Modeling and Optimization for Electric Vehicle Charging Infrastructure

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Abstract

We study how the electric vehicles (EVs) of today would perform in meeting the driving needs of vehicle owners, and propose an optimization model to find locations for charging stations needed to support EV usage. We take publicly available data from travel surveys that are person oriented and construct vehicle centric datasets. Chicago and Seattle metropolitan areas are selected as showcases for implementation. The statistical analysis of the datasets for these cities shows that a large majority of the vehicles travel less than the average range of EVs available in the marketplace. Since the distance traveled is not the only factor affecting EV range, we develop a user charging model that determines where and how to charge an EV given all the trips that the vehicle is supposed to make and the availability of the charging infrastructure. The vehicles that fail to complete all their trips are used as an input to an optimization model that yields optimal charging station locations. We present optimization results based on the Chicago and Seattle data.

Keywords: electric vehicles, charging station, location optimization

Introduction

Electric vehicles (EVs) have a long history, which even precedes the history of gasoline engine vehicles, going back as far as the mid 19th century Sulzberger (2004a). Although the dominance of EVs in the first decade of the 20th century was remarkable, it was short lived Sulzberger (2004b). The last decade has witnessed a growing interest in EVs, and many policy makers have created incentives to make EV ownership more attractive. Fluctuating oil prices and concerns over future oil supplies mean that EVs offer more stability in the cost of ownership than traditional gasoline vehicles. Advances in battery technology allows EVs to travel further than ever before on a single charge. Overall carbon emissions are much reduced if cars run on electricity produced at centralized power stations rather than on conventional gasoline engines. The environmental benefits of EVs may be further enhanced as electricity generation moves to renewable sources such as wind or solar. Moreover, these sources allow for local generation in microgrids at individual house/building or neighborhood/town level.

These advantages may be offset by a single important factor, *range anxiety* Wiederer and Philip (2010), which is the fear that the EV has insufficient charge, and the driver will be stranded. Unlike a gasoline vehicle which can refuel quickly, recharging depleted batteries can take hours. Thus a charging infrastructure may be crucial in the wider adoption of EVs.

For today's EV technologies, we study (i) how well EVs would support current driving patterns, and (ii) the charging infrastructure needed to reduce range anxiety. There are two key inputs to our study: EV specifications such as range and charging times (Section Basic EV Parameters); and data on driving patterns of vehicles. Unlike many other studies (e.g., Sweda and Klabjan (2011),Avci et al. (2012)) that use the National Household Travel Survey (NHTS) U.S. D.O.T., Federal Highway Administration (2009), we use the Metropolitan Travel Survey Archive (MTSA) University of Minnesota (2009) of the University of Minnesota. The surveys in the archive contain critical geographical data for the origin and destination of trips that one cannot find in the NHTS. We chose the Chicago 2007 and Seattle 2006 surveys. Since these surveys are person centric, we first converted the survey results into *vehicle tours*: all trips by a vehicle in chronological order with start/end times, origin/destination, distance traveled, trip purpose, etc. This step requires careful processing of the survey data to resolve inconsistencies. In Section Travel Databases, we introduce these travel databases and explain how to create vehicle tours.

Section Statistical Analysis of Driving Patterns uses statistical analysis of the vehicle tour data to see how well EVs may meet the driving needs of vehicle owners. We study distances traveled and how they compare to EV ranges. Then we analyze when vehicles travel for various purposes, and we infer potential times and locations for EV charging.

Next section, A Model for User Charging Decisions, provides a model for EV charging decisions during a vehicle tour. Instead of an elaborate optimization model that would be unrealistic and difficult to use, the "user charging model" chooses among three common charging methods available in North America (level I 120V-AC, level II 240V-AC, level III DC). Given a vehicle tour, initial charge, EV type and charging availability data, the user charging model determines where to charge with which method. If the vehicle tour cannot be completed, then this vehicle is considered to be a *failed* vehicle as an EV. An important purpose of the EV charging infrastructure is to create a network of charging stations that avoids such failures. Hence, in the following section, Optimal Placement of Charging Stations, we develop a mixed integer programming (MIP) model that determines locations for charging stations based on failed vehicle data. Given how many charging stations to open, the MIP model assigns each failed vehicle to a station by minimizing the total distance that needs to be traveled to and from the charging stations, which can be considered as a proxy for aggregate inconvenience.

