Optimal Location of Electric Vehicle Charging Stations Using Genetic Algorithm

Shuangshuang Chen, Yue Shi, Xingyu Chen, Feng Qi
State Key Laboratory of Networking and Switching Technology
Beijing University of Posts and Telecommunications
Beijing, China
chenss@bupt.edu.cn, yshi@bupt.edu.cn, chenxy@bupt.edu.cn, qifeng@bupt.edu.cn

***Abstract*—In this paper, we investigate the optimal location of electric vehicle (EV) charging stations. As one of the crucial infrastructures of EV, electric charging stations must be widely deployed to meet the growing needs of EV. In this study, we propose a locating method of charging station when considering economics, capacity, coverage and convenience. In order to solve the locating problem, an optimization model for charging stations location is established first, which minimizes the investment cost and transportation cost, meanwhile, the constraints of capacity, coverage and convenience should be satisfied simultaneously. Then, an improved genetic algorithm (GA) is proposed to solve the optimization problem. The simulation results indicate that the proposed locating method is effective and practical.**

Keywords—smart grid; electric vehicle; charging station; optimal location; coverage constraint; genetic algorithm

I. Introduction

As a new type of energy-saving transport, electric vehicles have gradually become the focus of world attention and inevitable trend of auto industry development [1]. As an important part of smart grid, electric vehicles must be coordinated with other areas to achieve common development. To break through bottleneck of the development of electric cars, it is extremely urgent to set up a batch of electric vehicle charging stations for users [2]. Therefore, research on placement of charging station is of great value.

In our work, we concentrate on the optimal placement of electric vehicle charging stations. We take into consideration many aspects and constraints in the model without excessive technical details so that the method can be applied to other scenarios. We study the locations where charging stations should be constructed so that we can diminish costs with coverage extended to the whole area and satisfy drivers' demand and convenience.

Charging stations placement is a location optimization problem. We consider in the model some constraints. Based on these goals, we first use the mixed integer linear programming model to determine the constraints and objective function. Since the placement problem is NP-hard problem, we adapt heuristic algorithm instead of an exact algorithm, which is not active for many variables and constraints. Finally, simulation results in MATLAB demonstrate that the proposed locating method is effective and practical.

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The rest of this paper is organized as follows. Section II reviews the related work. In section III, the formulation of the proposed model is laid down. In section IV, the design of GA solver is discussed. Simulation results are presented in Section V and this paper is concluded in Section VI.

II. Related Work

The affects of electric vehicles on the smart grid have already been extensively studied [3] [4]. Reference [3] proposed a full study of a photovoltaic (PV)-aided plug-in hybrid electric vehicles charging facility by investigating the two most challenging technical concerns: sizing of the local energy storage unit and control strategies of the facility. It discussed the combination of PV equipment into charging stations. Reference [4] presented a new SLM control strategy for coordinating PEV charging based on peak demand shaving, improving voltage profile and minimizing power losses.

Some existing work on EVs is correlated to station constructions based on some urban planning factors. Reference [5] proposed an optimized algorithm to locate electric vehicles charging stations. Reference [6] determined the location problem as an optimization model using greedy algorithm, on the basis of charging station coverage and capacity. The paper proved the problem NP-hard and proposed four solution methods to tackle the problem, such as greedy approach.

We find that most of works concentrate on technical details or some single sector. However, in this paper, we focus on charging stations location to achieve users demand and convenience.

III. Problem Formulation

A. Model

In this paper, we formulate the problem as an optimization problem. We consider in the model some constraints (investment cost, transportation cost, users demand, stations capacity, coverage of the whole area and convenience). Based on these goals, we use the mixed integer linear programming model to determine the constraints and objective function.

$I=\{1,\ldots,m\}$ is the set of demand points representing residential communities, $J=\{1,\ldots,n\}$ is the set of possible charging station locations. Each residential community is abstracted into a demand point. In our model, we take into account the following parameters:

- f_j : Investment cost of charging station j
- d_{ij} : Transportation cost of demand point i to charging station j
- x_j : Binary variable for charging station j
- z_{ij} : Binary variable of assigning demand point i to charging station j
- X_i : Demand for community i
- c_j : Charging station j capacity
- $D(j, k)$: Distance of charging station j to charging station k
- Q : Driving distance of electric vehicles charged in a certain charging station
- l_0 : The left flow not used by the graph, $l_0 \geqslant 0$
- y_{kl}: Traffic flow from charging station k to charging station l
- v : Size of V

