Modeling and Solving the Large Scale EV Charger Location Planning Problem

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Abstract

We develop a model for the Electric Vehicle (EV) charger location planning problem for cities. Using mixed integer programs with branch-and-bound techniques, the method provides solutions even for large cities. With a primary focus on vehicles used for daily commuting, EV users are assigned to charging stations that are within a short distance from their home or work. We systematically collect driver origin-destination information and solve this facility location problem with different objectives. We explore several model variants: serve all commuters, serve most commuters, and with added constraints to increase equity of access. Our model and methodology for data collection can be used for solving EV location charger placement problem for any city in the USA, and globally if similar data are available. Although we use data for the city of Atlanta, the solutions given by our models yield several general insights. When maximizing commuters served for a limited number of chargers, the optimal solution puts most chargers at work locations, serving commuters with short commutes and thus low charging needs. As the number of chargers increases, more are placed at larger distances from the city center, providing more commuters with charging near home. Assuming that those with home charging capability will charge at home, equity goals can be met with only minimal effect on the number of commuters served and the distribution of chargers.

Keywords: electric vehicles, equity, commuting, cities

1 Introduction

Many countries are transitioning from gasoline vehicles to electric vehicles. Electric vehicles must be charged. Most charging stations are privately built, although governments and utility regulators are providing assistance and incentives for the installation of charging stations. [1] Effective access to charging will be essential for electric vehicle adoption. As discussed in the literature review section below, several approaches to identifying the number and placement of Electric Vehicle (EV) chargers have been developed. Most of these approaches depend on heuristic techniques and have limitations for large city planning.

In this paper, we develop a mixed integer programming (MIP) model for the EV charger location planning problem for large cities, focusing primarily on the EVs used for daily commuting. We demonstrate solutions of this facility location problem with different objectives, including equity of access.

1.1 Literature Survey

Previous research on the problem of EV charger location has taken a number of methodological approaches. Dong et al. [2] estimate charger demand as a probability function of population, traffic, and the existence of points of interest and maximize the number of customers served. Akbari et al. [3] apply a genetic algorithm to the problem of station placement, with 50 demand points, minimizing the distance between settlements and charging stations. Zhou et al. [4] also use a genetic algorithm. Ahangar et al. [5] apply a Lagrangian relaxation approach to a model involving a bi-objective. Chen et al. [6] apply a genetic algorithm to the problem of station placement with 20 potential station locations, minimizing costs. Zhang et al. [7] maximize a multi-objective function with various components such as charging likelihood—function on a chosen subset of stations, charging willingness, charging demand served, coverage and distance between charger and points of interest. They compare several algorithms over a dataset with roughly 2,000 potential station locations, but do not attempt to solve exactly.

Previous research has also addressed different EV charger location problems. In the papers cited above, Dong et al. [2] maximize the number of customers served; some minimize the distance to charging stations (Akbari et al. [3]); some minimize costs (Chen et al. [6]). Notably, the paper by Brandstätte et al. [8] considers the EV vehicle location problem for a car-sharing system. They formulate a two-stage stochastic mixed integer program and attempt to solve it to optimality across different sizes of generated problems. Wang et al. [9] solve the problem of EV charger locations in dense city parking facilities as a MIP, with chance constraints used to mitigate the uncertainty in the demand for charging over time.

The model most widely used in the U.S., EVI-Pro Lite, developed by the US National Renewable Energy Laboratory, is not an optimization model. It serves all commuters, and lets the model choose whether to emphasize charging near home or charging near work. The full model, EVI-Pro, is also a simulation model, and cannot be run independently by users [10]. EVI-Pro also assumes drivers may charge during any time in which their vehicle would be stationary ("dwell times"), while we restrict planned charging to a commuter's origin or destination.

Equity of access to charging has been assessed based on the locations of charging stations that have already been built. For New York City, Khan et al. [11] found that EV charger locations are not correlated with population density, are heavily skewed away from disadvantaged communities, and skewed towards highway locations. For California, Hsu and Fingerman [12] found that there are race and income disparities in EV charger access, and that the access gap is larger at locations with more multi-unit dwellings. To our knowledge, the electric vehicle charger location models have yet to incorporate equity as a factor.

There are several works modeling commuter behavior in detail. For example, [13] predicts charging demand over time by simulating the behavior of six clusters of drivers. All three weekday clusters resemble a commute – a period of use, followed by a period of un-use, followed by a period of use – at different times of day. Similarly, among a set of self-recorded trips of households in the United Kingdom, a majority of actively-used vehicles record a commuting travel pattern [14].

1.2 Our Contributions

Our work differs from the above literature in four significant ways: (i) Large-scale optimal solutions: To the best of our knowledge, none of the above models are able to provide optimal solutions at the scale of a full city, without resorting to greedy algorithms or other heuristic methods. We solve a detailed mixed integer program (MIP) model that serves as many commuters as possible, rather than a fixed number of commuters. Moreover, we solve exactly over a large region with relatively detailed data on daily commute and availability of home chargers. (ii) Key new modeling features: While many models consider minimizing distance to EV chargers, they do not directly address the choice between charging near home versus charging near work. This either-or nature of the problem of EV charging - either at home or at work - introduces some interesting features beyond the standard facility location problem where each customer is represented using one location and distances are measured from this location. (iii) Equity: We address equity of access to EV charging from the lens of charger location and who is served. (iv) Use of data on work and home locations and potential for EV home charging. The EVI-Pro model uses different data, including those derived from GPS data, to infer home and work locations for commuters. Our use of census data for home and work locations provides additional analytic capability.

The rest of the paper is organized as follows. In Section 2 we present several mixed integer programming models that we use in this paper. In Section 3 we describe the methodology for collection and development of our data. We focus on the city of Atlanta, however, the methodology can be applied to any location especially in the USA. In Section 4, we report and analyze the results we obtained from our models. Finally, in Section 5 we present concluding remarks and discuss avenues of future research.

