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Mobile Battery Replacement Service Routing Problem for Shared Electric Bikes Based on Logistics Vehicles

TESI DI LAUREA MAGISTRALE IN MOBILITY ENGINEERING

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Abstract

As an emerging means of transportation, shared e-bikes have gradually become one of the favorite ways for Chinese urban residents to get around. However, there are few studies on the operation of shared bikes. At present, the power supply of shared electric bikes mainly relies on mobile service vehicles sent by operators for battery replacement. The service vehicle will go to the parking place of the shared electric bike where the battery needs to be replaced, collect the battery with insufficient power, and finally return to the battery warehouse.

The automobile industry is faced with the challenge of comprehensive electric transformation. Commercial vehicles are an essential source of carbon dioxide and air pollutants emission. And governments have put comprehensive electric transformation on the agenda. Currently, in China, the electrification of other commercial vehicles except buses is still in its initial stage. With the boost of relevant policies, the comprehensive electrification development of commercial vehicles will be accelerated.

This thesis's research object is the battery replacement operation system for shared e-bikes. The research content of this thesis is to select the electric logistics vehicle as the service vehicle and study the routing planning of its battery replacement service for shared e-bikes.

Firstly, after analyzing the actual situation and listing the assumptions, a linear programming model is established according to the constraints of transport cost, fast charging/battery-swapping cost, and service time cost. To solve the problem, genetic algorithm, particle swarm optimization, and chaotic particle swarm optimization are used to minimize the operating cost of replacing the shared electric bike battery.

Secondly, this thesis uses the Solomon benchmark as the dataset to test the algorithm and analyze the results. Compare the performance of genetic algorithm, particle swarm optimization, and chaotic particle swarm optimization. The optimal path provided by the three algorithms is used to analyze carbon dioxide emissions.

Finally, the sensitivity analysis is carried out to explore the factors that affect the experimental results, and the method of optimizing the decision scheme is proposed. According to the sensitivity analysis results, improved electric logistics load capacity, battery capacity, and reasonable arrangement of service vehicle fleet structure can improve the flexibility of vehicle operation in the system to a certain extent, reducing its total operating cost.

In the last part of this thesis, the work of this thesis is summarized step by step. The shortcomings of mobile replacement battery service are put forward, and the prospect is made.

Keywords: shared e-bikes, soft time window, routing planning, genetic algorithm, particle swarm optimization, chaotic particle swarm optimization

Abstract in italiano

Come mezzo di trasporto emergente, le e-bike condivise sono gradualmente diventate uno dei modi preferiti dai residenti urbani cinesi per spostarsi. Tuttavia, ci sono pochi studi sul funzionamento delle biciclette condivise. Attualmente, l'alimentazione delle bici elettriche condivise si basa principalmente sui veicoli di servizio mobili inviati dagli operatori per la sostituzione della batteria. Il veicolo di servizio si recherà al parcheggio della bici elettrica condivisa dove è necessario sostituire la batteria, ritirerà la batteria con potenza insufficiente e infine tornerà al magazzino batterie.

L'industria automobilistica deve affrontare la sfida di una trasformazione elettrica completa. I veicoli commerciali sono una fonte essenziale di emissioni di anidride carbonica e inquinanti atmosferici. E i governi hanno messo all'ordine del giorno una trasformazione elettrica completa. Attualmente, in Cina, l'elettrificazione di altri veicoli commerciali ad eccezione degli autobus è ancora nella sua fase iniziale. Con la spinta delle politiche pertinenti, lo sviluppo completo dell'elettrificazione dei veicoli commerciali sarà accelerato.

L'oggetto di ricerca di questa tesi è il sistema operativo di sostituzione della batteria per biciclette condivise. Il contenuto della ricerca di questa tesi è selezionare il veicolo logistico elettrico come veicolo di servizio e studiare la pianificazione del percorso del suo servizio di sostituzione della batteria per le e-bike condivise.

In primo luogo, dopo aver analizzato la situazione reale ed elencato le ipotesi, viene stabilito un modello di programmazione lineare in base ai vincoli del costo del trasporto, del costo di ricarica rapida/cambio batteria e del costo del tempo di servizio. Per risolvere il problema, vengono utilizzati l'algoritmo genetico, l'ottimizzazione dello sciame di particelle e l'ottimizzazione dello sciame di particelle caotiche per ridurre al minimo il costo operativo della sostituzione della batteria della bicicletta elettrica condivisa.

In secondo luogo, questa tesi utilizza il benchmark Solomon come set di dati per testare l'algoritmo e analizzare i risultati. Confronta le prestazioni dell'algoritmo genetico, dell'ottimizzazione dello sciame di particelle e dell'ottimizzazione dello sciame di particelle caotiche. Il percorso ottimale fornito dai tre algoritmi viene utilizzato per analizzare le emissioni di anidride carbonica

Infine, viene effettuata l'analisi di sensitività per esplorare i fattori che influenzano i risultati sperimentali e viene proposto il metodo di ottimizzazione dello schema decisionale. Secondo i risultati dell'analisi di

sensibilità, una migliore capacità di carico della logistica elettrica, la capacità della batteria e una disposizione ragionevole della struttura della flotta di veicoli di servizio possono migliorare in una certa misura la flessibilità del funzionamento del veicolo nel sistema, riducendone il costo operativo totale.

Nell'ultima parte di questa tesi, vengono esaminate le caratteristiche di diversi algoritmi e vengono riassunti i risultati della pianificazione del percorso. Vengono evidenziate le carenze del servizio di sostituzione della batteria mobile e viene fatta la prospettiva.

Parole chiave: e-bike condivise, finestra temporale morbida, pianificazione del percorso, algoritmo genetico, ottimizzazione dello sciame di particelle, ottimizzazione dello sciame di particelle caotiche

Contents

1 General Overview

Urban transport in China has experienced five stages of development:

(1) The period of transportation based on foot, water transport and animal rickshaw before the founding of the People's Republic of China.

(2) The period from the founding of the People's Republic of China to the 1980s when bicycles were an important means of transportation.

(3) During the rapid development of motorization from the 1980s to 2000, public transportation developed rapidly, and cars gradually entered families.

(4) During the rapid synchronous development of rail transit, bus and car from 2000 to 2010, bicycle traffic gradually shrank.

(5) After 2016, as the concept of shared bikes and electric vehicles began to emerge, non-motor vehicles showed their former vitality. Shared bikes and shared electric bikes have become important modes of transportation for urban residents.

As a component of the urban slow travel system, shared cycling plays an important role in satisfying basic travel, serving bus connections, facilitating public commuting, and improving transportation resilience[1][2][3] In recent years, shared e-bikes, as an emerging green mode of travel, have provided users with diversified choices for short and medium trips under their convenience, economy and sharing characteristics.

With China already committing to peak carbon dioxide emissions before 2030 and achieve carbon neutrality before 2060, the Central Economic Work Conference urged quicker steps to come up with an action plan that enables the peaking of emissions. It called for accelerated efforts to better the industry and energy structures and enable the peaking of coal consumption early while bolstering the development of new energy.

Currently, the shared electric bicycle system mainly adopts the operation method of manual battery replacement. The delivery vehicles carry electric bicycle batteries to provide battery replacement services for nodes in need in the urban road network. However, the delivery vehicles are mainly fuel vehicles. The increase in urban delivery will inevitably lead to an increase in the number of delivery vehicles and delivery times, which will indirectly harm urban environmental quality. The emergence of electric vehicles as logistics distribution vehicles realizes the concept of "zero emission and zero pollution" in the distribution process to improve the environment. The selection of electric vehicles as servo vehicles in the shared electric bike system helps promote the sustainable development of shared electric bikes and the environment.

This chapter will introduce the development of shared e-bikes in China, the advantages of shared e-bikes, the charging/changing strategy of shared e-bikes, and the development and advantages of electric logistics vehicles.

1.1. Development of shared e-bikes

1.1.1 Rapid growth

The shared e-bike is a new means of transportation, mainly for the Chinese city travel market of 3-10 kilometres. Since 2016, shared bikes have developed rapidly, with companies led by Mobike and ofo completing their financing and releasing many shared bikes in various places within a year. At the same time, e-bike sharing is also quietly taking off. The bikes are very convenient to use. After completing the registration, deposit and identity verification procedures by scanning the QR code on the bikes, users can unlock the bikes and use them and are charged according to the time.

Nanchang Hangkong University released its first batch of 40 e-bikes in mid-December 2016, and the operator said it made a profit on the first day. Since January 2017, shared electric vehicles have been launched in Beijing, Shanghai, Nanjing and other cities, such as the No. 7 electric bike, Mebike, electric zebra and Lieba.

