Optimizing EV Charging Infrastructure in Boston

15.C57 Optimization

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Abstract

This report addresses the challenge of expanding electric vehicle (EV) charging infrastructure in Boston, MA, to support the city's transition to zero-emission vehicles and its commitment to reducing greenhouse gas emissions. To meet the projected 2050 demand, this project identifies optimal locations for public and curbside Level 2 chargers, prioritizing accessibility, cost-effectiveness, and efficiency.

An optimization model was developed using data on existing chargers, geographic boundaries, and household demand from the 2020 Boston census. The model aims to ensure that all housing units are within a 0.5-mile radius of a charging station. Dorchester, Boston's largest and most diverse neighborhood, was used as a representative test case to evaluate the model's performance due to its size, population diversity, and varied infrastructure needs. The findings provide insights for scaling EV infrastructure planning citywide, with recommendations for improving accessibility and addressing demand in future deployments.

1 Introduction

The transition to electric vehicles (EVs) is a key strategy for combating climate change and reducing greenhouse gas emissions. Boston has set ambitious sustainability goals, including widespread adoption of zero-emission vehicles, but the city faces significant challenges in ensuring equitable access to EV charging infrastructure. The rapid growth of EV ownership has highlighted infrastructure gaps, particularly in underserved areas such as Dorchester, Boston's largest and most diverse neighborhood.

This project focuses on developing an optimization model to guide the placement and allocation of Level 2 EV chargers across Boston, with the goal of meeting projected demand by 2050. The model prioritizes accessibility, cost-effectiveness, and efficiency, ensuring that all housing units are within a 0.5-mile radius of a charging station. For evaluation, Dorchester was selected as a scaled-down test case due to its demographic diversity, size, and unique infrastructure needs, making it a representative setting for evaluating the model's effectiveness.

To achieve these objectives, we analyzed data from various sources, including existing charger locations, census data, and geographic boundaries. The optimization model identifies candidate locations and determines ideal placements and allocations for EV chargers to address Boston's future needs.

This paper outlines the methods, results, and implications of this analysis, emphasizing the lessons learned from applying the model to Dorchester. The findings support Boston's broader sustainability goals and highlight how this approach can be adapted to other neighborhoods and cities. Limitations and recommendations for further improvements in EV infrastructure planning are also discussed.

2 Methodology

This section outlines the methodology used in this project. First, we describe the data preprocessing steps, including how the data was cleaned, organized, and prepared for analysis. Then, we discuss the formulation of the optimization problem, including its rationale and the objectives it aims to achieve.

2.1 Data Overview

This project utilized data from multiple sources to guide the optimization of EV charging station placements and allocations in Dorchester, Boston, MA:

- **Alternative Fuels Data Center (AFDC):** Provided the current EV station locations (longitude, latitude) and the number of chargers at each station in Boston. This data was used to assess existing infrastructure, identify coverage gaps, and determine optimal locations for new charging stations. (1)
- **ChargePoint:** Supplied information on charging station and charger costs, enabling accurate cost estimation for the installation of new infrastructure. This data supported budgeting and financial planning for the proposed solutions. (2)
- **City of Boston (2020 U.S. Census):** Offered data on the number of residential units in each Boston neighborhood. Mapping this data allowed us to identify high-demand areas within a 10-minute walking radius of residential units, ensuring efficient and accessible charger placement. (3)
- **Mass.gov:** Provided funding information, specifying a $15 million budget constraint for the project. (4)

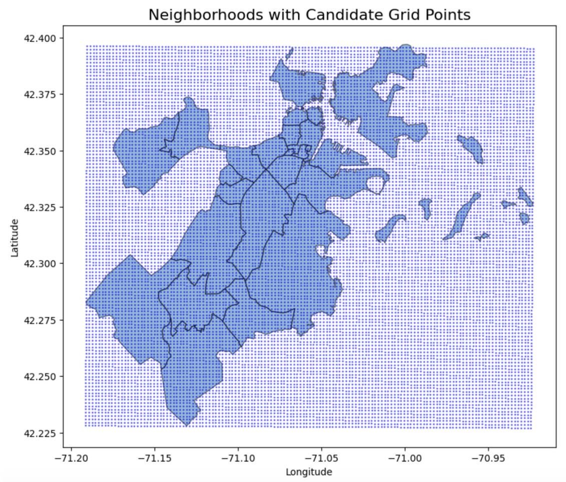
2.2 Data Preprocessing

2.2.1 Candidate Location Generation

To generate candidate locations for new EV chargers, we first filtered the dataset to include only public charging stations within Boston. Each charger was then labeled by its corresponding neighborhood to ensure neighborhood-specific analysis.

