THE ELECTRIC VEHICLE CHARGING STATION LOCATION PROBLEM: A PARKING-BASED ASSIGNMENT METHOD FOR SEATTLE

T. Donna Chen
The University of Texas at Austin
6.9E Cockrell Jr. Hall
Austin, TX 78712-1076
donna.chen@utexas.edu

Kara M. Kockelman
(Corresponding author)
Professor and William J. Murray Jr. Fellow
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
kkockelm@mail.utexas.edu
Phone: 512-471-0210

Moby Khan
Cambridge Systematics, Oakland, California
mobashwir@gmail.com
Word Count: 5123 plus 9 figures and tables = 7373 word-equivalents

The following paper is a pre-print, the final publication can be found in *Transportation Research Record* 1254: 28-36, 2013.

ABSTRACT

Access to electric vehicle (EV) charging stations will impact EV adoption rates, use decisions, electrified mile shares, petroleum demand, and power consumption across times of day. This work uses parking information from over 30,000 personal-trip records in the Puget Sound Regional Council's 2006 household travel survey to determine public (non-residential) parking locations and durations. Regression equations predict parking demand variables (total vehicle-hours per zone/neighborhood and parked-time per vehicle-trip) as a function of site accessibility, local jobs and population densities, trip attributes, and other variables available in most regions and travel surveys. Several of these variables are key inputs for a mixed integer programming problem, developed here for optimal EV-charging-station location assignments. The algorithm minimizes EV users' station access costs while penalizing unmet demand. This useful specification was used to determine top locations for installing a constrained number of charging stations within 10 miles of Seattle's downtown, showing how charging location schemes' access costs respond to parking demand and station locations. The models developed here are generalizable to data sets available for most any region, and can be used to make more informed decisions on station locations around the world.

Key words: Plug-in Electric Vehicles, Charging Stations, Location Assignment Problem, Mixed Integer Programming

BACKGROUND

As electric vehicles (EVs) enter the market, there is rising demand for public charging stations. Symbiotically, the demand for EVs is influenced by the availability of refueling infrastructure: "Without infrastructure, the vehicle of the future will remain just that – the vehicle of the future" (*1*). Provision of public charging stations can diminish owners' (potential and actual) range anxieties (*2*), thus increasing EV purchase and use decisions. Morrow et al. (*3*) showed how an EV-based transport system's overall cost can be reduced by providing more charging infrastructure instead of investing in bigger batteries (with greater range). They estimated that the marginal cost of increasing a car's all-electric range (AER) from 10 miles to 40 miles is $8,268, and the cost of installing an additional level-2 commercial charging station (including administrative and circuit installation costs, assuming 10 charge cords per facility) is $18,520. While the EV charging station location problem is a very new topic area, some important strides have been made in the past few years.

Wang et al. (*4*) created a numerical method for the layout of charging stations using a multi-objective planning model. Accounting for charging station attributes, distribution of gas-station demands (rather than parking decisions, as a proxy for charging demands), and power grid infrastructure, among other variables, the researchers tested and verified their model using data from Chengdu, China. Sweda and Klabjan (*5*) used an agent-based decision support system to identify patterns of residential EV ownership and driving activities to determine strategic locations for new charging infrastructure, with the Chicago region as a case study.

Most station location problems are based on existing optimization routines/heuristics. For example, Worley et al. (*6*) formulated the problem of locating stations and optimal EV routings as a discrete integer programming problem, based on the classic Vehicle Routing Problem (VRP). Ge et al. (*7*) proposed a method based on grid partition using genetic algorithms. Their routine focuses on minimizing users' loss or cost to access charging stations after zoning the planning area with a grid partition methodby choosing the best location within each partition, to reflect traffic density and station capacity constraints (which include charging power, efficiency, and number of chargers per station). Li et al (*8*) also used genetic algorithms to identify top locations for charging infrastructure. Their method is based on conservation theory of regional traffic flows, taking EVs within each district as fixed load points for charging stations. The number and distribution of EVs are forecasted, and the cost-minimizing charging station problem is (heuristically) solved using genetic algorithms.

Frade et al. (*9*) used Lisbon, Portugal as a case study, for application of a maximal covering location model (*10*) to maximize the EV charging demand served by an acceptable level of service. They determined not just the locations, but also the capacity of stations to be installed at each location. Finally, Kameda and Mukai (*11*) developed an optimization routine for locating charging stations, relying on taxi data and focusing on stations for Japan's recently introduced on-demand bus system.

This paper adds to the growing field of charging station location solutions by providing behavioral models to predict when and where vehicles are likely to be parked. It also takes a different approach for anticipating charging demand, using parking demand as a proxy. The optimization routine used recognizes parking demands across Seattle neighborhoods/zones, and ensures that stations are not too clustered, by minimizing total system travel distances to the closest charging station, after assuming a maximum cost for those parking beyond the limit of reasonable walk access. The mixed integer program (MIP) developed here is based on the "fixed-charge facility location model" (*12*), which identifies a set of facility sites to minimize the cost of serving a set of demands (located over space/across sites). This type of model has been used to design communication networks (*13*), locate off-shore drilling platforms (*14*), and locate freight distribution centers (*15*). Within the realm of EV charging station location work, the closest parallel to this research is likely Hanabusa and Horiguchi's (*16*) framework, minimizing EV travel costs while maintaining a minimum buffer distance around each charging station. Their EV travel cost is a function of travel time and waiting time at each charging station, and they define demand at each charging station via a traffic assignment algorithm (based on route choice behavior). The current paper attempts to best satisfy demand for public charging of EVs based on parking durations, land use attributes, and (in the case of individual parking durations) trip characteristics. Optimal station locations are determined as a function of parking demand and access (walk) distances/costs.