Figure 1. 1: Mebike

1.1.2. Industry winter

Due to the chaotic parking management of shared electric vehicles, the lack of supervision on the safety technology of electric vehicles, the lack of non-motorized lanes in cities and other reasons, the development of shared electric vehicles soon fell into a bottleneck. At the beginning of 2017, the transport commissions of Beijing, Shanghai and other places issued relevant documents, which clearly stated that the development of shared e-bikes should not be developed, and the development of shared e-bikes should not be temporarily implemented. In August 2017, the Ministry of Transport and other ten departments jointly issued the "Guidance on Encouraging and Regulating the development of Internet rental bikes," which pointed out that rental electric bikes are not encouraged. Subsequently, local governments have repeatedly stated that they do not encourage the development of shared electric bikes.

1.1.3. Rational development

In May 2018, the new mandatory national standard "Technical Specification for Safety of Electric Bicycles" was released and officially implemented on April 15, 2019. The new national standard will put safety first, from vehicle safety, electrical safety, speed, fire prevention tampering and other aspects of strict regulations. Implementing the new national standard has a mandatory normative effect on electric bicycle production, sale and use.

The new national standard provides clear instructions on the use, management and follow-up treatment of e-bikes nationwide, which means there will be rules to follow for the operation and management of shared e-bikes. At the same time, some local cities are gradually liberalizing the control of shared electric bikes, aiming to minimize the risk probability of civil electric bikes through sharing means.

Affected by the policy, the shared bike industry also ushered in development opportunities. 2020 is the first year of shared e-bike to resume development with many bike platforms entering the market of shared e-bikes. As shown in the pie chart below, Meituan, Didi and Hallo put 800,000, 650,000 and 550,000 e-bikes into the market in the first half year of 2020. Moreover, the annual put into the market is 2 million, 1.5 million and 1.3 million e-bikes, respectively. Hallo has 2.6 million e-bikes, Meituan has 2 million e-bikes, and Didi has 1.7 million e-bikes. The total share of the three companies is over 70%, and they are in an oligopoly situation. As shown in Figure 1.3, the revenue scale of China's shared e-bikes is 9.36 billion yuan in 2021, and it is expected to exceed 10 billion yuan in 2022. With the continuous expansion of the scale of shared e-bikes and the increasing public awareness of shared travel, the daily use rate of shared e-bikes will further improve, and the revenue scale of shared e-bikes is expected to exceed 20 billion yuan in 2025. In China, shared e-bikes, as an important supplement to two-wheeled transportation, still have great potential for development.

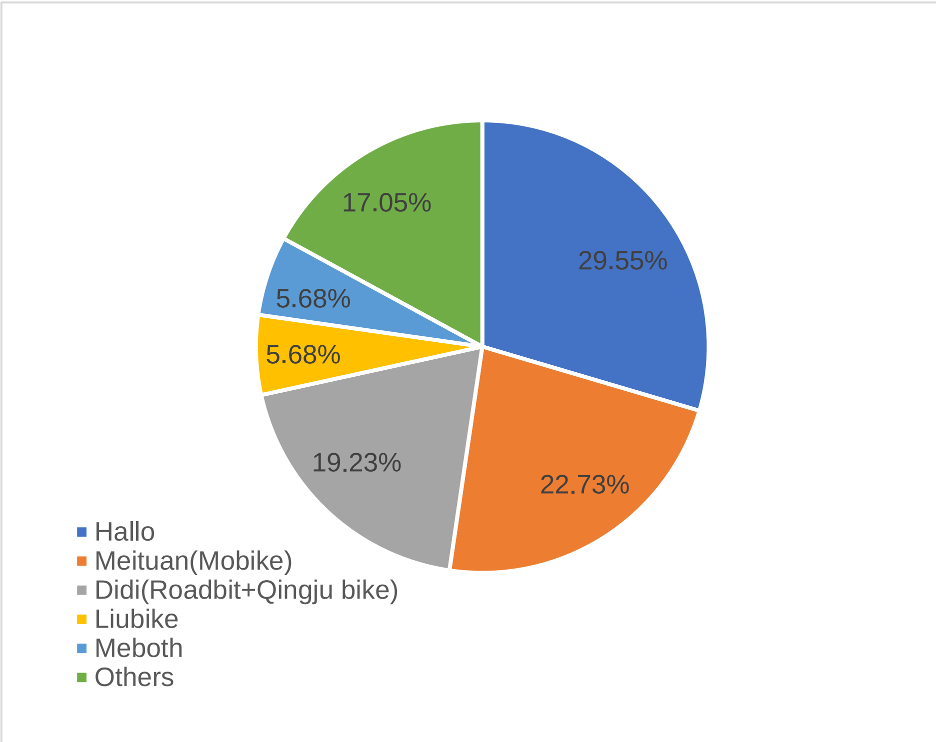

Figure 1. 2: Competition pattern of shared e-bike in 2020H1

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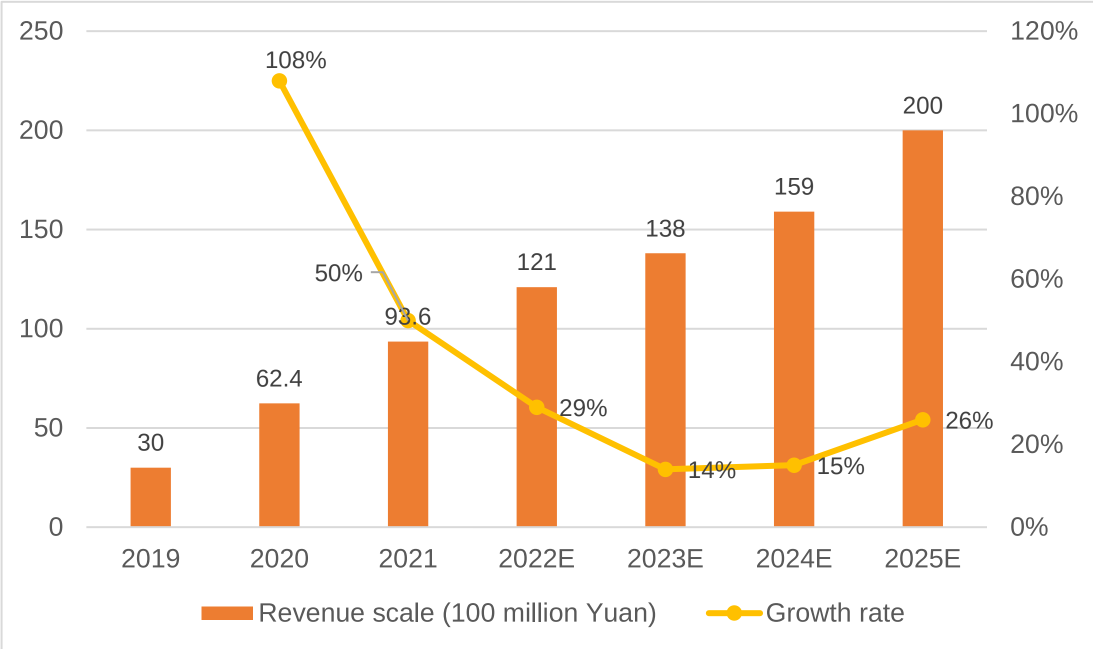

Figure 1. 3: The revenue scale of China's shared e-bikes

1.2. Advantages of sharing electric bikes

1.3. Charging/changing battery strategies for e-bikes

1.3.1. Shared charging station

Shared charging stations are usually found in urban neighbourhoods or convenience stores, where riders can recharge their bikes in their free time. According to the charging efficiency, shared charging stations can be divided into fast and slow charging stations. However, in the slow charging mode, it takes 4-6 hours to fill an e-bike, and few places in the urban road network can provide such charging equipment. Therefore, a large-scale shared electric bike system is not suitable for the situation of self-charging by users. In addition, the working voltage of fast charging equipment is relatively high, which also has high requirements for the charging facilities deployed. It is not easy to arrange large-scale in the shared e-bike network.

