MULTI-OBJECTIVE OPTIMIZATION FOR EV CHARGING INFRASTRUCTURE PLANNING

by Group 15

EFIMM0142 - Modelling Analytics

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Introduction

Background

Global warming and urban air pollution are driving the rapid development of electric vehicles(EVs). However, although the charging infrastructure network is expanding to accommodate the growing market share of electric vehicles (Erdogan et al., 2023), there is still uncertainty about private drivers' access to charging stations (Noel et al., 2020; Unterluggauer et al., 2022). Therefore, how to plan the charging infrastructure network so that it is highly accessible and efficient is crucial for government planners.

Question Formation

This study aims to provide planning departments with a decision support system by combining multi-criteria decision analysis, mixed integer programming(MIP) models, and multi-objective optimization. Three key optimization indicators—minimum total path, maximum coverage area, and minimum median number of service vehicles—are established to evaluate the suitability of EV charging stations. This study will enable government planners to have a more comprehensive understanding of how to develop intelligent data-driven plans for EV charging station site selection.

Model Development and Justification

Model Structure

The core of infrastructure location-allocation problem lies in facility placement and resource allocation, and the goal is usually to minimize costs, maximize services or achieve specific needs (Hakimi, 1964; Hakimi, 1965; Daskin, 1997). This study first uses the Dijkstra algorithm to calculate the shortest path matrix between supply and demand points (Dijkstra, 1959) as the basis for distance analysis. Subsequently, the candidate sites are screened by the AHP method to filter high-potential sites, which not only reduced computational complexity, but also improved optimization efficiency and decision-making quality (Yang and Lee, 1997; Alves et al., 2023). Combined with the Huff model (Huff, 1964), the demand distribution of electric vehicles in the region is estimated to guide resource allocation, which is widely used in business network analysis and travel demand estimation (Liang et al., 2020; Lin et al., 2016). Finally, the distribution of charging demand is optimized through a MIP model, and a sensitivity analysis is performed by adjusting the shortest-distance algorithms and distance decay parameter (β) of the Huff model to verify the robustness of the scheme (see Figure 1).

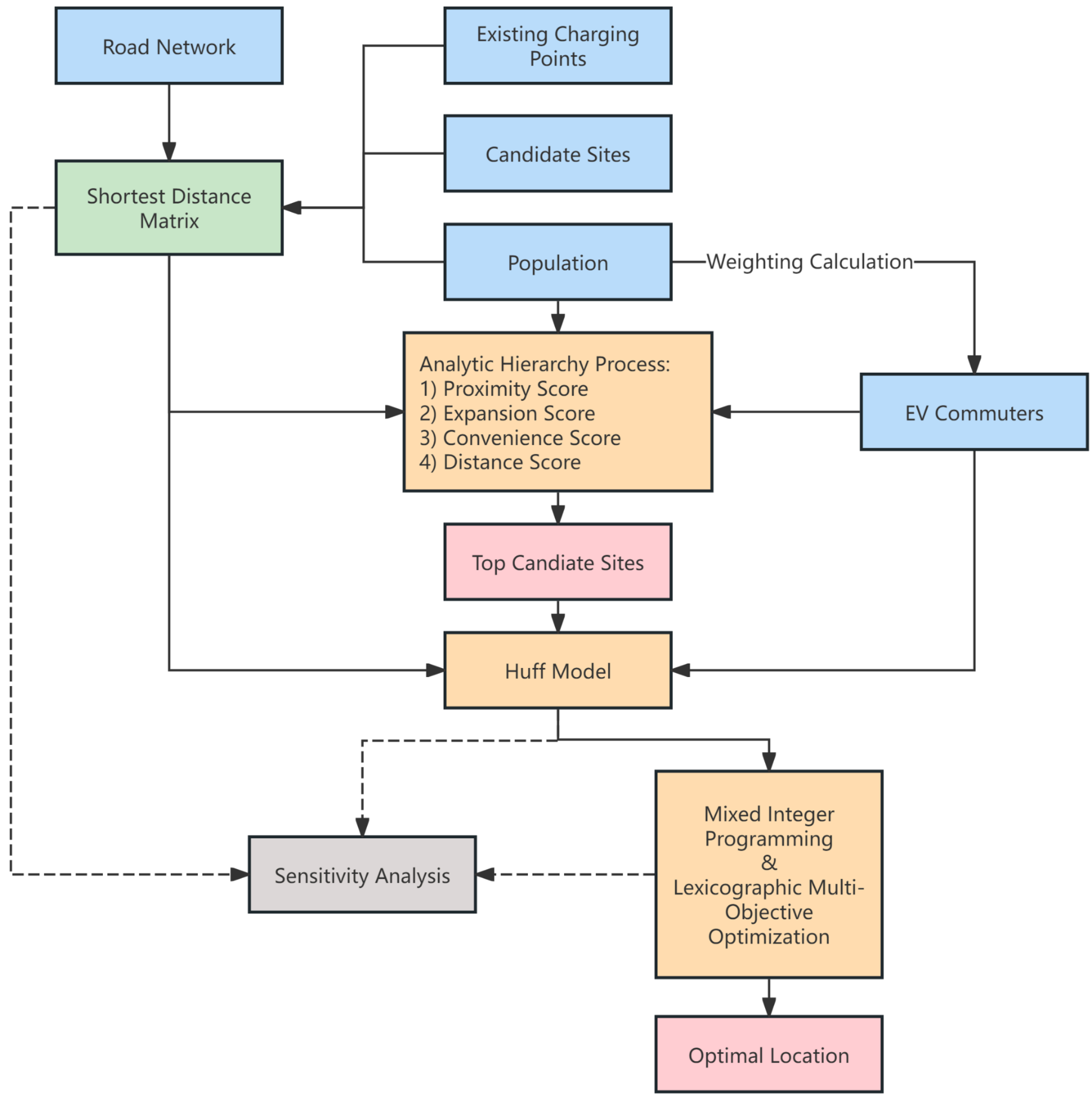

Figure 1. Model Structure Flow Chart

Mathematical Formula

All calculations and modelling in this study were performed in the Python environment(see Appendix B). The variables and formulas involved are as follows:

Table 1. Variables and Parameters

Notation	Description	Type
I	Set of population areas	Index
J	Set of charging stations, including existing sites and candidate sites	Index
$J_{existing}$	Set of existing charging stations	Index
$J_{candidate}$	Set of candidate charging stations	Index
d_{max}	The influence range of site j, the default is 1 mile	Input Parameter
d_{ij}	Distance between area i and station j	Input Parameter
D_i	EV commuter demand number of area i	Input Parameter
$major\_roads$	Main roads in Bristol city map	Input Parameter
$road$	Iterate through the index variable of the site collection major_roads	Input Parameter
k	Iterate over the site collection $J_{existing}$ index variable	Input Parameter
β	Distance attenuation coefficient	Input Parameter
x_{ij}	Expected number of vehicles from i to j	Continuous Variable
P_{ij}	Probability of area i choosing station j	Continuous Variable
y_j	Whether candidate site j is selected	Binary Variable

1) AHP

Through a review of existing studies (Hummler et al., 2022; Lazari and Chassiakos, 2023; Gazmeh et al., 2024; Suvittawat and Suvittawat, 2024), four dimensions: proximity, expansion, convenience, and distance, were selected. A final score was calculated for each candidate site based on these indicators to evaluate the potential of candidate sites.

Table 2. Definition of AHP Indicators

Indicators	Definition	Formula	Weight
Proximity Score	The total number of EV commuters within 1 mile	$proximity\_score_j = \frac{\sum_{i \in I} D_i}{\max_{j \in J_{candidate}} \sum_{i \in I} D_i}, \ d_{ij} \le d_{max}$	w_1 =0.35
Expansion Sore	The total young aged population within 1 mile	$expansion\_score_j = \frac{\sum_{i \in I}(age\_16\_29_i + age\_30\_49_i)}{\max_{j \in J_{candidate}} \sum_{i \in I}(age\_16\_29_i + age\_30\_49_i)},$	w_2 =0.25
Convenience Score	The distance from the site to the nearest major road	$convenience\_score_j = 1 - \frac{min(distance(j,road))}{\max_{j \in J_{candidate}} min(distance(j,road))}$	w_3 =0.25
Distance Score	The distance from the site to the nearest existing station	$distance\_score_j = \frac{min(distance(j,k))}{\max_{j \in J_{candidate}} min(distance(j,k))}, \ k \in J_{existing}$	w_4 =0.15

Note. All scores were min-max normalized.

The calculation formula for the final score of candidate points:

$$Score_j = (proximity\_score_j * W_1) + (expansion\_score_j * W_2) + (convenience\_score_j * W_3) + (distance\_score_j * W_4)$$

The weight of each indicator was set according to the priority of the evaluation criteria. All candidate sites were ranked in descending order based on their final scores, with top-ranked sites selected for subsequent modelling analysis. The final site set S comprises all existing sites and the top 30% of candidate sites based on their overall AHP scores.

$$S = J_{existing} \cup Top_{30\%}(J_{candidate})$$

2) **Huff Model**

The Huff Model was used to calculate the probability that users from area i will select station j based on the distance decay effect:

$$P_{ij} = \frac{A_{ij}}{\sum_{k \in S} A_{ik}} = \frac{A_j * d_{ij}^{\beta}}{\sum_{k \in S} A_k * d_{ik}^{\beta}}$$

Where:

- A_j is the attractiveness of station j (assumed equal for all stations).
- β is a distance decay parameter (negative value, typically −1.5).

The expected number of vehicles traveling from area i to station j is calculated as:

$$x_{ij} = P_{ij} * D_i$$

3) Objectives

Recent studies on charging infrastructure planning increasingly adopt multi-objective optimization to address diverse needs (Unterluggauer et al., 2022). This project utilizes a lexicographic multi-objective optimization approach to reflect real-world site selection challenges by ranking objectives in order of importance. The model prioritizes three key objectives in sequence, and the objective function is framed as:

1. **Minimizing Total Path Distance (Z_1):**

$$Z_1 = Min \sum_{i \in I} \sum_{j \in S} y_j * x_{ij} * d_{ij}$$

2. **Maximizing Coverage (Z_2)**

$$Z_2 = \frac{Max(\sum_{i \in I} y_j * 1)}{|I| * 1}$$

3. **Minimizing Median Vehicles per Station** (Z_3)

$$Z_3 = Min\ Median \sum_{i \in I} x_{ij}$$

subject to the constraints:

1. $\sum P_{ij} = 1,\ \forall i \in I, j \in S$
2. $x_{ij} \le y_j * M,\ \forall i \in I, j \in S$
3. $d_{ij} \le d_{max},\ \forall i \in I, j \in S$
4. $y_j \in \{0, 1\},\ \forall i \in I, j \in S$
5. $P_{ij} \ge 0,\ \forall i \in I, j \in S$
6. $x_{ij} \ge 0,\ \forall i \in I, j \in S$

Prototype Demonstration

Bristol, the second fastest-growing core city in England and Wales (Bristol City Council, 2024), has about 110,000 EV owners (Open Data Bristol, 2024; Office for National Statistics, 2024) and is investing £4.9 million to build 187 charging points by 2026 (Seabrook, 2024), making it an ideal area for research.

