



HAL
open science

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

Yue Zhang, Qi Zhang, Arash Farnoosh, Siyuan Chen, Yan Li

► **To cite this version:**

Yue Zhang, Qi Zhang, Arash Farnoosh, Siyuan Chen, Yan Li. GIS-Based Multi-Objective Particle Swarm Optimization of charging stations for electric vehicles. *Energy*, 2019, 169, pp.844-853. hal-02009151

HAL Id: hal-02009151

<https://ifp.hal.science/hal-02009151>

Submitted on 6 Feb 2019

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

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

Yue Zhang^a, Arash Farnoosh^b, Qi Zhang^a, Siyuan Chen^a

^aAcademy of Chinese Energy Strategy, China University of Petroleum-Beijing, Changping, Beijing 102249, China

^bIFP Energies Nouvelles, IFP School, 228-232 Avenue Napoleon Bonaparte, F-92852 Rueil-Malmaison, France

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

23 **1.Introduction**

24 According to BP statistics, in 2016 the consumptions of China's primary energy reached 3.053
25 billion tons of oil equivalent, accounting for 23% of the total primary energy consumption in the world.
26 In addition, the emissions of carbon dioxide reached 9.123 billion tons for the same year, accounting for
27 27.3% of the world's total emissions and making China the largest energy consumer and CO2 emitter in
28 the world.

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

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

43 As a relatively new type of clean transportation, the development of EVs in Beijing has met some
44 obstacles, such as the constraint of driven distance due to the battery capacity, the slow charging speed

45 and the inadequate constructions of charging facilities. The last one is the most urgent issue hinges the
46 personal purchases of EVs and greatly hampers their development in the city. Therefore, how to
47 reasonably plan the construction of charging facilities to meet the charging needs of EVs in Beijing has
48 become the most pressing problem.

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

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

60 Charging stations and power stations are mainly distributed along the road, especially highways
61 between cities. Aiming at quick charge within a short time span, their role is much more similar to the
62 gas stations for gasoline vehicles. This makes them suitable for EVs that need long-distance journey, so
63 they are conducive to break through the limited battery capacity of EVs and increase the travel distances.
64 But there is also a difference between the two types of facilities: the power stations have a higher
65 requirement of the facilities due to the need to satisfy most of battery specifications in the market. So,
66 power stations are mostly designed for the electric buses who possess only a few specifications. Various

67 specifications in the battery market make them not yet a practical solution for private EVs. However,
 68 charging station can meet most plugs of the EVs but the huge construction costs, high requirements of
 69 foot space and power grid make it not so prevailing as charging piles in China. The characteristics,
 70 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 |

71 Table 1: Summary of Different Charing Facilities

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

77 2.Literature review

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

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

98 Various types of methods were adopted to optimize the planning strategy of charging stations.
99 Jia,Long et al. (2016) estimated total demand of EVs based on the number and driving statistics, and
100 different charging facilities were used to satisfy different types of demands. A study of charging stations
101 in Italian highways was given by S. Micari et al. (Micari et al., 2017) using a two-stage method in order
102 to find the optimal locations of charging stations. With the development of computer science, bionic
103 algorithms were also widely used. For instance, the construction costs were optimized using Genetic
104 Algorithms (GA)(Alegre et al., 2017) and Quantum Particle Swarm Optimization (QPSO)(Liu,Zi Fa et
105 al., 2012) on a city in Spain and a virtual region separately. A. Awasthi et al. (Awasthi et al., 2017)
106 combined two popular bionic optimization algorithms: particle swarm optimization (PSO) algorithm was

107 used to reoptimize the suboptimal solution set obtained by GA. This method was applied to a planning
108 model of charging facility in India and the accuracy was greatly improved. Zhang,Di (2015) used a two-
109 objective model to study the alternative between the construction cost of charging facilities and the
110 improvement of the charging speed, and the standard normalization method was used to solved it. Besides,
111 among all cases in the literatures, virtual or simplified maps were widely used (Chen.Guang et al., 2014;
112 Zhang,Di, 2015).

