Location model of electric vehicle charging stations

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Abstract. Due to rapid development of the economy, resource scarcity and environmental contamination are becoming increasingly significant. Electric vehicles have become a main direction for positive development. Charging stations are an energy supplement infrastructure for electric vehicles. How to provide reasonable electric vehicle charging station locations and capacity plans for different regions is the theme of this article. Based on the idea of gradual cover and the location of the charging stations, we propose a distance satisfaction function to improve the model. As the supporting infrastructure for electric vehicles, the location of electric vehicle charging stations has highly important significance for the promotion of electric vehicles. To solve the problem of location selection of an electric vehicle charging station and fully cover the demand point, we used the set coverage model and distance satisfaction function to propose a set coverage model based on distance satisfaction.

1. Introduction

In recent years, with the influence of resources, the environment, and financial crisis, many countries have promoted electric vehicle industry development. Charging stations and their locations are important factors impacting the development of electric vehicles.

Although there are many solutions for selecting optimal locations for charging stations, they mainly include two aspects: graph theory and mathematical programming. Frade I et al. [1] proposed a location model based on maximal covering. Furthermore, Klastorin T. D. [2] illustrates how frequently encountered problems in achieving maximum coverage location raise general distribution issues for other discrete public and private location issues. Mehmet Cem Catalbas et al. [3] believed that charging station location is highly correlated with electric vehicle density and traffic density. They use data mining methods to estimate, and finally use the image processing method to eliminate clustering errors. S. Chen et al. [4] investigated the optimal location of a charging station as a candidate point. Then, they established the optimization model to solve optimization problems using a genetic algorithm. M. Cruz-Zambrano et al. [5] used two methods to search for fast charging stations. One is a classical flow-capturing optimization model involving only mobility needs. The other is an advanced flow-capturing optimization model including distribution network and location costs. A detailed discussion on this topic is in Church R. L. et al. [6]'s article. In 1986, Church R. L. and Weaver J. R. probed into theoretical links between median and coverage location problems. Considering energy sources, Mauri G. [7] studied the role of fast charging stations for electric vehicles in the integration and optimization of a distribution grid with renewable energy sources.

Although the maximal cover model can describe site selection well, at present, it is not suitable for sparsely populated areas. Furthermore, maximal coverage does not describe the type of charging pile
well. Now, people use more single-objective programming, which cannot describe the charging station construction plan due to a variety of factors.

In addition, Morns Brenna et al. [8] considered some constraints (open costs, distance between charging stations and customers, etc.). Hence, we proposed a model based on distance satisfaction.

2. Materials and methods

2.1. A logical problem of charging

Before introducing the model, we will present the charging characteristics of electric vehicles. The difference in location between a charging station in the location model and the location of a typical service facility influences the consumer’s choice of where to charge an electric vehicle while in the process of driving. This decision making describes the charging logic mentioned earlier. We analyzed charging characteristics using a simple electric vehicle driving process as an example.

![Figure 1](image1)

**Figure 1.** (a) is a schematic of a route without a charging station (b) is the route after point 3 is set as the charging station.

As shown in Figure 1, electric vehicles pass by three nodes between the starting point and end of the road. We used the Tesla electric car maximum mileage of 170 miles as a standard. It starts at full capacity and consumes 45 miles of energy from Start to point 1, which means there is no need to consider building a charging station at point 1. As long as the car has enough remaining energy to travel 75 miles from point 1 to point 2, it can successfully reach point 2. The car had enough remaining energy to travel the 25 miles from point 2 to point 3 but did not have enough to reach the End. Therefore, it is necessary to build a charging station at point 3 so that the car is able to reach the End.

Thus, the charging characteristics of the vehicle can be described with the following points:

Suppose vehicle \( m \) is going from point \( i \) to point \( j \), and its energy must satisfy the energy consumed between two points \( i \) and \( j \). Otherwise, a charging station should be built at point \( i \), which can be expressed by the formula characteristic \( B_{im} + R_{im} \geq d_{ij} \), where \( B_{im} \) represents the remaining amount of electricity of vehicle \( m \) at point \( i \), \( R_{im} \) represents the amount of electricity added by vehicle \( m \) at point \( i \), and \( d_{ij} \) represents the distance between two points \( i \) and \( j \).

The remaining amount of electricity at point \( j \) is equal to the remaining amount of electricity at point \( i \) plus the amount of electricity recharged at point \( i \) minus the distance between two points \( i \) and \( j \): \( B_{jm} = (B_{im} + R_{im}) - d_{ij} \).

If the vehicle is to be recharged at point \( i \), then its total charge after charging cannot exceed the maximum capacity of the vehicle battery itself: \( R_{im} \leq \beta - B_{im} \), where \( \beta \) represents the maximum capacity of the battery.

