GIS-Based Multi-Objective Particle Swarm Optimization of charging stations for electric vehicles

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GIS-Based Multi-Objective Particle Swarm Optimization of Charging Station for Electric Vehicles – Taking a District in Beijing as an Example

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Abstract

The rapid development of electric vehicles can greatly alleviate the environmental problems and energy tension. However, the lack of public supporting facilities has become the biggest problem hinders its development. How to reasonably plan the construction of charging facilities to meet the needs of electric vehicles has become an urgent situation in China. Different from other charging facilities, charging station could help to break the limitation of driving distance. It also has a special dual attribute of public service and high investment. So, this paper establishes a model with two objective functions of minimizing construction cost and maximizing its coverage and Particle Swarm Optimization was used to solve it. Besides, we take into account the conveniences of stations to charging vehicles and their influences on the loads of the power grid and GIS is used to overlay the traffic system diagram on power system diagram to find the alternative construction points. In this study, a district in Beijing is analyzed using the method and model we proposed. Finally, a planning strategy of charging station for Chinese market is suggested.

Keywords: Electric vehicle; Charging station; Multi-objective particle swarm optimization; GIS

MOPSO: Multi-objective particle swarm optimization
EV: Electric Vehicle

1.Introduction

According to BP statistics, in 2016 the consumptions of China's primary energy reached 3.053 billion tons of oil equivalent, accounting for 23% of the total primary energy consumption in the world. In addition, the emissions of carbon dioxide reached 9.123 billion tons for the same year, accounting for 27.3% of the world's total emissions and making China the largest energy consumer and CO_2 emitter in the world.

Huge energy consumption has brought two severe problems to China: one is the depletion of domestic fossil fuels which will also cause the issue of energy security; the other one is the air pollution. Therefore, one promising solution in transportation sector is the electric vehicles (EVs) which have become the focus of attention and the one with huge potential in China. The development of EVs can not only alleviate the environmental problems but also lower the noise caused by gasoline cars. Besides, combining with the renewable energy, they also have the advantages of enhancing renewable energy efficiency and smoothing the difference between the peak and valley of energy load, which will be beneficial to the whole electricity system (Hatton et al., 2009).

As the capital and one of the most developed cities of China, Beijing has drawn plenty of attention for its traffic and air pollution problems. And the promotions of EVs have achieved remarkable results since it was chosen to be the demonstrated city in 2009. According to local government statistics, by the end of 2015, the number of EVs in Beijing reached 35,900 and only the newly added EVs reached 55,100 in 2016. <Beijing Electric Vehicle Charging Infrastructure Planning (2016-2020)> predicts the number to be around 600,000 by 2020.

As a relatively new type of clean transportation, the development of EVs in Beijing has met some obstacles, such as the constraint of driven distance due to the battery capacity, the slow charging speed and the inadequate constructions of charging facilities. The last one is the most urgent issue hinges the personal purchases of EVs and greatly hampers their development in the city. Therefore, how to reasonably plan the construction of charging facilities to meet the charging needs of EVs in Beijing has become the most pressing problem.

Different specifications of EVs and different driving patterns make the charging needs different. So, various types of charging facilities are required (Jia,Long et al., 2016). There are mainly three categories of charging facilities in the market: charging pile, charging station and power station. They possess different characteristics, advantages and disadvantages.

Charging piles, which can be divided into private and public, are the most common charging facilities and have the highest coverage. The construction cost is not that huge, and it takes small foot space and mainly locates in the parking lots of residential areas, workplaces and commercial areas. The needs to construct charging piles are mainly led by owners of private EVs. The shortcoming of that is the relatively low charging speed, which makes its location limited in the parking lots within the city and is only suitable for short-journey EVs. As of the end of 2015, Beijing possessed 21,000 charging piles and most of them are private.

Charging stations and power stations are mainly distributed along the road, especially highways between cities. Aiming at quick charge within a short time span, their role is much more similar to the gas stations for gasoline vehicles. This makes them suitable for EVs that need long-distance journey, so they are conducive to break through the limited battery capacity of EVs and increase the travel distances. But there is also a difference between the two types of facilities: the power stations have a higher requirement of the facilities due to the need to satisfy most of battery specifications in the market. So, power stations are mostly designed for the electric buses who possess only a few specifications. Various specifications in the battery market make them not yet a practical solution for private EVs. However, charging station can meet most plugs of the EVs but the huge construction costs, high requirements of foot space and power grid make it not so prevailing as charging piles in China. The characteristics, advantages and disadvantages for the three charging facilities are concluded in Table 1.

Charing facilities	Characteristics	Advantages	Disadvantages
Charging pile	High coverage Locates in parking lots	Low construction cost Small foot space	Slow charging speed Limited location
Power station	Distributed along highways Suitable for public EVs	No waiting cost	Huge construction costs Land demand Battery facility requirement
Charging station	Distributed along highways Suitable for private EVs	Rapid charging speed Practical and sustainable	Huge construction costs Land demand Power grid requirements

Table 1: Summary of Different Charing Facilities

Charging stations can break the limitation of driven distance and greatly support the development of private EVs. But nowadays, most constructions of the charging stations in China still confine to demonstrations and lack of a set of theoretical tools to optimize the location and scale. So, expecting to promote the long-distance driving of EVs and therefore narrowing the gap with gasoline cars, this paper takes the charging station as an object of research and will attempt to find an optimal solution accordingly.

