POLITECNICO DI TORINO

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In Automotive Engineering

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The Location - Routing Problem of Electric Vehicles in City Logistics

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0. Abstract

Recent years, with the rapid development of transportation and the increasing number of vehicles, motor vehicles have become an important source of urban environmental pollution and traffic congestion problems. Currently, 25% of CO_2 come from transportation industry (Dablanc,2011). In response of side effects of the transportation sector on energy and the environment, many countries have adopted the development of new energy vehicles as a national strategy. As a representative of new energy vehicles, electric vehicles (EVs) with zero pollution and low energy consumption have been rapidly developed, it is also imperative to popularize EVs in the logistic sector, benefits from reducing harmful gas emissions and logistics costs.

Compared with the traditional fuel vehicles, the EVs distribution faces some difficulties such as battery capacity limitations, long charging time and few charging facilities. At present, the difficulty of charging seriously restricts the marketing promotion of EVs. Consummating the deployment of charging facilities are an important guarantee for the extensive use of EVs. The rational layout of charging stations is particularly important. The traditional vehicle routing problem cannot be directly applied to the EVs distribution system. The charging station location problem and the routing problem of EVs are interdependent.

This thesis mainly discusses:

- The problem of using EVs in logistics industry, especially in urban last mile delivery.
- Based on Genetic algorithm, design a model for solving optimization problems for both Charging Station Location Allocation Problem (CS-LAP) and for Electric Vehicle Routing Problem (E-VRP).
- Analyze some examples of scenario, compare the logistics costs between traditional vehicles and EVs.

1. Introductions to the related theories

1.1 City logistics

City logistics (urban freight distribution) generally is the logistic companies provide a series of logistics services to the customer points that distributed in urban area, these services includes processing, packaging, loading and unloading, distribution, etc. City logistics is an important activity that connects the exchange of goods between the city and the outside. It has a linking role in the entire logistics distribution system.

Mainly have the following contents and characteristics [1][2][3]:

1) The distribution area is relatively concentrated and fixed. The area is often bounded by the entire city boundary. So, it has the remarkable characteristic of short distribution distance.
2) The scale of urban logistics is huge. Urban logistics mainly occurs in densely populated and resource-intensive urban areas, so the customers' needs are various and huge amounts. The common distribution forms are small-batch and multi-frequency.
3) Urban logistics pay attention to customer service quality. It is directly facing to customers, so the quality of service directly affects the corporate image and reputation of company. Service quality is mainly embodied in whether the product packaging is intact, whether the delivery is on time, etc.
4) The vehicle speed is not high. In urban logistics, because the city traffic conditions are complicated, such as traffic congestion and road maintenance. Besides, under the control of traffic lights, the speed of distribution vehicles cannot be very high.
5) Low requirements for vehicle power performance. Due to the low speed restricted by urban roads, the requirements for vehicle power performance are generally low. Therefore, urban logistics companies pay more attention to the cargo loading capacity and operating costs when choosing the means of transport.

1.1.1 Last mile delivery

Delivery is the process of transporting goods from a source location to a predefined destination. The general process of delivering goods is known as distribution. Last mile delivery describes the movement of people and goods from a transportation hub to a final destination, it is the terminal distribution of urban freight distribution [4]. As a special type of distribution, last mile service provides short-distance and point-to-point distribution within cities, it can be divided into professional distribution and general merchandise distribution, as shown in

Figure 1.1:

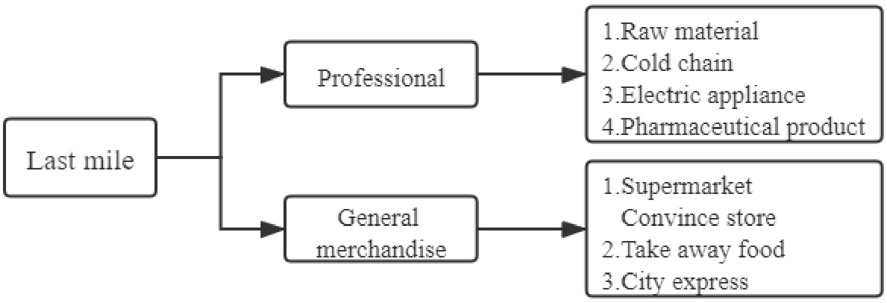


Figure 1.1 Last mile delivery classification

Professional distribution: the main customers are small and medium-sized enterprises and large supermarkets in the city. General merchandise distribution: this type of demands has a wide variety, high timeliness requirements, high distribution frequency and uneven distribution, the main customers are small enterprises, residents and individuals.

The distribution mode consists of four types [5]:

1) Self-delivery mode (direct delivery by suppliers);
2) Collaborative delivery mode (a number of logistics enterprises cooperated in a certain distribution area);
3) Outsourced delivery mode (the third-party logistics);
4) Integrated delivery mode (from production to transportation process comprehensively distribute goods by enterprises).

With the development of cities and the transformation of resident's consumption patterns, cities need more efficient distribution systems to support the daily operation of cities. At the same time, residents' higher pursuit of the urban living environment also requires logistics activities to reduce their negative impacts on environment and reduce energy consumption. Logistics is a key industry of the national economy, in China, logistic costs relative to GDP accounted for 14.6% in the first half of 2019 [6], and itself is also a major energy consumer and high emissions, so "Greening" logistic industry is imperative.

1.2 Green logistics

Green logistics refers to the use of advanced logistics technology to plan and implement logistics activities to restrain harm to environments and reduce resource consumption. The ultimate goal of green logistic is to minimize the impact of logistics activities on the environment and achieve sustainable development.

The significance of developing green logistics is not only in energy saving and emission reduction, for logistics companies, it can also reduce logistics costs and improve economic and social benefits. The development of green logistics is not only to achieve greening through technical means and management in a certain part of logistics. Moreover, the operation is carried out through all links in the logistics to realize the greening of the entire logistics system.

Green logistics is developed on the basis of traditional logistics, in term of operation process it is similar to traditional logistics. To realize a green logistics system, it is necessary to realize the greening of packaging, handling, transportation, storage, distribution, waste treatment, etc. Figure 1.2 shows the green logistics structure diagram [1]:

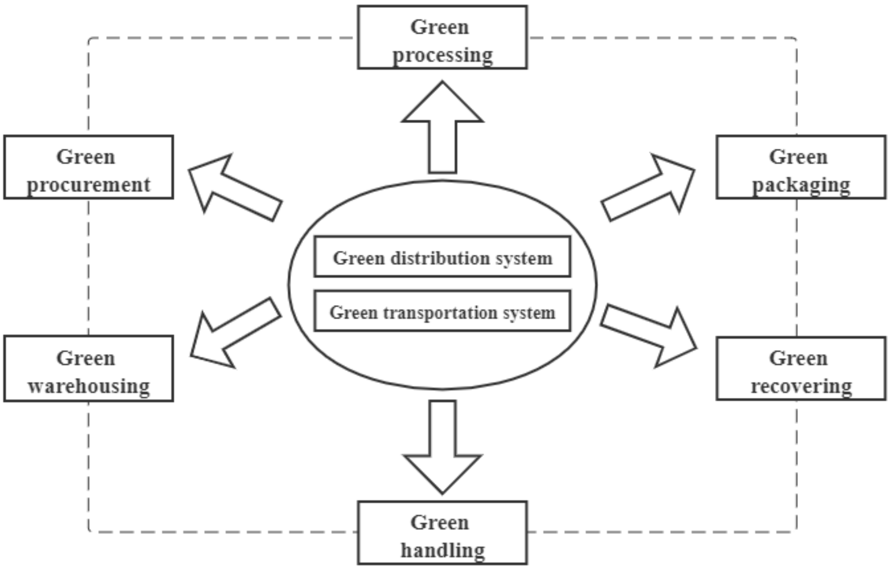


Figure 1.2 green logistic structure diagram

1.2.1 Low-carbon logistics

Green logistics is a concept with deep meaning, all methods and processes aimed at reducing the ecological environment impact during logistics process belong to the category of green logistics. While, low-carbon logistics emphasizes environmental protection, which can reduce the carbon intensity (the ratio of greenhouse gas emissions produced to GDP) during logistics. In terms of scope, green logistics includes low-carbon logistics, green logistics is richer in connotation [7].

The origin of low-carbon logistics is attributed to the low-carbon economy and the Copenhagen Environment Conference's advocacy of green issues. Low-carbon economy means that under the guidance of the concept of sustainable development, through technological innovation, institutional innovation, industrial transformation, new energy development and other means, as much as possible to reduce the consumption of high-carbon energy such as coal and petroleum, reduce greenhouse gas emissions, and achieve a win-win economic development pattern for social development and ecological environment protection.

Often most of the logistics cost lies in the transportation goods, and the carbon emissions caused by vehicle transportation also account for a large proportion of the carbon emissions of the entire logistics system.

1.2.2 Carbon emissions cost calculation

Carbon emission is an abbreviation for greenhouse gas emission, which is proposed under the background of global warming. Greenhous gases mainly include carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), ozone (O_3), chlorofluorocarbons (CFC_S), etc. The largest proportion is CO_2 among greenhouse gases [8]. Therefore, "Carbon" is used to represent greenhouse gas emissions. In this thesis, we mainly discuss the carbon dioxide gas, other gases are not considered due to small proportions. Because we study the electric vehicles routing problem of urban freight distribution, mainly consider two indicators for the calculation of the carbon emissions. One is the carbon emissions of the fuel in the upstream processing, and the other is the carbon missions caused by the exhaust emissions when the vehicle is driving. For electric vehicles and traditional fuel vehicles the carbon emissions sources are different [1][9]:

1) Fossil fuel vehicle CO_2 emissions calculation.

   The upstream process of fuel is mainly crude oil extraction and transportation, oil processing and transportation. We set a positive correlation between CO_2 emissions and vehicle fuel consumption. Through the mass conservation equation, the expression can be obtained as Eq. (1.1)

$$E = \sum F_k \cdot (\mu + \theta) \tag{1.1}$$

   $E =$ CO_2 emission for a fossil fuel vehicle in a single delivery

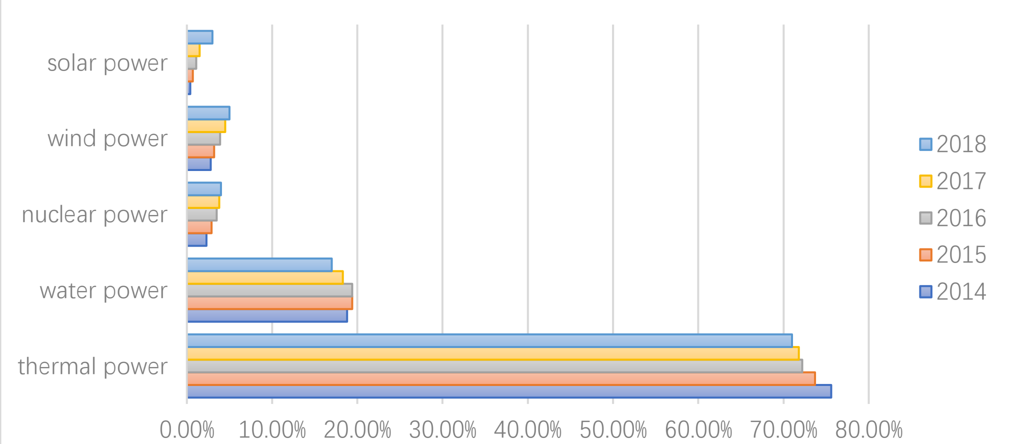
   $F_k =$ Fuel consumption per vehicle k, can be obtained by multiplying unit fuel consumption by the distance

   $\mu =$ Vehicle emission factor, used to calculate the carbon emissions caused by fuel consumption

   $\theta =$ Fuel conversion factor, carbon emissions caused by fuel production process.

2) Electric vehicle CO_2 emissions calculation.

   Electric vehicles do not produce exhaust emissions when driving, so here we only consider the carbon emission brought by the upstream power generation company's production process. According to statistics from China National Bureau of Statistics, power generation structure in the past five years as shown in Figure 1.3.



	thermal power	water power	nuclear power	wind power	solar power
2018	71%	17%	4%	5%	3%
2017	71.80%	18.30%	3.80%	4.50%	1.50%
2016	72.20%	19.40%	3.50%	3.90%	1.10%
2015	73.70%	19.40%	2.90%	3.20%	0.70%
2014	75.60%	18.80%	2.30%	2.80%	0.40%

Figure 1.3 annual power generation structure chart

We can see that thermal power generation has always accounted for the largest proportion, but the percentage has been declining. Thermal power generation accounted for 71% of total power generation in 2018. According to the climate home news, in EU, power generation coming from fossil fuels accounts for 34%. We ignore the carbon emissions caused by water power, wind power and nuclear power, only consider the carbon emissions caused by thermal power generation. According to the ratio of thermal power to the entire electricity and the mass balance equation, the expression can be obtained as Eq. (1.2):

$$E = \gamma \cdot \sum F_{ke} \cdot \lambda \tag{1.2}$$

$E =$ CO_2 emission for a fossil fuel vehicle in a single delivery

$\gamma =$ the proportion of thermal power in total power generation, here use 71% (2018)

$F_{ke} =$ electricity consumption per vehicle k, can be obtained by multiplying the unit power consumption by the distance

$\lambda =$ carbon emissions per unit of electricity production

When calculating the total logistic cost, the carbon emission cost of vehicles operation is also included in total cost. We consider the transportation distance, and converts the distance into the carbon emissions of fossil fuel vehicles and electric vehicles in the distribution process according to fuel consumption and electricity consumption through their respective conversion factors. Based on the unit carbon emission cost and the total carbon emission, calculate the carbon emission cost.

1.3 Incentive policies and measures

In the global transportation field, the CO_2 emissions caused by road transportation exceed 70% of the total emissions, of which the emissions from small vehicles (include light van and truck) account for more than 65%, become the main carbon emission source of the transportation industry, and forecasts project an increasing number of freight vehicles in city traffic [10]. In order to significantly reduce pollution and emissions from the transportation sector, some cities have announced that they will restrict internal combustion engine vehicles from entering the urban areas by delimiting zero-emission zones. Paris, London, Los Angeles, Oslo and Tokyo have already signed the *Fossil Fuel Free Streets Declaration*, commit to designate some core urban areas as zero-emission zones by 2030. Amsterdam announced that the urban central area will be designated as a zero-emission zone by 2025, allowing only zero-emission vehicles to pass, and plans to expand the zero-emission zone to the entire city area by 2030. These plans to set the zero-emission zone or the restricted zone for traditional fuel vehicles send a clear signal to companies and the public, that is, to encourage everyone to buy the electric vehicles [11].

In 2017, China ministry of transportation issued a road freight industry plan, which clearly pointed out that it is necessary to strengthen the technical management of urban distribution vehicles and provide convenience for electric vehicles. In January 2018, the State Council of China issued a document to promote the development of express logistics, encouraging the express logistics sector to accelerate the use of new energy vehicles or higher emission standard fuel vehicles, and gradually increase the proportion of new energy vehicles [12].

2. Electric vehicles applications in city logistics

In the urban last mile process, as the last link before the product reaches the customer, there are many customer points, complex distribution routes and congested road conditions that make traditional fuel vehicles run under uneconomical, high fuel consumption, low speed or idle conditions for a long time, namely causes a lot of carbon emissions, noise and vibration, and also increase the cost of vehicle. In today's low-carbon and environmental protection context, EVs have become the most promising alternative to current distribution vehicles with their zero-carbon emission, zero pollution and low noise characteristics, and are the main way to realize green logistics.

This chapter defines the related concepts of EVs and analyzes the characteristics and application status of EVs distribution.

2.1 Relevant concepts

2.1.1 Types of electric vehicles

An electric vehicle is an automobile that is propelled by one or more electric motors, using energy stored in rechargeable batteries [13]. EVs used in logistic sector can also be called—electric freight vehicles (EFVs). At present, because of their mileage limit, the application range of EFVs is relatively limited to the field of urban logistics distribution. There are mainly three types: electric minivans and vans, electric light trucks, electric refrigerated vehicles, shown in figure 2.1. Table 2.1 lists the using features of these three types [14].

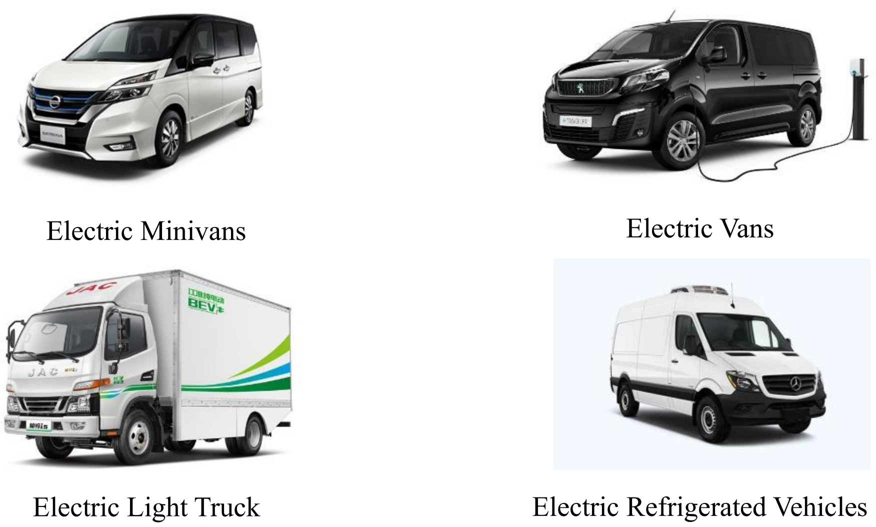


Figure 2.1 main types of EFVs

Types	Features
Electric minivans and vans	Small loading capacity, suitable for last mile delivery.
Electric light trucks	Large loading capacity, suitable for distribution from factory to distribution center (DC), master DC to regional/local DC and regional/local DC to dealers.
Electric refrigerated vehicles	Large capacity, suitable for transporting fresh food, fruits, etc.

