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Public Charging Opportunity for U.S. Cities based on Parking Lot Data

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Summary

The objective of this study is to evaluate the opportunity for public charging for a subset of US cities by using available public parking lot data. The capacity of the parking lots weighted by the daily parking occupancy rate is used as a proxy for daily parking demand. The city's public charging opportunity is defined as the percentage of parking demand covered by chargers on the off-street parking network. We assess this opportunity under the scenario of optimal deployment of public chargers. We use the maximum coverage model to optimally locate those facilities on the public garage network. We compare the optimal results to the actual placement of chargers. These empirical findings are of great interest to policymakers as those showcase the potential of increasing opportunities for charging under optimal charging location planning.

Keywords: charging, EV (electric vehicles), optimization, case-study

1 Introduction

Plug-in hybrid electric vehicles (PEVs) are gaining momentum since their first market introduction; it only took 36 months for reaching 160,000 sales, while hybrid vehicles only counted 60,000 sales after 36 months from their introduction(1). What is more, PEVs have reduced or zero tailpipe emissions compared to internal combustion engine conventional vehicles. Hence, PEVs operation results in low environmental externalities(2). Since PEVs operate with electricity from the grid, the deployment of

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public chargers in the transportation network is a crucial factor for their adoption and day-to-day operation. Plug-in hybrid electric vehicles have both fuel tank and battery so the unavailability of public charging might not hinder their daily trip making, but for sure it can reduce the increased electrified miles benefit. That is not the case for battery electric vehicles; charging is essential for their operation and the placement of such facilities in the existing transportation network should be carefully conducted in order to incentivize consumers to adopt PEVs and adequately cover the existing and future charging demand.

Numerous studies in the literature develop methodologies that place chargers on the transportation network. Those studies can be divided into the following categories: (a) studies that use heuristics to deploy chargers, (b) studies that optimize the location of the facilities in order to meet a cost associated objective, (c) studies that maximize the demand served by the chargers. Literature methodological approaches, representative of each category, are briefly mentioned below. In category (a), Liu et al. investigates charging opportunity for Seattle's metropolitan area by assigning chargers to the parking lots with the greater daily demand (i.e., a sorting algorithm is used) (3). Dong et al. also assesses the charging deployment considering activity-based travel patterns, using GPS data from Seattle (4). In category (b), He et al. optimally locates the chargers on urban networks by maximizing the social welfare and considering complete drivers daily tours (5). Also, Ghamami et al. develops an optimization framework for optimally locating chargers by minimizing the total cost of facility deployment and user spending (6). Chen et al. minimizes the cost of walking from the parking location of charging to the actual trip destination when optimally placing chargers on Seattle's parking lot network. In category (c), the recent study of S.Y. He et al. compares the results of max coverage and p-median facility location models for charging deployment in Beijing, China (7).

In our empirical study, public off-street parking lot location and capacity data are utilized in order to estimate the opportunity for public charging in US cities of different sizes and population counts. Seattle WA, San Francisco CA, New York City NY, Austin TX and Cambridge MA is the subset of US cities that we are looking into. The opportunity for public charging in this study is estimated as the percentage of demand covered by charging facilities placed on each city's parking lot network. The public parking lot capacity weighted by daily occupancy rates is used as a proxy for public parking demand. In some cases, due to unavailability of spatially disaggregated parking occupancy rates, the charging opportunity is hypothesized to be proportional to the parking lot capacity.

We investigate the charging opportunity under the assumption of optimal city provision for the placement of charging facilities. Therefore, we use the maximum coverage model to maximize the total demand covered. We compare the optimal planning results to the current levels of charging

opportunity from actual chargers location data. The proposed approach of estimating city-level opportunity of charging provides officials with insights relatively to the current public charging placement coverage and the optimization of the locations of chargers. This study aims to evaluate the potential of optimal charging placement on the off-street public parking network of cities. Better coverage of the parking demand on a city's network can definitely improve charging access for current electric vehicle drivers and promote electric vehicle adoption to all consumers.

