Multi-day Scenario Analysis for Battery Electric Vehicle Feasibility Assessment and Charging Infrastructure Planning

Anpeng Zhang[†], Jee Eun Kang[*†], and Changhyun Kwon[‡]

[†]Department of Industrial and Systems Engineering, University at Buffalo, SUNY
[‡]Department of Industrial and Management Systems Engineering, University of South Florida

December 11, 2019

Abstract

Multi-day activity-travel patterns help create potential vehicle usage profiles that contain vehicle operations and battery status under different scenarios with varying location-based charging opportunities, based on travel needs and charging availability/behaviors. Utilizing a multi-day data sampling method, analyses of scenarios are designed to provide insights on bounds of potential BEV market under different charging opportunities, including level 2 activity charging and level 3 trip charging. Single-day data results tend to overestimate travelers' BEV feasibility assuming that multi-day sample data provides accurate estimations. Facility utilization can be improved without affecting travelers' charging demand under correct pricing scheme for most cost-sensitive users. Smart grid charging strategy can greatly reduce the total number of operating chargers during the same time in a day, and BEV users' charging behaviors have minor impact on this improvement. Our numerical results indicate that an appropriate number of chargers installed in shopping and leisure locations should be more profitable and have higher charger utilization rate since those chargers help cover BEV users' trips.

Keywords: Activity-Travel Patterns; Battery Electric Vehicle; Charging Infrastructure Planning; Level 3 Charging

[*]Corresponding author; jeeeunka@buffalo.edu

1 Introduction and Background

Battery Electric Vehicles (BEVs) fully convert gasoline-based mobility to electricity-based mobility. For BEVs, the biggest challenge is whether a traveler's intended activity-travel choices (represented as activity-travel patterns) can be served by a BEV since BEVs have a shorter range and longer charging time. Although the coming generation of luxury BEVs such as the newest Tesla models has ranges much higher than 200 miles, most of BEVs on the market can drive around 80 miles to 150 miles with a full battery (Evrater, 2018). Thus, a traveler with travel needs over 100 miles may hardly be served by a BEV without charging during the day, and long-distance trips between cities are difficult to accomplish. Even for long-range BEVs, charging can be an issue. Travel activities on the next day will not be served successfully when long-range vehicles with low battery levels are not fully charged overnight due to slow charging speed at home. On the other hand, travelers may be able to fulfill their trip plans if charging opportunities are sufficiently available within the time frame of their travel activities. Thus, parking and charging infrastructures are critical to BEV users since their vehicles can be recharged when people are doing activities like working or shopping. Another challenge is the charging infastructure and power supply from increased charging demand. In a broader scope, BEVs may lead to benefit all ratepayers by reducing fixed costs while charged appropriately. However, a problem can arise during peak hours when BEVs charge simultaneously since it can lead to a heavy burden for the electrical grid.

Due to these reasons, an individual traveler's activity-travel patterns serve as a crucial input for assessing the feasibility, market potential, and promotion of BEVs. Full-day activity-travel patterns allow us to create potential vehicle usage profiles, which include vehicle operations and battery status under different charging scenarios based on travel needs and charging availability/behaviors. Adequate information on travelers' activities helps generate reliable charging profiles and insightful results can be derived related to charging infrastructure requirements and power demand estimations.

Many studies try to estimate the possibilities of substituting an BEV for a given conventional vehicle in households with single or multiple vehicles relying on one-day data. Several studies showed that those results could be limited since people can have quite distinct travel activities (habitual short trips or random long trips) on different days. Despite the commonly accepted claim based on one-day survey data that 78% of the commuters will be satisfied with a 40 mile range BEV, only 9% of vehicles did not exceed daily travel distance less than 100 miles for one year period based on multi-day GPS data (Pearre et al., 2011). Other studies also highlighted the need for using multi-day data (Dong et al., 2014; Smith et al., 2011).

Since people's travel patterns change substantially over time, multi-day data can provide more information than single-day data and more useful insights can be derived (Pendyala and Pas, 2000; Khan and Kockelman, 2012). Recent studies focus on BEV acceptance considering the multi-day perspective of the problem. Khan and Kockelman (2012) considered the covered days in a year as the estimation of BEV acceptance as well as the electrified miles as the estimation of PHEV acceptance, and switches between different cases were analyzed in multi-vehicle households. Their results suggested that BEVs with 100 miles of range should satisfy 50% of single-vehicle households and 80% of multiple-vehicle households. Tamor et al. (2013) defined a metric of BEV acceptance for individual travelers of a given range based on the number of days per year that EVs cannot fully replace conventional vehicles, and the cost of ownership was included to make the definition of acceptance more realistic. Their trip chain frequency distribution represented a combination of recurring habitual trips and random longer trips. Tamor and Milačić (2015) extended trip chain frequency distribution by considering the correlations of the single-day travel distance-frequency distributions for vehicles in the same household. They presented an analysis of prospective BEV acceptance and found that EVs ranging of 60 miles could be acceptable to nearly 90% of two-car households and cover one-third of all travels with similar acceptance assumptions in previous studies. In general, these works suggest that the acceptance of BEV is most influenced by occasional very long trips and most users may not be satisfied with a realistic BEV range of 100 miles unless other convenient alternative transportation means are available.

In this study, we extend the analysis of BEV acceptance to include activity purpose information so that we obtain more details on the usage of vehicles. Trip purpose is important information to understand people's travel behavior. This information indicates the destination/origin location of travel activities, which are hard to reveal in GPS data. Thus, charging assumptions in GPS-data-based studies are usually simple, including home charging and work charging. It is reasonable to assume that charging infrastructures are also available in locations other than home and workplaces, like shopping malls or even on highways. With multi-day travel data, more instructive charging scenario based on different locations can be developed and analyzed to derive insights on people's preferences on BEVs.

While multi-day travel data is important for BEV related analysis, this data is usually not available due to the expensive acquirement cost. There are different ways to reduce the cost of using multi-day data in research studies. Stopher et al. (2008) showed that the sample size can be significantly reduced to obtain meaningful results in multi-day surveys. Thus, multi-day data of smaller sizes may be less expensive and thus accessible for study. Another way to reduce the cost of using multi-day data is to generate multi-day samples based on single-day data, which involves a trade-off between data accuracy and data cost. In this study, we apply a multi-day sampling method from Zhang et al. (2018) and develop various parking-based charging scenarios. We compare the performance of generated multi-day sample with single-day data based on numerical experiments in later sections. Also, a scenario analysis is conducted to derive insights on feasibility of potential BEV users under different conditions and to provide suggestions on charging infrastructure planning.

Grid charging strategies are also considered along with BEV users' travel and charging behaviors in charging infrastructure planning. Smart charging can allow electric cars to interface with the electric grid, or smart grid (SG) with smart appliances, renewable energy resources as well as energy-efficient resources. Grid operators constantly monitor and manage electricity demand, supply, reserved backup capacity and the mix of electricity-generating technologies to ensure that everything runs smoothly, indicating that applying grid energy supply strategies is physically possible since the power supply in electricity grids is flexible (UCS, 2015).

Multiple previous works focused on the interaction between BEV charging and grid energy supply strategies. Shaukat et al. (2018) summarized the impact of BEVs charging on electricity grids, including electricity load capacity, power quality as well as economic and environmental issues. They also mentioned that the disordered charging of BEVs may increase the peak load demand while the smart charging plan of BEVs helps maintain a balanced load capacity and avoid installation of extra capacity. The economic and environmental impacts were studied based on a comparative analysis of controlled charging strategy versus uncontrolled charging strategy, considering a plug-in electric vehicle charging station located in a workplace parking garage (Tulpule et al., 2013).

Some other works advanced the study of BEVs' interaction within smart grids in the technical aspect and brought up the concept of vehicle-to-grid (V2G) technology (Lam et al., 2012; Richardson, 2013; Hota et al., 2014). The V2G technology is a promising solution for feeding the surplus energy back to the smart grid during high peak demand period, and thus intelligently scheduling BEV charging events is critical to maximizing the profit from BEVs (Shaukat et al., 2018). Sundstrom and Binding (2010) designed an algorithm to minimize the cost of electricity while avoiding distribution grid congestion and satisfying the individual vehicle owner's requirements. They tested the proposed algorithm in three different charging scenarios based on a simulated grid with only one type of charging facility as well as assumed perfect BEV trip prediction. Later, Sundstrom and Binding (2011) extended their previous work to handle voltage constraints and proposed a planning model concerning the charging service provider as well as its communication with other power system entities including the retailer and the distribution service operators. They aimed to force the charging load to follow the fluctuations in the preferred grid power supply load whenever the preferred limit tends to be exceeded. We also consider the grid charging strategies in this work, assuming that the flexibility in the electricity power supply can be utilized to reduce the operation cost for grid network operators to provide insights on the required supply capacity of charging facilities.

Our major contributions lie in that applying multi-day data to extract people's location-based charging behaviors, studying how users' charging cost concerns will affect their charging choices as well as BEV feasibility as well as providing charging infrastructure planning insights based on grid network charging strategies. In this study, we introduced our sampling method that generates multi-day travel data and defined multiple scenarios involving charging settings, user and grid charging strategies as well as BEV feasibility in Section 2. In Section 3, we conducted a series of scenario analysis to derive insights on BEV feasibility assessment as well as parking-based charging infrastructure planning. In Section 4, we present a summary of the paper as well as the conclusions of scenario analysis.

2 Scenario definitions and other concepts

In the following section, we briefly review the definitions of activity-travel pattern sequences, state of charge as well as the sampling method from Zhang et al. (2018). Later, we explain the detailed definition of various charging scenarios including BEV range, facility charging level and charging cost assumptions. We also introduced two charging strategies for two types of users with different pricing behaviors as well as multiple grid energy management strategies to how grid network supply power to BEVs. With a summary of all charging settings, we further define BEV feasibility and explain how it is different from the BEV market acceptance studied in previous literature.

2.1 Activity-Travel Pattern Sequence

An activity-travel pattern is a complex output of activity-travel decisions that contains the following information: activity decisions (e.g. activity type, durations, etc.), travel decisions (e.g. travel times, mode, accompanying persons, distances, etc.), and interacting activity/travel decisions (e.g. departure time, activity start times, locations, etc.).

We use a uni-dimensional activity-travel sequence as the basic representation of the data. We include ‘Home’, ‘Work’, ‘Shopping’, ‘Leisure’, ‘School’, ‘Personal Business’ and ‘Other’ as the activity types, and the time spent on traveling would be ‘Trip’ activity type. These activity types are identified based on the trip purposes from data, and abbreviated as H, W, S, L, C, P, O, and T, which serve as elements in the activity-travel pattern sequence array.

Since we have daily travel data as well as trip purposes for each person, we know the activity type and the time it happened. Each time slot of 6 min is labeled with one of the eight defined activity types. Thus, we achieve a daily vector of activity-travel pattern with 240 elements of activity types. Since activity types and participation duration include information on potential charging opportunities and times, ‘Trips’, as well as their durations, are used to infer travel distance that is critical for battery status.

2.2 State of charge definition

The state of charge (SOC) is the equivalent of a fuel gauge for the battery pack in a BEV, which we consider as the remaining battery level in a BEV for one person in this work.

