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An integrated optimization platform for spatial-temporal modeling of electric vehicle charging infrastructure

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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 significantly 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%) (US EPA, 2021). 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 (US EPA, 2021). Widespread adoption of plug-in electric vehicles (PEVs), which include both battery electric vehicles

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(BEVs) and plug-in hybrid electric vehicles (PHEVs), dominates the emerging revolutions in passenger transportation's transition to sustainable mobility (Sperling, 2018).

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) (Asensio et al., 2020; Coffman et al., 2017; Greene et al., 2020; Noel et al., 2020). Battery range constraints, both real and imagined, are one of the most significant barriers to large-scale acceptance of BEVs in the market (Mandys, 2021). Developing a dedicated recharging infrastructure system may alleviate range anxiety and encourage more consumers to purchase electric vehicles (Guo et al., 2018; McCollum et al., 2018). 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 (California Public Utilities Commission, 2019).

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 (Davidov, 2020; Ghamami et al., 2020; Kavianipour et al., 2021; Roni et al., 2019; Wang et al., 2018). 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 (Woods et al., 2017). Some utilize GPS travel survey data (Kontou et al., 2019), or empirical trip trajectory data from portable devices (Shahraki et al., 2015; Vazifeh et al., 2019). 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 (Wolbertus et al., 2021), vehicle attributes such as the initial state of charge variations, range anxiety, charging delay and queuing delay (Kavianipour et al., 2021), or a more nuanced model of the decision to charge that balances tradeoffs people make with regards to time, cost, convenience, and range anxiety (Sheppard et al., 2017). 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 (Pruckner et al., n.d.); 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 (Roni et al., 2019) 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 (Chakraborty et al., 2019). 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 (Awasthi et al., 2017; Liu et al., 2018; Pan and Zhang, 2016) 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 (Deb et al., 2018).

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 (Cai et al., 2014; Shahraki et al., 2015; Wolbertus et al., 2021), 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 (Sathaye and Kelley, 2013; Wang et al., 2018) 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 (Chen et al., 2013; Dong et al., 2014; Kontou et al., 2019), and the most common location for PEV charging is at home, followed by work, and then public locations (Hardman et al., 2018). 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 (Ghamami et al., 2020) only considered long-distance intercity trips; (Huang and Zhou, 2015) designed an optimization model only for workplace charging; and some other studies only optimized fast charging system (Kavianipour et al., 2021; Zhang et al., 2015). 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 (Yi et al., 2020) 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

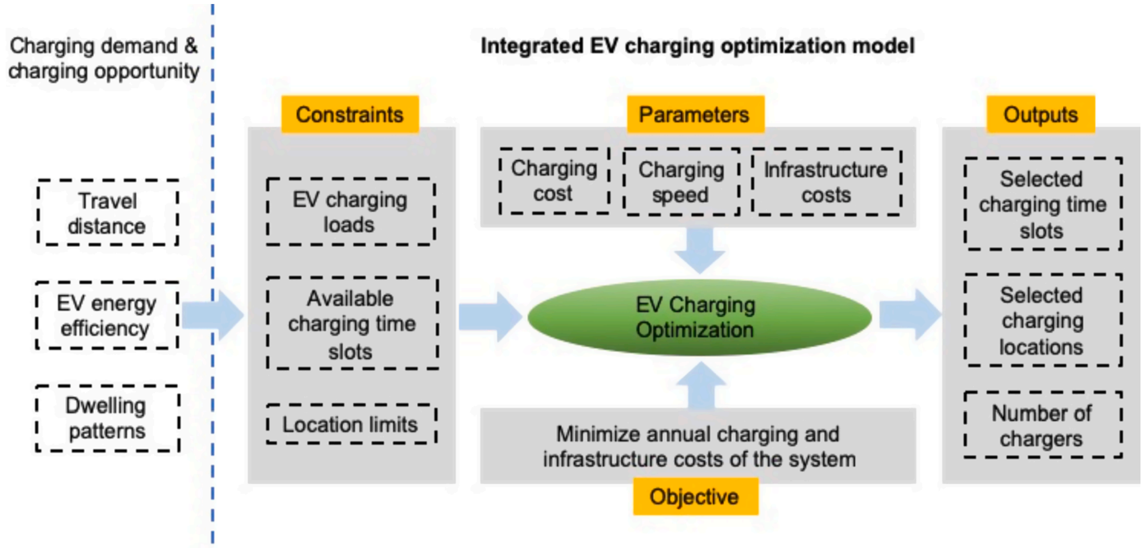

Fig. 1. A modeling framework for the Integrated Electric Vehicle Charging Optimization.

placement of charging infrastructures of all levels. Lastly, many existing models simply assume that vehicles are fully charged when leaving for work (Ghamami et al., 2020; Ji et al., 2015; Shahraki et al., 2015), but in reality, this is not always the case and BEV owners may have more complex charging behaviors (Lee et al., 2020).

