International Cartographic Association
Association Cartographique Internationale

Spatial Optimization for Electric Vehicle Charging Station Locations Using A GIS-Based Approach: A Case Study from Minnesota, USA

Xiaohuan Zeng [a,*]

[a] *University of Minnesota, Minneapolis, United States - zeng0170@umn.edu*

* Corresponding author

Abstract: The rapid growth of electric vehicles (EVs) necessitates the strategic placement of charging stations to support widespread adoption and ensure sustainable transportation. This study employs Geographic Information Systems (GIS) and spatial optimization techniques to address the site selection problem for electric vehicle charging stations (EVCS) in the state of Minnesota, United States. Specifically, it investigates how many and where new EVCSs should be added to complement the existing network and meet demand. Unlike previous studies focusing on urban areas, this research conducts a statewide analysis, accounting for spatial variations in EVCS distribution by applying different coverage radii for metropolitan and non-metropolitan areas. The results indicate that the selected sites enhance coverage, particularly in metropolitan regions. This research provides transportation practitioners with an adaptable framework validated through a case study in Minnesota, offering valuable insights into GIS-based site selection methods for EVCS.

Keywords: Geospatial Information System, Spatial Optimization, Electric Vehicle Charging Stations, Site Selection

1. Introduction

The growing adoption of electric vehicles (EVs) is critical for addressing climate change and achieving sustainability goals, particularly in reducing transportation-related greenhouse gas emissions. In Minnesota, transportation contributes about 25% of the state's emissions, with light-duty vehicles being the largest source. To mitigate these emissions, the state has set ambitious EV adoption targets, aiming for 5% of light-duty vehicles to be electric by 2025 and 65% by 2040. A crucial aspect of this transition is ensuring that the EV charging station (EVCS) network can meet the increasing demand across the state, thus supporting the widespread adoption of EVs. While recent studies have focused mainly on EV charging infrastructure in urban areas, rural regions, where EV adoption may be slower but still significant, have received less attention. Minnesota's National Electric Vehicle Infrastructure (NEVI) plan aims to deploy fast charging stations along Alternative Fuel Corridors (AFCs), yet a systematic approach for selecting the best sites is still lacking. This highlights the need for more comprehensive studies to determine the optimal locations for EVCS deployment statewide, addressing both metropolitan and non-metropolitan needs.

This study aims to address these research gaps in EVCS site selection by providing a case study of Minnesota. Utilizing GIS tools and spatial optimization techniques, the study identifies optimal locations for new EVCS, considering both urban and rural needs. The research evaluates three common optimization models for site selection, building on previous studies. The goal is to minimize travel distance and optimize coverage across varying demand densities. Additionally, the study introduces flexibility in the coverage radius of charging stations to accommodate the distinct characteristics of urban and rural areas, offering a more adaptable approach to EVCS deployment. The effectiveness of the site selection is evaluated through the coverage rate of registered EVs and the population. In conclusion, this study presents a state-wide analysis of EVCS site selection in Minnesota, providing valuable insights for stakeholders to optimize EV infrastructure and support the transition to a low-carbon transportation system.

1.1 Criteria for EVCS Site Selection

Previous studies and guidelines have summarized key criteria for optimal EVCS site selection, highlighting the need for a multi-dimensional analysis of technical, economic, environmental, and social factors (Banegas & Mamkhezri, 2023; Harshil & Nagababu, 2024). This paper consolidates these factors into three main categories: demand, cost, and equity. A thorough analysis of these elements is crucial to ensure effective site selection and alignment with the goals of sustainable and equitable transportation.

Demand is a primary criterion for EVCS site selection, influenced by charger type and technology (Great Plains Institute, 2019). For example, Direct-Current Fast Charging (DCFC or Level 3) enables rapid charging, reaching 80% capacity within an hour, but incurs higher construction costs, making it ideal for highways and busy roads to serve long-distance travelers (Tu et al., 2019).

Advances in Cartography and GIScience of the International Cartographic Association, 5, 36, 2025.
32nd International Cartographic Conference (ICC 2025), 17–22 August 2025, Vancouver, Canada. This contribution underwent double-blind peer review based on the full paper. https://doi.org/10.5194/ica-adv-5-36-2025 |

Level 2 and Level 1 Alternating-Current (AC) chargers, requiring several hours or days for similar charging levels (Dericioglu et al., 2018), are better suited for residential, workplace, and recreational areas. Social factors like travel patterns, population density, and EV ownership also influence demand. In the absence of ownership data, proxies such as income and education levels are used to forecast needs (He et al., 2016).

