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Toward Human-Cyber-Physical Systems: A Case Study in Transportation Electrification

By

Jiaman Wu

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

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in the

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of the

University of California, Berkeley

Committee in charge:

Associate Professor Marta C. Gonzalez, Chair

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Professor Scott J. Moura

Professor Joan L. Walker

Spring 2025

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Abstract

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Associate Professor Marta C. Gonzalez, Chair

Modern urban systems can be represented as large-scale cyber-physical infrastructures embedded in complex networks of human communications and interactions. While human dynamics plays a critical role in shaping system outcomes, it is often overlooked in system design. To address this gap, this dissertation introduces a framework that models human dynamics, connects human dynamics with physical system states, and devises policies to coordinate both. The framework is demonstrated in the context of transportation electrification.

The first part of this dissertation focuses on modeling human dynamics in urban systems. Specifically, Chapter 2 examines how spatial social networks influence plug-in electric vehicle (PEV) adoption using an agent-based Bass model applied at multiple spatial scales. The results demonstrate that integrating spatial and social connectivity leads to lower long-term forecasts than those from benchmark models, while also offering greater flexibility to account for the spatial autocorrelation observed in the empirical diffusion process. Furthermore, this part evaluates the effectiveness of various PEV marketing strategies under uncertainty, emphasizing the importance of aligning outreach efforts with social network structure.

The second part models how physical system states respond to human dynamics. Specifically, Chapters 3 and 4 use estimated human mobility patterns to inform the operation of private PEVs and commercial electrified fleets. For private PEVs, large-scale mobility traces are combined with empirical charging preferences to estimate individual charging behavior. The analysis shows that personalized, mobility-constrained charging recommendations can effectively reduce peak load stress on the power grid, providing valuable insights for charging infrastructure planning. For commercial fleets, the use case is extended to electric vertical take-off and landing aircraft. Using location-based service data, passenger travel demand is estimated and incorporated into a joint optimization of fleet dispatch and smart charging operations. This integrated approach is shown to improve power grid welfare without compromising optimal fleet dispatch.

The third part explores how system operators can design scalable and effective incentive mechanisms to coordinate human dynamics with physical system performance. In Chapter 5, we propose a cluster-based, appliance-level demand response program that utilizes large-scale energy consumption data to support the power grid's operation. By modeling appliance-level utility functions, the framework identifies distinct consumption patterns and captures user heterogeneity through clustering. A bi-level optimization model is developed to represent the interaction between individual consumers and the system operator. This approach demonstrates how fine-grained modeling of human dynamics can enhance market efficiency.

Together, this dissertation demonstrates how human activity data and algorithmic frameworks can be leveraged to advance the integration of human dynamics into transportation electrification. The unique contribution of this study lies in establishing a foundation for incorporating human dynamics into the modeling, control, and planning of any complex cyber-physical systems.

To my family, friends, and mentors.

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Chapter 1

Introduction

The widespread deployment of sensors, control systems, and communication technologies has led to the emergence of Cyber-Physical Systems (CPS) [1], where digital technologies interact with physical infrastructure. CPS is reshaping transportation systems [2, 3] and power grids [4, 5] by enabling more intelligent and adaptive operations. However, most CPS designs overlook one crucial element: explicitly modeling human system dynamics' influence. In reality, individuals are not passive users—they make decisions that influence, and are influenced by CPS. As such, a more complete framework is needed to integrate human system dynamics and CPS dynamics within a single modeling paradigm. To address this, I present the Human-Cyber-Physical System (HCPS) framework. The HCPS framework consists of three interconnected elements:

Human system dynamics, denoted as $\mathbf{s} = h(\mathbf{z}, \mathbf{x})$, describes how human system dynamics evolves in response to operator interventions ($\mathbf{z}$) and the state of the physical system ($\mathbf{x}$).

Physical system dynamics, denoted as $\mathbf{x} = f(\boldsymbol{\mu}, \mathbf{s})$, captures how the state of the physical system ($\mathbf{x}$) changes in response to direct operator controls ($\boldsymbol{\mu}$) and human system dynamics ($\mathbf{s}$).

Operator policy, denoted as $(\boldsymbol{\mu}, \mathbf{z}) = g(\mathbf{x}, \mathbf{s})$, specifies how the operator responds to the state of the physical system ($\mathbf{x}$) and human system dynamics ($\mathbf{s}$) by choosing control actions ($\boldsymbol{\mu}$) and interventions ($\mathbf{z}$).

Figure 1.1 illustrates the flow of influence among human system dynamics, physical system dynamics, and operator policy. Humans make decisions ($\mathbf{s}$), which influence physical system states ($\mathbf{x}$). The operator monitors both, and adjusts interventions ($\mathbf{z}$) or physical system control ($\boldsymbol{\mu}$) in response. In the meantime, physical system states ($\mathbf{x}$) and operator interventions ($\mathbf{z}$) also influence human system dynamics. This creates a closed-loop system where the human system, the physical system, and the operator evolve together.

Human-Cyber-Physical System

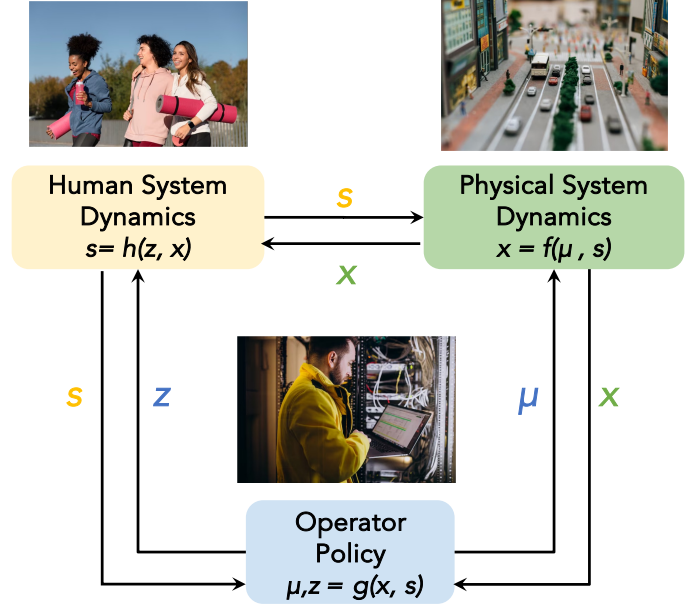
 s : Human system dynamics x : Physical system dynamics z : Operator actions to human system μ : Operator actions to physical system $h(.)$: Human dynamics model $f(.)$: Physical system dynamics model $g(.)$: Operator policy model

Figure 1.1: Framework of Human-Cyber-Physical System. The system captures influences among human system dynamics, physical system dynamics and the operator's policy.

1.1 Summary

The HCPS framework can be tailored to enhance system efficiency in one of the most crucial societal shifts of our era: the *electrification of transportation systems*. As electric vehicles (EVs) become increasingly prevalent, the transportation and power systems grows more interconnected. Yet, both systems are still largely designed without fully accounting for human system dynamics—particularly at scale. This dissertation applies the HCPS framework to the field of transportation electrification, addressing three key research questions aligned with the main components of the HCPS framework.

1.1.1 Human System Dynamics: How Do Social Networks Shape Electric Vehicle Adoption?

This part focuses on the human system dynamics model $s = h(z, x)$. Human system dynamics can be represented in various forms depending on the modeling context and data availability—ranging from simple scalars to probabilistic models. Conventional approaches rely on a limited amount of survey data to model the human system, which does not adequately account for the diversity in human system dynamics. Recently, advances in technology have provided access to extensive datasets related to human activities. These datasets facilitate a deeper understanding and modeling of microscale human activities at both individual and

collective levels. Chapter 2 shows how to model human system dynamics using large-scale datasets. Specifically, it answers one research question: How do social networks shape EV adoption?

Chapter 2 uses large-scale EV registration data to model EV diffusion on the spatial social network. The results reveal that incorporating social networks leads to lower adoption forecasts compared to traditional benchmark models. Moreover, the spatial social network-based model offers greater flexibility in capturing the spatial autocorrelation observed in empirical diffusion patterns. The chapter also evaluates the potential impacts of different EV marketing strategies. These insights are essential for charging infrastructure planning.

1.1.2 Physical System Dynamics: How Can We Link Charging Behavior to the Operations of Power and Transportation Systems?

This part focuses on the physical system dynamics model $\mathbf{x} = f(\boldsymbol{\mu}, \mathbf{s})$. Human system dynamics can be integrated into system models in various ways. In optimal control problems, they can serve as inputs for state estimation at future time steps, while in optimization problems, they may appear in objective functions or as constraints. When analytical solutions become infeasible due to system complexity, agent-based modeling provides a flexible alternative by enabling individual decision-making simulation with human system dynamics explicitly embedded. Chapters 3 and 4 illustrate the integration of human system dynamics within physical systems in the context of agent-based modeling and optimization problems. Specifically, it answers one research question: How can we link charging behavior to the operations of power and transportation systems?

Chapter 3 investigates how individual charging behaviors influence regional charging loads and explores the resulting policy implications. This includes modeling individual charging demand, evaluating the associated stress on the power grid, and informing the strategic deployment of charging infrastructure. Beyond private vehicles, knowledge of human system dynamics can also enhance the efficiency of electric fleet operations. Chapter 4 extends the analysis to electric vertical take-off and landing (eVTOL) aircraft fleets. Using location-based service (LBS) data, it estimates passenger travel demand and conducts a joint optimization of fleet dispatch and smart charging operations to maximize power grid social welfare. Together, these chapters illustrate how human system dynamics can inform the design of integrated power and transportation systems.

1.1.3 Operator Policies: How Can Operators Design Demand Response Programs to Increase Power Grid Revenue?

This part focuses on the operator policy model $(\boldsymbol{\mu}, \mathbf{z}) = g(\mathbf{x}, \mathbf{s})$, which determines how policies are selected based on the observed physical system and human system dynamics. In the HCPS framework, the operator aims to influence both physical system outcomes and

human system dynamics to achieve desired objectives. This requires mechanisms that are not only effective in dynamic physical systems but also scalable across diverse user groups. Chapter 5 addresses the question: How can operators design demand response programs to increase power grid revenue?

Chapter 5 develops a cluster-based demand response program that utilizes large-scale appliance-level energy consumption data. At the core of the approach is the utility model that distinguishes users based on their unique consumption behaviors. The distribution system operator (DSO) then designs group-level incentives to influence households' electricity consumption at the appliance level. By moving beyond one-size-fits-all pricing schemes and incorporating detailed human system dynamics modeling, the method offers a scalable and effective way to align human system dynamics with physical system-level goals.

1.2 Contributions

This dissertation introduces a novel approach to managing the HCPS. Overall, it offers four key categories of contributions:

Planning the Electric Vehicle Transition by Integrating Spatial Information and Social Networks (Chapter 2)

- *EV Diffusion Modeling on Spatial Social Networks:* In this work, we investigate how spatial social networks influence Plug-in EV (PEV) adoption forecasts by comparing the original Bass Model (BM) and the Social Network (SocNet) BM at different spatial scales (Chapter 2.3 and Chapter 2.4).
- *Impacts of Social Networks on EV Diffusion:* We find that both models can be calibrated to fit data up to 2022, but including or excluding social network effects leads to a threefold difference in adoption rate projections by 2050 (Chapter 2.5). We also demonstrate that the SocNet BM allows more flexibility to capture spatial autocorrelation of the empirical diffusion process than the State/County BM (Chapter 2.6).
- *Marketing Policy Implications:* We point out that promotion campaigns should be designed based on the understanding of spatial social network structure in the area of interest, as the effectiveness of campaigns is tied to the local socio-demographical structure (Chapter 2.7).

Planning Charging Stations for 2050 to Support Flexible Electric Vehicle Charging Demand (Chapter 3)

- *Individual Charging Demand Modeling:* We develop a framework that integrates individual mobility and charging data to generate realistic individual charging profiles.

Combining charging and mobility patterns enables the exploration of geographical patterns in charging demand, which is understudied in previous research (Chapter 3.2).

- *Personalized Charging Shifting Recommendation*: We implement personalized shifting recommendations to shift charging demand to off-peak periods to prevent EV charging load from contributing to increased power grid demand during peak periods (Chapter 3.3).
- *Charging Infrastructure Planning for 2050*: 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 (Chapter 3.4).

Integrating Urban Air Mobility into the Power Grid through Smart Charging Solutions (Chapter 4)

- *UAM Travel Demand Estimation*: We estimate the city-level mobility pattern using LBS data. Then we sample the urban air mobility (UAM) trips given a UAM penetration level based on this city-level travel demand (Chapter 4.2).
- *Transportation and Power System Nexus*: We calculate an optimal fleet dispatch policy with integer programming to maximize the fulfillment of day-ahead scheduled UAM travel demand (Chapter 4.3). Then, we model how fleet charging affects the power grid by employing the DC optimal flow model. Last, we maximize power system welfare through smart charging scheduling without changing fleet dispatch (Chapter 4.4).
- *Stochastic Characterization of UAM Operations*: We consider the uncertainty in UAM operations and propose charging schedules using chance-constrained MIP. We compare scenarios with and without uncertainty. This comparison helps us evaluate how uncertainty affects the effectiveness of smart charging in mitigating the negative impact of large-scale UAM on the power grid (Chapter 4.5).

A Cluster-based Appliance-level-of-use Demand Response Program Design (Chapter 5)

- *Data Empowered Appliance-level Utility Modeling*: We model the appliance-level utility as a quadratic function and use the discrete choice model (DCM) to estimate key parameters that distinguish users' usage patterns based on appliance consumption data. We then develop a strategy to combine appliance-level utility functions into a single utility function for the user (Chapter 5.2).
- *Demand Response Design to Offer Appliance-level Incentive*: Based on the proposed appliance-level model, we extend the conventional level-of-use demand response program to an appliance-level-of-use program, which leverages the bi-level structure and

offers users more specific and detailed incentives based on the use of each appliance (Chapter 5.3).

- *Heterogeneity Characterization to Improve Scalability and Efficiency*: To improve the scalability of the proposed program, we propose a cluster-based appliance-level-of-use program to capture the heterogeneity of different users by categorizing them into different groups (Chapter 5.4).

1.3 Dissertation Organization

This dissertation is organized as follows. Chapter 2 develops an agent-based diffusion model to study human system dynamics in the adoption of PEVs in the spatial social networks. Chapter 3 uses large-scale human mobility data to model private PEV charging behaviors and proposes personalized, mobility-aware charging strategies to reduce grid peak load. Chapter 4 extends the analysis to commercial electrified fleets by co-optimizing the dispatch and smart charging of eVTOL aircraft. Chapter 5 focuses on designing scalable demand response mechanisms that align individual user behavior with system-level objectives. Finally, Chapter 6 summarizes the main results of this dissertation, its broader implications, and possible future research directions.

Chapter 2

Planning the Electric Vehicle Transition by Integrating Spatial Information and Social Networks

The transition from gasoline-powered vehicles to PEVs presents a promising avenue for reducing greenhouse gas emissions. Spatial forecasts of PEV adoption are essential to facilitate this shift as they enable preparation for power grid adaptation. However, forecasting is hindered by the limited data availability at this early stage of adoption. Multiple model calibrations can match current adoption trends but yield divergent forecasts. By leveraging empirical data from places with leading adopters in the United States, this chapter shows that taking into account the spatial and social structure linking potential PEV adopters leads to forecasts of only a third of the benchmark predictions for 2050. Additionally, it demonstrates that a model with spatial social networks allows more flexibility to capture the spatial autocorrelation of the empirical diffusion process. At last, this chapter evaluates the potential impact of various PEV marketing campaigns under prevailing uncertainties, emphasizing the need to tailor strategies to network dynamics for effective PEV promotion.

2.1 Introduction

Modern techno-social systems consist of large-scale physical infrastructures embedded in a complex communication web whose dynamics are driven by human behavior [6]. This interplay is illustrated by the growing integration of PEVs –including both battery electric vehicles (BEVs) and plug-in hybrid vehicles (PHEVs)- into power systems. PEVs offer significant environmental advantages by reducing traffic-related air pollutants and cutting down greenhouse gas emissions [7, 8]. In addition, they provide economic benefits such as improved fuel efficiency and enhanced energy security [9]. Recognizing these advantages, the United States has enacted policies to encourage the uptake of PEVs. In 2022, the California Air Resources Board (CARB) approved the Advanced Clean Cars II regulation to ensure

that by 2035, all new cars and light trucks sold in California will be zero-emission vehicles (ZEVs) [10]. That same year, Washington state announced it would follow California and prohibit the sale of new gas-powered vehicles by 2035 [11]. Meanwhile, worldwide efforts to accelerate the adoption of PEVs are exemplified by the China mandate for new energy vehicles [12], the United Kingdom’s plan to transition to ZEVs [13], and the European Union’s CO₂ emissions regulations [14]. These initiatives are expected to substantially boost adoption in the near future. Aligned with this trend, modeling the geographical distribution of future PEV adopters becomes a pivotal task. This is because human decisions on when and where to adopt PEVs are linked directly to the regional electricity demands [15], the consequent pressure on the power grid [16], and the power system infrastructure planning [17]. Computational modeling approaches can provide predictability in complex technological systems if fed with the right data. Yet, modeling the spatial distribution of future PEV adopters is challenging. Despite increasing share in global vehicle sales [18], the adoption rate of PEVs is low [19] and with high regional disparities globally as well as within a country [20]. This early stage of adoption results in limited data to forecast the geographical distribution of PEV adopters.

The diffusion of PEVs exhibits significant differences across different demographic groups at the early stage. Evidence from the global PEV market indicates that early PEV adopters tend to have higher incomes [21], advanced education [22], and reside in non-apartment houses with home charging access [23]. In this regard, forecasting PEV adoption involves addressing the complex challenge of modeling the impact of various factors on adoption across diverse demographic segments. These factors can be broadly categorized as innovation-related and imitation-related. Innovation-related factors determine the extent to which consumers are inclined to adopt PEV without the impact of social influences, whereas imitation-related factors pertain to word-of-mouth effects from individuals who have already adopted or have experience with the PEV. Specifically, innovation is relevant to vehicle-specific attributes such as purchase cost and maximum driving range [24], mass media or advertising regarding PEV [25], the built environment such as the availability of public charging infrastructure [23] and grid infrastructure [26], availability of monetary incentives such as rebate upon purchase and tax reduction after purchases [27], and non-monetary incentives such as high-occupancy vehicle (HOV) lane access for adopters [28]. Imitation, on the other hand, is shaped by social influences from friends [29], online interactions [30] as well as neighborhood and workplace interactions [31, 32].

Previous studies establish a connection between aforementioned factors and the PEV diffusion projection utilizing aggregated and disaggregated data. The aggregated data is represented by the share of PEV vehicle sales at the country level [33], whereas the disaggregated data includes individual purchase records [34, 35] and surveys on travel behavior [36] or home charging access [37]. The spectrum of methodologies ranges from discrete choice models [38] to regression models [39]. For instance, Forsythe *et al.* [40] conduct a discrete choice experiment among new vehicle consumers in the United States. This study indicates that projected advances in BEV range and price may allow them to equal or exceed the consumer valuation of gasoline vehicles by 2030. Wu *et al.* [41] employ Bayesian models to predict

individual adoption probabilities and map the spatial distribution of charging demand of prospective adopters under varying adoption scenarios in the San Francisco Bay Area. They demonstrate that personalized shifting recommendations regarding charging schedules can reduce charging demand during power grid peak hours by 61% when achieving 90% PEV stock. Bayesian models can project the geographical distribution of future adopters given any adoption rate. However, it cannot output the time to reach such adoption. To provide temporal projections, the Bass model (BM) is widely used. The BM analyzes the market as a whole using two parameters (related to imitation and innovation factors, respectively). In 2009, Becker *et al.* [42] incorporate assumptions related to oil price fluctuations and incentives with BM and project that 65% of vehicle sales by 2030 will consist of PEVs. Jenn *et al.* [43] utilize sales data from 39 countries and explore PEV market expansion through BM. They find that it may be challenging to achieve targets such as 100 million electric vehicles worldwide by 2030. Lee *et al.* [44] use BM to predict the adoption dynamics of heterogeneous groups of PEV buyers. Their findings indicate that although high-income families currently constitute 49% of the PEV market, they form only 3.6% of households in California, suggesting this group may not remain the dominant PEV adopters. To sustain market growth, policymakers should account for the infrastructure and incentive requirements of consumers from mid/high- and middle-income groups. Despite the ability to provide temporal projections, BM does not provide the spatial distribution of future adopters. One limitation of the BM lies in that the formulation of BM implies homogeneity and global interconnectedness, i.e., each agent's probability of adoption is influenced uniformly by the adoption state of all other agents [45]. This leads to the omission of spatial information and characterization of heterogeneity in social influence. Another limitation of modeling adoption with the BM is that the model represents each demographic group in isolation and thus disregards any interaction the groups may have. To incorporate the role of geography and demographic characteristics in diffusion, we need models that consider both the spatial distribution of individuals and heterogeneity in the social network connections among different socio-demographic groups.

In this work, we investigate how spatial social networks influence PEV adoption forecasts by comparing benchmark adoption models at different spatial scales. We first aggregate individual purchase records at state, county, and census tract levels, and then we fit the empirical adoption trends at different levels of spatial aggregation in Washington and California. To that end, we consider two versions of the BM: the original BM and the Social Network BM (SocNet BM). Results reveal that both models can be calibrated to fit data up to 2022, but including or excluding social network effects leads to a threefold difference in adoption rate projections by 2050. Additionally, we demonstrate that the SocNet BM allows more flexibility to capture spatial autocorrelation of the empirical diffusion process than the State/County BM. This spatial information is critical for planning charging and grid infrastructure. At last, we point out that promotion campaigns should be designed based on the understanding of spatial social network structure in the area of interest as the effectiveness of campaigns is tied to the local socio-demographical structure. Altogether, the study offers insights on the forecast based on early adopters that is valuable to planning

power grid demand and the allocation of charging infrastructure.

2.2 Adoption Overview

California and Washington have the greatest market share of PEVs in the United States by the end of 2022 [46]. In this section, we use PEV purchase records in these two leading states for the adoption overview. The Clean Vehicle Rebate Project (CVRP) provides individual electric vehicle purchase records with adopters' home census tracts and the purchasing date in California between 2010 and 2022 [34]. The Electric Vehicle Title and Registration Activity (EVTRA) includes records of PEV ownership with adopters' home census tract and the purchasing date in Washington between 2010 and 2022 [35]. We get data on the number of passenger vehicles and household median incomes at the census tract level between 2010 and 2022 from the Census Bureau [47].

We empirically investigated the PEV adoption process from 2010 to 2022. On the state level, Fig. 2.1 (A) shows that the total adoption rate in Washington is around 1.9% in 2022 and the incremental adoption rate presents an increasing trend from 2010 to 2022. Fig. 2.1 (D) shows that California has a total adoption rate of around 2.0% in 2022. The incremental adoption rate reached local maxima in 2017. This may have happened due to rebate program policy changes at the end of 2016 [48]. Following the Diffusion of Innovation Theory [49], Rogers divides adopters as (1) innovators: first 2.5%, (2) early adopters: next 13.5%, (3) early majority: following 34%, (4) late majority: next 34%, and (5) laggards: last 16%. This locates current state-level adoption trends in the innovators' phase.

On the county level, Fig. 2.1 (B) shows that most PEV adopters from Washington live in King County and Pierce County. Fig. 2.1 (E) shows that most PEV adopters from California live in the Bay Area and Los Angeles County. These two maps indicate that PEV adoption started in metropolitan areas with a higher population and has not yet reached more rural areas. On the census tract level, we examine the correlation between socio-demographic characteristics and the total adoption rate. Fig. 2.1 (C,F) show, respectively, the adoption rate and the corresponding median household income of each census tract in Washington and California in 2022. Fitting the relationship between the adoption rate and the corresponding median household income results in similar slope coefficients of 0.04 ($R^2 = 0.52$) and 0.03 ($R^2 = 0.50$) for Washington and California. According to the correlation between adoption rate and income, we segment the potential market into low-, middle-, and high-income groups for adoption modeling purposes (see Methodology 2.8.1).

2.3 Calibration of PEVs Diffusion Models

We use the BMs at the state level and the county level as benchmarks, referred here as State/County BM (see Methodology 2.8.2). In BMs, the probability of every agent to adopt, given that it has not adopted so far, depends linearly on an independent innovation-related

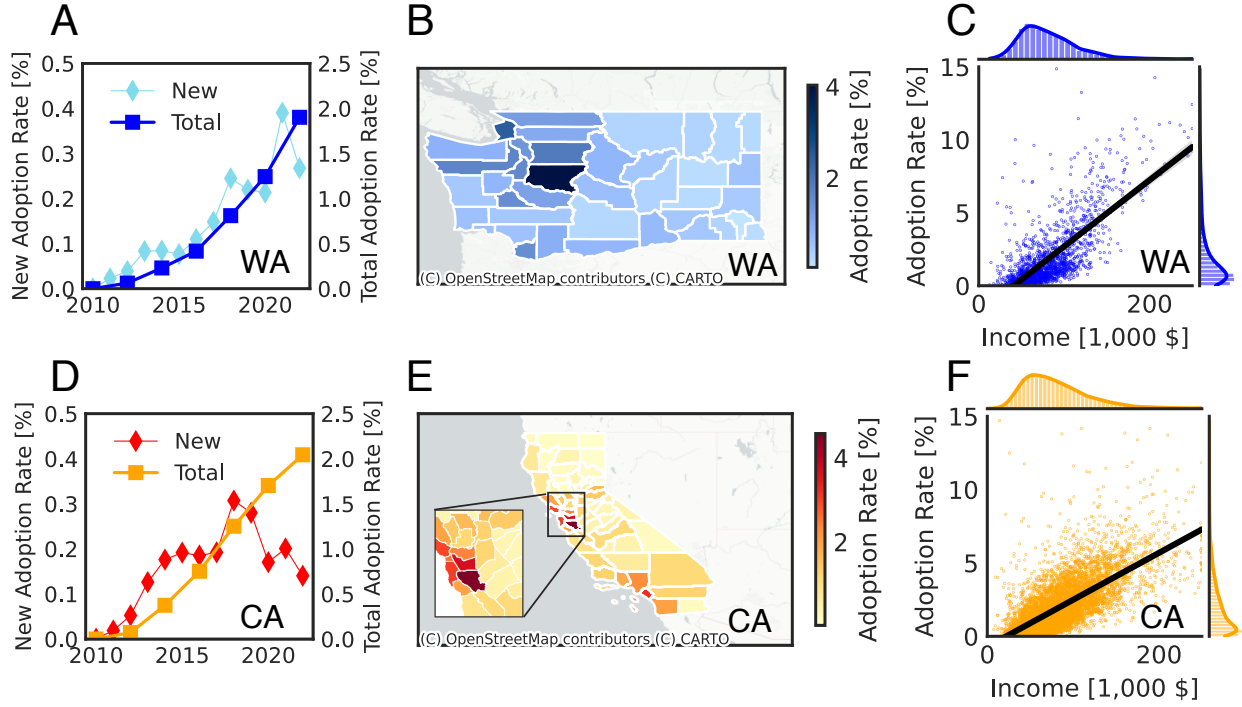


Figure 2.1: Overview of current PEV adoption. (A,D) State-level yearly total adoption rate (circle marker) and new adoption rate (square marker) in Washington (blue) and California (orange) from 2010 to 2022. (B,E) Maps of county-level cumulative adoption rate in Washington (blue) and California (orange) in 2022. A zoom-in adoption rate map in Bay Area is attached with (E). (C,F) Correlation between the adoption rate and the corresponding median household income of all census tracts in Washington (blue) and California (orange) in 2022. The black regression line given the adoption rate and the corresponding median household income are shown with points.

influence p and an imitation-related influence q that depends on the fraction of prior adopters [50]. This formulation implies homogeneity and global interconnectedness and fails to capture the heterogeneity in social connections among different socio-demographic groups from different locations.

Here, we further investigate the adoption spreading on a social network embedded with geographical and socio-demographic information via the SocNet BM (see Methodology 2.8.3). We start by creating social networks preserving preferential attachment connectivity and distance effects features following [51]. In a network, the concept of preferential attachment suggests that the likelihood of forming a connection with a node increases with its number of connections. Meanwhile, geographical effects indicate that nodes are more inclined to form connections with their geographically close neighbors. Therefore, in a network incorporating

both preferential attachment and geographical effects, any long-distance connections that do form are typically directed toward highly connected nodes. This suggests a dual influence on network growth: while local connections favor spatial proximity, distant connections seek out nodes that are significant in terms of their connectivity, creating a network characterized by both local clustering and scale-free properties [51]. With social networks, we fit SocNet BM parameters, namely p and q for low-, middle-, and high-income groups with empirical county-level aggregated PEV sales data (see Methodology 2.8.3). Considering that varying p and q can fit the data at this early stage (we defer detailed explanation in Section 2.6), we repeat the fitting process and report the median and uncertainty interval of results in this study. Afterward, we compare how well the State/County BM and SocNet BM fit the data by investigating fitting errors at the state, county, and census tract levels.

Fig. 2.2 (A,B) show the state-level aggregated adoption rate in Washington and California between 2010 and 2022. All models fit similarly well with the empirical data, i.e., State/County BM has a mean absolute error of 0.03% and SocNet BM of 0.08% in Washington. In California, the errors are 0.08% and 0.11%, respectively. Different from County BM and SocNet BM which directly outputs county-level forecasts, State BM fits and projects state-level adoption rates. To get the county-level aggregated adoption rate from State BM, we simulate PEV adoption growth curve on the state level based on fitted parameters and assign the PEV adopters to census tracts proportionally to the population. Fig. 2.2 (D,E) show the county-level aggregated cumulative adoption rate in Washington and California in 2022. We present the 15 most populated counties in each state and show the aggregated cumulative adoption rate for other counties in Appendix A.1. We find that County BM and SocNet BM fit the data similarly well. However, State BM underestimates adoption rates in more populated counties and overestimates adoption rates in less populated counties. For example, it underestimates the adoption rate in King County while overestimating the adoption rate in other counties in Washington. In California, State BM underestimates the adoption rate in Los Angeles, Orange, Santa Clara, and Alameda County while overestimating the adoption rate in other counties.

On the tract level, Fig. 2.2 (C) show the distribution of adoption rate error for three models. The adoption rate error values are the absolute difference between the simulated adoption rate and ground truth adoption rate in 2022. The errors for most tracts in Washington and California are within 2.5%. The tract-level error of SocNet BM has a higher variance than State/County BM (see Appendix A.2) since (1) it characterizes the adoption diffusion on an individual basis while State/County BM uses only three p and q sets (fitted from three socio-demographic groups) to characterize the adoption diffusion. (2) it characterizes the uncertainty in the adoption process by simulating it in an agent-based and probabilistic manner.

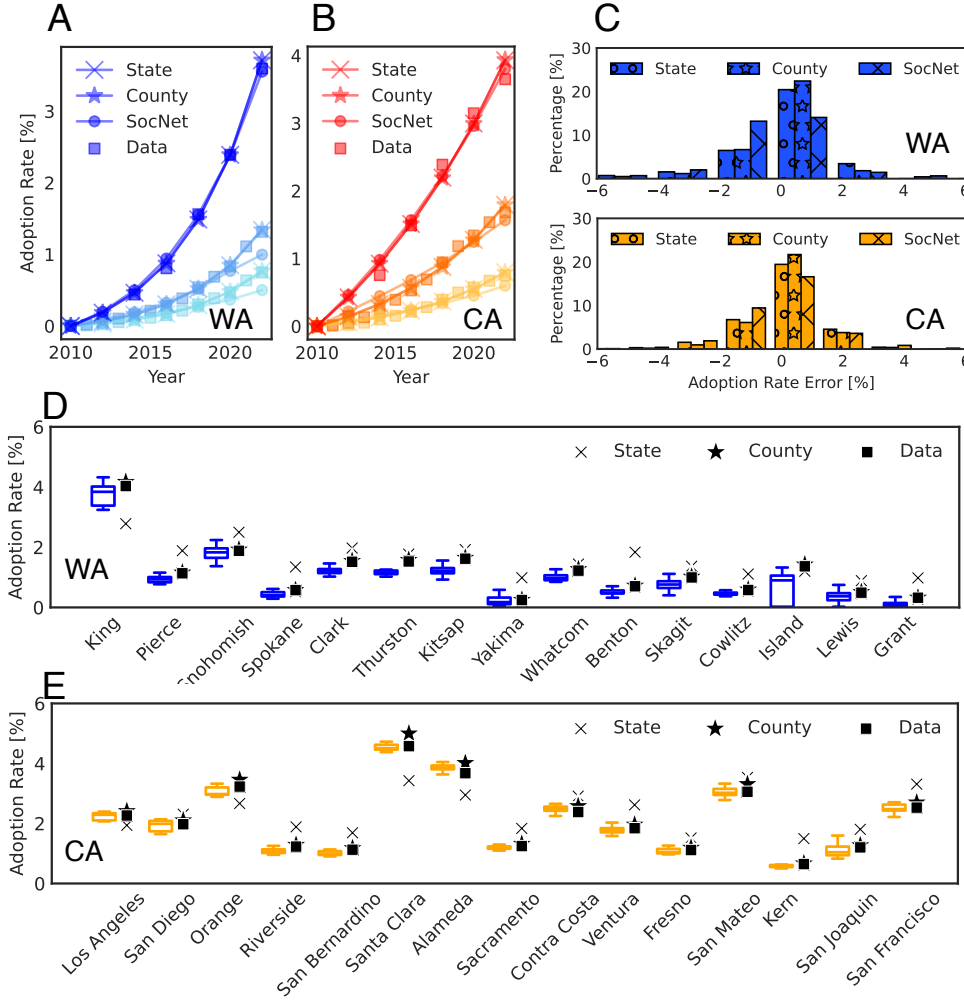


Figure 2.2: Comparison of State/County BM and SocNet BM's performance. (A, B) State-level fitted adoption curves of State BM (cross), County BM (star), SocNet BM (circle), and data (square) for low (light blue/yellow), middle (blue/orange), and high (dark blue/red) income groups in Washington and California from 2010 to 2022. Solid lines with markers show the median (50th percentile) adoption rate of income groups in states. (C) Distribution of tract level adoption rate error of State BM (cross), County BM (star), and SocNet BM (circle) in Washington (blue) and California (orange) in 2022. (D,E) County-level adoption rates of State/County BM and SocNet BM in the most populated 15 counties in Washington (blue) and California (orange) in 2022. The box shows the quartiles of the county-level adoption rates of SocNet BM while the whiskers extend to show the rest of the distribution. Cross markers show the adoption rate of State BM, star markers show the adoption rate of County BM, and square markers show the empirical data.

2.4 Parameters of PEVs Diffusion Models

The innovation parameter p reflects the extent to which consumers are willing to adopt new products without being affected by others. It is widely recognized that vehicle-specific attributes [24], mass media [25], the built environment [23, 28], availability of incentives [27] are relevant to the willingness of consumers to accept PEVs. However, to what extent these factors influence whether people adopt PEV remains an open question. The imitation parameter q describes the “word-of-mouth” effect [29, 30, 31, 32]. It captures how adopters are affected by the number of adopters in their social network. In general, a higher p indicates the new product will have more adopters from the beginning and a higher coefficient of imitation indicates that the diffusion will accelerate faster later.

We show the distribution of obtained parameters for State/County BM and SocNet BM for the three socio-demographic groups in Washington and California in Fig. 2.3 and attach median values of these parameters in Appendix A.3. Fig. 2.3 (A) shows that in Washington, the high-income group has the highest p and the low-income group has the lowest p for three models. Fig. 2.3 (B) shows that the q for State/County BM are similar across three groups in Washington. Similar to Washington, the high-income group in California has the highest p and the low-income group has the lowest p as shown in Fig. 2.3 (C). Compared with Washington, California has higher p for the three income groups at the state level. Fig. 2.3 (D) shows that in California, the q of the State/County BM and SocNet BM are similar across three groups. The difference between State/County BM and SocNet BM is that the fitted parameters of SocNet BM have more variance. This variance is brought by fitting with limited data, and also the probabilistic nature of the agent-based simulation process.

2.5 Divergence of PEVs Adoption Forecasts

We forecast PEV adoption rates from 2023 to 2050 with the calibrated models. In this section, we present the most optimistic adoption forecast by assuming that PEV users will not revert to internal combustion engine vehicles (ICEVs). The forecast considering the potential switching back to ICEVs by PEV users is deferred to Appendix A.4. Fig. 2.4 shows the comparison of State/County BM and SocNet BM’s prediction. Interestingly, we find that the social network model is three times more conservative in future forecasts, even though the three models all fit the empirical data well (as shown in Fig. 2.2).

Fig. 2.4 (A,C) show the adoption growth curves of State BM and County BM are similar as they all assume global interconnectedness in social network [45]. In contrast, SocNet BM has much lower adoption rate predictions than State/County BM. This is because the SocNet BM uses a social network model while individuals are influenced by the whole population in the State/County BM.