In order to achieve our goals, we provide the following conditions:

1) Costs: The construction of charging station greatly depends on initial investment costs, while drivers' transportation cost is also a necessary factor which is related to the distance from place of departure to charging station. So objective function contains two parts, which is defined as:

$$C = \sum_{j=1}^{j=n} f_j x_j + \sum_{i=1}^{i=m} \sum_{j=1}^{j=n} z_{ij} d_{ij} \quad (1)$$

$$x_j \in \{0,1\}, \forall j \in J \quad (2)$$

$$z_{ij} \in \{0,1\}, \forall i \in I, j \in J \quad (3)$$

x_j is not null if the charging station i is constructed. z_{ij} is not null if demand point i is served by charging station j.

2) Capacity: For each j,

$$K_{\mathrm{j}}^{\beta Q} = \{k \in J \,|\, D(j,k) \le \beta Q\} \quad (4)$$

Let $K_{\mathrm{j}}^{\beta Q}$ be the set of locations within distance βQ from j. For each charging station, we ensure that the total charging demand must be satisfied by the charging station capacity, i.e.,

$$\sum_{i=1}^{i=m} X_i z_{ij} \le c_j x_j, \forall j \in K_{\mathrm{j}}^{\beta Q} \quad (5)$$

Thus, we can guarantee that electric vehicle can get charged again within distance βQ away. β is a discount factor whose maximum value is one. The bigger β, the less conservative the model is, which means less charging stations should be deployed.

$$\sum_{j=1}^{j=n} z_{ij} = 1, \forall i \in I \quad (6)$$

$$z_{ij} \le x_j, \forall i \in I, j \in J \quad (7)$$

Equation (6) ensures that demand point i is charged only by one charging station. Equation (7) demonstrates that charging station can provide services when it is constructed.

3) Coverage: Based on condition 2, we model a graph $H=(V,E)$, where V means the set of charging stations that satisfy driver demand and E denotes edges between charging stations. To satisfy drivers convenience, an electric vehicle can access any charging station within its ability which makes electric vehicles drive anywhere in the area on being recharged. To do this, we use a traffic flow model based on the mixed integer linear programming method. Similar to [8], we adopt an example given in Fig.1 and Fig.2 to demonstrate the model. Suppose that an origin station has 9 unites of traffic flow. If the stations are not connected in feasible distance (βQ), the flow from origin station cannot get recharged and reach other stations. On the basis of capacity constrain, the coverage constrain is defined as:

$$l_0 + y_{0j} = v, \forall j \in V \quad (8)$$

$$x_j \sum_{k \in V} x_k = y_{0j}, \forall j \in V \quad (9)$$

$$y_{kl} \le v x_j x_l, \forall (k,l) \in E \quad (10)$$

$$x_j x_l + \sum_{p|(l,p)\in E} y_{lp} = \sum_{k|(k,l)\in E} y_{kl}, \forall j,l \in V \quad (11)$$

Equation (8) says that the left flow not used by the graph and the flow from origin station is v. (9) shows that the flow from origin station is equivalent to the flow absorbed by stations. (10) confines that flow can be absorbed only by one station. (11) guarantees that the total flow out of a station plus the amount for a station is equivalent to the total flow going to a station.

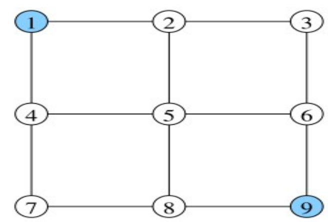

Fig.1. Original flow representation on a graph with 9 charging stations.

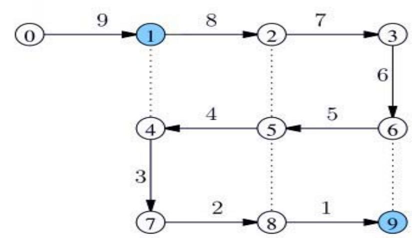

Fig.2. Feasible flow representation on a graph with 9 charging stations.

