ISSN: 2688-8645

# Site Selection and Capacity Determination for Urban New Energy Charging Stations Considering Road Network Resilience: A Multi-Objective Optimization Approach

Hua Qiu

School of Management Science and Engineering, Chongqing Technology and Business University, Chongqing 400067, China

1607229793@qq.com

## Abstract

**To enhance the resilience and coverage of urban charging infrastructure networks, this study investigates the site selection and capacity optimization problem for new energy charging stations by considering factors such as point-based demand, flow-based demand, capacity constraints, road network resilience, and disruptive events. A dual-objective 0-1 integer linear programming model was developed to describe the problem. The multi-objective problem was transformed into a single-objective problem using epsilon constraints and solved using the commercial solver Gurobi. The results indicate that: (1) The proposed decision-making scheme that considers network resilience outperforms the scheme that does not; considering road network resilience during the site selection phase is essential and can significantly improve the reliability of the urban charging network. (2) Increasing the number of charging stations can improve demand coverage and network resilience, but this will correspondingly increase construction costs.**

## Keywords

**Site Selection Optimization; Emergencies; Site Selection and Capacity Determination; Resilience; Charging Station Site Selection; Multi-objective Optimization.**

## 1. Introduction

Traditional charging station site selection problems are typically described using either a single point-demand model or a flow-demand model. Typical examples of point-demand models include the maximum coverage model, the set coverage model, the P-median model, and the P-center model [1]. The P-center model seeks to minimize the maximum distance from demand points to stations by selecting P stations such that the open stations can satisfy all demand. The P-center model does not account for heterogeneous demand levels at demand points, potentially leading to service failure risks[2]. The P-median model was first proposed by Hakimi[3] to determine the location of P charging stations under given candidate points, aiming to minimize the sum of demand-weighted distances. The set-coverage model was first proposed by Toregas et al.[4] to cover all demand points using the minimum number of stations. Wang et al. [5] employed mixed-integer programming to determine charging station locations, formulating a set-coverage model aimed at minimizing costs. Since the set-coverage model does not account for resource constraints at stations, Church et al. [6] proposed a maximum-coverage model to cover the greatest number of demand points using a finite number of stations. Hamed et al. [7] introduced stochastic parameters to forecast daytime and nighttime charging demand, studying the maximum-coverage site selection problem under various scenarios.

The point-demand model is now well-established and is commonly found in early research; however, in the site selection of charging stations, it is necessary to consider scenarios where vehicles visit charging stations to recharge due to low battery levels during their journeys. Consequently, the flow-demand model has gained widespread application. Hodgson [8] first proposed the interceptor site selection model in 1990, investigating the site selection scheme that maximizes intercepted traffic given a specific demand route and a fixed number of stations. The FCLM assumes that a single station can intercept all traffic along a route, ignoring the fact that a station's service radius is limited; for example, a new energy vehicle may run out of power while en route to the station[9]. To address this, Yang et al. [10] proposed a hybrid FCLM with a path demand service radius D. If the distance from a station to a node on the path does not exceed D, customers on the path are willing to deviate from their original route to use the new station's services and then return to their original route after charging. Kuby et al. [11] proposed an improved FCLM with traffic replenishment, which divides a path into several segments by combining two or more stations. A path is considered covered only when a set of stations is found that can support the vehicle in completing the entire journey.

The aforementioned studies all consider only single-mode demand, which does not reflect real-world conditions; therefore, some researchers have further proposed a site selection model that integrates point and flow demand [12]. Yang et al. [10] proposed a hybrid FCLM incorporating both path-based and fixed-radius service areas, aiming to maximize both the coverage of point-based demand and the interception of flow-based demand by establishing a fixed number of stations; however, this model did not account for the limited capacity of the stations. Xu et al. [13]proposed a capacity-constrained point-flow fusion model that combines the set-coverage model with the interception model, and also accounts for the uncertainty of charging demand.

Traditional research typically assumes that charging infrastructure networks are fully reliable; however, in real-world environments, charging facilities are susceptible to external factors, and their operational stability is subject to uncertainty. For example, the occurrence of sudden natural disasters such as large-scale destructive earthquakes or typhoons may cause a large number of urban charging stations to shut down, thereby triggering traffic congestion or even gridlock. To ensure that undamaged charging stations can still meet charging demand to the greatest extent possible during major disasters, it is essential to incorporate the concept of resilience into the site selection planning for charging stations. This will help enhance the resilience of urban transportation and provide a solid foundation for the sustainable development of new energy vehicles. Currently, only a few studies have considered resilience factors in the site selection of facilities such as emergency supply depots. For instance, Zhang et al. [14] investigated a two-level planning problem for the site selection of transportation service facilities that accounts for road network resilience. However, the site selection for these facilities differs significantly from that of urban new energy vehicle charging stations, as they do not simultaneously address both point and flow demands.