Beyond demand, cost is another critical consideration in Cost is another critical factor in EVCS placement. Integrating chargers into existing fuel stations or parking facilities reduces land acquisition costs (Great Plains Institute, 2019; He et al., 2016). Fast chargers, requiring industrial-grade power lines and transformers, entail higher electrical infrastructure costs, and their grid impact must be assessed. For new sites, terrain, geology, and construction feasibility are essential considerations. Operational costs and government subsidies also significantly affect the financial viability of EVCS. Subsidies can offset initial expenses, improving economic feasibility.

Social equity and environmental justice are equally vital. EVCS planning should address the needs of underserved communities, ensuring accessibility for low-income and environmentally burdened populations to promote inclusivity. Environmental considerations focus on reducing ecological impacts by prioritizing renewable energy and sustainable practices, like water recycling and permeable surfaces. Balancing these elements fosters equitable, sustainable EVCS development and broad community support for electric mobility.

1.2 GIS and Spatial Data Integration

EVCS site selection requires integrating spatial and non-spatial data (Banegas & Mamkhezri, 2023). Non-spatial data can be easily integrated, but geographic data requires advanced GIS techniques (Erbaş et al., 2018; Kłos & Sierpiński, 2023; Zhang et al., 2019). GIS combines datasets like charging station locations, road networks, and demographic information to create an analytical framework. For example, buffer analysis creates zones around existing stations to assess coverage and identify underserved areas. Overlay analysis merges spatial layers, revealing relationships between high EV ownership areas and charging station locations. Network analysis evaluates travel costs between sites, such as the distance to transportation hubs.

GIS also enhances decision-making with intuitive map visualizations that show the spatial distribution of charging stations, traffic, and population density. These maps help identify high-demand areas, assess station coverage, and evaluate accessibility. Moreover, they promote transparency and public engagement by illustrating the site selection process clearly.

1.3 Site Selection Methods

EVCS site selection involves multiple factors, making Multi-Criteria Decision-Making (MCDM) methods suitable (Dang et al., 2021). MCDM techniques like the Weighted Sum Model (WSM) and Analytic Hierarchy Process (AHP) decompose the problem into criteria and assign weights, with WSM using simple weighted summation and AHP using pairwise comparisons to assess criterion importance (Csiszár et al., 2019; Guler & Yomralioglu, 2020).

In addition, optimization models like Integer Linear Programming (ILP) and Mixed-Integer Linear Programming (MILP) are commonly used (Franco et al., 2015; Wang et al., 2016). These models mathematically formulate constraints and objectives, such as minimizing the number of stations while covering all demand points (He et al., 2016). ILP and MILP provide precise solutions but are computationally intensive and less flexible with uncertain data.

While MCDM methods are more subjective and better suited for multi-objective problems, they can be sensitive to weight assignments and expert opinions. A combined approach—using AHP and WSM for weight assignment and MILP for optimization—offers a flexible, comprehensive solution for EVCS site selection. Banegas and Mamkhezri (2023) provide a detailed overview of other methods, including genetic algorithms and agent-based simulations.

2. Methods

2.1 Study Area

The study area for this research is the state of Minnesota, United States. Transportation contributes roughly 25% of Minnesota's greenhouse gas emissions, primarily from light-duty vehicles with internal combustion engines (Claflin et al., 2023). Electrifying these vehicles is key to meeting the state's climate goals (Great Plains Institute & Bellwether Consulting, 2021). The Minnesota Department of Transportation (MnDOT) aims to achieve 5% EV registration among light-duty vehicles by 2025 and 65% by 2040 (MnDOT, 2024b). As of January 2024, Minnesota had 53,356 registered EVs, accounting for 1% of all light-duty vehicles (MnDOT, 2024b; MnPUC, 2024). While the state has not yet fully aligned with its long-term targets, the number of EV registrations continues to increase, as illustrated in Figure 1.

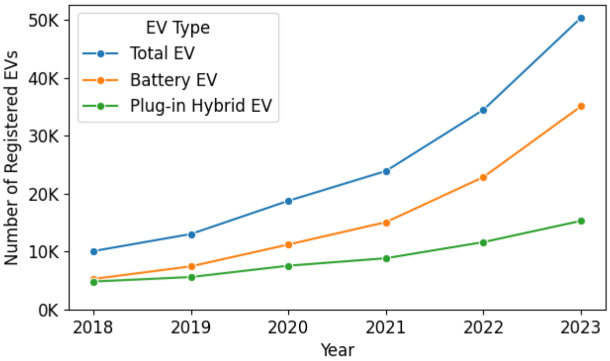

Figure 1. EV Registration Trends by Year in Minnesota (Data adapted from MnPUC, 2024).