In the above three conditions, \( B_{im} \) and \( R_{im} \) are greater than zero to ensure the smooth running of electric vehicles.
2.2. Traditional models
Set Cover Model:

\[
\begin{align*}
\text{minimize} & \quad \sum_{j \in M} c_j X_j \\
\text{s.t.} & \quad X_j \in \{0,1\} \quad \forall j \in M \\
 & \quad Y_{ij} \in \{0,1\} \quad \forall i \in N, j \in M \\
 & \quad \sum_{j \in M} Y_{ij} X_j \geq 1 \quad \forall i \in N \\
\end{align*}
\]

(1)

Maximum Cover Model:

\[
\begin{align*}
\text{maximize} & \quad \sum_{i \in N} H_i \\
\text{s.t.} & \quad X_j \in \{0,1\} \quad \forall j \in M \\
 & \quad Y_{ij} \in \{0,1\} \quad \forall i \in N, j \in M \\
 & \quad \sum_{j \in M} c_j X_j \leq C_1 \\
\end{align*}
\]

(2)

We show the meaning about notations in Table 1.

| Notations | Definitions |
|-----------|-------------|
| \( N \)   | Demand point sets |
| \( M \)   | Candidate point sets |
| \( i \)   | The \( i \)th demand point, \( i \in N \) |
| \( j \)   | The \( j \)th candidate station point, \( j \in M \) |
| \( d_{ij} \) | The distance of demand point \( i \) to station point \( j \) |
| \( X_j \) | If building station in point \( j \), then \( X_j = 1 \), else \( X_j = 0 \) |
| \( H_i \) | If demand point \( i \) is covered, then \( H_i = 1 \), else \( H_i = 0 \) |
| \( Y_{ij} \) | If demand point \( i \) can be covered by station point \( j \) in range \( R \) \((0 \leq d_{ij} \leq R)\), then \( Y_{ij} = 1 \), else \( Y_{ij} = 0 \) |
| \( H_i \) | If the demand at the demand point is satisfied, the demand point is covered, \( H_i = 1 \), otherwise \( H_i = 0 \) |
| \( c_1 \) | The average cost of building a charging station |
| \( C_1 \) | Tesla builds charging station budget in the area |
| \( R \)   | The coverage range radius of charging station |

2.3. Our model
The traditional set cover model and maximum cover model simply determine whether the demand point is covered by the distance from the demand point to the charging station. Only when the distance is less than the coverage radius can the requirement be fully covered. If the distance is larger than the coverage radius, it is not covered at all. This is inconsistent with real life. For this reason, Drezner,
Berman [9], and Orhan, Karaskal et al. [10] proposed a gradual cover model. Based on the idea of gradual cover and the location of the charging station, we proposed a distance satisfaction function.

The distance satisfaction function is defined as the degree of satisfaction from the demand point to the charging station distance. When the distance from the charging station to the demand point is longer, the satisfaction degree of the user at the demand point is lower. Therefore, the distance satisfaction function can be defined as a monotonically non-increasing function. We used the ridge-type time satisfaction function, which intercepts part of the cosine function curve from \(\pi/2\) to \(3\pi/2\).

The function expression is as follows:

\[
F(d_{ij}) = \begin{cases} 
1 & d_{ij} \leq L_i \\
\frac{1}{2} + \frac{1}{2} \cos \left( \frac{\pi}{U_i - L_i} \left( d_{ij} - \frac{U_i - L_i}{2} \right) + \frac{\pi}{2} \right) & L_i < t_{ij} \leq U_i \\
0 & d_{ij} > U_i 
\end{cases}
\] (3)

Here, \(F(d_{ij})\) represents the satisfaction level of the distance from the demand point \(i\) to the charging station \(j\). \(L_i\) is the farthest distance of demand point \(i\) when the distance satisfaction is one, and \(U_i\) is the shortest distance of the demand point \(i\) when time satisfaction is zero.

For the description of distance satisfaction, which is a very subjective concept, different customers have different levels of satisfaction in different demand points. The choice of the upper and lower limits for different customers makes different and reasonable selections of upper and lower limits, which is also very important.

Assume that the different users of each demand point have the same degree of satisfaction with distance perception at the charging station. Combined with the idea of the maximum cover model, we propose the maximum cover distance for the electric vehicle charging station model.

\[
\text{maximize} \sum_{i \in N} \sum_{j \in M} h_i F(d_{ij}) P_{ij} \\
\text{s. t.} \left\{ \begin{array}{l}
\sum_{j \in M} P_{ij} = 1 \quad \forall i \in N \\
\sum_{j \in M} c_j X_j \leq C_i \\
F(d_{ij}) X_j \geq Q_i P_{ij} \quad \forall i \in N, j \in M \\
P_{ij} \in \{0, 1\} \quad \forall i \in N, j \in M \\
X_j \in \{0, 1\} \quad \forall j \in M \end{array} \right. 
\] (4)

Among them, \(h_i\) is the number of electric vehicles at the demand point \(i\), \(F(d_{ij})\) is the distance satisfaction function of the demand point \(i\) to the charging station \(j\), and \(Q_i\) is the service quality level of the demand point \(i\). If the demand point \(i\) is charged at charging station \(j\), and \(F(d_{ij}) \geq Q_i\), then \(P_{ij} = 1\); otherwise, \(P_{ij} = 0\). The objective function represents the location of the charging station so that the covered demand point has the greatest number of vehicles when the distance satisfaction is as large as possible.

