Locating Electric Vehicle Charging Stations

Parking-Based Assignment Method for Seattle, Washington

T. Donna Chen, Kara M. Kockelman, and Moby Khan

Access to electric vehicle (EV) charging stations will affect EV adoption rates, use decisions, electrified mile shares, petroleum demand, and power consumption across times of day. Parking information from more than 30,000 records of personal trips in the Puget Sound, Washington, Regional Council's *2006 Household Activity Survey* is used to determine public (nonresidential) parking locations and durations. Regression equations predict parking demand variables (i.e., total vehicle hours per zone or neighborhood and parked time per vehicle trip) as a function of site accessibility, local job and population density, trip attributes, and other variables available in most regions and travel surveys. Several of these variables are key inputs to a mixed-integer programming problem developed to determine optimal location assignments for EV charging stations. The algorithm minimizes EV users' costs for station access while penalizing unmet demand. This useful specification is used to determine the top locations for installing a constrained number of charging stations within 10 mi of the downtown area of Seattle, Washington, and shows how the access costs of charging location schemes respond to parking demand and station location. The models developed here are generalizable to data sets available for almost any region and can be used to make more informed decisions about station locations around the world.

As electric vehicles (EVs) enter the market, demand for public charging stations is increasing. 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," says James Wehrman, senior vice president of Honda of America Manufacturing (*1*). The provision of public charging stations can diminish owners' (potential and actual) range anxieties and encourage EV purchase and use decisions (*2*). Morrow et al. show 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 (*3*). They estimate that the marginal cost of increasing a car's all-electric range from 10 mi to 40 mi 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. Even though the EV charging station location problem is a new topic, some important strides have been made in the past few years.

T. D. Chen and K. M. Kockelman, Department of Civil, Architectural, and Environmental Engineering, University of Texas at Austin, Ernest Cockrell Jr. Hall, Suite 6.9, 301 East Dean Keeton Street, Stop C1761, Austin, TX 78712-1076. M. Khan, Cambridge Systematics, Inc., Suite 1600, 555 12th Street, Oakland, CA 94607. Corresponding author: K. M. Kockelman, kkockelm@mail.utexas.edu.

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

Most station location problems are attributable to existing optimization routines or heuristics. For example, Worley et al. formulate the problem of locating stations and optimal EV routings as a discrete integer programming problem based on the classic vehicle routing problem (*6*). Ge et al. propose a method based on grid partition that uses genetic algorithms (*7*). Their routine focuses on minimizing users' loss or cost to access charging stations after zoning the planning area with a grid partition method by choosing the best location within each partition to reflect traffic density and station capacity constraints (e.g., charging power, efficiency, and number of chargers per station). Li et al. also use 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 (*8*). The number and distribution of EVs are forecasted, and the cost-minimizing charging station problem is (heuristically) solved with genetic algorithms.

Frade et al. (*9*) apply a maximal covering location model [defined by Church and ReVelle (*10*)] to Lisbon, Portugal, as a case study to maximize the EV charging demand served by an acceptable level of service. They determine not only the locations but also the capacity of stations to be installed. Finally, Kameda and Mukai develop an optimization routine for locating charging stations that relies on taxi data and focuses on stations for Japan's recently introduced on-demand bus system (*11*).

This paper adds to the growing literature on solutions for charging station locations by providing behavioral models to predict when and where vehicles are likely to be parked. It also takes a different approach to anticipating charging demand by using parking demand as a proxy. The optimization routine recognizes parking demand across Seattle, Washington, neighborhoods or 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 who park beyond the limit of reasonable walk access. The mixed-integer program (MIP) developed here is based on the fixed-charge facility location model, which identifies a set of facility sites to minimize the cost of serving a set of demands (located over space and across sites) (*12*). This type of model has been used to design communication networks (*13*) and to locate off-shore drilling platforms (*14*) and freight distribution centers (*15*).