2 Formulation

In this paper, we assume that most commuters would prefer to charge near either their home or their destination. This would give them somewhere convenient to wait while charging and reduce concern over running out of charge while driving.

We use census tracts as a means for modeling the commute pattern of the population and also for deciding the location of charging stations. A formal definition of 'census tract' is presented in Section 3. We assume there are N census tracts indexed as $\{1, ..., N\}$.

A commuter type is the set of all commuters who travel from the a given origin (or home) tract to a given destination (or work) tract and back each weekday. The set of commuter types is indexed $\{1, ..., M\}$. There are C_j commuters of each type j who could be served by assigning a location to charge back the power used by their daily commute distance, t_j. The charging time a commuter requires at a station is the equivalent amount of time to recharge their daily travel miles, including their commute.

Each census tract is considered as a potential location to install an EV charger station location (henceforth referred to as a station). We assume commuters are willing to use any station that is within a radius of r miles of either their origin or destination. The set of charging stations a customer type j is willing to use is denoted by S_j. Any established station can hold a number of fast chargers able to charge up to the equivalent of m driven miles per day (discussed in more detail in Section 3).

In the rest of this section, we develop five variants of our MIP model to solve for the EV charger location problem.

2.1 Serve All Commuters

Let z_i represent the number of chargers to be opened in block i; and let $x_{i,j}$ represent the number of commuters of type j to be served by a station in block i.

$$\begin{aligned}
\min \quad & \sum_{i=1}^{N} z_i && && (1)\\
\text{s.t.} \quad & \sum_{i \in S_j} x_{ij} = C_j && \forall j \in [M] && (2)\\
& \sum_{j=1}^{M} t_j x_{ij} \leq 2 m z_i && \forall i \in [N] && (3)\\
& z_i \in \mathbf{Z}_+ && \forall i \in [N] && (4)\\
& x_{ij} \in \mathbf{Z}_+ && \forall i \in [N], j \in [M]. && (5)
\end{aligned}$$

This model, *Serve-All*, minimizes the total number of chargers required to serve all commuters and resembles a facility location problem [15]. Here, rather than applying a cost based on travel distance, assignments are only permitted for facilities in two small regions for each commuter type.

We remind the reader that S_j is the set of potential locations where commuter type j can potentially charge. Constraint (2) ensures that all the commuters of type j are assigned to stations. Constraint (3) ensures that the total number of miles worth of charging required by commuters assigned to a charging station does not exceed the total capacity of the chargers established in that station. This constraint also ensures that commuters will not be assigned to charge in a given location if no chargers are established there.

2.2 Place a Limited Number of Stations

In this variation on *Serve-All*, which we will name *Station-Limit*, there are a limited number of chargers available to place, and we wish to serve as many commuters as possible. Up to B chargers in total may be placed.

$$
\begin{aligned}
\max \quad & \sum_{j=1}^{M} \sum_{i \in S_j} x_{ij} && && (6)\\
\text{s.t.} \quad & \sum_{i \in S_j} x_{ij} \leq C_j && \forall j \in [M] && (7)\\
& \sum_{j=1}^{M} t_j x_{ij} \leq m z_i && \forall i \in [N] && (8)\\
& \sum_{i=1}^{N} z_i \leq B && && (9)\\
& z_i \in \mathbf{Z}_+ && \forall i \in [N] && (10)\\
& x_{ij} \in \mathbf{Z}_+ && \forall i \in [N], j \in [M]. && (11)
\end{aligned}
$$

The objective is now to maximize the total number of commuters served. Constraint (7) is changed to require all customers be served, and the new Constraint (9) limits the number of stations placed.

2.3 Ensure at Least 40% of Stations Are Placed in Disadvantaged Areas

$$
\begin{aligned}
\max \quad & \sum_{j=1}^{M} \sum_{i \in S_j} x_{ij} && && (12)\\
\text{s.t.} \quad & \sum_{i \in S_j} x_{ij} \leq C_j && \forall j \in [M] && (13)\\
& \sum_{j=1}^{M} t_j x_{ij} \leq m z_i && \forall i \in [N] && (14)
\end{aligned}
$$

$$\sum_{i=1}^{N} z_i \leq B \tag{15}$$

$$\sum_{i \in S^U} z_i \geq \sum_{i=1}^{N} z_i \tag{16}$$

$$z_i \in \mathbf{Z}_+ \qquad \forall i \in [N] \tag{17}$$

$$x_{ij} \in \mathbf{Z}_+ \qquad \forall i \in [N], j \in [M]. \tag{18}$$

Here, modifying the *Station-Limit* model, we additionally require that at least 40% of the stations that are placed should be located in disadvantaged communities with Constraint (16), where S^U is the set of stations located in disadvantaged communities.

We could likewise add Constraint (16) to *Serve-All* for a model that minimizes the number of stations needed in order to serve all commuters while placing at least 40% of the stations in disadvantaged areas. We append "*40*" to either model name to indicate the inclusion of this constraint, as follows: *Serve-All-40*, *Station-Limit-40*.

