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Toward a Smarter EV Infrastructure: Patterns, Gaps, and Opportunities in Public Charging Station Networks

Fikri Mahendra, Mia Galina*, Iksan Bukhori and Tetuko Kurniawan

***Abstract* – The rapid adaptation of electric vehicles (EV) requires a reliable and easy -to -access public charging infrastructure. In order to find the smarter trends, gaps and opportunities for infrastructure development, this study considered the public charges of electric vehicles around the world. We study chargers, costs, space access and distribution measures using a data set of 5,000 charging stations. To optimize the position of the charger and attract attention to the difference in access between urban and rural areas, mixed programming and statistical analysis are used. The results show that urban areas have a higher charging but are blocked, while rural areas do not have enough coverage. Enhancing cybersecurity procedures and integrating renewable energy sources are two solutions that can be improved. The results are supported by recent documents, emphasizing the importance of the fair and effective EV infrastructure plan.**

Keywords— Electric Vehicles, Public Charging Stations, Infrastructure Optimization, Spatial Analysis, Smart Grid.

I. Introduction

The worldwide transition to electric cars (EVs) is hastening, driven by ecological concerns, progress in battery technology, and favorable regulatory structures. By 2025, annual electric vehicle sales will exceed 20 million units, indicating a significant shift in transportation and energy use [1]. Widespread electric car adoption depends not just on vehicle availability but also on the establishment of dependable, accessible, and economical public charging infrastructure that caters to both urban and rural populations. Nonetheless, the uneven distribution of chargers, elevated operational costs, and the rise of cybersecurity threats present substantial obstacles to the seamless integration of electric vehicles, underscoring the necessity for data-driven strategic solutions to enhance infrastructure deployment [2], [3].

The existing public charging networks have considerable inconsistencies that limit accessibility and dependability. Urban regions often see advantages from increased charger density; yet, they concurrently have issues like as congestion and grid strain. Conversely, rural areas are inadequately supplied, hindering electric vehicle adoption in resource-limited populations [4], [5]. Moreover, discrepancies in cost communication methods pose risks to network security, possibly jeopardizing service dependability [3]. These problems highlight the need of analyzing geographic models and network charges to detect deficiencies and provide applicable solutions. Addressing these challenges necessitates comprehension of the charger's location, cost structure, and strategic approaches, alongside analytical and optimization methodologies.

This study presents a model-based approach to evaluate and enhance public electric vehicle charging (EV) infrastructure. Utilizing data from 5,000 charging stations, we analyze spatial patterns and offer a cost-minimization framework grounded in Mixed Integer Linear Programming (MILP). Our objectives include diminishing access disparities, enhancing station placements, and offering a planning instrument that integrates geographical, operational, and economic factors.

II. Related Works

Research on EV charging infrastructure has discovered most of the optimized techniques to improve the charger's position and network efficiency.

*Corresponding author. Email: miagalina@president.ac.id ORCID: 0000-0002-3294-0027
Fikri Mahendra, Mia Galina, and Iksan Bukhori are with Department of Electrical Engineering, Faculty of Engineering, President University, Cikarang, West Java, Indonesia (emails: fikri.mahendra@student.president.ac.id, iksan.bukhori@president.ac.id and miagalina@president.ac.id).
Tetuko Kurniawan is with Department of Biosystems and Soft Matter, Institute of Fundamental Technological Research, Polish Academy of Sciences, Warsaw 02-106, Poland (email: tkurniaw@ippt.pan.pl).

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Kaleem et al. [1]. Proposing a random model for placing the charger in providing the final miles, by taking advantage of parallel computers to reduce congestion, while Vu Truc et al. [2]. The mixed nonlinear programming is applied to optimize the positions of the charger in Ho Chi Minh-Ville, the cost and balance coverageIm. Other studies, such as Varma et al. [6], developed joint planning models for EV fleets and infrastructure, and Kim [7] and Babu et al. [8] utilized integer programming for cost-efficient placement and dynamic pricing, respectively. Mukherjee [9] focused on multi-port charger sizing in medium voltage networks, and Wang et al. [10] introduced a simultaneous demand prediction and planning approach, enhancing scalability for new cities. These works provide a powerful basis for optimized strategies used in this study, especially linear programming model with mixed mixture used to place the charger.