Data Source

The datasets for this study come from various open data sources(see Table 3). A comprehensive data cleanup of existing charging points and candidate points was carried out, including only sites that are still in operation, non-private, and within the boundaries of Bristol.

Table 3. Data Sources

Data Name	Purpose	Source	Year	Type
Electric Vehicle Smart Charging Action Plan	Weight	GOV.UK	2023	REPORT
Quality of Life by Ward	Weight	Open Data Bristol	2018	CSV
Opinions and Lifestyle Survey: Electric vehicles	Weight	Office for National Statistics	2021	TEXT
Population Estimates by Single Year of Age and Sex by Output Area	Demand	Open Data Bristol	2021	SHP
Electric Vehicle Charging Points NCR	Supply	Open Data Bristol	2024	SHP
Designated Car Parks	Candidate	Open Data Bristol	2024	SHP
Bristol Boundary	Boundary	Open Data Bristol	2023	SHP
Road Networks of the City of Bristol	Distance	Open Street Map	2024	SHP

To simulate the potential demand, this study estimated the distribution of EV charging demand in Bristol(see Figure 2). The calculation formula can be expressed as follows:

*Number of EV Owners = Sum(Number of Population in Each Age Age Group * Proportion of EV Owner in Each Age Group)*

*Market Demand = (Number of EV Owners * Proportion of Who Drive to Work * Proportion of Who Need Access to Public Charging Stations)*

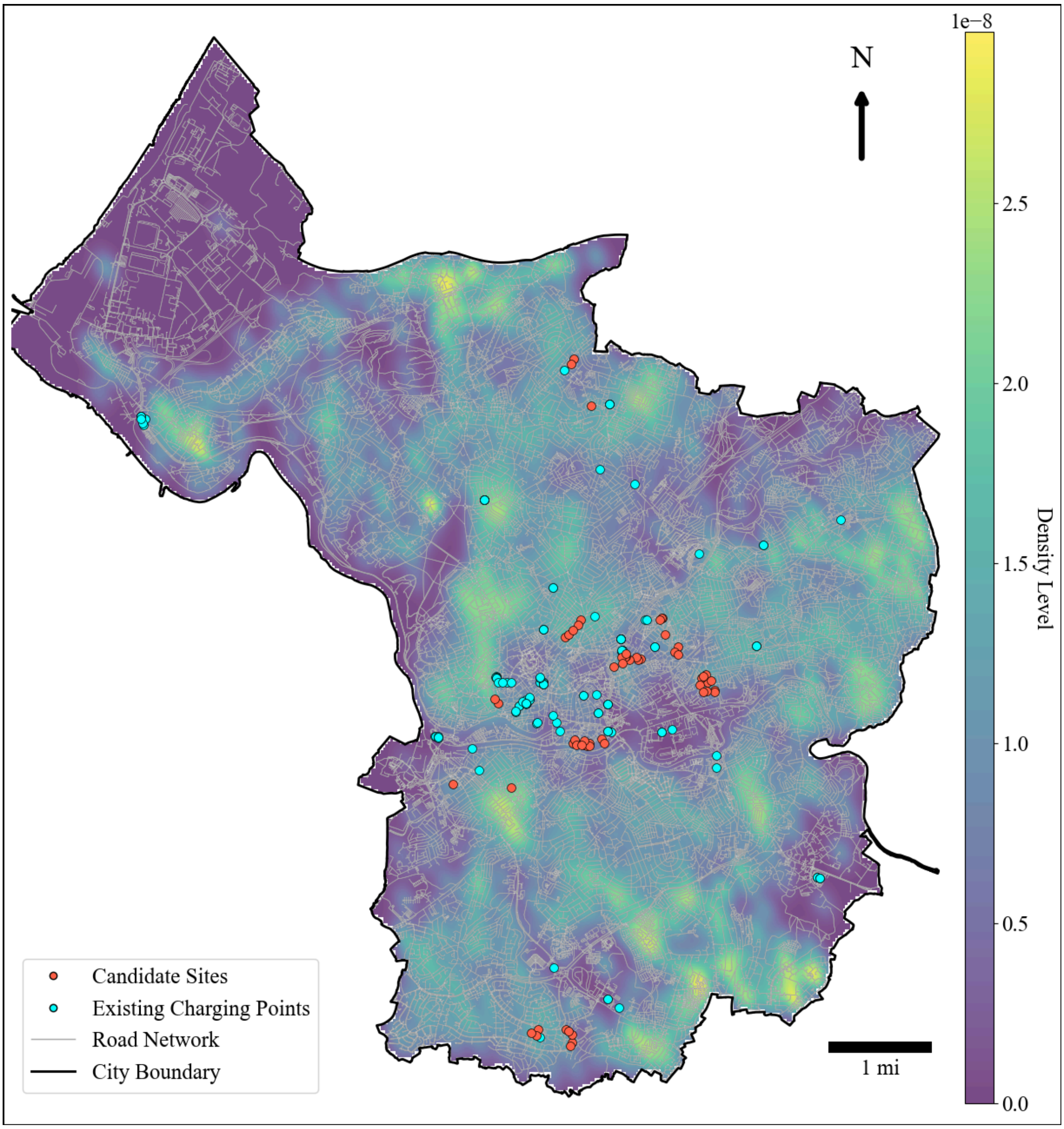

Figure 2. Distribution of Electric Vehicle Commuters in Bristol Who Need Access to Public Charging Points