2.Literature review

With the development of EV and its supporting facilities, a huge body of literatures related to the characteristics and problems of the charging facilities have been carried out for their future development and their optimal planning (Hatton et al., 2009; Jia,Long et al., 2016; Gao.Ciwei and Zhang.Liang, 2011). The planning process of charging stations was firstly divided into two independent parts by M. Densing et al. (Densing et al., 2012): one is to optimize the location and the other is to decide the scale of the charging station, and an example was optimized to find a least-cost solution based on the proposed principle.

Grouping the existing planning model of the charging station, many different objectives are considered according to its characteristics. Most of the literatures took economic as a starting point and considered different costs of charging station (Jia et al., 2012; Mehar and Senouci, 2013; Su et al., 2013; Moradi et al., 2015), including investment cost, operation cost, maintenance cost, electricity cost, waiting cost and etc. However, unlike charging piles, charging stations are large-scale electric facilities with a higher requirement on the power grid. So, the planning of the charging station needs to consider not only costs, but also its influence on the power grid and the coverage due to the function of service(Alhazmi et al., 2017; Du.Aihu et al., 2011; Wang,Hui et al., 2013; Chen.Guang et al., 2014; Xiong.Hu et al., 2012). For instance, Y. A. Alhazmi et al. (Alhazmi et al., 2017) took different driving modes into account and maximized the road trip success rate (TSR) to optimize the location of charging facilities in order to make it convenient for charging vehicles. A.Du (Du.Aihu et al., 2011) analyzed the physical characteristics of charging stations and considered them as high-power electric facilities and then optimized construction points considering the expansion costs of the power grid.

Various types of methods were adopted to optimize the planning strategy of charging stations. Jia,Long et al. (2016) estimated total demand of EVs based on the number and driving statistics, and different charging facilities were used to satisfy different types of demands. A study of charging stations in Italian highways was given by S. Micari et al. (Micari et al., 2017) using a two-stage method in order to find the optimal locations of charging stations. With the development of computer science, bionic algorithms were also widely used. For instance, the construction costs were optimized using Genetic Algorithms (GA) (Alegre et al., 2017) and Quantum Particle Swarm Optimization (QPSO) (Liu,Zi Fa et al., 2012) on a city in Spain and a virtual region separately. A. Awasthi et al. (Awasthi et al., 2017) combined two popular bionic optimization algorithms: particle swarm optimization (PSO) algorithm was used to reoptimize the suboptimal solution set obtained by GA. This method was applied to a planning model of charging facility in India and the accuracy was greatly improved. Zhang,Di (2015) used a two-objective model to study the alternative between the construction cost of charging facilities and the improvement of the charging speed, and the standard normalization method was used to solved it. Besides, among all cases in the literatures, virtual or simplified maps were widely used (Chen.Guang et al., 2014; Zhang,Di, 2015).

In summary, charging station is a large-scale electric facility so we should consider its impact on the power grid and take it as a constraint while the expansion costs of the grid should also be considered. Besides, charging stations have dual attributes of public service and high investment which are alternative. So, solely take one aspect as an objective to optimize the position of the charging station is unreasonable. Therefore, this paper adopts multi-objective optimization model to fully consider the two attributes of charging station, maximizing the coverage and minimizing the total costs at the same time. In addition, most literatures virtualized real map to simplify the optimization which makes the model unpractical in the real planning. To solve that, we propose a method to overlay the real grid and map using GIS, which makes the model has a stronger practicability.

3.Methodology

3.1 Multi-objective optimization model based on particle swarm optimization (MOPSO)

Multi-objective optimization is a more practical method when compared with single-objective optimization, because it considers two or more conflicting objectives and allows decision makers to set priority level according to different significances of different targets.

Among all the literatures related to multi-objective optimization, researchers mainly use two methods to deal with the problems. The first one is to convert multiple objectives into one function, and then treat it as a single-objective optimization. The transformation methods include setting different weights for different objective functions according to the priority, so as to form a single objective, or keeping one objective function and transferring others as penalty functions to the constraint set. However, the defect of this approach is that it is difficult to choose the weights properly which makes the optimization result extremely subjective. The second method is to determine a pareto solution set or its optimal representative subset that shows the substitutability between different targets (Konak et al., 2006). Among all methods to find the set, the most widely used are Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) (Konak et al., 2006). GA has long been the benchmark for solving such problems (Asl-Najafi et al., 2015). N. Srinivas (Srinivas and Deb, 1994) firstly proposed a Non-dominated Ranking Genetic Algorithm (NSGA) to obtain the optimal Pareto subset in a multi-objective optimization model. And K. Deb (Deb, 2000) improved it with elitist strategy (NSGA-II) which handles the problems of computational complexity and the lack of elites in the original algorithm. However, C. Dai et al. (Dai et al., 2015) argued that PSO is the most powerful contender of GA in terms of solving multi-objective optimization problems because it can significantly improve the processing efficiency in exchange for acceptable loss on the accuracy. Many studies optimistically proved the function of PSO in solving multi-objective model. S. Avril et al. (Avril et al., 2010) successfully adopted a PSO-based multi-objective model to minimize the total cost while ensuring the stability of the power grid and the constraints of consumers' demand were satisfied at the same time. G. Chen et al. (Chen et al., 2014) improved the approach based on chaos optimization and tried to find the equilibrium point among different targets. The simulation results showed that the model can find the optimal Pareto subset more efficiently. Therefore, in this paper, a multi-objective optimization model based on Particle Swarm Optimization (MOPSO) is used to optimize the planning of EV charging station with dual attributes.