To support EV adoption, Minnesota plans a robust statewide charging network. Through a $68 million NEVI allocation, fast-charging stations will be installed along

Alternative Fuel Corridors (AFCs) during FFY22-26 (FFY22-26), with stations spaced no more than 50 miles apart and within one mile of AFC exits (MnDOT, 2024a). This plan primarily targets Minnesota's two AFCs, Interstate 94 and Interstate 35. MnDOT's ongoing EV Infrastructure Needs Assessment (EVINA), to be completed by May 2025, will identify additional priority areas and develop optimization models for station placement (MnDOT, 2024c). This study aligns with EVINA's goals by focusing on spatial optimization and GIS methods.

2.2 Data

This study utilizes charging station data from the U.S. Department of Energy (USDOE, 2024), including longitude and latitude coordinates. As of December 2024, there are 894 publicly available EV charging stations within Minnesota. These comprise four stations with Level 1 chargers, 728 with Level 2 chargers, and 203 with fast chargers, with some stations hosting multiple charger types.

EV registration data for 2023 is segmented by zip code (MnPUC, 2024), with zip code centroids representing regional demand (Manson, 2020). This study focuses on current demand and its spatial distribution, not future demand forecasting, which requires advanced models (He et al., 2016). Figure 2 illustrates the spatial distribution of EV registrations and charging stations: blue dots indicate existing stations, with darker shades representing higher station density. The background shows EV registrations by zip code, with darker red indicating higher registration numbers, while the black boundary marks the seven-county metropolitan area. As shown in Figure 2, the densest concentrations of EV registrations and charging stations are located within the seven-county metropolitan area.

To identify potential new EVCS sites, this study utilizes the location data on 130 gasoline stations and 1,881 parking lots from a point-of-interest dataset (SafeGraph, 2024), aligning with cost-effective strategies from prior research (He et al., 2016). It is important to recognize, however, that the selection of potential locations can be adjusted depending on specific planning needs and available data. Population data at the block group level (Manson, 2020) and EV registration data are further utilized to evaluate coverage of current and proposed sites.

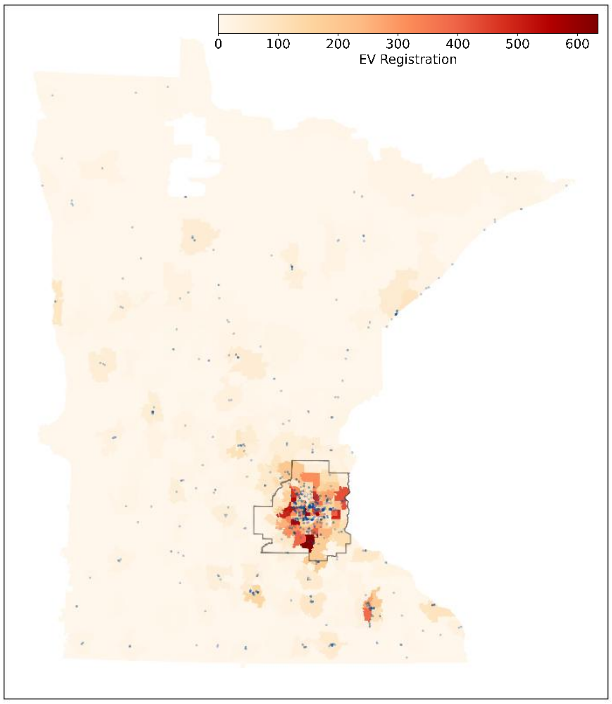

Figure 2. Spatial Distribution of Existing Charging Stations and EV Registrations.

2.3 Spatial Optimization

This study applies and compares three optimization methods for EVCS site selection: the Set Covering Model (SCM), the Maximal Covering Location Model (MCLM), and the P-Median Model (PMM) (He et al., 2016). A unified linear model is adopted to mathematically formulate these models (Hillsman, 1984).

Key sets and parameters:

- I: The set of demand locations.
- J: The set of locations for charging stations, including the existing and potential sites.
- J_{exist}: The set of already constructed charging stations.
- D_i: The maximum acceptable coverage radius or distance threshold for demand location i.
- d_{ij}: The Euclidean distance between demand location i and charging station j.
- p: The number of new charging stations to be established.
- w_i: The demand weight of the demand location i , represented by population.

