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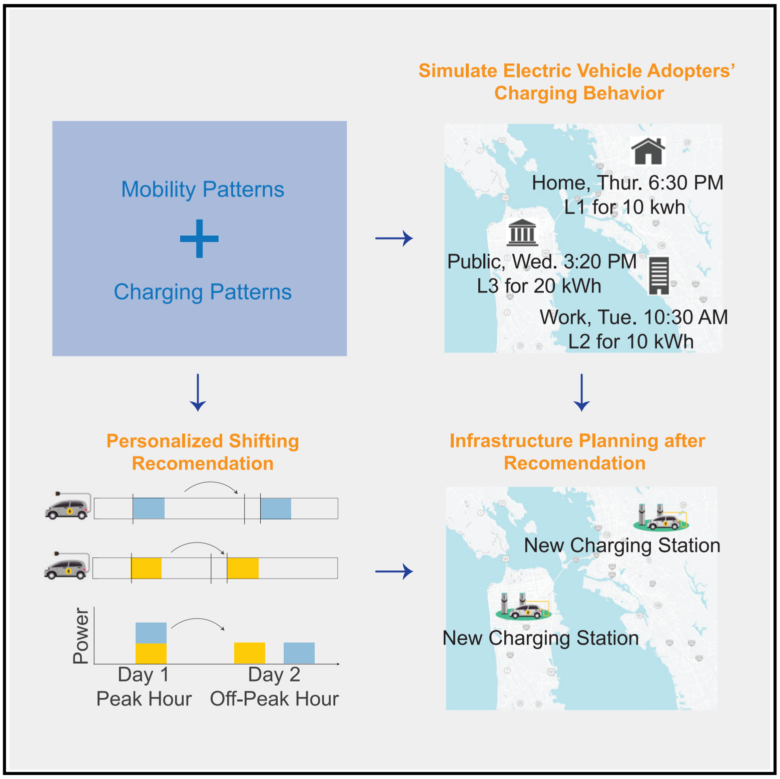
Planning charging stations for 2050 to support flexible electric vehicle demand considering individual mobility patterns

Graphical abstract



Highlights

- Individual mobility and charging patterns shape future electric vehicle demand
- Personalized shifting recommendations can effectively reduce peak-hour charging
- More public charging stations facilitate a shift away from the evening peak
- We recommend expanding daytime charging capacity in the San Francisco Bay Area

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In brief

Planning for electric vehicle (EV) charging stations must consider driver behavior and impacts on the power grid. Wu et al. reveal the value of personalized charging recommendations to shift EV charging away from grid peak hours in California. Daytime charging capacity should be expanded to maximize potential benefits.

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Planning charging stations for 2050 to support flexible electric vehicle demand considering individual mobility patterns

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SCIENCE FOR SOCIETY The electrification of transportation stands as a promising avenue for emissions reduction. To promote the widespread adoption of electric vehicles (EVs), we need to plan strategically their future charging infrastructure. To that end, we must account for diverse charging habits, mobility patterns, and effective grid management. Our research presents an approach to assess personalized recommendations that adapt charging schedules to alleviate the strain on the grid during its busiest evening hours. Based on data-informed activity patterns, we deploy public charging stations to support this shifted demand. The proposed framework offers strategies to cater to the needs of urban areas facing escalating demands of charging while taking into account the varying levels of EV adoption. Our findings reveal the potential for flexible EV charging scheduling without compromising driver mobility while highlighting the pivotal role of public charging in harnessing this newfound flexibility.

SUMMARY

With the widespread adoption of electric vehicles (EVs), it is crucial to plan for charging in a way that considers both EV driver behavior and the electricity grid's demand. Here, we integrate detailed mobility data with empirical charging preferences to estimate charging demand and demonstrate the power of personalized shifting recommendations to move individual EV drivers' demand on the grid out of peak hours. We find an unbalanced geographical distribution of charging demand in the San Francisco Bay Area, with temporal peaks in both grid off-peak hours in the morning and on-peak hours in the evening. Aligning with mobility patterns, our strategy effectively shifts demand to off-peak times. With the 2050 target of 90% EVs, this shifting reduces total on-peak charging demand by 61%, which could require over ∼18,000 additional level 3 chargers. We recommend building more charging stations and implementing shifting recommendations for EV grid integration.

INTRODUCTION

The transportation sector is a major contributor to global carbon emissions. In 2021, the energy consumed by transportation activities accounted for 38% of the total energy consumption worldwide, with a majority derived from fossil fuels.[1] The electrification of transportation is an essential part of global plans to reduce emissions,[2,3] and many countries have introduced policies to promote electric vehicle (EV) adoption.[4–6] The California Air Resources Board's recent roadmap sets the goal that 100% of new cars sold in California will be zero-emission vehicles by 2035,[7] demonstrating the state's increasing momentum and dedication toward the widespread adoption of EVs. Similarly, the Bay Area Air Quality Management District has set a target that 90% of vehicles, not just sales, will be zero emissions by 2050.[8] Rapid growth in the EV market will need to continue for that state to reach these goals, increasing from 19% of sales in 2022.[9]

However, the increasing number of EVs brings challenges to the electricity system. For one, the current charging infrastructure is insufficient to support the increasing charging demand.[10] The electricity grid's generation capacity must be considered in planning for future charging infrastructure.[11,12] With the increase in the number of EVs, peak demand on the grid will also increase. This can cause damage to grid infrastructure.[13] Moreover, when high peak demand coincides with periods of low renewable generation, as in the evening in California, adding demand can increase emissions.[14]

The strategy for planning future charging infrastructure considering its impacts on the grid focuses on the following two key elements: (1) estimating EV charging demand and (2) developing and testing a plan to manage this demand to protect the grid.

To estimate charging demand, we need to understand the mobility and charging patterns of EV adopters.[15] Previous research on mobility behaviors has primarily analyzed adopters based on Global Positioning System (GPS) travel histories of small numbers of drivers,[16,17] various surveys where drivers recount their recent trips,[18,19] or origin/destination matrix data of the territory.[20] This line of research is limited by the size and resolution of the data and does not capture the full variation observed in large-scale, real, individual-level mobility behavior. Other studies are focused on charging patterns, using statistical representations,[21,22] clustering of charging sessions,[23] or agent-based modeling,[24] to characterize individuals' charging patterns. Existing research on mobility and charging patterns finds that potential changes in plug-in behavior could most impact demand in urban areas[25] and that clustering effects in vehicle adoption at the local level could lead to areas with high plug-in electric vehicle (PEV) concentrations even before we see widespread adoption.[26]

However, none of these connect the rich, heterogeneous charging patterns and drivers' mobility patterns that can be obtained from empirical data. To bridge the gap between mobility-based studies and charging-based studies, we propose a framework that outputs individual spatial and temporal profiles of charging demand. Compared with previous research, the framework captures true and individual behavior patterns based on unique charging and mobility data sources. Combining charging and mobility patterns also enables the exploration of geographical patterns in charging demand, which is understudied in previous research.

Moreover, beyond understanding today's charging, studying future charging demand under widespread EV adoption presents significant challenges,[27,28] as it requires models that consider the different situations,[29] mobility diversity,[30] and charging patterns[31] among future adopters. As a result, few models of deep adoption scenarios try to capture the differences between today's drivers and future drivers. In this work, we incorporate data on income, housing type, charging access, mobility patterns, and charging patterns to capture the evolution of charging demand and infrastructure use in the Bay Area from 2019 to 2050.

After estimating the spatiotemporal charging demand of EVs, planners can leverage its flexibility for different objectives.[32,33] One approach widely used to mitigate the impact of EVs on the electricity grid is to treat them as centrally controlled, dispatchable assets, used for example to help manage peak demand,[34,35] reduce operation costs,[36–38] reduce the need for battery storage,[39,40] or integrate renewables.[41,42] Estimates of the value of such control in California range from $5.6 per driver in 2018[30] to as much as $87 per driver in 2s45.[43] This area of research has largely focused on aggregate-level analysis due to data limitations and associated modeling challenges.[44,45] Based on the individual variations observed in data, however, such aggregated approaches likely misrepresent charging demand.[46] Moreover, this approach almost always uses direct automated control that assumes the deployment of costly communications infrastructure and ignores social and regulatory barriers related to privacy concerns or loss of control.[47]

Recent developments have highlighted the power of other forms of control. Instead of relying on expensive communication infrastructure dedicated to centralized charging control, they suggest utilizing existing communication infrastructure and the deployment of different charging infrastructure to encourage drivers to shift home charging toward daytime charging[12] or to delay home charging and add workplace charging.[48] These two strategies both relieved pressure on the grid by avoiding peak evening hours and making better use of renewable generation. This strategy is complementary to the centralized control approach: Zhang et al. found that California needs more public and workplace charging stations to realize the full flexibility potential of California EV demand,[49] and Kara et al. found higher demand flexibility with fewer sessions per charging station.[50] Another stream of research looks at the benefits of charging flexibility under different electricity price designs. In a study of California in 2025, Szinai et al. found that controlled charging could reduce grid costs by up to 10% and recommended the use of daytime time-of-use pricing periods.[42] Focusing on San Diego, Li and Jenn found that time-of-use pricing with low overnight periods could decrease costs but increase emissions by as much as 20.2%.[51]

This focus on shifting within sessions and within a single day, however, misses an opportunity to leverage drivers' flexibility across plug-in events and across days. In a 2021 demonstration involving over 400 drivers from the California Bay Area, Spencer et al. found that 15%–30% of charging demand could be shifted into or out of a given hour, and drivers could plug in up to 46% more often, using just simple signals and small monetary incentives.[52] In the demonstration, participants received notifications, provided information, and opted in or out of control through a cellphone app.

Though many control studies have called for more public charging stations to increase EV demand flexibility, a few have quantified the increase needed. Most literature on public charging infrastructure focuses on its role in supporting EV adoption: Ledna et al. found that investments in public charging could be more cost-effective than purchase subsidies to boost EV adoption in California;[28] Levinson and West found that a national network of public charging could increase electrified mileage by 8%, although little of the infrastructure cost should be passed on to the drivers;[53] and Greene et al. found willingness to pay for a public charger in California in 2017 could range from $1,500 to $6,500.[54] In comparison with other leading markets, the United States has a low ratio of EVs to public charging

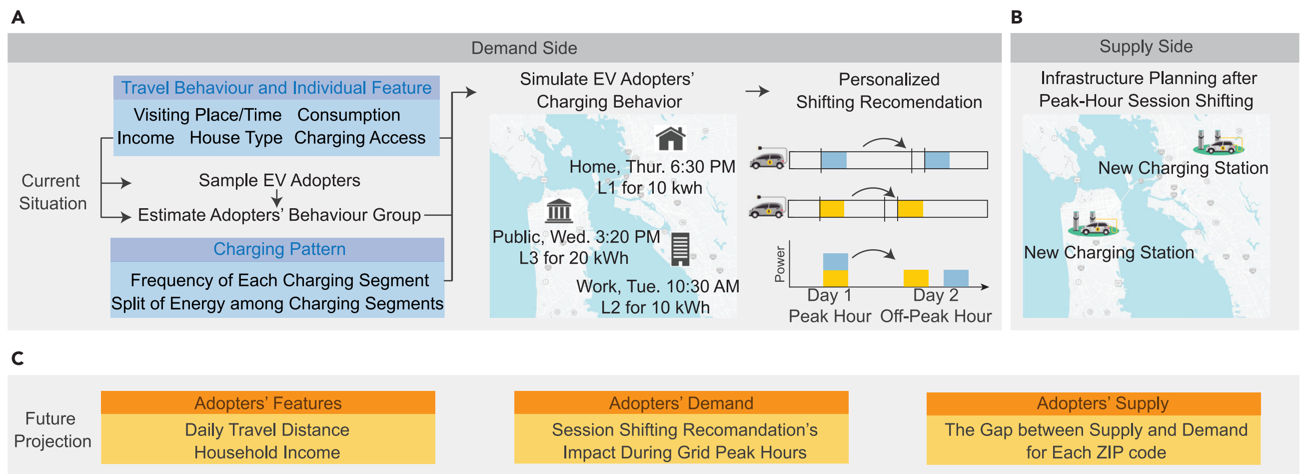

Figure 1. Overview of the proposed framework for understanding and planning future EV charging needs

(A) We analyze the current charging demand by extracting residents' travel behavior and individual features, including visiting places and time, energy consumption, income, house type, and charging access, to sample potential EV adopters and assign them a charging behavior group. Based on that, we simulate all EV adopters' charging behavior in a week, this includes charging location, session start and end time, energy, and power level. We propose personalized shifting recommendations to mitigate the impact of EV charging on grid peak hours. For example, EV adopters may shift their charging sessions from day 1 peak hour to day 2 off-peak hour when feasible.

(B) Supply-side management means planning for infrastructure capacity at the ZIP code level, considering demand both before and after the proposed personalized shifting recommendations.