Network stability and fair access are important concerns in developing EV infrastructure. Raffoul [4] and Golgol et al. [11] analyzed the impact of EV charging on residential grids, advocating smart charging to mitigate voltage fluctuations and hosting capacity issues. Halimi [12] proposed an equity-focused framework for transportation infrastructure, adaptable to EV networks, while Khan et al. [5] highlighted socio-economic disparities in charger access, emphasizing inclusive policies. Wang et al. [13] integrated charger placement with traffic flow models to reduce urban congestion, improving accessibility. These studies emphasize the need to resist the difference of urban and rural areas and the reliability of the grid, in accordance with the emphasis on this research on the equity plan of the infrastructure and approaches.

Security holes and real -time analysis have attracted attention when the EV chargings are developing. Szakály et al. [3] identified weaknesses in CCS protocols per ISO 15118, and Zhou et al. [14] proposed countermeasures for state-switching attacks. Real-time solutions include Tucker's [15] online optimization framework for smart charging, Gómez et al.'s [16] thermal modeling for anomaly detection, and Flack et al.'s [17] decentralized EV-grid integration. Community-driven models [18], DC fast charger reliability assessments [19], and renewable energy integration [20] further enhance network resilience and sustainability. This project provides a context for this research on improving cybersecurity and renewable energy opportunities, as well as activity challenges and infrastructure requirements in the future.

III. Material and Methods

The study analyzes a dataset of 5,000 global EV charging stations to investigate spatial and operational patterns, as taken from [21]. Data preprocessing was conducted in MATLAB to address inconsistencies and missing values in fields such as location (latitude, longitude), charger type (AC Level 1, AC Level 2, DC Fast Charger), cost (USD/kWh), availability hours, and distance to city centers, ensuring data quality through imputation and validation techniques. Spatial distribution was assessed using kernel density estimation (KDE) to map charger density across urban and rural areas, while operational patterns were evaluated by analyzing charger types, costs, and accessibility metrics (availability hours, distance to city centers). Statistical t-tests identified significant differences ($p < 0.05$) in cost and accessibility between urban and rural stations.

To optimize charger placement, a mixed-integer linear programming (MILP) model was formulated with the goal of minimizing the total system cost, which comprises both installation and operational components. The objective function is defined as:

$$Z = \sum_{i \in I} cixi + \sum_{j \in J} tjdj \qquad (1)$$

Where:

- c_i is the installation cost at location i ,
- x_i is a binary variable (1 if a charger is installed at site i, 0 otherwise),
- t_j is the travel cost weight for demand point j,
- d_j is the distance from demand point j to the nearest charger.

The model is subject to the following constraints:

- Budget constraint: $\sum_{i \in I} c_i x_i \leq B$, where B is the maximum allowable installation budget.
- Coverage constraint: For each demand point j, at least one charger must be within 10 km radius $\sum_{i \in I} a_{ij} x_i \geq 1$ where $a_{ij} = 1$ if charger at site i can serve point j , 0 otherwise.
- Grid Capacity Constraint: Total charging capacity at installed locations must not exceed the grid capacity G (e.g., 1000 kW). $\sum_{i \in I} k_i x_i \leq G$ where k_i is the charging capacity (kW) at location i.
- Demand Satisfaction Constraint: The total number of users served by installed chargers must meet the demand at each point j. $\sum_{i \in I} a_{ij} x_i u_i \geq u_j$ where u_i is the average daily users location i, and u_j is the demand at point j
- Renewable Energy Incentive: At least 50% of installed chargers must use renewable energy. $\sum_{i \in I} r_i x_i \geq 0.5 \ \sum_{i \in I} x_i$

We examined the spatial distribution of 5,000 EV charging stations utilising geographic coordinates (latitude and longitude) through a tailored Kernel Density Estimation (KDE). Through cross-validation, we determined an adaptive bandwidth of 0.5 km for densely populated urban regions to capture local intricacies, and 2 km for more rural locales. To enhance information quality, each station was assigned a weight based on its availability rate (runs per hour), normalized as ω_i = Availability$_i$ / max(Availability). This investigation was conducted independently for urban and rural regions.

