Charging Infrastructure Planning for Promoting Battery Electric Vehicles: An Activity-Based Approach Using Multiday Travel Data

Jing Dong (Corresponding author)
jingdong@iastate.edu
Department of Civil, Construction and Environmental Engineering
Iowa State University
350 Town Engineering Building
Ames, Iowa 50011
Phone: (515) 294-3957 Fax: (515) 294-8216

Changzheng Liu
liuc2@ornl.gov
Oak Ridge National Laboratory
National Transportation Research Center
2360 Cherahala Boulevard, Knoxville, TN 37932, USA
Phone: (865) 946-1306

Zhenhong Lin
linz@ornl.gov
Oak Ridge National Laboratory
National Transportation Research Center
2360 Cherahala Boulevard, Knoxville, TN 37932, USA
Phone: (865) 946-1308

Abstract

This paper studies electric vehicle charger location problems and analyzes the impact of public charging infrastructure deployment on increasing electric miles traveled, thus promoting battery electric vehicle (BEV) market penetration. An activity-based assessment method is proposed to evaluate BEV feasibility for the heterogeneous traveling population in the real world driving context. Genetic algorithm is applied to find (sub)optimal locations for siting public charging stations. A case study using the GPS-based travel survey data collected in the greater Seattle metropolitan area shows that electric miles and trips could be significantly increased by installing public chargers at popular destinations, with a reasonable infrastructure investment.

Keywords — Charging infrastructure; Battery electric vehicle; Range anxiety; GPS-based travel survey; Genetic algorithm.

1. Introduction

The continued growth in motor vehicle use worldwide will inevitably have consequences on global crude oil demand and CO_2 production. To avoid an increase in demand for oil proportional to the increasing number of vehicles, implementation strategies need to aim at the replacement of fossil fuels as the sole source of energy for automobiles. Within the U.S., the light-duty fleet, dominated by spark-ignited internal combustion engines that run on gasoline, accounts for more than 90% of the total U.S. gasoline consumption (Davis et al. 2012, EIA 2012). One of the pathways to sustainable petroleum displacement is a transition to the high-efficiency powertrain technologies, such as fuel-cell or battery-electric vehicles that could deliver better performance, higher efficiency, and zero tailpipe emissions (Kromer and Heywood, 2007; Lin et al., 2013). Electrification of light duty vehicles could reduce oil dependence and potentially reduce greenhouse gas emissions especially when implemented in conjunction with renewable energy generation to match the new electrical load. Consumer acceptance, technological advances, and policy measures are among the important factors for plug-in electric vehicle (PEV) market success. Many strategies have the potential to promote PEV deployment and market penetration, such as offering purchase subsidies and rolling out charging infrastructure in convenient locations in urban areas (Lin and Greene, 2011). More stringent regulations and technology-forcing mandates such as national highway traffic safety administration's new corporate average fuel economy (CAFE) standards and California air resources board's zero-emission vehicle mandate, have also been initiated, intended for reducing light-duty vehicles' petroleum use and mitigating negative environmental impacts from the transportation sector.

However, the fear that the vehicle has insufficient range to reach the destination, referred to as range anxiety has been shown to be a significant obstacle to market acceptance of battery electric vehicles (BEV). Range anxiety not only discourages consumer acceptance but also restrains the social benefits of BEV, as the early adopters of electric vehicles may be forced to use the vehicle for short trips and drive fewer annual miles, compared how they may travel without range anxiety. In fact, a state preference survey conducted in the United Kingdom revealed that higher income group is more likely to consider a BEV as a second vehicle (Skippon and Garwood, 2011). One way to mitigate range anxiety is through the deployment of public charging infrastructure. Like all the alternatives to gasoline vehicles, the initial costs of building the refueling/recharging infrastructure would be high and decrease as the number of alternative fuel vehicles increases. Shell Oil Company estimated a mature hydrogen refueling infrastructure in the U.S., serving 100 million hydrogen vehicles, might cost hundreds of billions of dollars, that is, several thousand dollars per vehicle served (Ogden, 2005). The National Research Council (2013) estimated a $3,000 per vehicle charging infrastructure investment cost for BEVs, including the costs for installing home, workplace, and public chargers. These costs, seemingly enormous, are actually of the same order of magnitude as the money spent to build and maintain the infrastructure for conventional transportation fuels (Ogden, 2005).

To assist policy makers efficiently allocate public resources in aiding the deployment of charging infrastructure a systematic approach is needed to quantify the benefit of offering public charging opportunities, as well as to determine where to site charging stations subject to vehicle travel range constraints (e.g. Shukla et al., 2011; Wang, 2007). Various mathematical models have been proposed to optimize hydrogen refueling, electric vehicle charging, and battery swapping station siting, including flow-capture (Kuby et al., 2009), p-median (Nicholas et al., 2004; Lin et al. 2008), set covering (Wang and Lin 2009, Frade et al. 2011), and agent-based (Sweda and Klabjan, 2011) approaches. In addition, the interaction of PEV charging with power grid infrastructure was considered in a few studies, such as the multi-objective charging station layout planning model proposed by Wang et al. (2010) and the stochastic program developed by Pan et al. (2010) that optimally sites battery swapping stations in a vehicle-to-grid system. Similar to refueling a conventional diesel or gasoline tank, hydrogen refueling and battery swap can be accomplished en route within a few minutes, though drivers might have to take a detour and travel some extra distance to find a hydrogen or battery swap station due to currently limited availability. Recharging the battery, however, takes a much longer time, from 30 minutes to several hours, depending on the charger power, battery size and its state of charge. Thus, it is preferred to charge a BEV at the activity destination where the vehicle is parked for a considerable period of time. However, most of the existing refueling and recharging station planning models ignore the constraints imposed by drivers' travel activities.

In this study we present a novel public charger infrastructure planning model that optimizes the location of public chargers while simulating driver travel and charging behavior. Installing chargers at the locations where many people park will not only increase the utilization but also increase the visibility, which might help to relieve range anxiety and promote BEV acceptance. Based on the multiday driving data collected from 445 instrumented gasoline vehicles in the Seattle metropolitan area, we simulate regional BEV drivers' travel and charging behavior so as to quantify the benefits of building public charging infrastructure in reducing range anxiety and increasing electric miles. Specifically, range anxiety is measured by the number of interrupted trips and the missed vehicle miles, given the originally intended trips by each driver. To reduce the number of interrupted trips, a charger location optimization problem is solved to determine a set of locations where public chargers should be installed, as well as the type of chargers to be installed at each location. In summary, contributions of this paper include: (1) assessing BEV feasibility based on the real world driving activities of the heterogeneous traveling population; (2) formulating the charger location optimization problem considering daily travel activity constraints; and (3) evaluating the impact of public charging infrastructure planning on promoting BEV consumer acceptance by simulating drivers' driving and charging behavior.

2. Background and assumptions

While BEV technology presents promising potential to displace gasoline with electricity, the limited range and charging constraints are among some significant drawbacks. The term "range anxiety" has been introduced to describe BEV drivers' omnipresent concern of becoming stranded with an empty battery, away from the charging infrastructure. The lack of public charging infrastructure and long charging time are among the critical hurdles for a widespread deployment of BEVs. By and large, there are two scenarios when a BEV has insufficient range to finish the planned trips: First, a single long trip exceeds the vehicle range. Such a long trip could be accomplished by a BEV if a charging station, preferably a high rate charger, is available along the travel route. However, the additional stops and waiting time would usually cause inconvenience and disrupt the original travel plan. Second, the accumulated distance of multiple trips exceeds the BEV range before returning home to charge the battery. This case might be circumvented by offering within day charging opportunities at public locations and is the primary focus of the present paper.