To maximize flexibility in identifying potential charger placements, we created a grid of candidate locations, setting the spacing between grid points to 0.1 miles. This grid was generated within the geographic boundaries of each neighborhood, ensuring that candidate locations were evenly distributed and representative of the entire area.

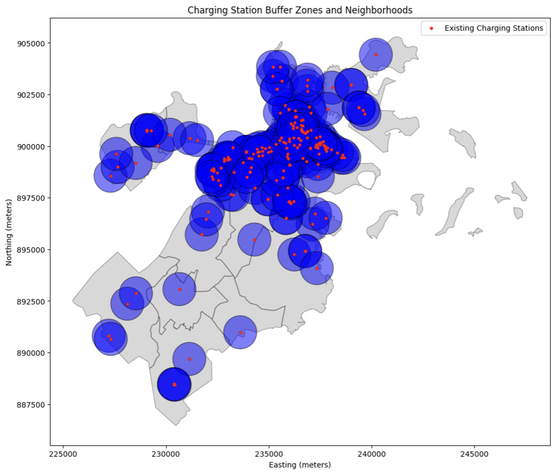
Figure 1: Candidate grid points (0.1-mile spacing) within Boston neighborhoods for potential EV charging station placements.



2.2.2 Selecting Candidate Locations in Uncovered Areas

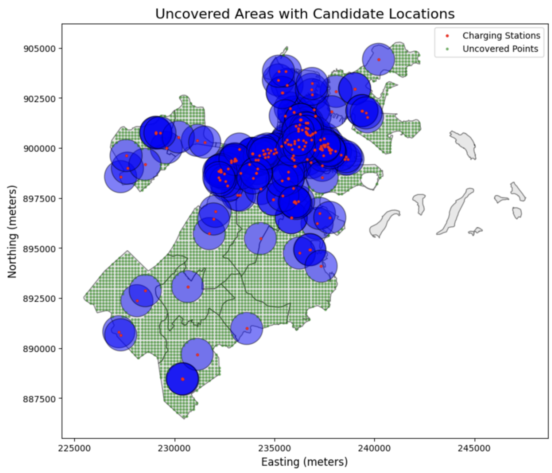
To ensure comprehensive coverage and address current gaps in EV infrastructure, we combined existing charging stations with the candidate grid locations generated earlier. A 0.5-mile buffer zone was established around each station to assess the overlap between existing infrastructure and candidate sites. These buffer zones help identify areas with sufficient coverage as well as underserved regions requiring additional stations. By integrating current and potential locations, this approach provides a more holistic framework for optimizing EV charger placements within Boston neighborhoods.

Figure 2: 0.5-mile Buffer Zones of Existing Stations



For areas outside the 0.5-mile buffer zones, candidate grid points were identified as potential locations for new EV chargers. These uncovered regions highlight the gaps in current infrastructure that need to be addressed to ensure equitable access to charging stations. By prioritizing these locations, the optimization model can focus on improving coverage and meeting the future demand for EV chargers effectively.

Figure 3: Candidate locations in uncovered areas

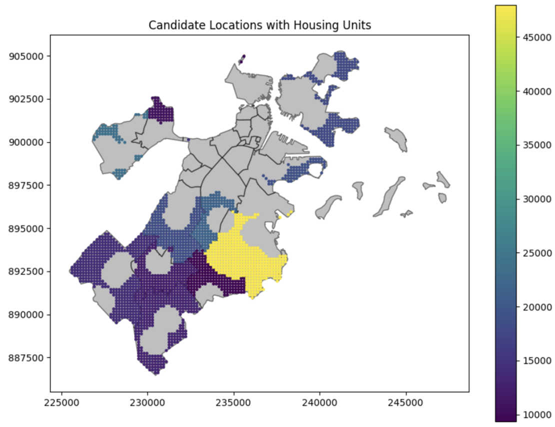


2.2.3 Analysis of Candidate Locations and Housing Units

This plot overlays candidate locations for EV chargers with the distribution of housing units across Boston neighborhoods. The color gradient represents the density of housing units, with areas like Dorchester showing significantly higher populations compared to other neighborhoods. Despite this, Dorchester remains severely underserved in EV charging infrastructure, highlighting a critical gap in coverage.