2.4 Ensure at Least 40% of Those Served Are Disadvantaged

We here introduce S^U, the set of commuters who live in disadvantaged communities. Constraint (19) below will ensure that at least 40% of commuters served should be those who live in disadvantaged communities. We can add it to either base model, referring to the resulting models as *Serve-All-40-Commuters* and *Station-Limit-40-Commuters*.

$$\sum_{j \in S^U} \sum_{i \in S_j} x_{ij} \geq 0.4 \sum_{j=1}^{M} \sum_{i \in S_j} x_{ij}. \tag{19}$$

Note that, in instances in which less than 40% of commuters live in disadvantaged areas, Constraint (19) prevents a feasible solution from serving all commuters. In this case, the model may be modified as follows by adding an additional binary variable so that, once all disadvantaged commuters are served, the constraint no longer applies. Here, C^D represents the total number of disadvantaged commuters in the dataset, C^M is the total number of non-disadvantaged commuters, and y is a new binary variable.

$$\sum_{j \in S^U} \sum_{i \in S_j} x_{ij} + 0.4 C^M y \geq 0.4 \sum_{j=1}^{M} \sum_{i \in S_j} x_{ij} \tag{20}$$

$$\sum_{j \in S^U} \sum_{i \in S_j} x_{ij} \geq C^D y \tag{21}$$

$$y \in \{0, 1\}. \tag{22}$$

2.5 Relaxation

We will also consider a relaxation of each model, in which charger placements are still integer decisions, but customers may be partially assigned, potentially to multiple different chargers. This version greatly reduces the number of integer variables under consideration, and so is easier to solve to optimality than the original. As an example, the relaxation of *Station-Limit* is as follows:

$$
\begin{aligned}
\max\ & \sum_{j=1}^{M} \sum_{i \in S_j} x_{ij} \\
\text{s.t.}\ & \sum_{i \in S_j} x_{ij} \leq C_j && \forall j \in [M] \\
& \sum_{j=1}^{M} t_j x_{ij} \leq 2m z_i && \forall i \in [N] \\
& \sum_{i=1}^{N} z_i \leq B \\
& z \in \{0,1\} \\
& x \geq 0.
\end{aligned}
$$

If we wish to find a feasible solution to *Station-Limit*, after solving the relaxation we can take the floor of $x_{i,j}$ for each i and j so that commuters are not assigned fractionally.

We can likewise consider a relaxation and build a feasible solution to the other models by relaxing their integrality constraint for x.

3 Data

In the table below, we describe some of the basic data. Note that the the values with a (*) are averages.

Parameter	Definition	Value
N	the number of potential charger locations; we will index stations using N	1,518
m	the charging capacity of a single charger, in terms of equivalent miles traveled	250×6
M	the total number of commuter types; we will index commuters by M	326,579
C_j	the number of commuters of type j	4*
t_j	the daily round-trip miles commuter type j travels	40*

3.1 Commuter Data

Our data is organized by census blocks, which partition census tracts. Census tracts usually contain a population of around 4,000 people; for a sense of scale, the state of

Georgia has roughly 2,000 census tracts and 300,000 census blocks. Census blocks are based on geographical features and vary more in population [16].

We use information from Longitudinal Employer-Household Dynamics (LEHD) from the U.S. Census Bureau, which releases yearly LEHD Origin-Destination Employment Statistics (LODES) [17]. Included in this data is the estimated number of commuters who travel from any census block to any other census block, based on their combination of census replies and Bureau of Labor Statistics employment data. We make the assumption that all commuters commute each day of the regular work week. This assumption overestimates in the cases of workers who may commute only some weekdays, and underestimates in the cases of workers who may drive more frequently (working more than five days a week, making additional trips during the workday, or making additional trips outside of work hours).

We treat origin or destination points within a census block as if they were placed at the geographic centroid of the block. We calculate distances by the spherical approximation from their latitude-longitude coordinates as a straight line. Commuters who travel farther are better represented with Euclidean distance. Since commuters who do not leave a city with a block structure likely are not traveling as far as those who travel outside of a major city, we choose to use Euclidean distance. Commuter travel distance is modeled as two times the number of miles the commuter travels between their origin and destination plus 23, the average number of non-commute miles traveled by Americans in 2022 [18].

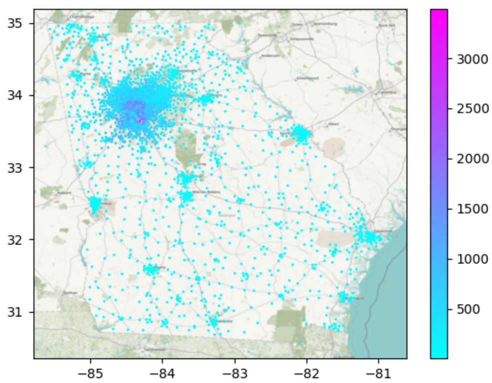

Fig. 1 The estimated number of commuters to and from Atlanta who live in each tract after aggregation and before filtering.

When we consider large geographic areas, we aggregate the block-level census data into tracts by summing commuter numbers and averaging latitude and longitude coordinates. As we will consider mainly commuters in the Atlanta area in this paper, we also focus on commuters who either travel to Atlanta, or from Atlanta. Specifically, we include all commuters who have an origin or a destination inside of the rectangular box containing the I-285 interstate, bounded by latitude-longitude pairs (33.923198,

-84.505798) and (33.613440, -84.227909) – about 1,000,000 commuters. We limit permissible stations to those within 50 miles of Atlanta, treated as the distance from latitude-longitude coordinate (33.769849, -84.389923), a point roughly in the center of Atlanta.

Figure 1 shows commuter distribution after the aggregation process. While most commuters who report commuting either to or from Atlanta do so within the neighboring areas, a few outliers who report commuting to or from Atlanta travel much farther–the maximum round-trip travel distance calculated is 563 miles. At a consistent speed of 60 miles per hour, that would equate to nearly a 9-hour round trip for a daily commute. Therefore, we remove such outlier commuters from our dataset. Table 1 includes summary statistics for aggregated data after removing either all commuters with a travel distance 2 standard deviations or 3 standard deviations away from the original data.

Table 1 Summary statistics for the Atlanta-area commuters.

		Average	Standard Deviation	Minimum	Maximum
Commuters of Each Type	Original	3.41	6.43	1	371
	Within 2 Standard Deviations	3.63	6.73	1	371
	Within 3 Standard Deviations	3.55	6.62	1	371
Travel Distance (miles)	Original	67.93	54.61	23	581
	Within 2 Standard Deviations	58.06	26.58	26	187
	Within 3 Standard Deviations	60.28	32.13	23	245

For the rest of the paper, we work with commuters whose travel distances fall within 2 standard deviations of the average. Figure 2 shows the distribution of these commuters.