Fig. 2.4 (B,D) demonstrate the predicted county-level adoption rate in 2050 for the three considered models. We present the most populated 15 counties in Washington and California and show other counties in Appendix A.5. Although State BM and County BM are similar

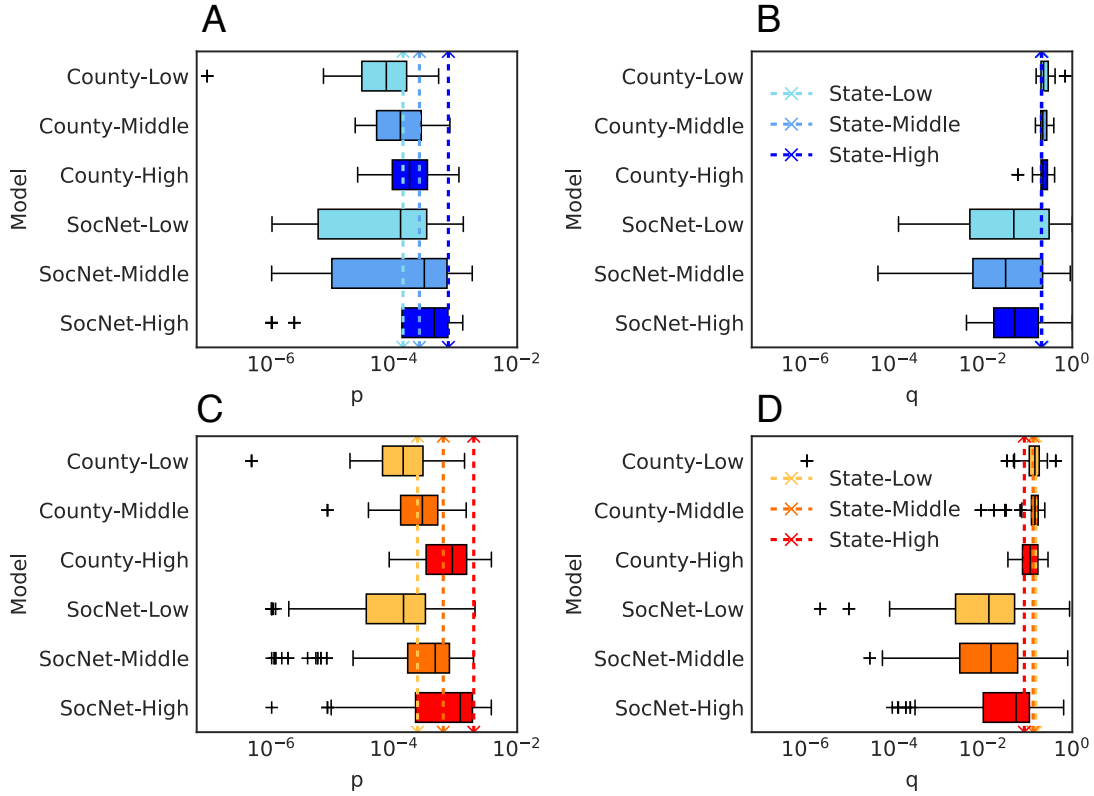


Figure 2.3: Calibrated parameters for socio-demographic groups using State/County BM and SocNet BM in Washington (blue) and California (orange). The box shows the quartiles of the county-level p and q parameters of County BM and SocNet BM while the whiskers extend to show the rest of the distribution, except for '+' which are determined to be outliers. The vertical dashed line denotes the p and q of State BM. The color denotes different socio-demographic groups, i.e., light color for the low-income group, default color for the middle-income group, and dark color for the high-income group. (A-B) p and q parameters of State/County BM and SocNet BM for low, middle, and high-income groups in Washington. (C-D) p and q parameters of State/County BM and SocNet BM for California's low, middle, and high-income groups.

when aggregated at the state level, they are very different at the county level. For instance, the adoption rate of King County using State BM is lower than using County BM while Pierce County using State BM is higher than using County BM. Similarly, the adoption rate of Orange County using State BM is lower than using County BM while Santa Clara County using State BM is higher than using County BM. This shows that when looking at a smaller geographical scale, the predictions are very different even if they show similar results on an aggregated level. In contrast to State/County BM, the prediction of SocNet BM has

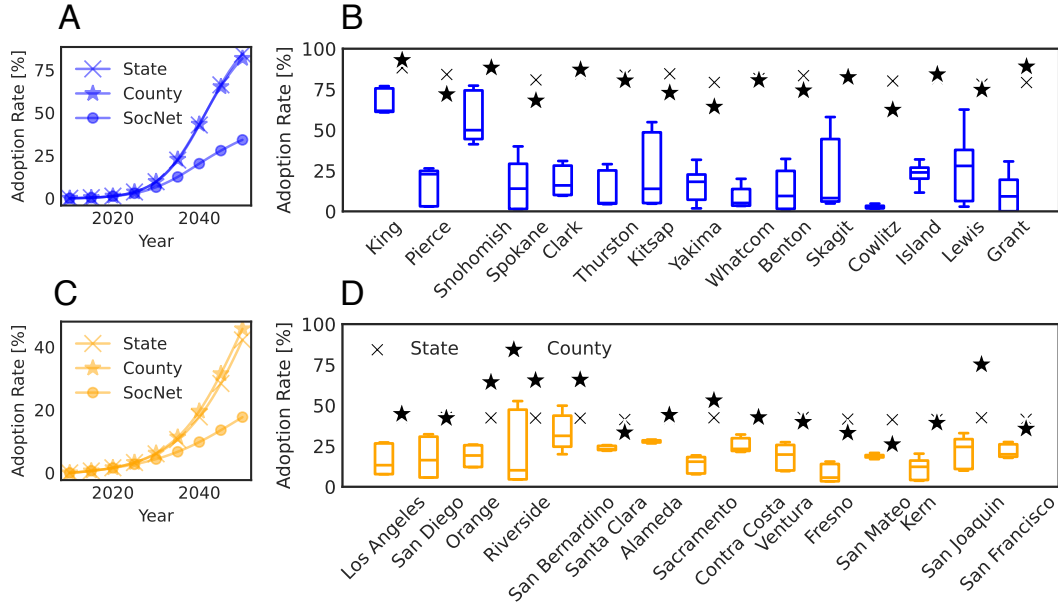


Figure 2.4: Comparison of State/County BM and SocNet BM’s adoption rate prediction. (A,C) State-level adoption rate growth curve from 2010 to 2050 for State/County BM and SocNet BM in Washington (blue) and California (orange). Lines with cross markers show the state-level adoption rate of State BM. Lines with star markers show the state-level adoption rate of County BM. Lines with circle markers show the median (50th percentile) state-level adoption rate of SocNet BM. (B,D) The county-level adoption rate from State/County BM and SocNet BM in the most populated 15 counties in Washington (blue) and California (orange) in 2050. The box shows the quartiles of the county-level adoption rates of SocNet BM while the whiskers extend to show the rest of the distribution. Cross markers show the adoption rate of State BM, star markers show the adoption rate of County BM, and square markers show the empirical data.

a much higher variance. This is due to two reasons. First, different combinations of p and q parameters give the same good fit with empirical data but will be very different as time increases. Second, even with the same p and q parameters, the probabilistic agent-based model itself brings variance to the prediction.

2.6 Effects of Network Structure on Spatial Diffusion

Knowing the spatial distributions of PEV adopters is important for charging station siting and grid capacity assessments. Since spatial information is embedded in the construction of the social networks, we test various network parameters $\gamma = 1, 3, 10$ for Los Angeles, where

γ is a parameter of the distance selection function (see Methodology 2.8.3). Higher γ favors links between nodes with a smaller distance. To further investigate the spatial characteristics of the adoption diffusion, we calculate Moran's I statistics [52] for State/County BM, and SocNet BM based on their output adoption rate for each census tract (see Methodology 2.8.4). Moran's I statistic is a commonly used spatial autocorrelation coefficient that is generally bounded between -1 and 1 [53]. A positive Moran's I statistic (or a positive spatial autocorrelation) indicates that similar adoption rates are from census tracts that are near to each other; while a negative one suggests dissimilar adoption rates are found from tracts near each other.

With networks with $\gamma = 1, 3, 10$, calibrated models show diverse adoption predictions in spatial characteristics. Fig. 2.5 (A) shows the adoption rates with corresponding Moran's I statistics under $\gamma = 1, 3, 10$ in Los Angeles. When $\gamma = 1$, Moran's I statistics first increase and then decrease with growing adoption rates. In contrast, with $\gamma = 3$ and 10 , Moran's I statistics monotonically increase with growing adoption rates. Fig. 2.5 (B) shows that Moran's I statistics of State/County BM are much higher than the data. For State/County BM, we only know the state/county-level aggregated adoption rate. To obtain census tract-level adoption rates, we assign adopters proportionally to the population in each census tract (see Methodology 2.8.2). In summary, Fig. 2.5 (A-B) demonstrate how different network structures influence the adoption by changing the γ of networks in the SocNet BM. As different social network structures lead to different spatial patterns of adoption, we can infer the best social network model to represent the adoption based on the spatial autocorrelation of the data. Specifically, in Los Angeles, $\gamma = 10$ appears to better characterize the social network associated with PEV adoption (see Appendix A.6 for results in other counties). Overall, the SocNet BM with a spatial social network allows more flexibility to capture the spatial autocorrelation of the empirical diffusion. Fig. 2.5 (C-E) further show the geographical distribution of Los Angeles' adopters in 2050 under $\gamma = 1, 3, 10$. We find that with increasing γ , the number of adopters decreases (especially from the low-income group). The diffusion with $\gamma = 3, 10$ is slowed down mainly because higher γ reduces social network effects on the low-income group. Specifically, when the diffusion starts, it is driven by innovation-related factors so high-income people adopt first. With higher γ , the high-income group is less likely to link with the low-income group who usually lives far away from them. Therefore, the adoption rate among the low-income group, whose adoption decisions are driven by social network effects, declines.

At last, we show that for SocNet BM, varying p and q can effectively fit the empirical data but show different predictions. Fig. 2.6 (A-C) show that for the three income groups, high p and low q , as well as high q and low p are all consistent with the data. However, these different combinations of p and low q will show remarkably different predictions. Fig. 2.6 (D) shows the Los Angeles adoption rate growth curve of varying p and q values, we can observe that all calibrations fit the data well. However, their predictions on adoption rate in 2050 varied between 10% to 40%.

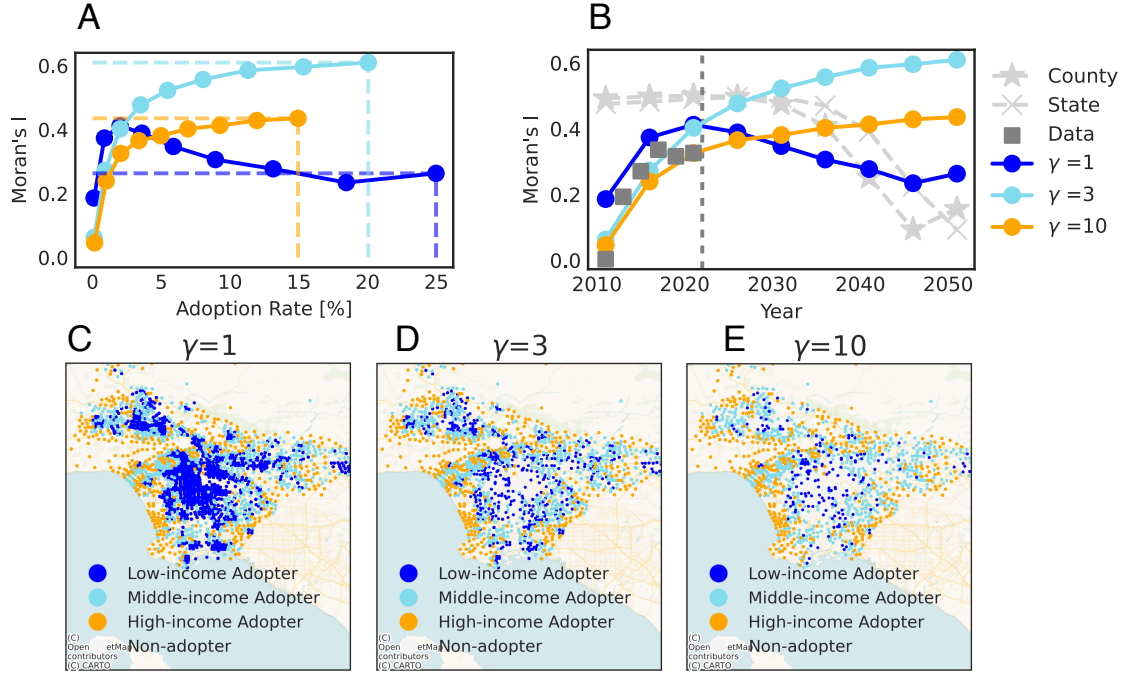


Figure 2.5: Comparison of State/County BM and SocNet BM's geographical pattern in prediction. (A) Adoption rate with corresponding Moran's I statistics under $\gamma = 1, 3, 10$. Solid lines with circle markers with dark blue, light blue, and orange represent the median (50th percentile) Moran's I statistics and the corresponding adoption rate under the network with $\gamma = 1, 3, 10$, respectively. Dashed lines to axis denote the median Moran's I statistics and the corresponding adoption rate in the year 2050. (B) Moran's I statistics for State/County BM and SocNet BM. For SocNet BM, we use the network with three γ s, i.e., 1, 3, 10. The fitting process is repeated for each γ and the median of predictions is reported. Solid lines with circle markers show the median (50th percentile) Moran's I statistics from SocNet BM. Dashed lines with cross markers and star markers show the Moran's I statistics from State/County BM; Squares show the Moran's I statistics calculated from empirical data on tract level. (C-D) Adopters' geographical distribution in Los Angeles in 2050 under $\gamma = 1, 3, 10$. Dark blue/light blue/orange points represent adopters from the low-/middle-/high-income group, respectively.

2.7 Promoting PEVs Adoption under Uncertainty

In this section, we aim to explore campaign strategies to promote PEV adoption through innovation-related approaches and imitation-related approaches with consideration of the uncertainty in modeling. We first propose an influencer strategy to promote PEV adoption. The influencer strategy refers to the campaign of distributing PEVs among influencers

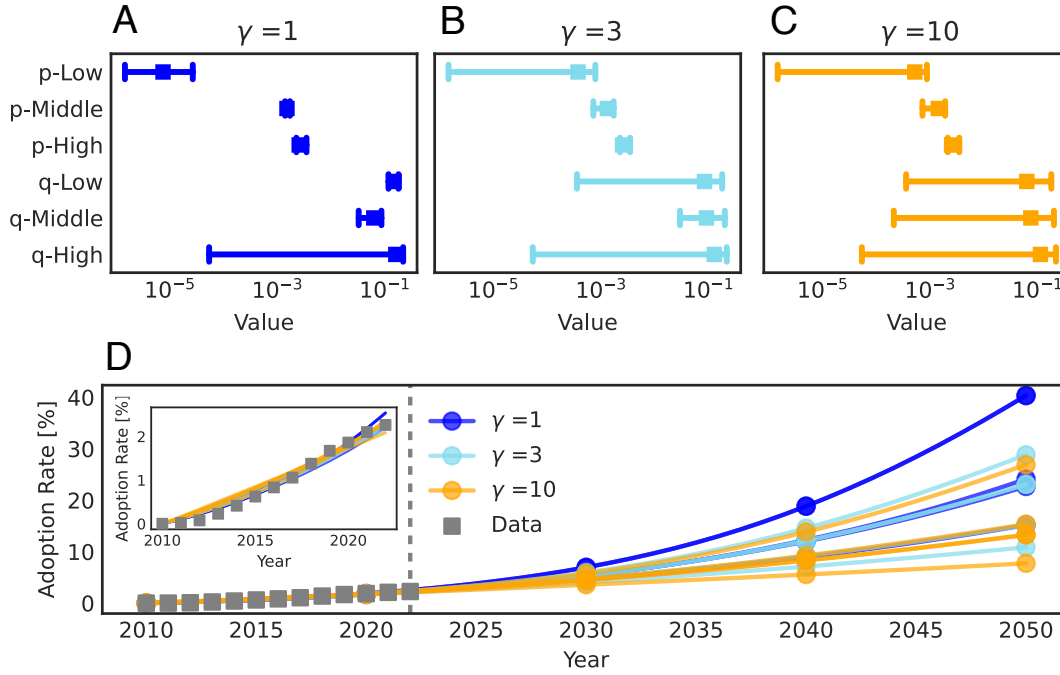


Figure 2.6: Comparison of calibrated SocNet BM’s p and q sets and corresponding adoption rate prediction. (A-C) Calibrated p and q values of low-/middle-/high- income group when using the network with three γ s, i.e., 1,3,10. Square markers show the mean value and the error bar indicates the min-max interval of p and q values. (D) County-level adoption rate growth curves using calibrated p and q sets of SocNet BM. Each Line with circle markers shows the adoption rates curve of one calibrated p and q set. The color of the lines indicates the network structure (γ) used for SocNet BM calibration. Squares show the empirical adoption rate growth curve. The inset is the same plot but with a zoom-in period from 2010 to 2022.

(agents with more connections in the social network) or asking them to recommend PEVs. Examples include sending PEVs or offering free leases of PEVs to influencers for a certain period, so as to let them share driving experience or advantages of PEVs to their followers. In this strategy, we choose influencers based on their target audience. The target audience is defined as the income group from which the influencer has the most connections. Here we have four strategies: choosing influencers targeting low-income groups (Low), middle-income groups (Middle), and high-income groups (High), or randomly choosing people from the whole population as influencers, ignoring their connectivity (Random). For Low, Middle and High strategies, we sort influencers by the number of connections to a target income group, then pick the top 100 and make them PEV adopters/advocates in 2023. We estimate the adoption rates with the four strategies in 2050.

Fig. 2.7 (A) shows the average adoption improvement of four strategies for various sets of p and q parameters calibrated from empirical data. The adoption improvement is calculated as the difference in adoption rates before and after the campaign in Los Angeles in 2050 divided by adoption rates before the campaign. We find that for networks with more distant connections ($\gamma = 1$), strategies targeting different socio-demographic groups (Low, Middle, High) have similar effects, which are all much better than the Random strategy. The similarity of Low, Middle, and High strategies is because (1) people who live close are more likely to have similar income levels, and (2) lower γ leads to more distant links. Therefore, people are more likely to have connections with different income groups when $\gamma = 1$. This leads to the situation that those influencers who have more connections with one group also have more connections with the other two groups. As γ keeps increasing, the network has less distant links and a higher level of spatial clustering, and thus influencers will have higher effects on one of three groups. Interestingly, we find that the adoption improvement is smaller with increasing γ . That means that if people in the region of interest have more distant connections, the influencer strategy is more efficient. In contrast, if people tend to connect with only nearby contacts the influencer strategy is less efficient.

Fig. 2.7 (B-D) compares innovation and imitation-related adoption boosting strategies, applied to the low-income group and for three pairs of $\hat{p}_{low}$ and $\hat{q}_{low}$ that fit current data. We represent the "innovation-related" strategy as an increase of $\hat{p}_{low}$ in a fixed factor, which modifies the global propensity of innovation adoption within the low-income group. We represent the "imitation-based" strategy by setting the first n agents with the highest degree as adopters. Each figure shows years to critical adoption rates (16%) resulting from the innovation-related and the imitation-related strategies for each pair $(\hat{p}_{low}, \hat{q}_{low})$. Fig. 2.7 (B) illustrates that with a relatively low fitted $\hat{p}_{low}$ and high $\hat{q}_{low}$, an imitation-related approach with more influencers can effectively boost adoption, whereas increasing the fixed factor (innovation-related strategy) does not have much effect. Conversely, Fig. 2.7 (D) depicts a scenario with a relatively high $\hat{p}_{low}$ and low $\hat{q}_{low}$, where increasing fixed factors significantly enhances adoption, but adding more influencers has a negligible effect. Fig. 2.7 (C) presents a middle ground, where combining both strategies achieves the highest adoption increase. It is crucial to note that the scenario where imitation-related strategies have a more significant impact does not imply that policies and actions seeking a global effect do not matter. On the contrary, initiatives such as consumer incentives or the development of charging infrastructure are essential for facilitating adoption in low-income areas or regions with limited charging stations. However, which are the best actions to increase the innovator rate is not clear. For example, Slowik *et al.* [28] assesses the PEV market in the 50 most populous metropolitan areas in the United States. They demonstrate that for areas with high PEV penetration, there is heterogeneity in the availability of policies, charging infrastructure, consumer incentives, and vehicle models. Altogether, Fig. 2.7 (B-D) shows that with different $\hat{p}_{low}$ and $\hat{q}_{low}$ effectively fitting the data, the year to reach critical adoption for different combinations of imitation-related strategy and innovation-related strategies varies as the contour of the year achieving critical adoption ranges from horizontally displayed and vertically displayed. In this regard, due to the small amount of data available, a conclusion

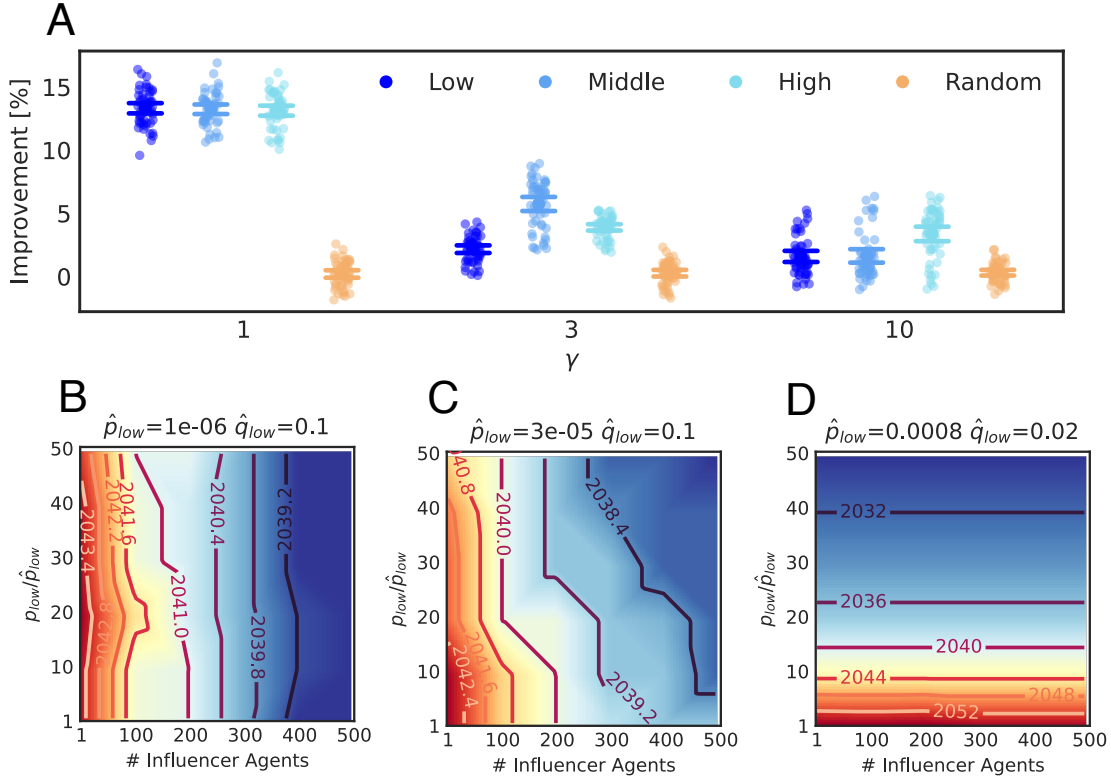


Figure 2.7: Campaign to promote PEV adoption under uncertainty in space and time. (A) Adoption improvement under different γ . For each γ , we show results for four campaign strategies: Using influencers targeting low-income group (Low), middle-income group (Middle), high-income group (High), or randomly picking influencers (Random). Points represent adoption improvement under various fitting and simulation processes. The error bars show the mean $\pm$ two standard errors among all points. (B-D) Heatmap and contour of the year to reach critical adoption (16%) with different p_{low} and the number of influencer agents. Here we show three cases of different $\hat{p}_{low}$ and $\hat{q}_{low}$. Three different $\hat{p}_{low}$ and $\hat{q}_{low}$ are obtained from fitting data.

on which combinations are the best is elusive. However, once we move beyond the early adoption stage (when adoption reaches the majority stage, and thus can obtain stable p and q from data), we can then identify whether an influencer strategy is appropriate as suggested by Fig. 2.7 (B-D), as well as find the best target audience according to Fig. 2.7 (A) by considering the network structure of the users.

2.8 Methodology

2.8.1 Market Segmentation

Previous research about understanding the driving forces behind PEV adopters' decisions highlights that adoption choices are related to household incomes [21, 44, 22]. Therefore, we divide the potential market into three socio-demographic groups: low-income group (income below 33% of the reference population of the state), middle-income group (income between 33% and 66% of the reference population of the state), and high-income group (income above 66% of the reference population of the state). The socio-demographic characteristics of the three groups are shown in Table 2.1. We justify the choice of this segmentation approach in Appendix A.7.

	Low-income Group	Middle-income Group	High-income Group
Washington Income Interval [US \$]	<66,685	66,685-92,830	>92,830
California Income Interval [US \$]	<64,623	64,623-95,587	>95,587

Table 2.1: Socio-demographic characteristics of the three groups.

2.8.2 Benchmark BM

We first revisit the BM and then illustrate the State/County BM and their fitting procedure.

Revisit BM

The Bass diffusion model enables us to investigate adoption dynamics [50]. This can be done by fitting the cumulative distribution function of adoption data with the cumulative distribution function of the model. The Bass cumulative distribution function is defined by

$$\frac{dy(t)}{dt} = (p + q/m \times y(t))(m - y(t)), \quad (2.1)$$

where $y(t)$ is the number of adopters at time t , p and q parameter of adoption and m is market size. This nonlinear differential equation can be solved by

$$y(t) = m \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}}. \quad (2.2)$$

State/County BM

The State/County BM fits empirical state-aggregated data for three socio-demographic groups. Specifically, For customers belonging to group i in state (county) j , the market size m_j^i is the number of vehicles of group i in state (county) j , and $t = 2010, \dots, 2022$. We obtain (p_j^i, q_j^i) where $i \in \{\text{Low, Middle, High}\}$ and $j \in \{\text{Washington, California}\}$ (or $j \in \{\text{Los Angeles, \dots, King}\}$) by fitting Eq. (2.2) through least squares method [54].

Assignment of State/County Adopters to Tracts

To obtain census tract-level adoption rates from State/County BM, we assigned aggregated adopters proportionally to the population in each census tract. Denote the number of adopters of group g in state (county) l as $y_l^g(t)$, and the number of vehicles of group g in state (county) l as m_l^g . Then for the tract h 's group g with m_h^g vehicles, the number of adopters in group g is calculated as:

$$y_h^g(t) = y_l^g(t) \times \frac{m_h^g}{m_l^g} \quad (2.3)$$

2.8.3 SocNet BM

In this section, we first explain how we construct the social networks. Then we present the SocNet BM's simulation and fitting procedure.

Social Network Construction

We construct social networks with ingredients of preferential attachment and distance selection by following [51]. For the region of interest, we sample nodes from data with expansion factor = 5 by keeping spatial distribution (an expansion factor is defined as the empirical number of vehicles from census / number of nodes). The sensitivity analysis for various expansion factors is available in the Appendix A.8. These nodes are in a two-dimensional space described by the longitude and latitude of potential adopters' home locations (the geographical resolution is at census tract level). Then we can calculate the distance between any adopter i and adopter j as d_{ij} . Once the nodes are distributed in this space, we construct links using the following algorithm: (1) Select at random a subset of n_0 initial active nodes. (2) Take an inactive node i at random and connect it with an active node j with probability:

$$prob_{i \rightarrow j} \propto \frac{K(k_j)}{D(d_{ij})}, \quad (2.4)$$

where k_j is the connectivity of node j , d_{ij} is the distance in kilometers between nodes i and j , $K(\cdot)$ and $D(\cdot)$ are given functions, and $prob_{i \rightarrow j}$ is then normalized up to a factor $\sum_{j \in \text{active nodes}} prob_{i \rightarrow j}$. For each inactive node, we sample $k_r = 3$ edges so that the average connectivity will be $\langle k \rangle = 2k_r$, and make the node i active. Finally (3), repeat (2) until all

nodes are active. To generate preferential attachment and empirical spatial features, we use $K(k) = k + 1$ and $D(d) = d^\gamma$, where $\gamma = 1, 3, 10$ (see Appendix A.9 for the rationale behind the selection of γ values). We illustrate the algorithm with an example in the Appendix A.5.

Simulation Procedure

This model consists of n agents indexed by $i \in \{1, \dots, n\}$, each of which is in either of two states: potential adopter or adopter. We use a set of variables $v(t)$ to describe the agents' adoption state (i.e., $v_i(t) = 1$ when agent i has adopted at t). Analogously to the BM, the probability of agent i to adopt depends linearly on an independent parameter p and a parameter q that depends on the fraction of prior adopted neighbors. Agent i 's probability to transition from non-adopter to adopter at t is as follows:

$$f_i(t) = (p + \frac{\sum_{j \in z_i} v_j(t)}{|z_i|} q)(1 - v_i(t)), \quad (2.5)$$

where z_i is the set of agents having connections with node i . This formulation implies that each agent's probability of adoption is influenced uniformly by the adoption state of all other neighbor agents.

A synchronous updating formulation of the BM is achieved by $\bar{v}_i(t)$ which is used to store the new state of the system until the end of the period when the actual updating occurs [55]. In each time $t \in \{2010, \dots, T\}$, the algorithm decides for each agent i whether or not it adopts based on the adoption probability according to Eq. 2.5 and a random value drawn from a uniform distribution $U(0, 1)$. If an agent adopts, the temporary variable $\bar{v}_i(t)$ is updated accordingly to 0 or 1. As soon as all agents have made their adoption decisions, the state of the system is updated as $v_i(t) = \bar{v}_i(t)$ for $i \in \{1, \dots, n\}$.

Fitting Procedure

We follow the method in [56]. Without loss of generality, we take one county as an example to illustrate the procedure. The procedure consists of two stages: locating the initial point and searching for the optimal solution.

Location of the initial point In this stage, we aim to determine the explicit connection between the BM and a particular SocNet BM in terms of parameters. In detail, for a given county, we generate adoption curves with all possible parameter pairs $(\mathbf{p}_{SocNet}, \mathbf{q}_{SocNet})$ using SocNet BM, where $p^{Low}, p^{Middle}, p^{High} \in \{1 \times 10^{-4}, 5.5 \times 10^{-4}, 1 \times 10^{-3}\}$ and $q^{Low}, q^{Middle}, q^{High} \in \{1 \times 10^{-3}, 5.5 \times 10^{-3}, 1 \times 10^{-2}\}$. Then we fit Eq.2.2 to all generated adoption curves with the nonlinear least squares method. Afterwards, we get estimated $(\mathbf{p}_{Bass}, \mathbf{q}_{Bass})$ pairs corresponding to the $(\mathbf{p}_{SocNet}, \mathbf{q}_{SocNet})$. We then estimate $\mathbf{C}$ and ϵ in the following linear model by ordinary least squares linear regression [57] to represent their relationship

$$\begin{bmatrix} \mathbf{p}_{SocNet} \\ \mathbf{q}_{SocNet} \end{bmatrix} = \mathbf{C} \cdot \begin{bmatrix} \mathbf{p}_{Bass} \\ \mathbf{q}_{Bass} \end{bmatrix} + \epsilon. \quad (2.6)$$

With this relationship, we fit the BM to the yearly sales data of PEVs from 2010 to 2022 in Washington and California using again the nonlinear least squares method. From this fit, we get $(\hat{\mathbf{p}}_{Bass}, \hat{\mathbf{q}}_{Bass})$. Substituting these values into Eq. 2.6, we get initial points as $(\hat{\mathbf{p}}_{SocNet}, \hat{\mathbf{q}}_{SocNet})$.

Searching for the optimal solution In this stage, we search for the optimal parameters around initial points using the Luus-Jaakola heuristic [58]. Starting out from $(\hat{\mathbf{p}}_{SocNet}, \hat{\mathbf{q}}_{SocNet})$ pair, we set up a grid search space as $\mathcal{X}$:

$$\mathcal{X} = \prod_{g=1}^G (\mathcal{X}_p^g \times \mathcal{X}_q^g), \quad (2.7)$$

where $\mathcal{X}_p^g$ and $\mathcal{X}_q^g$ are search space for p and q of for group g , respectively. Denote the search interval as $\Delta = 0.9$, search center as $\hat{\mathbf{p}}_{SocNet}^g$ and $\hat{\mathbf{q}}_{SocNet}^g$, we have

$$\mathcal{X}_p^g = \hat{\mathbf{p}}_{SocNet}^g \times \{1 - \Delta, 1, 1 + \Delta\}, \quad (2.8)$$

$$\mathcal{X}_q^g = \hat{\mathbf{q}}_{SocNet}^g \times \{1 - \Delta, 1, 1 + \Delta\}. \quad (2.9)$$

Then we run SocNet BM corresponding to the randomly sampled subsets $\mathbf{x}_i \in \mathcal{X}, i \in \{1, \dots, 50\}$ drawn from $\mathcal{X}$, and calculate the goodness of fit for $\mathbf{x}_i$ as

$$s(\mathbf{x}_i) = \max_{g=1, \dots, G} \frac{1}{T} \left| \sum_{t=1, \dots, T} (y^g(t, \mathbf{x}_i) - Y^g(t)) \right|^2, \quad (2.10)$$

where $y^g(t, \mathbf{x}_i)$ is simulated number of adopters with parameters $\mathbf{x}_i$ at time t , and $Y^g(t)$ is empirical number of adopters for group g at time t . Until the maximum number of 100 iterations is performed or the fitness is unchanged for 50 iterations, repeat the following: Denote optimal solution so far as $\mathbf{x}^*$ with goodness of fit $s(\mathbf{x}^*)$. If $s(\mathbf{x}_i) < s(\mathbf{x}^*)$, then update searching center points as $\mathbf{x}^* = \mathbf{x}_i$ and set $\Delta = 0.9$. Otherwise, set $\Delta = \Delta \times r$, where $r = 0.9$ is the searching decay rate, and update $\mathcal{X}$ with $(\hat{\mathbf{p}}_{SocNet}, \hat{\mathbf{q}}_{SocNet}) = \mathbf{x}^*$ and Δ .

To capture the uncertainty in the fitting process, we repeat the fitting procedure five times for each research area.

2.8.4 Measuring of Spatial Autocorrelation of Adoption

To measure spatial autocorrelation of the diffusion process, we calculate Moran's I statistics for each given time slot t based on:

$$I(t) = \frac{N}{\sum_{i=1}^N \sum_{j=1}^N w_{ij}} \frac{\sum_{i=1}^N \sum_{j=1}^N w_{ij} (F_i(t) - \bar{F}(t))(F_j(t) - \bar{F}(t))}{\sum_{i=1}^N (F_i(t) - \bar{F}(t))^2}, \quad (2.11)$$

where N denotes the number of census tracts; w_{ij} denotes the Euclidean distance between the centroid of census tract i and census tract j ; $F_i(t)$ denotes the adoption rate of census tract i at time t ; $\bar{F}(t)$ is the mean adoption rate of all census tracts at time t .

2.9 Conclusion

Modeling and projecting PEV adoption helps us plan resources to create a viable PEV ecosystem. However, forecasting PEV adoption is challenging because it is at a very early stage and even fitting simple models can be difficult. Today, a benchmark model for projecting adoption is the two-parameter BM. One important ingredient to be added is the role of spatial social networks in its forecast.

Our comparison of projections for future PEV adopters reveals that a more sophisticated diffusion model, fitted equally well to the same data, can produce results drastically different than the traditional BMs. The divergence of forecasts also indicates that it's important to consider the complexity of the current model design. While the more parameters in these models facilitate a closer fit to the available data, there is an inherent risk of overfitting. Furthermore, this study demonstrates that the SocNet BM with the spatial social network as an extra ingredient allows more flexibility to capture the spatial autocorrelation of the empirical diffusion process.

This work also explores PEV promotion campaigns' impact under uncertainty. We explore multiple possible social networks. Our analysis reveals that with more distant links in the social network, influencer strategies targeting different income groups yield similar adoption improvements by 2050. With more close links, the effectiveness of targeting specific income groups increases. Overall, the study emphasizes the need for adaptable, context-specific approaches that consider local socio-demographic contexts and social network structures when designing adoption-boosting strategies.

This study also provides implications for power system planning. Primarily, PEV adoption is uneven across regions. This framework provides a benchmark to predict the geographical distribution of PEV adopters. In areas with high PEV adoption, the stress on transmission and distribution networks intensifies. If the charging of these adopters remains uncoordinated, it may cause transformer overloading [59], overload transmission lines [60], early replacement of equipment [61]. This requires strategic control and infrastructure build-out to avoid bottlenecks and maintain reliable service [16]. Additionally, given demographic disparities in PEV adoption, equitable planning for charging infrastructure is crucial. The results show that middle- and low-income groups are less inclined to adopt PEVs due to innovation-related factors compared to the high-income group. To encourage PEV adoption among these communities, grid operators may need to offer lower electricity rates or enhance grid capacity to support new charging stations nearby. Moreover, the uncertainty in adoption forecasts demands integrating distributed energy resources, such as energy storage [62], renewables [63], vehicle-to-grid solutions [64] to bolster grid resilience.