We implement our approach with all charging from level II home chargers. Level II is the standard charging method recommended by automakers; and overnight home charging is expected to be the dominant charging scheme due to the limited availability of charging infrastructure in the early days of EV adoption and cheaper electricity at night Sioshansi (2012). We present the results based on the Chicago and Seattle data.

Finally, we conclude with a brief discussion of our results and directions for future research.

Basic EV Parameters

An EV is an automobile which is propelled by an electric motor that gets electricity from a battery pack. This general description includes both plug-in hybrid electric vehicles (PHEVs) and all-electric vehicles. A PHEV has a battery pack that stores electricity as well as a combustion engine that starts charging the battery pack when the state of charge hits a certain level. PHEVs now on the market include the Chevy Volt, Toyota Prius PHEV and Ford C-MAX Energi. Examples of mass produced all-electric vehicles are the Tesla Model S, Nissan Leaf, Ford Focus Electric and Mitsubishi i-MiEV.

The battery pack of an EV is the major component that determines the range and recharging times, and it tends to be heavy and expensive. Its capacity depends on the type and size of the vehicle: 16 kWh for the Volt (with only 10.4 kWh available for consumption), 24 kWh for Nissan Leaf, 23 kWh for Ford Focus Electric, and 53 kWh for the Tesla Roadster.

The range on battery power depends on multiple factors including weather (battery packs are sensitive to temperature change hence are thermally controlled), the use of climate control, speed, driving style, cargo weight and road conditions, Hayes et al. (2011). We have collected range data for Nissan Leaf and Chevy Volt from various sources. For example, we have used Hayes et al. (2011), Nissan's web site Nissan (2012), and data at Borba (2012) for Nissan Leaf.

Charging times depend on the charging type used:

- Level I: 120 V AC, 16 A (= 1.92 kW). Typical US residential grounded outlet
- Level II: 208-240 V AC, 12-80 A (= 2.5-19.2 kW). Requires installation of a special home charging dock
- Level III: 300-600 V DC, very high currents (100s of Amperes)

In a Volt, full charging takes about 10 hours at level I, and 4 hours at level II. Because of its higher capacity battery pack, the Leaf takes roughly 20 hours at level I, and 7 hours at level II. The Leaf's battery pack is expected to reach 80% of the capacity from a fully depleted state in 30 minutes using 480 volts DC 125 amps level III charging.

Travel Databases

A well known source of travel data is NHTS, U.S. D.O.T., Federal Highway Administration (2009). It gives specific details about the travels of 300,000 people from 150,000 households sampled across the US, where each household is surveyed about a single randomly chosen day. It gives starting and ending times for each trip and (unreliable) information about which vehicle is used for each trip. Unfortunately, trip endpoints do not have even approximate coordinates, and this limits its usefulness for our purposes.

Hence we concentrate on travel data from MTSA University of Minnesota (2009) for the cities of Chicago and Seattle, where each data source details the vehicle trips for a few thousand households. For such data sources, surveyed households are assigned a one or two day "diary period" over which they record their travels. The diary periods for Chicago's Regional Household Travel Inventory (CRHTI) cover 11 counties (3 of them in Indiana), and span the 12 months of 2007. The 4 counties of the Seattle metro area are covered by 11 separate surveys, but we are primarily interested in the one with diary periods from April through June of 2006, Puget Sound Regional Council (2006), Murakami and Watterson (1990).

The surveys for both cities are organized by household and give a series of "trips" for each person in a surveyed household; e.g., a trip goes from Point A to Point B starting at Time T_1 and ending at T_2. For Chicago, there are 10,552 households, 23,808 household members, and 159,856 trips. The corresponding numbers for Seattle (2006) are 4,746 households, 10,516 people and 87,600 trips.

