$0 \leq x_n(t_i) \leq r_n(t_i) = p_n(t_i) \times \overline{\Delta t_n(t_\iota)} \times \eta \tag{22}$$

If a PEV arrives home at 17:30 and leaves at 7:45 next day, and the time slot duration Δt is 1 hour (60 minutes), then the plugged in time for charging from 17:00 to

18:00, $\overline{\Delta t(t_{18})}$, is 0.5 and the plugged in time for charging from 7:00 to 8:00 in the next day, $\overline{\Delta t(t_{32})}$, is 0.75.

4. Assumptions on the variables:
   1) The span of plugged in time for each vehicle is fixed by the NTHS data. That is, each PEV controller knows the time for the first trip the next day.
   2) The electricity cost is not exactly the same in any two time intervals, i.e., $C(t_i)$ values are distinct.
   3) The charging power and AC to DC efficiency are assumed to be a constant and known.

7.4.1.1. Charging Profile

The key is the price made available to each PEV. At specific instants (e.g., every 30 minutes or after every 10,000 cars have \`registered' for the night), the grid operator sends the recently arrived vehicles a price profile $C(t_i)$. Start with the simplest option: $C(t_i)$ is simply the electricity net load (i.e. generation minus renewable) $D(t_i)$. In reality, the cost must have different values at different times.

Since the cost for a specific time slot is different than any other, optimizing the cost function in (20) above will choose the lowest point to charge and then jump to the second lowest one with the maximum charging power until the SOC reaches 100%. In this sense, the unrealistic partial rate charging [46, 47, 68, 69, 106] can be avoided. Indeed, there can be at most one partial charge time period, which means the charging stops partly through that period (e.g., 15 minutes into the a 60 minute period). The detailed proof is shown in the APPENDIX.

Figure 72, lower panel, shows charging profiles for two PEVs by assuming the charging cost on the top pane, which is obtained from the net load from day 98 to day 99. The two PEVs arrive home at 5:15 and 16:40, respectively. So PEV 1 decides to charge from 12:00 to 16:00 and late in the evening to guarantee full charge. For PEV 2, the lowest cost available occurs overnight so it decides to charge then with charging turned off for about 10 minutes, due to the small `bump' in price around 3 a.m. Note that this process does not prevent intermittent charging profiles, which can happen if the apparent cost to the PEV has multiple local (and similar in depth) peaks and valleys.

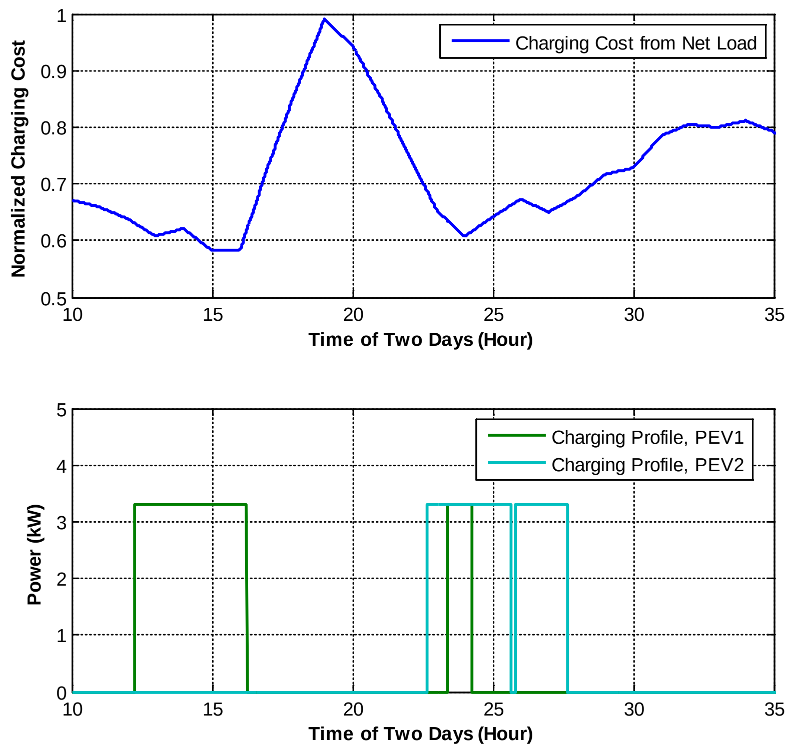


Figure 72. Charging profiles for two PEVs with different energy requirements and plug-in window.

The intermittent charging is considered to be a milder charging condition compared to continuous charging. In this pattern, battery temperature will be lower which has less impact on degradation, since temperature is the leading factor for degradation [48, 110, 111]. Similarly, intermittency will allow the converter and other electronics to cool down. If continuous charging has to be guaranteed, an alternative algorithm can be the following: 1), each PEV calculates its required charging time at arrival; 2), depending on the departure time in the next day, the PEV finds out all the feasible continuous charging windows (i.e. charging starting points); 3), according to the electricity cost broadcast, the PEV does a simple line search to determine the optimal charging window (i.e. charging starting point). Assuming a continuous window that accommodates the needed charge exists, it is easy to see that the algorithm leads to a continuous block.

Finally, note that the communication between grid operator and PEV is quite modest: one set of prices from grid operator, one set of charging values for PEV, once.

7.4.2. Cost Updating

Given that individual PEVs choose the lowest cost periods, the question becomes how to control/update the cost function such that the aggregated charging profile can be close to the optimum for grid operation. Intuitively, a simple approach would be based on a cost $C(t_i)$, where the original net load curve $D(t_i)$ can be used as the cost directly, as shown in the previous section. The basic scenario for cost updating is that the grid operator provides the net load forecast $D(t_i)$ each day and all PEVs will respond to the same signal.

Figure 73 shows the final result if the same net load is shared with the total population of PHEV40 (40 miles all electric range) for a typical day. The charging load exhibits a large peak at 2:00(26:00 on the graph) where the original net load has its minima. The incremental load is over 7 GW and lasts a short time. In this sense, the new peak will expose a significant extra burden on the grid.

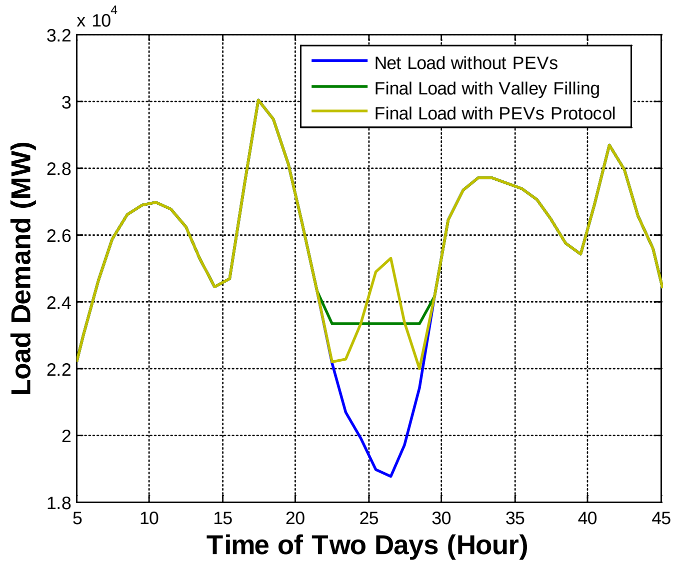


Figure 73. Update cost function every 24 hours with PHEV40 charging at 3.3 kW.

As shown in the introduction, the PEVs arrival time is well distributed so the new peak above was built up through a relatively long time (more than half day) by the individual decisions made at different times. A potential solution to lower the peak is for the grid operator to change the cost function periodically so that PEVs gradually fill the valleys in the updated cost function and avoid charging at the new peak. This process can be treated as a natural valley filling.

Given that a 3.3 kW maximum load for one PEV is trivial compared to the entire grid load, the updating of the cost can be accomplished such that a number of vehicles can register, obtain prices, select charging times and communicate the results with grid operator. A typical time interval T_{step}, or a set number of PEVs V_{step}, or a set amount of the net load change in a time window (e.g., 23:00 to 6:00 in the next day) can be used to trigger the updating. Below, the protocol's details and results will be shown based on the first two methods.

1. Updating the cost function

At each updating instant, the cost function is updated by adding the aggregated PEV charging profiles to the previous cost function.

$$C_k(t_i) = C_{k-1}(t_i) + s_{k-1}(t_i), \qquad C_0(t_i) = D(t_i) \tag{23}$$

2. Profile aggregating

As discussed before, this dissertation studies the mechanism for updating the cost: fixed time internals and fixed number of vehicles.

a. If fixed time interval is chosen, all of the individual profiles, generated from the PEVs that have arrival time, ta_n, in the interval $[T_{k-1}, T_k)$ are aggregated.

$$s_{k-1}(t_i) = \sum_n {x_n(t_i)}/{\eta} \;\forall\, n \quad s.t. \quad T_{k-1} \leq ta_n < T_k \tag{24}$$

$$T_k = T_{k-1} + T_{step}, \quad T_0 = 4am \tag{25}$$

b. If the fixed PEVs amount is chosen, each aggregation takes place with the interval of vehicle number (V_{k-1}, V_k).

$$s_{k-1}(t_i) = \sum_n {x_n(t_i)}/{\eta} \;\forall\, n \quad s.t. \quad V_{k-1} < n < V_k \tag{26}$$

$$V_k = V_{k-1} + V_{step}, \quad V_0 = 0 \tag{27}$$

In either case, it is important to limit the number of PEVs that will be aggregated between two cost broadcasts such that the load increment is small enough to accomplish smoothing of the overall load profile. This can be precisely controlled by T_{step} or V_{step}. In section 3.3, the tradeoff between more frequent (more communication) and less frequent (less smooth load profile) updates will be discussed.

7.4.3. Protocol Results and Analysis

7.4.3.1. One-Day Results

Figure 74 shows the results where T_{step} is 720 minutes (12 hours). The increment of the net load can be divided into two parts, the one before 16:00 and the one after, as shown in the red lines. As expected, the first one has the same trend as observed in Figure 73 and the second fills the two valleys to two smaller peaks, depicted in yellow lines.

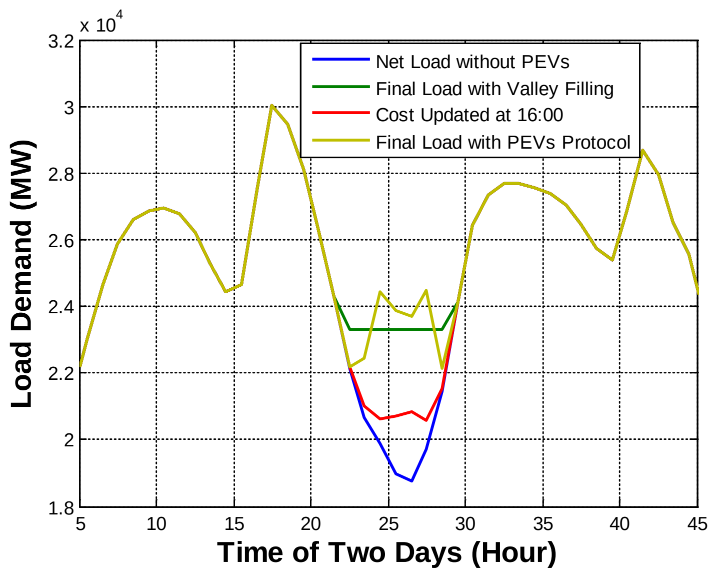


Figure 74. Update cost function every 12 hours.

Figure 75 shows the resutls when T_{step} are 360 and 240 minutes (6 hours and 4 hours) respectively. Each curve shows the load profile (cost function) after the charging profiles of the vehicles up to the corresponding time are incorporated. First, the final net load with PEV protocol becomes smoother with a decreased T_{step}. Second, the difference between two costs $C_k(t_i) - C_{k-1}(t_i)$ is small at the beginning which gets larger and eventually gets small again. This pattern is due to the distribution of the vehicles arrival times in Figure 69. With the same time interval, fewer PEVs arrive home in the morning and the late evening while more PEVs arrive home in the late afternoon and early evening.

That is why curves indicating costs are denser at the bottom and top, and less dense (i.e. larger change in each step) in the middle. Near the end of the process, i.e., very late evening, fewer PEV arrivals help smooth the demand curve.

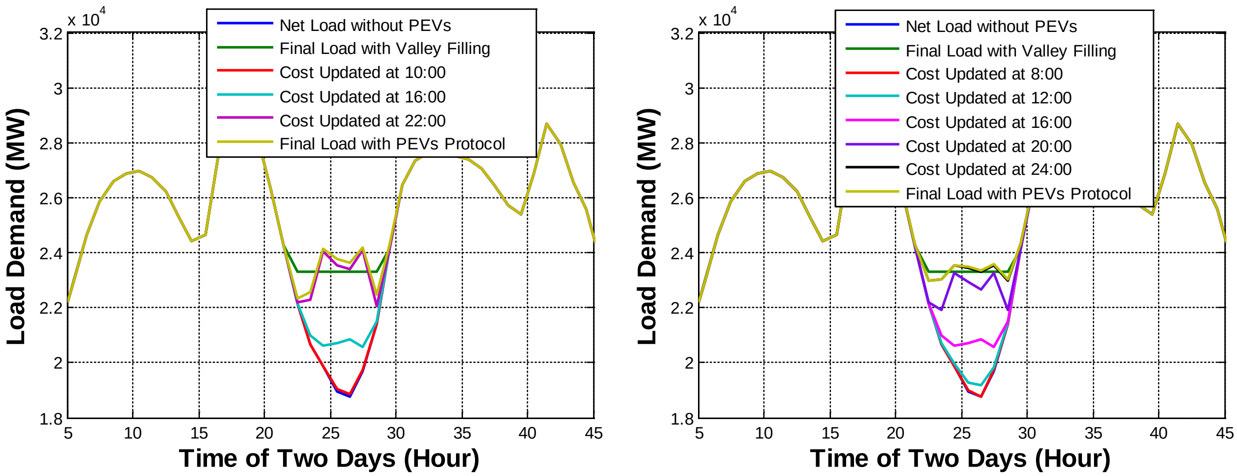


Figure 75. Update cost function every 6 hours (left) and 4 hours (right).

As shown in Figure 76, when T_{step} is reduced to 30 minutes the final curve is quite flat. The detailed examination on the right hand side indicates the variation of the curve is less than 200 MW from 23:00 to 4:00 in the next day. Thus, generators, especially load followers, can have a more steady operating condition overnight.

Another observation is the creation, and later filling, of new peaks and valleys in the cost function curve in successive steps. This is rather intuitive for this strategy. For example, all PEVs arrived between 16:00 and 16:30 are given the same cost function. They will optimize their own cost, i.e. they will try to be on where the cost is lowest. After updating, the new cost would be higher at those time slots and PEVs arriving between 16:30 and 17:00 will try to avoid charging at those time slots.

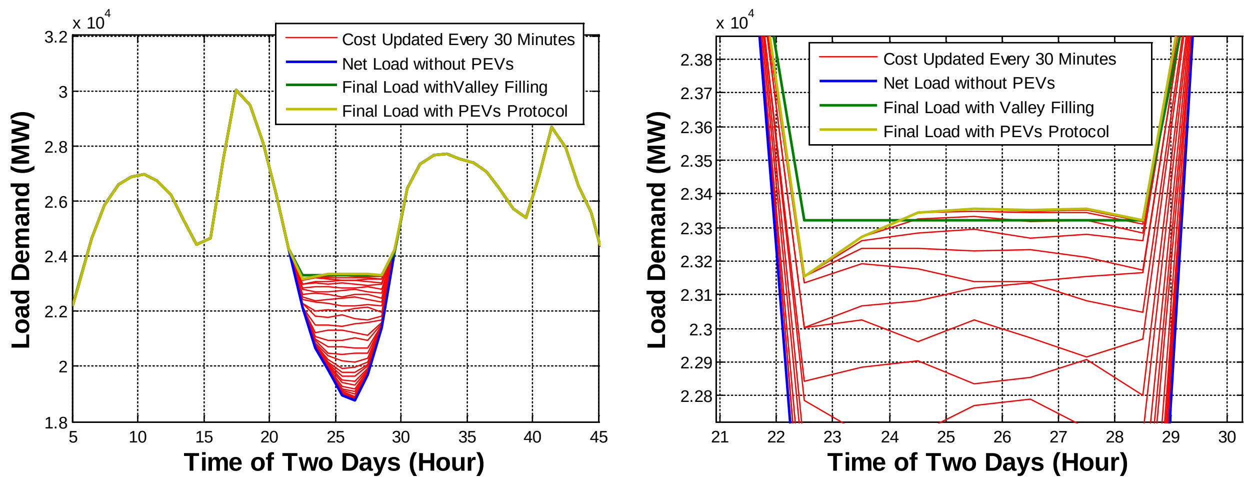


Figure 76. Update cost function every 30 minutes.