This research may be expanded in various ways. For instance, integrating technology, policy, and built-environment evolution into diffusion predictions could be one area of focus. Alternatively, planning for power and transportation infrastructure in response to varying forecasts of PEVs adoption represents another avenue. Lastly, this study uses data prior to 2023, but we note that the BEV stock in California was 3.8% by the end of 2023 [65], which crosses from the innovator phase into the early adopter phase. Larger numbers of adopters

will provide new opportunities to predict the diffusion in a more detailed way. For example, while segmentation based on consumer characteristics alone is a valid method for forecasting PEV adoption [66], the consideration of the vehicle models is crucial to connect adoption with the power grid. Currently, due to limited data, we focus on PEVs without distinguishing between BEVs and PHEVs. With more data, it will become feasible to predict the adoption of BEVs and PHEVs separately and to investigate the distinct implications for the power grid related to BEVs versus PHEVs, along with consumer profiles and their motivation.

Chapter 3

Planning Charging Stations in 2050 to Support Flexible Electric Vehicle Charging Demand

With widespread adoption of EVs, it is crucial to plan for charging in a way that considers both EV driver behavior and the electricity grid’s demand. In this chapter, 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 thousand additional Level 3 chargers. We recommend building more charging stations and implementing shifting recommendations for EV grid integration. The research reported in this chapter can be found in [41].

3.1 Introduction

The transportation sector is as 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 [67]. The electrification of transportation is as an essential part of global plans to reduce emissions [68, 69], and many countries have introduced policies to promote EV adoption [70, 71, 72]. 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 [73], 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 emis-

sions by 2050 [74]. Rapid growth in the EV market will need to continue for that state to reach these goals, increasing from 19% of sales in 2022 [75].

However, the increasing number of EVs brings challenges to the electricity system. For one, current charging infrastructure is insufficient to support the increasing charging demand [76]. The electricity grid’s generation capacity must be considered in planning for future charging infrastructure [77, 16]. With the increase in the number of electric vehicles, peak demand on the grid will also increase. This can cause damage to grid infrastructure [78]. Moreover, when high peak demand coincides with periods of low renewable generation, as in the evening in California, adding demand can increase emissions [79].

The strategy for planning future charging infrastructure considering its impacts on the grid focuses on 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 [80]. Previous research on mobility behaviors has primarily analyzed adopters based on GPS travel histories of small numbers of drivers [81, 82], various surveys where drivers recount their recent trips [83, 84], or, origin/destination matrix data of the territory [85]. 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 [86, 87], clustering of charging sessions [88], or agent-based modeling [89] 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 [90], and that clustering effects in vehicle adoption at the local level could lead to areas with high PEV concentrations even before we see widespread adoption [59].

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 [91, 92], as it requires models that consider the different situations [93], mobility diversity [94], and charging pattern [95] 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 [96, 97]. 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 [98, 99], reduce operation costs [100, 101, 102], reduce the need for battery storage [103, 104], or integrate renewables [105, 106]. Estimates of the value of such control in California range from 5.6 \$ per driver in 2018 [94] to as much as 87 \$ per driver in 2045 [107]. This area of research has largely focused on aggregate-level analysis due to data limitations and associated modeling challenges [108, 109]. Based on the individual variations observed in data, however, such aggregated approaches likely misrepresent charging demand [110]. Moreover, this approach almost always uses direct automated control which assumes the deployment of costly communications infrastructure and ignores social and regulatory barriers related to privacy concerns or loss of control [111].

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 [16], or to delay home charging and add workplace charging [112]. 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 [63], and Kara et al. found higher demand flexibility with fewer sessions per charging station [113]. 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 [106]. 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% [114].

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 2021 demonstration involving over 400 drivers from the California Bay Area, Spencer et al. found 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 [115]. 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, 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 [92]; Levinson and West found that a national network of public charging could increase electrified mileage by 8%, though little of the infrastructure cost should be passed on to the drivers [116]; and Greene et al. found willingness-to-pay for a public charger in California in 2017 could range from 1500 to 6500 \$ [117]. In comparison with other leading markets, the United States has a low ratio of EVs to public charging points [118] and a high dependence on home charging [66], but this is expected to change with increasing adoption by residents of apartments or multi-unit dwellings [37]. 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 states adoption targets [119].

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 EVs 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 3.1 depicts a summary of the proposed framework. Features of 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 p.m. to 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 [120], at the 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 to 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% up to 100% in future scenarios.

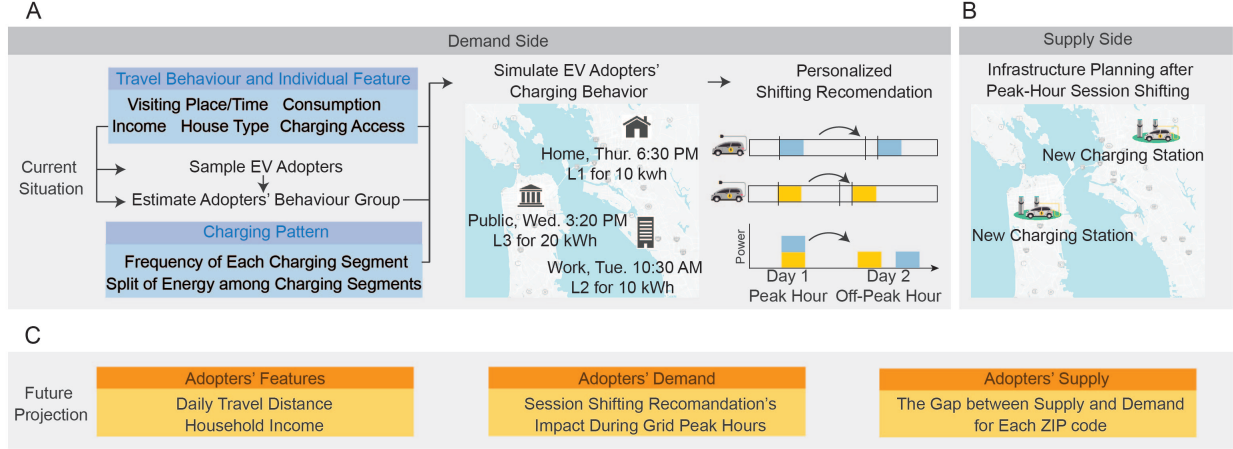


Figure 3.1: Overview of the proposed framework for understanding and planning future EV charging needs. (A) We analyze the current charging demand by extracting residents' travel behavior and individual features, including visiting places and time, energy consumption, income, house type, and charging 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.

3.2 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 two detailed, data-driven models: one for mobility and one for charging behavior groups (presented in full in the Methods section).

We extend the TimeGeo model proposed by Jiang et al. [121] 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 [121, 94]. First, we simulate the weekly charging profile for all estimated 129 thousand EV adopters in the Bay Area in 2019 [122]. In this research, we model all as battery electric vehicles and not plug-in hybrid electric vehicles. 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 United States Census and American Community Survey data from the year 2019 [123]. We use this to estimate the charging access of each EV adopter based on data from a recent California Home Charging Access Survey [37]. Finally, we extend the SPEECH model presented by Powell et al. [16] 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 3.2 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 drivers have work charging access [124]. However, if workplace charging access increases, the number of adopters choosing work charging may increase too. Based on present-day charging infrastructure availability, Figure 3.2 (A) shows that, on average, 58% of 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 3.2 (B) 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, while 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 3.2 (A), the validation data set contains more users belonging to Work charging groups and fewer drivers belonging to Home charging groups. As a result, home charging demand is lower than work charging demand in the validation test.

Figure 3.2 (C) 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 MW both in on-peak and off-peak hours. The range between the 25th and 75th percentile 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 3.2 (D) 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 [123]. 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, while 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.

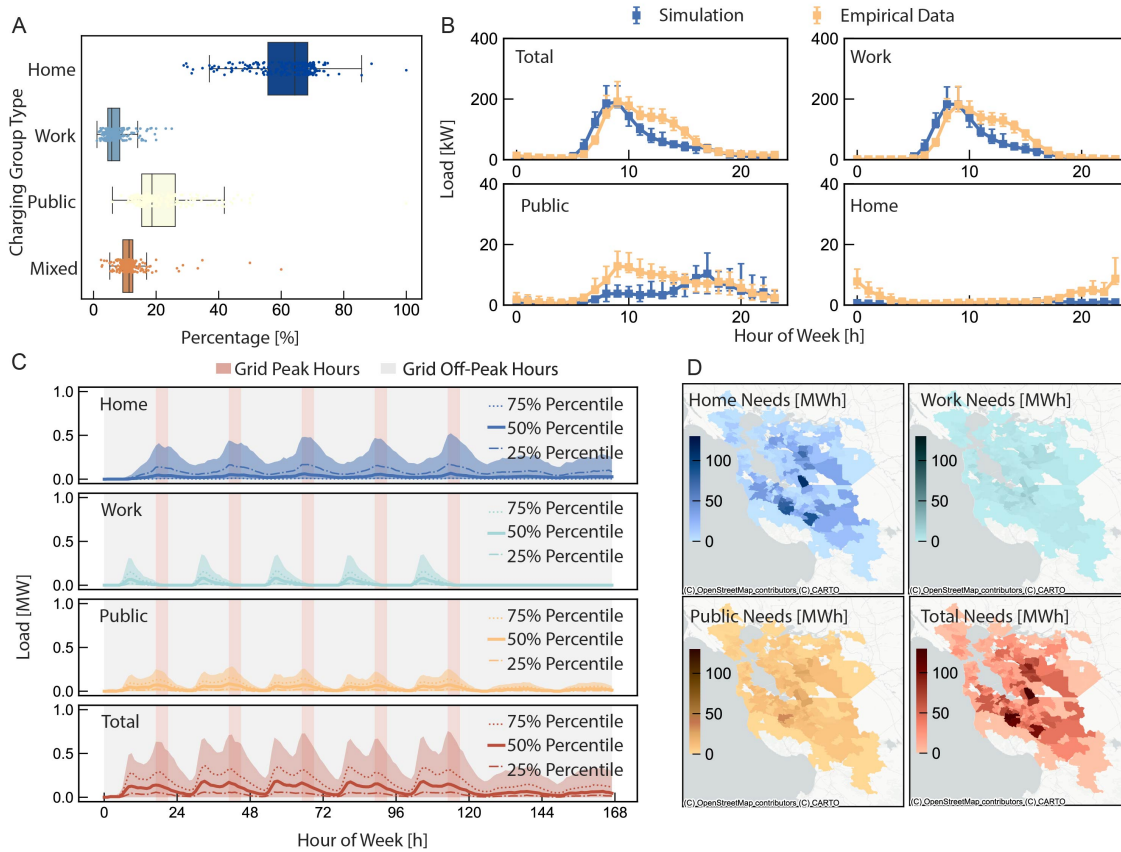


Figure 3.2: Analysis of EV charging demand. (A) Distribution of the four charging group types in each ZIP code. Each point represents the percentage of adopters belonging to a certain charging group type in one ZIP code. (B) Comparison between our charging demand simulations and real data. The solid 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 thousand simulated EVs; the full Bay Area fleet from 2019. The solid line, dotted line, and dash-dotted line show the 50th, 25th, and 75th percentile, respectively, of home, work, public, and total charging load, 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.

3.3 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? (2) would a shift to that stay be feasible given their individual travel plan? If a feasible alternative is found, we recommend the driver shift their session 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 new electric vehicles 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 the drivers 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 Appendix B.1).

Figure 3.3 (A) 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 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 3.3 (B) 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, while 16% are redirected to workplaces and 7% are shifted to other home stays. 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 3.3 (C) shows ZIP code level peak charging needs before and after our personalized shifting recommendations. Overall, the personalized shifting recommendations results 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 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.

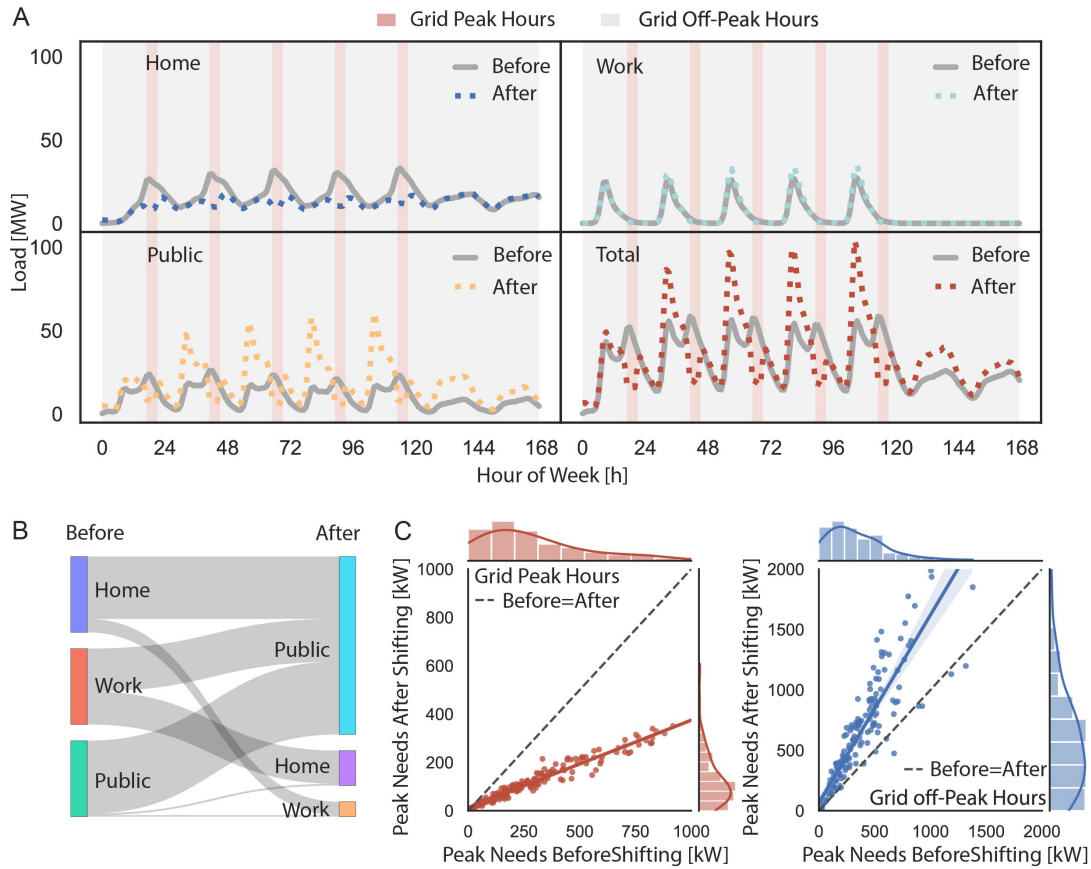


Figure 3.3: Impact of personalized shifting recommendations on charging demand. (A) Bay Area total charging load profile before and after implementing personalized shifting recommendations. The grey solid line displays the charging load before implementing personalized shifting recommendations, while 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 grey 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.

Figure 3.4 (A) 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 total public chargers, while Level 1 (L1) and Level 3 (L3) comprise 2% and 17%, respectively.

We use data from Open Charge Map [125] 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 3.4 (B) 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 find 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.

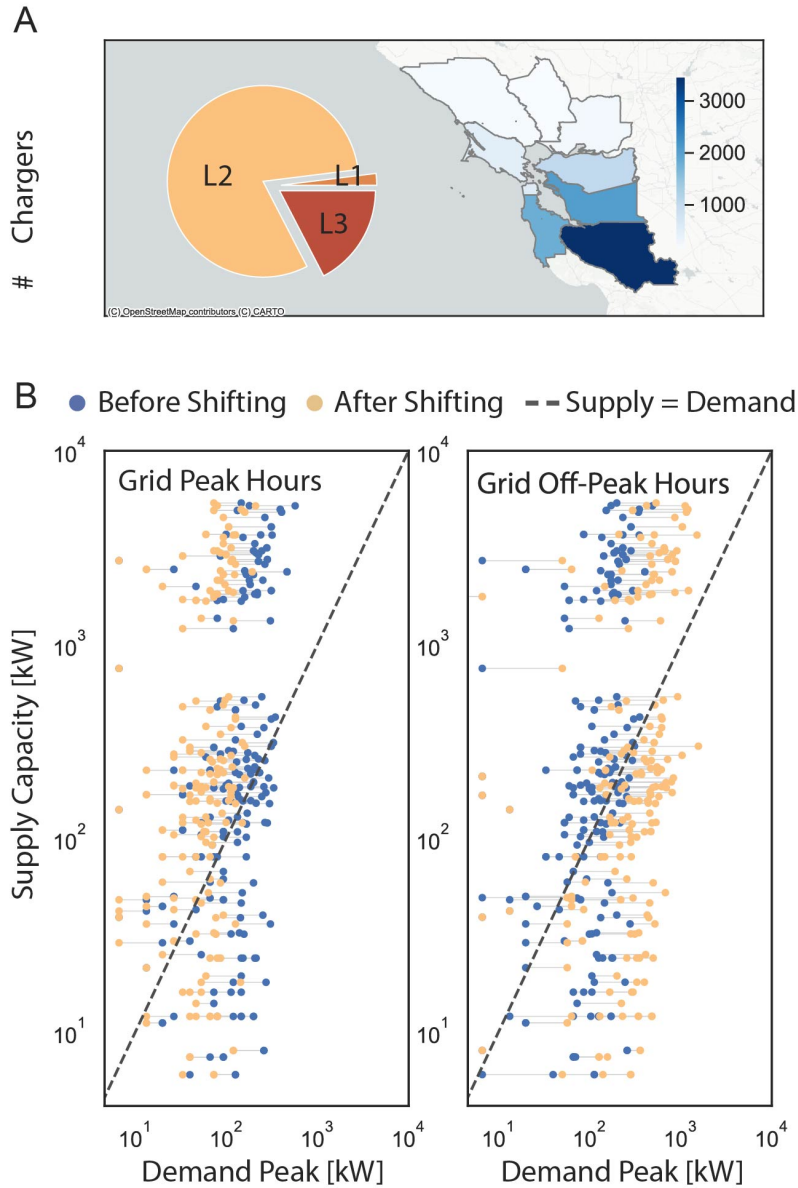


Figure 3.4: Impact of personalized shifting recommendations on charging infrastructure. (A) ZIP code level map showing the geographical distribution of existing public chargers. The pie plot indicates the percentage split of L1, L2, and L3 chargers in the Bay Area. (B) Comparison between public charging 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, while points above the diagonal line indicate that there is a surplus in the public charging station supply.

3.4 Projection of Deep Electric Vehicle 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 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 Fig. 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 3.5 (A) displays the daily travel distance and Figure 3.5 (B) 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, while 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, while 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 [126].

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 3.5 (C), the geographical distribution 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 (Appendix B.2). Figure 3.5 (D) 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, while 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 3.5 (E), 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, while 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 3.5 (F) 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 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 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 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 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 3.5 (G) shows that before personalized shifting recommendations, at an adoption rate of 20%, 70% of ZIP codes experience 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 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 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 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, while 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, though 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 electric vehicles. 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 adoption rate of 100% at 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 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 19 thousand L3 chargers (or 141 thousand 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 34 thousand (or 256 thousand L2 chargers with 6.6 kW) in 2050.

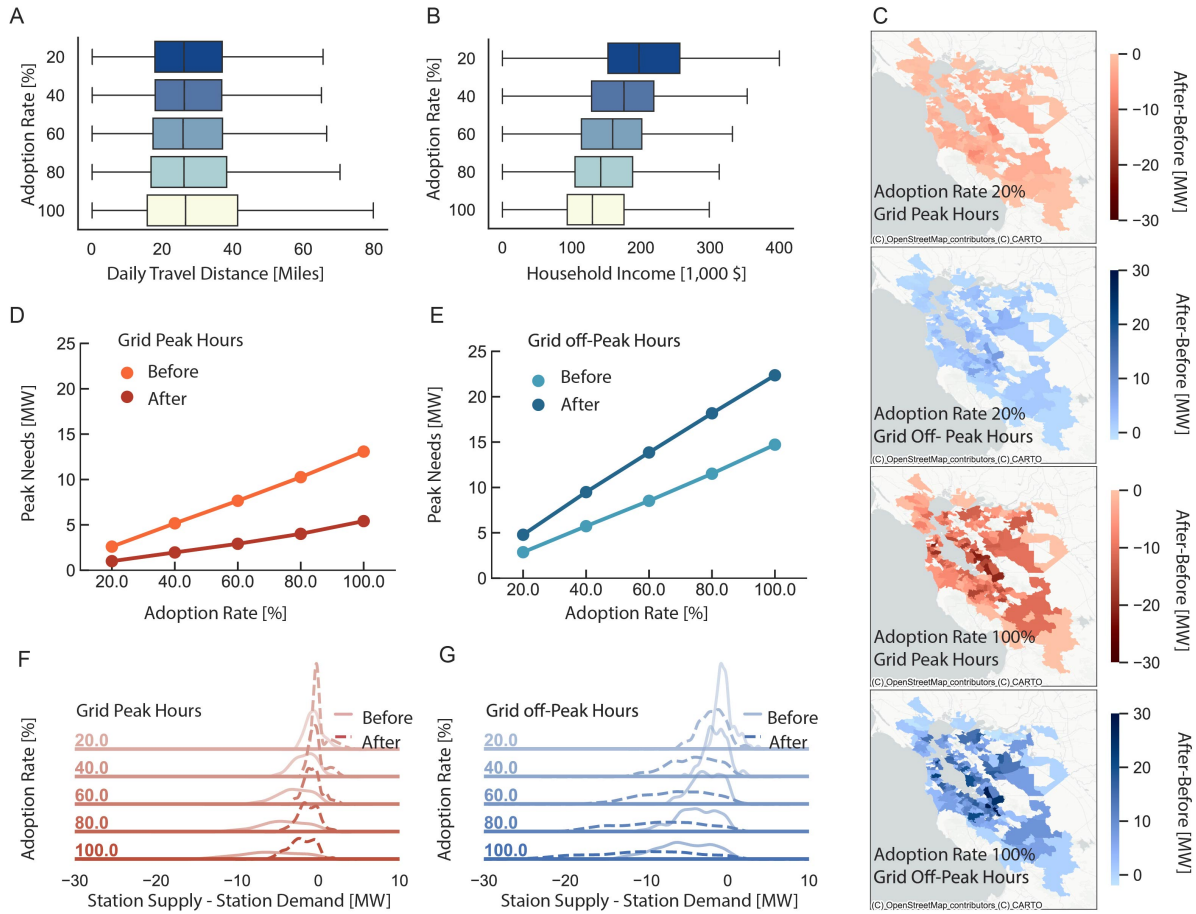


Figure 3.5: Results under future EV adoption. (A-B) The distribution of EV adopters' daily travel distance and household income when the adoption rate is increased. The box shows the interquartile range of all EV adopters, and the line that divides the box into two parts marks the median of EV adopters. (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, while negative values indicate an increase. (D-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-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, while positive values indicate sufficient charging infrastructure.

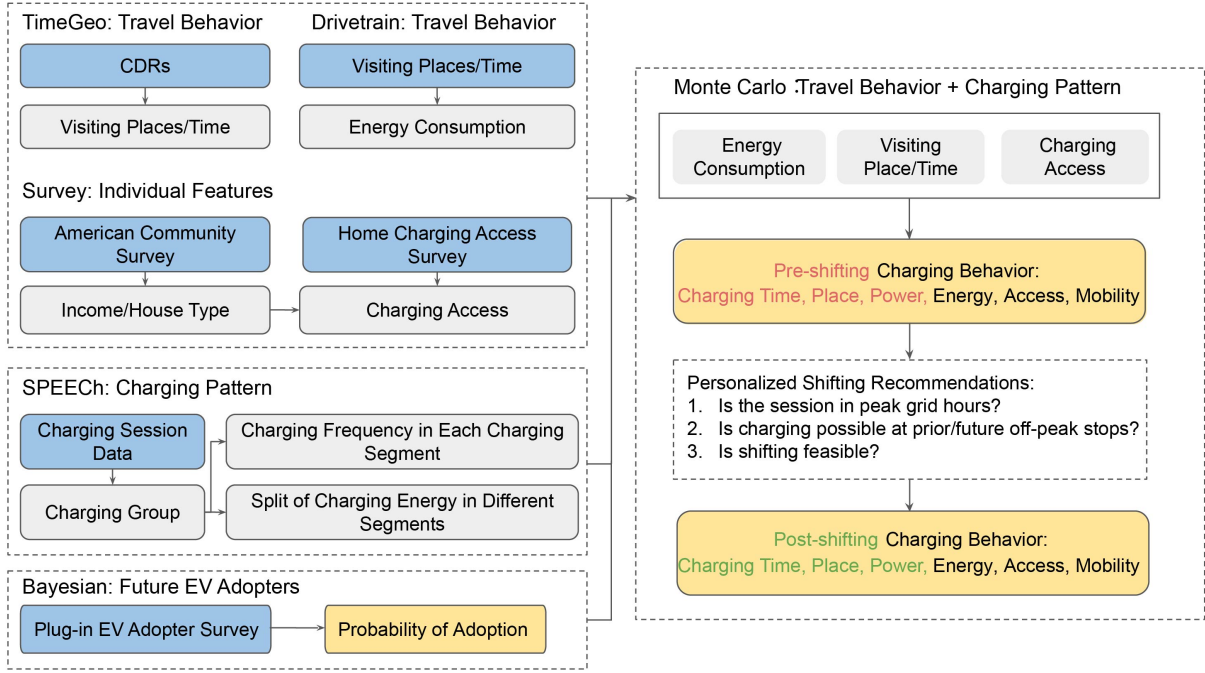


Figure 3.6: Methodology overview. Dashed frames represent models; blue frames represent the data sources; grey frames represent the intermediate output; and yellow frames represent ultimate output, i.e., original charging demand, charging demand after personalized shifting recommendations, and the probability of each driver being an EV adopter.

3.5 Methodology

3.5.1 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 SPEECCh 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 3.6 depicts the connection between the data source and models.

3.5.2 Datasets

We use four different datasets in this study: call detail records (CDRs), charging session records, charging infrastructure data, and survey data such as United States 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 [127]. 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 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 [121] 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 27.7 thousand electric vehicle adopters, recorded by a large charging station provider in the California San Francisco Bay Area in 2019 [16, 128]. 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 Level 2 (L2) charging, public L2 charging, public level 3 (L3) charging, Single Family Home (SFH) residential L2 charging, and Multi-Family Home (MFH) or Multi-Unit Dwelling (MUD) residential L2 charging. L2 charging occurs at 6.6 kW and Level 3 occurs at 50 kW. For detailed statistics and illustrations of the data we refer the reader to Powell et al. [16].

The charging station data collected from Open Charge Map [125] contains 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 Level 1 (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 United States Census Bureau American Community Survey [123]. The California Plug-in Electric Vehicle Adopter Survey [129] 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 [37], 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 electric vehicles in California between 2013 and 2019 [122]. This dataset provides EV adopters' home ZIP code, the purchasing date, and the purchasing model type.

3.5.3 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 [121]. The model divides each day of the week into 1008 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. [94] compared the aggregate performance of TimeGeo with that of the national household travel survey (NHTS) [130] and the California household travel survey (CHTS) [131].

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 APIs of Uber Movement [132] and OSMnx [133], respectively. Our analysis focuses on two popular EV models in the Bay Area: the Tesla Model 3 and Nissan Leaf. Appendix B.3 provides the number of adopters of each EV model.

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

$$E_{trip}^{Nissan} = f(V_{trip}) D_{trip}, \quad (3.1)$$

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 [77]. 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 [134]. That is,

$$E_{trip}^{Tesla} = 0.83f(V_{trip})D_{trip}. \quad (3.2)$$

The details of the simulated mobility pattern and energy consumption are in Appendix B.4.

3.5.4 EV Charging Behavior Simulation

Scalable Probabilistic Estimates of Electric Vehicle Charging (SPEECH) is a probabilistic framework for simulating large-scale EV charging loads that are grounded in real charging data [88, 16].

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 Appendix B.5).

SPEECH models the probability with which an adopter belonging to 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:

$$P(z | G)_i = N_{G,i}^z / N_{G,i}, \quad (3.3)$$

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:

$$P(c | G, z) = \sum_{k=1}^K P(c | k)P(k), \quad P(c | k) = \mathcal{N}(c | \mu_k, \sigma_k), \quad (3.4)$$

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 [123]. 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 [123]. The California Home Charging Survey [37] provides the distribution of home charging access given household income and housing type (details are in Appendix B.6). 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 [135]. We model the workplace charging access rate for those who have a workplace as 50% based on [124]. 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 Section 3.5.3. 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:

$$P(G | A, E) = N_{A,E}^G / N_{A,E}, \quad (3.5)$$

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 [128]. 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 Appendix B.7).

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 [136].

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:

$$\bar{c}(t) = c(t) - \max\{(s(t) - 100\%) * B, 0\}, \quad \bar{d}(t) = d(t) + \min\{s(t) * B, 0\} \quad (3.6)$$

Here, $\bar{c}(t)$ and $\bar{d}(t)$ 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 $s(t+1) = s(t) + \bar{c}(t) - \bar{d}(t)$ for all time slots t .

3.5.5 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_a^i , the departure time is t_d^i , and the charging end time is t_c^i . 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., $[t_a^i, t_c^i] \in T_{on}$ and $[t_a^j, t_c^j] \in T_{off}$.

4. Charging needs are satisfied: Charging energy needs should be met in the stay j , i.e., $e^i/r(z) \leq (t_d^j - t_a^j)$.
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 $c'(t) = r(z_i)$, $\forall t \in [t_a^j, t_c^j]$ and $c'(t) = 0, \forall t \in [t_a^i, t_c^i]$. We require $0 \leq s(t) \leq B, \forall t$.

3.5.6 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 $P(\text{EV} \mid I, D)$, 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:

$$P(\text{EV} \mid I, D) = \frac{P(I \mid \text{EV})P(D \mid \text{EV})P(\text{EV})}{P(I)P(D)} \quad (3.7)$$

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 $P(I \mid \text{EV})$ and $P(D \mid \text{EV})$, we use data from the California Plug-in Electric Vehicle Adopter Survey [129]. Once we estimate $P(\text{EV} \mid I, D)$, we use these probabilities to select EV adopters from all vehicular adopters.

Appendix B.8 compares the number of EVs estimated using the Bayesian method at each ZIP code with the number obtained from the CVRP dataset [122], demonstrating good agreement between the two methods. Additionally, Appendix B.9 shows the geographical distribution of EV drivers with increasing adoption rates.

3.6 Conclusion

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, while the other peak occurs during

on-peak hours and consists 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, while 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, 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 day-time parking events. Therefore, we recommend increases in daytime charging options, including public and workplace stations, where 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 [111]. 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 set-up 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, while 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.

Chapter 4

Integrating Urban Air Mobility into the Power Grid through Smart Charging Solutions

Adapting the existing power grid to support large-scale UAM operations using eVTOL aircraft presents a critical infrastructural challenge that needs to be tackled. To this end, this chapter presents a framework for estimating the potential of smart charging to improve power system welfare when integrating large-scale UAM into the power grid. We first estimate passenger travel demand for UAM from LBS data. Then we obtain the feasible charging window of aircraft by solving a fleet dispatching problem to maximize the fulfillment of scheduled UAM travel demand. With consideration of power grid dynamics, we optimize the timing and rate of charging in each feasible charging window to maximize power system welfare without disturbing optimal fleet dispatch. Finally, uncertainties in arrival times and charging demands are managed with chance-constrained optimization. This ensures the failure probability for meeting charging demand stays below a set confidence level. The efficacy of the proposed approach was demonstrated by case studies using a 9-bus transmission system.

4.1 Introduction

The advancement of eVTOL aircraft opens new opportunities for UAM. UAM offers a novel solution to meet passengers' travel needs, facilitate goods delivery, and provide rapid response in case of emergencies. Moreover, it is considered a strategy for mitigating the escalating traffic congestion in major urban areas [137]. Initially, the market held high expectations for UAM [138]. In addition to eVTOL companies like Joby Aviation [139], Uber initiated programs such as Uber Elevate to explore opportunities UAM [140]. However, recent projections have been adjusted downward as various potential barriers have been identified. These barriers include government intervention, public acceptance, and infrastructure limitations.

One of the infrastructure challenges that must be addressed for large-scale UAM oper-

ations comes from the power grid [141]. The success of UAM relies on the availability of electricity, as it involves the use of eVTOL aircraft. A reliable electricity supply is crucial for the daily operation of the eVTOL fleet, but the current power grid lacks the capacity for future large-scale eVTOL charging [142]. Additionally, the increasing number of EVs worsens the strain on the power supply. The projection suggests EV percentage of the ground fleet in the U.S. will grow to about 50% in 2050 with higher charging rates greater than 300 kilowatts (kW) [143, 144, 145]. The combination of more ground EVs and faster ground EV charging rates will utilize more of the electrical grid over the next several decades and thus reduce available electrical grid power capacity for UAM and constrain UAM operations if there are not enough upgrades of the power grid capacity.

Under the best-case assumption that electricity can be transmitted and distributed as needed within each interconnection (i.e., electrical grid), [146] estimates the maximum number of UAM aircraft that can be charged simultaneously by dividing the available electrical grid power capacity for UAM by the baseline UAM aircraft charging rate. The results show that the maximum number of UAM aircraft that can charge simultaneously in the continental United States will decrease by 20% by 2050 due to the projected increase in ground EVs. However, achieving even this scenario could cost trillions in grid distribution [147] and transmission [148] enhancements. Given the high cost of power network upgrades, an alternative solution is to intelligently coordinate aircraft charging. By aligning UAM charging with power system constraints, this coordination can minimize grid instability, such as overloads or voltage drops, without the need for costly infrastructure upgrades [149, 150, 151]. In this work, we aim to better understand the demand profiles of UAM fleets and develop smart charging strategies to optimally charge UAM fleets without overwhelming the electric grid.

Designing a smart charging schedule for the UAM fleet requires coordination between the power network and the transportation system. Controlling the UAM system involves two key tasks: (1) solving a dispatch problem to assign aircraft to fulfill trip requests and (2) monitoring the aircraft's SoC to manage the recharging of the aircraft battery. During this process, the electric UAM fleet represents a controllable load to the power grid in time and space. If well coordinated, this controllable load can improve grid social welfare even when considering power system operation constraints.

There is a growing body of work in UAM fleet dispatch. For example, Shihab *et al.* developed a model to decide whether to offer on-demand or scheduled flights and how to dispatch the fleet and schedule operations based on simulated market demand [152]. Munari *et al.* assigned aircraft to on-demand requests while accounting for maintenance events, allowing flight upgrades to reduce operational and repositioning costs [153]. Stouffer *et al.* designed a dispatching tool for UAM operations that enables a dispatcher to plan a UAM flight and check for issues before filing a flight plan [154]. Besides the fleet dispatch, another challenge comes from the charging strategies. Optimal charging strategies for fleet aircraft have received a lot of attention given the high cost of batteries for aircraft, several studies have examined how different recharging strategies can be optimized to help regulate the charge profile and enhance battery life [155, 156, 157, 158].

While previous studies have examined the UAM fleet as part of the transportation system,

they often focus solely on minimizing charging costs and overlook the impact on the power grid. To address this gap, some research has included the power system in the analysis. For example, Shihab et al. developed an optimal fleet dispatch framework for eVTOL aircraft aiming to boost fleet operators' revenue by securing extra income through offering frequency regulation services to the electricity market [159]. Thippavong documented an analysis of the available electrical grid power capacity for UAM [160, 146]. Additionally, Acera et al. proposed an optimization based on genetic algorithms to determine the number of eVTOL vehicles required to make vehicle-to-grid services profitable for different electrical systems [161]. Paudyal et al. conducted a grid impact study and analyzed infrastructure upgrade requirements for eVTOL charging on a realistic distribution grid through power flow simulation analysis [162]. However, these studies do not take into account, from the viewpoint of the power grid operator, how the smart charging of the eVTOL aircraft fleet could benefit the grid considering power flow dynamics. In this work, we aim to evaluate the benefits to the power grid by implementing smart charging schedules that consider grid constraints.

Most research on dispatching and scheduling algorithms for UAM have used deterministic frameworks. However, these models overlook the stochastic nature of aircraft charging [163]. This stochasticity is influenced by weather, temperature, and emergencies. As a result, deterministic models lead to ineffective schedules. Recent studies have started to address uncertainties in UAM operations. They consider uncertainty in deconfliction [164, 165], dispatch [166, 167], fleet sizing [168], routing [169], traffic flow management [170], and aircraft control [171]. However, these studies do not consider the impact of UAM operation uncertainty on the power grid. In this work, we use a chance-constrained optimization approach. This approach models the stochastic characteristics of aircraft operations using mixed-integer programming (MIP). The chance constraints ensure the failure probability of the UAM charging plan stays below a predetermined confidence level. Our objective is to improve the overall welfare of the power system by considering uncertainties in arrival timings and charging demands while not disturbing the optimal dispatch of eVTOL aircraft fleets that maximize the fulfillment of UAM demands.