The Chicago survey specifies 71,346 unique trip endpoint locations, but rounds their coordinates to census tract centroids to protect respondent identities. The Seattle survey rounds some of the coordinates to centroids of census tracts (or smaller regions), but it does not specify which were unique before rounding. To resolve such inconsistencies and provide a suitable framework for analysis, we preprocess the survey data to satisfy the following goals:

1. The data should be organized into vehicle tours that specify where each vehicle went on the diary day.
2. Trip endpoints should be specified as coordinates with uncertainty ranges.
3. Each trip should have a distance specified in terms of road mileage.
4. Each trip has a purpose, and starting and ending times.

Since Goal 1 requires vehicle tours, a natural way to proceed would be to use the "household vehicle number" to convert the (person-oriented) raw data. Both the Chicago survey and the 2006 Seattle survey have such a field, but using it to gather trips in order of claimed start time results in impossible vehicle tours whose trip endpoints do not match. Hence we created a graph problem by finding trip endpoints that do match, and looking for Euler paths that visit each trip in such a graph. When this failed, we organized trips by driver, collapsed sequences of non-car trips, and then used merging for cases when various household members took turns driving a vehicle.

Since the Chicago data are not consistent with Goal 3, and the Seattle data have distance from an unknown road mileage model, we recomputed all the distances based on the publicly available street-map data Bureau (2008). Instead of manually cleaning the data, we just dropped small connected components before running the shortest path algorithm. Paths were computed to minimize travel time for 60mph interstate highways, 50mph ramps, 40mph secondary highways, and 25mph local roads. Then the chosen routes were remeasured for distance.

Statistical Analysis of Driving Patterns

We used the Seattle and Chicago data to analyze driving patterns as follows:

- What is the total driving distance per day?
- How does the number of vehicles on the road depend on the hour of the day?
- How do these numbers change if we restrict the trip purpose (Shopping, Home, Work, Dining, etc.)?
- Are there any major differences between these two cities?

These data could help to estimate how many vehicle owners are potential EV users, and it could also tell when and where the charging would happen. For instance, we can find the time slots in which there is a high demand for charging near work locations.

Figure 1 gives the probability density function (pdf) of the total distance driven per day for Chicago (blue) and Seattle (red). The mean distance per day is 25.7 miles for Seattle and 28.6 miles for Chicago. About 2.6% and 6% of the vehicles traveled $>$ 73 miles per day in Seattle and Chicago, respectively. (The 73 mile cut-off is the EPA rated range for Nissan Leaf.) If range anxiety reduces the cut-off to 60 miles, the percentages become 6% and 10% for Seattle and Chicago.

We can also compute the number of vehicles on the road at a given time of the day; Figure 1 shows this with a 5 minute time granularity. The number of vehicles tends to peak in the morning and the afternoon, and the agreement between the distributions of both cities is quite good. As mentioned in the previous section, there is a purpose (work, home, shopping, dining, etc.) for each leg of the vehicle tour, so we can restrict to a specific purpose. Figure 2 shows the fraction of the vehicles on the road as a function of time for work, home and shopping related purposes. It appears that U.S. driving patterns do not depend strongly on the location—it would be interesting to compare with other cities and countries.

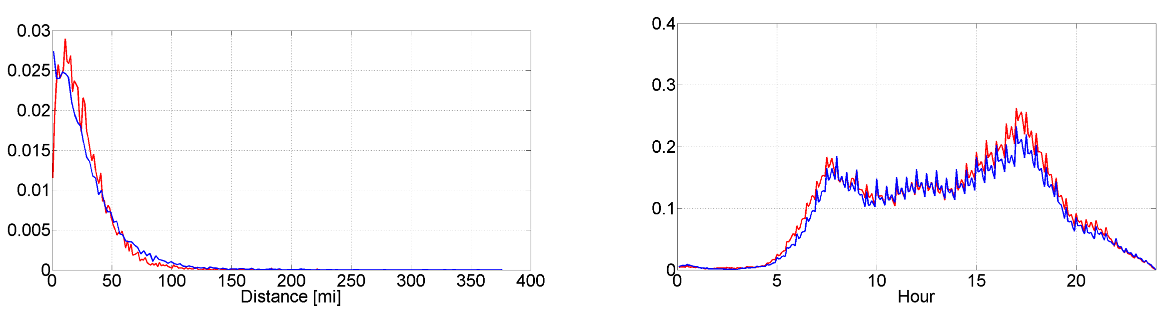

Figure 1: Left: The pdf of the driving distance per day for Chicago (blue) and Seattle (red). *Right:* The fraction of the total number of vehicles on the road as a function of time.