Within the realm of work related to EV charging station locations, the closest parallel to this research probably is the framework of Hanabusa and Horiguchi, which minimizes EV travel costs while maintaining a minimum buffer distance around each charging station (*16*). Their EV travel cost is a function of travel time and waiting time at each charging station, and demand at each charging station is defined with a traffic assignment algorithm (based on route choice behavior). The current paper attempts to best satisfy the demand for public charging of EVs on the basis of parking duration, land use attributes, and (in the case of individual parking duration) trip characteristics. Optimal station locations are determined as a function of parking demand and access costs (walk distances).

DATA DESCRIPTION

The data for this project were obtained from the Puget Sound, Washington, Regional Council (PSRC) *2006 Household Activity Survey* and other information available through the PSRC website (*17*). The data include the 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 2 consecutive days, both weekdays. The region consists of 3,700 traffic analysis zones (TAZs), illustrated 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 (ID); each household is 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 or radii around each parcel (*17*). Buffer-based variables include number of housing units, number 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 or 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 make this data set unusual and well suited for the analyses in this study.

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

METHOD

To relate the Seattle region household activity 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 for all stops that were at least 15 min in duration (i.e., those that would serve as plausible candidates for public charging, if an EV were driven). Parking duration information then was used for regression models that relate (*a*) zone-level parking demands (aggregated across sampled trips) to land use attributes and (*b*) trip-level parking demand to individual trip characteristics. Parking demands also were

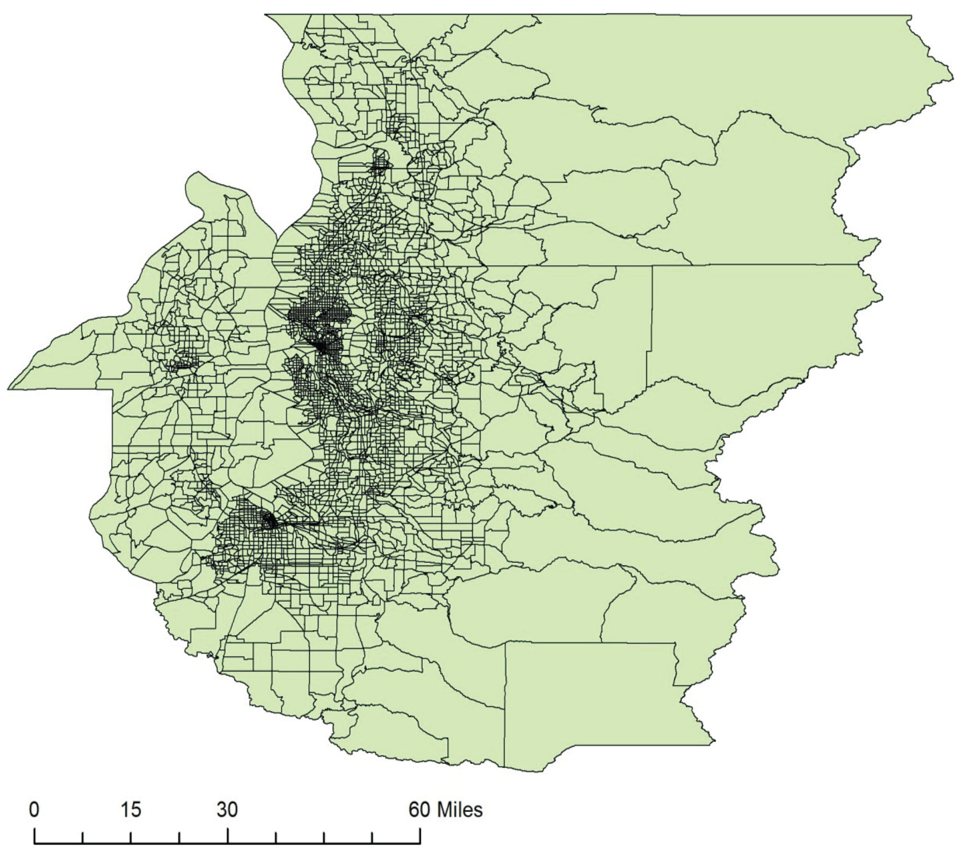

FIGURE 1 Seattle region's 3,700 traffic analysis zones.