We propose a framework to estimate the potential of smart charging to improve power system welfare when integrating large-scale UAM into the power grid. The framework begins with the operator estimating UAM travel demand using LBS data. Based on this estimated demand, the system operator determines fleet dispatch and models the impact of fleet charging on the power system by solving a DC optimal power flow problem. To account for uncertainties in arrival times and charging demands, we use a chance-constrained formulation. The framework is shown in Fig. 4.1.

The rest of the paper is organized as follows. Section 4.2 demonstrates the method for UAM travel demand estimation. Section 4.3 introduces the fleet dispatch algorithm. Section 4.4 and Section 4.5 provide both deterministic and stochastic frameworks to estimate the impact of the UAM fleet on the power grid under smart scheduling. Section 4.6 presents numerical studies and Section 4.7 concludes the paper.

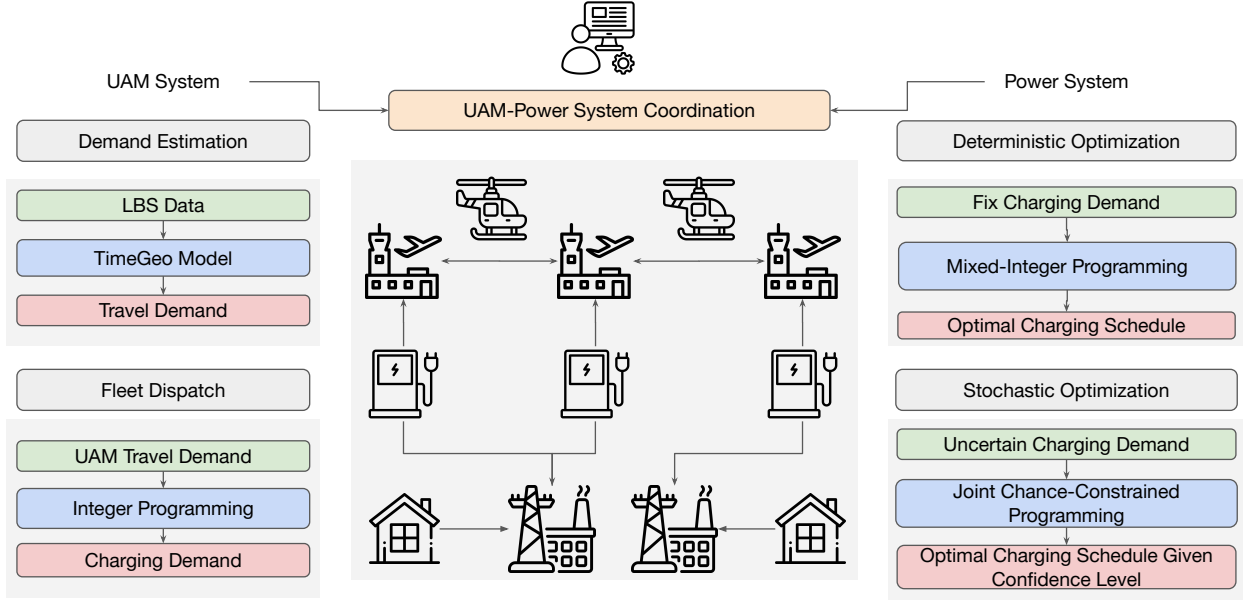


Figure 4.1: UAM–Power system coordination framework. This framework integrates UAM travel demand with power system operations. On the UAM side, LBS data is used to estimate travel demand via the TimeGeo model, which informs fleet dispatch and charging demand through integer programming. On the power system side, both deterministic and stochastic optimization approaches are used to compute optimal charging schedules, depending on whether charging demand is fixed or uncertain. The central coordination ensures efficient interaction between fleet operations and grid planning.

4.2 UAM Travel Demand Estimation

In this section, we first introduce the mobility generation model, then we illustrate how we estimate the UAM travel demand from the generated city-wide mobility trajectories.

4.2.1 Mobility Generation Framework: TimeGeo

We use TimeGeo [121] to generate individual trajectories for the entire city population. The purpose is to generate the urban-scale Origin-Destination (OD) travel flow from which we can estimate the demand for UAM services.

TimeGeo models each individual’s trajectory based on temporal and spatial choices: Temporal choices determine how long to stay and when to leave, while spatial choices decide which places to visit. Since the data covers only a portion of the population, we need to scale it to represent the entire population. The details on modeling these choices and expanding the data are provided below.

To model temporal choice, TimeGeo’s time-inhomogeneous Markov chain model defines three stay states: *home*, *work*, or *other*. It models *work* activities with predetermined arrival times and durations. *Home* is considered a less active state than *other* due to longer average stay durations.

For individuals at *home*, the probability of starting a trip within a specific time interval t is denoted as $n_w P^{rhy}(t)$. Here, n_w quantifies the number of trips originating from *home*, and $P^{rhy}(t)$ reflects the population’s overall travel circadian rhythm. The framework distinguishes between $P^{rhy}(t)$ for commuters and non-commuters. For non-commuters, $P^{rhy}(t)$ is the fraction of all trips of the population in interval t . For commuters, since work is modeled as a fixed activity, $P^{rhy}(t)$ does not include trips to or from work. The product $n_w P^{rhy}(t)$ defines the individual’s travel probability at a specific time interval t when they are at *home*.

For individuals at *other*, the intention to initiate a trip is modeled with two parameters: dwell rate β_1 and burst rate β_2 . Dwell rate β_1 measures how much more active the person is likely to travel when in state *other* compared to state *home*. Burst rate β_2 measures how much more active the person is likely to travel to an additional *other* location when in state *other* compared to state *home*. Specifically, the probability of traveling, when an individual is at state *other*, is defined as $\beta_1 n_w P^{rhy}(t)$. Next, if this individual chooses to move at time t , TimeGeo defines the probability that an individual travels to an additional *other* location as $\beta_2 n_w P^{rhy}(t) \beta_1 n_w P^{rhy}(t)$.

To model spatial choice, TimeGeo uses the rank-based exploration and preferential return (r-EPR) model. The temporal choice determines when to visit *home*, *work*, and *other*. While *home* and *work* are unique places, there are many possible *other* candidates. In spatial choice modeling, the framework aims to determine which *other* place to visit for each individual.

If the individual’s temporal choice is to go to an *other* state, she explores a new location with probability P^{new} or returns to a previously visited location with probability $1 - P^{new}$. Denote λ as the number of previously visited locations, the P^{new} is defined as:

$$P^{new}(\lambda) = \rho \lambda^{-\gamma}, \quad (4.1)$$

where ρ and γ are fitted from empirical data. If the individual decides to return to previously visited locations, she chooses a specific location l with probability $P^{rtn}(l)$. This probability is defined as the visitation frequency of location l . If the individual decides to explore a new location, she selects a destination based on the rank of locations. This rank represents the distance between each alternative destination and the current location. The shorter the distance, the higher the rank. Specifically, they choose a location l with rank κ with probability $P^{exp}(\kappa)$:

$$P^{exp}(\kappa) \sim \kappa^{-\alpha}, \quad (4.2)$$

where α is the fitted parameter from empirical data.

By combining temporal and spatial choices with estimated parameters, we simulate mobility for users in the dataset. Since the dataset represents only a sample of the entire population, the next step is to expand these users to represent the whole population for a city-wide simulation. TimeGeo calculates two sets of expansion factors to scale commuters

and non-commuters to match the real population. These factors determine how many times to replicate each commuter and non-commuter within each geographical unit (e.g., census tract, county).

4.2.2 UAM Fleet Demand

The simulated demand gives a holistic representation of the travel pattern in the city. However, not all of the demand will be satisfied by UAM. This section demonstrates a method to predict which trips will likely be served by UAM at a given penetration level.

Let the set of factors influencing people’s choices be denoted as $\mathcal{L}$. Those factors are ordered based on importance, producing a factor vector $\mathbf{L} = (L_1, L_2, \dots, L_m)$, where $L_1 \in \mathcal{L}$ is the most important factor, and $L_m \in \mathcal{L}$ is the least important. Examples of factors that significantly influence people’s decisions to choose eVTOL can be broadly classified into three categories, namely trip-related factors (e.g., travel time, cost, and distance), surface traffic congestion as a motivating factor to UAM, and acceptance-related factors (e.g., safety and security, privacy, and noise) [172]. In this work, we only consider trip-related factors due to data availability. However, the motivating factor and acceptance-related factors can be easily incorporated into the model once data is available. For each trip t , we compute its rank $r_L(t)$ with respect to each factor L . For example, if we define L as saved travel time, for a trip t_1 with a 30-minute saved travel time and a trip t_2 with a 20-minute saved travel time, we have $r_L(t_1) = 1$ and $r_L(t_2) = 2$. The synthetic rank of trip t is then represented as a tuple:

$$\mathbf{r}(t) = (r_{L_1}(t), r_{L_2}(t), \dots, r_{L_m}(t)), \quad (4.3)$$

where $r_{L_i}(t)$ denotes the rank of trip t based on factor L_i , with L_1 being the most important factor and L_m the least important. The tuple is sorted lexicographically to prioritize trips based on their ranks for each factor, with the most important factors influencing the order first.

We then select the top N^{trips} trips after lexicographic sorting of all $\mathbf{r}(t)$. The required number of aircraft is approximated by dividing the number of selected trips by the aircraft capacity C^{uam} , i.e., $N^{\text{trips}}/C^{\text{uam}}$. In the current setting we assume all users have “car-pooling” as the primary mode. That is, all users are comfortable taking rides with others. The pool rides are subjected to the capacity of the aircraft C^{uam} , and are only limited to customers who share the same origin and destination.

4.3 Aircraft Fleet Dispatch

In this section, we first introduce the fleet dispatch model, followed by the problem formulation and an efficient algorithm to solve it.

4.3.1 System Model

This system has three components: vertiports, aircraft, and travel demand requests. The operator manages several vertiports and aircraft. Each aircraft can land at or take off from a vertiport. Upon landing, an aircraft can choose to charge its battery at the vertiport. Each vertiport features a charging station equipped with several charging piles capable of accommodating multiple simultaneous charging sessions. We assume the fleet size and the number of vertiports are fixed, so not all travel demand can be satisfied. Passengers needing a UAM ride send a request a day in advance, and the operator decides which requests to accept and how to dispatch aircraft among vertiports after collecting all requests for the next day. For convenience, let $\mathcal{T}$ represent the discretized decision time intervals of the daily operation.

Vertiport. Denote $\mathcal{V}$ as the set of vertiports in a city where aircraft travel. Let $\mathcal{M}$ be the set of charging stations equipped at vertiports. Ideally, we need to constrain the number of chargers and parking spaces. However, in this work, we relax this constraint. This is because currently we are at a very early stage of UAM deployment and there is not so much infrastructure to give us a proper assumption of how many spaces are needed at each vertiport. In this regard, this formulation treats the infrastructure requirements as optimization variables. The results reveal what the ideal space each vertiport needs if we want to maximize the number of served trips. Let $o_{v,v'}$ denote the time cost between vertiports v and v' . Similarly, let $\mu_{v,v'}^t$ represent the energy cost between vertiports v and v' at time slot t . The time and energy required do not change with the number of passengers on the aircraft. However, these costs are different for each flight, as they are determined by the distance between departure and arrival vertiports along with the energy consumption per mile. The per-mile energy consumption varies due to external conditions that change throughout the day.

Aircraft. Denote $\mathcal{A}$ as the set of aircraft. Initially, all aircraft are assigned an initial vertiport according to fleet dispatch optimization results. During the time window after the arrival time of the current request and before the departure time of the next request, the aircraft can be charged to ensure operation. Note that aircraft is allowed not to charge if it doesn't increase the number of satisfied trips. At each time slot, one aircraft can be in one of three states: parked at vertiport, charging at vertiport, or in flight. We discrete the target SoC into U levels. To charge the aircraft from SoC $u - 1$ to SoC u at time t , the time cost is w_u^t . Each charging session has a predefined time window ω to provide flexibility in operation uncertainty.

Request. Denote $\mathcal{R}$ as the set of travel demand requests. For computational ease, we combine individual requests N^{trips} into group requests. Every group request accommodates C^{uam} trips. An aircraft is capable of handling only one group request at a time. The number of requests from vertiport v to vertiport v' at time t is $q_{v,v'}^t$. Each request $r \in \mathcal{R}$ is represented by a tuple $\langle t^d, t^a, v^o, v^d \rangle$, where $t^d \in \mathcal{T}$ is the departure time, $t^a \in \mathcal{T}$ is the

arrival time, $v^o \in \mathcal{V}$ is the origin vertiport, and v^d is the destination vertiport.

This section follows [168] to calculate the optimal aircraft dispatch and charging window to maximize the satisfied requests while considering the system dynamics.

4.3.2 Decision Variables

For each time slot t , denote the number of aircraft at vertiport v that begin to charge with an initial SoC of u and target SoC of u' as an integer variable $x_{v,u,u'}^t$. The number of aircraft departing for vertiport v' from vertiport v with SoC u is $y_{v,v',u}^t$. The number of parked aircraft at vertiport v of SoC u is $z_{v,u}^t$. We add one auxiliary integer variable $\iota_{v,v'}^t$ to represent the number of unserved travel demand.

4.3.3 Objective

We aim to minimize the number of requests denied by the UAM operator:

$$\sum_{v,v',t} \iota_{v,v'}^t. \quad (4.4)$$

4.3.4 Constraints

Lower Bound of SoC to Start Flight. Ensure that aircraft cannot be in flight when the level reaches reserve SoC.

$$y_{v,v',0}^t = 0, \quad \forall v, v', t. \quad (4.5)$$

Non-negative Unserved Orders. Ensure that the auxiliary integer variable $\iota_{v,v'}^t$ represents the number of unserved trips between vertiports. This doesn't prevent the head handing as $q_{v,v'}^t - \sum_u y_{v,v',u}^t$ can be negative when there is repositioning flights.

$$\iota_{v,v'}^t \geq 0, \quad \forall v, v', t. \quad (4.6)$$

$$\iota_{v,v'}^t \geq q_{v,v'}^t - \sum_u y_{v,v',u}^t, \quad \forall v, v', t. \quad (4.7)$$

Fleet size Limit. Ensures that the total number of aircraft in the system at the beginning equals the fleet size.

$$\sum_{v,u,u'} x_{v,u,u'}^0 + \sum_{v,u,u'} x_{v,u,u'}^0 + \sum_{v,u} z_{v,u}^0 = |\mathcal{A}|, \quad \forall v, v'. \quad (4.8)$$

System Dynamics. Ensure the number of aircraft in parked state at each vertiport at each time slot at each SoC level is determined by parked aircraft from the previous time slot, arrivals and departures in the vertiport, and charging status of aircraft in the vertiport. Denote $\mathcal{W}_{v,v'}^t = \{t' \in \mathcal{T} | t' + o_{v,v'}^{t'} = t\}$, the constraint is:

$$\begin{aligned} z_{v,u}^t &= z_{v,u}^{t-1} + \sum_{v' \in \mathcal{V} - \{v\}} \left(\sum_{t' \in \mathcal{W}_{v,v'}^t} y_{v',v,u+\mu_{v',v}^{t'}}^t - y_{v,v',u}^t \right) \\ &+ \sum_{u'=0}^{u-1} x_{v,u',u}^t (t - \omega - \sum_{u''=u'+1}^u w_{u''}) - \sum_{u''=u+1}^U x_{v,u,u''}^t, \quad \forall v, u, t. \end{aligned} \quad (4.9)$$

System Stationarity. Ensure that the aircraft scheduling and charging policies can be repeated everyday. Previous studies on human mobility [121] and travel surveys [36] indicate consistent daily travel demand. Thus, by default, the day is treated as a closed system. However, in more dynamic areas without clear patterns, this constraint can be lifted. We can then adjust the optimization problem using model predictive control (MPC) [173] to handle future demand prediction uncertainties.

$$x_{v,u,u'}^0 = x_{v,u,u'}^T, \quad y_{v,v',u}^0 = y_{v,v',u}^T, \quad z_{v,u}^0 = z_{v,u}^T. \quad \forall v, v', u, u'. \quad (4.10)$$

4.3.5 Optimization Problem

The optimization problem is:

$$\min \sum_{v,v',t} l_{v,v'}^t. \quad (4.11)$$

$$s.t. \quad y_{v,v',0}^t = 0, \quad \forall v, v', t, \quad (4.12)$$

$$l_{v,v'}^t \geq 0, \quad \forall v, v', t, \quad (4.13)$$

$$l_{v,v'}^t \geq q_{v,v'}^t - \sum_u y_{v,v',u}^t, \quad \forall v, v', t, \quad (4.14)$$

$$\sum_{v,u,u'} x_{v,u,u'}^0 + \sum_{v,u,u'} x_{v,u,u'}^T + \sum_{v,u} z_{v,u}^0 = |\mathcal{A}|, \quad \forall v, v', \quad (4.15)$$

$$\begin{aligned} z_{v,u}^t &= z_{v,u}^{t-1} + \sum_{v' \in \mathcal{V} - \{v\}} \left(\sum_{t' \in \mathcal{W}_{v,v'}^t} y_{v',v,u+\mu_{v',v}^{t'}}^t - y_{v,v',u}^t \right) \\ &+ \sum_{u'=0}^{u-1} x_{v,u',u}^t (t - \sum_{u''=u'+1}^u w_{u''}) - \sum_{u''=u+1}^U x_{v,u,u''}^t, \quad \forall v, u, t, \end{aligned} \quad (4.16)$$

$$x_{v,u,u'}^0 = x_{v,u,u'}^T, \quad y_{v,v',u}^0 = y_{v,v',u}^T, \quad z_{v,u}^0 = z_{v,u}^T. \quad \forall v, v', u, u'. \quad (4.17)$$

where the objective function of the optimization problem is to minimize the total number of unserved requests. Constraint (4.12) ensures aircraft of which the SoC is at reserve level

cannot fly. Constraint (4.13-4.14) ensures that only non-negative unserved requests are feasible. Constraint (4.15) states the number of aircraft in the system equals the fleet size. Constraint (4.16) describes the dynamics of the number of aircraft at various vertiports by modeling the dynamics of the operations. Constraint (4.17) ensures the stationarity of the state of the system. The solution of $x_{v,u,u'}^t$ gives the charging time window and energy requirements. The solutions for $x_{v,u,u'}^0$, $y_{v,v',u}^0$, and $z_{v,u}^0$ determine the initial allocation of aircraft to vertiports.

4.4 Charging Coordination Considering Power System Dynamics

In this section, we model the interaction between the UAM system and the power grid. We propose a joint model to capture the coupling between these two systems. Using the charging time window and energy requirements derived from the optimal UAM fleet dispatch, we calculate the optimal charging schedule while considering power grid dynamics. Our goal is to maximize power system welfare through smart charging. We begin by formulating the problem in a deterministic setting and then extend it to incorporate stochastic factors.

4.4.1 System Model

The system model includes both the UAM system and the power system. In the deterministic formulation, we assume that charging demand and the charging time window are known with certainty.

UAM System. At the vertiport charging station, each charging session n is characterized by its earliest and latest possible charging times, denoted by τ_n^s and τ_n^e , respectively. Here, τ_n^s is no earlier than the time τ_r^a when the aircraft completes its previous travel request and repositions to the origin vertiport for its next travel request, while τ_n^e no later than the time τ_r^d when the aircraft departs from the vertiport. An illustrative example of the charging window is shown in Fig. 4.2. The charging demand for session n is denoted by d_n . The parameters τ_n^s , τ_n^e , and d_n are obtained from the fleet dispatch. The binary parameter s_n^t indicates the available charging time slots as follows:

$$s_n^t = \begin{cases} 1, & \text{if } \tau_n^s \leq t \leq \tau_n^e, \\ 0, & \text{otherwise.} \end{cases} \quad (4.18)$$

Within the charging window, the operator must decide on the charging power for session n at time slot t as p_n^t , which is bounded by P^+ . The binary parameter $\phi_{n,m}$ indicates whether session n takes place at charging station m . The total charging capacity of station m is denoted by C_m^+ , meaning that the combined power of multiple concurrent charging sessions at the same station should not exceed C_m^+ .

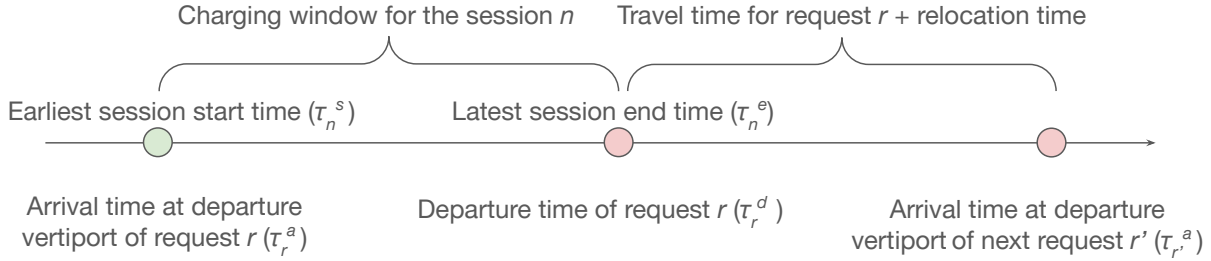


Figure 4.2: Illustrative example of a charging window. The window for session n spans from the earliest start time τ_n^s to the latest end time τ_n^e , bounded by the arrival time τ_r^a and departure time τ_r^d of request r .

Power System. The power system consists of buses and transmission lines as its fundamental components. Some buses function as generators, while others serve as loads. Buses that are neither generators nor loads act as interconnections. Generators produce power and deliver it to the network, while loads consume power from the network. The operator determines the energy generation at bus i during time slot t as g_i^t , which is constrained by the minimum and maximum generation limits G_i^- and G_i^+ . The difference in generation between two consecutive time slots is restricted by the ramp-down and ramp-up limits, denoted by R_i^- and R_i^+ . The generated power supplies the charging load of vertiports (with the binary indicator $\eta_{n,i}$ showing whether session n is a load for bus i) as well as the external load ℓ_i^t of bus i at time slot t . The voltage angle at bus i in time slot t is represented by δ_i^t , and the reactance of the transmission line between buses i and j is $b_{i,j}$. The voltage angle and reactance together determine the power flow between buses i and j , denoted by $f_{i,j}$, which is constrained by the transmission line's power flow limits, F_i^- and F_i^+ .

4.4.2 Decision Variable

We introduce variables at both the vertiport level and the power grid level. At the vertiport charging station level, the continuous decision variable is p_n^t , representing the charging power for session n at time slot t , and is bounded by P^+ . At the power grid level, the decision variables include the continuous variables for energy generation at bus i and time slot t as g_i^t , power flow between bus i and bus j at time slot t as $f_{i,j}^t$, and the voltage angle at bus i and time slot t as $\delta_{i,j}^t$.

4.4.3 Objective

The objective is to maximize power system welfare. Denote $\Psi(\cdot)$ as the generation cost function and $\Theta_i(g_i^t)$ as the benefit the system can obtain by using the generated power g_i^t at bus i , we have:

$$\max \quad \sum_t \sum_i \Theta_i(g_i^t) - \sum_t \sum_i \Psi_i(g_i^t), \quad (4.19)$$

4.4.4 Constraints

On the charging station level, there are charging demand constraints, charging window constraints as well as charging station capacity constraints.

Energy Demand Constraints. Ensure the charging demand for each session should be satisfied.

$$\sum_t p_n^t = d_n, \quad \forall n \in \mathcal{N}, \quad (4.20)$$

Charging Window Constraints. Ensure the power can be positive only during the charging window of the session. When the time t is out of the charging session n , i.e., $s_n^t = 0$, the constraint becomes $p_n^t = 0$. When the time t is in the charging session n , i.e., $s_n^t = 1$, the constraint becomes $0 \leq p_n^t \leq P^+$.

$$0 \leq p_n^t \leq s_n^t P^+, \quad \forall n \in \mathcal{N}, t \in \mathcal{T}, \quad (4.21)$$

Station Capacity Constraints. Ensure the maximal charging capacity of each vertiport is not exceeded. $\phi_{n,m} p_n^t$ is the total power at station m in time t . By enforcing $0 \leq \sum_n \phi_{n,m} p_n^t \leq C_m^+$, we ensure the total power at every station in every time slot doesn't its capacity C_m^+ .

$$0 \leq \sum_n \phi_{n,m} p_n^t \leq C_m^+, \quad \forall m \in \mathcal{M}, t \in \mathcal{T}, \quad (4.22)$$

On the grid level, we consider power flow dynamics, which need to consider (1) how the power injections are distributed along the power lines, and (2) how to ensure that the power flows do not exceed the capacity of the lines. To model flow dynamics, both the higher-fidelity AC model [174] and the simplified linear DC model [175] are commonly used. The AC model accurately captures the physical behavior of the network but becomes computationally prohibitive for large-scale optimization. On the other hand, the DC model, due to its linearity, is well-suited for large-scale problems. The linearity of the DC model relies on several key assumptions: (1) voltage magnitudes are constant, (2) reactive power and line resistances are neglected, and (3) phase angle differences between buses are assumed to be small. While these assumptions improve computational efficiency, they also limit the model's ability to handle voltage constraints in distribution networks [176]. Despite this, the DC model remains widely used in transmission-level application [177] and is appropriate for high-level analysis of control policies [178]. In this paper, we focus on the transmission-level application.

System Balance Constraints. Ensure the difference between outflow and inflow equals the net load generation minus load.

$$g_i^t - (\ell_i^t + \sum_n \eta_{n,i} p_n^t) = \sum_k f_{i,k} - \sum_j f_{j,i}, \quad \forall i \in \mathcal{I}, t \in \mathcal{T}. \quad (4.23)$$

$$f_{i,j}^t = b_{i,j}(\delta_i^t - \delta_j^t), \quad \forall i, j \in \mathcal{I}, t \in \mathcal{T}. \quad (4.24)$$

$$-2\pi \leq \delta_i^t \leq 2\pi, \quad \forall i \in \mathcal{I}, t \in \mathcal{T}. \quad (4.25)$$

Generation Capacity Constraints. Ensure the generation does not exceed generator capacity lower bound G_i^- and upper bound G_i^+ .

$$G_i^- \leq g_i^t \leq G_i^+, \quad \forall i \in \mathcal{I}, t \in \mathcal{T}. \quad (4.26)$$

Flow Capacity Constraints. Ensure the flow does not exceed transmission line capacity. The $F_{i,j}^-$ and $F_{i,j}^+$ has same absolute value but different sign, i.e, $F_{i,j}^- = -F_{i,j}^+$, which ensures for bi-directional flow doesn't exceed $F_{i,j}^+$.

$$F_{i,j}^- \leq f_{i,j}^t \leq F_{i,j}^+, \quad \forall i, j \in \mathcal{I}, t \in \mathcal{T}. \quad (4.27)$$

Ramping Capacity Constraints. Ensure the generation power gap between consecutive time intervals doesn't exceed the lower limit R_i^- and upper limit R_i^+ .

$$R_i^- \leq g_i^t - g_i^{t-1} \leq R_i^+, \quad \forall i \in \mathcal{I}, t \in \mathcal{T}. \quad (4.28)$$

4.4.5 Optimization Problem

The optimization problem is:

$$\max \quad \sum_t \sum_i \Theta_i(g_i^t) - \sum_t \sum_i \Psi_i(g_i^t) \quad (4.29)$$

$$s.t. \quad \sum_t p_n^t = d_n, \quad \forall n \in \mathcal{N}, \quad (4.30)$$

$$0 \leq p_n^t \leq s_n^t P^+, \quad \forall n \in \mathcal{N}, t \in \mathcal{T}, \quad (4.31)$$

$$0 \leq \sum_n \phi_{n,m} p_n^t \leq C_m^+, \quad \forall m \in \mathcal{M}, t \in \mathcal{T}, \quad (4.32)$$

$$g_i^t - (\ell_i^t + \sum_n \eta_{n,i} p_n^t) = \sum_k f_{i,k} - \sum_j f_{j,i}, \quad \forall i \in \mathcal{I}, t \in \mathcal{T}, \quad (4.33)$$

$$f_{i,j}^t = b_{i,j}(\delta_i^t - \delta_j^t), \quad \forall i, j \in \mathcal{I}, t \in \mathcal{T} \quad (4.34)$$

$$-2\pi \leq \delta_i^t \leq 2\pi, \quad \forall i \in \mathcal{I}, t \in \mathcal{T}, \quad (4.35)$$

$$F_{i,j}^- \leq f_{i,j}^t \leq F_{i,j}^+, \quad \forall i, j \in \mathcal{I}, t \in \mathcal{T}. \quad (4.36)$$

$$G_i^- \leq g_i^t \leq G_i^+, \quad \forall i \in \mathcal{I}, t \in \mathcal{T}, \quad (4.37)$$

$$R_i^- \leq g_i^t - g_i^{t-1} \leq R_i^+, \quad \forall i \in \mathcal{I}, t \in \mathcal{T}, \quad (4.38)$$

Eq. (4.29) maximizes the power system welfare of the system. Constraint (4.30) describes the charging requirement. Constraint (4.31) characterizes the maximal charging power of each session in each vertiport. Constraint (4.32) characterizes the maximal charging capacity of each vertiport. Constraints (4.33)-(4.35) denotes system balance. Constraints (4.36) describe the line capacity constraints. Constraint (4.37) denotes the generation capacity. Constraints (4.38) characterize the ramping constraints.

4.5 Charging Coordination Considering Uncertainty

The deterministic formulation focuses on cases where the aircraft's arrival time and demand are accurately estimated. However, in reality, the arrival time τ_n^s and charging demand d_n for each aircraft are stochastic. The uncertainty in the system affects the flexibility that smart charging can provide. For instance, a narrowed time window reduces the flexibility for adjusting the charging schedule. Similarly, if an aircraft consumes more energy than expected, the demand may be higher than anticipated.

4.5.1 Variables and Parameters

The stochastic formulation shares the same variables and parameters as the deterministic formulation. The difference between the deterministic and stochastic formulations lies in the randomness of the variables. For each session n , its demand d_n and start time τ_n^s are stochastic and are sampled from a joint distribution Ω_n , i.e., $d_n, \tau_n^s \sim \Omega_n$.

We assume the functions describe the probability of finite discrete realizations. Suppose we have $k \in \mathcal{K}$ realizations. A realization of the possible pattern is noted by the parameters $d_{n,k}$ and $s_{n,k}^t$ associated with the probability $\pi_{n,k}$. A binary variable $h_{n,k}$ is introduced for each pattern realization.

4.5.2 Objective

The objective is still to maximize the total power system welfare. Denote $\Psi(\cdot)$ as the generation cost function and $\Theta_i(g_i^t)$ as the benefit the system can obtain by using the generated power g_i^t at bus i , we have:

$$\max \sum_t \sum_i \Theta_i(g_i^t) - \sum_t \sum_i \Psi_i(g_i^t). \quad (4.39)$$

4.5.3 Constraints

The stochastic formulation retains the same constraints as the deterministic formulation, except for Constraints (4.30-4.31). In the stochastic formulation, the charging demand d_n and the earliest start time t_n^{str} for session n are treated as stochastic parameters influenced by

aircraft operations. We reformulate Constraints (4.30) and (4.31) using a chance-constrained framework as follows:

$$\Pr \left(\begin{array}{l} d_n^- \leq \sum_t p_n^t - d_n \leq d_n^+ \\ 0 \leq p_n^t \leq s_n^t P^+ \end{array}, \forall t \in \mathcal{T} \right) \geq 1 - \epsilon, \forall n \in \mathcal{N}, \quad (4.40)$$

where ϵ is a predefined confidence parameter for each session. This constraint ensures that the probability of failing to meet the charging requirements is below ϵ .

The distribution of stochastic parameters is hard to model by a continuous function. Also, these two parameters are correlated with each other. Here we assume that stochastic parameters have a finite discrete distribution, and then we can solve it by a mixed-integer programming method [179]. We can divide the pattern realizations into two sets.

Essential Requirements. The subset of possible pattern realizations with a probability over the confidence parameter is defined as:

$$\mathcal{K}_n^+ = \{k \in \mathcal{K}_n, \pi_{n,k} > \epsilon\}, \quad (4.41)$$

The binary variable for the realization k should be $h_{n,k} = 0$ when $\pi_{n,k} > \epsilon$. Since if this realization is true, the probability will exceed the ϵ . For realization $k \in \mathcal{K}_n^+$, the Constraints are as original:

$$d_n^- \leq \sum_t p_n^t - d_{n,k} \leq d_n^+, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}_n^+, \quad (4.42)$$

$$0 \leq p_n^t \leq s_{n,k}^t P^+, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}_n^+. \quad (4.43)$$

These constraints ensure all realizations with probability more than ϵ should be satisfied.

Nonessential Requirements. The subset of possible pattern realizations with a probability less than or equal to the confidence parameter is defined as:

$$\mathcal{K}_n^- = \{k \in \mathcal{K}_n, \pi_{n,k} \leq \epsilon\}. \quad (4.44)$$

For realization $k \in \mathcal{K}_n^-$, the Constraints can be reformulated as:

$$\sum_t p_n^t - d_{n,k} - h_{n,k} \left(\sum_t P^+ - d_{n,k} \right) \leq d_n^+, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}_n^-, \quad (4.45)$$

$$\sum_t p_n^t - d_{n,k} + h_{n,k} d_{n,k} \geq d_n^-, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}_n^-, \quad (4.46)$$

$$0 \leq p_n^t \leq P^+(s_{n,k}^t + h_{n,k}), \quad \forall n \in \mathcal{N}, k \in \mathcal{K}_n^-, t \in \mathcal{T}, \quad (4.47)$$

These constraints ensure all realizations with probability less or equal to ϵ can be selected to be compromised.

When the binary variable $h_{n,k} = 0$, Constraints are the same as the deterministic cases:

$$d_n^- \leq \sum_t p_n^t - d_{n,k} \leq d_n^+, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}_n^-, \quad (4.48)$$

$$0 \leq p_n^t \leq s_{n,k}^t P^+, \quad \forall n \in \mathcal{N}, t \in \mathcal{T}, k \in \mathcal{K}_n^- \quad (4.49)$$

When the binary variable $h_{n,k} = 1$, Constraints are relaxed as:

$$\sum_t p_n^t - d_{n,k} - \sum_t P^+ \leq d_n^+, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}_n^-, \quad (4.50)$$

$$\sum_t p_n^t \geq d_n^-, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}_n^-, \quad (4.51)$$

$$0 \leq p_n^t \leq P^+(s_{n,k}^t + 1), \quad \forall n \in \mathcal{N}, k \in \mathcal{K}_n^-, t \in \mathcal{T}, \quad (4.52)$$

Constraints (4.50) are guaranteed since $\sum_t p_n^t \leq \sum_t P^+ + d_{n,k} + d_n^+$ is always true. Since we have $d_n^- \leq 0$, we can guarantee Constraints (4.51) too. For Constraints (4.52), if $s_{n,k}^t = 0$, we have $0 \leq p_n^t \leq P^+$, which means even if the aircraft will not able to charge at time slot t , charging now is still a feasible solution in this optimization problem. If $s_{n,k}^t = 1$, we have $0 \leq p_n^t \leq 2P^+$, which means the aircraft can charge at time slot t . Together this constraint ensures that whether this time slot t is available for charging or not, a positive charging power solution is feasible.

Failure Probability Requirements. Ensures the summation of probability $\pi_{n,k}$ under all realizations for session n is less than ϵ . The subset of possible pattern realizations with a probability over the confidence parameter is defined as:

$$\sum_{k \in \mathcal{K}_n^+} (\pi_{n,k} h_{n,k}) \leq 0, \quad \forall n \in \mathcal{N}, \quad (4.53)$$

$$h_{n,k} \in \{0, 1\}, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}_n^+. \quad (4.54)$$

The subset of possible pattern realizations with a probability less or equal to the confidence parameter is defined as:

$$\sum_{k \in \mathcal{K}_n^-} (\pi_{n,k} h_{n,k}) \leq \epsilon, \quad \forall n \in \mathcal{N}, \quad (4.55)$$

$$h_{n,k} \in \{0, 1\}, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}_n^-. \quad (4.56)$$

4.5.4 Optimization Problem

We have the optimization problem as:

$$\max \quad \sum_t \sum_i \Theta_i(g_i^t) - \sum_t \sum_i \Psi_i(g_i^t) \quad (4.57)$$

$$s.t. \quad \text{Constraints (4.32) – (4.38)} \quad (4.58)$$

$$d_n^- \leq \sum_t p_n^t - d_{n,k} \leq d_n^+, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}_n^+, \quad (4.59)$$

$$0 \leq p_n^t \leq s_{n,k}^t P^+, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}_n^+. \quad (4.60)$$

$$\sum_{k \in \mathcal{K}_n^+} (\pi_{n,k} h_{n,k}) \leq 0, \quad \forall n \in \mathcal{N}, \quad (4.61)$$

$$h_{n,k} \in \{0, 1\}, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}_n^+. \quad (4.62)$$

$$\sum_t p_n^t - d_{n,k} - h_{n,k} \left(\sum_t P^+ - d_{n,k} \right) \leq d_n^+, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}_n^-, \quad (4.63)$$

$$\sum_t p_n^t - d_{n,k} + h_{n,k} d_{n,k} \geq d_n^-, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}_n^-, \quad (4.64)$$

$$0 \leq p_n^t \leq P^+(s_{n,k}^t + h_{n,k}), \quad \forall n \in \mathcal{N}, k \in \mathcal{K}_n^-, t \in \mathcal{T}, \quad (4.65)$$

$$\sum_{k \in \mathcal{K}_n^-} (\pi_{n,k} h_{n,k}) \leq \epsilon, \quad \forall n \in \mathcal{N}, \quad (4.66)$$

$$h_{n,k} \in \{0, 1\}, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}_n^-. \quad (4.67)$$

where Eq. (4.57) maximizes the power system welfare. Constraints (4.32)-(4.38) describe deterministic power system dynamics. Constraints (4.59)-(4.62) ensure the subset of possible pattern realizations with a probability over the confidence parameter should be satisfied. Constraints (4.63)-(4.67) ensure the summation of probability under all realizations for each session is less than the predetermined confidence level.

