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Charging station layout planning for electric vehicles based on ride-hailing vehicle travel patterns

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Abstract

An adequate quantity and strategically designed layout of charging stations (CSs) are essential to mitigate "range anxiety" among electric vehicle (EV) users in urban settings. This study introduces a sophisticated multi-method optimization approach for the spatial planning of CSs, leveraging ArcGIS spatial data analysis tools and real-world trajectory data from online ride-hailing EVs in a prototypical Chinese city, referred to here as City A. Initially, ArcGIS is utilized to transpose the spatial demand for EV charging from ride-hailing services onto a standardized coordinate grid, derived from travel trajectories. Subsequently, the P-median model is employed to preliminarily identify potential CS sites, prioritizing minimal distance and maximal effective coverage. Thereafter, the attractiveness of these candidate sites to drivers is assessed through the Huff model, which considers variables such as population density, road network density, and passenger travel volume, to further refine site selection by minimizing overlap in service areas and construction costs. The process concludes with the Slacks Based Measure (SBM) super-efficiency model, which isolates the most efficient layout configuration. A case study in City A demonstrates that this optimized approach can halve the number of CSs required compared to traditional, unoptimized layouts. The methodologies developed herein offer a robust framework for city-level CS site planning under multiple constraints.

Keywords: Online ride-hailing; electric vehicle; travel trajectory data; charging infrastructure planning; multi-model optimization

1. Introduction

The burgeoning proliferation of electric vehicles (EVs) in China, evidenced by a market penetration of 25.6% and sales surpassing 10 million units in 2022 (Canalys 2023), underscores an escalating demand for robust charging infrastructure. Despite the expansion in charging facilities, challenges such as suboptimal distribution of charging stations (CSs) and their underutilization persist, necessitating strategic enhancements in infrastructure planning (Canalys 2023; Thorgeirsson et al. 2021; Levinson and West 2018).

Charging an EV typically requires more time than refueling a conventional vehicle, and the resultant driving range often falls short of gasoline-powered counterparts, inducing "mileage anxiety" among users, especially in public transportation services (Zou et al. 2016). This anxiety is exacerbated by inadequately planned CS layouts. Urban planning entities and CS operators are thus compelled to account for vehicular travel patterns, driver-specific charging demands, and road network configurations in their site selection strategies.

This study zeroes in on the arrangement of public CSs in urban locales, with a focus on Beijing's Chaoyang District—a notable hub where 80% of online ride-hailing vehicles are EVs. We examine the spatio-temporal travel trajectories of ride-hailing EVs in City A, home to over 410,000 operational EVs. Employing an integrative approach that melds the P-median model, the Huff model, and the slacks-based measure super efficiency model (P-Huff-SBM), we advocate for an economically viable and highly efficient CS layout, poised to enhance coverage and service responsiveness.

The remainder of this paper is structured as follows: Section 2 outlines the methodology employed and details the data sources utilized. Section 3 presents the results and provides a comprehensive discussion of the findings. Finally, Section 4 offers concluding remarks and proposes policy recommendations based on the study's outcomes.

2. Modeling principles and data processing

2.1. Methodology framework

Utilizing the GAIA Open Dataset from DiDi Ltd., which maintains dynamic travel data of ride-hailing EVs across China (Wu Y, Yang X, Zheng Z 2017), this study extracted spatio-temporal trajectory data for City A. This data includes temporal order information and spatial trajectories, essential for analyzing travel patterns and charging demands.

The primary modeling process employs ArcGIS tools combined with several optimization models:

P-median model: Identifies optimal CS locations based on shortest distances to maximize service area coverage (Ko J, Shim J S 2016; Lin Z, Ogden J, Fan Y, Chen C W 2008; Jackson L E, Rouskas G N, Stallmann M F M 2007; Frade I, Ribeiro A, Gonçalves G, Antunes A P 2011).

Huff model: Assesses site attractiveness to drivers by considering population density, road density, and passenger travel density (Zhao Y, Guo Y, Guo Q, Zhang H, Sun H 2020).

SBM super-efficiency model: Determines the most cost-effective and efficient layout for CSs by integrating multiple factors including service coverage and investment costs (Tone K 2020; Charnes A, Cooper W W, Rhodes E 1978; Liu W B, Meng W, Li X X, Zhang D Q 2010).

2.2. Data Processing

Data from the GAIA dataset underwent cleaning to remove inconsistencies and was converted into the WSG-84 coordinate system for analysis. Key features such as the spatial and temporal distribution of charging demand were mapped based on the trajectories of ride-hailing EVs.