TABLE 1 Summary Statistics of PSRC Person- and Household-Level Attributes

Statistic	Mean	SD	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

NOTE: SD = standard deviation; min. = minimum; max. = maximum.

TABLE 2 Sample Snapshot of Trip Data, Household ID 2045

Person Number	Trip Number	Begin Time	End Time	Origin Parcel	Destin. Parcel	Home Parcel
1	1	10:40	11:00	8,009	12,543	12,543
1	2	14:20	14:50	12,543	4,532	12,543
1	3	20:00	20:55	4,532	12,543	12,543
2	1	8:10	9:00	12,543	10,093	12,543
2	2	15:00	15:40	10,093	12,543	12,543

NOTE: Destin. = destination.

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, 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 to determine where vehicles are parked in the region and for how long. The trip data consist of 87,600 person-trips, but not all were by car or light truck. After eliminating all passenger trips (to avoid duplicating driver trips) and keeping only trips made by light-duty vehicles, 48,789 trips remained in the data set. A snapshot of trip data is given in Table 2.

To estimate public charging demand at different parcels (and then at the TAZ level), the following steps were followed:

1. Consecutive trips were identified in which the destination of the earlier trip coincided with the origin of the later trip; the time between these two trips was when a vehicle was parked at that unique parcel.
2. No parking at one's home parcel was counted, because parking locations at home were not of interest for the location of public charging stations.
3. Parking durations of less than 15 min were removed, because they were not long enough for Level 2 charging. (Level 3 charging stations would not have this restriction.)

A MATLAB script was written to perform the above analysis for all 48,789 trips, and 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) then was aggregated by TAZ for neighborhood analyses of parking demand, as described later.

Forecasting Zone-Level Parking Demand

The demand for public EV charging may be roughly proportional to the total parking duration for all light-duty vehicles surveyed in each TAZ (excluding those that park at their home parcel). This parking duration was first normalized by dividing by parcel size, which yielded values of parking duration per square mile for each TAZ. Of the 3,700 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 duration and other variables of interest (as predictors of parking demand) of the remaining 3,692 TAZs are given in Table 3.

Table 4 lists the parameter estimation results of an ordinary least squares (OLS) regression of parking duration per square mile on covariates such as population and job density. All relevant land use,

TABLE 3 Summary Statistics of PSRC Zone Attributes

Variable	Mean	SD	Min.	Max.
Parking duration (min/mi^2)	2.41 E+04	1.18 E+05	0	2.43 E+06
Population density (persons/mi^2)	7.99 E+03	1.88 E+04	0	2.91 E+05
Employment density (jobs/mi^2)	1.26 E+04	8.27 E+04	0	2.07 E+06
Student density (students/mi^2)	1.64 E+03	2.48 E+04	0	1.02 E+06
Housing density (units/mi^2)	3.43 E+03	8.20 E+04	0	1.27 E+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
Number of 3-way intersections (½-mi radius)	45.8	22.52	0	119.3
Number of 4-way intersections (½-mi radius)	36.8	45.91	0	251.8
Number of express bus stops (¼-mi radius)	2.25	6.369	0	55.6
Number of bus stops (¼-mi radius)	6.21	9.016	0	69.6

NOTE: Parking duration is for surveyed vehicles only, which represent approximately 0.29% of Seattle's household-owned and -operated light-duty fleet over a 2-weekday period. n = 3,692.