The high density of housing units in Dorchester underscores the urgency of prioritizing this neighborhood for EV charger placement. By addressing this disparity, we can ensure equitable access to charging infrastructure for a large portion of Boston's population, aligning with the city's goals for increased EV adoption and reduced emissions. (5)

Figure 4: Candidate locations colored by housing density



2.2.4 Simulating Housing Unit Locations Across Boston

To simulate housing unit locations, the points were distributed uniformly at random within the geographic boundaries of each neighborhood in Boston. Using the total number of housing units reported for each neighborhood from the 2020 U.S. Census, we generated a corresponding number of random points within the boundaries of each neighborhood polygon. This process ensures that the simulated points are spread across the entire neighborhood while maintaining a one-to-one relationship with the actual housing unit count.

2.3 Problem Formulation

For this project, we based our formulation on the Boston Zero Emissions Roadmap, which provides projected EV adoption rates for 2050. These scenarios include a Low Scenario (54% adoption), a Baseline Scenario (62% adoption), and a High Scenario (71% adoption). For simplicity, we implemented a deterministic optimization problem using the Baseline Scenario of 62% adoption as our assumed rate.

The total budget for the project is set at $15 million, as outlined in the roadmap. Additionally, we assume a partial charging rate of 0.5, meaning each EV charges half a tank per session. These assumptions form the basis of our optimization model, guiding charger placement and allocation decisions to meet future demand within the budget constraints.

2.3.1 Overall Formulation

$$
\begin{aligned}
\min_{x,y,u,x',u'} \quad & \sum_{j\in F_k}\sum_{k\in N}(cx_{jk}+gu_{jk})+\sum_{j\in F'_k}\sum_{k\in N}(cx'_{jk}+gu'_{jk}) \\
\text{subject to} \quad & \sum_{j\in\Omega_k}\sum_{k\in N} y_{ijk}\geq 1, \quad \forall i\in\Omega_k \\
& y_{ijk}=x_{jk}, \quad \forall (i,j)\in\Omega_k, k\in N \\
& u_{jk}\leq 12x_{jk}, \quad \forall j\in F_k, k\in N \\
& u_{jk}\geq x_{jk}, \quad \forall j\in F_k, k\in N \\
& 2(u_{jk}+u'_{jk})\geq \frac{1}{24}a\cdot p\sum_{i\in H_k} y_{ijk}, \quad \forall j\in F_k, j\in F'_k, k\in N \\
& u'_{jk}\leq 12x'_{jk}, \quad \forall j\in F'_k, k\in N \\
& \sum_{j\in F_k}\sum_{k\in N}(cx_{jk}+gu_{jk})+\sum_{j\in F'_k}\sum_{k\in N}(cx'_{jk}+gu'_{jk})\leq B, \quad \forall j\in F_k, j\in F'_k, k\in N \\
& y_{ijk}\geq 0, \quad \forall (i,j)\in\Omega_k, k\in N \\
& u_{jk}, u'_{jk}\in Z_{\geq 0}, \quad \forall j\in F_k, j\in F'_k, k\in N \\
& x_{jk}, x'_{jk}\in\{0,1\}, \quad \forall j\in F_k, j\in F'_k, k\in N
\end{aligned}
$$

Let:

- $(i, j) \in \Omega_k$ if distance between housing unit i and station j is within a 0.5-mile radius in neighborhood k.
- N = set of neighborhoods in Boston.
- F_k = set of candidate station locations in neighborhood k, $k \in N$.
- F'_k = set of candidate overflow station locations in neighborhood k, $k \in N$.
- H_k = set of housing unit locations in neighborhood k.
- α = adoption rate (Baseline = 62%), the projected EV adoption rate in 2050 in Boston.
- p = partial charging rate (Baseline = 50%), assuming half a tank is charged for each car each time (battery capacity assumed).
- c = cost of installing a charging station for a dual-port level 2 charger (Base price of $7,200).
- g = cost of installing a level 2 charger (Estimated to be $12,000 per charger).
- B = budget ($15,000,000 according to the City of Boston).