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

122 **3.Methodology**

123 3.1 Multi-objective optimization model based on particle swarm optimization (MOPSO)

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

127 Among all the literatures related to multi-objective optimization, researchers mainly use two
128 methods to deal with the problems. The first one is to convert multiple objectives into one function, and

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

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

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

$$163 \quad X_i = (x_{i1}, x_{i2}, \dots, x_{iD}), i = 1, 2, \dots, N \quad (1)$$

164 The velocity of each particle can be expressed as:

$$165 \quad V_i = (v_{i1}, v_{i2}, \dots, v_{iD}), i = 1, 2, \dots, N \quad (2)$$

166 The optimal solution of each individual particle is:

$$167 \quad P_{best} = (p_{i1}, p_{i2}, \dots, p_{iD}), i = 1, 2, \dots, N \quad (3)$$

168 The global optimal solution of the population is:

$$169 \quad G_{best} = (p_{g1}, p_{g2}, \dots, p_{gD}) \quad (4)$$

170 The updated speed of the particle in each iteration is:

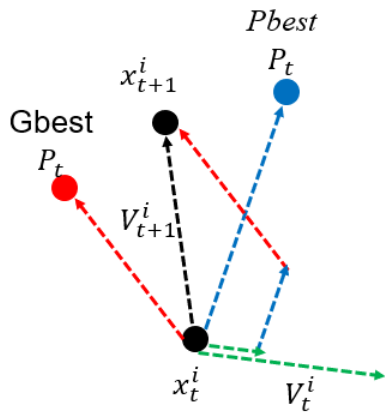
$$171 \quad v_{id} = w \times v_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 (p_{gd} - x_{id}) \quad (5)$$

172 Where w is inertia weight, c_1 , c_2 are learning factors, and r_1, r_2 are random numbers between 0

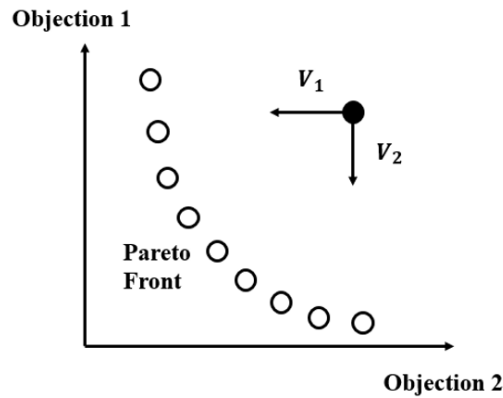
173 and 1. Formula (5) is mainly composed of the following three parts: The first part is the inertial part
 174 which reflects the motional pattern of particle and ensures the global convergence; the second part is the
 175 cognitive part that makes the particle moves according to their own memory; the last one is the social
 176 part, which reflects the collaboration among the particles and leads the optimization move towards the
 177 Gbest. The last two parts ensure the local convergence.

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

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



183
184 Figure 1: The Movement of Particle



185
186 Figure 2: Formation Process of Pareto Front

185 3.2 GIS

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

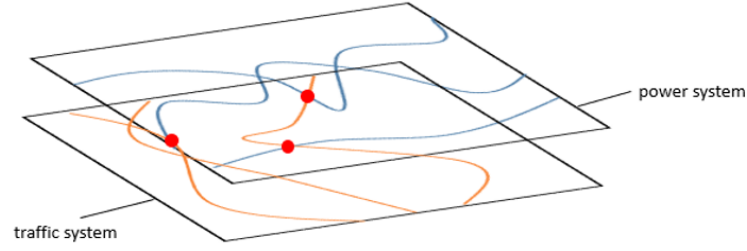


Figure 3: The Overlay Diagram of Traffic System and Power System

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:

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

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:

$$\text{CE}=\sum_i \sum_k C_L^i \times x_{k,i} + C_C^i \times x_{k,i} + C_G^i \times x_{k,i} \times [\text{PL}_i \times F_i - (\text{RPL}_k \times F_{k,\text{max}} - \text{IPL}_k \times F_k)] \quad (7)$$

Where,

C_L^i , C_C^i , C_G^i are respectively cost of land, construction and grid expanding; PL_i is power load of i -type of charging station; RPL_k is rated power load at node k ; IPL_k is power load before the construction at node k ; F_k and $F_{k,\text{max}}$ 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