Table 2.1 main features of EFVs

2.1.2 Characteristics of Electric vehicles

Compared with traditional fuel vehicles, the advantages of EVs are obvious:

1) They do not consume any fossil fuels or emit any CO_2 during delivery. Although part of the electrical energy in the charging process comes from thermal power plant, it generally centrally processes emissions which can also reduce carbon emissions. If their electricity comes from renewable sources, they are completely clean.
2) They make less noise than internal combustion engine vehicles, especially when driving at idle speed and low speed.
3) Many municipalities have adopted traffic controls for traditional freight vehicles entering the city center, they can only choose the fixed time period to enter the urban area or make a detour, this will increase the logistic cost. The advantages of EVs are reflected at this time. With the support of national policies, many cities have formulated separate traffic regulations for EVs, they get the priority right of way, do not subject to the same traffic restrictions as traditional freight vehicles.

Although there are great advantages of using EVs in environment, energy and services aspects, due to technical limitations, EVs still have some shortcomings:

1) Long charging time. Fast charging in 1 hour can be charged to about 80% of the full power, or it may take several hours or even twenty hours. While, fuel tanks can be filled up just in minutes.
2) Range anxiety. The limited range of EVs is often considered the most important barriers to EV adoption. From the data of the China Automotive Technology & Research Center's 2018 electric freight vehicle market analysis, it can be known that the range of EVs used for logistics transportation in China is concentrated in 200 km-250 km, the cumulative proportion is 56%. This greatly reduces the distribution scope of EFVs, and currently it can only focus on city logistics distribution. One is branch transportation with a mileage of 50-150 km, and the other is last mile delivery. The last mile in urban areas is characterized by small distance: it has been estimated that more than 80% of freight trips European cities are shorter than

80 km, which is compatible with the limited range of EFVs.

3) Backward planning of charging facilities. At present, EFVs have not been widely popularized, and they are still in the promotion period. The construction of supporting charging facilities means that a large amount of capital investment is required, but these investments cannot be profitable in the short term. From the government and enterprise level, there is a lack of motivation for the construction and improvement of charging facilities, resulting in an unreasonable ratio between the number of EFVs and charging station, and the problem of difficulty in charging.

2.1.3 Charging modes and charging infrastructures

EVs charging modes can be divided into on-board charging, ground charging, battery swapping and wireless charging modes. Each charging method has its own characteristics. Here we consider the public charging method [15]:

1) Fast charging (ground charging)

The direct current (DC) charging station charges the battery directly over a short period of time with a large current. It has high charging power (60 kw, 120 kw, 200 kw or higher). Charging time is short, usually takes 20mins to 2 hours, charging current is 150-400 A. Fast charging mode work and installation costs are higher than conventional charging mode. Due to the high current and large impact on the battery, easily heat the battery and may reduce the battery service life.

2) Normal charging

The alternating current (AC) charging pile delivers alternating current to charger, which converts its stored AC to DC to charge the battery. Because it is a two-stage power supply process, the charging speed is slow and usually takes 5 to 8 hours, some even reach 10-20 hours, charging current around 15 A. It is more suitable for charging in a fixed place or work place at idle time.

3) Wireless charging

The battery can be fast charged without the use of a cable to connect the power supply system. The technology is based on the electromagnetic induction principle, convert electrical energy into electromagnetic signals, the vehicle receives the signals and converts into electrical energy. This technology is not yet mature at present.

4) Battery swapping

Battery swapping means the electric vehicles supplement energy by replacing battery packs, eliminating the delay involved in waiting for charging battery. There are many restrictions of this mode. First, need a large-scale battery module to ensure the standardization and matching of battery replacement. Secondly, to achieve rapid and convenient battery replacement, require professional staffs and corresponding swapping stations, and the locations of stations must fully consider the mileage limit of electric vehicles. The battery swapping stations also require professional technical personnel or mechanical equipment to complete the battery replacement, charging and maintenance. Due to high investment costs, high technical requirements and lack of professionals, at present, this mode only used in a few special fields and is not feasible in public.

Battery charging stations are important infrastructures for cities in the future. At present, there are mainly two types:

1) Centralized charging stations

Provide electric energy supplement for EVs by establishing large-scale centralized professional charging facilities, similar to the current filling stations.

2) Distributed charging stations

Charing piles are installed in public places (public parking place, shopping mall, highway service area, etc.) and parking spaces of individual to achieve fast and convenient charging of EVs.

Besides, during the battery charging process, electric energy is converted into chemical energy and stored in battery. Due to the external environment affects and the chemical nature of the active materials inside battery, electrical energy cannot be converted into 100% of chemical energy, part of its consumed in other side reactions, so we need to consider the concept of charging efficiency.

The ratio of the discharged capacity to the input battery capacity when the battery is discharged to a certain cut-off voltage under certain conditions, this ratio is charging efficiency. Refer to the *Electric vehicle charging technical specifications* implemented in Shenzhen in 2011, as shown in Table 2.2.

Charger type	Charging efficiency
Off-board charger	$\geq 90\%$
On-board charger	$50\% \sim 100\%$

Table 2.2 charging efficiency standard

We mainly consider to use off-board chargers (fixedly installed on the ground, convert AC power from electricity gird to DC power) to charging battery, from the current mainstream charging equipment, the DC charging efficiency (fast charging) can reach 95%.

2.2 Application status

Many countries have begun to try and promote the use of EFVs in urban area. Next, we will introduce some applications in detail.

1) In Europe

FREVUE (Freight Electric Vehicles in Urban Europe), the European FP7 project, it is co-funded by the European Commission under the Seventh Framework Program. It demonstrates the use of EFVs in city logistics operation in eight European cities [16].

In Milan's project activity is to improve the urban distribution of goods within the pharmaceutical chain by implementing a logistics system which will coordinate supply and utilize EVs (e-NV200 Nissan) for delivery. The system is dedicated to the distribution of medicines to pharmacies located within the Area C (city center). In order to achieve this goal, Milan established a consolidation center on the outskirts of the city and procured a (refrigerated) electric freight vehicle for operation. In cooperation with the local freight operator which serve the 59 pharmacies located within Area C, the municipality of Milan estimates that their electric vehicle has the potential fulfil 20% of the pharmaceutical logistical needs. Through the use of an electric van for pharmaceutical deliveries, Milan intends to promote this model towards other Italian and European cities.

In Lisbon demonstration project, the Portuguese postal company CTT uses 10 small electric vans (Renault Kangoo ZOE) for post and parcel operations. EMEL (Lisbon's mobility and parking company) uses 5 small electric vans for maintenance of the on-street parking and charging facilities.

2) In China

In recent years, the annual growth rate of China's express delivery business has been maintained at around 50%. At present, the entire logistics industry has more than 20 million fuel freight vehicles in stock, the current market share of electric freight vehicles is only 2%, while the demand for short-distance delivery capacity in cities has continued to increase, which has created a huge market demand for electric commercial vehicles with zero emissions and suitable for short-distance distribution.

In November 2017, JD (one of the two massive B2C online retailers in China) logistics announced a joint test with a number of electric vehicle manufacturers across the country to jointly promote, develop, and introduce thousands of EVs, and put them into use in 16 large and medium-sized cities. In the next five years, JD logistics plans to replace all vehicles in the system with EFVs [17].

3) In USA

In September 2019, Amazon placed an order for 100,000 electric delivery vans from EV startup Rivian. The vans are expected to be on public roads by 2024, with the first coming as soon as 2021, prototypes possibly arriving as soon as 2020. This order came after Amazon led a 700-million-dollar investment round for Rivian, which could point to the two companies having a broader relationship as the e-commerce giant builds up a large electric fleet, this is the Amazon’s sweeping plan to tackle climate change.

In January 2020, UPS (American multinational package delivery and supply chain management company) said its venture capital arm, UPS Ventures, has completed a minority investment in Arrival, along with the investment in Arrival, UPS also announced a commitment to purchase 10,000 electric vehicles to be built for UPS with priority access to purchase additional electric vehicles. Arrival is the first commercial vehicle manufacturer to provide purpose-built electric delivery vehicles to UPS’s specifications and with a production strategy for global scale. Since 2016, UPS and Arrival have collaborated to develop concepts of different vehicles sizes. The company previously announced they would develop a state-of-the-art pilot fleet of 35 electric delivery vehicles to be trialed in London and Paris.

3. Vehicle distribution system relevant concepts

The research on EFVs is a new topic in recent years. The current research on electric vehicle distribution systems mainly focuses on the following three aspects: charging station location allocation problem (CS-LAP), electric vehicle routing problem (E-VRP) and electric vehicle location-routing problem (E-LRP). Therefore, this chapter will introduce the basic theory and model of the LAP, the VRP and the LRP respectively.

3.1 Location allocation problem (LAP)

This problem is to find numbers and locations for new facilities under specified constraints, like minimizing the delivery time from facilities to customers. The location decisions of public service facilities, warehouses, and distribution centers all belong to the category of LAP. According to different classification standards, LAP can be divided into different types, as shown in Table 3.1

Classifications	LAP types
Different demand points	Based on point demand: P-center, P-median, maximum coverage; Based on route demand: Flow interception problem
Time dimension	Static state LAP, dynamic LAP
Demand characteristics	Deterministic LAP, stochastic LAP
Facilities capacity	Deterministic LAP, uncertain LAP
Single/Multi-objective optimizations	Single-objective optimization LAP, multi-objective optimization LAP

Table 3.1 classification of LAP

According to the different customer needs, the charging facilities location model can be summarized into two categories: LAP considering point demand and LAP considering the route demand. Point demand mainly refers to that the service objects are fixed on the nodes in the research network, here we consider the simplified basic model (with Euclidean distance):

1) P-center model. This model mainly studies: on the premise that all demand points are served, how to select the number p facility locations in the network so that the sum of the total distances from demand points to facilities is the smallest. The model is shown in Eq. (3.1) - (3.5):

$$minZ = \sum_{i \in N} \sum_{j \in M} d_{ij} \cdot y_{ij} \tag{3.1}$$

s.t.

$$\sum_{j \in M} y_{ij} = 1, \forall i \in N \tag{3.2}$$

$$\sum_{j \in M} x_j = p \tag{3.3}$$

$$y_{ij} \leq x_j, \forall i \in N, j \in M \tag{3.4}$$

$$x_j, y_{ij} \in \{0,1\}, \forall i \in N, j \in M \quad (3.5)$$

$M =$ candidate facilities locations;

$N =$ customer points set;

$d_{ij} =$ distance from point i to j;

$p =$ numbers of facilities to be constructed;

$x_j = \begin{cases} 1 \\ 0 \end{cases}$ =1 build facility at point j;

$y_{ij} = \begin{cases} 1 \\ 0 \end{cases}$ =1 customer point i is covered by facility j;

Eq. (3.1) is the objective function of the facilities, which is to minimize the distance. Constraint (3.2) indicates all the customer points are assigned to a facility; Constraint (3.3) express the number of facilities to be built; Constraint (3.4) indicates that only open facility can provide services; Constraint (3.5) indicate the x_j, y_{ij} are 0-1 variables.

2) Maximum coverage location model. The goal of this model is to select a reasonable location of service facility to satisfy the largest demand, under the condition that the quantity and service radius of facilities are known. The model is shown in Eq. (3.6) - (3.10):

$$maxZ = \sum_{i \in N} \sum_{j \in M} d_i \cdot y_{ij} \quad (3.6)$$

s.t.

$$\sum_{j \in M} x_j \geq y_{ij}, \forall i \in N \quad (3.7)$$

$$\sum_{j \in M} x_j \leq m, \forall i \in N \quad (3.8)$$

$$y_{ij} \leq x_j, \forall i \in N, j \in M \quad (3.9)$$

$$x_j, y_{ij} \in \{0,1\}, \forall i \in N, j \in M \quad (3.10)$$

$M =$ candidate facilities locations;

$N =$ customer points set;

$d_{ij} =$ demand of point i;

$m =$ numbers of facilities to be constructed;

$x_j = \begin{cases} 1 \\ 0 \end{cases}$ =1 build facility at point j;

$y_{ij} = \begin{cases} 1 \\ 0 \end{cases}$ =1 customer point i is covered by facility j;

Eq. (3.6) is the objective function of the facilities, which is to maximize the demand points covered by facilities to be built. Constraint (3.7) indicates satisfy the customer point i just when facility build at point j;

Constraint (3.8) express the number of facilities to be built; Constraint (3.9) indicates that only open facility can provide services; Constraint (3.10) indicate the x_j, y_{ij} are 0-1 variables.

3) Flow interception location model. If customer demand is distributed on the traffic route in the network, this is a location model based on route demand. This model refers to how to select the service facilities location under the premise that the routes, the number of service facilities and the demand are known, so that the service facilities can intercept the maximum total demand. The model is shown in Eq (3.11) - (3.14):

$$maxZ = \sum_{q \in Q} f_q \cdot y_q \tag{3.11}$$

s.t.

$$\sum_{j \in V} x_j = m \tag{3.12}$$

$$\sum_{V_q \in A} x_j \geq y_q, \forall q \in Q \tag{3.13}$$

$$x_j, y_q \in \{0,1\}, \forall j \in V, q \in Q \tag{3.14}$$

$V =$ set of all nodes in the network;

$A =$ set of all arcs in the network;

$Q =$ set of all routes whose traffic flows are not 0;

$f_q =$ the traffic flow at q route;

$V_q =$ set of nodes at q route;

$m =$ numbers of facilities to be constructed;

$x_j = \begin{cases} 1 \\ 0 \end{cases}$ =1 build facility at node j;

$y_q = \begin{cases} 1 \\ 0 \end{cases}$ =1 at least build one facility on the route q;

Eq. (3.11) is the objective function, indicates that service facilities to be built can meet the largest demand in the routes. Constraint (3.12) express the number of facilities to be built; Constraint (3.13) indicates that only open facility can provide services; Constraint (3.10) indicate the x_j, y_q are 0-1 variables.

3.2 Vehicle routing problem

The vehicle routing problem, VRP, one of the classic combinatorial optimization problems. It was introduced in the scientific literature by Dantzig and Ramzer (1959). This problem can be described as: Assign vehicles depart from the distribution center to serve customers in different locations. By optimizing the delivery routes of vehicles under certain constraints to minimize the total transportation cost. The classic VRP is shown in Figure 3.1:

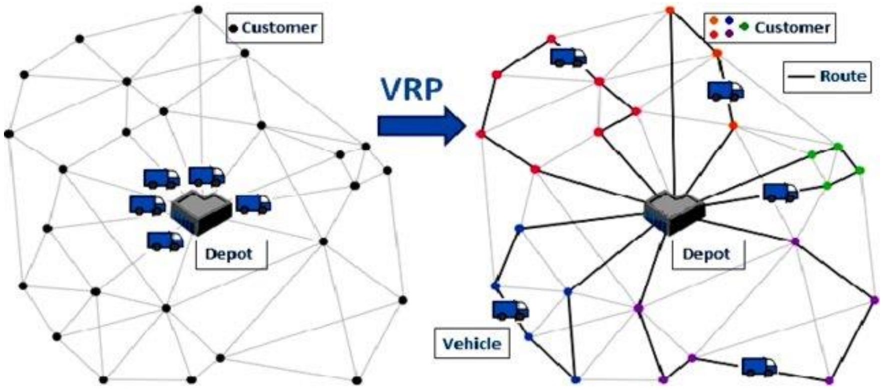


Figure 3.1 the schematic diagram of classic VRP

In a complete distribution network, generally a VRP includes [18]:

1) Distribution center

   The distribution center (DC) is an important node in logistics activities where logistic activities such as collection, assembly, packaging and sorting of goods are carried out. DC has the fleet of vehicles and the goods, and saves the location and demand information of all customers, completes the task of delivering goods to customers [19]. As the hub of the distribution process, the DC is the starting and ending point of the distribution task, vehicles depart from the DC and finally return to the DC.

2) Customers

   The service object of VRP is the customer, which is represented by the node in the problem. Each customer point contains typical characteristics such as service type and service time window. Service types represent the mode like delivery, pick up, or simultaneous pickup and delivery, this will affect the design of the distribution routes. Time window means the distribution vehicle should be completed within the earliest service time to the latest service time specified by the customer, otherwise should pay a certain waiting cost or penalty cost.

3) Cargo

   Cargo is the main distribution target of vehicle and the main part of customer demand. The main attributes are the size, weight, storage conditions, delivery location and time, etc.

4) Vehicles

In the VRP, the vehicles complete the task of goods distribution or collection service between the DC and customer points. VRP need to consider the attributes of vehicles and goods, and accurately arrange suitable vehicles, which can improve resource utilization and reduce distribution costs.

5) Constraints

Constraints refer to the conditions that must be satisfied during the vehicle delivery process. Basic constraints generally include loading capacity constraints, travel distance constraints, time window constraints, etc.

6) Objective functions.

The objective function is the purpose of the model, which can be divided into single-objective optimization and multi-objective optimization. In actual VRP, they are all multi-objective optimization problems. The optimization goals generally include: the shortest driving distance, the least cost, the least number of vehicles, etc.