Decision variables:

- $x_j \in \{0,1\}$: Binary variable; $x_j = 1$ if a charging station has been or will be constructed at the location j , and $x_j = 0$ otherwise. This study fixes this decision variable to 1 for all pre-existing charging stations, which means $x_j = 1$ for $\forall j \in J_{exist}$.

 https://doi.org/10.5194/ica-adv-5-36-2025 |

- $y_{ij} \in \{0,1\}$: Binary variable; $y_{ij} = 1$ if demand location i is covered by the charging station j (i.e., $d_{ij} < D_i$), and $y_{ij} = 0$ otherwise.
- $z_{ij} \in \{0,1\}$: Binary variable; $z_{ij} = 1$ if demand location i is assigned to the charging station j and station j is or will be established, and $z_{ij} = 0$ otherwise. Each location i can be assigned to at most one charging station j, and it must be the closest one.

Set-Covering aims to minimize the number of new charging stations needed and ensures each demand location $i \in I$ is covered by at least one charging station (Toregas et al., 1971). This can be mathematically formalized as follows:

$$Minimize \sum_{j \in J} x_j \tag{1}$$

$$S.T. \sum_{j \in J_i} y_{ij} \geq 1, \forall i \in I. \tag{2}$$

The objective function of **Maximum-Covering** is to maximize the total population covered by charging stations, while subject to the constraint on the number of new stations that can be built (Church & Velle, 1974). This can be mathematically formalized as follows:

$$Maximize \sum_{i \in I} w_i \cdot max_j y_{ij} \tag{3}$$

$$S.T. \sum_{j \in J \setminus J_{exist}} x_j \leq p. \tag{4}$$

P-Median seeks to minimize the total distance between demand locations and the nearest charging stations, weighted by the demand at each point, while subject to the constraint on the number of new stations that can be built (ReVelle & Swain, 1970). This can be mathematically formalized as follows:

$$Minimize \sum_{i \in I} \sum_{j \in J} w_i \cdot d_{ij} \cdot z_{ij} \tag{5}$$

$$S.T. \sum_{j \in J \setminus J_{exist}} x_j \leq p. \tag{6}$$

2.4 Evaluation of coverage ratio

To quantitatively assess the overall coverage of the charging stations J_m selected using different optimization methods (existing stations, SCP, MCLM, and PMP), this project calculates the coverage ratio of registered EVs and the population. Specifically, the coverage ratio represents the percentage of registered EVs w_i and the population p_i with the distance to the closest charging station smaller than or equal to a given distance threshold D_k. The set of distance thresholds (in kilometres) is defined differently for the metropolitan area ($D_k \in \{1,2,3,4,5,6,7,8\}$) and non-metro area ($D_k \in \{5,10,15,20,25,30,35,40,45\}$). The demand locations are the centroids of zip codes, and a demand location is covered if its distance to the closest charging station is smaller or equal to the distance threshold. Using the same notation as in Section 2.3, the coverage indicators are calculated as follows:

$$covered_{i,m,k} = \begin{cases} 1 \; if \, d_{ij} \leq D_k, \exists j \in J_m \\ 0 \; ohterwise \end{cases}; \tag{7}$$

$$R_{demand,m,k} = \frac{\sum_{i \in I} covered_{i,m,k} \cdot w_i}{\sum_{i \in I} w_i}; \tag{8}$$

$$R_{pop,m,k} = \frac{\sum_{i \in I} covered_{i,m,k} \cdot p_i}{\sum_{i \in I} p_i}. \tag{9}$$

These coverage ratios provide a quantitative evaluation of how well the proposed charging station networks serve both demand and population, offering insights into the effectiveness of different site selection methods.

3. Results

3.1 Sites Recommendation

This study categorizes demand locations into two types: within the seven-county metropolitan area and outside it, assigning different coverage radii based on location type. As shown in Figure 3, the potential station network in the metropolitan area is denser, with smaller coverage distances depicted in blue on the left. The maximum distance to the nearest potential station is set at 7,597 meters for metropolitan areas and 41,956 meters for non-metropolitan areas, as shown in the equation below. These thresholds ensure complete coverage using SCM optimization, as smaller distances could result in gaps in coverage. This flexible approach allows thresholds to be adjusted based on transportation experts' insights or specific contextual needs.

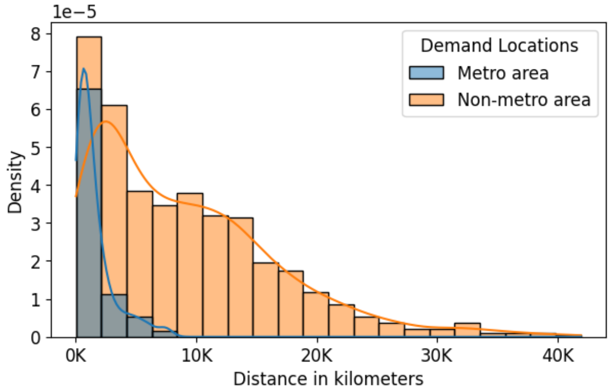

Figure 3. Distribution of distance to the closest existing or potential charging station, categorized by demand location type.