Decision Variables:

$$x_{jk} = \begin{cases} 1, & \text{if station } j \text{ is built in neighborhood } k, \\ 0, & \text{otherwise.} \end{cases} \quad \forall j \in F_k,\ \forall k \in N$$

$$y_{ijk} = \begin{cases} 1, & \text{if housing unit } i \text{ is within a 0.5-mi radius from station } j \text{ in neighborhood } k, \\ 0, & \text{otherwise.} \end{cases} \quad \forall (i,j) \in \Omega_k, k \in N.$$

$$u_{jk} = \text{number of chargers needed for station } j \text{ in neighborhood } k, \quad \forall j \in F_k, k \in N$$

$$u'_{jk} = \text{number of excess chargers needed for station } j \text{ in neighborhood } k, \quad \forall j \in F'_k, k \in N$$

$$x'_{jk} = \begin{cases} 1, & \text{if } u_{jk} > 0, \\ 0, & \text{otherwise.} \end{cases} \quad \forall j \in F'_k, k \in N$$

2.3.2 Rationale

Objective

The objective function minimizes the total cost of building and operating EV charging stations while accounting for excess demand. It consists of two main components:

1. **Cost of Building Stations and Installing Chargers (First Parenthesis):**
   - This component calculates the cost of constructing the planned charging stations (x_{jk}) and installing chargers (u_{jk}) at these stations across all neighborhoods.
   - The term $\sum_{j \in F_k} \sum_{k \in N} (cx_{jk} + gu_{jk})$ represents:
     - cx_{jk}: The cost of building station j in neighborhood k.
     - gu_{jk}: The cost of installing u_{jk} chargers at station j.
2. **Cost of Extra Stations and Chargers to Account for Excess Demand (Second Parenthesis):**
   - This component captures the additional cost required to handle excess charging demand by building overflow stations (x'_{jk}) and installing extra chargers (u'_{jk}) at these stations.
   - The term $\sum_{j \in F'_k} \sum_{k \in N} (cx'_{jk} + gu'_{jk})$ represents:
     - cx'_{jk}: The cost of building an overflow station j in neighborhood k.
     - gu'_{jk}: The cost of installing u'_{jk} chargers at the overflow station.

Constraints

1. **Coverage Constraint:**

   $$\sum_{j \in \Omega_k} \sum_{k \in N} y_{ijk} \geq 1, \quad \forall i \in \Omega_k$$

   This constraint ensures that every housing unit $i \in \Omega_k$ is covered by at least one station j within a 0.5-mile radius in neighborhood k.

2. **Logical Constraint:**

   $$y_{ijk} = x_{jk}, \quad \forall (i,j) \in \Omega_k, k \in N$$

   This constraint ensures that a housing unit i within a 0.5-mile radius from station j can only be covered by it if that station is built ($x_{jk} = 1$). If the station is not built ($x_{jk} = 0$), then $y_{ijk} = 0$.

3. **Maximum Charger Limit:**

$$u_{jk} \leq 12x_{jk}, \quad \forall j \in F_k, k \in N$$

This constraint sets a maximum limit of 12 chargers per station. If a station is not built ($x_{jk} = 0$), no chargers (u_{jk}) can be installed.

4. **Minimum Charger Requirement:**

$$u_{jk} \geq x_{jk}, \quad \forall j \in F_k, k \in N$$

This constraint ensures that at least one charger is installed at every built station ($x_{jk} = 1$).

5. **Demand Constraint:**

$$2(u_{jk} + u'_{jk}) \geq \frac{1}{24}\alpha \cdot p \sum_{i \in H_k} y_{ijk}, \quad \forall j \in F_k, k \in N$$

This constraint ensures that the total number of chargers (including excess chargers, u'_{jk}) is sufficient to meet the charging demand. The demand is calculated based on the EV adoption rate (α) and partial charging rate (p) over a 24h charging window.

6. **Overflow Station Charger Limit:**

$$u'_{jk} \leq 12x'_{jk}, \quad \forall j \in F'_k, k \in N$$

This constraint ensures that overflow stations are only built ($x'_{jk} = 1$) if there are excess chargers required ($u'_{jk} > 0$). If no excess chargers are needed ($u'_{jk} = 0$), then no overflow station is built ($x'_{jk} = 0$).