On the basic of classic VRP, it can be complicated by adding different constraints or other restrictive elements, the main classifications are shown in the table 3.2

Analysis elements	VRP types
Loading capacity	Capacitated VRP, VRP without restriction of loading capacity
Distribution center number	VRP with single DC, VRP with multiple DCs
Vehicles types	VRP with single vehicle type, VRP with multiple vehicle types
Customer time demand	VRP without time window, VRP with time window (soft/hard time window)
Distribution method	Delivery type, simultaneous delivery and pick up
Distribution information	Static VRP, dynamic VRP
Number of objective functions	Single-objective optimization, multi-objective optimization

Table 3.2 different classifications of VRP

The classic VRP model is shown in Eq. (3.6) - (3.12):

$$minZ = \sum_{i\in V}\sum_{j\in V} c_{ij} \cdot x_{ij} \quad (3.6)$$

s.t.

$$\sum_{i\in V} x_{ij} = 1, \forall j \in N \cup \{0\} \quad (3.7)$$

$$\sum_{j\in V} x_{ij} = 1, \forall i \in N \cup \{0\} \quad (3.8)$$

$$\sum_{i\in V} x_{i0} = K \quad (3.9)$$

$$\sum_{j\in V} x_{0j} = K \quad (3.10)$$

$$\sum_{i \notin S} \sum_{j \in S} x_{ij} \geq r(S), \forall S \subseteq V \backslash \{0\}, S \neq \emptyset \quad (3.11)$$

$$x_{ij} \in \{0,1\}, \forall i, j \in V \quad (3.12)$$

$\{0\} =$ distribution center node;

$c_{ij} =$ cost of going from node i to j;

$K =$ numbers of available vehicles;

$x_{ij} = \begin{cases} 1 \\ 0 \end{cases}$ =1 arc is going from node i to j;

$r(S) =$ the minimum number of vehicles needed to serve set S;

Eq. (3.6) is the objective function, indicates the minimum delivery cost; constraints (3.7), (3.8) state that exactly one arc enters and exactly one leaves each customer point, respectively; constraints (3.9), (3.10) indicate the number of vehicles leaving the depot is the same as the number entering; constraint (3.11) is the capacity cut constraints, which impose that the routes must be connected and that the demand on each route must not exceed the vehicle capacity; constraints (3.12) indicates x_{ij} is 0-1 variables.

3.3 Location-Routing problem

Location-routing problem (LRP) can be described as: given a series of customer points and several potential facilities locations, by comprehensively consider the LAP of the facilities and the VRP in the same problem, the goal is to obtain the facilities locations and vehicle routes with minimum cost or distance under the certain constraints. Classic LRP diagram is shown in Figure 3.2, Table 3.3 shows the classifications of LRP:

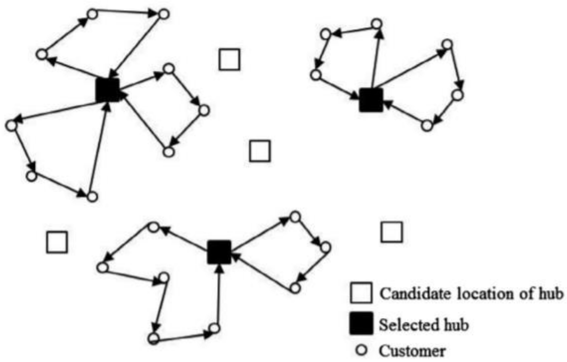


Figure 3.2 the schematic diagram of classic LRP

Analysis elements	LRP types
Facilities number	LRP with single facility, LRP with multiple facilities
Vehicles types	LRP with single vehicle type, LRP with multiple vehicles types
Time window	LRP without time window, LRP with time window (soft/hard time window)

Supply/demand characteristics	Static LRP, dynamic LRP
Number of objective functions	Single-objective optimization, multi-objective optimization

Table 3.3 classifications of LRP

Classical LRP model can be expressed as Eq. (3.13) – (3.20):

$$minZ = \sum_{i\in M} G_i y_i + \sum_{k\in K}\sum_{i\in S}\sum_{j\in S} c_{ij}x_{ijk} \tag{3.13}$$

s.t.

$$\sum_{k\in K}\sum_{i\in S} x_{ijk} = 1, \forall j \in N \tag{3.14}$$

$$\sum_{i\in S} x_{ipk} = \sum_{j\in S} x_{pjk}, \forall p \in S, k \in K \tag{3.15}$$

$$\sum_{i\in N\cup\{0\}}\sum_{j\in N} x_{ijk} \cdot q_j \le Q_k, \forall k \in K \tag{3.16}$$

$$\sum_{k\in K}\sum_{j\in N} x_{ijk} \ge y_i, \forall i \in M \tag{3.17}$$

$$\sum_{i\in M} y_i = p \tag{3.18}$$

$$x_{ijk} \in \{0,1\}, \forall i \in S, j \in S, j \ne i, k \in K \tag{3.19}$$

$$y_i \in \{0,1\}, \forall i \in M \tag{3.20}$$

$M =$ candidate distribution center locations;

$N =$ customer points set;

$S = M \cup N$;

$K =$ vehicles set;

$G_i =$ the cost of building a DC at point i;

c_{ij} = cost of going from point i to j;

$q_j =$ the demand of customer point j

$Q_k =$ the maximum loading capacity of vehicle k;

$p =$ numbers of DC to be constructed;

$x_{ijk} = \begin{cases} 1 \\ 0 \end{cases}$ =1 arc is going from node i to j;

$y_i = \begin{cases} 1 \\ 0 \end{cases}$ =1 build DC at node i;

Eq. (3.13) is the objective function, represents the minimum total cost of construction and transportation; Constraint (3.14) indicates each customer can only be served by one vehicle; Constraint (3.15) indicates exactly one arc enters and exactly one leaves each customer point, respectively; Constraint (3.16) indicates the loading capacity restriction; Constraint (3.17) ensures that the vehicle can only depart from the DC; Constraint (3.18) indicates that select total P number of DCs; Constraints (3.19), (3.20) ensure the x_{ijk}, y_i are 0-1 variables.

4. Location-routing problem of electric vehicles model formulation

4.1 Model description

With the improvement of people's awareness of environmental protection and the countries' promotion of new energy vehicles, EVs are expected to gradually replace traditional fuel vehicles and change the current status of cargo transportation. Therefore, for logistics companies, the problem is how to upgrade their transport vehicles with minimal cost. Meanwhile, because EFVs have not yet widely used, and the construction of charging stations is not complete, logistics companies need to consider where to charge when using EFVs for distribution.

Compared with traditional LRP, we consider the following elements in this model:

1) Distribution center.

   The distribution center is a distribution facility where goods are equipped according to customer requirements and delivered to users. In this model, we have one distribution center, as the starting point of transportations, equipped with a certain number of EFVs, they return to the distribution center after completing the delivery task. Different from traditional distribution centers, in this study have slow charging facilities in order to charging EFVs at night to save charging costs.

2) Electric freight vehicles.

   According to types of vehicles, LRP can be divided into single vehicle type and multiple vehicles types. Considering that there are not so many types of EFVs on the market at present, meanwhile, logistics companies are in the status quo of partial conversion of delivery vehicles from traditional fuel vehicles to EFVs, so companies generally choose one type of vehicle when purchasing EFVs. Therefore, we will consider only one type of vehicle in our model. EFVs distribution not only needs to consider the maximum load and maximum mileage, but also consider whether and where they need to be charged during delivery process. These also make the LRP of EFVs more complicated than traditional fuel vehicles.

3) Charging stations

   Unlike general LRP, the location problem of EVs is charging stations. Companies need to select suitable locations from several alternative locations where charging stations can be built. The EFVs can arrive at the charging station for power replenishment during delivery, while minimizing the total cost of location selection and transportation.

4) Customers

   In this model, the customer mainly including retail stores, supermarkets, etc. The positions of customers in the transportation network are important. The entire transportation network routes will change with the demand or time window of the customer points request.

Through the model introduction in section 4.1, we can know our LRP model is a special case of the traditional LRP model. The same point is both contain the location selection and routing arrangement, the difference is: in the traditional LRP model the location selection is distribution center, while the object of the electric vehicle LRP location selection is the charging station. Figure 4.1 (1), (2) part represents the classic LRP model and electric vehicle LRP model [20].

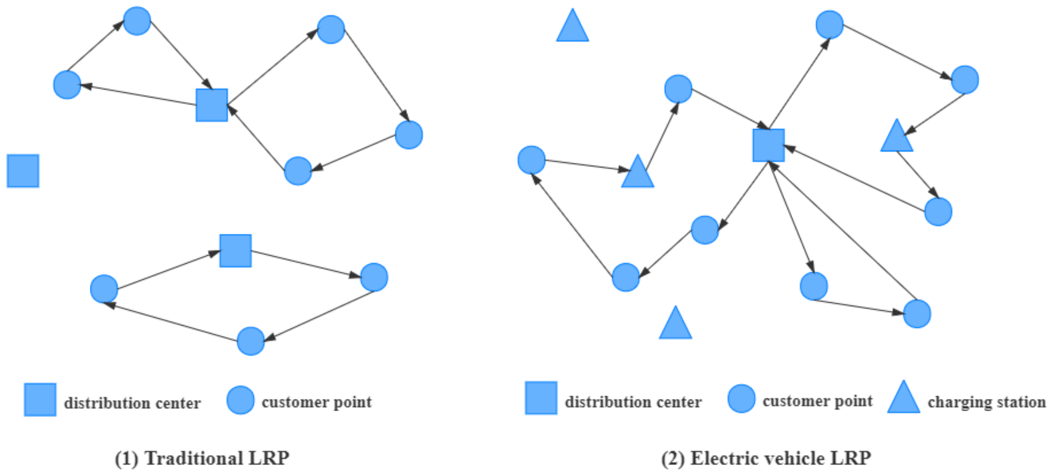


Figure 4.1 typical routes of traditional LRP and electric vehicle LRP

The mathematical model of the electric vehicle LRP with time windows is described as:

$G = \{V, E\}$ is a distribution network composed of point sets and arc sets, set $V = N \cup B \cup O$ includes all the nodes in the network. N is the set of customer nodes, B is the set of charging stations nodes, O is distribution center.

Since the current charging facilities are not yet complete, in the initial stage, company can also consider the location problem and choose the location and number of charging stations with lowest total cost from the alternative charging stations. The confirmed information of customer points including the locations, demand amounts and time windows. The setting value of objective function is the minimum total cost. Company arrange the EFVs depart from distribution center, to serve the customer points under the constraint of maximum load capacity; Meanwhile, EFVs need to visit all customer points within the specified time window, otherwise they should pay the waiting cost or penalty cost. In addition, due to the short mileage of EFVs, they perhaps need to visit charging stations for power replenishment, so that there is sufficient power to continue to deliver the next customer. Until all customer points have been visited, they will go back to the distribution center.

4.2 Assumptions and notations of model

Since the electric vehicles LRP model for urban freight distribution is derived from the traditional LRP model of traditional fuel vehicles, and considering the complexity of transforming actual problems into mathematical models, we make the following assumptions to reduce the complexity of calculations:

1) A single distribution center, multiple demand (customer) points.
2) All the customer points' locations, demand amounts and time windows are known quantitative data, and will not change dynamically.
3) A customer point can be served only once.
4) The demand amount of goods at customer points should not exceed the vehicle's capacity.
5) Vehicles depart from the distribution center, return to it after completing the distribution tasks.
6) All vehicles run at a constant speed, regardless of traffic conditions.
7) All vehicles are the same type, with the same capacity limitation, battery capacity and maximum mileage.
8) Vehicles is fully charged after leaving the distribution center or visiting the charging stations.
9) Vehicles have a fixed power consumption coefficient, and the power consumption is proportional to the driving distance.
10) The charging efficiency of vehicles at the charging station is fixed, the charging time is proportional to the required charging capacity.

In order to facilitate the accurate description of the model, the parameters and variables involved in model are defined in Table 4.1.

Symbols	Meanings
(1) Sets	
O	A single distribution center, $\{0\}$
N	Set of customers point (nodes), $N = \{1,2 \ldots n\}$
B	Set of battery charging stations, $B = \{1,2\ldots b\}$
V	Set of nodes, $V = N \cup B \cup O$
K	Set of vehicles, $K = \{1,2\ldots k\}$
(2) Decision variables	
x_{ijk}	When vehicle k finish task from point i to j: $= 1$
	Otherwise $= 0$
y_i	When a charging station is established at node i , $= 1$
	Otherwise $= 0$
(3) Variables	
arr_{ik}	The moment vehicle k arrives at node i
lev_{ik}	The moment vehicle k leaves from node i
$re1_{ik}$	The residual power of vehicle k when arrive at node i, unit is kwh
$re2_{ik}$	The residual power of vehicle k when leave from node i, unit is kwh

q_{ik}	The charging amount of vehicle k at station i, unit is kwh
t_{ik}	The charging time of vehicle k at station i, unit is min
Z_{ik}	Auxiliary variable
(4) Parameters	
d_{ij}	Distance between node i and j , unit is km
D_i	The weight of cargo required by customer i, unit is kg
L	The maximum load capacity of vehicle, unit is kg
e_i	The earliest time for customer point i
l_i	The latest time for customer point i
S_i	Service time at customer point i, unit is min
T_{ij}	Vehicle travel time from node i to j, unit is min
Q	Vehicle's battery capacity, unit is kwh
e_{low}	Minimum safe battery percent
M	Big positive number
H	Power consumption per unit mileage, unit is kwh/km
F	Fuel consumption per unit mileage, unit is L/km
μ	Carbon emission per unit liter of gasoline, unit is kg/L
θ	Carbon emission per unit of fuel production, unit is kg/L
B_c	Battery's charging factor
γ	Electric energy conversion coefficient
λ	Carbon emission per unit electricity, unit is kg/kwh
β	Percent of thermal power generation per unit electricity
f_i	Construction cost of charging station at node i, unit is $yuan$
C_F	Fixed cost for each vehicle, unit is $yuan$
C_T	Transport cost per unit distance, unit is $yuan/km$
C_E	Electricity price of charging facilities, unit is $yuan$
C_c	Environment cost per unit of carbon consumption, $yuan/kg$
P_e	The waiting cost per unit time of the vehicle arriving early, $yuan/mins$
P_l	The penalty cost per unit time of the vehicle arriving lately, $yuan/mins$

Table 4.1 Electric vehicle LRP model parameters and variable definition

4.3 Build the model

4.3.1 Determine the objective functions

EFVs are mainly used in commercial logistics distribution. From the perspective of a logistic company, the ultimate goal is to minimize the distribution costs and maximize benefits. For customers, they expect to have higher service quality. So, the logistic companies cannot just consider the lowest transportation cost, the customer service satisfaction is also a major factor in business survival. We use the time windows to quantify customer satisfaction.

With the increasing awareness of environmental protection, the goals pursued by the logistic companies are constantly updated, considering reducing the exhaust emissions of vehicles during delivery process.

Therefore, our goal is to minimize the total cost, which include the six costs as following:

1) The construction cost of charging station.

   In the research phase of location selection for EFVs charging stations, the construction cost of charging station is the most important expenditure. In reality, the construction cost is affected by many factors, such as the construction area of charging station. Here we consider the total cost of building the charging stations as shown in Eq. (4.1):

$$Z_{station} = \sum_{i \epsilon B} f_i \cdot y_i \tag{4.1}$$

2) The fixed cost per each vehicle

$$Z_{fixed} = \sum_{k \epsilon K} C_F \cdot k \tag{4.2}$$

3) The transport cost of vehicle

   The most common objective function in the VRP is the shortest distance or the lowest cost. Generally speaking, the transport cost will increase proportionally as the distance increases. The transport cost as Eq. (4.3):

$$Z_{transport} = \sum_{i \in V} \sum_{\substack{j \in V \\ i \neq j}} \sum_{k \in K} C_T \cdot d_{ij} \cdot x_{ijk} \tag{4.3}$$

4) The charging cost of vehicles

   If need battery charging during distribution process of using EFVs, we should consider the charging cost. Generally, the charging cost is related to the amount of charging required for EFVs. The charging cost represents as Eq. (4.4)

$$Z_{charging} = \sum_{i \in V} \sum_{k \in K} C_E \cdot q_{ik} \cdot y_i \tag{4.4}$$

5) The environmental cost

   The environmental costs are mainly reflected in carbon emissions, in section 1.2.2, we introduced in detail the calculation standards of carbon emissions for traditional fuel vehicles and EVs. The environment cost of fossil fuel vehicle and EVs are expressed as Eq. (4.5), (4.6):

$$Z_{carbon} = C_c \cdot (\mu + \theta) \sum_{k \in K} \sum_{i \in V} \sum_{\substack{j \in V \\ j \neq i}} x_{ijk} \cdot d_{ij} \cdot F \tag{4.5}$$

$$Z_{carbon} = \beta \cdot C_c \cdot \gamma \sum_{k \in K} \sum_{i \in V} \sum_{\substack{j \in V \\ j \neq i}} x_{ijk} \cdot d_{ij} \cdot H \tag{4.6}$$

6) The penalty cost of violating the time windows

Taking into account the timeliness requirements of customers for delivery services, we take the time effect cost that is caused by the violation of the customer's time window constraint, the penalty cost, into the total logistic cost. Time window restrictions can be divided into hard time windows and soft time windows. Considering the complexity of the actual delivery process, here we use the soft time window limit, $[e_i, l_i]$ represents the soft time window of customer i. P_e is the penalty cost per unit time for the early arrival of vehicle, P_l is the penalty cost per unit time for vehicle late arrival.