Particle swarm optimization algorithm was derived from the cluster of organisms in nature. It was first proposed in 1995 by American psychologist Kennedy and electrical engineer Eberhart based on the biopsychological model of Heppner (Chen et al., 2014). The mechanism of the algorithm is to simulate the behavior of the flock looking for food in a certain space. And it draws on the information mechanism that individuals share information in the community while retain their own (Liang,Jing, 2009). As shown in Figure 1, each particle competes and collaborates to find the global optimum in the search space. First it will initialize a set of random particles (random solutions) and then find the optimal solution by successive iterations. In each iteration, individual particles update their position through their own optimal solution (Pbest) and optimal solution among the population (Gbest). The update process shows as follows:

Assuming that the search space is D-dimension, and there are N particles in the population, each of which can be represented by a D-dimensional vector:

$$X_i = (x_{i1}, x_{i2}, \dots, x_{iD}), i = 1,2,\dots,N \quad (1)$$

The velocity of each particle can be expressed as:

$$V_i = (v_{i1}, v_{i2}, \dots, v_{iD}), i = 1,2,\dots,N \quad (2)$$

The optimal solution of each individual particle is:

$$P_{best} = (p_{i1}, p_{i2}, \dots, p_{iD}), i = 1,2,\dots,N \quad (3)$$

The global optimal solution of the population is:

$$G_{best} = (p_{g1}, p_{g2}, \dots, p_{gD}) \quad (4)$$

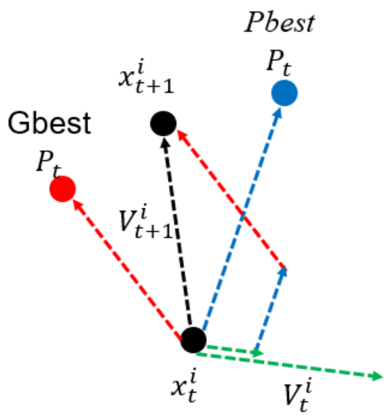
The updated speed of the particle in each iteration is:

$$v_{id} = \mathrm{w} \times v_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 (p_{gd} - x_{id}) \quad (5)$$

Where w is inertia weight, c_1, c_2 are learning factors, and r_1, r_2 are random numbers between 0 and 1. Formula (5) is mainly composed of the following three parts: The first part is the inertial part which reflects the motional pattern of particle and ensures the global convergence; the second part is the cognitive part that makes the particle moves according to their own memory; the last one is the social part, which reflects the collaboration among the particles and leads the optimization move towards the Gbest. The last two parts ensure the local convergence.

And the particles update their position according to $x_{id} = x_{id} + v_{id}$ at the end of each iteration.

In MOPSO, each particle has a different set of leaders; only one of them can be used to update the particle's position. Such leading particle is extracted and stored. Finally, it is expressed as the Pareto optimal curve as the final output of the algorithm (Delgarm et al., 2016). The movement trail is shown in Figure 2.



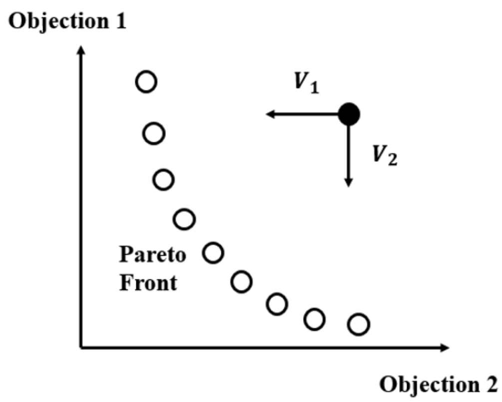


Figure 1: The Movement of Particle

Figure 2: Formation Process of Pareto Front

3.2 GIS

Since the charging station needs to serve as a public facility and it is also a high-power demand facility, it is necessary to consider the convenience to the EVs and its influence on the load of the power grid at the same time. In this paper, we use geographic information system to overlay the traffic system diagram on power system diagram and then find the geography intersections as the alternative points to construct charging stations (Figure 3). This would make the planning strategy more practical.

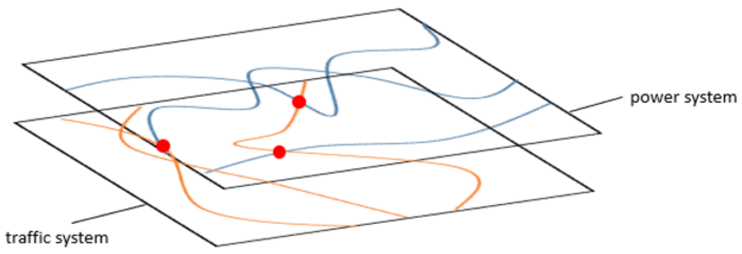


Figure 3: The Overlay Diagram of Traffic System and Power System

4. Model

4.1 Objectives

4.1.1 Minimization of the total costs

Total costs are composed of two parts: one is capital expenditure; the other is the charging cost:

$$\mathrm{Min(CE{+}CC)} \quad (6)$$

Capital expenditure (CE) includes: land cost, construction cost and the cost needed to expand the power grid due to the construction of the charging station:

$$\mathrm{CE}{=}\sum_i \sum_k \mathrm{C}_L^i \times x_{k,i} + \mathrm{C}_C^i \times x_{k,i} + \mathrm{C}_G^i \times x_{k,i} \times \left[\mathrm{PL_i} \times \mathrm{F_i} - \left(\mathrm{RPL_k} \times \mathrm{F_{k,max}} - \mathrm{IPL_k} \times \mathrm{F_k}\right)\right] \quad (7)$$