The fixed number of PEVs can also be used for triggering the updating of the cost (see Figure 77) when it is preferred to control the variation of the cost in each step. Because the charging power is fixed to be 3.3 kW, the maximum change between $C_k(t_i)$ and $C_{k-1}(t_i)$ is limited by the product of charging power and the PEVs number V_{step}. In this approach, the grid operator develops a queue, as PEVs arrive, and after each V_{step} vehicles, the cost is updated and shared with the next V_{step} vehicles. In the example shown here, V_{step} is set to be 100,000 such that the maximum change on the cost can be limited to 330 MW step by step. Figure 77 shows the results in comparison with the first method. The final variation lies within a 250 MW window from 23:00 to 4:00 in the next day. The cost function increment is more consistent and limited by 300 MW as expected in the analysis above.

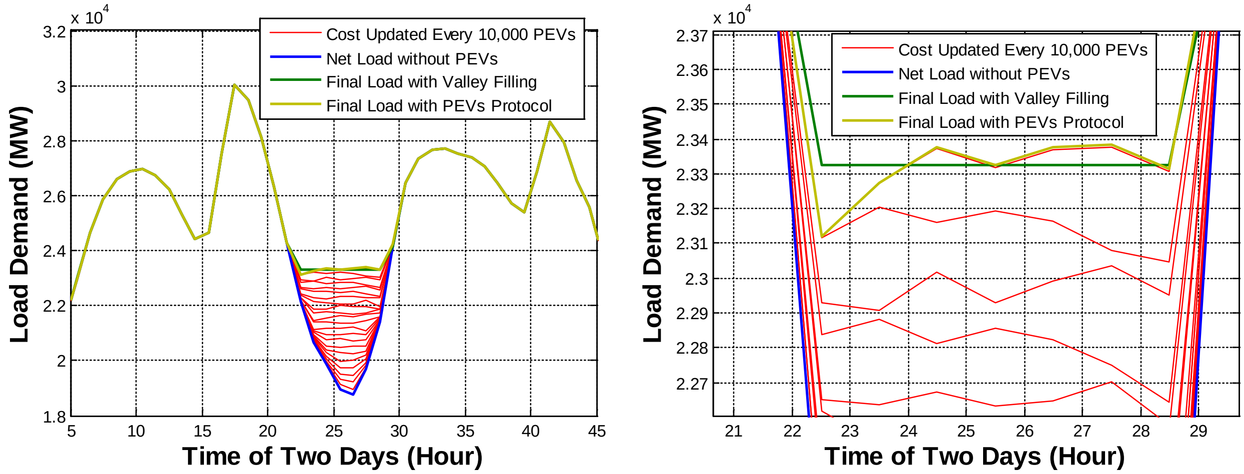


Figure 77. Update cost function every 10,000 PHEVs.

As discussed earlier, continuous charging can also be guaranteed by changing the algorithm to a simple line search of the charging start point for individual PEVs. The rest of the protocol can remain the same where costs are updated by T_{step} or V_{step}. Figure 78 shows the results of continuous charging with costs updated every 30 minutes, as a comparison to the results of the main protocol with intermittent charging in Figure 77. It can be observed that the final net load with PEVs is smooth, though not as flat as the one with intermittent charging. There exists a bump in the middle of the overnight valley. This is due to the fact that the average charging time is over 3 hours, for 3.3 kW power. Forcing continuous charging inevitably leads to a sizable number if PEVs having overlapping charging time, resulting in the shape seen in Figure 78. Higher charging power would mitigate this issue. On the right hand side of Figure 78, the results are shown with 6.6 kW charging power. As expected, the final load with PEVs is as flat as the intermittent 3.3 kW charging in Figure 76. However, 6.6 kW charging is not likely to be popular at least in the near future because it increases the component cost, makes the distribution network less stable, and has minimal benefits in reducing the operating cost [34, 73, 112, 113].

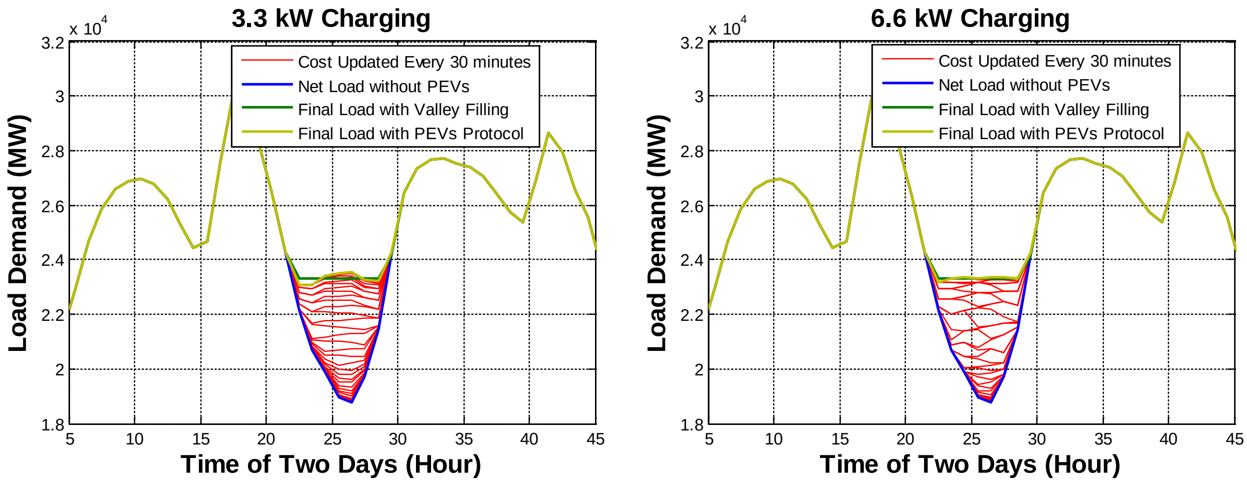


Figure 78. Continuous charging with cost updated every 30 minutes for 3.3 kW (left) and 6.6 kW (right) charging power.

7.4.3.2. Communication Effort

For the proposed protocol, either intermittent or continuous charging, each PEV receives the load curve (cost function), calculates its profile, and transmits the results one time, while the grid operator needs to receive all of the individual profiles in the set before updating. So the calculation effort is decentralized to individual PEVs while the receiving and aggregating efforts are on the grid operator, proportional to the PEVs population N. In Table 18, the amount of individual profiles received in a step and the frequency that the cost is updated are evaluated at the largest communication burden. To obtain the results shown in Figure 76, the cost is updated 48 times per day and no more than 167,000 PEV profiles are transmitted in 30 minutes. As for the results in Figure 77, the minimum updating interval is 18 minutes.

Table 18. One-day communication effort of the proposed protocol.

	Update Method	Max Arrival (PEVs per 15 Minutes)	Min Time Interval to Update (minute)	Max PEVs Aggregated in One Update	Update Times per Day
Analytical	**Fixed Time (T_{step})**	**4% × N**	**T_{step}**	**4% × N / 15 × T_{step}**	**1440/ T_{step}**
(N, population)	**Fixed PEVs (V_{step})**	**4% × N**	**V_{step} / (4% × N / 15)**	**V_{step}**	**N / V_{step}**
Example (T_{step} = 30 min	**Fixed Time (T_{step})**	**84000**	**30**	**167,000**	**48**
V_{step} = 100,000 N = 2.1 million)	**Fixed PEVs (V_{step})**	**84000**	**18**	**100,000**	**21**

Compared to methods in many existing publications [46, 47, 68, 69], the calculation and communication efforts offer advantages as: 1) one linear optimization calculated and one profile transmitted at the PEV side without any global information; 2) no more than 10% of profiles are aggregated in 30 minutes at the operator side; 3) the cost is updated no more than 50 times per day at the operator side; 4) further, PEVs do not have to wait until a specific time to participate, which increases the potential to change the net load in late morning and afternoon.

7.4.3.3. Annual Results

To understand the performance of the protocol for different net load curves, the same PEV charging requirements repeated each day with 30 minutes for T_{step} has been implemented in the simulations for the whole year. As a reference, the valley filling technique has been conducted separately. Figure 79 is the snapshot of the results from day 105 to day 120. The charging profiles from two methods are depicted at the bottom by the light blue and purple lines. The black line shows the upper bound of the charging power, and the green and yellow lines exhibit the final load with PEV charging.

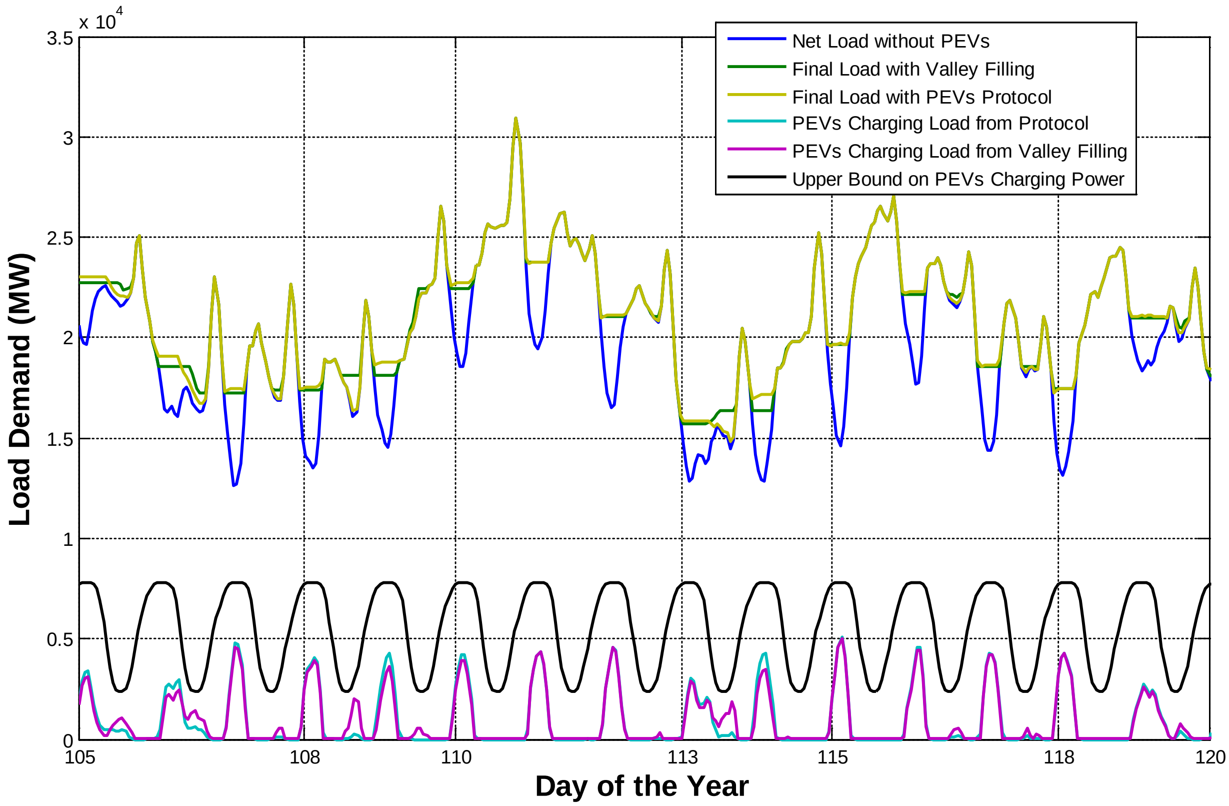


Figure 79. Annual results from valley filling and proposed protocol with 30 minutes updating interval.

The two charging profiles (i.e., valley filling and the protocol suggested here) are very close to each other especially when there is only one deep valley overnight. The correlation coefficient of the two profiles is 0.98 and the two resulting final loads exhibit less than 0.02% difference on the objective function in Equation (16). The only obvious difference occurs when there is another relatively deep valley in the afternoon as shown in the results from day 108 to 109 or day 113 to 114. In that case, the valley filling provides a result with two valleys filled up close to the same level while the proposed protocol does not fill the first valley in the afternoon and fills the overnight valley to a higher level. The main reason for that is the overnight valley is relatively deep, leading to a smaller cost function value so that PEVs participating in the protocol at the early steps will choose to charge overnight. When it is filled to a higher level than the afternoon, time has passed the first valley and the rest of the PEVs can still only choose overnight to charge. It needs to be noted that none of the existing research has addressed this since they require that most PEVs arrived home to initiate the protocol, often quite late in the day, e.g. midnight. Naturally, the afternoon valley cannot be filled in practice. However, for the proposed protocol in this chapter, one possible solution is to come up with a final net load curve (e.g., the valley filling results) as a target to approach and prioritize the afternoon valley by changing the cost function. The details for this approach are discussed in Section 7.5.

Another important aspect, to evaluate the performance of the proposed protocol, is the final net load variations for each night. First, a maximum variation of the final load curve is defined (e.g., 300 MW). Second, the length of the consecutive time window that meets this bound is found for every night of the year. This window indicates for how long the balancing generators can operate at a relatively constant condition. Figure 80 is the distribution of the width of this time window by setting the maximum variation to 300 MW. For most of the nights, the window width is above 7 to 8 hours and there is only one night with a 5-hour window and 21 days with a 6-hour window. The widest window reaches up to 13 to 14 hours. The widely spread distribution is due to the variety of the original net loads for different nights, shown in Figure 79. A narrower and deeper net load valley tends to have a shorter consecutive time of flat net demand, as day 118 shows, while a wider valley is likely to have a longer consecutive time of flat demand as day 119 shows.

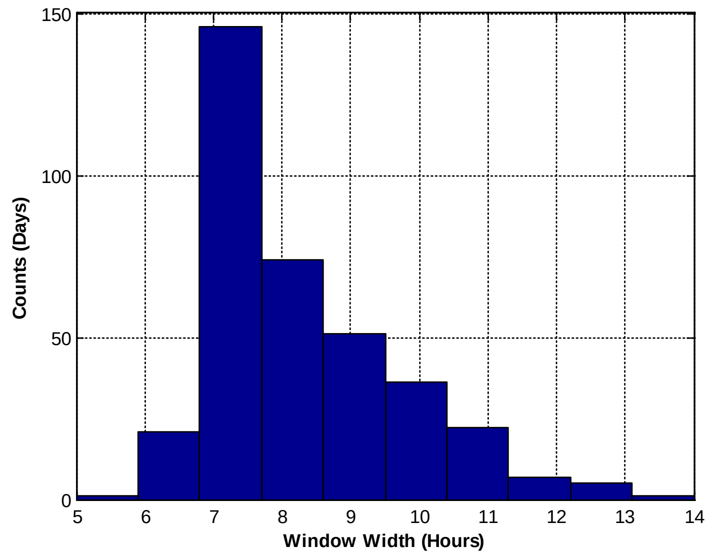


Figure 80. Histogram of the maximum consecutive time with load varying less than 300 MW.

In summary, in the proposed protocol, each PEV calculates its own optimal profile based on the broadcast cost function which is updated frequently. The charging load of PEVs can fill the overnight valley, often to a flat final net load curve. A valley in the afternoon imposes difficulty, however, as it lies outside of the most effective charging zone, from 20:00 to 7:00 in the next day, when a large number of PEVs are plugged in.

7.5. Modified Protocol for Target Load Following

When there exists a relatively large valley (or multiple valleys) in the afternoon due to large solar/wind generation (or intermittent solar/wind generation), it leads to the following potential scenario: power plants have to ramp up and down quickly to meet this particular load, increasing cost and generating more emissions or, alternatively, some of the solar/wind power is curtailed. It is therefore preferable to fill or smooth the afternoon valley(s). As shown in the left pane of Figure 81, the original protocol is not aimed at accomplishing this task and does not fill the first valley at all. As discussed in the Section

7.4.3.3 (Annual Results), this is due to the fact that overnight valley is more attractive than the afternoon one at the beginning. By the time the overnight valley is filled to the same level as the afternoon one, it is too late for enough PEVs to fill the first one. In order to fill the first valley, or more precisely, to approach a target load which the grid operator favors, here a modified version is built as follows: 1) grid operators define a target load by considering constraints at the grid level; 2) the cost broadcast is changed to be the current load minus the target load; 3) when appropriate, scaling is used to adjust the new cost function to ensure the desired overall charging profile. The local optimizations of individual PEVs along with the communication scheme remain the same as before. These steps will be described in detail below, followed by daily results.