3.2 Charger Information

For a fast charger, we estimate that a full charge takes an hour [19] and allows a range of 250 miles [20]; and a partial charge provides a range scaled linearly to charging time. We assume that a charger is actively charging for 12 hours each day, a conservative estimate to compensate for not modeling the queuing process. We assume a commuter will be willing to use a charger if it is within a radius of 1 mile of either their origin or their destination.

3.3 Home Charging

Approximately 52% of electric vehicle owners in the United States have access to home charging [21]. The Low-Income Energy Affordability (LEAD) tool from the US Department of Energy [22] gives an estimated number of units of different types of housing

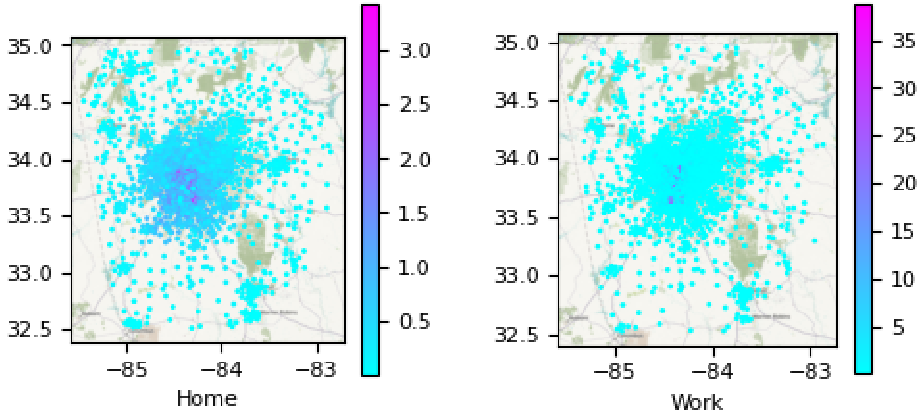

Fig. 2 The estimated number of commuters who live and work in each tract after filtering, in thousands. Note the difference in scale between the two figures.

(for example, single-unit detached homes, single-unit attached homes, apartment-style housing) in each census tract; and Axsen and Kurani [21] estimate the percentage of EV owners who have access to Level 1 charging (basic home charging) by the type of housing they live in.

For each census tract, we combine the two to get a weighted percentage of commuters originating in that tract who do not have access to home charging. Table 2 gives summary statistics for commuters after filtering to 2 standard deviations of travel distance (as in the previous section) and removing the estimated commuters who are able to charge at home, leaving only 304,907 commuters who are expected to require public charging in order to use an EV. There are a few tracts in Georgia that the LEAD data does not cover; for those tracts, the average estimated percentage of commuters in our dataset without access to Level 1 charging (roughly 28%) was used.

Table 2 Summary statistics for the Atlanta-area commuters who do not have access to Level 1 charging.

	Average	Standard Deviation	Minimum	Maximum
Commuters in Tract	1.03	2.21	0.0004	148.56
Travel Distance (miles)	55.89	20.48	23	187

Not all EV owners who are able to charge at home will choose to do so at all times. Assigning charger placement while assuming no EV owners will charge at home gives an upper bound on the number of chargers needed to allow those who might choose to charge at a fast charger to do so. Assuming that anyone with the opportunity to charge at home will do so, we will instead assign public charger placement only to

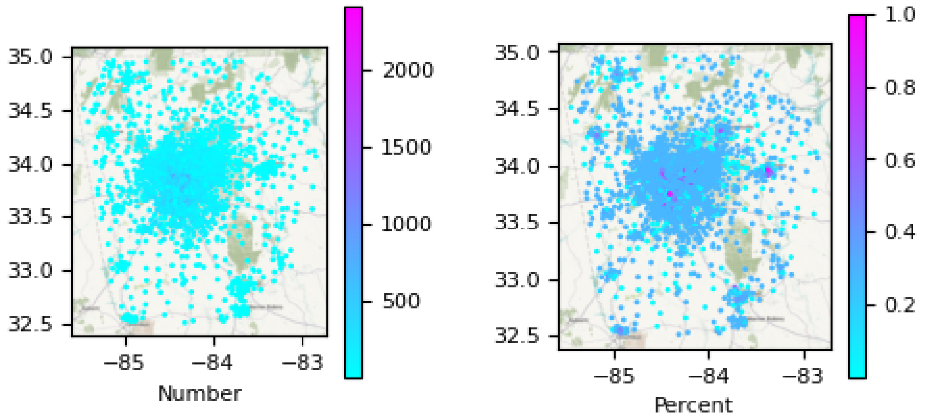

Fig. 3 The estimated number and percentage of commuters living in each tract who do not have access to Level 1 charging at home.

those commuters who cannot feasibly commute without access to a public charger and gives a lower bound on the number and placement of chargers needed.

3.4 Disadvantaged Communities

Disadvantaged communities and equity goals can be identified with a range of different criteria. Here we consider the implications of requiring at least 40% of charging access should go to disadvantaged communities [23]. Communities are determined to be disadvantaged based on factors including income, minority status, and neighboring disadvantaged communities. We use the set of communities determined to be disadvantaged by the Climate and Economic Justice Screening Tool (CEJST) [24] for this purpose.

As we use commuter data from 2020 for our experiments and the CEJST is based on census tracts in 2010, we calculate an estimated binary data point estimate of the disadvantaged status for each modified tract [25]. A 0/1 binary value for each 2010 tract's disadvantaged status is assigned by the CEJST, representing not disadvantaged and disadvantaged, respectively. The estimated disadvantaged status for each 2020 tract is the average disadvantaged value of its contributing 2010 tracts weighted by the land area overlap between each, rounded to the nearest of 0 or 1. For most tracts, the resulting disadvantaged status is unchanged by this process, as most tracts do not change much between 2010 and 2020.