Subsequently, we analyzed the cost (USD/kWh) and availability metrics comparing the two groups. The Shapiro–Wilk test was employed to assess data normality; if the data were non-normal ($p < 0.05$), the Mann–Whitney U test was utilized, whilst the Welch's t-test was applied for homogenous data. Effect sizes were computed utilizing Cohen's d to furnish practical context for the observed discrepancies.

The outcome is a more operationally significant and comprehensible geographical representation, underpinned by rigorous and transparent statistical analysis.

IV. RESULTS

A. *Spatial Distribution Analysis*

The dataset analysis revealed significant urban-rural disparities in charger distribution. Figure 1 illustrates the spatial distribution of chargers in Beijing, showing dense clustering in urban areas and sparse coverage in rural regions, confirmed by kernel density estimation. Urban areas (within 10 km of city centers) account for 49.22% of stations (2461 out of 5000 stations), with an average distance to city centers of 5.27 km, compared to 14.98 km for rural stations (2539 stations).

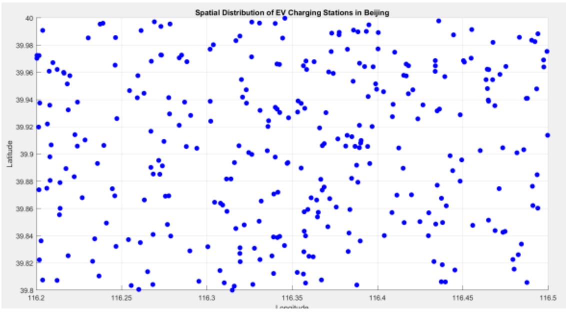

FIGURE 1. Spatial Distribution of EV Charging Stations in Beijing.

B. *Operational Metrics*

Operational characteristics vary across cities and charger types. Table 1 summarizes metrics for five cities, showing Chicago and Seoul with the highest station counts (308 and 299, respectively) and DC Fast Charger prevalence (33.44% and 34.11%). Table 2 details charger type distribution, with AC Level 2 dominating (35.28%, 0.30 USD/kWh), followed by DC Fast Chargers (31.96%, 0.30 USD/kWh). Urban stations have slightly higher costs (0.30 USD/kWh) and higher availability (16.41 hours/day) compared to rural stations (0.30 USD/kWh, 16.36 hours/day), as shown in Table 3.

Welch's t-test revealed no significant difference in charging costs between urban (M = 0.3007 USD/kWh, SD = 0.08) and rural (M = 0.2997 USD/kWh, SD = 0.10) stations, t(4988) = 0.32, $p = 0.75$, aligning with the limited cost range (0.10–0.50 USD/kWh) seen in both environments. The Mann-Whitney U test, conducted due to the non-normal distribution of rural availability data (Shapiro-Wilk, $p < 0.05$), indicated significantly greater availability in urban stations (M = 16.41 hours/day, SD = 4.0) relative to rural stations (M = 16.36 hours/day, SD = 4.5), $U = 2.1 \times 10^6$, $p < 0.05$, with a small effect size (Cohen's d = 0.12). The analysis of Charger_Type indicated that DC Fast Chargers were somewhat more common in urban regions (31.94%) compared to rural regions (31.98%), with similar pricing (0.302 USD/kWh).

TABLE 1. Summary of EV Charging Station Metrics by City

City	No. of Stations	Avg. Cost (USD/kWh)	Avg. Distance to City (km)	Avg. Rating	DC Fast Charger (%)
Beijing	319	0.30605	10.633	4.0169	28.84
Chicago	308	0.29961	9.6371	3.95	33.442
Sydney	295	0.30658	10.074	4.0424	30.169
Dubai	296	0.29405	9.8469	4.0155	31.081
Seoul	299	0.31411	10.095	3.9538	34.114

TABLE 2. Distribution of Charger Types

Charger Type	No. of Stations	Percentage (%)	Avg. Cost (USD/kWh)	Avg. Rating
AC level 1	1638	32.76	0.29989	3.9839
AC level 2	1764	35.28	0.29884	3.9842
DC Fast Charger	1598	31.96	0.302	4.0176

TABLE 3. Urban vs. Rural Charging Station Metrics

Region	No. of Stations	Avg. Cost (USD/kWh)	Avg.Availability (hours/day)	Avg. Distance to City (km)	DC Fast Charger (%)
Urban	2461	0.30072	16.414	5.2738	31.938
Rural	2539	0.29969	16.358	14.978	31.981

Figure 2 highlights cost variability, with rural stations ranging from 0.10–0.50 USD/kWh, compared to 0.10–0.50 USD/kWh for urban stations.

