## Title

Spatial-temporal Modeling of Electric Vehicles Charging Infrastructure and Management for a Sustainable Energy System



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# Spatial-temporal Modeling of Electric Vehicles Charging Infrastructure and Management for a Sustainable Energy System

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DISSERTATION

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## DEDICATION

I dedicate this dissertation to my dear family. A special feeling of gratitude to my loving parents, husband and son Aiden for their support and encouragement through all the difficulties and challenges.

## ABSTRACT

Transportation electrification is playing an increasingly essential role in mitigating climate change, especially coupled with a sustainable energy system. However, proper placement of charging infrastructures and management of charging activities is the key to ensuring the environmental benefits from the widespread adoption of electric vehicles. Existing literature on the emissions implications of vehicle electrification is often limited by neglecting the spatial and temporal diversity of the electricity grid, or by failing to respect individual heterogeneity. This dissertation research demonstrates the importance of assessing BEV charging infrastructure in an integrated perspective, focusing on key interactions between transportation, energy, and economy across individual patterns of travel behavior, dwelling constraints, pricing elasticity of consumers with regards to charging, and the temporal and spatial diversity in price and GHG intensity of electricity through three studies. Results from the charging infrastructure optimization study show that higher non-home charging opportunity informed by the empirical travel and dwelling patterns offers more potentials for a shared public charging system in San Diego, resulting in 14% - 30% lower in total system cost and 21% - 25% lower in emissions. This indicates that the heterogeneity in spatial and temporal travel and dwelling patterns substantially affect the design of the charging infrastructure system, and substantially change the energy, economic and environmental impacts of the system. The charging price strategies study considers the price elasticity of charging demand while investigating how different charging price strategies can affect the spatial and temporal distribution of charging activities and their energy, environmental and economic impacts. The results show that the ability of changing charging behavior to obtain environmental benefits depends on charging price strategies largely and the charging load profile is the result of various determinants including the dynamic electricity price, travel, and dwelling constraints, carbon price clustering effect, as well as exclusive home and shared non-home charging patterns. Lastly, results from the shared autonomous electric vehicle study indicate that SAEVs with exogenous charging would reduce GHG emissions by at least 75% compared to the internal combustion vehicles fleet in 2030, and the advantage expands to 97% if charging activities can interact with the grid when smart charging is available. The emission benefits of SAEVs are mainly dominated by vehicle electrification and grid development.

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# Chapter 1. Introduction

The transportation sector accounted for 28.5% of total greenhouse gas (GHG) emissions in the United States in 2016, overtaking electricity generation as the largest source of emissions. The majority of GHGs in transportation came from light-duty vehicles, which includes passenger cars (42.0%) and light-duty trucks (17.3%)[1]. The 2017 US National Household Travel Survey shows that 78.1% of US daily passenger miles of travel takes place in private vehicles for purposes such as commuting to or from work (16.9%), driving to shopping and errands (24.7%), and going to social and recreational activities (24.5%)[2]. Transportation electrification is playing an increasingly important role in dealing with climate change mitigation, especially considering that electricity GHG intensity has dropped significantly in recent years due to fuel switching to lower emitting sources of electricity production[1,3–6]. Widespread adoption of plug-in electric vehicles (PEVs), which include both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), dominates the emerging revolutions in passenger transportation's transition to sustainable mobility[7].

However, there are several challenges to realize widespread electrification of passenger vehicles, including the availability of electric vehicle supply equipment (EVSE, in other words charging infrastructure)[8,9]. The battery range constraints, both real and imagined, are identified as one of the most significant barriers to the large-scale acceptation of BEVs in the market[10–12]. Developing dedicated recharging infrastructure, may facilitate a release from 'range anxiety' and encourage more consumers to purchase electric vehicles[13,14]. Another potential barrier to widespread adoption of BEVs is its relatively high cost[10]. Incentives, such as the federal tax credits and state tax incentives[15] and manufacturer rebates, may be most effective to facilitate EV market[16] while environmental, performance and technological motivations are alternative motivations for adopting the high-end BEVs[17].

PEV charging increases demand to the electric grid and adds challenges for managing electric generation, transmission, and distribution[18]. However, they simultaneously bring market opportunities and facilitate the integration of non-dispatchable renewable energy sources for utilities since PEVs can operate as distributed storage technology or provide flexible loads[19,20]. Individual travel and charging patterns determine not only how much electricity is used, but the timing of the charging determines whether base or peak electricity will be used to charge the battery. Some studies find that PEV charging will not impact the generation and transmission of the electric grid in the short term but may need to be managed when the vehicles are deployed in greater numbers[21]. However, other studies show uncoordinated PEV charging could significantly change the shape of the aggregate residential demand, with impacts for electricity infrastructure, even at low adoption levels[22]. Proper management is critical because charging strategies may also significantly impact the environmental outcome of charging electric vehicles[23,24].

This research examines a large-scale, activity-based travel survey data in California[25] containing the mobility and dwelling information of 10,913 residents for one day. Dwelling, in this research, refers to the time a vehicle parks or “dwells” at a certain place. I explore the benefits of a comprehensive spatial and temporal optimization model to devise the best strategy for BEV infrastructure placement and charging management while minimizing the total system cost, investigating environmental outcomes of various charging price strategies, and informing the emissions benefits of a shared autonomous electric vehicle fleet. We show the importance of assessing BEV charging infrastructure in an integrated perspective, focusing on key interactions between transportation, energy, and economy across individual patterns of travel behavior, dwelling constraints, pricing elasticity of consumers with regards to charging, and the temporal and spatial diversity in price and GHG intensity of electricity.

## Chapter 2. Research Objectives

In general, my dissertation research focuses on electric vehicle charging infrastructure spatial modeling, and consists of three major phases: first, building an optimization model to identify the optimal EV charger placement and charging management while respecting individual mobility requirements and electricity diversity; second, investigating the energy and environmental implications of individual behavior under various charging strategies; finally, assessing the near-term emission benefits of SAEVs with EV-Grid Integration. **Figure 1.** The three phases of the research algorithm. shows the overall research algorithm.

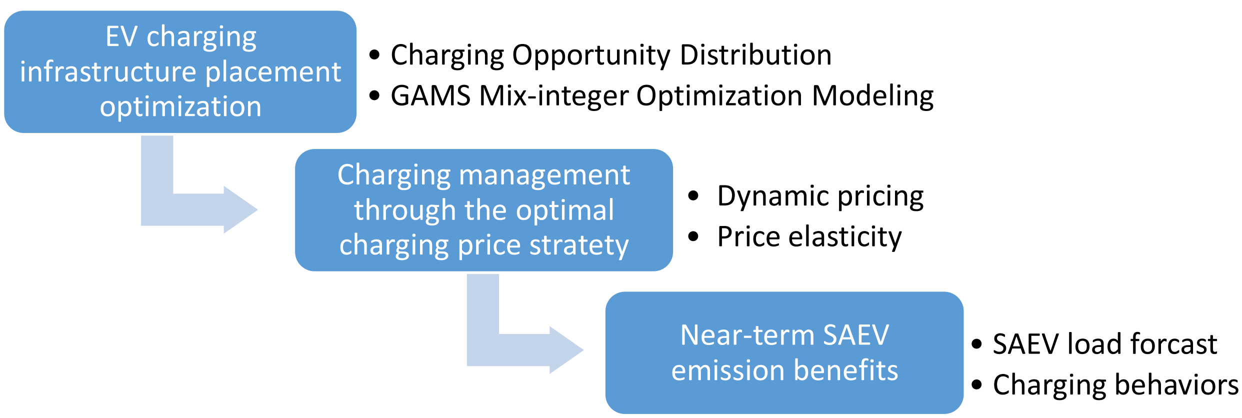


**Figure 1.** The three phases of the research algorithm.

**An Integrated Optimization Platform for Spatial-Temporal Modeling of Electric Vehicle Charging Infrastructure (Chapter 3);**

This section investigates how individual travel and dwelling patterns can affect the distribution of spatial and temporal charging opportunities as well as charging facility allocation to different locations. I design an optimization platform which takes into consideration the disconnect between electricity pricing and GHG intensity. Specifically, I address the following questions covering aspects of technology, environment, and policy:

1. Based on the individual travel and dwelling patterns, what locations have the best opportunities for charging infrastructure installation?
2. What is the best strategy for the government to allocate incentives to support of home versus non-home charging?
3. How many EV chargers of different types are required to support current PEV charging demand, and how do they compare with the existing ones?
4. What are the associated environmental impacts of the optimal charging strategy in California?

**Energy, Environmental, and Economic Impacts of Pricing on Charging Strategies for Electric Vehicles (Chapter 4);**

In this section, I will assess the impacts of various pricing strategies for charging on the grid and the environment. Then, I will optimize a charging pricing strategy that aligns with objectives of minimum GHG emissions without decreasing the profit to the charging suppliers (or electricity retailers depending on the business modes). Regional tier one flat rate of electricity will be used as a baseline and price elasticity will be considered in this study to answer the following questions:

1. What is the optimal dynamic pricing policy for the government to employ, so as to realize the maximum GHG mitigation?

2. What is the environmental implication of the dynamic pricing policy compared with the baseline flat rate one as it relates to the charging behave or policy?
3. To realize maximum GHG mitigation, how will the fuel cost to EV drivers change?
4. What are the energy and economic impacts of this pricing strategy? (Maximum GHG reduction while not decreasing profit to retailers)?

**Emissions Implications of Shared, Autonomous, and Electric Vehicle Fleets: A Case Study of California's Near Future (Chapter 5);**

The final section of my research is to estimate the impacts of a centrally operated, all-electric autonomous rideshare service on transportation emissions, climate change impacts and grid efficiencies in the Bay Area. In particular, we will answer the questions below:

1. What are the emissions benefits for a SAEV fleet at different rates of carbon intensity for electricity?
2. How do emissions benefits shift based on different vehicle occupancy rates (up to a maximum of 4)?
3. What are the emissions benefits of different levels of SAEV adoption compared to other modes?
4. What are policy recommendations that city and state officials can consider to support electrification of shared AV fleet?

# Chapter 3. An Integrated Optimization Platform for Spatial-Temporal Modeling of Electric Vehicle Charging Infrastructure


## Abstract

Vehicle electrification has been identified as one of the most important roles in decreasing greenhouse gas (GHG) emissions in transportation. Proper placement of charging infrastructures and management of charging activities is the key to ensuring the environmental benefits from the widespread adoption of electric vehicles (EVs). By employing empirical travel trajectory data, this paper investigates how individual travel and dwelling patterns can affect the distribution of spatial and temporal opportunities for electric vehicle charging, as well as charging infrastructure installation across regions. We formulate an integrated optimization platform for estimating electric vehicle charging infrastructure placement in home and non-home locations simultaneously that include infrastructure costs and dynamic electricity prices with a mixed-integer linear programming. We provide two case studies in the Great Sacramento Area and San Diego, California. The results show that higher non-home charging opportunity informed by the empirical travel and dwelling patterns offers more potentials for a shared public charging system in San Diego, resulting in 14% - 30% lower in total system cost and 21% - 25% lower in emissions. This indicates that the heterogeneity in spatial and temporal travel and dwelling patterns substantially affect the design of the charging infrastructure system, and substantially change the energy, economic and environmental impacts of the system. We also observe sensible timing of charging in non-home locations that correspond to daytime hours and a secondary peak in

charging at home locations during nighttime hours in both regions, emphasizing the importance of integrating grid dynamics into EV charging infrastructures planning process. Our model platform provides new insights on how to properly allocate EV charging infrastructures and manage charging activities from a comprehensive and disaggregated perspective combined with power grid smoothing.

## 1 Introduction

In 2019 the transportation sector accounted for 28.6% of total greenhouse gas (GHG) emissions in the United States, overtaking electricity generation as the largest source of emissions since 2017. The majority of GHGs in transportation comes from light-duty vehicles, which include passenger cars (40.5%) and freight trucks (23.6%) [26]. Transportation electrification is playing an increasingly important role in dealing with climate change mitigation, especially considering that electricity GHG intensity has dropped substantially in recent years due to fuel switching to lower-carbon sources of electricity production and increasing energy end-use efficiency [26]. Widespread adoption of plug-in electric vehicles (PEVs), which include both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), dominates the emerging revolutions in passenger transportation's transition to sustainable mobility [7].

However, there are several challenges to the widespread electrification of passenger vehicles, including the availability of electric vehicle supply equipment (EVSE, commonly known as charging infrastructure) [9,27–29]. Battery range constraints, both real and imagined, are one of the most significant barriers to large-scale acceptance of BEVs in the market [30]. Developing a dedicated recharging infrastructure system may alleviate range anxiety and encourage more consumers to purchase electric vehicles [14,31]. California is leading the revolution towards transportation electrification in the US and the world, and Governor Jerry Brown signed Executive Order B-48-18 in January 2018 setting a state target of having 5 million ZEVs on California roads by 2030 and deploying 250,000 charging stations, including 10,000 fast-charging stations, by 2025 [32].

The topic of EVSE deployment attracts research interest from a variety of fields. Studies stemming from traditional transportation disciplines often use methodologies such as facility location optimization and consider the placement of electric vehicle charging infrastructure as a location-allocation problem, which determines a set of new facilities from candidate sets [33–37]. Charging demand analysis is often the first and main step in existing studies. Some study is based on simple assumptions for travel distances, such as average annual or daily vehicle miles traveled (VMT), and defines various scenarios in charging behaviors [38]. Some utilize GPS travel survey data [39], or empirical trip trajectory data from portable devices [40,41]. Many other studies capture charging behavior and charging demand through constructing simulation models. For example, agent-based simulations are often constructed to model charging demand considering the empirically charging patterns [42], vehicle attributes such as the initial state of charge variations, range anxiety, charging delay and queuing delay [37], or a more nuanced model of the decision to charge that balances tradeoffs people make with regards to time, cost, convenience, and range anxiety [43]. Other types of simulation include accounting for  temporal utilizations of charging stations, such as the start time and duration of charging events during a discrete event simulation for different expansion strategies of public charging infrastructure [44]; identifying the optimal number of fast charging stations and the corresponding fleet vehicle downtime through simulating the fleet operations for free floating shared electric vehicles [36] or minimizing greenhouse gas emissions of electric delivery vehicles based on charging profiles simulations. These studies are limited because the transportation models are either unable to consider the energy, cost, or environmental impacts of the proposed deployment strategy for charging or simply assume constant electricity rates and uniform grid patterns. However, the operational costs and emissions of electric vehicles largely depend on the electricity they use, which is sensitive to both time and location. Studies based on empirical data show that differences in charging cost play an important role in the demand for charging location [45]. Electrical engineering studies are primarily concerned with finding the optimal location of the charging stations in the distribution network such that the impacts on the operation (e.g., voltage stability, reliability, and power losses) of the power network are minimized, but typically do not consider behavioral elements of EV owners [46–48] Therefore, it is very important to design a more comprehensive optimization model for electric vehicle charging infrastructure planning that combines strengths from transportation modeling approach while considering the dynamics of the grid. A review on the problem of charging infrastructure planning for EVs compares the scenarios of charging infrastructure development across countries and different approaches adopted in recent studies with a focus on optimization formation and the algorithms for solving the problem, emphasizing that the complexity and dynamics of the problem calls for extending existing models in the literature [49].

Past studies on PEV charging infrastructure placement are often limited to a set of select candidate sites, which are often assumed to be identical. Some studies choose existing gasoline stations as the candidate sites [41,42,50], but they neglect the behavioral implications of expecting drivers to wait at the gasoline station for a long time to charge their vehicles. Other studies using highway rest areas as candidate sites [35,51] suffer from the same problem. Some studies find that PEV drivers are more likely to charge their vehicles at the end of a trip rather than in the middle [39,52,53], and the most common location for PEV charging is at home, followed by work, and then public locations [21]. Our research is based on a more general assumption that people are more likely to charge their vehicles at the locations where they stay or dwell for a longer time, and our research contribute to the existing literature by considering how the distribution of dwelling times at different locations might affect the decision of how many, where, and what kind of chargers should be installed, as well as when and where BEV drivers should charge their vehicles.

Another limitation of previous studies is that they separate charging demand by either the type of location (e.g. home, work, or public charging) or based on the purpose of a trip (e.g. commute trips, long-distant trips or ride-share trips) and design the charging infrastructure system accordingly. For example, a study from [33] only considered long-distance intercity trips; [54] designed an optimization model only for workplace charging; and some other studies only optimized fast charging system [37,55]. In another study, a simulation model was proposed to analyze the charging demand distribution across residential area, working area, shopping entertainment area, social rest area and other functional areas [56] However, all of these studies fail to respect a simple fact that individuals may dwell and charge vehicles at the same place for different trip purposes. In other words, chargers at a certain location can be employed to satisfy various types of trips. For example, chargers placed at Walmart parking lots support both the staff and customers, but their trip purpose and dwelling time patterns are quite different. Sometimes it is hard to define whether or not a charging location belongs to “workplace charging” or “public charging", since users may park and charge at public parking lots near their office while working. Therefore, it can be inaccurate to separate the designation of non-home charging infrastructure into types of workplace and public charging. To our best knowledge, there is no existing study that comprehensively considers charging demand of all kinds and simultaneously optimizes the placement of charging infrastructures of all levels. Lastly, many existing models simply assume that vehicles are fully charged when leaving for work [33,41,57], but in reality, this is not always the case and BEV owners may have more complex charging behaviors [58].

To address these research gaps, we design an agent-based optimization model platform to identify the optimal EV charger placement of home and non-home charging across regions and charging management strategy at individual level while integrating grid dynamics. Compared to previous studies, our paper makes several unique contributions to the literature: 1) it demonstrates the importance of spatial distribution of dwelling times and the corresponding limits to charging opportunities by employing large-scale activity-based travel diary data, 2) it accounts for the spatial and temporal differences in prices and carbon intensity of the electricity, 3) it optimizes charging loads of a system comprehensively by considering four types of chargers while respecting the heterogeneity in home and non-home charging, and 4) it provides a higher level of resolution for charging infrastructure planning and management. This study is based on the mobility patterns of current vehicle drivers in California, but it may apply to other regions for which similar data are available and can be easily converted to new mobility with changing vehicle occupation rates under different scenarios such as shared mobility and/or medium and heavy-duty electrification.

The rest of the paper is organized as follows: Section 2 explains the methodology and data used in this research. Section 3 presents our results of the spatial-temporal charging opportunity distribution across California and compares case studies of optimal charging infrastructure system in San Diego and Great Sacramento Area. And in section 4, we conclude with a discussion of the major implications and outlook of our work.

## 2 Materials and method

We outline our study's approach as follows:

1) We assess the spatial-temporal distribution of 'charging opportunity' (defined in section 2.1) at the census tract level in California;

2) We construct an optimization model to investigate the optimal locations for PEV charging installation and the charging strategy of individual drivers by minimizing system cost.

Our integrated electric vehicle charging optimization (IEVCO) is able to demonstrate the optimal time and location to charge for each individual, and the number of EV chargers to install in each region. The overall modeling framework is shown in **Figure 2**. Data inputs include 1) spatial-temporal charging demand and availability (daily travel distance, vehicle energy efficiency, and dwelling time for each individual at each stop of a day) is based on a high-resolution individual activity-based travel diary data [25]; 2) available charging infrastructure characteristics (equipment and installation costs, power of the chargers) is cited from a study by the U.S. Department of Energy's National Renewable Energy Laboratory [59]; 3) charging cost (the price of charging at each hour of a day) refers to the dynamic locational marginal price reported by local transmission system operator [60]. The raw output of the optimization model is the assignment of charging time slots and locations for each individual included in the inputs, as well as the number of chargers required for each region.

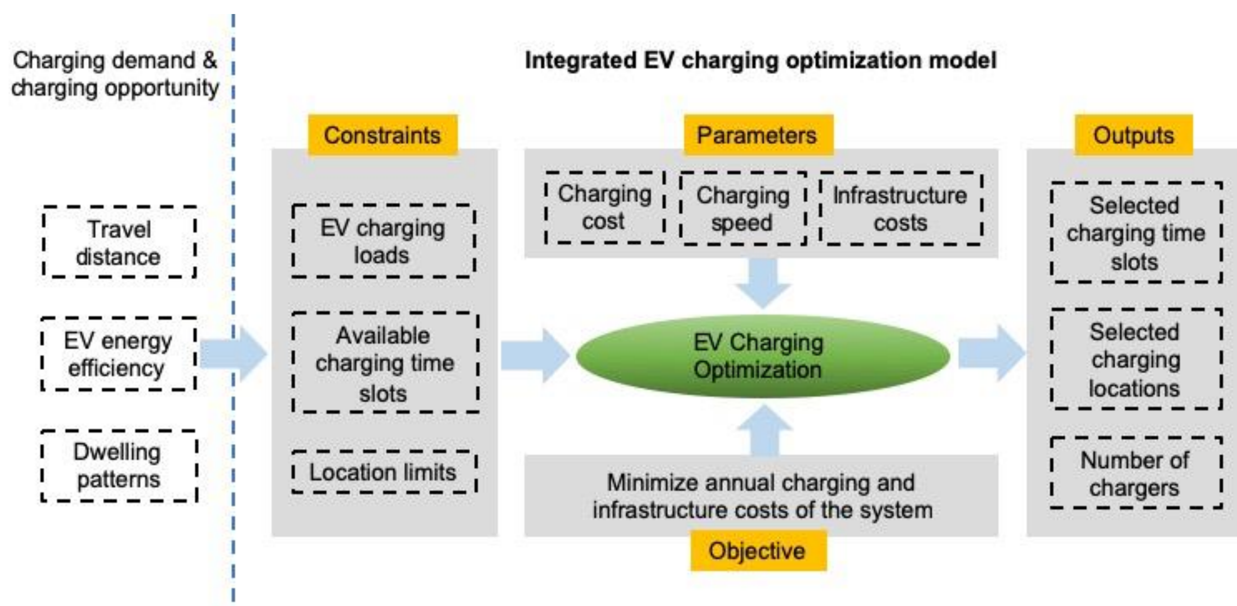


**Figure 2.** A modeling framework for the Integrated Electric Vehicle Charging Optimization.

### 2.1 Assessing the distribution of charging opportunity

Understanding spatial-temporal distributions of PEV owners' charging opportunities (CO) in the study area is the first step of modeling. We define the charging opportunity of an individual at a certain place as the time period they stay or dwell at that location, and define charging opportunity of a location as the sum-product of the number of people and their respective dwelling times at that location within a day. This definition is based on the general assumption that people are more likely to charge at places where they stay longer. Locations with more visitors also have a higher chance to support more charging activities than those with few visitors. **Figure 3** depicts an example of the charging opportunity of an individual as it relates to his/her daily activity. Vertical bars on the left graph represent activities and the dwelling time duration is the charging opportunity at that location. The disconnection between bars means the individual is traveling on the road. We separate charging opportunities into the home and non-home categories because the home charger is exclusive to EV owners, but chargers at non-home locations are shared by all users. Therefore, the model optimizes the time and location of each individuals' available charging time slots according to the cost associated with that time and location (shown by the color on the right graph: red means high cost while green means low cost).

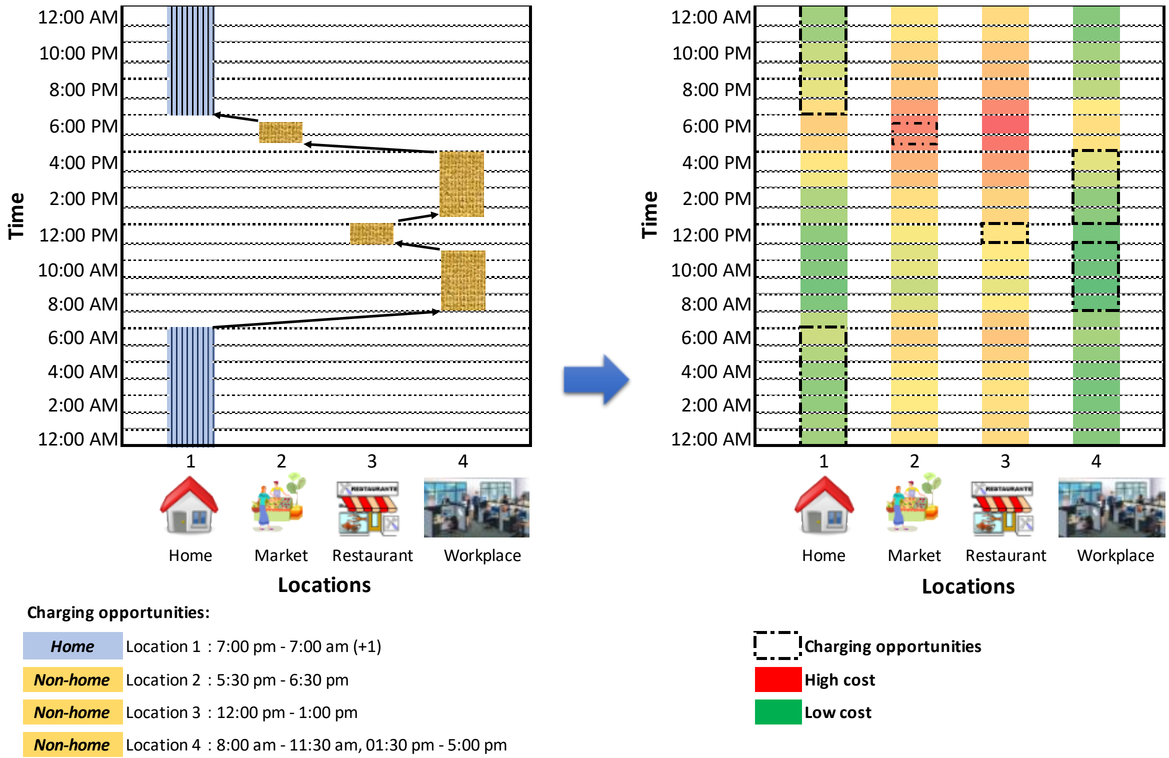


**Figure 3**. An illustration of charging opportunity

The left graph depicts a typical travel and dwelling time pattern of the sampled individual, who starts the commute trip at 7:00 am and arrives at the workplace at 8:00 am. His/her charging opportunity at that workplace is from 8:00 am - 5:00 am except for one hour at the restaurant during 12:00 pm -1:00 pm and the time for driving. After work, the driver spends one hour doing grocery shopping, leaving the charging opportunity at the market's parking lot from 5:30 pm - 6:30 pm. All the remaining time spent at home is the driver's home charging opportunity. Accordingly, the right image illustrates the basic logic of our IEVCO model: figuring out the optimal time slots and locations to charge within all the available charging opportunities for each sampled individual included in the inputs.

Our approach is advantageous for several reasons. First, it quantifies the charging opportunity of all locations (home or non-home) uniformly, allowing for all locations to be modeled simultaneously. Second, it enables us to analyze the available charging patterns of any possible locations based on the dwelling patterns of all the people who visit that location. For example, by measuring the distribution of daily dwelling times among all customers and workers in a shopping plaza, we are able to determine how many, and which level of chargers are suitable to install in its parking lot. Thirdly, since we only indicate the optimal charging strategy for BEV drivers within their charging opportunity, the model inherently avoids the problem of detouring to visit charging stations that commonly appear in other models.

## 2.2 Formulation of EV charging optimization

**NOMENCLATURE**

| | |
|---|---|
| **Sets** | |
| $i$ | individual within the study region, $i$ = {1, 2, 3, …, n} |
| $r$ | region, at census track level, r = {1, 2, …, m} |
| $t$ | time slot, refering to each hour of a day, $t$ = {1, 2, …, 24} |
| $l$ | level of chargers, $l$ = 1, 2 for home chargers and $l$ = 2, 3 for non-home chargers |
| **Variables** | |
| $y^{totalCost}$ | total system costs [$] |
| $x^{homeTime}_{irtl}$ | home charging time during time slot $t$ in region $r$ with level $l$ charger for driver $i$ [h] |
| $x^{nonhomeTime}_{irtl}$ | non-home charging time during time slot t in region r with level l charger for driver i [h] |
| $x^{homeCharger}_{rl}$ | number of home charger at level $l$ within in region $r$, integer variable |
| $x^{nonhomeCharger}_{rl}$ | number of non-home charger at level $l$ within in region $r$, integer variable |
| $x^{chosenCharger}_{irl}$ | a binary variable indicating if a level $l$ home charger being installed for individual $i$ at home location in region r (=1) or not (=0) |
| **Parameters** | |
| $e^{Demand}_{i}$ | daily total energy demand for individual $i$ [kWh] |
| $w_i$ | weight of sample individual $i$ |
| $c^{homeChargingPrice}_{trl}$ | home charging price at level $l$ charger in region $r$ during time $t$ [$/kWh] |
| $c^{nonhomeChargingPrice}_{trl}$ | non-home charging price at level $l$ charger in region $r$ during time $t$ [$/kWh] |
| $p^{homePower}_{l}$ | power of level $l$ chargers at home locations [kW] |
| $p^{nonhomePower}_{l}$ | power of level $l$ chargers at non-home locations [kW] |
| $c^{homeCharger}_{l}$ | equipment and installation cost for level $l$ home chargers [$/yr] |
| $c^{nonhomeCharger}_{l}$ | equipment and installation cost for level $l$ non-home chargers [$/yr] |
| $d^{homeDwellingTime}_{itr}$ | home dwelling time for individual $i$ during time slot $t$ in region $r$ [hr] |
| $d^{nonhomeDwellingTime}_{itr}$ | non-home dwelling time for individual $i$ during time slot $t$ in region $r$ [hr] |

Our IEVCO model is formulated as a mixed-integer optimization problem as follows: there are n EV drivers (i = {1, 2, 3, …, n}), each deciding the amount of time to recharge the vehicle in each of their available time slots $t$ among m regions ($r$ = {1, 2, …, m}), based on their daily activity patterns. The objective is to minimize total costs $y^{totalCost}$ with respect to the home and non-home charging time, $x^{homeTime}_{irtl}$ and $x^{nonhomeTime}_{irtl}$, during a specific time slots $t$, in region $r$ with level $l$ charger for BEV driver $i$, as well as the number of home and non-home chargers, $x^{homeCharger}_{rl}$ and $x^{nonhomeCharger}_{rl}$, being built at level $l$ within in region $r$. The total system cost, which is the sum of costs from fulfilling the charging demand of BEV owners and building the charging stations in the study domain, can reflect the expenditure that the society or system need at least to afford in building and running their charging infrastructure system. The model assumes: 1) individuals are rational price actors when they make the decision on where and how long to charge their vehicles and 2) their choice of PEV is sufficient to cover their average daily travel distances, and thus day-ahead charging is sufficient to support the next-day energy demand on average. Since our research focuses on the investigation of the optimal strategy to distribute charging stations in both home and non-home locations at all levels within the study area, as well as indicate the right time and location for each individual to charge their electric vehicles, we also assume instantaneous station installation and possible discontinuous charging with smart charging technology.