Where,

C_L^i, C_C^i, C_G^i are respectively cost of land, construction and grid expanding; $\mathrm{PL_i}$ is power load of i-type of charging station; $\mathrm{RPL_k}$ is rated power load at node k; $\mathrm{IPL_k}$ is power load before the construction at node k; $\mathrm{F_k}$ and $\mathrm{F_{k,max}}$ indicate the existing and the maximum current on node k respectively; F_i is the current of i-type of charging station; $x_{k,i}$=0 indicates do not construct i-type of charging station at node k, while $x_{k,i}$=1 leads to the opposite.

Charging cost (CC) is the cost to purchase electricity which is calculated by average industrial electricity price throughout the year

$$\mathrm{CC}{=}\sum_i \sum_k \mathrm{P_e} \times \mathrm{PL_i} \times \mathrm{T_{avg}} \times x_{k,i} \quad (8)$$

Where,

P_e is the average industrial electricity price; T_{avg} indicates the average use time of charging station.

4.1.2 Maximization of the coverage

Due to the characteristics of the expressway, the coverage cannot be measured by the service radius as the charging pile in the city. Therefore, this paper uses the average distance between every two adjacent charging stations on the same road to express the intensity.

$$\mathrm{Min}\ \ \alpha \times \sum_k D(x_{k+1}, x_k) \times x_{k+1} \times x_k \quad (9)$$

Where,

α is a parameter converts the distance between nodes to the actual distance ($\alpha > 1$); $D(x_{k+1}, x_k)$ represents the point to point distance between node k and node k + 1

4.2 Constraints

4.2.1 Demand Constraint

The capacities of all the charging nodes in the area should not be less than the total charging demands of EVs in this area.

$$\sum_i \sum_k PL_i \times x_{k,i} \geq D_{max} \quad (10)$$

Where,

D_{max} represents the total charging demand of EVs in the area.

4.2.2 Distance Constraint

Assuming that the charging vehicles will accept the charging service at the station until the battery is fully charged, this constraint ensures that the distance between two adjacent charging station nodes is not greater than the average maximum driving distance.

$$\alpha \times D(x_{k+1}, x_k) \times x_{k+1} \times x_k \leq L_{max} \quad (11)$$

Where,

L_{max} is the average maximum driving distance when the battery is fully charged.

4.2.3 Scale Constraint

The number of facilities in each charging station node shall not be less than the EVs that needs to be charged. Therefore, there will be no waiting cost.

$$x_{k,i} \times E_i \geq \beta \times \gamma \times Z_k \quad (12)$$

Where,

E_i is the number of charging facilities in i-type of station; β is the proportion of EVs that need to be charged in the traffic ($\beta < 1$); γ is the average proportion of EVs among all traffic flow ($\gamma < 1$).

4.3 Planning Process

Based on the MOPSO and GIS, the planning process of charging stations along the highway would be as follows:

First of all, setting the parameters in the model according to the statistics and assumptions.

Secondly, estimate the total charging demand of the region. We adopt the calculation method used by Jia,Long et al. (2016) which mainly based on the EVs fleet, battery capacity and average mileage:

$$D_{max} = N \times S \times B / L_{max} \quad (13)$$

Where,

N is the number of EVs in the region, S is the average travel mileage, B is the average battery capacity.

And then find the alternative construction points by using GIS to overlap the two diagrams. And establish the two-objective model according to formulas (6) - (12).

Finally, use Particle Swarm Optimization to get the optimal positions and specifications to construct.

The detail of the process can be found in the flow chart in Appendix B.

5. Case of Changping

Based on the proposed method and the model in sections 3 and 4, we select Changping - a district in Beijing - as a planning area to optimize the construction of charging stations on the surrounding highways.

The Beijing Traffic Management Bureau statistics show, as of April 2016, the EVs fleet in Changping District reached 2,191, ranked 5th in Beijing and the number is rapidly increasing recently. Besides, government of Changping actively promotes the development of electric taxi, with a point to facilitate the substitution of gasoline cars and alleviate the serious environmental problem in Beijing. The drivers of electric taxis will get subsidies and there are also plenty of preferential policies for them. Therefore, this district is selected as a planning region to optimize the scale and location of charging stations using the MOPSO we proposed. In addition, a scenario analysis is conducted to find the effects of the development of EVs on the charging stations.

5.1 Estimate the charging demand of the region

As we mentioned in 4.3, we adopt the method used by Jia,Long et al. (2016) to estimate the charging demand of Changping distinct which mainly bases on the EVs fleet, battery capacity and average mileage.

The sampling survey of EVs in Changping district shows the electric taxis account for 10.1% of the total EVs, with an average mileage of 425KM; while the private EVs account for 89.9%, with an average driving mileage of 68.49KM. So, the weighted average mileage of electric vehicles in the region would be 104.49KM.

In addition, we made a research in detail of the battery capacities in the market of EVs at this region. Different brands of EVs use different types of battery which possess different specifications. Weighted average method were used to get the average capacity according to the market share of different brands (Figure 4) and their battery specifications.