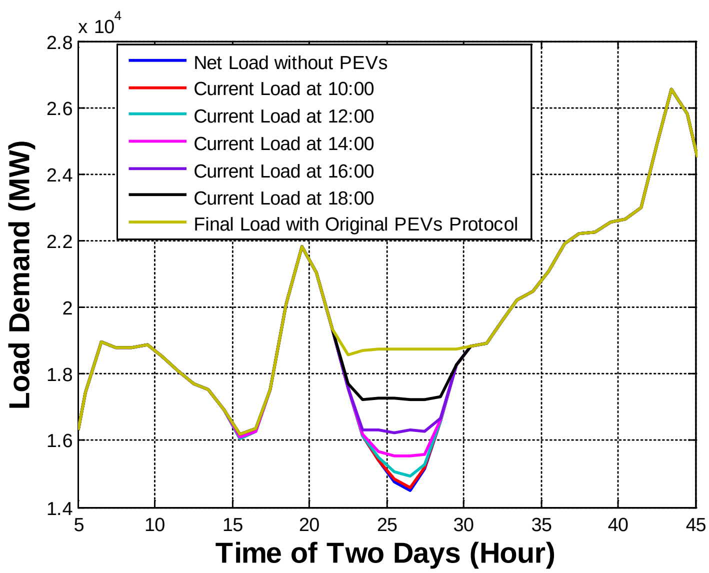


Figure 81. Final load of the original PEVs protocol for day 108 to day 109 and loads at different times.

7.5.1. Modified Protocol

For the first step, a target load curve with PEVs charging, $TL(t_i)$ is the summation of the known net load and the overall PEV charging load $X(t_i)$, which is unknown but bounded according to Equation (17) and inequality (19).

$$TL(t_i) = D(t_i) + X(t_i) \tag{28}$$

$$s.t. \begin{cases} \Delta t \times \sum_i X(t_i) = B = \sum_n b_n \\ X(t_i) \leq R(t_i) \end{cases}$$

One example for the target load is to use the solution of valley filling, formed by (16)(17)(19). The solution is depicted by the solid green line in Figure 82. Another example for the target load is the solution of ramp rate reduction, which is aimed at smoothing the final load for generation cost reduction [106]. In this study, the objective function for ramp rate reduction is shown in Equation (29), which minimizes the sum of squares of ramp rates between two consecutive time slots. The total energy and maximum power constraints associated with $X(t_i)$, in Equation (17) and (19), remain the same. The ramp rate problem consisting of (29),(17) and (19), is also a convex optimization problem and solvers, such as CVX and Quadratic Programming in MATLAB, can provide a solution fast and reliably. The solution to this problem is depicted by the dashed line in Figure 82.

$$min \sum_i \big(TL(t_{i+1}) - TL(t_i)\big)^2 = min \sum_i \Big(\big(D(t_{i+1}) + X(t_{i+1})\big) - \big(D(t_i) + X(t_i)\big)\Big)^2 \tag{29}$$

$$s.t. \begin{cases} \Delta t \times \sum_i X(t_i) = B = \sum_n b_n \\ X(t_i) \leq R(t_i) \end{cases}$$

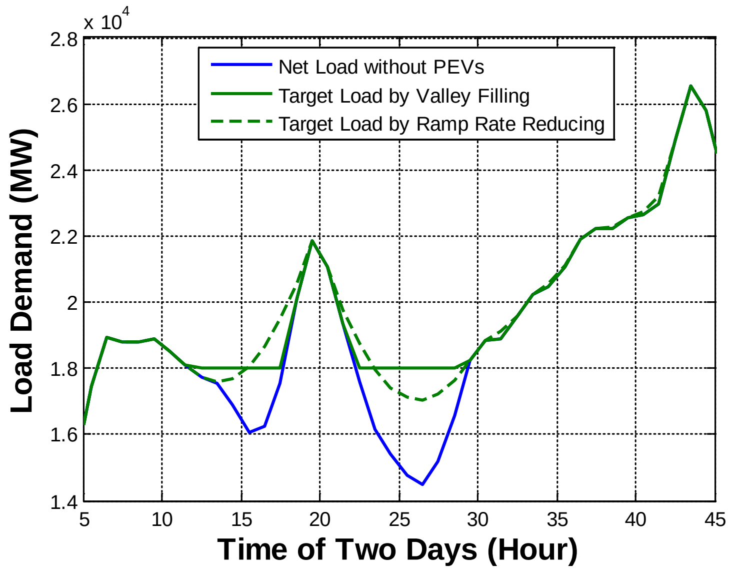


Figure 82. Two examples of the target loads, solution of valley filling and solution of ramp rate reducing.

For the second step, at each iteration, the cost function is modified by subtracting the target load from the cost function defined in Section 7.4.2. (i.e., the costs shown in Figure 76 and Figure 77). This modification, see Equation (30), results in a cost function that is essentially the gap between the current load and the target load. The current load is updated by receiving and aggregating PEV charging profiles $s_k(t_i)$ in each step exactly the same way as before while the target load is fixed.

$$TC_k(t_i) = C_k(t_i) - TL(t_i) \tag{30}$$

$$C_k(t_i) = C_{k-1}(t_i) + s_{k-1}(t_i), \qquad C_0(t_i) = D(t_i)$$

Generally, the modified cost function can be non-positive if the current load is less than the target level. The wider this gap in some time slots, the more attractive it is for the PEVs to charge. By the analysis shown in the APPENDIX, PEVs will choose the lowest cost periods, which leads initially to late night time slots due to the largest gap between the two curves. As joining PEVs select these time slots, the gap becomes small and the magnitude reaches the same as the ones in the afternoon, PEVs will then choose to charge at the first gap. However, by then there might not be enough PEVs available to fill the first gap, as the results show in Figure 83. It is exactly the same reason that the original protocol is not able to fill the afternoon valley in Figure 81. Thus, an additional step of modifying the cost is needed to guarantee the afternoon gap is filled first.

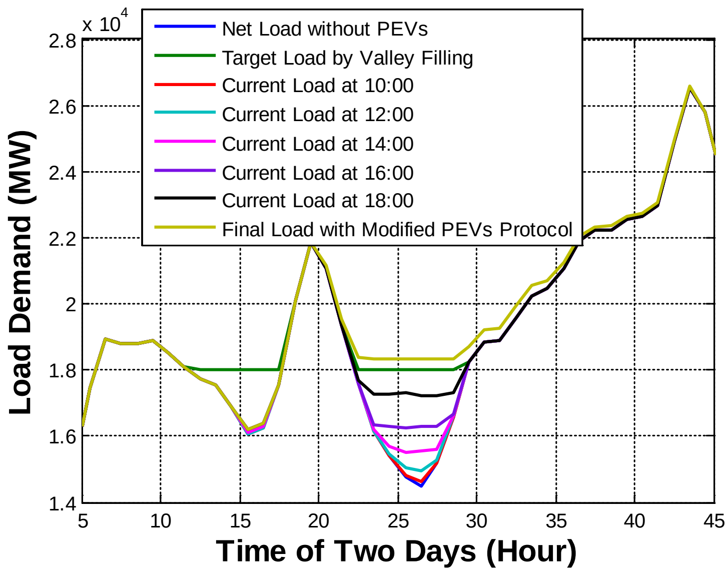


Figure 83. Results from modified protocol without prioritizing by using the valley filling solution as the target.

For the third step, in order to prioritize the afternoon time slots, Γ, grid operator can artificially scale the costs to be more attractive than those overnight. Equation (31) shows the formulation of the modified cost $PC_k(t_i)$, that will be broadcast to PEVs, along with some requirements.

$$PC_k(t_i) = TC_k(t_i)P(t_i) \tag{31}$$

$$\mathrm{P(t_i) = 1 \forall t_i \notin \Gamma, P(t_i) > 1 \forall t_i \in \Gamma}$$

$$\mathrm{PC_k(t_i) < PC_k(t_j) \;\forall \{\; TC_k(t_i) < 0, t_i \in \Gamma, t_j \notin \Gamma\}}$$

$$\mathrm{PC_k(t_i) < PC_k(t_{i+1}) \;\forall \{\; TC_k(t_i) < 0, t_i \in \Gamma, t_{i+1} \in \Gamma\}}$$

The scaling vector, $P(t_i)$, has to be larger than one when t_i belongs to Γ, the time slots that are to be prioritized, which is 11:00 to 18:00 in the example; it can be equal to one for the rest of the time slots. Second, from 11:00 to 18:00, the scaling values need to be greater than the ratio between the depth of the overnight gap and the depth of the afternoon gap, such that the afternoon gap is filled first. The scalar must be large enough that it produces lower costs in that window, even as the afternoon gap is partially filled. Third, for the first gap, from 11:00 to 18:00, the same problem discussed earlier can exist, that early PEVs will fill the deepest point, at around 15:00, and only then the rest of the gap. When the number of PEVs is small, there is a possibility that sufficient PEVs are not available to fill the early part of the gap. $P(t_i)$, therefore, should ensure the modified function $PC_k(t_i)$ has a more negative value for the earlier time slots in the prioritized window Γ. In other words, $PC_k(t_i)$ has to have a positive slope in terms of t_i if the target has not been reached. The last line in Equation (31) is the condition required to guarantee that the gap at the earlier time slots will be filled first by the PEVs. The precise values of $P(t_i)$ were manually tuned here, through a few trials, having the value on the order of 10E6 for 11:00 and 10E3 for 18:00, and gradually decreasing exponentially.

7.5.2. Results and Analysis

In this section, two sets of final results will be shown. First, following the above example in Figure 83, the solution of valley filling will be used as the target load. Second, the same modified protocol will be applied on the other target, the solution of ramp rate reducing.

7.5.2.1. Valley Filling as Target

Figure 84 shows the final load from the modified protocol with 11:00 to 18:00 prioritized. Due to the prioritizing, the gap in the small valleys is more negative than those of overnight valley, steering early arriving PEVs to toward the smaller valleys. As these are filled, or their different with the target becomes small, the updated cost function directs the PEVs to the overnight valley.

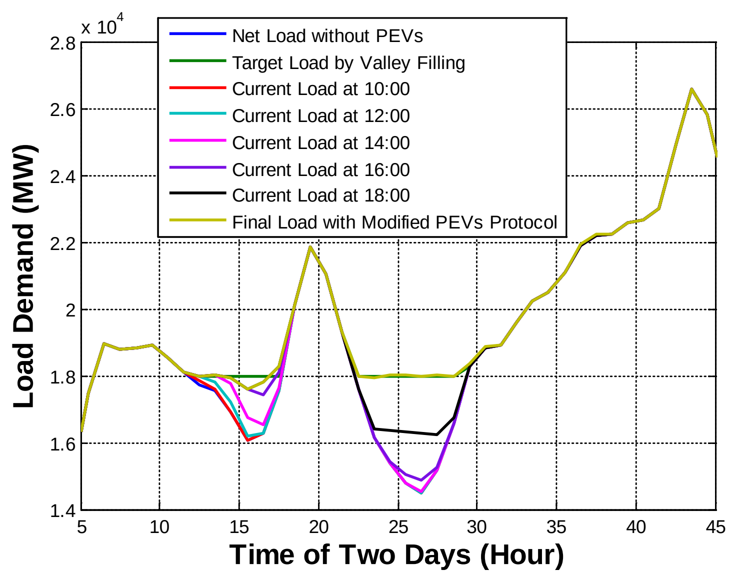


Figure 84. Results from modified protocol with time slots 11:00 to 18:00 prioritized by using the solution of valley filling as the target.

However, it ended up not filling the gap completely for the time slot 15:00 to 16:00. The reason is that the target load in the example is not feasible to achieve due to the small number of PEVs available. Note that the solution, in the green line, does not violate the maximum power constraint, but this constraint does not capture the actual challenge: some of the PEVs are already fully charged, so they are not able to take any more charge.

7.5.2.2. Ramp Rate Reducing as Target

In Figure 85, two 48-hour net loads in blue are shown with the left one the same as in the previous example and with the right one having multiple small valleys throughout the day. The big afternoon valley on the left pane implies substantial solar/wind generation during the day time while the two small valleys on the right pane indicate varying solar/wind generation. Compared to the example above, only the target load is changed in order to have the minimum ramp rate. The final loads with modified PEV protocol approached the targets very well. For the example on the left, the maximum difference from the target load is only 200 MW with only one exception at the time slot from 15:00 to 16:00. That difference is around 400 MW and due to the same reason mentioned before that the target is not feasible to achieve. As for the example on the right, this issue does not exist so the difference between final load and target is examined to be smaller than 200 MW for all time slots.

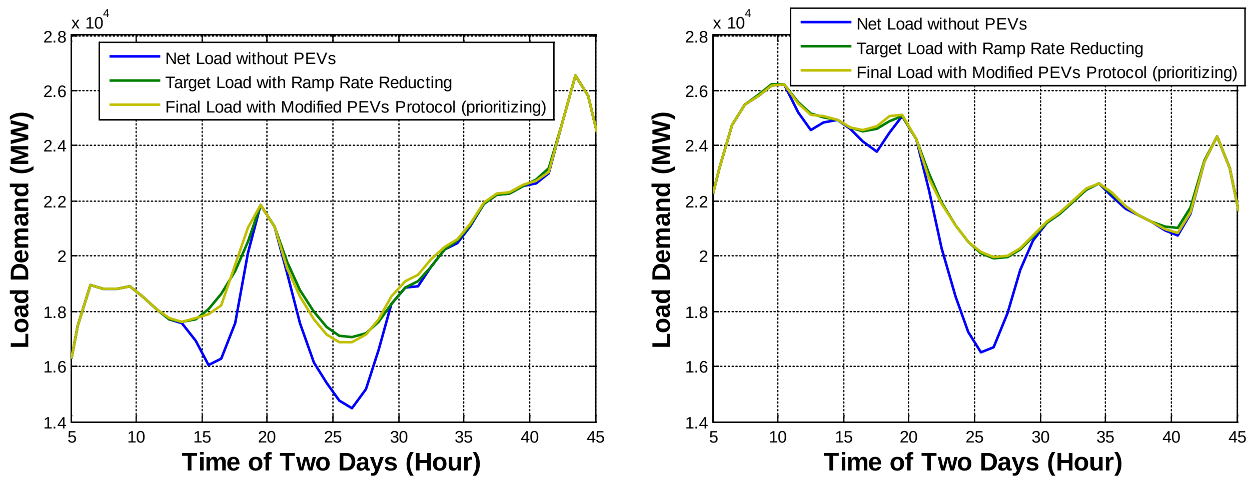


Figure 85. Two sets of Results from modified protocol with time slots 11:00 to 18:00 prioritized by using the solution of ramp rate reducing as the target.

In summary, by slightly changing the cost function broadcast and prioritizing the time slots during the day time, the final load with PEVs can be controlled to approach a target load. To form an achievable target, grid operators need to estimate the overall charging energy in (17), maximum charging power at each time slot in (19), and other possible constraints not included here. This modified protocol extended the capability of PEVs to change the grid load from valley filling to target load following.

7.6. Discussion

The results presented in this chapter often lead to Intermittent charging. As discussed in [102, 103, 106], there is little evidence that intermittent charging is undesirable, indeed the avoidance of excess heating due to continuous charging over a long period, could be an important benefit. Nevertheless, if continuous charging has to be guaranteed, individual PEVs can first estimate the required charging time and then perform a line search to understand the optimal starting point such that charging cost can be minimized. The rest of the protocol for cost updating will remain the same. For the overnight valley filling, this will show a very similar result compared to intermittent charging, but have a small bump in the middle of the valley. But if charging power is doubled to 6.6 kW, the flat valley filling overnight can also be achieved.

The actual charging power for a specific PEV depends on its SOC. Generally, the maximum constant charging power is sustained before the SOC reaches 80%~90% and lower charging power is applied until fully charged. In this study the algorithm to calculate individual charging profile does not consider the SOC dependent charging profile, but assumes maximum power can be applied all the time. However, a simple change on the algorithm can accomplish different charging profiles. For continuous charging, PEVs can estimate the SOC dependent charging profile, implement the line search to determine the charging starting point, and send back this profile. For intermittent charging, PEVs can overestimate the charging energy, implement the linear optimization to determine charging profile with constant power, tailor the end of the charging profile as the battery specifies, and send back the final profile. For the grid operator, the protocol to aggregate PEV profiles and update the cost function does not change at all.

Wind/solar power are subject to intermittency and difficult to predict [114-117]. If the forecast net load changes after most PEVs have arrived and committed, it is unlikely that any simple protocol can ensure a flat final load. In this case, a possible solution is to reschedule a certain number of PEVs. The rescheduling would require an accurate forecast of the renewable power, coupled with some ranking and identifying PEVs with flexibility to be re-scheduled. Such an approach would require significant extra communication and is beyond the scope of this dissertation, which is focused on simple protocols with minimal communication.