We denote the SOC of a person i at time t as $\mathrm{SOC}^i(t)$. For a BEV with range R during traveling activity, we assume the activity starting time is t_1, ending time is t_2 and the total trip distance is d. We have the following SOC relationship for BEVs during traveling activities.

$$\text{Traveling:}\quad \mathrm{SOC}^i(t) = \mathrm{SOC}^i(t_1) - \frac{t-t_1}{t_2-t_1}d,\ t \in [t_1, t_2] \tag{1}$$

On the other hand, BEV can stop and charge after traveling. Given charging rate as C, we have the following SOC relationship for BEVs during charging activities.

$$\text{Charging:}\quad \mathrm{SOC}^i(t) = \min(\mathrm{SOC}^i(t_1) + C(t-t_1), R),\ t \in [t_1, t_2] \tag{2}$$

According to this definition, BEV will stop charging at the end of an activity and the maximum charging time will be $t_2 - t_1$, if the capacity is not reached. On the other hand, if the capacity is reached at the time of t before the activity ends, $SOC^i(t)$ will remain at the level of full range since R will be smaller than $SOC^i(t_1) + C(t - t_1)$. For idle BEVs that are not charging, we can simply apply $C = 0$. In reality, SOC level should always be positive for BEVs to operate, and estimated SOC level below zero during a trip indicating that this travel activity cannot be finished under current charging scenarios. In this work, we allow negative SOC level so that we can observe the amount of time as well as the number of trips in a day that a person can be served by a BEV with positive SOC level, which is important information to estimate users' preferences for BEVs.

2.3 Sampling method

Suppose we have single-day activity-travel pattern sequence data for N persons as $P_{\text{single-day}} = [S_1, S_2, ..., S_N]$. We calculate the variability $v_{n,n'} = L(S_n, S_{n'})$ between all possible pairs of activity-travel pattern sequences S_n and $S_{n'}$; thus generate the $N \times N$ variability matrix V. Then, this variability matrix V is the input as the cost matrix for K-medoids algorithm for the clustering of all activity-travel patterns. We can also choose initial points manually by the major activity type to provide more accurate clustering results. Major activity type would be the type of activity that a person spends the most time outside the home. Thus, we can divide all activity-travel pattern vector S_i into K different clusters, obtaining a K-clustered result matrix C. Since we only have one day data ($M = 1$), our cluster result matrix $C = (c_{n,1} : n = 1, ..., N)$ is actually a vector. Thus, when we have $c_{n,1} = k$, we know the activity sequence S_n falls into the k-th cluster.

We can then generate a $K \times K$ transition probability matrix Ψ with the given defined method based on the activity-travel pattern clustering result K from multi-day activity-travel pattern data. We will only include transition counts from the same person, and take a summation of counted values from the whole population.

With the cumulative distribution of MIV for cluster k, we can randomly generate the intrapersonal variability MIV(n) for each person n by the inverse of the cumulative distribution function (cdf). We only need to generate $M - 1$ days of activity-travel pattern $\widetilde{S}_{n,m}, m = 2, 3, ..., M$, since we can use the original single-day data as the first-day data in our M-day sample. Thus, we can construct an M-day sample $\widetilde{S}_{n,m}, m = 1, 2, 3, ..., M$ for each person $n = 1, 2, ..., N$. Since we have the clustering results $c_{n,1}$ for $\widetilde{S}_{n,1}$, we can generate all $c_{n,m}, m = 2, ..., M$ based on the transition probability Ψ and the former day's clustering result $c_{n,m-1}$ for the same person. With the clustering results $c_{n,m}$ for the multi-day sample and intrapersonal variability MIV(n) for a person n, we can generate a sample pool from original data. Only activity-travel patterns that fall in the $c_{n,m}$-th cluster with MIV smaller than MIV(n) are allowed in the sample pool. We can also set an additional distance limit based on the daily travel distance from original single-day data. We use $f(\cdot)$ and $g(\cdot)$ to evaluate the maximum distance and minimum distance allowed in the sample pool. Then, we can randomly choose a single-day activity-travel pattern as our sample $\widetilde{S}_{n,m}$ for the n-th person on the m-th day. After repeating this process for all people, we can convert an N-person-single-day dataset to an N-person-M-day dataset of multi-day activity-travel patterns.

We summarize the sampling method as follows.

Step 1. Preprocessing of raw data to get single-day activity-travel pattern sequences of all persons.

Step 2. Use K-medoids algorithm to cluster the activity-travel patterns, taking Levenshtein distance matrix as input cost. Initial points could be chosen manually based on major activity type.

Step 3. Determine multi-day cluster results based on estimated transition probability as well as the original single-day cluster result for each person.

Step 4. Determine MIV for each person based on a single-day data clustering result as well as the corresponding MIV cdf or PIV cdf depending on the available data.

Step 5. Determine the sample pool for each person on each day based on the given MIV, clustering results and corresponding MIV cdf.

Step 6. Additional limits could be applied to activity-travel patterns in the sample pool based on the original single-day travel distance and constraint function of $f(\cdot)$ and $g(\cdot)$ for the maximum and minimum travel distance, respectively.

Step 7. Randomly choose a single-day activity-travel pattern for each person on each day until our multi-day dataset is fully constructed.

We also define a *single-day trivial method* that duplicates single-day's travel activities for multi-days to generate multi-day data. Thus, people's trips will always be the same on each day. More details can be referred to the work of Zhang et al. (2018).

2.4 Scenario definitions

In this work, we define various scenarios to compare people's preferences for BEVs under different charging/battery conditions, including the fastest DC level 3 charging in the current market. Our definition of scenarios is based on multiple aspects including BEV range, charging speed and cost as well as BEV user's charging behaviors and strategies, considering both the specifications of current BEVs on the market as well as facts from previous literature. The details are discussed in the following sections.

2.4.1 BEV range & charging level assumptions

BEV range is the maximum distance that a BEV can travel with full battery without charging, and we include three scenarios to consider the battery capacity of different BEV models in the current market. Some BEV models that can charge on level 3 chargers are listed in the following Table 1 (EVgo, 2019). Given the list of current BEVs on the market in Table 1, we define three different ranges covering most BEVs, and these ranges will be considered in our scenarios:

- 100 miles, 200 miles and 300 miles

Table 1: BEVs with level 3 charging availability in the market

BEV Models	**Range**	**Battery**	**Estimated Charging Time**
BMW i3	126 mi	42.2 kWh 352 V	7h (220V), 0.7h (440V)
Chevy Bolt	238 mi	60 kWh 350 V	9.3h (220V)
Chevy Spark	82 mi	19 kWh 400 V	20h (110V), 7h (220V)
Nissan LEAF	151 mi	40 kWh	35h (110V), 8h (220V), 0.75h (440V)
Ford Focus Electric	100 mi	33.5 kWh	20h (110V), 3.5h (220V), 0.5h (440V)
Hyundai Ioniq	124 mi	28 kWh 360 V	24h (110V), 4h (220V), 0.5h (440V)
Karma Revera	50 mi	20.8 kWh 347 V	10h (110V), 3h (220V), 0.42h (440V)
Kia Soul	111 mi	30 kWh 375 V	33h (110V), 5h (220V), 0.38h (440V)
Mitsubishi i-MiEV	62 mi	16 kWh 330 V	14h (110V), 7h (220V), 0.5h (440V)
Tesla Model S	285 mi	100 kWh 350 V	96.7h (110V), 10.72h (220V), 1.33h (440V)
Tesla X	250 mi	100 kWh 350 V	89h (110V), 10.72h (220V), 1.33h (440V)
Toyota Rav4	113 mi	41.8 kWh 386 V	44h (110V), 5h (220V)
Volkswagen e-Golf	125 mi	35.8 kWh 323 V	26h (110V), 3.7h (220V), 0.5h (440V)

In the US chargers are classified into different levels based on the charging power and speed (Hardman et al., 2018). Level 1 chargers are usually around 110V with the power of 1-3kW and are used for overnight home charging. Level 2 chargers are around 208-240V with power up to 43.5kW, and often installed at home, work or public places. DC level 3 chargers have the fastest charging time with much higher power demands (currently 50-150kW) and costs. Traut et al. (2013) mentioned that approximately 22% of all vehicles were parked close enough to an outlet sufficient to recharge overnight. However, multiple questionnaire survey studies have shown that home charging availability is the most influential factor in encouraging people to purchase PEVs (Bailey and Axsen, 2015; Dunckley and Tal, 2016; Hardman et al., 2018). Given the market share of electric vehicles in the US is only around 2%, it reasonable to assume most BEV owners have access to home charging facilities (Kane, 2018). There are multiple pieces of literature mentioned that around 50% to 80% of the charging events occurred at home (Franke and Krems, 2013; Hardman et al., 2018; Hu et al., 2019). We assume that home charging is available to all BEV users as level 1 or 2 charging facilities in this work. People tend to use level 2 chargers at the end of a trip or the beginning of activities given longer charging time. Although there are also level 3 chargers installed in public places in addition to corridors, people tend to use level 3 chargers during longer trips like interstate travels as a means to fulfill travel needs given less charging time and higher charging cost (Karner et al., 2016). Thus, we apply the following different charging levels for our scenarios, considering both charging infrastructure specifications as well as users' charging preferences. Here, we assume that public locations include shopping, school, and leisure where level 2 charging is available. In other words, level 2 charging infrastructures are not available in activity locations of 'Other' and 'Private business.' Comparing to other public places, locations of these activities are highly flexible and it is less likely for people to have access to level 2 charging opportunities during those activities.

Table 2: Charging level assumptions

Charging Level	Typical location	Power (kWh)	Hours to charge 100 mi	Charge rate (mi/h)
Level 1	Home	1.2	25	4
Level 2	Home, Work, Public	7.5	4	25
Level 3	Corridor	50	0.6	166.67

2.4.2 Charging cost assumptions

In this work, we focus on studying the charging cost of level 1 and level 2 charging events to explore the interactions between charging behaviors and charging costs. We do not involve the discussion of level 3 charging costs in this work since level 3 charging events are quite different from level 1 and level 2 charging events. Level 3 charging is usually necessary for people to finish trips even if they are much more expensive, and people can be more flexible while making charging decisions at level 1 or 2 charging locations. Thus, the interaction between level 3 charging events and charging behaviors should be discussed separately.

The cost of a charging event can be calculated based on the following equation:

$$c = P \times t \times r + c' \tag{3}$$

Here, we use c to denote the actual cost in a charging event; P to denote the power of various levels of chargers; t to denote the actual charging time; r to denote electricity pricing rate and c' to denote other miscellaneous expenses. We assume multiple pricing rates for electricity are considered for different scenarios, including flat rate and time-of-use (TOU) rate. Electricity price will not vary by time at the flat rate while price depends on time at the TOU rate. We assume the electricity price at home in flat rate is \$0.13 per kWh while TOU rate is \$0.13/kWh from 12am to 4PM, 9PM to 12AM; \$0.38/kWh from 4pm to 9pm according to a special plan for BEV users in California (Edison, 2019). Workplace charging cost is estimated at \$ 1.25/hour under level 2 charging according to Williams and DeShazo (2014)'s work, and this is equivalent to \$0.17/kWh as pricing rate (defined as higher work rate). Miscellaneous expenses may include other charging costs in addition to electricity costs. Users may need to pay a one-time service fee or a monthly membership fee to get access to public chargers, and the charging service cost is usually assumed as \$5 per charge (Francfort, 2015; Hu et al., 2019). For other activities, we assume that there are not miscellaneous expenses.

We assume home charging can only be flat rate or TOU rate without miscellaneous expenses; work charging can be free, flat rate or TOU rate without miscellaneous expenses; public charging can be flat rate or TOU rate with/without miscellaneous expenses.