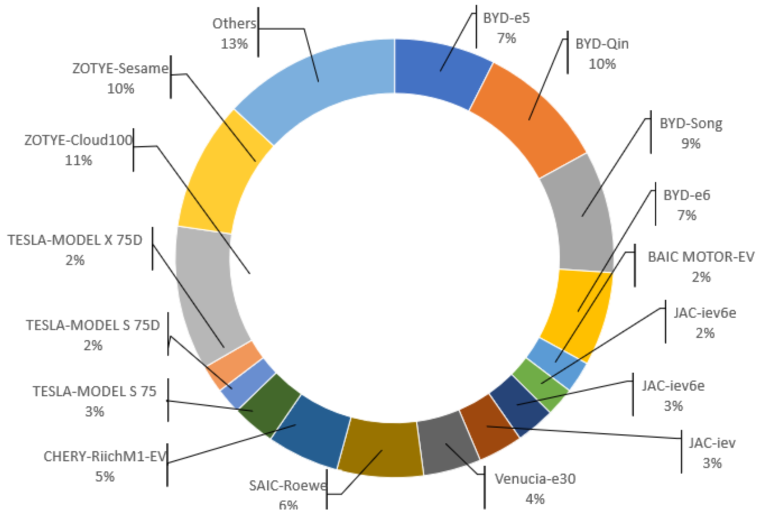


Figure 4: Proportions of Different Bands of EVs in Beijing

According to formula (13) and the data above, the total charge demand of Changping district is 1492047KWh.

5.2 Determination of the alternative construction points

As we mentioned, a charging station needs to serve as a public service facility as well as a high-power demand facility, so it is necessary to use geographic information system to consider the convenience as well as its influence on the power grid. In this paper, Arc GIS was used to overlay the traffic system diagram and the power system diagram. In order to reduce the costs of expanding power grid caused by the construction of charging station, the geography intersections of power grids and highways were selected as the alternative points for construction (Liu,Zi Fa et al., 2012). The data of traffic flow obtained from Beijing Traffic Management Bureau was used in the scale constraint. The result is shown in Figure 5. Thirteen candidate points were selected in this distinct. The details of the alternative points can be found in Table 2.

Figure 5: Candidate Construction Points in Changping

Number	Highway	Rated voltage	Number	Highway	Rated voltage
1	G110	220V	8	G6, 6th ring road	500V
2	G110	220V	9	6th ring road	220V
3	G6	220V	10	6th ring road	220V
4	G110, G6	220V	11	6th ring road	220V
5	G6	220V	12	G6	220V
6	6th ring road	500V	13	G6	220V
7	G7	500V			

Table 2: Specifications of alternative construction points

5.3 Scenario analysis

According to the national standard for electric vehicle charging system (GB/T 18487.1-2001"The general requirements for electric vehicle conductive charging system", GB/T 18487.2-2001"The connection requirements for electric vehicle conductive charging system and AC/DC power supply ", GB/T 18487.3-2001 "Electric vehicle conductive charging system and AC/DC charger (station)"), there are 4 types of charging stations which are presented in the Table 3. We take them as the alternative charging stations of the plan. And their costs are shown in Table 4.

Type	Service capability (cars/day)	Number of Chargers	Floor space (m^2)	Type of charger	Rated voltage	Maximum current
A	360	45	1085	DC Charger	380V±10% 50±1Hz	80/125/200/250
B	240	30	693	AC charger (>5KW)	380V±10% 50±1Hz	16/32/63
C	100	15	337	AC charger (<5KW)	220V±10% 50±1Hz	10/16/32
D	60	8	165	AC charger (<5KW)	220V±10% 50±1Hz	10/16/32

Table 3: The specifications of the alternative charging station

Type	Total construction cost (Ten Thousand Yuan)	Land cost (Ten Thousand Yuan)	Expansion cost of the grid (Yuan/KW)
A	690	136.71	553.6
B	520	87.218	553.6
C	310	42.462	553.6
D	210	20.79	553.6

Table 4: Costs of different charging stations

And Table 5 shows the average traffic flows at the 13 alternative construction points.

Number	Traffic flow (Thousand cars/day)	Number	Traffic flow (Ten thousand cars/day)
1	45.77	8	33.51
2	43.30	9	35.21
3	48.57	10	39.67
4	43.23	11	37.59
5	49.60	12	41.90
6	56.71	13	49.13
7	32.86		

Table 5: Traffic flow Data Alternative Point

On one hand, the development of EVs requires the support of the charging stations. On the other hand, the growing trend of EVs will determine the future constructions of the stations. So, in this paper we set two scenarios: one is the base-year scenario in 2016 and the other represents the future situation in 2020. And we made a comparison of the two scenarios, looking forward to finding the relationship between the development of EVs and the constructions of charging stations.

5.3.1 Scenario 1: Base-year Scenario

In the base-year scenario we set the values of parameters according to real data in 2016 from the Traffic Management Bureau. Besides, since no highway is totally straight, we adopted the empirical road conversion factor used by Liu et al. (2012) and set it as 1.2. This parameter is used to convert the point to point distance between nodes to the actual distance. And other parameters are shown in Table 6. N is the number of EVs in the planning region which has a strong influence on the charging demand. Up to 2016, the EVs fleet in Changping reached 91000. And according to the estimation in 5.1, the charging demand would be 1492047KWh in the planning area. β, which is 8.3% according to the survey, is the proportion of EVs that need to be charged in the traffic. γ is the average proportion of EVs among all traffic flows.