Solutions

The results showed that Site 57 was the optimal solution, with the shortest total distance of 3,537.03 miles and the highest total coverage of 70.89%, despite its seventh-lowest (10.97) in Median number of vehicles per station(see Table 4). In contrast, Site 54 ranked second in total distance (3,540.92 miles), but performed poorly (ranked eighth) in total coverage (70.18%) and number of vehicles per station (10.97). Similarly, Site

33 ranked third in path distance (3,541.16 miles) and second in coverage (70.39%), but ranked fourteenth in number of vehicles per station (10.98), weakening its overall suitability.

Table 4. The Top Three Results by Shortest Path Distance

Selected Site ID	Total Distance (miles)	Ranking	Total Coverage (%)	Ranking	Median Vehicles per Station	Ranking
57	3537.03	1	70.89	1	10.97	7
54	3540.92	2	70.18	8	10.97	8
33	3541.16	3	70.39	2	10.98	14

Table 5 further highlights the advantages of Site 57 in terms of total distance and total coverage. In comparison, Site 13 performs well in terms of the median number of vehicles per station (10.93, ranked first), but performs poorly in terms of path distance (3,544.81 miles, ranked ninth) and coverage (69.75%, ranked sixteenth).

Table 5. The Optimal Site for Each of The Three Objectives

Selected Site ID	Total Distance (miles)	Ranking	Total Coverage (%)	Ranking	Median Vehicles per Station	Ranking
57	3537.03	1	70.89	1	10.97	7
13	3544.81	9	69.75	16	10.93	1

In summary, Site 57 achieves the best ranking in most objectives, making it the optimal solution(see Figure 3). Although Site 13 and other stations have advantages in specific areas, they fail to achieve comparable overall performance.