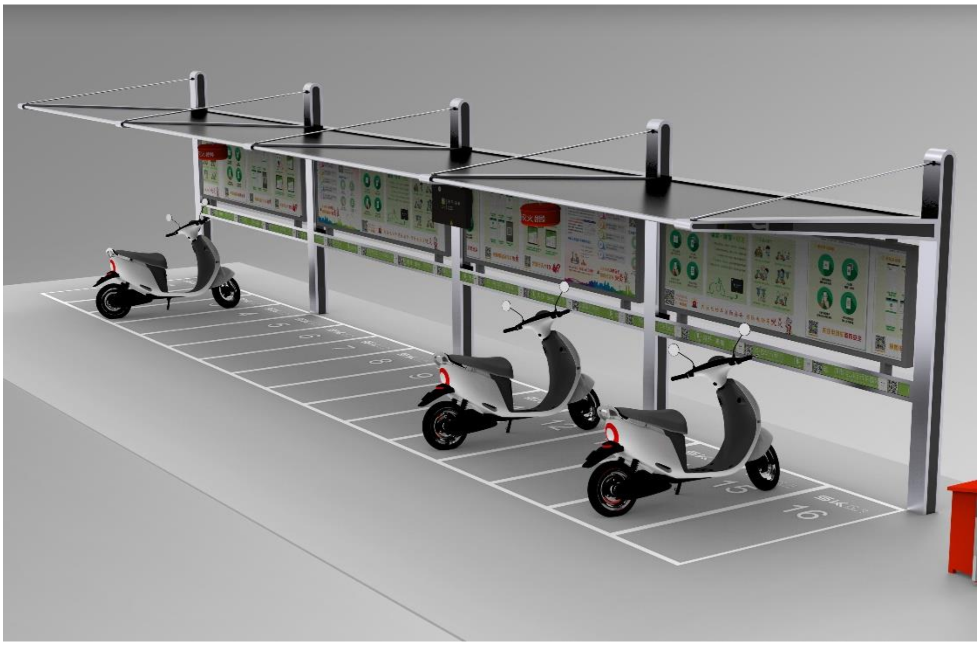

Figure 1. 15: Shared charging station

1.3.2. Shared battery changing cabinet

Shared battery changing cabinet is a new shared economy equipment. It solves the problems of unsafe battery charging, inconvenient charging and short battery life for users of e-bikes. Users need to scan the QR code, take out the fully charged battery, put the battery with insufficient power back into the changing cabinet, and finally put the new battery into the e-bikes, and then they can ride again.

Figure 1. 16: Shared battery changing cabinet

Currently, this mode is more popular with delivery riders, who need to refuel their bikes frequently. Instead, the battery recharge time after sharing the electric changing cabinet has changed from the original 4-6 hours to the current one minute to complete the battery changing. Shared battery changing cabinet not only saves the riders' time but also improves work efficiency.

However, there are still great difficulties in promoting the shared battery changing cabinet at this stage. On the one hand, for ordinary users, direct participation in battery replacement will reduce users' experience, and users are not willing to use the shared battery changing cabinet. On the other hand, for operating enterprises, the density of power changing outlets is not high at the present stage, and a large number of shared batterry changing cabinets are still needed. However, due to the natural asset-heavy property of shared battery changing cabinets, operators also face various problems of high operating costs such as site rent and commercial electricity price. So the speed of network construction cannot effectively accelerate the service for ordinary users.

1.3.3. Wireless charging

The traditional wired charging method is used regardless of the shared charging station or shared battery changing cabinet. In addition to easy-to-produce electric spark and plug wear, it is also easy to be affected by moisture, heat dissipation, dust, and other environmental problems that have certain impacts on the charging. In the complex outdoor environment, to better and safer charge electric bicycles, new charging methods are needed to meet the needs of the public. Wireless charging technology makes up for the shortage of wired charging to some extent.[4][5]

Wireless charging technology is mainly based on the magnetic field reaction, that is, inductive coupling. After the connected current passes through power factor correction (PFC) and high-frequency inverter power conversion, the high-frequency alternating current is generated to excite the transmitting coil to generate an alternating magnetic field. The receiving lock obtains energy in the alternating magnetic field to obtain an AC voltage, which is then provided to the battery load through the rectification link.

Presently, e-bike wireless charging product has progressed in China, mainly aiming at achieving more convenient wireless charging. In 2017, the company Xiangqi introduced wireless charging piles for e-bikes for the first time, which can be charged wirelessly by parking specific e-bikes at designated locations.

Figure 1. 17: Xiangqi wireless charging pile

Although the prospect of wireless charging piles will be very extensive, there are still many problems restricting the popularization of this technology. The first is the efficiency problem. Wireless charging leads to a significant reduction in charging efficiency. The second point is the cost. The cost is relatively high through the coil energy coupling to achieve energy transfer because the composition and structure are more complex than wired charging. Currently, the number of wireless charging piles is small, and the construction cost is high, so wireless charging piles cannot be put into large-scale commercial use quickly.

Lastly, there are safety issues caused by foreign bodies, such as heat and fire safety issues. And electromagnetic radiation biosafety issues.

1.3.4. Mobile services

Battery management of shared e-bikes is the core operation of the entire e-bikes project. Because the number of shared e-bikes in cities is limited, batteries must be replaced or recharged frequently. To adapt to the electric characteristics of shared e-bikes, most e-bike operating companies currently use mobile service vehicles to replace the batteries of e-bikes. The electric power of the shared e-bikes will be transmitted to the background server through the network, and the management personnel can determine the vehicle that needs to replace the battery according to the electric power displayed on the platform. The mobile battery replacement service is relatively simple, with the battery loading and unloading at the battery station and manual replacement at the e-bike parking station.

Figure 1. 18: Mobile service scenario

This thesis chooses mobile services to change the batteries for shared e-bikes. The research content is the path planning problem of replacing batteries of e-bikes in urban shared e-bike systems by mobile vehicles.

1.4. Development and advantages of electric vehicles for logistics distribution

1.4.1. Development of electric logistics vehicles

Urban logistics vehicles have the characteristics of short daily mileage and fixed round-trip, which is an important direction for the promotion of new energy vehicles after buses.

The development of new energy logistics vehicles cannot be achieved without the support of government policies. Since 2013, Beijing, Shanghai, Guangdong and other places have launched a series of new energy vehicle promotion plans, which have put forward the requirements of developing electric logistics vehicles to solve the urban end distribution.

Currently, China's policies on new energy logistics vehicles mainly focus on subsidies and the right of way. On the one hand, subsidies for purchasing new energy vehicles have been declining yearly. However, the subsidies for new energy logistics vehicles have been changed to subsidize the construction of charging piles and other infrastructure. On the other hand, new energy logistics vehicles are parking fee exemptions. Moreover, they also can share the city bus lanes.

The Figure 1.19 shows the changes in the number of new energy logistics vehicle sales over the period from 2018 to 2021. Affected by the decline in purchase subsidies and vehicle quality, China's sales volume of new energy logistics vehicles declined in 2019-2020. In 2021, with the release of the "carbon neutral" policy and the improvement of new energy battery technology, the sales volume of new energy logistics vehicles 2021 reached 132,000, with a year-on-year growth of 79.5%.

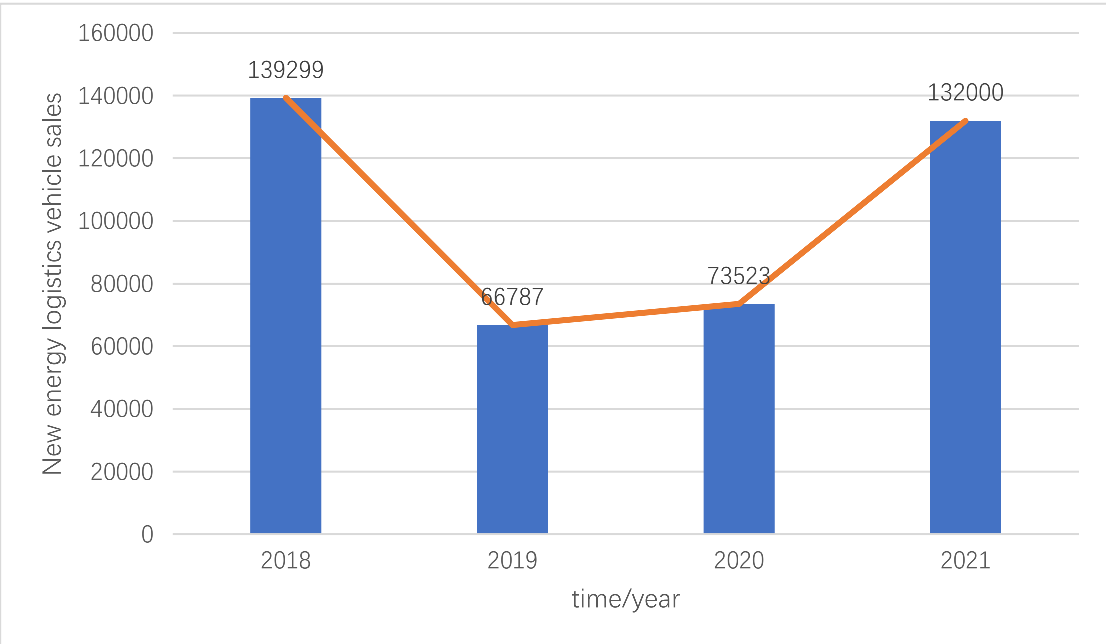

Figure 1. 19: New energy logistics vehicle sales in 2018-2021

Under the combined market demand and policy promotion action, the overall market of new energy vehicles will also perform well. It is expected that by 2025, the total sales volume of logistics vehicles in China will reach 4.19 million, with an annual growth rate of 4.36%. The penetration rate of new energy logistics vehicles can reach 20% in the optimistic scenario and 6.3% in the pessimistic scenario.