The penalty cost function is Eq. (4.7), (4.8):

$$P(arr_{ik}) = \begin{cases} P_e(e_i - arr_{ik}),\ arr_{ik} \le e_i \\ 0,\ e_i \le arr_{ik} \le l_i \\ P_l(arr_{ik} - l_i),\ arr_{ik} \ge l_i \end{cases} \tag{4.7}$$

$$Z_{penalty} = \sum_{i\in N} \sum_{k\in K} P(arr_{ik}) \tag{4.8}$$

4.3.2 Mathematical model

Based on the above model assumptions and notations, combined with the relevant analysis of the objective function, the mathematical model can be described as Eq. (4.9)

$$minZ = Z_{station} + Z_{fixed} + Z_{transport} + Z_{charging} + Z_{carbon} + Z_{penalty} \tag{4.9}$$

s.t.

$$\sum_{\substack{i\in V\\ i\neq j}} \sum_{k\in K} x_{ijk} = \sum_{\substack{i\in V\\ i\neq j}} \sum_{k\in K} x_{jik} = 1 \tag{4.10}$$

$$\sum_{j\in N\cup B} x_{0jk} = \sum_{j\in N\cup B} x_{j0k} \le 1, \forall k \in K \tag{4.11}$$

$$\sum_{\substack{i\in V\\ i\neq j}} \sum_{k\in K} x_{ijk} \le y_j \cdot M \tag{4.12}$$

$$\sum_{\substack{i\in V\\ i\neq j}} x_{ijk} = \sum_{\substack{i\in V\\ i\neq j}} x_{jik},\ \ \forall j \in N \cup B, k \in K \tag{4.13}$$

$$\sum_{\substack{i\in V\\ i\neq j}} \sum_{j\in B} D_i \cdot x_{ijk} \le L, \forall k \in K \tag{4.14}$$

$$x_{0jk} = 0, \forall j \in B, k \in K \tag{4.15}$$

$$lev_{ik} = arr_{ik} + S_i,\ \forall i \in N, k \in K \tag{4.16}$$

$$lev_{ik} = arr_{ik} + t_{ik},\ \forall i \in E, k \in K \tag{4.17}$$

$$arr_{jk} = \sum_{\substack{i\in V\\ i\neq j}} x_{ijk} \cdot \left(lev_{ik} + T_{ij}\right), \forall j \in N \cup B, k \in K \tag{4.18}$$

$$q_{ik} = t_{ik} \cdot B_c \cdot y_i, \forall i \in \{0\} \cup B, k \in K \tag{4.19}$$

$$re2_{0k} = Q, \forall k \in K \tag{4.20}$$

$$re2_{ik} = y_i \cdot Q, \forall i \in B, \forall k \in K \tag{4.21}$$

$$re2_{ik} = re1_{ik}, \forall i \in N, k \in K \tag{4.22}$$

$$re1_{ik} \geq 0, \forall i \in V, k \in K \tag{4.23}$$

$$re1_{jk} = \sum_{\substack{i \in V \\ i \neq j}} x_{ijk} \cdot (re2_{ik} - H \cdot d_{ij}), \forall j \in V, k \in K \tag{4.24}$$

$$re1_{jk} \geq e_{low} \cdot Q, j \in V, k \in K \tag{4.25}$$

$$q_{ik} = (\mathrm{Q} - re1_{ik}) \cdot y_i, \forall i \in B, k \in K \tag{4.26}$$

$$q_{ik} = 0,\ \forall i \in N, k \in K \tag{4.27}$$

$$\mathrm{e}_i \leq arr_{ik} \leq l_i, \forall i \in N \cup B, k \in K \tag{4.28}$$

$$Z_{ik} - Z_{jk} + n \cdot x_{ijk} \leq n - 1, \forall i \in V, j \neq i, j \in N, k \in K \tag{4.29}$$

$$Z_{ik} \geq 0, \forall i \in V, k \in K \tag{4.30}$$

$$x_{ijk} \in \{0,1\}, \forall i, j \in V, i \neq j, k \in K \tag{4.31}$$

$$y_i \in \{0,1\}, \forall i \in B \tag{4.32}$$

Eq. (4.9) is the objective function, indicates the minimum total distribution cost.

Constraint (4.10) states that each customer point can be served only once.

Constraint (4.11) states that each vehicle departs from DC, return to DC after completing the distribution tasks.

Constraint (4.12) indicates EV can only charging battery at the position where a charging station is built.

Constraint (4.13) exactly one arc enters and exactly one leaves each customer point.

Constraint (4.14) states that the demand on each route must not exceed the vehicle capacity.

Constraint (4.15) states that vehicle cannot go to charging station directly after departing from DC.

Constraint (4.16) express the moment of vehicle depart from the customer point i.

Constraint (4.17) express the moment of vehicle depart from the charging station i.

Constraint (4.18) is the moment of vehicle arriving customer point i.

Constraint (4.19) indicates the charging time of EFVs, affected by charging amount and charging efficiency.

Constraint (4.20), (4.21) indicates that vehicle depart from the DC and charging station at the maximum power.

Constraint (4.22) indicates that the electric quantity of vehicle will not change at customer point.

Constraint (4.23) ensures the electric quantity always positive at any nodes.

Constraint (4.24) calculates the remaining battery after vehicle arriving node.

Constraint (4.25) ensures the vehicle remaining power to each node is not less than the minimum safe power.

Constraint (4.26) calculates the electric quantity needed to charge when vehicle visit charging station.

Constraint (4.27) ensure that vehicle cannot be charged at customer point.

Constraint (4.28) is the time window constraint.

Constraint (4.29), (4.30) indicate the sub-loop elimination.

Constraint (4.31), (4.32) define the decision variable, x_{ijk}, y_i are both 0-1 variables.

5.Algorithm design for electric vehicle location-routing problem

5.1 Algorithm overview

We start from the perspective of using EFVs during distribution, meanwhile, conducts research on charging station location problem and distribution routes optimization, these problems can be called location-routing problem (LRP) of electric vehicle, which is derived from traditional LRP research.

Vehicle routing problem (VRP) was first introduced in the scientific literature 61 years ago, during this long time period, many scholars have studied VRP and its various derivative models and algorithms. It is one of the classic combinatorial optimization problems, and the NP-hard problem (non-deterministic polynomial-time hardness) [21]. The LRP of EVs is a combination of VRP and LAP, so LRP is also an NP-hard problem. The existing algorithms for solving NP-hard problems including two categories: Exact algorithms and heuristic algorithms. Heuristic algorithms can be divided into classical heuristic algorithms and metaheuristic algorithms. The exact algorithms are mainly used to solve small-scale problems, as the scale of the problem expands, heuristic algorithms are more useful [22].

5.1.1 Exact algorithms

An algorithm that can find the optimal solution of the problem is the exact algorithms. For difficult combinatorial optimization problems, when the scale of the problem is small, the exact algorithm can find the optimal solution within an acceptable time; when the scale of the problem is large, it can provide a feasible solution to the problem, meanwhile, give the initial solution for the heuristic method.

Exact algorithms mainly include enumeration method, branch and bound method, cutting plane method, dynamic programming method and so on, as Table 5.1:

Exact algorithm	Principles	Pros and Cons
Enumeration method	Enumerate all possible answers in inductive reasoning, reserve the answers that meet the constraints, discard the not satisfied answers.	Pros: the correctness of algorithm is easy to verify; easy to understand. Cons: large amount of calculation, long solution time and low efficiency.
Dynamic programming	Simplifying a complicated problem by breaking it down into simpler sub-problems in a recursive manner.	Pros: the algorithm structure is simple, small amount of calculation, short solution time. Cons: the sub-problems are not independent of each other, otherwise they will not have advantages.
Branch and bound method	Branch: split all feasible solution	Pros: can obtain quickly the optimal

	spaces repeatedly into smaller and smaller subsets. Bound: calculate a target boundary (for the minimum problem) for the solution set within each subset. After each branching, those subsets that exceed the known feasible solution target values are no longer further branched, so that many subsets can be ignored, which is called pruning.	solution of the problem. Cons: require large storage space, not suitable for solving large-scale calculation examples.
Cutting plane method	Relax the problem to a non-integer linear program, if the optimal solution is an integer, then stop, otherwise add new constraints to divide the feasible region.	Pros: short solution time. Cons: the scope of application is restricted to the integer linear programming.

Table 5.1 the main types of exact algorithms

5.1.2 Heuristics algorithms

Heuristic algorithm refers to the method of solving problems through inductive reasoning and experimental analysis of past experience, that is, by means of some intuitive judgment or heuristic method, to find the sub-optimal solution of the problem or to find its optimal with a certain probability solution. Generality, stability and faster convergence are the main criteria for measuring the performance of heuristic algorithms. Widely used classical heuristic algorithms include sweep algorithm, saving algorithms, hill climbing, etc.

1) Sweep algorithm

   This algorithm refers to Gillett and Miller's approach to solving VRP in 1974. This method uses polar coordinates to represent the location of each customer point, and then lets a customer point as the starting point, set its angle to zero degrees, to follow the clock or reverse clock direction, consecutive customers are assigned to a vehicle until capacity is reached. Then repeat for another vehicle.

2) Saving algorithm

   This algorithm uses the principle that the sum of any two sides of a triangle must be larger than the third side. The main idea is: taking the vehicle loading capacity as the constraint, sequentially merge the two initially formed transportation arcs, so that the reduction of distance after each merger is maximized, and repeat the process until obtain the final route.

3) Hill climbing.

This algorithm belongs to the family of local search. It is an iterative algorithm that starts with an arbitrary solution to a problem, then attempts to find a better solution by making an incremental change to the solution. If the change produces a better solution, another incremental change is made to the new solution, and so on until no further improvements can be found.

Table 5.2 list the Pros and Cons, application scope of these three algorithms:

Classifications	Pros	Cons	Application scope
Sweep algorithm	Can obtain a feasible solution in a short time	small probability of obtaining the optimal solution	Initial solution generation; optimization problem with fewer routes.
Saving algorithm	Easy to understand	Consider less the time factor	Suitable for simple optimization problem with stable demand or loose time.
Hill climbing	High search efficiency	It is a local search, easily fall into the local optimal solution	Suitable for small scale, small solution space optimization problem

Table 5.2 the introduction of main classical heuristic algorithm

5.1.3 Metaheuristics

The metaheuristic algorithm is an improvement of the heuristic algorithm, it solves the shortcomings of classical heuristic algorithms that are easy to fall into local optimal solution. Metaheuristic is an iterative generation process. Through the intelligent combination of different concepts, this process uses the heuristic algorithm to explore and develop the search space. In this process, learning mechanisms are used to obtain and master information in order to effectively find approximately optimal solutions.

Metaheuristic algorithms include simulated annealing algorithm, genetic algorithm, ant colony optimization algorithm, particle swarm optimization algorithm, artificial fish swarm algorithm, etc.

1) Simulated annealing algorithm (SA)

   The algorithm starts from a higher initial temperature, with the continuous decrease of temperature parameters, and randomly looks for the global optimal solution of the objective function in the solution space combined with the probability jump characteristics, that is, have the probability to jump out the local optimal solution and eventually tends to the global optimal solution.

2) Genetic algorithm (GA)

It is a stochastic global search and optimization method developed after imitating the biological evolution mechanism of nature, drawing on Darwin's evolution theory and Mendel's genetic theory. Its essence is an efficient, parallel, and global search method, which can automatically acquire and accumulate knowledge about the search space during the search process, and adaptively control the search process to obtain the best solution.

3) Ant colony optimization algorithm (ACO)

The walking path of ants is used to represent the feasible solution of the problem, and all the paths of the whole ant population constitute the solution space of the problem. The ants with shorter paths release more pheromones, and as time progresses, the concentration of pheromones accumulated on the shorter path gradually increases, and there will be more and more ants choosing the shorter path. Eventually, the entire ants will be concentrated on the optimal path under the effect of positive feedback, the optimal path is exactly the optimal solution of the optimization problem.

4) Particle swarm optimization algorithm (PSO)

This algorithm is a kind of swarm intelligence algorithm proposed by Kenndy and Ebeehart in 1995, which is derived from the research on bird predation behavior: A group of birds are searching for food randomly. If there is only one piece of food in this area, the easiest and most effective strategy to find food is to search the area around the bird closest to the food. In the PSO, the solution of each optimization problem corresponds to the position of a bird in the search space, and these birds are called “particles”. Each particle has its own position and velocity, and an adaption value determined by the optimization function.

5) Artificial fish swarm algorithm (AFSA)

This algorithm refers to a water area, fish can find nutrients on their own or trailing other fish, so the largest number of fish survival is generally the most nutrients in the waters, the algorithm is based on this characteristic, through the construction of artificial fish to imitate the fish foraging, grouping and tailing behavior, in order to achieve the optimal solution [23].

The five metaheuristic algorithms listed above have the similarities and differences. The same point is that they all use neighborhood search for optimization, and the convergence criteria can be set in the same way. The difference is that the natural phenomena simulated by each algorithm are different, the basic ideas for reference and the key parameter set are also different. For example, the SA needs to set the initial temperature and de-temperature function, GA needs to set the population size and genetic operators, while PSO needs to define the location and speed of swarms. Besides, these five algorithms have their own characteristics. Table 5.3 lists the characteristics and application scope of each algorithm:

Classification	Characteristics	Application scope
SA	Simple description, less restricted by initial conditions, not conducive to global search; Convergence speed slow.	Suitable for large-scale combinatorial optimization problems
GA	Easy to implement, strong processing constraint ability, strong global search ability, parallel search, strong robustness; Long running time, slow convergence.	Solve complex large-scale (linear/nonlinear) combinatorial optimization problems.
ACO	Adopt positive feedback mechanism, easy to obtain a local solution, strong robustness; The parameter setting will greatly affect the quality of solution, long running time, easy to fall into the local optimum.	Solve large-scale and complex (especially discrete problems) combinatorial optimization problems
PSO	Fast solution speed, simple description; easy to produce; Premature convergence, easy to fall into local optimal.	Solve the combinatorial optimization problems of continuous functions
AFSA	Low initial value and parameter setting requirements, strong robustness, strong global optimization ability, parallel search; Slow convergence speed, the accuracy of solution is not high.	Solve complex, large-scale combinatorial optimization problems that do not require high precision.

Table 5.3 characteristics and application scope of 5 metaheuristic algorithms

Combining the five algorithms listed in Table 5.3, we can conclude that all these algorithms can be used to solve combinatorial optimization problems, but for SA, the global search ability is poor, the ACO, PSO and AFSA are easy to converge to the local optimum, while GA can mutate with a certain probability, it has stronger global search ability, the ability to deal with constraints is also stronger.

Our electric vehicles LRP model with many constraints, even contains nonlinear constraints, need to calculate the time to reach each customer point, the remaining power and so on, which lead the problem more complex. Consider the characteristics of our model and various metaheuristics algorithms, we choose GA to solve the electric vehicles LRP. This is because GA has the processing power for a lot of constraints, strong robustness and code is easy to realization.

5.2 Genetic algorithm overview

5.2.1 Introduction

Genetic algorithm (GA) is an algorithm that simulates biological evolution to search for optimal solutions. In

1975, American professor J.Holland made a systematic explanation of this algorithm for the first time in his monograph [24]. The core idea of GA is: the solution set of the problem can be simulated as a biological population, and the chromosomes represent different individuals in the population. The optimization process starts from a certain chromosome in the initial population, according to the competition mechanism--survival of the fittest in nature, each chromosome has a certain probability to be selected, and this probability is fitness. At the same time, each chromosome receives crossover or mutation with certain probability, which makes the offspring easier to adapt the current living environment. After a certain number of evolutions, the final optimal chromosome can be decoded as the optimal solution.

5.2.2 Basic process

1) Coding and decoding

   In combinatorial optimization problems, the parameters and solutions of the problem are generally intuitionistic, which is called phenotype. In the simulated genetic process, they are all expressed in the form of chromosomes, so we need the conversion. Coding is to establish a mapping relationship from phenotype to genotype, decoding converts chromosomes (genotype) to phenotype. Coding and decoding are very important in the algorithm, choosing the suitable method will greatly simplify the complexity of the problem and increase the calculation speed.

2) Generating an initial population

   According to the determined coding method, an initial population is randomly generated with a certain number of individuals. The number of individuals in the population is called the population size.

3) Calculating fitness value

   Fitness is a measure of how well an individual adapts to the current environment. The fitness value will affect the probability of an individual being selected. Generally, we use the fitness function to calculate the fitness value of each individual.

4) Selection

   The essence of selection in the algorithm is the survival of the fittest in biological evolution. It is sorted according to the fitness value. The higher the value, the greater the probability of being selected. The individuals with the best fitness values in the current generation that are guaranteed to survive to the next generation. These individuals are called elite children. The default value of elite count is around 5% of the population size.

5) Crossover

The essence is to simulate the information exchange mechanism in biological evolution. The DNA is cut at the same position on the two chromosomes, and the front and back strings are combined to form two new chromosomes, increasing the population biological diversity.

6) Mutation

Several individuals in the population will have genetic mutations with a certain probability due to some reasons, resulting in new individuals and increasing population diversity.

7) Stopping criteria

Algorithm generally need to run multiple cycles for continuously searching the optimization value, so certain stopping criteria must be set to avoid infinite loop.