B. Problem formulation

According to the above constraints, the complete formulation for charging station location problem is proposed as follows:

$$\min C = \sum_{j=1}^{j=n} f_j x_j + \sum_{i=1}^{i=m} \sum_{j=1}^{j=n} z_{ij} d_{ij}$$

$$s.t. \begin{cases} \sum_{j=1}^{j=n} z_{ij} = 1,\ z_{ij} \le x_j, \forall i \in I, j \in J \\ \sum_{i=1}^{i=m} X_i z_{ij} \le c_j x_j, \forall j \in K_{\mathrm{j}}^{\beta Q} \\ l_0 + x_j \sum_{k \in V} x_k = v, \forall j \in V \\ y_{kl} \le v x_j x_l, \forall (k,l) \in E \\ x_j x_l + \sum_{p|(l,p)\in E} y_{lp} = \sum_{k|(k,l)\in E} y_{kl}, \forall j,l \in V \end{cases} \quad (12)$$

Since the placement problem is NP-hard problem, we adapt heuristic algorithm instead of an exact algorithm. A generic solution for multi-objective optimization problem is the improved genetic algorithm [9].

IV. A GENETIC ALGORITHM SOLVER

We use genetic algorithm since the location planning is considered as NP-hard problem. Genetic algorithms generate solutions to optimization complex problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover. In order to avoid the local optimum and maintain population diversity, the density function was presented based on standard GA [7].

A. Detail of GA solver

Chromosome coding: In this work, we use binary encoding format, and the charging stations are taken as genes of chromosomes. The length of chromosomes is the same to the number of possible charging station locations. For example, a chromosome g_u may encode as {1010101} for seven locations, where station 1, station 3, station 5 and station 7 are deployed (because of the gene is 1).

Initial population: In this process, we create a population of chromosomes, where chromosome is a binary string with a fixed length (depends on the amount of possible charging stations), and each bit of the binary is initialized randomly.

Fitness function: The fitness function consists of costs and constraints of capacity and coverage. The fitness of chromosome g_u is defined as follow:

$$F(\mathrm{g}_u) = \begin{cases} B - C(\mathrm{g}_u), \sum_{i=1}^{i=m} X_i z_{ij} \le c_j x_j, l_0 \ge 0, \\ 0, others \end{cases} \tag{13}$$

Where B is a large figure to ensure the value of $F(\mathrm{g}_u)$ always be positive, because of we use roulette wheel in the selection phase. It can be concluded that $F(\mathrm{g}_u)$ is positive only when the capacity and coverage constrains are satisfied, otherwise $F(\mathrm{g}_u)=0$.

Density function: We define chromosome g_u is similar to chromosome g_v as follow:

$$1-\varepsilon \le S(\mathrm{g}_u, g_v) \le 1+\varepsilon, (\varepsilon > 0) \tag{14}$$

Where ε denotes a small positive number; $S(\mathrm{g}_u, g_v)$ represents the similarity between chromosome g_u and chromosome g_v, defined as follow:

$$S(\mathrm{g}_u, g_v) = \frac{F(\mathrm{g}_u)}{F(\mathrm{g}_v)} \tag{15}$$

From (14) and (15), we can obtain *similar* (g_u ,g_v):

$$similar(\mathrm{g}_u, g_v) = \begin{cases} 1, 1-\varepsilon \le S(\mathrm{g}_u, g_v) \le 1+\varepsilon \\ 0, others \end{cases} \tag{16}$$

The density of chromosome s_v is calculated as the percentage of number in which the chromosomes are similar to s_v to the whole chromosomes:

$$density(\mathrm{g}_u) = \frac{1}{L} \cdot \sum_{v=1}^{L} similar(\mathrm{g}_u, \mathrm{g}_v) \tag{17}$$

where L denotes the population size.

Selection: After each successive generation, a proportion of the existing population is selected to foster a new generation. We define the selected probability is in direct proportion to the fitness value and in converse proportion to the density value:

$$M(s_v) = \frac{F(\mathrm{g}_u)}{\sum_{u=1}^{L} F(\mathrm{g}_u)} \cdot \frac{1}{density(\mathrm{g}_u)} \tag{18}$$

Equation (18) can make fitter chromosomes are more likely to be selected, meanwhile avoiding get into local optimum.

V. SIMULATION RESULTS

In this section, we first perform a series of simulations to verify the validity of the locating method. Then we perform a series of tests to check performance of the improved GA.

Based on research and investigation, the demand of a community is related to population size and the transportation cost rises as distance between user and charging station increases. So in the first test, we randomly generate 40 demand points and 10 possible charging stations in an area of 60 × 60 km^2, where we assign a random value in the range of [30, 50] vehicles to the demand X_i, and Q, f_j and c_j are set to 30 km, RMB 450*10^4 and 400 vehicles every day respectively. The layout of demand points and possible charging stations is depicted in Fig.3.