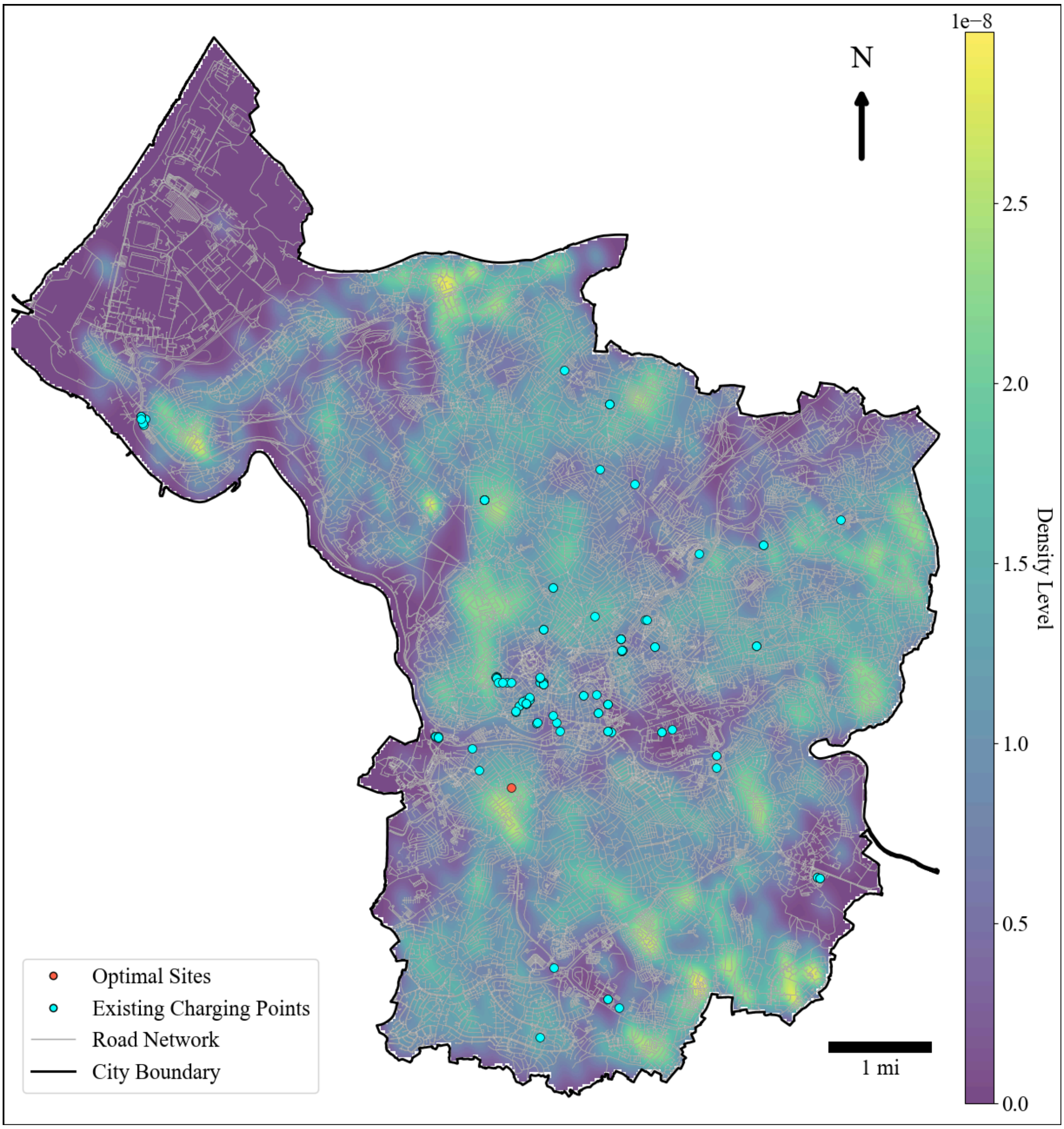

Figure 3. Location of the Optimal Solution

Sensitivity Analysis

This study assessed the robustness of results through two scenario models, to examine how constraint changes affect EV charging station performance by 1) altering the distance algorithm, and 2) modifying the distance decay parameter. Using a different algorithm accounts for real-world factors like road congestion, which can make the shortest path suboptimal (He et al., 2024). The distance decay parameter reflects user preferences, with some prioritizing cost savings over shorter travel or wait times (Habbal and Alrifaie, 2024).

These scenarios facilitate sensitivity analysis to evaluate site robustness under varying assumptions.

XGBoost was employed as an alternative to the shortest path algorithm due to its scalability, reliability, and efficiency (Bentéjac et al., 2020). It achieved a mean absolute error of 0.13 miles (see Appendix A) and its distance distribution closely matched actual data, introducing necessary randomness while maintaining accuracy(see Figure 4).

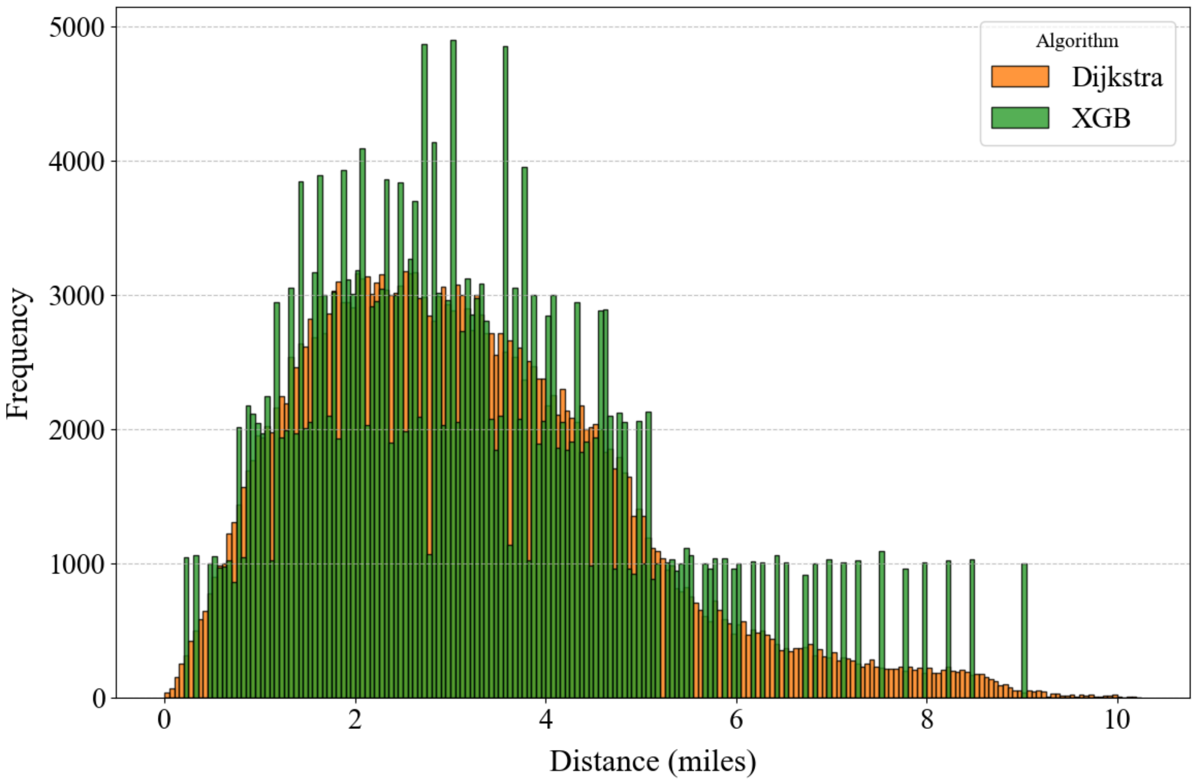

Figure 4. Distribution of Shortest Distance Results

Note. XGBoost is trained using 30% Dijkstra data.

The AHP analysis showed that both shortest-distance algorithms produced identical rankings of high-potential sites, mostly located in the city center and inner suburbs (see Appendix A; Figure 4).