(C) Future scenarios capture the evolution of EV adopters' demographic features, charging demand, and the public charging station supply for increasing adoption rates.

points[55] and a high dependence on home charging,[56] but this is expected to change with increasing adoption by residents of apartments or multi-unit dwellings (MUDs).[57] The latest California Energy Commission planning projects a need for nearly 1.2 million public and shared private chargers by the year 2030, just to support the adoption targets.[58]

It is critical that we better understand the connection between demand flexibility, individual mobility and charging patterns, and the build-out of public charging networks. To address this gap in this paper, we propose an approach of personalized shifting recommendations for EV adopters based on their original charging patterns and travel needs, which can reduce the burden on the grid during peak hours. The personalized shifting recommendations advise drivers to shift charging sessions rather than conducting automated control of the load profiles. As a type of control to move demand away from peak hours, the personalized shifting recommendations make use of charging demand flexibility that is quite unique to EVs in a way that is lower cost and more practical than automated control. It can also have higher possible benefits as it considers flexibility across multiple parking events or multiple days, whereas automated control works within a single session. We deep-dive into the implications for charging infrastructure and the number of new public chargers needed to enable this type of control.

In this work, we seek to couple planning for future public charging station supply with managing EV charging needs, aiming to prevent extreme charging demand from occurring during grid peak hours. First, we create a model to analyze the charging and mobility requirements of current EV drivers in the San Francisco Bay Area, California. Then, to prevent EV charging load from contributing to increased power grid demand during peak periods, we implement personalized shifting recommendations to shift charging demand to off-peak periods. Based on personalized recommendations, we quantify how valuable charging demand flexibility could be for reducing peaks and provide insights into the public charging infrastructure planning for 2050 through a model of future adoption.

Figure 1 depicts a summary of the proposed framework. Features of the existing residents are used to sample potential EV adopters, extract their daily mobility motifs, and estimate their charging behavior groups. The motifs provide the travel demand. Each charging behavior group is characterized by a specific charging pattern. Combining the travel demands and charging behavior groups, we can simulate the charging behavior of an EV adopter for a given week. To mitigate the impact that EV charging has on grid on-peak hours, we propose personalized shifting recommendations. The EVs' shifting is constrained by their motifs and charging patterns as we do not assume any change to their travel. We estimate the effects of these personalized shifting recommendations on grid peak (5–8 p.m. on weekdays) and off-peak hours (before 5 p.m. and after 8 p.m. on weekdays and all hours on weekends), as defined by the local utility,[59] at the Zone Improvement Plan (ZIP) code level. To support the changes in charging time, we also provide supply-side planning for charging stations by estimating the infrastructure charging demand and comparing it with the current infrastructure assessment. Finally, we extend our analysis of charging demand vs. public charging station supply analysis to future years, projecting EV adoption rates from 20% to 100% in future scenarios.

RESULTS

EV charging behavior simulation

First, we must understand EV charging demand. In this section, we estimate the demand across charging segments and locations by combining the following two detailed, data-driven models: one for mobility and one for charging behavior groups (presented in full in the experimental procedures section).

We extend the TimeGeo model proposed by Jiang et al.[60] to simulate mobility patterns. The model outputs the trajectories of approximately 6 million residents in the California Bay Area, using datasets of mobile phone activity from 1.39 million Bay Area residents as an input.[30,60] First, we simulate the weekly charging profile for all estimated $\sim$129,000 EV adopters in the Bay Area in 2019.[61] In this research, we model all as battery EVs and not plug-in hybrid EVs. To estimate each driver's energy demand from their travel trajectories, we use a drivetrain model. Second, we assign a home location to each EV driver and sample their demographic information (household income and housing type) based on US Census and American Community Survey data from the year 2019.[62] We use this to estimate the charging access of each EV adopter based on data from a recent California Home Charging Access Survey.[63] Finally, we extend the Scalable Probabilistic Estimates of Electric Vehicle Charging (SPEECh) model presented by Powell et al.[12] to simulate EV charging patterns. The model clusters 136 charging behavior groups and parameterizes these behavior groups on drivers' charging access, battery capacity, and energy needs. Each group represents a specific type of charging pattern including when, where, how, and how much drivers in the group typically charge. This dependence on charging access and energy needs as intermediate factors to assign the EV adopters' charging group lets us simulate the charging behavior of the modeled EV adopters in the Bay Area in 2019 and at future levels of adoption.

Figure 2 summarizes the results of the charging behavior simulations. We present the distribution of charging groups in each ZIP code. We classified the 136 charging behavior groups into four distinct charging group types based on their charging habits: primarily charging at home (home), primarily charging at work (work), primarily charging at public stations (public), and charging at two or more locations (mixed) on a regular basis. Currently, the number of adopters belonging to the work charging group is smaller than those belonging to public charging as less than 50% of the drivers have work charging access.[64] However, if workplace charging access increases, the number of adopters choosing work charging may increase too. Based on present-day charging infrastructure availability, Figure 2A shows that on average, 58% of the adopters fall in the home charging group, followed by 24% who fall in the Public charging group, 10% who fall in the mixed charging group, and 7% who fall in the workplace charging group.

We simulate when, where, how, and how much each adopter charges their car during a week by connecting the charging behavior group with the charging patterns. In order to validate our method, we sample 6% of the drivers and compare their charging load with a same-size sample of drivers from the original charging data (see experimental procedures). We sample drivers according to the charging group distribution of the data. Figure 2B shows the aggregated charging load profile of the data and our simulation, divided by charging location. The total charging load and work charging load match well, whereas the public charging load and home charging load have similar magnitudes but different timing of peak demand. Compared with the charging group distribution for all EV drivers shown in Figure 2A, the validation dataset contains more users belonging to Work charging groups and fewer drivers belonging to the home charging groups. As a result, home charging demand is lower than work charging demand in the validation test.

Figure 2C shows the weekly charging demand of all EV adopters in the Bay Area from 2019, separated by charging location. Home charging has a relatively high charging load during grid on-peak hours of 5–8 p.m. on weekdays. Work charging happens 8–10 a.m. on weekdays during grid off-peak hours. Charging happening in public places shows a more uniform charging load during the day. The combined charging load of the home, work, and public charging creates two peaks, one in off-peak hours and the other in on-peak hours on weekdays. The average maximum is 0.3 molecular weight (MW) both in on-peak and off-peak hours. The range between the 25th and 75th percentiles shown in the shaded areas reveals that for most ZIP codes, the home charging load is relatively flat, but for a few ZIP codes, the home charging load is very high.

Figure 2D depicts the weekly energy needs distributed around the Bay Area. It reveals substantial variation among ZIP codes. In the Bay Area, the average population per ZIP code is around 29,930.[62] We find that the weekly charging needs on the ZIP code level have a mean value of 21 MWh. Home charging needs are much higher than the work charging needs and the public charging needs. The highest home charging needs for a single ZIP code reach 111 MWh, whereas the highest work and public charging needs are 18 and 34 MWh, respectively. The charging energy demand is higher in Santa Clara, San Mateo, and Alameda counties, three adjacent counties located in the San Francisco Bay Area. Santa Clara County is known for its high-tech industry, as it is the location for the headquarters of many large technology companies.

Charging infrastructure planning after personalized shifting recommendations to mitigate peak charging demand based on individual charging and travel behaviors

The EV charging behavior simulation reveals that EVs will cause an additional charging demand peak during grid on-peak hours. To ensure stability and avoid the need for costly peaking plants, we propose a strategy that can reduce EV charging during grid on-peak hours. To achieve this, we consider the individual travel and charging patterns of adopters and customize personalized shifting recommendations for each driver (see experimental procedures). These recommendations identify the feasibility for drivers to move their original charging sessions from peak hours to other stops during off-peak hours by checking several rules. Namely, for a given session planned during grid peak hours, (1) does the driver have a stay at another location during grid off-peak hours within a short time window? And (2) would a shift to that stay be feasible given their individual travel plan? If a

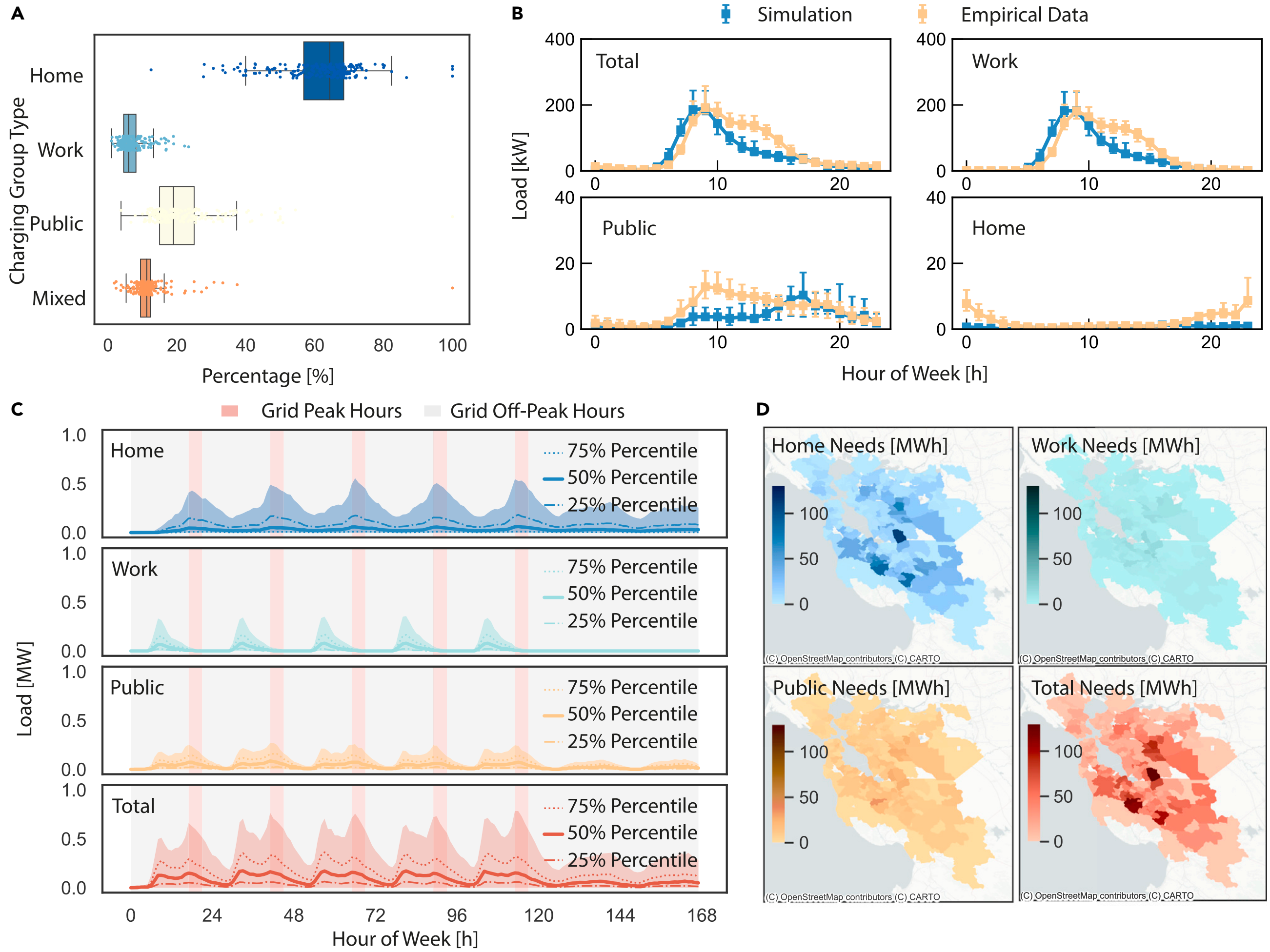

Figure 2. Analysis of EV charging demand

(A) Distribution of the four charging group types in each ZIP code. Each point represents the percentage of adopters belonging to a certain charging group type in one ZIP code.

(B) Comparison between our charging demand simulations and real data. The solid line shows the median of selected EV adopters' charging load, aggregated by ZIP code and charging location. The range from the 5th to the 95th percentile is represented by error bars, highlighting the variance among ZIP codes.

(C) Weekly charging load of ~129,000 simulated EVs; the full Bay Area fleet from 2019. The solid line, dotted line, and dash-dotted line show the 50th, 25th, and 75th percentiles, respectively, of home, work, public, and total charging loads, aggregated by ZIP code.

(D) Geographical distribution of charging needs aggregated by the ZIP codes where the charging sessions occur. We see total charging demand in 2019 is dominated by home charging.

feasible alternative is found, we recommend the drivers to shift their sessions accordingly.

These recommendations can be sent to drivers using existing communication infrastructure through either the vehicle interface or app, reducing a separate and expensive communication infrastructure dedicated to charging control. Most of the new EVs are already equipped with cellular connectivity, enabling them to communicate with backend systems for various services like remote monitoring, software updates, and vehicle diagnostics. We assume that the drivers will fully follow the recommendations. The amount of information shared and compliance with the recommendations would vary in different applications based on privacy regulations and user acceptance. Here, we analyze the best-case impact of the personalized shifting recommendations and estimate the charging infrastructure needed to support it (sensitivity analysis is in Note S1).