Using the defined distance thresholds, the study applies SCM and determines that adding a minimum of 25 new charging stations to the existing infrastructure covers all demand locations within the specified range. With $p =$

25 , MCLM and PMM are also solved to identify optimal station locations, minimizing their respective objective functions.

Intersection analysis (Table 1) shows that SCM and MCLM produce very similar results, where 13 out of 25 (52%) of their optimal locations overlap. Figure 4 and Figure 5 show the spatial distribution of the additional charging station selected by SCM and MCLM. Both models suggest the newly built charging stations should be spread out around the boundary of the metropolitan area and the state, particularly in regions where no existing stations are nearby, as seen in Figure 2. In contrast, PMM results differ significantly from SCM and MCLM, with only 1 and 2 overlapping stations, respectively. The locations selected by PMM are closer to high EV charging demand points, as the new stations are more concentrated in the metropolitan area, with only a few located in non-metropolitan areas, as shown in Figure 7. Thus, PMM prioritizes placing stations in locations that would be more accessible for the majority of potential EV users. These results align with prior research in Beijing (He et al., 2016).

	SCM	MCLM	PMM	total
SCM	11	13	1	25
MCLM	13	10	2	25
PMM	1	2	22	25

Table 1. Intersection analysis of the optimal charging station locations using SCM, MCLM, and PMM methods.

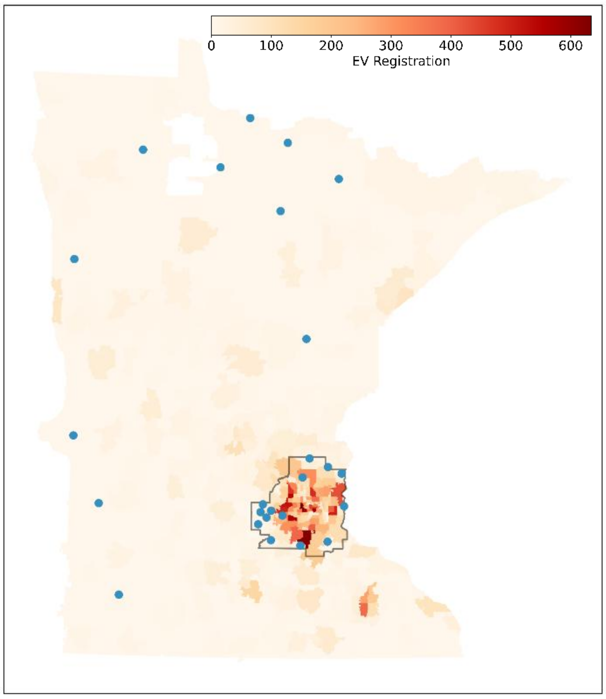

Figure 4. Locations of charging stations (blue dots) determined by SCM.

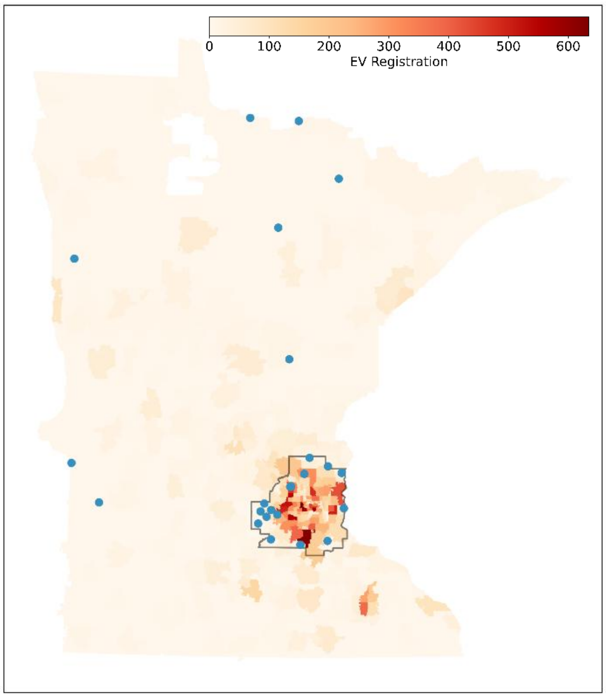

Figure 5. Locations of charging stations (blue dots) determined by MCLM.