4.6 Numerical Studies

We first introduce the dataset used and then present the UAM travel demand. Following this, we demonstrate the flexibility available in both the deterministic and stochastic settings.

4.6.1 Data Overview

We use LBS data to model the mobility trajectory of users. The datasets, as described in [180], cover Miami-Dade County in Florida and were collected over a two-month period from September to October 2022. The total number of users is approximately 100,000, and these users generated millions of records within the given region and timeframe. Each record consists of a user ID, a timestamp, a stay duration, and a pair of geographical coordinates.

For the power grid analysis, we utilize a synthetic 9-bus transmission system [181] to evaluate the performance of our framework. This system includes power flow data for nine buses, three of which are generators. The dataset comprises bus data, generator data, branch data, and generator cost data. Each bus can function as a generator or not; if it does, the data includes the maximum and minimum power outputs. Each generator has an associated cost represented by a quadratic function. For each branch between two buses, the dataset provides its reactance, as well as the lower and upper power capacity. Each bus has a load that must be satisfied, which is scaled from the data provided by [182]. This data offers hourly load information for a typical day in Florida.

4.6.2 Experiments Setting

Travel Demand. Denote the saved travel time compared to traditional cars as Δt and the travel distance as d , we define $\mathbf{L} = [\Delta t, d]$ as the factor vector to determine most possible 70,000 UAM trips. These trips satisfied $\Delta t > 30$ minutes and $d > 30$ miles.

Fleet Dispatch. Miami-Dade County is divided into hexagons with an edge length of 10 km, each containing a vertiport, resulting in a total of 27 stations. We assume the fleet size is 1500 and the flexible time window is set to be 20 minutes. The charging demand within the county is treated as the load for bus 1. The aircraft configuration is shown in Table 4.1. In the numerical study, we assume the energy consumption per mile is a constant that stays the same across the day.

Name	Charging Power [kW]	Battery Capacity [kWh]	Initial SoC [%]	Reserve SoC [%]	SoC Levels	Energy Rate [kWh/mile]	Passenger Capacity
Value	250	160	70%	20%	8	1	1

Table 4.1: Aircraft configurations

Power Grid. The generation capacity, ramping limits, line capacity, and reactance are derived from the 9-bus system data. In this case study, we set the generation function as a quadratic function, i.e., $\Psi(x) = \xi_1 x^2 + \xi_2 x + \xi_3$, where the ξ_1, ξ_2, ξ_3 is obtained from 9-bus system data. The benefit function is assumed to be $\Theta(x) = \sigma x$, where σ can be regarded as the amortized benefit the users can get from using one unit of electricity. Here we set it as the 0.1\$/kWh, which is at the same magnitude as the electricity price.

Uncertainty Modeling. For stochastic formulation, the confidence level is set as 0.05. The pattern realizations and probability for each session are listed in Table 4.2. In the table, we show the difference between the sampled arrival time (energy demand) and the mean arrival

Pattern Realizations	1	2	3	4	5	6	7	8	9
Arrival Time [min]	-10	-10	-10	+0	+0	+0	+10	+10	+10
Energy Demand [kWh]	-30	+0	+30	-30	+0	+30	-30	+0	+30
Probability	0.00020	0.0063	0.00020	0.029	0.93	0.029	0.00020	0.0063	0.00020

Table 4.2: Pattern realizations and probabilities

time (energy demand). The probability is sampled from a joint normal distribution with a mean value as the arrival time and energy demand in the deterministic formulation.

4.6.3 UAM Charging Demand

We analyze the differences between the city-wide mobility pattern and the UAM travel demand. Our comparison includes the departure timing distribution as well as maps of the origin and destination matrix for both general travel demand and UAM travel demand. Fig. 4.3 (A) illustrates that the departure timing for UAM and general travel demand have similar distributions. Fig. 4.3 (b-c) highlights the differences between general travel demand and UAM travel demand. The grey area represents the base map of Miami-Dade County. The green hexagons indicate areas, each containing one vertiport, represented by orange nodes. Links between vertiports signify travel demand between them, with the color of the edges indicating the flow of travel demand—the darker the color, the greater the flow. Our analysis reveals that while general travel demand covers the entirety of Miami-Dade County, UAM travel demand has more long trips between the northern and southern parts of the county.

Then we further show the charging session overview after optimal dispatch. Fig. 4.4 (A) shows the distribution of energy demand of charging sessions. Most charging sessions have to satisfy a charging demand of around 75 kWh. Fig. 4.4 (B) shows the distribution of charging start time, the travel demand distribution, and served travel demand distribution. Most charging session starts at late night and early morning. This is because the travel demand is low late night and early morning, allowing for time for charging. During the day, the charging demand doesn't increase with more travel demand. This is because all aircraft are active in serving travel demand. From 0:00 to 6:00, travel demand is low, allowing most aircraft to charge, resulting in numerous charging sessions. Around 8:00, during the 6:00 to 9:00 period, morning travel peaks occur, with many aircraft less available for charging due to active service. With full charges between 0:00-6:00, the fleet can meet trip demands, showing a served demand peak. From 9:00 to 15:00, demand drops, and so as the served demand. The 15:00-19:00 period has a second demand peak, but served demand does not rise due to limited fleet size and the morning peak depletes energy; aircraft charge only when SoC is critically low. From 19:00-24:00, demand decreases, allowing more charging time, and increasing charging sessions. This framework also provides important insights into optimizing capacity, the quantity of charging piles, and the allocation of parking spaces

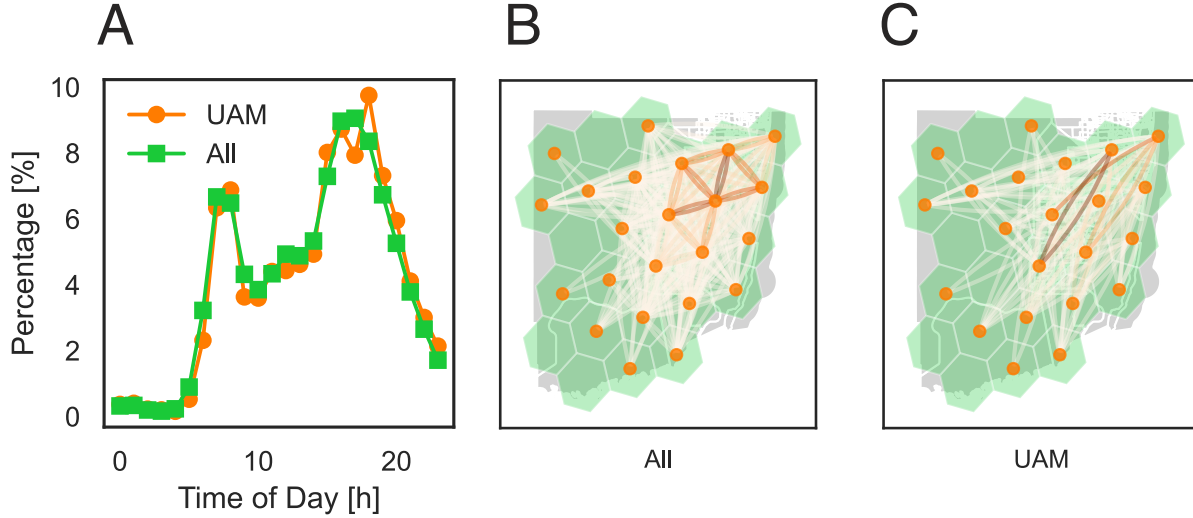


Figure 4.3: Comparison of all travel demand and the UAM demand. (A) Temporal distribution of the departure time of all trips and UAM trips. (B) Geographical distribution of all trips' OD. (C) Geographical distribution of UAM trips' OD.

to reduce unmet travel demand. Specifically, the number of simultaneous sessions varies from 1 to 192, indicating significant differences in vertiport size requirements across different locations.

4.6.4 Power Grid Flow

We analyze the power flow on transmission lines and the generation power at each generator for both deterministic and stochastic scenarios. Fig. 4.5 shows power flow in the system. The green nodes represent buses with generators, while the red nodes represent buses without generators. Arrows between two links indicate a flow on the transmission line, and the number on each arrow denotes the percentage of flow relative to the transmission line capacity. Similarly, the number on each node indicates the generation power relative to the generator's capacity. We define the peak hour as the time slot when the external load reaches its maximum and the off-peak hour as the time slot when the external load is at its minimum. Fig. 4.5 (A-C) display the off-peak hour power flow. In these scenarios, the stochastic scenario focusing on generation exhibits a lower generation than the deterministic scenario, while the stochastic scenario focusing on power system welfare shows a higher generation than the deterministic scenario. Fig. 4.5 (D-F) show the peak hour power flow. Similarly, during peak hours, the deterministic scenario has a generation between stochastic scenarios focusing on power system welfare and a scenario focusing on generation.

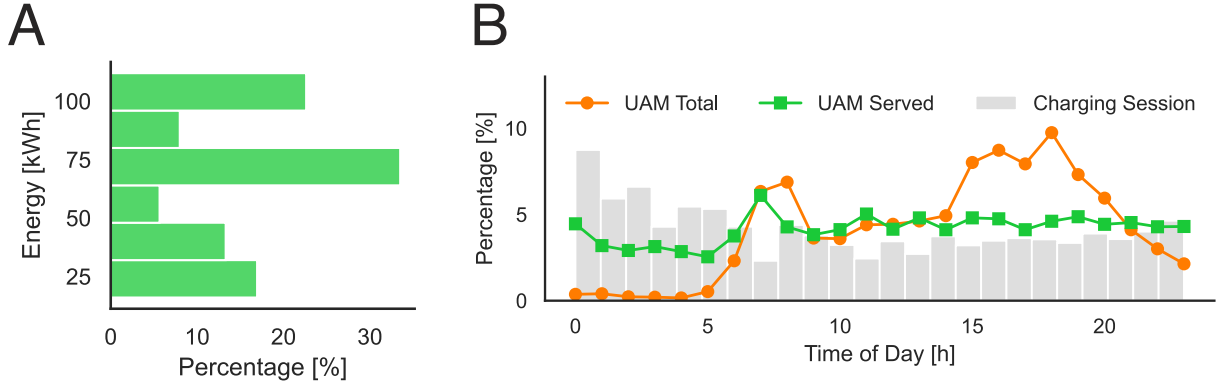


Figure 4.4: Charging session overview. (A) Histogram of charging session energy. (B) Histogram of charging session start time, UAM trip departure time distribution, and served UAM trip departure time distribution.

4.6.5 Power System Welfare

We present the load profile for both deterministic and stochastic scenarios, followed by the power system welfare that the operator can generate under these scenarios. Fig. 4.6 (A) illustrates the optimal charging schedule throughout the day. The red area highlights the power grid peak hours while the green area highlights the off-peak hours. The Deterministic case and ASAP case share the same area under curves because they are optimized without considering uncertainty in charging energy needs. However, the Stochastic (W)/Stochastic (G) case considers the uncertainty in energy consumption and thus has a different total charging demand. With a smart charging schedule (Deterministic/Stochastic), the charging profile becomes more flattened. This occurs because the generation cost is a quadratic function of power generation, meaning that a higher generation significantly increases the cost. Therefore, a good strategy is to shift high demand to time slots with lower demand. When comparing peak hours (times of high external load) with off-peak hours (times of low external load), we observe that the difference between the four methods becomes more pronounced during off-peak hours. For the stochastic cases, charging demand is uncertain, leading the operator to either charge more or less than the actual demand. In the power system welfare-focused case, the operator aims to maximize the benefit obtained by using the generated electricity minus the generation cost. In contrast, the generation-focused case aims to minimize generation costs only. The power system welfare-focused strategy is more aligned with economic benefits, while the generation-focused approach considers environmental factors. We find that under uncertainty, operators tend to charge more to increase power system welfare, even when generating less power could satisfy demand and reduce carbon emissions. Fig. 4.6 (B) shows the power system welfare change of Deterministic,

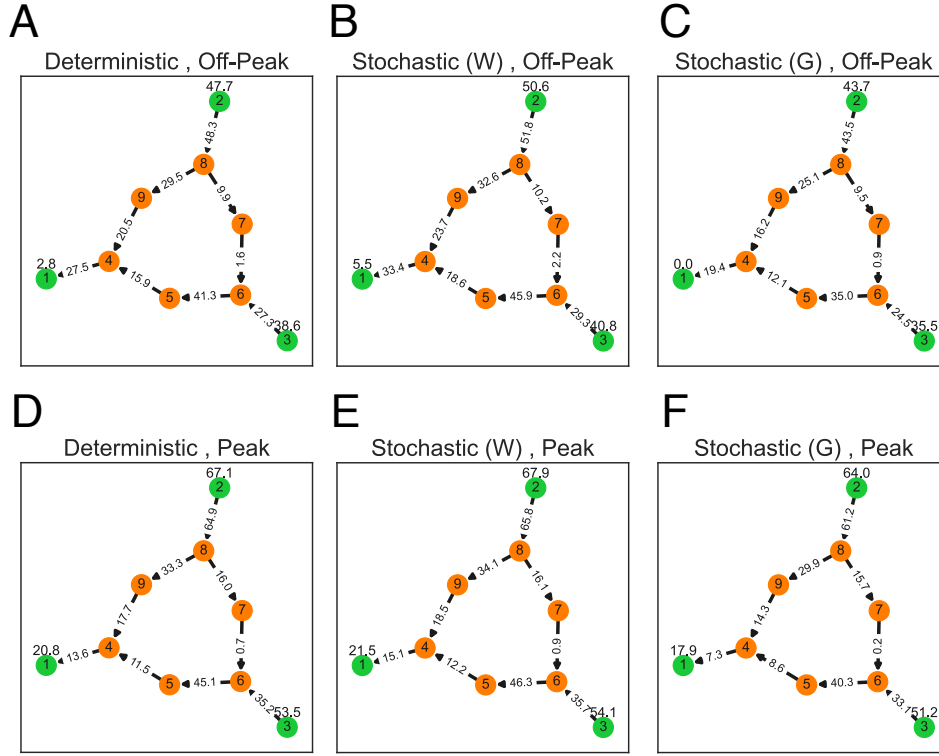


Figure 4.5: Power flow to line capacity and power generation to generator capacity under Deterministic and Stochastic (power system welfare) and Stochastic (Generation). (A-C) Peak hour case. (D-F) Off-peak hour case.

Stochastic (Welfare), and Stochastic (Generation) compared to without any control in AM (6:00-9:00), MD (9:00-15:00), PM (15:00-19:00), RD (19:00-6:00). The bar with '+' patterns indicates the change is positive and '/' indicates the change is negative. We find the change of Deterministic, Stochastic (Welfare) and Stochastic (Generation) is most significant in AM and RD when there are more charging sessions. While Deterministic, Stochastic (Welfare) provides positive changes, Stochastic (Generation) will reduce the power system welfare to improve environmental benefits. The simulation incorporating uncertainty reveals that areas with lower weather variability can be adequately managed through deterministic optimization, ensuring efficient charging operations. However, in regions with high weather-related uncertainties—where travel time and energy consumption exhibit significant fluctuations—deterministic approaches may be insufficient. In such cases, aircraft must overcharge to compensate for unpredictable energy demands, leading to lower effective service rates and a potential reduction in overall network efficiency. This highlights the importance of choosing launch sites for UAM services in areas with stable operational conditions. Additionally, it highlights the need for designing a UAM network that is resilient to external uncertainties,

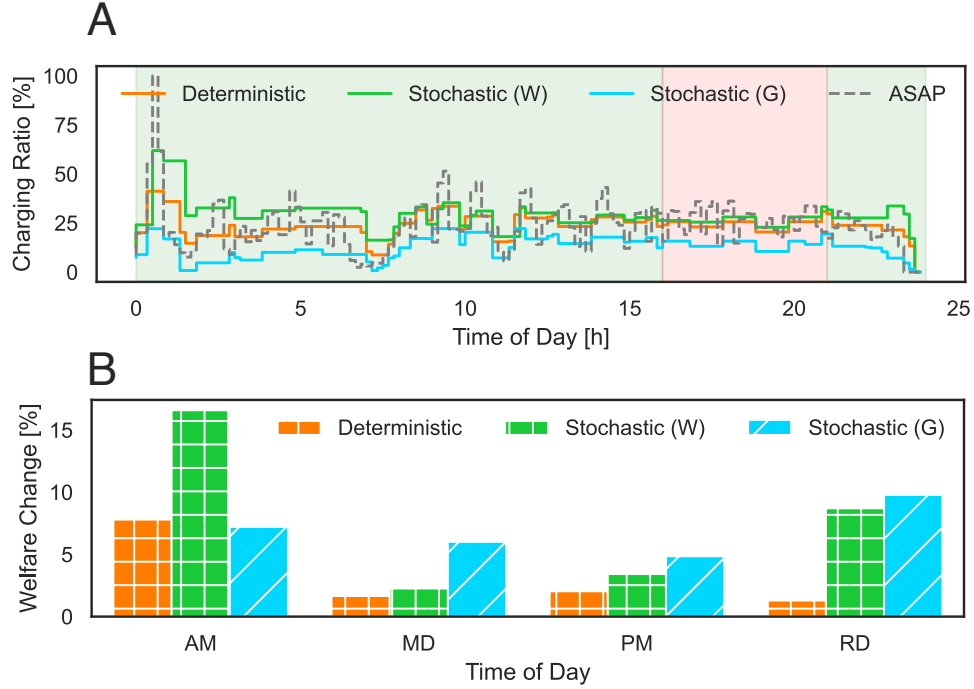


Figure 4.6: Charging power and power system welfare. (A) Charging schedule under ASAP, Deterministic, Stochastic (power system welfare), and Stochastic (Generation). (B) power system welfare change of Deterministic, Stochastic (power system welfare), and Stochastic (Generation) compared with ASAP. Patch '+' denotes the positive change and '/' denotes negative changes.

such as weather disturbances and unexpected delays.

4.7 Conclusion

The electrical grid is one of the many infrastructure challenges that must be overcome to enable large-scale UAM operations. This paper provides a framework to estimate the potential of smart charging to improve power system welfare when integrating large-scale UAM into the power grid. We first estimate UAM demand from LBS data. Then we construct a transportation and power system nexus by solving a fleet dispatch and an optimal power flow problem. The overall aim is to maximize the power grid welfare by smart charging management. At last, we incorporate the uncertainty of the charging time window and charging demand into the formulation through chance-constraint optimization. The results indicate

that smart charging effectively enhances power system welfare. Nevertheless, to incentivize vertiports to adhere to the operator's smart charging schedule, an appropriate pricing strategy must be established. Beyond smart charging, several alternatives for integrating UAM into the power grid we could explore include: (1) implementing renewable energy options like solar and wind power to meet some of the UAM charging needs, (2) utilizing energy storage systems, such as battery storage located at vertiports, to mitigate demand fluctuations and ensure grid reliability, and (3) exploring vehicle-to-grid capabilities to improve grid flexibility. UAM vehicles equipped with bidirectional charging systems could help stabilize the grid by discharging stored energy back into it during peak demand periods.

Chapter 5

A Cluster-based Appliance-level-of-use Demand Response Program Design

The ever-intensifying threat of climate change renders the electric power system undergoing a profound transition toward net-zero emissions. Energy efficiency measures, such as demand response, facilitate the transformation to jointly relieve consumers' financial burden and improve the operability of the electric power grid, in a carbon-free way. In this chapter, we design a cluster-based appliance-level-of-use demand response program, based on the massive volume of appliance consumption data, to expand the role demand response can play in the power grid's low-carbon transition. We systematically model the appliance-level utility function to distinguish consumers' distinct consumption patterns. We then develop a bi-level optimization model to capture the interactions between individual consumers and a DSO and enable appliance-level-of-use demand response functions. To further improve the efficiency and scalability of the proposed mechanism, we propose a cluster-based approach to capture the heterogeneity of users based on their energy consumption behaviors. Simulation results show that by capturing the detailed appliance-level response patterns, the proposed approach can systematically improve overall social welfare compared with conventional demand response mechanisms. The research reported in this chapter can be found in [183].

5.1 Introduction

The undergoing profound transition of the electric power industry toward net-zero emissions combats the climate change [184]. While the carbon emission responsibility has been traditionally attributed to energy generators for the combustion of fossil fuels, the active demand side is reshaping this conventional view [185]. The responsibility of carbon emission flows with electricity, transfers over the power delivery network, and eventually distributes

to consumers according to their electricity consumption activities. Therefore, encouraging low-carbon energy behaviors from the demand side, such as shifting their electricity use or adopting energy-efficient technology, could enable the decarbonization of the global economy [186, 187]. To this end, demand response, empowered by the ever-increasing amount of fine-grained energy consumption data collected by smart grid edge devices (e.g., smart meters), creates a win-win situation to combat climate change [188].

Demand response refers to the changes in electric usage by consumers in response to variations in the electricity price over time or across different energy sources. In this way, demand response could shave down demand peaks and smooth out power consumption across the grid, making it more reliable and versatile without requiring major investments in infrastructure upgrading [189]. Harnessing electricity demand can also help integrate variable renewable energy sources, like wind and solar power [190]. The year 2022 has witnessed several occasions where demand response from consumers effectively resolves system operability constraints. In the recent event of the California heat wave, electricity demand in the state climbed to a record high of more than 52,000 MW on September 6. At 5:45 pm, California’s Office of Emergency Services sent out an alert to targeted counties, and within minutes, demand dropped by 1,200 MW between 5:50 pm and 5:55 pm, which effectively ended the emergency [191]. Similarly, in May 2022, the Texas grid operator, ERCOT, asked residents to reduce their power use to prevent rolling blackouts due to a heat wave and the loss of several power generators, which successfully prevented the grid from falling below its safety margin of excess supply [192].

Despite the various advantages offered by demand response, traditional demand response programs fail to fully utilize the flexibility of consumers due to insufficient characterization of the consumers’ energy behaviors with different appliances. For instance, while a dryer can be run at different times, refrigerators must stay on constantly. Meanwhile, air conditioners are mostly needed during the hottest times of the day for homes and apartments. Therefore, a finer-level and more precise demand response empowers individual decisions at scale to fight climate change and maintain the integrity of the grid.

The deployment of advanced metering infrastructure, if expanded, offers the capability to monitor, record, and transmit data at unprecedented sampling rates [193]. Nevertheless, this expansion faces two primary challenges: the costs associated with installation and data collection and privacy concerns.

For the installation and data collection costs, recent technological advancements have paved the way for cost-effective, large-scale data collection. Utility operators are now focusing on optimizing smart meter deployment to reduce costs associated with deployment, maintenance, and data collection [194]. Innovations in smart meter infrastructure aim to decrease communication costs, and hardware expenses, and simplify network complexities [195]. A notable advancement is a low-cost smart meter design, offering a cost-efficient deployment strategy and receiving strong consumer support [196]. Additionally, the proliferation of smart home technologies such as Amazon’s Alexa®️, Google Home®️, Apple’s HomeKit®️, and Samsung SmartThings®️, has gained widespread popularity. These innovations have introduced novel methods for individually monitoring and controlling household

appliances, transforming how consumers interact with their home environments.

Addressing privacy concerns linked to smart meters involves three main strategies. First, distorts data before sending it to utilities using data aggregation [197], anonymization [198], and data obfuscation algorithms [199, 200, 201]. Second, estimates appliance use and consumption from aggregated data through applying non-intrusive load monitoring algorithms [202, 203, 204, 205]. Lastly, Decentralized frameworks, integrating cryptographic techniques [206, 207], offer functional and privacy-preserving solutions, ensuring essential services while protecting data privacy.

In summary, these technological improvements have rendered more detailed demand response programs not only feasible but also practical, offering both operators and consumers effective tools to manage energy usage more efficiently.

In this paper, to bridge the gap between high-resolution consumer data and demand response methods, we propose a cluster-based appliance-level-of-use demand response program design to expand the role demand response can play in facilitating and accelerating the power grid’s low-carbon transition.

Demand side management of the grid has been extensively studied in the previous literature to enhance the efficiency and reliability of the power system [208]. A key component of demand side management is the design of demand response programs, which have been extensively studied. These programs are typically categorized into two types: price-based and incentive-based demand response. Price-based demand response includes strategies like static time-of-use, critical peak pricing, and real-time pricing, with considerable research dedicated to designing optimal pricing schemes. For instance, Li *et al.* propose a dynamic pricing mechanism combining time-of-use and real-time pricing to tap the potential of demand response through flexibly guiding users’ energy consumption in [209]. Ruan *et al.* propose a graph deep learning-based retail dynamic pricing mechanism to incent consumers to adjust their daily energy consumption behaviors in [210]. On the other hand, incentive-based demand response programs are similar to critical peak pricing but reward customers for reducing their energy consumption during peak hours below a set baseline. There is extensive research focused on the design of incentive-based demand response programs. For instance, Wen *et al.* propose an incentive-based demand response program with modified deep learning and reinforcement learning [211]. Tsaousoglou *et al.* propose a demand response architecture including a mechanism based on Ausubel’s clinching auction and a communication protocol to guarantee both efficiency and truthful user participation in [212].

Various efforts have been made to study how to improve the design of price-based and incentive-based demand response programs based on a more accurate characterization of consumer behaviors. To this end, some of the previous literature made the effort to capture energy consumption patterns on the individual level to enhance the effectiveness of demand response. For instance, Samadi *et al.* analytically model each user’s preferences and energy consumption patterns and propose a mechanism for demand side management in [213]. Shafie-Khah *et al.* propose a stochastic model of a home energy management system to optimize the customer’s cost in different demand response programs in [214]. Muthirayan *et al.* propose a novel self-reported baseline mechanism and show that truthful reporting

of baseline consumption and marginal utility is a dominant strategy in [215]. Nikzad *et al.* employ bi-level stochastic programming to maximize the total social welfare for the smart microgrid in the presence of demand response programs in [216]. Zheng *et al.* develop a fully distributed multi-energy demand response approach based on the exchange alternating direction method of multipliers to reduce overall energy cost in [217]. Yu *et al.* present a novel framework for demand response resource trading between multiple service providers and end customers in [218]. However, one common drawback shared by these works is that they fail to differentiate the variance of different appliances within the design of the demand response program. As each kind of appliance has its own energy consumption and operation characteristics, it is evident that harnessing their unique energy consumption profiles and operation models can further improve the effectiveness of the demand response design [219].

To address this important concern, previous literature has investigated the mechanism and deployment of appliance-level demand response [220]. For instance, Aksanli *et al.* identify the relationship between human activities and the power demand of the house and generate power profiles to estimate users' flexibility when rescheduling appliances in [221]. Latifi *et al.* provide a detailed and practical characterization of the household appliances and improve the efficiency of the demand response [222]. Antunes *et al.* consider the power cost component and ways of dealing with user's discomfort and model detailed energy consumption models for different appliance categories [223]. Ruan *et al.* propose a non-interruptible appliance load reconstruction technique to restore the estimated electric energy consumption of appliances and proposes a demand-side smart dynamic pricing model to foster demand responses in [224]. However, these works were largely model-based and relied on empirical or numerical appliance models to capture the complex and dynamic human behaviors and uncertain environmental factors involved in daily energy consumption activities. While the aforementioned models were designed to reflect reality at their best, their validity can be affected by simplifying assumptions and abstractions. For a complex real-world problem characterized by noise and fluctuations, such as demand response, the massive volume of appliance-level consumption data, and how they can help unmask some of the patterns that we do not yet fully understand, have not been adequately explored in the literature.

The contributions of this paper are threefold. First, we propose a data-driven framework for appliance-level utility modeling by formulating utility as a quadratic function and estimating key parameters using a DCM. This approach distinguishes users' usage patterns based on appliance-level consumption data and integrates individual appliance utilities into a unified user-level utility function. Second, we extend the conventional level-of-use demand response program into an appliance-level-of-use design, leveraging the bi-level structure to offer users more specific and actionable incentives tied to the usage of individual appliances. Third, to enhance scalability and operational efficiency, we introduce a cluster-based version of the program that captures user heterogeneity by grouping users with similar appliance usage patterns.

The rest of this paper proceeds as follows: Section 5.2 introduces the appliance-level utility model for consumers. Section 5.3 illustrates the appliance-level-of-use program. After that, we present an extended version of the demand response program to enhance its scal-

ability in Section 5.4. At last, we show the efficiency of proposed programs in Section 5.5. Concluding remarks are demonstrated in Section 5.6.

5.2 Appliance-level Utility Function Estimation

In this section, we model the appliance-level utility function and employ the DCM to estimate function parameters. After that, we illustrate how we combine appliance-level utility functions to form an individual-level utility function for each consumer.

5.2.1 General Utility Model

The quadratic utility function is extensively utilized in power system research [213, 215] to articulate the diverse utility functions of users. This approach effectively captures essential utility function characteristics and achieves a balance between representing population heterogeneity and maintaining analytical simplicity. Originating from microeconomics' law of diminishing marginal utility (DMU) [225], the quadratic utility function embodies the principle that an individual's interest in consuming goods or services decreases when the consumption reaches its maximum level. According to this law, marginal utility is initially high and decreases to zero once consumption hits the saturation point. The utility function should satisfy the following three properties.

- The utility function is non-decreasing and continuous:

$$U'(x) \geq 0 \quad (5.1)$$

- Marginal benefit is non-increasing:

$$U''(x) \leq 0 \quad (5.2)$$

- Utility value is zero at zero power consumption:

$$U(0) = 0. \quad (5.3)$$

Following DMU law, we characterize a user's utility function of using a certain appliance with a piecewise quadratic function $U(x)$:

$$U(x) = \begin{cases} \gamma x - \frac{\alpha}{2} x^2, & 0 \leq x \leq \frac{\gamma}{\alpha}, \\ \frac{\gamma^2}{2\alpha}, & x \geq \frac{\gamma}{\alpha}, \end{cases} \quad (5.4)$$

where x is the energy consumption of the appliance, α and γ are constant parameters. We characterize consumers' personal preferences on energy consumption by estimating α and γ parameters for every appliance in different households.

To illustrate the meaning of these two parameters, we denote $\gamma = \frac{2a}{b}$ and $\alpha = \frac{2a}{b^2}$ and express the utility function as follows:

$$U(x) = \begin{cases} \frac{a}{b^2}x(2b - x), & 0 \leq x \leq b, \\ a, & x \geq b, \end{cases} \quad (5.5)$$

where a is a scale factor of the utility function. We can regard a as the maximum utility that the user can obtain from using a certain appliance. The parameter b denotes the threshold that the utility stops increasing with the energy consumption, which can also be interpreted as the maximum possible energy consumption associated with the appliance. Thus, we divide the utility function into two parts. The first part is the multiplier a , denoting the maximum utility that can be obtained from the appliance. The second part is $\frac{1}{b^2}x(2b - x) \in [0, 1]$, presenting how much the utility approaches to the maximum utility.

5.2.2 Parameter Estimation

To better characterize the utility function, we need to estimate parameters α and γ for each user's appliance. We have shown that these two parameters depend on the maximum utility a and maximum energy consumption b . For parameter b , we can directly estimate the maximum energy consumption $\bar{E}$ based on historical data. Therefore, we focus on estimating a in this section.

Specifically, we adopt the DCM [226] to estimate the maximum utility, followed by a three-step routine: model specification, model fitting, and parameter calculation.

Model Specification

DCM assumes that people choose the option that brings the maximal utility when facing a discrete set of options, and the utility of an option is a function of variables, an option-specific constant, and a random error term. For the distribution of error terms, we adopt the Logit model [227], which assumes choice probabilities follow sigmoid functions.

In our setting, the consumer chooses whether to use the appliance when confronted with different electricity payments and energy consumption. Therefore, for each user i 's appliance j , if the user chooses option m , the utility $U_{i,j,m}$ is specified as follows:

$$\begin{aligned} U_{i,j,m} &= V_{i,j,m} + \epsilon_{i,j,m} \\ &= \beta_{i,j,m}^c + \beta_{i,j,m}^{v\top} x_{i,j,m}^v + \epsilon_{i,j,m}, \end{aligned} \quad (5.6)$$

where $V_{i,j,m}$ is the net utility and $\epsilon_{i,j,m}$ is the random error. $x_{i,j,m}^v$ consists of variables that will influence the consumer's choice, and vector $\beta_{i,j,m}^v$ specifies the coefficients of $x_{i,j,m}^v$ whereas $\beta_{i,j,m}^c$ denotes option specific constants.

In this case, $x_{i,j}^{energy} \in x_{i,j}^v$ represents the general per-use energy consumption associated with the appliance and $x_{i,j}^{payment} \in x_{i,j}^v$ means the general per-use payment related to the appliance. The $\beta_{i,j}^{energy}$ and $\beta_{i,j}^{payment}$ are coefficients of $x_{i,j}^{energy}$ and $x_{i,j}^{payment}$.

Model Fitting

After specifying the model, we use maximum likelihood estimation and observation data to estimate the coefficients of variables, namely, $\beta_{i,j,m}^c$ and $\beta_{i,j,m}^v$.

For observation n of each user i 's appliance j , we define:

$$v_{i,j,m}^n = \begin{cases} 1, & \text{if observation } n \text{ chooses } m \\ 0, & \text{otherwise.} \end{cases} \quad (5.7)$$

Besides, for observation n we define $P_{i,j,m}^n$ as the probability of the user i to choose the option m for appliance j :

$$P_{i,j,m}^n = \frac{e^{V_{i,j,m}^n}}{\sum_{m' \in M} e^{V_{i,j,m'}^n}}. \quad (5.8)$$

Then the likelihood function for user i 's using appliance j is:

$$Lh_{i,j}^* = \prod_{n=1}^N \prod_{m=1}^M P_{i,j,m}^n v_{i,j,m}^n, \quad (5.9)$$

Finally, the coefficients of all variables can be derived as follows:

$$\hat{\beta}_{i,j,m}^c, \hat{\beta}_{i,j,m}^v = \arg \max_{\beta_{i,j,m}^c, \beta_{i,j,m}^v} \ln Lh^*(\beta_{i,j,m}^c, \beta_{i,j,m}^v). \quad (5.10)$$

Parameters Calculation

After estimating $\beta_{i,j,m}^c$ and $\beta_{i,j,m}^v$, we calculate the maximum utility by estimating the value of energy [228], denoted by VoE, which represents the average value of unit energy increase from a user's perspective. The VoE is calculated through:

$$VoE_{i,j} = \left| \frac{\partial x_{i,j}^{payment}}{\partial x_{i,j}^{energy}} \right| = \left| \frac{\partial U / \partial x_{i,j}^{energy}}{\partial U / \partial x_{i,j}^{payment}} \right| = \left| \frac{\beta_{i,j}^{energy}}{\beta_{i,j}^{payment}} \right|, \quad (5.11)$$

Next, the utility function $U_{i,j}(x)$ for user i 's appliance j when it consumes energy x is obtained by plugging maximum possible utility $a_{i,j}$ and energy consumption $b_{i,j}$ to get maximum possible utility into Eq. (5.5):

$$a_{i,j} = VoE_{i,j} \times \bar{E}_{i,j}, \quad (5.12)$$

$$b_{i,j} = \bar{E}_{i,j}. \quad (5.13)$$

5.2.3 Utility Function Combination

We can combine each user's appliance-level utility function into a single utility function.

Suppose we have $U_i(q_i) = \gamma'_i q_i - \alpha'_i q_i^2/2 + c$ as the total utility function to present $\sum_{j \in J} U_{i,j}(q_{i,j})$, where c is a constant, then we seek to solve the following optimization problem.

$$\begin{aligned} q_{i,j}^* &:= \max_{q_{i,j}} U_i(q_i) \\ \text{s.t. } U_i(q_i) &= \sum_{j \in J} U_{i,j}(q_{i,j}), \\ q_i &= \sum_{j \in J} q_{i,j}, \\ q_{i,j} &\geq 0, \forall j \in J. \end{aligned} \tag{5.14}$$

The Lagrange function is as follows:

$$L(q_{i,j}, \lambda, \mu_j) = \sum_{j \in J} U_{i,j}(q_{i,j}) + \lambda \left(\sum_{j \in J} q_{i,j} - q_i \right) + \sum_{j \in J} \mu_j q_{i,j}. \tag{5.15}$$

To obtain the optimizer, we check the Karush–Kuhn–Tucker conditions [229]:

$$\begin{cases} \gamma_{i,j} - \alpha_{i,j} q_{i,j} = -\lambda - \mu_j, \forall j \in J \\ q_i = \sum_{j \in J} q_{i,j}, \\ q_{i,j} \geq 0, \quad \mu_j \geq 0, \quad \mu_j q_{i,j} = 0, \quad \forall j \in J. \end{cases} \tag{5.16}$$

Solving the system of equations, we can present $q_{i,j}$ through a linear function of q_i . Replacing $q_{i,j}$ by the linear function of q_i in $U_{i,j}(q_{i,j})$, we have $U_i(q_i) = \sum_{j \in J} U_{i,j}(q_{i,j}) = \gamma'_i q_i - \alpha'_i q_i^2/2 + c$, where γ'_i and α'_i are represented by $\gamma_{i,j}$ and $\alpha_{i,j}$.