2.3. CS Site Layout with the P-median Model

The P-median model, implemented using ArcGIS, was utilized to optimize the spatial distribution of Charging Stations (CSs). By calculating median points for each grid, the model ensures that all potential charging demand points are within a 1 km radius, thereby effectively minimizing "mileage anxiety" among drivers. This optimization utilizes spatial operations and statistical processing tools within ArcGIS to ensure comprehensive coverage of all potential charging demand points, thereby enhancing the accessibility of CSs to meet driver needs efficiently(Ko J, Shim J S 2016; Lin Z, Ogden J, Fan Y, Chen C W 1990; Jackson L E, Rouskas G N, Stallmann M F M 2007; Frade I, Ribeiro A, Gonçalves G, Antunes A P 2011) .

Equation (1) computes the average coordinates of the grid locations ($\bar{X}$, $\bar{Y}$), which serve as the starting points for the median site determination:

$$\bar{X} = \frac{\sum_{i=1}^{n} x_i}{n}, \bar{Y} = \frac{\sum_{i=1}^{n} y_i}{n} \tag{1}$$

The optimal median center is subsequently identified through iterative adjustments, as outlined in Equation (2):

$$y_{i+1} = \left(\sum_{j=1}^{m} \frac{x_j}{\|x_j - y_i\|}\right) / \left(\sum_{j=1}^{m} \frac{1}{\|x_j - y_i\|}\right) \tag{2}$$

These calculated coordinates aim to strategically place CSs to minimize travel distances for EV drivers, efficiently addressing urban charging demands and further reducing the impact of range anxiety.

2.4. CS Site Optimization with the Huff Model

The Huff model optimizes the placement of charging stations (CSs) by assessing their attractiveness based on factors such as population density, road network density, and local demographic and infrastructural characteristics (Zhao Y, Guo Y, Guo Q, Zhang H, Sun H 2020). This model refines CS locations to enhance their economic efficiency and effectiveness, making adjustments to the scale and capacity of the CSs accordingly. Equation (3) defines the probability P_{IJ} of a driver choosing a specific CS, which is calculated based on the attractiveness S_{IJ} of the CS, the distance T_{IJ}, and the driver's sensitivity to distance λ:

$$P_{IJ} = \frac{S_J^{\mu} / T_{IJ}^{\mu}}{\sum_{J=1}^{n} S_J^{\mu} / T_{IJ}^{\lambda}} \tag{3}$$

This strategic optimization ensures that CSs are not only economically efficient but also strategically placed to maximize convenience and attractiveness, thereby enhancing driver satisfaction and operational efficiency.

2.5. CS Site Optimization with the SBM Super-Efficiency Model

The SBM model evaluated different CS layouts to identify the most effective configuration (Tone K 2020; Charnes A, Cooper W W, Rhodes E 1978; Liu W B, Meng W, Li X X, Zhang D Q 2010). This involved a detailed comparison of potential sites based on a series of criteria including construction costs, service coverage, and operational efficiency.

3. Results and discussion

3.1. Spatial and temporal distribution of charging demand of ride-hailing EVs

Analysis of the temporal charging patterns of ride-hailing EVs in City A reveals a pronounced preference for charging between 13:00 and 15:00 (Zou Y, Wei S, Sun F, Hu X, Shiao Y 2016). This timeframe corresponds with lower vehicle utilization and extended durations of no-load operation exceeding one hour, which strategically aligns with the need to alleviate range anxiety following morning and early afternoon peak usage. This temporal insight is integral to guiding the analysis of spatial charging demand, providing a foundation for optimizing CS deployment.

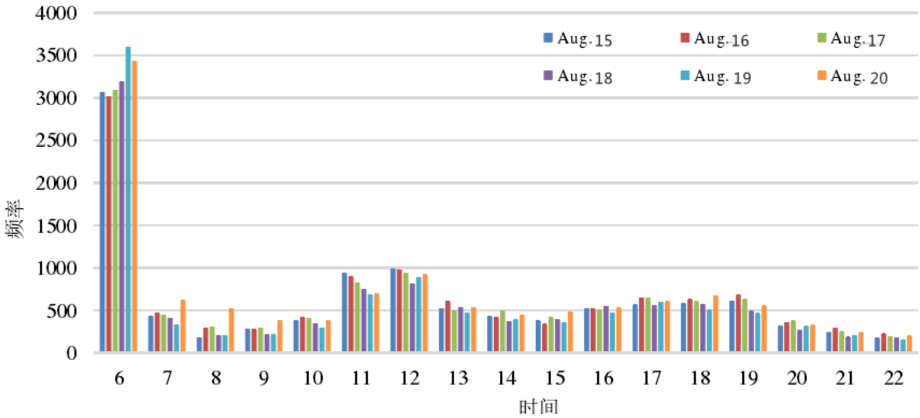

Fig. 1. The temporal distribution of the loading characteristics of the ride-hailing EVs in City A