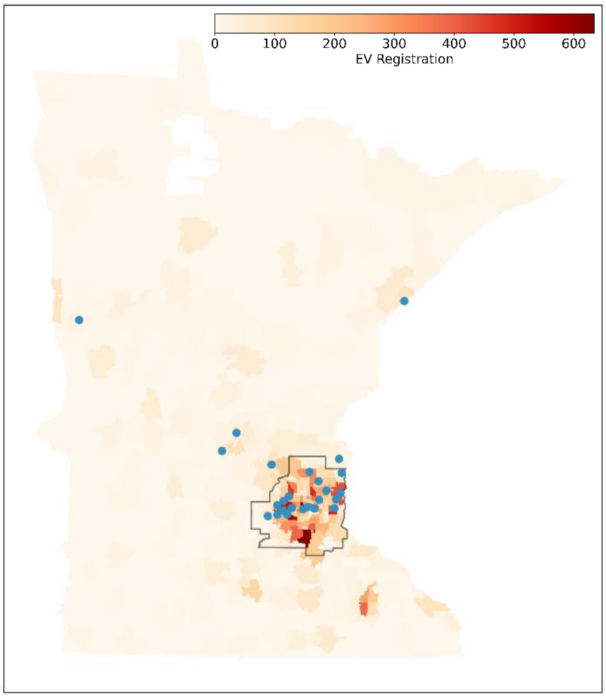

Figure 6. Locations of charging stations (blue dots) determined by PMM.

3.2 Evaluation of Coverage Ratio

Figure 7 shows the coverage ratio across different distance thresholds for existing charging stations and additional sites selected using the three optimization methods. The top and bottom rows of subplots represent the coverage ratios for registered EVs and population, respectively, while the left and right columns represent coverage in metropolitan and non-metropolitan areas. It is

32nd International Cartographic Conference (ICC 2025), 17–22 August 2025, Vancouver, Canada. This contribution underwent double-blind peer review based on the full paper. https://doi.org/10.5194/ica-adv-5-36-2025