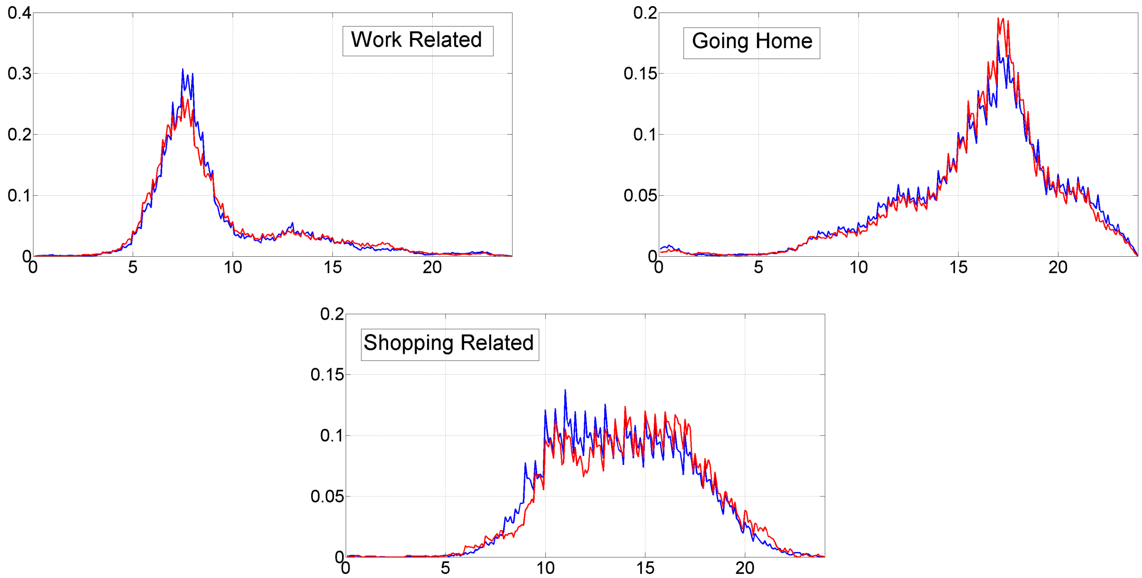

Figure 2: The fraction of the total number of vehicles with a specific trip purpose as a function of the hour of the day. (blue for Chicago and red for Seattle)

A Model for User Charging Decisions

In this section, we model EV owner charging decisions by assuming that they charge as much as possible at each stop, but they may have a choice of charging methods. Technological parameters such as battery capacity and charging times as discussed in Section Basic EV Parameters, and the driving patterns from the travel databases constitute the main inputs for a vehicle owner's charging decisions. There is no explicit treatment of alterations in travel schedules or destinations to facilitate charging. The model is general enough to allow any charging infrastructure (locations, charging methods, and charging access, i.e., public vs. private) and EV type (PHEV or all-electric vehicle). We conclude the section with numerical experiments where the model is implemented for a very specific charging infrastructure (only home charging with level II chargers) and EV vehicle pool (all Nissan Leaf).

Consider the "vehicle tour" of vehicle v, which consists of $\bar{i}$ individual legs (trips), see Figure 3. Let $L_{v,0}$, $L_{v,1}$, $\ldots$, $L_{v,\bar{i}}$ be the locations visited by vehicle v. For $i = 1, \ldots, \bar{i}$, the fraction of total battery capacity $\phi_{v,i}$ required for the ith leg from $L_{v,i-1}$ to $L_{v,i}$ depends on the driving condition (urban, suburban, highway), as well as ambient temperature, road mileage and the type of EV. However, it does *not* depend on the charging decisions.

The other key parameter is the fraction of total charge $\beta_{v,m,i}$ that can be added by using charging type m while at rest at $L_{v,i}$. We consider 3 types of charging: Level I charging ($m = 1$) uses 120V, Level II charging ($m = 2$) uses 240V, and Level III charging ($m = 3$) uses 480V DC. Of course $\beta_{v,m,i}$ depends on the time spent at location $L_{v,i}$, but that is part of the travel schedule independent of the charging decisions.