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

Where,

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

213 4.1.2 Maximization of the coverage

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

$$217 \quad \text{Min } \alpha \times \sum_k D(x_{k+1}, x_k) \times x_{k+1} \times x_k \quad (9)$$

218 Where,

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

221 4.2 Constraints

222 4.2.1 Demand Constraint

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

$$225 \quad \sum_i \sum_k PL_i \times x_{k,i} \geq D_{max} \quad (10)$$

226 Where,

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

228 4.2.2 Distance Constraint

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

$$232 \quad \alpha \times D(x_{k+1}, x_k) \times x_{k+1} \times x_k \leq L_{max} \quad (11)$$

233 Where,

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

235 4.2.3 Scale Constraint

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

$$238 \quad x_{k,i} \times E_i \geq \beta \times \gamma \times Z_k \quad (12)$$

239 Where,

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

242 4.3 Planning Process

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

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

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

$$248 \quad D_{\max} = N \times S \times B / L_{\max} \quad (13)$$

249 Where,

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

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

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

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

256 **5. Case of Changping**

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

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

268 5.1 Estimate the charging demand of the region

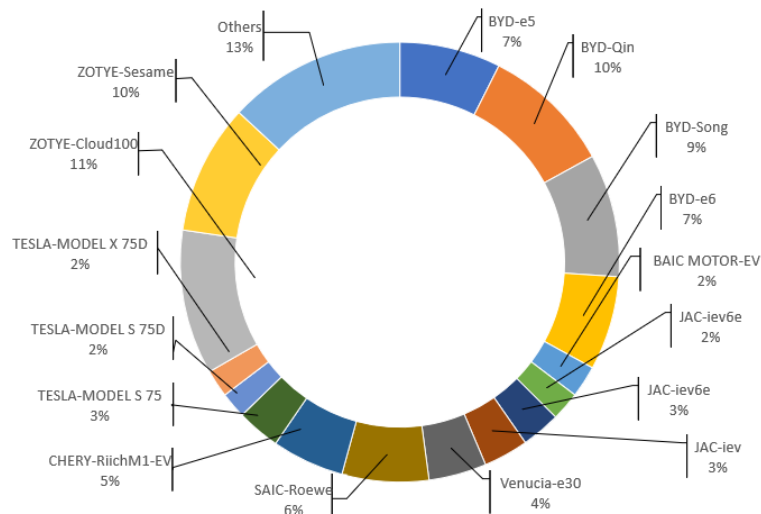
269 As we mentioned in 4.3, we adopt the method used by Jia,Long et al. (2016) to estimate the charging
270 demand of Changping district which mainly bases on the EVs fleet, battery capacity and average mileage.

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

275 In addition, we made a research in detail of the battery capacities in the market of EVs at this region.
276 Different brands of EVs use different types of battery which possess different specifications. Weighted

277 average method were used to get the average capacity according to the market share of different brands

278 (Figure 4) and their battery specifications.



279

280 Figure 4: Proportions of Different Bands of EVs in Beijing

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

282 1492047KWh.

283 5.2 Determination of the alternative construction points

284 As we mentioned, a charging station needs to serve as a public service facility as well as a high-

285 power demand facility, so it is necessary to use geographic information system to consider the

286 convenience as well as its influence on the power grid. In this paper, Arc GIS was used to overlay the

287 traffic system diagram and the power system diagram. In order to reduce the costs of expanding power

288 grid caused by the construction of charging station, the geography intersections of power grids and

289 highways were selected as the alternative points for construction (Liu,Zi Fa et al., 2012). The data of

290 traffic flow obtained from Beijing Traffic Management Bureau was used in the scale constraint. The

291 result is shown in Figure 5. Thirteen candidate points were selected in this district. The details of the

292 alternative points can be found in Table 2.