2 Data

Geographic information systems (GIS) datasets are collected in order to pinpoint the locations and acquire area and capacity values for the off-street public parking lots. Public charging station geographic coordinates have been acquired from Alternative Fuels Data Center (8) and processed in ArcMap 10.2.

For the cities of Seattle, San Francisco and Cambridge, we have complete data regarding exact off-street public parking lot locations and capacity(9–11). For the rest of the cities, we only have land use parcel data. We identify the parcels that are utilized as parking lots and estimate their parking capacity from the area in square feet that those cover. Specifically, we refer to each city's municipal parking regulations in order to come up with the average dimensions of parking spots, dimensions of driving corridors between those spots as well as entrances and exits. Then, we compute the average parking capacity in spots for each parking lot in the city, under the assumption that the facility represents a surface lot (only one floor of parking spots) (12, 13).

We analyze the public parking data of each city using JMP 12 statistical software (14). Descriptive statistics are provided, as shown on Table 1. The number of parking lots and the actual number of the charging stations that are currently deployed in each city are noted. The average parking lot capacity and the total capacity are also presented there.

Table 1: Descriptive Statistics

City	# Off-street Lots	Total Lot Capacity	Avg. Capacity per lot	St. Dev. Capacity	# Actual Chargers
Seattle WA	686	93,485	136	224	94
San Francisco CA	1,396	166,068	119	327	136
New York City NY	333	83,135	250	718	146
Austin TX	705	123,669	175	493	118
Cambridge MA	1,581	83,305	53	120	24

Figure 1 portrays the public parking lot and the public charging station locations at each city. The datasets used herein include only public off-street lots. The data completeness depends on the source.

Each charging station point signifies the actual location of charging equipment on the parking network of each city; each charging station stands for at least one or more chargers of different charging levels (e.g. Level 1, 2 or DC fast charging). The location of the existing charging equipment might or might not be within a public parking lot. Since we aim to evaluate the current charging availability for each city, we assume that parking lots that are within 0.25 miles from the existing public chargers are covered.