We define $\mathcal{C}^-_{v,i}$ as the state of charge when vehicle v completes leg i ($\equiv$ comes to rest at location $L_{v,i}$) , and $\mathcal{C}^+_{v,i}$ as the state of charge when vehicle v begins leg $i+1$ ($\equiv$ vehicle v's rest ends at location $L_{v,i}$). See Fig. 3 for a schematic description. It is reasonable to assume that if the driver of vehicle v decides to recharge at the end of leg i, then he/she picks at most one charging option at location $L_{v,i}$ and recharges as much as possible. Under this mild assumption, the dynamics for the state of charge are:

$$\mathcal{C}^-_{v,i} = \mathcal{C}^+_{v,i-1} - \phi_{v,i}, \ \text{ and } \ \mathcal{C}^+_{v,i} = \min(1, \mathcal{C}^-_{v,i} + \beta_{v,m,i}),$$

where m is in set M_i of charging options available at location $L_{v,i}$, and $\mathcal{C}^+_{v,0}$ is the initial charge at the

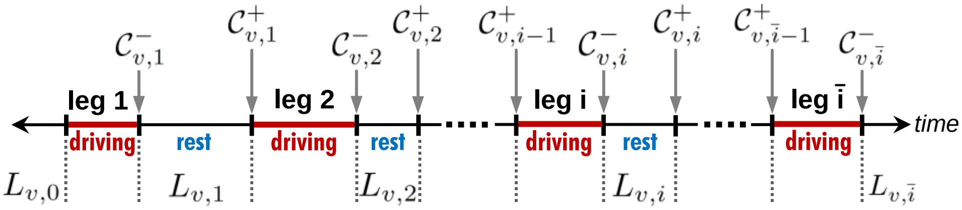

Figure 3: Schematic description of the vehicle tour of vehicle v.

beginning of the first leg. In practice, M_i is usually empty except when $L_{v,i}$ is v's home location. When it is empty, $m = 0$ and $\beta_{v,m,i} = 0$.

In case there is an i where the set $M_{v,i}$ has more than one charging option available, one of two preference lists apply:

$$\begin{aligned} \mathcal{N} &= (2,1,3) \qquad \text{i.e., try Level II, Level I, then Level III} \\ \mathcal{A} &= (3,2,1) \qquad \text{i.e., try Level III, Level II, then Level I.} \end{aligned}$$

The "aggressive" preferences list $\mathcal{A}$ minimizes the time needed for recharging, and the "normal" preferences $\mathcal{N}$ modifies this to avoid Level III if possible. (Manufacturers recommend this since such charging degrades the battery.) If using $\mathcal{N}$ for vehicle v at every charging opportunity would cause any $\mathcal{C}^-_{v,i}$ to drop below 0, we presume that the driver detects the pending problem while still at location $L_{v,0}$ and switches to $\mathcal{A}$. This is at best a rough approximation to human behavior, but it seems like a reasonable compromise between a totally naïve strategy and an elaborate economic optimization.

If $\mathcal{C}^-_{v,i} < 0$ for some leg i even under the aggressive preferences $\mathcal{A}$, then vehicle v is said to have *failed* as an EV. If vehicle v is a PHEV (like the Volt), we just compute how much of the distance from $L_{v,i-1}$ to $L_{v,i}$ has to be powered by gasoline in order to increase $\mathcal{C}^-_{v,i}$ to 0. This then gets added to a total gasoline-powered mileage for vehicle v.

If some vehicle n fails as an EV, it may be useful to determine whether hypothetical additional charging options could eliminate the problem, and if so, how much such charging is necessary. This information is an essential input to the problem of optimal placement of charging stations as discussed in the next section. Suppose a location $L_{v,i}$ is given charging options $M_{v,i}$ that are marked *hypothetical*. We can evaluate this situation using essentially the same rules as before, if we generalize some of the data structures:

- The scalar charge fraction $\beta_{v,m,i}$ obtainable at $L_{v,i}$ must be tagged with a fraction of the time spent at $L_{v,i}$ that must be devoted to type m charging in order to achieve $\beta_{v,m,i}$
- For $i' \geq i$, the state of charge $\mathcal{C}^+_{v,i'}$ becomes an interval where each end of the interval is tagged with a fraction of the $L_{v,i}$ time that is devoted to charging.
- $\mathcal{C}^-_{v,i'}$ needs such generalizations for $i' > i$.
- Generalizing to > 1 hypothetical charging location would complicate things considerably.