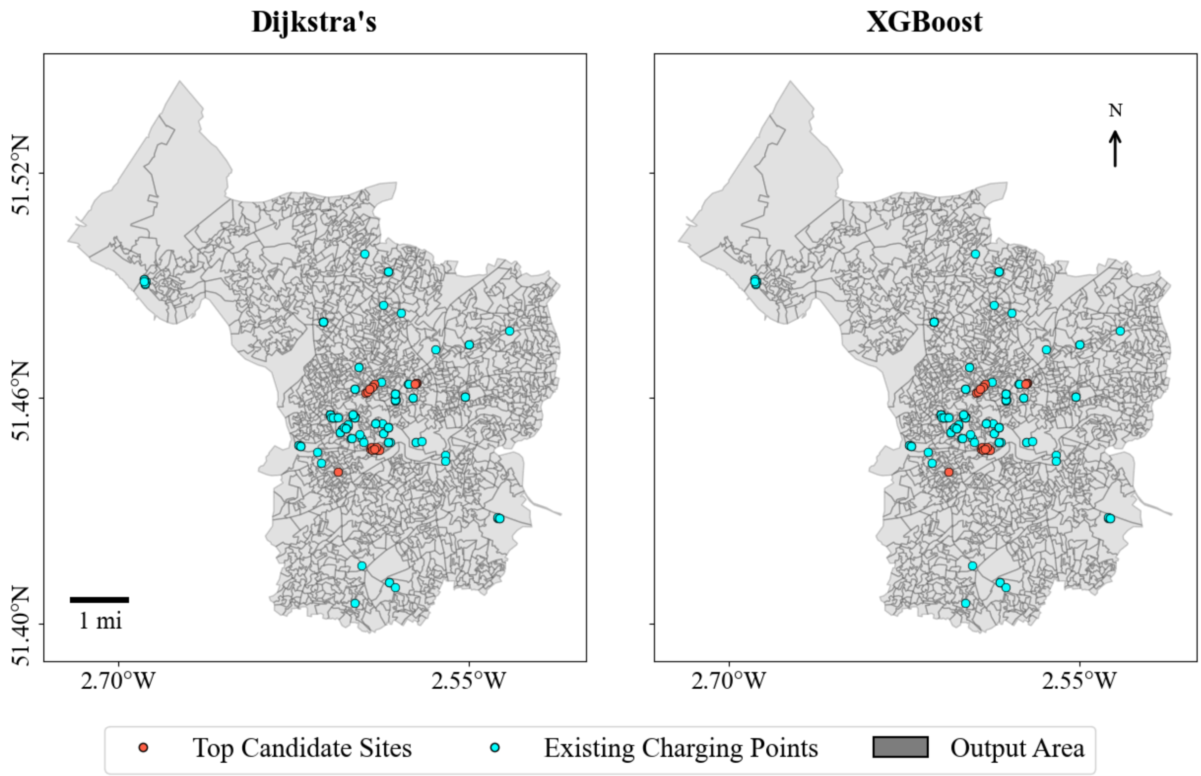

Figure 4. Distribution of High Potential Candidate Points

When β is between -3 and -1.2, Site 57 maintains the optimal solution. However, when β is between -1 and -0.1, Site 38 becomes the optimal point, indicating that it performs better when users tend to charge nearby. It is worth noting that when β is -1.1, Site 54 suddenly surpasses other Sites to become the optimal point. This phenomenon is very interesting and may reveal that this Site has certain advantages under certain conditions (see Figure 5).