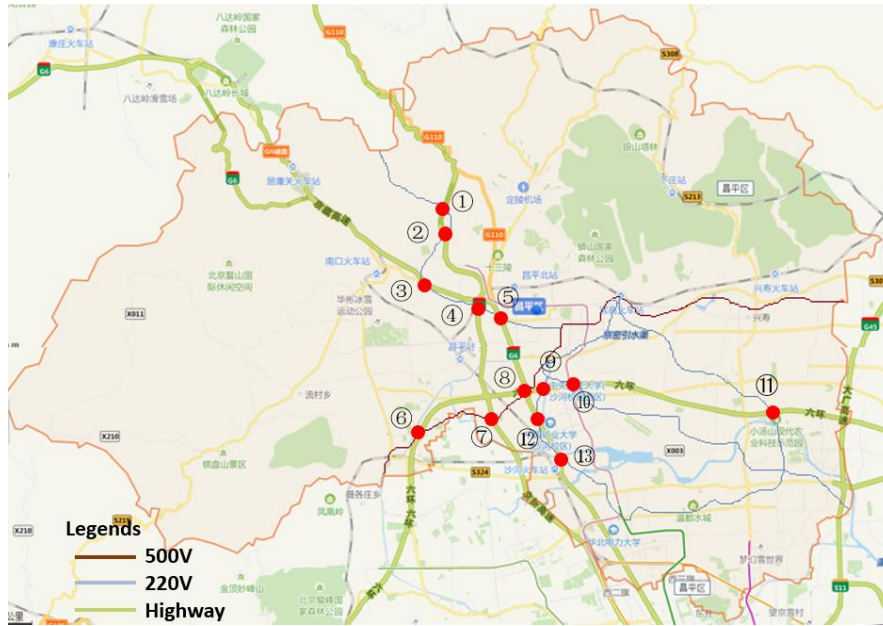


Figure 5: Candidate Construction Points in Changping

| 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 |

304 Table 3: The specifications of the alternative charging station

305

| 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 |

306 Table 4: Costs of different charging stations

307 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 | | |

308 Table 5: Traffic flow Data Alternative Point

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

313 between the development of EVs and the constructions of charging stations.

314 5.3.1 Scenario 1: Base-year Scenario

315 In the base-year scenario we set the values of parameters according to real data in 2016 from the
316 Traffic Management Bureau. Besides, since no highway is totally straight, we adopted the empirical road
317 conversion factor used by Liu et al. (2012) and set it as 1.2. This parameter is used to convert the point
318 to point distance between nodes to the actual distance. And other parameters are shown in Table 6. N is
319 the number of EVs in the planning region which has a strong influence on the charging demand. Up to
320 2016, the EVs fleet in Changping reached 91000. And according to the estimation in 5.1, the charging
321 demand would be 1492047KWh in the planning area. β , which is 8.3% according to the survey, is the
322 proportion of EVs that need to be charged in the traffic. γ is the average proportion of EVs among all
323 traffic flows.

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

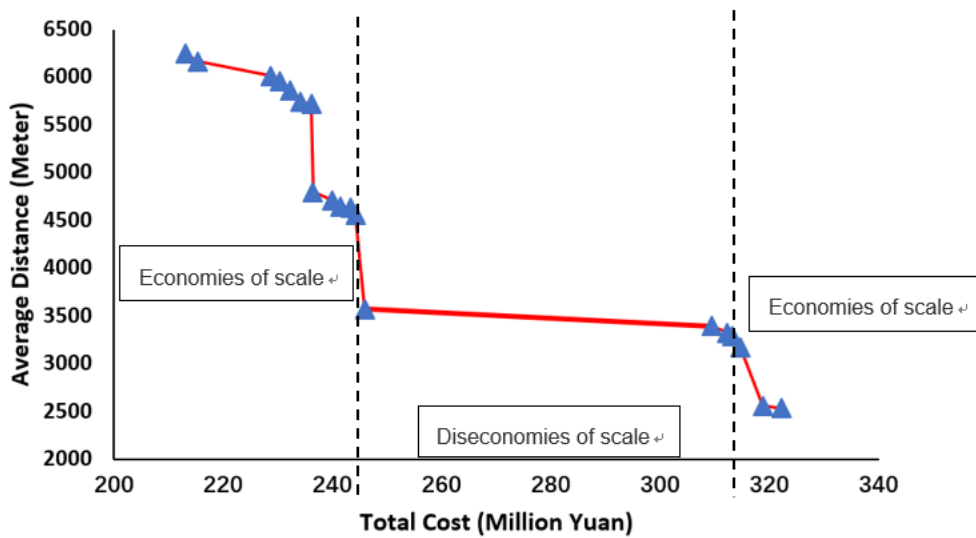
324 Table 6: Parameters in scenario 1

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

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

332 The Pareto curve also shows a change of scale economies effect. When only a few charging stations
333 were built, the slope is larger which means when more stations are constructed in the region, the costs