7. **Budget Constraint:**

$$\sum_{j \in F_k} \sum_{k \in N} (cx_{jk} + gu_{jk}) + \sum_{j \in F'_k} \sum_{k \in N} (cx'_{jk} + gu'_{jk}) \leq B$$

This constraint ensures that the total cost of building stations and installing chargers (including for overflow stations) does not exceed the allocated budget B.

8. **Non-Negativity:**

$$y_{ijk} \geq 0, \quad \forall (i,j) \in \Omega_k, k \in N$$

This constraint ensures that the variable y_{ijk}, which represents whether a housing unit is covered by a station, is non-negative. Since our other constraints inherently force y_{ijk} to take integer values, we can safely relax it to be continuous without altering the solution.

9. **Integer Charger Requirement:**

$$u_{jk}, u'_{jk} \in Z_{\geq 0}, \quad \forall j \in F_k, j \in F'_k, k \in N$$

This constraint ensures that the number of chargers is a non-negative integer.

10. **Binary Decision Variables:**

$$x_{jk}, x'_{jk} \in \{0,1\}, \quad \forall j \in F_k, j' \in F'_k, k \in N$$

This constraint ensures that station decision variables (x_{jk}, x'_{jk}) are binary, representing whether a station is built (1) or not (0).

Note: Selection of Overflow Stations (x')

The selection of overflow stations involved identifying stations with unmet demand and sampling new points within their 0.5-mile buffer zones to serve as overflow locations. This approach reflects how planners might use optimization results to guide additional infrastructure placement. Human oversight can refine the process by selecting points based on accessibility, feasibility, and local needs, ensuring a balance between model-driven optimization and practical implementation.

3 Results

Scaled-Down for Dorchester

Due to the large number of data points and computational complexity, we scaled down our analysis to focus on Dorchester. This allowed us to test our optimization model on a single neighborhood, providing insights into infrastructure planning while ensuring computational feasibility. Future iterations of the project can scale the methodology to include all neighborhoods in Boston.

k = 3 (Dorchester's neighborhood ID)
B = $15,000,000 \cdot 0.19$ (Dorchester's population is 19% of Boston)

3.1 Optimization Results

The optimization model identified 27 station locations in Dorchester, accommodating a total of 213 chargers at a cost of $1,936,800, which utilizes only 68% of the allotted budget for the area. This demonstrates that the model not only meets the coverage and demand requirements but also achieves significant cost savings. The selected locations effectively minimize coverage gaps while considering demand and accessibility. Overflow stations are strategically incorporated to handle excess demand, as shown in Figure 5. The results showcase an efficient and cost-effective distribution of EV infrastructure compared to a heuristic approach, ensuring better coverage with fewer stations. Detailed station and charger allocations are summarized in Table 1.

Figure 5: Selected Stations for Dorchester

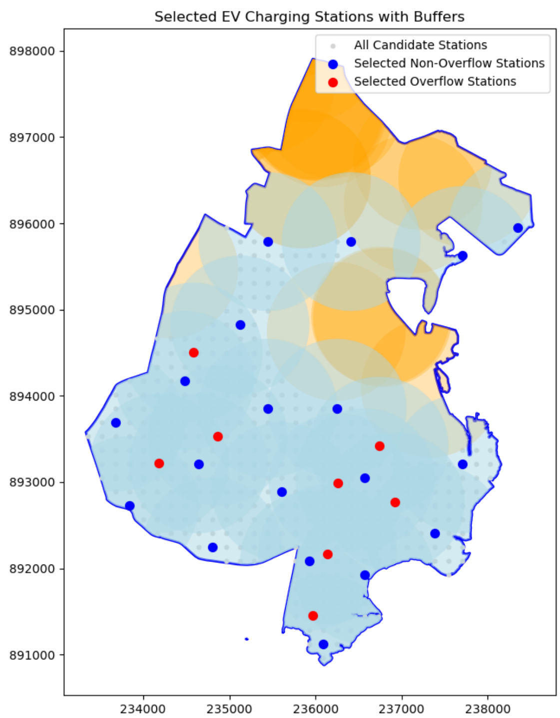


Table 1: Station and Overflow Station Charger Counts

Station ID	Charger Count	Overflow Station ID	Charger Count
Station 124	4.00	Station 124.1	12.00
Station 132	8.00	–	–
Station 162	3.00	–	–
Station 166	12.00	Station 166.1	2.00
Station 173	11.00	–	–
Station 251	12.00	–	–
Station 292	12.00	Station 292.1	5.00
Station 302	8.00	–	–
Station 307	12.00	Station 307.1	7.00
Station 315	6.00	Station 315.1	12.00
Station 342	12.00	–	–
Station 362	5.00	Station 362.1	12.00
Station 363	6.00	Station 363.1	12.00
Station 373	10.00	–	–
Station 376	12.00	–	–
Station 433	3.00	Station 433.1	12.00
Station 470	2.00	–	–
Station 507	10.00	–	–
Station 509	2.00	–	–

