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Finding the optimal location for public charging stations – a GIS-based MILP approach

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Abstract

Electric Vehicles (EVs) have achieved a significant development because of the continuous technology revolution and policy supports in recent years, which leads to a larger demand of charging stations. Strategies about how to find the optimal location for charging facilities are urgently needed in order to further assist the development of EVs. This paper focus on the return of investments on EV charging stations and proposes a Mixed Integer Linear Programming (MILP) model based on Geographic Information System (GIS) to identify the optimal location of charging stations in cities. Traffic flow data and land-use classifications are used as important inputs, and six important constraints are included in the MILP model with the objective function of maximizing the total profits of new charging stations. The effectiveness of the proposed method is then demonstrated by implementing a case study in Västerås, Sweden.

Keywords: EV, public charging startions; optimal location; GIS; MILP

1. Introduction

With the continuous technology revolution and government policy supports, electric vehicles (EVs) have achieved a significant development in recent years. Despite of the rapid growth of EVs, a number of barriers still

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exist, such as high purchase costs, limited range, long charging time and lack of widespread charging infrastructures [1].

As the EV market continuously develops, researches about the optimal size and location of EV charging infrastructures have been emerging. Although there are also some studies exploring the economics of charging facilities, most of them focus on the actual costs related to the construction of stations [2, 3], rather than the return of operations of the charging stations. However, studies on how to allocate charging stations geographically in order to gain maximal profits is also important, because higher returns on investment should encourage more investments, which indirectly might lead to higher adoption rates of EVs.

Therefore, in order to further boost installation of charging infrastructures, it is essential to pay more attention to the economics of charging infrastructures, which involves the optimal allocation of public charging stations. This paper focus on finding the optimal location of public charging stations while maximizing the return of investments on the charging station. A GIS-based MILP approach is proposed in order to find the optimal deployment of charging stations which is followed by a case study in Västerås, Sweden .

2. Methodology

GIS analysis is used as a powerful tool to integrate economic, social and technical variables with the geographic information. In this paper, the study district could be split into certain amounts of grids using GIS to identify the distribution of charging demand based on the land-use classification. In addition, some decision support system models are frequently used, and the most commonly used one is the linear/nonlinear programming model (LP/NLP) [2, 4, 5] because of its maturity and flexibility on optimization problems. The genetic algorithm is another popular method on this issue which usually finds out an optimal deployment based on the orientation-destination data [6, 7]. Besides, multi-objective decision model and multi-criteria decision model could handle multiple conflict objectives [8, 9] while figuring out the optimal location.

In this study, Mixed Integer Linear Programming (MILP) is adopted to obtain the optimal location and size of charging stations, with the objective of maximizing the overall profits and five important constraints. GIS is also chosen to process some important parameters related to geographical information in the MILP model, such as traffic flow and charging possibilities.

2.1. MILP model: the objective function

To achieve better returns of investment on the charging stations, an objective function of maximizing the total profits of all the new stations is adopted in the MILP model. Parking lot is a reasonable and convenient location to install chargers owing to its accessibility, so the alternative locations of charging station in this model are defined as the parking lots in the study area. The decision variables in this model are the locations of the charging stations; the number of fast or slow chargers needed to be installed in each station; and the charging demands met by each station. The profits of deploying the new stations are the revenues of charging EVs subtracted by the costs of building and maintaining the station, which gives the objective function

$$\text{Maximize } \Pr(x_j, n_j, q_j) = \sum_{j=1}^{J} [p_j * t_j * x_j * q_j - c_j], j = 1, 2, ..., J. \tag{1}$$

Where Pr is total profits of new stations in the study area; p_j is the charging price per minute in station j; t_j is the estimated charging duration of an EV being fully charged in station j; q_j is charging demand covered by each station j; c_j is the total cost of charging station j; and x_j represents the binary decision variable, which is defined as

$$x_j = \begin{cases} 1 & \text{if there is a station in parking lot j,} \\ 0 & \text{otherwise.} \end{cases} \quad j = 1, 2, ..., J. \tag{2}$$