The mathematical formulation of the optimization model is as follows:

Equation 1

$$\mathrm{Min}_{wrt\ x_{irtl}^{homeTime}, x_{irtl}^{nonhomeTime}, x_{rl}^{homeCharger}, x_{rl}^{nonhomeCharger}}\ y^{totalCost}$$

$$= (\sum_{irtl} c_{trl}^{homeChargingPrice} x_{itrl}^{homeTime} p_l^{homePower} w_i$$

$$+ \sum_{irtl} c_{trl}^{nonhomeChargingPrice} x_{itrl}^{nonhomeTime} p_l^{nonhomePower} w_i) * 365$$

$$+ \sum_{rl} c_l^{homeCharger} x_{rl}^{homeCharger} + \sum_{rl} c_l^{nonhomeCharger} x_{rl}^{nonhomeCharger}$$

To make the two cost components – capital cost for building charging stations and the electricity costs for charging electric vehicles, consistent and comparable, we define the objective total cost on an annual basis. The optimization model subject to a series of constraints:

1) Energy demand requirement and power constraint: the charging activities happening both at home and non-home locations should meet the average daily energy demand of EV driver *i*.

Equation 2

$$\sum_{trl}(x_{itrl}^{homeTime}p_l^{homePower} + x_{itrl}^{nonhomeTime}p_l^{nonhomePower}) \geq e_i^{Demand}, \forall i$$

2) Charging time constraints: charging time should not exceed one time slot, which is defined as one hour.

Equation 3

$$0 \leq x_{itrl}^{homeTime} \leq 1, \qquad 0 \leq x_{itrl}^{nonhomeTime} \leq 1$$

3) Dwelling time constraints: charging time should be within the available dwelling constraint.

Equation 4

$$x_{itrl}^{homeTime} \leq d_{itr}^{homeDwellingTime}, \qquad x_{itrl}^{nonhomeTime} \leq d_{itr}^{nonhomeDwellingTime}, \forall itr$$

4) Forcing constraints: non-home chargers are shared among users at non-home locations while each home charger is exclusive to an individual, which is specified in Equation 5-7. Specifically, forcing constraint Eq.5 ensures that during each hour $t$, the total number of installed level *l*

non-home charger in region *r* will be at least larger than the number of level *l* non-home charger being used in that hour. Therefore, charging activities will be optimally arranged and charging station queueing problem can be avoided endogenously by our model.

Equation 5

$$\sum_i x_{itrl}^{nonhomeTime} w_i \leq x_{rl}^{nonhomeCharger}, \forall rtl$$

Equation 6

$$x_{itrl}^{homeTime} \leq x_{irl}^{homeCharger}, \forall irl$$

Equation 7

$$x_{rl}^{homeCharger} = \sum_i x_{irl}^{chosenCharger} w_i$$

The model employs the activity-based travel diary data from the 2010-2012 California Household Travel Survey (CHTS) to simulate individuals' daily travel patterns and the travel information was collected every day for a full year [25]. The travel diary data provides the start and end times of trips as well as the location of individuals' daily activities taken by a sample of individuals across California (also implying the dwelling patterns of all sampled individuals). CHTS provides an "Expanded Person Weight" for each record of activity data to represent the total 36,969,200 persons residing in California. However, CHTS collects personal activity information from many travel modes and the weights in CHTS are calculated based on demographic attributes such as household size, income, age, number of household vehicles, and County of residents, but the weights in CHTS are not an accurate representation of BEV owners even if we only look at the driver trips. To address this issue, we use regional BEV ownership density from the Rebate Statistics of Clean Vehicle Rebate Project (CVRP) [61] to adjust the Expanded Person Weight in CHTS. Population data for the study area are employed from the US Census Bureau [62]. CVRP records the home address of the owners of alternative vehicles in California, and we subset the information of BEV drivers by 2019. As a result, the adjusted BEV weight is the number of BEVs that each sampled individual represents, and can be calculated as follows:

Equation 8

$$ABW_{i,r} = EPW_{i,r} \times \frac{BEV_r}{Pop_r}$$

where:

$ABW_{i,r}$: The adjusted BEV weight for sampled individual *i* with a home location belonging to region *r,* and the region here is defined at the census tract level.

$EPW_{i,r}$: The Expanded Person Weight in CHTS for sample individual *i* with home location belong to region *r*

$BEV_r$: Total number of BEVs in region *r*

$Pop_r$: The total population of region *r*.

We also use other resources to capture information on travel demand, the electric grid, and infrastructure costs in this study. Travel distance is calculated as the shortest driving distance between origins and destinations using Google API. We assume an average efficiency of 33.3 kWh per 100 miles for electric vehicles based on fuel economy data from FuelEconomy.gov [63] and EV sales data reported by the Transportation Research Center at Argonne National Laboratory [64]. To capture the temporal variation of electricity, we employ electricity generation costs as a proxy for charging price, which is based on the average real-time dispatch locational marginal price (LMP) over the entire year of 2017 in California ISO [60]. We do not estimate the electricity distribution and transmission costs and therefore underestimate real charging costs to some degree. We use LMP for both home and non-home charging prices since the model is focused on the outcome of social welfare as opposed to the benefits to customers or charging suppliers, and the LMP is a good representation of the marginal cost of the electricity at a specific time and location. The GHG impacts of charging use the average hour-of-day marginal emissions factors for CAISO in 2018 [65]. Parameters and costs of charging infrastructures are obtained from the U.S. Department of Energy's National Renewable Energy Laboratory's analysis on the refilling infrastructures for electric light-duty vehicles, which aggregates data for equipment and installation costs from various sources [59]. We levelize the charging station's capital and installation costs on an annual basis with a lifespan estimated as 10 years and an interest rate of 3%. Based on the costs and power of existing chargers, we define three scenarios. **Table 1** shows the assumptions for each type of charging infrastructures for the high, medium and low costs scenarios. Power of level 2 chargers in the low-cost scenario smaller than 6 kW is not sufficient for the model platform to achieve a feasible solution.

**Table 1.** Assumptions on the costs and power for chargers

| | | Level 1 Home | Level 2 Home | Level 2 Non-home | DC Fast |
|---|---|---|---|---|---|
| Annual equipment and installation cost ($/unit/year) | High | $112 | $378 | $729 | $11,958 |
| | Medium | $98 | $224 | $630 | $5,480 |
| | Low | $66 | $172 | $544 | $1,993 |

| | | | | | |
|---|---|---|---|---|---|
| | **High** | 1.9 | 19.2 | 19.2 | 90 |
| **Power (kw)** | **Medium** | 1.7 | 7.0 | 7.0 | 50 |
| | **Low** | 1.4 | 6.0 | 6.0 | 20 |
| **Charging price ($/kWh)** | | | LMP | | |

Note: 10-year lifespan with 3% discount rate.

Our optimization model is a Mixed Integer Linear Programming (MILP) problem, which we solve in GAMS with the Cplex solver. Although only private vehicle charging demand is evaluated in this study, shared mobility charging demand can be exogenously added to this optimization platform.

## 3 Results

### 3.1 Spatial-temporal Distribution of EV Charging Opportunity in California

**Figure 4** (top left) shows the timeshare for BEV owners in the whole state of California over the course of a day. Home dwelling time accounts for around 74% of the day on average and dwelling at non-home locations makes up 19%. On-road travel accounts for the remaining 7.3% of total time representing an average time of fewer than 2 hours. This result is consistent with other studies based on the National Household Travel Survey (NHTS) [24]. Non-home dwelling time durations are relatively short but vary from person to person. Non-home dwelling patterns of BEV owners are also shown in **Figure 4** (top right). The average BEV in California is parked 92.7% at either home or non-home locations of the time, which means there are lots of opportunities for BEV drivers to choose for charging the vehicle to fulfill their daily travel needs. Although the home charging opportunity is 54.3% higher than the non-home one, we still see the potential for charging demand management by shifting EV charging loads to cheaper and cleaner time periods during the daytime at non-home locations. We also observe that nearly 50% of the time durations in non-home locations are less than 40 min, indicating a large potential for fast charging facilities being used at non-home locations, which typically add 50 to 90 miles in 30 min for EVs. The other half of the non-home dwelling time durations are distributed from 60 min up to 10 hr. These properties of dwelling time patterns in non-home locations demonstrate the importance of considering dwelling patterns in designing the EV charging infrastructure system.

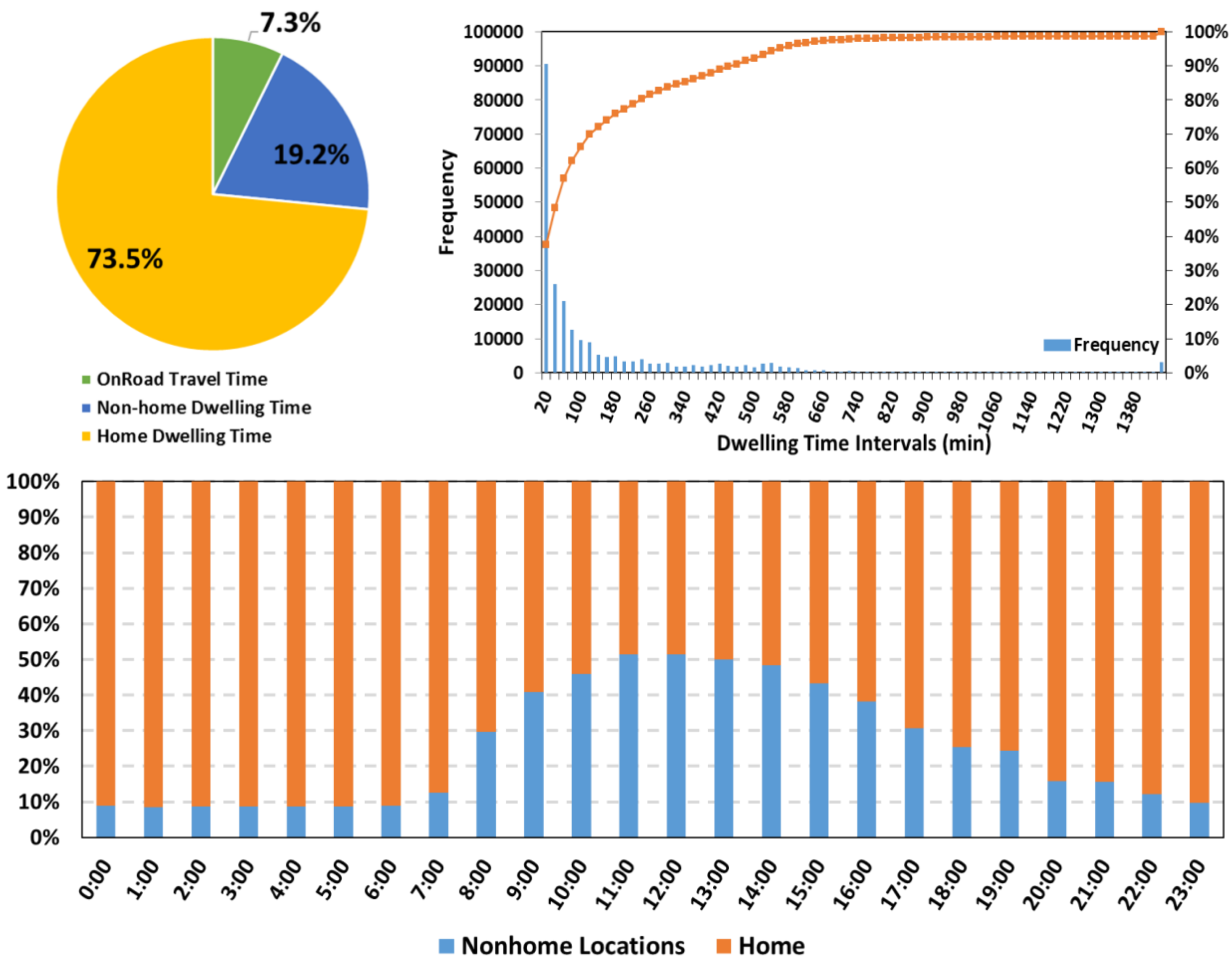


**Figure 4.** Timeshare and temporal charging opportunity distributions.

Investigating the charging opportunities distribution over the day is also important when considering the temporal change in price and GHG intensity of electricity. As seen in **Figure 4** (bottom), home locations have more charging opportunities in the off-peak period, running from 20:00 to 7:00 (next day), but charging opportunities at non-home locations are mostly distributed during the daytime period when the GHG impact and generation costs are pretty low in CAISO service territory. While we expect that home charging should still be the dominant charging pattern, there is potential for charging demand management by optimally scheduling charging activities into the charging opportunities—especially when considering the price differences of electricity at on- and off-peak hours.

### 3.2 Optimized Spatial Charging Infrastructure Platform

We conduct two case studies of the Greater Sacramento Area and San Diego, California to illustrate the outputs of our IEVCO platform. We choose these two areas because they are comparable in the amount of BEV drivers but with different spatial and temporal travel and dwelling patterns. We subset sample individuals with trip destinations in the study areas from CHTS: 2,452 sampled individuals, representing 15,789 BEV drivers in the CVRP dataset, with daily travel and dwelling patterns across 614 census tracts of San Diego, and 5,241 sample individuals, corresponding to 10,600 BEV drivers, representing 536 census tracts in the Greater Sacramento Area. **Figure 5** shows the daily dwelling locations of those BEV drivers. We observe that BEV drivers in the Greater Sacramento Area mostly stay near the center of the study domain and along the freeways of I-80 and US-50, but those in San Diego cluster along the coast since the eastern area is covered by the Santa Rosa Mountains. In aggregation, charging opportunity in home locations occupies 71.4% of the total among all locations in the Great Sacramento Area and the portion of home charging opportunity in San Diego is 68.8%.

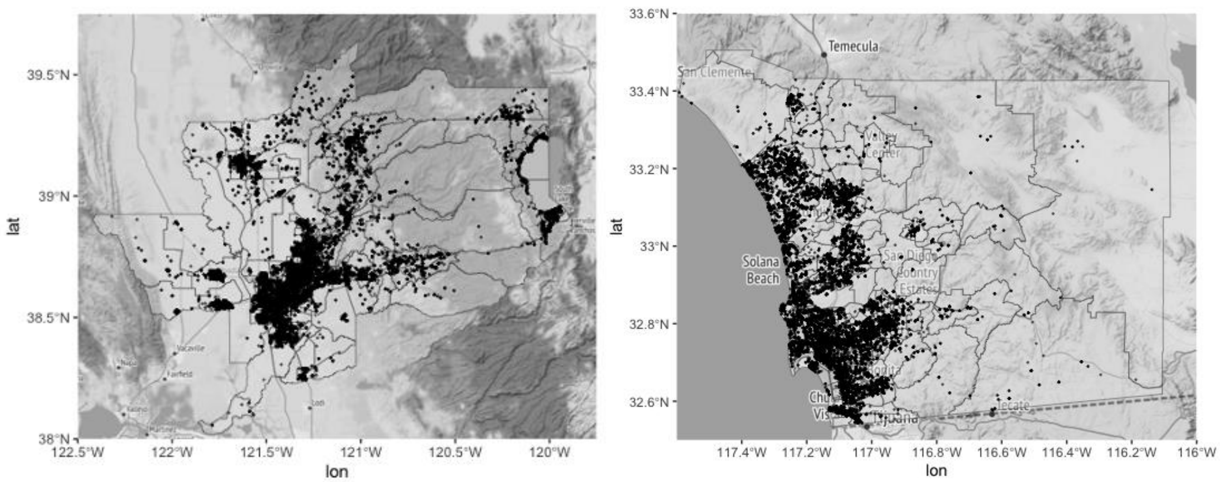


**Figure 5.** Daily dwelling locations of BEV drivers in the study areas: Greater Sacramento Area (left) and San Diego (right).

We display the optimal number of charging stations required under each cost scenario for both study domains in **Figure 6**. The high, medium, and low scenarios are corresponding to different levels of infrastructure equipment and installation costs and charging speed as seen in Table 1. We find that even though level 1 home charging dominates the charging patterns in both study domains, the components of charging stations are quite sensitive to the costs and efficiency of the charging infrastructures. The shares of level 1 chargers are 60.8%, 71.6%, and 79.4% for the high, medium, and low scenarios in the Great Sacramento Area, and 77.0%, 80.1%, and 82.2% in San Diego respectively. Generally, home charging (level 1 and level 2) is the dominant charging pattern, accounting for at least 70% of the total required chargers in all cost scenarios - despite the fact that many BEV drivers can fulfill their charging needs with only non-home chargers. The share of home chargers decreases as the infrastructure costs become higher. When the higher efficient but more expensive chargers are offered to the system, the optimal strategy would promote shared level 2 non-home charging. Comparing the two regions, we find that the share of level 1 home chargers in the Great Sacramento Area is much lower, accounting for 83.4% - 86.1% of all chargers at home, but 92.5% - 97.4% in San Diego.

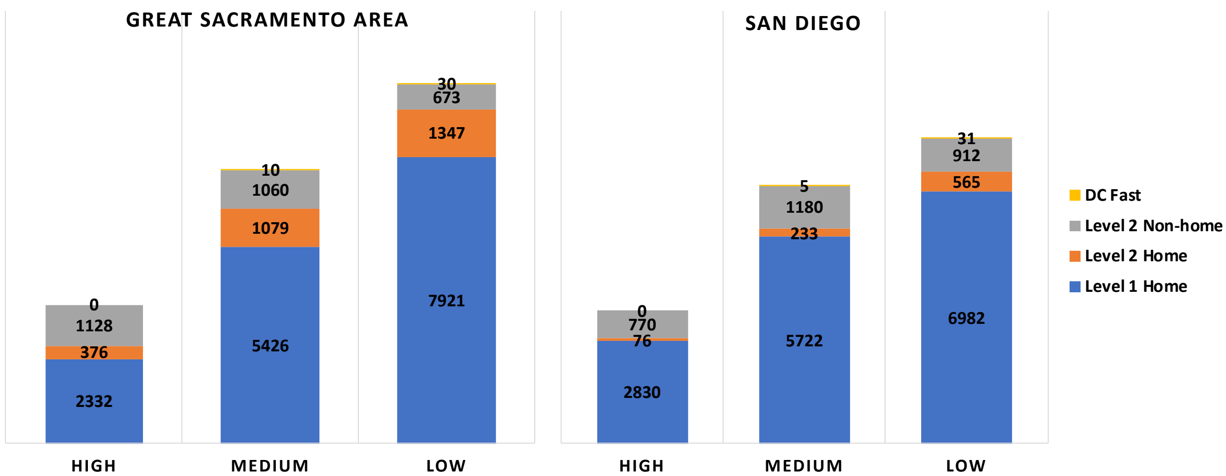


**Figure 6.** The optimal number of charging stations required under each scenario for both study domains.

*3.2.1 Costs and environmental impacts*

The total annual system costs and the GHG impacts for both study areas are compared in **Figure 7**. Dots represent GHG emissions (right axis), and bars refer to the total system costs (left axis). The annual system cost and GHG impacts of the charging infrastructure system in Great Sacramento Area are substantially higher than those in San Diego even if the number of BEV drivers in San Diego is higher, indicating that our general results are robust in that the spatial and temporal travel and dwelling patterns of BEV drivers substantially alter the economic and environmental impacts of the charging infrastructure system. While increasing the cost of charging infrastructure decreases the total number of charging stations required (regardless of charging speed), we find that the annual system cost is not necessarily highest in the high-cost scenario since our IEVCO platform will balance between charging cost and infrastructure installation cost in the system.

The constraints of spatial and temporal travel and dwelling patterns of BEV drivers also play an important role in determining the local charging system. Although the number of BEV drivers in San Diego is 48.9% higher than that in the Great Sacramento Area, the total economic and environmental impacts of the optimized charging infrastructure system are lower in San Diego. The annual system cost in the Great Sacramento Area ranges from $2,048,682 to $2,506,536, and the total GHG emissions from 14,709 $tCO_2e$ to 17,390 $tCO_2e$ due to different estimations of infrastructure costs and charging efficiency. In comparison, the annual system cost is 13.9% - 30.1% lower, and annual GHG emissions from the extra EV charging loads are 21.3% - 25.0% lower in San Diego County. The reason comes from the difference in the spatial and temporal travel and dwelling patterns of BEV drivers in two places. Due to a lower portion of charging opportunity in home locations, charging patterns in San Diego are more shared in public locations during the daytime when the cost and GHG intensity of electricity is lower. Therefore, the total cost and environmental impacts of charging system in San Diego is lower.

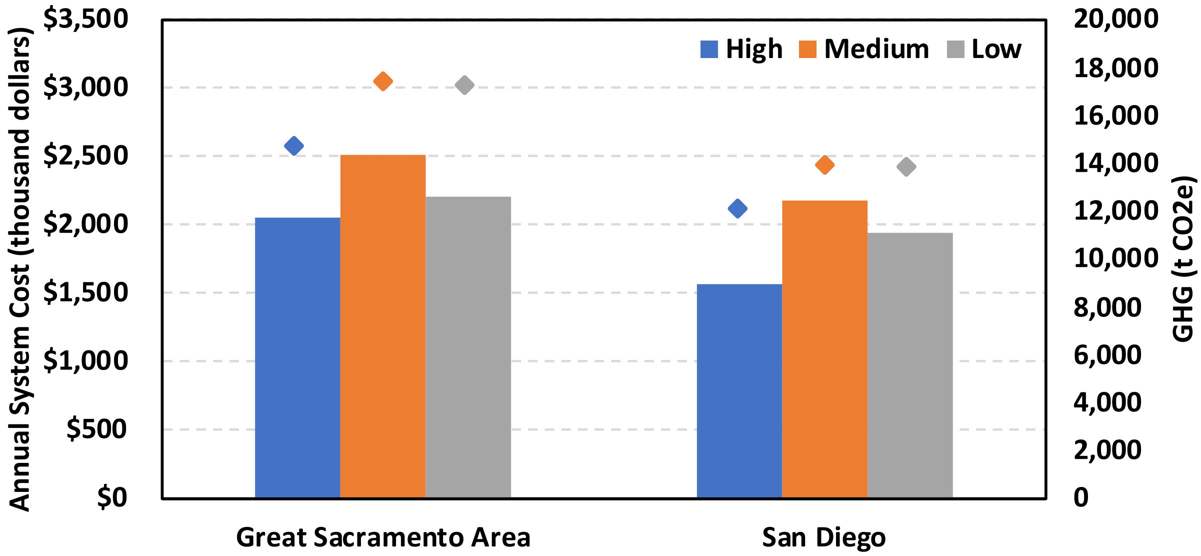


**Figure 7.** A comparison of charging infrastructure systems in total annual system costs (bars) and the GHG emissions (dots) between Great Sacramento Area and San Diego.

*3.2.2 Optimal locations of chargers*

To show the relative locations of the optimal distribution of charging stations, we show the results of the medium-cost scenario. As seen in **Figure 8**, the distributions of home and non-home charging stations are quite different. Non-home level 2 chargers are mainly located in Yolo County, Sacramento County, west of El Dorado County, and some regions in Placer County. DC fast chargers are mostly distributed in some small regions in south Sacramento and southeast Yolo County. Level 1 home chargers are distributed in all counties, except the southwest region of Sacramento County. Similar to level 1 home chargers, level 2 home chargers cover all counties, except the southwest region of Sacramento County and northwest of Yolo County. Interestingly, the region between highways in southwest Sacramento County does not necessitate investment of charging stations.

For chargers in San Diego County, level 1 home chargers cover most regions, while level 2 home chargers are distributed on the west side of the county and in some discrete regions along with the coast and download areas. Non-home level 2 chargers cover similar regions as level 1 home chargers, except it does not cover the center of San Diego County and most regions in the downtown area but shows up in the eastern part of the county.

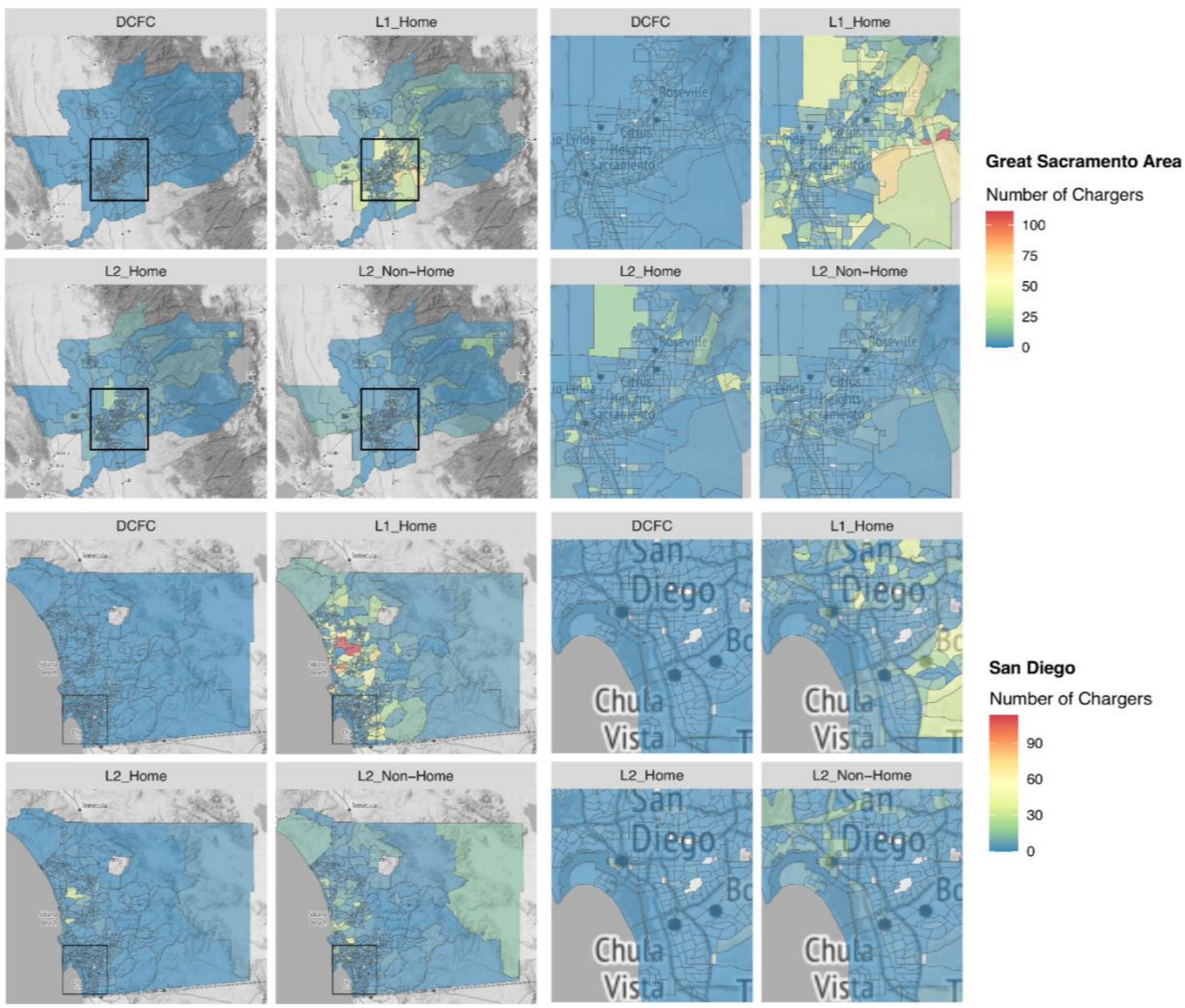


**Figure 8.** Distribution of chargers in the Great Sacramento Area (top) and San Diego (bottom), medium cost scenario.

*3.2.3 EV charging grid impacts*

**Figure 9** compares the distribution of the aggregate energy demand for each of the census tracts in both study areas for the medium-cost scenario. Most census tracts in both study domains will afford very low charging loads per day, but more census tracts in San Diego County will see the EV charging load as high as over 100 kWh per day. In other words, the energy impact from EV charging in San Diego is substantially different across census tracts and identifying those “hotspot” areas is very important especially as the electric vehicle fleet expands. Additionally, the source of charging loads is also quite different in the two study domains. In the median cost scenario, residential charging loads in San Diego are only 49.9%. But in the Great Sacramento Area, extra charging loads from home chargers contribute 63.1%. This finding is also consistent with our observations on charging opportunity of the two regions: the Great Sacramento Area has higher portion of home charging opportunity than that in San Diego.