From the perspective of power sources, new energy logistics vehicles can be divided into three categories: pure electric, plug-in hybrid and hydrogen fuel cells. The following graph shows that 73,032 pure electric logistics vehicles were sold in 2020, accounting for 99.33% of the new energy logistics vehicles market. The second is plug-in hybrid, with the sales volume of 345 units, accounting for 0.47% of the market; 146 hydrogen fuel cell logistics vehicles were sold, accounting for 0.20% of the new energy logistics vehicles market. Overall, the market performance of plug-in hybrid models and hydrogen fuel cells is weak, and pure electric vehicles are the main component of new energy logistics vehicles.

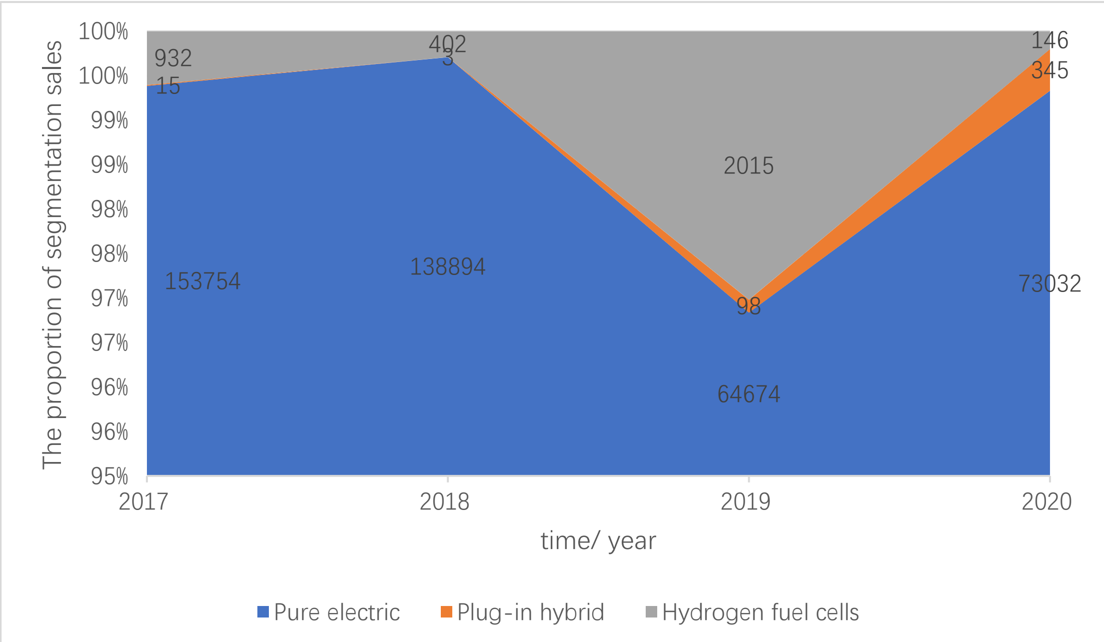

Figure 1. 20: New energy logistics vehicle segmentation sales 2017-2020

1.4.2. Advantages of electric logistics vehicles

Due to low power requirements, ideal low-speed torque characteristics, high braking regeneration ability, low noise, no pollution and other characteristics, the pure electric logistics vehicle is very suitable for urban driving. The application of electric logistics vehicles in logistics distribution helps alleviate air pollution, environmental noise and other problems.[6][7]

Electric logistics vehicles not only reduce the environmental impact but also bring more value to urban delivery:

(1) Easy to manage. Applying pure electric logistics vehicles can significantly reduce the number of vehicle managers, and electricity consumption management is easier than oil management.

(2) Oil and electricity price difference. The oil price is relatively stable, with little room for fluctuation. In contrast, electricity prices vary significantly in different regions and periods, so there is a large space for cost optimization.

(3) Data collection. Electric logistics vehicles are generally equipped with a complete data acquisition system and are online in real-time. The data generated during their operation will be of great significance to optimizing enterprise efficiency and reducing operating costs in the future.

(4) Right-of-way advantage. Because electric logistics vehicles do not produce air pollution in the place where they operate, they can obtain more advantages in the right-of-way and reduce costs for enterprises.

In this thesis, electric logistics vehicle is selected as the service vehicle for battery replacement of shared e-bikes. In the network of the research content, electric logistics vehicles replace usable batteries for shared e-bikes at each node. When the number of onboard batteries is insufficient, they need to go to the battery station with a fixed location to load usable batteries. When serving new energy vehicles, the vehicle running in the road network needs to consider not only the load capacity but also its electricity. When its electricity is not enough to continue the service, it needs to go to the charging station to supplement the electricity.

2 The basic theory

The vehicle routing problem (VRP) and its variants have been extensively studied over the decades since Dantzig and Ramser (1959) [8]put it forward. The most representative VRP variants include VRP with time windows and capacitated vehicle routing problem. [9]Due to the increasingly severe environmental pollution, many people have begun to pay attention to the sustainable development of the logistics industry, which gradually derived all kinds of VRP variants. Nowadays, the research of green VRP has significantly been developed.

2.1. The basic theory of vehicle routing problem

VRP can be described as the traditional delivery vehicle of a logistics enterprise carrying goods from a single distribution centre and successively visiting customer points with different goods needs. Distribution vehicles must deliver to all customer points and arrange distribution routes reasonably according to the location of customer points. Delivery vehicles must visit customer points one by one and return to the distribution center after completing all customer points in the path. The specific diagram of traditional vehicle path planning is shown in Figure 2.1.

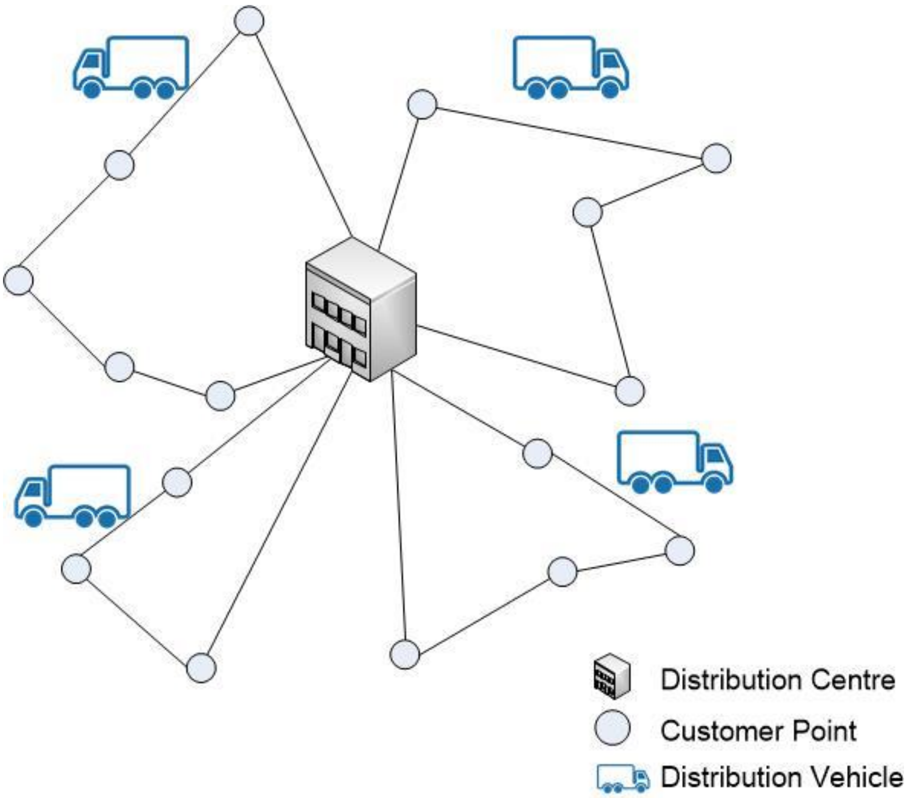

Figure 2. 1: Schematic diagram of traditional vehicle routing problem

Vehicle routing problem has different variation problems. Different variants of the problems in the distribution process need to meet different constraints and the pursuit of goals and tasks of different. According to the research content of this thesis, the capacitated vehicle routing problem and VRP problem with time window will be mainly introduced.