TABLE 4 OLS Regression Results of Parking Demand (min/mi²)

Variable	Parameter Estimate	Standardized Coefficient	*t*-Statistic
Constant	3,268	na	1.06
Density			
Population (residents/mi²)	−0.294	−0.047	−3.50
Employment (jobs/mi²)	0.583	**0.408**	27.0
Student (students/mi²)	0.226	0.047	4.11
Average parking prices (within ¼ mi) for daily paid parking ($)	2.22	**0.193**	11.0
Transit access and network connectivity			
No. of 3-way intersections (½-mi radius)	−158.0	−0.030	−2.41
No. of 4-way intersections (½-mi radius)	160.8	0.062	2.94
No. of express bus stops (¼-mi radius)	1,537	0.083	3.29
No. of bus stops (¼-m radius)	1,624	**0.124**	4.17

Note: All coefficients shown are statistically significant at the 5% level (p-value < .05). Response variable 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. Values in boldface type are the most practically significant of the covariates. Number of observations = 3,692 TAZs; adjusted R^2 = .521; na = not applicable; no. = number.

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 also are shown to highlight levels of practical significance. They represent the number of standard deviation (SD) changes in the response variable (parking duration per square mile) following a 1-SD change in the associated covariate (evaluating all parameter values at their means).

According to the model's standardized coefficients, parking demand intensity per square mile is most associated with employment (job) density; parking price and transit access are relevant but secondary. Increased student density and network connectivity (i.e., more four-way intersections) also appear to play meaningful roles in increasing a zone's total parking demand.

Forecasting Trip-Level Parking Duration

Parking durations for individual drivers or 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 min) with average parking duration for various activity types and trip purposes. Work is the most common activity (27% of total trips) and has the longest away-from-home parking duration, averaging 380 min or 6.33 h per trip.

Table 6 presents the 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 regressors statistically significant at the .05 level were retained in the final model. Table 6 offers a range of interesting results and many practically significant predictor variables. Because individual trips provide a large data set, t-statistics are high; fortunately, model fit also is strong (R^2_{adj} = .590). Apparently, activity type at one's destination is what most heavily influences parking duration, with work trips and kindergarten through 12th-grade (K–12) school trips having roughly equal and long parking durations, on average [for those who drive for such activities (rare for K–12 trips, because most of these students do not drive themselves)].

Long parking durations are evident for college, religious or community, recreation, and social activities. Predictably, trips to pick up and drop off incur the shortest average parking durations. Interestingly, job density is not statistically significant in this model even though the correlation between the work trip purpose indicator and job density is low ($\rho = +.11$).

Trips involving passengers are predicted to require slightly shorter parking durations than single-occupant-vehicle trips, and long-distance trips increase duration (by about 3.4 min/mi, everything else constant), as expected. 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 on arrival of an EV can be paramount for station success (by encouraging additional EV adoption and future EV trips to that station).

Anticipating Best Sites for Public Charging Stations

The modeling results discussed above illuminate various factors that contribute to (or at least are associated with) zone-level and trip-level parking demand, in statistically and practically significant ways. To select highly accessible, high-demand locations for the 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 TAZs. Here, EV charging demand is assumed to be proportional to (i.e., well proxied by) light-duty-vehicle parking demand, as reported directly in the sample data. Optimization ensures a minimum distance between charging stations to avoid clustering of the not-inexpensive charging infrastructure in adjacent zones with high parking demand. Such problems are solved with MIPs, which are common in transportation applications such as airline crew scheduling, vehicle routing, and pipeline design (e.g., *18–20*). MIPs usually are solved with branch-and-bound techniques (*21*).