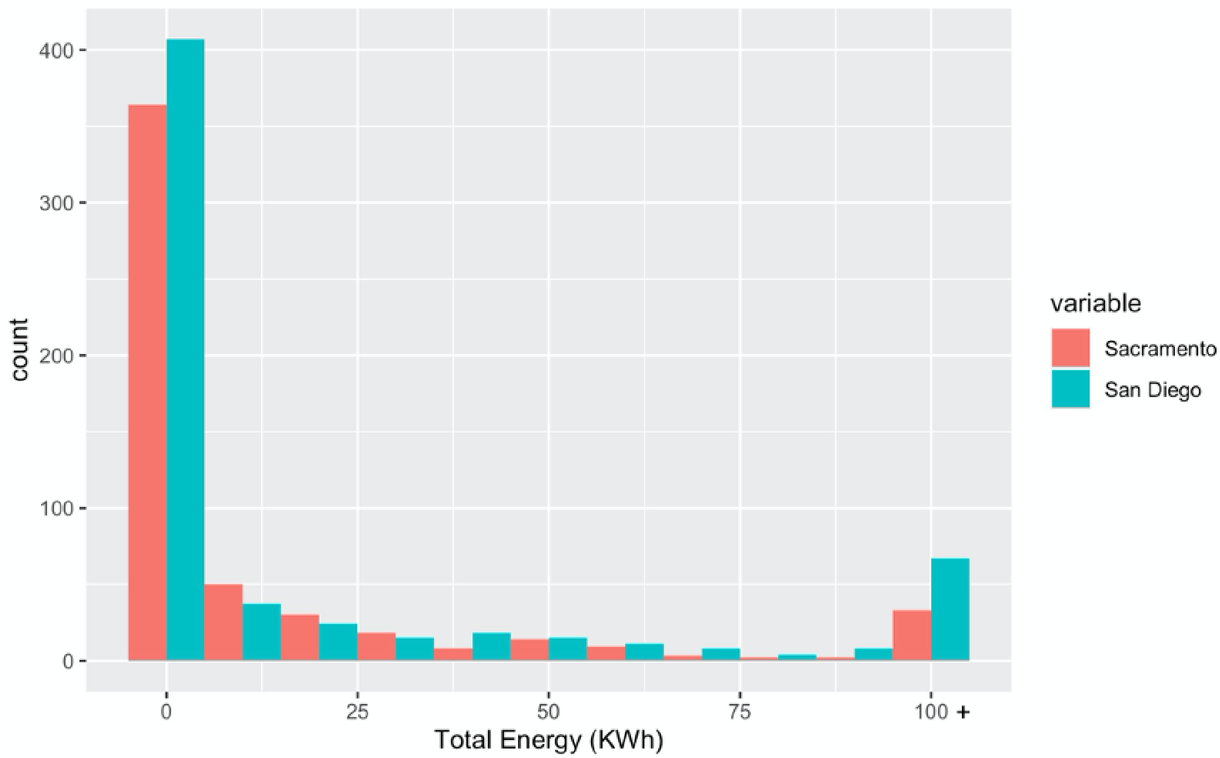


**Figure 9.** Total extra charging loads impact at census tract level, medium cost scenario.

To evaluate the impact of EV charging loads on the grid, we are also able to estimate the power requirement from charging in each time period. **Figure 10** shows the timing of charging across different power levels. We find that charging is concentrated over two time periods that align with off-peak periods on the grid under the optimized strategy in both regions. There are two peaks from EV charging: the first peak occurs between 11:00 pm to 4:00 am and the second peak corresponds to non-home charging between 8:00 am to 2:00 pm. We also find the distinction of the peak demand component between the two study domains. The grid in the Greater Sacramento Area (**Figure 10**, top) is affected most with concurrent charging loads as high as 17.7 MW in the early morning from 3:00 am - 4:00 am (mainly for home charging). In San Diego County

(**Figure 10**, bottom), the electricity grid experiences extra charging loads as high as 10.7 MW in the morning from 9:00 am - 10:00 am with the biggest contribution from level 2 non-home charging. Additionally, DC fast charging appears between 9:00 am to 12:00 pm in the Greater Sacramento Area, while in San Diego County, DC fast charging only appears at 9:00 am.

Although the Greater Sacramento Area and San Diego County share similar temporal charging patterns, the contributions from different charger levels vary. Overall, the share of non-home charging in San Diego is higher than that in the Great Sacramento Area. Non-home level 2 charging has a similar contribution with level 1 home charging during the nighttime peak in the Great Sacramento Area, while level 1 home chargers contribute to charging load the most during the nighttime peak in San Diego County. But during the daytime peak, non-home level 2 charging accounts for the highest share of EV charging load in both regions. The results indicate again that higher non-home charging opportunity informed by the empirical travel and dwelling patterns offers more potentials for a shared public charging system.

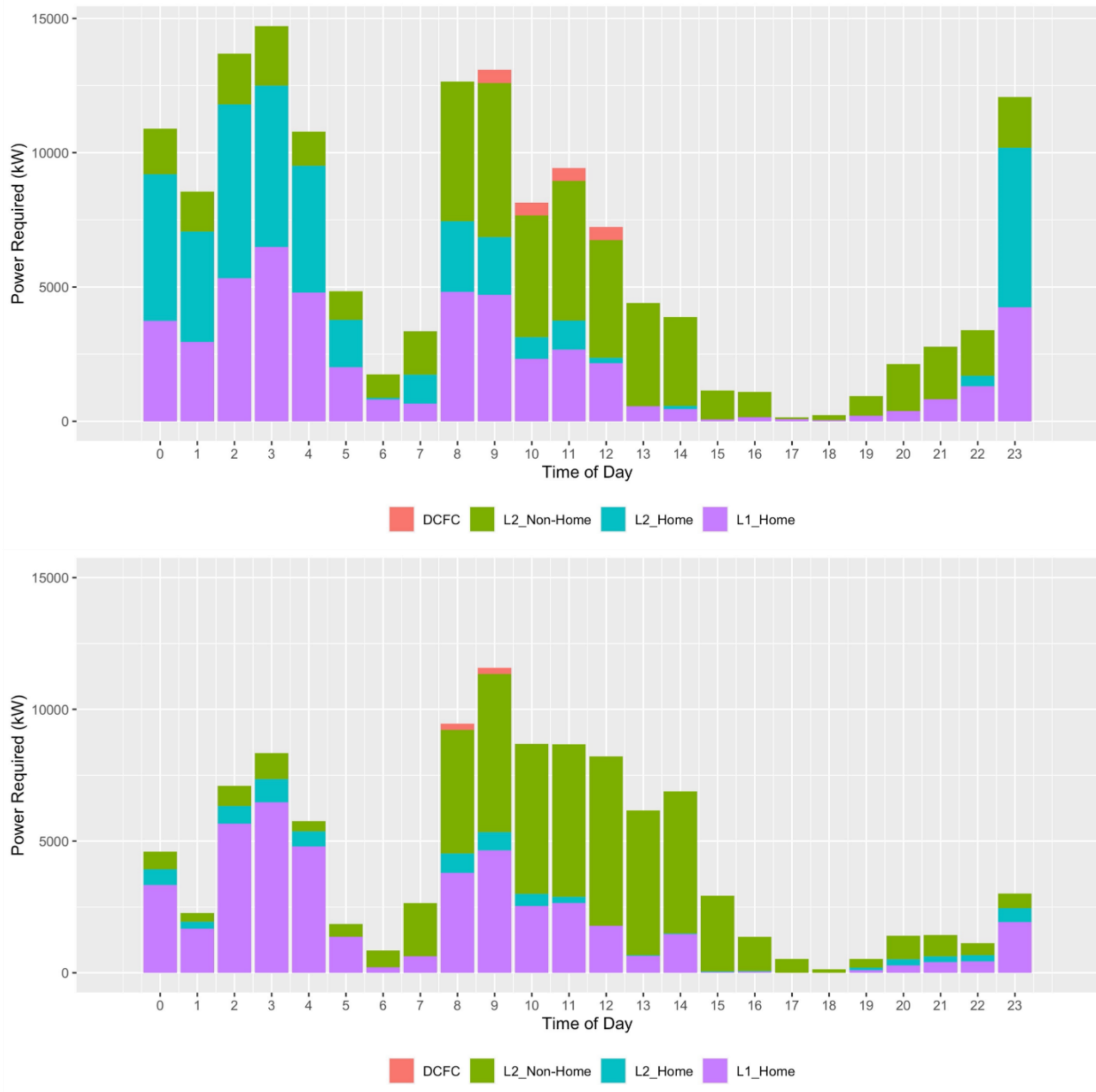


**Figure 10.** EV charging power demands in the Great Sacramento Area (top) and San Diego (bottom), medium cost scenario.

## 4 Conclusions and discussion

In this study, we formulate an optimization model to explore how many of which type charging stations should be installed at which locations and to determine the optimal charging strategies for BEV drivers within the system that minimize total system costs based on their travel and dwelling behavior, as well as dynamic electricity price of the study domain. The high-resolution individual activity-based travel diary data provides empirical information on travel and dwelling behavior, which offers opportunities to develop new spatial and temporal optimization models for EV charging infrastructure planning and charging management. We also introduce the concept of "charging opportunity" to represent the potential of charging availability. Charging opportunity distributions in California demonstrate the dominance of home charging but reveal the importance of dwelling patterns in designing the EV charging infrastructure system as well as the potential for fast-charging facilities at non-home locations.

Our IEVCO model platform is implemented for the Greater Sacramento Area and San Diego County in California as case studies to illustrate the energy, economic and environmental impacts of the optimized EV charging infrastructure systems with sensitivity to high, medium, and low scenarios of infrastructure equipment and installation cost, as well as charging efficiency. We find that we are able to determine the optimal distribution of charging activities and the number of chargers of different levels in the study regions at the census tract level. The results show that home charging accounts for over 70% of EV charger types in both study regions. Compared with the Great Sacramento Area, the annual system cost of the charging infrastructure system is 14%

- 30% lower, and annual GHG emissions from the extra EV charging loads is 21% - 25% lower even if the number of BEV drivers is 48.9% higher in San Diego. In terms of energy impact, charging is concentrated over two time periods that align with off-peak periods on the electric grid, but the grid in San Diego County will be less impacted by the extra EV charging loads due to more shared public charging among BEV drivers. Spatially, the energy impact from EV charging in San Diego is more diverse such that the number of census tracts with high extra charging load is higher, emphasizing the importance of identifying those "hotspot" areas, especially with electric vehicles fleet expansion.

Our work affirms that the spatial and temporal travel and dwelling patterns of BEV drivers substantially affect the design of the EV charging infrastructure system. The majority of charging infrastructure planning focuses primarily on origin-destination trip data for locating chargers. However, we show the importance of including dwelling patterns of individuals on the decision-making process of optimal charger placement. These considerations will be critical moving into the future, as an improper framework may prevent the system from adequately reducing costs to users or integrating with the electricity grid.

The optimization model results may underestimate the number of non-home chargers because we assume all BEV drivers are completely responsive to charging price and turnovers are assumed to happen with perfect efficiency. However, the case studies demonstrate the minimum requirements of the local charging infrastructure system to meet the current EV load demand.

The optimal solution may not represent what is happening in practice due to factors such as land-use constraints, grid availability, and financial subsidies, which can play a vital role in charging infrastructure investment. However, the optimal charging strategy from our model combines power grid smoothing, charging management, and avoiding unnecessary grid upgrades. The modeling platform developed in this paper provides new insights to both policymakers and researchers on how to properly allocate electric vehicle charging infrastructure and manage charging activities with the least total system cost. Future work will consider factors that may affect BEV drivers charging behavior by introducing the price elasticity of charging demand into our model platform and investigate the potential to use price signals to manage EV owners' charging loads.

# Chapter 4. Energy, Environmental, and Economic Impacts of Pricing on Charging Strategies for Electric Vehicles


## Abstract

While utilizing price signals to affect charging behaviors has been identified as a promising strategy to manage charging loads as needed, few studies discuss their impacts comprehensively. In this paper, we investigate how different charging price strategies can affect the spatial and temporal distribution of charging activities at the individual level, as well as the required charging infrastructure system, to evaluate their energy, environmental and economic impacts. We utilize an integrated optimization platform for EV charging management and infrastructure placement in home and non-home locations in San Diego, California that include charging price strategies, infrastructure costs, and mobility demand patterns. Three pricing scenarios are evaluated: flat rate scenario, real-time pricing scenario, and existing EV time of use residential rates plus public EV charging rates scenario. Considering the price elasticity of charging demand, our model indicates the charging behaviors with respect to different pricing strategies. Our results show that the ability of changing charging behavior to obtain environmental benefits depends on charging price strategies largely. The charging load profile with our optimized charging platform is the result of various determinants including the dynamic electricity price, travel, and dwelling constraints, carbon price clustering effect, as well as exclusive home and shared non-home charging patterns.

SYNOPSIS: Our research shows that the ability of changing charging behavior to obtain environmental benefits depends largely on charging price strategies, indicating the importance of considering EV charging price when making climate policies.

## 1 Introduction

The transportation sector is the largest source of emissions in the United States, accounting for 28.6% of total greenhouse gas (GHG) emissions in the year of 2019. The majority of GHGs in transportation comes from light-duty vehicles, which includes passenger cars (40.5%) and freight trucks (23.6%)[26]. Vehicle electrification has identified as one of the most important way to reduce transport related GHG emissions due to higher efficiency of electrified powertrains and lower emission rate of electricity[66,67]. Individual travel and charging patterns not only determine how much electricity is used, but the timing of the charging decides whether base or peak electricity will be used to charge the battery. Some studies find that plug-in electric vehicle (PEV) charging will not impact the generation and transmission of the electric grid in the short term but may need to be managed when the vehicles are deployed in greater numbers[21]. However, other studies show uncoordinated PEV charging could significantly change the shape of the aggregate residential demand, with impacts for electricity infrastructure, even at low adoption levels[22]. Proper management is critical because charging strategies may also significantly impact the environmental outcome of charging electric vehicles[23,24].

Previous research points to the promising prospect of managing EV charging load through price mechanisms to act as a flexible demand response resource. Using price signals to manage charging is one of the cheapest strategies to implement in order to achieve the traditional regulatory goals of a safe, reliable, and affordable service while advancing system efficiency, enhancing environmental sustainability, and facilitating renewable resources integration[68,69]. Some studies have demonstrated the benefits of dynamic pricing for EV charging to decrease the expenditure of distribution grid operators and/or the charging cost of EV owners[70–73], or to reduce the overlaps between residential and EV charging loads[74]. Dong et al. developed a charging price strategy of EV fast charging stations to minimize the total voltage magnitude deviation of distribution networks[75]. Dutta et al. proposed a new energy pricing controlled EV charging and discharging strategy in home energy management system to acquire maximum financial benefit of EV owners using real load profile of a house in Melbourne and associated electricity rates[76].

Recent studies discussed the EV driver's response to the charging price in order to shift the charging loads to the off-peak time period[77–80], or to reduce the charging costs[71,81,82]. Although there has been substantial work investigating the economic or operational benefits of optimizing EV charging loads with an appropriate price strategy, few studies have been explicitly designed to explore the environmental benefit of shifting consumers' charging loads with various price signals. Previous studies examined the GHG emissions of several charging strategies considering the variation in electricity emissions factors but ignored the impact of electricity prices on charging behaviors[83,84]. Additionally, many EV charging optimization models do not consider the travel and dwelling constraints of EV drivers[70,71]. It is unrealistic to expect the EV drivers to charge the vehicles during the time when they are not available or at the places where they are not there only to accommodate with the grid needs. Moreover, managing EV charging loads without considering the availability of electric vehicle charging infrastructure is also inappropriate. We develop a unique approach that simulates EV charging behavior to internalize environmental damages (across diverse sets of electricity rates and GHG intensities) while simultaneously optimizing for electric vehicle charging infrastructure planning and respecting the dynamics of individual mobility demand.

Many studies take a naive approach in assuming that EV owners are completely rational in changing their charging behaviors in response to price changes[69,70,81]. While some studies have shown that electricity consumption is relatively inelastic[85–87], there are studies demonstrating that the availability of smart technology can increase price elasticity and grid efficiency[88,89]. Since the price elasticity of EV charging demand is rarely estimated using empirical data, price elasticity of residential electricity demand is often used as a proxy in previous studies. Ding et al estimated the dynamic price elasticity for PHEV charging demand from the literature and applied to three price response patterns[90].

Our study employs estimated pricing elasticity of charging demand from a recent empirical study by San Diego Gas & Electric Company (SDG&E)[91]. The authors conducted a randomized control trial experimental study on estimating the effect of time-of-use (TOU) price signals on the home charging behavior of early BEV adopters in San Diego. 430 BEV consumers were randomly assigned to the three experimental TOU rates, each of which has three periods: peak, off-peak and super off-peak. The results showed that EV consumers are responsive to price signals, especially the on-peak and off-peak prices. Their own-price elasticities were estimated in the range of -0.3 to -0.5. Our work improves upon a large body of literature that treats charging behavior independent from electricity pricing and employ price elasticities with respect to charging behavior to analyze response to a carbon tax price signal.

The purpose of this study is to understand the energy, economic and environmental performance of various pricing scenarios based on data from San Diego, California in controlling the charging behavior of consumers and designing the appropriate charging infrastructure system. Our paper is unique in the literature because it 1) utilizes a comprehensive optimization model platform to identify optimal EV charger placement while managing charging activities, and by 2) considers price elasticity of charging demand into the optimization model.

## 2 Method and materials

We utilize an electric vehicle infrastructure planning and charging management model platform to investigate the implications of charging price strategies when integrating climate damage and price elasticity of charging demand in emission reductions, grid impacts, infrastructure deployment as well as costs breakdown. The optimization model platform was designed based on a previous study[92] to determine the optimal strategy for electric vehicle charging infrastructure placement at different levels for both home and non-home locations, as well as the optimal charging time slots and locations for each BEV drivers within the study domain given a set of constraints such as travel demand and dwelling patterns of each driver.

We propose three default charging pricing scenarios and apply three carbon prices for each. The overall flow of our study's approach is as follows:

1. We assess the optimal charger distribution and charging time under an objective of the minimal total system cost based on the tier-two flat rate (FR) of the electricity, real-time (RT) price of the grid, as well as the existing residential EV time-of-use (TOU) rates and public charging rates in San Diego.
2. We analyze the environmental benefits of the charging system when we internalize the climate damage by applying different carbon prices to each default pricing scenarios.
3. We evaluate the grid and cost impacts of the nine scenarios: three default charging price each with three carbon price levels.

As shown in **Figure 11**, the overall modeling framework consists of four modules: travel demand, charge pricing, infrastructure characteristics, and impacts evaluation. Charge pricing and impacts evaluation are the core modules of this model. The charge pricing is determined by a specific pricing scenario that is related to the electricity price at charging stations during each time period, and the carbon price internalized. According to different charging prices, the optimization model platform indicates the optimal time, location and charging power for each

EV drivers in the system. According to the outputs of the optimization platform, we calculate the GHG emissions, total costs and impacts to the regional distribution system through the GHG intensity, the charge pricing, and the energy consumption of EVs during each time period.

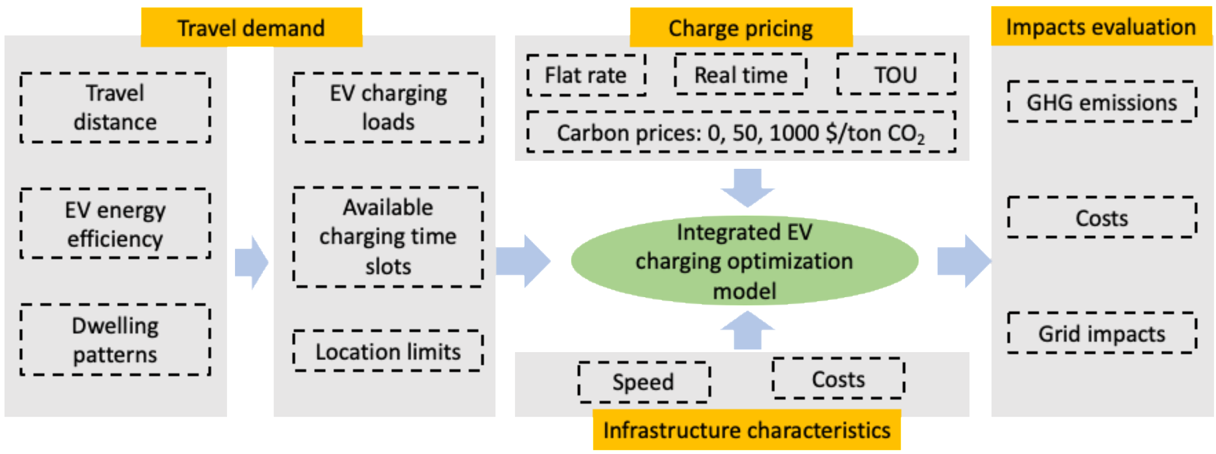


**Figure 11.** Modeling framework for the integrated pricing strategy analysis.

Note: Three charging pricing scenarios are proposed, and we outline our study's approach as follows: 1) based on the tier two flat rate (FR), real-time (RT) price of electricity, as well as the existing residential EV time-of-use (TOU) rates and public pricing rates in San Diego, we identify the optimal charger locations and charging time for the least total system cost; 2) we analyze the environmental impacts of the charging system when we minimize the total social cost, which incorporates the carbon prices into the total system cost; 3) we evaluate the energy and economic impacts of the three default charging price scenarios with various carbon prices.

**EV charging demand.** We simulate individuals' daily travel and dwelling patterns by employing the activity-based travel diary data from the 2010-2012 California Household Travel Survey

(CHTS)[25], which provides the start and end times, as well as the location of individuals' daily activities taken by a sample of individuals across California. Based on that, we figure out the dwell time of each sampled individual at each stop. CHTS provides an Expanded Person Weight for each record of activity data to represent the total 36,969,200 persons residing in the State of California. However, CHTS collects personal activity information from many travel modes and the weights in CHTS are calculated based on demographic attributes such as household size, income, age, number of household vehicles, and county of residents, but unfortunately the weights in CHTS are not a good representation of BEV owners. To address this issue, we first subsample individuals with travel model of driving and then use regional BEV ownership density from the Rebate Statistics of Clean Vehicle Rebate Project (CVRP) [61] to adjust the Expanded Person Weight in CHTS. Population data for the study area are employed from the US Census Bureau [62]. We subset sample individuals with trip destinations in San Diego, California from CHTS: 2,452 sampled individuals, representing 15,789 BEV drivers in CVRP dataset, with daily travel and dwelling patterns across 614 census tracts of San Diego.

Travel distance is calculated as the shortest driving distance between origins and destinations using Google API. Electric vehicle efficiencies are from FuelEconomy.gov [63] and we assume the average efficiency as 33.3 kWh per 100 miles for electric vehicles based on fuel economy data from FuelEconomy.gov[63] and EV sales data reported by Transportation Research Center at Argonne National Laboratory[93]. Daily dwelling locations and travel distance of those BEV drivers within the study area are shown in Supporting Information Figures S1. We observe that BEV drivers in San Diego cluster along the coast, and their daily travel distance is mostly below 100 miles with an average value of 22 miles.

**Charging Price Scenarios.** We define three default pricing scenarios. In the first, charging cost refers to the tier two flat price of electricity in San Diego Gas & Electric (SDG&E). The tier two flat rate will be charged when the energy in each billing period hits 130% of the baseline allowance (234 kWh during summer and 343 kWh during winter in San Diego). The second default pricing scenario is real-time pricing, which is estimated based on the daily average real-time dispatch locational marginal price (LMP) over the entire year of 2018 in California ISO[60]. Because the LMP does not include upstream electricity distribution and transmission costs, it is an underestimate of retail rates and ultimately real charging costs and cannot be directly compared with other pricing scenarios which are based on retail rates. Therefore, we estimate real-time pricing (RTP) by using a price*quantity approach such that the sum of RTP*electricity quantity would equal to the total energy demand multiplied by the default tier two flat rates to ensure that the utility would net revenue at whatever the RTP would be compared to the flat rate.

Equation 9

$$\sum_{t}^{24}(RTP_t \times electricity_t) = FR \times \sum_{t}^{24} electricity_t$$

In this way, our RTP both reflects the price of electricity generation in the system while maintaining identical level of revenue for the operating utility. The last scenario is constructed to evaluate the existing charging price strategy in San Diego. Residential charging is based on the EV TOU rates of SDG&E company[94]. Charging rates at the public level 2 stations is based on the electricity rates for small business set by SDG&E Company. DC fast charging rates refers to the "Pay As You Go" rates of EVGo (a charging network provider) for the San Diego area[95]. We note this scenario as "TOU" for short.

To capture the charging behaviors of BEV drivers more precisely, we also consider the pricing elasticity of charging demand of BEV drivers. A study from D. Chakraborty, D. Bunch, J. Lee et al[45] calculated the elasticity of choosing each alternative charging type with respect to the cost of charging at home based on a cohort survey of PEV owners in California conducted in the years 2016 and 2017. They observed that a 10% increase in the cost of charging at home yields a 3.6% decrease in probability of home charging for BEV owners while the probability of workplace charging goes up by 1.5%. We choose to use -0.36 and 0.15 as the pricing elasticities of charging demand for home and non-home charging, respectively in our model and the tier two flat rate of SDG&E as the baseline. Then the new charging demand for each BEV driver in each region $x_{ir}^{chargingDemand}$ under each alternative pricing scenario could be expressed in the following equation:

Equation 10

$$x_{ir}^{chargingDemand}$$

$$= \sum_{tl} x_{itl}^{nonhomeTime,flatRate} p_l^{nonhomePower} \left[1 + \frac{\beta^{nonhome}\left(c_{tl}^{homeChargingPrice} - c_{tl}^{flatRate}\right)}{c_{tl}^{flatRate}}\right]$$

$$+ \sum_{tl} x_{itl}^{homeTime,flatRate} p_l^{homePower} \left[1 + \frac{\beta^{home}\left(c_{tl}^{homeChargingPrice} - c_{tl}^{flatRate}\right)}{c_{tl}^{flatRate}}\right], \forall ir$$

where $x_{itl}^{nonhomeTime,flatRate}$ and $x_{itl}^{homeTime,flatRate}$ are the non-home and home charging time for individual *i* during time *t* at level *l* charger under the baseline tier two flat rate scenario; $p_l^{nonhomePower}$ and $p_l^{homePower}$ are the non-home and home charging power at level *l* charger; $\beta^{home}$ and $\beta^{nonhome}$ are the pricing elasticity of charging demand for home and non-home locations; $c_{tl}^{homeChargingPrice}$ and $c_{tl}^{flatRate}$ are the customers' alternative home charging price and the tier two flat rate during time *t* with level *l* charger, respectively.

To investigate the environmental, energy and economic impacts of internalizing the climate damage, we incorporate two carbon prices into the total cost. We utilize a social cost of carbon (SCC) of \$50/ton $CO_2$[96] (in 2020 dollars) and a carbon price of \$1000/ton $CO_2$ for calculating climate change damages. Such a high pricing level of carbon does not indicate any realistic policy implementation, but we just want to show the effect of the extreme case as well as the trend of potential change of charging behavior. Therefore, the total social cost, which is the sum of charging cost, infrastructure cost and environmental damage, indicates the total cost that the whole society need to pay for the charging system.

**Figure 12** compares all the default pricing strategies for charging in our model. Real-time pricing reflects the temporal change of electricity with trend aligning with its generation and transmission costs. DCFC has the highest pricing most of the day except during 16:00 to 20:00, when residential TOU reaches the peak pricing. During the lowest pricing period of residential TOU, which is between midnight and 5:00, charging at home is \$0.1/kWh cheaper than the public level 2 pricing. Overall, joining the residential EV-TOU plan of SDG&E is more economical if avoiding home charging during 16:00 to 20:00, when tier two flat rate is lower, for BEV drivers.

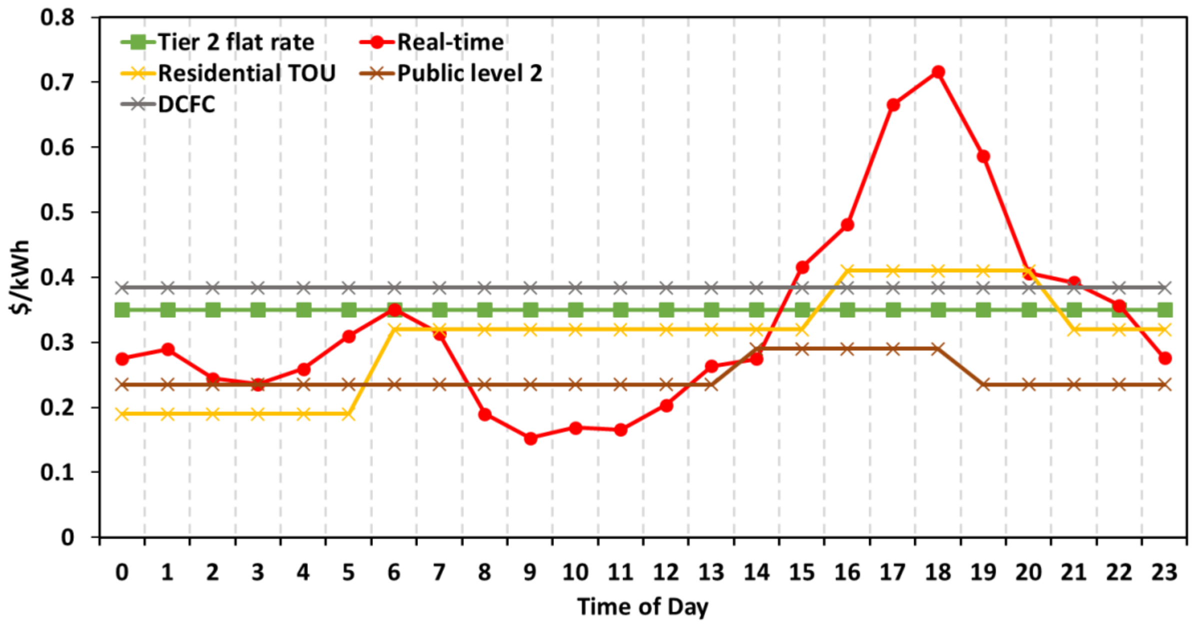


**Figure 12.** Pricing strategies for charging in the hourly manner.

Note: Real time rate mostly aligns with the GHG intensity of the grid. DCFC has the highest pricing most of the day except during 16:00 to 20:00, when residential TOU reaches the peak pricing. During the lowest pricing period of residential TOU, which is between midnight and 5:00, charging at home is $0.1/kWh cheaper than the public level 2 pricing. Overall, joining the residential EV-TOU plan of SDG&E is more economical if avoiding home charging during 16:00 to 20:00, when tier two flat rate is lower, for BEV drivers.

