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.

I. 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 [1]. Although the dominance of EVs in the first decade of the 20th century was remarkable, it was short lived [2]. 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 cars. Advances in battery technology mean that EVs can go 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 referred to as the range anxiety [3], which is the fear that the EV has insufficient charge to make its trip(s) and would thus be stranded. Unlike a gasoline vehicle which can get at least 200 more miles of range via a quick refueling operation, recharging depleted batteries can take multiple hours. Thus a charging infrastructure may be crucial in the wider adoption of EVs.

Given the current EV technologies, we study (i) how EVs would perform in supporting the driving patterns of vehicle owners, and (ii) the charging infrastructure needed to reduce range anxiety and enhance EV adoption. There are two key inputs to our study. One is the data on EV specifications such as range and charging times, which is discussed in Section II. The other is the data on driving patterns of vehicles. Unlike many other studies (e.g., [4],[5]) that use the National Household Travel Survey (NHTS) [6], we use the Metropolitan Travel Survey Archive (MTSA) [7] of the University of Minnesota. The surveys in the archive contain critical geographical data (latitude and longitude) 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 sets of vehicle tours. A vehicle tour consists of all the trips by a vehicle in chronological order with start/end times, origin/destination, distance traveled, trip purpose, etc. This step requires a careful processing of the survey data to check for and resolve inconsistencies. In Section III, we introduce these travel databases and discuss in detail how we create the datasets of vehicle tours.

In Section IV, we aim to get a rough idea of how well EVs may meet the driving needs of vehicle owners by a statistical analysis of the vehicle tour data. We study the distances traveled by vehicles, and compare them against the driving range of EVs. Further, we analyze the times that the vehicles travel during the course of a day and the trip purposes to infer about the potential times and locations the vehicles can charge.

Section V provides a model for EV charging decisions, which takes vehicle tours as an input. Instead of an elaborate optimization model that would be unrealistic and difficult to use, we develop a “user charging model” that 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 state-of-charge, EV type and availability of different charging methods at each location visited, the user charging model determines where to charge with which method. If the entire vehicle tour cannot be completed with the given input and the resulting charging decisions, 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 Section VI, we develop a mixed integer programming (MIP) model that determines locations for charging stations by taking the failed vehicles of the user charging model as an input. For a given number of charging stations to be opened, 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 station by all vehicles, which can be considered as a proxy for aggregate inconvenience.

We implement all the steps of our approach for a plausible charging scenario where all charging is restricted to be only at home with level II chargers. The motivation for this scenario is two-fold: (i) Level II is the standard charging method recommended by automakers, and (ii) 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 [8]. We present the results based on the Chicago and Seattle data in Sections V-A and VI-A.

Finally, we conclude in Section VII with a brief discussion on our results and the direction for future research.

II. BASIC EV PARAMETERS

An EV is an automobile which is propelled by an electric motor that uses electrical energy stored in 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. Some of the PHEVs in the market place are Chevy Volt, Toyota Prius PHEV and Ford C-MAX Energi. Examples of all-electric vehicles that are mass produced are Tesla Roadster and 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. The capacity of the battery pack varies depending on the type and size of the vehicle. There is a 16 kWh capacity battery for Volt, but only 10.4 kWh of the full capacity (65%) is available for consumption. The Nissan Leaf, Ford Focus Electric and Tesla Roadster have 24 kWh, 23kWh and 53 kWh capacity battery packs, respectively.

The range on battery power depends on multiple factors including weather (battery packs are sensitive to temperature changes and must be thermally controlled), the use of climate control, speed, driving style, total weight (cargo) and road conditions, [9]. We have collected range data for Nissan Leaf and Chevy Volt from various sources. For example, we have used [9], Nissan’s web site [10], and data at [11] for Nissan Leaf.