DATA DESCRIPTION

The data used for this project was obtained from the Puget Sound Regional Council's (PSRC) 2006 household travel survey. The trip data contains trip information of 4,741 households and 10,510 individuals residing in the King, Kitsap, Pierce and Snohomish counties of Washington State. Each respondent was asked to keep a travel diary for two consecutive days, all of which were weekdays. The region consists of 3,700 Traffic Analysis Zones (TAZs), as shown in Figure 1.

The entire region consists of 1,177,140 parcels, and each trip in the trip file is connected to an origin and destination parcel identification number or "ID". Each household is also connected to its home-location parcel ID. In contrast to other regions' TAZ-based land use data sets, PSRC land-use information is available *for each parcel*, and each trip in the Seattle data is associated with an origin parcel and a destination parcel, along with parking, transit and land use attributes within quarter-mile and half-mile buffers/radii around each of these parcels. Buffer-based variables include number of housing units, numbers of jobs (by sector: education, food service, government, industrial, medical, office, construction, retail and service), average costs of nearby parking (both hourly and daily), number of free off-street parking spaces, number of intersections (by type: four-way, three-way, and "point" nodes/dead-ends), number of local and express bus stops, (network) distance to nearest bus stop, and other variables. The wealth and resolution of information provided makes this data set unusual and well suited for analyses performed in this paper.

Table 1 shows various descriptive statistics for Seattle's surveyed persons and households. The average respondent is 42 years old, and 47% of respondents are males. 78 percent are licensed drivers, and the average numbers of persons, workers and vehicles in each household are 2.22, 1.13 and 1.89, respectively.

METHODOLOGY

In order to relate the Seattle region household travel survey data to optimal charging station locations for parked EVs, this study took a three step approach. First, parking locations (by parcel, then aggregated by TAZ) and durations were determined for all trips away from home and of at least 15 minutes in duration (i.e., those that serve as plausible candidates for public charging, if an EV had been used). This parking duration information was then used for regression models that relate (1) zone-level parking demands (aggregated across sampled trips) to land use attributes and (2) trip-level parking demand to individual trip characteristics. Parking demands were also used as inputs for identifying optimal charging station locations, to satisfy as much demand as possible, subject to certain constraints (on access and station supply). The formulation of a mixed-integer optimization problem is presented here, along with an illustrative application to 900 TAZs near the region's center.

Determining Parking Locations and Duration

Parcel-level parking information was extracted from the trip data file in order to determine where vehicles are parked in the region and for how long. A snapshot of the trip data is shown in Table 2.

The trip data consist of 87,600 person-trips, but not all were by car or light truck. After eliminating all passenger trips (in order to avoid duplicating driver trips) and keeping only trips made by light-duty vehicles, 48,789 trips remained in the data set. To estimate public charging demand at different parcels (and then at the level of TAZs), the following steps were used:

1. Consecutive trips were identified, where the destination of the earlier trip coincides with the origin of the later trip. The time between these two trips is when a vehicle is parked at that unique parcel.
2. No parking at one's home parcel is counted, since parking locations at home are not of interest for locating public charging stations.
3. Parking durations of less than 15 minutes were removed, since those are not enough for Level II charging. (Level III charging stations would not have this restriction.)

A MATLAB script was written to perform the above analysis for all 48,789 trips. As a result, 30,085 candidate parking durations for public charging emerged. The output consists of tripmaker ID, parking parcel ID, and parking duration. The parking information (at the parcel level) was then aggregated by TAZ for neighborhood analyses of parking demand, as described below.

Forecasting Zone-Level Parking Demand

The demand for public EV charging in each TAZ may be roughly proportional to the total duration of parking for all surveyed light-duty vehicles at that TAZ (outside of those that park at their home parcels). This parking duration was first normalized, by dividing by parcel size, resulting in values of parking duration per square mile, for each TAZ. Out of the 3700 TAZs in the Seattle region, eight did not contain any parcels identified with land use attributes and were not used in the zone-based analyses. Summary statistics for total surveyed parking durations and other variables of interest (as predictors of parking demand) of the remaining 3692 TAZs are shown in Table 3.

Table 4 shows the parameter estimation results of an ordinary least squares (OLS) regression of parking duration (per square mile) on covariates like population and jobs densities. All relevant land use, access, and network connectivity variables were tested as covariates in initial regression model specifications, with statistically significant regressors (at the .05 level) retained in the final model. Standardized coefficients are also shown, to highlight levels of practical significance. These represent the number of standard deviation (SD) changes in the response variable (parking duration per square mile) following a one SD change in the associated covariate (evaluating all parameter values at their means).

Based on the model's standardized coefficients, parking demand's intensity (per square mile) is most associated with employment (jobs) density. Parking prices and transit access are also relevant**, but** secondary. Increased student density and network connectivity (via more four-way intersections) also appear to play meaningful roles in increasing a zone's total parking demand for the zone.