2.1. Electric Vehicle Charger

Three charging levels were codified in the National Electric Code (NFPA, 2011) for charging plug-in electric vehicles. Level 1 charger, using a standard 120 voltage, 15 or 20 ampere branch circuit that is commonly found in residential and commercial buildings in the United States, is suitable for overnight home charging and possibly workplace charging. Level 2 charger, typically considered as the preferred method for charging BEVs, specifies a 240 voltage, single-phase, 30 ampere branch circuit. A system upgrade might be required to install a Level 2 charger at private and public facilities. Level 3 charger, also referred to as fast charger, is a high voltage and high-current charging implementation. By delivering direct current (DC) directly to the vehicle's battery pack, a BEV's battery pack can be charged at a much higher rate. For example, a Level 3 charger allows a Nissan Leaf's battery to be charged to its 80% capacity in 30 minutes. The cost of such a specialized charger is dramatically higher, as its installation involves changes in the power infrastructure—requiring new transmission, sub-transmission, and distribution lines and so on (Lemoine et al., 2008; Hadley and Tsevetkova, 2008). Table 1 lists the charging power (Morrow, 2008) and costs (NRC, 2013), including both equipment and installation costs, of different types of chargers.

Table 1 Electric Vehicle Charger Specification

	Level 1	Level 2-Commercial	Level 3 DC Fast Charger
Charging circuit	120 V, 15 A	240 V, 30 A	50 V, 200 A
Power (kW)	1.44	6	90
Cost (US dollars)	700	5,000	50,000

### 2.2. GPS based travel survey data

GPS based travel survey data, collected from conventional gasoline vehicles and represents real world travel activities, provide a basis for assessing market potential and estimating energy consumption of plug-in electric vehicles. For example, one day travel

activities collected from GPS-instrumented vehicles in St. Louis metropolitan area (Gonder et al., 2007) and Austin, TX (Dong and Lin, 2012) have been used for analyzing Plug-In Hybrid Electric Vehicle energy efficiency. In addition, multiday vehicle data have also been used to analyze BEV range requirements in selected areas, including Winnipeg, Canada (Smith et al., 2011) and the Atlanta, Georgia greater metropolitan area (Pearre et al., 2011).

In this study, we use longitudinal travel data collected from conventional gasoline vehicles and assume that the motorists' travel behavior remains unchanged when switching to BEV technologies. In addition to simplicity, this assumption is also justified by its market and policy relevance. First, travel adaptation is usually associated with an added cost or certain inconvenience. Over time, drivers might get used to the new norm and disregard the inconvenience. However, from the perspective of the industry, it is meaningful for the charger suppliers to understand how to satisfy charging demand without forcing behavioral changes. Whether this is cost effective or not is worth debating. Second, from policy makers' perspective, one objective baseline for consensus infrastructure cost estimation is to assume no behavioral adaptation. Otherwise, infrastructure cost estimates may vary greatly depending on the level of behavioral adaptation assumed. At the current stage, there is no clear evidence on how BEV drivers will adapt to the limited vehicle range and long charging time. Therefore, assuming no behavior adaptation might be a practical and relevant approach for market assessment and policy discussion.

3. Data description

Puget Sound Regional Council (PSRC) conducted a household travel choice study, aiming to study how travelers change their travel behavior in response to tolling that varies by the location and time of day. The Traffic Choices Study (PSRC, 2008) recorded driving activities of 275 volunteer households in the Seattle metropolitan area for approximately an 18-month period (from November 2004 to April 2006). Among the participating households, 45% of the households own one vehicle, 48% own 2 vehicles and 7% own 3 or more vehicles, resulting in a total of 445 vehicles. On average each vehicle makes 4.8 trips and travels 30 miles per day. Figure 1 shows the map of the central Puget Sound region. The region includes five major cities—Seattle and Bellevue in King County, Tacoma in pierce County, Everett in Snohomish County and Bremerton in Kitsap County. The home locations of the instrumented vehicles and the popular destinations such as shopping malls and work places are plotted on the map. The majority of the volunteer households are located in Seattle, their travel destinations are in a much wider area.
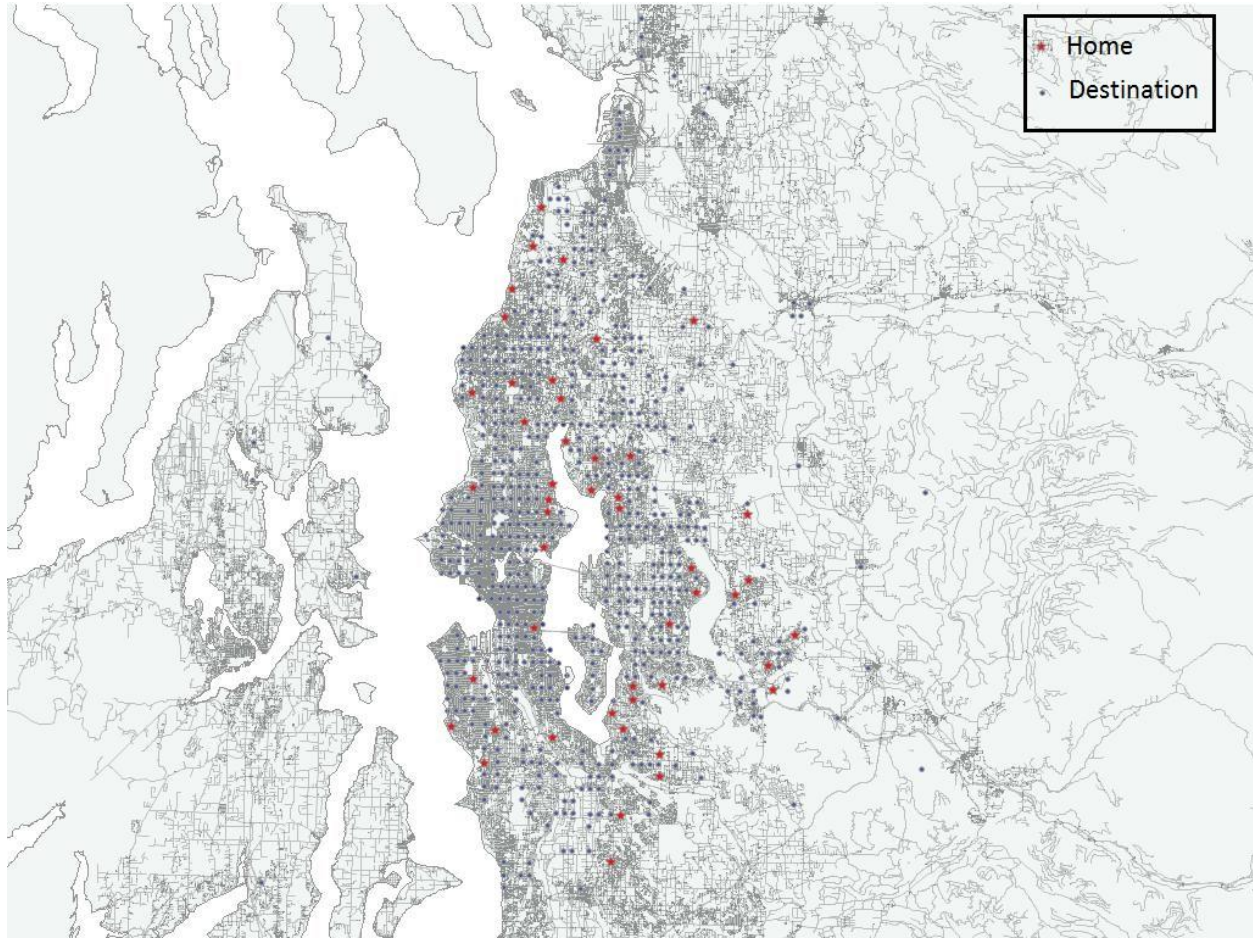
Figure 1 The greater Seattle metropolitan area map.