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 BEV 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 Fig. 1. 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 (California Department of Transportation, 2013); 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 (Melaina, 2014); 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 (California ISO, 2020). 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.

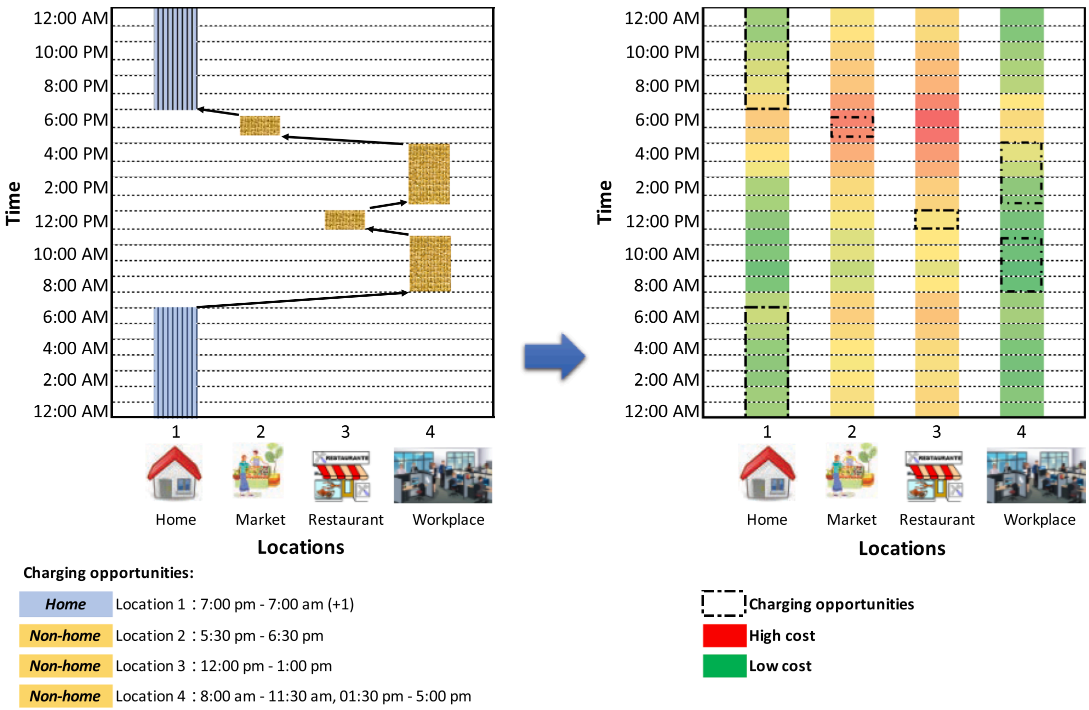

Fig. 2. An illustration of charging opportunity.

2.1. Assessing the distribution of charging opportunity

Understanding spatial-temporal distributions of BEV 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. Fig. 2 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).

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 to 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 to 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

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Sets	
i	individual within the study region, $i = \{1, 2, 3, \ldots, n\}$
r	region, at census track level, r = {1, 2, …, m}
t	time slot, refering to each hour of a day, $t = \{1, 2, \ldots, 24\}$
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, $x_{irtl}^{homeTime}$ 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 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 BEV 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:

$$\mathrm{Min}_{wrt x_{irtl}^{homeTime}, x_{irtl}^{nonhomeTime}, x_{rl}^{homeCharger}, x_{rl}^{nonhomeCharger}} y^{totalCost} \tag{1}$$

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

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

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

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, which is calculated based on average daily travel distance and the efficiency of electric vehicles.

$$\sum_{trl} (x_{itrl}^{homeTime} p_l^{homePower} + x_{itrl}^{nonhomeTime} p_l^{nonhomePower}) \geq e_i^{Demand}, \forall i \tag{2}$$

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

$$0 \leq x_{itrl}^{homeTime} \leq 1, 0 \leq x_{itrl}^{nonhomeTime} \leq 1 \tag{3}$$

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	$1,993
Power (kw)	**High**	1.9	19.2	19.2	90
	Medium	1.7	7.0	7.0	50
	Low	1.4	6.0	6.0	20
Charging price ($/kWh)			LMP		

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

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

$$x_{itrl}^{homeTime} \le d_{itr}^{homeDwellingTime}, x_{itrl}^{nonhomeTime} \le d_{itr}^{nonhomeDwellingTime}, \forall itr \tag{4}$$

(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 Eqs. (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.

$$\sum_i x_{itrl}^{nonhomeTime} w_i \le x_{rl}^{nonhomeCharger}, \forall rtl \tag{5}$$

$$x_{itrl}^{homeTime} \le x_{irl}^{homeCharger}, \forall irl \tag{6}$$

$$x_{rl}^{homeCharger} = \sum_i x_{irl}^{chosenCharger} w_i \tag{7}$$

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 (California Department of Transportation, 2013). 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) (California Air Resources Board, 2019) to adjust the Expanded Person Weight in CHTS. More details on the BEV weight correction can be find in Supporting Information.