The main methods used in algorithm process is listed in table 5.4, basic structure diagram is shown in figure 5.1:

Table 5.4 GA: the method of basic flow

Process	Main methods
Coding and decoding	Binary coding, Floating point coding, Symbol coding
Generate initial population	Randomly generate samples
Calculate fitness	Transform the objective function, includes: linear transformation, dynamic linear transformation, logarithmic transformation, etc.
selection	Roulette wheel selection, Optimal saving strategy, Stochastic tournament, Deterministic sampling selection, etc.
Crossover	One-point crossover, Multi-point crossover, Uniform crossover, etc.
Mutation	Simple Mutation, Uniform Mutation, etc.
Stopping criteria	Iterations number reach a certain value, fitness value no longer changes, the optimal individual fitness value reaches a certain value.

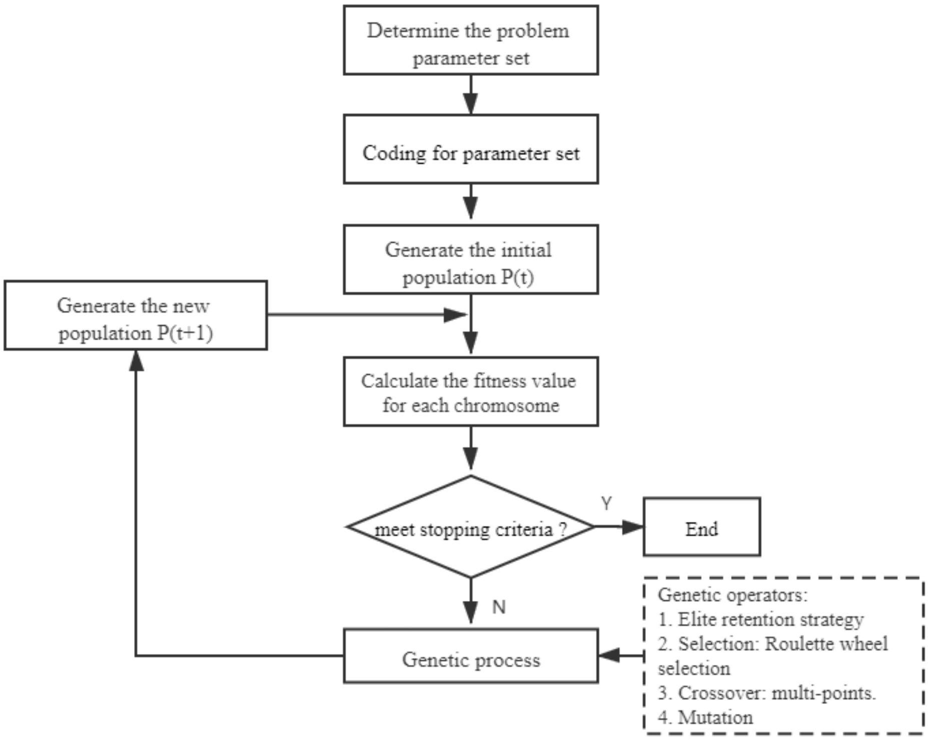


Figure 5.1 GA basic structure diagram

5.2.3 Determine the parameters

Whether the parameter setting is reasonable or not directly affects the solution speed and convergence of the algorithm. GA requires predetermined parameters including the following four items:

1) Population size

   Size refers to the number of generated chromosomes, which will greatly affect the performance of algorithm. The population size cannot be too large, otherwise the solution speed will be reduced and the efficiency will be affected. The population size also cannot be too small, will be easily fall into the local optimum. Generally, this value can be set to 10-500 [25].

2) Crossover probability

   Simulating the generation of offspring during biological evolution, we generally set the crossover probability relatively large. However, if this value is too large, although the diversity of children is guaranteed, it will also increase the possibility of excellent individuals being damaged; If this value is too small, also easily fall into the local optimum. We can set the value 0.7-0.9 [26].

3) Mutation probability

The probability of mutation is to change the value of one or more genes in the gene segment so that new children can be produced. Like biological mutation, this probability is very low, we can set the value 0.001-0.1 [26].

4) Numbers of iterations

Among the 3 stopping criteria listed in table 5.4, setting a reasonable number of iterations is the most commonly used. Generally, this number can be set to 50-800 [25][26].

5.2.4 Advantages and disadvantages of genetic algorithm

The GA simulates the evolution process of natural organisms, adopts the competition mechanism of survival of the fittest, and has great advantages in convergence, calculation time and robustness. In addition, the advantages of GA in random fast search and scalability also make the algorithm widely used.

However, GA also have some shortcomings in application: the selection of crossover and mutation probability in genetic operators has a greater impact on the algorithm. The algorithm is relatively dependent on the initial population.

Taking into account the dependence on the initial population in the iterative process of traditional GA, the idea of greed is incorporated into the process of generating the initial population, and the choice of crossover probability and mutation probability may destroy the existing optimal solution. Join the elite retention strategy to improve the performance of the algorithm.

5.3 Algorithm process design

There are two main ideas when using metaheuristics algorithm to solve LRP:

1) Split the LRP, solve the LAP first, then bring the obtained results into the VRP for optimization.
2) The LRP taken as a whole, and obtain the result of comprehensive optimization of location and routes at the same time.

The (1) idea is just a simple superposition of two problems, will not consider some constraints, we choose the (2) idea to solve the LRP based on genetic algorithms.

5.3.1 Chromosome coding and decoding

The model in this thesis aims to provide reasonable arrangements of EFVs to offer distribution services for logistics companies, and to go to the charging station for replenishment when the power is insufficient during delivery. We use a greedy search operation in the genetic algorithm to solve this problem, and apply a hybrid coding method to represent a feasible solution with the coding of customers, distribution center and charging stations together. Natural number $1 \sim N$ represent customers, natural number $N+1 \sim N+M$ represent charging stations, distribution center is 0, the number of vehicles owned by the distribution center is K.

1) Coding: First generate the chromosome sequence, composed of routes and charging station locations.

①. The first part is the driving routes. First generate a full array of customer points and charging stations $(C_1, C_2, \cdots, C_N, C_{N+1}, \cdots, C_{N+M})$, then randomly generate a number of distribution centers and insert them into the customer points sequence. The number of distribution center represents the same number of vehicles departing from the distribution center $(C_1, C_2, \cdots, C_a, 0, C_{a+1}, C_{a+2}, \cdots, C_l, 0, C_{l+1}, \cdots, C_{N+M})$. Add the closed loop conditions to generate $chrome(0, C_1, C_2, \cdots, C_a, 0, C_{a+1}, C_{a+2}, \cdots, C_l, 0, C_{l+1}, \cdots, C_{N+M}, 0)$ sequence.

②. The second part is the charging station locations. Randomly generate 0-1 variables with number of M to indicate whether the charging station is selected, where 1 is the charging station is selected, and 0 represents not selected.

2) Decoding: decoding is essentially the reverse process of coding. First, customers and charging stations are allocated to vehicles, and then the array $chrome1$ is used to store the decoded chromosome sequence.

We illustrate the process of coding and decoding by using 10 customer points, 3 charging stations and 3 EFVs (1 to 10 represents customers, 11 to 13 represents charging stations) as shown in Figure 5.2, the sequence indicates that there are three vehicles for distribution and two charging stations selected, 10 and 13 respectively.

The first vehicle departs from the distribution center and serves No.5,3,1 customers in turn, after finish the service of No.3 customer, charging at the No.13 charging station, then continuing to service customer point No.1 and return to the distribution center; The second vehicle serve No.8,4,9,2 these four customers, before No.9, 2 customer service should go to No.11 charging station charging battery and eventually return to the distribution center; The third vehicle serve No.10,6,7 three customers, finally return the distribution center.

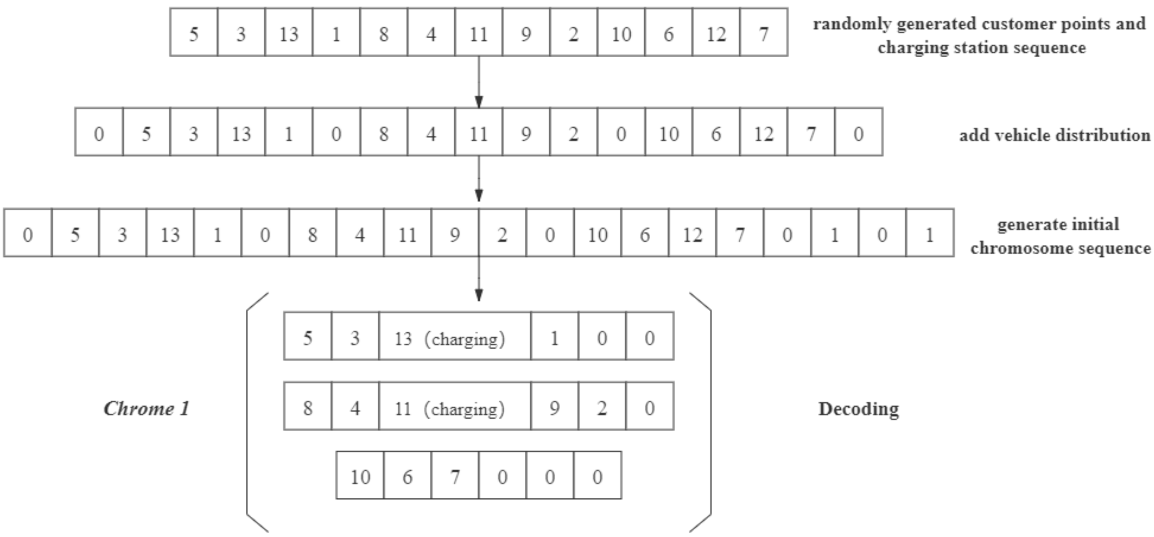


Figure 5.2 chromosome coding and decoding diagram

5.3.2 Generate initial population

The genetic algorithm relies heavily on the initial population during iterating, and we use the Greedy algorithm to generate the initial population. Assuming that there are K EFVs in the distribution center that can provide cargo delivery services, that there are N customers and M charging stations can be used to replenish the battery during delivery.

The initial population generation method used is: according to the complexity and scale of the problem to set a reasonable population size $sizepop$, the chromosomes is composed of two parts: the driving routes and charging station locations. The generation steps of first part is:

$Step1$: Randomly generate the first customer point among the N customer points, and then find the point closest to the first point as the next point according to the greedy idea until the N customers and M charging stations are generated in full arrangement. For example, there are 10 customers that need to be serviced and 3 alternative charging stations, if the first customer point 5 is randomly generated, the closest to 5 is 3, the closest to 3 is 13, and so on, until the sequence is generated $(5,3,13,1,8,4,11,9,2,10,6,12,7)$

$Step\ 2$: Randomly select $k-1$ locations and sequence them in descending order in the first part of the chromosome sequence generated by $Step1$, and then insert 0 at these locations of the chromosome sequences to indicate addition to the vehicle schedule, allowing different customers to be delivered by different vehicles. For example, if the distribution center has 3 vehicles, two locations are randomly generated, and if two positions are $(4,9)$ and sorted down $(9,4)$, then if the sequence of chromosomes dispatched by the vehicle becomes $(5,3,13,1,0,8,4,11,9,2,0,10,6,12,7)$.

$Step\ 3$: Insert 0 at the beginning and end of the chromosomal sequence generated by $Step2$, indicating the addition of closed-loop conditions, which eventually results in a chromosomal sequence $(0,5,3,13,1,0,8,4,11,9,2,0,10,6,12,7,0)$.

The second part of the chromosome randomly generates the $M-bit$ 0-1 variable to indicate whether the charging station is selected, and the complete chromosome sequence is $(5,3,13,1,8,4,11,9,2,10,6,12,7,0,1,0,1)$

Finally, the chromosome sequence is judged by loading weight, customer point remaining battery, and time window constraints. If the constraints are not satisfied, the chromosome sequence is discarded and the new chromosome sequence is regenerated until the $sizepop$ chromosome that satisfy the conditions.

5.3.3 Fitness function

The fitness function is used to calculate the fitness value of each chromosome, which has a great influence on the solution speed and the quality of the solution. Since the objective function of this model is to minimize the total cost, and the larger the fitness value indicates that the chromosome is better, therefore, the function is set to the inverse of the objective function, which is both eligible and convenient for calculation. The specific formula is shown in the Eq. (5.1):

$$F(i) = \frac{1}{Z(i)} \tag{5.1}$$

$F(i)$ is the fitness value of chromosome i, $Z(i)$ is the objective function value of i.

5.3.4 Genetic operators

We incorporate the elite retention strategy with the proportional selection method, before the proportional selection, the fitness values are sorted in descending order, the first 2% chromosomes are directly retained as elite individuals into the new population, and the remaining 98% of the chromosomes of the new population are produced by proportional selection.

1) Selection operators

The algorithm selects a group of individuals in the current population, called parents, who contribute their genes—the entries of their vectors—to their children. The algorithm usually selects individuals that have better fitness values as parents. At present, the widely used selection operators are proportional selection (roulette wheel selection), optimal saving strategy and deterministic sampling selection. We choose the roulette wheel selection. The basic idea is that the probability of any individual being selected to the next generation is equal to the ratio of its fitness value to the sum of all individuals' fitness value. Assuming that the population size is $sizepop$ and the fitness value of each chromosome is $F(i)$, the probability $P(i)$ of the selected is calculated as shown in Eq. (5.2).

$$P(i) = \frac{F(i)}{\sum_{i=1}^{sizepop} F(i)} \tag{5.2}$$

After calculating the probability of each chromosome being selected, the probability is summed to form the roulette, sum operation cumulative probability $N(j)$ calculation as shown in the Eq. (5.3), each sector of the roulette disk represents a chromosome, the angle size of the sector is proportional to the cumulative probability of the chromosome, indicating that the chromosome fitness value accounts for the percentage of the roulette, as shown in Figure 5.3.

$$N(j) = \sum_{i=1}^{sizepop} P(i) \tag{5.3}$$

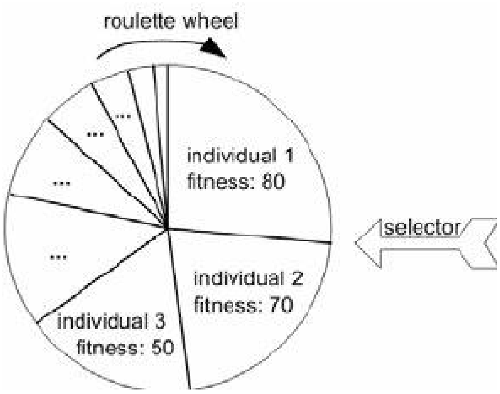


Figure 5.3 roulette wheel selection

Starting from the fitness value, randomly choosing the $sizepop$ chromosomes to form a new population. The specific steps are as follows:

$Step$ 1: Sort the fitness values in descending order, retaining the first 2% of chromosomes as elite individuals into the new population;

$Step$ 2: Calculate the probability of each chromosome being selected, calculate the Eq. (5.2);

$Step$ 3: Calculate the cumulative probability of each chromosome being selected by Eq. (5.3);

$Step$ 4: Randomly produce the $x \in [0,1]$ and compared with $N(j)$, if $x \leq N(1)$, then the first chromosome in the population will be selected into the next generation; if $N(i-1) < x \leq N(i)$, the i-th chromosome will be selected into the next generation.

$Step$ 5: Repeat $step$ 4 until the remaining 98% of the individuals are generated, merging with the previous elite individuals to form a new population, with a $sizepop$ size.

2) Crossover operators

To increase the population diversity, genetic algorithms simulates the evolution of natural organisms that recombine chromosomes to generate the crossover children through the mating between parents, which is the main way to produce new chromosomes. According to the different coding methods, different crossover strategies can be used, commonly used crossover strategies include single-point cross, two-point crossover and multi-point crossover, etc. Using single-point crossover or two-point crossover will make the number of calculations increase and convergence speed is slow, so we use the multipoint crossover, so the algorithm will converge faster, but this method may destroy the existing good solution, so we incorporate the elite retention strategy.

According to the two parts of chromosome, the crossover will operate separately. The specific steps are:

$Step$ 1: Select the crossover parent. Randomly combine all chromosomes that in the population in pairs.

Form $\left[{}^{sizepop}/_{2}\right]$ sets of parents, choose one set inside $\left[{}^{sizepop}/_{2}\right]$ to crossover;

$Step$ 2: Randomly generate $x \in [0,1]$, compared with P_c (crossover probability, generally < 1), if $x \leq P_c$, implement the multi-point crossover. The specific processes are:

①. Remove all 0 genes in the driving route (inside the first part) of the parent chromosome, and record the locations of these 0 genes;

②. In the range$[1, N+M]$ randomly generate m numbers as crossover points;

③. Exchange the genes at the intersection of the two parent chromosomes;

④. Test respectively the repeated genes in the children and replace them with the missing genes. The sequence is consistent with the gene sequence in the middle of the original chromosome intersection.

⑤. Add the 0 genes at the recorded positions.

We illustrate the process of coding and decoding by using 10 customer points, 3 charging stations and 3 EVs. So, $N = 10, M = 3$, the crossover points $m = 3$. The first part of two parent chromosomes are $(0,5,3,13,1,0,8,4,11,9,2,0,10,6,12,7,0)$ and $(0,6,3,0,11,7,10,8,5,12,1,2,0,4,9,13,0)$. The first parent chromosome randomly generate 3 crossover points are $(2,4,11)$, the second parent chromosome's crossover points are $(1,4,7)$, the two children obtained by crossover are $(0,5,6,13,7,0,8,4,11,9,2,0,10,1,12,3,0)$ and $(0,3,5,0,11,10,8,6,12,7,2,0,4,9,13,0)$.