2.1.1. Capacitated vehicle routing problem

Capacitated vehicle routing problem[10] is the most basic variant of VRP. It is described explicitly that each distribution vehicle of a logistics enterprise has a specific capacity limit for loading goods. The distribution vehicles carry goods from the single distribution centre and visit customer points with different goods demands in turn. The sum of goods demands of all visiting customer points should not exceed the loading capacity of the distribution vehicles. Distribution routes should be reasonably arranged according to the locations of customer points. Delivery vehicles should visit customer points in order and return to the distribution center after completing the distribution tasks of all customer points in the path. The goal of the problem is to minimize the distribution cost.

Before the model, the capacitated vehicle routing problem generally exists the following basic assumptions:

(1) A single distribution centre distributes goods to multiple customers.

(2) The fleet of delivery vehicles with uniform capacity.

(3) All distribution vehicles start from the distribution centre and must return to the distribution centre after completing the task. Vehicles only deliver goods without receiving goods from customers.

(4) The geographical location and demand of all customer points are known, and each customer point is only served once.

(5) Stable traffic conditions and no extraordinary circumstances occur during the distribution of vehicles.

(6) The demand of any customer point is less than the maximum load of the delivery vehicle.

According to the capacitated vehicle routing problem description, there are a single distribution center O and m distribution vehicles with load capacity Q. The set of distribution vehicles is $K = \{k_1, k_2 \dots k_m\}$, the delivery vehicle is responsible for delivering to n customer points, and the customer set is $I = \{I_1, I_2 \dots I_n\}$, where the quality of goods demanded by each customer point i is q_i. C_{ij} represents the variable cost of the delivery vehicle from i to point j, where $C_{ij} = vd_{ij}$, v is the unit cost of vehicle travel,d_{ij} is the distance from i to point j, and w is the fixed cost of the vehicle. The set of all nodes in the model is $V = I \cup \{I_0\} \cup \{I_{n+1}\}$. Optimising logistics resource allocation and minimising the total transportation cost under the premise of meeting the constraint of maximum vehicle capacity is the goal of this problem. Accordingly, a detailed CVRP model can be established as follows:

$$minZ = \sum_{k \in K} \sum_{i \in V} \sum_{j \in V} Cij \cdot x_{ij}^{k} + \sum_{k \in K} \sum_{i \in V} w \cdot x_{0i}^{k} \tag{2.1}$$

subject to

$$\sum_{k \in K} y_i^k = 1, \qquad i \in I \tag{2.2}$$

$$\sum_{i,j \in V, i \neq j} x_{ij}^k = \sum_{i,j \in V, i \neq j} x_{ji}^k, k \in K \tag{2.3}$$

$$0 \leq \sum_{i \in I} y_i^k q_i \leq Q, k \in K \tag{2.4}$$

$$x_{ij}^k \in \{0,1\}, i.j \in V, k \in K, i \neq j \tag{2.5}$$

$$y_i^k \in \{0,1\}, i \in I, k \in K \tag{2.6}$$

The objective function (2.1) represents the minimization of logistics transportation costs, where the first term is the variable transportation cost of the vehicle, which depends on the length of the driving distance; The second is the fixed transport cost of the vehicle, depending on the number of delivery vehicles. Constraint (2.2) means that each customer i must be served once by a delivery vehicle; Constraint (2.3) indicates that the number of vehicles arriving at and leaving any node is equal to ensure the continuity of the route. Constraint (2.4) means that the loading mass of the delivery vehicle shall not exceed its maximum capacity. Constraints (2.5) and (2.6) are binary decision variables. If $x_{ij}^k = 1$ means delivery vehicle k goes from node i to node j. And if $y_i^k = 1$ means customer point i is delivered by delivery vehicle k.

2.1.2. Vehicle routing problem with time windows

Vehicle routing problem with time windows (VRPTW) [11] is the extension of the CVRP. This problem is specifically described as that each distribution vehicle of a logistics enterprise has a specific capacity limit for loading goods. The distribution vehicle carries goods from a single distribution center and visits customer points with different cargo demands and time window demands in turn. The sum of goods demands of all visiting customer points should not exceed the loading capacity of the distribution vehicle. When planning the customer point distribution route, the first task is to arrive and deliver the goods within the time window of the customer point. If arriving at the customer point outside the time window, different degrees of penalty costs will be paid. This type of problem aims to maximize customer satisfaction and minimize transportation costs. Usually, the VRPTW occur in the following three situations when it is delivered to the customer: In the first case, the delivery vehicle has arrived before the specified customer delivery time window, and the unloading can not begin until the customer delivery time starts, so that the waiting cost will be paid. In the second case, the delivery vehicle arrives within the specified customer delivery time window, and the unloading service can be carried out directly to the customer so that no cost will be paid. In the third case, the delivery vehicle arrives later than the specified customer delivery time window. At this point, if the customer refuses to accept the goods, is the vehicle routing problem with hard time windows (VRPHTW). However, if the customer receives the goods, the price is to pay the penalty, which is the vehicle routing problem with soft time windows (VRPSTW). Reducing the waiting and penalty costs and improving customer satisfaction are the goals of this optimization problem. In reality, the VRPSTW is more in line with the actual situation, which will be discussed clearly.

Before the model, the vehicle routing problem with soft time windows generally exists the following basic assumptions:

(1) A single distribution centre distributes goods to multiple customers.

(2) The fleet of delivery vehicles with uniform capacity.

(3) All distribution vehicles start from the distribution centre and must return to the distribution centre after completing the task. Vehicles only deliver goods without receiving goods from customers. And the departure time of delivery vehicles is 0.

(4) The geographical location, demand of all customer points and time windows are known, and each customer point is only served once.

(5) Stable traffic conditions and no extraordinary circumstances occur during the distribution of vehicles.

(6) The demand of any customer point is less than the maximum load of the delivery vehicle.

The goal of the vehicle routing problem with soft time windows is to minimize logistics transportation costs, including time window penalty costs. In addition to the above basic symbolic description of CVRP, there are the following symbolic descriptions: The time window satisfying customer point i is$[E_i, L_i]$. Distribution center has hard time window $[E_0, L_0]$; Customer service time (unloading time) is s_i; The distance and time from i to j are d_{ij} and t_{ij}; π_1 and π_2 are penalty coefficients in advance and delay, respectively. $S(T_i^k)$ is the service time cost function, T_i^k is the moment that the delivery vehicle k arrives at point i, $T_i'^k$ is the moment that the delivery vehicle leaves at point i, and WT_i^k is the waiting time at point i. The function of service time cost is shown in Equation (2.7).

$$S(T_i^k) = \begin{cases} \pi_1(E_i - T_i^k), & T_i^k < E_i \\ 0, E_i \le T_i^k \le L_i, & i \in I, k \in K \\ \pi_2(T_i^k - E_i), & T_i^k > L_i \end{cases} \tag{2.7}$$

Accordingly, a detailed VRPSTW model can be established as follows:

$$minZ = \sum_{k\in K}\sum_{i\in V}\sum_{j\in V} C_{ij}\cdot x_{ij}^{k} + \sum_{k\in K}\sum_{i\in V} w\cdot x_{0i}^{k} + \sum_{k\in K}\sum_{i\in I} S\left(T_i{}^{k}\right) \tag{2.8}$$

Subject to

$$\sum_{k\in K} y_i^k = 1, \qquad i \in I \tag{2.9}$$

$$\sum_{i,j\in V, i\neq j} x_{ij}^k = \sum_{i,j\in V, i\neq j} x_{ji}^{\prime k}, \qquad k \in K \tag{2.10}$$

$$0 \leq \sum_{i\in I} y_i^k\, q_i \leq Q, \qquad k \in K \tag{2.11}$$

$$T_i^{\prime k} = T_i^k + WT_i^k + s_i, \qquad i \in V, k \in K \tag{2.12}$$

$$T_j^k = \sum_{i\in V}\sum_{j\in V, i\neq j} x_{ij}^k\left(T_i^{\prime k} + t_{ij}\right), k \in K \tag{2.13}$$

$$WT_i^k = max\left[0, \left(E_i - T_i^k\right)\right], \qquad i \in I \tag{2.14}$$

$$x_{ij}^k \in \{0,1\}, \qquad i,j \in V, k \in K, i \neq j \tag{2.15}$$

The objective function (2.8) represents the minimum total logistics cost. The first two items are the variable and fixed transportation costs of vehicles, and the third is the service time cost. Constraint (2.9) indicates that each customer i must be delivered once by a delivery vehicle. Constraint (2.10) indicates that the number of vehicles arriving at and leaving any node is equal to ensure the continuity of the route. Constraint (2.11) means that the loading mass of the delivery vehicle must not exceed its maximum capacity. Constraint (2.12) indicates that the time leaving f is the sum of the time arriving at f, waiting time, and service time. Constraint (2.13) represents the sum of the time to j from i and the travel time of arc (j). Constraint (2.14) represents the wait time at customer point f. The constraint (2.15) is expressed as a binary decision variable.