The traffic choice study dataset contains the time-stamped spatial information at the resolution of 4 records per minute. The geographic positioning system (GPS) receiver uses radio signals sent from satellites to determine the vehicle's position. The spatial coordinates in latitude and longitude are stored in the on board unit and periodically communicated to a central computer using cellular wireless communications. To record and transmit data on a regular basis, the GPS devices instrumented on the participant vehicles are automatically turned on/off when turning on/off the ignition. This allows for continuous collection of vehicles' daily travel activities, which is an essential requirement for the BEV feasibility analysis. Note that there is still possible discontinuity in the GPS tracking data due to temporary device failure, satellite signal loss or wireless communications interruption.

Over 700,000 trips were collected. Table 2 describes the data fields of the trip record used in this paper. Though the GPS tracking data of the entire trip are available, we only consider the start and end locations of each trip, as well as the dwell time between two consecutive trips. Ideally, a trip's start location should match the end location of the previous trip. However, gap exists in some cases. This is because, when it is turned on, a GPS device might

need some time to warm up before working properly. On the other hand, the end location of a trip, recorded by a GPS device, is more reliable. Therefore, the end locations are considered as a "stop". In the dataset, the locations of trips are recorded by the latitude and longitude coordinates. As a driver may not always park at the same spot in a parking lot, some nearby latitude-longitude coordinate pairs might be associated with the same activity destination, such as a shopping mall or the driver's workplace. Moreover, if a charger is available near a BEV driver's destination, he/she might be willing to park at the charging station and walk a few minutes to the destination. Therefore, instead of using the exact geographic locations, each trip end is assigned to a grid cell. When a charger is placed in the grid cell, the driver can charge the BEV at the stop if necessary. The dwell time determines the time available to charge the battery. In particular, in the downtown area, each grid cell covers 0.5 by 0.5 miles; in suburbs, each grid cell covers 1 by 1 mile; and in outer suburbs, each grid cell covers 5 by 5 miles. As a result, the entire Seattle metropolitan area is divided into 4129 grid cells, containing all the trip ends.

Table 2 GPS Travel Data Description

| Data field	Description
Vehicle ID	The unique ID of the vehicle
Travel day	The date when the trip was recorded
Trip number	Trips taken by an individual on a travel day are numbered sequentially by a trip number
Start time	The start time of the trip
End time	The end time of the trip
Start location	GPS coordinates of the starting point of the trip
End location	GPS coordinates of the end point of the trip
Travel distance	Vehicle miles traveled on the trip
Dwell time	Time spent at the destination while the vehicle is parked

4. Methodology

To assess the impact of deploying charging infrastructure on promoting consumer acceptance of BEVs, an evaluation framework is presented in Figure 2, includes charging infrastructure planning, travel and charging activity simulation, and measures of performance. Charging infrastructure planning determines the placement of electric vehicle chargers at home, work and other convenient locations. In this study, we assume that all BEV drivers have access to level 1 chargers at home. Based on the recorded vehicle activities, specifically, travel distances and dwell times, public charger placement problem is formulated and solved using genetic algorithm (GA). The placement of charging stations, together with travel patterns, determines battery's state of charge (SOC) and charger availability at travelers' activity destinations. BEV drivers' driving and charging behavior can then be simulated to evaluate whether a traveler can complete all the planned travel activities, provided a charging

infrastructure plan. Some collective effects can also be evaluated. In particular, the following performance measures are defined to quantify the benefits of deploying charging infrastructure.

Missed trips: when the trip distance is longer than the remaining battery range, the trip is considered as a missed trip. The subsequent trips will also be missed, until the vehicle is recharged, presumably at home. The precedent trips, however, are assumed to be unaffected in the present study.

Missed miles: the vehicle miles traveled (VMT) associated with the missed trips.
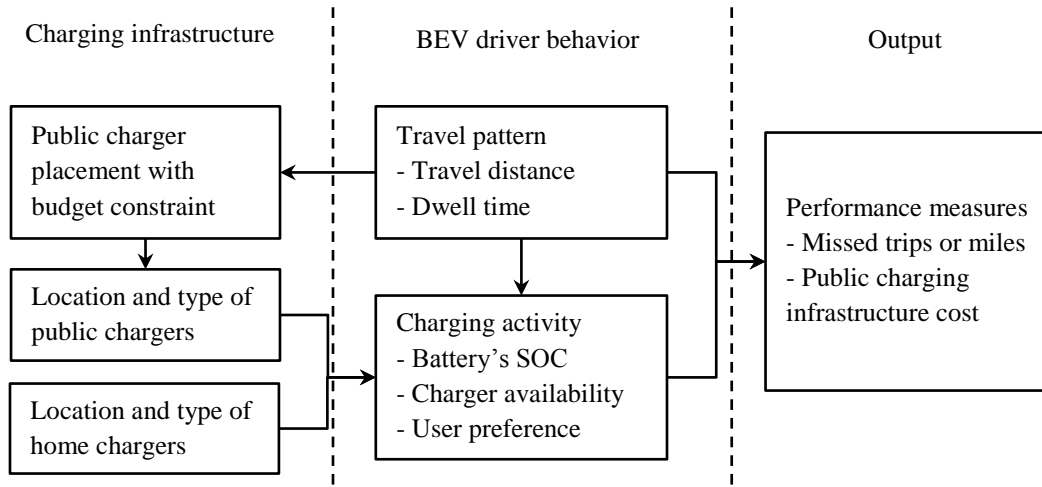
Figure 2 Methodology framework.

4.1. Problem formulation

Consider a set of candidate sites $I = \{1, 2, \cdots, m\}$ for installing charging stations, and a set of BEV drivers $J = \{1, 2, \cdots, n\}$. The public charger placement problem is to determine the locations and the types of the chargers to be installed in the planning network so as to minimize the number of missed trips, subject to a budget constraint.

Drivers' travel activities, including trip distances and the dwell time between two consecutive trips, and BEV characteristics, including the electric range and electricity consumption rate, are known. These input variables are defined as follows.

$s_{jd(k)}$	Travel distance of driver j's k-th trip on day d	[mile]
$t_{jd(k)}$	Dwell time after driver j's k-th trip on day d	[hour]
$l_{jd(k)}$	Destination of driver j's k-th trip on day d	[-]
R_j	Electric range of driver j's BEV	[mile]
r_j	Electricity consumption rate of driver j's BEV	[kW h/mile]

In the case study, the entire fleet is assumed to be BEVs with a 100 mile range (i.e. $R_j = 100, \forall j$). And the electricity consumption rate is 300 W h per mile (i.e. $r_j = 0.3, \forall j$).