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 (US DOE, 2019) and EV sales data reported by the Transportation Research Center at Argonne National Laboratory (Gohlke and Zhou, 2020). 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 (California ISO, 2020). 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 (Azevedo et al., 2019). 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 (Melaina, 2014). 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.

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.

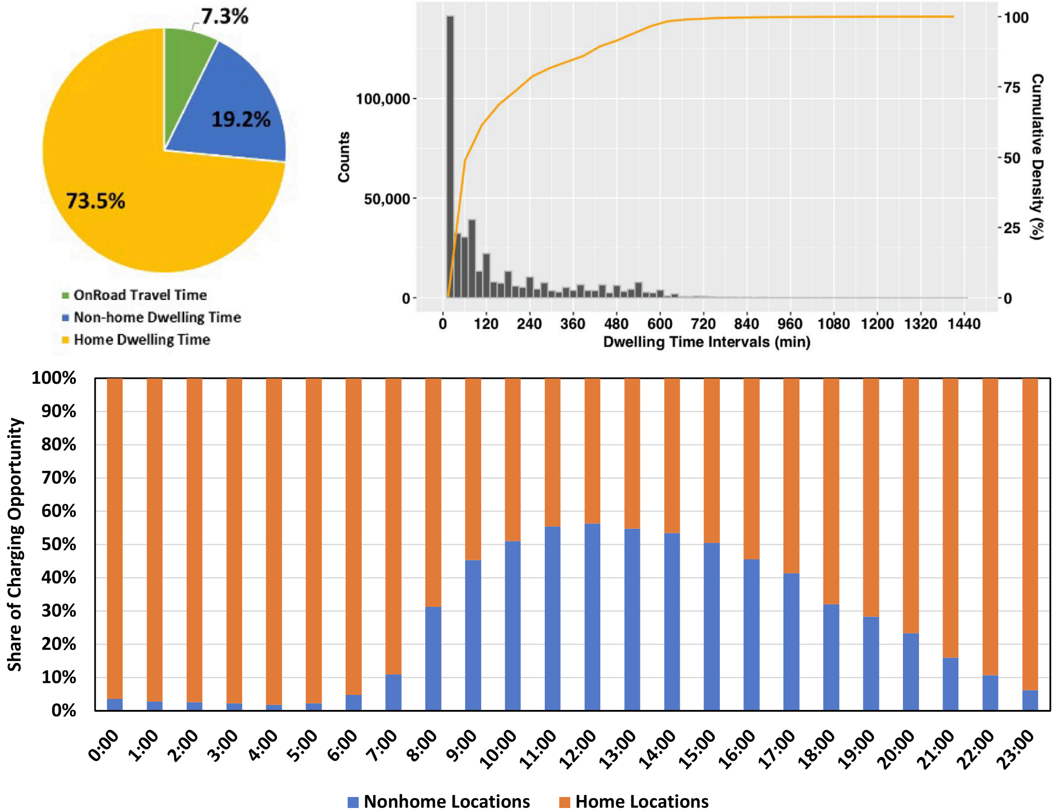

Fig. 3. Timeshare and temporal charging opportunity distributions.

3. Results

3.1. Spatial-temporal distribution of EV charging opportunity in California

Fig. 3 (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 h. This result is consistent with other studies based on the National Household Travel Survey (NHTS) (Zhang et al., 2011). 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 Fig. 3 (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.

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 Fig. 3 (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

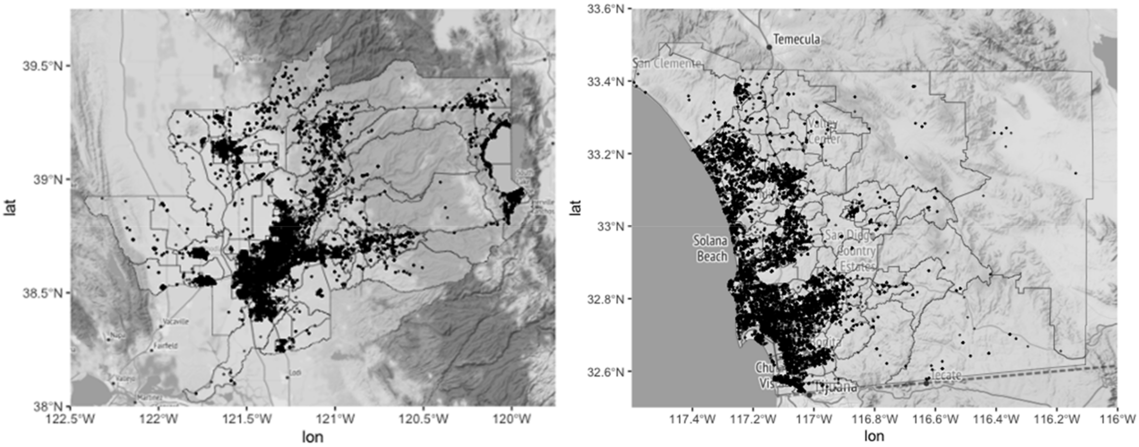

Fig. 4. Daily dwelling locations of BEV drivers in the study areas: Greater Sacramento Area (left) and San Diego (right).