The following set of equations defines the problem solved here using the General Algebraic Modeling System (GAMS), software designed for mathematical programming and optimization tailored for large-scale modeling applications. Nonproprietary

TABLE 5 Summary Statistics of PSRC Trip Attributes

Variable	Mean	SD	Min.	Max.	Avg. Parking Duration (min per trip)
Parking duration (min/trip)	142.0	199.5	15.0	2,120	na
Trip distance (miles)	6.71	7.14	0.230	67.6	na
Passengers (excluding driver)	0.421	0.811	0	6	na
Activity					
Work	0.271	0.445	0	1	379.7
School (K–12)	6.87 E–03	0.083	0	1	338.8
College	7.63 E–03	0.087	0	1	222.5
Eating out	0.071	0.257	0	1	46.1
Personal business	0.179	0.384	0	1	46.8
Everyday shopping	0.168	0.374	0	1	27.7
Major shopping	0.016	0.127	0	1	47.6
Religious–community	0.019	0.138	0	1	116.8
Social	0.040	0.197	0	1	127.6
Recreation–participate	0.057	0.232	0	1	103.5
Recreation–watch	0.016	0.126	0	1	107.4
Accompany someone	8.88 E–03	0.094	0	1	58.8
Pick up–drop off	0.133	0.340	0	1	15.5
Turn around	4.52 E–03	0.094	0	1	53.0
Vehicle					
Car	0.560	0.496	0	1	147.2
SUV	0.194	0.395	0	1	133.2
Van	0.119	0.324	0	1	103.3
Truck	0.089	0.285	0	1	173.7
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 min are included. Avg. = average; K–12 = kindergarten through 12th grade.

and noncommercial freeware available for solving MIPs includes ABACUS and bonsaiG (*21*).

Mixed-Integer Optimization Problem

The objective function in this MIP 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 mi in this application) because drivers are unlikely to walk long distances for parking [similar to transit access experiences (*22*)]. Zones i and j index the set of zones for all potential destination TAZs and the assignment of individual charging stations, respectively. In this setup, the number of charging stations one can allocate to zones (L) is less than the number of zones (i) because of budget constraints. Then, for EVs whose destination is some zone i not equipped with a charging station, parking demand must be satisfied by a (hopefully nearby) charging station in zone j. So, y_{ij} represents 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 proportionally to parking demand.

Another key decision variable is x_j, which takes a value of 1 for zones with charging stations and 0 for zones without, representing the set of optimal charging location zones. Other parameters include the parking demand at zone i (d_i) and the travel costs (c_{ij}). 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), 0 otherwise. A large number for M (an arbitrary number) allows all parking demand to be assigned to charging stations, hopefully ensuring that locally parked EVs can be accommodated by the nearest charging stations.

Objective function:

$$\min \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} y_{ij}$$

Constraints:

Parking demand constraint:

$$\sum_{j=1}^{n} y_{ij} = d_i \qquad \forall j \in J \tag{1}$$

Charging supply constraint:

$$\sum_{i=1}^{n} y_{ij} \le M x_j \qquad \forall i \in I \tag{2}$$

Charging station availability constraint:

$$\sum_{j=1}^{n} \le L \qquad \forall j \in J \tag{3}$$

Charging station spacing constraint:

$$\sum_{i=1}^{n} \delta_{ij} x_j \le 1 \qquad \forall i \in I \tag{4}$$

TABLE 6 OLS Regression Results of Individual Parking Durations (min/trip)

Variable	Parameter Estimate	Standard. Coefficient	t-Statistic
Constant	372.2	na	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)	−9.075 E–05	−0.008	−1.99
Employment density (per mile^2)	8.173 E–05	−0.048	12.1
Student density (per mile^2)	−3.189 E–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[a]			
School (K–12)	−21.28	−0.009	−2.37
College	−157.6	−0.069	−18.4
Eating out	−306.6	**−0.396**	−95.0
Personal business	−313.2	**−0.603**	−135.6
Everyday shopping	−324.5	**−0.609**	−133.9
Major shopping	−308.0	**−0.196**	−51.5
Religious–community	−246.3	**−0.170**	−44.6
Social	−241.9	**−0.238**	−60.7
Recreation–participate	−259.7	**−0.302**	−75.6
Recreation–watch	−254.2	**−0.161**	−41.8
Accompany someone	−298.9	**−0.141**	−37.2
Pick up–drop off	−344.1	**−0.587**	−127.3
Turn around	−303.8	**−0.102**	−27.5
Vehicle[b]			
Van	−13.87	−0.023	−5.82
SUV	−4.101	−0.008	−2.12
Truck	−1.367	−0.002	−0.51
Other	−17.88	−0.016	−4.22