2.4.3 User charging strategies and pricing behaviors

In this work, we assume that BEV users can use level 1 or 2 charging at home during night time, and have access to other level 2 charging opportunities at workplaces, shopping places, etc (Hardman et al., 2018). Philipsen et al. (2016) mentioned that gas stations were highly preferred as locations for fast-charging infrastructure by both users and non-user of electric vehicles, and it is likely that BEV users may stop and charge in the middle of a long trip. For level 3 charging, we assume BEV users may stop and perform level 3 charging with additional time during longer trips. People can stop and charge multiple times during long trips, as Sun et al. (2016) mentioned there exists an increase in the proportion of stays for fast-charging when the trip duration is longer than one hour. However it is less likely for BEVs to charge frequently before battery runs out, we assume 1.5-hour, which is approximately 100 miles in travel distance on highways with a speed limit of 65 mph, is the minimum time a BEV will travel before it needs another charge since highway speed limit can be higher than 65 mph. Given the fact that level 3 charging time is not considered in our current dataset, we simply assume that level 3 charging events will be inserted as an additional 30-min travel activity without affecting the total travel time of long-distance trips. This is a less realistic assumption, but people usually take breaks in service areas on highways in the middle of a long trip of hours, and these breaks may not be reported in travel activity surveys. Considering the breaking time, we believe this assumption will not greatly affect our current study results, and we will investigate the rationality of this assumption later if related data is available.

According to Franke and Krems (2013)'s work, many users charged their BEV even with substantial battery life remaining and some users charged at charge levels that were associated with battery warnings. Sun et al. (2018) also mentioned that people may charge immediately after arriving at home or charge at the cheapest time at home. Considering the psychological dynamics underlying sustainable BEV battery charging behavior, we believe different people may choose different charging strategies for different purposes. Some people may charge immediately at available charging opportunities regardless of remaining SOC level, while some people only charge when there is not sufficient battery to finish their trips.

Based on the former assumptions, we define the following two different charging strategies to describe whether users stop and charge at an activity location as well as how long they want to charge during each stop.

Maximum SOC strategy Immediate charging for as much as one can at level 1 or level 2 stations; Level 3 charging during a trip when SOC level lower than 5%.

Minimum cost strategy Optimal charging based on trip planning to minimize cost while keeping SOC level higher than 5%; when it is impossible to keep SOC level higher than 5%, users will tend to keep higher (maybe negative) SOC level as much as possible.

Here, we make a less realistic assumption that users tend to keep a higher SOC level as much as possible when the trip can not be satisfied by the current BEV range and may instead be covered by other means of transportations. Additional trips may be satisfied by BEVs with longer range and we want to consider that since we have multiple BEV range scenarios.

Charging decisions are trivial in maximum SOC strategy since BEV users will always charge immediately at available stations. BEV users' decisions can be much more complicated in the real world, since there are other factors, including charging cost, can affect their charging behaviors. Thus, we define BEV users' minimum cost strategy as an optimization problem trying to minimize the total charging cost while satisfying travel demands. We define a binary variable x_{ij}, where $x_{ij} = 1$ denotes charging event of type i happens during the j-th time interval (or time interval j); otherwise $x_{ij} = 0$. Given this definition, we can use a linear variable t_{ij} to denote the amount of time the BEV is actively charging in time interval i.

Given these variables, charging decisions for a BEV user in multiple days can be obtained based on the following mathematical formulation:

$$\min \sum_{i \in Q,\ j \in T} r_i P_i t_{ij} + \sum_{i \in Q,\ j \in T} c_i' x_{ij} \tag{4}$$

subject to:

$$x_{ij} = 0 \qquad \forall (i,j) \notin \hat{Q} \tag{5}$$

$$\sum_{i \in P} x_{ij} \leq 1 \qquad \forall j \in T \tag{6}$$

$$t_{ij} \leq \tau_j x_{ij} \qquad \forall i \in P,\ j \in T \tag{7}$$

$$\lambda_j^s + \sum_{i \in P, k \leq j} r_i t_{ik} \leq R \qquad \forall j \in T \tag{8}$$

$$\lambda_j^e + \sum_{i \in P, k \leq j} r_i t_{ik} \geq \lambda^l \qquad \forall j \in T \tag{9}$$

In objective function (4), we use Q to denote the set of all activity types, T to denote all activity time intervals for this person and P_i to denote the charging power at locations of activity type i. Thus, the total cost of charging, including electricity cost $r_i P_i t_{ij}$ and miscellaneous cost $c_i' x_{ij}$ including public charging fixed cost as well as non-charging penalty cost, is minimized for this person as the objective. In constraint (5), we ensure that BEV user may only charge at locations of activity type i during time interval j when type i events happen within time interval j, and we use $\hat{Q}$ to denote the set containing all pairs of (i, j) where the person has activity type i during time interval j. Constraint (6) ensures that BEV users can charge at only one activity location, or otherwise do not charge, within each time interval. Given τ_j denoting the length or maximum charging time in time interval j, constraint (7) ensures that BEV user will charge at the correct activity location of type i during time interval j. Then, we use λ_j^s and λ_j^e to denote the starting and ending SOC level during time interval j, and we assume λ^l is the lowest SOC level that BEV user can accept before recharging. Note that based on our former assumptions, we have $\lambda^l = 0.05R$ as 5% of BEV range R. Based on these notations, constraint (8) ensures that charging will not exceed range limit, and constraint (9) ensures that BEV users will charge before they run out of battery.

However, the above problem may be infeasible when the travel demand of a given person can not be satisfied by BEV with SOC level greater than λ. According to our minimum cost charging assumption, BEV users will try to keep sufficient SOC level, and they have no choice but keep charging in this case where some trips can not be satisfied. Thus, we modify the problem by replacing constraint (9) as follows, and optimize by maximizing the lowest SOC level λ^-. Different from constant value of λ^l in original formulation, λ^- is a linear variable less than BEV range R.

$$\lambda_j^e + \sum_{i \in Q, k \leq j} r_i t_{ik} \geq \rho \qquad \forall j \in T \tag{10}$$

People's charging behaviors are complicated as electricity pricing will affect people's willingness to charge. Xiong et al. (2016) proposed a practical solution to leverage charging price considering travel cost as well as queuing cost, and adjust BEV users' charging behavior so that the efficiency of charging networks can be improved. Their work involved a game-theoretic perspective constructing the problem on a non-atomic congestion game played by BEV users, and Nash equilibrium was adopted as the solution concept. A more recent work from Sun et al. (2018) explored choice behaviors of 24-km-range PHEV users after arriving at home under a dynamic electricity pricing scheme. Multiple charging strategies are presented with mixed logit models, and results suggested that electricity prices significantly affect choices to charge at the cheapest time for all users in addition to driving distance.

In this work, we consider two different types of user behaviors related to the effect of pricing:

Cost sensitive Users tend to minimize the cost of charging with minimum cost strategy

Cost insensitive Users tend to maximize the utilization of charging opportunities with maximum SOC strategy

Here, we assume that there may be both types of people among all BEV users, and we set a ratio of $\rho_\mathrm{c} \in [0, 1]$ as the proportion of cost insensitive population. Higher ρ_c values indicating that more BEV users are sensitive to charging cost, and they tend to apply min-cost charging strategies to control travel costs during daily activities. While an inelastic charging demand case under the cost insensitive behavior seems reasonable by a non-sophisticated BEV driver with probably higher income, some people may argue that cost sensitive behavior can be less common for travelers since it may be time-expensive and requires planing ahead. First, it is common for people to avoid refueling their vehicles in downtown areas before a trip to suburban areas since they know gas prices are usually lower there, and the fact reveals the cost sensitive behaviors of travelers. In addition, the planning itself may not be time-expensive since there may be smartphone apps (many apps including google map can show gas prices now) to help people check real-time charging times and it will be easier for people to find a charging station that is relatively cheaper in a specific area before they run out of battery.

2.4.4 Grid charging strategies

Different from the above users' charging strategies, we also define multiple *grid energy management strategies* or *grid charging strategies* to describe grid energy management or how grid network supply power to BEVs that need to be charged during the planned time interval. BEV users' charging strategies describe how user's charge BEVs during five-day period, identifying the amount of time t_{ij} they want to spend on charging at location of activity i within a time interval j. Grid charging strategies describe how chargers supply power to BEVs within each time interval, identifying the power supply distribution along time so that enough power is provided within given time. For example, BEV user may decide to charge from 1:00PM to 3:00PM while BEV can be fully charged within 1 hour. Then, grid energy management helps to decide whether power is supplied from 1:00PM to 2:00PM or from 2:00PM to 3:00PM.

We use *actual charging time* to denote the amount of time that power is supplied from a grid network and the SOC level is increasing before reaching full battery since power supply distribution can vary depending on the actual charging time. In this work, we estimated the grid network supply in the same activity locations as integer or real number of chargers working with full or fractional power. For example, 0.5 work chargers with a charging power of 25 mi/h during an hour is equivalent to a total charged SOC of 12.5mi in the same time, and the actual charging time is 0.5 hours. Based on these assumptions, we define four different gird charging strategies and summarize as follows.

Immediate charging (IC) Power is supplied as soon as BEV is connected to the charger; Numbers of chargers are integers.

Optimal charging (OC) Power supply within each charging time interval of all BEVs is arranged optimally to minimize the number of chargers in use at the same time; Number of chargers are integers.

Fractional average charging (FIC) Actual charging time is the same as activity time; Numbers of chargers needed are estimated in average as a fractional value.

Fractional optimal charging (FOC) Power supply within each charging time interval of all BEVs is arranged optimally to minimize the number of chargers in use at the same time; Number of chargers needed is estimated in average as a fractional value.

For average charging, we estimate the average number of chargers people use during different activities based on the fractional actual charging time. Suppose a person has activity time interval $[s, u]$ and actual charging time τ, the average number of chargers used for this person in average charging is $\frac{\tau}{u-s}$ during the whole activity. We sum the average number of chargers used at the same time for each person to obtain the total number of people charging at the same time.

For immediate charging, we assume that charging starts as soon as BEV users' activity begins and charging ends when BEV battery is full. Suppose a person have activity time interval $[s, u]$ and actual charging time τ, the number of chargers used for this person in maximum SOC strategy is 1 during time interval $[s, s+\tau]$ and 0 during time interval $[s+\tau, u]$.

For optimal charging, we assume that the actual charging time can be optimally scheduled for every person so that the total number of chargers needed at the same time is minimized. Sundstrom and Binding (2011) noted that grid network operators, retailer and charging service providers could be a single entity and share the same objective of minimizing the cost of energy for the charging service providers. In that case, attractive products can be provided to BEV owners, and charging service providers need to interact with the grid network operators by following the peak hour power supply penalty and optimizing their charging infrastructure network. Thus, we set our goal in this optimization problem is to minimize the largest number of chargers since it should help reduce peak hour power usage, even though multiple stakeholders with different objectives are involved.

We count the total number of chargers at the same activity locations during the same time to estimate the total power supply needed in the local area. Approximately, we consider the SOC level of each 20-min time interval instead of continuous-time during a 5-day-period to simplify the problem. Based on the current assumptions, we have 360 time intervals and we can find the minimum value of the maximum number of chargers in use among the whole population in different scenarios based on the optimization problem formulated mathematically.