**Infrastructure characteristics.** We obtain the equipment and installation costs of charging infrastructures from the medium cost scenario of U.S. Department of Energy's National Renewable Energy Laboratory (NREL) analysis on the refilling infrastructures for electric light-duty vehicles [59]. We annualized the charging stations capital costs assuming a lifespan of 10 years and a discount rate of 3%. We assume the charging stations have no maintenance cost.

Level 2 and DC fast chargers (DCFC) are potentially available at all non-home locations while home chargers are restricted to level 1 and 2. **Table 2** shows the assumptions for each type of charging infrastructures in our model.

**Table 2.** Assumptions on the costs and power for chargers

| | **Level 1 Home** ($p_{l=1}^{homePower}$) | **Level 2 Home** ($p_{l=2}^{homePower}$) | **Level 2 Non-home** ($p_{l=1}^{nonhomePower}$) | **DC Fast charger** ($p_{l=2}^{nonhomePower}$) |
|---|---|---|---|---|
| Annualized equipment and installation cost ($/unit/year) | $98 | $224 | $630 | $5,480 |
| Power (kW) | 1.7 | 7 | 7 | 50 |

Note: 10-year lifespan with 3% discount rate.

**EV charging optimization.** The EV charging optimization platform is based on our IEVCO model[92], which is formulated as follows: there are n EV drivers (*i* = {1, 2, 3, …, n}), each deciding the amount of time to recharge the vehicle in each of their available time slots *t* among m regions (*r* = {1, 2, …, m}), based on their daily activity patterns. The objective is to minimize total costs $y^{totalCost}$ with respect to the home and non-home charging time, $x_{irtl}^{homeTime}$ and $x_{irtl}^{nonhomeTime}$, during a specific time slots *t*, in region *r* with level *l* charger for BEV driver *i*, as well as the number of home and non-home chargers, $x_{rl}^{homeCharger}$ and $x_{rl}^{nonhomeCharger}$, being built at level *l*. The total system cost, which, in the default pricing scenarios, is the sum of costs from fulfilling the charging demand of BEV owners and building the charging stations in the study domain, can reflects the expenditure that we need at least to afford in building and running their charging infrastructure system. When internalizing the climate damage, the total cost should also include the associated carbon cost and the total cost becomes the total social cost, which indicates the total cost that the whole society need to pay for the charging system. The objective function for our model is provided in the Equation 11 below:

Equation 11

$$\mathrm{Min}_{wrt\, x_{itrl}^{homeTime}, x_{itrl}^{nonhomeTime}, x_{rl}^{homeCharger}, x_{rl}^{nonhomeCharger}}\; y^{totalCost}$$

$$= (\sum_{irtl} c_{trl}^{homeChargingPrice} x_{itrl}^{homeTime} p_l^{homePower} w_i$$

$$+ \sum_{irtl} c_{trl}^{nonhomeChargingPrice} x_{itrl}^{nonhomeTime} p_l^{nonhomePower} w_i) * 365$$

$$+ \sum_{rl} c_l^{homeCharger} x_{rl}^{homeCharger} + \sum_{rl} c_l^{nonhomeCharger} x_{rl}^{nonhomeCharger}$$

$$+ [\sum_{irtl} (x_{itrl}^{homeTime} p_l^{homePower} + x_{itrl}^{nonhomeTime} p_l^{nonhomePower}) g_t w_i] c^{carbonPrice} * 365$$

where $g_t$ is the average GHG intensity of electricity in CAISO[97] and $w_i$ is the weight of sample individual *i.* The total cost is on an annual base to make the three cost components consistent.

The model is subject to major constraints: first, charging activities happening both at home and non-home locations should meet the average daily energy demand of BEV driver *i*; second, charging time should within the available dwelling constraint; finally, non-home chargers are shared among users while each home charger is exclusive to an individual. Major constraints for the optimization model can be found in **Table 3**.

**Table 3.** Major constraints and parameters for the optimization model

| Constraints | Descriptions |
|---|---|
| $\sum_{trl}(\boldsymbol{x_{itrl}^{homeTime}} \boldsymbol{p_l^{homePower}} + \boldsymbol{x_{itrl}^{nonhomeTime}} \boldsymbol{p_l^{nonhomePower}}) \geq \sum_{r} \boldsymbol{x_{ir}^{chargingDemand}}, \forall \boldsymbol{i}$ | Charging activities happening both at home and non-home locations should meet the average daily charging demand of BEV driver *i*. |
| $\boldsymbol{x_{itrl}^{homeTime}} \leq \boldsymbol{d_{itr}^{homeDwellingTime}}$, $\boldsymbol{x_{itrl}^{nonhomeTime}} \leq \boldsymbol{d_{itr}^{nonhomeDwellingTime}}, \forall \boldsymbol{itr}$ | $d_{itr}^{homeDwellingTime}$ is the home dwelling time for individual *i* during time slot *t* in region *r*, and $d_{itr}^{nonhomeDwellingTime}$ is the non-home dwelling time. |
| $\sum_{i} \boldsymbol{x_{itrl}^{nonhomeTime}} \boldsymbol{w_i} \leq \boldsymbol{x_{rl}^{nonhomeCharger}}, \forall \boldsymbol{rtl}$ <br> $\boldsymbol{x_{itrl}^{homeTime}} \leq \boldsymbol{x_{irl}^{homeCharger}}, \forall \boldsymbol{irl}$ <br> $\boldsymbol{x_{rl}^{homeCharger}} = \sum_{i} \boldsymbol{x_{irl}^{homeCharger}} \boldsymbol{w_i}$ | Non-home chargers are shared among users while each home charger is exclusive to an individual. $x_{irl}^{homeCharger}$ is a binary variable indicating if a level *l* home charger being installed for individual *i* at the home location in region r ($x_{irl}^{homeCharger}$=1) or not ($x_{irl}^{homeCharger}$=0). |

We also use other resources to capture information on some constraints of this model, including travel distance and vehicle efficiency. Travel distance is calculated as the shortest driving distance between origins and destinations using Google API. We assume an average efficiency of 33.3 kWh per 100 miles for electric vehicles based on fuel economy data from FuelEconomy.gov[63] and EV sales data reported by Transportation Research Center at Argonne National Laboratory[93]. More details including the remaining equations of the optimization platform could be find in the working paper[92]. The optimization model is a Mixed Integer Linear Programming (MILP) problem, which we solve in GAMS with the Cplex solver.

**Impact evaluation.** Evaluating the impacts of various charging pricing strategies relies on other resources to provide information on the cost and GHG intensity of electric grid, as well as infrastructure costs. Specifically, the GHG impacts of charging is based on the hour-of-day average emissions factors for CAISO in 2018[97]. The average GHG emissions factor in CAISO, compared with the net load profile of the grid in SDG&E service territory in the year of 2018 can be find in Supporting Information Figure S2. We notice a green period of time from 7am to 5pm during the day for using the electricity, and this green period aligns with the second off-peak period in net load of the grid, indicating a “double-win” of reducing the risk of the grid and GHG impacts of charging together with appropriate charging management strategy through pricing.

## 3 Results

We organize our results into four sections, each corresponding to the impacts of various pricing strategies on the energy and electricity grid, environmental benefits, costs components, and infrastructure deployment.

### 3.1 Energy impact

The energy impacts provide insights into how the pricing mechanism affects the energy and electricity grid. We investigate how different charging pricing scenarios may change the mix of energy required for different levels of home and non-home charging, as well as the temporal impacts to the electricity grid. **Figure 13** shows the results of our analysis for the energy requirement from BEV drivers under the three default pricing scenarios with a comparison of carbon price changes in San Diego. The total amount of energy demand is fixed (determined by the total travel distance of all drivers in the study domain), but the distribution of charging load over time across the four categories – level 1 home, level 2 home, level 2 non-home, and DCFC, are totally different according to pricing scenarios. In general, level 2 non-home charging is the largest contributor in all nine scenarios. Among the three default pricing scenarios, the baseline tier two flat rate shares similar proportions of home and non-home charging loads, while the time-of-use strategy has higher share of non-home charging loads and the real time pricing scenario even higher.

After internalizing climate change damages by applying various carbon rates, the share of non-home charging increases due to the low carbon intensity of the electricity during the daytime from 6am to 6pm. A carbon price of $50/tons $CO_2$ leads to 8.7%, 0.2% and 15.4% increase of non-home charging compared to the default flat rate, real-time and time-of-use scenarios respectively, and an extremely high carbon price of $1000/tons $CO_2$ results in 41.9%, 5.6% and 59.9% increase. In the flat rate scenarios, level 1 and level 2 home charging decrease while level 2 non-home charging and DC fast charging increase as carbon price increases. However, only the share of DC fast charging increases with the carbon price change in the real time pricing scenario, and only level 2 non-home charging increases in the time-of-use scenario.

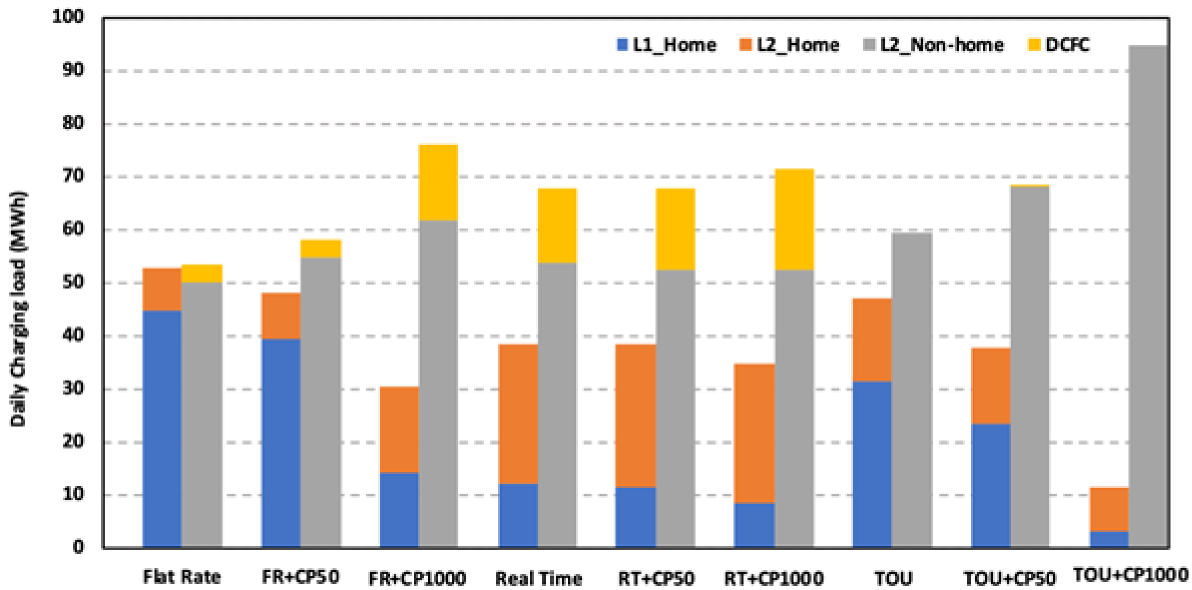


**Figure 13.** Energy impacts of the three charge pricing scenarios with carbon price change.

Note: Ratio of non-home charging loads increase from 50.4% to 71.5%, 63.8% to 67.3%, and 55.8% to 89.2% for the tier two flat rate, real-time pricing, and time-of-use rate scenarios respectively as carbon price increases from 0 to 1000 \$/tons $CO_2$.

We further break down the energy demand by hour-of-day for each of the charging scenarios in **Figure 14**. By employing the tier two flat rate as charging price, we observe relatively even distribution of the charging loads over a day in general, but sensible timing of charging in non-home locations that correspond to daytime hours when BEV drivers are away from home and have higher non-home charging opportunities, which emphasizes the importance of considering the staying and travel constraints into the charging strategies optimization. In addition, we see two peaks of charging in the real-time pricing scenario: the first one happening during the daytime with level 2 non-home charging as the major pattern and a secondary peak in charging at home locations during nighttime hours from midnight to 5:00, aligning with the two off-peak periods of the grid. This indicates the impact of the dynamic electricity rates in managing EV charging loads.

The EV charging load profile under the existing time-of-use charge pricing strategy in San Diego is dramatically different from that under the scenario of real-time one. Level 2 public charging is the major charging strategy for EV drivers since the price for Level 2 public charging is always the lowest except for the time period from midnight to 5:00. In the TOU scenario, level 2 public charging accounts for 55.8% of the total EV charging demand and dominates the energy requirement between 6:00 and 23:00. However, we still observe a small fraction of home charging during time periods from 6:00 to 11:00 and 21:00 to 23:00, indicating that the empirical travel and dwelling pattern of EV drivers constrains the availability and capacity of pricing management of charging loads. DCFC has no contribution to the charging demand under TOU scenario, since level 2 public charging is always preferable in price. Among the three default charging scenarios, the local distribution system in San Diego is affected most in the real-time pricing scenario with the extra charging load as high as over 26.0 MW during 9:00 to 10:00 with the biggest contribution from level 2 non-home charging, while the peak load of time-of-use scenario is around 10.4 MW and flat rate one 6.2 MW mainly from home charging during the midnight.

More importantly, we also observe a clustering effect on the charging load profiles by integrating the carbon prices, which makes charging activities more cluster around daytime hours when the GHG intensity of the grid is lower. Internalizing the climate change damage will not only decrease the environmental impact of EV driving, but also help smooth the grid by shifting EV charging loads towards off-peak hours during the day. The share of non-home charging (level 2 public and DCFC) increases from 50.4% to 71.5%, 63.8% to 67.3%, and 55.8% to 89.2% for flat rate, real time pricing, and time-of-use rate scenarios with the implementation of a carbon price, shifting overnight home charging (especially level 1 home) to shared public level 2 charging during the day when the GHG intensity of the electricity is lower. In sum, the charging load profile with our optimized charging platform is the result of various determinants including the dynamic electricity price, travel and dwelling constraints, carbon price clustering effect, as well as the exclusive home versus shared non-home charging.

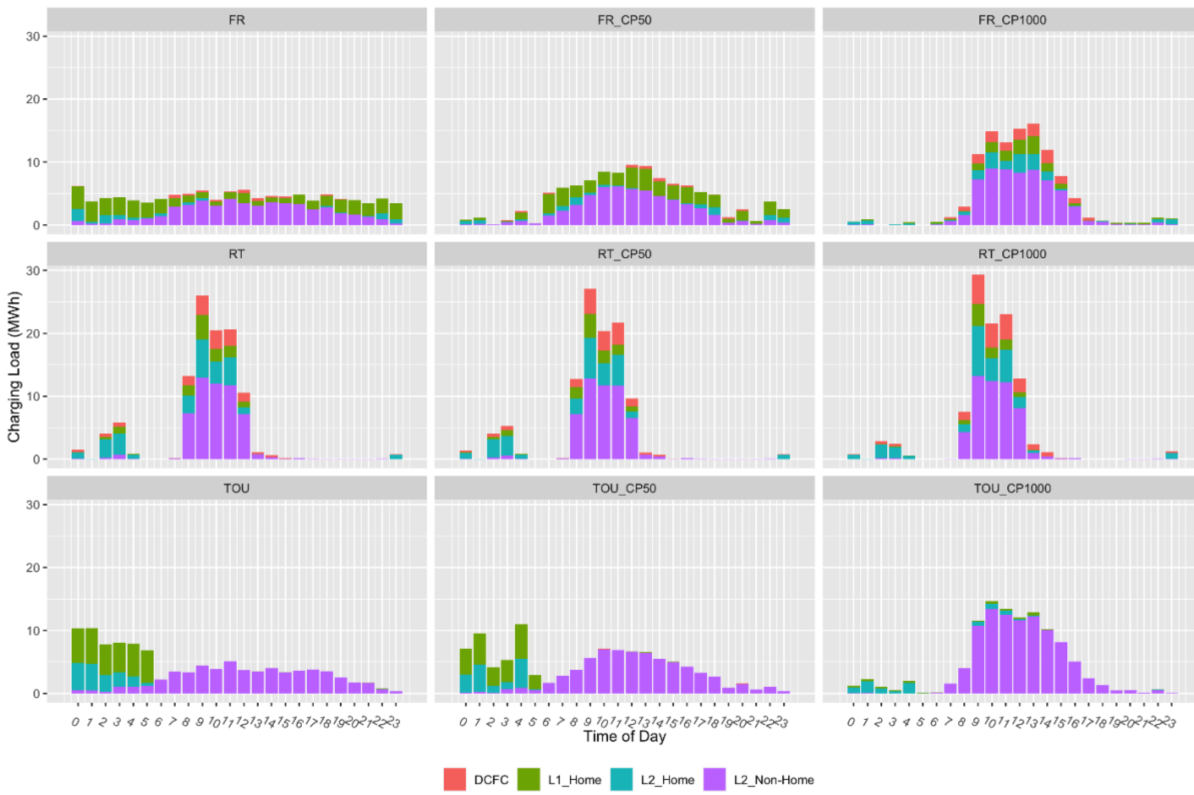


**Figure 14.** Temporal change in charging loads of the three charge pricing scenarios with carbon price change.

Note: In flat rate scenarios, charging loads distribute evenly over a day in general, but showing sensible timing of charging in non-home locations; in real time pricing scenarios, two peaks of charging align with the two off-peak periods of the grid; in the time-of-use scenarios, level 2 public charging is the major charging strategy except for the time period from midnight to 5:00. There is a clustering effect on the charging load profiles by integrating the carbon prices, making charging activities more cluster around daytime hours when the GHG intensity of the grid is lower.

### 3.2 Environmental impact

Charging behavior of EV drivers is changed when the climate change damage is internalized. **Figure 15** depicts the changes in environmental impacts before and after we introduce the carbon prices into the optimization model. Overall, the total GHG emissions of the charging system in San Diego under the default time-of-use scenario is the highest. The flat rate one and the real time pricing one is 3.9% and 24.1% lower respectively. The shape of hourly emission profile of the default real-time pricing scenario (**Figure 15b**) is generally consistent with the hourly GHG intensity of the grid – daytime charging peak aligning with the off-peak period in GHG intensity. Therefore, the shape of the emission profile in the real-time pricing scenario does not change too much after introducing carbon prices, and only an extremely high carbon price of $1000/ton $CO_2$e lower the secondary peak value of carbon emissions during the nighttime hours. In **Figure 15a**, the blue line, which shows the hourly GHG emissions under the default flat rate, is flat across a day. However, only a carbon price of $50/ton $CO_2$ eq shifts the charging activities into the daytime hours from 6am to 6pm (**Figure 15a** green line) and decrease the total emissions by 12.33% as a result. For comparison, we do not see an obvious "cluster effect" in the time of use scenarios when applying a carbon price of $50/ton $CO_2$ eq and the GHG emissions only decrease by 7.27%. When applying a carbon price of $1000/ton $CO_2$ eq, the benefit of charging during the low emissions daytime hours offsets the relative higher level 2 non-home charging price, therefore we see a dramatic shift from overnight home charging emissions towards daytime ones. As a result, the total GHG emissions decrease by 24.9%.

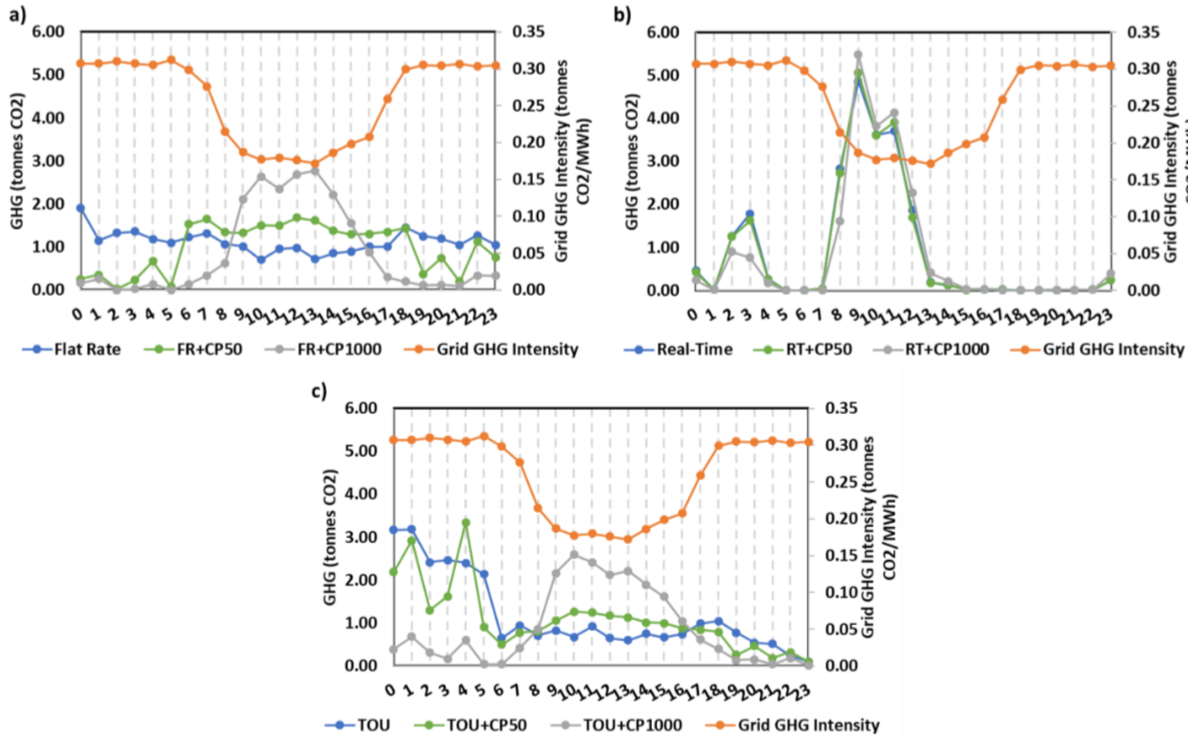


**Figure 15.** Temporal change in charging emissions with carbon price change for (a) flat rate scenario, (b) real time pricing scenario, and (c) time-of-use scenario.

**Table 4** shows the effect of applying different carbon prices on the environmental outcome for EV charging load. We find that the environmental impact of EV charging load is the lowest in the real time pricing scenario, and the existing time-of-use pricing strategy in San Diego is the highest. They are 21% lower and 4.1% higher compared with the annual GHG emissions under the flat rate scenario, which is about 10,899 tons $CO_2e$.

We also find that the effectiveness of carbon price in mitigating GHG emissions depends on the default pricing strategy. In the real time pricing scenarios, daytime charging is the major charging strategy in the default scenario and there is no much room to improve after introducing carbon prices. Therefore, the mitigation cost is extremely high accordingly. On the contrary, the mitigation costs of shifting EV charging load towards daytime hours by applying carbon prices are remarkably lower in the flat rate scenario, and we only see a significant improvement in GHG mitigation when the carbon price is high in the time-of-use scenario.

**Table 4.** GHG emissions of charging pricing scenarios modeling

| | Flat Rate | FR +CP50 | FR +CP1000 | Real Time | RT +CP50 | RT +CP1000 | TOU | TOU +CP50 | TOU +CP1000 |
|---|---|---|---|---|---|---|---|---|---|
| **GHG (tons $CO_2$e)** | 10,899 | 9,555 | 8,215 | 8,608 | 8,571 | 8,261 | 11,342 | 10,518 | 8,517 |
| **GHG mitigation (tons $CO_2$e)** | - | 1,344 | 2,684 | - | 37 | 347 | - | 824 | 2,825 |
| **Mitigation cost ($/tons $CO_2$e)** | - | 261 | 3,159 | - | 12,995 | 24,340 | - | 716 | 3,294 |

### 3.3 Cost and infrastructure deployment

**Figure 16** compares the distributions of the required charging infrastructure in four types under the three default charge pricing scenarios with carbon price change. Flat rate scenario requires the largest total number of charging infrastructures, in which level 1 home charger contributes the most, accounting for about 74.2%. By introducing carbon prices, the total number of charging infrastructures decreases, but the share of the required level 2 home chargers and DCFC increases. In the TOU scenario, the total number of charging infrastructure is the smallest among all three default scenarios, and level 2 non-home chargers account for 20%. No DCFC is required to be built in the TOU scenario. We also see an increase in the share of non-home chargers and decrease in the total amount of chargers required after introduction of carbon prices. However, in the real time pricing scenarios, the share of non-home chargers stabilizes at about 29% and the total number of chargers increases with carbon price change.

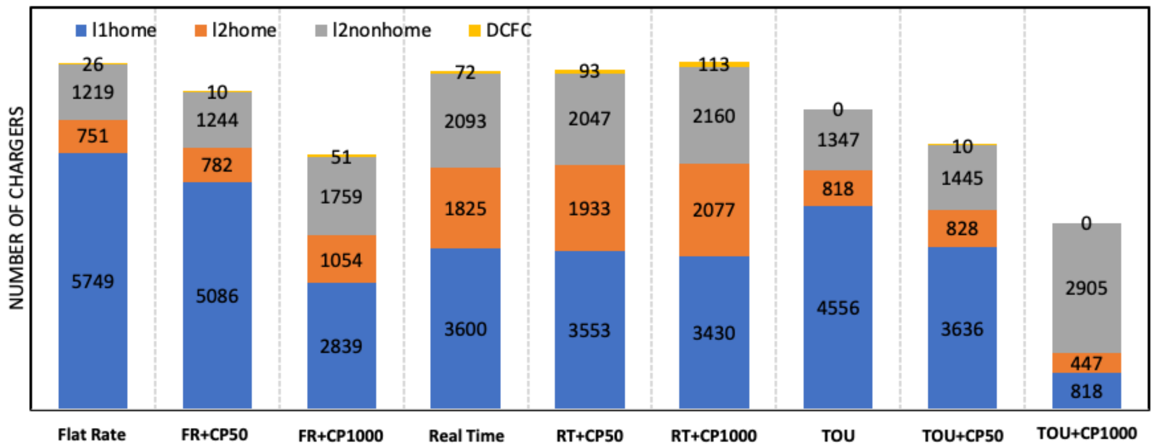


**Figure 16.** Charging infrastructure requirement for the three charge pricing scenarios with carbon price change.

Note: Home chargers are the main charging types in all three baseline pricing scenarios (with zero carbon price), but the flat rate scenario is the highest. Under the time-of-use rate scenario, the total number of infrastructures required is the lowest, due to higher ratio of more efficient chargers are installed.

**Table 5** compares the cost impact among charge pricing scenarios. Time-of-use scenario has the lowest total costs, which is 8.97 million dollars annually. Real time pricing and flat rate scenario are 6.9% and 69.7% higher. The higher total cost in the flat rate scenario comes from a much higher cost from charging due to higher charging rates, which is \$0.35/kWh in the flat rate scenario while about \$0.18/kWh and \$0.19/kWh in the real time and time of use scenarios on average. Although flat rate scenario requires the largest number of total charging infrastructure among all three default scenarios, the infrastructure cost is not the highest since the major type of charging infrastructure is level 1 home charger, which is much cheaper than others. Similarly, real time scenario has the highest infrastructure costs, but the total number of charging infrastructure is not the highest since it requires much more level 2 home and non-home charging infrastructures than other two scenarios.

We also see a balance among charging cost, infrastructure cost and carbon cost under the optimization. The model output for the time of use case is optimized by selecting higher charging cost and lower infrastructure cost than the output for the real time case, which means the model optimally choose to charge during a higher rate period instead of installing more or higher efficient charging infrastructures to meet the system total charging demand. After introducing a carbon price of \$50/tons $CO_2e$, more charging activities cluster in daytime hours with level 2 chargers but there is no requirement for many DCFC yet, resulting in more required shared level 2 chargers but less exclusive level 1 home charger and expensive DCFC. Therefore, the total infrastructure cost decreases in the flat rate scenario. But in the scenario of baseline flat rate with a carbon price of \$1000/tons $CO_2e$, the extremely high carbon cost makes charging in the daytime, during which the grid GHG intensity is lower, more preferable. As a result, the share of the highly efficient DCFC and level 2 chargers increases, and the total infrastructure increases.

Generally, the total carbon cost of the charging system are 0.43 to 0.53 million dollars by implementing a carbon price of \$50/tons $CO_2e$, and 8.22 to 8.52 million dollars with a carbon price of \$1000/tons $CO_2e$.