In light of this, this paper integrates point-to-point and flow-based demands and incorporates road network resilience to construct a dual-objective optimization model for the site selection and capacity determination of urban new energy charging stations that accounts for resilience. This model can effectively simulate various potential outage scenarios and generate a set of alternative solutions—including optimal and non-inferior solutions—for each scenario, significantly expanding the richness and flexibility of the decision-making space. When addressing complex disaster risks and diverse urban demands, decision-makers need not be confined to a single "optimal" solution but can, based on their risk preferences, select the resilience-oriented layout strategy that best fits the actual context from among multiple high-quality solutions. Furthermore, a series of comparative experiments with traditional site selection models demonstrates that, in most simulated scenarios, the model proposed in this paper exhibits significant advantages in key performance metrics. This validates its superiority in enhancing the disaster resilience of urban new energy charging infrastructure networks and

ISSN: 2688-8645

ensuring the effective operation of transportation systems during emergencies, thereby providing a more practical reference for decision-making regarding the planning and layout of charging facilities.

# 2. Establishing a Dual-Objective Model for Site Selection and Capacity Determination of Urban Renewable Energy Projects Considering Resilience

## 2.1. Problem Description

During the planning phase of urban new energy charging stations, it is essential to consider the possibility of sudden station outages caused by large-scale destructive natural disasters and to establish an efficient and resilient charging network. We define the problem on a network G = (Y, E), where Y is the vertex set consisting of demand points i and charging stations j, and E is the edge set representing demand flow paths. Figure 1 illustrates the charging behavior of point-demand users. Points A, B, C, D, and E represent the travel destinations of point-demand users, and the areas within the circles indicate the coverage ranges of charging stations. When charging stations are operational, point-demand users can choose any charging station covering their travel destination to charge; when a charging station is out of service, users will switch to other open charging stations covering their destination to charge. Figure 2 illustrates the charging behavior of flow-demand users. When no charging stations are out of service, users can choose any charging station along their travel route to charge; when a charging station is out of service, users proceed to other open charging stations along their travel route to charge. This paper aims to maximize both the demand covered by charging stations and the resilience of the urban road network through rational site selection and capacity determination decisions.

Set multi-level capacity thresholds for the number of charging points each station must serve. Let c denote the capacity level of a candidate charging station, and b denote the capacity level of an existing charging station. When making site selection decisions, the optimization of capacity determination (and expansion) for charging stations is also integrated.

The problems to be addressed are: How many new charging stations should be built? Where should they be located? How should their capacities be determined? How should the capacity of existing charging stations be expanded? Which charging station should serve point-based demand? Which charging station should capture flow-based demand?

This paper makes the following assumptions:

(1) Under the point-based demand model, users select a charging station within the service area to receive service.

(2) Under the flow-based demand model, users choose the shortest path between the origin and destination for their trip.

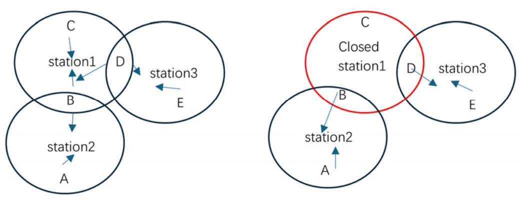


**Fig 1.** Schematic Diagram of Point-to-Point Traffic Demand

ISSN: 2688-8645

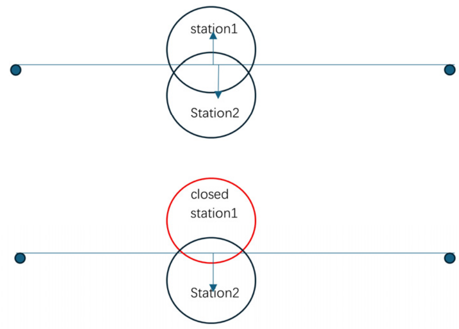


**Fig 2.** Schematic Diagram of Flow Demand

## 2.2. Symbol

Set:

$Q$ denotes the set of trips in the road network $q \in Q$;

$I$ denotes the set of demand points, $i \in I$;

$J$ denotes the set of all charging stations, $j \in J$;

$J_e$ denotes the set of existing charging stations;

$J_n$ denotes the set of candidate locations for new charging stations;

$J_n / M$ denotes the set of unaffected candidate charging stations when a disruptive event occurs;

$J_e / M$ denotes the set of unaffected, already-built candidate charging stations when a disruptive event occurs;

$C$ denotes the set of charging station capacity levels, $c \in C$;

$B$ denotes the set of expansion levels for existing charging stations, $b \in B$;

$E$ denotes the set of catastrophic event scenarios, $e \in E$

Parameters:

$D_i$ denotes the charging demand at demand point $i$;

$D_q$ represents the charging demand for the trip;

$U$ represents the service capacity of a single charging station;

$P_c$ represents the charging capacity of charging stations at candidate locations;

$P_b$ represents the number of charging stations added to existing charging stations of a certain grade;

$M$ represents the number of charging stations to be built;

$N$ represents the number of charging stations already built;

$O$ represents the capacity of the existing charging stations;

$e^q$ denotes a destructive event;

$t^{i,j}$ represents the travel time for an electric vehicle from node $i$ to node $j$ when no disruptive events occur;

$t_e^{i,j}$ represents the travel time from node $i$ to node $j$ for an electric vehicle when a disruptive event occurs;

γ represents the average waiting time for electric vehicles at a charging station;

$l_{ij}$ represents the distance from demand point $i$ to candidate charging station j;

$l_{qj}$ denotes the shortest path distance from flow source $q$ to charging station candidate $j$ ;

$a_{ij}^{e}$ indicates that, in scenario $e$ , if demand point $i$ is within the service area of charging station $j$ and is not out of service is 1; otherwise is 0;

$b_{qj}^{e}$ indicates that, under scenario e, if the flow demand $q$ is within the service area of charging station $j$ and the station is not out of service is 1; otherwise is 0;

$W_{j}^{e}$ represents the availability of charging station $j$ under scenario $e$ . For existing charging stations, they are assumed to be available by default but may become unavailable due to events; for new charging stations, they contribute capacity only when they are built and available.

Decision variables:

$X_{jc}$ Let $X_{jc}$ be a variable taking values between 0 and 1; it is 1 if a charging station with capacity $c$ is built at location $j$, and 0 otherwise.

$X_{kb}$ Let $X_{kb}$ be a variable taking values between 0 and 1. If an expansion of level $b$ is performed at an existing charging station $k$, $X_{kb}$ is 1; otherwise, $X_{kb}$ is 0.

$Y_{i}^{e}$ Let $Y_{i}^{e}$ be a variable taking values between 0 and 1. If demand point $i$ at location e is served by charging station $j$, $Y_{i}^{e}$ is 1; otherwise, $Y_{i}^{e}$ is 0.

$Z_{q}^{e}$ Let $Z_{q}^{e}$ be a variable taking values between 0 and 1; it is 1 if the flow demand is captured by charging station $j$ in scenario $e$, and 0 otherwise.

## 2.3. A Dual-Objective Optimization Model for Site Selection and Capacity Determination in Point-Flow Integration

Construct a dual-objective optimization model for the site selection and capacity determination of urban new energy charging stations that integrates point and flow demand. Objective function (1) maximizes the sum of point and flow demand coverage:

$$z=\sum_{i\in I}D_{i}Y_{i}^{e}+\sum_{q\in Q}D_{q}Z_{q}^{e},\forall e\in E \tag{1}$$

In Equation (1), the first term represents the demand for points covered under scenario e, and the second term represents the demand for flows covered under scenario e.

$$\max f_{1} \tag{2}$$

$$f_{1}\le z,\forall e\in E \tag{3}$$

The objective function (2) aims to maximize the total coverage requirement under the worst-case scenario.

Equation (3) indicates that $f_1$ does not exceed the actual coverage requirement under any scenario e.