Charging demand is one of the important variables when maximizing the profits. It is calculated by partitioning the whole study area into identical small grids, the centroids of which are regarded as demand nodes. The further information about the partition of the study area will be discussed in part 2.3. It is also assumed that the expected

EV adoption rate in the traffic flow is u, and a charging possibility v_i is defined to show the different charging possibilities of the electric cars in different grids. Further discussion about charging possibility will also be presented in part 2.3. The charging demands could be calculated as formula (3).

$$d_i = u * v_i * f_i, i = 1,2,3,...I \tag{3}$$

Where d_i represents the charging demand of EV in grid i, and f_i is the average traffic flow in grid i calculated by formula (14) in part 2.3.

The concept of service area is defined with the basic assumption that a charging station could only serve the traffic flow in that certain area. In this paper, the service radius of a station is set as L meter, which is similar with length of side of the grid. A binary variable r_{ij} is adopted to describe the demand coverage level of station j on demand node i, whose value is 1 when demand node i could be covered by station j, otherwise the value is 0, that is

$$r_{ij} = \begin{cases} 1 & s_{ij} \le L \\ 0 & s_{ij} > L \end{cases}, i = 1,2,...,I; j = 1,2,...J. \tag{4}$$

Where r_{ij} represents the demand coverage level of station j on demand node i, and s_{ij} is the distance between station j and demand node i.

The EV charging equipment which has been located in the city should be considered in the model because part of the demands has been met by them. Suppose there are Z stations which have been installed in the district and he remaining charging demands in cell i are

$$dr_i = d_i - \sum_{z=1}^{Z} d_{iz}, i = 1,2,...,I, z = 1,2,...,Z. \tag{5}$$

Where dr_i is the remaining demands in cell i and d_{iz} is the demand in cell i covered by the existing station z.

The definition of demand coverage level and remaining demands will be used to estimate the optimal charging demands covered by each station by formula (7) and (8).

It is assumed that fast chargers and slow chargers are chosen according to the function of the land-use, and the costs, charging price and the charging time are different for two types of chargers. The costs of a station consists of rent costs, equipment costs, installation costs, maintenance and operation costs, and electricity costs, which vary with the number and the type of chargers. The rent costs for places to install the chargers and park cars are calculated based on the opportunity costs of the parking spot, which is the parking fee the owner should have if it is used for charged parking. It is also assumed that the maintenance and operating costs are 10% of the equipment costs and installing costs [10]. Therefore, the total cost of building one station is calculated by equation (6).

$$c_j = (c_j^r + c_j^e + c_j^i + 10\% * c_j^e + 10\% * c_j^i) * n_j + p_e * \alpha * q_j, j = 1,2,...,J. \tag{6}$$

Where c_j stands for the total costs for station j; n_j is the number of chargers in station j; c_j^r represents the parking fee per day of parking lot j; c_j^e and c_j^i represents the price of a charger and the costs of installing one charger in station j respectively. p_e is the price of purchasing electricity from the power grid; α stands for the capacity of the EV battery; and q_j is the total remaining demand covered by station j. And they are all transformed into daily costs.

2.2. MILP model: the constraints

With the purpose of achieving the maximum profits, there are some constraints needed to be satisfied in the model, including the capacity constraint (7), demand constraint (8), assignment constraint (9), limitation of number of chargers in each station (10; 11) and the total number of stations (12). In addition, the non-negative and integer requirements of the decision variables (13) are also necessary. The formulas of the constraints are shown below