Figure 3A illustrates how our personalized shifting recommendations reshape charging load profiles. We observe a total charging peak load reduction of 36 MW during grid on-peak hours and an increase of 39 MW during grid off-peak hours. Home charging accounts for 57% of the total charging peak load reduction in grid peak hours, as it contributes the majority of charging load in peak hours, the hours that are targeted for shifting. Workplace charging comprises 11% of the total charging peak load increase in grid off-peak hours; this fraction is low as workplace charging access is low, and not many sessions can be moved to workplaces. Public charging accounts for 39% of the total charging peak load reduction for grid peak

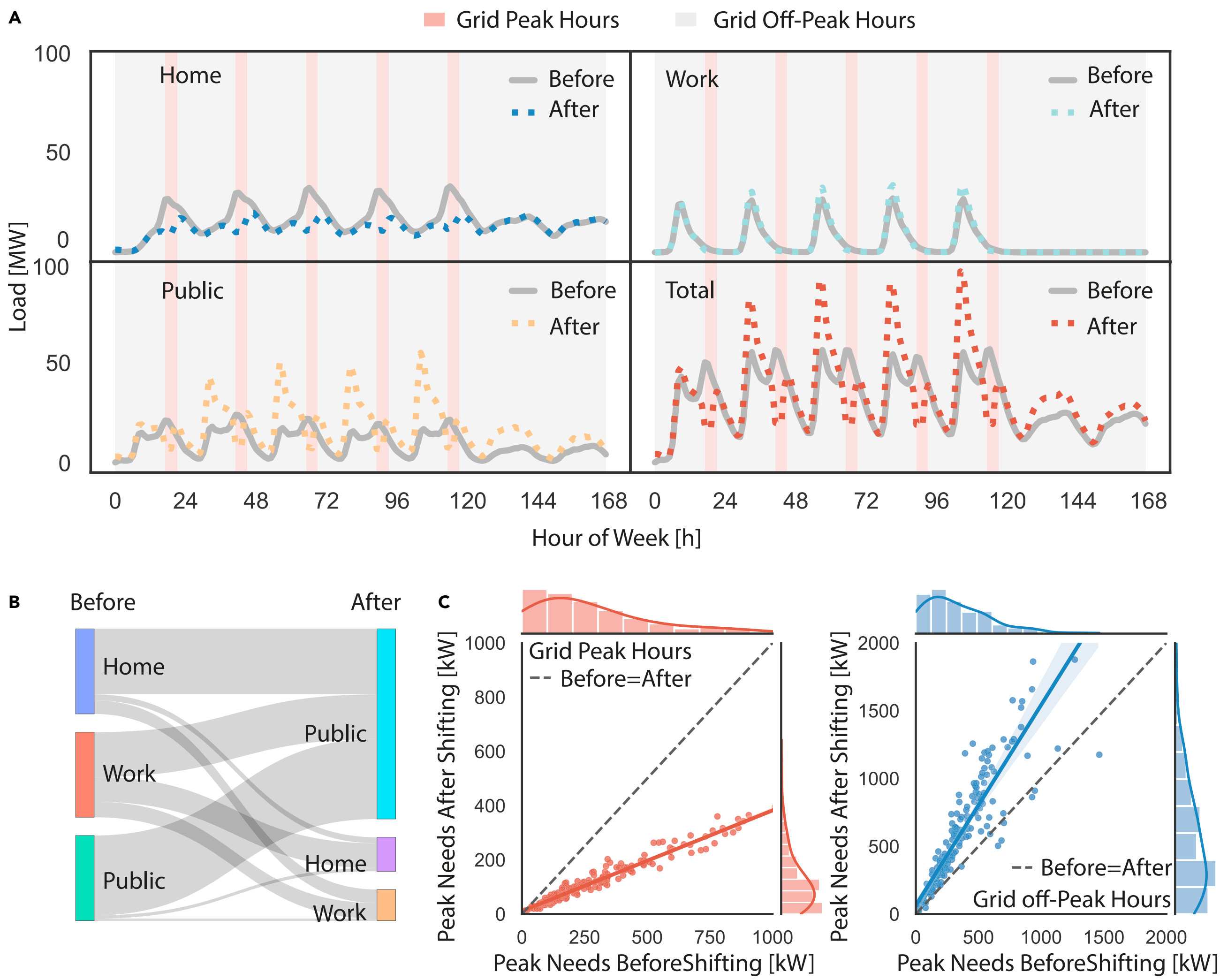

Figure 3. Impact of personalized shifting recommendations on charging demand

(A) Bay Area total charging load profile before and after implementing personalized shifting recommendations. The gray solid line displays the charging load before implementing personalized shifting recommendations, whereas the dotted line shows the charging load after the implementation of our personalized shifting recommendations.

(B) Charging locations before and after implementing personalized shifting recommendations. Blocks on the left side and the right side represent locations, where charging sessions take place before and after implementing the personalized shifting recommendations. If a block on the left side is connected to a block on the right side by a thick gray flow, it means that a number of charging sessions have shifted from the former location to the latter due to the recommendations.

(C) ZIP code level impact of personalized shifting recommendations. The points below the diagonal line show ZIP codes with a drop in peak demand after session shifting while points above the diagonal line indicate an increase in peak demand after session shifting.

hours and 89% of the total charging peak load increase for grid off-peak hours. We assume public charging access is open to everyone, thus providing more flexibility for moving sessions.

Figure 3B presents the impact of personalized shifting recommendations on the distribution of charging sessions across various locations. We only depict the shifted demand; some sessions were not shifted after implementing the recommendations if they occurred outside peak hours or if they could not be moved due to drivers' travel constraints. According to our observations, a significant majority of 77% of the charging sessions previously taking place at home are now shifted to public places, whereas 16% are redirected to workplaces and 7% are shifted to other homestays. Additionally, we found that 53% of workplace charging sessions are now shifted to public places and 29% are redirected to home places. Notably, most public charging sessions are still conducted in public places, albeit at different times, with a small percentage 6% being relocated to the workplace or home. The results indicate that to reduce the strain EVs put on grid peak hours, we need more public charging capacity.

Figure 3C shows ZIP code level peak charging needs before and after our personalized shifting recommendations. Overall, the personalized shifting recommendations result in a 0.1 MW reduction per ZIP code on average during grid on-peak hours and a 0.2 MW increase per ZIP code on average during grid

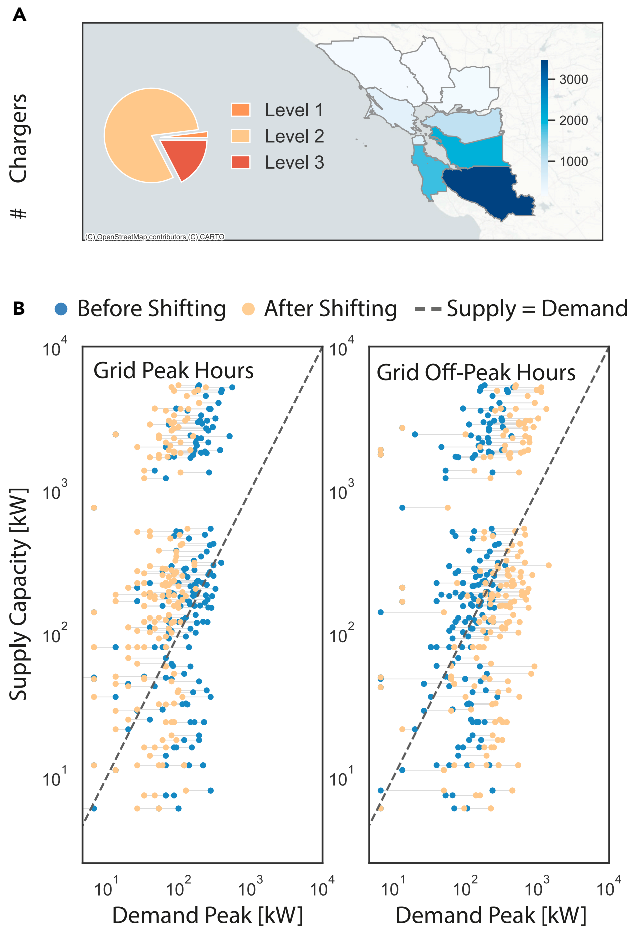

Figure 4. Impact of personalized shifting recommendations on charging infrastructure

(A) ZIP code level map showing the geographical distribution of existing public chargers. The pie plot indicates the percentage split of L1, L2, and L3 chargers in the Bay Area.

(B) Comparison between public charging station supply and peak public charging needs at the ZIP code level. Each pair of points represents the before- and after-shifting peak demand for one ZIP code. Points below the diagonal line indicate that the public charging station supply is insufficient, whereas points above the diagonal line indicate that there is a surplus in the public charging station supply.

off-peak hours. These results imply that EV charging peak load will decrease during grid on-peak hours at the cost of increasing charging peak load during grid off-peak hours. We note that high electricity demand during off-peak hours is acceptable in this case from the generation perspective as it aligns with peak solar generation; net grid demand, i.e., grid load deducts renewables, is the main concern. This increase in charging peak load, however, requires extra charging capacity to be supplied.

Figure 4A shows the geographical distribution of current public chargers. There are 36 chargers on average for each ZIP code. One ZIP code in Santa Clara shows the highest number of chargers at 454. Level 2 (L2) chargers comprise 81% of the total public chargers, whereas level 1 (L1) and level 3 (L3) comprise 2% and 17%, respectively.

We use data from Open Charge Map[65] to assess the public charging station supply vs. our estimated public charging demand, where the public charging station supply is the sum of the maximum charging rate for all chargers in the ZIP code. Figure 4B shows the current public charging demand during on-peak and off-peak hours per ZIP code compared with the public charging station supply. Blue points below the diagonal dashed line show ZIP codes with insufficient charging capacity. Namely, 62 ZIP codes during grid off-peak hours and 61 ZIP codes during grid on-peak hours. This indicates that for the current Bay Area, a number of ZIP codes are not able to support adopters' intrinsic public charging demand. However, overall, with the current public charging station supply in Bay Area, there is 125 MW more public charging capacity than needed before personalized shifting recommendations; this reflects that public charging demand is concentrated in fewer ZIP codes than public charging infrastructure. After implementing the personalized shifting recommendations, we found that 31 ZIP codes have insufficient public charging station supply during grid on-peak hours, and 112 ZIP codes have insufficient public charging station supply during grid off-peak hours.

Projection of deep EV adoption

In this section, we examine the period beyond 2019. To simulate future EV charging demand, we probabilistically sample EV drivers from the full pool of 6 million residents in the Bay Area for scenarios featuring EV adoption rates of 20%, 40%, 60%, 80%, and 100% of the total residents. By adoption, we refer to stock, not sales: at an EV adoption rate of 20%, 20% of all personal vehicles are EVs. To accomplish this, we first sample vehicular adopters from all residents using census tract-level vehicle usage rates. Next, we utilize household income and daily route distance to estimate the likelihood that each vehicle is an EV (see experimental procedures): the higher the probability, the earlier we assume they adopt an EV. The results presented in Figure 5 show how charging demand will evolve and how our personalized shifting recommendations will change demand at each level of adoption to protect the grid from any additional charging loads.