The crossover method of the second part (charging station locations) is similar with the first part, the only difference is that there is no need to remove the 0 gene position, but directly crossover. For example, the two parent chromosomes' second parts are $(1,0,1)$ and $(0,0,1)$, the crossover point generated randomly are both at 1. So the complete chromosomes after crossover are $(0,5,6,13,7,0,8,4,11,9,2,0,10,1,12,3,0,0,0,1)$ and $(0,3,5,0,11,10,8,6,12,7,2,0,4,9,13,0,1,0,1)$. The complete crossover process is shown in Figure 5.4:

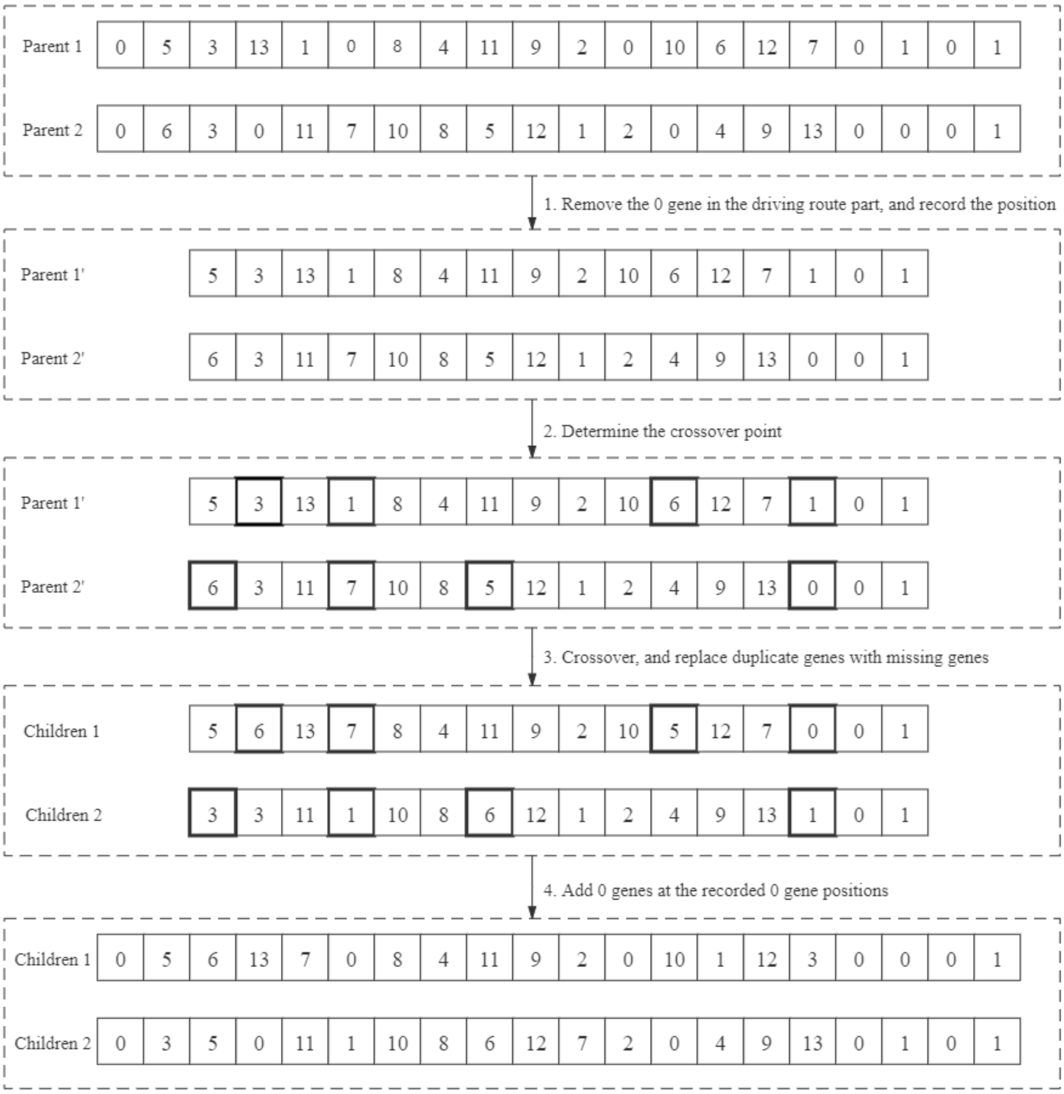


Figure 5.4 crossover process schematic diagram

3) Mutation operators

Simulated biological evolution may occur in the natural phenomenon of genetic mutations, in the genetic algorithm, mutation refers to the generation of diverse populations, some individuals in the population will produce genetic mutations with a small probability, this change will make the population diversity increase, but may also destruct previous excellent chromosome, so the probability of mutation will generally be set not too large, the value is between 0.001 to 0.1. Because we have adopted the elite retention strategy for good solution of the genetic, it is appropriate to increase the probability of mutation in order to increase population diversity. The first part of the chromosome driving routes using interchange mutation, the second part of the charging station selection using the basic bit variation idea, as follows:

$Step$ 1: Randomly select an individual, as the mutant parent;

$Step$ 2: Randomly generate $x \in [0,1]$, compared with P_m, if $x \leq P_m$, implement the mutation. The specific processes are:

①. Remove all 0 genes in the driving route (inside the first part) of the parent chromosome, and record the locations of these 0 genes;

②. In the range$[1, N+M]$ randomly generate 2 numbers as mutation points of the first part, meanwhile, the second part adopts the simple mutation;

③. Operate the gene mutation of two parts at the mutation points separately;

④. Add the 0 genes at the recorded positions.

Assume the mutated chromosome is the crossover children 1 $(0,5,6,13,7,0,8,4,11,9,2,0,10,1,12,3,0,0,0,1)$, the random mutation point of the driving route is $(4,6)$, the mutation point of the charging station location is 2, the mutation processes as figure 5.5 shows:

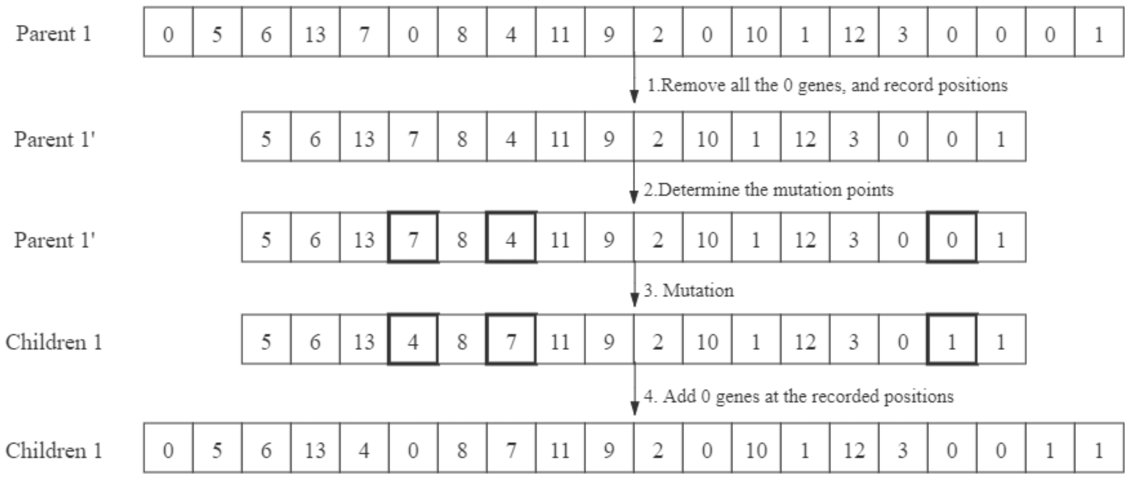


Figure 5.5 mutation process schematic diagram

Step 3: Calculate the fitness value of each chromosome respectively, and select individuals with high fitness values as the new generation population.

4) Stopping criteria

There are two types of stopping criteria commonly used: the first type is to judge by fitness value. If the fitness value is equal to the given threshold, or if the fitness value changes very little in successive iterations, the operation will terminate. The second type is the operation numbers reach the given iteration numbers. According to the scale and complexity of the problem, we chooser the second type of criteria, set a reasonable number of iterations, the algorithm will stop after running enough times. The specific steps of the GA of our model are shown in figure 5.6:

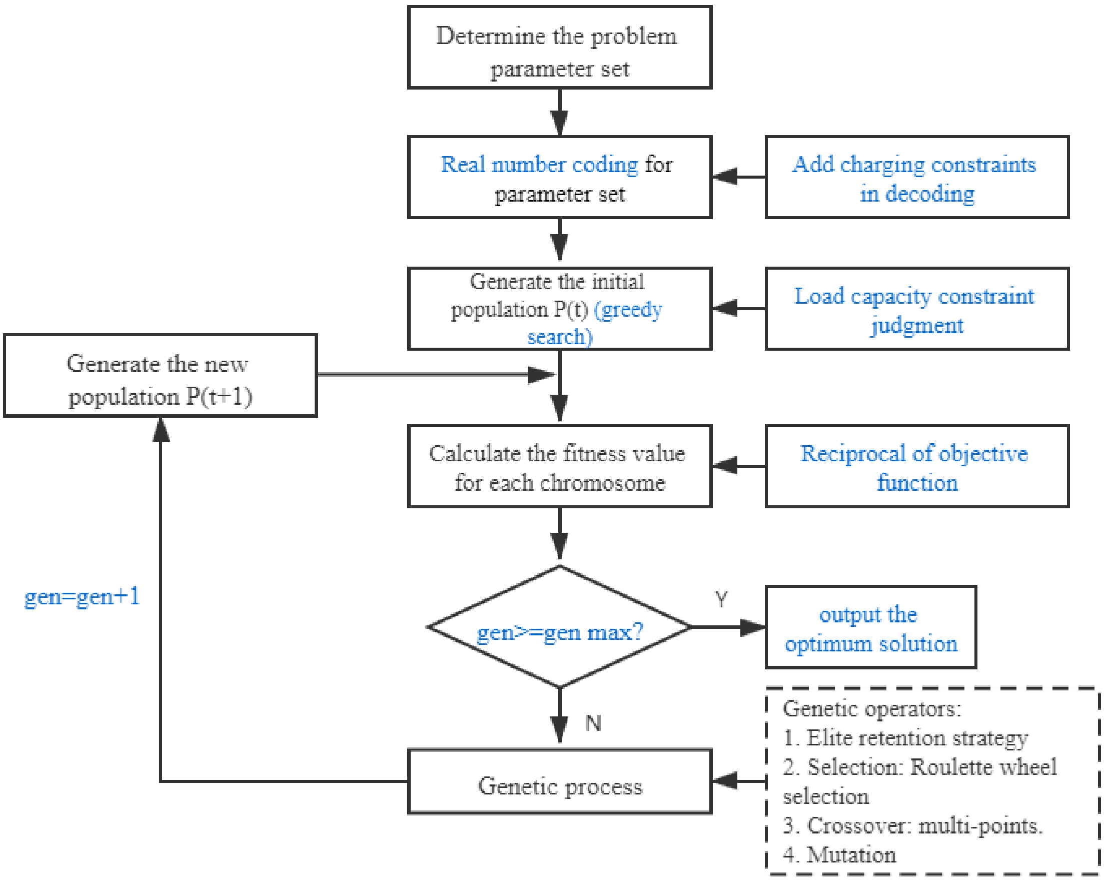


Figure 5.6 GA flowchart

6. Case analysis

The vehicles used for urban distribution are traditional fuel vehicles and EFVs, at present, fossil fuel vehicles are still the main distribution method, with a market share of 98% in China [27]. While, the characteristics of zero pollution and low energy consumption of EFVs have made it popular in recent years. In order to confirm the accuracy and effectiveness of the electric vehicles LRP model and genetic algorithm proposed in this thesis, this section will use medium and large-scale cases to verify the model.

6.1 Algorithm implementation

All calculation cases are performed on the computer: Intel (R) Core (TM) i7-8550U CPU @ 1.80GHz, 8GB RAM, Windows 10 operation system. Genetic algorithm codes are implemented on the MATLAB R2020a.

In the coding process, I think the most difficult point is the design of the crossover process. the routes part and the charging station selection part are crossover separately, then duplicate parts are eliminated, the detailed process is as follows:

Crossover process codes

S1: if rand (1) < pcross

generate randomly $x \in [0,1]$, compared with P_c, if $x \leq P_c$, implement the multi-point crossover

```
S2:   ppc1 = pcross1(1: length(pcross1)-Nstation);
      ppc2 = pcross2 (1: length(pcross1)-Nstation);
```

Remove the 0 genes in the routes part (first part)

```
   zeropos1= find(ppc1==0);
   ppc1 (zeropos1) = [];
   zeropos2= find(ppc2==0);
   ppc2 (zeropos2) = [];
```

Record all the positions of 0 genes, for later recovery

S3: generate randomly 3 numbers $\in [1, N+M]$ as the crossover points

```
   crosspos1 = sort(randperm(length(pop1),3),'ascend');
   crosspos2 = sort(randperm(length(pop1),3),'ascend');
```

S4: exchange the genes at each crossover point of the two parents, keep one of the genes as the output of cross

```
   p1cross(crosspos1) = p2cross(crosspos2);
   p2cross(crosspos2) = ptemp(crosspos1);
```

S5: separately check the repeated genes in the children

```
   ptime = setdiff(pop1, p1cross); postime = zeros(1,length(ptime));
for i = 1: length (ptime)
  postime(i) = find(pop1==ptime(i));
end
```

Replace the repeated genes with the missing genes, the sequence is same with the gene sequence in the middle

```
of the orginal chromosome intersection
postime = sort(postime,'ascend'); cnt = 1;
for i = 1:length(p1cross)
    if ~ismember(p1cross(i),ptemp)
        ptemp = [ptemp,p1cross(i)];
    else
        p1cross(i) = pop1(postime(cnt));
        cnt = cnt+1;
    end
end
```

6.2 Basic data

The current examples for verifying the VRP or LRP models are mainly Solomon benchmark problems, which are divided into three series: R, C, and RC. In this thesis, we randomly generate the customer points sequence, meanwhile, the time window is relatively loose in actual delivery, so we choose R112 examples as the data source. In addition, based on the defined customer points coordinates, we use the P-center method (the total distance between the charging stations and the customer points is the smallest) to determine 6 candidate locations of charging stations filter from 20 locations for two cases (listed in Appendix attached list 1). We divide the data of R112 example into customer points and charging stations, and assume the distance between customer points is Euclidean distance.

6.2.1 Charging station

The charging station here we consider 380V50kw vertical DC fast charger (as shown is figure 6.1), the cost of one DC charger is about 0.5 yuan/w, so a single 50kw DC fast charger equipment cost is about 25,000 yuan, the initial investment cost is listed in table 6.1(the relevant data comes from Guosheng Securities Research Institute):

Figure 6.1 380V 50kw vertical DC fast charger

Single 50kw DC charger investment cost		
Total cost	Charging equipment + power distribution equipment + civil construction cost	57,000-60,000
Charging equipment cost	Contains monitoring, charger module, assemblies box, relay, etc.	25,000
Civil construction cost	Building operations, electric wire, etc.	10,000-13,000
Power distribution equipment cost	low-voltage apparatus, electricity meter, etc.	22,000

Table 6.1 single DC fast charger investment cost

Consider the slow charger is cheap, and the investment in civil engineering and power distribution equipment is less, assuming that the investment of one slow charger is 0.5 yuan/w, the total investment cost of one fast charger is calculated as 1.2 yuan/w. Suppose the equipment depreciation period is 10 years, the average annual maintenance cost is 3% of the initial investment, and the average annual operating and labor costs are 6% of the initial investment. The average annual fixed cost is listed in table 6.2:

Costs	7.5kw	50kw
Single charger initial investment	4000	60,000
Annual depreciation expense (10 years)	400	6,000
Annual equipment maintenance cost	100	1,800
Average annual operating labor cost per pile	200	3,600
Total annual fixed expenses (regardless of venue)	700	11,400

Table 6.2 average annual fixed cost per one DC charger pile

6.2.2 Vehicle relevant parameters

The basic parameter settings of EFVs refer to the configuration parameters of Nissan e-NV200 (Figure 6.2), specific parameters listed in table 6.3, other parameters are shown in table 6.4 (the relevant data comes from Guosheng Securities Research Institute):

Figure 6.2 Nissan e-NV200

Parameters	Values
Maximum loading capacity	700kg
Maximum mileage	200km
Battery capacity	40kwh
Vehicle speed	30km/h
Consumption of battery per km	0.143kwh/km
Charging factor	60kwh/h

Table 6.3 e-NV 200 configuration parameters

Parameters	Values
Service time for one customer	10 mins
Electric conversion coefficient	0.94
Electricity fee	0.55 yuan/kwh
Minimum safe battery percent	20%
Fixed cost	100 yuan/vehicle
Transport cost	2 yuan/km
Carbon emission price	0.5 yuan/kg
Waiting cost for vehicle arriving early	1 yuan/mins
Penalty cost for vehicle arriving late	2 yuan/mins

Table 6.4 other parameters

As comparison, the traditional fuel vehicle's basic parameter refers to the Nissan NV 200 (Figure 6.3, same model as electric vehicle), relevant parameters list in table 6.5:

Figure 6.3 Nissan NV 200

Parameters	Values
Engine	1.6 L
Maximum load capacity	700 kg
Fuel consumption	0.07 L/km
Carbon emission per unit liter of gasoline	2.3 kg/L
Oil price	6.13 yuan /L