Note that for the first condition we only consider the $x \leq b$ for $U_{i,j}(q_{i,j})$, since $x > b$ will not be reached: When x exceeds the maximum possible energy consumption b , the utility will not increase while the energy cost builds up, which leads to lower revenue for the user, contradicting users' rationality.

5.3 Bi-level Model for Appliance-level Demand Response Program

The Level-of-Use Program (LoUP) process, a general framework for demand response, aims to maximize the revenue of the DSO by setting appropriate π_r and z . The program adopts a three-phase process: Firstly, the DSO sends the pricing information $\{\pi^h, \pi^r, z\}$ to users, where π^h is the electricity price and π^r is a reward price for users who reduce their energy consumption below the threshold z . Secondly, user i decides the energy $q_{i,j}$ it will consume on each appliance j . Thirdly, the payment is calculated depending on the amount of energy the user consumes. This section aims to extend the general framework to an appliance-level demand response framework. We term this framework the appliance-level-of-use program (ALoUP).

5.3.1 Program Overview

The ALoUP aims to maximize the revenue of DSO by setting appropriate π_j^r and z_j for every appliance. Given the pricing information $\{\pi^h, \pi_j^r, z_j\}$, the payment of each appliance is calculated as follows:

- If $q_{i,j} \leq z_j$, then the payment for the user i is:

$$\pi^h q_{i,j} - (\pi^h - \pi_j^r)(z_j - q_{i,j}). \quad (5.17)$$

- If $q_{i,j} > z_j$, then the payment for the user i is:

$$\pi^h q_{i,j}. \quad (5.18)$$

The sum of payments for all appliances is straightforwardly defined as the total payment.

5.3.2 User Side Model

User's revenue refers to the utility that a user benefits from consuming energy minus the payment she makes for the energy consumption.

For the utility part, we define the utility of user i from using appliance j based on the discrete choice modeling. Specifically, when user i consumes $q_{i,j}$ for appliance j , its utility is:

$$U_{i,j}^{user} = U_{i,j}(q_{i,j}). \quad (5.19)$$

For the payment part, we define the user's payment under ALoUP. Therefore, when the user i consumes $q_{i,j}$ for appliance j , the payment is:

$$C_{i,j}^{user} = \begin{cases} \pi^h q_{i,j} - (\pi^h - \pi_j^r)(z_j - q_{i,j}), & q_{i,j} \leq z_j \\ \pi^h q_{i,j}, & q_{i,j} > z_j. \end{cases} \quad (5.20)$$

Combining them together, for each user i , we have her revenue R_i^{user} as:

$$R_i^{user} = \sum_{j \in J} (U_{i,j}^{user} - C_{i,j}^{user}). \quad (5.21)$$

Based on the revenue, user i can calculate her optimal energy consumption plan by solving the following optimization problem:

$$\begin{aligned} q_{i,j} &:= \max_{q_{i,j}} R_i^{user} \\ \text{s.t. } & q_{i,j} \geq 0. \end{aligned} \quad (5.22)$$

The optimal response of user i given $\{z_j, \pi_j^r\}$ is:

$$q_{i,j}^* = \max_{q_{i,j}^*} R_i^{user}. \quad (5.23)$$

Remark: In this study, we focus on establishing a foundational framework, thereby restricting our analysis to the continuous energy consumption of interruptible appliances. To effectively integrate uninterruptible appliances into our model, we propose to employ a binary variable alongside the per-use energy consumption $h_{i,j}a_{i,j}$ to substitute the continuous variable $q_{i,j}$ for representing the energy consumption of the user i on appliance j . This replacement means that instead of consuming a continuous amount of energy $q_{i,j}$, the user has the option to either utilize the appliance and consume $a_{i,j}$ or not use it at all, consuming 0. We defer the details in Appendix C.1.

5.3.3 Operator Side Model

The revenue of DSO is the profit it gains from users minus the generation cost to satisfy users' demand.

For the profit part, we assume it equals the sum of the users' payments for energy:

$$U^{dso} = \sum_{i \in I} \sum_{j \in J} C_{i,j}^{user}. \quad (5.24)$$

For the generation cost part, we assume it is a convex function $g(\cdot)$ of total energy demand [230]:

$$C^{dso} = g\left(\sum_{i \in I} \sum_{j \in J} q_{i,j}\right). \quad (5.25)$$

For DSO, we denote the revenue R^{dso} as:

$$R^{dso} = U^{dso} - C^{dso}. \quad (5.26)$$

Then the DSO seeks to solve the following optimization problem to set the optimal π_j^r and z_j :

$$\begin{aligned} \max_{z_j, \pi_j^r} \quad & R^{dso} \\ \text{s.t.} \quad & z_j, \pi_j^r \geq 0, \quad \forall j \in J. \end{aligned} \quad (5.27)$$

We denote the optimal solution of DSO by

$$z_j^*, \pi_j^{r*} = \max_{z_j, \pi_j^r} R^{dso}. \quad (5.28)$$

5.3.4 Solution Analysis

The bi-level model consists of a lower-level model and an upper-level model as shown in Figure 5.1.

The lower level focuses on the user side. Given the pricing scheme $\{\pi^h, \pi_j^r, z_j\}$, the optimal energy consumption $q_{i,j}^*$ can be obtained by maximizing Eq. (5.21) :

$$q_{i,j}^* = \begin{cases} \frac{\gamma_{i,j} - 2\pi^h + \pi_j^r}{\alpha_{i,j}}, & z_j \geq \frac{2\gamma_{i,j} - 3\pi^h + \pi_j^r}{2\alpha_{i,j}} \\ \frac{\gamma_{i,j} - \pi^h}{\alpha_{i,j}}, & z_j \leq \frac{2\gamma_{i,j} - 3\pi^h + \pi_j^r}{2\alpha_{i,j}}. \end{cases} \quad (5.29)$$

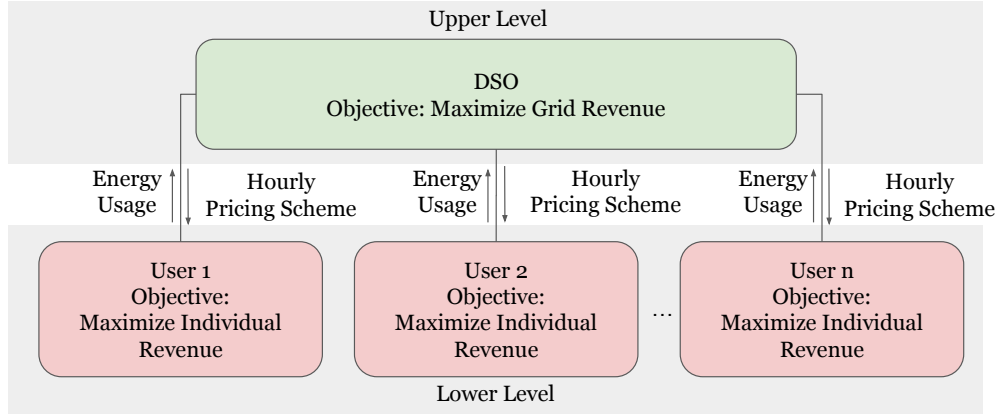


Figure 5.1: The upper-level DSO sets hourly prices to maximize grid revenue, while lower-level users respond by adjusting their energy usage to maximize individual revenue. This hierarchical structure captures the interactive decision-making between the grid and users.

In the upper level, the DSO makes the decision. With the solution from the lower-level model, we can obtain the optimal solution for the upper-level model. The profit the DSO gets from the consumer is the sum of all payments from users:

$$C_{i,j}^{user} = \begin{cases} \frac{(2\pi^h - \pi_j^r)(\gamma_{i,j} - 2\pi^h + \pi_j^r)}{\alpha_{i,j}} - (\pi^h - \pi_j^r)z_j, & z_j \geq \frac{2\gamma_{i,j} - 3\pi^h + \pi_j^r}{2\alpha_{i,j}} \\ \frac{\pi^h(\gamma_{i,j} - \pi^h)}{\alpha_{i,j}}, & z_j \leq \frac{2\gamma_{i,j} - 3\pi^h + \pi_j^r}{2\alpha_{i,j}} \end{cases} \quad (5.30)$$

Plugging C_i^{user} into Eq. (5.24) yields that:

$$U^{dso} = \sum_{i \in I} \sum_{j \in J} C_{i,j}^{user}. \quad (5.31)$$

For the generation cost, since we know the energy consumption of every user, by plugging $q_{i,j}^*$ into Eq. (5.25), we have:

$$C^{dso} = g \left(\sum_{i \in I} \sum_{j \in J} q_{i,j}^* \right). \quad (5.32)$$

We use the big- M method [231] to formulate the decision-making. According to the Eq. (5.30), the $C_{i,j}^{user}$ is determined by z_j and $\bar{z}_{i,j}$, where $\bar{z}_{i,j}$ is:

$$\bar{z}_{i,j} = \frac{2\gamma_{i,j} - 3\pi^h + \pi_j^r}{2\alpha_{i,j}}. \quad (5.33)$$

The big- M formulation needs two sets of auxiliary variables, $y_{i,j,1}$ and $y_{i,j,2}$. When $z_j \geq \bar{z}_{i,j}$, we set $y_{i,j,1} = 1$. And when $z_j \leq \bar{z}_{i,j}$, we set $y_{i,j,2} = 1$. Then the generation cost and users' payment can be represented as the function of y (Details are deferred to Appendix C.2).

To find the optimal $\{\pi_j^r, z_j\}$, we need to solve the following optimization problem.

$$\begin{aligned}
 \max_{z, \pi^r, y} \quad & U^{dso} - C^{dso} \\
 \text{s.t.} \quad & \bar{z}_{i,j} - z_j \leq M(1 - y_{i,j,1}), \quad \forall i \in I, \forall j \in J \\
 & z_j - \bar{z}_{i,j} \leq M(1 - y_{i,j,2}), \quad \forall i \in I, \forall j \in J \\
 & y_{i,j,1} + y_{i,j,2} = 1, \quad \forall i \in I, \forall j \in J \\
 & y_{i,j,1}, y_{i,j,2} \in \{0, 1\}, \quad \forall i \in I, \forall j \in J \\
 & z_j \geq 0, \quad \forall j \in J
 \end{aligned} \tag{5.34}$$

5.3.5 Algorithm to Solve Problem (5.34)

Problem (5.34) is hard to solve due to its cubic objective function. We make modifications to the original optimization problem and transform the mixed integer cubic programming problem¹ into the mixed integer linear programming problem. Specifically, we first discretize the reward price to reduce the cubic problem to a quadratic problem, then introduce more auxiliary variables to transform the quadratic problem into a linear problem.

Discretization of Reward Price

We discretize the reward price to several segments. That is, for each appliance j , we set $\pi_j^r \in \{\pi_{1,j}^r, \pi_{2,j}^r, \dots, \pi_{k,j}^r\}$, and introduce auxiliary variable $\{x_{1,j}, x_{2,j}, \dots, x_{k,j}\}$. If the k_{th} price is chosen, then $x_{k,j} = 1$. After the discretion, the problem becomes a quadratic problem.

Auxiliary Variable

To further reduce the quadratic problem to a linear mixed-integer programming problem, we introduce several auxiliary variables:

$$\begin{aligned}
 a_{k,i,j}^{xy} &= x_{k,j} y_{i,j,1}, & k \in K, i \in I, j \in J \\
 a_{k,i}^{xyz} &= a_{k,i,j}^{xy} z_j, & k \in K, i \in I, j \in J \\
 a_{i,j}^{yz} &= y_{i,j,1} z_j, & i \in I, j \in J.
 \end{aligned} \tag{5.35}$$

With these auxiliary variables, this problem is transformed from mixed-integer quadratic programming to mixed-integer linear programming and can be solved efficiently via commercial solvers, e.g., Gurobi [232].

¹The cubic structure comes from the objective function. See Appendix C.2 for details.

5.4 Cluster-based Bi-level Model for Demand Response Program

We can straightforwardly customize the LoUP and ALoUP by setting the customized threshold z_i and price π_i^r for every customer i , or the threshold $z_{i,j}$ and price $\pi_{i,j}^r$ for every user i 's appliance j . We term them individual-based level-of-use program (ILoUP) and individual-based appliance-level-of-use program (IALoUP). However, IALoUP could be very time-consuming. This section aims to improve the scalability of the proposed demand response program. We cluster the customers based on their electricity consumption patterns and then use the centroids to approximate the heterogeneity among all users. We term this kind of framework the cluster-based level-of-use program (CLoUP) and the cluster-based appliance-level-of-use program (CALoUP).

Figure 5.2 illustrates the cluster-based bi-level model. Each household $i \in [1, I]$ computes its household-level utility function parameters (α_i, γ_i) and appliance-level utility function parameters $(\alpha_{i,j}, \gamma_{i,j})$ for appliance $j \in [1, J]$. These parameters are reported to the DSO for clustering, ensuring that the DSO does not access individual energy consumption data, thereby preserving user privacy. Upon receiving these parameters, the DSO employs K-means clustering. For CLoUP, clustering is performed on household-level parameters (α_i, γ_i) , assigning a cluster label n_i and determining the cluster center $(\alpha'_{ni}, \gamma'_{ni})$ for each household. This results in the pricing scheme $\pi_h, \pi^r n_i, z_{n_i}$. CALoUP clusters appliance-level parameters $(\alpha_{i,j}, \gamma_{i,j})$, providing cluster center parameters $(\alpha'_{ni,j}, \gamma'_{ni,j})$ for use in pricing scheme design. This results in a pricing scheme $\pi_h, \pi^r n_i, j, z_{n_i,j}$. Finally, the DSO communicates the respective pricing schemes to each household.

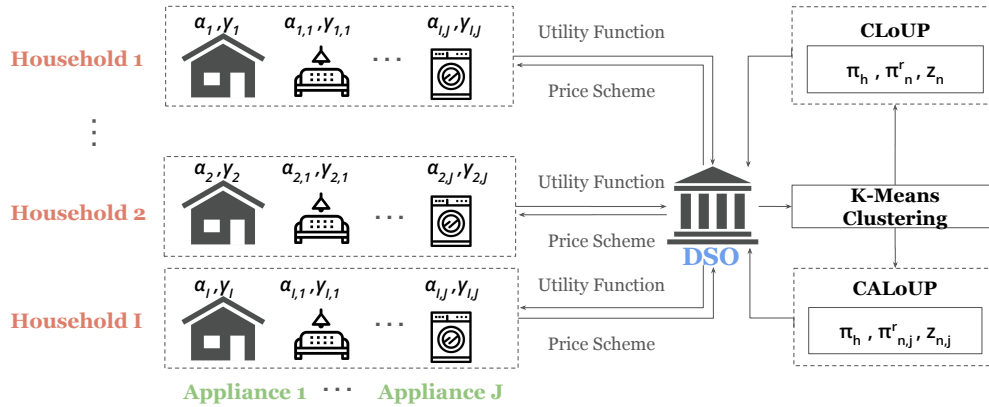


Figure 5.2: Households make appliance-level energy decisions based on utility functions and pricing schemes provided by the Distribution System Operator (DSO). The DSO clusters households using K-means and implements either cluster-level (CLoUP) or cluster-appliance-level (CALoUP) optimization to improve scalability and pricing efficiency.

5.4.1 Usage Pattern Clustering

The K -Means clustering method [233] is adopted here to differentiate different classes of usage patterns. The K -Means algorithm clusters data by trying to separate samples into n groups of equal variance, minimizing a criterion known as the inertia or within-cluster sum-of-squares. This algorithm requires the number of clusters to be specified. It scales well to a large number of samples and has been used across a large range of application areas in many different fields.

The K -Means algorithm divides samples into disjoint clusters. After clustering, the algorithm returns m clusters with c_m users in each cluster, each described by the center of the samples in the cluster $\mu_m = [\alpha_m, \gamma_m]$. These clustering results serve as the basis for characterizing the cluster-based demand response problem.

5.4.2 Demand Response based on Approximation

We only describe CALoUP in detail and the CLoUP can be obtained by extending LoUP in the same manner. The CALoUP aims to maximize the utility of DSO by setting appropriate $\pi_{n,j}^r$ and $z_{n,j}$ for every appliance of the group. Given the pricing information $\{\pi^h, \pi_{n,j}^r, z_{n,j}\}$, the payment of each appliance is computed depending on the energy that users consume:

- If $q_{n,j} \leq z_{n,j}$, then the payment for the user n is:

$$\pi^h q_{n,j} - (\pi^h - \pi_{n,j}^r)(z_{n,j} - q_{n,j}). \quad (5.36)$$

- If $q_{n,j} > z_{n,j}$, then the payment for the user n is:

$$\pi^h q_{n,j}. \quad (5.37)$$

The summation of all appliances leads to the total payment. Similarly, the optimal $\{\pi_{n,j}^r, z_{n,j}\}$ can be obtained through the mixed-integer linear programming.

5.4.3 Solution Analysis

Similarly, denote the profit the DSO gets from the users as U^{dso} :

$$\begin{aligned} U^{dso} = & \sum_{n \in N} \sum_{j \in J} \frac{(2\pi^h - \pi_{n,j}^r)(\gamma_{n,j} - 2\pi^h + \pi_{n,j}^r)}{\alpha_{n,j}} y_{n,j,1} c_n \\ & - \sum_{n \in N} \sum_{j \in J} \left((\pi^h - \pi_{n,j}^r) z_j y_{n,j,1} - \frac{\pi^h(\gamma_{n,j} - \pi^h)}{\alpha_{n,j}} y_{n,j,2} \right) c_n. \end{aligned} \quad (5.38)$$

The generation cost is C^{dso} :

$$C^{dso} = g \left(\sum_{n \in N} \sum_{j \in J} \left(\frac{\gamma_{n,j} - 2\pi^h - \pi_{n,j}^r}{\alpha_{n,j}} y_{n,j,1} + \frac{\gamma_{n,j} - \pi^h}{\alpha_{n,j}} y_{n,j,2} \right) c_n \right). \quad (5.39)$$

We also set $\bar{z}$ as:

$$\bar{z}_{n,j} = (2\gamma_{n,j} - 3\pi^h + \pi_{n,j}^r)(2\alpha_{n,j})^{-1}. \quad (5.40)$$

To find the optimal $\{\pi_{n,j}^r, z_{n,j}\}$, we need to solve the following optimization problem.

$$\begin{aligned} \max_{z,x,y,a} \quad & U^{dso} - C^{dso} \\ \text{s.t.} \quad & \bar{z}_{n,j} - z_{n,j} \leq M(1 - y_{n,j,1}), \quad \forall n \in N, j \in J \\ & z_{n,j} - \bar{z}_{n,j} \leq M(1 - y_{n,j,2}), \quad \forall n \in N, j \in J \\ & y_{n,j,1} + y_{n,j,2} = 1, \quad \forall n \in N, \forall j \in J \\ & y_{n,j,1}, y_{n,j,2} \in \{0, 1\}, \quad \forall n \in N, j \in J \\ & z_{n,j} \geq 0, \quad \forall n \in N, j \in J \end{aligned} \quad (5.41)$$

5.4.4 Algorithm to Solve the Problem (5.41)

We follow the algorithm for ALoUP and transform our optimization problem as follows. Denote the profit the DSO gets from the users as U^{dso} , we have:

$$\begin{aligned} U^{dso} = \sum_{n \in N} \sum_{j \in J} & \left(\frac{(2\pi^h y_{n,j,1} - \sum_{k \in K} \pi_{k,n,j}^r a_{k,n,j}^{xy})(\gamma_{n,j} - 2\pi^h)}{\alpha_{n,j}} \right. \\ & + \frac{2\pi^h \sum_{k \in K} \pi_{k,n,j}^r a_{k,n,j}^{xy}}{\alpha_{n,j}} - \frac{\sum_{k \in K} (\pi_{k,n,j}^r)^2 a_{k,n,j}^{xy}}{\alpha_{n,j}} \\ & \left. - (\pi^h a_{n,j}^{yz} - \sum_{k \in K} \pi_{k,j}^r a_{k,n,j}^{xyz}) + \frac{\pi^h (\gamma_{n,j} - \pi^h)}{\alpha_{n,j}} y_{n,j,2} \right) c_n. \end{aligned} \quad (5.42)$$

The generation cost C^{dso} can be described as:

$$C^{dso} = g \left(\sum_{n \in N} \sum_{j \in J} \left(\frac{(\gamma_{n,j} - 2\pi^h) y_{n,j,1}}{\alpha_{n,j}} - \frac{\sum_{k \in K} \pi_{k,n,j}^r a_{k,n,j}^{xy}}{\alpha_{n,j}} + \frac{\gamma_{n,j} - \pi^h}{\alpha_{n,j}} y_{n,j,2} \right) c_n \right). \quad (5.43)$$

We set $\bar{z}_{n,j}$ as follows:

$$\bar{z}_{n,j} = \frac{2\gamma_{n,j} - 3\pi^h + \sum_{k \in K} \pi_{k,n,j}^r x_{k,n,j}}{2\alpha_{n,j}}. \quad (5.44)$$

We can then transfer the problem as follows:

$$\begin{aligned}
 \max_{z,x,y,a} \quad & U^{dso} - C^{dso} \\
 \text{s.t.} \quad & \bar{z}_{n,j} - z_{n,j} \leq M(1 - y_{n,j,1}), \\
 & z_{n,j} - \bar{z}_{n,j} \leq M(1 - y_{n,j,2}), \\
 & \sum_{k \in K} x_{k,n,j} = 1, z_{n,j} \geq 0, \\
 & y_{n,j,1} + y_{n,j,2} = 1, \\
 & y_{n,j,1}, y_{n,j,2} \in \{0, 1\}, \\
 & a_{k,n,j}^{xy} \leq x_{k,n,j}, a_{k,n,j}^{xy} \leq y_{n,j,1}, \quad \forall k \in K \\
 & a_{k,n,j}^{xy} \leq x_{k,n,j} + y_{n,j,1} - 1, \quad \forall k \in K \\
 & a_{k,n,j}^{xyz} \leq a_{k,n,j}^{xy}, a_{k,n,j}^{xyz} \leq z_{n,j}, \quad \forall k \in K \\
 & a_{k,n,j}^{xyz} \leq z_{n,j} - \bar{U}(1 - a_{k,n,j}^{xy}), \quad \forall k \in K \\
 & a_{n,j}^{yz} \leq y_{n,j,1}, a_{n,j}^{yz} \leq z_{n,j}, \\
 & a_{n,j}^{yz} \leq z_{n,j} - \bar{U}(1 - y_{n,j,1}), \\
 & a^{xy}, a^{xyz}, a^{yz}, x_{n,k,j} \in \{0, 1\}, \quad \forall k \in K.
 \end{aligned} \tag{5.45}$$

Note that all the constraints are $n \in N, j \in J$. We omit them for the sake of brevity.

5.5 Numerical Studies

This section first conducts the parameter estimation of the utility function and specifies the distribution of the utility function among all users. Then we compare the four different demand response programs based on estimation results.

5.5.1 Data Overview

To construct utility functions for various appliances, we utilize two datasets from Austin, Texas: one detailing electricity usage time series and the other showing electric tariffs. The Pecan Street Dataport [234] provides high-resolution data from instruments installed in users' homes, covering around 750 houses in Texas. This dataset offers anonymized power data for each household, identified by a unique Data ID, with appliance-level data recorded at one-minute intervals throughout 2018. We have appliances categorized into four groups: cooking, cleaning, HVAC, and working appliances. Additionally, Austin Energy provides a Time-of-Use (ToU) electric tariff option [235], which complements the electricity usage data by offering insights into the cost implications of appliance use at different times.

5.5.2 Utility Function Estimation

We demonstrate the calibrated utility function in this section. Figure 5.3 (A) illustrates the energy consumption required for users to achieve maximum utility ($\bar{E}$) for different appliances. It reveals that HVAC appliances are the largest consumers of energy, followed by cleaning appliances, due to their longer operation times. Cooking appliances consume less energy due to shorter usage durations, while working appliances, typically having lower rated power, consume the least energy. The distribution of $\bar{E}$ shows that HVAC appliances exhibit higher variance, indicating diverse user behaviors when making decisions. Users need to consider the payment and the energy consumption when they make decisions, and their decisions reflect how they value the energy consumption associated with the appliance, i.e., the VoE. Figure 5.3 (B) explores the VoE for different appliances, highlighting that working and HVAC appliances, often linked to essential activities, possess higher VoE values. The variance in VoE for working and HVAC appliances is particularly notable, suggesting varying usage patterns across households. With the knowledge of energy consumption and VoE, we visualize the utility function with median $\bar{E}$ and VoE among all users in Figure 5.3 (C). Figure 5.3 (C) shows that HVAC appliances typically offer higher utility compared to others. In terms of energy consumption to reach maximum utility, HVAC appliances again lead, while working appliances show the lowest maximum energy consumption to reach maximum utility. This analysis indicates the diversity of appliance types on energy consumption patterns.

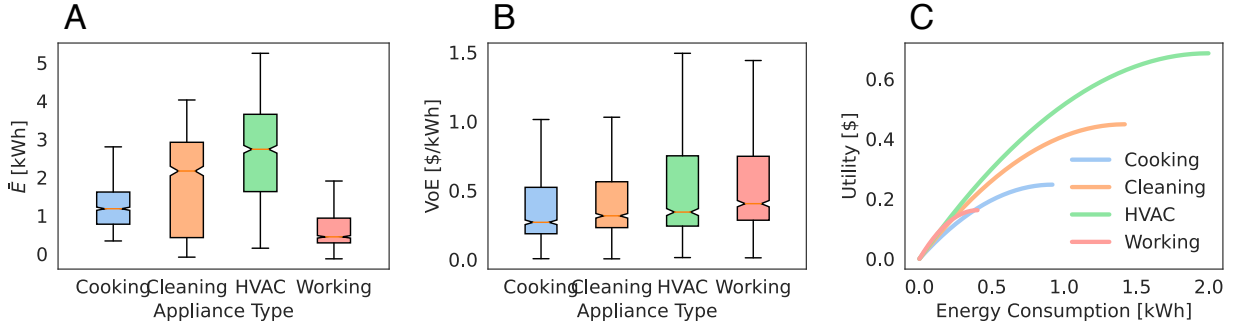


Figure 5.3: Utility function estimation for different appliance types. (A) shows the estimated energy required to achieve maximum utility ($\bar{E}$) across appliance types. (B) presents the VoE across appliance types. (C) visualizes the median utility functions for each appliance type.

5.5.3 Efficiency Evaluation

We evaluate the performance of the different algorithms listed below. To ensure the robustness of the results, we add uniform-distributed noise to consumers' utility function parameters and repeat each method several times to show the uncertainty level of the results.

- **No Demand Response Program (NDR):** No demand response program is applied.
- **Classic Price-based Demand Response Program (PDR):** PDR implements time-of-use pricing, ToU@Low and ToU@High, with peak hours prices at 1.1 and 1.2 times the current rate, respectively.
- **Incentive-based Demand Response Program (IDR):** IDR offers incentives for reduced usage during peak hours, with a reported baseline set at 0.6 (Bid@Low) and 0.8 (Bid@High) times the energy leading to maximum utility.
- **Our Demand Response Program (ODR):** LoUP, ALoUP and CALoUP.

Figure 5.4 shows the improvement of ToU@Low, ToU@High, Bid@Low, Bid@High, LoUP, ALoUP, and CALoUP compared with NDR. For total revenue, the value denotes the increase compared with NDR while for generation cost and user payment, the values indicate the reduction compared with the NDR. All values are normalized by maximum values among all methods. CALoUP stands out as the leading solution, achieving the highest revenue and reducing generation costs, thereby lowering user payments through substantial energy consumption reductions. ALoUP outperforms LoUP by integrating appliance-level pricing, showcasing the effectiveness of our proposed models. Although ToU@High and Bid@Low exhibit performances comparable to ALoUP, ToU@High unintentionally raises user payments without significant energy savings, and Bid@Low lacks efficiency relative to CALoUP. This evaluation highlights CALoUP’s superior capability in improving demand response effectiveness.

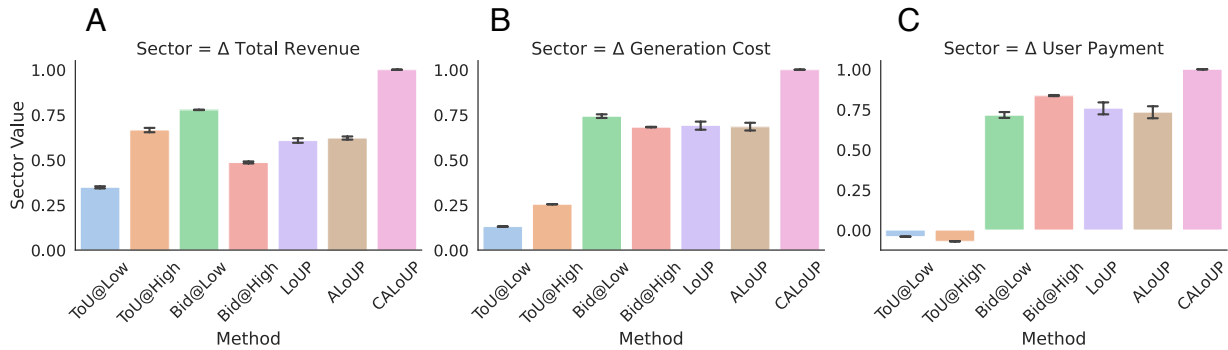


Figure 5.4: Efficiency evaluation across pricing methods. The three panels compare the change in total revenue, generation cost, and user payment under different methods. Cluster-appliance-level optimization (CALoUP) achieves the highest system revenue but also results in the highest generation cost and user payment, while simpler pricing schemes like ToU@Low yield lower system performance with minimal user cost.

5.5.4 Robustness Evaluation

We assess the robustness of our framework by testing the algorithm across two scenarios: varying user diversity levels and different numbers of clusters. User diversity reflects the variance in utility functions, with higher levels indicating a wider range of utility function shapes among participants. The choice of cluster numbers indicates the precision in characterizing these utility functions, where more clusters equate to finer accuracy. Figure 5.5 (A) reveals that as user diversity increases, the total revenue improvement compared with NDR for DSO decreases. Additionally, CALoUP outperforms ALoUP, highlighting the efficacy of cluster-based appliance-level pricing in enhancing demand response programs. On the other hand, Figure 5.5 (B) shows an increase in the number of clusters leads to higher DSO revenue improvement (compared with NDR). However, a higher number of clusters also results in greater computational costs, the operator needs to consider the trade-off between computational efficiency and the performance benefits of the framework.

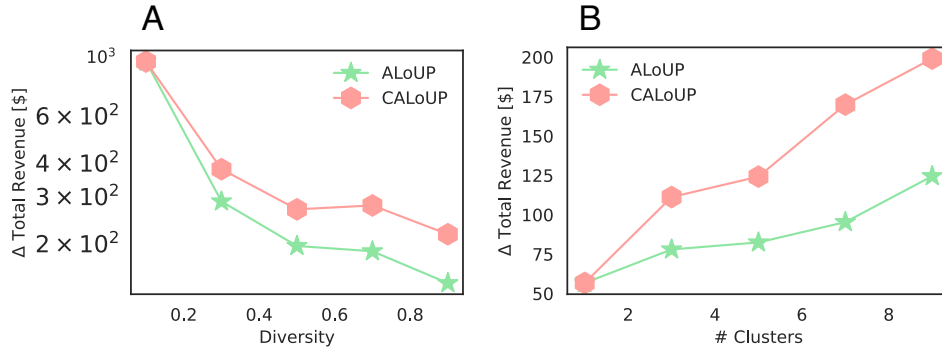


Figure 5.5: Robustness evaluation under user diversity and clustering levels. (A) shows that total revenue improvements decrease with increasing user diversity, with CALoUP consistently outperforming ALoUP. (B) illustrates that increasing the number of clusters enhances DSO revenue improvement.

5.6 Conclusion

In this work, we model the appliance-level utility function as a quadratic function and estimate the key parameters using the discrete choice model. Leveraging the proposed model, we extend the level-of-use program to an appliance-level-of-use program to enable more specific demand-side management. Furthermore, we propose a cluster-based approach to reduce the computational complexity of the proposed appliance-level demand response program and improve its scalability and efficiency. The numerical studies highlight the strength of the proposed demand response programs as they significantly improve social welfare compared

with the no-demand response scenario. In addition, the appliance-level demand response programs outperform the individual-level demand response in the case of generation cost and user payment. Our work can be extended in several ways. For instance, one can expand the proposed demand response design to cover not only consumers that consume energy, but also prosumers equipped with appliances such as energy storage devices.

Chapter 6

Conclusion

This chapter concludes the dissertation by summarizing the key contributions, discussing their impact on related research, and outlining potential directions for future work.

6.1 Summary

This dissertation introduces a framework for incorporating human system dynamics into the design and operation of CPS, with a particular focus on the electrification of transportation systems. By integrating human system dynamics, physical system dynamics, and operator policy, the framework provides a foundation for more adaptive, efficient, and resilient HCPS.

The first part of the dissertation focuses on estimating human system dynamics using real-world data. Specifically, it examines how spatial social networks influence PEV adoption forecasts. A comparison of benchmark diffusion models reveals that models—despite fitting the same historical data well—can produce drastically different forecasts, highlighting the risk of overfitting at the early stage of EV adoption. Besides, incorporating spatial social networks improves the model’s ability to capture observed spatial autocorrelation in the adoption patterns. This part also explores the role of uncertainty and network topology in shaping the effectiveness of PEV promotion strategies. These findings emphasize the need for adaptive, context-aware policies that consider both local social network structures.

The second part investigates how human system dynamics influence physical system dynamics. For private EVs, human mobility data is combined with charging session data to model spatiotemporal charging demand in the San Francisco Bay Area. Then, personalized mobility-constrained shifting recommendations are proposed to alleviate peak demand on the power grid. Simulations suggest that such strategies can significantly flatten load curves, but their effectiveness depends on complementary infrastructure—particularly at workplaces and public destinations during daytime hours. For commercial fleets, the analysis extends to UAM. A framework is developed to integrate UAM travel demand with power grid operations using smart charging. Results suggest that smart charging can benefit the power system without compromising the optimal fleet dispatch.

The third part focuses on how system operators can coordinate human system dynamics and physical system dynamics through policy design. This part proposes an appliance-level demand response program that models user utility functions using a quadratic form estimated through discrete choice models. The program enables fine-grained control at the appliance level. To improve scalability and reduce computational complexity, a cluster-based approach is introduced that groups users based on similar consumption patterns. Numerical experiments show that the proposed mechanism improves social welfare relative to baselines and outperforms traditional individual-level demand response programs in terms of both generation costs and user payments.

Together, these three parts demonstrate the value of incorporating human system dynamics into the operation of CPS. The proposed HCPS framework offers practical insights to enable a more responsive and sustainable electrification of transportation systems.

6.2 Impacts on Related Efforts

The work presented in this dissertation has broader impacts across several domains. Below, we summarize four key areas.

Extending Human System Dynamics Modeling to Diverse HCPS Domains. While this dissertation focuses on transportation electrification, the outputs and modeling approaches developed are broadly applicable to other HCPS domains. For example, mobility simulations and energy usage patterns can be used to improve traffic simulation, smart grid control, and transportation-energy system coordination. These generalizations open up new pathways for applying human system dynamics modeling to address challenges in urban systems.

Advancing Privacy-Preserving System Design. The reliance on fine-grained behavioral data in HCPS raises critical privacy concerns. This dissertation motivates the need for privacy-aware algorithm design in system operations, as well as further development of frameworks that incorporate privacy-preserving and incentive-compatible mechanisms. These directions are particularly relevant for scaling HCPS in data-sensitive environments such as health care systems, mobility platforms, and smart grids, where balancing utility with user trust is essential.

Enhancing System Robustness under Human Uncertainty. The stochastic nature of human decision-making can destabilize HCPS operations if not properly accounted for. In the context of transportation electrification, this dissertation reveals the importance of integrating renewable energy sources, energy storage systems, vehicle-grid integration technologies to buffer demand-side uncertainty. These efforts can collectively support the development of robust optimization frameworks in HCPS.

Promoting Equitable and Resilient Infrastructure Planning. This dissertation provides a framework to model where charging demand will grow, helping utilities and planners

target grid upgrades and charging station deployments. Furthermore, this research allows for the identification of systemic disparities in EV adoption and access to charging stations. As a result, it can aid in shaping policies focused on a fair transition, such as equitable subsidy initiatives or strategic placement of infrastructure in underserved communities. These contributions provide a data-driven basis for integrating equity and resilience into infrastructure planning.