334 will not increase by a lot. This may partly due to the learning effect and economical efficiencies of raw
 335 material, transportation and construction. But as more stations are built, the Pareto curve gradually slows
 336 down, which leads to the opposite to the economies of scale. And the reason is that when more stations
 337 are constructed and concentrated, the burden on the grid will greatly increase and more costs will incur
 338 to expand the capacities of grid which result in a dramatic increase on the total cost. The changes of scale
 339 economies follow the bottleneck effect: when the number of stations reach a certain amount, the
 340 economies of scale will appear again which may be the result of great expansion of the grid.



341

342

Figure 6: Pareto Curve in Scenario 1

343 Due to the fact that the result of MOPSO is a Pareto optimal set, we used the Displaced Ideal Model
 344 to obtain the only compromise solution. We assumed that for the planning of a charging station, the two
 345 objective functions are of the same importance. Therefore, the internal factors of each objective function
 346 are identical, that is, $w = (w_1, w_2) = (1/2, 1/2)$.

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

348

349

| 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 |

350
351

Table 7: Optimal planning results of Charging station



352

Figure 7 : Optimal planning results of Charging station

353

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

357 The model claims that four of the eleven points should construct two or more types of charging

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

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

368 5.3.2 Scenario 2: 2020 scenario

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

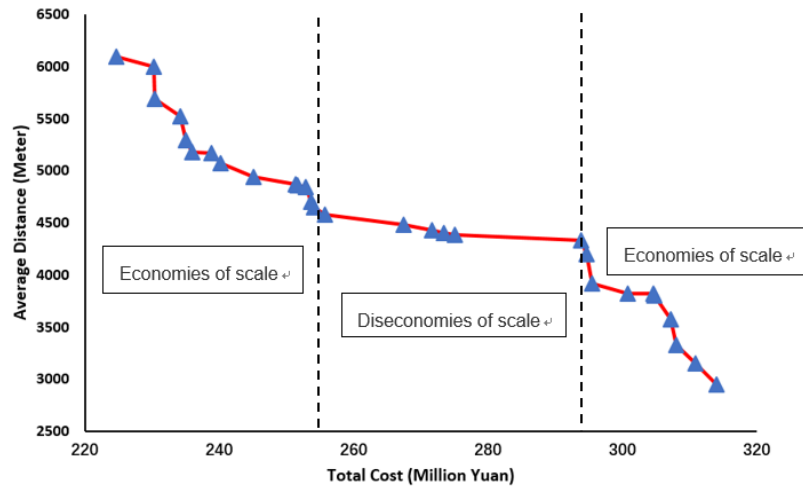
372 In this scenario, we set the number of EVs in the planning region (N) as 180,000 which is derived
 373 from <Special Planning of Electric Vehicle Charging Infrastructure in 2020>. So, the charging demands
 374 in 2020 are supposed to be 2951303 KWh. And we made reasonable hypotheses that the driving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

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

377 Table 8: Parameters in scenario 2

378 We set up the model similarly and used MOPOS to solve it. The Pareto curve is shown in Figure 8.

379 We can find that it possesses the same properties as in the first scenario.



380

381

Figure 8: Pareto Curve in Scenario 2

382

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 |

383

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



384

385

Figure 9 : Change of Optimal Planning Results

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

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

403 **6. Conclusion**

404 The results of the case in Changping point out that the Pareto curve between the total costs and the
405 coverage shows a change of scale economies effect. The constructions of charging stations will
406 experience a process from economies of scale to diseconomies of scale and back to economies of scale
407 again. As the growing trend of EVs and the increase of charging demands are inevitable, it is better for

408 us to break through the bottleneck effect at earlier stage of constructions, so as to make the updates in
409 the near future easier and more economical. For the 2020 scenario of Changping, the optimal solution is
410 in the area of diseconomies of scale. If we take a perspective of long term and consider the bright future
411 of EVs, a better strategy could be more constructions of charging stations and push the solution to the
412 second stage of economies of scale while the increase on the total costs would not be so high.