The issue of the actual cost of energy, charged to the customer, by the utility is also not investigated. If the protocol is focused on overnight charging, a low uniform pricing policy is likely, though secondary valleys (reflecting intermittent renewables) may lead to more complex pricing models. Another issue, not directly addressed, is possible distribution network constraints, given that the data used reflect statewide numbers. The concept here can be used in relatively small networks and grids, with little to no modifications. The implementation on the residential transformer is shown in Chapter 8.

7.7. Conclusions

Realistic electric demand from CAISO for 2005 and solar and wind power under 30% renewable penetration assumptions were used to generate the net load profile for the state of California. The 2009 National Household Travel Survey data and parameterized PEVs operating and charging model were used to simulate the charging demand and constraints with 2.1 million PEVs (10% penetration). Optimization on the aggregated profile was formed in terms of valley filling and ramp rate reducing. Optimization on individual PEV charging was formed, as well, for the objective of minimizing charging cost. Two methods on cost function updating were performed along with results for both daily and annual basis. The proposed protocol in this chapter shows a promising result in terms of overnight valley filling and target load approaching. Based on the data, model and results above, the following conclusions can be drawn:

1. At the demonstrated renewable penetration, the net load curve shows the biggest valley almost every night. The most effective time for charging is the windows from20:00 to 7:00 in the next day, corresponding to the availability of 80% of the

total number of vehicles. With significant PEV market penetration (10%) shown in this chapter, coordination between individual PEVs and the grid has to be made to avoid additional and prohibitively expensive peak power periods.

2. Using grid load directly as the cost function and updating it frequently enough, by either a fixed time interval or vehicle amount, will lead to a flat final net load overnight for a relatively large time window. Updating the cost function every 30 minutes results in less than 300 MW variations on the final load during more than 7 hours, for 90% of the days in a year. Also, the correlation of the aggregated charging loads from grid level valley filling and the proposed protocol is greater than 0.98.
3. The computation and communication efforts required by the proposed protocol are very modest. Each PEV needs to compute its charge profile only once, performing a simple linear optimization problem. It also needs to send the charging profile back to the grid operator, where individual profiles are aggregated and loads are updated periodically.
4. Using the gap between the current load and final target load as the modified cost function and prioritizing the earlier time slots if necessary, a desired target net load can be approached similar to overnight valley filling.

Chapter 8. SOLUTION FOR RESIDENTIAL TRANSFORMER

In Chapter 7, the proposed decentralized charging protocol shows a good performance to fill the net load valley or to follow a target final load for the entire state of California. This chapter utilizes the same decentralized protocols directly and compares results with a centralized protocol for cost reduction and demand leveling in a smaller region. The region is identified to be the area under residential transformer. Electric demand of the residential transformer, electricity cost from multiple utilities and representative travel behavior data are used to evaluate the proposed protocols in terms of reducing the peak demand, the power losses and money cost for PEV charging. Two un-coordinating charging strategies, the immediate charging and the immediate charging with cost, are also simulated to provide references.

8.1. Introduction and Literature Reviews

Plug-in electric vehicles shift the energy consumption from oil to electricity. The electricity flows from the power plants, transmission lines to the distribution circuits to feed the PEVs. In Chapter 7, the results show that with the proposed coordinating charging strategy, the extra demand of the 10% PEVs in California will not increase the electric net load at the peaking times. The majority of previous studies, which focused on the impact of PEVs on the generation side of the electric grid also conclude that with controlled charging, building new power generation infrastructure will not be required [63, 118-122]. Thus, the power generation will not face substantial problems with controlled PEV charging in the near future. However, the distribution circuits may face more challenges due to the following reasons. First, 80% of the charging energy by PEVs will draw from home, which can be seen from the model results in section 4.3.2.2 and the report from the actual EV project [101]. Second, the local PEV penetration can reach to a very high level although the average penetration cross the state grows slowly [118]. It is possible that all households in a neighborhood own and operate at least one PEV.

In the residential distribution circuits, several impacts have been identified associated with PEV charging, including the thermal impact on the power lines, the transformer overload, failure and aging, the power losses in the network and the voltage deviations [112]. Also, several factors have been identified to contribute to those impacts, comprising of the driving patterns, the charging characteristics, the charging timing control and the PEV penetrations [112].

Some studies utilize the transformer demand in southern California plus the simulated charging demand from the National Household Travel Survey (NHTS) to evaluate the possible final demand on the transformer. Combined with a thermal model of a transformer, the hot spot temperature and the aging factor can be calculated [73, 118]. Results show that the uncontrolled charging can reduce transformer life dramatically although the immediate failure may not happen. Simple control strategy was investigated to achieve off-peak charging which had significant impact on transformer aging factor. Another study also utilizes the transformer aging model and Monte Carlo simulation to estimate thermal aging in a fully loaded 25 kVA overhead distribution transformer serving 12 homes and 6 PEVs, with ambient temperature data from Phoenix, Arizona and Burlington, Vermont [71]. Results indicate that warmer temperature can increase the aging effect and the smart charging in general can substantially reduce transformer aging. The study also proposed a temperature-based smart charging algorithm. In another study [72], the same author further investigated a decentralized charging algorithm to avoid transformer overloading by denying the charging request when it can potentially overload the transformer.

In addition to the impact on the transformer, one study utilizes a large-scale distribution planning model for evaluating the impact of different levels of PEV penetration on distribution network investment and incremental energy losses [113]. Obtained results show that depending on the charging strategies, investment costs can increase up to 15% of total actual distribution network investment, and energy losses can increase up to 40% in off-peak hours for a scenario with 60% of total vehicles being PEV. It is also shown that the smart charging can decrease the simultaneity factor, consequently to reduce power losses and investment. Another study utilizes the detailed IEEE 34 node test grid to assess the power losses with uncontrolled charging [123]. A centralized quadratic optimization is formulated to evaluate the impact of coordinated charging, which actually reduces the power losses and voltage deviations.

From the existing studies above, it can be summarized that the uncontrolled charging with high PEV penetrations will potentially reduce transformer life, incur the network upgrade and increase the power losses in the network. Coordinated charging can potentially mitigate all those issues by leveling the demand, in particularly at the transformer level. In this chapter, four charging strategies are evaluated for different PEV penetration levels, including immediate charging, immediate charging with TUO price, decentralized coordinated charging and centralized coordinated charging. The peak demand of a residential transformer, the power losses and the charging cost are the metrics to be investigated.

8.1.1. The Irvine Smart Grid Demonstration (ISGD) Project

UC Irvine is hosting one of the country's largest smart grid demonstration programs, the Irvine Smart Grid Demonstration (ISGD). ISGD will evaluate various aspects of the future smart grid through a public-private partnership led by Southern California Edison (SCE) and the U.S. Department of Energy with UC Irvine's Advanced Power and Energy Program as a research partner, and Facilities Management, Campus and Environmental Planning, and Transportation and Distribution Services as partners also. The ISGD program is comprehensive in that it spans from regional grid intelligence technologies, to the substation and distribution circuit level, down to individual homes that will be outfitted with smart appliances, solar panels, and electric vehicles to help understand how the grid will need to interact with the home of the future [124]. One objective of the ISGD project is reducing energy cost to costumers by shifting usage load to off-peak hours. There are two ways to do so. One is when the electric demand is not flexible, the energy storage installed at the individual house or at the transformer level can function to level the demand, i.e., charging during off-peak hours and discharging during peak hours. The other is when some of the electric demand is flexible, a control algorithm can move the demand to the off-peak time directly. Charging PEVs overnight is identified to be the controllable demand.

Figure 86 shows the layout of the ISGD project. In the MacArthur substation, the electric voltage is stepped down from the transmission level to the distribution level. In the figure, two circuits, Arnold and Rommel, feed the power from the substation to the residential areas, where the ISGD region is connected to the Arnold circuit. There are four blocks under four residential transformers which are connected to the Arnold circuit. There are 9, 8, 9, 20 houses in the four blocks and served by those residential transformers respectively. Different technologies are deployed in the four blocks. For instance, block 1 is the zero net energy (ZNE) group; block 2 utilizes the energy storage for each houses (home storage); block 3 has a larger energy storage for the entire street (community storage). In addition to the energy storage, solar panels, smart appliances and plug-in electric vehicles are also deployed for the three blocks. Block 4 serves as a control group to provide reference.

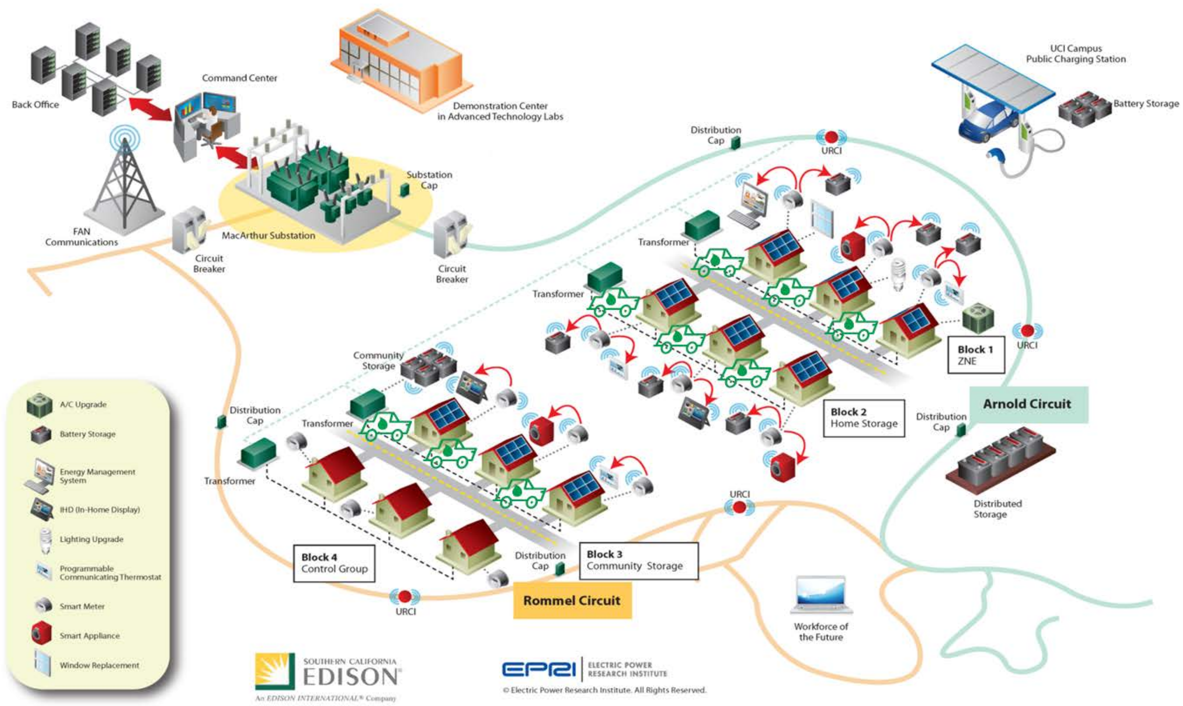


Figure 86. Layout of the Irvine Smart Grid Demonstration (ISGD) project.

Figure 87 shows the electric load at the transformer of the control group for the first two days in September in the year of 2013. September is the time period when the peak demand occurs in the entire year. The minute resolved profile indicates a lot of fluctuations which cannot be estimated accurately. However, the profile does show the diurnal pattern, the same as observed in section 7.2.3 for the electric demand of California.

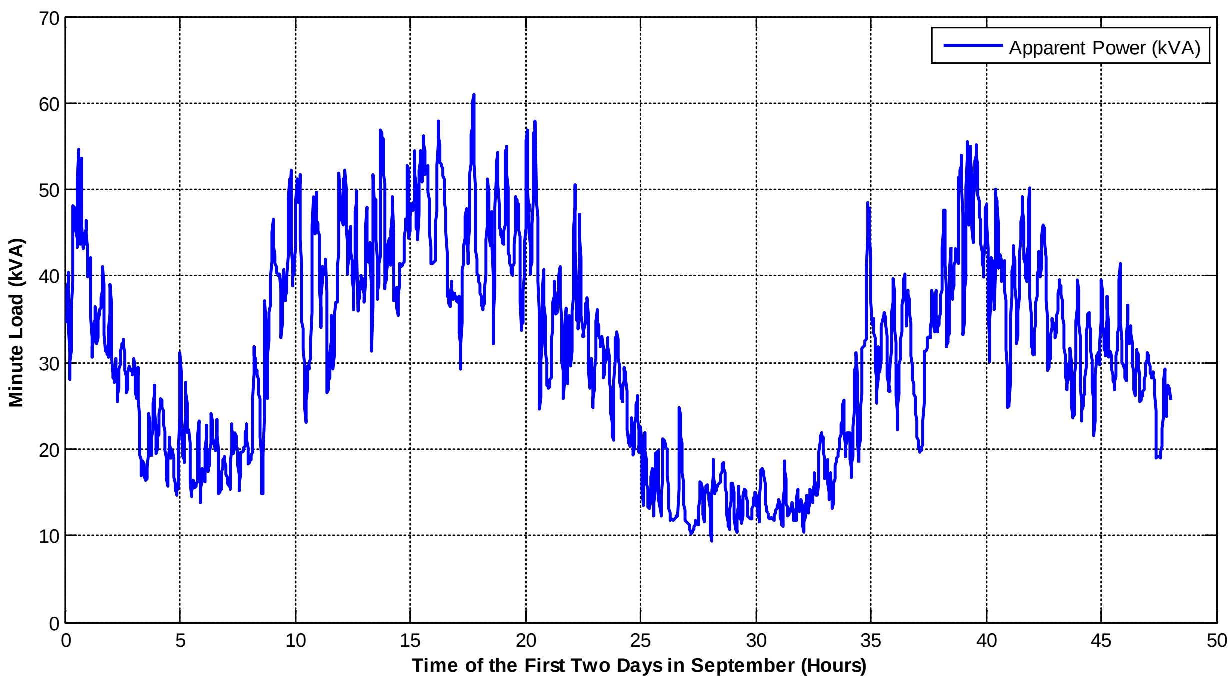


Figure 87. ISGD control group electric load in one-minute resolution for the first two days in September 2013.

In order to better understand this pattern, the hourly average profile is calculated, as shown in Figure 88. The curve shows a valley from midnight to 8 am and a peak around the late afternoon and early evening. It is obvious that this sine wave shaped profile follows people's activities at home. For the two days shown, the hourly peak load is about 50 kVA, which is lower than the 75 kVA rated capacity of the transformer. In Figure 89, it can be seen that for the entire month, the transformer has never overloaded.

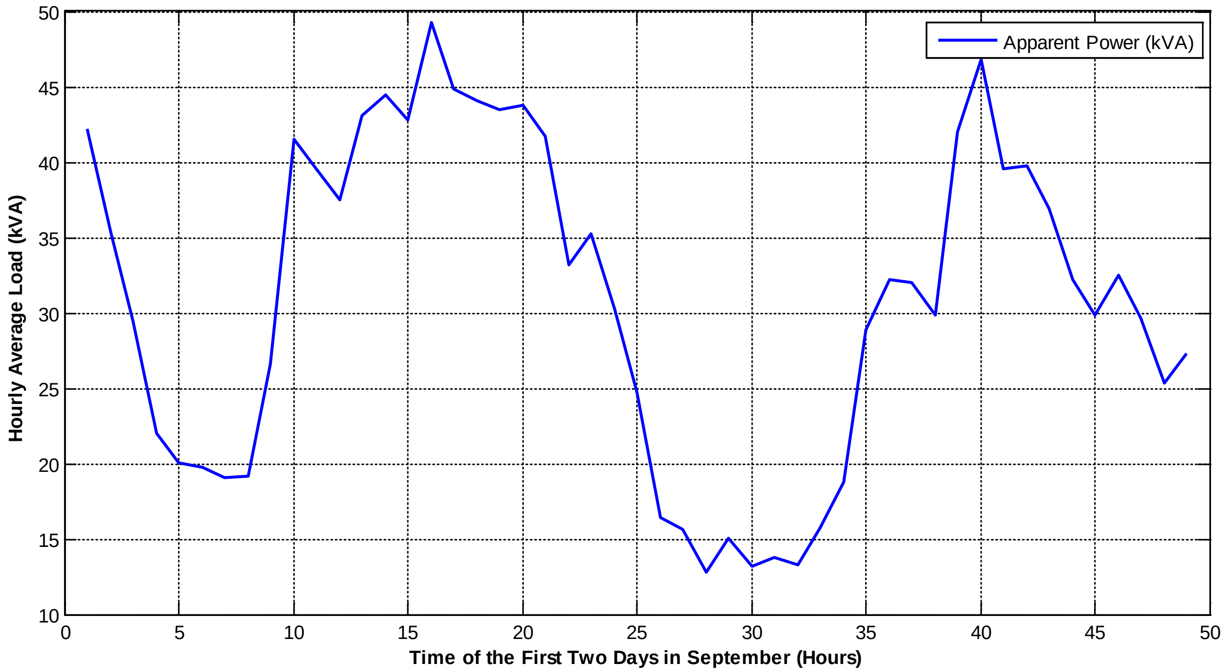


Figure 88. Hourly average ISGD control group electric load for the first two days in September 2013.