4 Experiments

Each of the following experiments is performed on the tract-aggregated version of the Atlanta area data with commuters whose calculated travel distance is within 2 standard deviations of the mean, using Python with Gurobi as a MIP solver, and solving to a 1% optimality gap. The relaxation discussed in Section 2.5 is solved, and the number of customers assigned to any given charger is rounded down. All computations are done on a computer with a i7-12700KF CPU and a rtx-4090 GPU, with 64 GB RAM.

4.1 Station Placement for All Commuters

The *Serve-All* model is run on tract-level data for all commuters in the Atlanta area. The solution places 41,423 chargers and serves 1,076,376 commuters. As shown in the left-hand side of Figure 4, without an upper bound, the maximum is 655 chargers in a tract, although 87% of tracts are allocated 50 or fewer chargers. This may not be a desirable outcome.

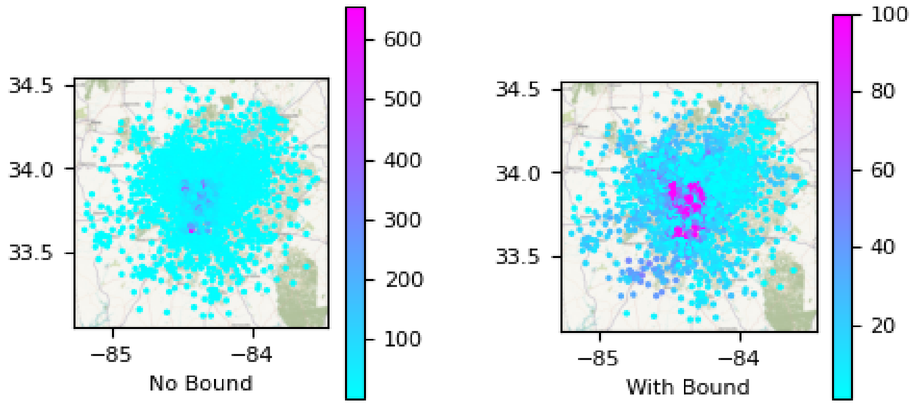

Fig. 4 Chargers placed in each tract by *Serve-All* without an upper bound and with an upper bound of 100 stations per tract.

Serve-All is run again, with an upper bound of 100 chargers per tract. The right-hand side of Figure 4 shows the resulting placement of chargers, placing 41,020 chargers to serve all commuters, similar to the unbounded result. On average, 27 chargers are placed in tracts that are assigned chargers. All following experiments will include the 100-charger upper bound.

4.2 Varying Available Chargers

Here we solve *Station-Limit* with different values of B (the number of chargers that can be placed), serving any of the full set of commuters both with and without home charging access.

Figure 5 shows the locations of chargers placed when 5,000, 20,000, and 25,000 chargers are available alongside the solution to *Serve-All*. No explicit constraint was placed to encourage charger placement inside of the city, but at smaller values of B, chargers are placed mostly inside the city – serving first commuters who commute

Table 3 *Station-Limit* results.

Stations Placed	Commuters Served	Commuters/Stations Ratio	Percentage at Work
5,000	238,559	47.7	53.2
10,000	415,461	41.5	56.8
15,000	567,026	37.8	57.7
20,000	697,906	34.9	54.3
25,000	813,307	32.5	32.8
30,000	914,306	30.5	48.6
35,000	999,119	28.5	46.2
41,020	1,068,414	26.0	39.6

within the city and therefore don't travel as far or need as much charging capacity, and expanding outside of the city once those commuters are served.

When fewer stations are permitted, maximizing the number of commuters who are able to charge encourages the model to serve commuters who have a shorter commute (and therefore require a shorter estimated charging time). Most stations are placed near the city, and near workplaces, until more than 25,000 stations are permitted – at this point, our model shows many more stations placed outside the city, suggesting a point exists where establishing stations outside the city becomes more valuable than before. After this point, we see a drop in the percentage of commuters who are assigned to charge at work, because they are instead charging at home, outside of the city. We can see that some intermediate solutions before this point, as with 12,500 permitted chargers, place many chargers very close to Atlanta that do not continue to be placed in the same area in solutions with more chargers; but after this point, the placement of chargers seems to grow more smoothly, without removing and replacing as many "previous" chargers.

4.3 Station Placement with Home Charging

Here we incorporate home charging into our model by assigning only commuters who cannot charge at home to fast charging stations.

As many of the commuter types (origin-destination pairs) contain very few commuters and a few commuter types contain many commuters, rounding to get an integer percentage in the type's home tract would bias our analysis, as tract pairs with a single commuter. To solve over the dataset of commuters who do not have access to home charging, we let x_{ij} (the number of commuters of a given type assigned to a given charger) be linear rather than integer, and we do not round down as before to find a feasible integer solution. Instead, consider fractional customer numbers as an abstraction of existing commuters–e.g., if 1 commuter traveled a given route and 60% of commuters in their home tract have access to home charging, our scaled data would have $C_j = 0.6$, representing that with 60% probability, there is a commuter who travels this route who cannot charge at home. The change to fractional variable values does mean that it is possible in this model to assign commuters partially to multiple different chargers; in other words, that we might assign a single commuter to charge partially at home and partially at work, or that we might only partially charge a given commuter. These results should therefore be viewed as a relaxation of the previous