Based on the toughness calculation method proposed in Reference [14], the maximum toughness target for the charging station can be expressed as:

$$\max R\left(u',e^{q}\right)=\frac{F\left(u,e^{q}\right)-F\left(u',e^{q}\right)}{F\left(u,e^{q}\right)-F\left(u\right)} \tag{4}$$

In Equation (4), $u$=( $Y_i$ , $X_{jc}$ , $X_{kb}$ ),is a vector composed of decision variables $Y_i$ , $X_{jc}$ and $X_{kb}$,corresponding respectively to whether demand point $i$ is covered by a charging station, whether to build a charging station with capacity $c$ at candidate point $j$ and whether to perform a level $b$ expansion at existing charging station $k$ . $u$ and $u'$ represent the two charging station configurations that do not consider and do consider a disruptive event, respectively., $F(u)$ denotes the total time consumed by all electric vehicles before the occurrence of the disruptive event $e^q$ , $F\left(u,e^q\right)$ denotes the total time spent by electric vehicles in system configuration $u$ after the occurrence of the disruptive event $e^q$ , $F\left(u',e^q\right)$ denotes the total time spent by electric vehicles in the resilient design configuration $u'$ during the occurrence of the disruptive event $e^q$ ,Maximizing the resilience function $R\left(u',e^q\right)$ is equivalent to minimizing the function $F\left(u',e^q\right)$ via the decision variable $u'$ .Therefore, the objective function for maximizing resilience can be simplified to minimizing $f_2$ :

$$\begin{aligned} minf_2 = \sum_{i\in I} D_i t_{,}^{i,j} a_{ij}^e y_i^e + \\ \gamma \mathrm{U}\left(\sum_{j\in J_n/M} \sum_{i\in I} \sum_{c\in C} P_c a_{ij}^e X_{jc} + \sum_{k\in J_s/M} \left(\sum_{i\in I} \sum_{b\in B} P_b a_{ik}^e X_{kb} + ON\sum_{i\in I} a_{ik}^e\right)\right) \end{aligned} \tag{5}$$

Objective function (5) represents the time spent by the vehicle in the resilient configuration when a disruptive event occurs. The first term represents the travel time for the electric vehicle en route to the charging station; the second term represents the waiting time while queuing at a candidate charging station; and the sum of the third and fourth terms represents the waiting time while queuing at an existing charging station.

$$\sum_{c\in C} X_{jc} \le 1, \forall j \in J_n \tag{6}$$

Equation (6) indicates that only one capacity class of charging station can be established at each candidate site.

$$\sum_{b\in B} X_{kb} \le 1, \forall k \in J_e \tag{7}$$

Equation (7) indicates that each existing charging station can be expanded only once.

$$\sum_{c\in C} \sum_{j\in J_n} X_{jc} = M \tag{8}$$

Equation (8) represents the construction of M new charging stations.

$$\sum_{j\in J_n} \sum_{c\in C} a_{ij}^e X_{jc} + \sum_{j\in J_e} \left(\sum_{b\in B} a_{ij}^e X_{jb} + a_{ij}^e\right) \ge Y_i^e, \forall i \in I, e \in E \tag{9}$$

Equation (9) indicates that, in scenario $e$ , demand point $i$ is covered if and only if at least one available charging station (new or existing) is within its service area.

$$\sum_{j\in J_n} \sum_{c\in C} b_{qj}^e X_{jc} + \sum_{j\in J_e} \left(\sum_{b\in B} b_{qj}^e X_{jb} + b_{qj}^e\right) \ge Z_q^e, \forall q \in Q, e \in E \tag{10}$$

Equation (10) indicates that, in scenario $e$, the flow demand $q$ is met if and only if at least one available charging station is within its service area.

$$\sum_{i\in I} D_i Y_i^e + \sum_{q\in Q} D_q Z_q^e \le U\left(\sum_{j\in J_n} \sum_{c\in C} P_c X_{jc} W_j^{\mathrm{e}} + \sum_{k\in J_{\mathrm{e}}} \left(O + \sum_{b\in B} P_b X_{kb}\right) W_k^{\mathrm{e}}\right), \quad \forall e \in E \tag{11}$$

Equation (11) indicates that, under scenario $e$, the total service demand does not exceed the total service capacity of available charging stations. Here, $W_j^e$ represents the availability of charging station j under scenario $e$, ensuring that only available stations contribute to the capacity.

$$X_{jc} \in \{0,1\}, \forall j \in J_n, c \in C \tag{12}$$

$$X_{kb} \in \{0,1\}, \forall k \in J_e, b \in B \tag{13}$$

$$Y_i^e \in \{0,1\}, \forall i \in I, e \in E \tag{14}$$

$$Z_q^e \in \{0,1\}, \forall q \in Q, e \in E \tag{15}$$

Equations (12), (13), (14), and (15) specify the constraints on the ranges of the decision variables.