We use the following integer programming problem to find the minimum value of the maximum number of chargers in use while the actual charging time is optimally scheduled for the same activity type q in *Optimal charging* scenario.

$$\min y^q \tag{11}$$

subject to:

$$\sum_{j=s_k^q}^{u_k^q} x_{ij}^q = \tau_k^q \qquad \forall (k,i) \in \hat{K}, i \in M \tag{12}$$

$$\sum_{i=1}^{|M|} x_{ij}^q \leq y^q \qquad \forall j \in N \tag{13}$$

$$x_{ij}^q \in \{0,1\} \qquad \forall i \in N, t \in T \tag{14}$$

$$y^q \in \mathbb{Z}^+ \tag{15}$$

where $\mathbb{Z}^+$ denotes the set of non-negative integers. We want to minimize the number of people charging (or chargers in use) within each 20-min time interval for the same activity type in the objective function. We use a binary variable of $x_{ij}^q = 1$ to denote that a person i is charging during time interval j with activity type q, and we use an integer variable y^q to denote the maximum number of people charging at the same time with activity type q. Here, we have different activity types of home, work, shopping, school, and leisure, and we count the total number of chargers needed separately for different activity types. We use N to denote the set of time intervals and M to denote the set of all people. We assume that an activity k with activity type q starts at time s_k^q

Table 3: Charging settings

Type	**Property**	**Values**
Infrastructure	Home	None; Level 1; Level 2
	Public	None; Level 2
	Long distance trip	None; Level 3
Vehicle	Starting SOC level	Fixed; Random
	Ranges (miles)	100; 200; 300
Charging strategies	BEV users	Max SOC; Min cost
	Grid network	IC; OC; FIC; FOC

and ends at time u_k^q, and the actual charging time during this activity is τ_k^q. We use $\hat{K}$ to denote the set of pairs (k, i) where activity k belongs to person i. Thus, constraint (12) ensures that a person gets enough charging time during an activity and constraint (13) ensures that the total number of people charging at the same time does not exceed the limit.

For *fractional optimal charging*, we can modify the model so that the chargers may work at lower power and it can be formulated as a linear problem with the same objective and constraints (11) to (13). Instead of a binary variable, we define a linear variable $x_{ij}^q \in [0, 1]$ as the fractional power of the charger that a person i is charging during time interval j with activity type q. Similarly, we also relax y^q as a linear variable to denote the average number of people charging at the same time with activity type q.

Although the number of operating chargers in fractional average charging and immediate charging scenarios can be easily calculated according to the given equation, we can also replace constraints in the optimal charging model so that all scenarios are compared in the same discrete time unit. We can replace (12) by the following constraint (16) to model *fractional average charging* scenario.

$$x_{ij}^q = \frac{\tau_k^q}{u_k^q - s_k^q} \qquad \forall (k, i) \in \hat{K}, i \in M, j \in [s_k^q, u_k^q] \tag{16}$$

Note that x_{ij}^q andy^q are linear variables in fractional average charging scenario. For *immediate charging* scenarios, we can add the following constraint (17) to ensure travelers keep charging as soon as possible until battery is full.

$$x_{i,j}^q - x_{i,j+1}^q \geq 0 \qquad \forall (k, i) \in \hat{K}, i \in M, j \in [s_k^q, u_k^q] \tag{17}$$

This constraint ensures that travelers can only charge from the beginning of the activity.

2.4.5 Summary of charging settings

We summarize the charging settings in our assumptions in Table 3. Based on the charging settings of infrastructure, we can define the following charging availability scenarios in Table 4. We use H_1

Table 4: Scenario descriptions

Available locations	**Scenario name**	**Details**
Home only	$S(H_1)$	Home Lv1
	$S(H_2)$	Home Lv2
	$S(H_2, T_3)$	Home Lv2, Trip Lv3
Work only	$S(W_2)$	Work Lv2
Shop only	$S(S_2)$	Shop Lv2
School only	$S(C_2)$	School Lv2
Leisure only	$S(L_2)$	Leisure Lv2
Home & Work	$S(H_2, W_2)$	Home Lv2, Work Lv2
	$S(H_2, W_2, T_3)$	Home Lv2, Work Lv2, Trip Lv3
Home & Public	$S(H_1, A_2)$	Home Lv1, Activity Lv2
	$S(H_2, A_2)$	Home Lv2, Activity Lv2
	$S(H_1, A_2, T_3)$	Home Lv1, Activity Lv2, Trip Lv3
	$S(H_2, A_2, T_3)$	Home Lv2, Activity Lv2, Trip Lv3
No home or public	$S(Nc)$	No home or activity charging
	$S(Nc, T_3)$	Trip Lv3

to denote level 1 home charging and H_2 to denote level 2 home charging, and similar assumptions are applied in other cases. We use A_2 to denote level 2 charging available in locations of all activities including work as well as public activities (shop, school, and leisure). We use T_3 to denote level 3 charging can be inserted during the trips, and other charging opportunities may be also available depending on scenario definitions.

We also include the following other minor assumptions to define our scenarios:

1. The starting battery level of each vehicle is random (from 0 to full battery) or half of the full battery, depending on different assumptions in charging scenarios.

2. People are divided into groups of low MIV ($\leq$ 20 percentile), medium MIV and high MIV ($\geq$ 80 percentile).

Our current charging scenarios set up should involve multiple stakeholders, including BEV users, charging facility constructors, charging service providers, grid network operators. Some stakeholders may involve in multiple roles in the reality, and their objective may be complex. Deaton (2019) mentioned both government or policymakers and private firms are encouraged to build charging infrastructure for public or private usage in New York City, Iowa, and Austin. Thill (2019) also claimed that utilities, private developers, and business owners may all play a role in Illinois state's BEV infrastructure construction depending on facility location, and different incentives exist for different investors and equipment owners. Utilities like ComEd and Ameren may invest in charging infrastructure in different places than other companies like Tesla, whose equipment only works with its own cars.

Many stakeholders emphasize that charging infrastructure planning should incentivize efficient charging behaviors even different stakeholders have different objectives. ChargePoint argued for the ability to set charging prices for drivers to maximize effective utilization whether they own the equipment on the land or not (Thill, 2019). Bagdasarian (2018) revealed a demand charge fee, which usually occurs during peak hour power supplies, can be responsible for around 90 percent of a public charging station's monthly utility bill. Fast BEV charging service operators that regularly use spurts of electricity can have a conflict with electricity rate structures from grid networks that were designed to keep the flow of electrons on the grid steady. Since the high cost of electricity on charging service providers during peak hours from grid networks may easily be passed to travelers as a higher price, we believe the optimized charging infrastructure planning plays a key role in reducing peak-hour power usage and can be critical to all stakeholders including BEV users.

2.5 BEV feasibility assumptions

Many studies have focused on the potential impact on energy consumption, emissions profiles, and potential changes of operating PHEVs and BEVs (Axsen et al., 2011; Dong and Lin, 2012; Gonder et al., 2007; Kang and Recker, 2009; Zhang et al., 2011; Dong et al., 2014; Kang and Recker, 2014b; Khayati and Kang, 2015). There are also works using activity-travel patterns and their flexibility of modeling complex activity-travel decisions as inputs for refueling/recharging station siting studies (Dong et al., 2014; Jung et al., 2014; Kang and Recker, 2014a; Xi et al., 2013). In these works, scenario analysis assumed different charging availability and charging behaviors. These analyses generated temporal vehicle operations and charging profiles that served to understand the electricity demand and emissions. For PHEVs, studies showed the change in energy consumption and electricity charging demand does not alter the activity-travel patterns since PHEVs have no range limitation. When the same approach is applied for travel-range-limited BEVs, travel behavioral assumptions are made to deal with trips when battery is depleted. Dong et al. (2014) assumed that a traveler misses out on activities and travels if the battery is depleted. Kang and Recker (2014b) assumed that 1) delay occurs for the duration of time that is sufficient to make the next trip possible, or 2) travelers are willing to reschedule their intended activity-travel patterns within their scheduling flexibility. Khayati and Kang (2015) assumed that intra-household interactions of vehicle allocation and activity allocation occur to compensate for the limited range of BEVs as well as to utilize lower operating cost of BEVs.

Previous literature suggests that electric vehicle driving ranges, travel patterns, and charging placement are correlated and cost considerations need to be included in order to extract BEV adoption insights. Neubauer and Wood (2014) examined the sensitivity of BEV utility based on a simulation tool considering range anxiety and different charging infrastructure scenarios. Simple time-based availability is considered for chargers in different activity locations and arbitrarily selected decaying rate is used to demonstrate the impacts of fast-charging battery wear. Kontou et al. (2017)

focused on minimizing the societal cost of replacing gas-powered household passenger cars with BEVs centrally. They considered multiple aspects including operational costs of heterogeneous driving patterns' cars, the government investments for charging deployment and monetized environmental externalities or gasoline emission. Their results indicated that the time-frame for the socially optimal conversion of 80% of the sample vehicles can take 6 to 12 years. More recently, Björnsson et al. (2018) compared multiple objectives to find a fleet-optimized PHEV battery range under different techno-economic conditions, and drivers are assumed to choose PHEVs when these are economically beneficial given a driver's movement pattern. However, they assumed that the battery is recharged only and fully in every parking period of at least 10 hours, which is greatly different from our work.

However, we assume that travelers' scheduled activities are not affected by charging activities or vehicle battery status in this study. The properties of BEVs can affect travelers' behaviors and travelers are more likely to accept BEVs if their intended travel demand can be well satisfied. This interactive relationship may take place as the BEV market share grows over time, but we believe whether BEVs can serve travelers' original activities in the early stages is quite important. Thus, we focus on the problem of BEV adoption without considering travelers' major behavior changes, and all daily activities are required to be served as scheduled by BEVs.

Studies focusing on BEV market acceptance found that considering trip coverage, multi-vehicle households, long-distance trips as well as the cost of ownership (Pearre et al., 2011; Khan and Kockelman, 2012; Tamor et al., 2013; Tamor and Milačić, 2015). According to their findings, occasional very long trips greatly affect the acceptance of BEVs and most users may not be satisfied with a realistic BEV range of 100 miles without other convenient alternative transportation means. However, BEVs ranging of 60 miles could be accepted by nearly 90% of two-car households and cover one-third of all travels assuming 'BEV as a second-car' according to the study of Tamor and Milačić (2015). In that case, longer trips are covered by conventional vehicles or other means of transportation, and a large fraction of shorter daily trips can be satisfied by electric vehicles with modest range.

Motivated by this idea, we consider a similar concept of *BEV feasibility* in this study. People may have different attitudes and preferences towards longer non-habitual trips, either using BEV, conventional vehicle or other transportation means. Thus, different people may have different views on whether a BEV should help them finish the limited number of long-distance trips. However, people are less likely to consider buying a BEV if their shorter daily travel demand cannot be served. Thus, we assume that a BEV is feasible to a person if all or most of the daily habitual trips can be served regardless of long-distance trips. We consider these people as potential buyers of BEV since most of their short daily trips can be satisfied by a modest range. Note that these are only the potential buyers of BEV or an upper bound of the BEV market, and the actual acceptance of BEV will be less than the feasibility of BEV in the same area.

3 Scenario Analysis: Multi-Day Battery Electric Vehicle (BEV) Feasibility Assessment

The objective of this scenario analysis is to assess BEV feasibility of daily usage based on our generated multi-day data. Comparing the BEV feasibility results of daily habitual usage, we can extract insights on travelers' attitudes towards BEV range as well as charging opportunities and show that our sampling method is applicable in real-world applications. Given limitations in BEV range, an area with adequate charging opportunities may greatly improve the user experience of local travelers since they can recharge vehicles during activities. We develop various charging scenarios and analyze the maximum number of chargers needed to derive insights on charging infrastructure planning.

3.1 Data Description

We apply our models based on the household travel data from the 2010−2012 California Statewide Household Travel Survey provided by the California Department of Transportation (Kunzmann, 2013). The survey included much socio-economic information including trip travel time and activity duration time from 42,431 households from various counties and regions. We extracted the activity-travel patterns as well as travel distances based on the activity information provided by the dataset. We can easily define different clusters of activities according to the activity purpose given in the dataset. We have a total of 108,778 people in this single-day dataset. Among those people, we have 72,400 employed people with at least one trip each day, and we randomly choose 2000 of them as our sample data in order to shorten the computational time for generating multi-day sample data. Based on the chosen sample data, we generate a 5-day sample data with our sampling method with the assumption that all travel activities happen during weekdays.