6.3 Future Directions

The methodologies and findings presented in this dissertation contribute to operations of HCPS, particularly in the context of transportation electrification. Nonetheless, several promising research directions remain. These can be grouped into four key areas:

Human System Dynamics as a Public Asset. This dissertation develops models of human system dynamics using network science, statistical physics of complex systems, and probabilistic agent-based approaches. The approaches as well as outputs are valuable for various applications [236, 237]. However, for non-specialists, it remains difficult to apply these methods directly. Future work should focus on making knowledge human system dynamics more accessible by publishing standardized datasets with high-resolution spatiotemporal coverage on mobility [238] and energy section [234]. Additionally, building an open-source software library with tools for modeling human activity [239] could further foster interdisciplinary research.

Privacy-Preserving and Incentive-Compatible HCPS. The effective operation of HCPS often requires detailed, real-time data on human activity, such as smart meter readings or mobility traces. However, privacy concerns remain a significant barrier to data sharing. Future research should investigate mechanisms that both protect individual privacy and incentivize engagement. This includes the development of privacy-preserving algorithms based on differential privacy [240], correlated randomness [241], and encryption techniques [242]. Designing privacy-preserving and incentive-compatible frameworks that align individual interests with system-level objectives is critical for broader adoption [243].

Robust Operations under Human System Uncertainty. Human decision-making can introduce significant uncertainty into physical world operations. While prior work on system management has largely focused on uncertainties from the physical environment [244, 245, 246], future research should address how to manage uncertainties in human system dynamics. Approaches such as stochastic dynamic programming [247], chance-constrained optimization [248], robust optimization [249], and deep reinforcement learning [250] hold promise. Moreover, developing a theoretical framework to mathematically characterize the impact of human behavioral uncertainty on physical system performance can provide valuable insights for enhancing the robustness of system operations.

Equitable and Resilient Infrastructure Planning. This dissertation demonstrates how

modeling human system dynamics improves the precision of infrastructure planning. Looking forward, extending these models to forecast future human behavior—shaped by socioeconomic, environmental, and technological changes—will be essential. On the technical side, such forecasts can improve grid planning by providing detailed demand-side information and supporting the integration of distributed energy resources for greater resilience. On the socioeconomic side, predicting and addressing disparities in infrastructure access is critical for advancing justice and inclusion. For example, future work could explore co-optimization frameworks for charging infrastructure placement that balance both equity [251] and resilience [252].

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Appendix A

Supplementary Information for Chapter 2

A.1 Fitting Error on County Level

Figure A.1 shows 2022 county-level adoption rates for Washington and California (excluding the 15 most populated counties) from data and simulations of State BM, County BM, and SocNet BM.

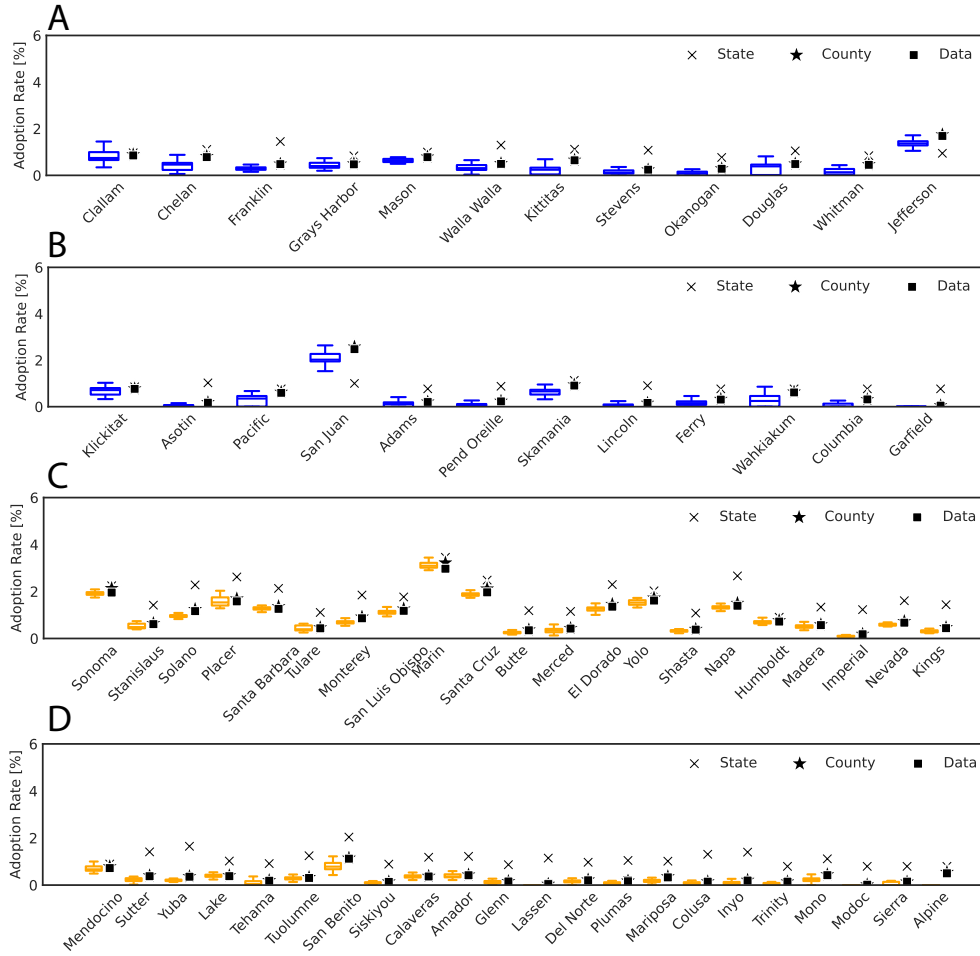


Figure A.1: County-level adoption rates of data, State/County BM and SocNet BM in 2022. The box shows the quartiles of the county-level adoption rates of SocNet BM while the whiskers extend to show the rest of the distribution. Cross markers show the adoption rate of State BM, star markers show the adoption rate of County BM, and square markers show the empirical data. (A-B) demonstrate results in Washington (blue) and (C-D) demonstrate results in California (orange).

A.2 Fitting Error on Tract Level

Tract-level fitted adoption rates from State BM, County BM, SocNet BM, and data in 2022 are shown in Fig. A.2.

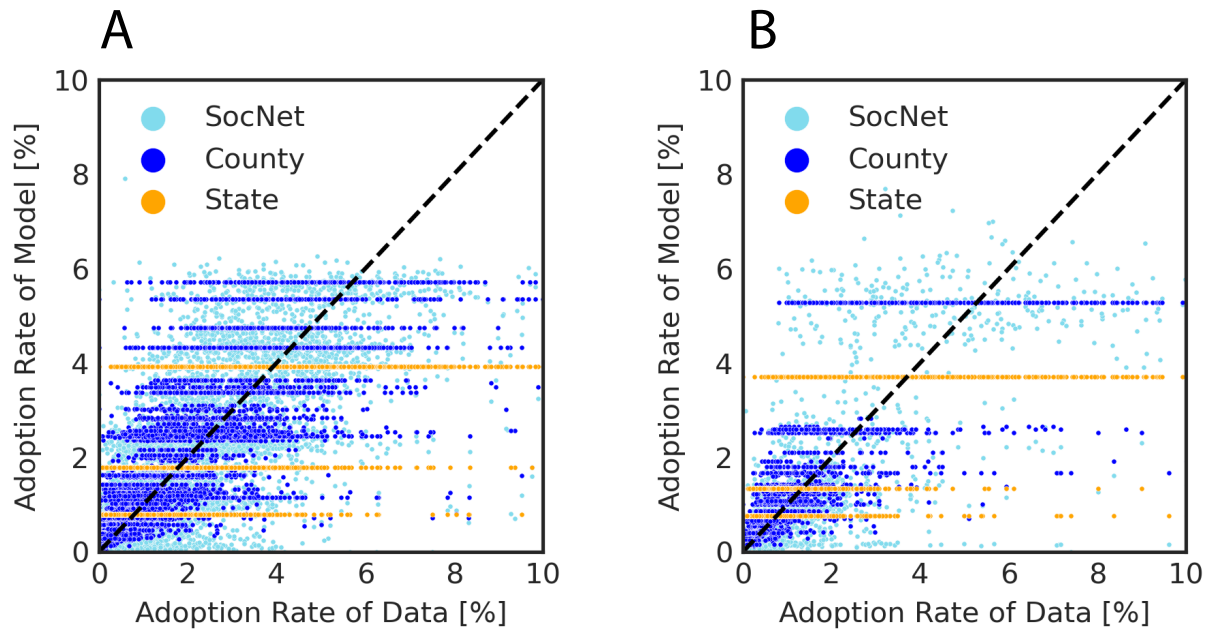


Figure A.2: Tract-level adoption rate comparison between empirical data and simulations of State BM (orange), County BM (dark blue), and SocNet BM (light blue) in 2022. Each point presents the fitted tract-level adoption rate and the corresponding empirical adoption rate. The diagonal line indicates fitted adoption rate is the same as the empirical data. (A) demonstrates results in Washington and (B) demonstrates results in California.

A.3 Coefficients of State/County BM and SocNet BM.

Table A.1 demonstrates fitted p and q values from State/County BM and SocNet BM.

	p^{Low}	p^{Middle}	p^{High}	q^{Low}	q^{Middle}	q^{High}
Washington State	1.4×10^{-4}	2.6×10^{-4}	7.6×10^{-4}	0.21	0.21	0.20
Washington County	7.4×10^{-5}	1.3×10^{-4}	1.8×10^{-4}	0.23	0.22	0.22
Washington SocNet	1.5×10^{-4}	3.4×10^{-4}	4.0×10^{-4}	0.02	0.03	0.03
California State	2.3×10^{-4}	6.2×10^{-4}	2.0×10^{-3}	0.15	0.13	0.08
California County	1.4×10^{-4}	2.9×10^{-4}	8.8×10^{-4}	0.14	0.14	0.11
California SocNet	1.2×10^{-4}	4.7×10^{-4}	1.2×10^{-3}	0.02	0.01	0.05

Table A.1: Median p and q values of State/County BM and SocNet BM (units for BM parameters are $year^{-1}$).

A.4 Forecast Considering “Switching Back to Internal Combustion Engines Vehicles (ICEVs)”.

Various elements—including fluctuations in fuel/electricity prices, the availability of charging stations, and changes in consumer tastes—may cause a reversal towards older technology. According to [253], approximately 46% of current PEV users in the United States may consider reverting to ICE vehicles. Our model allows for the simulation of “Switching Back to ICEVs” by assigning a likelihood that users will abandon PEVs after several years of use. We examine different scenarios by adjusting two parameters: *Year* indicates the number of years before users start to consider transitioning back to ICEVs, while *Prob* expresses the probability of this switch. For example, “*Year* = 5 and *Prob* = 0.5” indicates that after 5 years of adoption, the adopter will have a probability of 0.5 of switching back to ICEVs every year thereafter. Our settings include *Year* = 5, 10, 15 and *Prob* = 0.1, 0.3, 0.5. Setting “No Return” represents the baseline where customers do not switch back to ICEVs. Fig. A.3 (A-B) demonstrates how a smaller *Year* and a larger *Prob* slows down the PEV diffusion in Los Angeles.

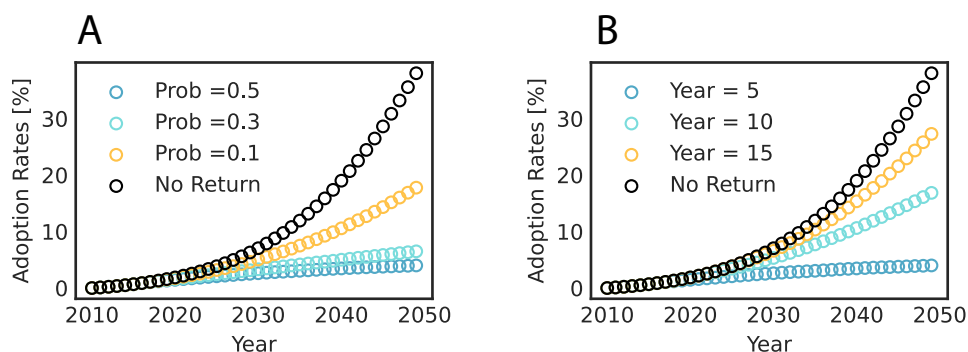


Figure A.3: PEV diffusion forecast accounting for “Switching Back to ICEVs”. (A) demonstrates adoption forecast based on varying timeframes (in years) before users begin considering a transition back to ICEVs (*Year* set as 5). (B) demonstrates adoption forecast based on different probabilities of switching back to ICEVs (*Prob* set as 0.5).

A.5 Forecasts on County Level

Figure A.4 shows 2050 county-level adoption rates for Washington and California (excluding the 15 most populated counties) from data and simulations of State BM, County BM, and SocNet BM.

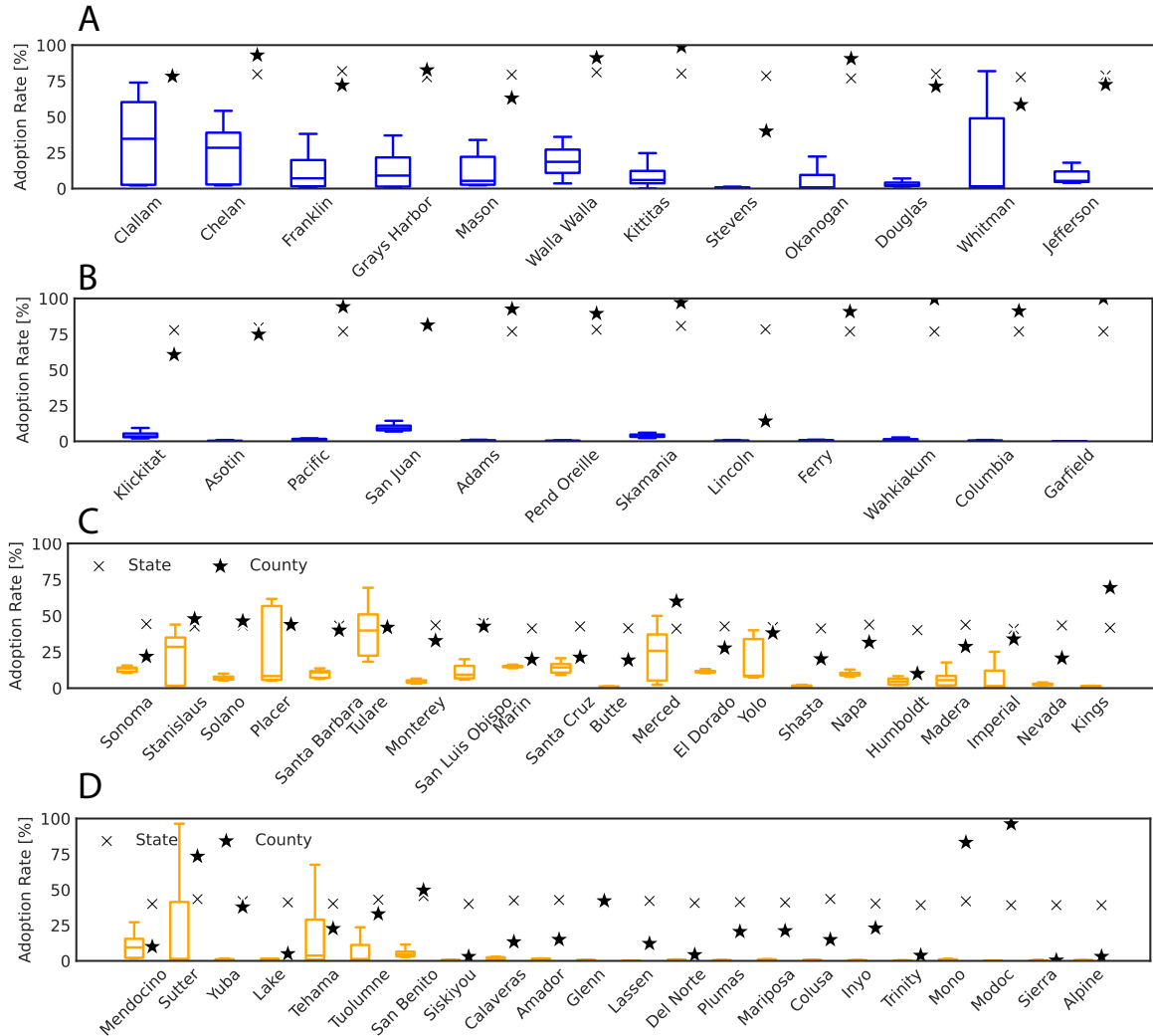


Figure A.4: County-level adoption rates of data, State/County BM and SocNet BM in 2050. The box shows the quartiles of the county-level adoption rates of SocNet BM while the whiskers extend to show the rest of the distribution. Cross markers show the adoption rate of State BM, star markers show the adoption rate of County BM, and square markers show the empirical data. (A-B) demonstrate results in Washington (blue) and (C-D) demonstrate results in California (orange).

A.6 Urban Layout and Diffusion Process

The urban layout of the area directly affects the spatial and social structures of areas, which can further affect PEV adoption. This section provides an analysis of the correlation between urban spatial/social structures and adoption diffusion patterns. Regarding spatial structure, we consider the geographical autocorrelation of population density, the geographical autocorrelation of income, and the overall population density at the county level. Concerning the social structure of areas, we take into account various γ values that determine the social network structure.

In terms of spatial structure, Fig. A.5 demonstrates that counties with greater population and higher geographical autocorrelation in terms of income and population density typically exhibit higher adoption rates in present and forthcoming adoption trends.

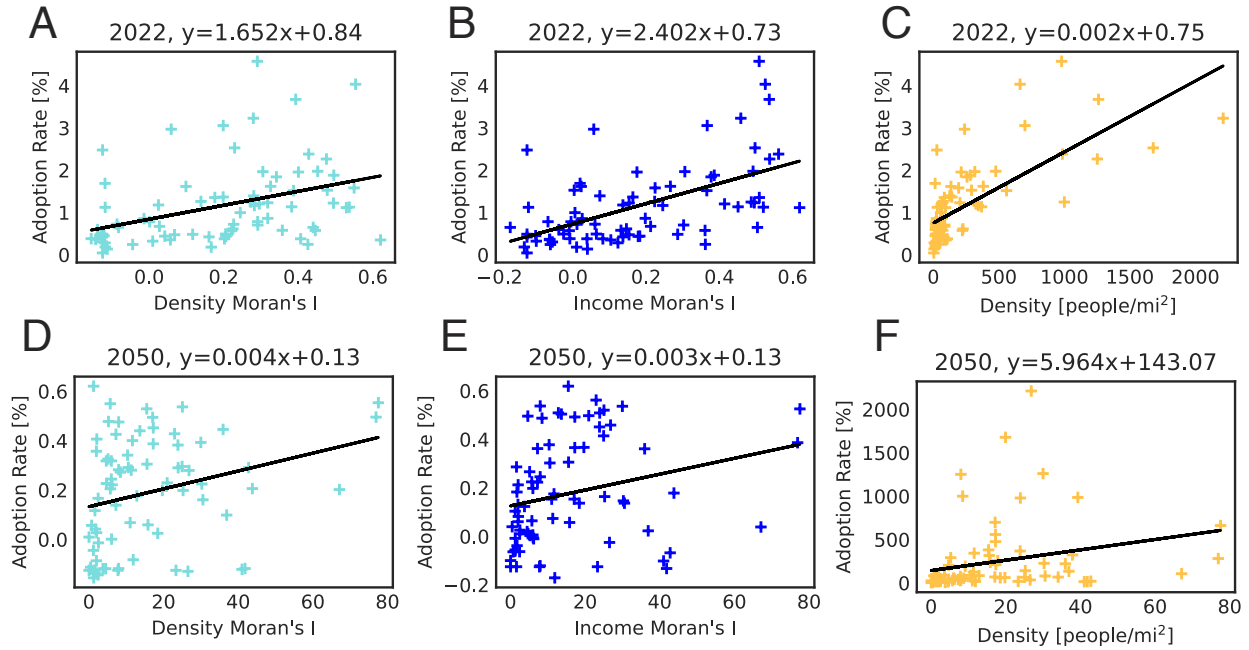


Figure A.5: Spatial structure and diffusion process. Each circle represents one county in Washington and California. The solid line denotes the linear regression results of circles. (A-C) plot the county-level adoption rate and corresponding population density Moran's I, Income Moran's I, and overall population density in 2022. (D-F) plot county-level adoption rate and corresponding population density Moran's I, Income Moran's I, and overall population density in 2050.

In terms of social structure, Fig. A.6 (A-C) display the Moran's I statistics for State/County BM and SocNet BM across three counties in Washington, while Fig. A.6 (D-F) show the same in California. In California and Washington's most populous counties, specifically

King and Los Angeles, we can identify a social network structure parameter (γ) that closely replicates the observed Moran's I statistics. Nonetheless, counties such as Santa Clara and Pierce have no γ value that can accurately replicate the empirical Moran's I statistics.

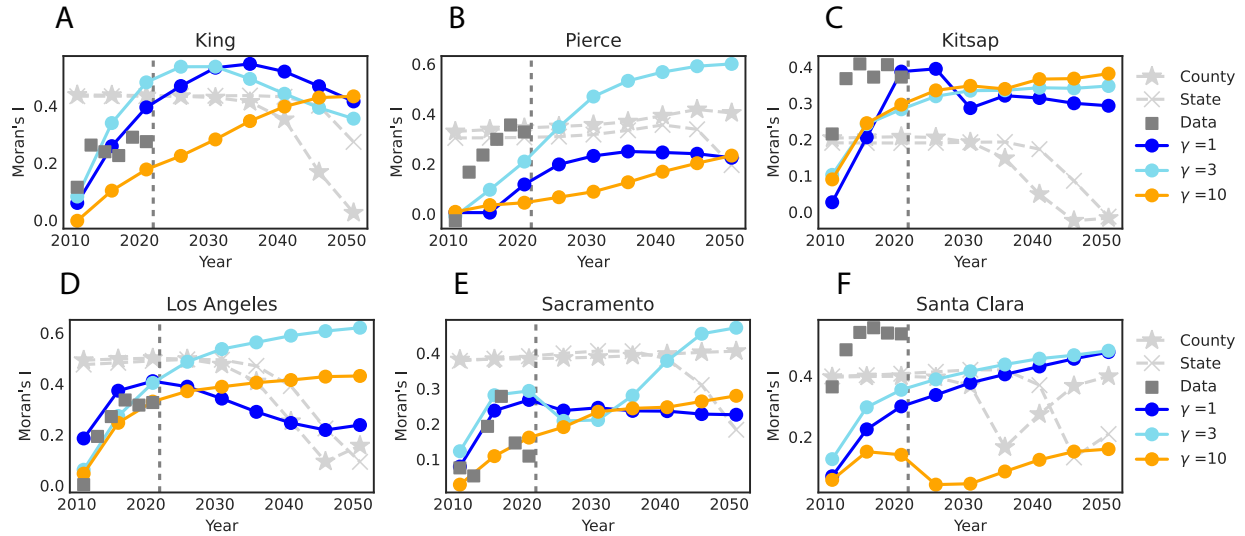


Figure A.6: Moran's I statistics for State/County BM and SocNet BM in 6 counties in Washington and California. For SocNet BM, we use the network with three γ s, i.e., 1,3,10. The fitting process is repeated for each γ and the median of predictions is reported. Solid lines with circle markers show the median (50th percentile) Moran's I statistics from SocNet BM. Dashed lines with cross markers and star markers show the Moran's I statistics from State/County BM; Squares show the Moran's I statistics calculated from empirical data on tract level.

A.7 Justification of Market Segmentation

In this study, we divide the potential market based on income. Other related segmentation factors include educational background, home ownership, and housing type. In Fig. A.7, we show that these three variables exhibit correlations. The figure illustrates the association of these three variables with income. Besides, with only three income groups, the fitted p and q already demonstrate significant variability due to limited data at the early adoption stage. Hence, despite the potential for more advanced applications to incorporate additional market segmentation with more socio-demographic parameters [44] or varying levels of the variables[254], we select income as the sole segmentation criterion.

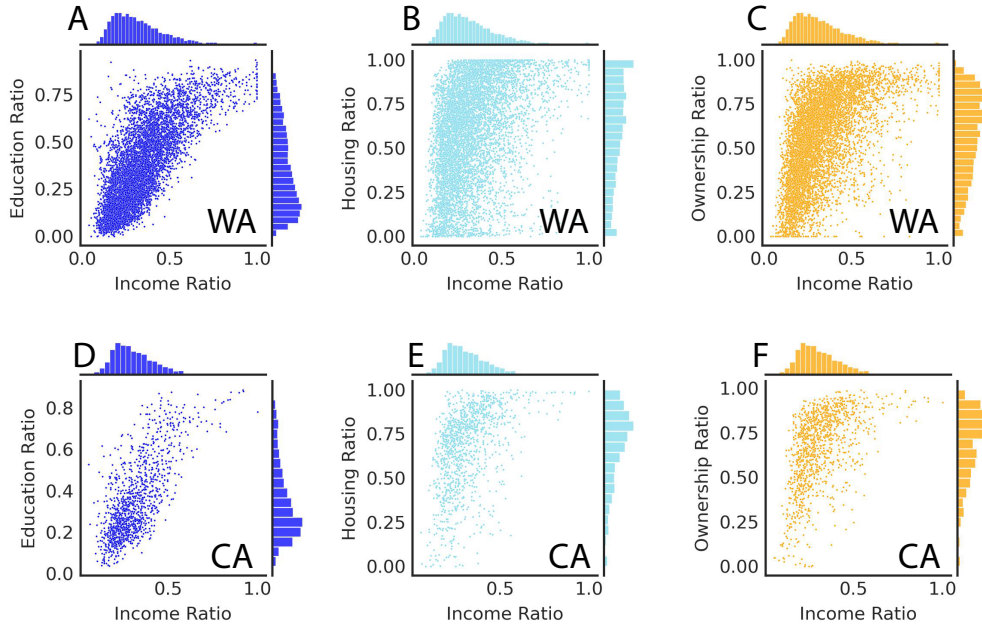


Figure A.7: Correlation plots of socio-demographic variables related to adoption. The income ratio represents the normalized income relative to the highest income across all tracts. (A,D) demonstrate correlation between the education ratio and income in Washington and California. The education ratio is defined as the proportion of the population aged 25 or older who have at least a Bachelor's degree, relative to the total population aged 25 and older. (B,E) demonstrate correlation between ownership ratio and income in Washington and California. The ownership ratio refers to the percentage of owner-occupied units among all housing units. (C,F) demonstrate correlation between the housing ratio and income in Washington and California. The housing ratio indicates the percentage of detached single-family units among total housing units.

A.8 Sensitivity Analysis on Network Size

This sensitivity analysis illustrates the impact of varying network sizes on the social network structure, adoption rate, and Moran’s I for the adoption rate. We configure various network sizes by selecting expansion factors of 5, 10, 15, 25, and 100 in Los Angeles. As presented in Table A.2-A.4, an increase in the expansion factor results in reduced network size, characterized by fewer nodes and edges. Our analysis also demonstrates how average degree, average geographical distance between two nodes, clustering coefficient, and assortativity vary across different expansion factors.

Expansion Factor	# Nodes	# Edges	Average Degree	Average Distance	Clustering Coefficient	Assortativity
5	1,189,150	3,567,441	6	21.67	0.0001	0.07
10	594,480	1,783,431	6	21.68	0.0002	0.07
15	396,364	1,189,083	6	21.66	0.0002	0.07
25	237,827	713,472	6	21.70	0.0004	0.07
100	59,453	178,350	6	21.76	0.0012	0.07

Table A.2: Expansion factor and corresponding social network structure summary ($\gamma = 1$)

Expansion Factor	# Nodes	# Edges	Average Degree	Average Distance	Clustering Coefficient	Assortativity
5	1,189,150	3,567,441	6	1.95	0.01	0.65
10	594,480	1,783,431	6	1.96	0.02	0.65
15	396,364	1,189,083	6	1.97	0.02	0.65
25	237,827	713,472	6	1.99	0.03	0.64
100	59,453	178,350	6	2.14	0.08	0.62

Table A.3: Expansion factor and corresponding social network structure summary ($\gamma = 3$)

We further illustrate the impact of varying expansion factors on adoption rates and Moran’s I. Figure A.8 (A-C) shows that smaller expansion factors result in higher Moran’s I, whereas Fig. A.8 (D-F) indicates that the expansion factor has minimal effect on adoption rates. Consequently, we decide to use the smallest feasible expansion factor, which is 5.

Expansion Factor	# Nodes	# Edges	Average Degree	Average Distance	Clustering Coefficient	Assortativity
5	1,189,150	3,567,441	6	0.71	0.04	0.96
10	594,480	1,783,431	6	0.71	0.07	0.96
15	396,364	1,189,083	6	0.72	0.10	0.95
25	237,827	713,472	6	0.72	0.14	0.95
100	59,453	178,350	6	0.78	0.33	0.92

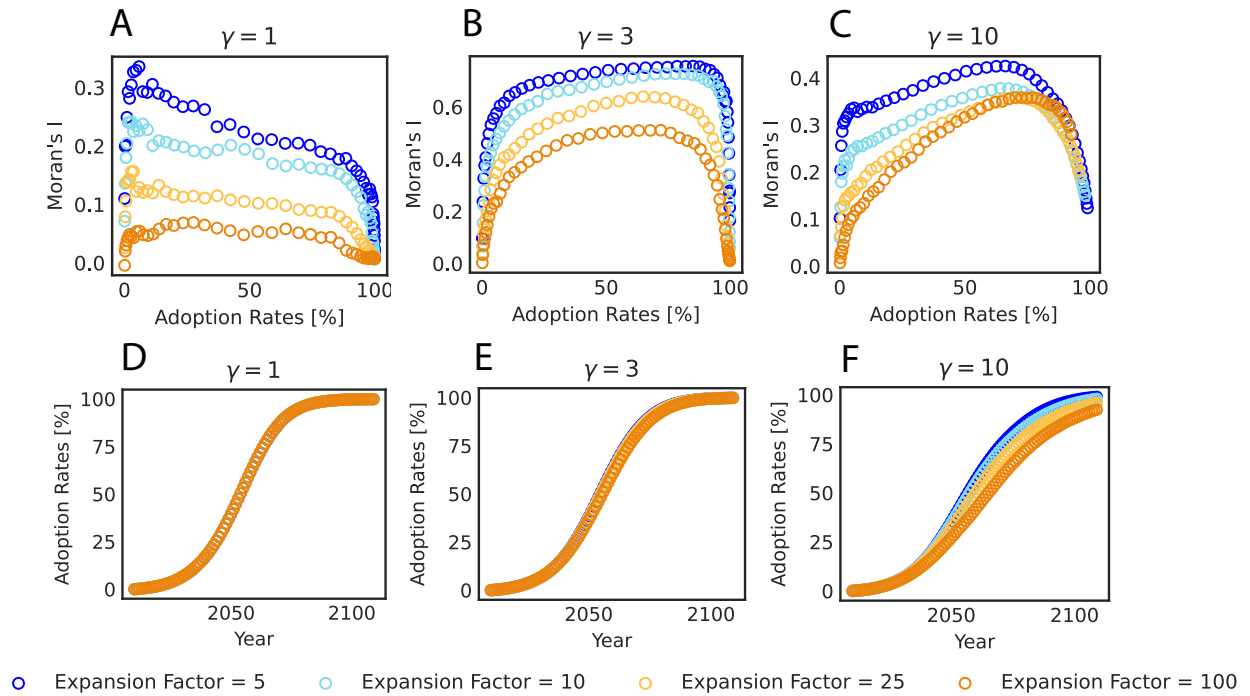
Table A.4: Expansion factor and corresponding social network structure summary ($\gamma = 10$)

Figure A.8: Network expansion factors' influence on diffusion patterns. The dots present the median results of multiple repetitions of simulation using a predefined p and q set. (A-C) demonstrate the correlation of adoption rates and corresponding Moran's I across various expansion factors (Expansion Factor = 5, 10, 25, 100) and different network structures ($\gamma = 1, 3, 10$). (D-F) demonstrate adoption rates evolution across various expansion factors (Expansion Factor = 5, 10, 25, 100) and different network structures ($\gamma = 1, 3, 10$).

A.9 Justification of Values of γ s

We calculate clustering coefficient [255], assortativity [256], the distribution of degree, and distribution of the geographical distance between nodes in Los Angeles. Table A.5 and Fig. A.9 show the overview of social network characteristics with different γ . We find that higher γ leads to higher clustering coefficients, assortativity, $P(k)$ exponents, and $P(r)$ exponents.

Previous research finds for the social network inferred from blogs [257], location-based social networks [258][259] or mobile phone data [260][261][262], the distribution of geographical distance between nodes follows a power law, with exponents between -1 and -2. Therefore, we explore social networks with $\gamma = 1, 3, 10$, which leads exponents between 0 to -3. Also, we set $\gamma = 10$ for the default social network for analysis as it leads to a clustering coefficient closer to empirical values in social networks.

γ	Clustering Coefficient	Assortativity	P(k) Power Law Fitted Exponent	P(r) Power Law Fitted Exponent
1	0.0001	0.07	-3	-0.3
3	0.01	0.65	-3	-2.1
10	0.04	0.96	-3	-3.0

Table A.5: Social network characteristics with different γ

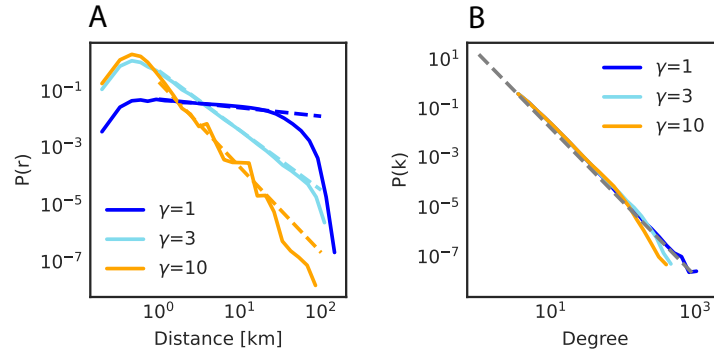


Figure A.9: Distance distribution $P(r)$ and Degree distribution $P(k)$ of social network with $\gamma = 1, 3, 10$. (A) Distance distribution of various social network structures. The solid line indicates the data distribution and the dashed line with the same color indicates the fitted power law distribution. (B) Degree distribution of various social network structures. The solid line indicates the data distribution and the grey dashed line indicates the fitted power law distribution.

A.10 Social Network Construction Process

Fig. A.10 depicts the procedure for constructing a social network. Subfigures (A-C) illustrate the assignment of geographical information to nodes based on census data [47], while (D-F) illustrate the process of forming edges among nodes.

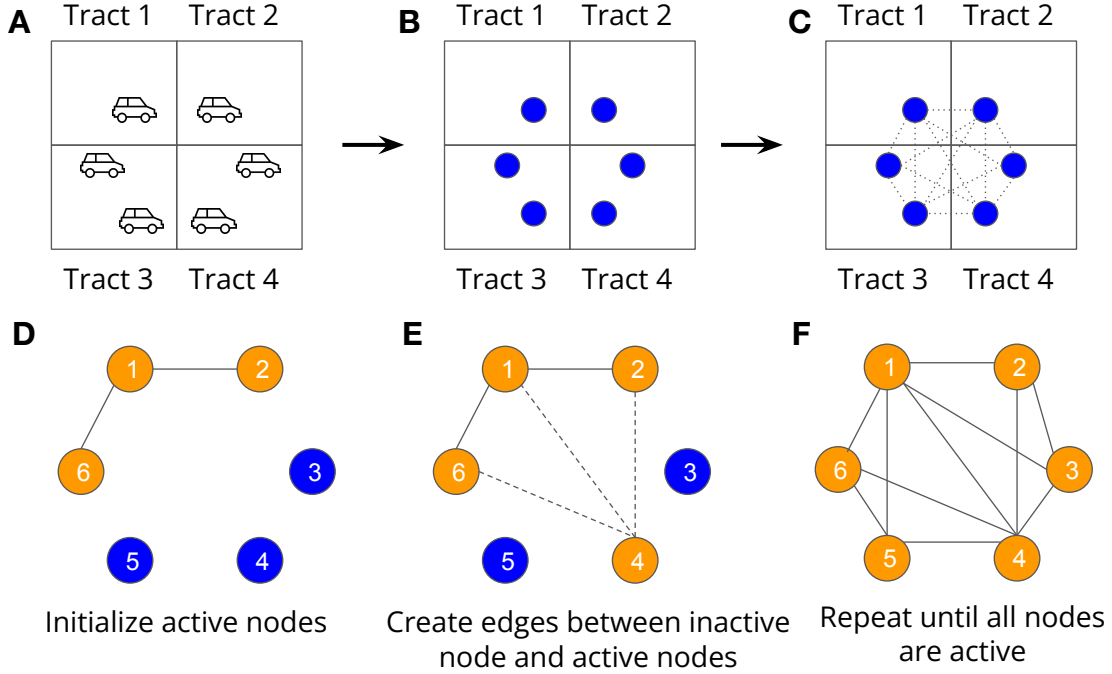


Figure A.10: Social network construction process. (A) Number of vehicles in each census tract (obtained from the census tract data). (B) Each node represents one node (when the expansion factor is 1). The latitude and longitude for each node are set as centroid coordinates of its respective census tract. (C) Based on the latitude and longitude for each node, the distance d_{ij} between any two nodes, i and j , can be computed. For nodes residing within the same census tract, the distance is set as half the square root of the census tract's area. (D) Nodes 1, 2, and 6 are selected as the active nodes set, leaving nodes 3, 4, and 5 as inactive. (E) Inactive node 4 is randomly chosen, and $prob_{4 \rightarrow j}$ is calculated and normalized where $j \in \{1, 2, 6\}$. For example, for node 4 and node 1, $k_4 = 0$ and d_{41} is the distance between the centroid of census tract 4 and census tract 1. Based on $prob_{4 \rightarrow j}$, $m = 3$ edges are created linking node 4 to nodes in the active nodes set. Node 4 is then marked as active. This step is repeated for the remaining inactive nodes until all are active. (F) This process is executed for nodes 3 and 5 to finalize the social network.