Whether to install an electric vehicle charger at a candidate site or not is denoted as the decision variable.

x_i Charger placement at candidate site $i \in I$ (= 0, if no charger installed; = 1, 2, or 3, if level 1, 2 or 3 charge is installed)

Accordingly, the charging power and cost of each candidate site can be determined based on Table 1. These derived variables are defined as follows.

P_i Charging power at candidate site $i \in I$ is a function of x_i.

C_i Charger cost at candidate site $i \in I$ is a function of x_i.

If a BEV driver's activity destination is in the candidate sites, that is, $l_{\text{jd}(k)} \in$ I, the available charging power is $P_{l_{jd(k)}}$. If the destination does not belong to the candidate charging station site, or no charger is installed at the candidate site, $P_{l_{jd(k)}} = 0$.

When the BEV range is sufficient to finish the driver's all-day travel activities, that is, $\sum_k s_{jdk} \le R_j$, We assume that the driver will not use public chargers and only charge the battery when returning home. This assumption is made to simplify the calculation and represents the majority of current BEV adopters' behavior. It can be relaxed and will not affect the solution. When daily VMT exceeds the BEV range, drivers can take advantage of public chargers and charge the battery at some trip destinations. The energy increase in the battery, measured in miles, can be determined based on the battery's state of charge, charging power and dwell time at the destination.

$$R_{jd(k)} = min\left\{R_j - R_{soc,jd(k)} \quad , \quad \frac{P_{l_{jd(k)}} \cdot t_{jd(k)}}{r_j}\right\} \tag{1}$$

$R_{jd(k)}$ Energy increase of the battery from the recharge at the destination of   [mile]
          driver j's k-th trip on day d

$R_{soc,jd(k)}$ Battery's pre-charging SOC at the destination of driver j's k-th trip on   [mile]
          day d, which is measured after finishing trip k and before a possible
          recharging at the destination.

The pre-charging SOC of the BEV at the destination of the k-th trip ($R_{soc,jd(k)}$) can be calculated on the basis of battery level at the previous stop, possible recharge, and trip distance.

$$R_{soc,jd(k)} = R_{soc,jd(k-1)} + R_{jd(k-1)} - s_{jd(k)} \tag{2}$$

A negative pre-charging SOC ($R_{soc,jd(k)}$) indicates that the range of the BEV is insufficient to complete the daily travel. Thus, the k-th trip and all the subsequent trips on the travel day are considered as missed trips. Let y_{jd} denote the number of missed trips for driver j on day d. Thus, the objective function can be written as minimizing the total number of the missed trips of all the BEV drivers on all the travel days.

$$\min f(x) = \sum_j \sum_d y_{jd} \tag{3}$$

The total cost of building the charging infrastructure needs to be within the maximum allowable budget. The budget constraint is written as follows.

$$\sum_i C_i \leq B \tag{4}$$

B　　　　The total budget for installing chargers in the entire study area　　　　[$]

4.2. Activity-based assessment

An activity-based assessment approach is proposed to describe BEV drivers' driving and charging behavior and quantify range anxiety phenomenon associated with limited-range vehicles. One day travel activities of a sample vehicle and different charging scenarios are illustrated in Figure 3. In this particular example, a BEV with 100-mile range and a level 1 home charger cannot finish all the trips before returning home. However, since the vehicle is parked at work and another public place for a relative long time during the day, the battery could be recharged, if chargers exist. Two alternative strategies are considered: providing a level 1 charger at work, or installing a level 3 charger at the public location. Both scenarios will avoid the battery being stranded before returning home.
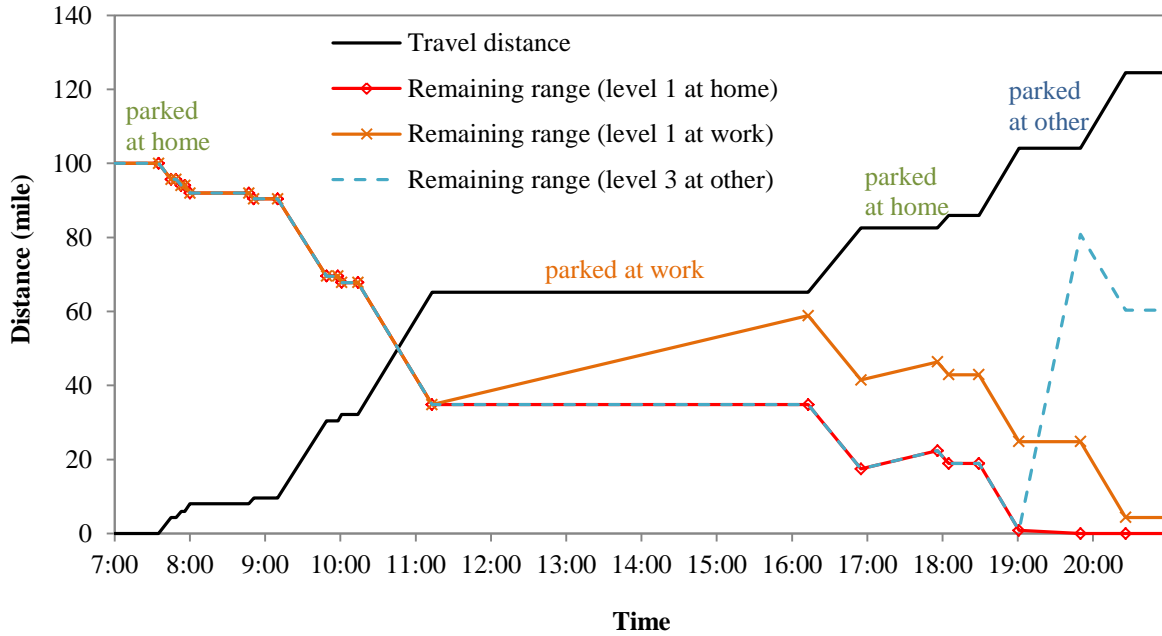
Figure 3 Travel and charging behavior.

The objective function Eq. (3) can be evaluated based on real world driving activities (i.e. the input variables) and the energy consumption calculated using Eq. (1) and Eq. (2). The activity-based assessment method provides the basis for implementing the genetic algorithm that seeks optimal locations for installing charging stations in the study area.

4.3. Genetic algorithm-based optimization

Location and type of public chargers are found using a genetic algorithm (GA)-based optimization model that minimizes missed trips subject to the budget constraint. Genetic algorithm (Holland, 1975) is considered as a mature artificial intelligence technology that has been applied to solve many real world problems, including some recent applications in solving electric vehicle charger location problems (Ge et al. 2011, Li et al. 2011). The Evolver module of the @risk software, an advanced commercial GA-based optimizer developed by Palisade Corporation, is used to solve the proposed charger location optimization problem. Simulating charging behavior and evaluating the objective (or fitness) function require the use of lookup tables and databases, which makes the optimization problem non-smooth and difficult for hill-climbing routines to find optimal solutions. Evolver is chosen for it can find good solutions for problems involving large, interrelated tables, and does not require continuity in the functions that it evaluates.