N (Ten thousand cars)	β (%)	γ (%)
9.1	8.3	6.39

Table 6: Parameters in scenario 1

Based on the parameters and formulas (6) to (13), we set up the model and solved it using MOPOS.

Figure 6 shows the Pareto curve between the two objective functions. We can find that there is a clear alternative between the goals of minimizing the total costs and maximizing the coverage: in order to make the charging facilities more intensive, more charging stations need to be built, which will definitely increase the costs accordingly; on the other hand, to reduce the total costs, the number of charging stations should decrease as much as possible and the coverage will also be limited at the same time.

The Pareto curve also shows a change of scale economies effect. When only a few charging stations were built, the slope is larger which means when more stations are constructed in the region, the costs will not increase by a lot. This may partly due to the learning effect and economical efficiencies of raw material, transportation and construction. But as more stations are built, the Pareto curve gradually slows down, which leads to the opposite to the economies of scale. And the reason is that when more stations are constructed and concentrated, the burden on the grid will greatly increase and more costs will incur to expand the capacities of grid which result in a dramatic increase on the total cost. The changes of scale economies follow the bottleneck effect: when the number of stations reach a certain amount, the economies of scale will appear again which may be the result of great expansion of the grid.

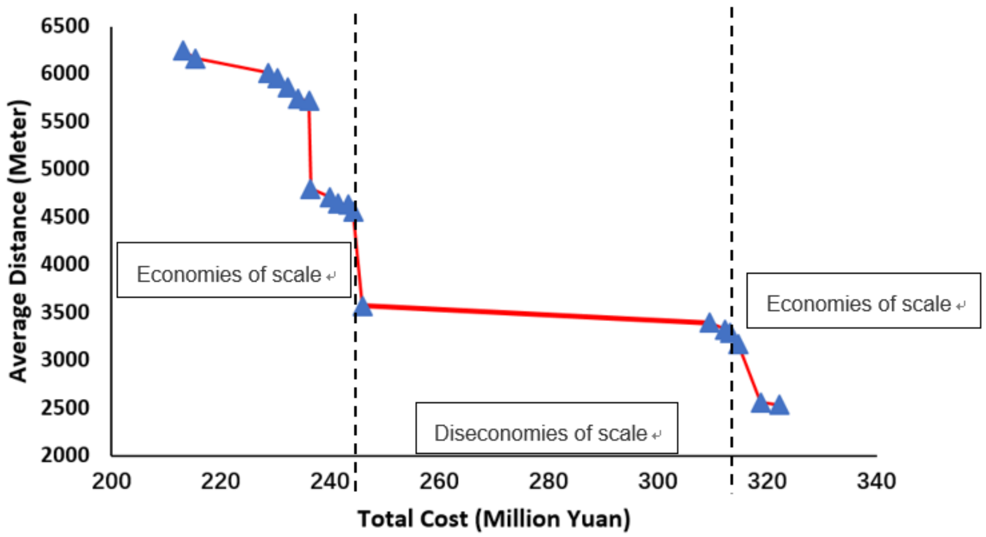


Figure 6: Pareto Curve in Scenario 1

Due to the fact that the result of MOPSO is a Pareto optimal set, we used the Displaced Ideal Model to obtain the only compromise solution. We assumed that for the planning of a charging station, the two objective functions are of the same importance. Therefore, the internal factors of each objective function are identical, that is, w = (w1, w2) = (1/2, 1/2).

The final results of the optimal planning are shown in Table 7 and Figure 7.

Alternative Point	Type of charging station			
	Type A	Type B	Type C	Type D
1	0	0	0	0
2	0	0	1	0
3	0	0	0	1
4	0	1	1	0
5	0	0	1	0
6	0	1	1	1
7	0	0	0	0
8	0	0	1	0
9	0	1	0	0
10	0	0	1	0
11	0	1	0	0
12	1	1	0	0
13	0	1	1	0

Table 7: Optimal planning results of Charging station

Figure 7 : Optimal planning results of Charging station

Among the 13 alternative points, the model chose 11 points to construct charging stations. The total construction cost is 241.4 million yuan, and the average distance between every two adjacent nodes on the same road is 4.64 kilometers.

The model claims that four of the eleven points should construct two or more types of charging stations. Two main reasons could be found: one is the limitation of scale. For example, at point 6, the model chose to construct 3 stations (type B, C and D) which is due to the huge traffic flow at this point and therefore a large charging demand. The combination of B, C and D has 48 chargers with a service ability of 400 cars/day which exceeds type A with 45 chargers. The other reason is the cost. At node 4, we chose to build stations B and C rather than A with the same service ability and this could be the result that the total construction costs of B and C (10.33 million yuan) are much cheaper than A (22.47 million yuan) who possesses lager expansion cost (14.2 million yuan) at this point.

Besides, B and C generate less expansion costs under the circumstance that the EVs in the distinct are not that much and the charging demand is relatively weak, while type D has limited service capability. So, most of the 11 construction points selected type B and C.

5.3.2 Scenario 2: 2020 scenario

Since the development of EVs requires the support of charging stations and that will also determine the constructions of the stations, we set a future scenario of 2020 to test the mutually determined relationship between them.

In this scenario, we set the number of EVs in the planning region (N) as 180,000 which is derived from <Special Planning of Electric Vehicle Charging Infrastructure in 2020>. So, the charging demands in 2020 are supposed to be 2951303 KWh. And we made reasonable hypotheses that the driving patterns and the technology of battery will not change a lot in such a short time span. Besides, other parameters are shown in Table 8.