### 2.4. A Multi-Objective Optimization Algorithm Based on Epsilon Constraints

The Epsilon-constraint algorithm is a classic method for solving multi-objective problems. It transforms a given objective function into a set of constraints, thereby converting a multi-objective problem into a single-objective problem for solution. This paper employs an Epsilon-constraint-based multi-objective algorithm for the solution, with the specific steps outlined below:

Step 1: Set the maximum value of the worst-case coverage requirement $max f_1$ as the primary objective, and minimize user time consumption $min f_2$ as a secondary objective;

Step 2: Determine the range of ε as [$f2_{min}$, $f2_{max}$] by calculating the independent minimum $f2_{min}$ and independent maximum $f2_{max}$ of $f_2$, set the step size to Δ (set to 1 in this paper), and define the set of candidate Pareto-optimal solutions as P ≠ ∅;

Step 3: Convert f2(x) into a constraint, transform the two-objective problem into a single-objective problem to solve for f1(x), and incorporate the solved values of f1(x) and f2(x) into P.

$$max f_1$$

S.t.

$$f_2 \le \varepsilon \tag{16}$$

constraint (3)(6)-(16)

Step 4: If $\varepsilon < f2_{max}$ , then ε ← ε + Δ; return to Step 3 and continue the loop; otherwise, proceed to Step 5;

Step 5: Process the set of candidate Pareto-optimal solutions P to remove the dominated solutions, thereby obtaining the problem's Pareto front.

## 3. Case Study Analysis

### 3.1. Case Study on the Transportation Network in Chaoyang District, Beijing

#### 3.1.1. Example Network and Parameter Settings

Using data from Reference [13], specifically the charging station network in Chaoyang District, Beijing, we conduct a practical case study analysis. The dataset includes 30 demand points and 10 candidate charging station locations, with 5 origin-destination (OD) pairs selected as sources of traffic demand. The distribution of candidate charging station locations is shown in Table 1, and the geographic distribution of demand points is shown in Table 2. Eight charging station candidate sites and two existing charging stations are defined. The existing charging stations are designated as I and J, each with a capacity of 15 charging piles; the remaining sites are candidate sites. The expansion level for the existing charging stations and the capacity level for the candidate sites are both set to 5, with the number of charging piles at each level being (2, 3, 4, 5, 6) and (10, 12, 14, 16, 18), respectively. The daily service capacity U of a single charging is 9 vehicles, and the service radius of a single charging station is 3.5 kilometers. The average waiting time $\gamma$ for an electric vehicle at a charging station is 30 minutes. Following a disruptive event, the average travel speed of electric vehicles is 20 km/h, and $t_{r}^{i,j} = 3 * l_{ij}$ minutes. Twenty random outage scenarios for charging stations are generated.

**Table 1.** Geographical Distribution of Potential Charging Station Locations

| No | CoordinatesX | CoordinatesY | No | CoordinatesX | CoordinatesY |
|---|---|---|---|---|---|
| A | 3.75 | 7.05 | F | 6.90 | 2.30 |
| B | 3.84 | 5.08 | G | 9.20 | 1.97 |
| C | 7.18 | 5.13 | H | 13.05 | 5.57 |
| D | 4.41 | 2.13 | I | 15.61 | 4.90 |
| E | 8.44 | 3.30 | J | 15.24 | 1.17 |

### 3.1.2. Analysis of the Calculation Results

The model was solved using Gurobi 11.1. Table 4 presents the results for some typical Pareto-optimal solutions. The analysis indicates that even if a catastrophic event causes the charging station to shut down, the site selection schemes generated by this model can still meet the majority of both point and flow demands under worst-case scenarios, demonstrating strong road network resilience. Furthermore, the model provides multiple sets of site selection schemes, capable of meeting the diverse decision-making needs of decision-makers with varying preferences and risk tolerances.