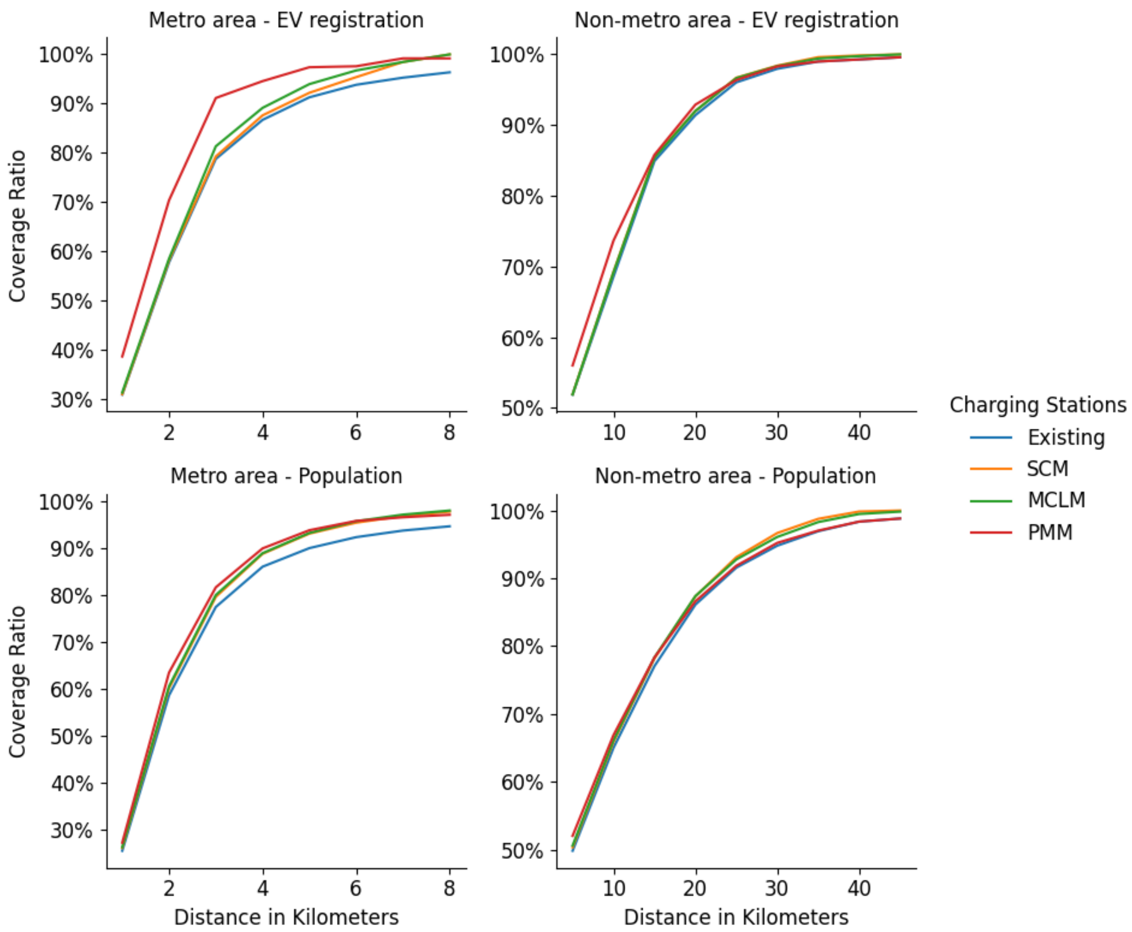

Figure 7. Evaluation of coverage ratio of registered EVs and population by site selection methods and demand location types.

clear that as the distance threshold increases, the coverage ratio gradually increases and approaches 100%. Furthermore, after adding more charging stations using the three optimization methods, the coverage exceeds that of the scenario, considering only the existing charging stations. This improvement is more noticeable in metropolitan areas (left subplots) and when using EV registration data to measure coverage (upper subplots). This is likely because, in our optimization, the objective function relies on the location and demand derived from the EV registration data, without integrating population data into the optimization process. In non-metropolitan areas, the four curves are very close to each other or even overlap, likely due to the lower number of EV registrations and population in these areas, as well as the larger range of distance thresholds. Additionally, as shown in the top-left subplot, the PMM method results in greater coverage improvement when the distance threshold is set to a relatively small value. This is because the PMM optimization considers both demand and distance, unlike the other two methods.

4. Discussion

This study presents a flexible framework for optimizing the allocation of charging station locations using GIS and three spatial optimization models: the Set Covering Model (SCM), Maximal Covering Location Model (MCLM), and P-Median Model (PMM). Unlike prior studies focused on urban areas, this research analyses both metropolitan and non-metropolitan areas across Minnesota, highlighting trade-offs in coverage, demand, distance, and budget. SCM and MCLM produced balanced statewide station distributions, while PMM concentrated stations in metropolitan areas. Adding the optimized stations significantly improved coverage, especially in urban regions with high EV registrations. This GIS-based framework is replicable and supports sustainable transportation planning by integrating diverse data sources and addressing regional variations.

Despite these advancements, the study has limitations. First, while EV registration data served as a proxy for demand, future growth in EV adoption was not considered. Incorporating demand forecasting could improve long-term planning. Additionally, this study did not differentiate between charger types, such as Level 2 and DC fast chargers. Future research could optimize site selection based on specific charging needs.

Second, the optimization models primarily addressed coverage, demand, and distance but omitted other important factors. Future work could incorporate local climate impacts, such as how Minnesota's harsh winters affect EV infrastructure. Using road network distances instead of Euclidean distances could also improve accuracy, especially in areas with limited road connectivity.

Lastly, the evaluation metrics focused on EV and population coverage but did not consider equity or accessibility for disadvantaged communities. Future studies could include these factors to ensure fairness in infrastructure deployment. Balancing efficiency and equity remains a critical challenge, especially in resource-limited contexts.

To enhance practical applications, future research could develop interactive decision-support tools for stakeholders, allowing for dynamic visualization of site selection factors and scenario-based adjustments. Collaborating with transportation agencies could also align optimization models with regional planning priorities, ensuring realistic and actionable outcomes.

5. References

Banegas, J., & Mamkhezri, J. (2023). A systematic review of geographic information systems based methods and criteria used for electric vehicle charging station site selection. *Environmental Science and Pollution Research*, *30*(26), 68054–68083.

Church, R., & Velle, C. R. (1974). The maximal covering location problem. *Papers in Regional Science*, *32*(1), 101–118.

Claflin, A., Coleman, N., Hagan, L., Gaffney, K., & Trudeau, L. (2023). *Greenhouse Gas Emissions in Minnesota: 2015-2020*. Minnesota Pollution Control Agency Minnesota, USA. https://www.pca.state.mn.us/air-water-land-climate/climate-change-trends-and-data

Csiszár, C., Csonka, B., Földes, D., Wirth, E., & Lovas, T. (2019). Urban public charging station locating method for electric vehicles based on land use approach. *Journal of Transport Geography*, *74*, 173–180.