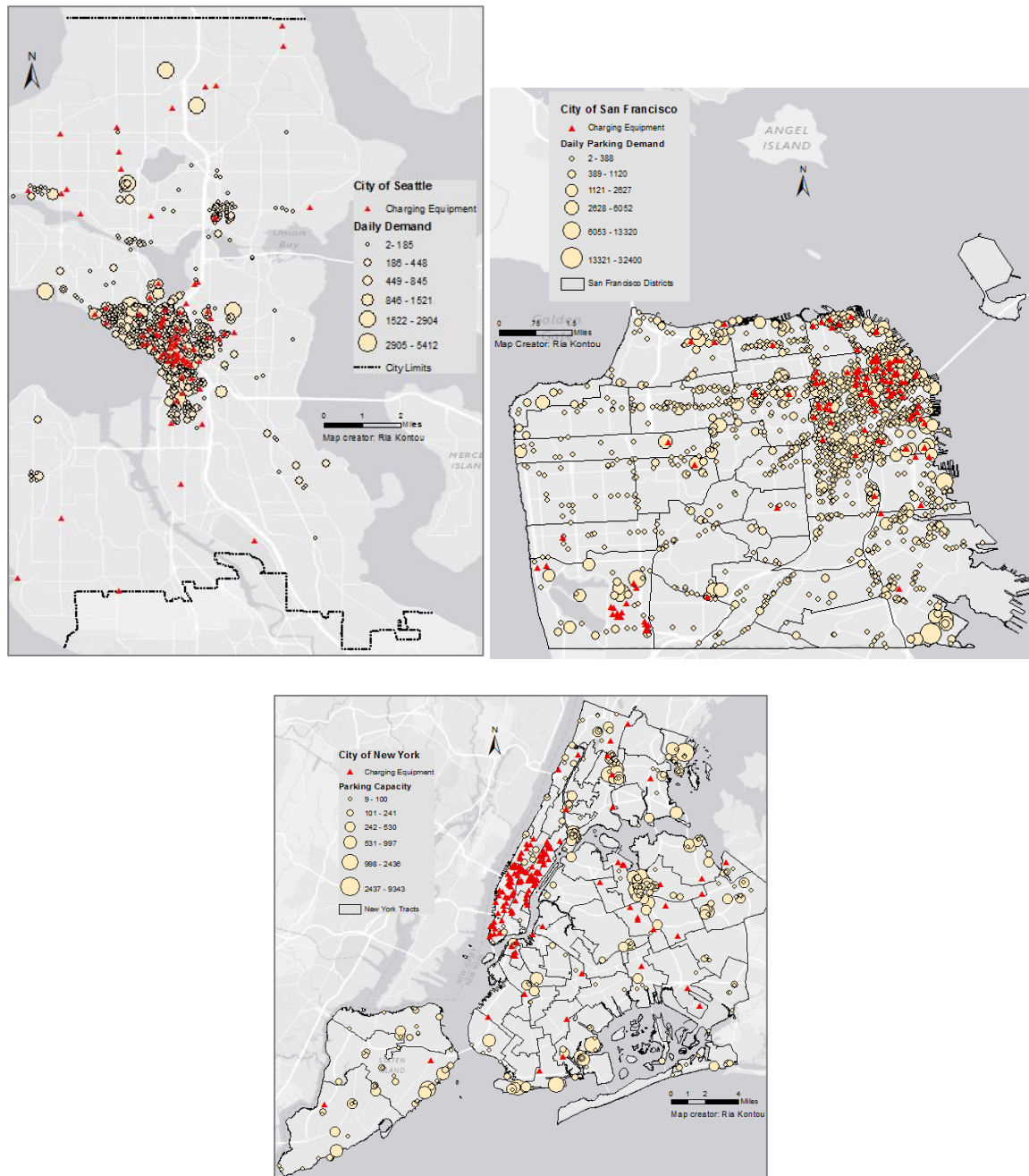


Figure 1(a): Parking lots and actual charging locations for US cities.

