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► **To cite this version:**

Chuan Li, Shunyu Zhao, Vincent Gauthier, Hassine Moun gla. Large-scale optimization of electric vehicle charging infrastructure. The 32nd ACM International Conference on Advances in Geographic Information Systems (SIGSPATIAL '24), Oct 2024, Atlanta GA USA, France. pp.725-728, 10.1145/3678717.3700830 . hal-04810316

HAL Id: hal-04810316

<https://hal.science/hal-04810316v1>

Submitted on 6 Dec 2024

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Large-Scale Optimization of Electric Vehicle Charging Infrastructure

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Abstract

The rapid adoption of electric vehicles (EVs) is driving increasing demand for efficient and strategically placed charging stations. While numerous studies have explored optimization methods for the placement of EV charging stations, most focus on smaller geographic areas, leaving the challenge of optimizing station distribution across larger regions unresolved. This paper presents a novel approach for optimizing both the placement and capacity of EV charging stations using the H3 spatial grid system and queuing theory. By leveraging the hexagonal structure of the H3 grid, we accurately model spatial data and analyze EV charging demands in both urban and non-urban areas. Queuing theory is employed to predict station utilization and optimize the allocation of charging points, minimizing user wait times and ensuring efficient resource distribution. The proposed method is adaptable to future growth in EV adoption and addresses infrastructure needs in both high-demand and underserved regions. This paper outlines the framework developed for the 13th SIGSPATIAL Cup (GISCUP 2024), which achieved top-1 performance. Results based on real-world data demonstrate the model's effectiveness in enhancing the spatial distribution of charging stations, improving accessibility and efficiency in EV infrastructure.

CCS Concepts

• **Applied computing** → **Transportation**; • **Computing methodologies** → **Machine learning**; • **Information systems** → **Geographic information systems**.

Keywords

Large-Scale Optimization, Electric Vehicle Charging, Smart Spatial Grid, Queuing Theory, Spatial Optimization, Geospatial Data Processing, EV Infrastructure Planning

1 Introduction

With the global rise in electric vehicle (EV) adoption, building an efficient, accessible, and scalable network of charging stations has

become a critical infrastructure challenge. Urban centers, where traffic density is high, demand more charging stations to meet growing needs[1], while rural or underserved areas require strategic placements to support EV users in less populated regions[2]. Addressing these diverse needs calls for an intelligent system that balances demand, accessibility, and future scalability.

The problem of optimal EV charging station placement has been widely studied. Existing methods primarily include multi-criteria decision-making (MCDM) and mathematical programming approaches. For example, [3] utilized hexagonal grids to determine optimal charging station locations using the MCDM approach. Although MCDM is effective, mathematical programming tends to offer more precision, although at a higher computational cost, especially when applied to large-scale road networks[4].

Mathematical programming approaches for planning charging infrastructure can be divided into three main categories[5]: the Charging Station Owner (CSO) approach[6],[7], the Distribution Network Operator (DNO) approach[6], and the Electric Vehicle Users (EVU) approach[8],[7]. As EV adoption grows and charging technology advances, it becomes increasingly necessary to incorporate queuing models to account for situations where demand exceeds the station's charging capacity. For example, [9] integrates queuing theory into the EV charging station optimization problem to address this.

This paper introduces a novel optimization model that leverages the H3 spatial grid system and queuing theory to address EV charging station placement. The H3 grid system, with its hexagonal structure, facilitates seamless aggregation and analysis of geospatial data. Unlike traditional grids, H3 dynamically adjusts resolution, making it adaptable to varying population densities and regional demands.

Queuing theory enhances this model by optimizing station capacity, minimizing user wait times, and ensuring cost-effective infrastructure investments. By simulating charging station behavior under different demand scenarios, we determine the optimal number of charging points per station based on expected utilization, balancing efficiency and scalability.

Building upon prior work in spatial optimization and infrastructure planning, this research combines geospatial analysis with operational efficiency models. Our approach not only addresses current EV charging needs but also adapts to projected future growth, offering a scalable, future-proof solution.

2 Data Processing

This study integrates multiple data sources to improve the spatial analysis of Electric Vehicle (EV) charging infrastructure across Georgia. We utilize the H3 spatial grid system[10] at resolution 8, dividing the state into 282,771 hexagonal cells. Each H3_8 cell aggregates features such as demographic data, traffic flow[11], Points of Interest (POIs), power infrastructure, and geospatial attributes, including building area, main route overlap, EV adoption rates, and night-time light intensity. The H3 framework supports 16 resolutions, where each finer resolution divides the area of the coarser resolution approximately into seven smaller hexagons, as the figure 1 shows. Despite the approximation, the system enables efficient indexing by truncating the identifiers of the child cells to find their parent cell.