Appendix B

Supplementary Information for Chapter 3

B.1 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. B.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. B.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. B.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.

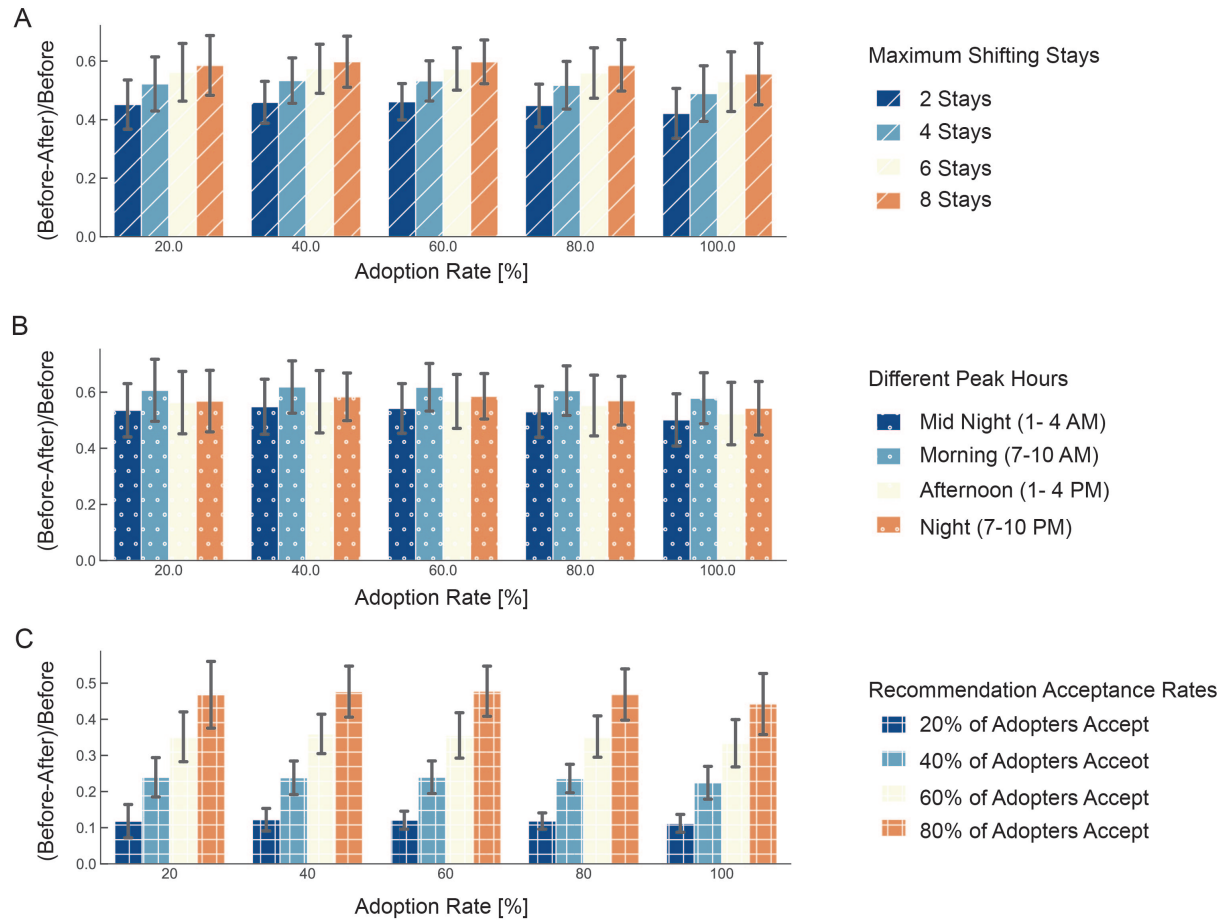


Figure B.1: Sensitivity analysis of personalized shifting recommendations. We show ZIP code level differences between before and after our personalized shifting recommendations in the ratio of before recommendations under different EV adoption rates. The error bar highlights the variance among ZIP codes. (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.

B.2 Unbalanced Demand with Increasing Adoption Rates

With increasing adoption rates, ZIP codes in the 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 B.2 and Figure B.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 B.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 B.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 B.2 (B) 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 B.3 (A-B) indicate more sublinear increases in South Bay Area and more superlinear increases in the North Bay Area. The difference among ZIP codes implies the unbalanced development of EV charging demand in the Bay Area. Figure B.3 (C) indicates that the recommendations reduce the number of ZIP codes with sublinear increases in the South Bay Area during grid peak hours. Figure B.3 (D) shows that the recommendations reduce the number of ZIP codes with superlinear increases in the North Bay Area and increase the number of ZIP codes with sublinear increases in the South Bay Area during grid off-peak hours.

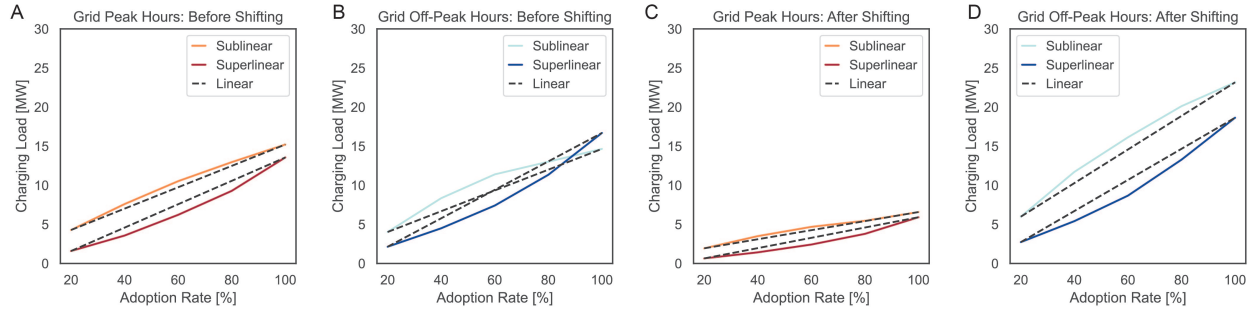


Figure B.2: Charging load growth under sub-linear, linear, and super-linear adoption patterns. (A) and (B) show average peak and off-peak charging loads before applying shifting strategies, while (C) and (D) present the corresponding results after shifting. The dashed line indicates linear growth; solid lines represent average loads for ZIP codes with sub-linear (above) and super-linear (below) increases.

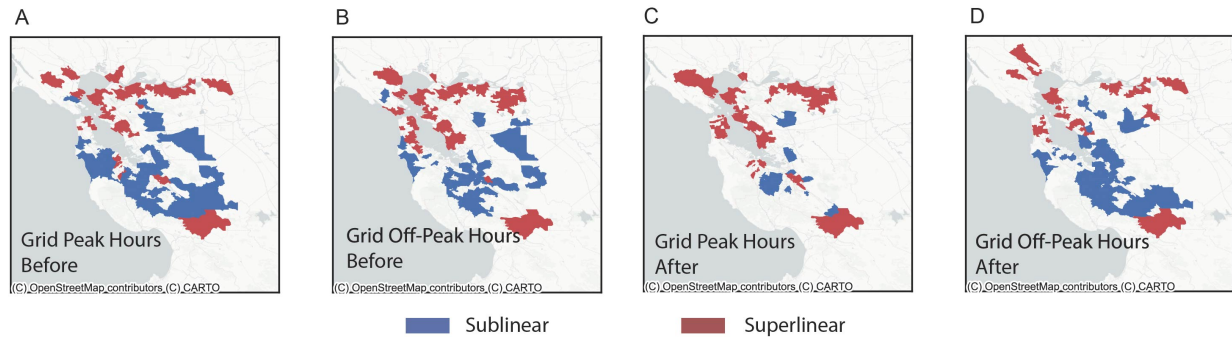


Figure B.3: Spatial distribution of sub-linear and super-linear charging load growth in the Bay Area. (A) and (B) show ZIP codes with sub-linear (blue) and super-linear (red) peak load growth before demand shifting, during grid peak and off-peak hours, respectively. (C) and (D) present the same classification after shifting.

B.3 EV Models Market Share

Figure B.4 shows the market share of battery-operated EVs used in this study [122]. 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 [136].

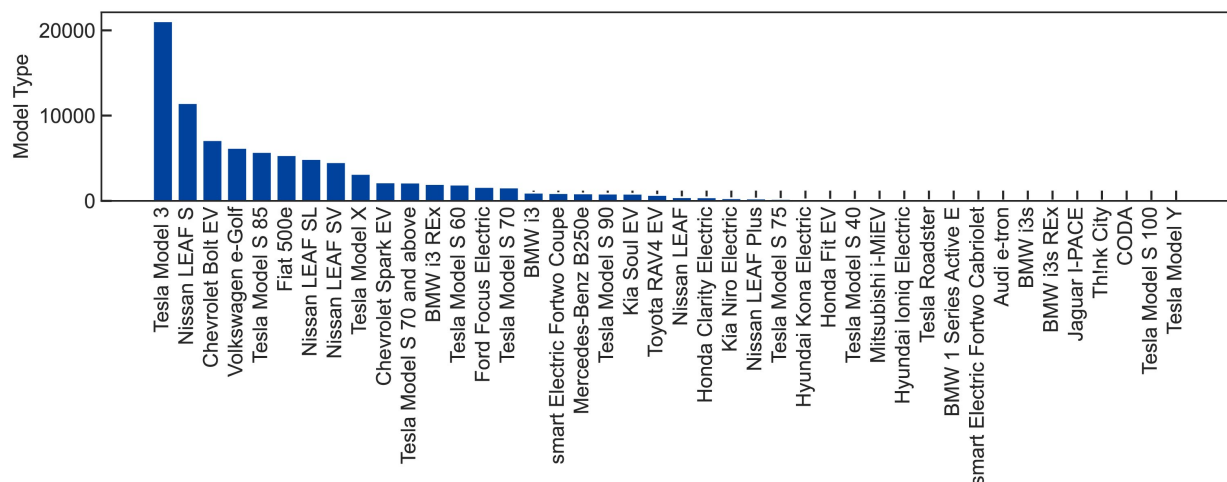


Figure B.4: Market share of battery electric vehicle (BEV) models used in this study. The Tesla Model 3 and Nissan LEAF S are the most common models among users, followed by the Chevrolet Bolt EV and Volkswagen e-Golf.

B.4 Travel Behavior of EV Drivers

Figure B.5 (A) 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 B.5 (B) 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. B.5 (C). Most people consume less than 25 kWh a day. Figure B.5 (D) shows the number of stays during the day. Most people visit two places during the day.

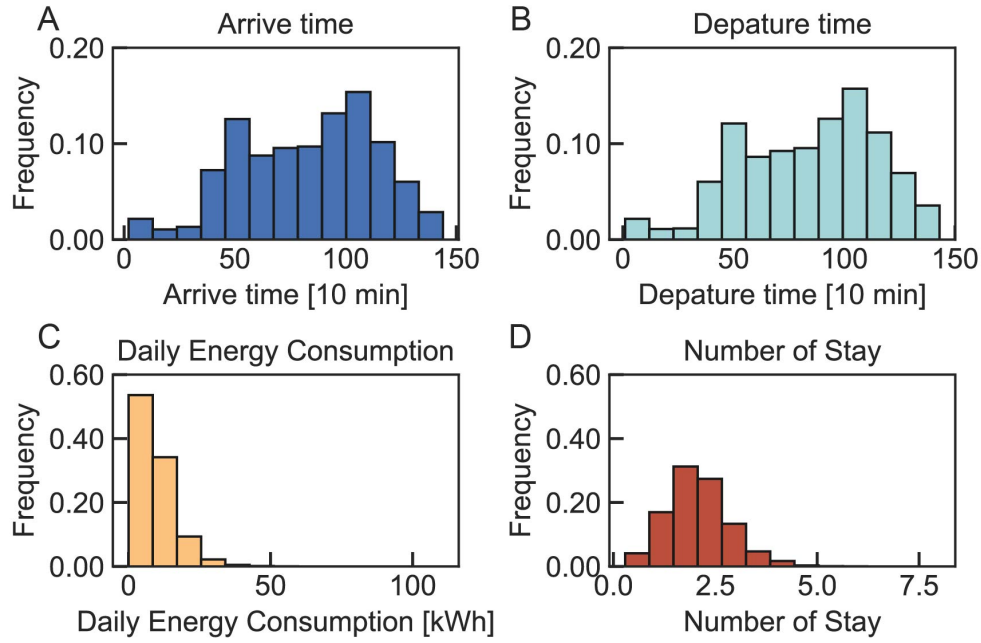


Figure B.5: Distributions of simulated EV driver travel behavior. (A) and (B) show the distributions of arrival and departure times, revealing two travel peaks around 9 a.m. and 7 p.m., with similar shapes due to short dwell times. (C) displays the daily energy consumption, where most users consume less than 25 kWh per day. (D) shows the number of stops per day, with the majority of users making two or fewer visits.

B.5 Speech Groups Data

The dendrograms in Fig. B.6 and Fig. B.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.

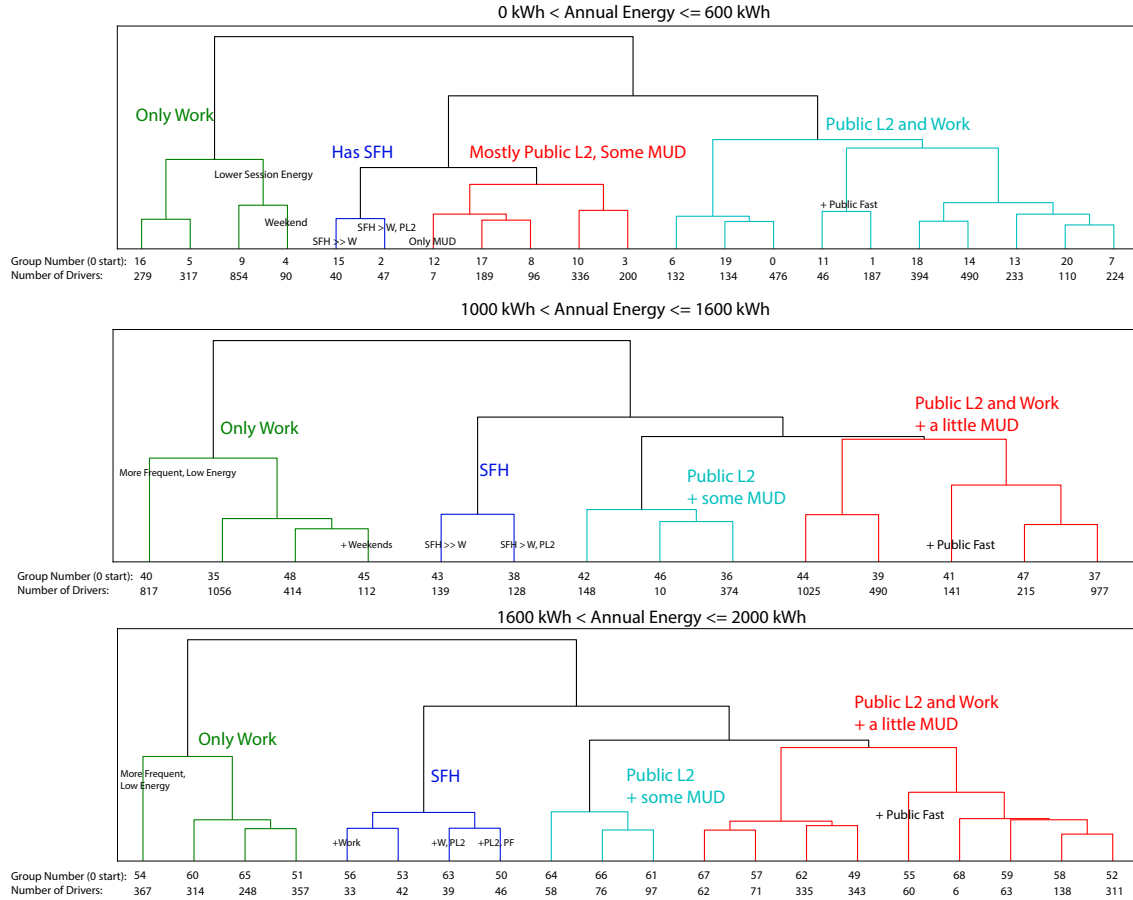


Figure B.6: Clustering dendrograms of EV charging groups (groups 1–68). Dendrograms represent hierarchical clustering results of 68 EV charging groups based on charging behavior and energy use. The data is segmented into three energy usage tiers: (top) 0–600 kWh, (middle) 1000–1600 kWh, and (bottom) 1600–2000 kWh of annual energy consumption. Labels such as “Only Work,” “Public L2 and Work,” and “Mostly Public L2, Some MUD” describe common charging patterns and living types (e.g., SFH = single-family home, MUD = multi-unit dwelling).

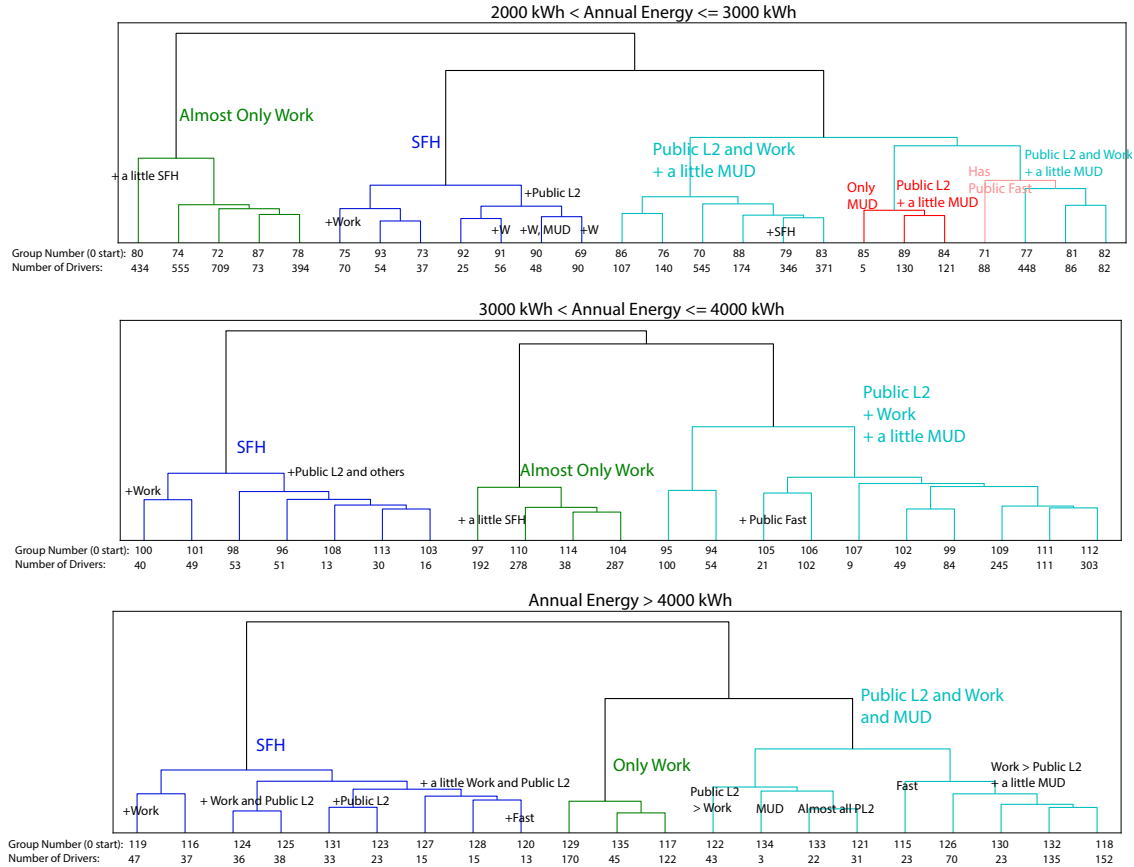


Figure B.7: Clustering dendrograms of EV charging groups (groups 69–136). Dendrograms represent hierarchical clustering results for EV user groups with annual energy consumption above 2000 kWh, separated into three tiers: 2000–3000 kWh (top), 3000–4000 kWh (middle), and over 4000 kWh (bottom). Labels such as “Almost Only Work,” “Public L2 and Work,” and “SFH + Public L2” summarize shared traits including charging location (e.g., work, public Level 2, fast charging), and dwelling type (e.g., SFH = single-family home, MUD = multi-unit dwelling).

B.6 Home Charging Access Survey Data

Table B.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 [37]. 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 B.1: Potential home charging access by housing type and income level. The table presents the percentage of vehicles with potential access to home charging based on data from the California Energy Commission’s Home Charging Access Survey.

B.7 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 $G \in [1, \dots, 136]$;

e : weekly energy consumption of the adopter;

$\mathbf{t}$: stay period of the adopter, where $\mathbf{t}_i = (t_i^a, t_i^d)$ with t_i^a and t_i^d as arrival time and departure time, respectively, $t_i^a, t_i^d \in [1, \dots, 1008]$;

$\mathbf{l}$: stay place of the adopter, where $\mathbf{l}_i = (l_i^{type}, l_i^{coordinates})$ with $l_i^{type} \in [\text{home}, \text{work}, \text{public}]$;

Output: $\mathbf{t}^*$; $\mathbf{l}^*$: when and where the adopter charges;

$\mathbf{c}^*$: energy charged in the stay;

$\mathbf{z}^*$: charging segment in the stay.

```

1: for stay  $i$  in all stays do
2:
3:   # When and where charging happens
4:    $\mathbf{t}_i^* = \mathbf{t}_i; \mathbf{l}_i^* = \mathbf{l}_i$ 
5:
6:   # How to charge (charging segment in the session)
7:   if  $\mathbf{l}_i^* \in [\text{home}]$  then
8:      $\mathbf{z}_i' = [\text{SFH L1}, \text{SFH L2}, \text{MFH L2}, \text{Public L2}, \text{Public L3}]$ 
9:   else if  $\mathbf{l}_i^* \in [\text{work}]$  then
10:     $\mathbf{z}_i' = [\text{Work L2}, \text{Public L2}, \text{Public L3}]$ 
11:  else if  $\mathbf{l}_i^* \in [\text{public}]$  then
12:     $\mathbf{z}_i' = [\text{Public L2}, \text{Public L3}]$ 
13:  end if
14:   $\mathbf{z}_i^* = \max_{\mathbf{z}_i' \in \mathbf{z}_i'} P(\mathbf{z}_i | G)$ .
15:  Sample if the driver charges charges in segment  $\mathbf{z}_i^*$  with probability  $P(\mathbf{z}_i^* | G)$ .
16:
17:  # How much to charge (charging energy in the session)
18:  if the driver charges in segment  $\mathbf{z}_i^*$  then
19:    Sample the energy charged with Gaussian mixture model  $\mathbf{c}_i^* = P(\mathbf{c}_i | G, \mathbf{z}_i^*)$ .
20:  else
21:     $\mathbf{c}_i^* = 0$ 
22:  end if
23: end for
24:  $\mathbf{c}_i^* = (\mathbf{c}_i^* / \sum_j \mathbf{c}_j^*) \times e$ 
25: return  $\mathbf{t}^*, \mathbf{l}^*, \mathbf{c}^*, \mathbf{z}^*$ 

```

B.8 Validation for Adoption Model in 2019

Figure B.8 shows a comparison between the CVRP data [122] and our simulation. Figure B.8 (A) and B.8 (B) show the geographical distribution of CVRP and our simulation. The distributions are similar in most ZIP codes. Figure B.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.

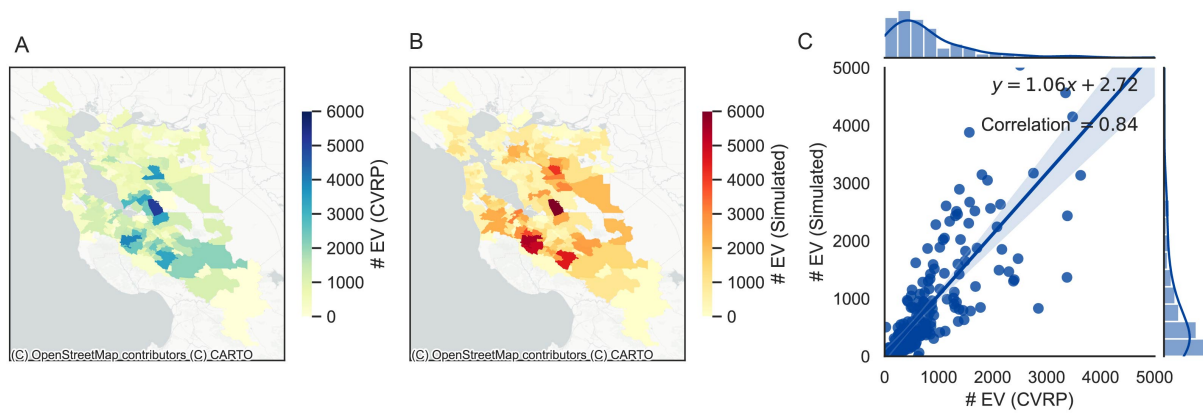


Figure B.8: Validation of the EV adoption model for the year 2019. (A) shows the geographical distribution of EV counts based on California’s CVRP data, and (B) presents the corresponding simulation results from the proposed adoption model. (C) illustrates the correlation between CVRP data and simulated EV counts

B.9 Geographical Distribution of EV Adopters with Increasing Adoption Rate

Figure B.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. B.9 (A-C). When the adoption rate keeps increasing, there will be more EV adopters in the North Bay Area, as shown in Fig. B.9 (D-F).

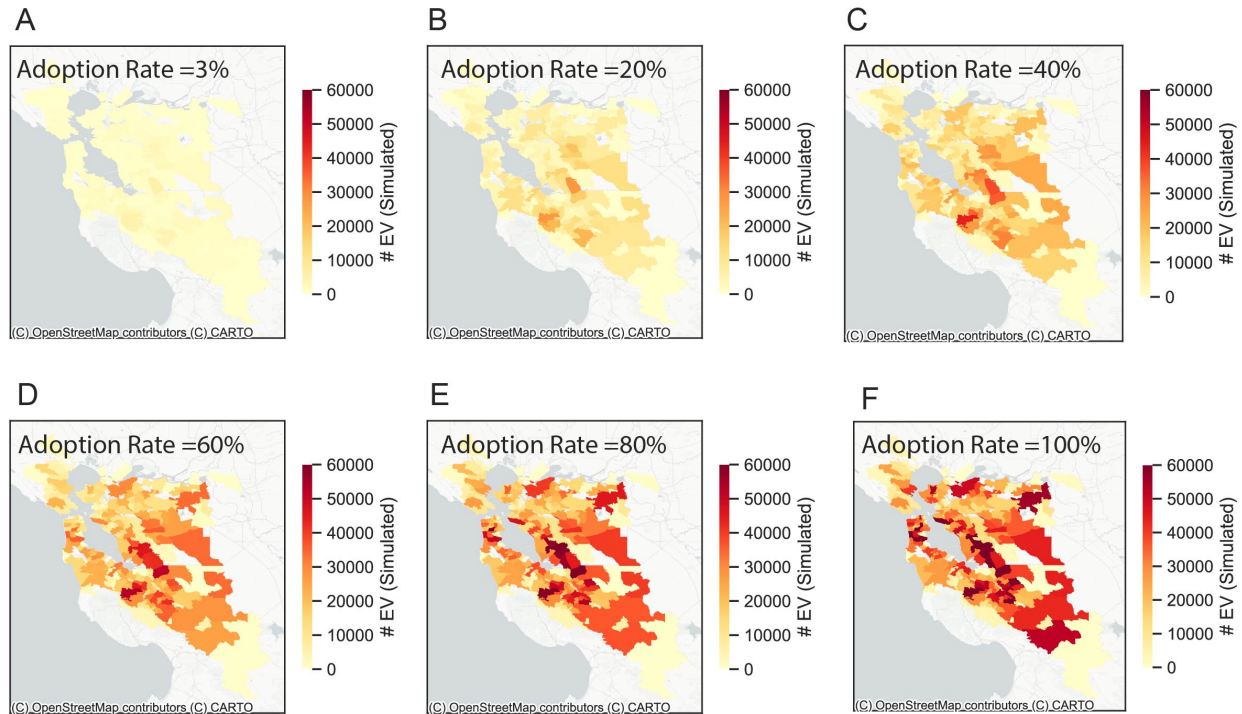


Figure B.9: Simulated spatial distribution of EV adopters under increasing adoption rates. Maps (A) through (F) show the number of electric vehicle adopters across ZIP codes in the Bay Area at adoption rates of 3%, 20%, 40%, 60%, 80%, and 100%, respectively.

Appendix C

Supplementary Information for Chapter 5

C.1 User Side Model for Uninterruptible Appliances.

Here, we demonstrate the method to derive the optimal solution on the user side with $h_{i,j}$, which constitutes the lower level of the bi-level optimization.

The user aims to maximize its revenue by calculating optimal $h_{i,j}$. User revenue refers to the utility that a user benefits from consuming energy minus the payment she makes for the energy consumption.

For the utility part, when user i consumes $q_{i,j}$ for appliance j , its utility is:

$$U_{i,j}^{user} = \bar{U}_{i,j} h_{i,j}, \quad (C.1)$$

where $h_{i,j}$ is a binary variable that indicates if the user chooses to use the appliance, i.e., $h_{i,j} = 1$ represents that the user chooses to use the appliance, and $\bar{U}_{i,j}$ denotes the utility the user can obtain when deciding to use the appliance. For the payment part, we define the user's payment under ALoUP as an example. Therefore, when the user i consumes $a_{i,j} h_{i,j}$ for appliance j ($a_{i,j}$ is the energy consumption per use for appliance j of user j), the payment is:

$$C_{i,j}^{user} = \begin{cases} \pi^h a_{i,j} h_{i,j} - (\pi^h - \pi^r)(z_j - a_{i,j} h_{i,j}), & a_{i,j} h_{i,j} \leq z_j \\ \pi^h a_{i,j} h_{i,j}, & a_{i,j} h_{i,j} > z_j. \end{cases} \quad (C.2)$$

Combining them together, for each user i , we have her revenue R_i^{user} as:

$$R_i^{user} = \sum_{j \in J} (U_{i,j}^{user} - C_{i,j}^{user}). \quad (C.3)$$

Based on the revenue, user i can calculate her optimal energy consumption plan by solving the following optimization problem:

$$\begin{aligned} h_{i,j} &:= \max_{h_{i,j}} R_i^{user} \\ \text{s.t. } & h_{i,j} \in \{0, 1\}. \end{aligned} \quad (C.4)$$

The optimal response of user i given $\{z_j, \pi_j^r\}$ is:

$$h_{i,j}^* = \max_{h_{i,j}^*} R_i^{user}. \quad (C.5)$$

Given the pricing scheme $\{\pi^h, \pi_j^r, z_j\}$, the optimal choice $h_{i,j}^*$ can be obtained by maximizing Eq. (C.3).

- When $\bar{U}_{i,j} - \pi^h a_{i,j} < 0$, we have:

$$h_{i,j}^* = \begin{cases} 1, & z_j \geq \frac{\pi^h a_{i,j} - \bar{U}_{i,j}}{\pi^h - \pi_j^r} + a_{i,j} \\ 0, & z_j \leq \frac{\pi^h a_{i,j} - \bar{U}_{i,j}}{\pi^h - \pi_j^r} + a_{i,j}. \end{cases} \quad (C.6)$$

- When $\bar{U}_{i,j} - \pi^h a_{i,j} \geq 0$, we have $h_{i,j}^* = 1$.

In the upper level, the DSO makes the decision. With the solution from the lower-level model, we can obtain the optimal solution for the upper-level model.

C.2 Transformation for ALoUP

In the original optimization problem, we have U^{dso} as:

$$U^{dso} = \sum_{i \in I} \sum_{j \in J} \left(\frac{(2\pi^h - \pi_j^r)(\gamma_{i,j} - 2\pi^h + \pi_j^r)}{\alpha_{i,j}} y_{i,j,1} - (\pi^h - \pi_j^r) z_j y_{i,j,1} + \frac{\pi^h(\gamma_{i,j} - \pi^h)}{\alpha_{i,j}} y_{i,j,2} \right). \quad (C.7)$$

Note that the term $(\pi_j^r)^2 y_{i,j,1}$ in U^{dso} is cubic, so we make modifications to the original optimization problem to reduce the cubic programming to linear programming.

We denote the profit the DSO gets from the users as U^{dso} :

$$\begin{aligned} U^{dso} = & \sum_{i \in I} \sum_{j \in J} \left(\frac{(2\pi^h y_{i,j,1} - \sum_{k \in K} \pi_{k,j}^r a_{k,i,j}^{xy})(\gamma_{i,j} - 2\pi^h)}{\alpha_{i,j}} \right. \\ & + \frac{2\pi^h \sum_{k \in K} \pi_{k,j}^r a_{k,i,j}^{xy}}{\alpha_{i,j}} - \frac{\sum_{k \in K} (\pi_{k,j}^r)^2 a_{k,i,j}^{xy}}{\alpha_{i,j}} \\ & \left. - (\pi^h a_{i,j}^{yz} - \sum_{k \in K} \pi_{k,j}^r a_{k,i,j}^{xyz}) + \frac{\pi^h(\gamma_{i,j} - \pi^h)}{\alpha_{i,j}} y_{i,j,2} \right). \end{aligned} \quad (C.8)$$

The generation cost is C^{dso} :

$$C^{dso} = g \left(\sum_{i \in I} \sum_{j \in J} \left(\frac{(\gamma_{i,j} - 2\pi^h) y_{i,j,1} - \sum_{k \in K} \pi_{k,j}^r a_{k,i,j}^{xy}}{\alpha_{i,j}} + \frac{\gamma_{i,j} - \pi^h}{\alpha_{i,j}} y_{i,j,2} \right) \right). \quad (C.9)$$

We set $\bar{z}_{i,j}$ as follows:

$$\bar{z}_{i,j} = \frac{2\gamma_{i,j} - 3\pi^h + \sum_{k \in K} \pi_{k,j}^r x_{k,j}}{2\alpha_{i,j}}. \quad (\text{C.10})$$

Then the optimization problem becomes:

$$\begin{aligned} \max_{z,x,y,a} \quad & U^{dso} - C^{dso} \\ \text{s.t.} \quad & \bar{z}_{i,j} - z_j \leq M(1 - y_{i,j,1}), \quad \forall i \in I \\ & z - \bar{z}_{i,j} \leq M(1 - y_{i,j,2}), \quad \forall i \in I \\ & \sum_{k \in K} x_{k,j} = 1, z_j \geq 0, \\ & y_{i,j,1} + y_{i,j,2} = 1, \quad \forall i \in I \\ & y_{i,j,1}, y_{i,j,2}, x_{k,j} \in \{0, 1\}, \quad \forall i \in I, k \in K \\ & a_{k,i,j}^{xy} \leq x_{k,j}, a_{k,i,j}^{xy} \leq y_{i,j,1}, \forall i \in I, k \in K \\ & a_{k,i,j}^{xy} \leq x_{k,j} + y_{i,j,1} - 1, \forall i \in I, k \in K, \\ & a_{k,i,j}^{xyz} \leq a_{k,i,j}^{xy}, a_{k,i,j}^{xyz} \leq z_j, \forall i \in I, k \in K, \\ & a_{k,i,j}^{xyz} \leq z_j - \bar{U}(1 - a_{k,i,j}^{xy}), \forall i \in I, k \in K \\ & a_{i,j}^{yz} \leq y_{i,j,1}, a_{i,j}^{yz} \leq z_j, \forall i \in I \\ & a_{i,j}^{yz} \leq z_j - \bar{U}(1 - y_{i,j,1}), \forall i \in I \\ & a_{k,i,j}^{xy}, a_{k,i,j}^{xyz}, a_{i,j}^{yz}, x_{k,j} \in \{0, 1\}, \forall i \in I, k \in K. \end{aligned} \quad (\text{C.11})$$

Note that all the constraints are also $\forall j \in J$. We omit this condition for the sake of brevity.