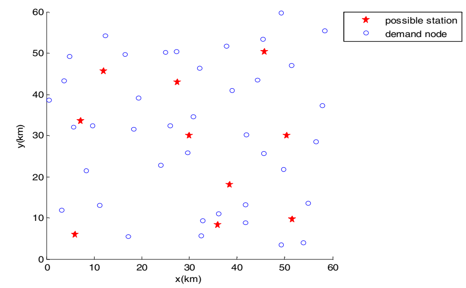

Fig.3. Layout of demand points and possible charging stations.

The population size of GA is 100, and the maximum number of generations is 400, the probability of crossover and migration are 0.6 and 0.1, respectively. The simulations were performed with MATLAB R2012a.

By changing ß (i.e., letting ß is 0.9 and 0.8), we can obtain the selected locations and allocation of demand points shown in Fig.4 and Fig.5.

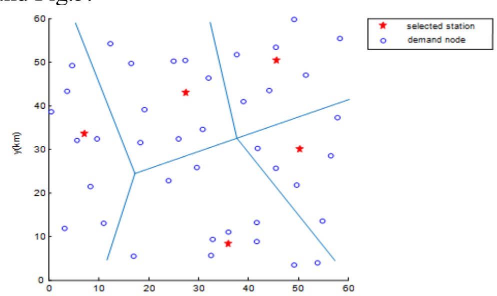

Fig.4. selected locations and allocation of demand points (ß =0.9).

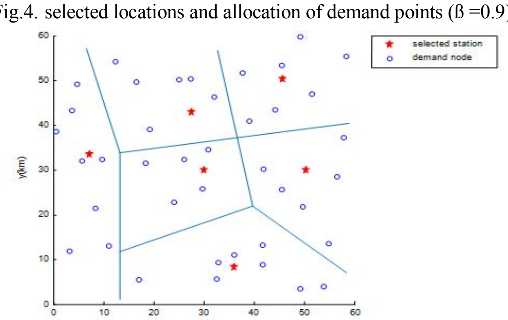

Fig.5. selected locations and allocation of demand points (ß =0.8).

It is observed from the two figures that the proposed locating method is practical. Each electric vehicle can access a charging station when the capacity constraint is satisfied. Moreover, an electric vehicle can access any charging station within its driving ability which makes electric vehicles drive anywhere in the area on being recharged. When ß decreases, the number of selected charging stations will increase as constraint (5) becomes stronger.

As discussed above, we designed three groups of experiments to test the proposed location method, the data used for them listed in test I. Note that the values of ß are set to 0.9, 0.8and 0.7, respectively.

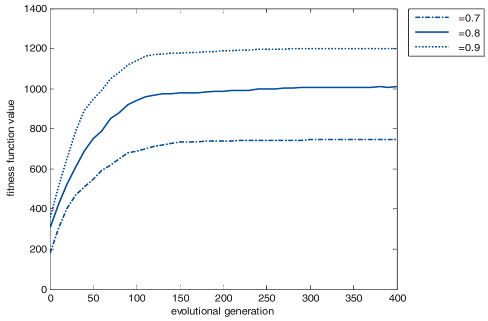

Fig.6. algorithm performance

Fig.6. shows the performance curves of the three experiments. It can be seen that each curve moving up rapidly in initial time, and has convergence in the last runs of algorithm. It proved that the proposed planning mechanism has good performance under various constraint conditions, so it has high flexibility. When ß decreases, the costs will increase so the fitness function value decreases.

We test the proposed locating method over lager area to evaluate the scalability. We randomly generate 65 demand points and 16 possible charging stations in an area of 100 × 100 km^2. The GA's parameter unchanged. We perform simulations with β (1, 0.8, and 0.6) in Table I. where the objective function values and the numbers of stations constructed are shown. It proved that the proposed locating method has high scalability, when applied to larger area.

TABLE I. SIMULATION RESULTS FOR m=65 and n=16

β	Number of stations constructed	Objective function value
1	8	6225.0820
0.8	10	6602.6540
0.6	12	7158.3810

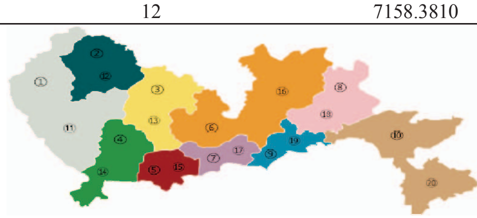

Fig.7. The layout of charging station locating in city

In the third test, we test how the methods perform in a city. We decide locations in a real city. The city in China is made up of ten districts and we select two locations in each district for potential charging station. The layout of 20 possible locations is shown in Fig.7. The distance between locations is attained from data supported by Baidu Map [16].