The charging times depend on the charging type used. There are three common charging methods in the US:

- 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 a special charging dock to be installed at households
- Level III: 300-600 V DC, very high currents (100s of Amperes)

In a Volt, full charging is estimated to take 10 hours at level I, and about 4 hours at level II. Because of its higher capacity battery pack, the Leaf takes roughly 20 hours at level I, and approximately 7 hours at level II (depending on amperage). 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.

III. TRAVEL DATABASES

A well known source of travel data is NHTS, [6]. 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 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 12 months starting in January, 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, [12], [13].

The surveys for both cities are organized by household, and they 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 called “traffic analysis zones”), 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 household 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
When this failed, we organized trips by driver, collapsed sequences of non-car trips, and then used a merging process to look for cases where 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 [14]. 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 based on 60mph interstate highways, 50mph ramps, 40mph secondary highways, and 25mph local roads. Then the chosen routes were remeasured solely on distance.

IV. STATISTICAL ANALYSIS OF DRIVING PATTERNS

We used the collected data from Seattle and Chicago to analyze some of the main characteristics of the driving patterns. We are particularly interested in the following questions:

• 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.)?
• Is there any significant difference between the cities?

These data could help to estimate the percentage of vehicle owners that are candidate for EVs, and it could also give an indication of when and where the charging would happen. For instance, we could find the times when there should be a high demand for charging near work locations.

Figure 1 gives the probability density function (pdf) of the total distance driven per day for the two cities (blue for Chicago and red for Seattle). The mean distance per day is 25.7 miles for Seattle and 28.6 miles for Chicago. While 2.6% of the vehicles travel more than 73 miles in a day in Seattle, and about 6% travel that far in Chicago. (The 73 mile cut-off comes from the EPA rated range for the Nissan Leaf.) If range anxiety reduces the cut-off to 60 miles (80% of the “typical” range), then the percentages become 6% and 10%, respectively.

Using this data, we can also compute the number of vehicles on the road at a given time of the day. Figure 1 shows the pdf of this quantity with a time granularity of 5 minutes. The number of vehicles tends to peak in the morning and the afternoon, and the agreement between the distributions of both cities is surprisingly good. As mentioned in Section III, the surveys also give a trip purpose (work, home, shopping, dining, etc.) for each leg of the vehicle tour. We repeated the same analysis but this time restricting to a specific purpose. Figure 2 shows the pdfs of vehicles on the road as a function of time for work, home and shopping related purposes. It appears that human driving patterns in the US might not depend strongly on the location and that a thorough analysis of one or two cities could yield information about the driving patterns in the rest of the country. It would be interesting to compare with other cities and countries.

Fig. 1. Top: The driving distance per day for Chicago (blue) and Seattle (red). Bottom: The pdf of the total number of vehicles on the road.

Fig. 2. The pdf of the number of trips as a function of time for different trip purposes. (blue for Chicago and red for Seattle)
V. A MODEL FOR USER CHARGING DECISIONS

In this section, we model the charging decisions of EV owners in order to estimate the charging needs in different regions of a metropolitan area. Technological parameters such as battery capacity and charging times as discussed in Section II, 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). In Section V-A, we discuss 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 $i$ individual legs (trips), see Figure 3. Let $L_{v,0}, L_{v,1}, \ldots, L_{v,i}$ be the locations visited by vehicle $v$. For $i = 1, \ldots, i$, the fraction of total battery capacity $\phi_{v,i}$ required for the $i$th 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 $C_{v,i}^-$ as the state of charge when vehicle $v$ completes leg $i$ ($\equiv$ comes to rest at location $L_{v,i}$), and $C_{v,i}^+$ as the state of charge when vehicle $v$ begins leg $i+1$ ($\equiv$ vehicle $v$’s rest ends at location $L_{v,i}$). See Figure 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:

$$C_{v,i}^- = C_{v,i-1}^- - \phi_{v,i},$$

$$C_{v,i}^+ = \min(1, C_{v,i}^- + \beta_{v,m,i}),$$

where $m$ is in set $M_v$ of charging options available at location $L_{v,i}$, and $C_{v,0}^-$ is the initial charge at the beginning of the first leg. In practice, $M_v$ 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:

$$N = (2, 1, 3) \quad \text{i.e., try Level II, Level I, then Level III}$$

$$A = (3, 2, 1) \quad \text{i.e., try Level III, Level II, then Level I}$$

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

If $C_{v,i}^+ < 0$ for some leg $i$ even under the aggressive preferences $A$, 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 $L_{v,j}$ has to be powered by gasoline in order to increase $C_{v,i}^+$ 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 Section VI. Suppose a location $L_{v,j}$ is given charging options $M_{v,j}$ 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 $C_{v,i'}^+$ 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.
- $C_{v,i'}^-$ 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 $C_{v,i,i-1}^+$ 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 $f_0 + (\phi_{v,i'} - c_0)(f_1 - f_0)$

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 $C_{v,j}^-$. 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 I

**OUTPUT FOR THE HOME CHARGING SCENARIO**

<table>
<thead>
<tr>
<th></th>
<th>Chicago 2007</th>
<th>Seattle 2006</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>13176</td>
<td>6647</td>
</tr>
<tr>
<td>unique households</td>
<td>8880</td>
<td>6674</td>
</tr>
<tr>
<td>1-day diary period</td>
<td>7578</td>
<td>277</td>
</tr>
<tr>
<td>2-day diary period</td>
<td>5598</td>
<td>6370</td>
</tr>
<tr>
<td>Failed</td>
<td>679</td>
<td>190</td>
</tr>
<tr>
<td>unique households</td>
<td>626</td>
<td>180</td>
</tr>
<tr>
<td>1-day diary period</td>
<td>294</td>
<td>5</td>
</tr>
<tr>
<td>2-day diary period</td>
<td>385</td>
<td>185</td>
</tr>
</tbody>
</table>

A. **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 per day. Such long charging times, the 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 km² 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. We refer to such a vehicle as a **failed** vehicle.

Table I 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 a very high percentage of the vehicles in both datasets is able to complete the vehicle tours with only home charging. While only 5.2% of the vehicles fail in Chicago, 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 vehicle touring. However, 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 \(t\). Let \(CO\) be the set of all charging options, and or 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. A total of \(p\) charging stations will be selected. 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.

\[
\begin{align*}
\text{min} & \quad \sum_{(v,t,j) \in CO} d_{v,t,j} x_{v,t,j} \\
\text{s.t.} & \quad \sum_{(v,t,j) \in CO} x_{v,t,j} = 1, \quad \forall v \in V \\
& \quad x_{v,t,j} \leq y_j, \quad \forall (v, t, j) \in CO \\
& \quad \sum_{(v,s,j) \in CO} x_{v,t,j} \leq Q_j y_j, \quad \forall j, t \in T \\
& \quad \sum_{j \in J} y_j = p \\
& \quad x_{v,t,j} \in \{0,1\}, \quad \forall (v, t, j) \in CO \\
& \quad y_j \in \{0,1\}, \quad \forall j \in J 
\end{align*}
\]

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 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.

A. **Home Charging Scenario (cont.)**

The hypothetical charging options for failed vehicles in Section V is used to generate the input data for the optimization model. Each hypothetical charging option gives the resting location and 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 $t$. The distance 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 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 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 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 recharge on the spot increases as shown by the ‘zero-distance’ curve. The solving time in Cplex is roughly similar for different $p$, and decreases when $p$ gets really large. 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.

![Figure 4](image_url)

**Fig. 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)

**VII. DISCUSSION AND CONCLUSIONS**

Range anxiety is perceived to be a major road block to large scale EV adoption [3]. 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 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 when simulated 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. Opening 100 public charging stations corresponds to an approximate $200,000 investment in level II charging docks [15], excluding the cost of installation and renting space. If these cities follow a careful planning practice that places each station on public grounds, which would eliminate the space costs, then this would be a minor investment for such large cities.

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.
REFERENCES