2.1 Converting Spatial Data to H3 Grid System

The section outlines a method for standardizing spatial data using the H3 hexagonal grid system, which simplifies the analysis of geographic features. Irregular polygons are converted into H3 indexes based on their centroids, and raster data (e.g., night light intensity) is aggregated within H3 cells. Key features, such as main route overlap length, building area, and population, are also integrated at the H3_8 level. This approach facilitates scalable geospatial analysis by providing a uniform grid structure that enhances the understanding of urbanization patterns and infrastructure needs.

2.2 POI Classification and Scoring

To systematically classify and score the 385,233 POIs in Georgia, we used a zero-shot classification approach using the LLM model. This method facilitated the categorization of diverse POI data into predefined categories relevant to EV infrastructure, improving the spatial analysis for optimal charging station placement. The classification process involved: 1. Extracting and cleaning unique POI categories from the dataset. 2. Mapping each POI to a set of candidate labels representing high-level categories (e.g., Commercial, Residential, Transportation). 3. Assigning a priority score to each category based on its relevance to EV charging demand, with higher scores indicating greater importance. The priority score for each H3_8 cell was then calculated by summing the scores of all POIs within the cell. This scoring mechanism enabled the identification of high-priority areas where EV infrastructure is likely to be more beneficial. By leveraging AI-based classification, our approach provided a flexible and scalable solution for handling large-scale POI datasets, facilitating more effective spatial optimization of EV charging station placement.

3 Method

To optimize the placement of EV charging stations, it is essential to distinguish between Urban, Suburban, and Rural areas, as their infrastructure requirements vary significantly. In Suburban and

Rural regions, where Points of Interest (POIs) and traffic flow may be sparse, safety and accessibility can be ensured by providing at least one station with five DC Fast Charging (DCFC) piles within a 50 km radius. Conversely, in Urban and Suburban areas, placement strategies rely more heavily on each grid's geospatial features and origin-destination (OD) traffic patterns 3.2, allowing for a data-driven approach tailored to local demand.

3.1 Clustering Urban, Suburban, and Rural Areas

To categorize areas into Urban, Suburban, and Rural, we applied K-Means clustering based on spatial features that capture variations in population density, infrastructure, and night-time light intensity.

3.1.1 Feature Selection and Standardization. We selected the following features: - x_1 : Census Population (number of residents). - x_2 : Building Area (total built-up space). - x_3 : Total POI Score (sum of priority scores for Points of Interest). - x_4 : Average Night-Time Light Intensity. The features were standardized using:

$$X_{\text{scaled}} = \frac{X - \mu}{\sigma} \quad (1)$$

where μ and σ are the feature's mean and standard deviation.

3.1.2 Clustering and Area Type Mapping. We applied the Elbow Method to determine $k = 3$ clusters by minimizing the within-cluster sum of squares:

$$WCSS = \sum_{i=1}^k \sum_{j \in C_i} \|X_j - \mu_i\|^2 \quad (2)$$

K-Means then assigned each data point to one of three clusters based on proximity to cluster centroids. Clusters were labeled as "Urban," "Suburban," and "Rural" by sorting cluster centers based on the population metric x_1 , higher populations indicate urban areas

3.1.3 Result Interpretation. The clusters represent and verification: Urban: High x_1, x_2, x_4 ; uburban: Intermediate feature values; Rural: Low x_1, x_2, x_4 . The clustering results segment geographic regions into "Urban," "Suburban," and "Rural" effectively, with urban areas exhibiting higher population, building area, and night light intensity values. Verification using thresholds for night light intensity, inspired by VIIRS DNB methods, shows consistency with established techniques for urbanization detection. Specifically, we employed a threshold of 8 nW/cm²/sr for the night light feature, based on careful examination of stable lights within urban areas as suggested in [12]. A Pearson correlation of 0.7761 between the night light intensity and the classified area types further validates our approach, indicating a strong relationship between night light data and the level of urbanization. Discrepancies in the suburban classification suggest potential areas for refining the thresholds to enhance accuracy.

3.2 Queuing model

In order to determine the optimal number of service channels at each station, we employ an M/M/c queuing model. This model assumes that electric vehicles arrive at charging stations following a Poisson process with a rate of λ vehicles per hour, and that each station can service vehicles at an exponential rate of μ vehicles