3.2 BEV feasibility insights

Based on our range and charging opportunity scenarios, we show the number of people covered (among the whole population of 2000) in percentage value in the following Tables 5 and 6. We assume that if a person can finish all trips and the percentage of time with positive SOC level in five days is higher than a threshold, we say the person is covered (or feasible for BEV adoption). Here, we set the threshold values as 80%, 90% and 100%, assuming that a person needs to have at least 80%/90%/100% of time with positive SOC level to be considered feasible for BEV adoption.

Based on the results in Tables 5 and 6, we can see that starting SOC level has little effect on the estimation of BEV feasibility since the results of fixed starting level and random starting level are similar. Comparing to other charging locations, home charging is quite effective and helps most people to cover most trips even with low BEV range. As the range increases, the number of people with home charging that could be fully served (with 100% positive SOC level) will grow fast. In general, 90% of the trips of most people can be covered with either high range BEV or good charging infrastructures.

Table 5: Percentage of people covered with fixed starting SOC level

Coverage(%)	Range 100			Range 200			Range 300		
	80%	90%	100%	80%	90%	100%	80%	90%	100%
$S(Nc)$	10.8	5.9	0.2	39.5	29.6	6.0	62.7	55.1	22.4
$\boldsymbol{S(H_2)}$	95.9	90.2	64.5	97.4	94.9	86.0	98.1	96.4	90.6
$S(W_2)$	48.3	38.3	14.4	70.2	63.1	38.4	80.6	76.0	54.7
$S(S_2)$	25.3	17.7	2.3	51.2	42.8	14.0	70.0	63.9	33.3
$S(C_2)$	35.0	24.2	7.6	59.2	51.1	26.0	74.7	68.5	44.1
$S(L_2)$	47.6	38.9	13.0	69.9	64.2	36.2	84.2	79.9	57.9
$\boldsymbol{S(H_2, W_2)}$	96.4	90.9	67.8	98.1	95.3	86.9	98.3	96.9	90.8
$\boldsymbol{S(H_2, A_2)}$	98.3	95.1	76.5	98.8	97.1	90.2	98.9	98.2	92.8

Table 6: Percentage of people covered with random starting SOC level

Coverage(%)	Range 100			Range 200			Range 300		
	80%	90%	100%	80%	90%	100%	80%	90%	100%
$S(Nc)$	14.4	9.8	0.6	37.8	31.6	7.6	52.0	46.0	17.6
$\boldsymbol{S(H_2)}$	95.8	90.0	64.2	97.3	94.6	85.8	97.8	96.2	90.0
$S(W_2)$	48.0	38.6	14.2	65.2	58.0	33.0	75.0	70.2	47.7
$S(S_2)$	26.2	19.8	2.9	46.8	40.8	13.2	61.6	56.4	27.4
$S(C_2)$	34.2	25.6	7.8	55.8	48.2	24.2	65.8	60.4	36.6
$S(L_2)$	46.3	38.6	12.7	65.0	59.4	33.0	75.2	71.5	48.4
$\boldsymbol{S(H_2, W_2)}$	96.4	90.8	67.8	97.8	95.0	86.4	98.4	96.6	90.3
$\boldsymbol{S(H_2, A_2)}$	98.3	95.0	76.4	98.6	97.1	90.0	98.8	97.9	92.4

We also include the number of people covered (with 100% positive SOC level) with Level 1 chargers available at home in the following table 7. In table 7, we use $S(H_1, \cdot)$ to denote scenarios where level 1 home charging is used and $S(H_2, \cdot)$ to denote scenarios where level 2 home charging is used. Charging availability in various locations is listed in different columns, denoting various scenarios: home only, home and work locations, home and activity locations.

According to the table, the differences in the number of covered people between level 1 home charging scenario and level 2 home charging scenario are less significant regarding total coverage, especially when BEVs with higher ranges are available. We can conclude that most people may be well served by Level 1 home chargers and they have no need to upgrade their home chargers to level 2.

3.3 Compared with single-day data results

Based on the multi-day sample data, we can calculate the percentage of time when SOC level remains positive for each person i in 5 days, denoted as P^i_{multi}. For single-day sample data, we can calculate the percentage of time when SOC level remains positive for each person i in one

Table 7: Level 1/level 2 home charging comparison results

Scenario	Range 100			Range 300		
	Home	Home & Work	Home & Act	Home	Home & Work	Home & Act
$S(H_1, \cdot)$	966	1130	1410	1540	1638	1792
$S(H_2, \cdot)$	1284	1356	1528	1800	1806	1848
Difference	318	226	118	260	168	56
$S(H_1, \cdot, T_3)$	1418	1557	1728	1863	1889	1924
$S(H_2, \cdot, T_3)$	1580	1648	1759	1918	1918	1933
Difference	162	91	31	55	19	9

day, denoted as P^i_{single}. By comparing these two values, we can define the following three different comparison results for person i.

Same ($M \approx_i S$)**:** We say BEV feasibility comparison results are the *same* for person i if $|P^i_{\text{multi}} - P^i_{\text{single}}| \leq 5\%$, and we use $M \approx_i S$ to denote this comparison result.

Overestimation ($M \lesssim_i S$)**:** We say BEV feasibility estimation results are *overestimated* for person i if $P^i_{\text{single}} - P^i_{\text{multi}} > 5\%$, and we use $M \lesssim_i S$ to denote this comparison result.

Underestimation ($M \gtrsim_i S$)**:** We say BEV feasibility estimation results are *underestimated* for person i if $P^i_{\text{multi}} - P^i_{\text{single}} > 5\%$, and we use $M \gtrsim_i S$ to denote this comparison result.

Thus, estimation results can be calculated for each person i based on multi-day sample data and original single-day data, and we count the fraction of travelers that fall in the three comparison results as percentage value in Table 8. We assume that if multi-day sample data provides correct estimation results of BEV feasibility, then we use $M \approx S$ to denote the amount of correct estimations based on original single-day data; we use $M \lesssim S$ to denote the amount of people whose BEV feasibility is overestimated based on original single-day data; we use $M \gtrsim S$ to denote the amount of people whose BEV feasibility is underestimated based on original single-day data. In addition to our sampling method, we can easily generate multi-day data from single-day data by duplicate the travel activities of one day to all other days and we use *trivial sample* to refer to the sample data generated by this method. Similar assumptions are applied to achieve the comparison results of $M \approx T$, $M \lesssim T$ and $M \gtrsim T$ between multi-day sample data and trivial sample data, and the results are shown in Table 9.

According to the results in table 8, we can see significant overestimation in single-day BEV feasibility results, especially when charging opportunities and BEV range are limited. The error in BEV feasibility estimation can be reduced when we have more charging infrastructures and larger BEV range. Comparing with Table 9, the performance of the trivial sampling method is different from the performance of using original single-day data alone. An interesting observation is that the percentage of underestimations increase in trivial sample results, and the number of overestimations and underestimations are similar. We believe trivial method may provide a good

Table 8: Multi-day results vs Single-day results

MvsS(%)	Range 100			Range 200			Range 300		
	$M \approx S$	$M \gtrsim S$	$M \lesssim S$	$M \approx S$	$M \lesssim S$	$M \lesssim S$	$M \approx S$	$M \gtrsim S$	$M \lesssim S$
$S(H_2)$	84.35	6.25	9.40	92.70	3.25	4.05	94.45	2.55	3.00
$S(W_2)$	35.50	5.75	58.75	55.95	2.85	41.20	68.20	2.10	29.70
$S(S_2)$	17.05	0.75	82.20	37.35	0.35	62.30	53.05	0.45	46.50
$S(C_2)$	23.75	5.45	70.80	46.00	2.90	51.10	58.10	2.20	39.70
$S(L_2)$	35.20	4.55	60.25	56.55	2.90	40.55	68.75	2.05	29.20
$S(H_2, W_2)$	85.55	5.65	8.80	93.15	3.25	3.60	94.60	2.45	2.95
$S(H_2, A_2)$	90.90	3.55	5.55	94.95	2.15	2.90	96.50	1.55	1.95
$S(Nc)$	7.90	0.00	92.10	27.65	0.00	72.35	42.15	0.00	57.85

Table 9: Multi-day sample results vs Trivial sample results

MvsT(%)	Range 100			Range 200			Range 300		
	$M \approx T$	$M \gtrsim T$	$M \lesssim T$	$M \approx T$	$M \gtrsim T$	$M \lesssim T$	$M \approx T$	$M \gtrsim T$	$M \lesssim T$
$S(H_2)$	84.75	6.25	9.00	92.25	4.10	3.65	93.55	3.85	2.60
$S(W_2)$	35.90	29.95	34.15	47.20	25.30	27.50	57.50	21.75	20.75
$S(S_2)$	28.05	26.95	45.00	33.25	24.60	42.15	44.25	23.60	32.15
$S(C_2)$	29.40	31.05	39.55	38.65	30.55	30.80	46.35	26.30	27.35
$S(L_2)$	33.95	28.25	37.80	47.40	23.45	29.15	57.15	20.55	22.30
$S(H_2, W_2)$	85.65	6.05	8.30	93.05	3.70	3.25	94.20	3.25	2.55
$S(A_2)$	91.05	3.60	5.35	95.30	2.05	2.65	96.70	1.60	1.70
$S(Nc)$	23.55	27.50	48.95	26.95	27.60	45.45	33.50	27.35	39.15

bound for potential BEV market estimation, and we may focus on utilizing both multi-day samples as well as trivial samples to provide more reliable BEV feasibility assessment in future works. Multi-Day data is required while studying people's travel patterns since results based on single-day data will overestimate the BEV feasibility. Note that single-day data may work as well when we have good charging opportunities and BEV range since most people can be covered.

3.4 Level 3 charging insights

In this work, we assume that level 3 charging activities can be inserted during trip activities, and the charging time does not affect later activity schedules. People may stop and rest after hours of driving, and BEVs can be recharged. Given such assumptions, we show the number of trips with different length in hours under various charging scenarios in Table 10. We only include results based on scenarios $S(H_2, T_3)$, $S(H_2, W_2, T_3)$ and $S(Nc, T_3)$ since other scenarios (like $S(H_2, A_2, T_3)$) show similar observations. We also show the number of people inserting level 3 charging activities during their trips in the same table. Most of the trips last less than two hours, and only a few trips last longer than 3 hours. The results show that the number of trips with level 3 charging is similar to the number of people inserting level 3 charging activities, indicating that most people may only need level 3 charging in one of their daily trips.

Table 10: Trips with level 3 charging activities

Number of trips					
Trip duration	$\leq$2h	2h–3h	3h–4h	4h–5h	$\geq$5h
$S(H_2, T_3)$	219	179	50	42	65
$S(H_2, W_2, T_3)$	213	177	50	42	64
$S(Nc, T_3)$	534	272	69	54	94
Number of vehicles					
Trip duration	$\leq$2h	2h–3h	3h–4h	4h–5h	$\geq$5h
$S(H_2, T_3)$	202	142	46	41	63
$S(H_2, W_2, T_3)$	196	141	46	41	62
$S(Nc, T_3)$	395	227	63	52	89

Based on the assumption of level 3 charging activities, we analyze the number of people with negative SOC level under different level 2 charging scenarios (denoted as uncovered), the rate in percentage comparing to MIV group population as well as the number of level 3 charging activities inserted during trips. We list the number of people uncovered with level 2 charging only as well as the number of level 3 chargers they required during long-distance trips. We also show the origin and destination of the trips where level 3 charging activities are inserted. Note that we did not include scenarios of $S(H_2, W_2, T_3)$ and $S(H_2, A_2, T_3)$ since the results are similar to that of $S(H_2, T_3)$. The results are listed in the following Table 11.