In Figure 89, the electric load exhibits similar style for the first seven days in terms of the maximum and minimum value. Those are some of the extremely hot days in a year. Other than that, the electric load fluctuates between 5 kVA and 30 kVA and exhibits multiple peaks during the day time. The first peak is in the early morning and the second peak is in the early evening, both are associated with people's activities. However, the load in the noon time is even lower than the night, due to the power generation of solar panels on the roof of two houses. Thus, this electric load is literally the net load at the the residential transformer. It will be called the base load hereafter. It is favorable that the charging load can fill the valley of the base load to avoid additional peaks and reduce power losses.

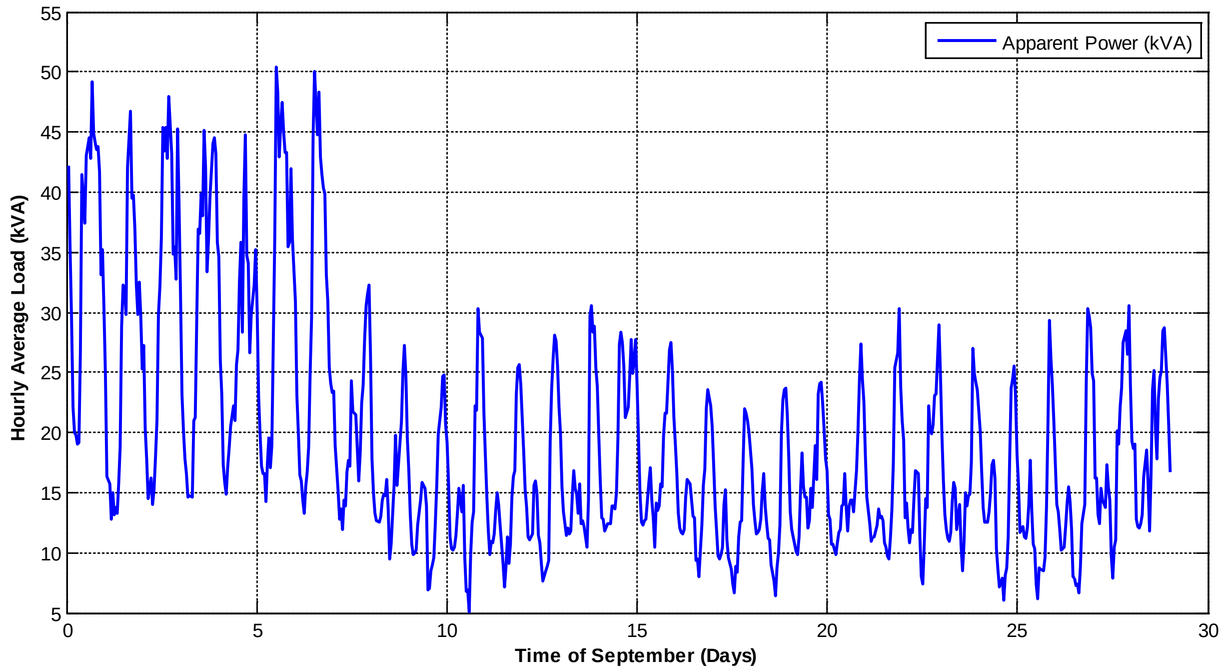


Figure 89. Hourly average ISGD control group electric load in September 2013.

One 75 kVA transformer serving for 20 houses is not the typical case in southern California. It is more representative to have 10 to 12 household served by a 25 or 37.5 kVA transformer [73, 118]. Thus, the electric load observed by one of the two windings of the transformer is used as the base load and ten households are assumed to be served.

8.1.2. Vehicle

It is ideal to utilize the actual travel behaviors from the control group. However, there is no survey taken by those residents to record the driving log. Thus, the survey data from 2009 NHTS is used to represent the travel pattern. As introduced before, PEV penetrations vary from 0% to 100%. 100% penetration means each household has one PEV. A maximum of ten vehicles' driving behavior data is required. Table 19 shows the daily VMT, end time of the last trip, the overnight dwelling time for the selected samples.

They are chosen from the region of southern California and have the average VMT, end time and dwelling time the same as the fleet-wide average.

Table 19. Travel behaviors of the ten selected samples from 2009 NHTS in southern California.

	VMT	End Time (hour)	Dwelling Time (hour)	AC Consumption For PHEV35 (kWh)	AC Consumption For BEV100 (kWh)
Car1	37.22	19.33	11.92	12.76	13.58
Car2	54.32	17.92	12.92	12.76	19.81
Car3	22.13	17.50	14.67	8.07	8.07
Car4	38.68	18.67	12.33	12.76	14.11
Car5	16.10	17.75	13.92	5.87	5.87
Car6	30.18	15.83	14.67	11.01	11.01
Car7	40.28	18.00	12.00	12.76	14.69
Car8	35.33	19.00	12.83	12.76	12.89
Car9	61.37	19.50	13.17	12.76	22.38
Car10	45.27	18.33	13.50	12.76	16.51
Average	38.09	18.18	13.19	11.43	13.89

Two types of PEVs are incorporated in this study, PHEV35 and BEV100. The electric consumption from the grid are shown in Table 19, assuming 0.34 kWh/mile, 0.31 kWh/mile respectively and a 0.85 AC to DC efficiency.

8.1.3. Charging Power and Rate Structures

3.3 kW, 6.6 kW and 9.6 kW are the charging power to be assessed. It is concluded in Chapter 4 and Chapter 6 that the Level 1 home charging is all needed for PHEV. The higher power charging in this chapter is aimed to evaluate the more severe condition for the residential transformer.

In order to guide PEV users to conduct the off-peak charging, all utilities have introduced the TOU electricity price for PEV charging or for household electric consumption. In the territory of Southern California Edison (SCE), there are three options available for PEV charging, including the residential plan, the home & electric vehicle plan and the electric vehicle plan. The residential plan has four tiers of energy costs, which are 13 cents, 16 cents, 27 cents and 31 cents per kWh. Only the total energy consumption has impact on the cost, so it is anticipated that user will charge PEVs immediately given this rate structure.

Figure 90 shows the TOU rates of the electric vehicle plan. The peak and off-peak time periods are the same for summer, winter, weekday and weekend. In summer, peak price is higher than that in the winter while the off-peak price is lower than that in the winter. The off-peak hour spans for a long time from 9 pm to 12 pm in the next day, which provides enough time to fully charge PEV with the EVSE power shown before. To utilize this rate structure, it is required to install a separate meter for the PEV, which increases the cost for the users and may not be compensated by the savings of the charging cost.

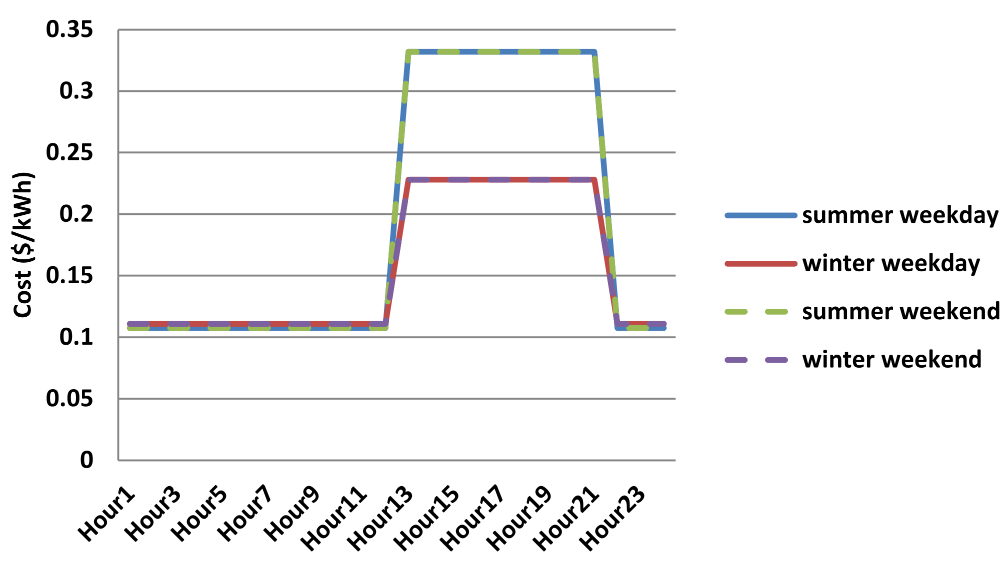


Figure 90. SCE TOU price for electric vehicle.

Figure 91 shows TOU price of the home and electric vehicle plan, which uses a single meter to measure the electricity used by the entire home. It offers "super low" rates from midnight to 6 am, low off-peak rates from 6 am to 10 am and from 6 pm to midnight, and high on-peak rates on weekdays between 10 am and 6 pm. This rate plan is often selected by people who are able to shift both their household electricity consumption and their electric vehicle charging to off-peak, evening, and overnight hours [125]. Similar like the residential plan, this plan has two tiers. Tier 2 rates apply when the home and PEV usage exceeds 130% of the region's baseline allocation.

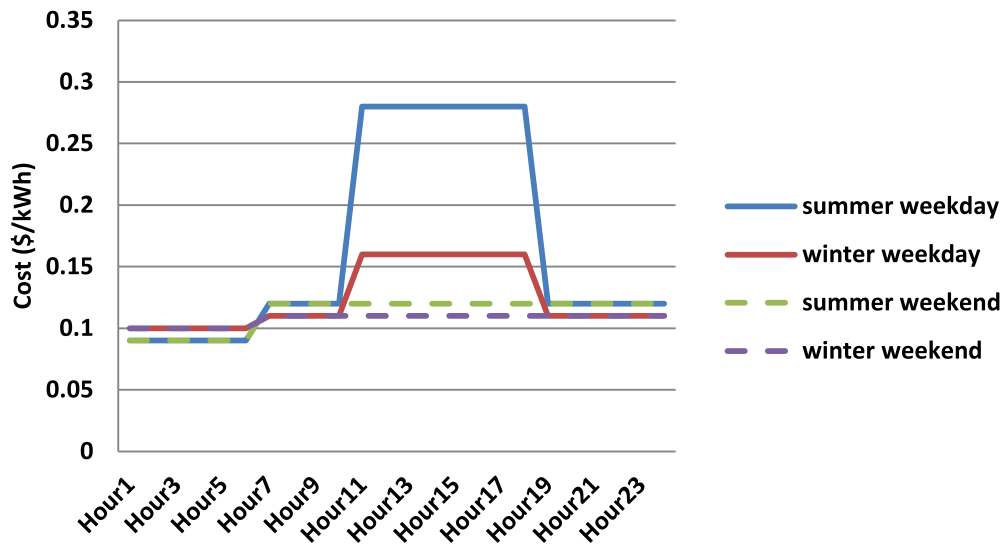


Figure 91. SCE TOU price for home and electric vehicle.

The report of the EV project has shown that people's charging behaviors are highly influenced by the rate structure [101]. Basically, those behaviors are intended to minimize the money cost with other factors being satisfied. Thus, the impact of the two TOU rate structures on the charging profiles is evaluated in this chapter.

8.2. Charging Strategies and Objectives

This section discusses the objectives for PEV charging and introduces the uncoordinated charging strategies as well as the proposed coordinated charging strategies.

There are four items considered to be the objectives, as shown in Table 20. They are minimizing the time cost, minimizing the money cost of energy, leveling the demand and minimizing the battery degradation. It needs to be noted that the battery degradation depends on a number of factors, such as temperature, SOC and the C rate, so there is not a simple function which can represent it. In this study, it is not taken into account directly rather than analyzed qualitatively.

Table 20. Charging strategies, charging objectives and the form of the objective functions in the optimization.

	Time Cost	Energy Cost (TOU)	Demand Leveling	Battery Degradation
Immediate	**Linear**	**N/A**	**N/A**	**N/A**
Immediate with TOU	**Linear**	**Linear**	**N/A**	**N/A**
Decentralized (Protocol 1)	**N/A**	**Linear**	**Linear**	**N/A**
Centralized (Protocol 2)	**N/A**	**Linear**	**Quadratic**	**N/A**

Generally, the time cost conflicts with the other three objectives. To minimize the charging time, high power immediate charging is required, which can potentially increase the energy cost, as discussed in the previous section, create more peaking demands and leave the battery at a high SOC for a longer time, which impose more degradations [48, 111]. To implement the immediate charging strategy, a linear function with the value increasing by the time can be used as the objective function. As shown in (32), $T(t_i)$ is the function associated with time while $x_n(t_i)$ is the energy charged into the battery in each time slot. The constraints are the same as before in Chapter 7, i.e., the required charge and charging power limit. Thus, the PEV will choose the lowest cost of time to charge, which is a continuous time period immediately after plugged in.

$$minimize \sum_i T(t_i) \times x_n(t_i) \tag{32}$$

$$\sum_i x_n(t_i) = b_n$$

$$0 \le x_n(t_i) \le r_n(t_i) = p_n(t_i) \times \overline{\Delta t_n(t_i)} \times \eta$$

The second un-coordinated charging strategy is named as Immediate with TOU, which incorporates the time cost and the energy cost. In (33), $T(t_i)$ and $M(t_i)$ are the time cost and money cost of the energy. They are multiplied by two weighting factors W_T and W_M respectively. For this strategy, energy cost should dominate the objective function so W_M needs to be large enough to ensure that the second term in (33) is much greater than the first one.

$$minimize\ W_T \sum_i T(t_i) \times x_n(t_i) + W_M \sum_i M(t_i) \times x_n(t_i) \tag{33}$$

$$\sum_i x_n(t_i) = b_n$$

$$0 \le x_n(t_i) \le r_n(t_i) = p_n(t_i) \times \overline{\Delta t_n(t_i)} \times \eta$$

The coordinated charging strategies take money cost and demand leveling into account while ignore the time cost but just ensure required charge before the next departure. The details are explained in the next two sections.

8.2.1. Decentralized Control

The decentralized control (protocol 1) used here is the same as described in section 7.4 with an additional item $M(t_i)$ for the money cost, as shown in (34). The first term represents the cost associated with transformer loading while the second one is for the money cost. The two terms are multiplied by two weighting factors, which will be changed for investigating different preferences. The estimated load D_k is the summation of the base load D_0 and the future charging load from the k arrived PEVs. As shown in (34), this estimated load is updated every time that one PEV is plugged in. This updating pattern was introduced in section 7.4 with the updating interval to be one vehicle. Constraints of the charge required before the next departure and the charging power are the same as before.

$$
\begin{aligned}
&minimize\ W_D \sum_i D_{k-1}(t_i) \times x_n(t_i) + W_M \sum_i M(t_i) \times x_n(t_i) \\
&D_k(t_i) = D_0(t_i) + \sum_{n=1}^{k} x_n(t_i) \\
&\sum_i x_n(t_i) = b_n \\
&0 \le x_n(t_i) \le r_n(t_i) = p_n(t_i) \times \overline{\Delta t_n(t_\imath)} \times \eta
\end{aligned}
\tag{34}
$$

8.2.2. Centralized Control

The centralized control (protocol 2) is not feasible for a large amount of PEVs coordinating with the entire grid while it is possible to be implemented in a small region, such as the area under the residential transformer. Each vehicle sends its charging requirements, including the required energy, EVSE power and the available time for charging, to a central control unit. After all of the PEVs or the majority are plugged in and finish sending charging requirements, the central control unit calculates the charging command for each individual PEVs according to (35) and sends them back. The format of the objective function is similar like the decentralized control but the first term is quadratic in order to directly level the demand. In addition, the $X(t_i)$ is the aggregated charging profile from all the individual PEVs. The equality and inequality constraints do not change.

$$
\begin{aligned}
&minimize\ W_D \sum_i (D(t_i) + X(t_i))^2 + W_M \sum_i C(t_i) \times X(t_i) \\
&D(t_i) = D_0(t_i) \\
&X(t_i) = \sum_n x_n(t_i) \\
&\sum_i x_n(t_i) = b_n \\
&0 \le x_n(t_i) \le r_n(t_i) = p_n(t_i) \times \overline{\Delta t_n(t_i)} \times \eta
\end{aligned}
\tag{35}
$$

8.3. Results

The simulation results for PHEV35 are shown in this section in terms of the charging profile and the consequent final load, the summary of peak load, power losses and money cost for the whole month. The impact of different TOU rates on demand leveling is also investigated.