N (Ten thousand cars)	β (%)	γ (%)
18	12	15

Table 8: Parameters in scenario 2

We set up the model similarly and used MOPOS to solve it. The Pareto curve is shown in Figure 8. We can find that it possesses the same properties as in the first scenario.

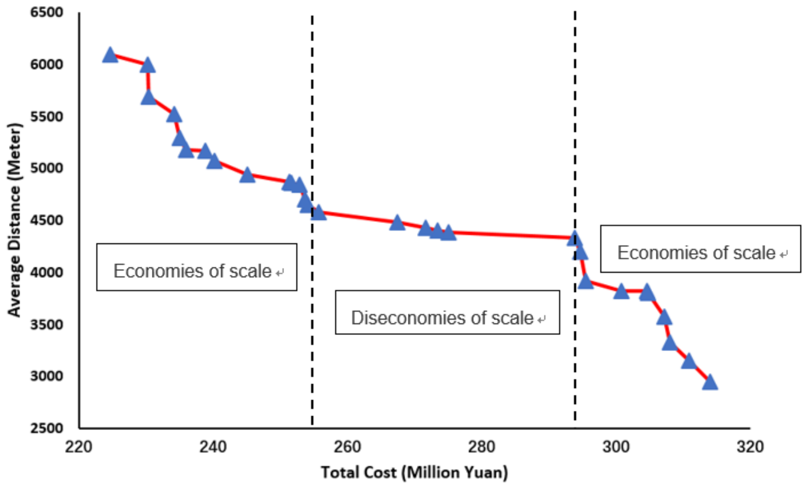


Figure 8: Pareto Curve in Scenario 2

The following Table 9 and Figure 9 show the results of the optimal planning in 2020 scenario.

Alternative Point	Scenario 1	Scenario 2
1	Null	B
2	C	C
3	D	B+C
4	B+C	B+C
5	C	A
6	B+C+D	B+C+D
7	Null	B+D
8	C	Null
9	B	A+C
10	C	B+C
11	B	A+B+C
12	A+B	A+D
13	B+C	A+C+D
Total Cost (Million Yuan)	241.40	273.44
Average Distance (Meter)	4641.50	4104.69

Table 9: Comparison of Optimal Planning Results in Scenario 1 and 2

Figure 9：Change of Optimal Planning Results

In scenario 2, the model chose 12 of the 13 alternative nodes to construct charging stations. The total cost will be 273.44 million yuan. And if we assume the constructions are based on the results in the base-year scenario and there is no abandon cost, the update cost will be only 32.04 million yuan. Besides, the average distance between two adjacent nodes on the same road is narrowed to 4.1 kilometers.

The results of the two scenarios partly show the characteristic of consecutiveness. Seven nodes get updates in year 2020. The reason is that the second scenario shows the development of the EVs in 2020 and that requires more charging stations with stronger service abilities to satisfy the increasing charging needs. However, there is an interesting fact at nodes 7 and 8. In base-year scenario, the model chose not to build at node 7 and a type C station at 8. Nevertheless, in 2020, two stations (B and C) are supposed to construct at node 7 while no station at 8. To figure it out, we also need to take nodes 4 and 6, which are in the same roads with the two nodes, into account. Node 6 possesses traffic flows far beyond others and with the increase of the charging demand, the three stations built in 2016 may not satisfy the needs. So, the model selected node 7, who is closest to 6, to build two charging stations to share the burden and we do not update at 8 because of the expansion costs of B and C are much higher than B and D at node 7. Besides, there is no station along the north part after node 4 in scenario 1, so stations are necessary at node 7. And the model did not update node 4 because node 7 is on a grid with larger capacity. This can be also adopted similarly to the situation at node 12.

6. Conclusion

The results of the case in Changping point out that the Pareto curve between the total costs and the coverage shows a change of scale economies effect. The constructions of charging stations will experience a process from economies of scale to diseconomies of scale and back to economies of scale again. As the growing trend of EVs and the increase of charging demands are inevitable, it is better for us to break through the bottleneck effect at earlier stage of constructions, so as to make the updates in the near future easier and more economical. For the 2020 scenario of Changping, the optimal solution is in the area of diseconomies of scale. If we take a perspective of long term and consider the bright future of EVs, a better strategy could be more constructions of charging stations and push the solution to the second stage of economies of scale while the increase on the total costs would not be so high.

According to the comparations of the two scenarios, development of EVs and constructions of the stations have a mutually determined relationship. The total costs in both scenarios are above 200 million yuan and the construction process could be tough, so the government should lead the planning and financing processes rather than completely marketize them. Some preferential policies are also necessary. Such as low loan interest rate, better electricity price than industrial one and etc. Besides, only 3 nodes remain at the same scales and 8 nodes require updates or new stations in a 4-year development plan of EVs. And if we ignore the abandon costs, the costs of updates will be approximately 32.04 million yuan which only account for 11.72% of the total cost. The main reason is that the expansion costs take up a large part and that was already finished in the base-year scenario. So, when the government plans the construction of charging stations, they should have a long run perspective in case of frequent updates and the expansion costs should be fully considered since they take a huge part and the safety of gird is vital. When making a construction plan of charging stations, a better strategy is based on the estimated or planned data in the near future rather than the real data. For instance, in the case of Changping, the government could propose the construction plan of 2016 according to the 2020 scenario. In that case, the abandon costs would be saved, and we have plenty of time for the grid expansion.