In general, the uncovered rate for different MIV groups are similar, and higher MIV groups are slightly less covered in its group population comparing to lower MIV groups. With home charging, the major demand for level 3 charging would be leisure origin trips and home destination trips. Higher MIV people have higher demand in other activities, indicating their highly multi-purpose trips. However, home charging availability can still greatly reduce the need for level 3 charging events, even for a high MIV population that travel a lot.

3.5 Parking-based charging infrastructure planning

In this section, we study the demand as well as energy management in grid networks, and we evaluate the charging infrastructure needed in different activity locations based on the demand for power supply.

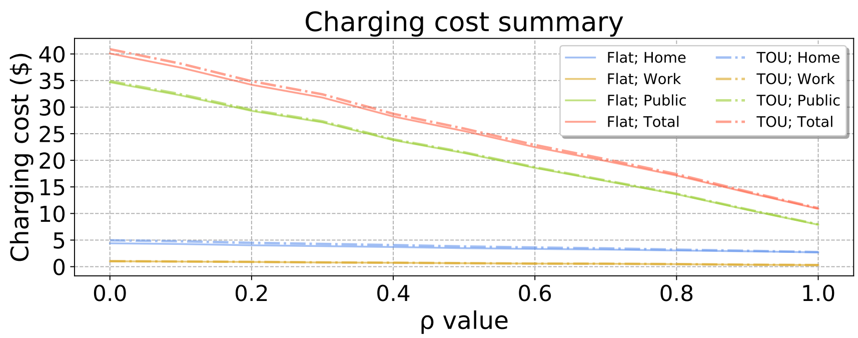
BEV charging demand is concerned to avoid heavy burden in the power grid, and this is critical in charging infrastructure planning. Multiple aspects including time-of-use rates as well as dynamic pricing can change travelers' charging behaviors and alter them to avoid peak charging demand, and charging when grid power costs are lower will help to increase the utilization of grid assets and to avoid investments in additional peak generation capacity, renewable energy generators or

Table 11: Number of charges at activity locations under various scenarios

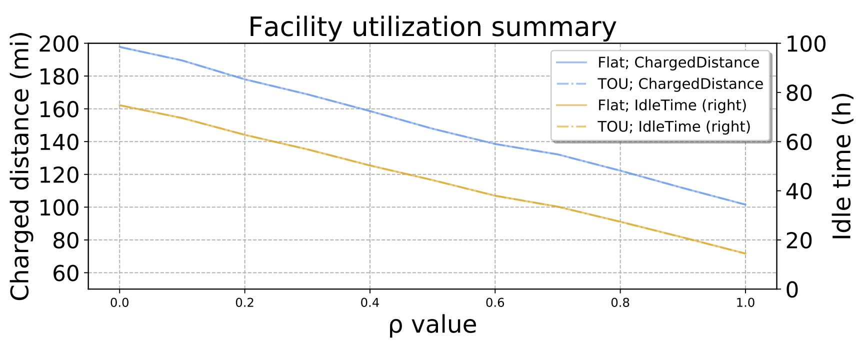
$S(H_2, T_3)$ with home charging only										
Origin	*Uncovered*	*Rate*	*Lv3 inserted*	H	W	S	C	L	O	P
Low MIV	180	44.1%	23	3	2	3	0	12	2	1
Med MIV	534	44.6%	173	40	7	4	0	61	46	15
High MIV	181	45.7%	234	71	4	6	8	53	73	19
Destination	*Uncovered*	*Rate*	*Lv3 inserted*	H	W	S	C	L	O	P
Low MIV	180	44.1%	23	18	1	1	0	2	0	1
Med MIV	534	44.6%	173	76	4	1	5	41	36	10
High MIV	181	45.7%	234	77	1	3	0	62	68	23
$S(Nc, T_3)$ with only level 3 charging										
Origin	*Uncovered*	*Rate*	*Lv3 inserted*	H	W	S	C	L	O	P
Low MIV	387	94.9%	112	42	23	6	3	24	10	4
Med MIV	1139	95.2%	830	264	82	30	21	209	177	47
High MIV	384	97.0%	773	257	32	27	19	141	251	46
Destination	*Uncovered*	*Rate*	*Lv3 inserted*	H	W	S	C	L	O	P
Low MIV	387	94.9%	112	53	6	20	0	20	9	4
Med MIV	1139	95.2%	830	305	40	27	29	173	207	49
High MIV	384	97.0%	773	229	20	34	9	205	221	55

distribution system upgrades (Fitzgerald et al., 2017). Thus, we include detailed scenarios of BEV users' travel behaviors and charging strategies as well as grid charging strategies to consider the contribution to the burden for a power grid so that we can derive charging infrastructure planning insights.

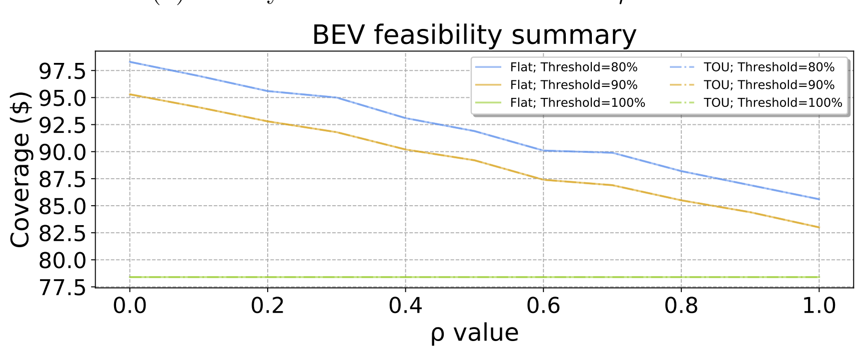
We have explored BEV feasibility based on whether their travel demand can be satisfied, as well as charging infrastructure utilization in different activity locations. However, the cost is also an important factor affecting people's decisions, and BEV user's travel cost is closely related to electricity price that is related to grid network demand. Electricity prices at home and public locations do not vary with time in *Flat* scenarios, while TOU rate is applied for home and public charging in *TOU* scenarios. Work charging rates are the same in both charging scenarios, and more details on pricing and rates can be referred to the previous section 2.4.2. In the following Figure 1, we show the results of average charging cost spent in different activity locations, the average amount of distance charged as well as average vehicle idle time and BEV feasibility for all users in five days. Here, idle time is defined as the amount of time a vehicle is parked but not charged during a charging event time interval. For example, a vehicle is charged from 2:00 PM to 4:00 PM and it reaches full battery at 3:00 PM, then we have idle time for this time interval as 1 hour. In Figure (1a), limited changes occur in home and work charging activities while public charging cost is greatly reduced if there are more cost-sensitive users in the group, probably due to the higher charging cost at public locations. We have a higher facility utilization rate when there are more cost-sensitive people in the population since average idle time is decreasing in Figure (1b), and there is less burden on the grid power supply since the charged distance also decreases. There is a decreasing trend in BEV feasibility as more people are cost-sensitive and are less willing to spend too much on charging in Figure (1c). In all figures, resemblances can be observed among Flat and TOU scenarios for charging cost, facility utilization, and BEV feasibility. From these results, we can conclude that travelers' cost-sensitive behaviors will have an impact on their charging decisions and BEV acceptance while the differences between the current flat pricing and TOU pricing are not enough to change travelers' behaviors.



(a) Charging cost based on various ρ values



(b) Facility utilization based on various ρ values



(c) BEV feasibility based on various ρ values

Figure 1: Overall system affects with different number of cost sensitive users in the population

To understand how the decreasing trend in BEV feasibility happens, we compare the charging cost and facility utilization between $\rho = 0$ and $\rho = 1$ with flat pricing for 3 different groups of users in the following Table 12. We use 'Flat, $\rho = 1$; Same' to denote the group of users whose SOC level coverage remains unchanged as ρ value varies. We use 'Flat, $\rho = 1$; ¡=20%' to denote the group of users whose SOC level coverage decreases within 20% when users become cost-sensitive, and 'Flat, $\rho = 1$; ¿20%' to denote the group of users whose SOC level coverage decreases for more than 20% similarly. The results from 'Flat, $\rho = 1$; Same' indicate that 1636 people have the same SOC level when they become cost-sensitive and the public charging cost will be decreased by 32.15 with a higher facility utilization rate since idle time is negative. Thus, we can conclude that as more people are cost-sensitive, there will be more efficient charging facility usage activities without affecting their daily travel activities for some people. On the other hand, the reason why we have users facing significant SOC level coverage decrease for more than 20% is that our current assumption is to maximize the lowest SOC level in objective (10) for minimum cost charging strategies. However, some people may have negative lowest SOC level and some trips can not be satisfied. In that case, the strategy will ignore the need for charging and maintain the SOC level around the minimum lowest negative SOC level, leading to a lower SOC coverage rate with a significantly decreased charging distance of 179.93. We believe the results are reasonable to reveal an expected charging facility usage since it is less likely for these users to buy a BEV when their trips can not be satisfied easily. The majority in this group may not use charging facilities since they will not own a BEV, so it is acceptable to have a lower estimated charging distance involved in grid power supply calculation.

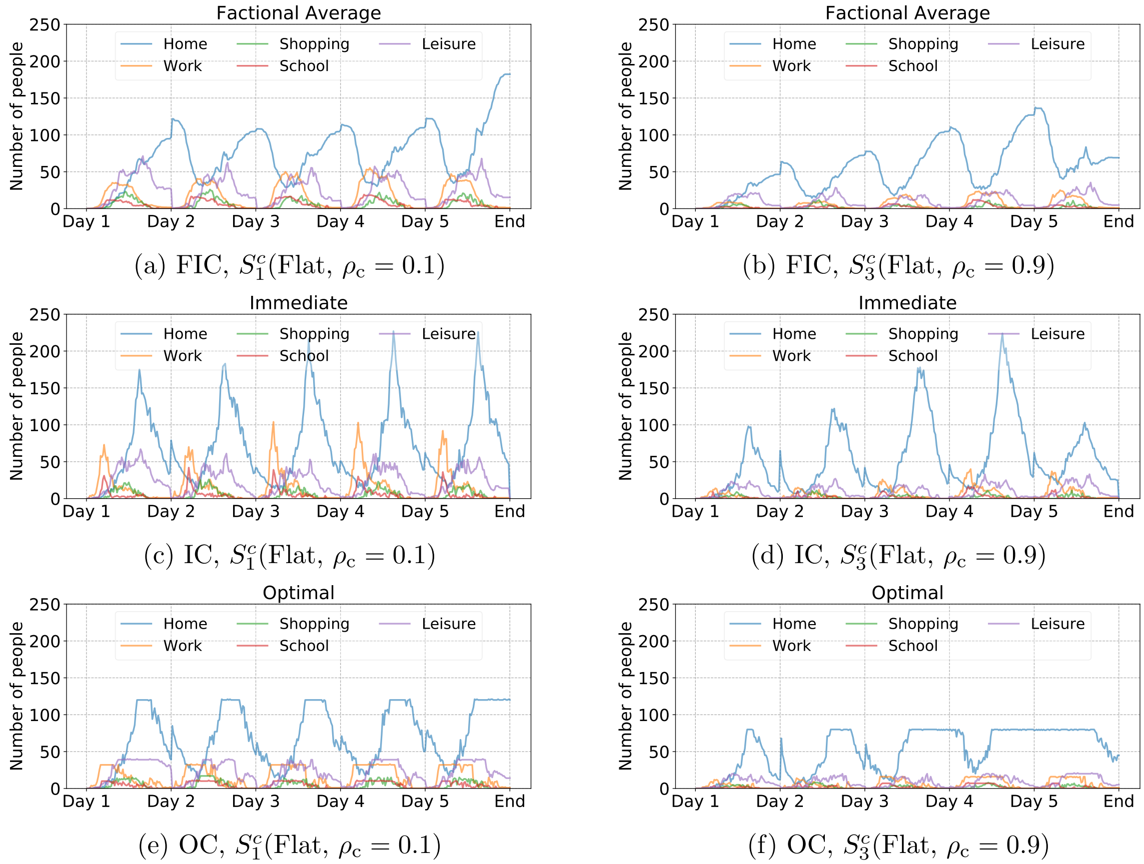
Table 12: Charging cost and facility utilization difference between $\rho = 0$ and $\rho = 1$

Scenario	**Pop.**	**H ($)**	**W ($)**	**P ($)**	**Total ($)**	**Dist. (mi)**	**Idle (h)**
Flat, $\rho = 1$; Same	1636	-0.93	-0.82	-32.15	-33.89	-84.18	-64.60
Flat, $\rho = 1$; $<= 20\%$	108	-1.42	-0.12	-22.14	-23.68	-80.17	-44.03
Flat, $\rho = 1$; $> 20\%$	256	-3.96	-0.20	-22.97	-27.12	-179.93	-39.59

Given these scenarios indicating BEV users' behaviors related to cost, we further consider the maximum number of chargers being used at the same time in different activity locations, hoping to provide guidelines for parking-based charging infrastructure planning. We visualize the total number of travelers charging, or the gird network demand, during different activities in multiple days in the following Figures 2.