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

428 Moreover, in both scenarios the model chose to build more than one type of station in some nodes.
429 In 2020 scenario, 9 of the 12 constructed nodes would propose two or more types of stations and most

430 of them take type A as an optimal choice. One reason is that the specifications of existing stations could
431 not satisfy the increasing needs. The other one would be the expansion costs are so expensive that the
432 model prefers the combination of two or more small stations to make it economical. But the problem is
433 that they take larger foot space than one station with the same service ability. So, the government should
434 invest more on the relevant technology in order to have some new types of stations possess of better
435 ability. This would be helpful to satisfy the rapidly increasing charging needs without bringing too much
436 burden on the grid.

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

440 **Acknowledgement**

441 This research did not receive any specific grant from funding agencies in the public, commercial,
442 or not-for-profit sectors. And we would like to take the opportunity to thank those people who have
443 provided helpful suggestions during the research. We also gratefully acknowledge the editors for kind
444 help and the anonymous reviewer for their beneficial comments and encouragement.

445

446 **Appendix A: Nomenclature**

447 Indices:

448 i : set of charging stations

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

450 Parameters:

451 CE: capital expenditure

452 CC: cost to purchase electricity every year

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

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

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

456 RPL_k : rated power load of node k

457 IPL_k : power load before the construction on node k

458 PL_i : power load of i -type of charging station

459 F_k : current on k node

460 F_i : current of i -type of charging station

461 $F_{k,max}$: maximum current on k node

462 $F_{k,max}^A$: maximum current after the expansion on k node

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

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

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

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

467 Z_k : traffic flow on k node

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

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

470 P_e : average industrial electricity price

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

472 Variables:

473 $x_{k,i}$: $\left\{ \begin{array}{l} 0, \text{ do not construct i-type of charging station at the k-node} \\ 1, \text{ construct i-type of charging station at the k-node} \end{array} \right.$