Moreover, in both scenarios the model chose to build more than one type of station in some nodes. In 2020 scenario, 9 of the 12 constructed nodes would propose two or more types of stations and most of them take type A as an optimal choice. One reason is that the specifications of existing stations could not satisfy the increasing needs. The other one would be the expansion costs are so expansive that the model prefers the combination of two or more small stations to make it economical. But the problem is that they take larger foot space than one station with the same service ability. So, the government should invest more on the relevant technology in order to have some new types of stations possess of better ability. This would be helpful to satisfy the rapidly increasing charging needs without bringing too much burden on the grid.

At the end we should emphasize that there is a limitation in the study: the comparation of the two scenarios is insufficient since the abandon costs caused by the updates are not considered. And it is due to the unavailability of the data. This shall be taken in to account and overcome in the future research.

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Appendix A: Nomenclature

Indices:

i: set of charging stations

k: set of the alternative points to construct the charging stations

Parameters:

CE: capital expenditure

CC: cost to purchase electricity every year

C_L^i: cost of land for the charging station of type i

C_C^i: cost of construction for the charging station of type i

C_G^i: cost of expand grid for the charging station of type i

RPL_k: rated power load of node k

IPL_k: power load before the construction on node k

PL_i: power load of i-type of charging station

F_k: current on k node

F_i: current of i-type of charging station

$F_{k,max}$: maximum current on k node

$F_{k,max}^A$: maximum current after the expansion on k node

L_{max}: the average maximum driving distance when the battery is fully charged

D_{max}: total charge demand of EVs in the region

α: parameter that converts the distance between nodes to the actual distance ($\alpha > 1$)

β: proportion of EVs that need to be charged in the traffic ($\beta < 1$)

Z_k: traffic flow on k node

γ: average proportion of electric vehicles among all traffic flows ($\gamma < 1$)

E_i: number of facilities in the i-type of charging station

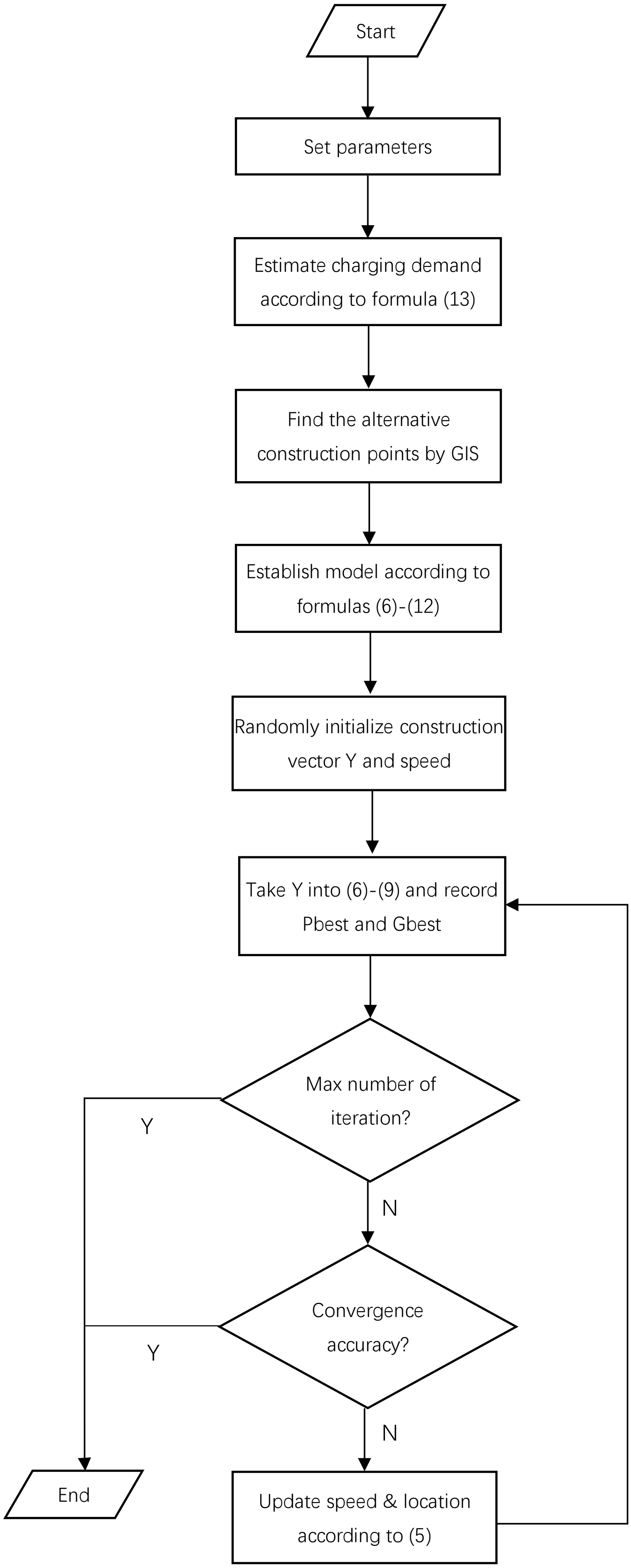
P_e: average industrial electricity price

T_{avg}: average use time of the charging station

Variables:

$$x_{k,i}: \begin{cases} 0, \text{ do not construct i-type of charging station at the k-node} \\ 1, \text{ construct i-type of charging station at the k-node} \end{cases}$$

Appendix B: Flow-Chart of Planning Process



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