The rules for manipulating these data structures are not difficult. Suppose the interval for $\mathcal{C}^+_{v,i'-1}$ is $[c_0, c_1]$ and the time fractions for c_0 and c_1 are (respectively) f_0 and f_1. Subtracting $\phi_{v,i'}$ gives $[c_0 - \phi_{v,i'}, c_1 - \phi_{v,i'}]$ with the same f_0 and f_1 unless $c_0 - \phi_{v,i'} < 0$. In that case, we get $[0, c_1 - \phi_{v,i'}]$ with

$$f_0 + \frac{(\phi_{v,i'} - c_0)(f_1 - f_0)}{c_1 - c_0}$$

in place of f_0. Similarly, recharging can cause f_1 to be reduced if adding $\beta_{v,m,i}$ to c_1 would make it > 1.

The primary result of evaluating the model with a hypothetical charging location is the minimum recharge fraction f_0 for $\mathcal{C}^-_{v,\bar{i}}$. This is the fraction of the time spent at location $L_{v,i}$ that must be spent charging in order to prevent vehicle v from failing as an EV.

Table 1: Output for the Home Charging Scenario

		Chicago 2007		Seattle 2006	
All	vehicle tours	13176	100%	6647	100%
	unique households	8880	100%	4223	100%
	1-day diary period	7578	57.5%	277	4.2%
	2-day diary period	5598	42.5%	6370	95.8%
Failed	vehicle tours	679	5.2%	190	2.9%
	unique households	626	7.0%	180	4.3%
	1-day diary period	294	43.3%	5	2.6%
	2-day diary period	385	56.7%	185	97.4%

Numerical Experiments: Home Charging Scenario

EV manufacturers recommend level II charging over level III due to the detrimental effect of fast charging on the batteries. Otherwise level II charging is the fastest option, and it typically requires multiple hours. Such long charging times, a lack of charging infrastructure, and cheaper electricity at night make overnight home charging at level II the most common charging behavior by households. We can test this home charging scenario by applying the user charging model to the vehicle tours from Chicago 2007 and Seattle 2006.

Suppose each household has a level II charger and all charging must be at home. Since PHEV owners have essentially no range anxiety (due to their combustion engines), we assume that all vehicles in the datasets are type "Nissan Leaf". We also assume that vehicles start their first leg of their vehicle tours with a full battery. Further, we declare census tracts to be urban if population per km^2 exceeds 2000, rural if it is below 20, and otherwise suburban. If a subsegment of a vehicle tour spans multiple census tracts, we make this determination for a single census tract midway along. Implementing the user charging model with these assumptions identifies each vehicle that cannot complete its vehicle tour, which we refer to as a failed vehicle.

Table 1 shows some statistics from the results. There are a total of 13176 (6647) vehicle tours in Chicago (Seattle) dataset. Almost all the vehicles in Seattle have 2-day diary periods, only 43.2% of the vehicles in Chicago fall into this category. It is remarkable that only 5.2% of the vehicles fail in Chicago and this figure drops to 2.9% in Seattle. As the figures suggest, even without a charging infrastructure, a high percentage of the vehicle owners can make their daily trips by only charging at home with the current charging and vehicle technology.

Optimal Placement of Charging Stations

This section develops an optimization model for locating charging stations based on the travel datasets and the user charging model introduced in the previous sections.

Consider a finite time horizon T, divided into equal (e.g., one minute) periods indexed by t. During T, a set of vehicles V need to recharge at p charging stations chosen from a set of candidate locations J. For each vehicle $v \in V$, there are a number of charging options available at various periods and locations. Each charging option is denoted as a triple (v, t, j) that says vehicle v can be charged at location j in period t. Define CO as the set of all charging options. For any $(v, t, j) \in CO$, let $d_{v,t,j}$ be the distance between the location of v in period t and location j, where $\tau_{v,t,j}$ is the duration of charging required.