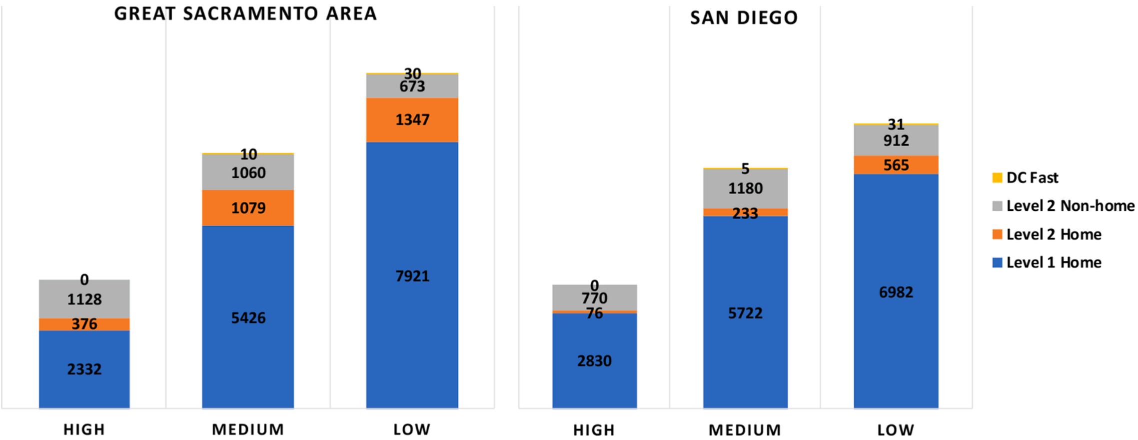

Fig. 5. The optimal number of charging stations required under each scenario for both study domains.

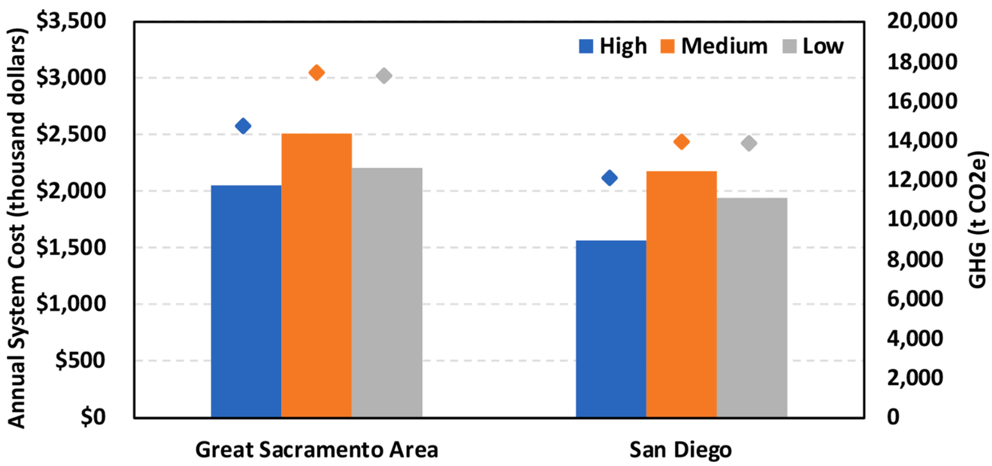

Fig. 6. A comparison of charging infrastructure systems in total annual system costs (bars) and the GHG emissions (dots) between Great Sacramento Area and San Diego.