NOTE: All coefficients shown are statistically significant at the 5 percent level (p-value < .05) except those for trucks. Values in boldface type are the most practically significant of covariates. Number of observations = 30,085; adjusted R^2 = .590; CBD = central business district.
[a]Base case = work.
[b]Base case = car.

Nonnegativity constraint on parking demand:

$$y_{ij} \geq 0 \qquad \forall i \in I, j \in J \tag{5}$$

Binary variable constraint for charging station selection:

$$x_j \in \{0,1\} \qquad \forall j \in J \tag{6}$$

Minimum spacing between stations:

$$\delta_{ij} = \begin{cases} 1 & \text{if } C_{ij} < r \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

Maximum access cost:

$$c_{ij} \leq W \tag{8}$$

The formulation of this optimization problem introduces some challenges. Capacity for each charging station is undefined here because parking demand currently is without a time-of-day dimension, and the objective function might overly favor the long parking durations of work and school trips. 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 specified MIP is a step toward the efficiency of locating charging stations, as illustrated in the Seattle case study.

Charging Station Allocation: Application to the Seattle Area

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 mi (network distance) of the Seattle central business district were considered. (Inclusion of all 3,700 zones resulted in a large matrix that caused the GAMS software to time out in searching for a solution.) With relatively small size (5% of the average PSRC TAZ) and high population density (three times that of the average PSRC TAZ), these relatively central TAZs are good candidates for EV charging stations with interzonal parking access. (Large, low-density peripheral zones cause problems for the GAMS algorithm because they have no or few neighboring zones within the 2-mi maximum distance for parking access. For such applications, zones with larger areas can be split, with zones of approximately equal sizes being the optimal condition for seeking a set of solutions.)

L was limited to 80, and r was set to 1 mi because ½-mi access or walk distances (the worst-case scenario for an EV owner parked between such stations) often are reasonable, especially for workers who intend to park for many hours. Network walking distances (as given by the PSRC, whose data exclude freeway links and certain bridges considered unsafe for pedestrian use) were used to represent C_{ij}. As noted earlier, the maximum walk penalty W was limited to 2 mi to reflect a cap on reasonable access costs. Using the COIN-OR branch-and-cut 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 assignments to charging stations within a 2-mi access distance. The algorithm arrived at a solution in approximately 8 min and 45 s 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 on that demand.

As shown in Table 7, many of these zones rank high in parking demand, so a charging station scores well by serving them directly.

TABLE 7 Charging Station Assignments and Their In-Zone Parking Demands

TAZs Assigned a Station (ID number)	Survey Parking Demand (min)	Parking Demand Rank (900 zones)	TAZs Assigned a Station (ID number)	Survey Parking Demand (min)	Parking Demand Rank (900 zones)
305	29,266	1	745	1,076	310
873	26,473	2	828	1,005	335
709	13,972	7	882	1,005	335
808	11,489	8	783	996	337
674	10,184	13	675	983	341
70	8,959	18	834	839	373
30	6,449	33	246	823	379
878	5,909	41	719	796	387
804	5,311	47	270	773	392
351	5,154	50	56	749	398
384	4,305	70	339	722	403
735	4,040	72	93	678	410
844	3,587	83	884	677	411
859	3,317	92	446	631	425
721	3,314	93	781	605	432
815	3,237	96	199	603	433
701	3,097	105	348	593	435
387	2,669	125	769	537	448
557	2,517	137	591	496	457
101	2,445	144	665	417	486
31	2,311	153	371	401	488
728	2,284	155	753	385	494
332	2,120	170	676	361	497
670	2,035	175	381	325	516
803	1,985	179	84	310	521
632	1,854	198	888	310	521
679	1,798	204	298	200	581
702	1,655	223	809	198	585
17	1,513	244	692	145	621
53	1,481	247	811	135	631
141	1,481	247	717	126	644
117	1,264	271	65	118	653
2	1,249	274	12	115	654
864	1,248	275	169	61	702
416	1,209	283	176	18	750
872	1,191	286	623	18	750
757	1,099	301	329	15	754
331	1,089	303	290	0	761
428	1,084	306	754	0	761
42	1,077	309	893	0	761