The grid cells in the network are ranked by number of trips that end in the grid. Top 500 popular destinations, are selected as potential locations for public chargers. Since the charging station capacity constraint is not considered in the proposed optimization model, the potential charging congestion, that is, a vehicle arrives at a charging station when all chargers are

occupied, is ignored. At an early market with a small number of BEVs on the road, charging congestion may be rare. Based on the driving activities of 445 vehicles in the greater Seattle metropolitan area, only 3.7% of the trips end at a location (i.e. one of the top 500 popular destinations) where another vehicle has already parked. If two chargers are provided at these destinations, the charging conflict percentage drops to 0.5%. With more BEVs on the road, it is likely that smart grid technologies will be used to coordinate queuing and charging for multiple vehicles. Consideration of queuing and charger capacity will significantly increase the complexity of the optimization problem and is an important issue to be addressed in the future research.

An integer representation of the genetic solutions is used in the evolutionary computation method: $x_i = 0$ represents no charger at node i, and $x_i = 1, 2, or\ 3$, if level 1, 2 or 3 charger is installed at the node, respectively. The optimization model that minimizes the total number of missed trips is solved using Evolver at various budget levels.

5. Results

5.1. Travel patterns
To illustrate real world driving patterns and the implication on range anxiety phenomenon associated with limited-range vehicles, Figure 4 plots cumulative distributions of trip lengths and daily VMTs of two fleets. The trip length distribution curves, derived from the Austin (229 vehicles on one travel day) and Seattle (445 vehicles on multiple travel days) travel survey data, show that very few trips exceed the typical BEV range, that is, 80 to120 miles. The cumulative distribution curves of daily VMTs, on the other hand, show a higher percentage of unfinished trips beyond the BEV range. Since we assume that driver will not change their original travel plans in this study, providing additional charging opportunities at work and other convenient locations will only eliminate some of the unfinished short trips. To use a BEV on a trip longer than the vehicle's range, drivers need to make changes to their trip plans and charge at a public charger along the travel route, preferably a fast one.
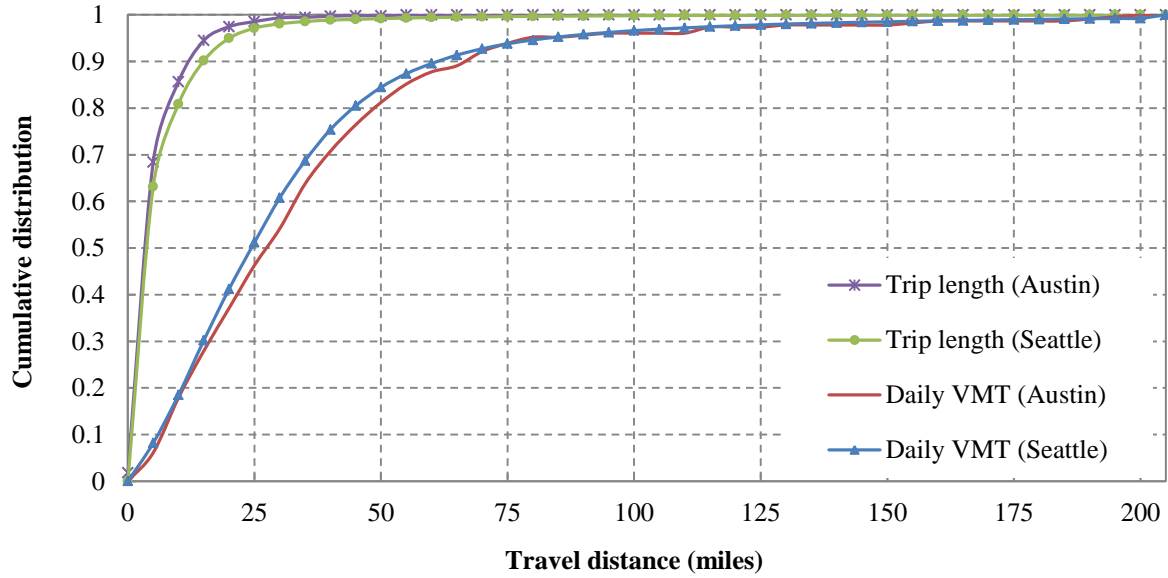
Figure 4 Trip length and daily VMT distribution.

5.2. Home charging

Each vehicle's home location is available in the Seattle travel survey database (See Figure 1). The base case scenario assumes that level 1 charger is available at home and that BEV is charged when the vehicle is parked at home for more than 1 hour, that is to say, the chargeable range is more than 4.8 miles. No public chargers are considered in this scenario.
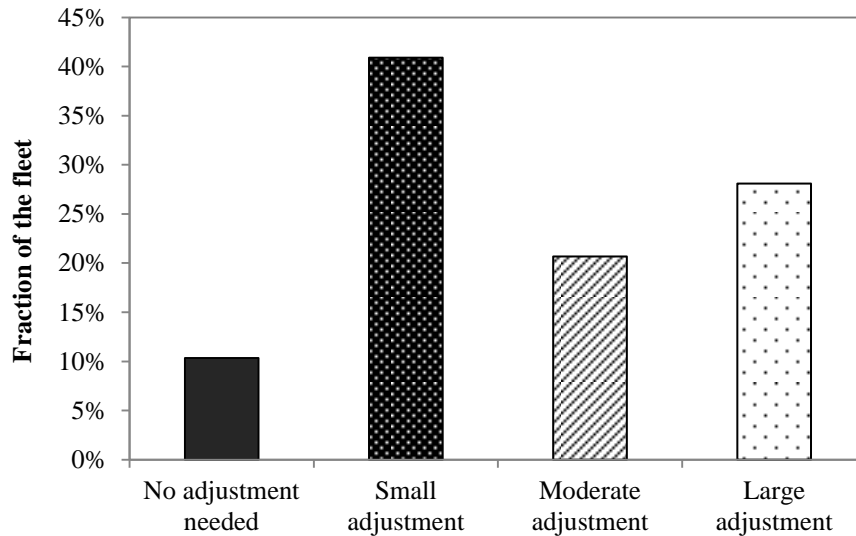

Figure 5 Travel adaptation.

The sample (445 participants) is segmented according to how much travel adjustment they would have to do if they were driving BEVs. An adjustment, either using a substitute

gasoline vehicle or changing travel plans, is needed if a participant's accumulative daily travel distance exceeds the 100 mile BEV range. As shown in Figure 5, provided with home chargers, 10% (i.e. 46 vehicles out of 445) of the drivers can accomplish all the planned travel activities using a BEV with 100 mile range (i.e. no adjustment needed). This observation is similar to the study by Pearre et al. (2011), which reported, based on data collected in the Atlanta metropolitan area that 9% of the vehicles in the sample never exceeded 100 miles in one day. It is worth noting that there is no significant difference in terms of vehicle ownership per household and vehicle model and year in the "no adaption" subset compared to the entire sample set. For 41% of the sampled population, adjustment is needed for less than 5% of the travel days (i.e. small adjustment); 21% of the fleet need adjustment on 5%-10% of the travel days (i.e. moderate adjustment); and the rest 28% of the fleet cannot complete their planned daily driving activities for more than 10% of the travel days (i.e. large adjustment).