8.3.1. Charging Profiles and Final Load

As introduced previously, there are three rate structures which can be used for charging PEVs. In this section, the TOU rate with off-peak time from 9 pm to 12 pm, which is dedicated for PEV and requires a separate meter, is used. The weighting factor W_M is 10,000 times greater than the weighting factor W_M in order to prioritize the impact of the money cost.

Figure 92 shows the base load on the transformer, the final loads with the four charging strategies and the rated capacity of the transformer. 10% PEV penetration is presented, i.e., only one PHEV35 is assigned for the 10 houses. The charging profiles of immediate charging and immediate charging with TOU do not change from day to day since the vehicle is assumed arriving home at the same time, having the same dwelling time and required energy every day. Thus, the increments on the base load, depicted by the green lien and the red line, remain the same for each day. Depending on the base load at different days, additional peaks with different magnitudes have been incurred by both of the two un-coordinated charging strategies. However, there still is a gap between the peak load and the rated capacity of the transformer given such a low PEV penetration rate.

For the protocol 1 and protocol 2, they both exhibit that the charging occurs after midnight when both the money cost and the base load are at their lowest values. Due to the two different formats of the cost of demand leveling in the objective function, one is linear and the other is quadratic, protocol 2 shows a completely flat final load curve while protocol 1 has variations. Those results indicate that protocol 2 provide slightly better performance for demand leveling but requires partial charging power.

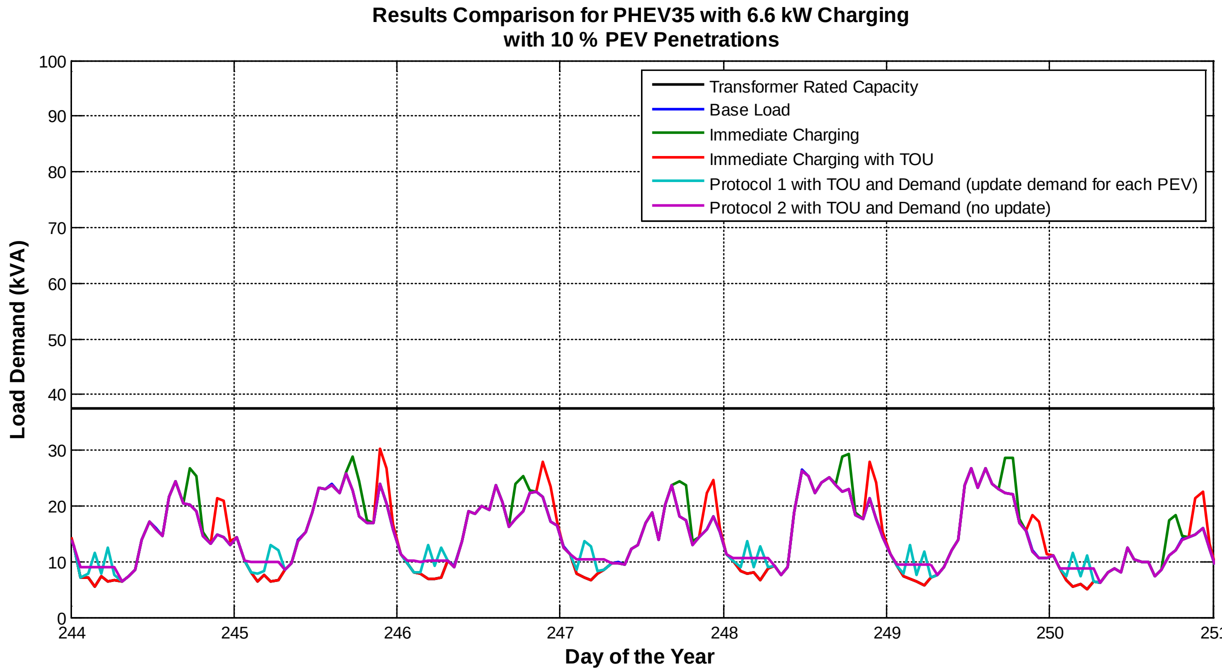


Figure 92. Comparison of the final load of different charging strategies for PHEV35 with 6.6 kW charging at 10% PEV penetrations.

Figure 93 shows the results with 30% PEV penetration, i.e., three PHEV35 for the ten households. In the seven days shown, there are already three days when the immediate charging with TOU overloads the transformer. The TOU price drops down at 9 pm by which all the vehicles have arrived. It is expected that people set up a timer to initiate charging at this time point so that the charging cost can be minimized with the least charging time consumed. Consequently, the load increment from 9 pm to 10 pm is approximated to be the product of the PEV number and the maximum charging power. The load increment from immediate charging is not as concentrated as the immediate charging with TOU, since different vehicles arrive home at different times. This diversification factor can slightly mitigate the overloading issue. Similar like the previous case, protocol 1 and protocol 2 are able to allocate charging load during the off-peak time. Final load from protocol 1 has small variations along the final load from protocol 2.

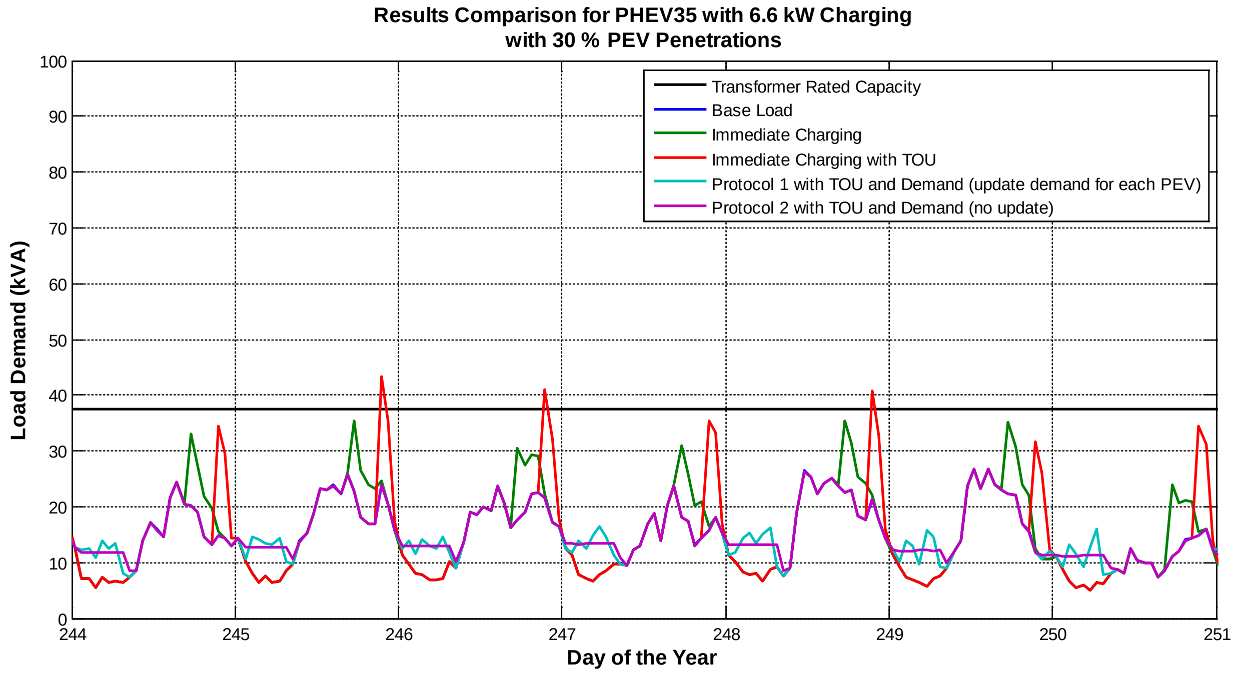


Figure 93. Comparison of the final load of different charging strategies for PHEV35 with 6.6 kW charging at 30% PEV penetrations.

In the case of 50% PEV penetrations, as shown in Figure 94, the immediate charging with TOU continues to increase the peak load to more than 50 kVA while the final load from immediate charging slowly increases to the rated capacity of the transformer. Protocol 1 and protocol 2 have not increased the peak load rather than increasing the load overnight. The overnight final loads are below 20 kVA and 15 kVA for the two protocols respectively.

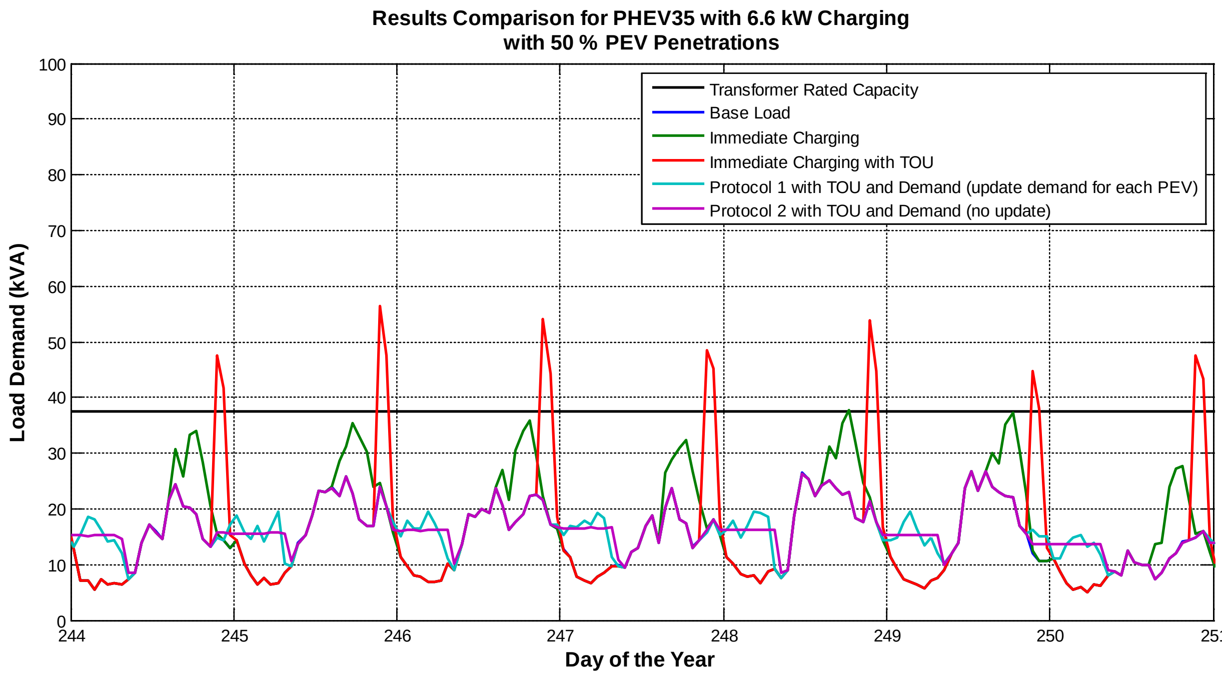


Figure 94. Comparison of the final load of different charging strategies for PHEV35 with 6.6 kW charging at 50% PEV penetrations.

Figure 95 shows the results for 70% PEV penetration. In the day 245, the immediate charging with TOU has the final load increased to 75 kVA, which is double the magnitude of the transformer rated capacity. This may cause the immediate failure of the transformer. The immediate charging also overloads the transformer each day in the seven days shown. The two coordinated strategies do not increase the peak load but have an additional valley created in the morning, when the charging load has disappeared while the base load has not jumped up.

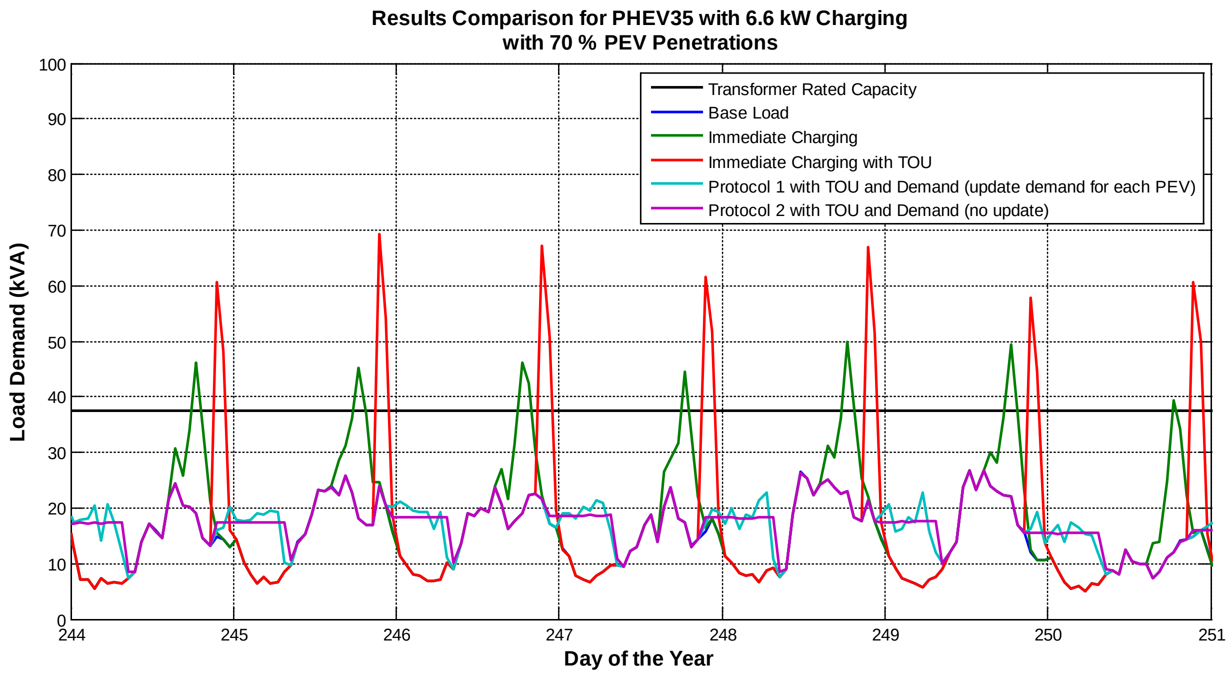


Figure 95. Comparison of the final load of different charging strategies for PHEV35 with 6.6 kW charging at 70% PEV penetrations.

In the 100% PEV penetration case, as shown in Figure 96, immediate charging with TOU overloads the transformer significantly from 9 pm to 10 pm every day. The impact of immediate charging also reaches to the worst point. In the seven day shown, protocol 1 and protocol 2 maintain the peak of the final load overnight smaller than the peak of the base load. In other words, they do not create any additional peaks for those days. However, one concern arias that the load increment overnight does not provide the typical cooling time for the transformer and is anticipated to maintain the temperature at a high level continuously. This can reduce the life time of the transformer, which can be evaluated by the thermal and aging models of the transformer as seen in the literatures [71, 73, 118].

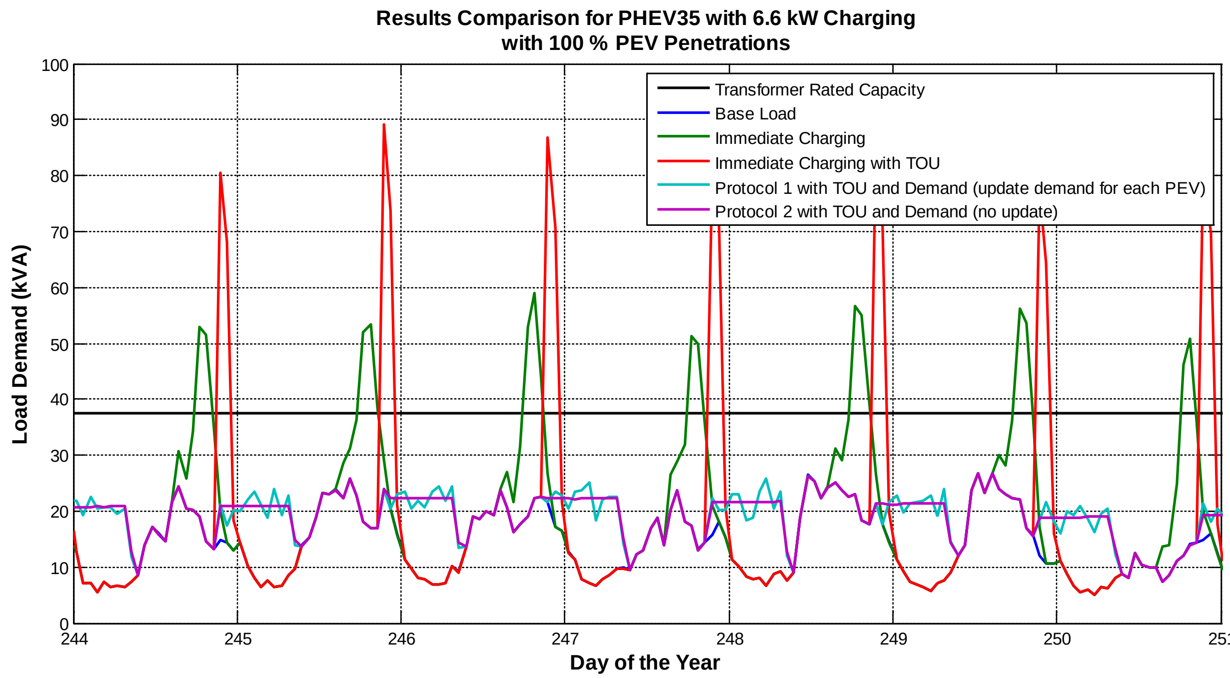


Figure 96. Comparison of the final load of different charging strategies for PHEV35 with 6.6 kW charging at 100% PEV penetrations.