Figure 5A displays the daily travel distance, and Figure 5B presents the household income of the set of EV adopters at each stage of adoption. At an adoption rate of 20%, the median daily travel distance is 26 miles with a standard deviation of 16, whereas the median household income is $197,299, with a standard deviation of $74,452. On the other hand, at an adoption rate of 100%, the median daily travel distance is 27 miles, with a standard deviation of 19 miles, whereas the median household income is $130,037, with a standard deviation of $63,509. Our analysis indicates that individuals with higher daily travel distances and those with lower incomes tend to be later adopters of EVs. Recent research based on customer surveys has found that this reflects issues including range anxiety and high upfront costs.[66]

The increasing adoption of EVs leads to changes in the charging demand profile in the Bay Area, necessitating the use of personalized shifting recommendations to mitigate the negative impact of increasing EV charging loads during grid peak hours. As depicted in Figure 5C, the geographical distribution

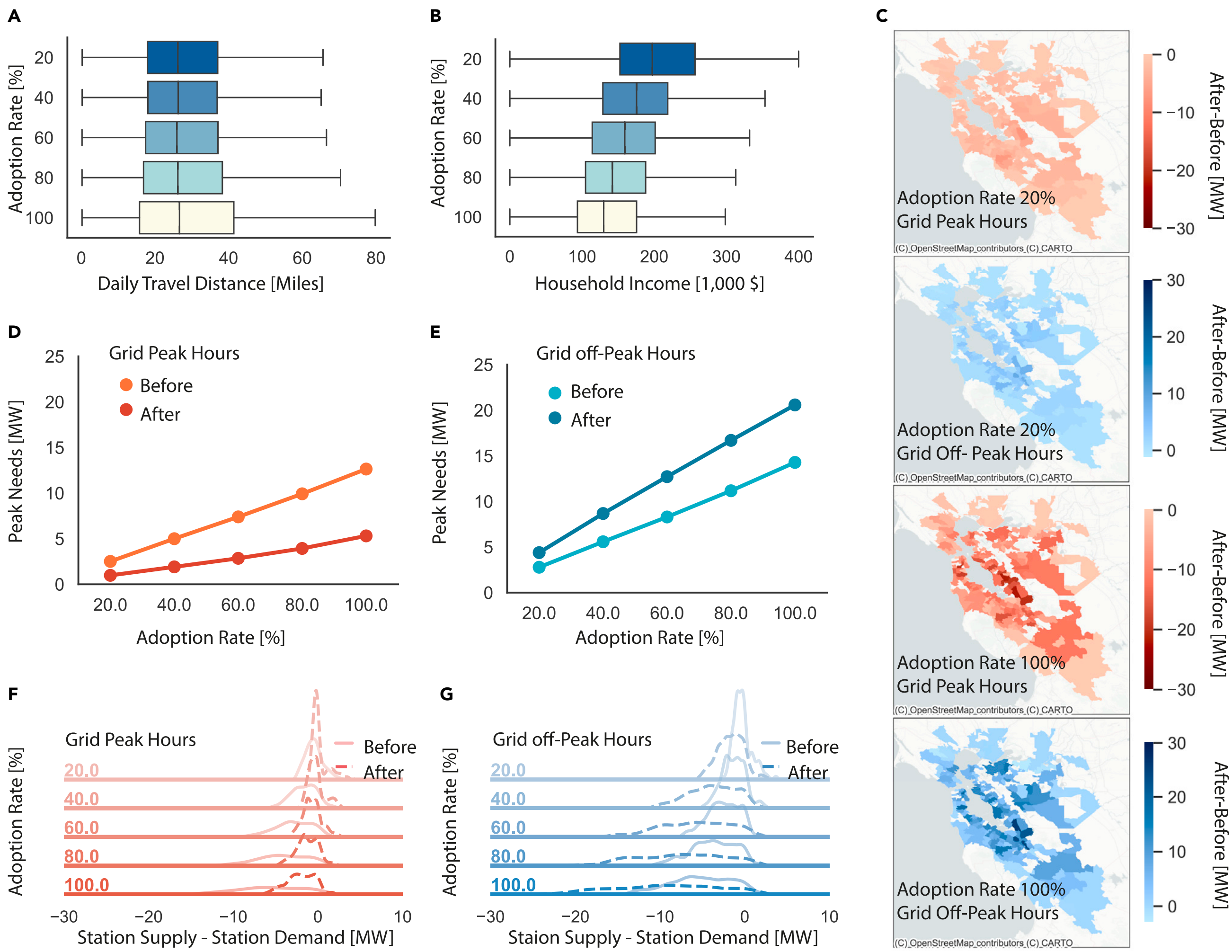

Figure 5. Results under future EV adoption

(A and B) The distribution of EV adopters' daily travel distance and household income when the adoption rate is increased. The box shows the interquartile range of all EV adopters, and the line that divides the box into two parts marks the median of EV adopters.

(C) Maps of EV peak charging need differences between after and before our personalized shifting recommendations, highlighting the geographic impact at adoption rates of 20% and 100%. Positive values indicate a decrease in peak charging needs, whereas negative values indicate an increase.

(D and E) Impact of personalized shifting recommendations on EV peak needs with increasing adoption rates, with points indicating the mean of peak needs among ZIP codes.

(F and G) Comparison between public charging station supply and peak charging needs with increasing adoption rates, showing the current public charging station supply minus EV peak charging needs under different adoption rates. Negative values indicate insufficient public charging station supply, whereas positive values indicate sufficient charging infrastructure.

of peak shaving results is more concentrated in the South Bay Area when the adoption rate is 20%, but it extends to include hot spots in the North Bay Area, East Bay Area, and San Francisco when the adoption rate reaches 100%. During grid peak hours, implementing the personalized shifting recommendations reduces peak-hour charging loads by at least 30% in 177 ZIP codes with 20% adoption and in 179 ZIP codes with 100% adoption. However, the decrease in peak charging load during on-peak hours results in higher charging peak demand during grid off-peak hours. The personalized shifting recommendations can increase peak charging loads during off-peak hours by at least 30% in 136 to 143 of the ZIP codes.

In addition to analyzing EV charging demand in the Bay Area, we also investigated the charging needs at the ZIP code level. As the adoption rates increase, different ZIP codes exhibit different patterns in charging demand evolution (Note S2). Figure 5D illustrates the EV charging peak loads for each ZIP code during grid on-peak hours before and after implementing the personalized shifting recommendations. When the adoption rate is 20%, our personalized shifting recommendations result in an average reduction of 59% in ZIP code level charging peak loads, whereas with 100% adoption, the average reduction is around 56%. The average reduction is approximately 1.5 MW at 20% adoption rate and around 7.3 MW at 100%

adoption rate for each ZIP code. Next, we examine the charging demand during grid off-peak hours. As shown in Figure 5E, when the adoption rate is 20%, the personalized shifting recommendations can lead to an average increase of 57% in the charging peak loads of the ZIP codes in off-peak hours, whereas with 100% adoption rate, the average increase is around 39% of charging peak loads. The lower increase in the 100% case may be a sign of lower flexibility or higher off-peak demand among later adopters. In absolute terms, the average increase per ZIP code is approximately 1.6 MW at 20% adoption and 6.3 MW at 100% adoption.

To support the growing adoption of EVs, it is necessary to increase the number of public charging stations as more people increase the demand for charging. Figure 5F illustrates the gap between public charging station supply today and public charging demand with increasing adoption rates during grid on-peak hours. Before personalized shifting recommendations, when the adoption rate is 20%, 71% of the ZIP codes experience insufficient public charging station supply, with an average insufficiency of 0.4 MW and a standard deviation of 1.2 MW. At an adoption rate of 100%, this number increases to 94% of the ZIP codes, with an average insufficiency of 6.3 MW and a standard deviation of 4.9 MW. After personalized shifting recommendations, when the adoption rate is 20%, 61% of the ZIP codes experience insufficient public charging station supply. On average, the surplus per ZIP code is 0.3 MW and a standard deviation of 1.2 MW. At an adoption rate of 100%, 88% of the ZIP codes experience insufficient public charging station supply, with an average insufficiency of 2.2 MW and a standard deviation of 2.0 MW.

Meanwhile, during off-peak hours, more public charging capacity is needed than before personalized shifting recommendations were implemented. Figure 5G shows that before personalized shifting recommendations, at an adoption rate of 20%, 70% of the ZIP codes experienced insufficient public charging station supply, with an average insufficiency of 0.2 MW and a standard deviation of 1.2 MW. This number increases to 94% of the ZIP codes at an adoption rate of 100%, with an average insufficiency of 5.5 MW and a standard deviation of 4.2 MW. After personalized shifting recommendations, at an adoption rate of 20%, 86% of the ZIP codes experience insufficient public charging station supply, with an average insufficiency being 1.7 MW and a standard deviation of 1.8 MW. This number increases to 94% of the ZIP codes at an adoption rate of 100%, with an average insufficiency of 10.6 MW and a standard deviation of 7.8 MW.

Therefore, although personalized shifting recommendations are effective in reducing peak charging needs during grid on-peak hours, they lead to a net increase in the need for public charging stations. That is, although fewer public charging stations are needed in on-peak hours after the shifting, that is outweighed by the many more public charging that must be added in off-peak hours. In all cases, we find more charging capacity is needed to meet the increased public charging demand resulting from the higher adoption rates of EVs. The average increase in public charging station insufficiency caused by applying the personalized shifting recommendations is 27 L3 chargers with 50 kW (or 198 L2 chargers with 6.6 kW) at an adoption rate of 20% and 83 L3 chargers with 50 kW (or 628 L2 chargers with 6.6 kW) at an adoption rate of 100% at the ZIP code level. This insufficiency could also be met by a mix of L2 and L3 chargers, as in the simulation results.

To achieve the Bay Area Air Quality Management District's 2050 objective of having 90% of the personal vehicle fleet consist of EVs, it is necessary to meet the interim goals of 1.5 million EVs by 2030 and 5 million EVs by 2050. According to our model, at the 2030 target, there would be a reduction of 414 MW in charging needs during on-peak hours from following the personalized shifting recommendations. However, this would also result in an increase of 437 MW in charging needs during off-peak hours, necessitating new infrastructure in over 90% of the ZIP codes. Once the 2050 objective is met, our model estimates that the EV charging demand could reach 2 GW during grid peak hours in 2050. In this case, the Bay Area is missing $\sim$19,000 L3 chargers (or $\sim$141,000 L2 chargers with 6.6 kW) to support the demand in 2050. If we assume adopters follow the personalized shifting recommendations, there will be a 61% decrease in total charging demand during on-peak hours, but the number of missing L3 chargers will be around $\sim$34,000 (or $\sim$256,000 L2 chargers with 6.6 kW) in 2050.

DISCUSSION

In this work, we first combined mobility patterns with charging behavior group features to model the charging behavior of EV adopters in the San Francisco Bay Area. Then, we provided personalized shifting recommendations to users based on their intrinsic charging behavior and mobility constraints to reduce the charging peak load during grid peak hours. Finally, we simulated future scenarios to see how the charging demand and required public charging station supply evolve with increasing adoption rates under our recommendations.

For the charging demand simulation, the results show that the daily charging load shapes are similar with two peaks for most ZIP codes. One peak occurs during off-peak hours and mainly consists of work charging and public charging, whereas the other peak occurs during on-peak hours consisting of home charging and public charging. The magnitude of weekly charging needs in the Bay Area varies greatly at the ZIP code level, with the highest charging demand in the ZIP codes of the South Bay and the lowest charging demand in the North Bay in 2019. Home charging demand is the largest share in 2019, whereas work charging is the smallest.

We propose personalized shifting recommendations to mitigate charging load during peak hours on the grid. We find that these result in a considerable reduction of the peak by shifting home and public charging sessions from peak to off-peak hours at other stops. Demand is largely shifted to daytime parking sessions, adding to the peak in off-peak hours. In this study, we assumed fixed access to workplace charging and found that public charging at non-workplace and non-home locations was used to serve the shifted demand. However, workplace charging occurs at similar off-peak times, and if more workplace charging were available, it could similarly serve the shifted demand. Our results can be best interpreted as a shift from evening to daytime parking events. Therefore, we recommend increases in daytime charging options including public and workplace stations, where

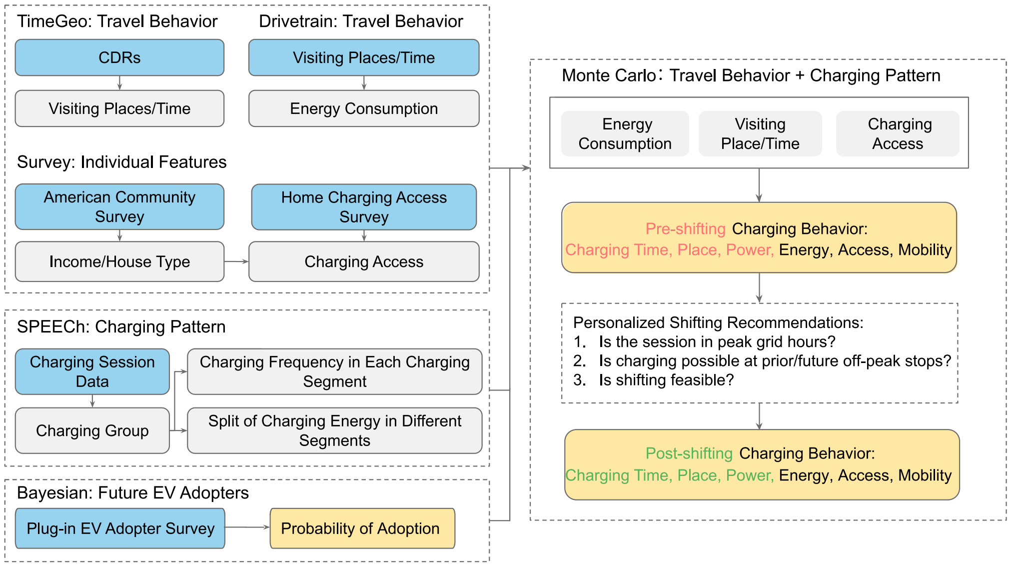

Figure 6. Methodology overview

Dashed frames represent models; blue frames represent the data sources, gray frames represent the intermediate output, and yellow frames represent ultimate output, i.e., original charging demand, charging demand after personalized shifting recommendations, and the probability of each driver being an EV adopter.

possible, to facilitate more flexibility in EV charging. To implement and fully leverage the benefits of our proposed personalized shifting recommendations, it will be necessary to increase daytime charging capacity in most ZIP codes, which will involve the installation of new charging infrastructure.