**Table 5.** Cost's breakdown of charging pricing scenarios modeling

| | Flat rate | FR+ CP50 | FR+ CP1000 | Real time | RT+ CP50 | RT+ CP1000 | TOU | TOU+ CP50 | TOU+ CP1000 |
|---|---|---|---|---|---|---|---|---|---|
| **Total cost (Million dollars)** | 15.22 | 15.57 | 23.70 | 9.59 | 10.07 | 18.03 | 8.97 | 9.56 | 18.28 |
| **Charging cost (Million dollars)** | 13.58 | 13.58 | 13.58 | 7.11 | 7.07 | 6.99 | 7.49 | 7.52 | 7.75 |
| **Infrastructure cost (Million dollars)** | 1.64 | 1.51 | 1.90 | 2.47 | 2.58 | 2.78 | 1.48 | 1.51 | 2.01 |
| **Carbon cost (Million dollars)** | - | 0.48 | 8.22 | - | 0.43 | 8.26 | - | 0.53 | 8.52 |

## 4 Conclusions and discussion

In this study, we utilize an integrated optimization platform for EV charging infrastructure planning and charging management to investigate the energy, economic and environmental impacts of three default charge pricing scenarios in San Diego: tier two flat rate, real time pricing, and existing EV time of use residential rate and public EV charging rates. Additionally, we introduce the climate change damage by applying carbon prices of \$50/tons $CO_2e$ and \$1000/tons $CO_2e$ in each of the default pricing scenarios. More importantly, we consider the price elasticity of charging demand into the model, which gives a more precise estimation on the effect of pricing signals. The high-resolution activity-based travel diary data provides empirical data on travel and dwelling behavior of EV drivers, which offers opportunities to conduct a more accurate impact analysis for managing EV charging loads through appropriate price signals. The output of the optimization model platform reveals the optimal spatial-temporal distribution of charging activities and the required number of chargers of four levels in San Diego at the census tract level.

The results show that the charging load profile with our optimized charging platform is the result of various determinants including the dynamic electricity price, travel and dwelling constraints, carbon price clustering effect, as well as the exclusive home and shared non-home charging. In general, level 2 non-home charging is the largest contributor in all nine scenarios. After internalizing the climate change damage by applying various carbon prices, the ratio of non-home charging loads increases from 50.4% to 71.5%, 63.8% to 67.3%, and 55.8% to 89.2% for the tier two flat rate, real-time pricing, and time-of-use rate scenarios respectively. We also observe a clustering effect by integrating the carbon prices, which means charging activities more cluster around daytime hours when the GHG intensity of the grid is lower. Therefore, internalizing the climate change damage will not only decrease the environmental impact of EV driving, but also help smooth the grid by shifting EV charging loads towards off-peak hours during the day.

Our research also shows that the GHG impacts of EV charging load depends largely on charging price strategies, and the mitigation cost of internalizing climate change damage also varies accordingly, indicating the importance of considering the default EV charging price strategy when making climate policies. Overall, the total GHG emissions of the charging system in San Diego under the default time-of-use scenario is the highest and the flat rate one and the real time pricing one is 3.9% and 24.1% lower respectively. The mitigation costs of shifting EV charging load towards daytime hours by applying carbon prices is extremely high in the real time pricing scenario and are remarkably lower in the flat rate scenario. We only see a significant improvement in GHG mitigation when the carbon price is extremely high in the time-of-use scenario. The ability of changing charging behavior to obtain environmental benefits is a combination of the carbon price and default charging price, and the optimization platform will balance among charging price, carbon price, and infrastructure costs. Therefore, the extreme carbon pricing of $1000/ton does not substantially help in certain scenarios.

The model results may underestimate the number of DCFC and the associated impacts because we only subsample the EV drivers who have home address within the area of San Diego, failing to consider the charging demand from drivers passing through the study domain. They often have long distance trips, but short dwell times. However, this case study reveals the minimum impacts of the local charging infrastructure system under various charging price strategies. In this study, we regard the EV drivers as price takers since the extra charging load from existing EV fleet are too small to affect generator dispatching. However, California has set a state target of having 5 million ZEVs on California roads by 2030 and deploying 250,000 charging stations, including 10,000 fast-charging stations, by 2025[32]. The next step in our research is to investigate the potential impacts of charge pricing mechanism in future scenarios in which the EV fleet is large.

This paper provides new insights to both policymakers and researchers on how to evaluate the impacts of various charge pricing strategies with an integrated optimization model which assess the charging behaviors and planning for the required charging infrastructure system simultaneously. Results of this research not only provide policy guidance for charging management and infrastructure planning in San Diego, California but may be applicable to other regions for which similar data are available. Compared to previous studies, this study is the first of this kind to combine both individual mobility dynamics and charging pricing mechanism and consider charging activities management and infrastructure planning together in a comprehensive optimization to explore the economic, energy and environmental impacts. Considering the price elasticity of EV charging demand into the price strategy impacts analysis is another innovation aspect of our study. This study is based on the mobility of current light-duty vehicle drivers, but it can be easily converted to new mobility with changing vehicle occupation rates under different scenarios such as shared mobility and/or medium and heavy-duty electrification.

# Chapter 5. Emissions Implications of Shared, Autonomous, and Electric Vehicle Fleets: A Case Study of California's Near Future


## Abstract

Shared autonomous electric vehicles (SAEVs) are potentially one of the most promising ways to reduce the transportation greenhouse gas (GHG) emissions on a per-vehicle basis. However, measuring their effect on emission savings requires a careful simulation of their travel and charging behaviors, as well as a sophisticated integration with an ever-evolving power system. In this paper, we conduct an analysis by forecasting market penetration of SAEVs and integrating it with a grid dispatch model, while considering various charging strategies and travel patterns based on empirical data. We find that SAEVs with exogenous charging would reduce GHG emissions by at least 75% compared to the internal combustion vehicles fleet in 2030, and the advantage expands to 97% if charging activities can interact with the grid when smart charging is available. The emission benefits of SAEVs are mainly dominated by vehicle electrification and grid development.


## 1 Introduction

In 2019, California statewide greenhouse gas (GHG) emissions reached 418.2 MMTCO2e, and the transportation sector accounted for 39.7%, in which passenger vehicles are the major source contributing 28.5%[98]. The state's GHG emissions have dropped below the 2020 GHG limit required by the California Global Warming Solutions Act (Assembly Bill 32) since 2016 and the state has continued its commitment to reduce emissions to at least 40 percent below 1990 levels required by 2030 Senate Bill 32. To reach the goal, many efforts have been made including establishing vehicle emission standards and fuel carbon intensity requirements.

In 2018, the state of California passed Senate Bill 1014 which requires the California Air Resources Board (CARB) to regulate transportation network companies (TNCs) such as Uber and Lyft to transition vehicles in their fleets to become zero emission vehicles (ZEVs). The rules formed by CARB are known as the Clean Miles Standard (CMS). These requirements will help to reduce greenhouse gas emissions from some of the highest travel intensity passenger vehicles within the state. However, the TNCs also face the difficult prospect of turning over a fleet of vehicles that they do not own. Shared, autonomous, and electric vehicles (SAEVs) offer a potential solution for TNCs as the vehicles would follow the CMS requirements while simultaneously operating under a different ownership structure where TNCs would likely own and operate the vehicles themselves. This study examines the differences in travel and charging behavior by SAEVs, and the resultant emissions impacts associated with their use.

Previous studies have investigated the environmental impacts of vehicle automation, electrification, and ridesharing. Some studies indicated that the environmental outcomes and energy consumption of autonomous vehicles with internal combustion engines could be deeply uncertain, ranging from extremely negative to highly positive [99,100]. Combining ridesharing with autonomous vehicles might decrease the energy use and GHG emissions in the transportation sector [101]. A study assessing 12 combinations of penetration scenarios among shared, electric and autonomous vehicles found that system $CO_2$ emissions range from -22% to +6% [102]. Coupled with vehicle electrification, an SAEV fleet could achieve a 70% reduction in GHG emissions compared with a private EV fleet [103]. These research and other studies, at first glance, indicate a promising future of electrifying the shared autonomous vehicle fleet in terms of emission reduction. However, some questions are still unsolved: how does the emission benefits change with the development of the grid, and how charging behaviors or vehicle occupancy affect the emission performance of the SAEV fleet?

In the past decade, many studies have investigated the upstream emissions from electricity generation that correspond to EV charging. In the studies that compare life cycle emissions from EV with that from internal combustion vehicle (ICV), this part of emissions is usually calculated using general average [104,105] or marginal [106] emission factors of electricity generation, which is a very rough estimation neglecting the temporal fluctuation of emission rate and the difference in the time of charging. Gai et al. and Fang et al. matched hourly charging load with hourly emission factors to investigate the performance of different temporal charging patterns [107,108]. But this method still omits the complexity in the dynamic interaction between the supply and demand sides of the power system. To address this, several studies have established economic dispatch models based on real-world power systems in PJM Interconnection [109], Beijing [110], Germany [111], Italy [112], all over the U.S. [113] , and all over Europe [114]. But none of them have focused on SAEV charging load specifically, nor have any endogenized future renewable capacity expansion into the optimization models. Furthermore, the investigation into different charging strategies is still not sufficient. Most previous studies focus on the general comparison between controlled and uncontrolled charging [109,111–113]. A few studies address rough categorizations of uncontrolled charging patterns such as day or night charging [114], fast or slow charging [107], home and workplace charging [110]. More detailed discussion is needed for SAEVs since the fleet is operated by the service providers, and there is more flexibility for managing their charging activities.

To address the research gaps above, we evaluate the emission benefits of an SAEV fleet against travel and charging patterns, utilizing a unique data set to cover real TNC trips across the San Francisco Bay Area in California, and incorporating hourly charging profiles drawing on information from various sources including real-world charging activities from electric vehicle data loggers and public charging suppliers, ride requests from TNCs, and netload profiles from the utility. 162 scenarios are defined based on three possible market penetration levels, seven charging strategies, and four vehicle occupancy rates with annual projections from 2022 to 2030. This work performs a bottom-up investigation into the consequential emissions of SAEVs by building a power system dispatch model, with an optimized projection of future generation mix in compliance with policy requirements for future renewable capacity expansion.

## 2 Simulating the travel pattern of SAEV fleet

To simulate the travel behavior of an SAEV fleet, we assume that SAEVs operate in the same manner as existing TNC services when providing trips. Our model employs a unique dataset of both Uber and Lyft in period 3 operation (driving a passenger from an origin to destination) that allows us to replicate the distribution of distances travelled per trip and frequency of demand throughout the period of a day. Since these miles only account for operation when driving passengers, we scale the miles by a deadheading factor of 38.5% to represent the additional miles travelled in periods 1 and 2 (driving in search of passengers and driving to pick-up matched passengers respectively) according to the estimation of deadhead miles based on the TNC data in 2018 from California Air Resources Board[115].

Accurate simulation of daily travel patterns of an SAEV fleet is fundamental to estimate the associated electricity consumption. In this research, we utilize a bootstrapping algorithm to simulate the hourly travel distances of a single SAEV based on a given distribution of trip distances for each hour of a day from the existing TNC fleet. The result is extrapolated based on an exogenously specified number of vehicles, thus providing a total number of daily miles travelled. The probability density function of the trip distances for each hour, which is shown in **Figure 17**, is dominated by short trips which are less than 25 miles in general but indicates variability across hours of a day.

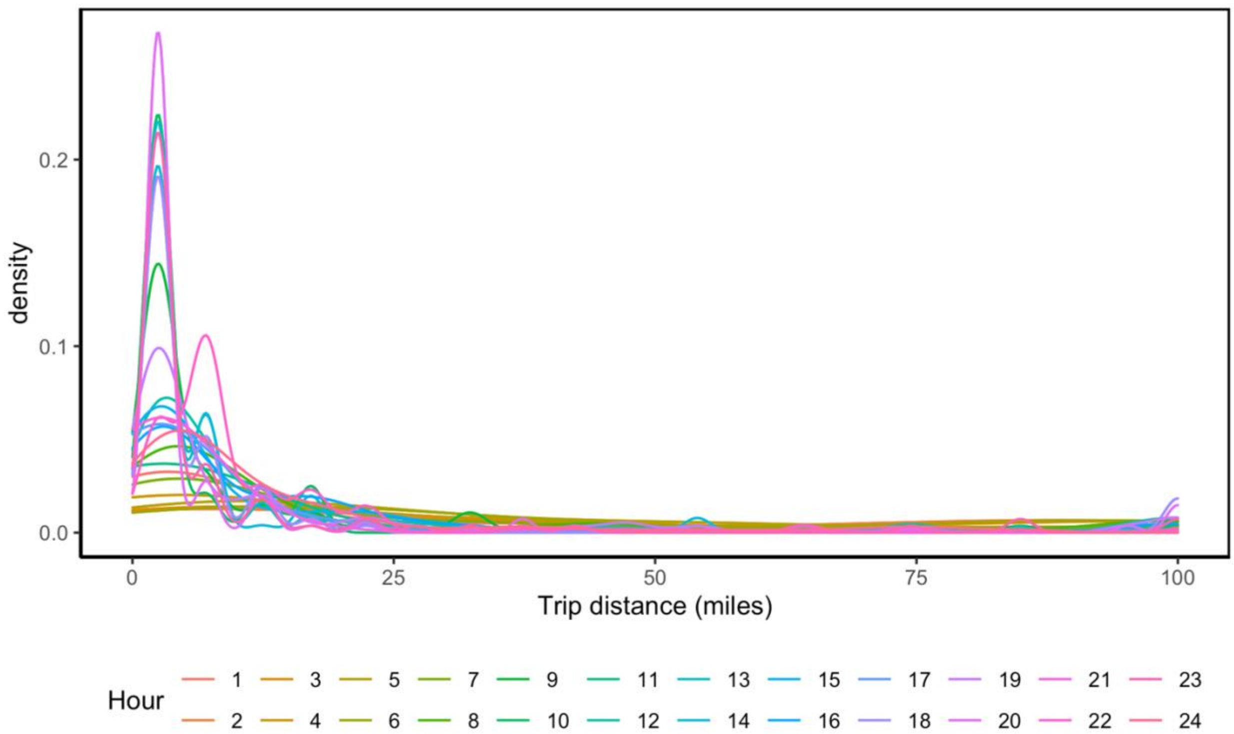


**Figure 17.** Trip distances distribution by hour.

**Figure 18** shows the bootstrapping simulation result for daily travel pattern of an SAEV in the base case, in which the vehicle occupancy is consistent with that of a TNC vehicle. We find that there are two peaks in the hourly vehicle miles travelled: one from 7am to 12pm, and the other from 3pm to 9pm. The average daily vehicle miles travelled of an SAEV is 213 miles including deadheading.

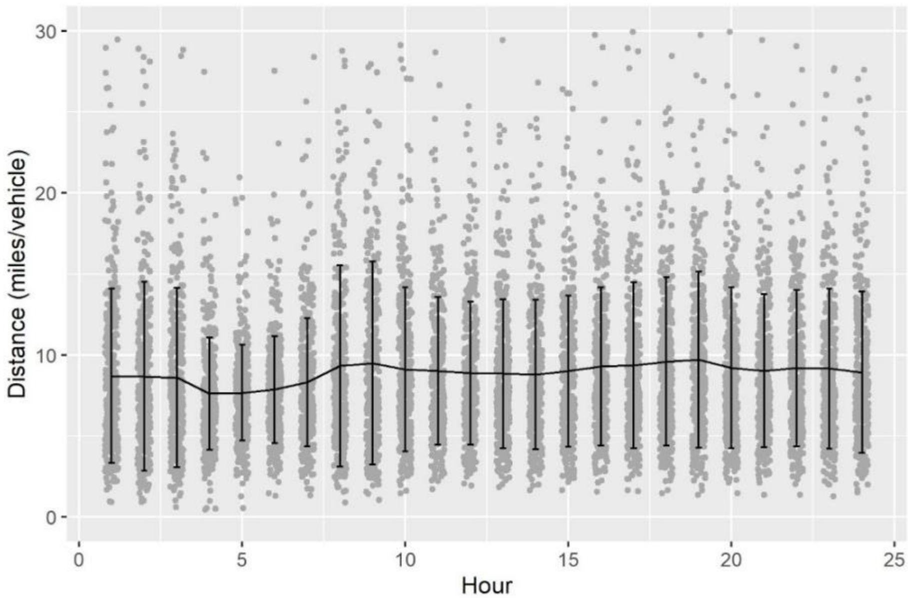


**Figure 18.** Simulation result for SAEV daily travel pattern, deadhead included.

We defined three scenarios for the growth of the SAEV adoption based on the proportion of current Uber and Lyft market size, which is around 96,000 vehicles in the San Francisco Bay Area of California. The medium adoption scenario assumes that the SAEV fleet will be as large as 10% of current TNC market by 2030, and the SAEV fleet in the low and high scenario corresponds to 5% and 25% respectively. Given that the average vehicle occupancy of a TNC vehicle is 1.55 [116], total travel demand for the SAEV fleet through 2030 is estimated as 0.58 to 2.90 trillion passenger miles in the low and high adoption scenarios respectively.

To investigate the environmental benefits of the SAEV fleet under different adoption and charging strategy scenarios, we compare their total GHG emissions to the four counterfactual scenarios, which are defined as “private internal combustion vehicles”, “TNC internal combustion vehicles", "private electric vehicles" and "TNC electric vehicles". The average vehicle occupancy is 1.55 and 1.54 for TNC and private vehicles respectively based on the 2017 National Household Travel Survey[117]. According to the design of the prospective autonomous vehicles providing shared rides, the Cruise Origin for example, we defined the average occupancy from a range of one to four passengers per trip for the SAEV fleet following a uniform distribution.

Private vehicle scenarios assume that the travel demand of the SAEV fleet is fulfilled by private vehicles, and as a result, there are no deadhead miles in the two cases. Since deadheading is assumed to contribute 38.5% to the total miles in the SAEV and TNC scenarios, the total passenger miles will be lower. Private vehicle scenarios not only excludes deadhead miles, but also removes effects from induced demand and passengers shift from other modes as many studies concern[118,119]. We assume the impact from induced miles and mode shifts of TNCs and SAEVs ranges from 5% to 35% increase in passenger miles following a uniform distribution. Considering mode shifts and induced miles will further reduce the environmental benefit of SAEVs but provides a more precise estimation of net emission savings. **Figure 19** compares the daily travel distance for SAEVs, TNCs and private vehicles in 2030 at medium adoption level. The total daily vehicle miles of the SAEV fleet have larger variance since the vehicle occupancy rates ranges larger compared with the other two modes. To fulfil the same level of travel demand, the total daily vehicle miles using TNC services is the highest due to high deadhead ratio and induced miles compared with that using private vehicles. The vehicle miles of SAEV fleet are lower than that of TNC fleet due to this higher vehicle occupancy rate on average.

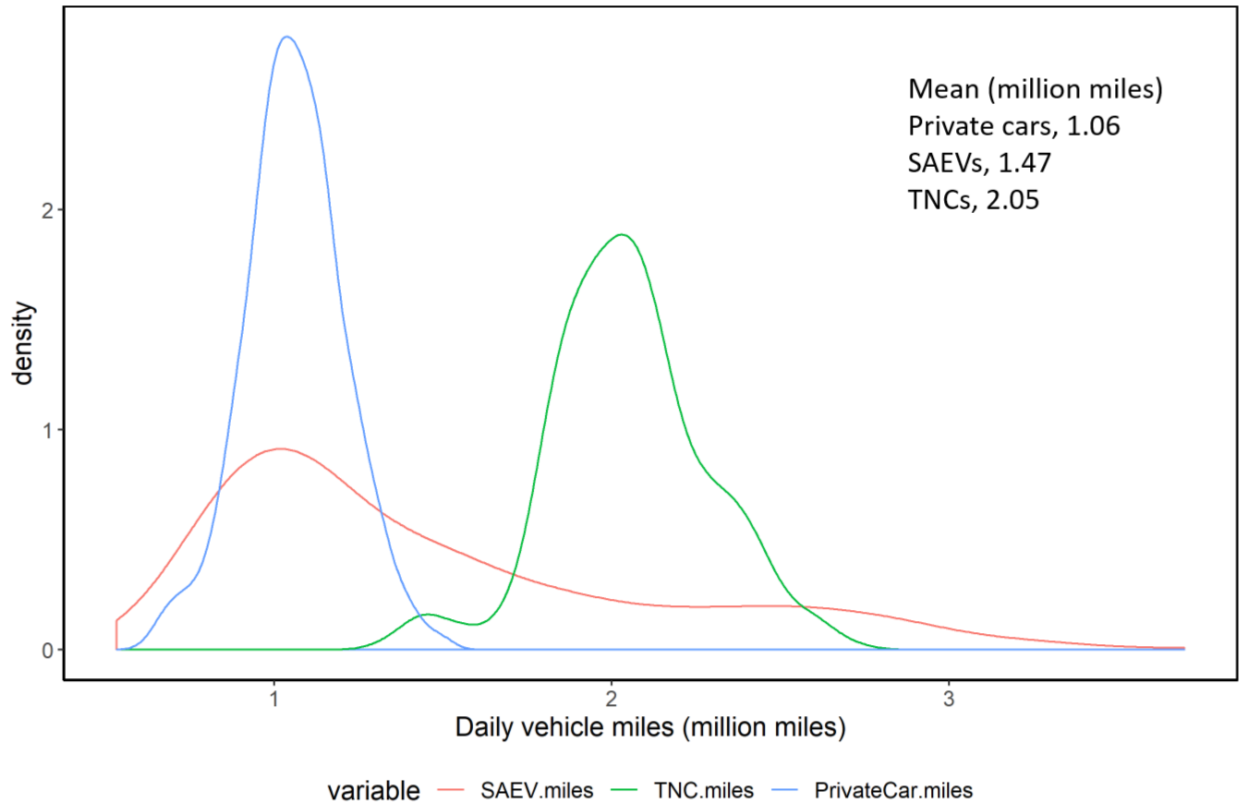


**Figure 19.** A comparison of daily travel distance for SAEVs, TNCs and private vehicles in 2030 at medium adoption level.

## 3 Characterizing SAEVs charging behavior

The energy efficiency of SAEVs is calculated considering the general EV energy efficiency and power draw of SAEVs, which is the energy consumption from other electronic devices such as board computing, radar or cooling devices. We assume that the energy efficiency of a typical SAEV is 0.3kWh/mile and power draw is 8.3 kW. Overall, the total energy efficiency of SAEVs is 0.58 kWh/mile, which is nearly double than that of a private or TNC electric vehicle

(0.33kWh/mile). The aggregate hourly charging profile of SAEVs is obtained by allocating the total daily energy demand into each hour under different charging strategies.

We define six exogenous charging strategies and one endogenous strategy. Exogenous charging strategies assume that charging stations have no communication or interaction with the grid, and thus could only schedule charging according to pre-set daily charging probability patterns, instead of being able to adapt charging according to real-time grid conditions. Patterns of "*Nighttime Charging*", "*Daytime Workplace Charging*", "*Daytime Public Charging*" are extracted from real-world charging data from the Electric Vehicle Miles Traveled (eVMT) project of UC Davis. The eVMT project established a platform that monitors the day-to-day usage patterns and charging behavior of EVs over the course of a single year (per logged vehicle) that includes in aggregate over 2 million miles travelled and over 55,000 charging events [58,120,121]. The pattern of "*Charging Inverse to Netload* '' is defined according to data from California Independent System Operator (CAISO). The seasonal typical netload patterns of 2020 are extracted and standardized. Then the inverse pattern is taken to be the charging probability. Scheduling charging under this pattern is aimed at flattening demand profile and consuming excess intermittent renewable generation. The pattern of "*Charging Inverse to Ride Requests*" is defined according to data from Lyft. Using the number of trips started in each hour as ride requests, we standardize and invert this hourly pattern to define the charging probability. This strategy schedules less charging when there are more ride requests, which is expected to be beneficial for the ride hailing service provider. Lastly, the "*Uniform Charging*" is a flat pattern without any specific strategy.

To simulate the day-to-day variability of the charging profile, we add a random variation into each hour of the charging probability pattern. For a single day, the variation in each hour is sampled from a normal distribution, with the expectation being zero and the variance derived from the real-world charging data of EVgo. The charging data in California from 2014 to 2019 is normalized by day, and the variance of all the charging loads in each hour is calculated respectively, to be used for the distribution of the variation. The daily charging probability patterns are then multiplied with the daily energy needed to form daily charging profiles. An example of charging load profiles of the six exogenous charging strategies are depicted in **Figure 20**.

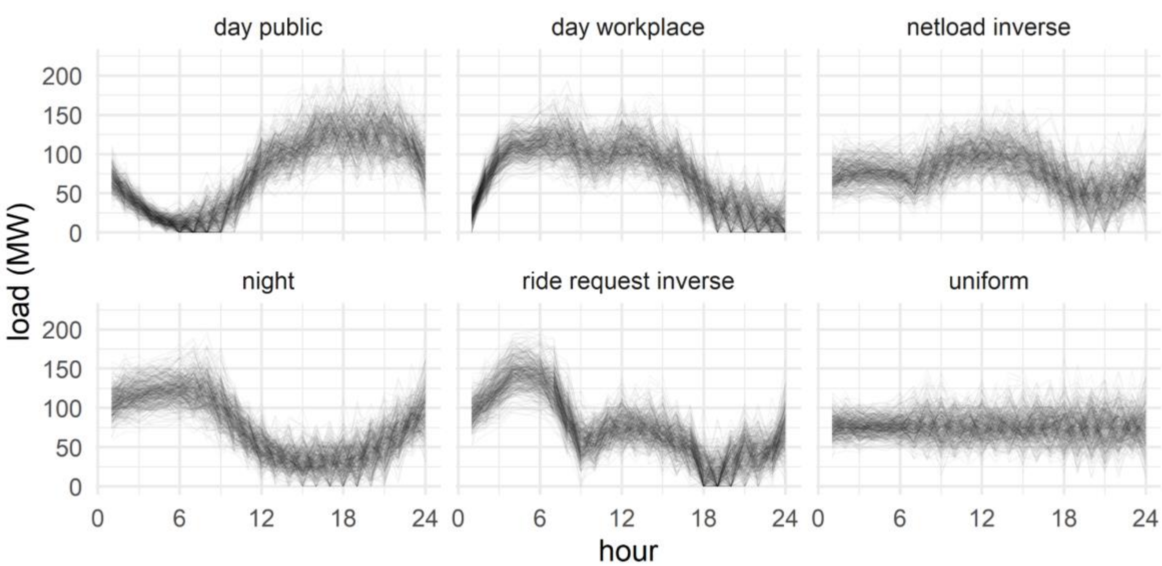


**Figure 20.** SAEV hourly charging profiles of exogenous charging strategies, covering each day of 2030, at medium adoption level.

The endogenous charging strategy is "smart charging", which assumes that charging stations can schedule the charging of SAEVs in response to the temporal price changes in the electricity wholesale generation market. We also assume that the charging schedule is completely flexible throughout a day if all the energy consumed in this day is charged by the end of the day. The charging profiles of the exogenous strategies will be part of the demand side input into the grid simulation model. The charging profile of the endogenous strategy is instead an output variable from the model when smart charging is allowed. Apart from SAEV charging loads, the charging loads of other EVs are also included in the demand side input. The scale of it is derived from the projection of yearly miles travelled from eVMT data. And the pattern of the charging load is assumed to be a combination of 80% nighttime charging, 10% daytime public charging, and 10% daytime workplace charging.

### 4 Emissions implications of SAEVs

To calculate emissions generated from the power grid that correspond to SAEV charging loads, the average emission rate per hour is calculated and multiplied with the charging load in each hour. In **Figure 21,** the total annual $CO_2$ emissions from SAEVs under different charging strategies are shown over the years from 2022 to 2030. For non-smart charging strategies, total emissions increase by year, because of the gradual increase in SAEV fleet size. Nighttime charging and daytime public charging perform the worst, because both strategies mainly charge at the times without a lot of solar generation. Charging inverse to ride requests emits $CO_2$ at a similar scale as uniform charging. Charging inverse to netload is the second cleanest strategy, but not ideal since the netload patterns are from 2020, which does not correspond to the future netload patterns as more and more renewable generation is integrated. The daytime workplace charging is the least carbon intensive among all exogenous strategies because it best utilizes the solar generation during the day. By adjusting the SAEV charging strategy without interaction with the electricity wholesale market, there can be an incremental $CO_2$ emission benefit of up to 20,000 tonnes in 2030.

Generally, switching from non-smart charging to smart charging reduces emissions more drastically than changing between exogenous strategies. The reduction could be more than 60,000 tonnes of $CO_2$ in 2030. However, the trend of total emissions over the years under smart charging is not consistent with the exogenous strategies. This is because the smart charging pattern is affected by the renewable penetration level. In early years, when there is less renewable capacity in the grid, the hourly electricity price does not change very significantly with the fluctuation of renewable availability. In this way, the charging is scheduled more randomly throughout the day, and could take place in hours with higher emission rates. The increase in SAEV fleet size could then cause an increase in emissions in early years. In fact, in 2022 and 2023, smart charging performs slightly worse than charging inverse to netload and daytime workplace charging. However, with the increase in renewable capacity over the years, the price of electricity tends to drop more significantly when there is a large amount of renewable generation during the day. Since the charging is scheduled during hours with lower electricity prices, smart charging patterns tend to follow renewable generation and relieve curtailment. Thus, the charging load corresponds to lower emissions in later years, and smart charging reveals a more significant advantage compared with the other strategies.