3. Results and discussion

Each state in the United States has its own unique administrative divisions. For our preliminary work, we divided the entire territory of the United States into three categories: urban, suburban and rural. According to the results of the 2010 Census published by the United States Census Bureau, the Census Bureau’s urban-rural classification is fundamentally a delineation of geographical areas that identifies individual urban and rural areas of the U.S. The Census Bureau’s urban areas represent densely developed territory and encompass residential, commercial, and other non-residential urban land uses. The Census Bureau identifies two types of urban areas: one is urbanized areas (UAs) of 50,000 or
more people, and the other is urban clusters (UCs) of at least 2,500 but less than 50,000 people. Therefore, in our model, we define UAs as cities, UCs as suburbs, and the rest as villages.

Because of the large differences in the sizes of U.S. cities, to make the model more accurate, we further divided the urban areas into three categories. Based on the results of the GAWC Research Network, we used populations of 500,000 and one million as the cut-off point. Metropolitan cities with a population of over 1 million are artificially set as 1st-tier cities, cities with a population of 500,000 to 1 million are 2nd-tier, and cities with a population of 500,000 or less are 3rd-tier (the result can be easily seen in table 2).

| Area          | Category          | Population   | Number | Example        |
|---------------|-------------------|--------------|--------|----------------|
| Urban         | 1st-tier Cities   | ≥1,000,000   | 42     | Houston, TX    |
|               | 2nd-tier Cities   | 200,000-1,000,000 | 137   | Oklahoma, OK   |
|               | 3rd-tier Cities   | 50,000-200,000 | 320   | Wilson, NC     |
| Suburban      |                   | 2,500-50,000  | 3,102  | Ada, OK        |
| Rural areas   |                   |              |        |                |

Based on this principle, we first selected the location of the candidate charging stations within a certain area and then used the maximum cover location model to centrally determine the true charging station building points at the candidate sites. The goal of the plan is to establish a certain number of charging stations, thereby maximizing the service of charging stations.

It should be noted that when calculating the distance from the demand point to the candidate point, the Hami distance (city distance) is used instead of the European distance, which is more in line with actual driving situations of the vehicles in the city, and the calculation amount is reduced. We first chose Houston as a specific case study for first-tier cities. Based on Houston's city planning, we divide it into nine districts.

![Figure 2. Houston's urban divisions.](image)

We used Houston's West Houston District as an example a community with a highly concentrated population within the city, which we treated as the charging demand points. For the 10 charging candidate points, we used the above maximum cover algorithm and finally obtained 6 charging station locations, as shown in figure 2.
For a first-tier city with uneven population density distribution into divisions such as residential areas, administrative regions, economic zones, and so on, we extracted the population density area (red dot in figure 3). We focused on meeting the charging needs of the majority of people within a city population and calculating a solution to meet this demand using integer programming. The average number of charging stations for first-tier cities was 84.

This model can also be used to determine the number of charging stations necessary to meet the demands of second- and third-tier cities; the results were 59 and 36 charging stations, respectively.

Unlike urban areas, the population density of suburban and rural areas is already very small and can no longer be considered. The main factor to consider is distance traveled and determining whether people can meet their travel needs in rural and suburban areas. From Tesla's planning map, we can see that general suburbs and rural areas belong to a transitional area between cities. Tesla generally serves electric vehicles traveling long distances and needs to provide charging stations for the traveling population. The number of travelers does not need a high number of charging stations; a main trunk charging station can be set based on the distance between cities. The distribution of charging stations in rural and suburban regions should be more decentralized to meet the vehicle charging needs as much as possible.

Finally, we selected an approximate average for each urban and suburban area and estimated the number of charging stations throughout the United States based on the ratio of 1st-tier, 2nd-tier, 3rd-tier and suburban areas. At the same time, we should also consider the connection between cities. There should also be a certain number of intercity charging stations. We attributed rural areas to intercity divisions based on the description of road sections. Furthermore, we think charging stations on highway sections should follow a similar distribution as that of existing gas stations. Within our assumptions, we perform the result about charging station number that we forecast in table 3.

Table 3. Charging station number forecast table.

|                  | 1st-tier Cities | 2nd-tier Cities | 3rd-tier Cities | Suburb | Rural |
|------------------|-----------------|-----------------|-----------------|--------|-------|
| Numbers          | 42              | 137             | 320             | 3,102  | —     |
| Average Charging Stations | 84              | 59              | 36              | 10     | —     |
| Charging Stations | 3,528           | 8,083           | 11,520          | 31,020 | 117,000 |
4. Conclusions
To address the problem of location selection during electric vehicle charging station planning, this paper proposes a location method based on regional information and user demand. According to the battery life of an electric vehicle, we determined the service range of a charging station. Based on the cost constraints, we determined the number of charging stations, combined with the distance satisfaction function to determine the optimal location for an electric vehicle charging station. The method proposed in this paper can obtain the ideal charging station planning scheme that meets requirements and provides a guiding significance and application value for the location and constant volume of the electric vehicle charging station.

Researching the entire United States, we divided the territory based on population densities by area. To some extent, we could describe people’s needs more accurately. Significantly, we were able to analyze specific issues and add different factors to the forecast model.

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