### 3.1.3. Results of the Sensitivity Analysis on the Number of Charging Stations

**Table 2.** Geographical Distribution of Demand Points

| No | CoordinatesX | CoordinatesY | Point demand | No | CoordinatesX | CoordinatesY | Point demand |
|---|---|---|---|---|---|---|---|
| 1 | 0.90 | 8.62 | 33 | 16 | 11.94 | 5.71 | 40 |
| 2 | 2.46 | 7.15 | 35 | 17 | 14.91 | 6.27 | 33 |
| 3 | 5.17 | 7.41 | 22 | 18 | 12.62 | 4.31 | 25 |
| 4 | 6.13 | 6.47 | 29 | 19 | 14.11 | 5.38 | 28 |
| 5 | 2.81 | 5.38 | 28 | 20 | 18.14 | 6.83 | 24 |
| 6 | 3.77 | 3.66 | 24 | 21 | 16.98 | 6.18 | 30 |
| 7 | 5.32 | 5.12 | 37 | 22 | 16.14 | 4.20 | 29 |
| 8 | 8.10 | 5.47 | 37 | 23 | 15.33 | 2.83 | 30 |
| 9 | 5.52 | 3.47 | 30 | 24 | 14.56 | 1.64 | 23 |
| 10 | 4.89 | 2.08 | 40 | 25 | 16.09 | 0.99 | 22 |
| 11 | 7.17 | 1.87 | 23 | 26 | 9.57 | 2.58 | 27 |
| 12 | 6.87 | 4.05 | 38 | 27 | 8.39 | 1.04 | 33 |
| 13 | 8.53 | 4.22 | 26 | 28 | 9.42 | 0.72 | 24 |
| 14 | 12.05 | 7.10 | 29 | 29 | 10.61 | 1.27 | 33 |
| 15 | 13.32 | 7.50 | 33 | 30 | 12.23 | 0.62 | 25 |

A sensitivity analysis of the number of charging stations was conducted for various random outage scenarios. The results are shown in the figure. As shown in Figures 3, in the event of a disruptive incident, the demand that charging stations can cover under the worst-case scenario increases as the number of operational charging stations increases. For the same level of demand coverage, establishing more charging stations can enhance the resilience of the urban transportation network, but it also leads to higher costs. Therefore, the planning phase must balance safety and economic considerations based on actual conditions.

**Table 3.** Distribution of Demand and Demand Volume

| Flow | List of Potential Charging Station Locations | Flow demand |
|---|---|---|
| 1 | A,B,D | 35 |
| 2 | A,H,I | 25 |
| 3 | B,C,J | 32 |
| 4 | D,F,G | 40 |
| 5 | H,I,J | 50 |

**Table 4.** Selected optimization results

| | Requirements for worst-case scenario coverage | Resilience | Site Selection Results | Capacity Selection | Results of Capacity Expansion for Existing Charging Stations |
|---|---|---|---|---|---|
| Solution1 | 504<br>Coverage:48% | 2905318 | A C D G H | 10,10,16,10,10 | 0,0 |
| Solution2 | 630<br>Coverage:60% | 3384049 | A C D G H | 18,10,18,10,14 | 0,0 |
| Solution3 | 764<br>Coverage:73% | 4071199 | A D E G H | 18,18,18,14,18 | 0,2 |
| Solution4 | 810<br>Coverage:78% | 4383516 | A D E G H | 18,18,18,18,18 | 0,6 |

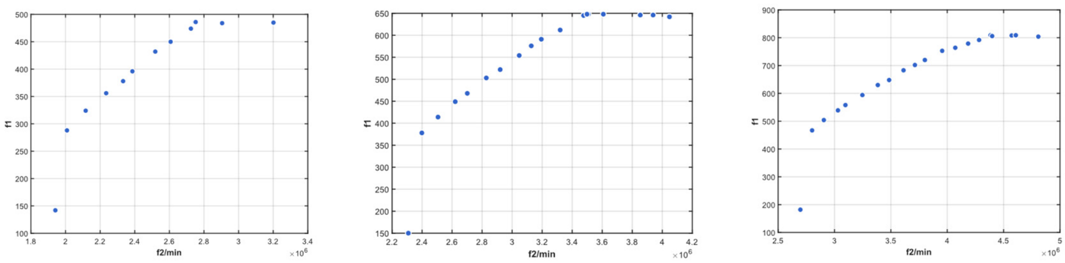

Fig. 3-1 Pareto solution when m = 3 Fig. 3-2 Pareto solution when m = 4 Fig. 3-3 Pareto solution when m = 5

**Fig 3.** Sensitivity Analysis of Different Numbers of Charging Stations

### 3.1.4. Comparison of Decision Outcomes with and without Resilience

To further evaluate the optimization performance of the model presented in this paper, we set m=5 and compared the results obtained with and without considering resilience. The results are shown in Table 5. As shown in Table 5, when a catastrophic event causes a random charging station to shut down, the site selection results that incorporate resilience outperform those that do not. The bolded data in the table indicate superior performance for that specific metric. A solution is considered a “superior solution” if it excels on both metrics, a “non-inferior solution” if it excels on one and is inferior on the other, and an “inferior solution” if it is inferior on both. The results indicate that the model yields 3 non-inferior solutions, 1 superior solution, and 0 inferior solutions. Decision-makers may select the superior solution for charging station deployment. Under the same demand coverage target, the superior solution achieves a 5.8% improvement in the resilience target.