Table 6.5 NV 200 parameters

6.3 Result analysis

6.2.1 medium-scale case result analysis

We select a medium-scale example for research, data comes from Solomon benchmark problem R112, forming a distribution system with 1 distribution center, 25 customers and 6 charging stations. The relevant data of coordinates of candidate charging stations and customer points are listed in Appendix attached list 2 and attached list 3. Table 6.6 lists the basic parameters setting of GA:

Parameters	Meanings	Value
$sizepop$	Population size	50
$tournamentSize$	Elite size	2
$Nite$	Iterations number	100
P_c	Crossover probability	0.9
P_m	Mutation probability	0.1

Table 6.6 SA basic parameters

As the scale of the case increases, the possibility of the metaheuristic algorithm to obtain the optimal solution will gradually decrease, because the solution obtained is generally an approximate optimal solution. Therefore, we repeat 10 times for the experiment, take the minimum value from the 10 results as the optimal solution of the case. Figure 6.3 shows the iteration process, the algorithm converges after approximately 100 iterations, and the optimal solution obtained at this time has stabilized, the routes distribution is shown in figure 6.4 and the solution is listed in table 6.7:

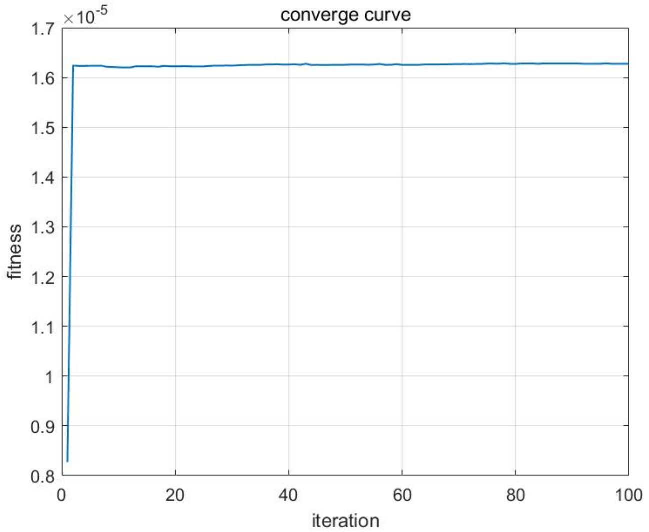


Figure 6.4 iteration process for medium-scale case

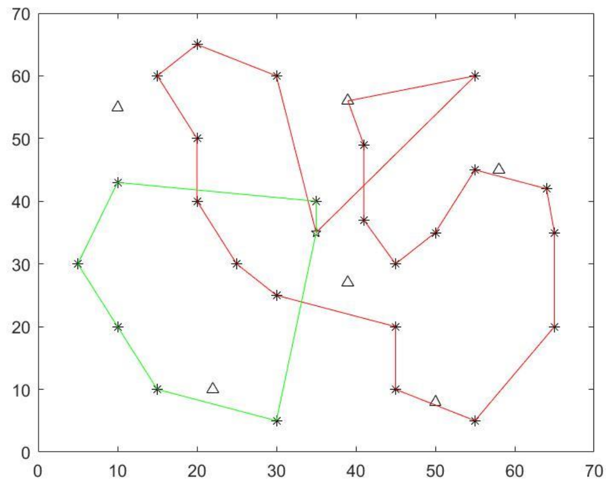


Figure 6.5 EFVs optimal routes distribution diagram

Indicators	Values
Optimal solution	60837.88 yuan
Optimal distribution cost (without CS cost)	837.88 yuan
Routes	● 0--7--8--16--4--15--3--10--17--18--19--21--20--25--2--9--22--24--1--29(charging)--6 (red line) ● 0--23--5--14--13--11--12--0 (green line)
Fixed cost	200 yuan
Transport cost	592.27 yuan (296.14 km)
Charging cost	16.30 yuan
Environment cost	14.45 yuan
Penalty cost	14.86 yuan

Table 6.7 Results of calculation case

According to figure 6.5 and table 6.7, in the given 4 alternative charging stations, No.29 node, coordinate (58,45), is chosen to build a charging station. Besides, in order to verify the stability of the algorithm, we run the calculation examples 10 times, obtain the 10 optimal solution for each time and calculate the deviation value, as shown in table 6.8:

Time	Optimal value	Deviation value
1	60850.21	0.02%
2	**60837.88**	--
3	60861.31	0.04%
4	60842.10	0.01%
5	60911.32	0.12%
6	60892.80	0.09%
7	60945.82	0.18%
8	60946.56	0.18%
9	60851.65	0.02%
10	60874.28	0.06%
Average	60881.39	0.07%

Table 6.8 calculation examples results of 10 run times

In 10 run times, the average value of the solution is 60881.39, and the average deviation of the solution is 0.07%. During operation, appears 1 optimal solution – 60837.88, and all solutions deviation are controlled within 1%, and the maximum deviation is 0.18%. As a whole, we can see that the quality of the solutions obtained in

10 run times is good, the deviations are all within a reasonable range, indicating that the genetic algorithm model is stable.

Then we compare the result of EFVs distribution with traditional fuel vehicle. For the convenience of comparison, consider the traditional fuel vehicles costs contain: fixed cost, transportation cost, fuel cost, environmental cost and time window penalty cost. The calculation examples used is same with EFVs case. The experiment is repeated 10 times, and the optimal solution is the minimum value in the 10 results, the optimal path is shown in the figure 6.7:

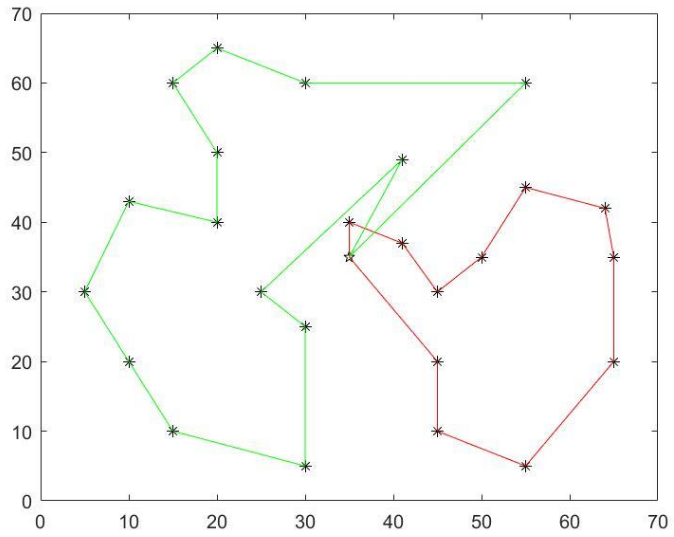


Figure 6.6 fuel vehicle optimal routes distribution diagram

Compare the solution results of fuel vehicle distribution with the results of EFVs distribution, the comparison items are listed in table 6.9:

Indicators	Electric freight vehicle	Traditional fuel vehicle
Optimal solution (without CS cost)	837.88 yuan	939.81 yuan
CS construction cost	60,000yuan	--
Fixed cost	200 yuan	200 yuan
Transport cost	592.27 yuan (296.14 km)	565.34 yuan (282.67km)
Charging cost/fuel cost	16.30 yuan	121.29 yuan
Environmental cost	14.45 yuan	41.26 yuan
Time window penalty cost	14.86 yuan	11.92 yuan
Distribution routes	● 0--7--8--16--4--15--3--10--17--18--19--21--20--25--2--9--22--24--1--29(charging)--6 (red line)	● 0--17--18--19--21--20--25--2--9--22--24--23--0 (red line)

	● 0--23--5--14--13--11--12--0 (green line)	● 0--6--7--8--16--4--15--5--14--13--11--12--10--3--1--0 (green line)

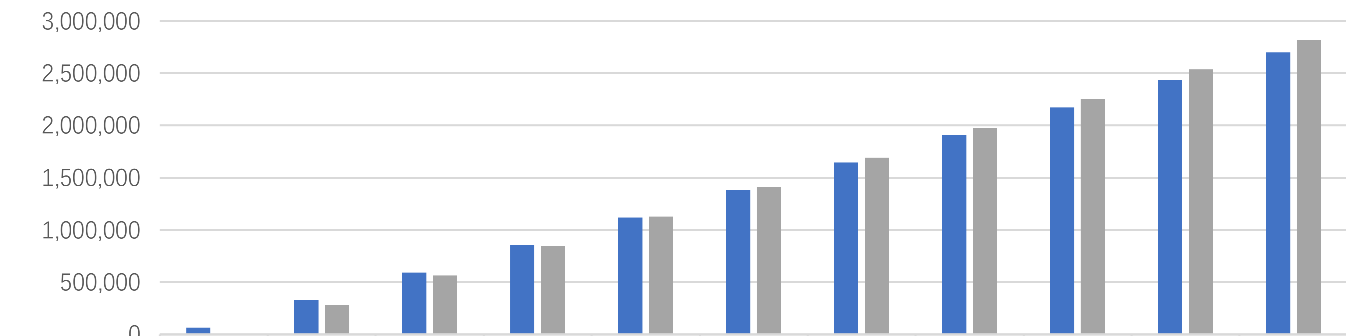
Table 6.9 results comparison of EFVs and fuel vehicles

From the above table, we can know that for one mission, the distribution cost of using EFVs (excluding charging station relevant costs) is less than that using fuel vehicles, so if we use EFVs for distribution, we can pay less 101.93 yuan for each mission, save an average of 0.36 yuan/km. Because the needs for battery replenishment during delivery, the transportation distance and cost are higher than that of fuel vehicles, the exceed cost is16.93 yuan. The time window penalty cost of using EFVs is a little larger than that of fuel vehicles. While, the charging cost is significantly lower than the fuel cost of fuel vehicle, only account for 13.4% of fuel cost, and carbon emission costs are also reduced by 65%. Therefore, from the perspective of economic and environmental benefits, EFVs have obvious advantages.

Then, we consider the total cost (plus charging station relevant costs), from section 6.2.1, we know that:

1) One 7.5kw slow charger investment cost is 4000 yuan, the average annual fixed cost is 700 yuan, logistics company should have slow charging facilities in order to charging EFVs at night to save charging costs, here we consider one 7.5kw slow charger in DC;
2) One 50kw DC fast charger investment cost is about 60,000 yuan and the average annual fixed cost is 11,400 yuan, the upfront investment in self-built charging station is huge, we build one DC fast charger at point (39,56).

Suppose vehicles drive 300 days a year, and one distribution mission per day. The distribution cost is 837.88 yuan/mission for using EFVs and 939.81 yuan/mission for using traditional fuel vehicles, the distribution cost saved by using EFVs is 30,579 yuan/year. The total annual cumulative cost is shown in figure 6.7:



	0	1	2	3	4	5	6	7	8	9	10
EFVs	64,000	327,464	590,928	854,392	1,117,856	1,381,320	1,644,784	1,908,248	2,171,712	2,435,176	2,698,640
Fuel vehicles	0	281,943	563,886	845,829	1,127,772	1,409,715	1,691,658	1,973,601	2,255,544	2,537,487	2,819,430

EFVs Fuel vehicles

Figure 6.7 comparison of total logistics cumulative cost between EFVs and traditional fuel vehicles

From the above figure, we can see that starting from the 4th year, the total logistics cost of using EFVs has become less than that of using fuel vehicles. In other words, at least 4 years before investors can actually earn a profit. Until the 10th year of using EFVs, the logistic company can save 120,790 yuan (≈15,098 euro) totally in distribution cost, the total cost saved is not much, so in this medium-scale case of customer demand, the self-built charging station mode of company cannot bring huge benefits. Company is profitable because the annual cost savings by using EFVs distribution is larger than the annual cost of the charging stations, all costs of the charging station are borne by logistics company, the utilization rate of the charging station is low, so the charging station is always operating at a loss, especially the high cost of fast charging station, the total investment payback period is long.

If the fast charging station we build can be used publicly or shared with other logistics companies, then the charging station operation can be profitable, and the total investment payback period of logistics company will also be accelerated. At present, the most basic profit method for charging stations is collect charging electricity and service fees. We consider the charging service fee is 0.55 yuan/kw, charging station operates 330 days a year, if the utilization rate of a single 50kw DC fast charger is 7% (1.68 hours per day), the payback period of investment will take 15.6 years, if the utilization rate increase to 30% (8 hours per day), the payback period will be 0.98 years, table 6.10 lists payback period under different utilization rates:

Utilization rate	7%	10%	15%	20%	30%	50%
Hours/day	1.68	2.4	3.6	4.8	7.2	12
Payback period (years)	15.60	5.78	2.82	1.87	1.11	0.62

Table 6.10 payback period under different utilization rates

From the above table, we can know that the payback period of single charger is greatly affected by the utilization rate (= annual accumulated charging time / total time of a year). For example: if the fast charging station can be used for EFVs belongs to other logistics companies, during the 300 delivery times for a year, the utilization rate is 10%, the charging station daily service EFVs number is 4 (including 3 EFVs from other companies), then the company will be profitable in the 1.9th year. We can see the payback period is much shorter than before, and at the 10th year, the logistic company can save 269,290 yuan totally in total cost, around 2.2 times as before.

6.2.2 large-scale case result analysis

The large-scale example uses the 61 nodes in the Solomon benchmark problem R112, forming a distribution system with 1 distribution center, 60 customers and 6 alternative charging stations. The relevant data of coordinates of charging stations and customer points are shown in Appendix attached list 2 and attached list 4. Table 6.11 lists the basic parameters setting of genetic algorithms:

Parameters	Meanings	Value
$sizepop$	Population size	100
$tournamentSize$	Elite size	2
$Nite$	Iterations number	150
P_c	Crossover probability	0.9
P_m	Mutation probability	0.1

Table 6.11 GA basic parameters

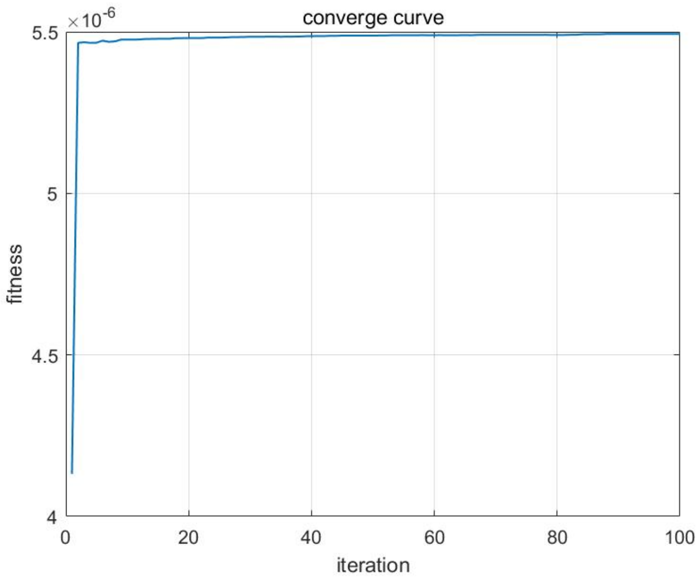


Figure 6.8 iteration process for large-scale case

Figure 6.8 shows the iteration process of using EFVs to distribution, the algorithm converges after approximately 150 iterations, and the optimal solution obtained at this time has stabilized, the routes distribution is shown in figure 6.9 and the solution is listed in table 6.12:

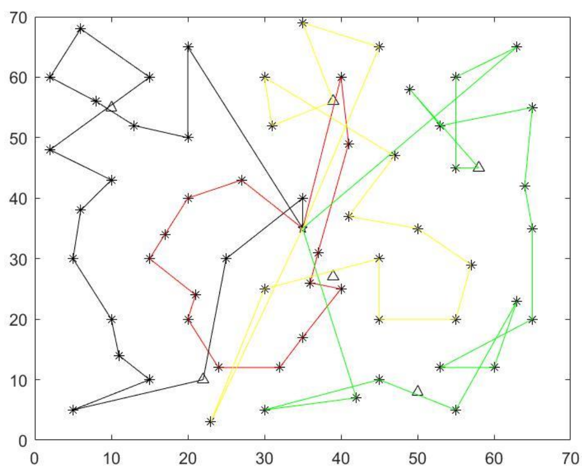


Figure 6.9 EFVs optimal routes distribution diagram

Indicators	Values
Optimal solution	181799.44 yuan
Optimum distribution cost (without CS cost)	1799.44 yuan
Charging station cost	60,000 yuan × 3
Routes	● 0--52--18--60--5--59--37--42--57--2--40--58--53--1--30--0 (red line) ● 0--41--15--22--23--55--39--56--25--24--29--34--33--51--66(charging)--3--9--35--0 (green line) ● 0--11--7--48--47--36--49--19--46--8--45--17--16--44--14--38--61(charging)--6--27--0 (black line) ● 0--43--13--26--21--4--54--12--28--50--10--31--64(charging)--32--20--0 (yellow line)
Fixed cost	400 yuan
Transport cost	1270.18 yuan (635.09 km)
Charging cost	51.76 yuan
Environment cost	30.48 yuan
Penalty cost	47.02 yuan

Table 6.12 Results of calculation case

According to figure 6.9 and table 6.12, in the given 6 alternative charging stations, No.61,64 and 66 nodes, coordinate (22,10), (39,56) and (58,45), are chosen to build charging stations. Besides, in order to verify the stability of the algorithm, we run the calculation examples 10 times, obtain the 10 optimal solution for each time and calculate the deviation value, as shown in table 6.13:

Time	Optimal value	Deviation value
1	181932.70	0.07%
2	181970.85	0.09%
3	182023.40	0.12%
4	181830.93	0.02%
5	181837.25	0.02%
6	**181799.44**	--
7	181859.62	0.03%
8	182009.60	0.12%
9	182184.29	0.21%
10	181946.76	0.08%
Average	181939.48	0.07%

Table 6.13 calculation examples results of 10 run times

In 10 run times, the average value of the solution is 181939.48, and the average deviation of the solution is 0.07%. During operation, appears 1 optimal solution – 181799.44, and 9 solutions deviation are controlled within 1%, and the maximum deviation is 0.21%. From these results, the algorithm model is relatively stable.