Forecasting Trip-Level Parking Durations

In addition to examining total parking demand per zone, parking durations for individual drivers/parked vehicles, in minutes per destination, can be modeled as a function of trip and destination characteristics. Table 5 presents summary statistics of these individual trip attributes (parked away from home, for at least 15 minutes), along with average parking durations for various activity types/trip purposes. As can be seen, work trips are the most common trip type (27 percent of the total) and command the longest parking durations (among away-from-home parking experiences), averaging 380 minutes or 6.33 hours each.

Table 6 presents OLS regression estimates for these trips. All relevant zone characteristics (including regressors tested in the zone-level parking demand model, such as parking prices, transit, and network characteristics) and trip-level variables were tested as covariates in initial models, but only statistically significant regressors (at the .05 level) were retained in the final model.

Table 6's results offer a wide range of interesting results, with many very practically significant predictor variables. Since individual trips provide a very large data set, t-statistics are high; fortunately, model fit is also strong ($R^2_{adj} = 0.590$). Apparently, activity type at one's destination is what most heavily influences parking duration, with work trips and K-12 school trips having roughly equal and very long parking durations, on average (for those who drive for such activities [very rare for K-12 trips, since most of these students are not driving themselves to school]).

Longer parking durations are also evident for college, religious/community, recreational, and social activities. Predictably, trips made for the purposes of picking up/dropping off passengers entail the shortest parking durations, on average. Interestingly, job density is not statistically significant in this model despite the fact that the correlation between work-trip purpose indicator and job density is low ($\rho = +0.11$).

Trips involving passengers are predicted to require slightly shorter parking durations than single-occupant-vehicle (SOV) trips, while longer-distance trips increase durations, as expected (by about 3.4 minutes per mile, everything else constant). Such information is useful for charging station owners and operators, who will want to anticipate how many people can and will charge at a station or set of stations, and for how long. Station availability, upon arrival of an EV, can be paramount for station success (by encouraging further EV adoption and future EV trips to that station).

Anticipating Best Sites for Public Charging Stations

The modeling results discussed above illuminate a variety of factors that contribute to (or at least are associated with) zone-level and trip-level parking demand, in statistically and practically significant ways. In order to select highly accessible, high-demand spots for installation of public charging stations, an optimization problem was specified, with an objective function that seeks to minimize the total access costs (walk distances) from the charging stations to drivers' ultimate destination zones (TAZs). Here, EV charging demands are assumed proportional to (i.e., well proxied by) light-duty-vehicle parking demands, as reported directly in the sample data. The optimization ensures a minimum distance between charging stations, to avoid clustering of the not-inexpensive charging infrastructure in adjacent high-parking-demand zones. Such problems are solved using mixed-integer programs (MIPs), which are common in transportation applications, such as airline crew scheduling, vehicle routing, and pipeline design (e.g., *17, 18, 19*). MIPs are generally solved using branch and bound techniques (*20*).

The following set of equations defines the problem solved here using the General Algebraic Modeling System (GAMS), a software designed for mathematical programming and optimization tailored for large-scale modeling applications. Outside of proprietary programs, noncommercial freeware is also available for solving MIPs, such as ABACUS and bonsaiG (*20*).

The Mixed-Integer Optimization Problem

The objective function in this MIP (shown below) aims to reduce total access cost as a function of walk distance between zones i and j (c_{ij}) weighted by parking duration. The walk penalty c_{ij} is limited to a maximum distance or cost, W (set to 2 miles in this application), since drivers are unlikely to walk long distances for parking (similar to transit-access experiences [*21*]). Here i and j index the set of zones for all potential destination TAZs and assignment of individual charging stations, respectively. In this set up, the number of charging stations (L) is less than the number of zones (i) due to budget constraints. Then, for

EVs whose destination is some zone i not equipped with a charging station, the parking demand will have to be satisfied by a (hopefully close by) charging station in zone j. In other words, y_{ij} represents the parking demand for zone i met by a charging station in zone j. Assuming that overall parking demand is likely proportional to EV parking demand, the objective function penalizes longer parking access distances proportional to parking demand.

In addition to y_{ij}, another key decision variable is x_j, which takes on a value of 1 for zones with charging stations and zero for zones without, representing the set of optimal charging location zones. Other parameters include d_i, the parking demand at zone i, and L, which is the limit on the total number of charging stations one can allocate to zones. To ensure that charging stations are sufficiently spaced out, the indicator δ_{ij} takes on a value of 1 if the distance between i and j is less than a specified minimum spacing r and zero otherwise. A large number M allows all parking demand to be assigned to charging stations, hopefully ensuring that locally parked EVs can be accommodated by their nearest charging station.

Objective function:

$$\min \sum_i \sum_j c_{ij}\, y_{ij}$$

Constraints:

1. $\sum_j y_{ij} = d_i, \forall\, j \in J$ (parking demand constraint)
2. $\sum_i y_{ij} \leq Mx_j, \forall\, i \in I$ (charging supply constraint)
3. $\sum x_j \leq L, \forall\, j \in J$ (charging-station availability constraint)
4. $\sum_i \delta_{ij} x_j \leq 1, \forall\, i \in I$ (charging station spacing constraint)
5. $y_{ij} \geq 0\ \forall\, i \in I, j \in J$ (non-negativity constraint on parking demand)
6. $x_j \in \{0,1\}\ \forall\, j \in J$ (binary variable constraint for charging station selection)
7. $\delta_{ij} = \begin{cases} 1\ if\ C_{ij} < r \\ 0 \text{ otherwise} \end{cases}$ (minimum inter-station spacing)
8. $c_{ij} \leq W$ (maximum access cost)

The formulation of this optimization problem also introduces some challenges. Capacity for each charging station is undefined here, since parking demand is currently without a time-of-day dimension and the objective function may overly favor work and school trips, with their long parking durations. Here, the optimization simply aims to locate optimal zones with a reasonable spread under the assumption that EV parking patterns will imitate overall parking demand. Nonetheless, the MIP specified here is a step towards efficiency of locating charging stations, as illustrated in the Seattle application below.