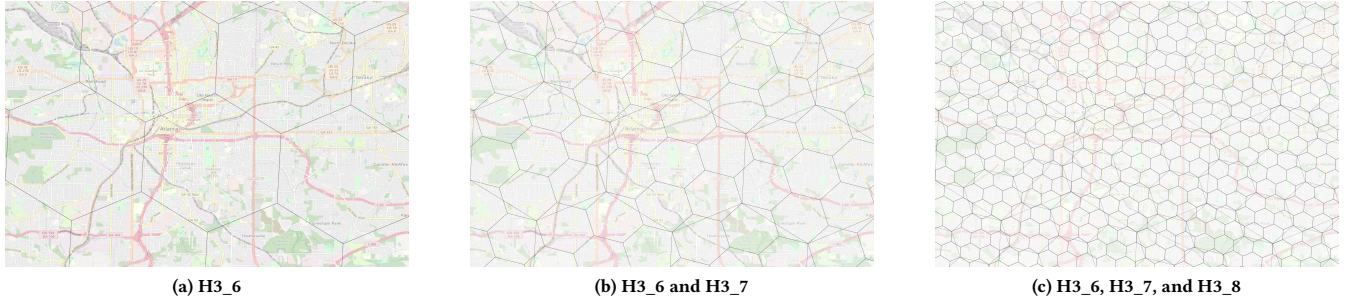


Figure 1: H3 enables the user to subdivide areas into smaller hexagons, increasing the resolution for finer spatial analysis.

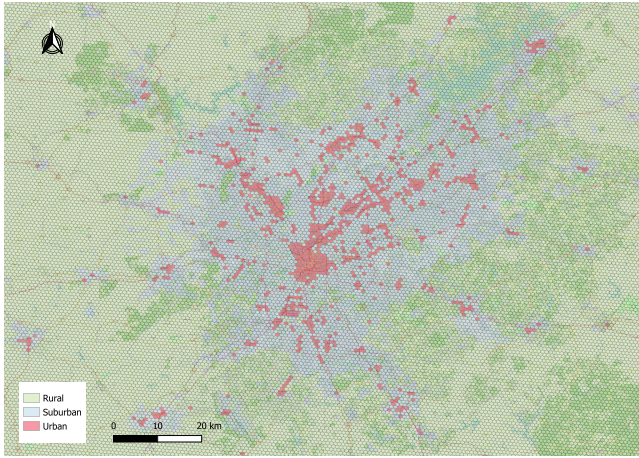


Figure 2: Urban, Suburban and Rural

per hour. The goal is to minimize the average waiting time while maintaining a reasonable utilization rate. To account for charging station outages[13], we introduce the concept of an outage rate (p), which adjusts the total number of available charging stations (c).

$$p = \frac{\sum(O_d \times H_d)}{H_{\text{total}} \times D_{\text{total}}} \quad (3)$$

Where, O_d = Outage days, H_d = Affected households per day, H_{total} = Total households, D_{total} = Total days. The effective number of charging stations (c_{eff}) is given by:

$$c_{\text{eff}} = c \times (1 - p) \quad (4)$$

where c is the total number of stations, and p is the outage rate. The effective utilization rate (ρ_{eff}) is then calculated as:

$$\rho_{\text{eff}} = \frac{\lambda}{c_{\text{eff}} \cdot \mu} = \frac{\lambda}{c \cdot (1 - p) \cdot \mu} \quad (5)$$

where λ is the EV arrival rate, and μ is the service rate per charging station.

The objective is to minimize the average waiting time (W_q), which is a function of the average queue length (L_q). The probability

of zero vehicles in the system (P_0) can be computed as:

$$P_0 = \left(\sum_{n=0}^{\lfloor c_{\text{eff}} \rfloor - 1} \frac{(\lambda/\mu)^n}{n!} + \frac{(\lambda/\mu)^{\lfloor c_{\text{eff}} \rfloor}}{\lfloor c_{\text{eff}} \rfloor! \cdot (1 - \rho_{\text{eff}})} \right)^{-1} \quad (6)$$

Using P_0 , the average queue length (L_q) is:

$$L_q = \frac{P_0 \cdot (\lambda/\mu)^{\lfloor c_{\text{eff}} \rfloor} \cdot \rho_{\text{eff}}}{\lfloor c_{\text{eff}} \rfloor! \cdot (1 - \rho_{\text{eff}})^2} \quad (7)$$

Finally, the average waiting time in queue (W_q) is given by:

$$W_q = \frac{L_q}{\lambda} \quad (8)$$

Optimization Goal: The goal is to determine the optimal number of charging stations (c) that minimizes the average waiting time (W_q), subject to the constraint that the utilization rate (ρ_{eff}) remains below a reasonable threshold (e.g., 0.9). The optimization problem can be formulated as:

$$\min_c W_q = \frac{L_q}{\lambda} \quad \text{subject to} \quad \rho_{\text{eff}} \leq 0.9 \quad (9)$$

To estimate the EV arrival rate λ , we calculate the number of vehicles arriving per hour at a given location, n_t , and multiply this by the percentage of EVs in the local market, β_i , to get the EV arrival rate $\gamma_{ti} = n_t \times \beta_i$. The peak period (e.g., 8am to 8pm) is used to compute the average EV arrival rate, λ , during the busiest time of day. Different types of charging stations have varying service rates (μ). For DC Fast Chargers (DCFC), the average service rate is approximately 2 vehicles per hour (assuming a full charge in 30 minutes). For Level 2 chargers, the service rate is lower, at approximately 0.25 vehicles per hour (assuming a charge time of 4 hours).