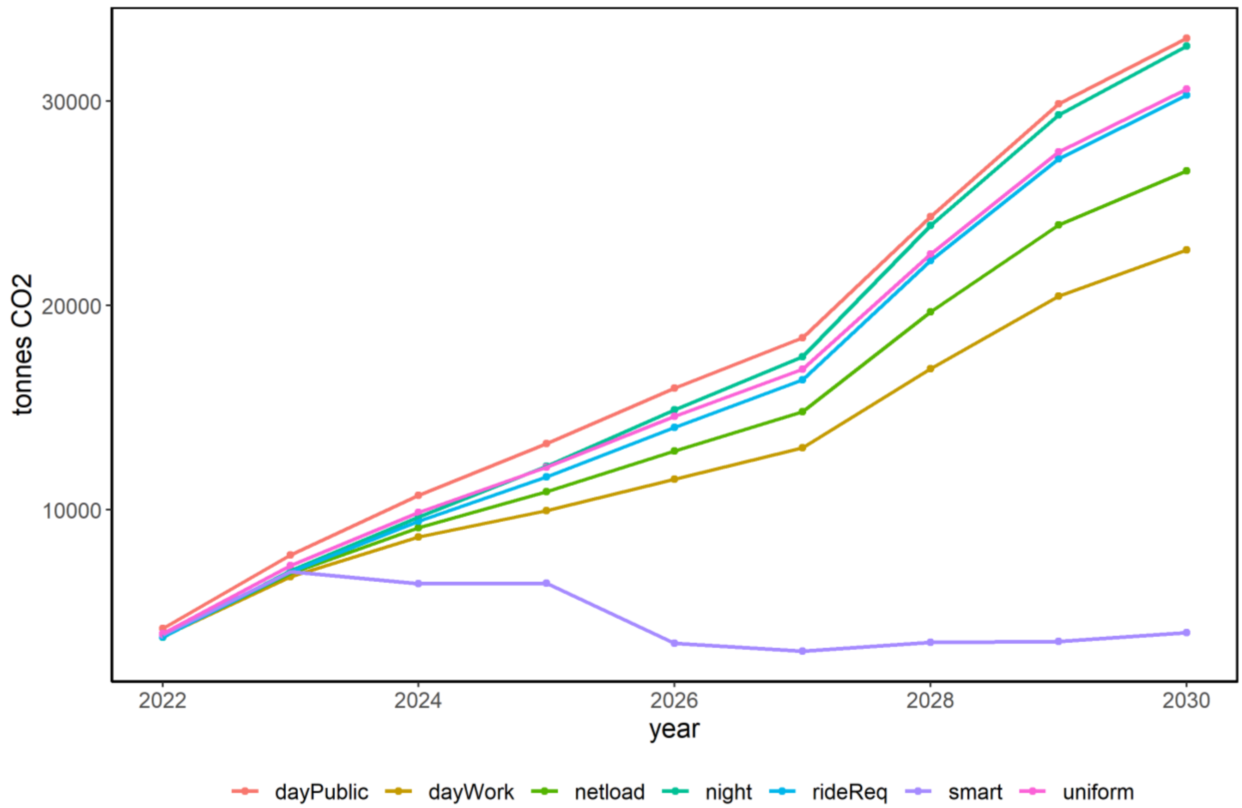


**Figure 21.** Total annual $CO_2$ emission from SAEVs in California at medium adoption level.

**Figure 22** compares the daily GHG emissions from the SAEV fleet under different charging strategies with the four counterfactual scenarios. We find that TNC combustion vehicles have the highest emissions due to high deadheading and low occupancy rate. The emission benefit from SAEV fleet varies largely depending on the charging strategies. Smart charging will make SAEV the most environmentally friendly across all scenarios. Compared to private combustion vehicles, the SAEV fleet could reduce GHG by at least 75% in 2030, and the emission benefits will expand to at least 85% compared to the combustion TNC fleets.

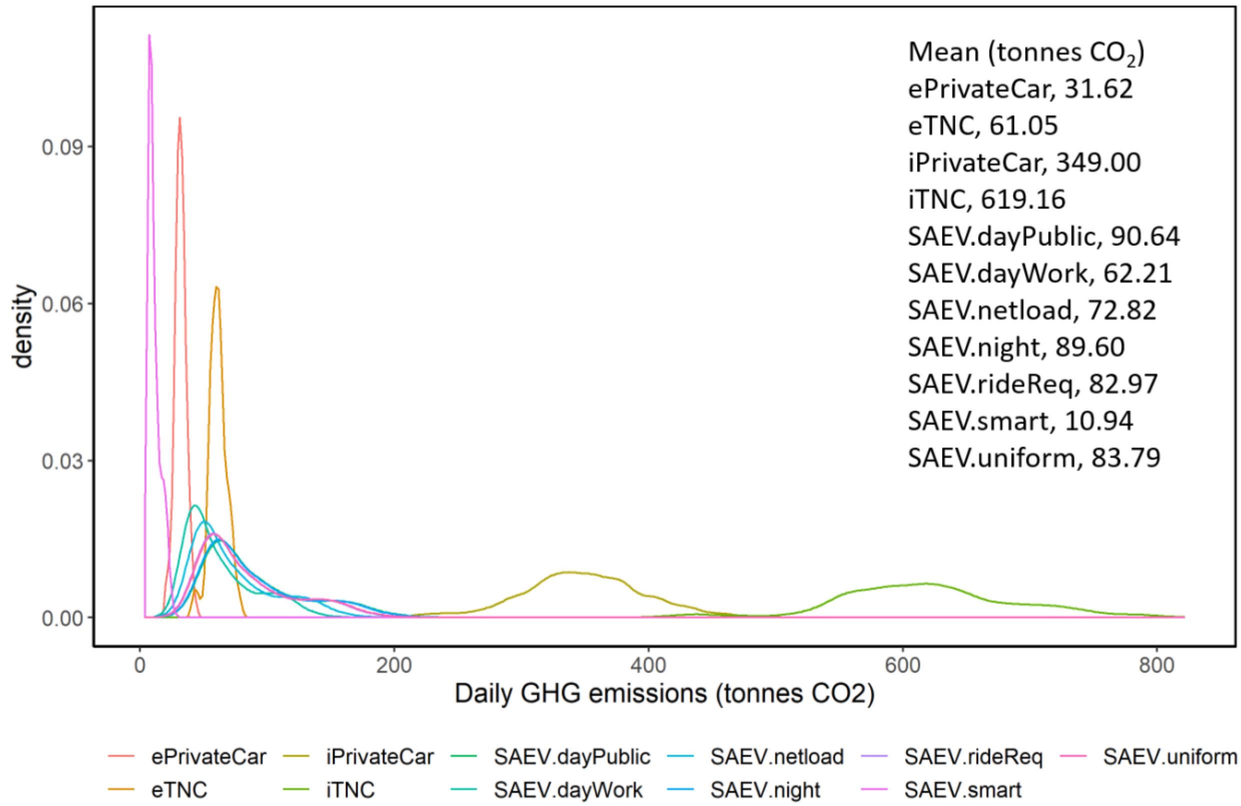


**Figure 22.** A comparison of total annual CO2 emissions for SAEVs, TNCs and private vehicles in 2030 under medium adoption scenario, in which the travel demand corresponds to 14,880 TNC vehicles with an average vehicle occupancy of 1.55.

In aggregate, the annual change in total GHG emissions under three adoption levels are shown in **Figure 23**. We find that the counterfactual emissions from combustion vehicles only vary depending on the level of adoption, and the emission benefits of SAEVs are dominated by electrification, especially considering the offset effects from less mileage travelled in the private combustion vehicle scenario. Annual emissions from the SAEV fleet under daytime workplace charging are 73% and 85% lower than those from the private combustion vehicle and combustion TNC scenarios in 2022, and the benefits become 82% and 90% in 2030. The reason is that the renewable capacity expands due to the RPS, and the average GHG intensity of the electricity in the grid decreases over the years accordingly. Smart charging strategy further increases the advantages of SAEVs to 97% and 98% compared with the private combustion vehicle and combustion TNC scenarios in 2030 because the extra SAEV loads happen during even cleaner hours of a day compared with other charging strategies. The annual emissions from electric TNC vehicles and SAEV fleet under daytime workplace charging strategy are similar, indicating that the benefit from higher occupancy rate of SAEVs is offset by the lower general efficiency due to the power draw. The annual emission from private electric vehicles is the lowest before 2025. However, after 2025, benefit from a cleaner electric grid and smart charging technology, SAEV becomes the best mode in terms of GHG emissions even when considering deadheading, effects from induced miles, and mode shifts as well as the power draw of autonomous vehicles.

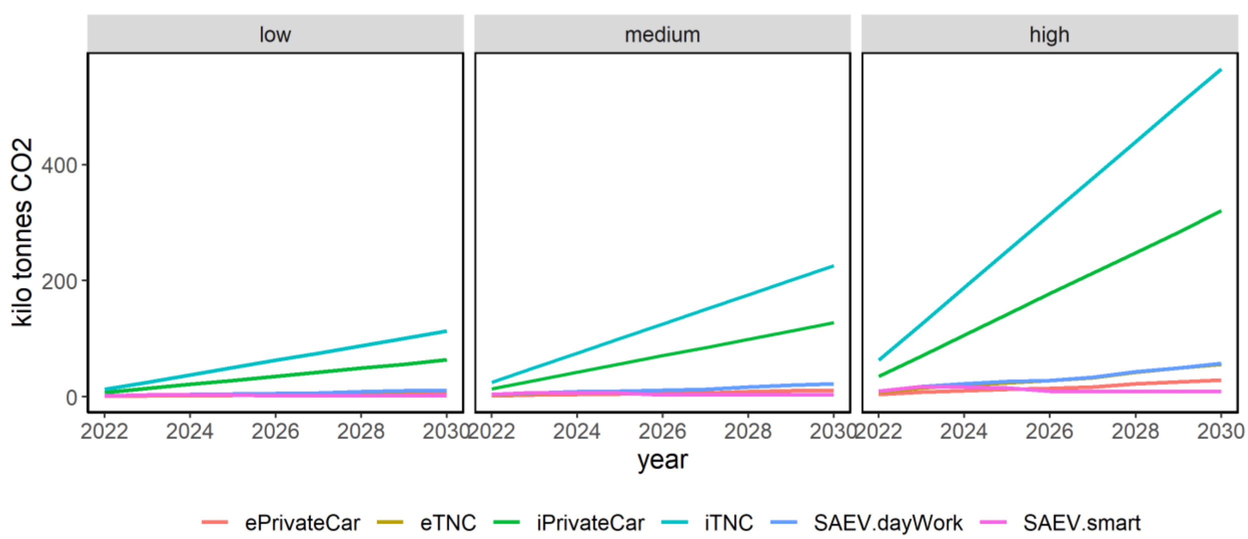


**Figure 23.** Total GHG emissions from the counterfactual scenarios and SAEV scenarios with different adoption levels and charging strategies.

## 5 Conclusions and discussion

In this study, we aim to investigate the environmental benefits of SAEVs with respect to grid development, market penetration as well as travel and charging behaviors. By using a bottom-up economic dispatch model with expansion constraints for future renewable capacity, we are able to forecast the consequential emissions of SAEVs through 2030. The unique real-world TNC vehicle travel data, and the empirical charging activity data offer opportunities to conduct more precise simulations of SAEV driving and charging patterns, based on which, a more accurate estimation of emission outcomes is made.

The results show that, compared with the two counterfactuals with combustion vehicles, vehicle electrification dominates the emission benefits of SAEVs. Emissions from an SAEV fleet are tremendously smaller than a counterfactual fleet, and the benefits expand with time as the grid becomes cleaner, and the SAEV adoption level becomes higher. Appropriate charging strategies and higher occupancy help the SAEV fleet achieve greater benefits. Our study also strongly reveals the advantage of synergizing SAEVs with the electricity grid. Among charging strategies without interaction with the grid, the daytime workplace charging pattern accounts for the least emissions. But emission benefits are way more significant if SAEV charging can be managed according to signals from the grid.

Our analysis may overestimate the emission benefits of SAEV in the smart charging scenarios because we did not consider the constraints from charging infrastructure capacity and battery size of the vehicle. Furthermore, in the counterfactual scenarios, we assume that the ICV efficiency is fixed over the years, but in fact the efficiency could be increasing with technology development, which could also shrink the emission savings of SAEVs. We will fix the limitations above in the future research. The next step in our research also includes conducting more sensitivity analysis on the mode shift, deadhead, and induced demand for future SAEV fleet, as well as considering the environmental impacts from other air pollutants like $CH_4$, $NO_x$, and $SO_2$.

## 6 Methods

We employ the Grid Optimized Operation Dispatch (GOOD) model to simulate the operation of electricity generators that respond to electricity load demand [103,113]. The GOOD model is an economic dispatch optimization model that turns on power generators one at a time based on the cost of operation (fuel costs plus operating costs) until total load demand is fulfilled. For renewable power sources, the model contains constraints that limit generation based on the timing of resource availability (when the sun shines or wind blows).

While our study is focused on the operation of vehicles within the San Francisco Bay Area, the electricity grid operation is substantially more interconnected, and we therefore simulate the operation of the entire Western Interconnect (WECC). By including all of WECC, we are able to accurately capture imports and exports of electricity to better account for emissions impacts of charging events in California. The model also contains constraints for renewable capacity expansion to comply with Renewable Portfolio Standards (RPS). We run our model for four representative weeks in each season, on an hourly basis, for each year from 2022 through 2030. The RPS requirements for each year linearly increase up to 60% in 2030 from approximately 30% in 2020 in accordance with SB100.

*Objective Function: Total cost of the system*

The objective function describes the total cost of the electricity system across all generators *g*, time periods *t*, and regions *r* (with alias set *o*). The cost is comprised of the total cost of electricity generation, wheeling charges related to transmission of electricity across different balancing zones, and the cost to install new solar, wind, and storage capacity. The total cost in the system varies as a function of how generators are dispatched; electricity is imported/exported from different regions; the charging load patterns from electric vehicles; new capacity of solar, wind, and storage assets; and the operation of grid storage—all of which are determined endogenously by the GOOD model.

Equation 12

$$\min_{\substack{x_{gt}^{\text{gen}},x_{rto}^{\text{trans}},x_{rt}^{\text{ev.flexLoad}},\\ x_r^{\text{new.solar}},x_r^{\text{new.wind}},\\ x_r^{\text{storage.cap}},x_{rt}^{\text{storage.soc}},\\ x_{rt}^{\text{storage.in}},x_{rt}^{\text{storage.out}}}} \left( \begin{array}{l} \sum_g \sum_t x_{gt}^{\text{gen}} c_g^{\text{gen.cost}} + \sum_r \sum_t \sum_o x_{rto}^{\text{trans}} c_{ro}^{\text{trans.cost}} + \\ \sum_r x_r^{\text{new.solar}} c^{\text{solarCost}} + x_r^{\text{new.wind}} c^{\text{windCost}} + x_r^{\text{storage.cap}} c^{\text{storageCost}} \end{array} \right)$$

*Constraint 1a: Generation must equal load with regular charging behavior*

This constraint is active when modeling the scenario with "regular" SAEV charging behavior defined by exogenous charging strategies. In each time period *t* and region *r*, the generation (plus net import/exports and net storage input/output) of electricity must meet the total demand load. The demand load is comprised of two exogenous parameters: baseload demand and charging load demand from SAEVs as determined by the mobility portion of our modeling system. The charging load from other EVs is included in the baseload demand.

Equation 13

$$\begin{pmatrix} \sum_{g \in gtor_{gr}} x_{gt}^{\text{gen}} + \sum_{o} x_{otr}^{\text{trans}} c^{\text{transLoss}} - \sum_{p} x_{rtp}^{\text{trans}} - \\ x_{rt}^{\text{storage.in}} + x_{rt}^{\text{storage.out}} c^{\text{storage.out}} - \left( c_{rt}^{\text{demandLoad}} + c_{rt}^{\text{evHourlyLoad}} \right) \end{pmatrix} = 0, \forall t, r$$

*Constraint 1b: Generation must equal load with smart charging behavior*

This constraint is active when modeling the scenario with "smart" EV charging behavior, which is the endogenous charging strategy. It is identical to 1a, except that the charging load demand from EVs is now a decision variable (the GOOD model determines the best time that EVs should charge).

Equation 14

$$\begin{pmatrix} \sum_{g \in gtor_{gr}} x_{gt}^{\text{gen}} + \sum_{o} x_{otr}^{\text{trans}} c^{\text{transLoss}} - \sum_{p} x_{rtp}^{\text{trans}} - \\ x_{rt}^{\text{storage.in}} + x_{rt}^{\text{storage.out}} c^{\text{storage.out}} - \left( c_{rt}^{\text{demandLoad}} + x_{rt}^{\text{evFlexLoad}} \right) \end{pmatrix} = 0, \forall t, r$$

*Constraint 2: Maximum solar generation*

This constraint takes information about representative solar profiles across all regions *r* in all time periods *t* and limits the maximum generation from all solar resources in the model based on the maximum initial capacity of solar generators plus newly installed capacity of solar resources in the year being run by the GOOD model.

Equation 15

$$\left( c_{rt}^{\text{maxSolar}} \sum_{solar \in gtor_{solar,r}} c_{solar}^{\text{maxGen}} + x_{r}^{\text{new.solar}} c_{rt}^{\text{maxSolar}} - \sum_{solar \in gtor_{solar,r}} x_{solar,t}^{gen} c_{solar}^{\text{maxGen}} \right) \geq 0, \forall t, r$$

*Constraint 3: Maximum wind generation*

This constraint takes information about representative wind profiles across all regions *r* in all time periods *t* and limits the maximum generation from all wind resources in the model based on the maximum initial capacity of wind generators plus newly installed capacity of wind resources in the year being run by the GOOD model.

Equation 16

$$\left( c_{rt}^{\text{maxWind}} \sum_{wind \in gtor_{wind,r}} c_{wind}^{\text{maxGen}} + x_{r}^{\text{new.wind}} c_{rt}^{\text{maxWind}} - \sum_{wind \in gtor_{wind,r}} x_{wind,t}^{gen} c_{wind}^{\text{maxGen}} \right) \geq 0, \forall t, r$$ M

*Constraint 4: Balancing flexible EV load under an EV smart charging scenario*

This constraint provides guidance on how often the GOOD model must fulfill the aggregate charging demand from EVs. The hourly demand is allowed to be determined endogenously but the aggregate demand must be fulfilled within a larger time window.

Equation 17

$$\sum_{t \in ttod_{td}} x_{rt}^{\text{evFlexLoad}} - c_{rd}^{\text{evDailyLoad}} \geq 0; \forall r, d$$

*Constraint 5: Renewable Portfolio Standards renewable generation requirement*

This constraint specifies the proportion of in-state (within California) generation that must be fulfilled by renewable resources.

Equation 18

$$\sum_{ca,t}\left(\sum_{solar\in gtor_{solar,ca}} x^{\mathrm{gen}}_{solar,t} + \sum_{wind\in gtor_{wind,ca}} x^{\mathrm{gen}}_{wind,t}\right) - c^{\mathrm{RPS}}\sum_{ca,t}\left(\sum_{g\in gtor_{g,ca}} x^{\mathrm{gen}}_{gt}\right) \geq 0$$

*Constraint 6: Tracking storage state of charge*

This constraint tracks the aggregate energy state of grid storage batteries. In each time period, the energy balance is achieved by adding the energy input minus the energy output to the previous time period's energy level.

Equation 19

$$x^{\mathrm{storage.soc}}_{rt} - x^{\mathrm{storage.soc}}_{r,t-1} - x^{\mathrm{storage.in}}_{r,t-1} c^{\mathrm{storageLoss}} + x^{\mathrm{storage.out}}_{r,t-1} = 0; \forall r, t$$

*Constraint 7: Maximum storage capacity*

This constraint specifies the maximum amount of energy that can be stored in the grid battery storage based on the installed capacity of storage.

Equation 20

$$x^{\mathrm{storage.cap}}_{r} - x^{\mathrm{storage.soc}}_{rt} \geq 0; \forall r, t$$

*Constraints 8 & 9: Storage input/output limits*

This pair of constraints limits the amount of energy that can be transferred in and out of the grid storage within one time-period.  Based on the performance of current lithium-ion batteries, we allow for a charging/discharging limit equal to 25% of the total capacity of the storage device.

Equation 21

$$.25x_{r}^{\text{storage.cap}} - x_{rt}^{\text{storage.in}} \geq 0; \forall r, t$$

Equation 22

$$.25x_{r}^{\text{storage.cap}} - x_{rt}^{\text{storage.out}} \geq 0; \forall r, t$$

# Chapter 6. Conclusions

By employing three studies, this research demonstrates that integrating the heterogeneity of individual travel, dwelling, and charging behaviors and the development of the grid dynamics can improve the charging infrastructure planning while ensuring the environmental benefits from widespread vehicle electrification. The major conclusions drawn from this research include:

1. **Spatial and temporal travel and dwelling patterns of BEV drivers substantially affect the design of the EV charging infrastructure system.**

Traditional methodologies charging infrastructure planning focuses primarily on origin-destination trip data for locating chargers but failing to consider the charging opportunity indicated by the dwelling constraints of BEV drivers in trip stops. Our study on the integrated charging infrastructure optimization platform (Chapter 3) shows the importance of including individuals dwelling patterns on the decision-making process of optimal charger placement and charging activity management. These considerations will be critical moving into the future because an improper framework may prevent the system from adequately reducing costs or interacting with the electricity grid.

2. **The GHG impacts of EV charging load depends largely on charging price strategies, and the mitigation cost of internalizing climate change damage varies accordingly.**

Comparing the energy, economic and environmental impacts of three default charge pricing scenarios in San Diego (Chapter 4), we observe that the ratio of non-home charging loads increases from 50.4% to 71.5%, 63.8% to 67.3%, and 55.8% to 89.2% for the tier two flat rate, real-time pricing, and time-of-use rate scenarios respectively after internalizing the climate change damage by applying various carbon prices. This indicates that considering the default EV charging price strategy is critical when making climate policies. The ability of changing charging behavior for enhancing environmental benefits is a combination of the carbon price and default charging price, and affected by other factors including dynamic electricity price, travel and dwelling constraints, carbon price clustering effect, as well as the exclusive home and shared non-home charging. Our study emphasizes the importance of a more accurate impact analysis for managing EV charging loads through appropriate price signals.

**3. Vehicle electrification dominates the emission benefits of SAEVs, and appropriate charging strategies and higher occupancy help the SAEV fleet achieve greater benefits.**

The study of investigating the environmental benefits of SAEVs with respect to grid development, market penetration as well as travel and charging behaviors reveals that the emissions from an SAEV fleet are 97% and 98% smaller compared with the private combustion vehicle and combustion TNC scenarios in 2030, and the benefits expand with time as the grid becomes cleaner, and the SAEV adoption level becomes higher. Emission benefits are way more significant if SAEV charging can be managed according to signals from the grid with appropriate smart charging technology.

# Chapter 7. Supporting Information

## 1 Supporting Information for Chapter 3

### 1.1 Convergence of the average results for spatial charger distributions

Due to the extensive physical memory requirements and complexity of our optimization, we have devised a new method to solve a smaller system while maintaining reliable results. We subsampled 500 individuals from the sampled individual pool of the California Household Travel Survey (CHTS) dataset, run the model for each subset, and repeat this process 99 times. The median case among the 99 trials is selected as a representative solution for the model. We show the distribution of the solutions in terms of the per capita system cost of these 99 trials and the median value in Figure SI- 1.

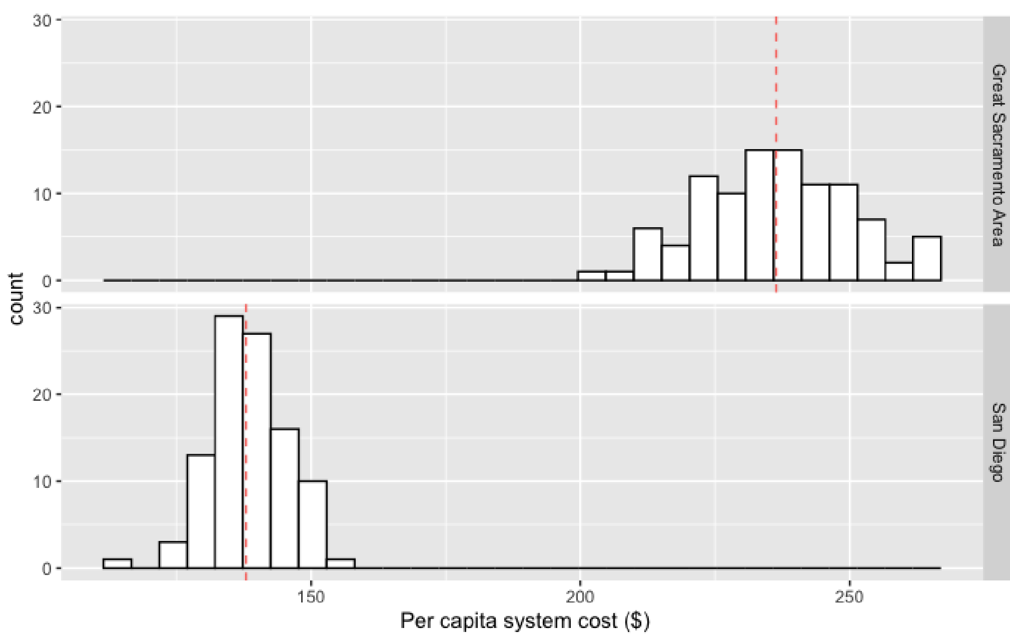


Figure SI- 1. Per capita system cost distribution of the 99 trials. The red lines show the median values of the solutions for each of the study areas.

Figure SI- 2 and Figure SI- 3 show the cumulative average of the number of the optimized charging stations for each census tract converged in med-cost scenario as the number of trials increases for Great Sacramento Area and San Diego respectively. We use the cumulative average value of the 99 trials to calibrate the spatial distribution of the chargers in the estimation of the model results with the median case.

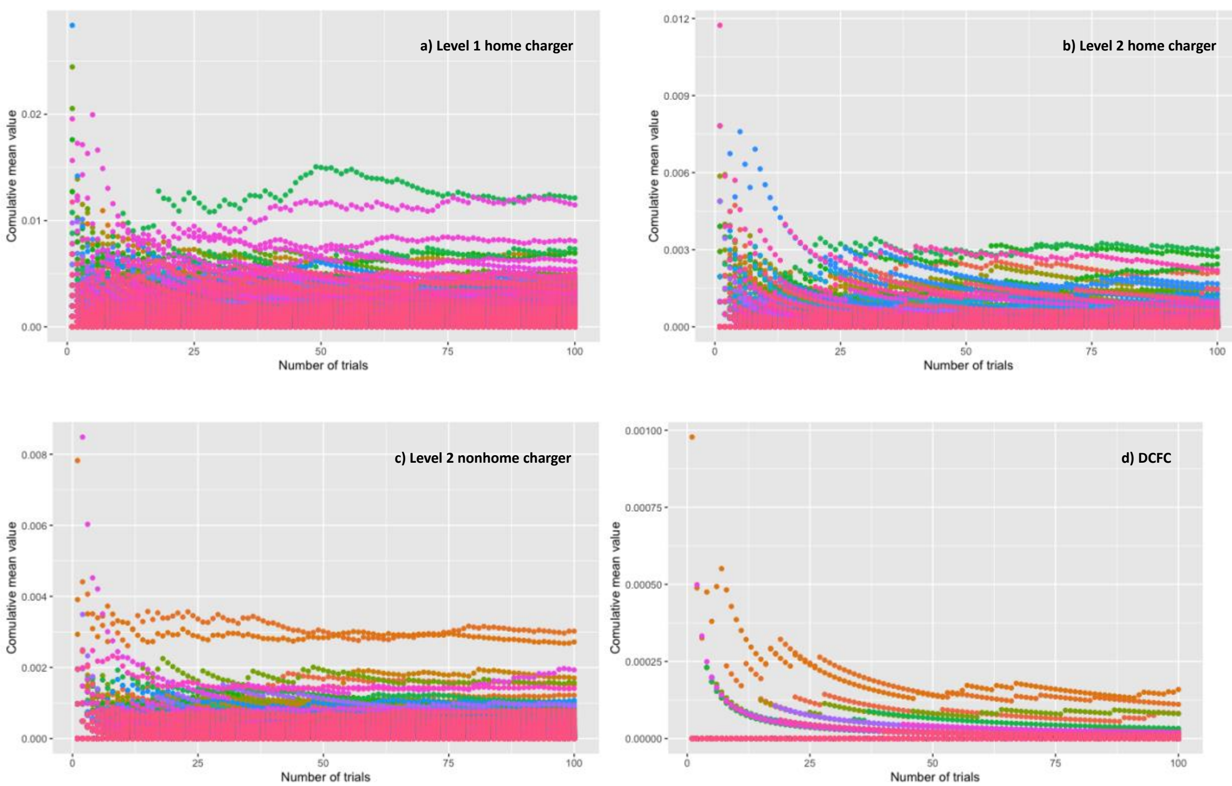


Figure SI- 2. Average of the optimized charging stations converged in the medium cost scenario in Great Sacramento Area for a) level 1 home charger; b) level 2 home charger, c) level 2 non-home charger, and d) DCFC, respectively.