5.3. Public charging

In addition to having level 1 charger at home, BEV drivers may have access to public chargers. The charging location optimization model is run using different budget constraints. In particular, the per vehicle infrastructure cost is assumed to vary from $500 to $5,000, which is consistent with the alternative fuel vehicle infrastructure cost estimates suggested by Ogden (2005) and NRC (2013). Figure 6 summarizes the optimal number of level 1, 2 and 3 chargers at each given budget. When the budget increases beyond $1,000 per vehicle, the total number of chargers is close to the maximum number, namely 500, but more level 2 and 3 chargers are deployed with a larger budget. No level 3 charger is planned when the budget is below $3,000 per vehicle. A few level 3 chargers are planned at higher budget levels. The solutions suggest that with limited budget, it is preferred to install more low-cost and low power chargers than fewer expensive and high power chargers.
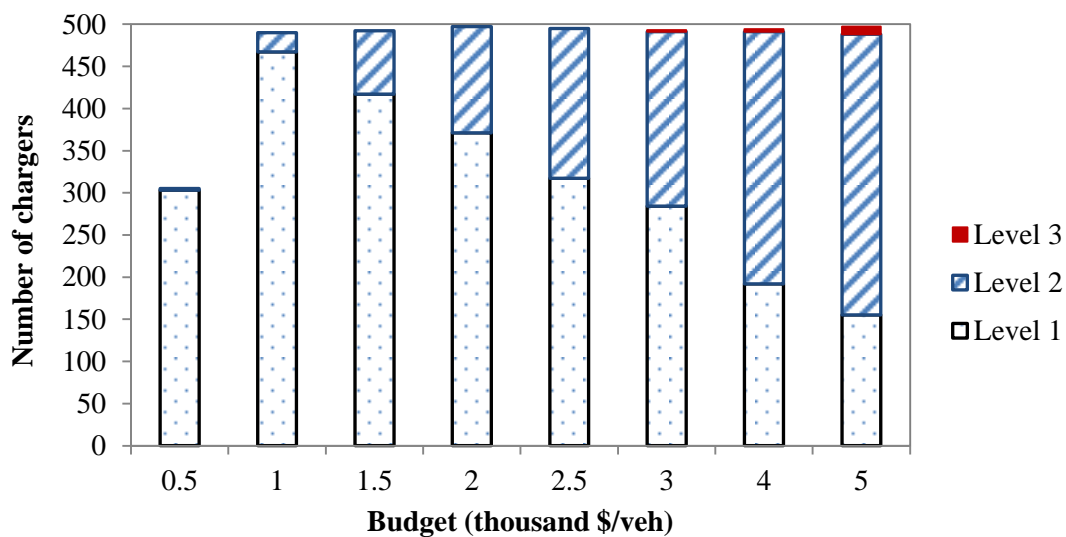
**Figure 6 Number of chargers at varying budget levels.**

As an example, Figure 7 shows charger locations at the $2,000 per vehicle budget level. The solution suggests installing chargers in the major cities, including Seattle and Bellevue, and along highway corridors, such as Interstate 5 and Interstate 90.
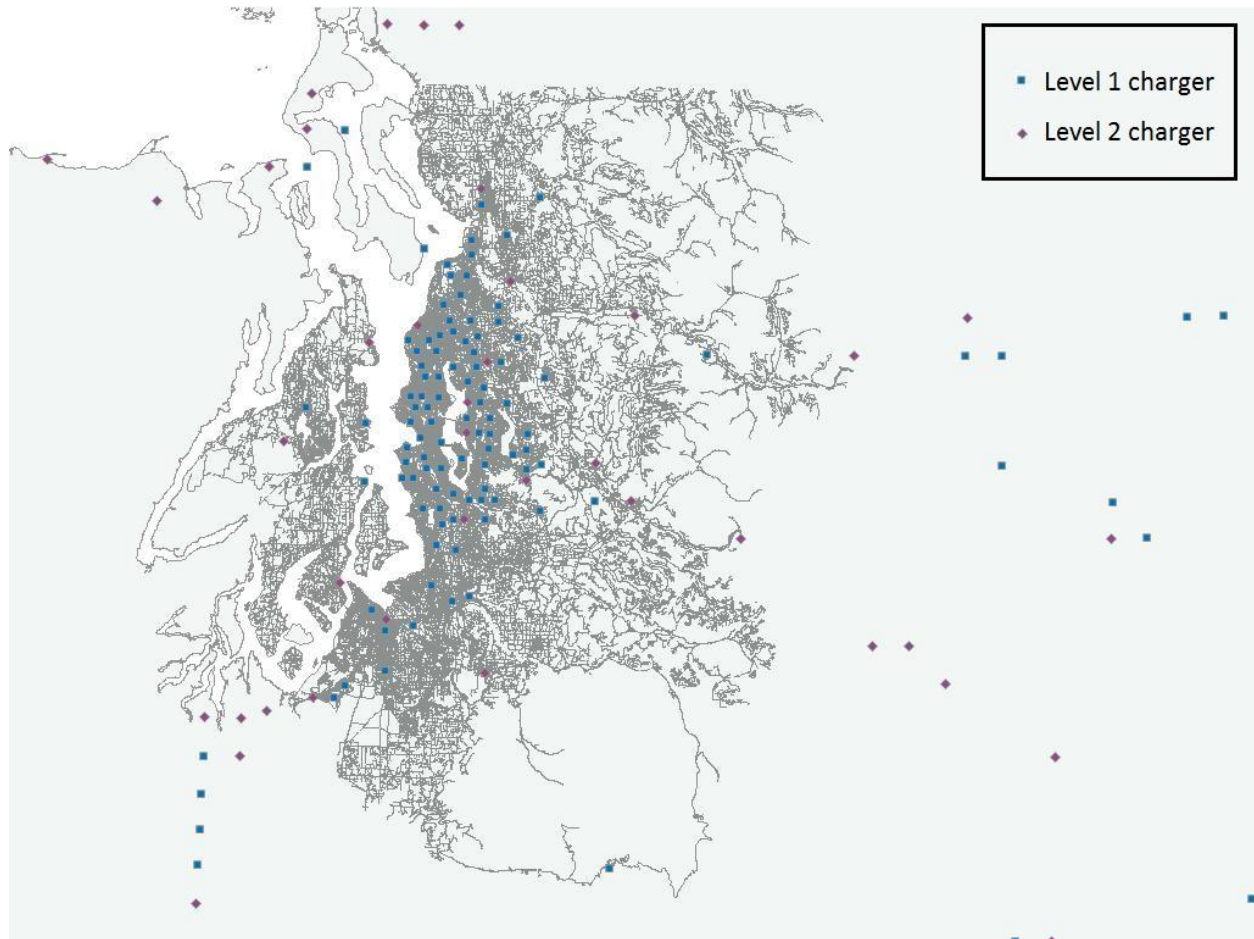
**Figure 7 Charger locations (budget $2,000 per vehicle)**