2.2. Basic theory of electric vehicle routing problem

Today, greenhouse gas emission has become a severe environmental problem. Significant emissions have been attributed in part to the transport sector across industries. Spurred by government policies, some logistics companies seek alternatives to traditional fuels. With the development of battery technology, electric vehicles have been developed as a promising alternative to conventional cars.

The electric vehicle routing problem (EVRP) [12][13] is the expansion of the VRP, the VRP of distribution vehicles to the electric vehicle fleet. For EVRP, the logistics enterprises provide electric cars with specific loading cargo capacity limits and power limit constraints. The distribution vehicle starts from a single distribution center to carry goods and deliver goods to customers with different needs in turn. The total demand for goods at all customer points should not exceed the loading capacity of the delivery vehicle. On the way, if the electric vehicle's power is not enough to support the next customer point, then select the nearest charging station to charge, and continue to serve the remaining customer points after charging until returning to the distribution center.

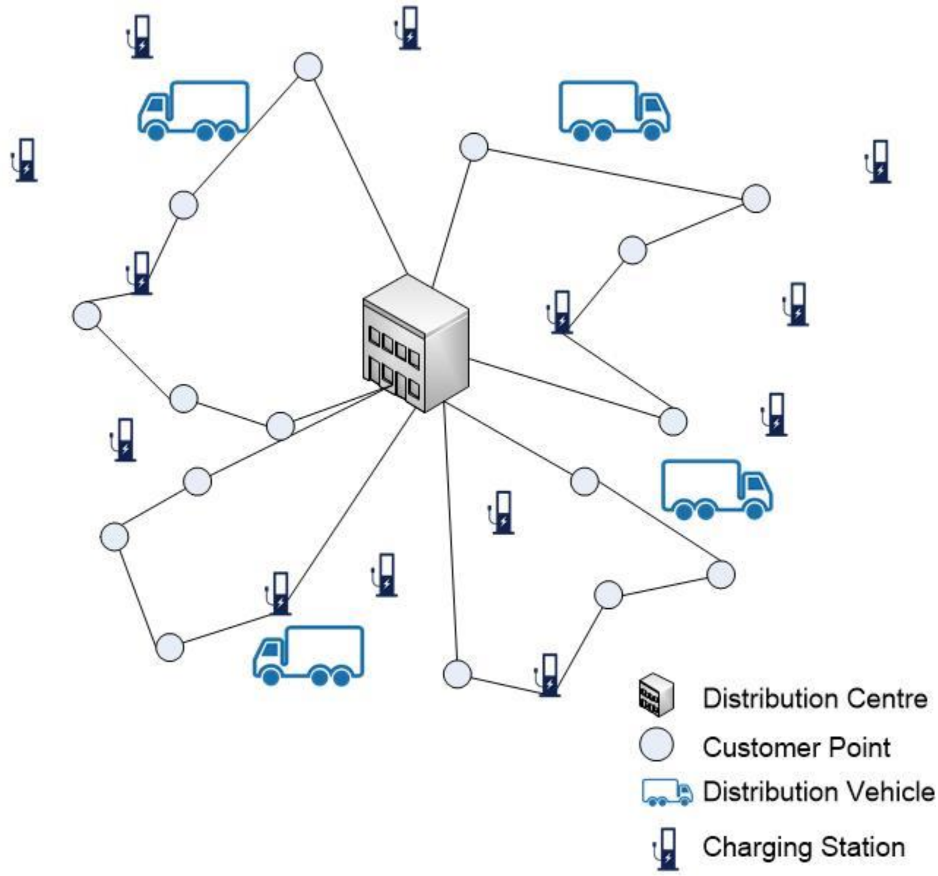

Figure 2. 2: Schematic diagram of electric vehicle routing problem

In the construction of the EVRP model, in addition to satisfying the basic assumptions of the traditional vehicle routing problem, the most important thing is to meet the constraints of electric vehicle batteries. During the delivery of electric vehicles, the following situations may occur:

(1) The electric vehicle drives into the nearest charging station to charge before the power consumption is complete and then delivers to other

customers until it returns to the distribution center.

(2) When the electric power consumption ends, it still does not reach the charging station or back to the distribution center, leading to the failure to complete the following distribution tasks, resulting in increased enterprise costs.

(3) Electric cars have more charge but not enough to reach the nearest charging station.

How to plan the distribution path of electric vehicles so that they can return to the distribution center smoothly after completing the proper distribution task is one of the critical problems to be solved in the route planning of electric vehicles.

2.3. Basic theory of classic algorithms for electric vehicle routing problem

EVRP is a typical NP-hard problem with two main difficulties in solving it. The first one is that sufficient time and exemplary configuration are needed to provide computing conditions due to the complexity and large amount of calculation. Secondly, the solution of various algorithms is more likely to fall into the optimal local solution, and the solution results of the algorithm need to be constantly optimized, so it is necessary to jump out of the optimal local solution and adopt the global search method. Currently, the solution methods applied to EVRP can be divided into precise and heuristic methods.

When the problem size is small, the precise algorithm can obtain the optimal solution within an acceptable time. However, when the problem size is large, the time required by the exact algorithm to solve the optimal solution increases exponentially. At present, the methods used by most EV vehicle path optimization researchers are various heuristic-solving algorithms. The meta-heuristic algorithm is the most mainstream intelligent optimization algorithm used to solve EVRP, including the genetic algorithm, ant colony algorithm, particle swarm optimization algorithm, simulated annealing algorithm, and tabu search algorithm.

Genetic algorithm (GA)[14] is a kind of evolutionary algorithm. It uses natural biological selection and the natural genetic mechanism of the random search algorithm. Its basic principle is modeled on "natural selection, survival of the fittest" in nature. This algorithm is very suitable for dealing with complex and nonlinear problems that are challenging to solve by traditional heuristic algorithms. The problem's parameters are encoded in this algorithm, and the corresponding data is the chromosome. Then, a series of operations such as selection, crossover, and mutation are used to carry out genetic iteration on the chromosome. After iteration, the chromosome is superior to the next generation, and the chromosome that meets the optimization goal is finally output.

Ant colony algorithm (ACA) is a new emulated evolution algorithm. This algorithm is in the 1990 s by M. Dorigo [14] put forward according to the foraging behavior of ant colonies. The solution of the ant colony algorithm for the VRP is as follows: the path of each ant represents one of the feasible solutions of VRP, and the whole ant population is the feasible solution space. Ants on shorter paths release more pheromones and thus attract more ants. Finally, the ant population will find the optimal path under the positive feedback effect, which is the optimal feasible solution of the VRP.

Particle swarm optimization (PSO) is a swarm intelligence optimization algorithm that Kennedy and Eberhart put forward in 1995. [16] The algorithm was also inspired by the behavior characteristics of the biological population (bird predation), and it is widely used to solve optimization problems. In this algorithm, each particle corresponds to a potential solution, which is determined by the fitness value calculated by the fitness function, and the particle's speed

determines the particle's moving position. Each particle will dynamically adjust its position according to the position of other particles. The process is repeated and expected to move the swarm toward the best solutions.

Simulated annealing (SA) [17]was designed by Metropolis based on the similarity between annealing processes of fixed substances in physics and general optimization problems. The physical annealing process is the heating process, isothermal process, and cooling process, which correspond to the set initial temperature of the algorithm, the Metropolis sampling process, and the decrease of control parameters, respectively. Setting the Metropolis criterion is the key to whether the algorithm can obtain the optimal global solution. This algorithm is gradually developed into an iterative adaptive heuristic probabilistic search algorithm.

The above classical meta-heuristic algorithms have different advantages and disadvantages in obtaining feasible solutions for different optimization problems. Because the optimality of feasible solutions cannot be fully guaranteed, many scholars have begun to improve the meta-heuristic algorithm according to its advantages and disadvantages, forming a hybrid heuristic algorithm.