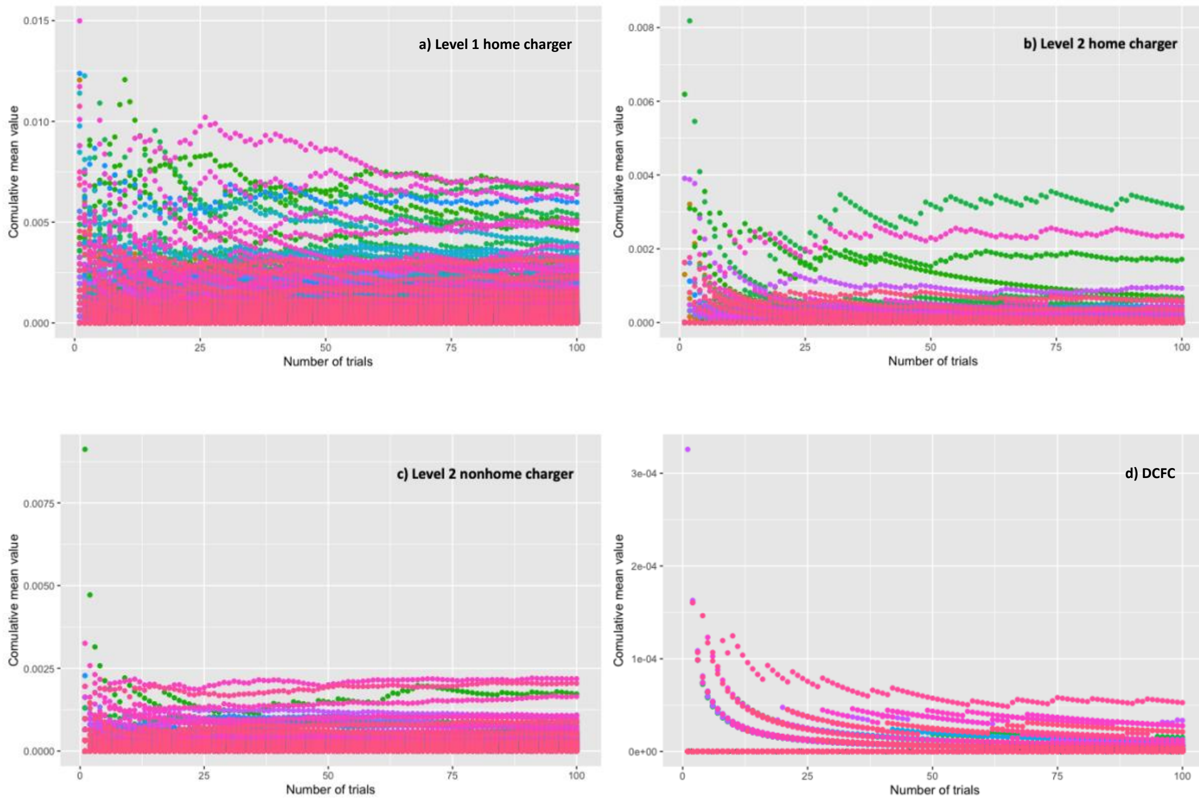


Figure SI- 3. Average of the optimized charging stations converged in the medium cost scenario in San Diego for a) level 1 home charger; b) level 2 home charger, c) level 2 non-home charger, and d) DCFC, respectively.

**1.2 Spatial and temporal distribution of energy demand**

We list the top 50 values of the energy demand among all census tracts at each hour of the day with the four charger levels for med-cost scenario in the tables below to show our model outputs in terms of energy demand. For example, census tract 170.32 in San Diego County, California will see the highest extra charging demand in the hour of 10 from level 2 non-home charging. This allows for the spatial and temporal "hotspots" of the energy demand as well as their sources to be easily identified with our model.

Table SI- 1. Top 50 values of the energy demand in San Diego, med-cost scenario

| Region | Time | Level of charger | value (kWh) |
|---|---|---|---|
| Census Tract 170.32, San Diego County, California | start_hr10 | L2_Non-Home | 196.00 |
| Census Tract 170.32, San Diego County, California | start_hr9 | L2_Non-Home | 196.00 |
| Census Tract 170.35, San Diego County, California | start_hr0 | L2_Home | 126.71 |
| Census Tract 170.35, San Diego County, California | start_hr2 | L2_Home | 126.71 |
| Census Tract 170.35, San Diego County, California | start_hr23 | L2_Home | 126.71 |
| Census Tract 54, San Diego County, California | start_hr10 | L2_Home | 79.03 |
| Census Tract 54, San Diego County, California | start_hr3 | L2_Home | 79.03 |
| Census Tract 54, San Diego County, California | start_hr8 | L2_Home | 79.03 |
| Census Tract 54, San Diego County, California | start_hr9 | L2_Home | 79.03 |
| Census Tract 83.03, San Diego County, California | start_hr0 | L1_Home | 77.79 |
| Census Tract 83.03, San Diego County, California | start_hr1 | L1_Home | 77.79 |
| Census Tract 83.03, San Diego County, California | start_hr2 | L1_Home | 77.79 |
| Census Tract 83.03, San Diego County, California | start_hr23 | L1_Home | 77.79 |
| Census Tract 83.03, San Diego County, California | start_hr3 | L1_Home | 77.79 |
| Census Tract 83.03, San Diego County, California | start_hr4 | L1_Home | 77.79 |
| Census Tract 83.03, San Diego County, California | start_hr5 | L1_Home | 77.79 |
| Census Tract 83.48, San Diego County, California | start_hr10 | L2_Non-Home | 70.00 |
| Census Tract 83.48, San Diego County, California | start_hr3 | L2_Non-Home | 70.00 |
| Census Tract 83.48, San Diego County, California | start_hr4 | L2_Non-Home | 70.00 |
| Census Tract 83.48, San Diego County, California | start_hr5 | L2_Non-Home | 70.00 |
| Census Tract 83.48, San Diego County, California | start_hr7 | L2_Non-Home | 70.00 |
| Census Tract 83.48, San Diego County, California | start_hr8 | L2_Non-Home | 70.00 |
| Census Tract 83.48, San Diego County, California | start_hr9 | L2_Non-Home | 70.00 |
| Census Tract 83.48, San Diego County, California | start_hr11 | L2_Non-Home | 69.37 |
| Census Tract 170.32, San Diego County, California | start_hr11 | L2_Non-Home | 69.01 |
| Census Tract 215, San Diego County, California | start_hr2 | L1_Home | 64.37 |
| Census Tract 215, San Diego County, California | start_hr3 | L1_Home | 64.37 |

| | | | |
|---|---|---|---|
| Census Tract 215, San Diego County, California | start_hr4 | L1_Home | 64.37 |
| Census Tract 83.24, San Diego County, California | start_hr10 | L1_Home | 61.17 |
| Census Tract 83.24, San Diego County, California | start_hr11 | L1_Home | 61.17 |
| Census Tract 83.24, San Diego County, California | start_hr12 | L1_Home | 61.17 |
| Census Tract 83.24, San Diego County, California | start_hr2 | L1_Home | 61.17 |
| Census Tract 83.24, San Diego County, California | start_hr3 | L1_Home | 61.17 |
| Census Tract 83.24, San Diego County, California | start_hr4 | L1_Home | 61.17 |
| Census Tract 215, San Diego County, California | start_hr8 | L1_Home | 56.64 |
| Census Tract 83.65, San Diego County, California | start_hr0 | L1_Home | 54.71 |
| Census Tract 83.65, San Diego County, California | start_hr1 | L1_Home | 54.71 |
| Census Tract 83.65, San Diego County, California | start_hr13 | L1_Home | 54.71 |
| Census Tract 83.65, San Diego County, California | start_hr14 | L1_Home | 54.71 |
| Census Tract 83.65, San Diego County, California | start_hr2 | L1_Home | 54.71 |
| Census Tract 83.65, San Diego County, California | start_hr23 | L1_Home | 54.71 |
| Census Tract 83.65, San Diego County, California | start_hr3 | L1_Home | 54.71 |
| Census Tract 83.65, San Diego County, California | start_hr4 | L1_Home | 54.71 |
| Census Tract 54, San Diego County, California | start_hr2 | L2_Home | 51.78 |
| Census Tract 83.06, San Diego County, California | start_hr12 | L1_Home | 51.56 |
| Census Tract 51, San Diego County, California | start_hr10 | DCFC | 50.00 |
| Census Tract 51, San Diego County, California | start_hr11 | DCFC | 50.00 |
| Census Tract 51, San Diego County, California | start_hr12 | DCFC | 50.00 |
| Census Tract 51, San Diego County, California | start_hr8 | DCFC | 50.00 |

Table SI- 2. Top 50 values of the energy demand in Great Sacramento Area, med-cost scenario

| Region | Time | Level of charger | Value (kWh) |
|---|---|---|---|
| Census Tract 3, San Diego County, California | start_hr12 | L2_Non-Home | 161.00 |
| Census Tract 3, San Diego County, California | start_hr13 | L2_Non-Home | 161.00 |
| Census Tract 3, San Diego County, California | start_hr14 | L2_Non-Home | 161.00 |

| | | | |
|---|---|---|---|
| Census Tract 3, San Diego County, California | start_hr15 | L2_Non-Home | 154.73 |
| Census Tract 170.21, San Diego County, California | start_hr14 | L1_Home | 135.91 |
| Census Tract 170.21, San Diego County, California | start_hr2 | L1_Home | 135.91 |
| Census Tract 170.21, San Diego County, California | start_hr3 | L1_Home | 135.91 |
| Census Tract 170.21, San Diego County, California | start_hr4 | L1_Home | 135.91 |
| Census Tract 170.21, San Diego County, California | start_hr8 | L1_Home | 135.91 |
| Census Tract 170.21, San Diego County, California | start_hr0 | L1_Home | 91.89 |
| Census Tract 85.11, San Diego County, California | start_hr10 | L2_Non-Home | 91.00 |
| Census Tract 85.11, San Diego County, California | start_hr11 | L2_Non-Home | 91.00 |
| Census Tract 85.11, San Diego County, California | start_hr12 | L2_Non-Home | 91.00 |
| Census Tract 85.11, San Diego County, California | start_hr13 | L2_Non-Home | 91.00 |
| Census Tract 85.11, San Diego County, California | start_hr14 | L2_Non-Home | 91.00 |
| Census Tract 85.11, San Diego County, California | start_hr15 | L2_Non-Home | 91.00 |
| Census Tract 85.11, San Diego County, California | start_hr7 | L2_Non-Home | 91.00 |
| Census Tract 85.11, San Diego County, California | start_hr8 | L2_Non-Home | 91.00 |
| Census Tract 85.11, San Diego County, California | start_hr9 | L2_Non-Home | 91.00 |
| Census Tract 170.20, San Diego County, California | start_hr9 | L2_Home | 89.79 |
| Census Tract 83.03, San Diego County, California | start_hr0 | L1_Home | 77.79 |
| Census Tract 83.03, San Diego County, California | start_hr1 | L1_Home | 77.79 |
| Census Tract 83.03, San Diego County, California | start_hr2 | L1_Home | 77.79 |
| Census Tract 83.03, San Diego County, California | start_hr23 | L1_Home | 77.79 |
| Census Tract 83.03, San Diego County, California | start_hr3 | L1_Home | 77.79 |
| Census Tract 83.03, San Diego County, California | start_hr4 | L1_Home | 77.79 |
| Census Tract 83.03, San Diego County, California | start_hr5 | L1_Home | 77.79 |
| Census Tract 170.21, San Diego County, California | start_hr9 | L1_Home | 70.67 |
| Census Tract 215, San Diego County, California | start_hr2 | L1_Home | 64.37 |
| Census Tract 215, San Diego County, California | start_hr3 | L1_Home | 64.37 |
| Census Tract 215, San Diego County, California | start_hr8 | L1_Home | 64.37 |
| Census Tract 215, San Diego County, California | start_hr9 | L1_Home | 64.37 |
| Census Tract 83.01, San Diego County, California | start_hr9 | L1_Home | 64.29 |

| | | | |
|---|---|---|---|
| Census Tract 83.24, San Diego County, California | start_hr2 | L1_Home | 61.17 |
| Census Tract 83.24, San Diego County, California | start_hr3 | L1_Home | 61.17 |
| Census Tract 83.24, San Diego County, California | start_hr4 | L1_Home | 61.17 |
| Census Tract 83.33, San Diego County, California | start_hr9 | L1_Home | 57.81 |
| Census Tract 170.52, San Diego County, California | start_hr0 | L2_Home | 56.80 |
| Census Tract 170.52, San Diego County, California | start_hr2 | L2_Home | 56.80 |
| Census Tract 170.52, San Diego County, California | start_hr23 | L2_Home | 56.80 |
| Census Tract 170.52, San Diego County, California | start_hr3 | L2_Home | 56.80 |
| Census Tract 170.52, San Diego County, California | start_hr4 | L2_Home | 56.80 |
| Census Tract 170.52, San Diego County, California | start_hr8 | L2_Home | 56.80 |
| Census Tract 83.29, San Diego County, California | start_hr10 | L2_Non-Home | 56.00 |
| Census Tract 83.29, San Diego County, California | start_hr11 | L2_Non-Home | 56.00 |
| Census Tract 83.29, San Diego County, California | start_hr12 | L2_Non-Home | 56.00 |
| Census Tract 83.29, San Diego County, California | start_hr13 | L2_Non-Home | 56.00 |
| Census Tract 83.29, San Diego County, California | start_hr14 | L2_Non-Home | 56.00 |
| Census Tract 83.29, San Diego County, California | start_hr8 | L2_Non-Home | 56.00 |
| Census Tract 83.29, San Diego County, California | start_hr9 | L2_Non-Home | 56.00 |

### 1.3 Spatial and temporal distribution of power requirement

To evaluate the impact of the EV charging loads to the grid, we are also able to see the power requirement from charging in each time period for each census tract region. Figure SI- 4 and Figure SI- 5 show the temporal change of the power requirement within the study areas. Under optimized charging strategies, the charging is concentrated in two time periods, aligning with the off-peak periods on the grid.

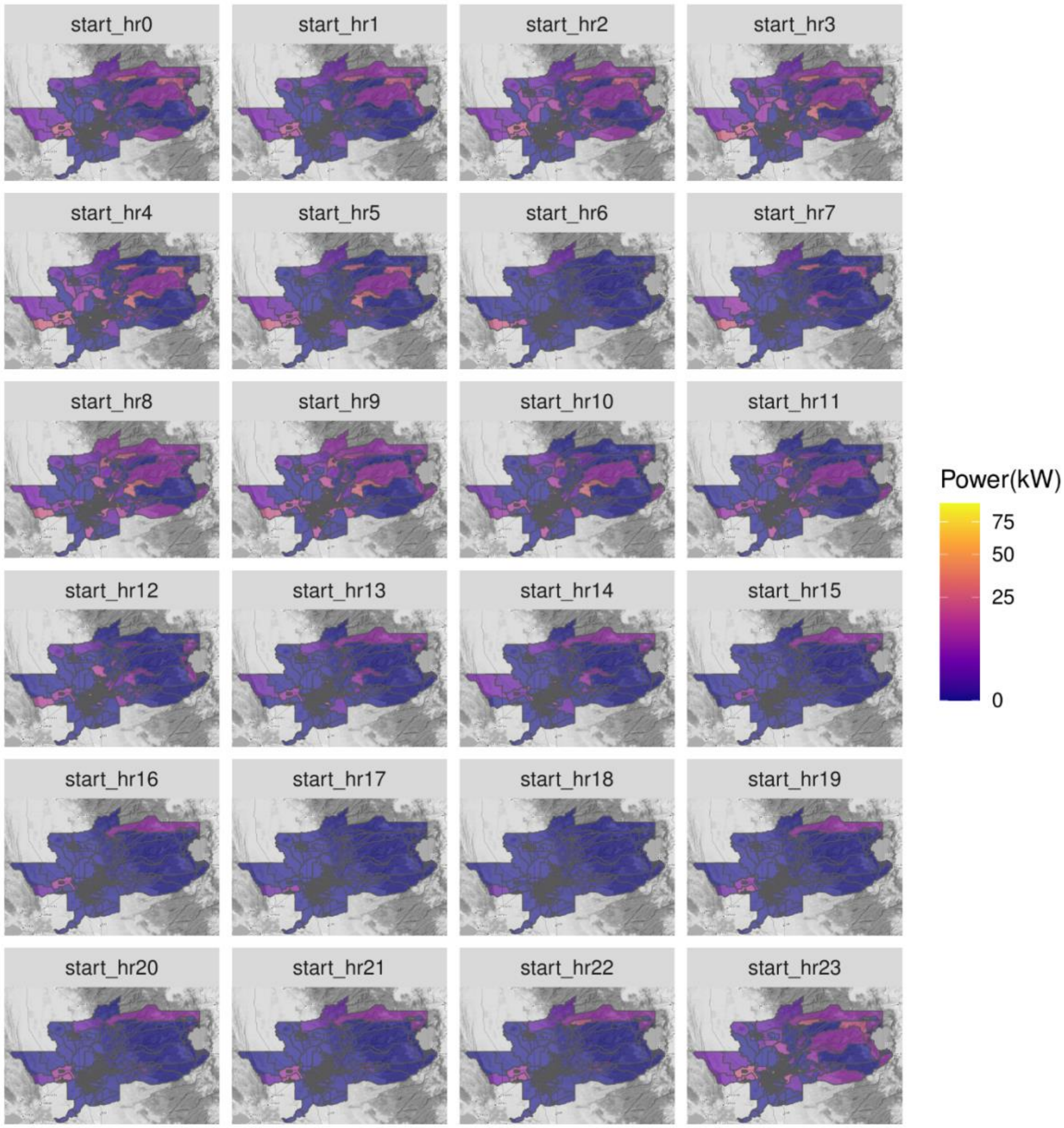


Figure SI- 4. Spatial and temporal distribution of power requirements in the medium cost scenario in Great Sacramento Area

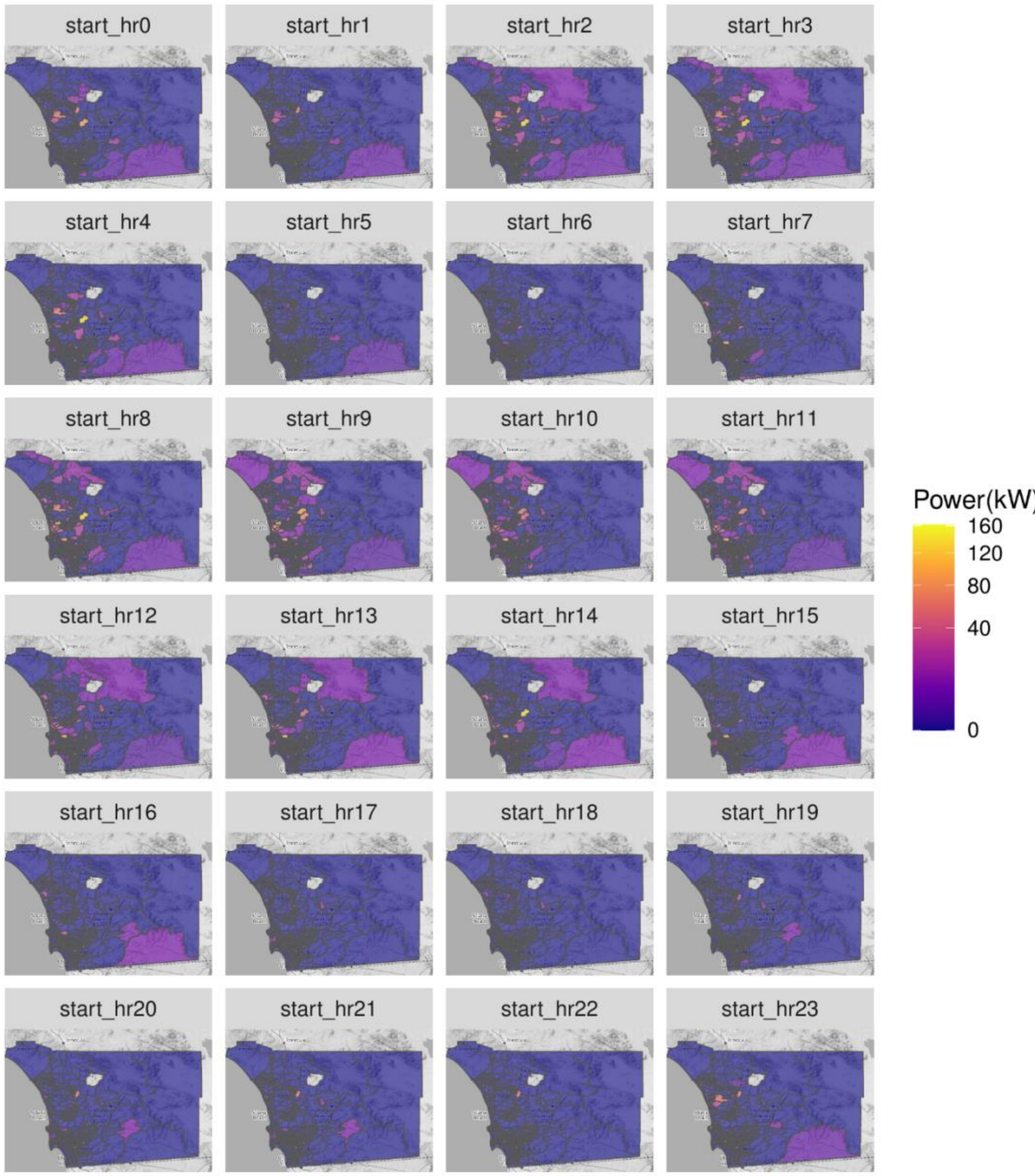


Figure SI- 5. Spatial and temporal distribution of power requirements in the medium cost scenario in San Diego

## 2 Supporting Information for Chapter 4

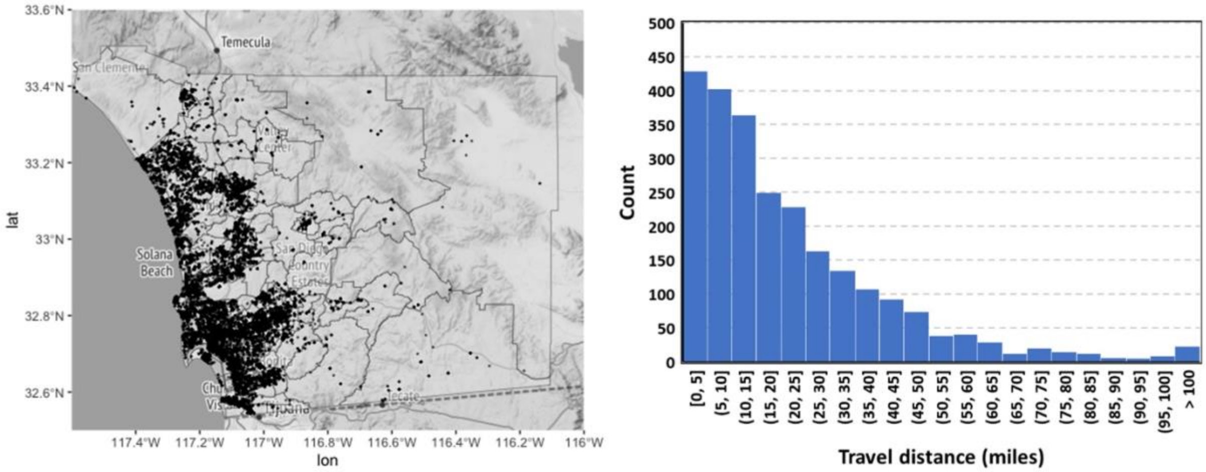


Figure SI- 6. Daily dwelling locations and travel distance of BEV drivers in San Diego.

Note: BEV drivers in San Diego cluster along the coast, and their daily travel distance is mostly below 100 miles with an average value of 22 miles.

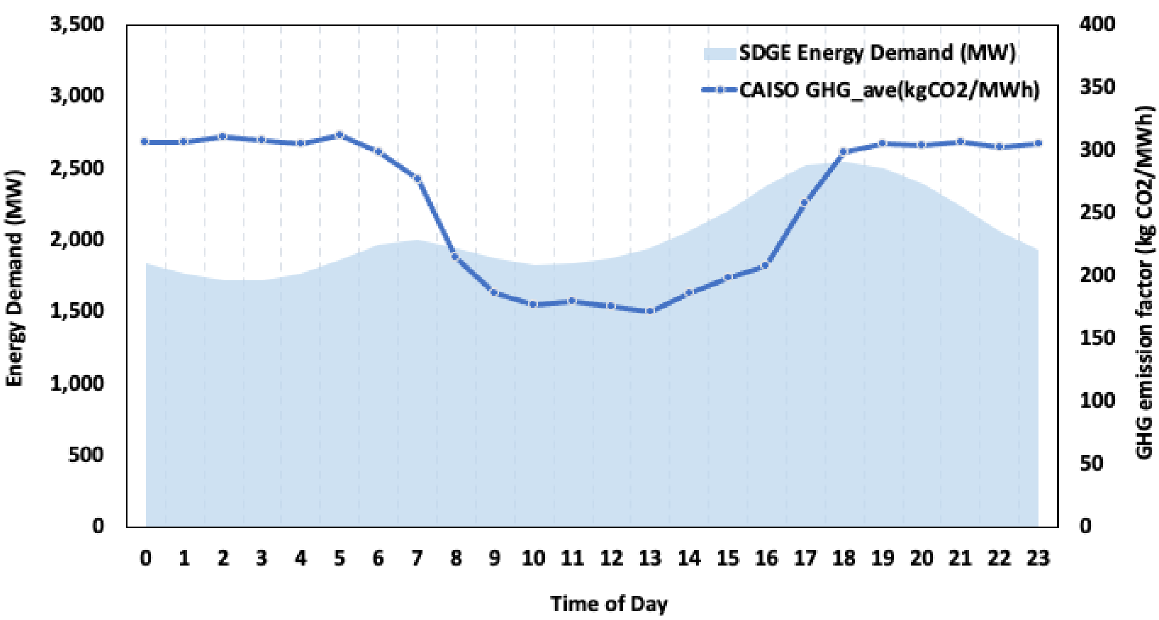


Figure SI- 7. GHG emission intensities and load profile of the grid in the hourly manner.

Note: There is a green period of time from 7am to 5pm during the day for using the electricity, and this green period aligns with the second off-peak period in net load of the grid.

# Chapter 7. References


(1) US Environmental Protection Agency. *Invetory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2016*; 2018. https://doi.org/EPA 430-R-18-003.

(2) US Federal Highway Administration. *Summary of Travel Trends: 2017 National Household Travel Survey*.

(3) Williams, J. H.; Debenedictis, A.; Ghanadan, R.; Mahone, A.; Moore, J.; Iii, W. R. M.; Price, S.; Torn, M. S. The Technology Path to Deep Greenhouse Gas Emissions Cuts by 2050: The Pivotal Role of Electricity. *Science (80-. ).* **2012**, *335* (6064), 53–59. https://doi.org/10.1126/science.1208365.

(4) Davis, S. J.; Lewis, N. S.; Shaner, M.; Aggarwal, S.; Arent, D.; Azevedo, I. L.; Benson, S. M.; Bradley, T.; Brouwer, J.; Chiang, Y. M.; Clack, C. T. M.; Cohen, A.; Doig, S.; Edmonds, J.; Fennell, P.; Field, C. B.; Hannegan, B.; Hodge, B. M.; Hoffert, M. I.; Ingersoll, E.; Jaramillo, P.; Lackner, K. S.; Mach, K. J.; Mastrandrea, M.; Ogden, J.; Peterson, P. F.; Sanchez, D. L.; Sperling, D.; Stagner, J.; Trancik, J. E.; Yang, C. J.; Caldeira, K. Net-Zero Emissions Energy Systems. *Science*. 2018. https://doi.org/10.1126/science.aas9793.

(5) Kennedy, C. A.; Ibrahim, N.; Hoornweg, D. Low-Carbon Infrastructure Strategies for Cities. *Nat. Clim. Chang.* **2014**, *4* (5), 343–346. https://doi.org/10.1038/nclimate2160.

(6) Chu, S.; Majumdar, A. Opportunities and Challenges for a Sustainable Energy Future. *Nature* **2012**. https://doi.org/10.1038/nature11475.

(7) Sperling, D. *Three Revolutions: Steering Automated, Shared, and Electric Vehicles to a*

*Better Future*; Island Press, 2018.

(8) Bonges, H. A.; Lusk, A. C. Addressing Electric Vehicle (EV) Sales and Range Anxiety through Parking Layout, Policy and Regulation. *Transp. Res. Part A Policy Pract.* **2016**, *83*, 63–73. https://doi.org/10.1016/j.tra.2015.09.011.

(9) Coffman, M.; Bernstein, P.; Wee, S. Electric Vehicles Revisited: A Review of Factors That Affect Adoption. *Transp. Rev.* **2017**, *37* (1), 79–93. https://doi.org/10.1080/01441647.2016.1217282.

(10) Egbue, O.; Long, S. Barriers to Widespread Adoption of Electric Vehicles: An Analysis of Consumer Attitudes and Perceptions. *Energy Policy* **2012**, *48* (2012), 717–729. https://doi.org/10.1016/j.enpol.2012.06.009.

(11) Rezvani, Z.; Jansson, J.; Bodin, J. Advances in Consumer Electric Vehicle Adoption Research: A Review and Research Agenda. *Transp. Res. Part D Transp. Environ.* **2015**, *34*, 122–136. https://doi.org/10.1016/j.trd.2014.10.010.

(12) Franke, T.; Krems, J. F. What Drives Range Preferences in Electric Vehicle Users? *Transp. Policy* **2013**, *30*, 56–62. https://doi.org/10.1016/j.tranpol.2013.07.005.

(13) Tran, M.; Banister, D.; Bishop, J. D. K.; McCulloch, M. D. Realizing the Electric-Vehicle Revolution. *Nat. Clim. Chang.* **2012**, *2* (5), 328–333. https://doi.org/10.1038/nclimate1429.

(14) McCollum, D. L.; Wilson, C.; Bevione, M.; Carrara, S.; Edelenbosch, O. Y.; Emmerling, J.; Guivarch, C.; Karkatsoulis, P.; Keppo, I.; Krey, V.; Lin, Z.; Broin, E.; Paroussos, L.; Pettifor, H.; Ramea, K.; Riahi, K.; Sano, F.; Rodriguez, B. S.; van Vuuren, D. P. Interaction of Consumer Preferences and Climate Policies in the Global Transition to Low-Carbon Vehicles. *Nat.*

*Energy* **2018**, *3* (8), 664–673. https://doi.org/10.1038/s41560-018-0195-z.

(15) US DOE. Electric Vehicles: Tax Credits and Other Incentives https://www.energy.gov/eere/electricvehicles/electric-vehicles-tax-credits-and-other-incentives.