Figure 8 shows the percentage of the total budget allocated for each type of charger. The majority of the budget is allocated to level 1 charges when the budget level is low and to level 2 chargers when the budget is high. At budget levels between $1,500 and $3,000 per vehicle, the majority of chargers are level 1 but the majority of the fund is allocated to level 2 chargers.
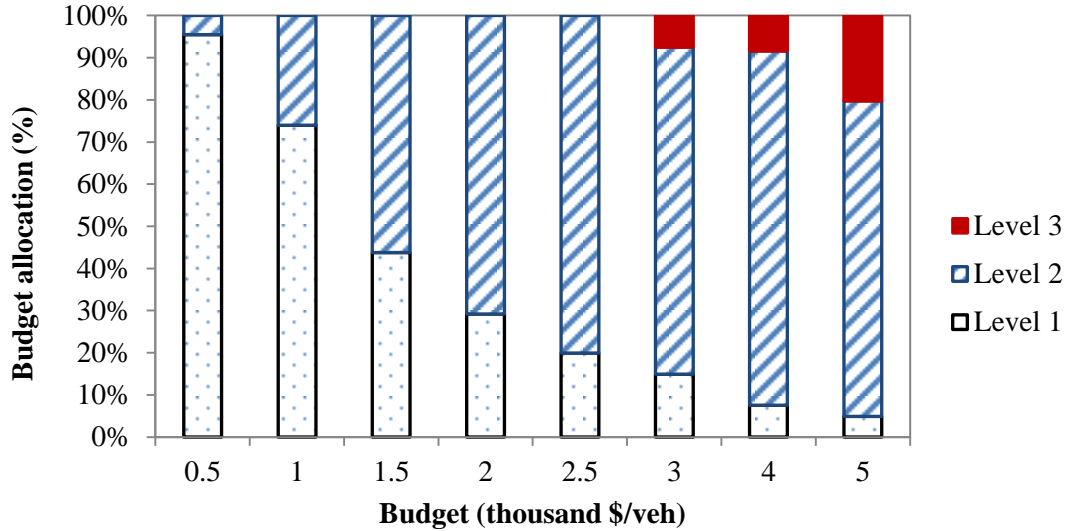
Figure 8 Percentage of the total budget used for each type of charger.

Impacts of different budget levels on missed trips and miles are demonstrated by Figure 9. If no public charger is built, corresponding to the home charging scenario discussed in Section 5.2, about 10% of all trips and 20% of VMT will be missed. As shown in Figure 5, the majority of the observed drivers (i.e. 72% of the fleet) would not need to adapt in more than 90% of travel days. Yet, the 28% of the fleet that needs large adjustment account for more than 31% of the total number of trips traveled and 38% of total VMT. Some of these vehicles need adaption on half of their travel days, which significantly contribute to the total number of missed trips. Both missed trips and VMTs reduce nonlinearly relative to the increase of budget. Public chargers funded up to $2,000 per vehicle are able to reduce missed trips to 2.58%. The marginal benefits decreases with additional investment. The curve is relatively flat beyond $2,000, suggesting that the $5,000 per vehicle budget is a sufficient upper bound for the present study.
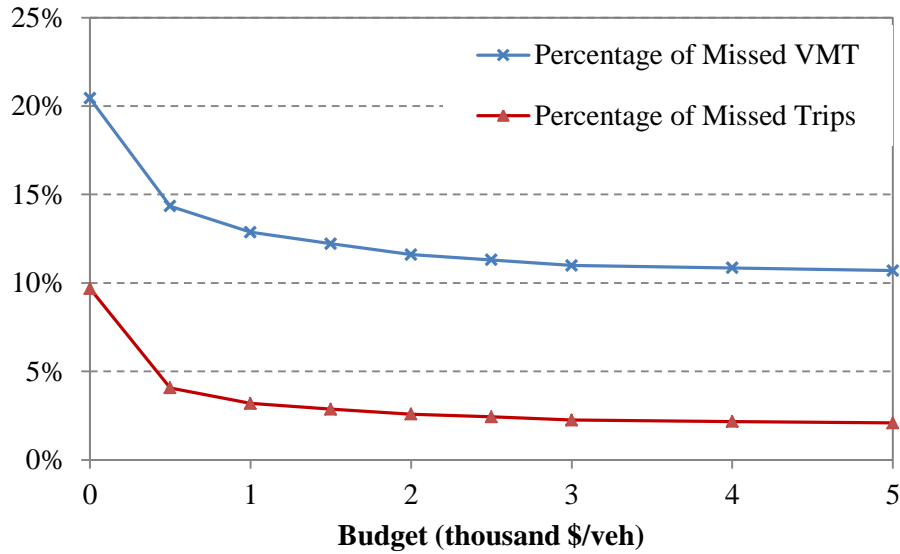
Figure 9 Missed trips and VMT under different budget level.

As the total number of chargers to be deployed in a region, together with the available budget, is usually determined at the strategic planning stage, a set of 500 candidate charger locations are predefined before solving the tactical optimization problem. Nevertheless, the number of candidate locations would influence the solution and constraint the reduction of the missed trips. For example, at the $5,000 per vehicle budget level, increasing the number of candidate sites from 500 to 1,000 can reduce the number of missed trips by an additional 0.3% (i.e. from 2.1% to 1.8%). Figure 10 shows the solutions considering different number of candidate sites. Similar to the observation from Figure 6, more low power chargers are planned when more candidate sites are considered.
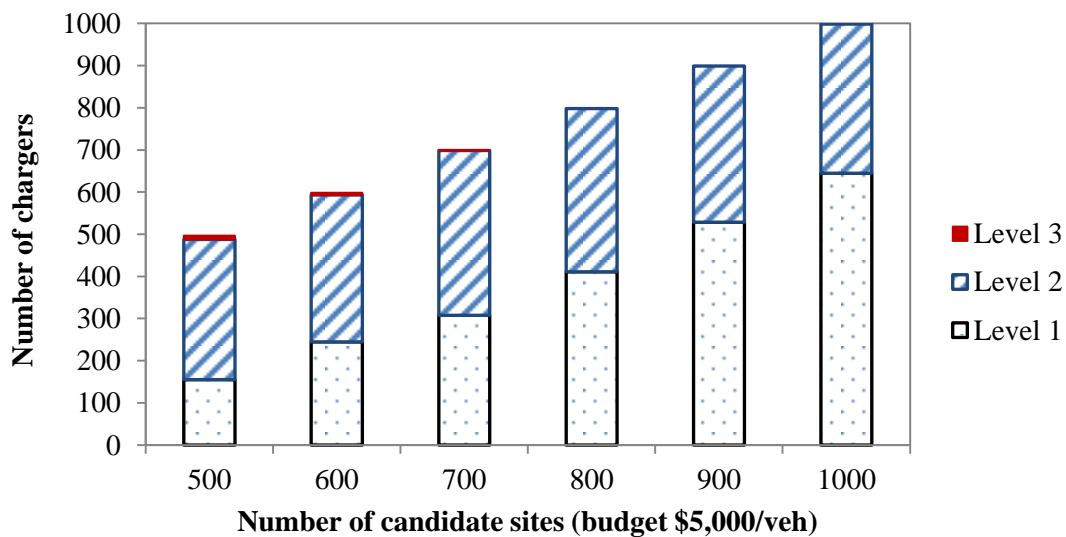
Figure 10 Solutions considering varying number of candidate sites

6. Conclusions and discussions

This paper examines the impact of different deployment levels of public charging infrastructure on reducing BEV range anxiety using an optimization model that places chargers at candidate locations, considering charging behavior and the budget constraint. GPS tracking data shows that very few trips exceed the typical BEV range; while daily VMT has a higher likelihood of exceeding the range. More public chargers, when optimally located, could effectively reduce range-constrained days and trips for BEV drivers. The optimized public charger planning strategies suggest that, with a small budget, level 1 chargers are preferred, as they can provide the necessary network coverage at a low cost. Due to its high cost, level 3 charging is less attractive. However, installing fast chargers along the interstate corridors is essential in order to facilitate BEV drivers to conduct intercity travel.