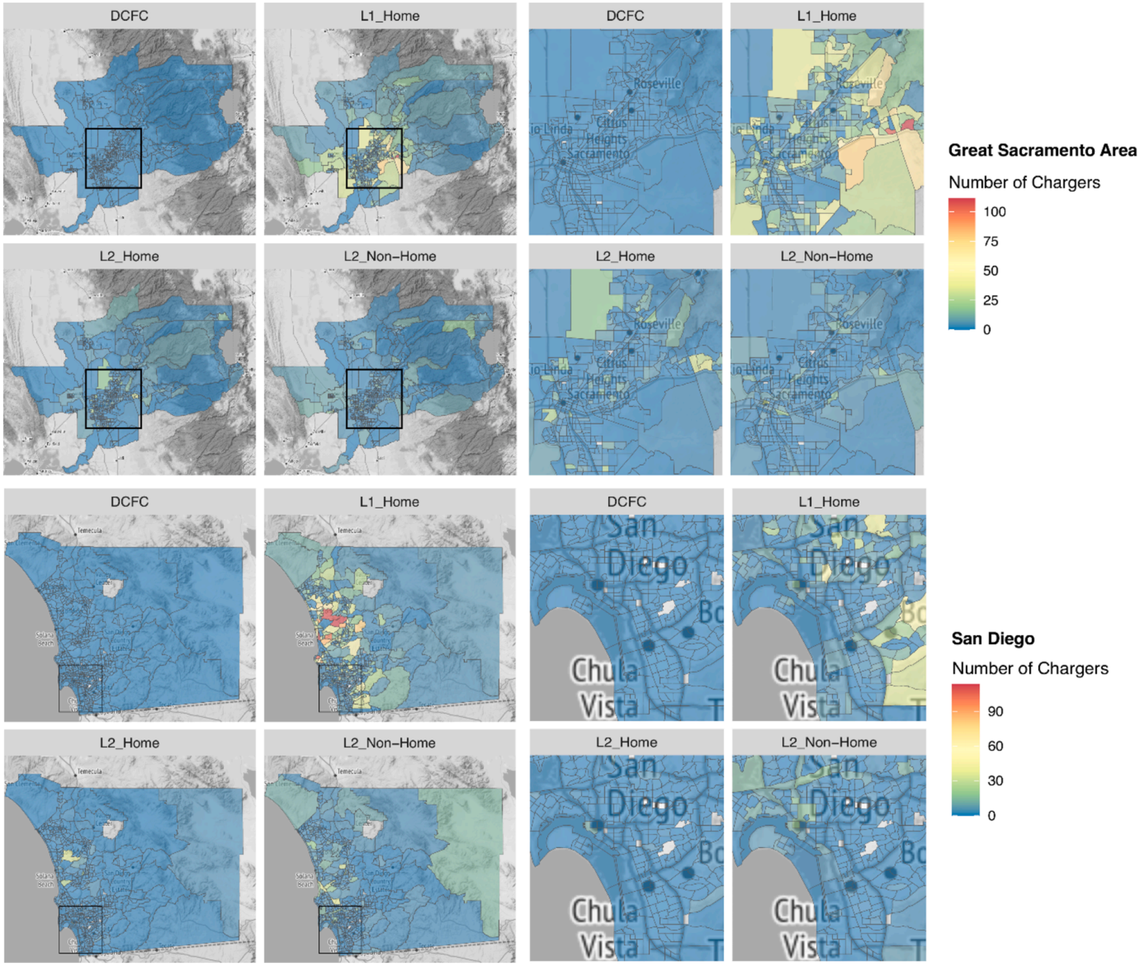

Fig. 7. Distribution of chargers in the Great Sacramento Area (top) and San Diego (bottom), medium cost scenario.

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. Fig. 4 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%.

We display the optimal number of charging stations required under each cost scenario for both study domains in Fig. 5. 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.

3.2.1. Costs and environmental impacts

The total annual system costs and the GHG impacts for both study areas are compared in Fig. 6. 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,

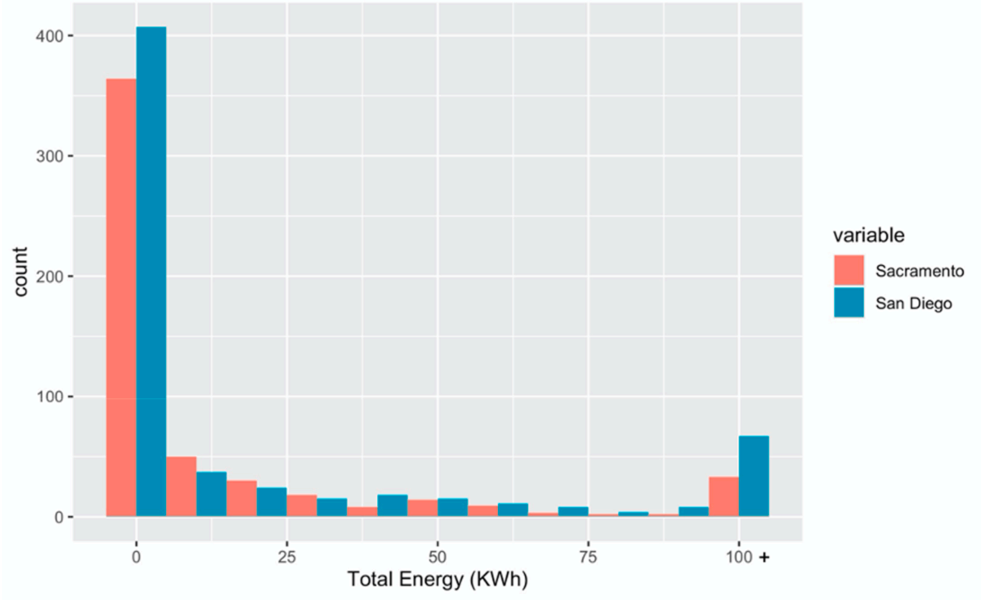

Fig. 8. Distributions of census tract charging loads in the Great Sacramento Area (red) and San Diego (blue), medium cost scenario. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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.