8.3.2. Peak, Power Losses and Cost

Given the final load profiles from different charging strategies, the peak load for each day can be calculated with regard to different PEV penetrations and charging power. The monthly average peak is shown in Figure 97 for the base load and the final loads with the four charging strategies.

As shown in Figure 97 and analyzed in the previous section, the general trend of the peak load for the un-coordinated charging strategies is that it increases with the increased PEV penetrations. For protocol 1 and protocol 2, the monthly average peak does not diverge from the base load until 40% PEV penetrations. Result in section 8.3.1 indicates that there is not any peak increment from coordinated charging for the seven days shown. Those are the days with high electricity demand as shown in Figure 89, meaning that in the rest of the month, even the coordinated charging strategies increase the original peak at high PEV penetrations. The reason is because the size of the base load valley is smaller compared to the first seven days in that month.

Charging power has significant impact on increasing electric load peaks for the uncoordinated charging strategies. From 3.3 kW to 9.6 kW EVSE power, the average peak of immediate charging with TOU doubles the magnitude. For the immediate charging, the average peak increases most from 3.3 kW to 6.6 kW. Protocol 1 and protocol 2 are not sensitive to the charging power, having the average peaks almost the same for all three EVSE scenarios.

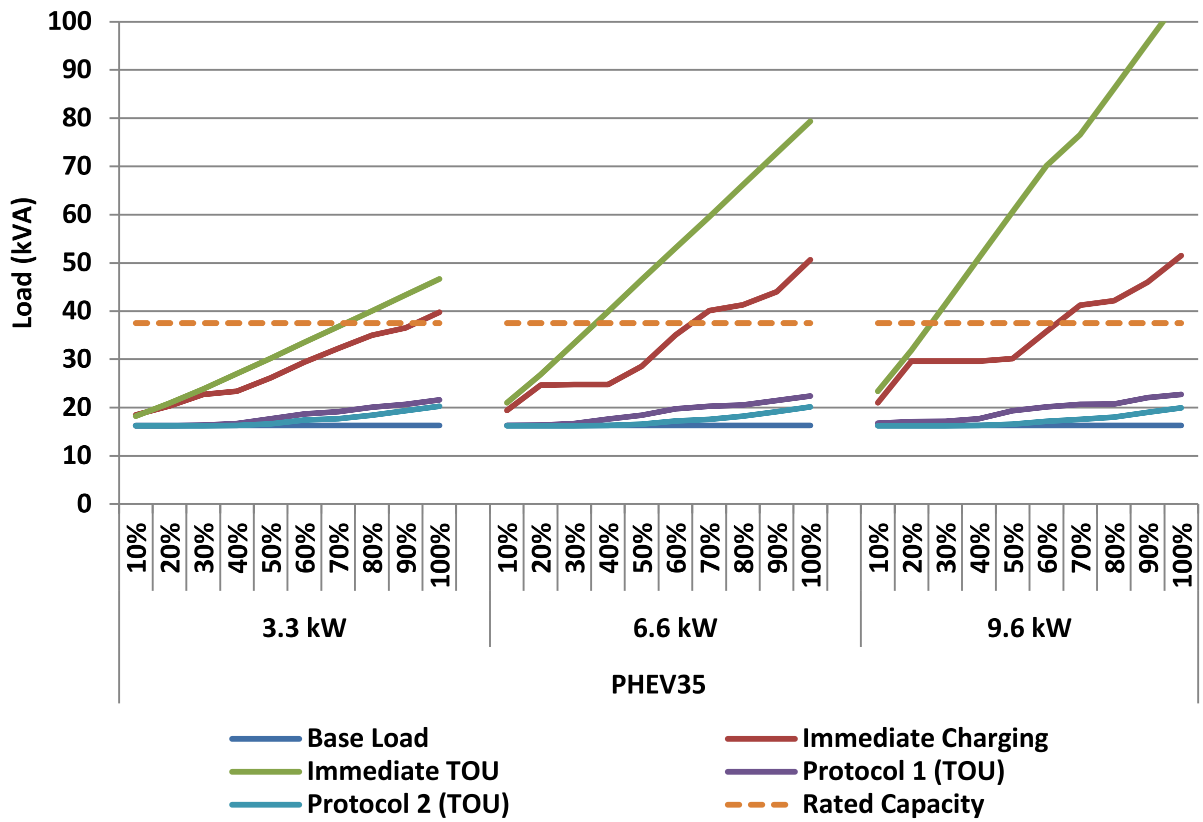


Figure 97. The average peak of each day in September.

In the distribution network, power losses are paid by the utility, since the costumer is only billed according to the electric meter which is installed at the end of the distribution network. Leveling the load not only reduces the transformer aging problem but also decreases the power losses which benefits the utilities and essentially benefit all costumers for the long term. To calculate the power losses accurately, the detailed information is required in terms of the power line impedance, length and the instantaneous current. The information is not accessible at current phase of this study. Thus, the power losses are estimated and normalized to the power losses by the base load. The sum of squares of the hourly resolved base load is normalized to be one. The sum of squares of other final loads is divided by the sum of squares of the base load. The results are shown in Figure 98, with different PEV penetrations and charging power.

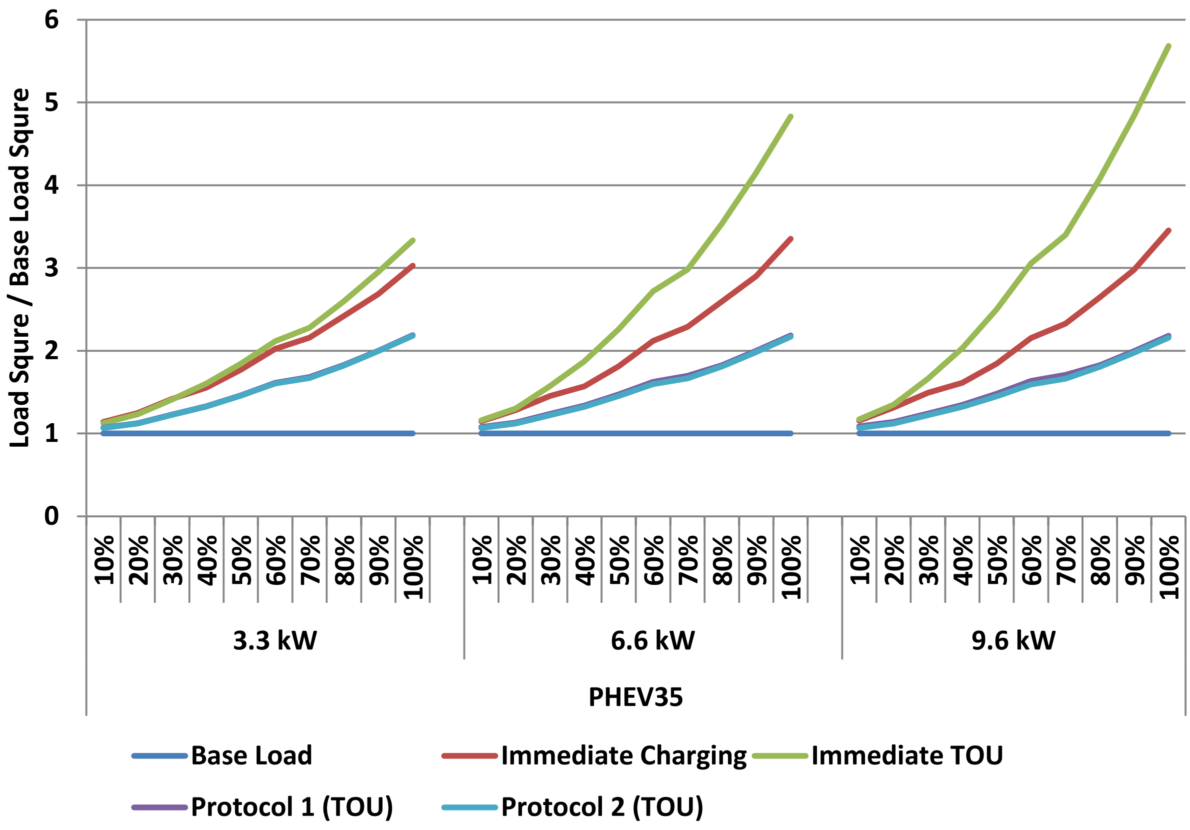


Figure 98. The power losses estimation of the four charging strategies.

The immediate charging with TOU has the highest losses followed by the immediate charging and the other two coordinated strategies for all scenarios. It is the same as the plot of the monthly average peak load that the power losses increase continuously with PEV penetrations. The trend of increase appears to have a quadratic pattern. Protocol 1 and protocol 2 exhibit almost the same result and lies in the middle of the curves of the immediate charging and the base load. Only the immediate charging with TOU is very sensitive to the charging power, incurring three, five and six times greater power losses than the base load at 3.3 kW, 6.6 kW and 9.6 kW charging with 100% PEV penetration.

8.3.3. Impact of TOU Rates

In this section, the TOU rate from home and electric vehicle plan is used, as shown in Figure 91. This rate structure has three levels during weekdays, including a relatively short super off-peak time period, from 12 am to 6 am, compared to the other TOU price presented in the previous section. Thus, the final loads from protocol 1 and protocol 2 are expected to be different from the previous results.

Figure 99 shows results, having the money cost prioritized and the demand leveling prioritized respectively for both protocol 1 and protocol 2. Protocols with TOU and Demand in the figure (green and light green lines) is to prioritize the money cost, having W1, the weighting factor for the money cost, to be 10,000 and W2, the weighting factor for the demand leveling, to be one. Protocols with Demand in the figure (red and purple lines) is to prioritize the demand leveling, having W1 to be zero and W2 to be one.

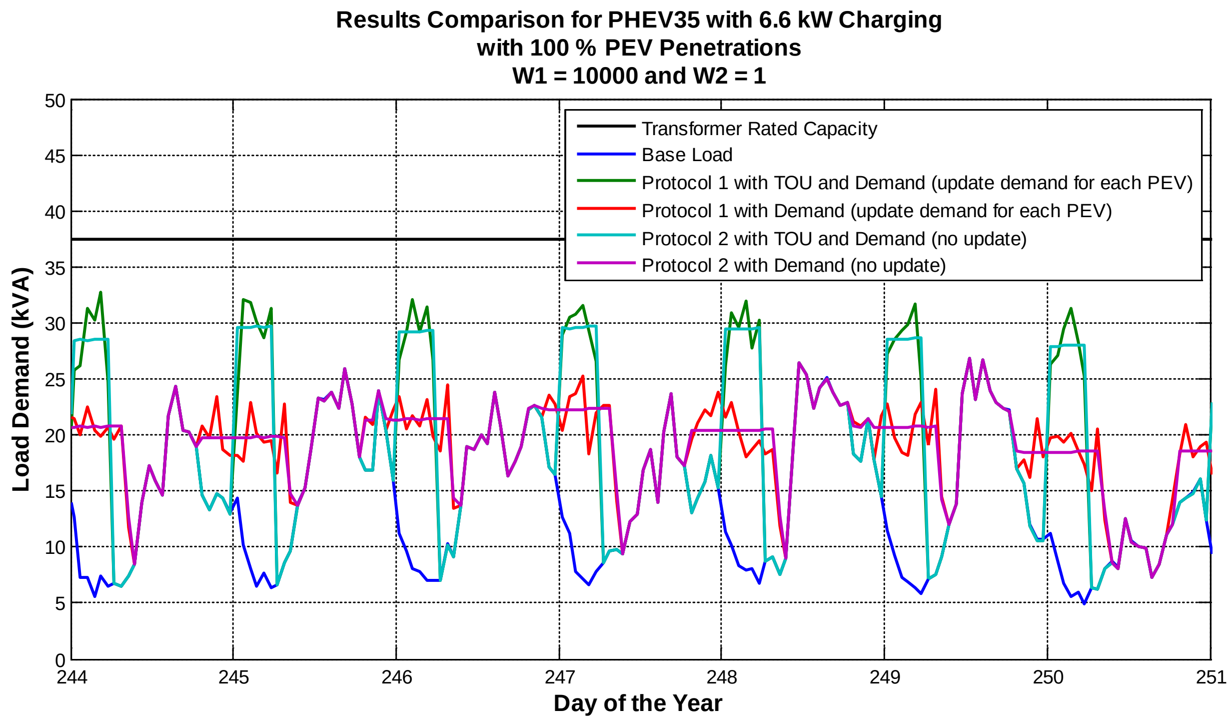


Figure 99. Final loads of the two protocols having money cost or the demand leveling as the priority with SCE home and electric vehicle plan and 6.6 kW EVSE.

When the money cost is prioritized, the charging only happens between 12 am and 6 am, so a high plateau is aggregated, as shown by the green and light green lines. When the weighting factor for the money cost decreases down to zero, the protocols intend to level the demand to the largest extent, as shown by the red and purple lines, which are similar like the results in section 8.3.1 using the first TOU price. In other words, the first TOU price does not affect the final loads of the two protocols significantly if different weighting factors are used. The reason is because the first TOU rate provides a very large window for low electricity price.

Figure 100 is the corresponding Pareto plot of the charging cost and power losses with different combinations of the two weighting factors for the second TOU price. It better illustrates the tradeoff between money cost and demand leveling shown in Figure 99. The normalized power losses and charging cost are ranged from 2.5 to 2.15 and from $0.09/kWh to $0.104/kWh respectively. From the optimization perspective, any points on this Pareto front are considered to be an optimal solution. However, it is expected that all the users will choose the charging with the lowest cost since the power losses and generation cost are not their direct concerns. Thus, the 15% more power losses need to be covered by the utilities as well as the potentially extra cost to purchase the power from the generation side. Those facts indicates that even with the coordinated charging strategies implemented, the second TOU rate will have negative impact for demand leveling, when the PEV penetration is high. It is due to the mismatch among the length of the low electricity price window, the size of the based load valley and the charging energy required of all these PEVs.

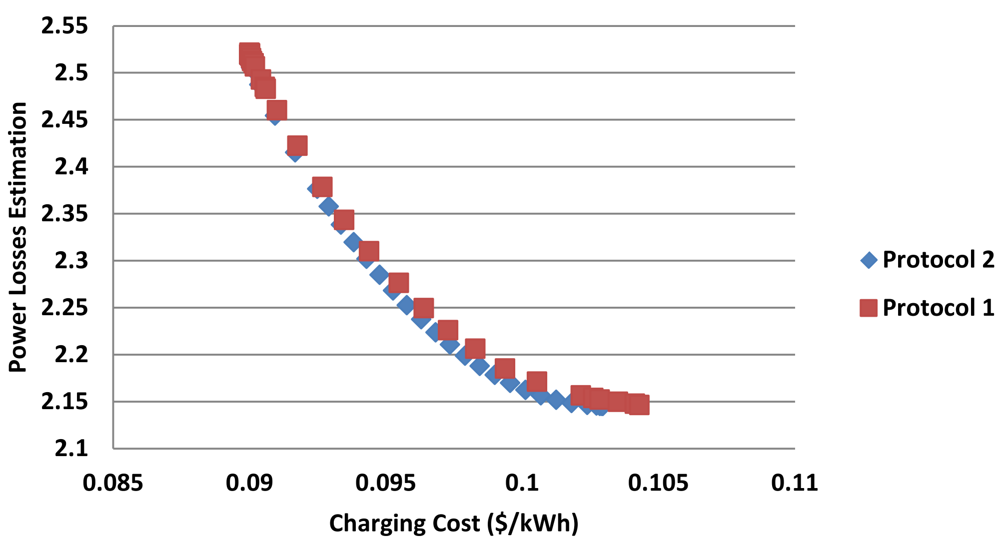


Figure 100. Pareto plot of the charging cost and power losses for TOU rate of the home and electric vehicle plan with 100% PEV penetration.