3.2. CS Site Layout with P-Median Model

Utilizing the P-median model (Upchurch C, Kuby M 2010; Li Z 2019; Ko J, Shim J S 2016; Lin Z, Ogden J, Fan Y, Chen C W 2008; Hodgson M J 1990), we initially identified 947 optimal candidate points for CSs to cover all identified charging demand points, albeit without weighting the intensity of each demand. This initial model resulted in excessive coverage in lower-demand areas. Optimization through ArcGIS led to a refined count of 847 CSs, achieving balanced service coverage in high-demand zones. A further reduction to 447 CSs slightly diminished coverage efficiency, illustrating the inherent trade-off between optimizing coverage and conserving resources.

3.3. CS Site Optimization with Huff Model

The application of the Huff model (Zhao Y, Guo Y, Guo Q, Zhang H, Sun H 2020) refined the CS layout by evaluating site attractiveness based on demographic and infrastructural factors. This optimization produced a more economically efficient layout, reducing construction costs while marginally increasing total charging distance impedance. The adjustments made via the Huff model effectively redistributed charging demand points, enhancing driver convenience and maintaining robust service coverage without significant detriments.

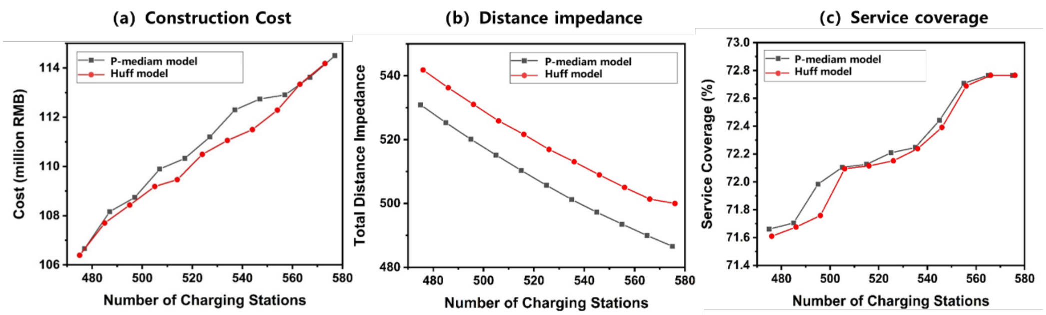

Fig. 2 Comparison of CS layout options based on the P-median model and Huff model

3.4. CS Site Optimization with SBM Super-Efficiency Model

Using the SBM super-efficiency model, we evaluated the efficiency of various CS layout options (Tone K 2002; Charnes A, Cooper W W, Rhodes E 1978; Liu W B, Meng W, Li X X, Zhang D Q 2010). The model identified six options with super-efficiency values greater than 1, indicating effective planning solutions. Notably, the layout with 476 CSs emerged as the most efficient, offering the lowest cost and highest overall effectiveness, thus balancing investment with service coverage and user satisfaction.

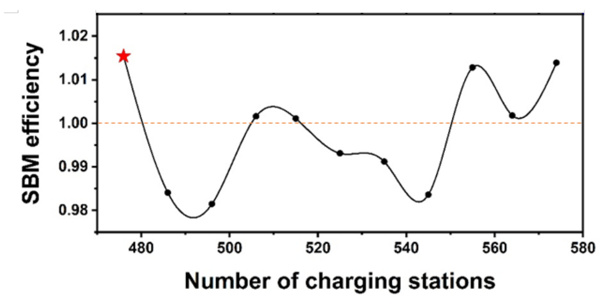

Fig.3 SBM efficiency for different CS site layout options

4. Concluding remarks

This study demonstrates the importance of a scientifically planned layout of public charging stations (CSs) for fostering the adoption of electric vehicles (EVs). By utilizing comprehensive spatio-temporal data from ride-hailing EVs in City A, we developed a multi-model-based approach for optimizing urban public CS layouts. This approach integrates the P-median, Huff, and SBM super-efficiency models to effectively address the spatial and temporal dynamics of travel demand, road network structure, and charging needs.

Our findings indicate that the optimized layout of 476 CSs can significantly enhance charging convenience for ride-hailing EV drivers within a 1 km radius, effectively alleviating "mileage anxiety" and reducing the number of CSs by half compared to the initial unoptimized scheme of 947 CSs. The strategic deployment not only caters to peak demand times but also optimizes resource use by reducing unnecessary coverage.

This method proves to be flexible, practical, and replicable, offering a robust framework for urban charging infrastructure development that can be adapted to other cities facing similar challenges.