In this thesis, the most classical and adaptable genetic algorithm is used to solve the problem. Because genetic algorithm has good global search ability and can search all the solutions in the solution space quickly, without falling into the trap of fast decline of the local optimal solution. And using its inherent parallelism, it can be convenient to carry out distributed computing and speed up the solving speed.

In addition, particle swarm optimization (PSO) is one of the most popular meta-heuristic algorithms recent years. It has fast convergence speed, strong optimization searching ability, high quality of feasible solutions, and good solving effect when solving optimization group problems, so it is widely used in path planning. In this thesis, particle swarm optimization (PSO) is also used to study EVRP, and the random and ergodic characteristics of the chaotic search are used to improve the standard PSO. Moreover, the algorithm is applied to the path optimization solution of the electric vehicle changing the battery for e-bikes.

2.4. The summary of this chapter

This chapter introduces the two variants of the vehicle routing problem and the characteristics, basic assumptions, and models.

Then transits to the electric vehicle routing problem, which lays a solid foundation for the following path optimization model construction. Moreover, the related algorithm of EVRP is introduced for the subsequent design algorithm to provide a basis.

3 Model building

When the electric vehicle works for the mobile service, it must supplement the electric energy in time if the remaining power is insufficient to continue working. How to realize the optimal management of electric vehicles and the logistics distribution network under a series of constraints has become the biggest challenge, which is precisely the focus of the research on the routing problem of electric vehicles.

This thesis is inspired by the growing popularity of fast charging and battery-swapping stations and considers the importance of quality customer service. The introduction of fast charging stations, battery-swapping stations, and soft time windows expanded the electric vehicle routing problem (EVRP). Moreover, build the electric vehicle routing problem with the soft time window - fast charging/ battery-swapping (EVRPSTW -FC/BS).

EVRPSTW-FC/BS not only takes into account the overall logistics operation cost but also adds a penalty function considering the cost of customer waiting time according to the customer satisfaction demand of the shared e-bike parking point.

3.1. Problem description

EVRPSTW-FC /BS is described as fully charged electric vehicles that transport goods from an e-bike battery warehouse and access the shared e-bike parking points with different e-bike battery quantity requirements and time windows requirements in turn. If the electric vehicle arrives at the e-bike parking point before or after the time window, it will pay different penalty costs. Due to the limitation of battery capacity, if the residual electric power of the electric vehicle is not enough to support it to go to the following e-bike parking points, it must go to the charging station or battery-swapping station to supplement the electric power. After that, the electric vehicle continues along its designated route, completing the task of replacing the e-bike batteries until it returns to the e-bike battery warehouse.

The goal is to plan each electric vehicle service path and makes the operation cost of mobile battery replacement minimum, the following hypothesis:

(1) Single e-bike battery warehouse. There is only one e-bike battery warehouse, which provides fully charged batteries for all the shared e-bike parking points and receives the electric bike batteries that are low in charge.

(2) The fleet of electric vehicles with uniform load and battery capacity. And the number of electric vehicle is limited.

(3) Using fast charging stations and battery-swapping stations. Since the conventional charging mode usually takes a long time and is not suitable for the timeliness of logistics distribution, this thesis chooses the fast charging mode and the battery-swapping mode for electric vehicles.

(4) Every fully charged electric vehicle starts from the e-bike battery warehouse. During driving, if the battery power is insufficient to serve following shared e-bike parking points, it must swap the fully charged battery at the battery-swapping station or enter the charging station for charging. When an electric car enters a charging station for charging, by default, it will be fully charged.

(5) All electric vehicles only provide fully charged batteries for the shared bikes and recycle the low batteries. Electric vehicles do not take the fully charged battery away from the shared e-bike parking points.

(6) The geographical location, battery demand, and time window of each

shared e-bike parking point are known, and the location of the e-bike battery warehouse is also known. Furthermore, the unified departure time of electric vehicles is 0.

(7) Stable traffic conditions and no extraordinary circumstances occur during the distribution of vehicle. Moreover, electric vehicles in the process of mobile service speed are constant.

According to the description of the problem and basic assumptions, the schematic diagram of EVRPSTW-FC /BS is shown in Figure 3.1.

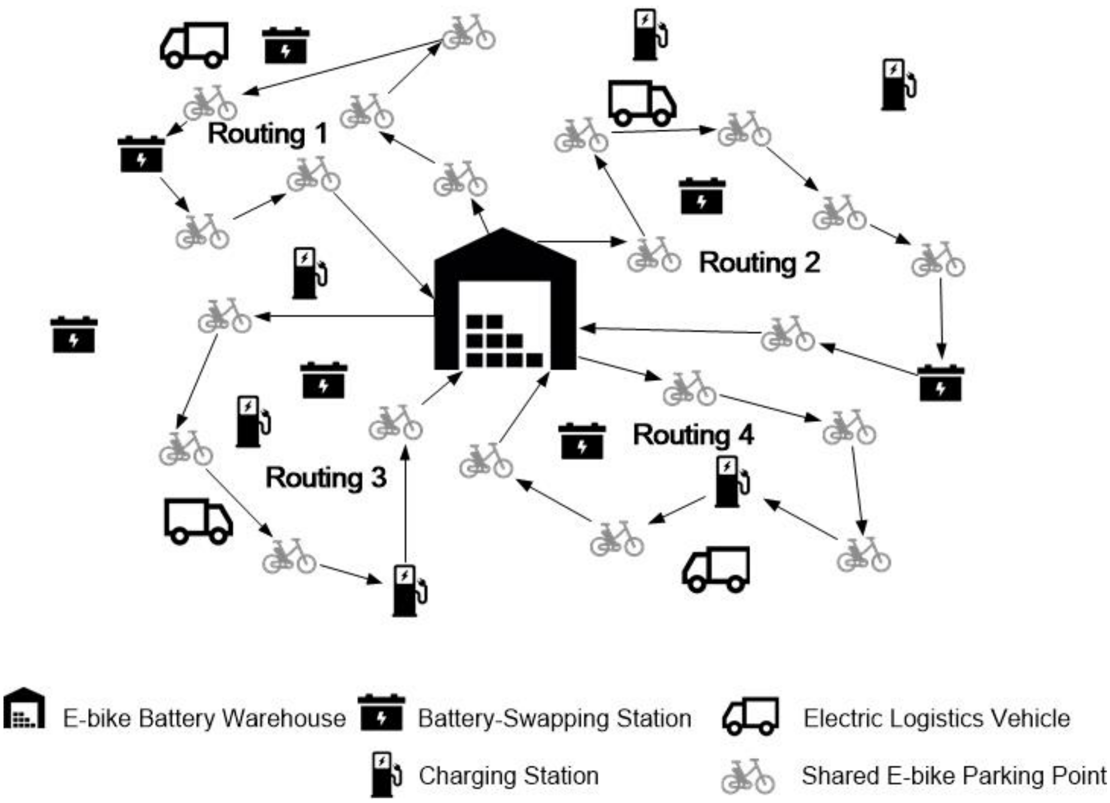

Figure 3. 1: Schematic diagram of EVRPSTW-FC /BS

3.2. Mathematical model of EVRPTW-FC/BS

3.2.1. Definition of variables and parameters

According to the above problem description and basic assumptions, the routing network of EVRPTW-FC/BS contains four types of parameters:

(1) E-bike battery warehouse is I_0, which is also the starting point of the electric vehicle, and the virtual endpoint is I_{n+1}.

(2) I is the set of shared e-bike parking points. $I = \{I_1, I_2, \dots I_n\}$, which includes n shared e-bike parking points.

(3) F is the set of fast charging stations or battery-swapping stations. $F = \{f_1, f_2, \dots f_u\}$, which includes u fast charging stations or battery-swapping stations.

(4) K is the set of electric vehicles operating for mobile services. $K = \{k_1, k_2, \dots k_m\}$, which includes m electric vehicles.

EVRPTW-FC/BS can be defined on complete directed graph $G = (V, H)$. $V = I \cup F \cup \{I_0\} \cup \{I_{n+1}\}$is the set of above four type parameters. $H = \{(i,j)|i,j \in V, i \neq j\}$ is arc set. Each shared e-bike parking point $i \in V$ is associated with its time window $[E_i, L_i]$ and the service time s_i. Electric vehicles only serve each shared e-bike parking point once. In addition, each shared e-bike parking point has a demand q_i, and the total demand of all parking points on route q_i cannot exceed the maximum capacity Q of each vehicle. Transport costs are divided into variable costs $C_{ij}(C_{ij} = vd_{ij})$ and fixed costs w, where v is the unit cost of running each electric vehicle.