$$q_j \le n_j * m_j, j = 1,2,...,J. \tag{7}$$

$$q_j \le \sum_{i=1}^{I} r_{ij} * dr_i, i = 1,2,...,I, j = 1,2,..,J. \tag{8}$$

$$\sum_{j=1}^{J} x_j * r_{ij} \le 1, i = 1,2,...,I, j = 1,2,...,J. \tag{9}$$

$$n_j \ge x_j, j = 1,2,...,J. \tag{10}$$

$$n_j \le l_j * x_j, j = 1,2,...,J. \tag{11}$$

$$\sum_{j=1}^{J} x_j = N, j = 1,2,...,J. \tag{12}$$

$$x_j, n_j \ge 0 \text{ and are integers}, j = 1,2,...,J. \tag{13}$$

Where q_j is the amounts of cars charged by station *j*; n_j is the number of chargers in station *j*; m_j is the maximum serving times of each charger per day in station *j*; r_{ij} represents the demand coverage level of station *j* on demand node *i*; dr_i is the remaining demands in cell *i* ; l_j stands for the upper bound of chargers in station *j*; and *N* is the number of the total stations which will be installed.

It is assumed that each charger is possible to charge *m* cars at most per day, and constraint (7) and (8) make sure that the cars charged in the station are less than both the capacity of the station and the charging demand. Constraint (9) means that the remaining demands in grid *i* are in the service area of only one station, which ensures that different demand nodes are distributed to different charging stations. Formula (10) and (11) ensure that each station would have at least one charger and at most l_j chargers, determined by the loads of the power grid. And the constraints also have the logical implication that if there is no station, there is no charger, vice versa. Also, the budget of allocating charging stations may be limited, so at most *N* stations would be allocated in the city according to formula (12). Constraint (13) makes sure all the decision variables should be integers and nonnegative.

2.3. GIS: the partition of study area and charging possibilities

In the MILP model, some important parameters are related to geographical information in the study area, such as the traffic flow and charging possibility, so GIS is also employed to find out the optimal locations of the charging stations. With the objective of maximizing overall profits, the optimal locations of charging stations are highly influenced by the distribution and amount of charging demands. In this model, charging demands are calculated based on the daily traffic flow in different measurement points. Because the measurement points of traffic flow is not evenly distributed and may be missing in some area, a grid network is constructed to make effective use of traffic flow data. The target district could be divided into *I* identical small grids with the side of *L* meters and take the centroid of every grid as the demand node, on which average traffic flow could be calculated by formula (14). For those grids that do not include any measurement points, the traffic flow would be the average of the surrounding grids.

$$f_i = \frac{1}{K_i} * \sum_{k_i=1}^{K_i} f_{k_i}, i = 1,2,...,I. \tag{14}$$

Where f_i is the average traffic flow in grid *i;* K_i represents the number of traffic flow measurement points in grid *i*; and f_{k_i} is the daily traffic flow in measurement point k_i.

Different land-use classifications including residential with villa, residential with apartment, working, commercial, mixed land-use and other area are also identified using GIS to diversify type of charger and the charging possibilities of EVs in different locations. It is assumed that fast chargers would be installed in commercial area or mixed functional area, while slow chargers are allocated in working or apartment area. Besides, in the districts where citizens have high possibilities to stop and stay, including commercial, working and residential districts (except residential parts with villas because people live there usually have home chargers), the charging possibility of an EV is v_0. But in the districts where people barely stay for long time, such as forests or farmlands, the charging possibility is 0. Several types of land-use could be included in one grid, so as equation (15) shown, the overall charging possibility in each cell should be calculated according to the area of each type of land-use.

$$v_i = \frac{A_i}{A} * v_0, i = 1, 2, 3, ..., I \tag{15}$$

Where v_i is the charging possibility of an EV in cell *i; A* is for total area of cell *i;* and A_i stands for sum of area of residential, working and commercial parts in cell *i*.

3. Case study

3.1. Description of study area and parameters

The selected study area is the central part of Västerås and its overall area is 67 km^2. As shown in Fig.1, it is split into 268 identical small grids (I=268) for the convenience of study, and the side of the grid and service radius of a charging station is both 500 meters (L=500) because the willing walking distance of drivers to charge a car is considered as 500 meters. And 532 parking lots in this area are regarded as the alternative locations of charging stations (J=532). The daily traffic flow data derived from the website of traffic administration of Västerås is used to calculate the charging demand in each cell, including data from 245 traffic flow measurement points, range from 253 to 18,458 vehicles per day. And it is estimated that the 8 charging stations (Z=8) with 40 chargers installed already could cover the charging needs of 234 electric cars per day in its service area.