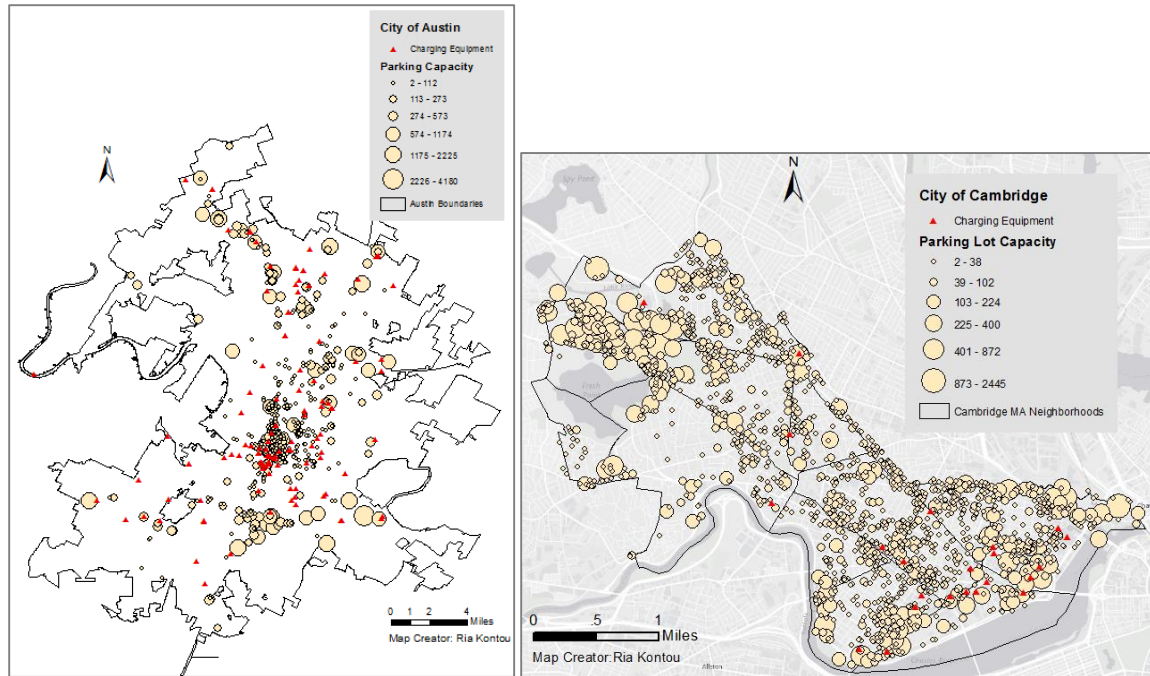


Figure 1(b): Parking lots and actual charging locations for US cities.

Our study overcomes the hurdle of collecting data on actual demand by using parking lot capacities weighted by the daily occupancy levels as proxy for the average daily parking demand of the parking lots on the network. This process significantly decreases the time that officials can assess opportunity of charging on their current public parking lot network.

Table 2 presents estimates of the daily occupancy rates from various literature sources. For Seattle WA and San Francisco CA we have available spatial disaggregated data on average hourly parking occupancy rates for certain neighborhoods. We utilize those to weight the capacity of each parking lot in the city and estimate the demand for public garage parking. We assume that the average daily hours of off-street parking is the upper bound of parking hours allowed during the daily peak period (4 hours) (15).

Neighborhood parking occupancy rates are not available for New York City, Austin and Cambridge; in that case, we make the assumption that the parking demand is only proportional to the parking capacity. Hence, for those cities, we use the parking lot capacity as a proxy for the demand.

Table 2: Average daily parking lot occupancy rates

City	Neighborhood	Average hourly parking occupancy rate
Seattle WA (10)	Uptown	85%
	First Hill	80%
	University District	52%
	Ballard Retail District	61%
	Chinatown	67%
	Pike-Pine	50%
	All the rest	66%
San Francisco CA (16, 17)	Downtown, Financial District	80%
	All the rest	60%
New York City NY		n.a.
Austin TX		n.a.
Cambridge MA		n.a.

For accurate demand estimation, officials should request the average occupancy rate for each public parking lot and proceed with the analysis as follows.

3 Methodology

As it was mentioned in the introductory section, we use the maximum coverage location model to optimally locate charging stations. We estimate the centroid of each polygon parking lot in ArcGIS and calculate the Euclidian distance from each parking lot (node) to every other parking lot in Matlab 2015b. The Euclidian distance can be multiplied by a factor to account for actual road network distances. We assume that the number of charging facilities to be placed in each city is exogenously determined; officials can set this number according to the city's budget availability for charger installation.

The set of public parking lots is a given set of locations $I = \{1, 2, \dots, n\}$, $J = \{1, \dots, n\}$ is the set of potential public charging facility locations, and c_i the public parking demand for each public parking lot j . The distance between candidate public charging facility node i and the public parking lot j is d_{ij} . Assume N_i , subset of J , where $N_i = \{j | d_{ij} \leq w\}$, with w the walking distance. Note that if a charger is placed in a lot, the demand of all the lots that are within w walking miles from this garage destination is considered covered. The total number of public charging facilities to be located is k . The decision variables of this program are integer: y_i is 1 when parking lot i is covered, otherwise 0, and x_j is 1 when public charging station is assigned to j , otherwise 0.

We determine the optimal public charger locations such that the demand covered to be maximized, under the constraint of placing a specific number of charging infrastructure on the network. The optimization framework is presented below:

$$\max \sum_{i=1}^n c_i y_i \quad (1)$$

subject to:

$$\sum_{j \in N_i} x_j \geq y_i, \forall i \in I \quad (2)$$

$$\sum_{j \in J} x_j = k, \quad (3)$$

$$y_{ij} \in \{0, 1\}, x_j \in \{0, 1\}, \quad \forall i, \forall j \quad (4)$$

where the first constraint ensures that if one charging facility is located within w miles from a parking lot, then the parking lot's demand is covered, otherwise y_i is set to zero. The second constraint ensures that k public charging facilities will be located and the second constraint ensures integrality of the decision variable.