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 Fig. 7, 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.

3.2.3. *EV charging grid impacts*

Fig. 8 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

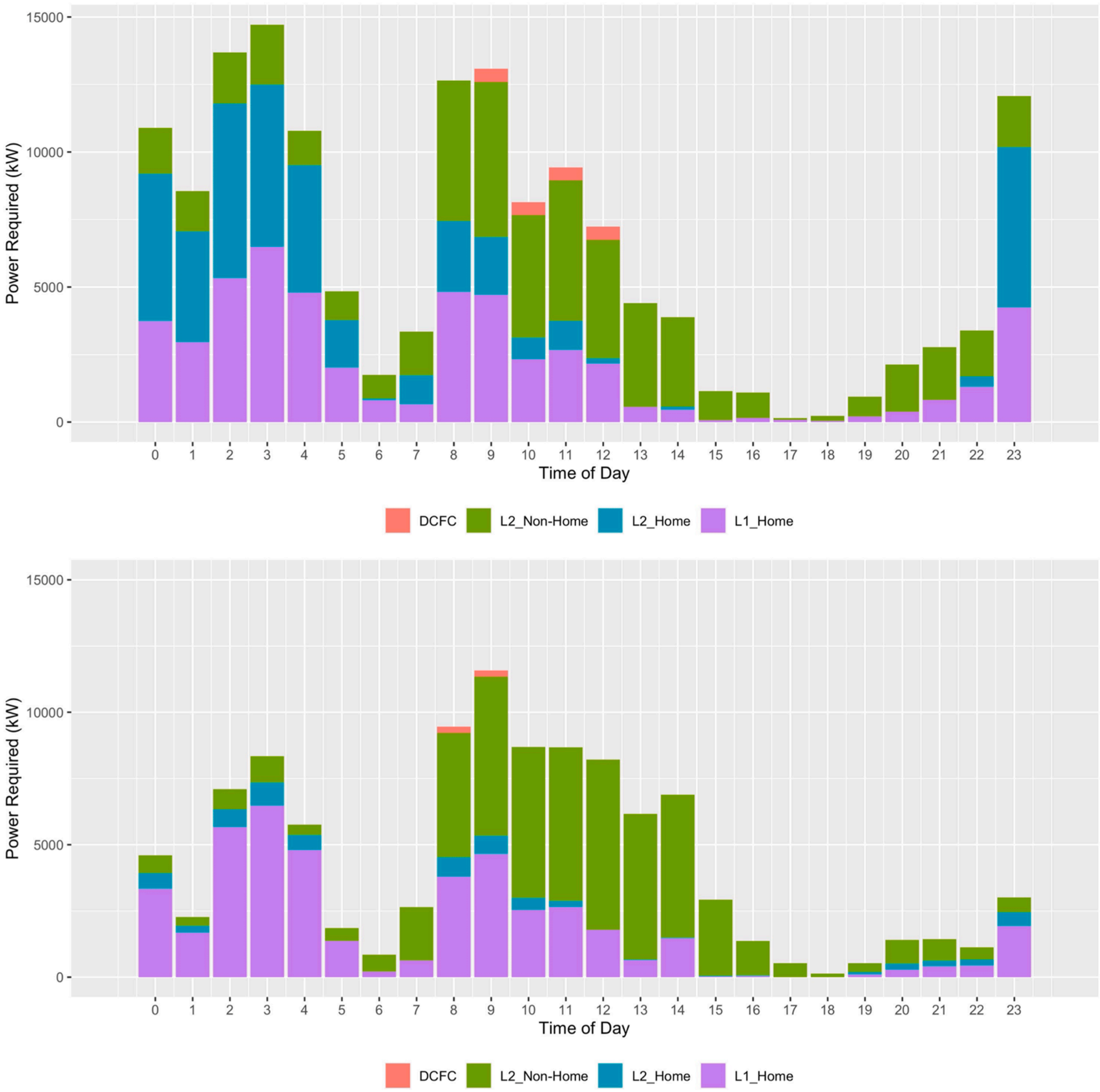

Fig. 9. EV charging power demands in the Great Sacramento Area (top) and San Diego (bottom), medium cost scenario.

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.

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. Fig. 9 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 (Fig. 9, 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 (Fig. 9, 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.

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.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting Information

BEV weight correction (Eq.S1); Convergence of the average results for spatial charger distributions (Figure SI-1, Figure SI-2, and Figure SI-3); Top 50 values of the spatial and temporal distribution of the energy demand (Table S1-1 and Table SI-2); Spatial and temporal power requirements of the med-cost scenario (Figure SI-4 and Figure SI-5). Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2022.103177.

References

Asensio, O.I., Alvarez, K., Dror, A., Wenzel, E., Hollauer, C., Ha, S., 2020. Real-time data from mobile platforms to evaluate sustainable transportation infrastructure. Nat. Sustain. 3 (6), 463–471. https://doi.org/10.1038/s41893-020-0533-6.