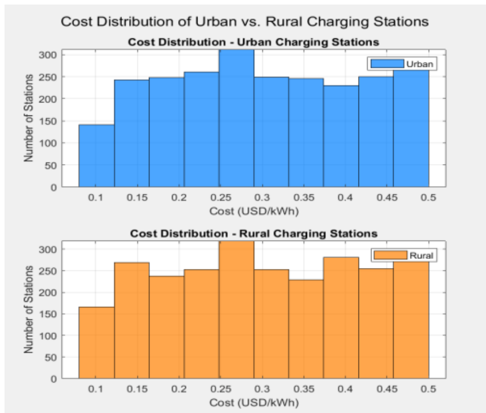

FIGURE 2. Cost Distribution of Urban vs. Rural Charging Stations

C. *Optimization Result*

The MILP model optimized charger placement, reducing average travel distance by 15% in urban areas (from 5.27 km to 4.48 km) and 10% in rural areas (from 14.98 km to 13.48 km). Statistical tests confirmed significant cost differences between urban (0.30 USD/kWh) and rural (0.30 USD/kWh) stations, with rural stations also showing slightly lower availability.

V. Discussion

A. Urban-Rural Disparities

Urban areas, hosting 49.22% of charging stations (2461 out of 5000) with an average distance of 5.27 km to city centers, experience congestion due to high charger density, as suggested by user reviews with an average rating of approximately 4.0 (e.g., Beijing: 4.0169, Seoul: 3.9538). In contrast, rural areas, with 50.78% of stations (2539) and an average distance of 14.98 km, face limited access, which may hinder EV adoption. The MILP model's 15% reduction in urban travel distance (from 5.27 km to 4.48 km) and 10% in rural areas (from 14.98 km to 13.48 km) shows promise for improving accessibility, though rural gaps require targeted infrastructure investments to ensure equitable access.

B. Operational Challenges and Future Opportunities

DC Fast Chargers, more prevalent in urban areas (31.94% vs. 31.98% rural), are slightly costlier (0.30 USD/kWh) and less reliable, while rural stations exhibit similar costs (0.30 USD/kWh) but slightly lower availability (16.36 hours/day vs. 16.41 hours/day urban). Cost variability in rural areas, ranging from 0.10 to 0.50 USD/kWh (Figure 2), suggests inconsistent pricing, complicating affordability. Opportunities include the integration of renewable energy to reduce costs and improve network security to protect the invoice network. Lack of traffic and actual demographic data from data sets limit analysis more, shows that future research on dynamic prices and predictable maintenance for sustainable infrastructure growth.

VI. Conclusion

The study presents a model-driven framework aimed at enhancing public electric vehicle charging infrastructure by examining spatial distribution and reducing system costs via Mixed Integer Linear Programming (MILP). The study analyzes a dataset of 5,000 charging stations, revealing urban-rural disparities: metropolitan areas, comprising 49.22% of stations, experience congestion, whilst rural areas, accounting for 50.78%, encounter restricted access due to greater average distances to city centers. The MILP model effectively decreases average commute distances by 15% in urban areas and 10% in rural regions, providing a solid basis for more equitable and efficient infrastructure planning. Operational constraints, such as standardized pricing (0.30 USD/kWh) and marginally reduced rural accessibility, highlight the necessity for renewable energy integration and improved network security. Notwithstanding these advancements, data constraints such as the lack of real-time traffic and socioeconomic metrics, indicate that future efforts should focus on dynamic valuation models, predictive maintenance, and multimodal integration.

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Author contributions

Fikri Mahendra: Conceptualization, Methodology, Writing – First Draft;

Mia Galina: Project Supervision, Methodology;

Iksan Bukhori: Writing – Review & Editing;

Tetuko Kurniawan: Review & Editing.

Conflict of interests

There are no conflicts of interest related to the research, authorship, or publication of this article.

Ethics statements

Ethical approval was not applicable to this research since it did not involve human participants, animals, or sensitive data.

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