As EV adoption rates increase, the profile of EV adopters will change, with a larger proportion of low-income residents and those with higher daily travel distances owning EVs. We showed that implementing personalized shifting recommendations to shift charging sessions away from on-peak hours was effective at all levels of EV adoption. As adoption, demand, and its grid impacts increase, the benefits of this approach will become more widespread. However, to support this strategy for managing the increase in demand, additional charging infrastructure will be necessary.

There are several important avenues for expanding upon this work. Future research could explore changes in population and travel behavior in the future. We assume all drivers follow the personalized shifting recommendations in this work. In practice, adopters may not follow the personalized shifting recommendations for personal reasons, e.g., drivers are not willing to accept charging recommendations to shift to public charging due to more cost and less convenience.[47] In this case, future research should evaluate how uncertainty in human behavior could influence the efficacy of personalized shifting recommendations and how to customize the recommendation based on drivers' preferences. To further promote the adoption of recommendations, we can explore the design of incentive reward programs that can provide discounts, priority access, or loyalty benefits for utilizing specific charging stations or charging during off-peak hours. Also, to address concerns and misconceptions about public L3 charging, personalized recommendations can be accompanied by educational materials and resources. The whole setup depends on receiving some information about drivers' travel patterns and responses to the recommendations; future research could explore how the optimization could still be conducted under limited information scenarios. Finally, although we targeted evening on-peak hours based on constraints at the generation level, we recognize that EV charging can also impact the distribution grid. Both the increased use of fast public charging and the new morning off-peak peak in demand caused by our personalized shifting recommendations could pose localized challenges to distribution grid infrastructure. These impacts could be mitigated by the installation of new collocated sources of renewable energy or batteries and should be the focus of future work.

EXPERIMENTAL PROCEDURES

Resource availability

Lead contact

Further information and requests for resources and materials should be directed to and will be fulfilled by the lead contact, Marta C. Gonzalez. (martag@berkeley.edu).

Materials availability

This study did not generate new unique materials.

Data and code availability

The code used for the analysis presented in this paper is available at https://zenodo.org/badge/latestdoi/624661479.

Overview

The methodology includes four parts. We first use TimeGeo and a drivetrain model to estimate the travel behavior and energy consumption of each vehicle in the sample. Second, we connect the travel behavior and SPEECh model by energy consumption and charging access to obtain the original charging behavior of EV adopters. Third, we identify the feasibility of drivers moving their original sessions from peak hours to off-peak hours by checking several rules. Last, we use a Bayesian model to estimate the probability of each driver adopting an EV based on their income and travel distance. Figure 6 depicts the connection between the data source and models.

Datasets

We use four different datasets in this study: call detail records (CDRs), charging session records, charging infrastructure data, and survey data such as US Census Bureau American Community Survey, the California Plug-in Electric Vehicle Adopter Survey, the California Home Charging Access Survey, and the Clean Vehicle Rebate Project (CVRP) data.

The CDRs, mobile phone activity data, play a crucial role in mobility modeling.[67] We use CDRs for the Bay Area, including data from around 1.39 million users and over 200 million calls made during a period of 6 weeks. Each record contains the anonymized user identification (ID), timestamp, duration, and geographic location of the associated cell tower. We discretize the spatial resolution to the service areas of 892 distinct cell towers. With this information we develop the TimeGeo[60] mobility model for all 6 million residents in the Bay Area, giving detailed travel patterns for a typical week.

The charging session records contain over 2.8 million charging sessions from 27,700 EV adopters, recorded by a large charging station provider in the California San Francisco Bay Area in 2019.[12,68] Each session is associated with a unique adopter ID and includes the start time, end time, energy, charging rate, and location category for each session. The sessions cover five segments: workplace L2 charging, public L2 charging, public L3 charging, single family home (SFH) residential L2 charging, and multi-family home (MFH) or MUD residential L2 charging. L2 charging occurs at 6.6 kW and L3 occurs at 50 kW. For detailed statistics and illustrations of the data we refer the reader to Powell et al.[12]

The charging station data collected from Open Charge Map[65] contain information on the location of each station, the number of charging piles, and charger types in each charging station. The location is represented by longitude and latitude, while the charger type covers L1, L2, and L3. We collect data on the number of each charger type.

We use multiple surveys to compile information on Bay Area residents' demographics, EV charging access, and EV adoption behavior. We obtain data on the number of passenger vehicles at the census tract level, the distributions of housing types, and household incomes from the US Census Bureau American Community Survey.[62] The California Plug-in Electric Vehicle Adopter Survey[69] provides the income and daily travel distance distributions of EV adopters. We model access to residential charging based on the California Home Charging Access Survey,[63] which surveys the relationship between home charging access and demographics, i.e., household income and house type. The annual household income has three bins: up to $60,000, between $60,000 and $100,000, and greater than $100,000. The house type has two bins: SFH and MFH. For each combination of household income bin and house type bin, the California Home Charging Access Survey provides the corresponding home charging access rate. To model EV adoption, we use CVRP data on over 400,000 purchases of EVs in California between 2013 and 2019.[61] This dataset provides EV adopters' home ZIP code, the purchasing date, and the purchasing model type.

Estimating travel behavior of EV adopters

Using the CDRs data, we extract information on the visited places and times for each user. The TimeGeo models and integrates the flexible temporal and spatial mobility choices of the individuals.[60] The model divides each day of the week into 1,008 discrete intervals, resulting in 10-min intervals. For each interval, the individual decides whether to stay or move, and if she chooses to move, where to go next.

To represent the movement mechanisms, TimeGeo introduces a time-inhomogeneous Markov chain model with three individual-specific mobility parameters: a weekly home-based tour number (n_w), a dwell rate (β_d), and a burst rate (β_b), as well as a global travel circadian rhythm of the population in an average week ($p(t)$) that differs for commuters and non-commuters.

For the temporal movement choices, TimeGeo initializes the individual's probability to move as $n_w p(t)$ if she makes a trip originating from home in a time-interval t of a week, and $\beta_d n_w p(t)$ for a trip not originating from home. If the individual decides to move, she goes to public places with probability $\beta_b n_w p(t)$ and returns home with probability $1 - \beta_b n_w p(t)$.

For the spatial movement choices, TimeGeo uses a rank-based exploration and preferential return to determine the individual's next destination. When the individual chooses to move to another place, she can either return to a visited place or explore a new location. The model assumes that the individual explores a new place with probability $P_n = \rho S^{-\gamma}$, where S represents the number of previously visited locations, and ρ and γ control the user's tendency to explore a new location based on empirical data. If the individual decides to return, the return location is selected from the visited locations according to her visiting frequency. If she decides to explore a new location, the alternative destinations are selected based on the distance to her origin with probability $P(k)k^{-\alpha}$, where k represents the rank of alternative destinations.

To validate the simulation of individual mobility in the Bay Area, Xu et al.[30] compared the aggregate performance of TimeGeo with that of the National Household Travel Survey (NHTS)[70] and the California Household Travel Survey (CHTS).[71]

Using the mobility model, we estimate energy consumption by utilizing a drivetrain model. A drivetrain model establishes the relationship between energy consumption and two aggregate properties of the trip, namely, average travel speed and route distance. We estimate these properties using the Application Programming Interfaces (APIs) of Uber Movement[72] and OSMnx,[73] respectively. Our analysis focuses on two popular EV models in the Bay Area: the Tesla Model 3 and Nissan Leaf. Note S3 provides the number of adopters of each EV model.

The drivetrain model for the Nissan Leaf can be represented as:

$$E_{trip}^{Nissan} = f(V_{trip}) D_{trip}, \quad \text{(Equation 1)}$$

where V_{trip} and D_{trip} represent the average speed and route distance of the trip, respectively. The function $f(V_{trip})$ indicates the consumed power per mile (kWh/mile) when the EV is traveling at speed V_{trip} (mile/h). The value of $f(V_{trip})$ varies among different EV models. To estimate the energy consumption of the two EV models in our study, we first use a piecewise linear function based on data observed from the Nissan Leaf.[11] Then we scale the consumption of the Nissan Leaf in the same trip by 0.83 to estimate the energy consumption of the Tesla Model 3, as the Tesla Model 3 consumes, on average, 17% less energy than the Nissan Leaf.[74] That is:

$$E_{trip}^{Tesla} = 0.83 f(V_{trip}) D_{trip}. \quad \text{(Equation 2)}$$

The details of the simulated mobility pattern and energy consumption are in Note S4.

EV charging behavior simulation

SPEECh is a probabilistic framework for simulating large-scale EV charging loads that are grounded in real charging data.[12,23]

This version of the SPEECh model clusters drivers into 136 charging behavior groups, based on real charging data from a large charging station provider in the Bay Area. Each group of drivers has unique characteristics in multiple charging segments with different frequencies and patterns of behavior (see Note S5).

SPEECh models the probability with which an adopter belonging to a charging behavior group G will charge in segment z on a given day by sampling from the charging frequencies of all drivers in that group in the historical data:

$$P(z|G)_i = N_{G,i}^z \big/ N_{G,i}, \quad \text{(Equation 3)}$$

where $N_{G,i}$ denotes the number of sessions by driver i in group G, and $N_{G,i}^z$ denotes the number of sessions in segment z by driver i in group G.

The distribution of energies for a session in each segment, for a driver in each group, charging on a weekday or weekend, is modeled using the historical charging session data of all drivers in that group. For each group G and charging segment z, SPEECh models the joint distribution of charging energy in a session c using a Gaussian mixture model, as follows:

$$P(c|G,z) = \sum_{k=1}^{K} P(c|k)P(k), P(c|k) = \mathcal{N}(c|\mu_k, \sigma_k), \quad \text{(Equation 4)}$$

where each component k in the mixture model is a Gaussian distribution with weight $P(k)$, representing a pattern of charging energy that occurs in the sessions observed in segment z for adopters in group G. The mean and standard deviation of component k are denoted by μ_k and σ_k, respectively.

We use SPEECh to estimate the charging segment and per-session charged energy of each driver. To achieve that, the first step is to estimate adopters' charging behavior group (G) based on their charging access (A) and annual energy consumption (E). Then we simulate the charging segment (z) and session charged energy (c) of adopters based on the charging behavior group and SPEECh model, i.e., $P(z|G)$ and $P(c|G,z)$. This step allows us to represent future adopters based only on today's data, by assuming that future adopters with the same energy consumption and access to charging will follow the same distribution of charging patterns.

We divide adopters' charging access A into four bins: no home or workplace charging access, home charging access only, workplace charging access only, and both home and workplace charging access. Home charging access includes SFH L1 charging, SFH L2 charging, and MFH L2 charging, while workplace charging access includes only workplace L2 charging. We model home charging access based on household income and housing type. Income is a random variable that follows a standard normal distribution centered at the median income of the residential tract. The median income information at the tract scale is from census data.[62] Each house type in a census tract has a corresponding probability, and we assign the house type according to the probability in the census data.[62] The California Home Charging Survey[63] provides the distribution of home charging access given household income and housing type (details are in Note S6). The survey does not distinguish between L1 and L2 charging; we assume the split between L1 and L2 is 0.38 : 0.45 based on.[75] We model the workplace charging access rate for those who have a workplace as 50% based on.[64] Combining the home charging access and workplace charging access gives us overall charging access, A.

Annual energy consumption E is equally divided between 19 bins from 0 to 4,750 kWh. We calculate energy consumption in a typical week using a drivetrain model described in estimating travel behavior of EV adopters. Multiplying weekly energy consumption by 52 (the number of weeks in a year) gives the annual energy consumption E.

The probability of an adopter belonging to group G, given charging access A and energy consumption E, is estimated directly from the charging groups of adopters in the historical data:

$$P(G|A,E) = N^G_{A,E} \Big/ N_{A,E}, \qquad \text{(Equation 5)}$$

Here, $N_{A,E}$ denotes the number of adopters with access A and annual energy consumption E, and N^G denotes the number of adopters in group G. $N_{A,E}$ and N^G are calculated directly from the charging data.[68] Based on charging access A and energy consumption E, we assign the adopter to a charging behavior group with $P(G|A,E)$.

Using the estimated charging group G and SPEECh model, i.e., $P(z|G)$ and $P(c|G,z)$, we simulate the charging behavior of all EV adopters by the Monte Carlo method (see Note S7).