Declaration of Competing Interest

The authors declare no competing financial interests or personal relationships that could have influenced the work reported in this paper.

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Data Availability

Further data are available from the corresponding author upon reasonable request.

Appendix

A.1. ZS Calculation

The charging capacity of fast public CS is assumed to be up to 80 kW. The battery capacity of the online ride-hailing EV is set at 52 kW, which can fully charge to 80% in about 30 minutes, according to the capacity of the charging piles.

The service life of many DC fast-charging facilities is around ten years, and the average land price is about 36,520 RMB in City A. Since the service lifetime of public service facilities in the central city is 50 years. We can get the CS calculation as follows.

$$\mathrm{C_s} = \left(\frac{\text{Investment cost}}{\text{Usage time}} + \frac{\text{Land cost}}{\text{Land use time}} + \text{Electricity Cost} \right) \times \mathrm{C}h\text{arging time}$$

The suspended operation loss due to queuing Cw needs to be estimated according to the mileage of EVs in City A. The starting price of a ride-hailing service is 9 RMB/2 km, i.e. 1.9 RMB per mile, assuming that the ride-hailing EV travels 40 km per hour and the parking time of each EV is about half an hour. Then the parking loss of 20 km is about 44 RMB, i.e. the maintenance cost of the CS per unit of time, and then we can get the customer in each time due to queuing of suspended operation loss Cw.

Reference

[1] Canalys. Global EV market grew 55% in 2022 with 59% of EVs sold in Mainland China, https://www.canalys.com/newsroom/global-ev-sales-2022; 2023 [accessed 22 June 2023].
[2] Thorgeirsson A T, Scheubner S, Fünfgeld S, Gauterin F. Probabilistic prediction of energy demand and driving range for electric vehicles with federated learning. IEEE Open J. Veh. Technol. 2021; 2: 151-161. https://doi.org/10.1109/OJVT.2021.3065529
[3] Levinson R S, West T H. Impact of public electric vehicle charging infrastructure. Transp. Res. Part D Transp. Environ. 2018; 64: 158-177. https://doi.org/10.1016/j.trd.2017.10.006
[4] Zou Y, Wei S, Sun F, Hu X, Shiao Y. Large-scale deployment of electric taxis in Beijing: A real-world analysis. Energy 2016; 100: 25-39. https://doi.org/10.1016/j.energy.2016.01.062
[5] Ko J, Shim J S. Locating battery exchange stations for electric taxis: A case study of Seoul, South Korea. Int. J. Sustainable Transp. 2016; 10(2): 139-146. https://doi.org/10.1080/15568318.2013.871612
[6] Lin Z, Ogden J, Fan Y, Chen C W. The fuel-travel-back approach to hydrogen station siting. Int. J. Hydrogen Energy 2008; 33(12): 3096-3101. https://doi.org/10.1016/j.ijhydene.2008.01.040
[7] Wu Y, Yang X, Zheng Z. Research on Parking Spots Optimization of Car Sharing Based on Improved Genetic Algorithms. Logist. Sci. Technol. 2017; 40(12):78-82+91. (in Chinese) 10.13714/j.cnki.1002-3100.2017.12.020.
[8] Jackson L E, Rouskas G N, Stallmann M F M. The directional p-median problem: Definition, complexity, and algorithms. Eur. J. Oper. Res. 2007; 179(3): 1097-1108. https://doi.org/10.1016/j.ejor.2005.06.080
[9] Zhao Y, Guo Y, Guo Q, Zhang H, Sun H. Deployment of the electric vehicle charging station considering existing competitors. IEEE Trans. Smart Grid 2020; 11(5): 4236-4248. https://doi.org/10.1109/TSG.2020.2991232
[10] Frade I, Ribeiro A, Gonçalves G, Antunes A P. Optimal location of charging stations for electric vehicles in a neighborhood in Lisbon, Portugal. Transp. Res. Rec. 2011; 2252(1): 91-98. https://doi.org/10.3141/2252-12
[11] Tone K. A slacks-based measure of super-efficiency in data envelopment analysis. Eur. J. Oper. Res. 2002; 143(1):32-41. https://doi.org/10.1016/S0377-2217(01)00324-1
[12] Charnes A, Cooper W W, Rhodes E . Measuring the efficiency of decision making units. Eur. J. Oper. Res. 1978; 2(6):429-444. https://doi.org/10.1016/0377-2217(78)90138-8
[13] Liu W B, Meng W, Li X X, Zhang D Q. DEA models with undesirable inputs and outputs. Ann. Oper. Res. 2010; 173: 177-194. https://doi.org/10.1007/s10479-009-0587-3