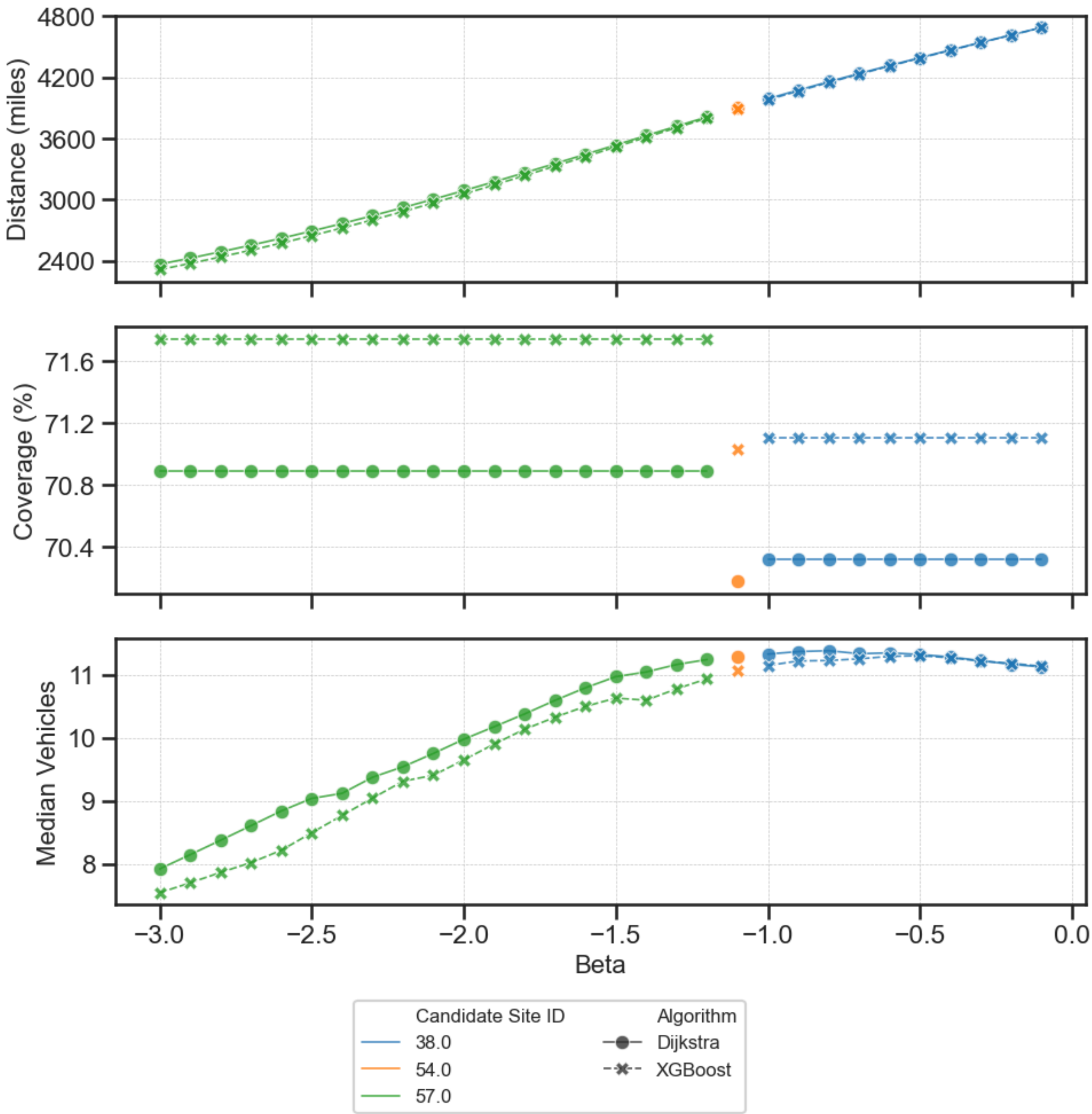

Figure 5. The Optimal Point Changes with Beta Under Different Shortest Path Algorithms

Conclusions and Limitations

Discussion

This study addresses the modelling challenges of EV charging station site selection by combining multi-criteria decision analysis, mixed integer programming, and multi-objective optimization. Using Bristol as a case study, the effectiveness of the proposed framework in selecting sites that meet different user needs and planning objectives is demonstrated. Sensitivity analysis further demonstrates the adaptability of the model under different assumptions (e.g., user behaviour and traffic patterns), highlighting the importance of adopting optimization modelling methods in infrastructure planning. Resulting a replicable framework to support the development of sustainable, user-focused EV charging network systems.

Limitations and Future Improvement

Nevertheless, there are also some limitations. To begin with, the Huff model assumes uniform distance preferences across all regions, which differs from reality. Consumers' preferences vary by purpose (Drezner et al., 2020) and area (Gong et al., 2020). Future research could validate β values across regions through enhanced sensitivity analysis. Moreover, multi-objective optimization often involves conflicts, such as minimizing path distance versus maximizing coverage. The Pareto frontier method (Husarek et al., 2021; Zhang et al., 2024) and fuzzy objective optimization (Gulia et al., 2023) can be combined to better address trade-offs and uncertainties, offering more flexible solutions. Additionally, commercial sustainability was not fully addressed. Factors like maintenance costs and utilization fluctuations might impact operations (Abdi et al., 2022; Alanazi, 2023). Future studies could integrate sustainability indicators, such as cost-benefit analysis (Olcay and Cetinkaya, 2023), demand forecasting (Rashid et al., 2024), and market volatility resilience (Bao et al., 2021).

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Appendix A

Table A1. Comparison of Shortest Path Models

Algorithm	Running Time (Seconds)	MAE (miles)
Dijkstra	250.62	/
XGBoost	165.85	0.13

Table A2. AHP Results Using Dijkstra's Algorithm

Candidate ID	Proximity Score	Expansion Score	Convenience Score	Distance Score	Final Score
29	0.9874	0.9991	0.8970	0.4473	0.8867
27	0.9849	0.9990	0.9066	0.4316	0.8858
26	0.9946	1.0000	0.9079	0.3968	0.8846
28	0.9751	0.9801	0.8777	0.3194	0.8536
25	1.0000	0.9941	0.8537	0.2423	0.8483
38	0.8378	0.7849	0.9893	0.3732	0.7928
55	0.8128	0.7637	0.9846	0.4435	0.7881
37	0.8462	0.8260	0.9611	0.2999	0.7879
34	0.8436	0.7936	0.9739	0.3205	0.7852
33	0.7931	0.7525	0.9768	0.4637	0.7795
57	0.8772	0.6058	0.9072	0.6272	0.7794
12	0.8743	0.7811	0.9293	0.2439	0.7702
54	0.7727	0.7532	0.9571	0.4385	0.7638
13	0.8642	0.7856	0.9261	0.2226	0.7638
53	0.7792	0.7396	0.9747	0.4030	0.7617
35	0.7647	0.7329	0.9758	0.4385	0.7606
11	0.8527	0.7581	0.9242	0.2630	0.7585