We solve the aforementioned the mathematical program in GAMS 23.3(18) using the integer linear CPLEX 12.1.0 solver.

More detailed and realistic charging location optimization frameworks have been proposed in the literature [e.g., (19), (5), (20), (6)]. The aim herein is not to propose a new formulation but to use the public charger location optimal results so as to calculate the percentage of parking lot demand that is covered, under the assumption of $x\%$ of lots have at least one charger. We solve the optimization model for scalars k that correspond to certain percentages of coverage of parking lots with chargers,

such as 1%, 5% and 10%. For each optimal solution, we estimate the percentage of the opportunity of charging under optimal planning.

4 Results

4.1 Charging Opportunity for Major US Cities

For each city, we solve the integer linear program Eqs. (1-4) for alternate number of chargers k on the parking lot network. Two alternative cases of acceptable walking distance are considered ($w \leq 0.25$ and $w \leq 0.15$ miles) (21). We expect that charging opportunity is higher when walking distance acceptance upper bound is higher, because greater parking lot demand is expected to be covered by the placement of a charger at a specific parking node.

4.1.1 Charging opportunity for Seattle WA

The charging opportunity for Seattle is portrayed at Figure 2. The public charging opportunity percentage is estimated both for the optimal public charging deployment and the current placement of chargers on the network.

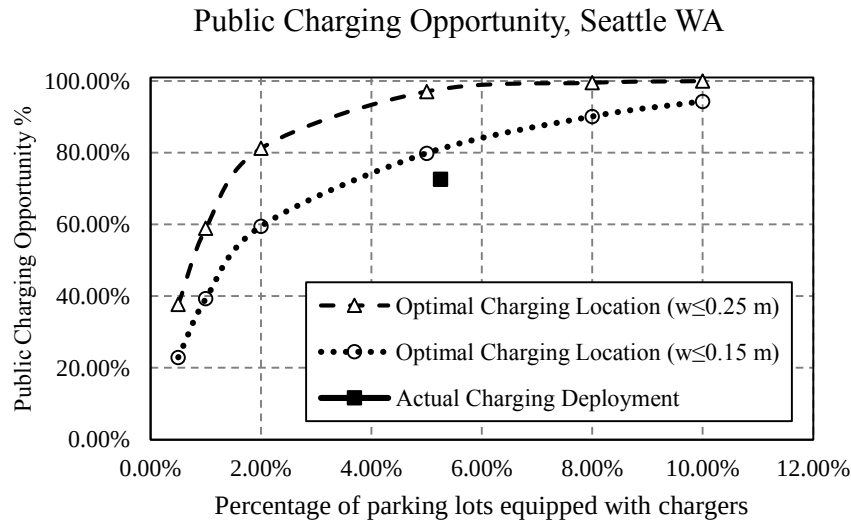


Figure 2: Charging opportunity; optimal deployment versus actual placement for Seattle

Figure 2 shows that 2% coverage of Seattle's parking lots with chargers is enough to achieve 80% coverage of the total public parking demand. Under the optimal charging location scenario, only 12% parking lot charging coverage is required in order to provide 100% parking opportunity to the parking demand. Figure 2 also portrays that the current 5.25% deployment of charging stations in parking lots covers approximately 72.6% of the parking demand. We speculate that this point belongs on a curve

of a lower than 0.15 miles upper bound of walking distance acceptance. The shape of the curve also confirms other literature findings (3), as it showcases decreasing marginal benefits of installation of chargers on the parking network.

4.1.2 Charging opportunity for San Francisco CA

In a similar manner, Figure 3 portrays the opportunity for public charging at San Francisco in California. Note that California is the state with the largest adoption of PEVs in the US(22).