Charging Station Allocation: A Seattle Area Application

To demonstrate the mixed-integer optimization problem, total daily parking demand in minutes (d_i) across 900 TAZs (i = 900, j = 900) within approximately 10 miles (network distance) of the Seattle CBD were considered. (Inclusion of all 3,700 zones resulted in a large matrix that caused the GAMS software to time out in the search for a solution.) With relatively small size (just 5 percent area of the average PSRC TAZ) and high population density (three time that of the average PSRC zone), these relatively central TAZs are good candidates for inter-zonal parking access of EV charging stations. (Large, low-density peripheral zones cause problems for the GAMS algorithm because they have no or few neighboring zones within the 2-mile maximum parking-access distance. For such applications, the zones with larger areas can be split, with all zones of approximate equal size being the optimal condition for seeking a set of solutions.)

The total number of charging stations was limited to L = 80, and the minimum distance between charging stations was set to r = 1 mile, since ½-mile access/walk distances (the worst-case scenario for an EV owner parked between such stations) are often reasonable, especially for workers intending to be parked for many hours. Network walking distances (as given by the PSRC, which exclude freeway links and certain bridges considered unsafe for pedestrian use) were used to represent the travel costs, C_{ij}. As noted earlier, the maximum walk penalty, W, was limited to 2 miles, to reflect a cap on reasonable access costs. Using the Coin- or Branch-and-Cut (CBC) solver, a straightforward GAMS code inputted the travel cost matrix. To reduce the GAMS-required memory, the large travel cost matrix was filtered to restrict parking assignment to charging stations within a 2 mile access distance. The algorithm arrived at a solution in approximately 8 minutes and 45 seconds on a standard desktop computer. The mixed-integer problem selected optimal parking station locations in the 80 zones listed in Table 7 (and shown in Figure 2), with PSRC travel survey parking demands and associated zone ranks (based simply on that demand) shown alongside.

As shown in Table 7, many of these zones rank high in parking demand, so a charging station scores well by serving them directly. But many others were also selected, despite very low in-zone parking demand, thanks to their strategic locations – nestled among other zones with high parking demands. Figure 2 provides maps of this solution set for charging station locations (left side) versus a simple assignment approach, where chargers are placed in the 80 zones with highest parking demands (right). As illustrated in Figure 2, optimal station locations are much more scattered throughout the 900-zone region, versus the simple demand-based assignment method, which concentrates stations in the region's central business district. When clustered together, high parking demand zones, under the optimal solution, are sometimes served by a low- to medium-demand zone, nestled among them.

The optimized solution yielded a total (minimized) cost (z) of 842,413 mile-minutes, with a weighted-average parking access cost of 0.69 miles (weighted by total parking duration of station-assigned zones). 79.9 percent of parking demand was able to access a charging station within 1 mile of the destination TAZ, with a maximum walk-access distance of 1.90 miles. In contrast, if charging stations were placed purely based on parking demand (in the top 80 TAZs, where parking demand is highest), the total cost (z) would be 890,135 mile-minutes (5.7 percent higher than the optimal solution found here), the average parking access cost would be 0.73 miles, and the maximum access distance would more than double, to 3.96 miles. Under this simplified approach, 78.0 percent of parking demand appears able to access a charging station within 1 mile of the destination TAZ.

Such results suggests there is some merit to simple, demand-based assignment (with no more than one station per zone, though that station may have multiple chargers available). However, for implementations where zones are even smaller in size (with greater opportunity for interzonal parking access), the benefits of this paper's optimization approach are more striking. For example, when 20 charging stations are strategically located across the City of Seattle's 218 zones, the routine returns an optimal solution in under 1 second, placing 94.5 percent of parking demand within 1 mile a station – rather than meeting just 79.6 percent of parking demand (within 1 mile) under the simple assignment rule (allocating public chargers to zones with highest parking demands).

CONCLUSIONS

A key factor for long-term EV success involves simplifying the logistics of charging one's vehicle away from home. Thoughtful siting of public charging stations can ease consumer range anxiety while offering a lower cost approach to integrating EVs into the transportation market (versus investing in longer-range batteries). This study relied on household travel survey data from the Seattle region to investigate parking demands (by zone and by trip) and then identify optimal station locations using a rigorous MIP.

Parking demand was examined in two ways, based on land-use characteristics for a zone and trip (and traveler) characteristics for individual trips. Land use and access attributes were used in an OLS regression model to predict total parking times per zone. Parking demand (per square mile) at the TAZ level rose significantly with jobs and student densities. More connected and transit-served zones, characterized by more nearby four-way intersections and bus stops, were also found to experience higher parking demand. At the trip level, trip purposes were by far the most significant predictor of parking durations. Models revealed that work and school trips require the longest parking periods while regular errands (personal business, shopping, eating out, and picking up and dropping off passengers) necessitated the shortest parking durations, with social and recreational activities falling somewhere in between. Trip distance and use of a car (rather another vehicle type) also lengthened average parking durations.