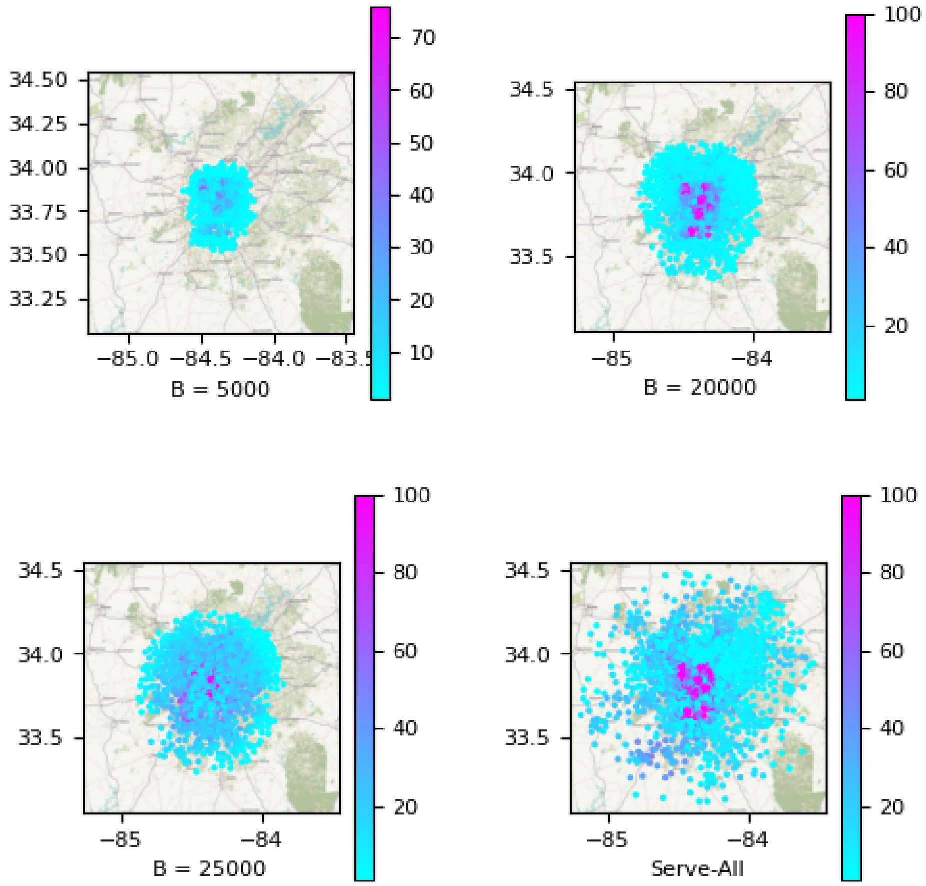

Fig. 5 Charger placement with 5,000, 20,000, and 25,000 chargers available, with *Serve-All* placement repeated here for comparison.

model. Remember that naturally there are fewer commuters to serve when removing those with access to home charging.

As those living in apartments have a lower probability of having access to home charging (9.1%) than those living in detached houses (78.3%) [21], and apartments are much more common within the city than outside of it, more charging demand lies inside of Atlanta. This model consequently places most chargers inside of the city and close to the city compared to when serving all commuters.

4.4 Equity Considerations

Figure 7 plots the percentage of the commuters in each tract who do not have access to Level 1 charging as a function of the average income of the tract. Tracts with

Table 4 Results from *Station-Limit* and *Serve-All* when placing stations for only commuters without home charging access.

Stations Placed	Commuters Served	Commuters/Stations Ratio	Percentage at Work
2,000	87,637	43.8	43.3
4,000	152,715	38.2	56.7
6,000	205,357	34.3	36.0
8,000	248,516	31.1	33.5
10,349	284,877	27.5	55.2

incomplete home charging data were excluded from this figure. The figure shows that commuters in higher income tracts tend to have more access to EV charging at home.

Table 5 Commuters served by *Station-Limit-40* and *Station-Limit-40-Commuters*, serving only commuters who do not have home charging access.

Stations Placed	*Station-Limit-40*	*Station-Limit-40-Commuters*
2,000	88,717	88,371
4,000	152,742	152,151
6,000	210,247	202,311
8,000	247,634	214,055
10,000	278,784	216,126

In Table 5, we show the commuters served by the results of the *Station-Limit-40* and *Station-Limit-40-Commuters* models on the set of commuters who do not have home charging access, the same set used for Table 4. For *Station-Limit-40-Commuters* we include the optional binary constraint discussed in that section–after all disadvantaged commuters are served, the requirement that 40% of served commuters be disadvantaged is no longer enforced. When fewer than 4,000 chargers are placed, both versions of equity requirement don't significantly affect the number of commuters who can be served; recall that each solve is done within a 1% optimality gap.

Station-Limit-40, in the instances where fewer stations are allowed, returns a slightly better solution than does *Station-Limit*, despite introducing a new constraint. While (naturally) not outside of the 1% optimality gap permitted, the difference is fairly consistent. As more disadvantaged commuters live inside of the city, requiring station placement near disadvantaged communities seems to encourage station placement inside the I-285 perimeter of Atlanta.

4.5 Notes on Model Solutions in Atlanta Communities

Figures 8 and 9 display the number of stations placed in each tract of central Atlanta when the model is run as in Table 3 and when we add the equity constraint 16 to the same data, respectively. Here, as we zoom in to the center of Atlanta, we are able to show tract boundaries (colored to represent the number of stations placed in the district, with the same color scale as in Figure 6).

The optimization model does not enforce any continuity in station placements between differing numbers of available stations. Indeed, as we saw in Subsection 4.2