We consider gird network charging strategies (IC, FIC, OC) as well as user charging behaviors S_1^c and S_3^c from Table 12 related to cost-sensitive population ratio and electricity cost rate. TOU scenarios are omitted since the results are similar to those under Flat scenarios. FOC results are also omitted due to its similarity to OC results. For each subgraph, the total number of travelers charging is shown in the y-axis while the time of day is shown on the x-axis.

In Figure (2a), we can observe a higher home charging demand at the end of the fifth day, which is obvious compared to the demand peak in the other four days. The reason is that usually BEV



(a) FIC, S_1^c(Flat, $\rho_c = 0.1$)

(b) FIC, S_3^c(Flat, $\rho_c = 0.9$)

(c) IC, S_1^c(Flat, $\rho_c = 0.1$)

(d) IC, S_3^c(Flat, $\rho_c = 0.9$)

(e) OC, S_1^c(Flat, $\rho_c = 0.1$)

(f) OC, S_3^c(Flat, $\rho_c = 0.9$)

Figure 2: Operating chargers (grid network demand) during different activities based on Scenario $S(H_2, A_2)$

users return to home at the end of each day, and have several hours of home charging in the next day. While we have no data after the fifth day, the average charging time at home is less than that in the other four days and the average number of chargers during this time increases since the amount of time to charge the same amount of battery decreases.

Comparing Figures (2a), (2c) and Figure (2e), we can see that the number of chargers needed under optimal grid strategy is much less than fractional average or immediate grid strategy. Average charging scenarios represent the theoretical charging efficiency during an activity since it indicates the actual power supply from the grid network within a unit time. Suppose we have two persons with 40 mins of actual charging time during a one-hour activity, the average number of chargers they needed is around 1.33; Either immediate charging or optimal charging will require at least 2 chargers to serve both people during the activity for at least 20 mins. In other words, some chargers may operate lower than the maximum load for a longer time to finish charging demand and the total power supply of all chargers may be reduced. Thus, these results of average charging represent the expectation of the electric grid power supply. With optimal scheduling of charging time or minimum cost strategies, we can see in Table 13 that the number of chargers needed under S_1^c drops from 227 to 121 for home chargers and significant decreases can be observed in other scenarios. This

S^c_1 **(Flat, $\rho_c = 0.1$)**					
Scenarios	FIC	IC	OC	FOC	IC/OC
Home	182.22	227	121	121.58	53.30%
Work	55.29	104	33	32.40	31.73%
Shopping	25.96	26	17	15.59	65.38%
School	19.09	42	11	11.27	26.19%
Leisure	71.35	67	40	39.69	59.70%
S^c_3 **(Flat, $\rho_c = 0.9$)**					
Scenarios	FIC	IC	OC	FOC	IC/OC
Home	137.29	224	80	80.14	35.71%
Work	25.09	40	16	15.69	40.00%
Shopping	11.90	11	8	7.56	72.73%
School	12.02	16	8	7.13	50.00%
Leisure	35.47	33	21	20.48	63.64%
S^c_4 **(TOU, $\rho_c = 0.9$)**					
Scenarios	FIC	IC	OC	FOC	IC/OC
Home	132.36	221	77	77.10	34.84%
Work	24.98	41	17	16.80	41.46%
Shopping	12.39	14	10	8.54	71.43%
School	12.40	17	8	8.10	47.06%
Leisure	36.12	34	22	22.48	64.71%

Table 13: Number of people charging (grid network demand) during different activities

indicates that charging can greatly improve the efficiency in utilizing charging infrastructures in addition to travelers' charging choices.

Comparing IC and FIC scenarios with OC scenarios, we can see that optimal strategy can always reduce the maximum number of chargers needed among the whole population regardless of the ratio of cost-sensitive users. In Figures (2b) and (2d), we can see the number of people using chargers has an increasing trend among 5 days for $\rho = 0.9$ scenarios since more people are cost-sensitive and they only charge when they need. Fewer people are charging in earlier days when they have enough battery to finish their trips leading to the fact that more people are charging in later days. The number of chargers needed under $\rho = 0.9$ scenarios is similar to that from $\rho = 0.1$ scenarios, and the results as 227 and 224 in Table 13. However, the minimum cost strategy can reduce the maximum number of chargers used to around 80 in both $\rho = 0.9$ scenarios and 121 in $\rho = 0.1$ scenario according to the findings in Table 13. Thus, even if BEV users have different charging behaviors as a react of pricing, a correct grid energy management strategy will still greatly help reduce the general grid network burden.

Besides, we summarize the maximum number of chargers needed as well as the average rate of operating chargers per traveler in different activity locations in the following Table 13. These results are based on the charging scenario $S(H_2, A_2)$ that level 2 charging is available in all activity locations, and the results are also similar when level 3 charging insertions are available. Note that the maximum number of chargers in use at home in FOC scenarios is slightly larger than that in OC scenarios while theoretically results from FOC should be the lower given fractional value is applied. This is because we are estimating the power supply with 20-min time intervals, and this leads to an inaccurate calculation in OC cases where less accurate results are present. However, we can observe the similarity between the results of OC and FOC scenarios even if inaccurate results exist, showing that an optimal charging strategy can help reduce power supply burdens in grid networks. We use the IC/OC rate in Table 13 to denote the utilization rate of the chargers in different activity locations as well as scenarios. According to the results, level 2 home, shopping and leisure chargers are more needed than chargers at work and school locations, since the charger utilization rate is higher. Considering that the miscellaneous expense in public charging leads to higher charging costs, this indicates that BEV users' travel demands need to be satisfied with the chargers in those locations. It is possible that people are willing to pay more and use chargers in those locations, and it may be more profitable to install chargers in shopping and leisure locations. On the other hand, we can observe a higher utilization rate in work and school locations as well as a lower number of chargers for $\rho = 0.9$ scenarios, indicating that more cost-sensitive people tend not to charge at those locations if SOC level is enough to satisfy travel demands. In general, we can observe the differences caused by BEV users' charging behavior differences, but the power supply burden in grid networks may still be resolved as long as energy management strategies are applied.

Besides, the charging strategies connecting travelers and electric grid network may be more complicated than the three scenarios that we have defined in this work. Daina et al. (2017) developed a random utility model to integrate BEV drivers' activity-travel scheduling and charging choices for energy systems analysis. As the market grows, we need to consider BEV users' charging behavior preferences as well as their response to charging strategies in power grid networks with more complicated assumptions.

4 Conclusion

In this paper, we apply a sampling method considering intrapersonal variability information to generate multi-day samples based on single-day travel data from Zhang et al. (2018), and developed various charging scenarios for BEV feasibility assessment. Different from previous studies, we focus on people's weekly habitual trips and aim to estimate the upper bound of the BEV market.

We design various charging scenarios considering properties of charging infrastructures and vehicles, allowing level 1 home charging, level 2 activity charging and level 3 trip charging. In addition, we consider interactions between BEV users' charging behaviors and gird charging strategies under different cost-sensitive population and pricing settings. Based on a California dataset, we conduct several scenario analysis trying to estimate travelers' feasibility to BEV under different conditions. According to numerical experiment results, the starting level of BEV has little impact on the estimation of BEV feasibility. For most people, 90% of the trips can be satisfied with either a high-range BEV or well-covered charging infrastructures. Results also indicate that a large number of people can be well served by level 1 home chargers, and less number of people require level 2 home chargers. We also compare the results based on multi-day sample data as well as based on original single-day data, showing that estimation error in BEV feasibility can be reduced after considering the potential intrapersonal information in single-day data. Home charging greatly reduces the need for level 3 charging even for people with high travel demands, and those demands usually come from leisure trips. Also, we consider multiple grid-charging strategies under different BEV user charging strategies and estimate the maximum number of chargers needed in different locations. Even overall BEV feasibility is decreasing when more people are cost-sensitive, grid network operators may choose optimal strategy to help most users improve facility utilization efficiency without affecting their daily travel charging demands. According to our experimental results, the number of required chargers can be greatly reduced if grid energy supply can be well scheduled, and this improvement is less dependent on BEV users' charging behaviors. Higher charger utilization rates in shopping and leisure locations are observed in all scenarios even if the miscellaneous expense in public charging will lead to higher charging costs. This fact indicates that BEV users' travel demands need to be satisfied with the chargers in those locations, and it is more recommended to install chargers in shopping and leisure locations.

Although insightful results related to BEV feasibility are derived based on multi-day sample data, there are several limitations in our work. The assumptions of level 3 charging activities are less realistic since we do not allow travelers to delay their activities. Although we consider a min-cost BEV user charging strategy, people may have more flexible travel options other than charging under low SOC level or whenever charging opportunities are available in maximum SOC strategy. For example, they may choose to include other means of transportation, which is also a reasonable assumption. Thus, building various charging profiles involving taxi options for different groups of people may increase the accuracy of BEV feasibility assessment. Currently, only a few longer non-habitual trips can be captured based on our applied sampling method. Although this method may still be applicable in charging infrastructure studies or other studies where mainly daily habitual trips of travelers are considered (e.g., Dong et al., 2014), we believe better sampling methods will help us provide better bounds on potential BEV market.

There are more factors for us to study to improve our findings. Autonomous technology may be an important factor that would affect how people charge and how grid networks react in the future. Yi and Shirk (2018) mentioned that the introduction of autonomous technology presents a driver-free environment for EVs to reach nearby charging stations since the challenge of co-locating charging infrastructure with driver destinations no longer needs to be considered. They provided an optimal charging decision-making framework for autonomous electric vehicles, considering personal daily itineraries and existing charging infrastructure. They designed an energy cost prediction model as well as multistage charging decision-making models to find optimal charging strategies based on dynamic programming. This can significantly change the charging behavior of electric vehicles and is an effective way to control BEVs' charging behavior to achieve optimality.

We will improve our scenario analysis given more accurate multi-day samples or datasets, considering more realistic charging profiles for both vehicles and travelers.