Total Number of Stations: 27
Total Number of Chargers: 213
Total Costs: $1,936,800

3.2 Evaluation

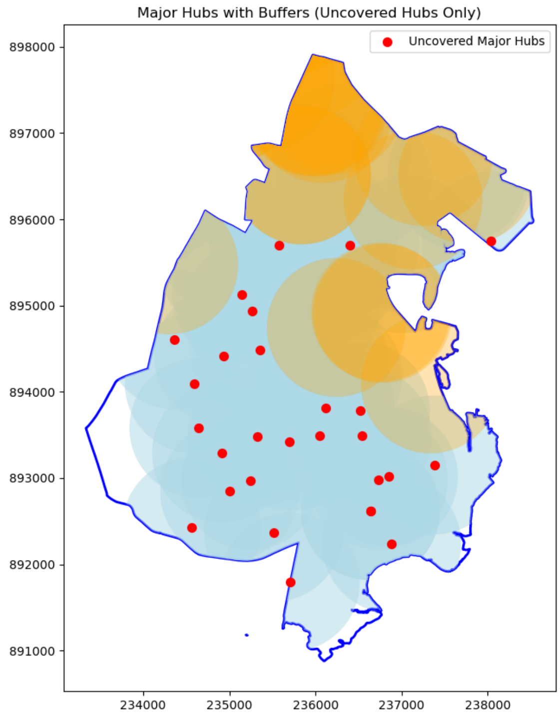
To assess our model's performance against straightforward yet comprehensive strategies, we compared the optimized station locations with a simpler approach: building stations at major community hubs. For this comparison, we identified all public parks, libraries, and schools in Dorchester as potential station locations under the simple strategy.

Without considering the pre-existing 10 buffer zones, building stations at these major hubs would result in 63 stations while still failing to cover all residential units in Dorchester. This indicates that the hub-based approach is suboptimal for selecting station locations.

Even after excluding locations already covered by pre-existing stations, constructing stations at the remaining uncovered major hubs would result in 28 stations, yet some areas of Dorchester would still lack coverage. Additionally, this method does not account for the demand each station can accommodate, as it provides no guidance on the number of chargers to allocate per station. Furthermore, we observed clustering near the center, which may not align with actual demand distribution.

While this hub-based method may appear reasonable with human oversight, it ultimately proves far less efficient compared to the optimized approach generated by our model.

Figure 6: Selecting Major Hubs in Dorchester



4 Discussion & Future Directions

The optimization model developed for Dorchester demonstrates the potential for efficient and cost-effective EV charging infrastructure planning. By strategically placing 27 stations with 213 chargers, the model achieves comprehensive coverage while utilizing only 68% of the allocated budget. This approach significantly outperforms simpler heuristic methods, such as placing chargers at community hubs, which would require more stations and still fail to provide adequate coverage.

To expand this model to the entire city of Boston, an iterative scaling approach can be employed. Each neighborhood can be added sequentially to the optimization problem, allowing for adjustments and refinements as the model grows in complexity. This gradual expansion will help maintain computational feasibility while ensuring that inter-neighborhood dynamics and citywide patterns are captured effectively.

For future enhancements, implementing an adaptive formulation to account for different EV adoption scenarios would be valuable. This could involve assigning probability distributions to various adoption rates and incorporating stochastic optimization techniques. Such an approach would provide more robust solutions that can adapt to uncertainties in future EV uptake and charging demands.

Additionally, integrating real-time data on charging patterns, traffic flow, and grid capacity could further improve the model's accuracy and responsiveness to changing urban dynamics. Collaboration with utility companies and city planners would be essential to incorporate these factors and ensure that the charging infrastructure aligns with broader urban development goals.

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