The first regression model's outputs provide key inputs for determining efficient charging station locations, as specified here via a mixed integer optimization program. Taking into consideration budget constraints (which limit total number of charging stations to be deployed), and avoiding resource clustering (by specifying minimum station spacings), the optimization problem assigned 80 public charging stations thoughtfully across 900 TAZs within 10 miles of Seattle's downtown center. As designed, these were spaced at least one mile apart, with wide ranging access and parking demand characteristics, illustrating both the importance of parking intensity and access. This optimal charging location scheme was compared to one based focused on top-ranked zones, in terms of parking demand, and yielded clearly better results in multiple ways, like average access distances (in addition to minimizing total access costs).

The work presented here has certain limitations. It assumes that LDV parking demand is a strong proxy for EV charging demands, which may not reflect actual charging demands, particularly while EV market shares are still small. As compared to the general U.S. population, early EV adopters are disproportionately younger, male, more educated, and more environmentally sensitive (*22*). Over time, as EV market shares grow, parking demands may more closely reflect EV charging demands. Introducing a time-of-day dimension to the optimization problem, to reflect the dynamic nature of charging demand levels, would also serve as a useful extension. While this work's MIP identifies optimal zones for charging station placement, specific station locations within identified zones are not defined. Such location choices are likely to be highly influenced by visibility, accessibility, and installation costs, which vary from $2000 to $5000 for wall-mounted stations in parking garages to $15,000 or more for stations which require utility service and infrastructure upgrades, according to Austin Energy staff (*23*).

Nonetheless, the models developed here provide a basic framework for readers to anticipate parking demands and more efficiently locate EV charging infrastructure in new settings and/or subject to different constraints (on access costs and station availability). This framework can be quickly adapted to other cities and regions, with similar data sets, for making more optimal decisions on station locations around the world.

ACKNOWLEDGEMENTS

The authors are grateful to the National Science Foundation for financial sponsorship of this work through the University of Texas at Austin and Texas A&M's Industry-University Research Center for PEVs. Crucial support in the form of optimization formulation aid by Tarun Rambha, GAMS guidance by Christopher Melson and Dr. David Morton, and administrative assistance by Annette Perrone also helped make this investigation possible. The suggestions of several anonymous reviewers are also appreciated.

REFERENCES

1. Wehrman, J. (2013). Senior vice president of Honda of America Manufacturing. As quoted by A. Lienert in *Alt-Fuel Vehicle Infrastructure is Stumbling Block, Honda Tells Lawmakers*. Edmunds.com, March 6, 2013. Article available online at http://www.edmunds.com/car-news/alt-fuel-vehicle-infrastructure-is-stumbling-block-honda-tells-lawmakers.html
2. Aoki, H. (2010). *The Standardization of Electric Mobility Towards CO_2 Reduction*. Slideshow developed for The Tokyo Electric Power Company.
3. Morrow, K., Karner, D. and Francfort, J. (2008) Plug-in hybrid Electric Vehicle Charging Infrastructure. *Final Report Idaho National Laboratory*. INL/EXT-08–15058.
4. 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*.
5. 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.
6. Worley, O., Klabjan, D. and Sweda, T. (2012) Simultaneous Vehicle Routing and Charging Station Siting for Commercial Electric Vehicles. *IEEE International Electric Vehicle Conference*, Greenville, NC.
7. 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.
8. 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.
9. Frade, I., Ribeiro, A., Goncalves, G. and Antunes, A.P. (2011) Optimal Location of Charging Stations for Electric Vehicles in a Neighborhood in Lisbon, Portugal. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2252*: 91-98.
10. Church, R. L., and ReVelle, C. (1974) The Maximal Covering Location Problem. *Papers of the Regional Science Association* (32): 101-118.
11. Kameda, H. and Mukai, N. (2011) Optimization of Charging Station Placement by Using Taxi Probe Data for On-Demand Electrical Bus System. *Lecture Notes in Computer Science* 6883: 606-615.
12. Drezner, Z. and Hamacher, H.W. (Eds.). (2004) *Facility Location: Application and Theory* (2nd ed.). New York: Springer.
13. Mirzain, A. (1985) Lagrangian Relaxation for the Star-Star Concentrator Location Problem: Approximation Algorithm and Bounds. *Networks* 15: 1-20.
14. Balas, E. and Padberg, M.W. (1976). Set Partitioning: A Survey. *SIAM Review* 18: 710-760.
15. Nozick, L.K. and Turnquist, M.A. (1998) Integrating Inventory Impacts into a Fixed Charge Model for Locating Distribution Centers. *Transportation Research Part E* 31(3): 173-186.
16. Hanabusa, H. and Horiguchi, R. (2011) *Lecture Notes in Computer Science* in *Knowledge-based and Intelligent Information and Engineering Systems*, Volume 6883/2011, pp. 596-605.
17. Brimberg, J., P. Hansen, K.W. Lih, N. Mladenović and M. Breton (2003) An Oil Pipeline Design Problem. *Operations Research* 51(2): 228-239.
18. Barnhart, C., A. Cohn, E. Johnson, D. Klabjan, G. Nemhauser and P. Vance (2003) *Airline Crew Scheduling,* chapter 14 in *Handbook of Transportation Science*: International Series in Operations Research & Management Science 56 (5): 517-560.
19. Kaufman, D., J. Nonisb, R. Smith (1998) A Mixed-Integer Linear Programming Model for Dynamic Route Guidance. *Transportation Research Part B* 32 (6): 431-440.
20. Linderoth, J. and T. Ralphs (2004) Noncommercial Software for Mixed-Integer Linear Programming. Technical Report 04T-023, Department of Industrial and Systems Engineering, Lehigh University. Available at http://homepages.cae.wisc.edu/~linderot/papers/Linderoth-Ralphs-05-TR.pdf.
21. Transportation Research Board (2003). *Transit Capacity and Quality of Service Manual*, 2nd Edition. Transit Cooperative Research Program (TCRP) Report 100.