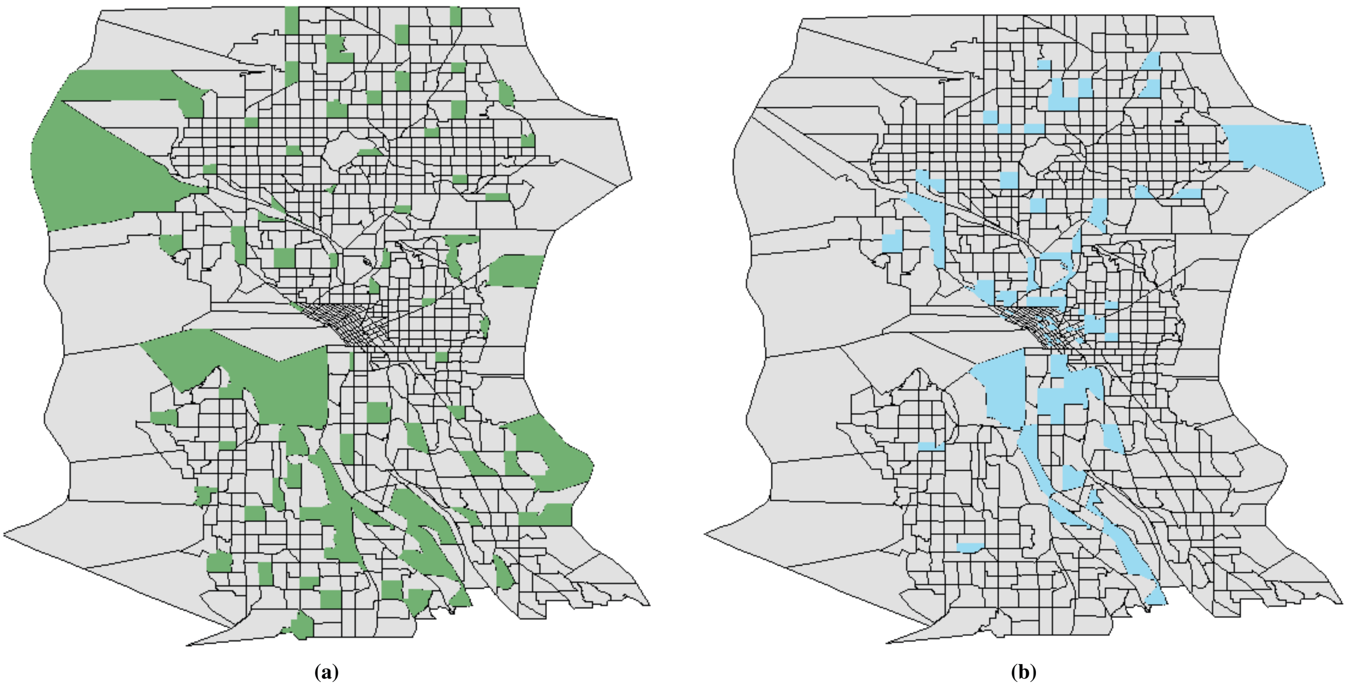

FIGURE 2 Seattle maps of (*a*) optimal locations for charging stations and (*b*) charging stations located in zones with highest parking demand (*i* and *j* = 900; *L* = 80).