Each candidate location j has a capacity Q_j that gives the number of vehicles that can charge there simultaneously. Let y_j be a binary decision variable that is 1 if a charging station is opened at location j, and 0 otherwise. Similarly, $x_{v,t,j}$ is a binary variable that is 1 if vehicle v is charged with option (v, t, j).

A MIP model for this problem is given below.

$$\min \sum_{(v,t,j)\in CO} d_{v,t,j} x_{v,t,j} \tag{1}$$

$$s.t. \sum_{(v,t,j)\in CO} x_{v,t,j} = 1, \qquad \forall v \in V \tag{2}$$

$$x_{v,t,j} \leq y_j, \qquad \forall (v,t,j) \in CO \tag{3}$$

$$\sum_{\substack{(v,s,j)\in CO \\ s\leq t\leq s+\tau_{v,s,j}}} x_{v,t,j} \leq Q_j y_j, \qquad \forall j \in J, t \in T \tag{4}$$

$$\sum_{j\in J} y_j = p \tag{5}$$

$$x_{v,t,j} \in \{0,1\}, \qquad \forall (v,t,j) \in CO \tag{6}$$

$$y_j \in \{0,1\}, \qquad \forall j \in J \tag{7}$$

The objective is to minimize the total distance traveled by all vehicles to access the selected charging stations. Constraint 2 ensures that each vehicle is charged by selecting only one charging option. Constraint 3 is a feasible cut introduced for computational purposes—it says vehicle v can charge at location j only if a charging station is opened there. Constraint 4 ensures that the number of vehicles assigned to a charging station at location j is not beyond the capacity of that location in any period. Finally, constraint 5 makes sure that exactly p charging stations are opened.

Home Charging Scenario (cont.)

The hypothetical charging options for failed vehicles, which are discussed in the previous section, are used to generate the input data for the optimization model. Each hypothetical charging option gives the resting location and start/end time of a vehicle, the amount of charging the vehicle needs and a maximum distance the vehicle can travel to access a charging station. To generate the set CO of charging options in the optimization model, we need to augment the hypothetical charging options with the candidate locations of charging stations. And we need to do so under the constraint that the candidate locations are within the maximum travel distances of vehicles.

We use the resting locations of all failed vehicles as the set J of candidate locations. In the travel database, the coordinates of the resting locations are anonymized to those of the census tracts they reside. Thus even though some of the resting locations such as homes or companies may not be suitable for placing charging stations, it should be feasible to find nearby locations in the same census tracts that are suitable. For vehicle v in period t, the distance between its resting location and candidate location j is calculated as the great-circle or orthodromic distance between the coordinates of the two places. If the distance is within the maximum travel distance, a charging option is generated for vehicle v at candidate location j in period t, i.e., (v, t, j). The distance ($d_{v,t,j}$) is attached to this charging option. The amount of charging needed to cover the round trip to candidate location j is added to the original amount of charging. This sum serves as the duration $\tau_{v,t,j}$ in the charging option.

We solve the optimization problem with the datasets for Chicago 2007 and Seattle 2006. Among all the failed vehicles, we focus on those that can complete their tours with just 1 additional hypothetical charging. In the Chicago data, there are 376 such vehicles, 396 candidate locations and 7544 charging options. In Seattle data, there are 101 such vehicles, 197 candidate locations and 933 charging options. We implement the model in AMPL and solve it to optimality with the CPLEX solver. Figure 4 shows the solution for Chicago with $p = 50$; each blue paddle corresponds to a charging station opened. The red lines denote the trips between the vehicle resting places and the charging stations. Figure 4 also shows