Awasthi, A., Venkitusamy, K., Padmanaban, S., Selvamuthukumaran, R., Blaabjerg, F., Singh, A.K., 2017. Optimal planning of electric vehicle charging station at the distribution system using hybrid optimization algorithm. Energy 133, 70–78. https://doi.org/10.1016/j.energy.2017.05.094.

Azevedo, I., Donti, P., Horner, N., Schivley, G., Siler-Evans, K., Vaishnav, P., 2019. Electricity Marginal Factor Estimates [WWW Document]. Cent. Clim. Energy Decis. Making. Pittsburgh Carnegie Mellon Univ. URL http://cedmcenter.org.

Cai, H., Jia, X., Chiu, A.S.F., Hu, X., Xu, M., 2014. Siting public electric vehicle charging stations in Beijing using big-data informed travel patterns of the taxi fleet. Transp. Res. Part D Transp. Environ. 33, 39–46. https://doi.org/10.1016/j.trd.2014.09.003.

California Air Resources Board, 2019. Clean Vehicle Rebate Project Rebate Statistics [WWW Document]. URL https://cleanvehiclerebate.org/eng/rebate-statistics.

California Department of Transportation, 2013. 2010-2012 California Household Travel Survey Final Report 1–349.

California ISO, 2020. Market price maps [WWW Document]. URL http://www.caiso.com/PriceMap/Pages/default.aspx.

California Public Utilities Commission, 2019. Zero-Emission Vehicles [WWW Document]. URL http://www.cpuc.ca.gov/zev/.

Chakraborty, D., Bunch, D.S., Lee, J.H., Tal, G., 2019. Demand drivers for charging infrastructure-charging behavior of plug-in electric vehicle commuters. Transp. Res. Part D Transp. Environ. 76, 255–272. https://doi.org/10.1016/j.trd.2019.09.015.

Chen, T.D., Kockelman, K.M., Khan, M., 2013. Locating Electric Vehicle Charging Stations. Transp. Res. Rec. J. Transp. Res. Board 2385 (1), 28–36. https://doi.org/10.3141/2385-04.

Coffman, M., Bernstein, P., Wee, S., 2017. Electric vehicles revisited: a review of factors that affect adoption. Transp. Rev. 37 (1), 79–93. https://doi.org/10.1080/01441647.2016.1217282.

Davidov, S., 2020. Optimal charging infrastructure planning based on a charging convenience buffer. Energy 192, 116655. https://doi.org/10.1016/j.energy.2019.116655.

Deb, S., Tammi, K., Kalita, K., Mahanta, P., 2018. Review of recent trends in charging infrastructure planning for electric vehicles. Wiley Interdiscip. Rev. Energy Environ. 7 (6) https://doi.org/10.1002/wene.2018.7.issue-610.1002/wene.306.

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

Ghamami, M., Kavianipour, M., Zockaie, A., Hohnstadt, L.R., Ouyang, Y., 2020. 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. 120, 102802. https://doi.org/10.1016/j.trc.2020.102802.

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

Greene, D.L., Kontou, E., Borlaug, B., Brooker, A., Muratori, M., 2020. Public charging infrastructure for plug-in electric vehicles: What is it worth? Transp. Res. Part D Transp. Environ. 78, 102182. https://doi.org/10.1016/j.trd.2019.11.011.

Guo, F., Yang, J., Lu, J., 2018. The battery charging station location problem: Impact of users' range anxiety and distance convenience. Transp. Res. Part E Logist. Transp. Rev. 114, 1–18. https://doi.org/10.1016/J.TRE.2018.03.014.

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

Huang, Y., Zhou, Y., 2015. An optimization framework for workplace charging strategies. Transp. Res. Part C Emerg. Technol. 52, 144–155. https://doi.org/10.1016/j.trc.2015.01.022.

Ji, W., Nicholas, M., Tal, G., 2015. Electric vehicle fast charger planning for metropolitan planning organizations: Adapting to changing markets and vehicle technology. Transp. Res. Rec. 2502 (1), 134–143.

Kavianipour, M., Fakhrmoosavi, F., Singh, H., Ghamami, M., Zockaie, A., Ouyang, Y., Jackson, R., 2021. Electric vehicle fast charging infrastructure planning in urban networks considering daily travel and charging behavior. Transp. Res. Part D Transp. Environ. 93, 102769. https://doi.org/10.1016/j.trd.2021.102769.

Kontou, E., Liu, C., Xie, F., Wu, X., Lin, Z., 2019. Understanding the linkage between electric vehicle charging network coverage and charging opportunity using GPS travel data. Transp. Res. Part C Emerg. Technol. 98, 1–13. https://doi.org/10.1016/j.trc.2018.11.008.

Lee, J.H., Chakraborty, D., Hardman, S.J., Tal, G., 2020. Exploring electric vehicle charging patterns: Mixed usage of charging infrastructure. Transp. Res. Part D Transp. Environ. 79, 102249. https://doi.org/10.1016/j.trd.2020.102249.