22. Carley, S.R., R.M. Krause, B.W. Lane and J.D. Graham (2013) Intent to Purchase a Plug-In Electric Vehicle: A Survey of Early Impressions in Large American Cities. *Transportation Research Part D*18 (1): 39-45.
23. Freberg, Cameron (2012). Conservation Program Associate, Electric Vehicles and Emerging Technologies, Austin Energy. Email to Kara Kockelman. November 9.

LIST OF TABLES

LIST OF FIGURES

Table 1: Summary Statistics of PSRC Person- and Household-level Attributes

	Mean	**St Dev.**	**Min**	**Max**
Person Records (N=10,510)				
Age (years)	41.9	21.8	0	99
Male Indicator	0.47	0.50	0	1
Driver’s License Indicator	0.78	0.42	0	1
Student Indicator	0.21	0.4	0	1
Household Records (N=4,741)				
Household Size	2.22	1.21	1	8
Household Number of Workers	1.13	0.85	0	5
Household Number of Vehicles	1.89	1.07	0	10
Number of Licensed Drivers	1.69	0.73	0	5
Household Income ($/year)	71,400	42,300	5,000	175,000

Table 2: Snapshot of Trip Data

Household #	Person #	Trip #	Begin Time	End Time	Origin parcel	Destin. parcel	Home parcel
2045	1	1	1040	1100	8009	*12543*	12543
2045	1	2	1420	1450	*12543*	**4532**	12543
2045	1	3	2000	2055	**4532**	*12543*	12543
2045	2	1	810	900	*12543*	**10093**	12543
2045	2	2	1500	1540	**10093**	12543	12543

Table 3: Summary Statistics of PSRC Zone Attributes

Variable (n = 3962)	**Mean**	**Std. Dev.**	**Min**	**Max**
Parking duration (mins/mile^2)	2.41E+04	1.18E+05	0	2.43E+06
Population density (persons/mile^2)	7.99E+03	1.88E+04	0	2.91E+05
Employment density (jobs/mile^2)	1.26E+04	8.27E+04	0	2.07E+06
Student density (students/mile^2)	1.64E+03	2.48E+04	0	1.02E+06
Housing density (units/mile^2)	3.43E+03	8.20E+04	0	1.27E+05
Average price of daily paid parking within zone ($)	0.145	1.027	0	21.3
Average price of hourly paid parking within zone ($)	0.066	0.465	0	11.0
3-way intersections (1/2 mile radius)	45.8	22.52	0	119.3
4-way intersections (1/2 mile radius)	36.8	45.91	0	251.8
Express bus stops (1/4 mile radius)	2.25	6.369	0	55.6
Bus stops (1/4 mile radius)	6.21	9.016	0	69.6

Note: The parking duration is of surveyed vehicles only, which represent approximately 0.29 percent of Seattle’s household-owned and operated light-duty fleet over a two-weekday period.

Table 4: Parking Demand (min/mile^2) Regression Results (OLS)

Variable	Parameter Estimate	Standardized Coef.	t-stat
Constant	3268		1.06
Density			
Population density (residents/mile^2)	-0.294	-0.047	-3.50
Employment density (jobs/mile^2)	0.583	**0.408**	27.0
Student density (students/mile^2)	0.226	0.047	4.11
Parking Prices (within ¼ mile)			
Average price of daily paid parking ($)	2.22	**0.193**	11.0
Transit Access & Network Connectivity			
#3-way intersections (within ½ mile)	-158.0	-0.030	-2.41
#4-way intersections (within ½ mile)	160.8	0.062	2.94
#Express bus stops (within ¼ mile)	1537	0.083	3.29
#Bus stops (within ¼ mile)	1624	**0.124**	4.17
Number of Observations	3,692 TAZs		
Adjusted R-squared	0.521		

Note: All coefficients shown are statistically significant at the 5-percent level (p-value < 0.05). Y is the zone's total parking duration of surveyed drivers (away from home, and longer than 15 min duration). Other covariates tested in Table 4's model are all land use, network, pricing, and transit attributes shown in Table 3.

Table 5: Summary Statistics of PSRC Trip Attributes

Variable	Mean	Std. Dev.	Min	Max	Avg Parking Duration (min. per trip)
Parking duration (min/trip)	142.0	199.5	15.0	2120	-
Trip distance (miles)	6.71	7.14	0.230	67.6	-
Passengers (excluding driver)	0.421	0.811	0	6	-
Activity: Work	0.271	0.445	0	1	379.7
Activity: School (K-12)	6.87E-03	0.083	0	1	338.8
Activity: College	7.63E-03	0.087	0	1	222.5
Activity: Eating out	0.071	0.257	0	1	46.1
Activity: Personal business	0.179	0.384	0	1	46.8
Activity: Everyday shopping	0.168	0.374	0	1	27.7
Activity: Major shopping	0.016	0.127	0	1	47.6
Activity: Religious/community	0.019	0.138	0	1	116.8
Activity: Social	0.040	0.197	0	1	127.6
Activity: Recreation-participate	0.057	0.232	0	1	103.5
Activity: Recreation-watch	0.016	0.126	0	1	107.4
Activity: Accompany someone else	8.88E-03	0.094	0	1	58.8
Activity: Pick up/drop off	0.133	0.340	0	1	15.5
Activity: Turn around	4.52E-03	0.094	0	1	53.0
Vehicle: Car	0.560	0.496	0	1	147.2
Vehicle: SUV	0.194	0.395	0	1	133.2
Vehicle: Van	0.119	0.324	0	1	103.3
Vehicle: Truck	0.089	0.285	0	1	173.7
Vehicle: Other	0.034	0.181	0	1	145.1