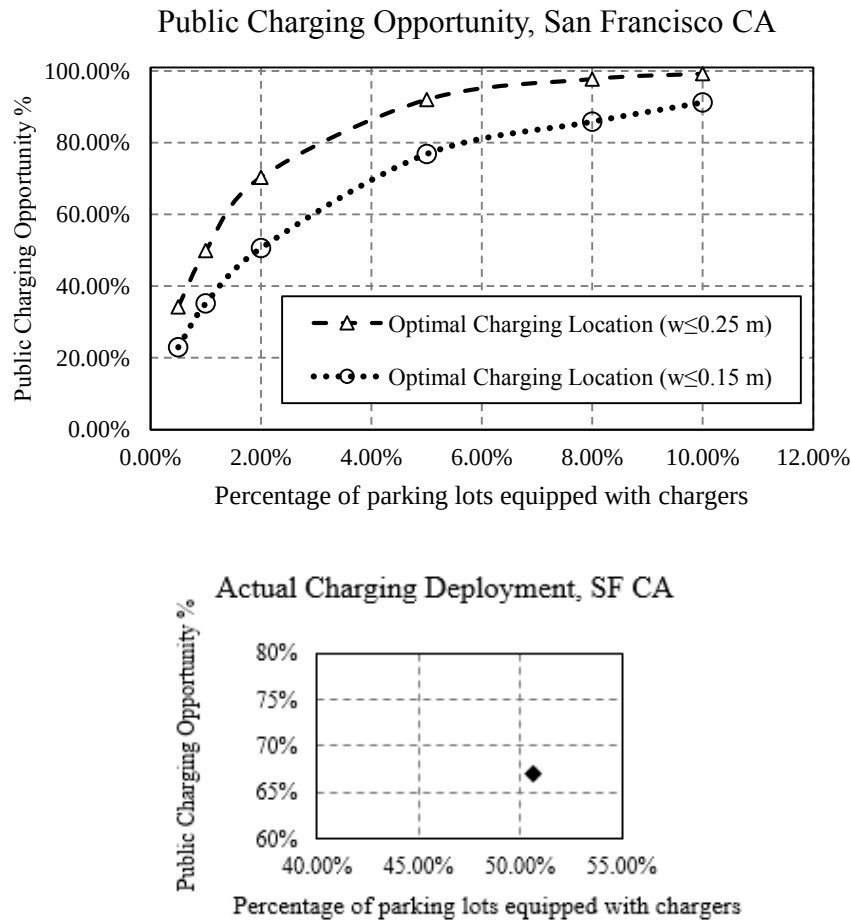


Figure 3: Charging opportunity; optimal deployment versus actual placement for San Francisco

For San Francisco, 2% optimal coverage of parking lots with chargers can result in 70% charging opportunity when the acceptable maximum walking distance is 0.25 miles and in approximately 50% when that distance is 0.15 miles. Interestingly, the current coverage of charging demand is high, reaching 67% with 51% of coverage of lots with chargers. Our findings pinpoint that the concentration of charging equipment in just 4% of the parking lots could increase the opportunity to charge publicly compared to the current charging placement.

4.1.3 Charging opportunity for New York City NY

Figure 4 portrays the opportunity for charging results for New York City.

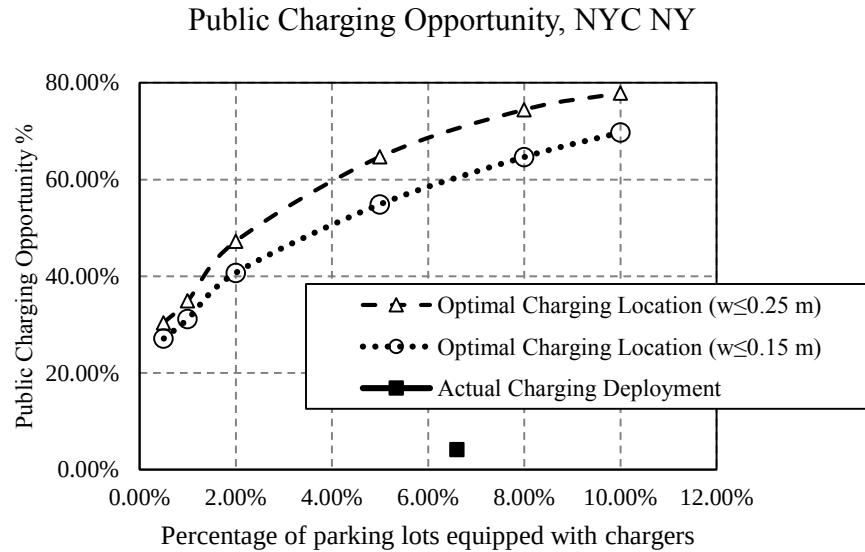


Figure 4: Charging opportunity; optimal deployment versus actual placement for NYC