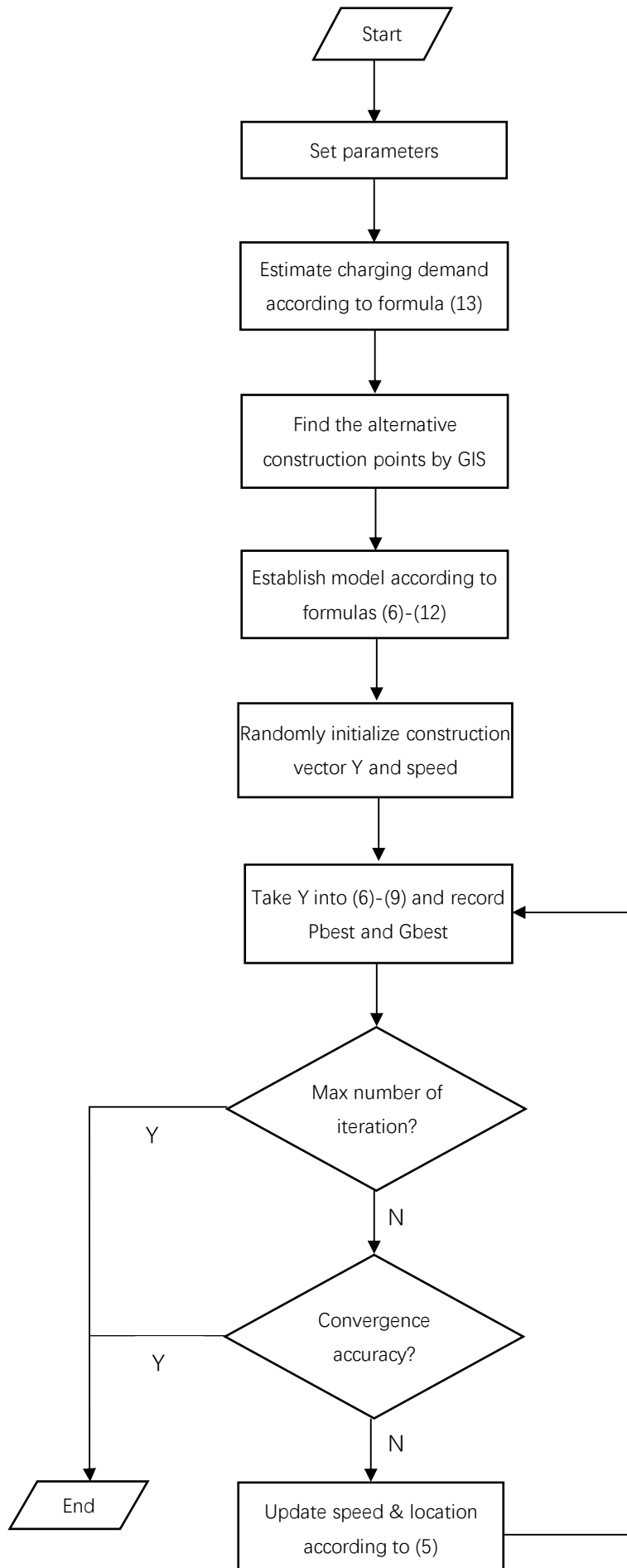
475

476 **Appendix B: Flow-Chart of Planning Process**

477

478

479



480 **Reference**

- 481 Alegre, S., Míguez, J.V., Carpio, J., 2017. Modelling of electric and parallel-hybrid electric vehicle using
482 Matlab/Simulink environment and planning of charging stations through a geographic
483 information system and genetic algorithms. *Renewable & Sustainable Energy Reviews* 74,
484 1020–1027.
- 485 Alhazmi, Y.A., Mostafa, H.A., Salama, M.M.A., 2017. Optimal allocation for electric vehicle charging
486 stations using Trip Success Ratio. *International Journal of Electrical Power & Energy Systems*
487 91, 101–116.
- 488 Asl-Najafi, J., Zahiri, B., Bozorgi-Amiri, A., Taheri-Moghaddam, A., 2015. A dynamic closed-loop
489 location-inventory problem under disruption risk. *Computers & Industrial Engineering* 90, 414–
490 428.
- 491 Avril, S., Arnaud, G., Florentin, A., Vinard, M., 2010. Multi-objective optimization of batteries and
492 hydrogen storage technologies for remote photovoltaic systems. *Energy* 35, 5300–5308.
- 493 Awasthi, A., Venkitesamy, K., Sanjeevikumar Padmanaban, Selvamuthukumar, R., Blaabjerg, F., Singh,
494 A.K., 2017. Optimal Planning of Electric Vehicle Charging Station at the Distribution System
495 Using Hybrid Optimization Algorithm. *Energy* 133.
- 496 Chen, G., Liu, L., Song, P., Du, Y., 2014. Chaotic improved PSO-based multi-objective optimization for
497 minimization of power losses and L index in power systems. *Energy Conversion &
498 Management* 86, 548–560.
- 499 Chen, Guang, Mao, Zhaolei, Li, Jiyuan, Wang, Dongju, Zhou, Hao, 2014. Multi-objective Optimal
500 Planning of Electric Vehicle Charging Stations Consider Carbon Emission. *Automation of
501 Electric Power System* 38, 49–53.
- 502 Dai, C., Wang, Y., Ye, M., 2015. A new multi-objective particle swarm optimization algorithm based on
503 decomposition. Elsevier Science Inc.
- 504 Deb, K., 2000. A fast elitist multi-objective genetic algorithm: NSGA-II. *IEEE Transactions on
505 Evolutionary Computation* 6, 182–197.
- 506 Delgarm, N., Sajadi, B., Kowsary, F., Delgarm, S., 2016. Multi-objective optimization of the building
507 energy performance: A simulation-based approach by means of particle swarm optimization
508 (PSO). *Applied Energy* 170, 293–303.
- 509 Densing, M., Turton, H., Bäuml, G., 2012. Conditions for the successful deployment of electric vehicles
510 – A global energy system perspective. *Energy* 47, 137–149.
- 511 Du, Aihu, Hu, Zechun, Song, Yonghua, Wu, Junyang, 2011. Distribution Network Planning Considering
512 Layout Optimization of Electric Vehicle Charging Stations. *Power System Technology* 35, 35–
513 42.
- 514 Gao, Ciwei, Zhang, Liang, 2011. A Review on the Impact of Electric Vehicle on Power Grid. *Power
515 System Technology* 35, 127–131.
- 516 Hatton, C.E., Beella, S.K., Brezet, J.C., Wijnia, Y.C., 2009. Charging Stations for Urban Settings the
517 design of a product platform for electric vehicle infrastructure in Dutch cities. *World Electric
518 Vehicle Journal* 1.
- 519 Jia, L., Hu, Z., Song, Y., Luo, Z., 2012. Optimal Siting and Sizing of Electric Vehicle Charging Stations.
520 *Automation of Electric Power Systems* 36, 54–59.
- 521 Jia, Long, Hu, Ze Chun, Song, Yong Hua, 2016. Planning of Charging Facilities for Electric Vehicles in
522 Cities Considering Different Types of Charging Demand. *Power System Technology* 40, 2579–