To ensure that the simulation results adhere to the capacity constraints of the vehicles, we need to consider two factors: (1) the charged energy should be enough to support the travel needs, and (2) the charged energy should not exceed the capacity of the vehicle's battery. To achieve this, we first simulate the initial state of charge (SoC) of all the vehicles. However, due to limited information from charging session data, we are unable to infer the initial SoC of each vehicle from the data. To address this issue we make an assumption that all vehicles start the week mostly charged: we sample the initial SoC based on a Gaussian distribution with a mean of 80% of the maximum capacity B kWh and a standard deviation of 20% of the maximum capacity. We model the maximum capacities of a Tesla Model 3 and Nissan Leaf as 82 kWh and 40 kWh, respectively.[76]

We denote the SoC of a given time slot t as $s(t)$, the energy charged at time slot t as $c(t)$ kWh, and the energy consumption at time slot t as $d(t)$ kWh. As c and d are generated from different models, in rare cases the values are outside the acceptable range. To ensure that the capacity constraints of the vehicles are met, we map the charging and energy consumption according to:

$$\overline{c}(t) = c(t) - \max\{(s(t) - 100\%) * B, 0\}, \overline{d}(t) = d(t) + \min\{s(t) * B, 0\} \qquad \text{(Equation 6)}$$

Here, $\overline{c}(t)$ and $\overline{d}(t)$ represent the mapped charging and energy consumption values, respectively. The term $\max\{s(t) - B, 0\}$ ensures that the charged energy does not exceed the battery's capacity, while the term $\min\{s(t), 0\}$ ensures that the charged energy is enough to support the vehicle's travel needs. We can then calculate the SoC of the next time slot as $s(t+1) = s(t) + \overline{c}(t) - \overline{d}(t)$ for all time slots t.

Personalized shifting recommendations to reduce the peak

To allow for session shifting, we establish a set of rules based on EV adopters' original travel and charging patterns. For travel behavior, we do not require adopters to change their usual travel patterns. For charging patterns, we limit session shifting to a maximum tolerable period of a few stays from the original charging session. Furthermore, we ensure that the shift session will be completed during the stay after shifting.

We assume EV adopters share similar travel and charging patterns among weeks and choose a typical week for study. We divide the week into 10-minute intervals, with each week beginning at $t = 0$ and ending at $t = 1008$. We define on-peak hours as T_{on} and off-peak hours as T_{off}. The charging rate is a function of charging segment z and is denoted as $r(z)$ (e.g., 1.2 kW for home L1 charging). Suppose an adopter needs to charge e_i during stay i and can tolerate a shift if the new charging session happens within h stays from the original charging session. In this analysis, we set h equal to 10 here to make full use of the demand flexibility. The arrival time of stay i is t^i_a, the departure time is t^i_d, and the charging end time is t^i_c. We shift the charging session from stay i to stay j if j satisfies the following conditions:

(1) Consistent with driver's original charging frequency: the target session j must be within the threshold h of the original session. The user can choose to move the session forward, i.e., $j < i, |i - j| < h$, or the user can choose to delay the session, i.e., $i < j, |i - j| < h$.
(2) Consistent with driver's original charging level preference for a given location.
(3) On-peak hours to off-peak hours: only shift sessions that happen in grid on-peak hours to grid off-peak hours, i.e., $[t^i_a, t^i_c] \in T_{on}$ and $[t^j_a, t^j_c] \in T_{off}$.
(4) Charging needs are satisfied: charging energy needs should be met in the stay j, i.e., $e^i / r(z) \le (t^j_d - t^j_a)$.
(5) Feasible given all travel plans: if the adopter shifts the session from stay i to stay j, the charging load and SoC will be updated as $s(t+1) = s(t) + c'(t) - d(t)$, where $c'(t) = r(z_i), \forall t \in [t^j_a, t^j_c]$ and $c'(t) = 0$, $\forall t \in [t^i_a, t^i_c]$. We require $0 \le s(t) \le B, \forall t$.

Predicting potential EV adopters

To sample EV users from all vehicular adopters in the Bay Area, we first extract vehicular adopters from the entire population using vehicle usage rates at the census tract scale. Then, we assign each vehicular adopter a probability of using an EV, denoted by $P(\text{EV}|I,D)$, based on their household income I and daily driving distance D. We assume that I and D are independent random variables for a given trip maker.

To estimate the probability of using an EV, we use a Bayesian approach:

$$P(\text{EV}|I,D) = \frac{P(I|\text{EV})P(D|\text{EV})P(\text{EV})}{P(I)P(D)} \qquad \text{(Equation 7)}$$

where $P(I)$ and $P(D)$ are the probability densities of household income and daily travel distance of all trip makers in the Bay Area, respectively. We set $P(\text{EV})$ to 2%, based on the share of EVs within all cars in the Bay Area in 2019 according to the CVRP dataset. For future scenarios, we vary $P(\text{EV})$ from 20% to 100% to observe how charging demand evolves. To estimate $P(I|\text{EV})$ and $P(D|\text{EV})$, we use data from the California Plug-in Electric Vehicle Adopter Survey.[69] Once we estimate $P(\text{EV}|I,D)$, we use these probabilities to select EV adopters from all vehicular adopters.

Note S8 compares the number of EVs estimated using the Bayesian method at each ZIP code with the number obtained from the CVRP dataset,[61] demonstrating good agreement between the two methods. Additionally, Note S9 shows the geographical distribution of EV drivers with increasing adoption rates.

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.crsus.2023.100006.

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AUTHOR CONTRIBUTIONS

J.W., S.P., Y.X., R.R., and M.C.G conceived the research. J.W., S.P., Y.X., R.R., and M.C.G. developed the methodology. S.P. and Y.X. provided data. J.W. and S.P. processed the data. J.W. implemented the methodology. J.W., S.P., Y.X., R.R., and M.C.G analyzed the results. J.W. S.P. and Y.X. performed visualization. J.W. and M.C.G. prepared the original draft. J.W., S.P., Y.X., R.R., and M.C.G. edited and revised the manuscript. R.R. and M.C.G. supervised the research.

DECLARATION OF INTERESTS

The authors declare no competing interests.

INCLUSION AND DIVERSITY

We support inclusive, diverse, and equitable conduct of research.

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Supplemental information

Planning charging stations for 2050 to support flexible electric vehicle demand considering individual mobility patterns

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Supplemental Experimental Procedures

Note S1: Sensitivity Analysis

We test the performance of our personalized recommendations with three parameters, i.e., maximum shifting stays, different peak hours, and recommendation acceptance rates.

- **Maximum Shifting Stays**: Maximum shifting stay is the maximum number of stays we assume each session can be shifted from the original charging session. We set different maximum shifting limits to test how shifting by fewer stays would influence the success of the peak shaving results. We find in Fig. 1 (a) that, consistently under different EV adoption rates, larger maximum shifting stays enable more peak shaving, and even with a maximum displacement of 2 stops (stays) the recommendations are able to achieve more than 40% shaving.
- **Different Peak Hours**: Different peak hours are the possible period of grid peak hours. In the future, the increasing production from renewables and the availability of other system management assets will cause the peak of the net load on the grid to occur at different times of day. In this sensitivity analysis, we test how different peak hours will influence the success of the algorithm's peak shaving results. We test four cases: morning, afternoon, evening, and late-time peak periods. We find in Fig. 1 (b) that the morning peak hour benefits from the most shaving and the midnight peak hour benefits from the least shaving. This happens because the current uncontrolled charging peak occurs in the morning or afternoon/evening, so the morning/afternoon/evening peak has more potential to be shaved. Also, since current home charging access is higher than work charging access, moving workplace charging (which usually happens in the morning) to home charging (which usually happens in the afternoon/evening) is easier than moving home charging to workplace charging.
- **Recommendation Acceptance Rate**: Recommendation acceptance rate is the ratio of drivers who follow the recommendations. In the base case we assume all drivers follow the personalized shifting recommendations in this work. In practice, adopters may not follow the personalized shifting recommendations for personal reasons. We vary the ratio of drivers who follow the recommendations to test how different levels of compliance will influence the peak shaving results. We confirm in Fig. 1 (c) that with an increasing fraction of drivers following the recommendations, peak shaving is more successful. When the acceptance rate is just 20%, the recommendations can still achieve over 10% shaving. Designing incentives and education programs to increase recommendations following ratio is necessary to realize the full potential of this demand flexibility.

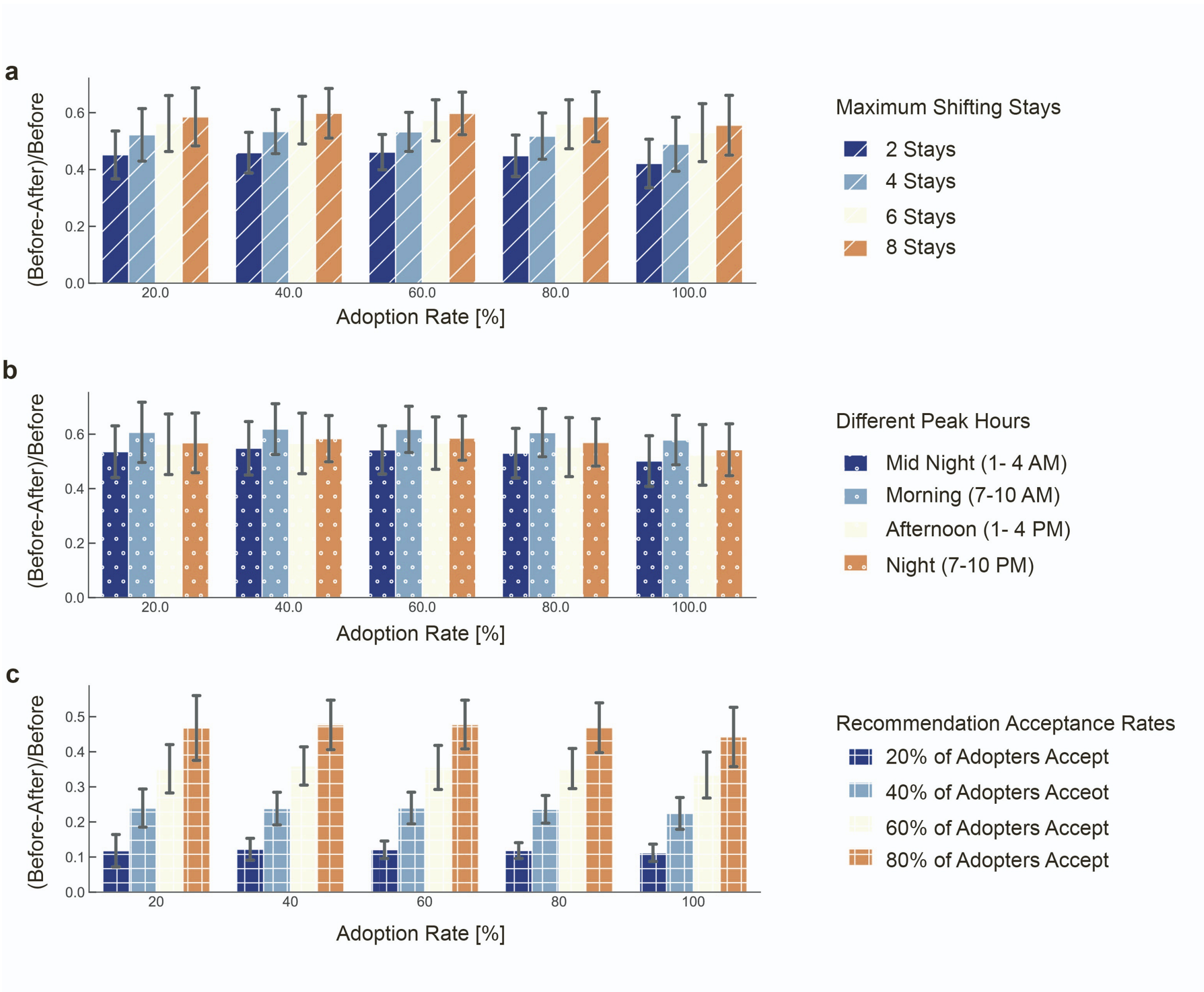

Figure 1: Sensitivity analysis of personalized shifting recommendations. We show ZIP code level differences between before and after our personalized shifting recommendations in the ratio of before recommendations under different EV adoption rates. The error bar highlights the variance among ZIP codes. (a) Peak shaving effects under different maximum numbers of shifting stays. (b) Peak shaving effects under different peak hours. (c) Peak shaving effects under different recommendation acceptance rates.

Note S2: Unbalanced Demand with Increasing Adoption Rates

With increasing adoption rates, ZIP codes in Bay Area show sub-linear increases and super-linear increases in peak charging loads. We identify sub-linear and super-linear increases in peak charging load on the ZIP code level and visualize the increases in Figure 2 and Figure 3. Sub-linear growth in a given ZIP code indicates there is less EV demand there from early adopters and more from later adopters; super-linear growth means the opposite.

Figure 2 shows the average peak charging loads with increasing adoption rates for ZIP codes with sub-linear and super-linear increases in load respectively. The dashed line shows the linear increase of the peak charging load. The solid line above the dashed line represents the average load of ZIP codes with sublinear increases while the solid line below the dashed line represents the average load of ZIP codes with superlinear increases. Figure 2 a and c show that during grid peak hours, the shifting strategy narrows the gap of load between sub-linear increasing ZIP codes and super-linear increasing ZIP codes. In contrast, Figure 2b and d show that during grid off-peak hours, the shifting strategy enlarges the gap of load between sub-linear increasing ZIP codes and super-linear increasing ZIP codes.

Figure 3a-b indicate more sublinear increases in South Bay Area and more superlinear increases in North Bay Area. The difference among ZIP codes implies the unbalanced development of EV charging demand in the Bay Area. Figure 3c indicates that the recommendations reduce the number of ZIP codes with sublinear increases in South Bay Area during grid peak hours. Figure 3d shows that the recommendations reduce the number of ZIP codes with superlinear increases in North Bay Area and increase the number of ZIP codes with sublinear increases in South Bay Area during grid off-peak hours.