One of the caveats of this study is the assumption that current activity patterns with gasoline powered vehicles will not change when switching to electric vehicles. Nevertheless, travelers might have access to another vehicle, use alternative travel modes, change their itineraries, or make short detours to public chargers, thus reducing the number of unfinished trips. Although changes in their travel behavior are expected, at the present stage, it is not well understood how drivers will react to range limitation. Our assumption has been made to facilitate model calculation, which provides a useful reference point for market assessment and policy discussion. Further observations and understanding of BEV drivers' behavior are recommended in the future research. Moreover, the deployment of smart meters that can measure electricity consumption during certain time periods and enable the billing of time-of-use tariffs will influence the charging behavior of PEV fleet—allowing for potential energy cost savings through information and communication technologies-controlled PEV charging (Goebel, 2012). Subsidized work charging and free charging opportunities provided to customers by various businesses might also encourage public charging even though there is sufficient power left in the battery to return home. Furthermore, based on the spatial and temporal distribution of BEV charging activities, the electric demand profile can be estimated as a means to assess the impact on the quality and stability of the power system (Mullan et al. 2011).

References

Davis, S.C., Diegel, S.W. and Boundy, R.G. (2012) Transportation Energy Data Book: Edition 31, Oak Ridge National Laboratory, Oak Ridge, TN.

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

(EIA) U.S. Energy Information Administration (2012) U.S. Product Supplied of Finished Motor Gasoline. Accessed on October 8, 2012. http://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=pet&s=mgfupus1&f=a

Frade, I., Anabela, R., Goncalves, G., Antunes, A. P. (2011) Optimal location of charging stations for electric vehicles in a neighborhood in Lisbon, Portugal. *Transportation Research Record* 2252, 91–98.

Ge, S., Feng, L. and Liu, H. (2011) The Planning of Electric Vehicle Charging Station Based on Grid Partition Method. IEEE Electrical and Control Engineering Conference, Yichang, China.

Goebel, C. (2012) On the business value of ICT-controlled plug-in electric vehicle charging in California. *Energy Policy*, http://dx.doi.org/10.1016/j.enpol.2012.06.053.

Gonder, J., Markel, T., Simpson, A. and Thornton, M. (2007) Using GPS travel data to assess the real world driving energy use of plug-in hybrid electric vehicles (PHEVs). Presented at the Transportation Research Board (TRB) 86th Annual Meeting, Washington, D.C.

Hadley, S.W., Tsevetkova, A. (2008) *Potential Impacts of Plug-in Hybrid Electric Vehicles on Regional Power Generation*. U.S. Department of Energy, Washington D.C.

Holland, J.R. (1975). Adaptation in natural and artificial systems. Ann Arbor, MI: University of Michigan Press.

Kromer, M.A. and Heywood, J.B. (2007) Electric Powertrains: Opportunities and Challenges in the U.S. Light-Duty Vehicle Fleet. MIT Laboratory for Energy and the Environment, Cambridge, Massachusetts.

Kuby, M., Lines, L., Schultz, R., Xie, Z., Kim, J.-G., Lim, S., (2009) Optimization of hydrogen stations in Florida using the flow-refueling location model. *International Journal of Hydrogen Energy* 34, 6045–6064.

Lemoine, D.M., Kammen, D.M., Farrell, A.E. (2008) An innovation and policy agenda for commercially competitive plug-in hybrid electric vehicles. *Environmental Research Letters* 3, 1–10.

Li, Y., Li., L, Yong, J., Yao, Y. and Li, Z. (2011) Layout Planning of Electrical Vehicle Charging Stations Based on Genetic Algorithm. Lecture Notes in Electrical Engineering, 1, Volume 99, Electrical Power Systems and Computers: 661- 668.

Lin Z., Dong, J. and Greene, D.L. (2013) Hydrogen vehicles: Impacts of DOE technical targets on market acceptance and societal benefits. Forthcoming in *International Journal of Hydrogen Energy*.

Lin, Z. and Greene, D.L. (2011) Promoting the Market for Plug-in Hybrid and Battery Electric Vehicles: Role of Recharge Availability. *Transportation Research Record*, No. 2252, pp. 49-56.

Lin, Z., Ogden, J., Fan, Y., Chen, C.-W. (2008) The fuel-travel-back approach to hydrogen station siting. *International Journal of Hydrogen Energy* 33, 3096–3101.

Morrow, K., Karner, D., Francfort, J. (2008) U.S. Department of Energy Vehicle Technologies Program–Advanced Vehicle Testing Activity: Plug-in Hybrid Electric Vehicle Charging Infrastructure Review. Report # INL/EXT-08-15058.

Mullan, J., Harries, D., Bräunl, T. and Whitely, S. (2011) Modelling the impacts of electric vehicle recharging on the Western Australian electricity supply system. *Energy Policy* 39, pp. 4349–4359.

(NFPA) National Fire Protection Association. The 2011 Edition of National Electrical Code, Article 625.

(NRC) National Research Council (2013) *Transitions to Alternative Vehicles and Fuels*. Washington, D.C.: The National Academies Press.

Nicholas, M. A., Handy, S. L., Sperling, D. (2004) Using geographic information systems to evaluate siting and networks of hydrogen stations. *Transportation Research Record* 1880, 126–134.

Ogden, J. (2005). The transition to hydrogen. *Access* 27, pp. 10–16.

Pan, F., Bent, R., Berscheid, A., Izraelevitz, D. (2010) Locating PHEV exchange stations in V2G. In: Proceedings of 1st IEEE International Conference on Smart Grid Communications (SmartGridComm), pp. 173–178.

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

Puget Sound Regional Council (2008). *Traffic Choices Study - Summary Report*.

Shukla, A., Pekny, J., and Venkatasubramanian, V. (2011) An optimization framework for cost effective design of refueling station infrastructure for alternative fuel vehicles. *Computers and Chemical Engineering*, 35, pp. 1431-1438.

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

Skippon, S. and Garwood, M. (2011) Responses to battery electric vehicles: UK consumer attitudes and attributions of symbolic meaning following direct experience to reduce psychological distance. *Transportation Research Part D*, 16, pp. 525–531.

Sweda, T. and Klabjan, D. (2011) An Agent-Based Decision Support System for Electric Vehicle Charging Infrastructure Deployment. 7th IEEE Vehicle Power and Propulsion Conference, Chicago, Illinois.

Wang, H., Huang, Q., Zhang, C. and Xia, A. (2010) A Novel Approach for the Layout of Electric Vehicle Charging Station. Apperceiving Computing and Intelligence Analysis Conference.

Wang, Y.-W. (2007) An optimal location choice model for recreation-oriented scooter recharge stations. *Transportation Research Part D*, 12, pp. 231-237.

Wang, Y.-W., Lin, C.-C. (2009) Locating road-vehicle refueling stations. Transportation Research Part E: Logistics and Transportation Review 45, 821–829.