And different land-use classifications are drawn according to OpenStreetMap and Google Earth, the whole study area is split into six types of land-use area, including residential with villa, residential with apartment, working, commercial, mixed land-use and other area. Considering people live in villas usually possess home charger so public chargers are unnecessary for them, residential area with villa is not considered as the optimal alternative location for charging facilities. As shown in Fig.2, 25% of the whole area is suitable for allocating a charging station, including apartment, working, commercial and mixed area.

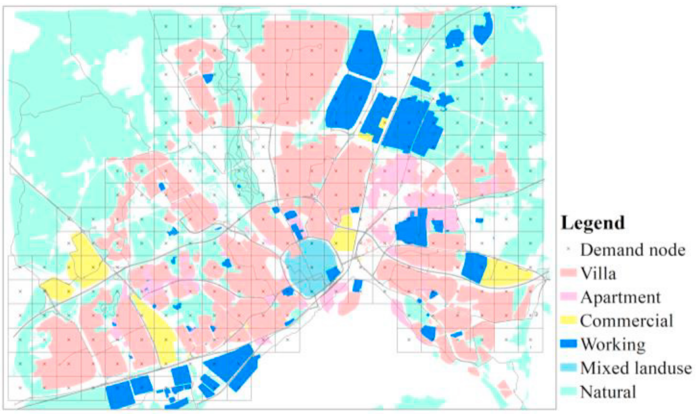

Fig. 1 The grid and demand nodes in the study area

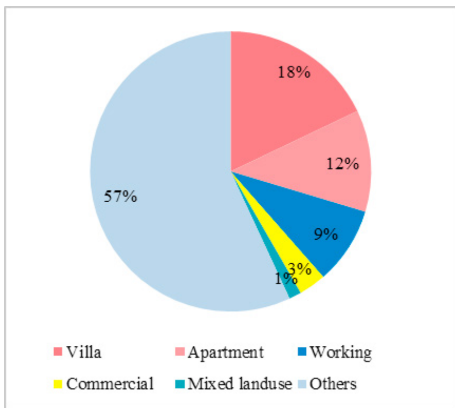

Fig. 2 Percentage of different land-use types

It is also assumed that the EV penetration rate in Vasteras is 5%, and the charging possibility for an EV passing by the functional district is 5%. And the charging time to refuel a car is estimated to be 30 minutes and 240 minutes for fast charger and slow charger respectively. Every fast charger is estimated to serve 16 cars per day, while every slow charger can only charge 2 EVs at most per day. And the charging price and cost of equipment are also different for fast and slow chargers as table 1 shown.

Table 1. Assumption of input parameters in the model

Parameters	Value	
EV penetration rate (u)	5%	
Charging possibility for functional districts(v_0)	5%	
Price of electricity(p_e)	0.5 SEK/Kwh	
Upper bound of chargers in a station (l_j)	10	
	Fast chargers	**Slow chargers**
Serving times of one outlet per day (m)	2	16
Price of charging (p)	2 SEK/min	0.2 SEK/min
Charging time for an EV (t)	30 min	240 min
Price of equipment (including installation)	\$5,525	\$54,525

3.2. The results

The results of optimal location of the charging stations are presented in two cases. It is defined to install 3 and 10 new stations in the study area in case I and II respectively. The optimal locations of new stations and type of chargers are shown in Fig. 3. The green spots represent the existing EV charging stations in Västerås, and the red points stand for the parking lots selected for allocating the new fast chargers, while the red triangles are the parking lots selected for allocating the new slow chargers. It is shown in case I that to maximize the profits, fast charging stations in commercial area are considered first, and as the stations to be built increase as in case II, slow chargers in the working and residential area are adopted, and all the stations scatter in the city to cover more charging demand.