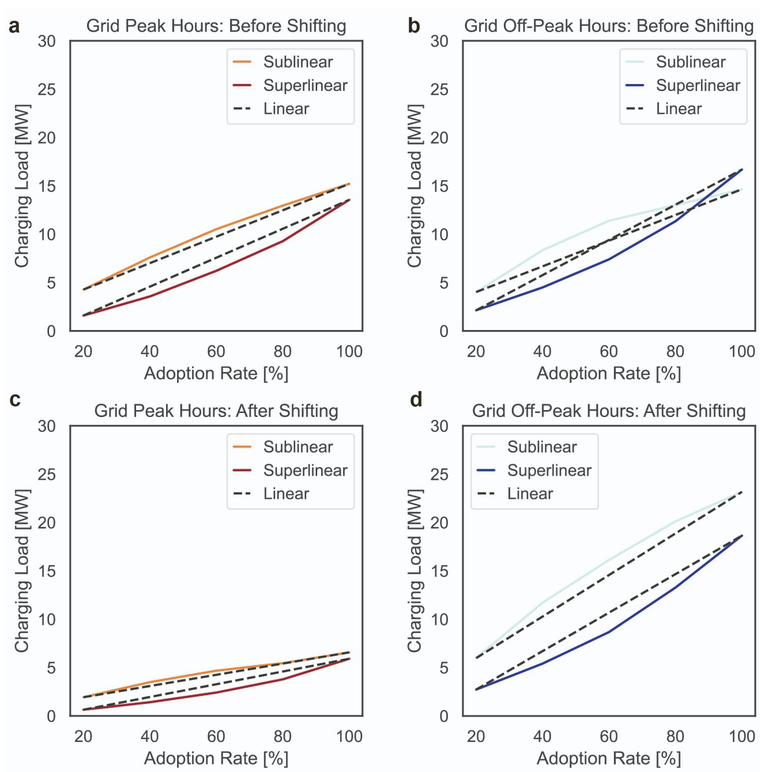

Figure 2: Sub-linear increase and super-linear increase in peak charging needs.

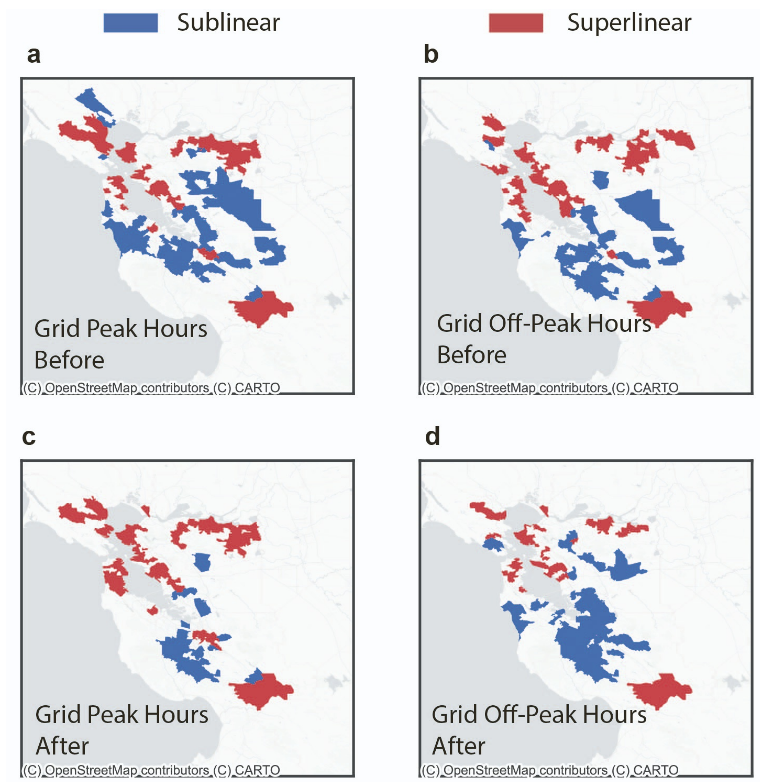

Figure 3: Sub-linear increase and super-linear increase in peak charging needs.

Note S3: EV models market share

Figure 4 shows the market share of battery-operated EVs used in this study [1]. We observe that Tesla Model 3 and Nissan LEAF S are the most popular model. The Tesla Model 3 has a battery capacity of 50-82 kWh and Nissan LEAF S has a battery capacity of 40 kWh [3].

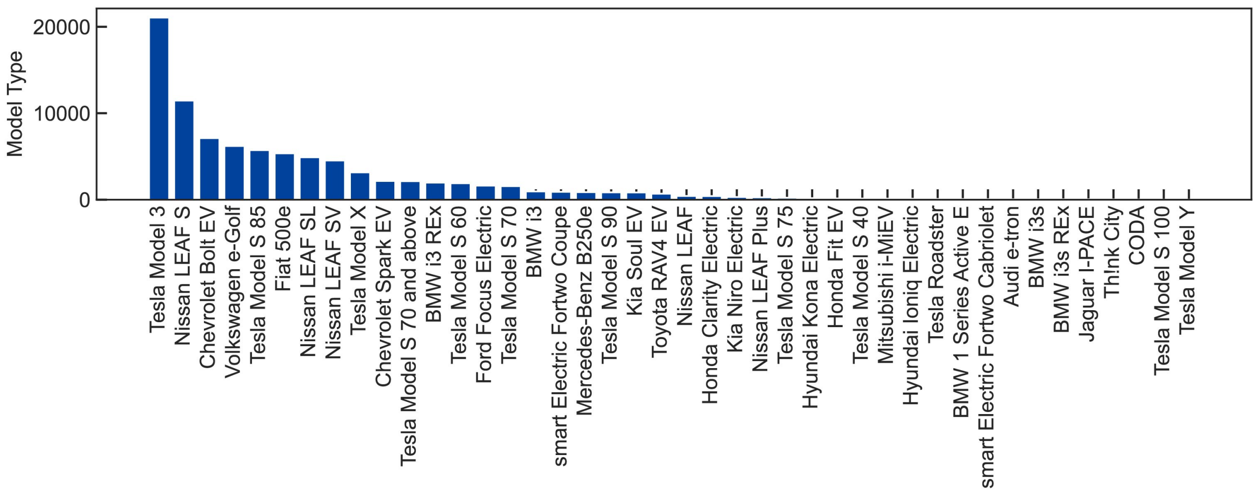

Figure 4: BEV models market share.

Note S4: Travel behavior of the EV drivers

Figure 5a shows the distribution arrival time for EV drivers in the year 2019. There are two peaks during the day. One happens at around 9 a.m. in the morning, while the other happens at around 7 p.m. at night. Figure 5b shows the departure time distribution. The distribution of arrival time and departure time are similar since people spend little time on the way. The histogram of daily energy consumption is shown in Fig. 5c. Most people consume less than 25 kWh a day. Figure 5d shows the number of stays during the day. Most people visit two places during the day.

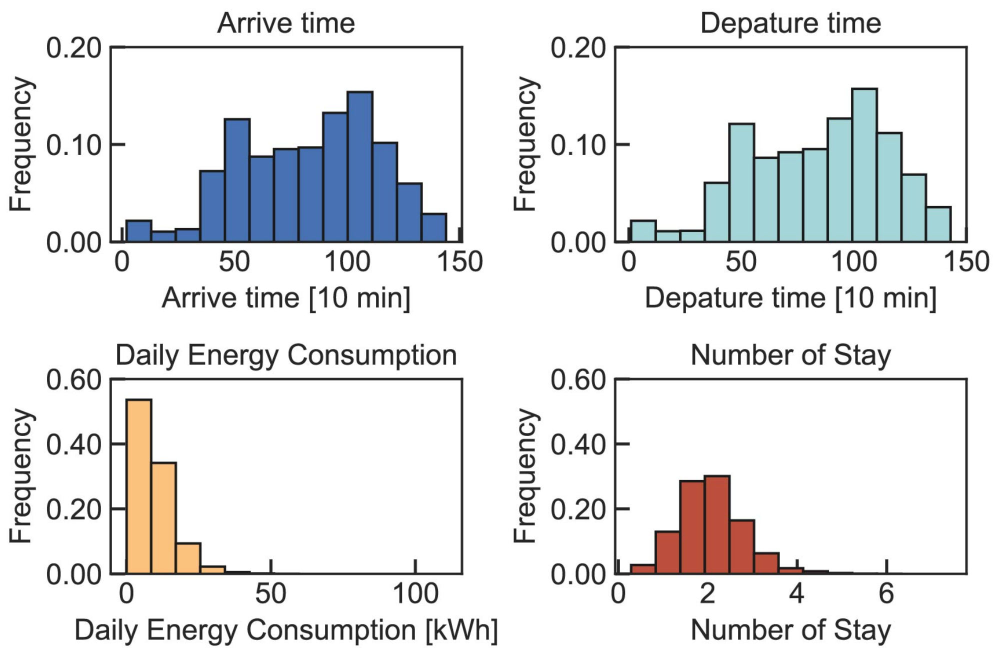

Figure 5: Statistics illustrating the simulated travel behavior of all users.

Note S5: Speech Groups Data

The dendrograms in Fig. 6 and Fig. 7 illustrate the result of the hierarchical clustering on real charging data with 136 charging groups. Some statistics are annotated to support the labeling interpreting the clustering results.

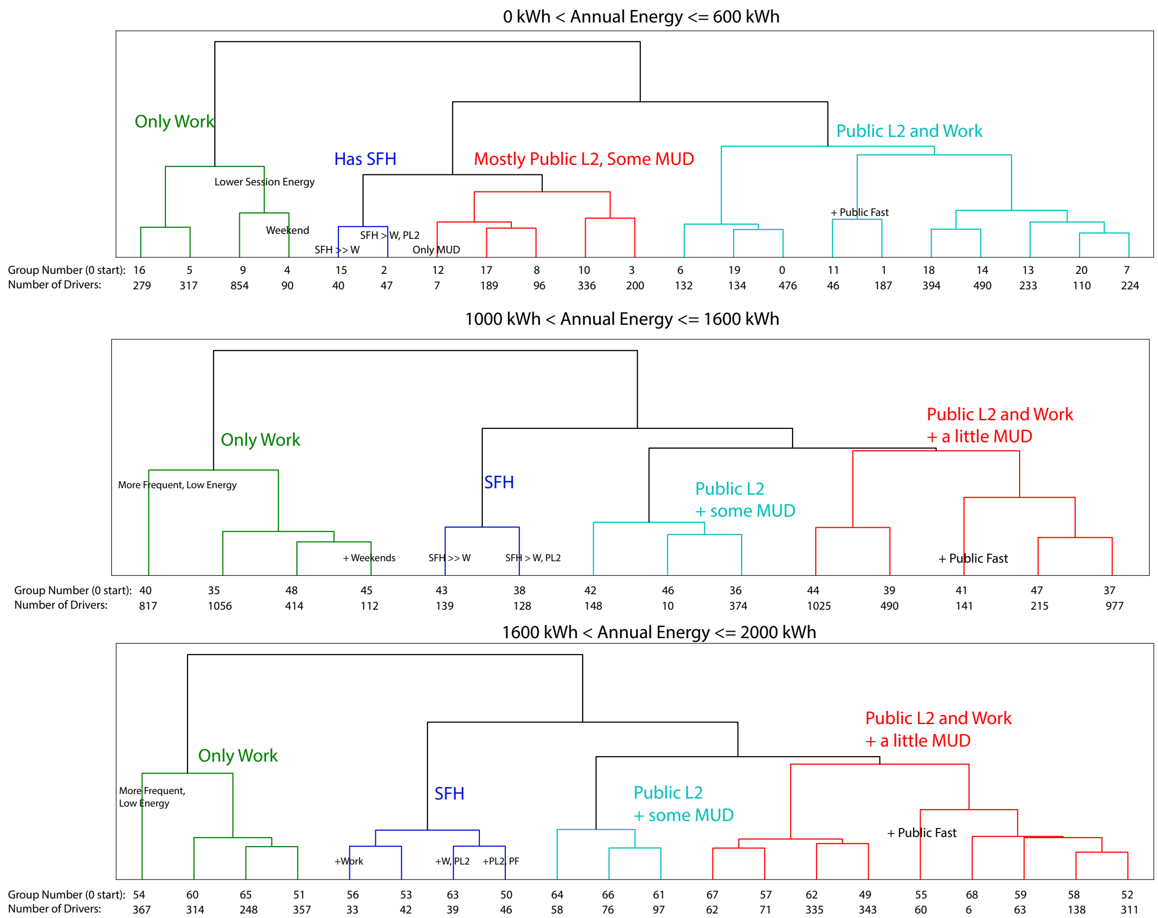

Figure 6: Speech Groups Clustering Dendrograms (Group from 1 to 68)