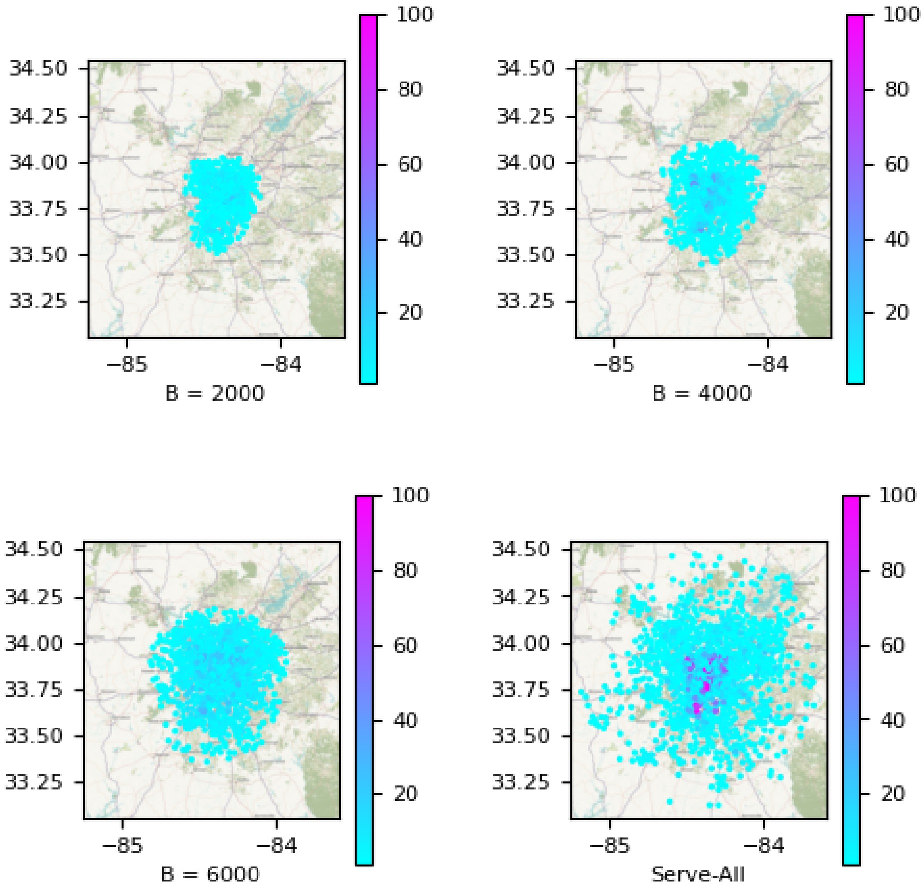

Fig. 6 Placement of chargers for only those commuters who do not have home charging access with 2,000, 4,000, and 6,000 chargers available alongside the placement by *Serve-All*.

and here in greater detail in Figure 8, increasing the number of chargers placed may result in solutions that remove great numbers of chargers from tracts where they were placed when we permitted fewer chargers. For example, in Figure 8, when we place 15,000 chargers we can see that several tracts in the city have more than 80 chargers assigned to them which are no longer assigned so many chargers when we place 25,000 chargers. This is an understandable but undesirable result of independent solves of the model.

However, when applying Constraint 16, we can see in 9 a more natural growth in charger placement. It could be more efficient to implement these solutions over time as demand for chargers grow.

Most tracts show a steady and organic growth in charger placement in Figure 9, as opposed to a much more variable pattern in Figure 8. Overall, with the equity

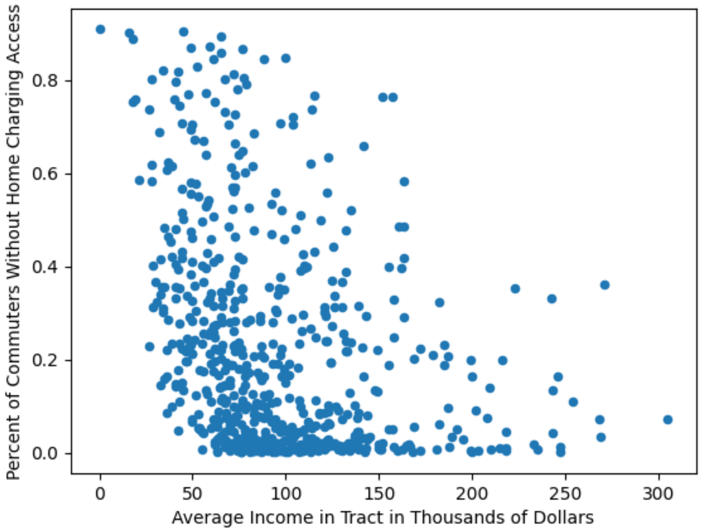

Fig. 7 Average percent of commuters in a tract without home charging access by average yearly income within the tract.

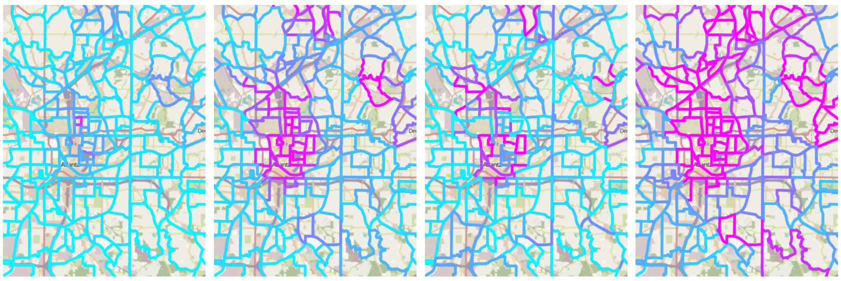

Fig. 8 *Station-Limit* placements in Atlanta, with varying numbers of stations placed. Left to right: 5,000, 15,000, 25,000, and 35,000 stations placed.

constraint applied, the model places stations in a way that grows monotonically in this case and in metro Atlanta. This is an interesting possible beneficial side effect of the 16 constraint.

5 Conclusion and Future Work

We introduce our MIP models and associated relaxations for the EV charger location planning problem, and two types of constraint to improve equity of solutions. Our model can easily be applied to any area in the US, as the census data and Level 1 charging estimates are available for the entire US. The model can also be applied outside the US if similar input data are available We share the related code and data via GitHub [26].

Fig. 9 *Station-Limit-40* placements in Atlanta, with varying numbers of stations placed. Left to right: 5,000, 15,000, 25,000, and 35,000 stations placed.

Cities and urban regions can benefit from considering both types of model: the EVI Pro-Lite simulation and the optimization model proposed here. EVI-Pro-Lite provides a result that serves all commuters and allows the modeler to decide the extent to which commuters will be served near home or mear work; our model provides a lowest cost solution, and also allows planners to determine how to place chargers if the budget is insufficient to serve all.