Our data show that the actual NYC charging opportunity is surprisingly low, having about 6.5% of the lots with access to charging equipment and achieving just a 5% coverage of demand. Optimal provision for the installation of chargers can have a positive impact regarding the off-street parking demand coverage. The trajectories of the opportunity to charge for the two alternate acceptable walking distances are closer when the percentage of public lots equipped with chargers is less than or equal to 2%. For greater values than 2% charging coverage, the distance between those curves increases, showcasing that when $w \leq 0.25$ miles the optimal charging locations cover parking demand faster.

Comparing NYC's optimal charging deployment results with Seattle and San Francisco, we actually see that 10% coverage of lots with chargers just results in less than 80% demand coverage. This was not the case for the two other cities, where almost 100% of demand coverage was reached with optimal charging provision. This result can be attributed to NY City's greater spatial parking dispersion.

4.14 Charging opportunity for Austin TX

Figure 5 portrays the opportunity for charging results for Austin TX.

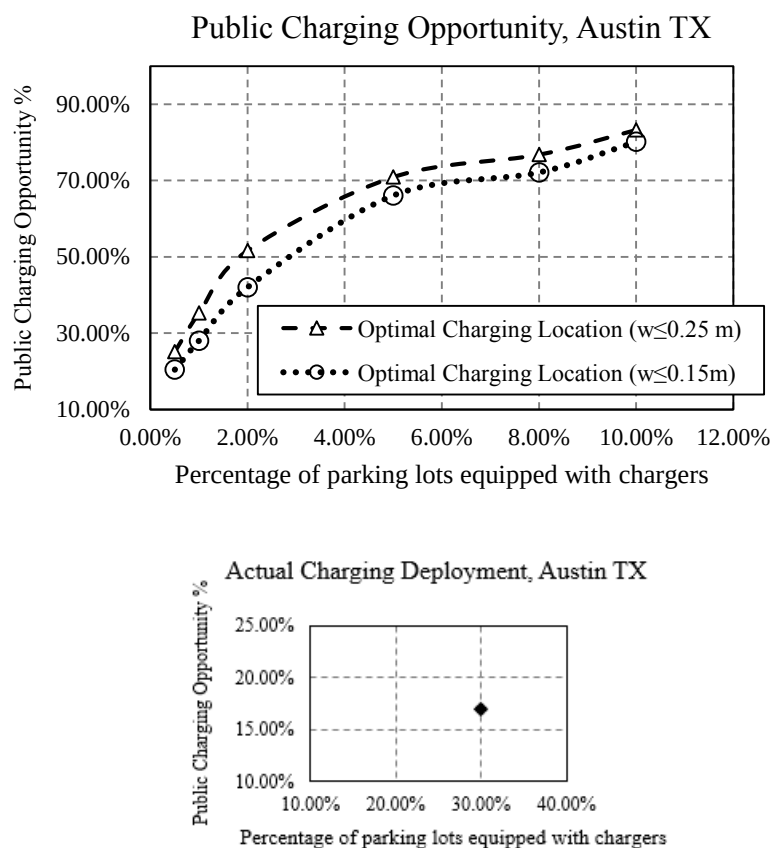


Figure 5: Charging opportunity; optimal deployment versus actual placement for Austin

Interestingly, the current percentage of garages covered with charging equipment is almost 30%. However, only 16% of the public parking demand is covered with this placement plan. If the officials have optimally located those equipment, they could have achieved the same demand coverage percentage with just 1% lots coverage with chargers. The curves for the two alternate acceptable walking distance results are closer compared to other cities. This result showcases that for the city of Austin the walking distance acceptance estimation might not lead to significant changes in demand coverage.