(16) Krupa, J. S.; Rizzo, D. M.; Eppstein, M. J.; Brad Lanute, D.; Gaalema, D. E.; Lakkaraju, K.; Warrender, C. E. Analysis of a Consumer Survey on Plug-in Hybrid Electric Vehicles. *Transp. Res. Part A Policy Pract.* **2014**, *64*, 14–31. https://doi.org/10.1016/j.tra.2014.02.019.

(17) Hardman, S.; Tal, G. Exploring the Decision to Adopt a High-End Battery Electric Vehicle: Role of Financial and Nonfinancial Motivations. *Transp. Res. Rec. J. Transp. Res. Board* **2016**, *2572* (1), 20–27. https://doi.org/10.3141/2572-03.

(18) Green, R. C.; Wang, L.; Alam, M. The Impact of Plug-in Hybrid Electric Vehicles on Distribution Networks: A Review and Outlook. *Renew. Sustain. Energy Rev.* **2011**, *15* (1), 544–553. https://doi.org/10.1016/j.rser.2010.08.015.

(19) Tan, K. M.; Ramachandaramurthy, V. K.; Yong, J. Y. Integration of Electric Vehicles in Smart Grid: A Review on Vehicle to Grid Technologies and Optimization Techniques. *Renew. Sustain. Energy Rev.* **2016**, *53*, 720–732. https://doi.org/10.1016/j.rser.2015.09.012.

(20) Geske, J.; Schumann, D. Willing to Participate in Vehicle-to-Grid (V2G)? Why Not! *Energy Policy* **2018**, *120* (July 2017), 392–401. https://doi.org/10.1016/j.enpol.2018.05.004.

(21) Hardman, S.; Jenn, A.; Tal, G.; Axsen, J.; Beard, G.; Daina, N.; Figenbaum, E.; Jakobsson, N.; Jochem, P.; Kinnear, N.; Plötz, P.; Pontes, J.; Refa, N.; Sprei, F.; Turrentine, T.; Witkamp, B. A Review of Consumer Preferences of and Interactions with Electric Vehicle Charging

Infrastructure. *Transp. Res. Part D Transp. Environ.* **2018**, *62* (April), 508–523. https://doi.org/10.1016/j.trd.2018.04.002.

(22) Muratori, M. Impact of Uncoordinated Plug-in Electric Vehicle Charging on Residential Power Demand. *Nat. Energy* **2018**, *3* (3), 193–201. https://doi.org/10.1038/s41560-017-0074-z.

(23) García-Villalobos, J.; Zamora, I.; San Martín, J. I.; Asensio, F. J.; Aperribay, V. Plug-in Electric Vehicles in Electric Distribution Networks: A Review of Smart Charging Approaches. *Renew. Sustain. Energy Rev.* **2014**, *38*, 717–731. https://doi.org/10.1016/j.rser.2014.07.040.

(24) Zhang, L.; Brown, T.; Samuelsen, G. S. Fuel Reduction and Electricity Consumption Impact of Different Charging Scenarios for Plug-in Hybrid Electric Vehicles. *J. Power Sources* **2011**, *196* (15), 6559–6566. https://doi.org/10.1016/j.jpowsour.2011.03.003.

(25) California Department of Transportation. 2010-2012 California Household Travel Survey Final Report. **2013**, No. June, 1–349.

(26) US EPA. *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2019*; 2021; Vol. 76.

(27) Noel, L.; Zarazua de Rubens, G.; Kester, J.; Sovacool, B. K. Understanding the Socio-Technical Nexus of Nordic Electric Vehicle (EV) Barriers: A Qualitative Discussion of Range, Price, Charging and Knowledge. *Energy Policy* **2020**, *138*. https://doi.org/10.1016/J.ENPOL.2020.111292.

(28) Asensio, O. I.; Alvarez, K.; Dror, A.; Wenzel, E.; Hollauer, C.; Ha, S. Real-Time Data from Mobile Platforms to Evaluate Sustainable Transportation Infrastructure. *Nat. Sustain.* **2020**, *3* (6), 463–471. https://doi.org/10.1038/s41893-020-0533-6.

(29) Greene, D. L.; Kontou, E.; Borlaug, B.; Brooker, A.; Muratori, M. Public Charging Infrastructure for Plug-in Electric Vehicles: What Is It Worth? *Transp. Res. Part D Transp. Environ.* **2020**, *78* (October 2019), 102182. https://doi.org/10.1016/j.trd.2019.11.011.

(30) Mandys, F. Electric Vehicles and Consumer Choices. *Renew. Sustain. Energy Rev.* **2021**, *142*. https://doi.org/10.1016/J.RSER.2021.110874.

(31) Guo, F.; Yang, J.; Lu, J. The Battery Charging Station Location Problem: Impact of Users' Range Anxiety and Distance Convenience. *Transp. Res. Part E Logist. Transp. Rev.* **2018**, *114*, 1–18. https://doi.org/10.1016/J.TRE.2018.03.014.

(32) California Public Utilities Commission. Zero-Emission Vehicles http://www.cpuc.ca.gov/zev/.

(33) Ghamami, M.; Kavianipour, M.; Zockaie, A.; Hohnstadt, L. R.; Ouyang, Y. Refueling Infrastructure Planning in Intercity Networks Considering Route Choice and Travel Time Delay for Mixed Fleet of Electric and Conventional Vehicles. *Transp. Res. Part C Emerg. Technol.* **2020**, *120* (September), 102802. https://doi.org/10.1016/j.trc.2020.102802.

(34) Davidov, S. Optimal Charging Infrastructure Planning Based on a Charging Convenience Buffer. *Energy* **2020**, *192*. https://doi.org/10.1016/j.energy.2019.116655.

(35) Wang, Y.; Shi, J.; Wang, R.; Liu, Z.; Wang, L. Siting and Sizing of Fast Charging Stations in Highway Network with Budget Constraint. *Appl. Energy* **2018**, *228* (July), 1255–1271. https://doi.org/10.1016/j.apenergy.2018.07.025.

(36) Roni, M. S.; Yi, Z.; Smart, J. G. Optimal Charging Management and Infrastructure Planning for Free-Floating Shared Electric Vehicles. *Transp. Res. Part D Transp. Environ.* **2019**, *76*,

155–175. https://doi.org/10.1016/j.trd.2019.09.021.

(37) Kavianipour, M.; Fakhrmoosavi, F.; Singh, H.; Ghamami, M.; Zockaie, A.; Ouyang, Y.; Jackson, R. Electric Vehicle Fast Charging Infrastructure Planning in Urban Networks Considering Daily Travel and Charging Behavior. *Transp. Res. Part D Transp. Environ.* **2021**, *93* (March), 102769. https://doi.org/10.1016/j.trd.2021.102769.

(38) NREL; Woods, E.; Rames, C.; Muratori, M.; Raghavan, S.; Melaina, M.; NREL. National Plug-In Electric Vehicle Infrastructure Analysis. **2017**, No. September. https://doi.org/10.13140/RG.2.2.25881.93280.

(39) Kontou, E.; Liu, C.; Xie, F.; Wu, X.; Lin, Z. Understanding the Linkage between Electric Vehicle Charging Network Coverage and Charging Opportunity Using GPS Travel Data. *Transp. Res. Part C Emerg. Technol.* **2019**, *98*, 1–13. https://doi.org/10.1016/j.trc.2018.11.008.

(40) Vazifeh, M. M.; Zhang, H.; Santi, P.; Ratti, C. Optimizing the Deployment of Electric Vehicle Charging Stations Using Pervasive Mobility Data. *Transp. Res. Part A Policy Pract.* **2019**, *121*, 75–91. https://doi.org/10.1016/J.TRA.2019.01.002.

(41) Shahraki, N.; Cai, H.; Turkay, M.; Xu, M. Optimal Locations of Electric Public Charging Stations Using Real World Vehicle Travel Patterns. *Transp. Res. Part D Transp. Environ.* **2015**, *41*, 165–176. https://doi.org/10.1016/j.trd.2015.09.011.

(42) Wolbertus, R.; van den Hoed, R.; Kroesen, M.; Chorus, C. Charging Infrastructure Roll-out Strategies for Large Scale Introduction of Electric Vehicles in Urban Areas: An Agent-Based Simulation Study. *Transp. Res. Part A Policy Pract.* **2021**, *148* (April), 262–285.

https://doi.org/10.1016/j.tra.2021.04.010.

(43) Sheppard, C.; Waraich, R.; Campbell, A.; Pozdnukhov, A.; Gopal, A. R. *Modeling Plug-in Electric Vehicle Charging Demand with BEAM*; 2017.

(44) Pruckner, M.; German, R.; Eckhoff, D. Spatial and Temporal Charging Infrastructure Planning Using Discrete Event Simulation. *Proc. 2017 ACM SIGSIM Conf. Princ. Adv. Discret. Simul.* https://doi.org/10.1145/3064911.

(45) Chakraborty, D.; Bunch, D. S.; Lee, J. H.; Tal, G. Demand Drivers for Charging Infrastructure-Charging Behavior of Plug-in Electric Vehicle Commuters. *Transp. Res. Part D Transp. Environ.* **2019**, *76* (February), 255–272. https://doi.org/10.1016/j.trd.2019.09.015.

(46) Liu, J. peng; Zhang, T. xi; Zhu, J.; Ma, T. nan. Allocation Optimization of Electric Vehicle Charging Station (EVCS) Considering with Charging Satisfaction and Distributed Renewables Integration. *Energy* **2018**, *164*, 560–574. https://doi.org/10.1016/j.energy.2018.09.028.

(47) Pan, Z. J.; Zhang, Y. A Novel Centralized Charging Station Planning Strategy Considering Urban Power Network Structure Strength. *Electr. Power Syst. Res.* **2016**, *136*, 100–109. https://doi.org/10.1016/j.epsr.2016.01.019.

(48) Awasthi, A.; Venkitusamy, K.; Padmanaban, S.; Selvamuthukumaran, R.; Blaabjerg, F.; Singh, A. K. Optimal Planning of Electric Vehicle Charging Station at the Distribution System Using Hybrid Optimization Algorithm. *Energy* **2017**, *133*, 70–78. https://doi.org/10.1016/j.energy.2017.05.094.

(49) Deb, S.; Tammi, K.; Kalita, K.; Mahanta, P. Review of Recent Trends in Charging

Infrastructure Planning for Electric Vehicles. *Wiley Interdiscip. Rev. Energy Environ.* **2018**, *7* (6), e306. https://doi.org/10.1002/WENE.306.

(50) Cai, H.; Jia, X.; Chiu, A. S. F.; Hu, X.; Xu, M. Siting Public Electric Vehicle Charging Stations in Beijing Using Big-Data Informed Travel Patterns of the Taxi Fleet. *Transp. Res. Part D Transp. Environ.* **2014**, *33*, 39–46. https://doi.org/10.1016/j.trd.2014.09.003.

(51) Sathaye, N.; Kelley, S. An Approach for the Optimal Planning of Electric Vehicle Infrastructure for Highway Corridors. *Transp. Res. Part E Logist. Transp. Rev.* **2013**, *59*, 15–33. https://doi.org/10.1016/j.tre.2013.08.003.

(52) Chen, T. D.; Kockelman, K. M.; Khan, M. Locating Electric Vehicle Charging Stations. *Transp. Res. Rec. J. Transp. Res. Board* **2014**, *2385* (1), 28–36. https://doi.org/10.3141/2385-04.

(53) Dong, J.; Liu, C.; Lin, Z. Charging Infrastructure Planning for Promoting Battery Electric Vehicles: An Activity-Based Approach Using Multiday Travel Data. *Transp. Res. Part C Emerg. Technol.* **2014**, *38* (January), 44–55. https://doi.org/10.1016/j.trc.2013.11.001.

(54) Huang, Y.; Zhou, Y. An Optimization Framework for Workplace Charging Strategies. *Transp. Res. Part C Emerg. Technol.* **2015**, *52*, 144–155. https://doi.org/10.1016/j.trc.2015.01.022.

(55) Zhang, L.; Shaffer, B.; Brown, T.; Scott Samuelsen, G. The Optimization of DC Fast Charging Deployment in California. *Appl. Energy* **2015**, *157*, 111–122. https://doi.org/10.1016/j.apenergy.2015.07.057.

(56) Yi, T.; Zhang, C.; Lin, T.; Liu, J. Research on the Spatial-Temporal Distribution of Electric Vehicle Charging Load Demand: A Case Study in China. *J. Clean. Prod.* **2020**, *242*, 118457. https://doi.org/10.1016/J.JCLEPRO.2019.118457.

(57) Ji, W.; Nicholas, M.; Tal, G. Electric Vehicle Fast Charger Planning for Metropolitan Planning Organizations: Adapting to Changing Markets and Vehicle Technology. *Transp. Res. Rec. J. Transp. Res. Board* **2015**, No. 15–5942.

(58) Lee, J. H.; Chakraborty, D.; Hardman, S. J.; Tal, G. Exploring Electric Vehicle Charging Patterns: Mixed Usage of Charging Infrastructure. *Transp. Res. Part D Transp. Environ.* **2020**, *79*, 102249. https://doi.org/10.1016/j.trd.2020.102249.

(59) Melaina, M. W. Retail Infrastructure Costs Comparison for Hydrogen and Electricity for Light-Duty Vehicles. In *SAE Technical Paper Series*; 2014; Vol. 1. https://doi.org/10.4271/2014-01-1969.

(60) California ISO. Market price maps http://www.caiso.com/PriceMap/Pages/default.aspx.

(61) California Air Resources Board. Clean Vehicle Rebate Project Rebate Statistics https://cleanvehiclerebate.org/eng/rebate-statistics.

(62) United States Census Bureau. 2012 American Community Survey One-year Estimates https://factfinder.census.gov/faces/nav/jsf/pages/download_center.xhtml.

(63) US DOE. Fuel Economy Guide https://www.fueleconomy.gov/feg/printGuides.shtml.

(64) Gohlke, D.; Zhou, Y. *Assessment of Light-Duty Plug-in Electric Vehicles in the United States, 2010 – 2019*; Argonne, IL (United States), 2020. https://doi.org/10.2172/1642114.

(65) Azevedo, I.; Donti, P.; Horner, N.; Schivley, G.; Siler-Evans, K.; Vaishnav, P. Electricity Marginal Factor Estimates http://cedmcenter.org.

(66) Laberteaux, K. P.; Hamza, K. A Study on Opportune Reduction in Greenhouse Gas Emissions

via Adoption of Electric Drive Vehicles in Light Duty Vehicle Fleets. *Transp. Res. Part D Transp. Environ.* **2018**, *63*, 839–854. https://doi.org/10.1016/J.TRD.2018.07.012.

(67) Tamayao, M.-A. M.; Michalek, J. J.; Hendrickson, C.; Azevedo, I. M. L. Regional Variability and Uncertainty of Electric Vehicle Life Cycle CO2 Emissions across the United States. *Environ. Sci. Technol.* **2015**, *49* (14), 8844–8855. https://doi.org/10.1021/ACS.EST.5B00815.

(68) Zethmayr, J.; Kolata, D. Charge for Less: An Analysis of Hourly Electricity Pricing for Electric Vehicles. *World Electr. Veh. J.* **2019**, *10* (1), 6. https://doi.org/10.3390/wevj10010006.

(69) Schwarz, M.; Auzepy, Q.; Knoeri, C. Can Electricity Pricing Leverage Electric Vehicles and Battery Storage to Integrate High Shares of Solar Photovoltaics? *Appl. Energy* **2020**, *277*, 115548. https://doi.org/10.1016/J.APENERGY.2020.115548.

(70) Canizes, B.; Soares, J.; Vale, Z.; Corchado, J. M. Optimal Distribution Grid Operation Using DLMP-Based Pricing for Electric Vehicle Charging Infrastructure in a Smart City. *Energies* **2019**, *12* (4). https://doi.org/10.3390/en12040686.

(71) Subramanian, V.; Das, T. K. A Two-Layer Model for Dynamic Pricing of Electricity and Optimal Charging of Electric Vehicles under Price Spikes. *Energy* **2019**, *167*, 1266–1277. https://doi.org/10.1016/j.energy.2018.10.171.

(72) Zhang, L.; Zhao, Z.; Xin, H.; Chai, J.; Wang, G. Charge Pricing Model for Electric Vehicle Charging Infrastructure Public-Private Partnership Projects in China: A System Dynamics Analysis. *J. Clean. Prod.* **2018**, *199*, 321–333. https://doi.org/10.1016/j.jclepro.2018.07.169.

(73) Zhang, X.; Liang, Y.; Liu, W. Pricing Model for the Charging of Electric Vehicles Based on System Dynamics in Beijing. *Energy* **2017**, *119*, 218–234. https://doi.org/10.1016/j.energy.2016.12.057.

(74) Moghaddam, Z.; Ahmad, I.; Habibi, D.; Masoum, M. A. S. A Coordinated Dynamic Pricing Model for Electric Vehicle Charging Stations. *IEEE Trans. Transp. Electrif.* **2019**, *5* (1), 1–1. https://doi.org/10.1109/tte.2019.2897087.

(75) Dong, X.; Mu, Y.; Xu, X.; Jia, H.; Wu, J.; Yu, X.; Qi, Y. A Charging Pricing Strategy of Electric Vehicle Fast Charging Stations for the Voltage Control of Electricity Distribution Networks. *Appl. Energy* **2018**, *225* (92), 857–868. https://doi.org/10.1016/j.apenergy.2018.05.042.

(76) Datta, U.; Saiprasad, N.; Kalam, A.; Shi, J.; Zayegh, A. A Price-Regulated Electric Vehicle Charge-Discharge Strategy for G2V, V2H, and V2G. *Int. J. Energy Res.* **2019**, *43* (2), 1032–1042. https://doi.org/10.1002/er.4330.

(77) Hu, Z.; Zhan, K.; Zhang, H.; Song, Y. Pricing Mechanisms Design for Guiding Electric Vehicle Charging to Fill Load Valley. *Appl. Energy* **2016**, *178*, 155–163. https://doi.org/10.1016/j.apenergy.2016.06.025.

(78) Davis, B. M.; Bradley, T. H. The Efficacy of Electric Vehicle Time-of-Use Rates in Guiding Plug-in Hybrid Electric Vehicle Charging Behavior. *IEEE Trans. Smart Grid* **2012**, *3* (4), 1679–1686. https://doi.org/10.1109/TSG.2012.2205951.

(79) Tang, D.; Wang, P. Nodal Impact Assessment and Alleviation of Moving Electric Vehicle Loads: From Traffic Flow to Power Flow. *IEEE Trans. Power Syst.* **2016**, *31* (6), 4231–4242. https://doi.org/10.1109/TPWRS.2015.2495254.

(80) Xu, X.; Niu, D.; Li, Y.; Sun, L. Optimal Pricing Strategy of Electric Vehicle Charging Station for Promoting Green Behavior Based on Time and Space Dimensions. *J. Adv. Transp.* **2020**, *2020*, 1DUMMMY. https://doi.org/10.1155/2020/8890233.

(81) Iacobucci, R.; McLellan, B.; Tezuka, T. Optimization of Shared Autonomous Electric Vehicles Operations with Charge Scheduling and Vehicle-to-Grid. *Transp. Res. Part C Emerg. Technol.* **2019**, *100* (July 2018), 34–52. https://doi.org/10.1016/j.trc.2019.01.011.

(82) Latifi, M.; Rastegarnia, A.; Khalili, A.; Sanei, S. Agent-Based Decentralized Optimal Charging Strategy for Plug-in Electric Vehicles. *IEEE Trans. Ind. Electron.* **2019**, *66* (5), 3668–3680. https://doi.org/10.1109/TIE.2018.2853609.

(83) Woody, M.; Vaishnav, P.; Craig, M. T.; Lewis, G. M.; Keoleian, G. A. Charging Strategies to Minimize Greenhouse Gas Emissions of Electrified Delivery Vehicles. *Environ. Sci. Technol.* **2021**, *55* (14), 10108–10120. https://doi.org/10.1021/ACS.EST.1C03483.

(84) Xu, L.; Yilmaz, H. Ü.; Wang, Z.; Poganietz, W. R.; Jochem, P. Greenhouse Gas Emissions of Electric Vehicles in Europe Considering Different Charging Strategies. *Transp. Res. Part D Transp. Environ.* **2020**, *87*. https://doi.org/10.1016/J.TRD.2020.102534.

(85) Arisoy, I.; Ozturk, I. Estimating Industrial and Residential Electricity Demand in Turkey: A Time Varying Parameter Approach. *Energy* **2014**, *66*, 959–964. https://doi.org/10.1016/j.energy.2014.01.016.

(86) Woo, C. K.; Liu, Y.; Zarnikau, J.; Shiu, A.; Luo, X.; Kahrl, F. Price Elasticities of Retail Energy Demands in the United States: New Evidence from a Panel of Monthly Data for 2001–2016. *Appl. Energy* **2018**, *222* (September 2017), 460–474.

https://doi.org/10.1016/j.apenergy.2018.03.113.

(87) Lijesen, M. G. The Real-Time Price Elasticity of Electricity. *Energy Econ.* **2007**, *29* (2), 249–258. https://doi.org/10.1016/j.eneco.2006.08.008.

(88) Quillinan, J. D. Pricing for Retail Electricity. *J. Revenue Pricing Manag.* **2011**, *10* (6), 545–555. https://doi.org/10.1057/rpm.2011.22.

(89) Faruqui, A.; Sergici, S.; Akaba, L. The Impact of Dynamic Pricing on Residential and Small Commercial and Industrial Usage: New Experimental Evidence from Connecticut. *Energy J.* **2014**, *35* (1), 137–160.

(90) Ding, Z.; Lu, Y.; Zhang, L.; Lee, W. J.; Chen, D. A Stochastic Resource-Planning Scheme for PHEV Charging Station Considering Energy Portfolio Optimization and Price-Responsive Demand. *IEEE Trans. Ind. Appl.* **2018**, *54* (6), 5590–5598. https://doi.org/10.1109/TIA.2018.2851205.

(91) Jonathan Cook; Rchwell, C. C.; George, S. Final Evaluation for San Diego Gas & Electric's Plug-in Electric Vehicle TOU Pricing and Technology Study. **2014**.

(92) Li, X.; Jenn, A. *An Integrated Optimization Platform for Spatial-Temporal Modeling of Electric Vehicle Charging Infrastructure*; 2021.

(93) Argonne National Laboratory. Light Duty Electric Drive Vehicles Monthly Sales Updates https://www.anl.gov/es/light-duty-electric-drive-vehicles-monthly-sales-updates.

(94) SDG&E. Electric vehicle time-of-use (TOU) pricing plans https://www.sdge.com/residential/pricing-plans/about-our-pricing-plans/electric-

vehicle-plans.

(95) EVgo. Level 2 and DC Fast Charging Plans https://www.evgo.com/charging-plans/.

(96) US Environmental Protection Agency. The Social Cost of Carbon https://19january2017snapshot.epa.gov/climatechange/social-cost-carbon_.html.

(97) California ISO Outlook platform.

(98) Global, T.; Solutions, W. *California Greenhouse Gas Emissions for 2000 to 2011 – Trends of Emissions and Other Indicators*; 2021.

(99) Greenwald, J. M.; Kornhauser, A. It's up to Us: Policies to Improve Climate Outcomes from Automated Vehicles. *Energy Policy* **2019**, *127*, 445–451. https://doi.org/10.1016/J.ENPOL.2018.12.017.

(100) Taiebat, M.; Stolper, S.; Xu, M. Forecasting the Impact of Connected and Automated Vehicles on Energy Use: A Microeconomic Study of Induced Travel and Energy Rebound. *Appl. Energy* **2019**, *247* (November 2018), 297–308. https://doi.org/10.1016/J.APENERGY.2019.03.174.

(101) Greenblatt, J. B.; Shaheen, S. Automated Vehicles, On-Demand Mobility, and Environmental Impacts. *Curr. Sustain. Energy Reports 2015 23* **2015**, *2* (3), 74–81. https://doi.org/10.1007/S40518-015-0038-5.

(102) Fernandes, P.; Bandeira, J. M.; Coelho, M. C. A Macroscopic Approach for Assessing the Environmental Performance of Shared, Automated, Electric Mobility in an Intercity Corridor. *J. Intell. Transp. Syst.* **2021**, 1–17.

https://doi.org/10.1080/15472450.2021.1945453.

(103) Sheppard, C. J. R.; Jenn, A. T.; Greenblatt, J. B.; Bauer, G. S.; Gerke, B. F. Private versus Shared, Automated Electric Vehicles for U.S. Personal Mobility: Energy Use, Greenhouse Gas Emissions, Grid Integration, and Cost Impacts. *Environ. Sci. Technol.* **2021**, *55* (5), 3229–3239. https://doi.org/10.1021/acs.est.0c06655.

(104) Ellingsen, L. A. W.; Singh, B.; Strømman, A. H. The Size and Range Effect: Lifecycle Greenhouse Gas Emissions of Electric Vehicles. *Environ. Res. Lett.* **2016**, *11* (5). https://doi.org/10.1088/1748-9326/11/5/054010.

(105) Wu, Z.; Wang, M.; Zheng, J.; Sun, X.; Zhao, M.; Wang, X. Life Cycle Greenhouse Gas Emission Reduction Potential of Battery Electric Vehicle. *J. Clean. Prod.* **2018**, *190*, 462–470. https://doi.org/10.1016/j.jclepro.2018.04.036.

(106) Ma, H.; Balthasar, F.; Tait, N.; Riera-Palou, X.; Harrison, A. A New Comparison between the Life Cycle Greenhouse Gas Emissions of Battery Electric Vehicles and Internal Combustion Vehicles. *Energy Policy* **2012**, *44*, 160–173. https://doi.org/10.1016/j.enpol.2012.01.034.

(107) Gai, Y.; Wang, A.; Pereira, L.; Hatzopoulou, M.; Posen, I. D. Marginal Greenhouse Gas Emissions of Ontario's Electricity System and the Implications of Electric Vehicle Charging. *Environ. Sci. Technol.* **2019**, *53* (13), 7903–7912. https://doi.org/10.1021/acs.est.9b01519.

(108) Fang, Y.; Asche, F.; Novan, K. The Costs of Charging Plug-in Electric Vehicles (PEVs): Within Day Variation in Emissions and Electricity Prices. *Energy Econ.* **2018**, *69*, 196–203. https://doi.org/10.1016/j.eneco.2017.11.011.

(109) Weis, A.; Michalek, J. J.; Jaramillo, P.; Lueken, R. Emissions and Cost Implications of

Controlled Electric Vehicle Charging in the U.S. PJM Interconnection. *Environ. Sci. Technol.* **2015**, *49* (9), 5813–5819. https://doi.org/10.1021/es505822f.

(110) Chen, X.; Zhang, H.; Xu, Z.; Nielsen, C. P.; McElroy, M. B.; Lv, J. Impacts of Fleet Types and Charging Modes for Electric Vehicles on Emissions under Different Penetrations of Wind Power. *Nat. Energy* **2018**, *3* (5), 413–421. https://doi.org/10.1038/s41560-018-0133-0.

(111) Jochem, P.; Babrowski, S.; Fichtner, W. Assessing CO2 Emissions of Electric Vehicles in Germany in 2030. *Transp. Res. Part A Policy Pract.* **2015**, *78* (2015), 68–83. https://doi.org/10.1016/j.tra.2015.05.007.

(112) Bellocchi, S.; Gambini, M.; Manno, M.; Stilo, T.; Vellini, M. Positive Interactions between Electric Vehicles and Renewable Energy Sources in CO2-Reduced Energy Scenarios: The Italian Case. *Energy* **2018**, *161* (2018), 172–182. https://doi.org/10.1016/j.energy.2018.07.068.

(113) Jenn, A.; Clark-Sutton, K.; Gallaher, M.; Petrusa, J. Environmental Impacts of Extreme Fast Charging. *Environ. Res. Lett.* **2020**, *15* (9), 094060. https://doi.org/10.1088/1748-9326/ab9870.

(114) Arvesen, A.; Völler, S.; Hung, C. R.; Krey, V.; Korpås, M.; Strømman, A. H. Emissions of Electric Vehicle Charging in Future Scenarios: The Effects of Time of Charging. *J. Ind. Ecol.* **2021**, 1–15. https://doi.org/10.1111/jiec.13144.

(115) California Air Resources Board. Clean Miles Standard 2018 Base-Year Emissions Inventory Report. **2019**, No. December, 8.

(116) California Air Resources Board. *Proposed Clean Miles Standard Regulation Staff Report :*

*Initial Statement of Reasons*; 2021.

(117) National Household Travel Survey https://nhts.ornl.gov/ (accessed Aug 1, 2021).

(118) Taiebat, M.; Brown, A. L.; Safford, H. R.; Qu, S.; Xu, M. A Review on Energy, Environmental, and Sustainability Implications of Connected and Automated Vehicles. *Environ. Sci. Technol.* **2018**, *52* (20), 11449–11465. https://doi.org/10.1021/acs.est.8b00127.

(119) Bauer, G. S.; Greenblatt, J. B.; Gerke, B. F. Cost, Energy, and Environmental Impact of Automated Electric Taxi Fleets in Manhattan. *Environ. Sci. Technol.* **2018**, *52* (8), 4920–4928. https://doi.org/10.1021/acs.est.7b04732.

(120) Tal, G.; Srinivasa Raghavan Vaishnavi Chaitanya Karanam Matthew Favetti Katrina May Sutton Jade Motayo Ogunmayin Jae Hyun Lee, S. P.; Nitta, C.; Kurani, K.; Chakraborty, D.; Nicholas, M.; Turrentine, T. *Advanced Plug-in Electric Vehicle Travel and Charging Behavior Final Report (CARB Contract 12-319)*; 2020.

(121) Nicholas, M. A.; Tal, G.; Turrentine, T. S. Advanced Plug-in Electric Vehicle Travel and Charging Behavior Interim Report. **2017**.