3.3 Geospatial Optimization of Charging Station Distribution

We use the H3 hierarchical grid system to standardize the spatial representation of geographic regions, optimizing the placement of EV charging stations based on urbanization levels and infrastructure needs across Urban, Suburban, and Rural areas.

3.3.1 *Grid-Based Spatial Analysis Using H3 Indexes.* Administrative polygons are converted to H3 indexes at resolution 8 (H3_8) for standardized analysis, with approximately 2 km spacing between cells. If an H3_8 cell’s site capacity exceeds 30 charging stations, we subdivide it into H3_9 cells to enable finer placement decisions. POI-based prioritization helps identify the top H3_9 cells, and K-Means clustering is used to optimize placement considering POI distribution and socio-economic factors.

3.3.2 *Optimizing Placement for Suburban and Rural Areas.* For larger suburban and rural polygons, we adopt a hierarchical approach. Suburban Areas: aggregate H3_8 cells into parent H3_7 cells, then subdivide into child H3_8 cells. Prioritize based on POI scores, with K-Means clustering used for placement optimization. Rural Areas: Aggregate H3_8 cells into H3_6, then subdivide into child H3_8 cells. The top-ranked cells are selected for placement using a similar approach.

Table 1: Priority Scores for POI Categories

POI Category	Priority Level
Commercial and Retail Centers	1
Parking Facilities	2
Transportation Hubs	3
Workplaces and Offices	4
Government and Public Services	5
Residential Areas	6

3.3.3 *POI-Based Prioritization.* Each H3 cell’s priority is determined by the types and quantities of POIs, with scores assigned based on relevance to EV users. Table 1 outlines the priority levels for various POI categories. The priority level for an H3 cell is ranked for all POIs within that cell.

3.3.4 *Additional Considerations for Optimal Placement.* Optimal H3 cells should ideally include existing infrastructure (e.g., power towers, streetlights) and be located near main transportation routes to enhance accessibility. This concise approach retains the core methodology while streamlining the explanation for clarity.

4 Results and discussions

The results indicate that the H3 hierarchical grid system effectively tailors the placement of EV charging stations to the specific needs of Urban, Suburban, and Rural areas. In Urban regions, prioritizing high-density zones near essential POIs optimized accessibility based on traffic patterns, while in Suburban and Rural areas, the strategy balanced coverage with local demand and safety needs, providing coverage within a 50 km radius. An important enhancement identified is the potential for further optimization through a more fine-grained H3 resolution that incorporates land use data. This approach could significantly improve siting accuracy but would require increased computational resources to manage the finer spatial analysis. Future work could focus on leveraging these fine-grained data to refine placement decisions dynamically, based on evolving usage patterns.

On the other hand, the results show that the optimization model based on queuing theory can generate appropriate capacity numbers for EV charging stations. Future research could consider more conditions, such as the grid’s capacity limitations and the actual costs of setting up charging stations, to make the results more accurate. More complex optimization methods, such as meta-heuristic approaches, could also be explored to estimate the optimal solution.

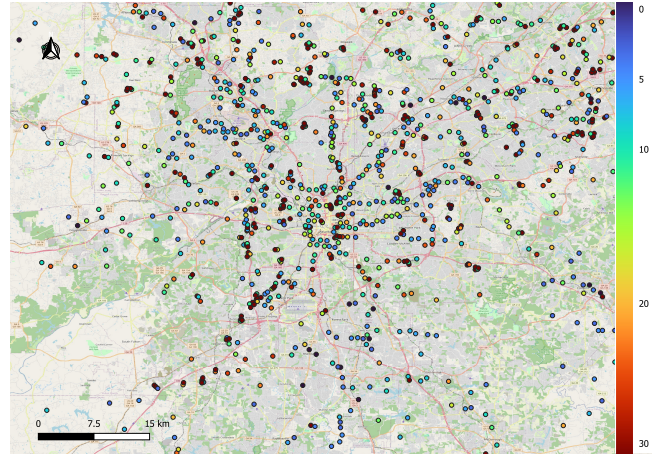


Figure 3: Charging station distribution

The optimized EV charging station placements across Georgia can be explored on this [interactive map link](#), showcasing tailored strategies for urban, suburban, and rural areas.

5 Acknowledgments

We extend our sincere gratitude to all those who have dedicated their time and effort to organizing the 32th ACM SIGSPATIAL Conference and the 13th GISCU competition in 2024. Your hard work has been invaluable in bringing this event to life.

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Received 10 October 2024; revised 11 October 2024; accepted 16 October 2024