523 2587.

524 Konak, A., Coit, D.W., Smith, A.E., 2006. Multi-objective optimization using genetic algorithms: A
525 tutorial. *Reliability Engineering & System Safety* 91, 992–1007.

526 Liang,Jing, 2009. Research on Dynamic Multi-Objective Optimization Algorithm Based on Particle
527 Swarm Optimization. University of Electronic Science and Technology of China.

528 Liu, Z., Wen, F., Ledwich, G., 2012. Optimal Planning of Electric-Vehicle Charging Stations in
529 Distribution Systems. *IEEE Transactions on Power Delivery* 28, 102–110.

530 Liu,Zi Fa, Zhang,Wei, Wang,Ze Li, 2012. Optimal Planning of Charging Station for Electric Vehicle
531 Based on Quantum PSO Algorithm. *Proceeding of the CSEE* 39–45.

532 Mehar, S., Senouci, S.M., 2013. An optimization location scheme for electric charging stations, in:
533 *International Conference on Smart Communications in Network Technologies*. pp. 1–5.

534 Micari, S., Polimeni, A., Napoli, G., Andaloro, L., Antonucci, V., 2017. Electric vehicle charging
535 infrastructure planning in a road network. *Renewable & Sustainable Energy Reviews* 80, 98–
536 108.

537 Moradi, M.H., Abedini, M., Tousi, S.M.R., Hosseinian, S.M., 2015. Optimal siting and sizing of
538 renewable energy sources and charging stations simultaneously based on Differential Evolution
539 algorithm. *International Journal of Electrical Power & Energy Systems* 73, 1015–1024.

540 Srinivas, N., Deb, K., 1994. Multiobjective Optimization Using Nondominated Sorting in Genetic
541 Algorithms. MIT Press.

542 Su, C.L., Leou, R.C., Yang, J.C., Lu, C.N., 2013. Optimal electric vehicle charging stations placement in
543 distribution systems, in: *Industrial Electronics Society, IECON 2013 - Conference of the IEEE*.
544 pp. 2121–2126.

545 Wang,Hui, Wang,Gui Fu, Zhao,Jun Hua, 2013. Optimal Planning for Electric Vehicle Charging Stations
546 Considering Traffic Network Flow. *Automation of Electric Power System* 37, 63–69.

547 Xiong.Hu, Xiang.Tieyuan, Zhu.Yonggang, Song.Xudong, Chen.Hao, 2012. Electric Vehicle Public
548 Charging Stations Location Optimal Planning. *Automation of Electric Power System* 36, 65–
549 70.

550 Zhang,Di, 2015. Research on Recharge/Battery Swap Facility Location Problem of Electricity Vehicles.
551 Huazhong University of Science and Technology.

552