Future work could improve this modeling approach. The EVI Pro model, while a simulation model rather than an optimization model, includes a number of features that we have not included, including the charging demand at different times of day, the resulting load on the electric grid, and the interest in Level 2 version fast charging. Plans for EV charging infrastructure would benefit from similar model enhancements and comparisons.

Home charging is more available outside of areas of dense population, and therefore serving only commuters who do not have home charging access tends to place stations mostly inside the city, especially around multi-unit housing.

This model has assumed that all commuters travel by car. Walking, biking, and public transit have been ignored. Future work could consider the effects of walking, biking, and public transportation on the need for and placement of EV chargers.

Acknowledgments

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Appendix

As more stations are placed, the locations of stations with higher proportions of commuters assigned to charge at their work locations (shown in purple in Figure 10) align with major highways. This makes sense if we consider that more workplaces could

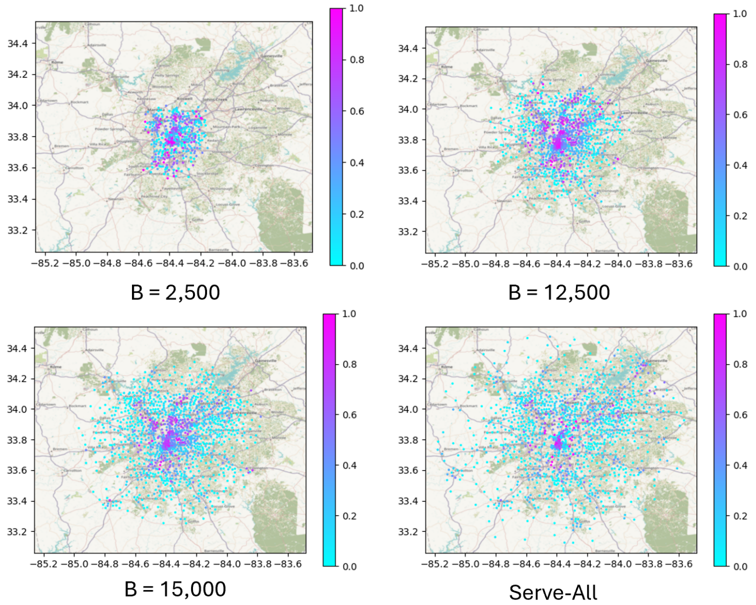

Fig. 10 Fraction of assigned commuters at a placed charger who are charging at their workplace rather than their home with 2,500, 12,500, 15,000, and 20,862 chargers available.

be close to highways, and housing areas often branch out away from them. It also means that, even though the model did not consider road geography, it places a solid percentage of chargers near major highways, which is a desirable quality.

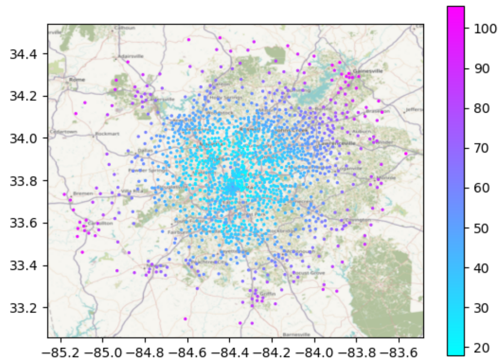

Fig. 11 Average travel distance (miles) assigned to each placed charger in the solution from Model 2 with upper bound.

In Figure 11, we see that the average travel distance of customers assigned to chargers increases with distance from Atlanta. Since we include both commuters who

Table 6 Bounding box used for each additional city.

City	W Longitude	E Longitude	N Latitude	S Latitude
Seattle, WA	-122.434624	-122.243736	47.734521	47.493823
Boston, MA	-71.190850	-70.986709	42.397731	42.226543
Chicago, IL	-87.753866	-87.521962	42.002429	41.644020
Denver, CO	-105.140602	-104.769395	39.906613	39.587375
Phoenix, AZ	-112.323980	-111.927099	33.919566	33.288199
Houston, TX	-95.557577	-95.191757	29.934059	29.604466

Table 7 Commuter distance statistics and *Serve-All* results for each additional city.

City	Commuters	Average Distance	Standard Deviation	Stations Placed
Seattle, WA	705,750	37.87	62.43	22,198
Boston, MA	749,783	25.78	28.49	25,274
Chicago, IL	1,043,975	36.15	58.23	47,887
Denver, CO	1,125,725	36.90	52.67	33,846
Phoenix, AZ	1,447,273	44.74	61.44	49,804
Houston, TX	1,524,600	74.40	132.09	67,114

travel into Atlanta and who travel from Atlanta to elsewhere, the larger travel distance assigned inside Atlanta is explained partially by commuters who travel from Atlanta to farther cities or suburbs. Additionally, only stations within 50 miles of Atlanta are considered, so commuters who travel from a home farther than 50 miles from Atlanta must be assigned to charger at their work location in Atlanta.

As demonstration of the application of the model to any US state, we run *Serve-All* on a set of additional US cities. As in our Atlanta data, the data set for each city here is all commuters who commute into or out of the city boundaries, inclusive. We allow station placement in any tract within 30 miles of the center of the bounding box drawn, and filter out any commuter with a travel distance greater than one standard deviation above the average for their city's data set. Note that this is slightly stricter than the filtering applied to the Atlanta dataset. We add 23 miles to each commuter's daily travel distance as we did with Atlanta. Table 6 gives the bounding boxes used, chosen to roughly align with each city's geographic borders while including minimal excess area. All are solved under the same conditions as in Section 4.

Our results, shown in Table 7, show a correlation between commuter population and number of stations needed, as one would expect. Houston, Texas is an interesting case, as the estimated commute length and standard deviation are much larger than our other considered cities, and extra stations are placed there to cover the additional charging needed.