8.4. Discussion

Battery degradation is considered to be another important aspect in addition to the time cost, money cost and demand leveling. Generally, temperature and SOC are the two main factors that mostly contribute to battery degradation. Higher temperature and higher SOC will significantly shorten battery life by increasing the resistance growth rate [48, 49, 51, 110]. In this sense, immediate charging will have the most negative impact on battery life due to the continuous high power charging, consequently the high temperature incurred, and a longer time accumulated with high SOC since fully charged. Immediate charging with TOU should potentially reduce the degradation because it is some form of delayed charging. The proposed protocols, due to the intermittent charging or the partial power charging, should have lower impact on battery degradation. However, the quantitative impacts from these charging strategies need to be evaluated in experiments or battery degradation model.

The proposed protocols satisfy the charging time constraints rather than considering the time cost directly. An issue exits when users need to change the original plan to depart early or require more charge. A solution is to implement the same protocol based on the current condition with the updated constraints on dwelling time and required charge. If it is an emergency, BEVs might be stranded on the way to the destination due to the insufficient charge while PHEVs can still function as the conventional vehicles. Although there is such a low possibility for the emergencies, it requires attentions for a solution.

The proposed protocols can level the overnight demand so that the power losses can be minimized as well as the peak load under a certain rate structure. They provide the optimal solution from the perspective of reducing power losses and peak load. However, the actual impact on the transformer aging is not clear. The existing diurnal demand pattern of a residential transformer allows it to have a long time during the night to cool down when the temperature is relatively low. PEVs fill the night valley, which increase the temperature for the entire night, as seen in [118]. In literatures, controlled charging almost imposes no observable transformer aging issue compared to the base load in the coast of California [73, 118]. Thus, it is expected that the valley filling results from the protocols should have a similar impact on the transformer.

This study has covered the condition of the extremely high base load for a whole year in the ISGD project. Results show that the transformer overloading has never happened. It is valuable to assess more severe conditions, with higher base load and smaller transformer. If a constraint of the transformer capacity is considered, the PEVs may not be fully charged by the departure time. In this case, the optimal charging proposed in Chapter 4 can be utilized to guide users to have more charging at other locations during the day time so the burden on residential transformer can be mitigated.

8.5. Summaries and Conclusions

This chapter utilizes the Irvine Smart Grid Demonstration (ISGD) project as a study platform to evaluate the impact of charging load from PEVs on the residential transformer. Ten vehicle samples from 2009 NHTS were used to simulate the charging requirements for ten households. The electric load on the first winding of the 75 kVA transformer for the control group was obtained to represent the base load of a 37.5 kVA transformer. Four charging control strategies, including immediate charging, immediate charging with TOU, protocol 1 and protocol 2 were investigated. Protocol 1 is the decentralized strategy, proposed in Chapter 7 with the cost updated after each PEV arrives while protocol 2 is proposed in this chapter as a centralized strategy. Both are aimed to balance the minimization between charging cost and demand leveling, given individual users' charging requirements taken into account. Immediate charging intents to finish the required charge as soon as possible while immediate charging with TOU considers the charging cost more important than the finishing time. From the results, analysis and discussions, following are the conclusions.

1. The immediate charging with TOU overloads the transformer with only 30% PEV penetration at 6.6 kW charging; immediate charging overloads the transformer with 70% PEV penetration; proposed protocols can well fill the demand valley, consequently do not overload the transformer for all times.
2. The peak load is very sensitive to the charging power for the un-coordinated charging strategies but does not change for protocol 1 and protocol 2.
3. Power losses are highly influenced by PEV penetration. Immediate charging with TOU is the worst case and very sensitive to the charging power; the proposed protocols exhibit more than 50% losses reduction compared to the un-coordinated strategies.
4. The TOU price with a narrow off-peak time window has negative impact for demand leveling when PEV penetration is high. It is suggested that utilities should collaborate with automakers for new rate structure designing.

Chapter 9. CONCLUSIONS

A vehicle based personal transportation model was developed by considering the actual travel behavior in California. The characteristics of real plug-in electric vehicles (PEVs) and electric vehicle supply equipment (EVSE), and the current and future grid operations were utilized to provide model input. The model can be used for exploring the energy impact of PEVs, the distributions of Level 1 and Level 2 EVSE, the allocation and utilization of the Level 3 DC fast charging stations, and the charging impact on the electric grid. Following are the highlighted results from this dissertation. These results can be used by automakers, utilities, EVSE operators, individual PEV users or policy makers, who are interested in optimizing PEV operation and its infrastructure.

9.1. Energy Impact

- **Deploying PHEV can reduce fuel consumption dramatically**

PHEVs with 16 and 40 miles all-electric range can reduce fuel consumption by 46% and 74% respectively, compared to HEVs with the same MPG at hybrid mode. These reductions are achieved by using only Level 1 1.44 kW home recharging. Adding more EVSE at non-home locations and increasing the charging power can future reduce the fuel consumption for the fleet, however, the extra reduction is very limited.

- **Fuel reduction rate of BEV is highly dependent on the all-electric range and infrastructure availability**

The current BEV with 60 miles all-electric range, combined with the insufficient non-home charging infrastructure, can only replace 50% to 60% of the fleet-wide fuel consumption with electric energy. The rest long-distance travels still have to be covered by the conventional vehicles or hybrids.

9.2. Operating Cost

- **PHEVs show a significant operating cost reduction compared to HEVs**

All charging infrastructure options show substantial operating cost reduction for PHEVs compared to hybrid electric vehicles of 10 dollars/100 miles. The operating cost of PEHVs has large variation, from 3.5 to 7.5 dollars/100 miles. The advanced charging time strategy results in the largest reduction in operating cost. The uncontrolled immediate charging exhibits the highest cost, followed by the mild-controlled delayed and average charging. The well-controlled smart charging and advanced-controlled optimal charging can have the best performance.

Although the use of more non-home charging locations can further reduce the fuel reduction and operating cost for PHEVs, the extra benefit is limited to 0.5 dollar per 100 miles. However, at the same time, a number of EVSE have to be installed at non-home locations which require large-scale investment for the government. Higher charging power will increase the cost with uncontrolled charging strategy and slightly reduce the cost for the controlled cases.

- **The operating cost of BEVs is also much lower compared to HEVs and highly influenced by the electricity rate structure**

BEVs results in an operating cost less than 4 dollars/100 miles for different ranges and charging power with the optimal charging strategy. The Level 2 3.3 kW charging can cut the operating cost down by 10% compared to 1.44 kW Level 1 charging. With further higher power charging, the changes on cost will not be observed.

The rate structure from different utilities or the same utility released in different years can have significant impact on the operating cost. A rate structure published by PG&E in 2011, which has lower TOU price in the night time can further reduce the cost down to 2.5 dollars/100 miles for BEVs.

9.3. Level 1 and Level 2 Infrastructure Requirements

- **Level 1 home charging is all needed for PHEVs**

The fuel reduction analysis indicates that 1.44 kW home charging can decrease fuel consumption significantly. The extra benefit from non-home charging and higher charging power is limited. The charging profiles implies that high charging power can cause higher demand in the peak hour when charging is not well controlled, and more non-home charging locations can increase the demand during the day time. The operating cost analysis also shows that charging time strategy is most important to reduce cost, compared to high charging power and more non-home locations. Considering all those facts above, it is concluded that home Level 1 1.44 kW charging is all that needed for PHEVs.

- **All BEVs require home EVSE and Level 2 is preferred**

The optimal charging strategy was proposed to minimize the operating cost given the constraints on the all-electric range and EVSE availability. Result shows that all home based travels (first trip from home, last trip back to home) have charging activities at home and draw most charging energy from home. This indicates that home EVSE is required for BEV deployment. The result also shows that Level 2 EVSE can continuously increase BEV feasibility with increased all-electric range. At the same time, Level 2 EVSE can decrease operating cost when the TOU price is used.

- **25 non-home EVSE per 100 BEVs is an upper bound for the long term**

Utilizing the optimal charging model, the charging activities at other location categories were calculated so that the approximated number of EVSE at those locations can be known as well. Results show that for one hundred BEV60, there should be 25 EVSE installed outside home to achieve the highest BEV feasibility, which is 96%. BEVs with longer range will require a smaller number of EVSE, so 25 non-home EVSE per one hundred BEVs is considered to be an upper bound. However, in the near future, when the penetration of BEVs is still very small, more EVSE per 100 BEVs is needed to fulfill the travel demands.

The EVSE cost was evaluated on a per-BEV basis. Result implies that based on the current EVSE hardware and installation costs, 1,200 dollars investment is required for one BEV at non-home locations, in which the public locations only need about 700 dollars. In the same manner as the number of EVSE required, those numbers for costs are underestimated when the volume of BEV is still very small.

9.4. Level 3 Infrastructure Requirements

- **Optimized DC fast charging station network increases BEV feasibility**

A methodology to optimize the allocation of Level 3 DC fast charging stations was developed by identifying the candidate charging routes, the candidate charging locations, and consequently solving a set-covering problem to minimize the number of the candidates. Using all the gasoline stations and shopping centers as the candidates, BEV60 requires 265 locations in California to achieve the highest feasibility, which is 95% assuming one fast charge per day or 98% assuming multiple fast charges per day. The increased all-electric range leads to fewer locations and higher feasibility. BEV200 requires only 40 locations throughout the entire California and has only one infeasible day for every four years.

Sixteen chargers are needed for 1,000 BEV60, resulting in 1,600 dollars investment required on a per-BEV basis. This number is considered to be an upper bound for both short term and long term, since the current BEV penetration has already required 200 to 300 locations in the state of California. More BEV in the future will just increase the number of chargers linearly.

- **Charging time and extra waiting time depend on charging power, full charge or sufficient charge, and station selection strategy**

Fast charging needs people to change their behaviors, in particularly to detour to the station from the original route, to wait as the vehicle is being charged or wait extra time if in a line. Model results show that higher charging power, up to 2 C, can reduce the charging time to 20 minutes and 10 minutes for full charge and sufficient charge respectively. A reservation system is highly recommended for its effect to decrease the extra waiting time. Those technologies are worth more investigation for mitigating the inconvenience incurred by fast charging.

9.5. Grid Coordination

- **Utilizing the proposed decentralized protocol, the charging load of PEVs can fill the electric load valley during the night time and follow a feasible target load**

A decentralized charging protocol has been proposed for PEVs with grid operators updating the command signal. Each PEV calculates its own optimal charging profile only once, after it is plugged in, and sends the result back to the grid operators. Grid operators only need to aggregate charging profiles and update the load. Using the net load on the grid directly as the cost function and updating it frequently enough, by either a fixed time interval or vehicle amount, will lead to a flat final net load overnight for a relatively large time window. For instance, updating the cost function every 30 minutes results in less than 300 MW variations on the final load during more than 7 hours, for 90% of the days in a year. Also, the correlation of the aggregated charging loads from grid level valley filling and the proposed protocol is greater than 0.98.

In the case that some other form of the final load is more preferred than the valley filling result, this final load can be treated as a target load for the PEVs to follow. Using the gap between the current load and final target load as the modified cost function and prioritizing the earlier time slots if necessary, the desired target load can be approached similar to overnight valley filling.

- **Centralized and decentralized protocols surpass the un-coordinated charging strategies on reducing peak load and power losses for residential transformer**

The same decentralized protocol coordinating individual PEV charging with the grid can be utilized for the demand leveling of a residential transformer. The real money cost was added into the objective combined with the demand leveling. A centralized protocol has also been formulated for a central control unit to calculate the charging commands of all PEVs. The finishing time was considered as a constraint rather than an objective.

One of the un-coordinated charging strategies, the immediate charging with TOU, overloads the transformer with only 30% PEV penetration at 6.6 kW charging; another one, immediate charging overloads the transformer with 70% PEV penetration; proposed protocols can fill the demand valley well and do not overload the transformer for all times. Power losses are highly influenced by PEV penetration. Immediate charging with TOU is the worst case and very sensitive to the charging power; the proposed protocols are not sensitive to the charging power and achieve more than 50% losses reduction compared to the un-coordinated strategies.

APPENDIX

Here presents the main properties of the optimization algorithm in (20)-(22). Each PEV will minimize its costs associated the following cost function.

$$\sum C(t_i)x(t_i)$$

Subject to

$$\begin{cases} \sum x(t_i) = b \\ x(t_i) \geq 0 \\ x(t_i) \leq r(t_i) \end{cases}$$

The Lagrangian is

$$\mathcal{L} = C^T x - \nu\left(\sum x(t_i) - b\right) - \lambda^T x + \mu^T(x - r)$$

Applying the standard approach, KTT condition (which are both necessary and sufficient due to convexity)

$$\frac{\partial \mathcal{L}}{\partial x} = C(t_i) - \nu - \lambda(t_i) + \mu(t_i) = 0$$

$$\nu\left(\sum x(t_i) - b\right) = 0$$

$$\lambda(t_i)x(t_i) = 0$$

$$\mu(t_i)(x(t_i) - r(t_i)) = 0$$

From

$$\lambda(t_i)x(t_i) = 0 \rightarrow \lambda(t_i) = 0 \; or \; x(t_i) = 0$$

Since charging time is the only interest, consider

$$x(t_i) \neq 0$$

Then

$$\lambda(t_i) = 0$$

Then the KTT conditions become to

$$\begin{cases} C(t_i) - \nu + \mu(t_i) = 0 \\ \nu\left(\sum x(t_i) - b\right) = \quad 0 \\ \mu(t_i)(x(t_i) - r(t_i)) = 0 \end{cases}$$

If

$$\mu(t_i) \neq 0 \rightarrow x(t_i) = r(t_i)$$

i.e., charging at maximum power. If

$$\mu(t_i) = 0 \rightarrow x(t_i) can\ be\ different\ than\ r(t_i)\ but\ C(t_i) = \nu$$

So the KTT condition shows either $x(t_i) = r(t_i)$ or $C(t_i) = \nu$.

If $C(t_i)$'s are distinct, then $\mu(t_i) = 0$ is possible for one time slot only, since there is only one ν.

This shows that all other $x(t_i)'s$ are at maximum value with possible exception of 1.

Claim: assuming distinct prices for each time slot, the algorithm above picks the lowest cost time slots. Furthermore, the partial time slot has the highest price among time slots used (but lower than those not used).

Proof: Start with the first part of the claim. We use the following notation for the charging and non-charging time slots, respectively

$$I_c = \{j | x(t_j) \neq 0\}$$

$$I_{nc} = \{j' | x(t_{j'}) = 0\}$$

From the main property of the optimization in (6)-(8), for all $j \in I_c$, we have $x(t_j) = r(t_j)$ except at most one; i.e., maximum charge in all time slots with at most one partial charge.

Now assume there exists some $j' \in I_{nc}$ such that $C(t_{j'}) < C(t_k)$ for some $k \in I_c$; i.e., one of the time slots with no charge has lower price than at least one of the charging times slots.

Then consider the following:

$$C(t_{j'})\varepsilon + C(t_k)(x(t_k) - \varepsilon) = [C(t_{j'}) - C(t_k)]\varepsilon + C(t_k)x(t_k) < C(t_k)x(t_k)$$

i.e., shifting the charging to the $t_{j'}$ time slot reduces the cost, which is not possible as it contradicts the optimality of the solution. This shows the optimized solution picks the lowest cost time slots.

For the last part of the claim, we follow the same logic: suppose t_j was associated with partial charging, i.e., $x(t_j) < r(t_j)$. Suppose there exist t_k such that $C(t_j)< C(t_k)$ and $x(t_k) = r(t_k)$. Clearly, there exists $\varepsilon > 0$ small enough such that

$$\begin{cases} 0 < x(t_j) + \varepsilon \leq r(t_j) \\ 0 \leq x(t_k) - \varepsilon < r(t_k) \end{cases}$$

Similar to above, we note that

$$C(t_j)(x(t_j) + \varepsilon) + C(t_k)(x(t_k) - \varepsilon) = [C(t_j) - C(t_k)]\varepsilon + C(t_j)x(t_j) + C(t_k)x(t_k)$$
$$< C(t_j)x(t_j) + C(t_k)x(t_k)$$

Which means shifting from t_k to t_j reduces the cost, which contradicts optimality of the solution, implying that $C(t_j) > C(t_k)$ for all $\{k \neq j | k \in \mathrm{I}_c\}$.

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