Dang, R., Li, X., Li, C., & Xu, C. (2021). A MCDM framework for site selection of island photovoltaic charging station based on new criteria identification and a hybrid fuzzy approach. *Sustainable Cities and Society*, *74*, 103230.

Dericioglu, C., YiriK, E., Unal, E., Cuma, M. U., Onur, B., & Tumay, M. (2018). A review of charging technologies for commercial electric vehicles. *International Journal of Advances on Automotive and Technology*, *2*(1), 61–70.

Erbaş, M., Kabak, M., Özceylan, E., & Çetinkaya, C. (2018). Optimal siting of electric vehicle charging stations: A GIS-based fuzzy Multi-Criteria Decision Analysis. *Energy*, *163*, 1017–1031.

Franco, J. F., Rider, M. J., & Romero, R. (2015). A mixed-integer linear programming model for the electric vehicle charging coordination problem in unbalanced electrical distribution systems. *IEEE Transactions on Smart Grid*, *6*(5), 2200–2210.

Great Plains Institute. (2019). *Charging Station Site Selection Guidelines*. Great Plains Institute. https://driveelectricmn.org/wp-content/uploads/2019/10/electric-vehicles-charging-site-selection.pdf

Great Plains Institute & Bellwether Consulting. (2021). *2021 Minnesota Electric Vehicle Assessment*. Minnesota Department of Transportation Minnesota, USA. https://edocs-public.dot.state.mn.us/edocs_public/DMResultSet/Urlsearch?columns=docnumber,docname&folderid=19994055

Guler, D., & Yomralioglu, T. (2020). Suitable location selection for the electric vehicle fast charging station with AHP and fuzzy AHP methods using GIS. *Annals of GIS*, *26*(2), 169–189.

Harshil, B., & Nagababu, G. (2024). Strategies and models for optimal EV charging station site selection. *IOP Conference Series: Earth and Environmental Science*, *1372*(1), 012106.

He, S. Y., Kuo, Y.-H., & Wu, D. (2016). Incorporating institutional and spatial factors in the selection of the optimal locations of public electric vehicle charging facilities: A case study of Beijing, China. *Transportation Research Part C: Emerging Technologies*, *67*, 131–148.

Hillsman, E. L. (1984). The p-median structure as a unified linear model for location—Allocation analysis. *Environment and Planning A*, *16*(3), 305–318.

Kłos, M. J., & Sierpiński, G. (2023). Siting of electric vehicle charging stations method addressing area potential and increasing their accessibility. *Journal of Transport Geography*, *109*, 103601.

Manson, S. M. (2020). *IPUMS national historical geographic information system: Version 15.0*.

MnDOT. (2024a). *2024 MN Electric Vehicle Infrastructure Plan*. Minnesota Pollution Control Agency Minnesota, USA. https://www.dot.state.mn.us/nevi/

MnDOT. (2024b). *Minnesota Electric Vehicles Performance Measure Dashboard*. Minnesota Department of Transportation Minnesota, USA. https://www.dot.state.mn.us/measures/electric-vehicles.html

MnDOT. (2024c). *MN EV Infrastructure Needs Assessment*. Minnesota Department of Transportation Minnesota, USA. https://talk.dot.state.mn.us/mnevina

MnPUC. (2024). *Minnesota Electric Vehicles Registration Data*. Minnesota Public Utilities Commission Minnesota, USA. https://mn.gov/puc/activities/economic-analysis/electric-vehicles/

ReVelle, C. S., & Swain, R. W. (1970). Central facilities location. *Geographical Analysis*, *2*(1), 30–42.

SafeGraph. (2024). *Global Points of Interest (POI) Data* [Dataset]. https://www.safegraph.com/products/places

Toregas, C., Swain, R., ReVelle, C., & Bergman, L. (1971). The location of emergency service facilities. *Operations Research*, *19*(6), 1363–1373.

Tu, H., Feng, H., Srdic, S., & Lukic, S. (2019). Extreme fast charging of electric vehicles: A technology overview. *IEEE Transactions on Transportation Electrification*, *5*(4), 861–878.

USDOE. (2024). *Alternative Fuels Data Center* [Dataset]. U.S. Department of Energy. https://afdc.energy.gov/stations

Wang, X., Yuen, C., Hassan, N. U., An, N., & Wu, W. (2016). Electric vehicle charging station placement for urban public bus systems. *IEEE Transactions on Intelligent Transportation Systems*, *18*(1), 128–139.

Zhang, Y., Zhang, Q., Farnoosh, A., Chen, S., & Li, Y. (2019). GIS-based multi-objective particle swarm optimization of charging stations for electric vehicles. *Energy*, *169*, 844–853.