**Table 5.** Comparison of Decision Outcomes with and without Resilience

| Without considering the resilience configuration | | Consider resilience configuration | |
|---|---|---|---|
| Worst-case demand coverage | Resilience | Worst-case demand coverage | Resilience |
| 810 | 4653603 | 504 | **2905318** |
| | | 630 | **3384049** |
| | | 764 | **4071199** |
| | | **810** | **4383516** |

## 3.2. Random Large-Scale Traffic Network Case Study

### 3.2.1. Network and Settings

This section presents a case study analysis of a larger-scale simulated traffic network to evaluate the effectiveness of the testing method in such networks. In a 50×50 km grid, 100 demand points, 34 candidate charging station locations, and 6 existing charging stations were randomly generated. For traffic demand, following the approach in Reference[13], the Nguyen-Dupuis network was used to generate demand, and 10 paths were selected from the results. The charging demand for each demand point is randomly generated within the range [20, 30], and the charging demand for each path is randomly generated within the range [40, 80], All existing charging stations have a capacity of 15 charging points. The expansion level for existing charging stations and the capacity level for candidate charging station sites are both set to 5, with the number of stations at each level being (2, 3, 4, 5, 6) and (10, 12, 14, 16, 18), respectively. The daily service capacity U of a single charging point is 9 vehicles, and the service radius of a single charging station is 3.5 kilometers. The average waiting time $\gamma$ for an electric vehicle at a charging station is 30 minutes. Following a disruptive event, the average travel speed of electric vehicles is 20 km/h, and $t_r^{i,j}=3*l_{ij}$ minutes. Twenty random scenarios of charging station outages are generated.

### 3.2.2. Sensitivity Analysis

A sensitivity analysis was conducted on the number of charging stations under the assumption that 10 stations were randomly taken out of service; the results are shown in Figure 4. The results indicate that as the number of charging stations increases, the required coverage demand also increases. For a given coverage demand, establishing a larger number of charging stations enhances the resilience of the urban road network, consistent with the results of the practical example in the previous section.

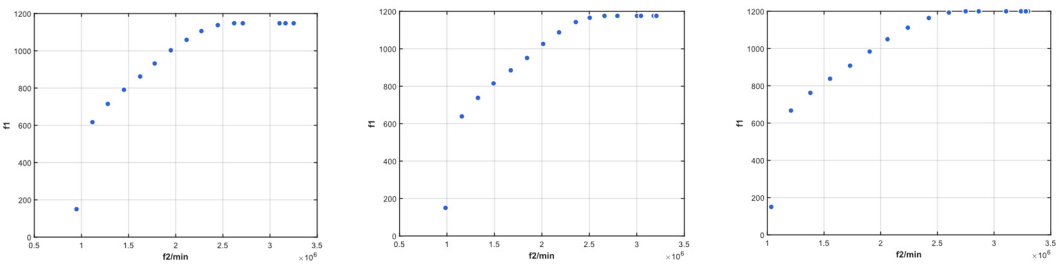


Fig.4-1 Pareto solution when m = 12 Fig.4-2 Pareto solution when m = 13 Fig.4-3 Pareto solution when m = 14

**Fig 4.** Sensitivity Analysis of the Number of Charging Stations Built

The following section compares the computational results for configurations that account for resilience with those that do not; the results are presented in Table 6. The results indicate that when a disruptive event causes a charging station to shut down, the resilience-based configuration performs significantly better than the non-resilience-based configuration, yielding 4 optimal solutions, 3 non-suboptimal solutions, and 0 suboptimal solutions. The superior solutions achieve an average 33% improvement in resilience metrics while maintaining the same level of demand coverage. Under the premise of meeting the same demand coverage, the resilience-considered configuration scheme can significantly enhance the resilience level of the urban road network. Furthermore, the solutions derived from this scheme are more diverse, providing planning departments with greater flexibility in making trade-off decisions between demand coverage and road network resilience.