4.1.5 Charging opportunity for Cambridge MA

The city of Cambridge in Massachusetts is also examined. The results for the optimal charging opportunity potential and the actual demand coverage are presented in Figure 6.

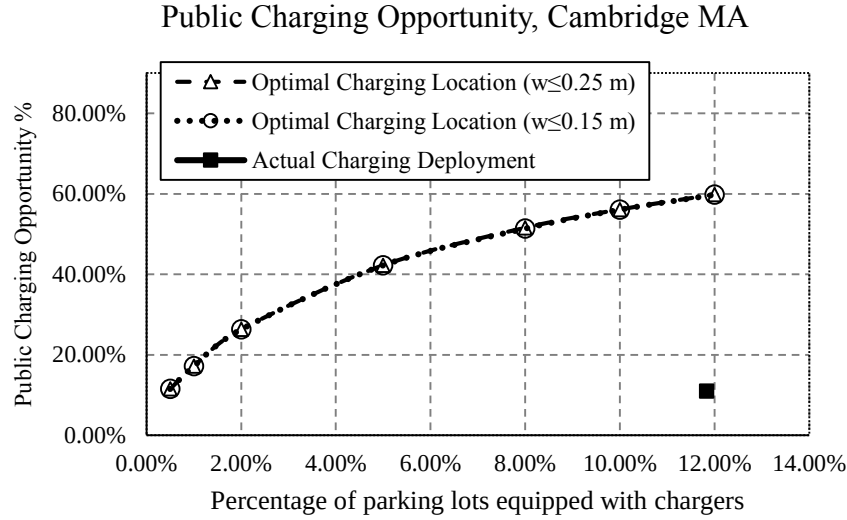


Figure 6: Charging opportunity; optimal deployment versus actual placement for Cambridge MA

Even though 12% of the existing parking lots are equipped with public chargers, the city of Cambridge achieves just 11% coverage of the parking demand. With optimal facility location deployment, the city could achieve 60% of public parking demand coverage. Surprisingly, our findings show that the upper bound of acceptable walking distance does not impact the percentage of the opportunity for charging. Therefore, the demand coverage results are not expected to be impacted by w , when $w \in [0.15, 0.25]$.

For Cambridge, the spatial dispersion of lots is greater than that of the cities of San Francisco and Seattle, where a 10% coverage of lots with chargers results in an almost 100% demand coverage.

5 Conclusions

Our empirical study examines the levels of charging opportunity for a diverse subset of US cities. The opportunity of charging is defined as the percentage of public parking demand covered when a certain percentage of parking lots is equipped with chargers. The demand for public parking is either estimated using parking capacity data weighted by daily average occupancy rates or by assuming that the parking demand is only a function of the lot's capacity.

We compare the actual parking demand coverage to the results of optimal charging placement on the parking lot network. We use the maximum coverage model to place the charging facilities on the network. The results indicate that the cities can substantially increase the levels of demand covered when optimally planning for the charging infrastructure deployment. The results also pinpoint that the parking lots locations are highly concentrated on the city level and, thus, great demand coverage can

be achieved with just a few lots equipped with chargers. As we have shown, even low charging coverage for all cities can result in substantial charging opportunity. Due to exploiting spatial concentration of parking lots, even low investments for chargers adoption, optimal facility location planning can lead to good charging opportunity levels.

This study does not consider charging capacity and assumes that potentially all the parking spots of a lot would have charging availability. Also, for the cases of New York City, Austin, and Cambridge the capacity of the parking lots is assumed as a proxy for the parking demand. This is not the case though as the spatial difference of occupancy rates plays an important role on the demand estimation and the placement of chargers on the off-street public parking network for the cities of Seattle and San Francisco. Future research should focus on getting detailed parking occupancy information for all the cities evaluated in such a study.

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