Table A3. AHP Results Using XG Boost Algorithm

Candidate ID	Proximity Score	Expansion Score	Convenience Score	Distance Score	Final Score
29	0.9874	0.9991	0.8970	0.4473	0.8867
27	0.9849	0.9990	0.9066	0.4316	0.8858
26	0.9946	1.0000	0.9079	0.3968	0.8846
28	0.9751	0.9801	0.8777	0.3194	0.8536
25	1.0000	0.9941	0.8537	0.2423	0.8483
38	0.8378	0.7849	0.9893	0.3732	0.7928
55	0.8128	0.7637	0.9846	0.4435	0.7881
37	0.8462	0.8260	0.9611	0.2999	0.7879
34	0.8436	0.7936	0.9739	0.3205	0.7852
33	0.7931	0.7525	0.9768	0.4637	0.7795
57	0.8772	0.6058	0.9072	0.6272	0.7794
12	0.8743	0.7811	0.9293	0.2439	0.7702
54	0.7727	0.7532	0.9571	0.4385	0.7638
13	0.8642	0.7856	0.9261	0.2226	0.7638
53	0.7792	0.7396	0.9747	0.4030	0.7617
35	0.7647	0.7329	0.9758	0.4385	0.7606
11	0.8527	0.7581	0.9242	0.2630	0.7585

Table A4. Optimal Results of Sensitivity Analysis Using Dijkstra's Algorithm

Beta	Selected Site ID	Total Distance (miles)	Total Coverage (%)	Median Vehicles per Station	Ranking		
					Goal 1	Goal 2	Goal 3
-3.0	57	2366.79	70.89	7.92	1	1	1
-2.9	57	2425.98	70.89	8.15	1	1	1
-2.8	57	2488.08	70.89	8.37	1	1	1
-2.7	57	2553.11	70.89	8.61	1	1	1
-2.6	57	2621.10	70.89	8.84	1	1	1
-2.5	57	2692.06	70.89	9.04	1	1	1
-2.4	57	2765.95	70.89	9.12	1	1	1
-2.3	57	2842.70	70.89	9.37	1	1	1
-2.2	57	2922.21	70.89	9.54	1	1	1
-2.1	57	3004.33	70.89	9.75	1	1	1
-2.0	57	3088.84	70.89	9.98	1	1	1
-1.9	57	3175.51	70.89	10.18	1	1	3
-1.8	57	3264.03	70.89	10.38	1	1	7
-1.7	57	3354.05	70.89	10.60	1	1	8
-1.6	57	3445.19	70.89	10.80	1	1	8
-1.5	57	3537.03	70.89	10.97	1	1	7
-1.4	57	3629.13	70.89	11.05	1	1	2
-1.3	57	3721.07	70.89	11.16	1	1	17
-1.2	57	3812.42	70.89	11.24	1	1	17
-1.1	54	3902.78	70.18	11.28	1	8	7
-1.0	38	3990.68	70.32	11.33	1	5	7
-0.9	38	4075.03	70.32	11.37	1	5	1
-0.8	38	4157.43	70.32	11.38	1	5	3
-0.7	38	4237.85	70.32	11.34	1	5	7
-0.6	38	4316.38	70.32	11.35	1	5	7
-0.5	38	4393.21	70.32	11.32	1	5	7
-0.4	38	4468.60	70.32	11.28	1	5	1
-0.3	38	4542.87	70.32	11.23	1	5	1
-0.2	38	4616.34	70.32	11.17	1	5	1
-0.1	38	4689.33	70.32	11.13	1	5	1

Table A5. Optimal Results of Sensitivity Analysis Using XGboost Algorithm

Beta	Selected Site ID	Total Distance (miles)	Total Coverage (%)	Median Vehicles per Station	Ranking		
					Goal 1	Goal 2	Goal 3
-3.0	57	2314.03	71.74	7.54	1	1	12
-2.9	57	2374.35	71.74	7.70	1	1	15
-2.8	57	2437.74	71.74	7.86	1	1	16
-2.7	57	2504.24	71.74	8.02	1	1	16
-2.6	57	2573.87	71.74	8.22	1	1	7
-2.5	57	2646.65	71.74	8.49	1	1	7
-2.4	57	2722.53	71.74	8.77	1	1	7
-2.3	57	2801.47	71.74	9.04	1	1	8
-2.2	57	2883.33	71.74	9.31	1	1	8
-2.1	57	2967.98	71.74	9.41	1	1	7
-2.0	57	3055.19	71.74	9.65	1	1	6
-1.9	57	3144.68	71.74	9.90	1	1	8
-1.8	57	3236.09	71.74	10.14	1	1	7
-1.7	57	3329.04	71.74	10.33	1	1	2
-1.6	57	3423.04	71.74	10.50	1	1	2
-1.5	57	3517.61	71.74	10.63	1	1	4
-1.4	57	3612.25	71.74	10.60	1	1	3
-1.3	57	3706.46	71.74	10.78	1	1	3
-1.2	57	3799.80	71.74	10.94	1	1	3
-1.1	54	3891.23	71.03	11.07	1	6	2
-1.0	38	3980.05	71.10	11.15	1	3	1
-0.9	38	4065.88	71.10	11.22	1	3	2
-0.8	38	4149.61	71.10	11.23	1	3	1
-0.7	38	4231.26	71.10	11.26	1	3	1
-0.6	38	4310.93	71.10	11.29	1	3	1
-0.5	38	4388.82	71.10	11.31	1	3	1
-0.4	38	4465.20	71.10	11.27	1	3	1
-0.3	38	4540.36	71.10	11.22	1	3	1
-0.2	38	4614.62	71.10	11.18	1	3	1
-0.1	38	4688.29	71.10	11.14	1	3	1

Appendix B