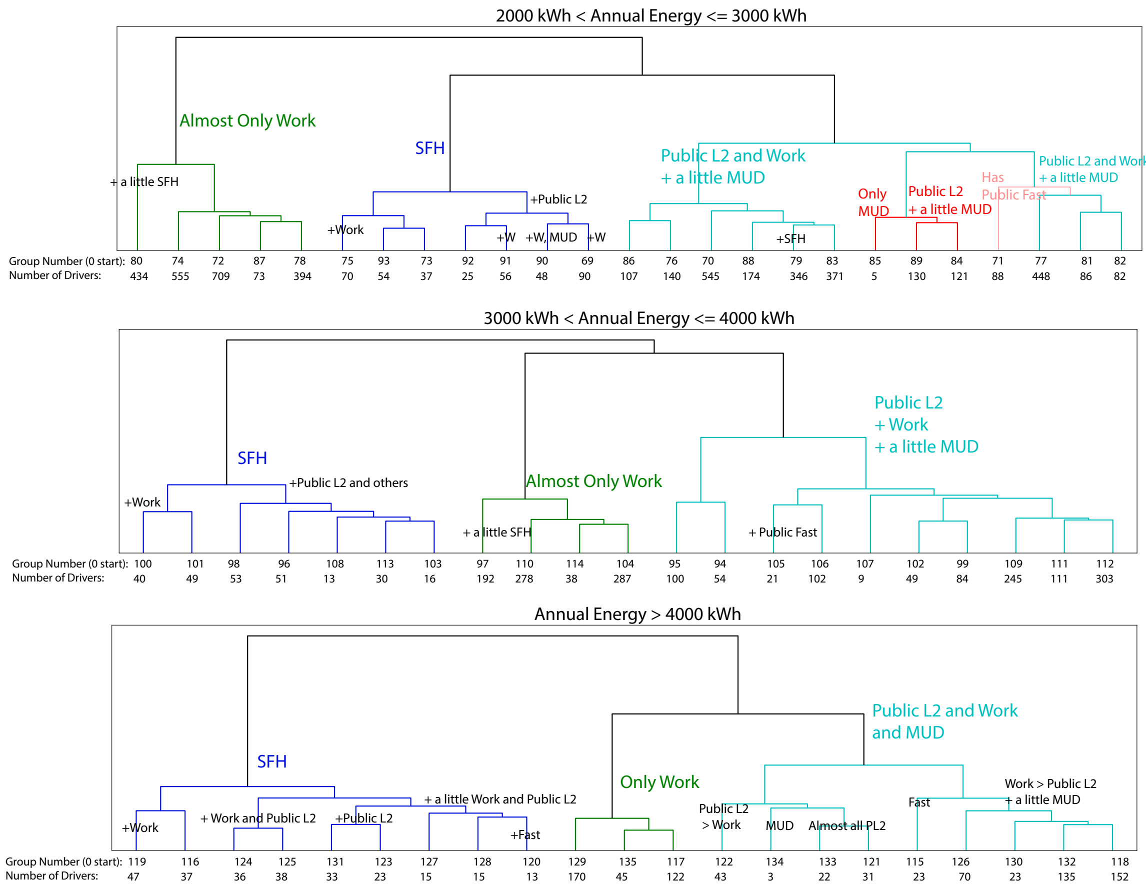

Figure 7: Speech Groups Clustering Dendrograms (Group from 69 to 136)

Note S6: Home charging access survey Data

Table 1 shows the share of vehicles that currently park near 120V electricity or could park in locations where respondents think new electrical installation could occur [2]. We observe that people living in SFH with higher household incomes have a higher probability to have home charging access.

Household Income	$ 60,000 or less	$ 60,000 or less	$ 60,000 to $100,000	$ 60,000 to $100,000	$ 100,000 or More	$ 100,000 or More
Housing Type	SFH	MFH	SFH	MFH	SFH	MFH
Potential Access with Parking Behavior Modification	72%	29%	78%	36%	85%	43%

Table 1: Data from the California Energy Commission's Home Charging Access Survey [2].

Note S7: Monte Carlo simulation

For each EV adopter, TimeGeo estimates when and where the adopter visit during the week. We apply the Algorithm 1 to estimate the charging behavior of a given EV adopter.

Algorithm 1 Monte Carlo simulation for one EV adopter

Input: G: charging group of the adopter, where $G \in [1, ..., 136]$;
e: weekly energy consumption of the adopter;
$\boldsymbol{t}$: stay period of the adopter, where $\boldsymbol{t}_i = (t_i^a, t_i^d)$ with $\boldsymbol{t}_i^a$ and $\boldsymbol{t}_i^d$ as arrival time and departure time, respectively, $\boldsymbol{t}_i^a, \boldsymbol{t}_i^d \in [1, ..., 1008]$;
$\boldsymbol{l}$: stay place of the adopter, where $\boldsymbol{l}_i = (\boldsymbol{l}_i^{type}, \boldsymbol{l}_i^{coordinates})$ with $\boldsymbol{l}_i^{type} \in$ [home, work, public];
$P(z \mid G)$: the probability of an adopter charging in the charging segment z given the charging behaviour group G in a day, where $z \in$ [SFH L1, SFH L2, MFH L2, Work L2, Public L2, Public L3];
$P(c \mid G, z)$: the Gaussian mixture model of charging energy of an adopter in a given group G charging in each segment z on a day, where $c \in \mathbb{R}^+$.

Output: $\boldsymbol{t}^*; \boldsymbol{l}^*$: when and where the adopter charges;
$\boldsymbol{c}^*$: energy charged in the stay;
$\boldsymbol{z}^*$: charging segment in the stay.

for stay i in all stays **do**

  // **When and where charging happens**
  $\boldsymbol{t}_i^* = \boldsymbol{t}_i; \boldsymbol{l}_i^* = \boldsymbol{l}_i$

  // **How to charge (charging segment in the session)**
  if $\boldsymbol{l}_i^* \in$ [home] **then**
    $\boldsymbol{z}_i' =$ [SFH L1, SFH L2, MFH L2, Public L2, Public L3]
  else if $\boldsymbol{l}_i^* \in$ [work] **then**
    $\boldsymbol{z}_i' =$ [Work L2, Public L2, Public L3]
  else if $\boldsymbol{l}_i^* \in$ [public] **then**
    $\boldsymbol{z}_i' =$ [Public L2, Public L3]
  end if
  $\boldsymbol{z}_i^* = \max_{\boldsymbol{z}_i^* \in \boldsymbol{z}_i'} P(\boldsymbol{z}_i \mid G)$.
  Sample if the driver charges charges in segment $\boldsymbol{z}_i^*$ with probability $P(\boldsymbol{z}_i^* \mid G)$.

  // **How much to charge (charging energy in the session)**
  if the driver charges in segment $\boldsymbol{z}_i^*$ **then**
    Sample the energy charged with Gaussian mixture model $\boldsymbol{c}_i^* = P(\boldsymbol{c}_i \mid G, \boldsymbol{z}_i^*)$.
  else
    $\boldsymbol{c}_i^* = 0$
  end if
end for
$\boldsymbol{c}_i^* = \left(\boldsymbol{c}_i^* / \sum_j \boldsymbol{c}_j^*\right) \times e$
return $\boldsymbol{t}^*, \boldsymbol{l}^*, \boldsymbol{c}^*, \boldsymbol{z}^*$

Note S8: Validation for adoption model in the year 2019

Figure 8 shows a comparison between the CVRP data [1] and our simulation. Figure 8a and 8b show the geographical distribution of CVRP and our simulation. The distributions are similar in most ZIP codes. Figure 8c shows the correlation between CVRP data and our simulation, which implies a good agreement between the number of EVs obtained via the Bayesian estimates and the mobility model versus the ground truth of EV usage.

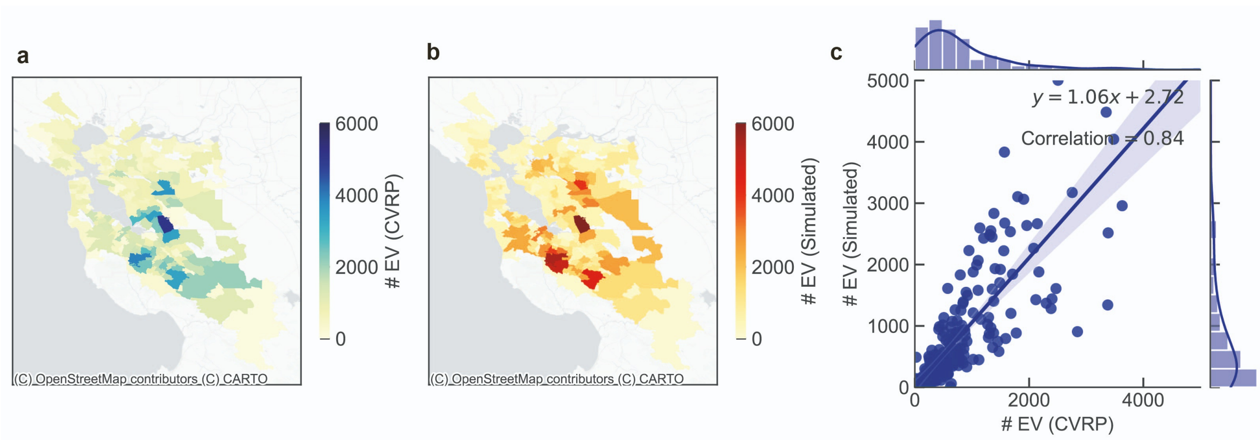

Figure 8: Validation for adoption model in the year 2019.

Note S9: Geographical distribution of EV adopters with increasing adoption rate

Figure 9 shows the number of EV drivers with an increasing adoption rate. The early EV adopters locate in the South Bay as shown in Fig. 9a-c. When the adoption rate keeps increasing, there will be more EV adopters in the North Bay Area as shown in Fig. 9d-f.

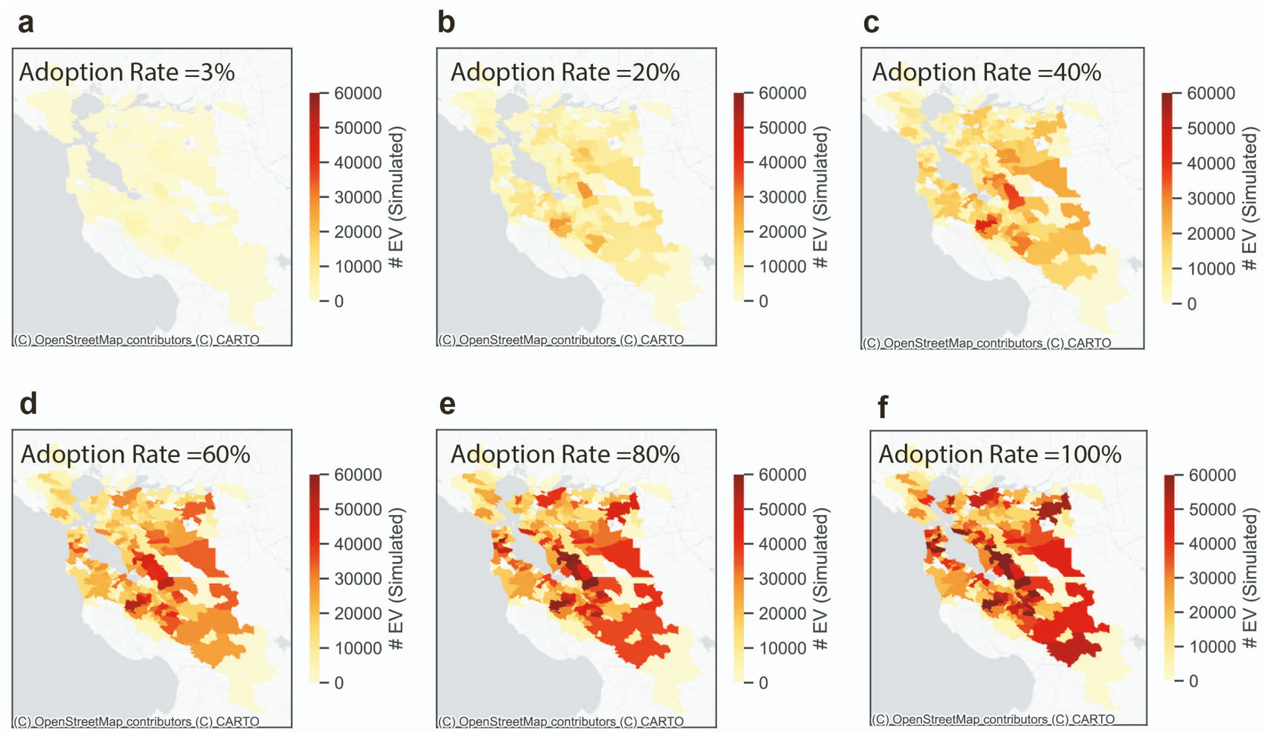

Figure 9: Geographical distribution of EV adopters with increasing adoption rate

References

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