Acknowledgment

This work was, in part, supported by Region II University Transportation Research Center (UTRC). Authors are grateful for their generous support. Authors would like to thank Dr. Joan Lucas (SUNY Brockport) for her support and Dr. Will Recker (UC Irvine) for insightful comments and discussions on this work.

References

Axsen, J., K. S. Kurani, R. McCarthy, C. Yang. 2011. Plug-in hybrid vehicle ghg impacts in california: Integrating consumer-informed recharge profiles with an electricity-dispatch model. *Energy Policy* **39**(3) 1617–1629.

Bagdasarian, A. 2018. Steep utility fees are killing electric-car charging stations. URL `https://www.greenbiz.com/article/steep-utility-fees-are-killing-electric-car-charging-stations`.

Bailey, J., J. Axsen. 2015. Anticipating pev buyers' acceptance of utility controlled charging. *Transportation Research Part A: Policy and Practice* **82** 29–46.

Björnsson, L.-H., S. Karlsson, F. Sprei. 2018. Objective functions for plug-in hybrid electric vehicle battery range optimization and possible effects on the vehicle fleet. *Transportation Research Part C: Emerging Technologies* **86** 655–669.

Daina, N., A. Sivakumar, J. W. Polak. 2017. Electric vehicle charging choices: Modelling and implications for smart charging services. *Transportation Research Part C: Emerging Technologies* **81** 36–56.

Deaton, J. 2019. Everybody wants ev charging stations, but barely anyone is building them. URL `https://www.fastcompany.com/90321889/everybody-wants-ev-charging-stations-but-barely-anyone-is-building-them`.

Dong, J., Z. Lin. 2012. Within-day recharge of plug-in hybrid electric vehicles: energy impact of public charging infrastructure. *Transportation Research Part D: Transport and Environment* **17**(5) 405–412.

Dong, J., C. Liu, Z. Lin. 2014. Charging infrastructure planning for promoting battery electric vehicles: An activity-based approach using multiday travel data. *Transportation Research Part C: Emerging Technologies* **38** 44–55.

Dunckley, J., G. Tal. 2016. Plug-in electric vehicle multi-state market and charging survey. *EVS29* 1–12.

Edison, S. C. 2019. Rate options for clean energy technology. URL `https://www.sce.com/residential/rates/electric-vehicle-plans`.

EVgo. 2019. Battery electric vehicles, bev, evs, hevs, bhev's. URL `https://www.evgo.com/why-evs/types-of-electric-vehicles/`.

Evrater. 2018. The electric vehicle list: An up-to-date list of current and future full-electric cars. URL `https://evrater.com/evs`.

Fitzgerald, G., C. Nelder, J. Newcomb. 2017. Electric vehicles as distributed energy resources URL `https://rmi.org/insight/electric-vehicles-distributed-energy-resources/`.

Francfort, J. E. 2015. The ev project price/fee models for publicly accessible charging. Tech. rep., Idaho National Lab.(INL), Idaho Falls, ID (United States).

Franke, T., J. F. Krems. 2013. Understanding charging behaviour of electric vehicle users. *Transportation Research Part F: Traffic Psychology and Behaviour* **21** 75–89.

Gonder, J., T. Markel, M. Thornton, A. Simpson. 2007. Using global positioning system travel data to assess real-world energy use of plug-in hybrid electric vehicles. *Transportation Research Record: Journal of the Transportation Research Board* (2017) 26–32.

Hardman, S., A. Jenn, G. Tal, J. Axsen, G. Beard, N. Daina, E. Figenbaum, N. Jakobsson, P. Jochem, N. Kinnear, et al. 2018. A review of consumer preferences of and interactions with electric vehicle charging infrastructure. *Transportation Research Part D: Transport and Environment* **62** 508–523.

Hota, A. R., M. Juvvanapudi, P. Bajpai. 2014. Issues and solution approaches in phev integration to smart grid. *Renewable and Sustainable Energy Reviews* **30** 217–229.

Hu, L., J. Dong, Z. Lin. 2019. Modeling charging behavior of battery electric vehicle drivers: A cumulative prospect theory based approach. *Transportation Research Part C: Emerging Technologies* **102** 474–489.

Jung, J., J. Y. Chow, R. Jayakrishnan, J. Y. Park. 2014. Stochastic dynamic itinerary interception refueling location problem with queue delay for electric taxi charging stations. *Transportation Research Part C: Emerging Technologies* **40** 123–142.

Kane, M. 2018. 2018 july us plug-in electric car sales charted: Market share exceeds 2. URL `https://insideevs.com/news/338839/2018-july-us-plug-in-electric-car-sales-charted-market-share-exceeds-2`.

Kang, J. E., W. Recker. 2009. An activity-based assessment of the potential impacts of plug-in hybrid electric vehicles on energy and emissions using 1-day travel data. *Transportation Research Part D: Transport and Environment* **14**(8) 541–556.

Kang, J. E., W. Recker. 2014a. Strategic hydrogen refueling station locations with scheduling and routing considerations of individual vehicles. *Transportation Science* **49**(4) 767–783.

Kang, J. E., W. W. Recker. 2014b. Measuring the inconvenience of operating an alternative fuel vehicle. *Transportation Research Part D: Transport and Environment* **27** 30–40.

Karner, D., T. Garetson, J. Francfort. 2016. Ev charging infrastructure roadmap. Tech. rep., Idaho National Lab.(INL), Idaho Falls, ID (United States).

Khan, M., K. M. Kockelman. 2012. Predicting the market potential of plug-in electric vehicles using multiday gps data. *Energy Policy* **46** 225–233.

Khayati, Y., J. E. Kang. 2015. Modeling intra-household interactions for the use of battery electric vehicles. *Transportation Research Board 94th Annual Meeting*. 15-4052.

Kontou, E., Y. Yin, Z. Lin, F. He. 2017. Socially optimal replacement of conventional with electric vehicles for the us household fleet. *International Journal of Sustainable Transportation* **11**(10) 749–763.

Kunzmann, M. 2013. 2010-2012 california statewide household travel survey final report. *California Department of Transportation* URL `http://www.dot.ca.gov/hq/tpp/offices/omsp/statewide_travel_analysis/files/CHTS_Final_Report_June_2013.pdf`.

Lam, A. Y., K.-C. Leung, V. O. Li. 2012. Capacity management of vehicle-to-grid system for power regulation services. *2012 IEEE Third International Conference on Smart Grid Communications (SmartGridComm)*. IEEE, 442–447.

Neubauer, J., E. Wood. 2014. The impact of range anxiety and home, workplace, and public charging infrastructure on simulated battery electric vehicle lifetime utility. *Journal of power sources* **257** 12–20.

Pearre, N. S., W. Kempton, R. L. Guensler, V. V. Elango. 2011. Electric vehicles: How much range is required for a day's driving? *Transportation Research Part C: Emerging Technologies* **19**(6) 1171–1184.

Pendyala, R., E. Pas. 2000. Multiday and multiperiod data for travel demand modeling. *Invited Resource Paper in Transport Surveys: Raising the Standard, Proceedings of an International Conference on Transport Survey Quality and Innovation.Transportation Research Board, National Research Council* II–B/1 – II–B/22.

Philipsen, R., T. Schmidt, J. Van Heek, M. Ziefle. 2016. Fast-charging station here, please! user criteria for electric vehicle fast-charging locations. *Transportation research part F: traffic psychology and behaviour* **40** 119–129.

Richardson, D. B. 2013. Electric vehicles and the electric grid: A review of modeling approaches, impacts, and renewable energy integration. *Renewable and Sustainable Energy Reviews* **19** 247–254.

Shaukat, N., B. Khan, S. Ali, C. Mehmood, J. Khan, U. Farid, M. Majid, S. Anwar, M. Jawad, Z. Ullah. 2018. A survey on electric vehicle transportation within smart grid system. *Renewable and Sustainable Energy Reviews* **81** 1329–1349.

Smith, R., S. Shahidinejad, D. Blair, E. Bibeau. 2011. Characterization of urban commuter driving profiles to optimize battery size in light-duty plug-in electric vehicles. *Transportation Research Part D: Transport and Environment* **16**(3) 218–224.

Stopher, P., K. Kockelman, S. Greaves, E. Clifford. 2008. Reducing burden and sample sizes in multiday household travel surveys. *Transportation Research Record: Journal of the Transportation Research Board* (2064) 12–18.

Sun, X.-H., T. Yamamoto, T. Morikawa. 2016. Fast-charging station choice behavior among battery electric vehicle users. *Transportation Research Part D: Transport and Environment* **46** 26–39.

Sun, X.-H., T. Yamamoto, K. Takahashi, T. Morikawa. 2018. Home charge timing choice behaviors of plug-in hybrid electric vehicle users under a dynamic electricity pricing scheme. *Transportation* **45**(6) 1849–1869.

Sundstrom, O., C. Binding. 2010. Planning electric-drive vehicle charging under constrained grid conditions. *Power System Technology (POWERCON), 2010 International Conference on*. 1–6.

Sundstrom, O., C. Binding. 2011. Flexible charging optimization for electric vehicles considering distribution grid constraints. *IEEE Transactions on Smart Grid* **3**(1) 26–37.

Tamor, M. A., C. Gearhart, C. Soto. 2013. A statistical approach to estimating acceptance of electric vehicles and electrification of personal transportation. *Transportation Research Part C: Emerging Technologies* **26** 125–134.

Tamor, M. A., M. Milačić. 2015. Electric vehicles in multi-vehicle households. *Transportation Research Part C: Emerging Technologies* **56** 52–60.

Thill, D. 2019. The need for charging stations is clear, but who should own them is not. URL `https://energynews.us/2019/02/15/midwest/the-need-for-charging-stations-is-clear-but-who-should-own-them-is-not/`.

Traut, E. J., T. C. Cherng, C. Hendrickson, J. J. Michalek. 2013. Us residential charging potential for electric vehicles. *Transportation Research Part D: Transport and Environment* **25** 139–145.

Tulpule, P. J., V. Marano, S. Yurkovich, G. Rizzoni. 2013. Economic and environmental impacts of a pv powered workplace parking garage charging station. *Applied Energy* **108** 323–332.

UCS. 2015. How the electricity grid works. URL `https://www.ucsusa.org/clean-energy/how-electricity-grid-works`.

Williams, B., J. DeShazo. 2014. Pricing workplace charging: financial viability and fueling costs. *Transportation Research Record* **2454**(1) 68–75.

Xi, X., R. Sioshansi, V. Marano. 2013. Simulation–optimization model for location of a public electric vehicle charging infrastructure. *Transportation Research Part D: Transport and Environment* **22** 60–69.

Xiong, Y., J. Gan, B. An, C. Miao, Y. C. Soh. 2016. Optimal pricing for efficient electric vehicle charging station management. *Proceedings of the 2016 International Conference on Autonomous Agents & Multiagent Systems*. International Foundation for Autonomous Agents and Multiagent Systems, 749–757.

Yi, Z., M. Shirk. 2018. Data-driven optimal charging decision making for connected and automated electric vehicles: A personal usage scenario. *Transportation Research Part C: Emerging Technologies* **86** 37–58.

Zhang, A., J. E. Kang, K. Axhausen, C. Kwon. 2018. Multi-day activity-travel pattern sampling based on single-day data. *Transportation Research Part C: Emerging Technologies* **89** 96 – 112. doi: https://doi.org/10.1016/j.trc.2018.01.024. URL `http://www.sciencedirect.com/science/article/pii/S0968090X18301062`.

Zhang, L., T. Brown, G. S. Samuelsen. 2011. Fuel reduction and electricity consumption impact of different charging scenarios for plug-in hybrid electric vehicles. *Journal of Power Sources* **196**(15) 6559–6566.