We get the city data information from Wikipedia. We relate the population amount to the demand Xi and the urban residents disposable income to the cost f j . We set the capacity c j abversely proportional to the density with constant. The related data are shown in Table II.

We execute simulations with several mixtures of D(40, 50, and 60 km) and β (1 and 0.8) and the simulation results of the method are listed in Table III where the best investment costs are shown and the numbers of stations constructed are put in table.

TABLE II. DATA IN THE CITY

District	Population(10^4)	Density(/km^2)	PCDI	c j
1&11	268.44	6738	41763	148.412
2&12	49.18	3164	31709	316.0556
3&13	140.86	8023	33035	124.6417
4&14	110.85	5976	49085	167.336
5&15	133.05	16915	54116	59.11913
6&16	192.69	4969	42754	201.2477
7&17	93.64	11889	46418	84.11136
8&18	31.68	1897	31651	527.1481
9&19	21.26	2848	42224	351.1236
10&20	13.09	444	27300	2252.252

TABLE III. SIMULATION RESULTS FOR THE CITY CASE

β	*Q*	Number of stations constructed	investment cost
1	40	9	34524
1	50	8	30624
1	60	6	22864
0.8	40	10	47536
0.8	50	9	42184
0.8	60	8	30624

The third test to a real environment proved that the method is practical and the method can potentially have impact in real-life problem of optimal location of EVs.

VI. CONCLUSIONS AND FUTURE WORKS

In this paper, we focus on charging stations location to achieve users demand and convenience. The future work is aimed at considering the distance between substation and charging station as an additional design constraint. Also, we plan to investigate the complexity of our contribution and compare it with the existing work.

REFERENCES

[1] Dharmakeerthi, C.H., Saha, T.K., "Modeling and Planning of EV Fast Charging Station in Power Grid" IEEE Power and Energy Society General Meeting, pp. 1–8, Jul. 2012.

[2] Masoum, A.S. , Abu-Siada, A., Islam, S. ,"Impact of Uncoordinated and Coordinated Charging of Plug-In Electric"IEEE PES.ISGT., pp. 1–7, Nov. 2011.

[3] F. Guo, E.Inoa, W.Choi, and J. Wang, "Study on global optimizationand control strategy development for a PHEV charging facility," IEEETrans. Veh. Technol., vol. 61, no. 6, pp. 2431–2441, Jul. 2012.

[4] A. S. Masoum, S. Deilami, P. S. Moses, M. A. S. Masoum, andA. Abu-Siada, "Smart load management of plug-in electric vehicles indistribution and residential networks with charging stations for peakshaving and loss minimisation considering voltage regulation," IETGener. Transmiss. Distrib., vol. 5, no. 8, pp. 877–888, Aug. 2011.

[5] S. Mehar and S-M. Senouci. An optimization location scheme for electric charging stations. IEEE SaCoNet, pp 1–5, 2013.

[6] Lam, A.Y.S., Yiu-Wing Leung and Xiaowen Chu, "Electric Vehicle Charging Station Placement: Formulation, Complexity, and Solutions" IEEETrans.smart grid., vol.5, no. 6, pp. 2846–2856, Nov. 2014.

[7] T. D. Chen, K. M. Kockelman, and M. Khan, "The electric vehicle charging station location problem: A parking-based assignment method for Seattle," in Proc. 31st USAEE/IAEE North Amer. Conf., Austin, TX, USA, Nov. 2012, pp. 1–14.

[8] J. M. Conrad, C. P. Gomes, W.-J. van Hoeve, A. Sabharwal, and J. F. Suter, "Wildlife corridors as a connected subgraph problem," J. Environ. Econ. Manag., vol. 63, no. 1, pp. 1–18, Jan. 2012.

[9] Wang, David Tse-Chi, Ochoa, Luis.F, Harrsion, G.P, "Modified GA and Data Envelopment Analysis for Multistage Distribution Network Expansion Planning Under Uncertainty," IEEE Transcations on Power Systems, vol.26, no.2, pp.897-904, May.2011.

[10] Yue Shi, Shaoyong Guo, Qiu Xue-song and Feng Qi, "Optimal planning of power distribution communication network using genetic algorithm" ICC. communications., pp. 3676–3681, June. 2014.