Liu, J.-P., Zhang, T.-x., Zhu, J., Ma, T.-N., 2018. Allocation optimization of electric vehicle charging station (EVCS) considering with charging satisfaction and distributed renewables integration. Energy 164, 560–574. https://doi.org/10.1016/j.energy.2018.09.028.

Mandys, F., 2021. Electric vehicles and consumer choices. Renew. Sustain. Energy Rev. 142, 110874. https://doi.org/10.1016/j.rser.2021.110874.

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.Ó., Paroussos, L., Pettifor, H., Ramea, K., Riahi, K., Sano, F., Rodriguez, B.S., van Vuuren, D.P., 2018. Interaction of consumer preferences and climate policies in the global transition to low-carbon vehicles. Nat. Energy 3 (8), 664–673. https://doi.org/10.1038/s41560-018-0195-z.

Melaina, M.W., 2014. Retail Infrastructure Costs Comparison for Hydrogen and Electricity for Light-Duty Vehicles, in: SAE Technical Paper Series. https://doi.org/10.4271/2014-01-1969.

Noel, L., Zarazua de Rubens, G., Kester, J., Sovacool, B.K., 2020. Understanding the socio-technical nexus of Nordic electric vehicle (EV) barriers: A qualitative discussion of range, price, charging and knowledge. Energy Policy 138, 111292. https://doi.org/10.1016/j.enpol.2020.111292.

Pan, Z.J., Zhang, Y., 2016. A novel centralized charging station planning strategy considering urban power network structure strength. Electr. Power Syst. Res. 136, 100–109. https://doi.org/10.1016/j.epsr.2016.01.019.

Pruckner, M., German, R., Eckhoff, D., n.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.

Roni, M.S., Yi, Z., Smart, J.G., 2019. Optimal charging management and infrastructure planning for free-floating shared electric vehicles. Transp. Res. Part D Transp. Environ. 76, 155–175. https://doi.org/10.1016/j.trd.2019.09.021.

Sathaye, N., Kelley, S., 2013. An approach for the optimal planning of electric vehicle infrastructure for highway corridors. Transp. Res. Part E Logist. Transp. Rev. 59, 15–33. https://doi.org/10.1016/j.tre.2013.08.003.

Shahraki, N., Cai, H., Turkay, M., Xu, M., 2015. Optimal locations of electric public charging stations using real world vehicle travel patterns. Transp. Res. Part D Transp. Environ. 41, 165–176. https://doi.org/10.1016/j.trd.2015.09.011.

Sheppard, C., Waraich, R., Campbell, A., Pozdnukhov, A., Gopal, A.R., 2017. Modeling plug-in electric vehicle charging demand with BEAM.

Sperling, D., 2018. Three revolutions: steering automated, shared, and electric vehicles to a better future. Island Press.

US DOE, 2019. Fuel Economy Guide [WWW Document]. URL https://www.fueleconomy.gov/feg/printGuides.shtml.

US EPA, 2021. Inventory of U.S. greenhouse gas emissions and sinks. 1990–2019, Federal Register.

Vazifeh, M.M., Zhang, H., Santi, P., Ratti, C., 2019. Optimizing the deployment of electric vehicle charging stations using pervasive mobility data. Transp. Res. Part A Policy Pract. 121, 75–91. https://doi.org/10.1016/J.TRA.2019.01.002.

Wang, Y., Shi, J., Wang, R., Liu, Z., Wang, L., 2018. Siting and sizing of fast charging stations in highway network with budget constraint. Appl. Energy 228, 1255–1271. https://doi.org/10.1016/j.apenergy.2018.07.025.

Wolbertus, R., van den Hoed, R., Kroesen, M., Chorus, C., 2021. 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. 148, 262–285. https://doi.org/10.1016/j.tra.2021.04.010.

Woods, E., Rames, C., Muratori, M., Raghavan, S., Melaina, M., NREL, 2017. National Plug-In Electric Vehicle Infrastructure Analysis. https://doi.org/10.13140/RG.2.2.25881.93280.

Yi, T., Zhang, C., Lin, T., Liu, J., 2020. Research on the spatial-temporal distribution of electric vehicle charging load demand: a case study in China. J. Clean. Prod. 242, 118457. https://doi.org/10.1016/j.jclepro.2019.118457.

Zhang, L.i., Brown, T., Samuelsen, G.S., 2011. Fuel reduction and electricity consumption impact of different charging scenarios for plug-in hybrid electric vehicles. J. Power Sources 196 (15), 6559–6566. https://doi.org/10.1016/j.jpowsour.2011.03.003.

Zhang, L., Shaffer, B., Brown, T., Scott Samuelsen, G., 2015. The optimization of DC fast charging deployment in California. Appl. Energy 157, 111–122. https://doi.org/10.1016/j.apenergy.2015.07.057.