Note: n=30,085. Only trips ending away from home, with origin and destination zones in the region and parked durations exceeding 15 minutes, are included here.

Table 6: Individual Parking Durations (min/trip) Regression Results (OLS)

Variable	Parameter Estimate	Standard. Coef.	t-stat
Constant	372.2		125.5
Destination TAZ Characteristics			
Land-use entropy (balance or mix index)	-42.63	-0.047	-11.9
Distance to CBD (miles)	-0.204	-0.013	-3.34
Population density (per mile^2)	-9.075E-05	-0.008	-1.99
Employment density (per mile^2)	8.173E-05	-0.048	12.1
Student density (per mile^2)	-3.189E-05	-0.010	-2.48
Trip Characteristics			
Trip distance (miles)	3.461	**0.124**	31.8
Passengers (excluding driver)	-2.715	-0.011	-2.68
Activity: Work (base case)	-	-	-
Activity: School (K-12)	-21.28	-0.009	-2.37
Activity: College	-157.6	-0.069	-18.4
Activity: Eating out	-306.6	**-0.396**	-95.0
Activity: Personal business	-313.2	**-0.603**	-135.6
Activity: Everyday shopping	-324.5	**-0.609**	-133.9
Activity: Major shopping	-308.0	**-0.196**	-51.5
Activity: Religious/community	-246.3	**-0.170**	-44.6
Activity: Social	-241.9	**-0.238**	-60.7
Activity: Recreation-participate	-259.7	**-0.302**	-75.6
Activity: Recreation-watch	-254.2	**-0.161**	-41.8
Activity: Accompany someone else	-298.9	**-0.141**	-37.2
Activity: Pick up/drop off	-344.1	**-0.587**	-127.3
Activity: Turn around	-303.8	**-0.102**	-27.5
Vehicle: Car (base case)	-	-	-
Vehicle: Van	-13.87	-0.023	-5.82
Vehicle: SUV	-4.101	-0.008	-2.12
Vehicle: Truck*	-1.367	-0.002	-0.51
Vehicle: Other	-17.88	-0.016	-4.22
Number of Observations	30,085		
Adjusted R-squared	0.590		

Note: All coefficients shown are statistically significant at the 5 percent level (p-value < 0.05) except those shown with an asterisk (*). Bolded standardized coefficients indicate the most practically significant of covariates.

Table 7: Charging Station Assignments and their In-Zone Parking Demands

TAZs Assigned a Station (ID #)	**Survey Parking Demand** (minutes)	**Parking Demand Rank** (out of 900 zones)
305	29266	1
873	26473	2
709	13972	7
808	11489	8
674	10184	13
70	8959	18
30	6449	33
878	5909	41
804	5311	47
351	5154	50
384	4305	70
735	4040	72
844	3587	83
859	3317	92
721	3314	93
815	3237	96
701	3097	105
387	2669	125
557	2517	137
101	2445	144
31	2311	153
728	2284	155
332	2120	170
670	2035	175
803	1985	179
632	1854	198
679	1798	204
702	1655	223
17	1513	244
53	1481	247
141	1481	247
117	1264	271
2	1249	274
864	1248	275
416	1209	283
872	1191	286

757	1099	301
331	1089	303
428	1084	306
42	1077	309
745	1076	310
828	1005	335
882	1005	335
783	996	337
675	983	341
834	839	373
246	823	379
719	796	387
270	773	392
56	749	398
339	722	403
93	678	410
884	677	411
446	631	425
781	605	432
199	603	433
348	593	435
769	537	448
591	496	457
665	417	486
371	401	488
753	385	494
676	361	497
381	325	516
84	310	521
888	310	521
298	200	581
809	198	585
692	145	621
811	135	631
717	126	644
65	118	653
12	115	654
169	61	702
176	18	750
623	18	750