**Table 6.** Comparative Analysis of Resilient and Non-Resilient Configurations in the Event of a Disruptive Incident

| Without considering the resilience configuration | | Consider resilience configuration | |
|---|---|---|---|
| Worst-case demand coverage | Resilience | Worst-case demand coverage | Resilience |
| 1148 | 4154038 | 617 | **1116277** |
| | | 791 | **1450804** |
| | | 932 | **1776546** |
| | | **1148** | **2619733** |
| | | **1148** | **2711614** |
| | | **1148** | **2711886** |
| | | **1148** | **3.100861** |

## 4. Summary

This chapter considers road network resilience, integrates point-of-demand and flow-of-demand factors, and employs a worst-case coverage model to study the site selection and capacity determination of urban new energy charging stations. The aim is to design a charging network that combines a wide coverage of charging demand with a high level of urban road network resilience. Whether under normal conditions or during sudden disruptive events, the site selection scheme proposed in this paper—which incorporates resilience considerations—performs better than schemes that do not, in terms of both demand coverage capability and road network resilience.

Sensitivity analysis results indicate that: (1) increasing the number of charging stations can effectively enhance demand coverage capacity during facility outages, but this leads to higher costs, requiring a comprehensive trade-off based on the marginal benefits of facility configuration; (2) while maintaining the same level of demand coverage, increasing the number of charging stations helps improve road network resilience, but correspondingly raises construction costs, requiring decision-makers to balance cost investments against the benefits of demand coverage and resilience enhancement.

Future research could explore robust optimization models that account for demand uncertainty. Additionally, a two-level optimization model could be developed by integrating the operator as the upper-level decision-maker and users as the lower-level decision-makers, thereby maximizing the expected utility for both supply and demand sides.

ISSN: 2688-8645

# References


[1] Wang Z P, Zhang J, Liu P, et al. A Review of Research on Electric Vehicle Charging Station Planning [J]. Journal of Chinese Highway and Transport, 2022, 35(12): 230–252.

[2] Yi W F, Yu Y Z, Zhang Y W, et al. Optimization Planning of Energy Stations in Regional Integrated Energy Systems Based on the p-Median Model [J]. Automation of Electric Power Systems, 2019, 43 (04): 107–112.

[3] HAKIMI S L. Optimum locations of switching centers and the absolute centers and medians of a graph[J]. Operations Research, 1964, 12(3): 450-459.

[4] TOREGAS C, SWAIN R, REVELLE C, et al. The location of emergency service facilities[J]. Operations Research, 1971, 19(6): 1363-1373.

[5] WANG Y W, WANG C R.Locating passenger vehicle refueling stations[J].Transportation Research Part E:Logistics and Transportation Review,2010,46(5):791-801.

[6] CHURCH R, REVELLE C.The maximal covering location problem[C]//Papers of the Regional Science Association.[S.l.]:Springer-Verlag,1974,32(1):101-118.

[7] HAMED M M, KABTAWI D M, Al-Assaf A, et al. Random parameters modeling of charging-power demand for the optimal location of electric vehicle charge facilities[J]. Journal of Cleaner Production, 2023, 388: 136022.

[8] HODGSON M J. A flow-capturing location-allocation model[J].Geographical Analysis,1990, 22 (3): 270-279.

[9] Zhang C Y. A Study on a Site Selection Model for Electric Vehicle Charging Stations Considering Charging Choice Behavior and Range Anxiety [D]. Jilin University, 2021.

[10] Yang J, Zhang M, Chen X. A Service Station Interception Location-Allocation Problem with Service Radii [J]. Theory and Practice of Systems Engineering, 2006, (01): 117–122.

[11] KUBY M, LIM S. The flow-refueling location problem for alternative-fuel vehicles[J]. Socio-Economic Planning Sciences, 2005, 39(2): 125-145.

[12] HODGSON M J, ROSING K E. A network location-allocation model trading off flow capturing and p-median objectives[J]. Annals of Operations Research, 1992, 40(1): 247-260.

[13] Xu W, Lu W J, Chen Z Q. A Robust Optimization-Based Model for the Integrated Location Selection of Electric Vehicle Charging Stations [J]. Journal of Systems Management, 2024, 33(04): 901–913.

[14] ZHANG X, HU Z, MAHADEVAN S. Bilevel optimization model for resilient configuration of logistics service centers[J]. IEEE Transactions on Reliability, 2020, 71(1): 469-483.