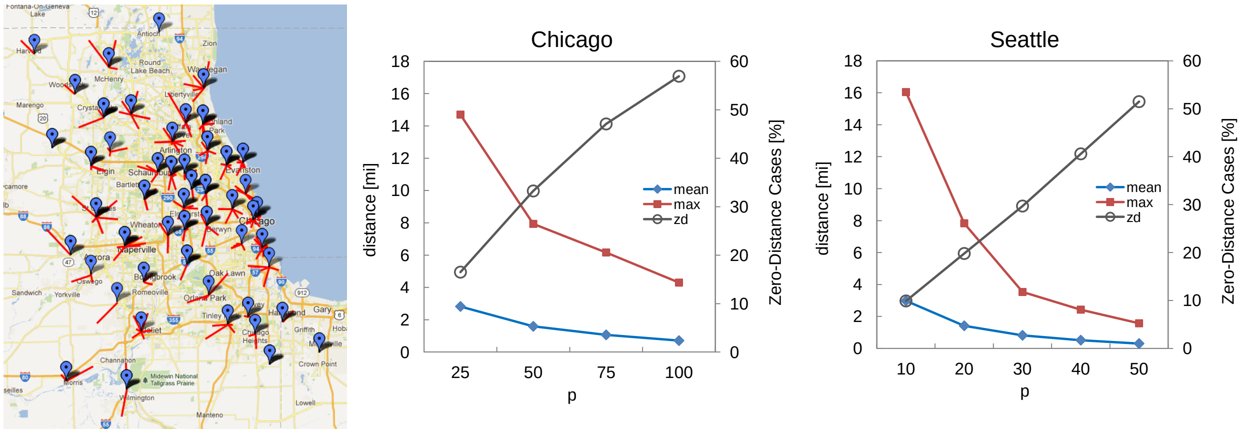

Figure 4: Left: The solution for Chicago with $p = 50$. *Right:* Results of the numerical experiments for Chicago and Seattle. (mean: average distance, max: maximum distance, zd: zero-distance)

the optimization results and particularly how the results change when we change the number of charging stations opened. Both the average and maximum distance decrease as p is increased. In parallel, the percentage of the vehicles that can get recharged on the spot increases as shown by the 'zero-distance' curve. Even though we only run the optimization on the failed vehicles from the travel database, we can scale up the solutions when more data become available.

Discussion and Conclusions

Range anxiety is perceived to be a major road block to large scale EV adoption Wiederer and Philip (2010). In this paper, we study how well EVs can support the driving patterns of vehicle owners. Moreover, we propose a methodology to optimize the charging infrastructure needed in a metropolitan area. We implemented our approach for Chicago and Seattle by using the travel surveys from MTSA.

The statistical analysis of the datasets we have created from the survey results shows that average distance traveled per day is 29 and 26 miles in Chicago and Seattle, respectively. Almost 90% (94%) of the vehicles in Chicago (Seattle) drive less than 60 miles per day. These figures indicate that a high percentage of vehicles travel much less distance than the range of some mass produced EVs like Nissan Leaf with a 73 mile EPA rated range. Nevertheless, these statistics shed some light to the question of whether drivers would be able to make their trips with today's EVs.

Next, we developed a user charging model and implemented it to see what fraction of the vehicles can make their trips without being stranded. Assuming that all vehicles were Nissan Leaf, we created a stress test where vehicles were restricted to charge only at home with level II AC chargers. Remarkably, we found that 94% and 97% of the vehicles were able to complete their trips in Chicago and Seattle, respectively. This may be an indication that the range anxiety may not be well-founded for the majority of vehicle drivers since they should be able to sustain their driving patterns with the current EV technology in the marketplace.

Finally, we determined charging station locations for both cities via a MIP model that we have developed. Its main input is the vehicles that fail to complete their trips, which are determined by the user charging model. The charging station locations are chosen from a set of candidate locations such that the total distance traveled by these "failed vehicles" to the selected charging stations is minimized. Driving to a charging station is considered as a measure of inconvenience for a vehicle driver. The results show that as the number of charging stations are increased, mean and maximum inconvenience experienced by the vehicles drop rapidly. For example, if 100 (50) stations each having 10 level II chargers are opened in Chicago (Seattle) Metropolitan Area, the maximum and mean inconvenience are 4.3 (1.6) and 0.7 (0.3) miles, respectively.

There are interesting directions for future research. One is to analyze the impact of EV charging on the power grid by geography and time of the day. Another topic of interest is to analyze in detail the output of the user charging model for the home charging scenario to look for common characteristics of failed vehicles.

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