329	15	754
290	0	761
754	0	761
893	0	761

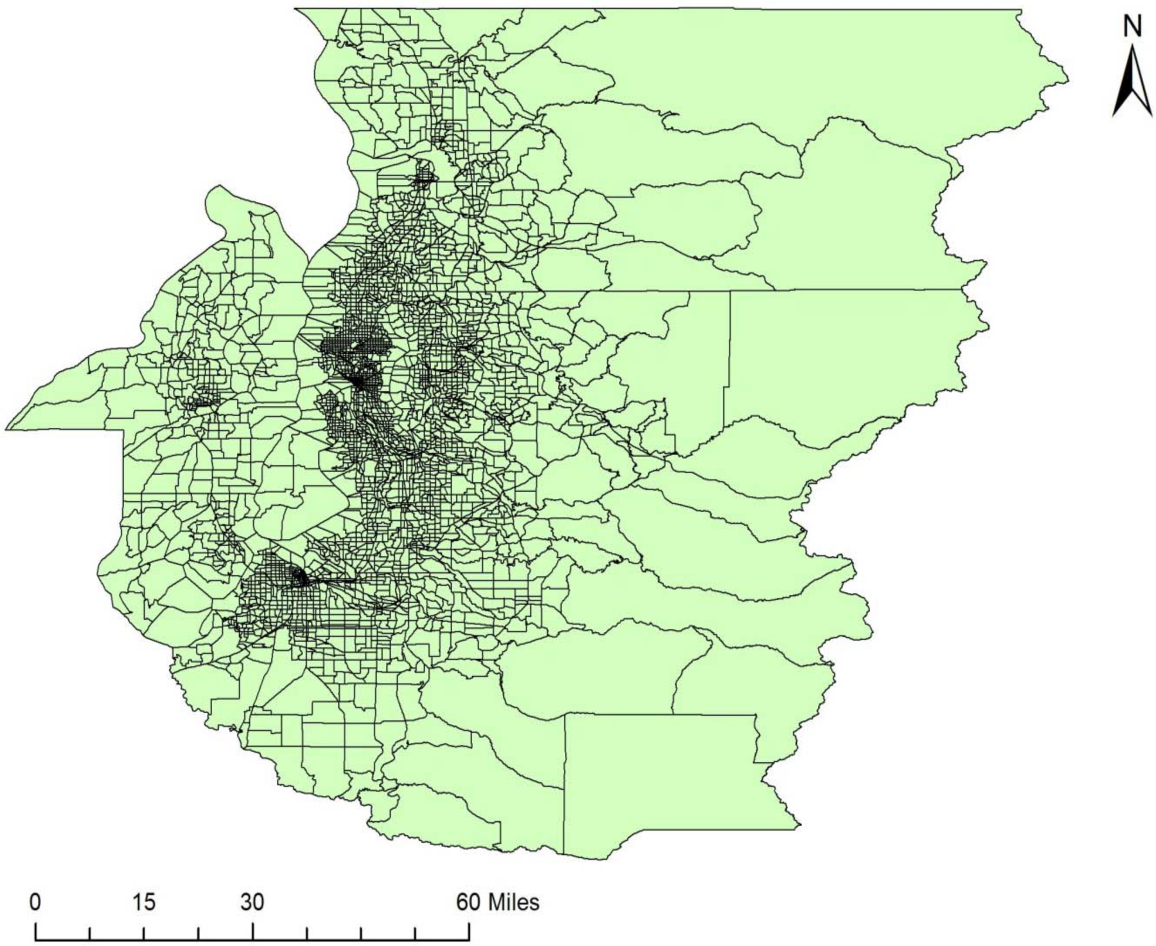

Figure 1: **Map of the Seattle Region's 3,700 Traffic Analysis Zones**

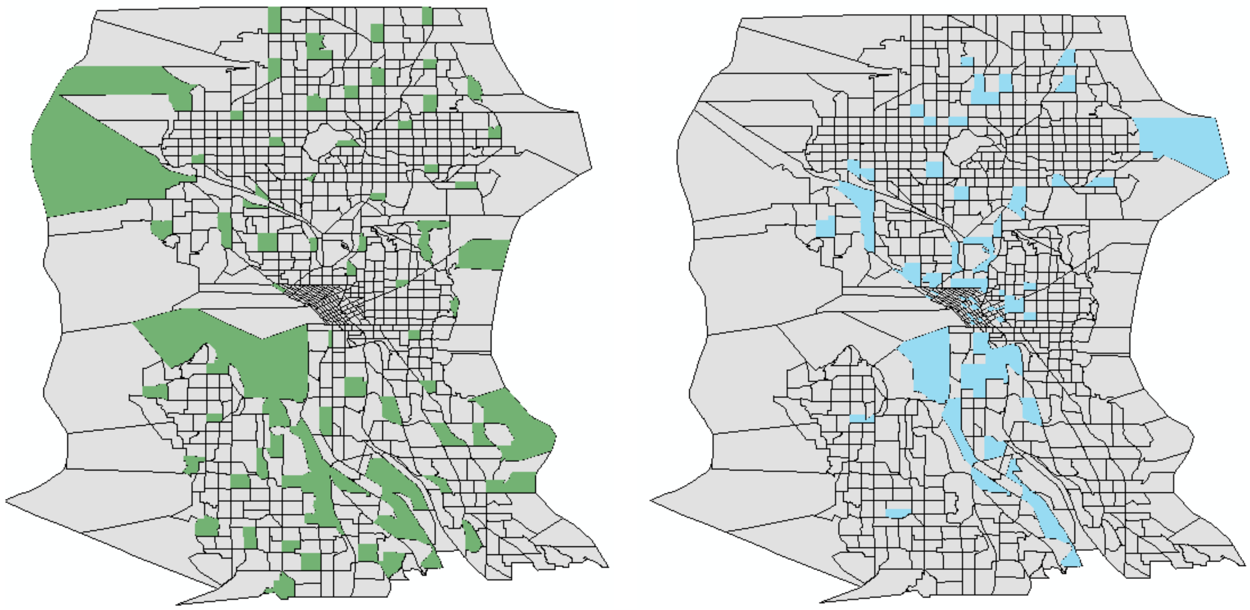

Figure 2. Map of Optimal Charging Station Locations in Seattle vs. Top Parking Demand Zone Charging Station Locations (*I* & *J* = 900, *L*=80)