But many others also were selected, despite low in-zone parking demand, because of their strategic locations—nestled among other zones with high parking demand. Figure 2*a* shows maps of this solution set for charging station locations versus a simple assignment approach, where chargers are placed in the 80 zones with the highest parking demand (Figure 2*b*). Optimal station locations are more scattered throughout the 900-zone region; however, the demand-based assignment method concentrates stations in the central business district. Under the optimal solution, zones with high parking demand that are clustered together sometimes are 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 mi (weighted by total parking duration of station-assigned zones). Of parking demand, 79.9% were able to access a charging station within 1 mi of the destination TAZ, with a maximum walk-access distance of 1.90 mi. In contrast, when charging stations were placed purely according to parking demand (in the top 80 TAZs, where parking demand is highest), then the total cost (z) was 890,135 mile-minutes (5.7% higher than the optimal solution), the average parking access cost was 0.73 mi, and the maximum access distance was more than double (3.96 mi). Under this simplified approach, 78.0% of parking demand appears to be able to access a charging station within 1 mi of the destination TAZ.

Such results suggest that simple, demand-based assignment (with no more than one station per zone, but that station may have multiple chargers available) has some merit. However, for implementations where zones are smaller (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 Seattle's 218 zones, the routine returns an optimal solution in under 1 s, placing 94.5% of parking demand within 1 mi of a station—rather than meeting only 79.6% of parking demand within 1 mi under the simple assignment rule (i.e., allocating public chargers to the zones with the highest parking demand).

CONCLUSIONS

One 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 relies on household travel survey data from the Seattle region to investigate parking demands (by zone and by trip) and then identify optimal station locations with a rigorous MIP.

Parking demand was examined in two ways, on the basis of 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. TAZ-level parking demand per square mile increased significantly with jobs and student density. More highly connected and transit-served zones, characterized by more nearby four-way intersections and bus stops, also experienced higher parking demand. At the trip level, trip purpose was by far the most significant predictor of parking duration. Model results reveal that work and school trips require the longest parking durations; regular errands (i.e., personal business, shopping, eating out, and picking up and dropping off passengers) necessitate the shortest parking durations; and social and recreational activities fall somewhere in between. Trip distance and use of a car (rather than another vehicle type) also lengthened average parking duration.

The outputs of the first regression model provide key inputs for determining efficient charging station locations, as specified here via a mixed-integer optimization program. Considering budget constraints (which limit the total number of charging stations to be deployed) and avoiding resource clustering (by specifying minimum station spacing), the optimization problem thoughtfully assigned 80 public charging stations across 900 TAZs within 10 mi of Seattle's downtown center. As designed, stations were spaced at least 1 mi apart, with wide-ranging access and parking demand characteristics to illustrate the importance of both parking intensity and access. This optimal charging location scheme was compared with one based on zones ranked in terms of highest parking demand and yielded clearly better results in many ways, including average access distance and total access cost.

The work presented here has certain limitations. It assumes that the parking demand of light-duty vehicles is a strong proxy for EV charging demand, which may not reflect actual charging demand, particularly while EV market shares are still small. Compared with the general U.S. population, early EV adopters are disproportionately younger, male, more educated, and more sensitive to environmental concerns (*23*). Over time, as EV market shares grow, parking demand may more closely reflect EV charging demand. Introducing a time-of-day dimension to the optimization problem to reflect the dynamic nature of charging demand levels also would be a useful extension. Even though 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 $2,000 to $5,000 for wall-mounted stations in parking garages to $15,000 or more for stations that require utility service and infrastructure upgrades (personal communication from Cameron Freberg, conservation program associate, Electric Vehicles and Emerging Technologies, Austin Energy, to Kara Kockelman, Nov. 9, 2012).

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

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