In case I, parking lot ① is in the central part of the city, which is a mixed functional area of commercial and working land-use, and offices, shopping mall, movie theatre and restaurants are gathered nearby. Although the rent costs are high, the high daily traffic flow and charging possibilities leads to high profits. Parking lot ② and ③ are both in the commercial area, where there are some shopping mall, supermarkets and restaurants. Also, location ② is near the highway E18, so high traffic flow will also lead to a high charging demand. In addition, only fast chargers are selected in this case, 6 chargers should be evenly distributed in three new stations.

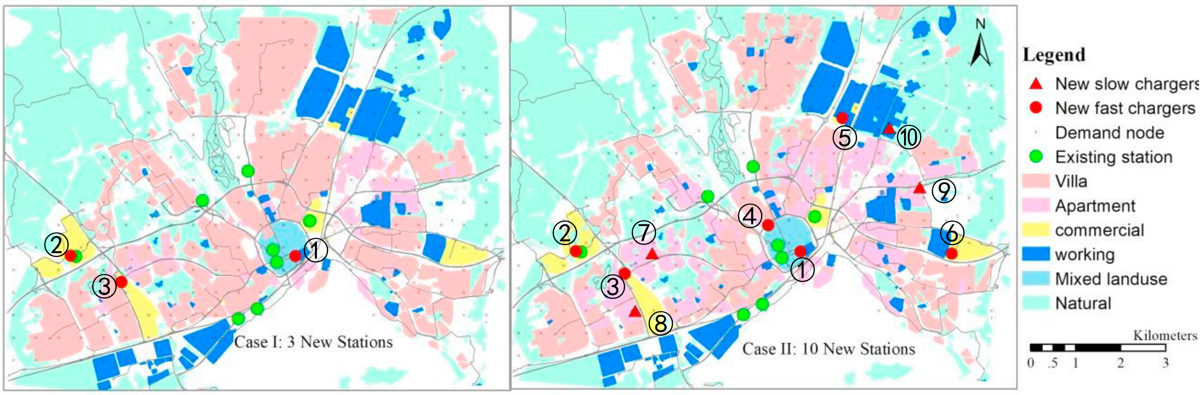

Fig.3 Optimal locations and type of new charging stations

In Case II, parking lot ①-⑥ are all in the commercial area and a lot of visitors in the day would create EV charging demands; ⑦ -⑨ are in the residential area with high density of apartments, where home chargers maybe technically impossible and public chargers are needed to meet the charging demands; and ⑩ is in the working area where many offices gathered together and employees would like to charge their car during working time. In addition, most of the selected locations are near main roads or highway with a high traffic flow. And 12 fast chargers should be installed in the commercial area and 40 slow chargers are needed in the residential and working area.

4. Discussion and conclusions

The results of the case study demonstrate the effectiveness of the deployment model built in this paper, and the framework could be easily applicable in different cities as long as the data of geographical information, traffic flow and other related information could be accessible for the target city. The optimal location of the charging stations in this model is mainly determined by the geographical distribution of traffic flow and different charging possibilities based on the land-use classification, so the geographical information plays an important role in the optimization process. The optimal locations in the result ensure optimal profits of the charging stations, which could encourage more initiative investments and therefore a better EV penetration. However, there are also some limitations in the present model, and some parameters could be considered in more details. In the future study, different of size of the grid would be considered to find out its sensitivity. And the arrival patterns of the vehicles could be took into consideration to calculate the daily serving times of a charger, and Queuing Theory may be used in the further analysis. And the structure of traffic flow data used in the model is relatively simple and it's impossible not identify the origin and destination of vehicles, so we could not estimate the state of battery of the EVs in each demand node and charging possibility may not be accurate enough. Therefore, the charging demand used in the model might be unreliable. In the future study, more improvement will be implemented to get a better result.

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