Then, same process as before, we compare the result of EFVs distribution with traditional fuel vehicle. The calculation case used is same with EFVs. The experiment is repeated 10 times, and the optimal solution is the minimum value in the 10 results, the optimal path is shown in the figure 6.10:

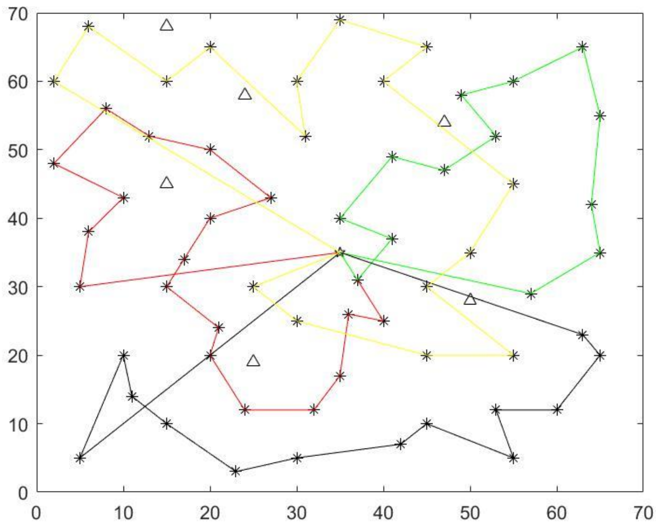


Figure 6.10 fuel vehicle optimal routes distribution diagram

Compare the distribution costs of using fuel vehicles and using EFVs, the comparison items are listed in table 6.14, the route, the detailed routes are shown in table 6.15:

Indicators	Electric freight vehicle	Traditional fuel vehicle
Optimal solution(without CS cost)	1799.44 yuan	1801.48 yuan
Charging station cost	180,000 yuan	--
Fixed cost	400 yuan	400 yuan
Transport cost	1270.18 yuan (635.09 km)	993.54 yuan (496.77km)
Charging cost/fuel cost	51.76 yuan	222.01 yuan
Environmental cost	30.48 yuan	150.66 yuan
Time window penalty cost	47.02 yuan	35.27 yuan

Table 6.14 results comparison of EFVs and fuel vehicles

EFVs optimal routes	● 0--52--18--60--5--59--37--42--57--2--40--58--53--1--30--0 (red line) ● 0--41--15--22--23--55--39--56--25--24--29--34--33--51--66(charging)--3--9--35--0 (green line)

	• 0--11--7--48--47--36--49--19--46--8--45--17--16--44--14--38--61(charging)--6--27--0 (black line) • 0--43--13--26--21--4--54--12--28--50--10--31--64(charging)--32--20--0 (yellow line)
Fuel vehicles optimal routes	• 0--17--45--8--46--47--48--7--52--18--60--5--59--37--42--57--2--58--40--0 (red line) • 0--53--28--27--1--50--33--51--9--35--34--29--24--54--0 (green line) • 0--55--25--39--56--23--22--41--15--43--14--44--16--38--0 (black line) • 0--6--13--21--4--26--12--3--30--20--32--10--31--11--19--49--36--0 (yellow line)

Table 6.15 optimal distribution routes comparison

From the feasible solution obtained in the above tables, it can be seen that in the large-scale case (long-distance transportation process), the use of EFVs distribution and the use of traditional fuel vehicle distribution required costs are not much different, the difference value is only 2.04 yuan for each mission. Meanwhile, EFVs need to be charged in the distribution process, resulting in transportation cost (distance) and time window penalty cost are higher than the use of traditional fuel vehicle distribution. But the EFVs' charging costs and environmental costs are much lower than the fuel vehicles, where the environmental cost reduced by 79.77%, Therefore, the total cost of using EFVs for the same mission almost same with using fuel vehicles.

Then, consider we should build 3 charging stations (50kw DC fast charger) in this large-scale case, the initial investment is 180,000 yuan, average annual fixed cost increasing 34,200 yuan. The distribution cost saved by using EFVs is 2.04yuan/mission. In this large-scale case, self-built charging station of company have no benefits. Same as before, we consider the 3 charging stations available for the EFVs of other logistics companies, under the same assumptions as previous, if the utilization rate of each charging station is 10%, each charging station daily service EFVs number is 4 (including 3 EFVs from other companies), then the company will be profitable in the 7th year, much longer than before. If the utilization rate is 20%, it means each charging station daily service EFVs number is around 8, then the company will be profitable in the middle of the 1st year. The key is to increase the utilization rate of charging stations, reasonably open charging stations for public.

6.4 Conclusions

This thesis integrates the charging station cost, charging cost and environmental cost into the electric vehicle LRP model, and designs the genetic algorithm to solve the model, so some corresponding conclusions are drawn. According to the two scale of examples, Table 6.16 lists the saved cost of using EFVs with respect of fuel vehicles:

	Saved distribution costs	Saved total costs (300 missions/year)	Saved environmental costs
Medium-scale (25 customers,1 charging stations, 2 vehicles)	101.39 yuan/mission (0.36 yuan/km)	18,317 yuan/year	24.81 yuan/mission (64.98%)
Large-scale (60 customers, 3 charging stations, 4 vehicles)	2.04 yuan/mission (0.004 yuan/km)	-34,288 yuan/year	121.73 yuan/mission (80.7%)

Table 6.16 comparison of costs

In summary, considering the aspects of distribution costs and environmental costs, EFVs distribution has certain advantages, but with the increase in total distribution distance and customer points, the average total cost savings reduced, This is because fuel vehicles are not subject to the same mileage limits as EFVs due to the number of customers, the increase in distribution distance and the limitations of the customer's time window, so they have more freedom of choice for customer service priorities, thereby reducing transportation costs and time window penalty costs to offset some of the environmental costs; Meanwhile, since the EFVs in delivery do not produce carbon emission, so the EFVs environmental costs than the use of fuel vehicles savings of an average of about 64.98%.

However, taking into account the total cost, if logistics company prepare to self-building charging stations and not open to the public, in the case of medium distribution scale, from a sustainable development perspective, using EFVs for distribution has advantages, both economic and environmental benefits are better than fuel vehicles. Due to the high initial investment cost of charging stations, when the scale of the distribution becomes larger and the increasing number of charging stations needed to be established, and electric vehicles no longer have an obvious distribution cost advantage, the total logistic cost of using EFVs will be higher than using fuel vehicles. If the charging station built by the logistics company can be opened to the public, the charging stations can be profitable, company can quickly compensate for the excessive upfront investment of using EFVs for distribution.

Considering the limitation of research time and the difficulty of data acquisition, there are still some shortcomings in this thesis that need to be perfected and improved:

1) Taking into account the difficulty of obtaining customer locations, time windows, demands and related data of distribution vehicles from the actual enterprise, we do not use the actual research data in the electric vehicles LRP model, but on the basis of the Solomon benchmark problems to make reasonable assumptions

about the relevant data. Therefore, if the actual experimental data can be obtained, it can make the research more convincing.

2) The research object is relatively single, limited to the EFVs that use fast charging mode in distribution. Therefore, in future studies, the charging route of hybrid vehicles may be considered, and other charging methods (partial charging, wireless charging, etc.) can also be studied.

3) Simplify the electric vehicles LRP model during model building process. Although the integration of charging station cost, charging cost and environmental cost makes the model more realistic, but like the variety of vehicle types, real traffic conditions and distance, dynamic demand of customers, and other factors are not taken into account.

4) In the design process of electric vehicle LRP genetic algorithm, although the idea of the greedy algorithm and elite retention strategy have improved the performance of the algorithm, but the optimal solution number of the algorithm in solving the case studies is not many, indicating that there are still some shortcomings in algorithm convergence.

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APPENDIX

Attached list 1 coordinates where charging stations can be built

Number	x coordinate	y coordinate
1	4	14
2	22	10
3	50	8
4	62	23
5	39	27
6	28	35
7	4	37
8	35	17
9	55	20
10	15	30
11	31	52
12	46	39
13	39	56
14	65	61
15	10	55
16	58	45
17	25	19
18	24	58
19	15	45
20	18	68

Attached list 2 charging station coordinates

number	x coordinate	y coordinate
1	22	10
2	50	8
3	39	27
4	39	56
5	10	55
6	58	45

Attached list 3 medium-scale case: customer points data

Number	x coordinate	y coordinate	Demand	Starting time	Ending time
0	35	35	0	0	8
1	41	49	46	2.4	7.1
2	55	45	24	0	5.7
3	25	30	72	1.3	6.5
4	20	50	24	0.5	6.2
5	10	43	52	1.2	5.8
6	55	60	30	0	7.5
7	30	60	26	2.2	6.5

8	20	65	63	0.5	6.5
9	50	35	30	0.3	5.6
10	30	25	23	1.9	7.5
11	15	10	58	0.5	6.8
12	30	5	45	0.8	5.8
13	10	20	35	0.5	5
14	5	30	52	2	6.3
15	20	40	61	0.5	4.8
16	15	60	29	1	5.5
17	45	20	30	0.5	4.5
18	45	10	48	1.6	5.1
19	55	5	29	1.2	5.6
20	65	35	51	1.2	7
21	65	20	25	1.8	6.2
22	45	30	91	2.5	6.2
23	35	40	45	0.1	4.7
24	41	37	29	0.2	5
25	64	42	61	0.5	5.5

Attached list 4 large-scale case: customer points data

Number	x coordinate	y coordinate	Demand	Starting time	Ending time
0	35	35	0	0	480
1	41	49	52	144	426
2	35	17	23	0	390
3	55	45	15	0	342
4	55	20	23	90	450
5	15	30	26	12	390
6	25	30	14	78	390
7	20	50	35	30	372
8	10	43	61	72	348
9	55	60	49	0	450
10	30	60	26	132	390
11	20	65	35	30	390
12	50	35	18	18	336
13	30	25	23	114	450
14	15	10	20	30	408
15	30	5	26	48	348
16	10	20	48	30	300
17	5	30	27	120	378
18	20	40	38	30	288
19	15	60	83	60	330
20	45	65	43	60	480
21	45	20	52	30	270
22	45	10	51	96	306

23	55	5	15	72	336
24	65	35	72	72	420
25	65	20	46	108	372
26	45	30	26	150	372
27	35	40	37	6	282
28	41	37	48	12	300
29	64	42	73	30	330
30	40	60	46	12	414
31	31	52	29	0	390
32	35	69	41	18	468
33	53	52	11	6	408
34	65	55	14	72	402
35	63	65	37	24	480
36	2	60	34	30	432
37	20	20	36	72	474
38	5	5	61	48	390
39	60	12	56	12	456
40	40	25	26	18	414
41	42	7	36	48	480
42	24	12	47	0	390
43	23	3	44	90	444
44	11	14	18	60	390
45	6	38	16	12	456
46	2	48	41	72	468
47	8	56	27	12	450
48	13	52	36	66	414
49	6	68	30	78	402
50	47	47	13	72	480
51	49	58	10	12	336
52	27	43	25	0	414
53	37	31	71	48	432
54	57	29	26	126	468
55	63	23	36	36	480
56	53	12	16	96	474
57	32	12	49	48	408
58	36	26	30	78	480
59	21	24	62	0	456
60	17	34	15	72	468

P-center code

```
disbak = dis; ite = 0;
valite = [];

while 1
```

```
    ref = zeros(N,1);
    k = size(dis,1);
    ite = ite+1;

    for i = 1: N
        coor = client(i,2:3);
        [val,ind] = min(sum((dis(:,2:3)-repmat(coor,k,1)).^2,2));
        ref(i) = ind;
    end
    disite = 0;
    % calculate the total distance
    for i = 1: N
        disite = disite + sum((dis(ref(i),2:3)-client(i,2:3)).^2);
    end
    valite = [valite,disite];

    klist = unique(ref);
    if length(unique(ref)) ==p
        break;
    end

    if length(unique(ref))>p
        % drop
        addval = zeros(length(unique(ref)),1);
        for i = 1: length(unique(ref))
            droppoint = klist(i);
            clientdrop = find(ref==droppoint);
            % find other closer location
            for j = 1: length(clientdrop)
                coor = client(clientdrop(j),2:3);
                disleft = dis;
                disleft (droppoint, :) = [];
                addval(i) = addval(i) + min(sum((disleft(:,2:3)-repmat(coor,length(disleft(:,2:3)),1)).^2,2)) -
sum((coor-dis(droppoint,2:3)).^2);
            end
        end
        [~, ii] = min(addval);
        dis (ii, :) = [];
    end
end
```

Main Program Code

```
clear all
close all
```

```
%% GENETIC ALGORITHM INITIALIZATION
Nite = 150; % iteration number
Npop = 100; % population size
pcross = 0.9; % crossover probability
pmutate = 0.1; % mutation probability

% Generating initial population
population = zeros (Npop, Nclient+2*Nstation+Kvehecal+1);
offspring = zeros (Npop, Nclient+2*Nstation+Kvehecal+1);
bestfitness = zeros (Nite, 1);
bestpop = zeros (Nite, Nclient+2*Nstation+Kvehecal+1);
cnt = 1;
while 1
    [p1,p2,p3] = popinit;
    fff = checkroute(p3);
    if checkroute(p3)
        population (cnt, :) = p3;
        cnt = cnt+1;
    end
    if cnt > Npop
        break;
    end
end

for ite = 1: Nite
    fprintf('ite %d\n',ite)
    fval = zeros(Npop,1);
    for i = 1: Npop
        fval(i) = fitness (population(i, :));
    end

% Selection
%   Sort the fitness values in descending order, keep the top 2% chromosomes as elite individuals in the new generation.
    [fvalnew,Ipos] = sort(fval,'descend');
    tournamentSize=2;
    for k=1: Npop
        for i=1: tournamentSize
            randomRow = randi(Npop);
            tourPopDistances(i) = fval(randomRow);
        end
        parent1 = max(tourPopDistances);
        [parent1X, ~] = find (fval==parent1,1, 'first');
        parent1Path = population (parent1X, :);
```

```
        for i=1:tournamentSize
            randomRow = randi(Npop);
            tourPopDistances(i) = fval(randomRow);
        end
        parent2 = max(tourPopDistances);
        [parent2X, ~] = find (fval==parent2,1, 'first');
        parent2Path = population (parent2X, :);

% Crossover
%    Select the crossover parents, randomly combine all the chromosomes in the population in pairs to form a parent group, and select one group from it for crossover;
    parent1Pathcross = parent1Path;
    if rand(1) <pcross
        while 1
            indcross = randperm(Npop,2);
            pcross1 = parent1Path;
            pcross2 = parent2Path;
            ppc1 = pcross1(1:length(pcross1)-Nstation);
            ppc2 = pcross2(1:length(pcross2)-Nstation);
            zeropos1 = find(ppc1==0);
            ppc1 (zeropos1) = [];
            zeropos2 = find(ppc2 == 0);
            ppc2(zeropos2) = [];
            [pppc1,pppc2] = crossover(ppc1,ppc2);

            start = 1;p1new = zeros(1,length(ppc1));
            for i = 1:length(zeropos1)-1
                p1new(zeropos1(i)+1:zeropos1(i+1)-1) = pppc1(start:start+zeropos1(i+1)-zeropos1(i)-2);
                start = start+zeropos1(i+1)-zeropos1(i)-1;
            end
            p1new = [p1new,0];
            p1new = [p1new,pcross1(length(pcross1)-Nstation+1:end)];
            start = 1;p2new = zeros(1,length(ppc2));
            for i = 1:length(zeropos2)-1
                p2new(zeropos2(i)+1:zeropos2(i+1)-1) = pppc2(start:start+zeropos2(i+1)-zeropos2(i)-2);
                start = start+zeropos2(i+1)-zeropos2(i)-1;
            end
            p2new = [p2new,0];
            p2new = [p2new,pcross2(length(pcross2)-Nstation+1:end)];
            if checkroute(p1new) && checkroute(p2new)
                parent1Pathcross = p1new;
                break
            end
        end
    end
```

```
% Mutation
    if rand(1)<pmutate
        while 1
            indmutate = randi(Npop);
            pmutate = parent1Pathcross;
            indzero = find(pmutate(1:length(pmutate)-Nstation)==0);
            pmutate1 = pmutate(1:length(pmutate)-Nstation);
            pmutate2 = pmutate(length(pmutate)-Nstation+1:end);
            p1list = find(pmutate1 > 0 & pmutate1 <= Nclient);
            mutatepos = randperm(length(p1list),2);
            temp = p1list(mutatepos(1));
            p1list(mutatepos(1)) =    p1list(mutatepos(2));
            p1list(mutatepos(2)) = temp;
            if Nstation >1
                m2pos = randi(Nstation);
                if pmutate2(m2pos) == 0
                    pmutate2(m2pos) = 1;
                else
                    pmutate2(m2pos) =0;
                end
            end
            pmutate = [pmutate1,pmutate2];
            if checkroute(pmutate)
                parent1Pathcross = pmutate;
                break;
            end
        end
    end
    offspring(k,:) = parent1Pathcross;
    end

% Record iteration
    bestfitness(ite) =    fvalnew(1);
    bestpop(ite,:) = population(Ipos(1),:);
    population = offspring;
end
```