Table 3.1 summarizes all the symbols that need to be used.

Table 3. 1: Variables and parameters in EVRPTW-FC/BS model

parameter delimiter	**parameter definition**
$\boldsymbol{I_0, I_{n+1}}$	shared e-bike battery warehouse (starting point), virtual end point
$\boldsymbol{I}$	the set of shared e-bike parking points
$\boldsymbol{F}$	the set of fast charging or battery-swapping stations
$\boldsymbol{K}$	the set of electric vehicles
$\boldsymbol{V}$	the set of above four type parameters
$\boldsymbol{E_i}$	the earliest service time which e-bike parking point can accept
$\boldsymbol{L_i}$	the latest service time which e-bike parking point can accept
$\boldsymbol{S_i}$	the time for EV to replace the battery at e-bike parking point i
$\boldsymbol{T_i^k}$	the time of electric vehicle k accesses to e-bike parking point i
$\boldsymbol{T'^k_i}$	the time of electric vehicle k lefts from e-bike parking point i

$\boldsymbol{WT_i^k}$	the waiting time of electric vehicle k at e-bike parking point i
$\boldsymbol{q_i}$	the demand of battery of e-bike parking point i
$\boldsymbol{t_{ij}}$	the time from i to j for electric vehicles
$\boldsymbol{d_{ij}}$	The distance from i to j
$\boldsymbol{b_i^k}$	SOC of electric vehicle k at e-bike parking point i
$\boldsymbol{C_{ij}}$	the variable cost of electric vehicle k from i to j
$\boldsymbol{Q}$	the max loading capacity of each electric vehicle
$\boldsymbol{A}$	the power consumption rate of electric vehicles
$\boldsymbol{B}$	the max electric capacity of each electric vehicle
$\boldsymbol{v}$	the unit transport cost
$\boldsymbol{w}$	the fixed cost of each electric vehicle operating
$\boldsymbol{P_f, P_s}$	the cost of fast charging and battery-swapping
$\boldsymbol{\pi_1, \pi_2}$	the punishment cost coefficient
$\boldsymbol{x_{ij}^k}$	the routing decision variable of electric vehicle k from i to j
$\boldsymbol{y_{ij}^k}$	the supplementary electricity decision variable of electric vehicle k from i to j

3.2.2. Objective function

In order to solve the EVRPTW-FC/BC, the objective function Z can be established based on the total operating cost. The model aims to minimize the operating cost of battery replacement service for e-bikes.

The objective function consists of three parts: transport cost of electric vehicles, cost of quick charging or power change and penalty or time cost for violating the customer's time window.

The specific objective function is as follows:

$$Z = Z_1 + Z_2 + Z_3 \tag{3.1}$$

(1) Transport cost of electric vehicles: Transport cost is the sum of the variable cost between two points of each electric vehicle and the fixed cost of starting the electric vehicle. The variable cost is related to the distance the vehicle travels. The longer the distance, the greater the variable cost; The fixed cost refers to the usage fee per electric vehicle, which is settled in days. Therefore, the total transport cost function is shown in Formula (3.2).

$$Z_1 \sum_{k \in K} \sum_{i \in V} \sum_{j \in V} C_{ij} \cdot x_{ij}^k + \sum_{k \in K} \sum_{j \in V} w \cdot x_{0j}^k \tag{3.2}$$

(2) Cost of fast charging or battery swapping: The cost of charging or battery swapping is the sum of the cost of charging or battery swapping and the conversion cost of waiting time required for charging or battery swapping. When the electric vehicle runs low during the service, it needs to go to the nearest charging station or battery swapping station to replenish the electric power, so it needs to pay the cost of charging or battery-swapping. The time spent replenishing the power will affect the battery replacement service of the remaining shared e-bike parking point, thus affecting the routing change. So the time spent waiting for a charge or battery swapping needs to be factored into the operating costs. The charge or battery swapping cost function is shown in Formula (3.3).

$$Z_2 = \sum_{k \in K} \sum_{i \in I} \sum_{j \in F} t \cdot y_{ij}^k (P + \pi) \tag{3.3}$$

(3) Service time cost: Each shared e-bike parking point requires electric vehicles to provide service for a limited period by the mobile service. However, the operator cannot fully ensure that the mobile service is within the time window due to vehicle scheduling. This model sets a soft time window limit. Electric vehicles can reach the shared e-bike parking point outside the time window but at a specific cost. If an electric vehicle arrives before the time window, the operator must pay for the waiting time. If an electric vehicle arrives late to the time window, it needs to pay a specific penalty cost. If an electric vehicle arrives at the shared e-bike parking point within the time window of the shared e-bike parking point, there is no need to pay the service time cost. Therefore, the service time cost function is established as shown in Formula (3.4a) and (3.4b).

$$S(T_i^k) = \begin{cases} \pi_1 (E_i - T_i^k), T_i^k < E_i \\ 0, E_i \le T_i^k \le L_i \qquad i \in I, k \in K \\ \pi_2 (T_i^k - E_i), T_i^k > L_i \end{cases} \tag{3.4a}$$

$$Z_3 = \sum_{k \in K} \sum_{i \in I} S(T_i^k) \tag{3.4b}$$

3.2.3. Constraints

In this thesis, the model's constraints are divided into four categories: node access constraints, load capacity constraints of electric vehicles, soft time window constraints, and battery capacity constraints of electric vehicles.

(1) The node access constraints

Generally, node access constraints include unique node constraints, path selection constraints, and traffic balance constraints. Based on these original constraints, the following constraints are established according to the characteristics of EVRPSTW-FC/BS. Firstly, it is necessary to ensure the uniqueness of the service. Each shared e-bike parking point is only served by the electric vehicle once, as shown in Constraint (3.5). Secondly, when electric vehicles serve shared e-bikes, they do not have to access the charging or battery-swapping station, as shown in Constraint (3.6). Thirdly, it is necessary to ensure the balance of node flow. After arriving at a node, the electric vehicle will start from that node and return to the e-bike battery warehouse, as shown in Constraint (3.7). Fourth, ensure the non-repeatability of the fasting charging and battery-swapping stations. The electric vehicle is not allowed to pass through the fast charging or battery-swapping station for more than two consecutive times in the routing, as shown in Constraint (3.8). Finally, routing decision variables must be set to determine electric vehicle access to the node, as shown in Constraint (3.9) and (3.10).

$$\sum_{k\in K}\sum_{j\in I_{n+1}\cup I\cup F, i\neq j} x_{ij}^k = 1,\ \ i \in I \tag{3.5}$$

$$\sum_{k\in K}\sum_{j\in I_{n+1}\cup I\cup F, i\neq j} x_{ij}^k \leq 1,\ \ i \in F \tag{3.6}$$

$$\sum_{k\in K}\sum_{i,j\in V, i\neq j} x_{ij}^k = \sum_{k\in K}\sum_{i,j\in V, i\neq j} x_{ji}^k \tag{3.7}$$

$$\sum_{k\in K}\sum_{j\in F} x_{ij}^k = 0 \tag{3.8}$$

$$x_{ij}^k \begin{cases} 1, & The\ k\ vehicle\ goes\ from\ i\ to\ j \\ 0, & else \end{cases} \quad i,j \in V, k \in K \tag{3.9}$$

$$y_{ij}^k \begin{cases} 1, & vehicle\ k\ from\ i\ to\ j\ for\ charging\ or\ battery\ changing \\ 0, & else \end{cases} \tag{3.10}$$

(2) The vehicle capacity constraints

Electric vehicles should meet load capacity constraints and vehicle number constraints. The maximum number of electric vehicles in this thesis is limited to 8. Every electric vehicle has a maximum load limit, so the e-bike battery's weight should not exceed the maximum load when the electric vehicle is ready to depart from the e-bike battery warehouse. The capacity constraints of the electric vehicle are shown in Constraint (3.11).

$$0 \leq \sum_{j\in I, i\neq j} q_j \sum_{i\in I_0 \cup I \cup F} x_{ij}^k \leq Q, \qquad k \in K \tag{3.11}$$

(3) The time window constraints

Time window constraints are divided into hard and soft time window constraints. Most of the existing EVRP studies with time windows focus on meeting the customer's hard time window constraints. However, due to the complexity of the transportation process, the hard time window lack practicability. Therefore, soft time window constraints are adopted in this thesis. When electric vehicles arrive earlier or later than the time window, waiting or penalty costs will be paid. Specific constraints include (3.12), (3.13), and (3.14).

$$T_i'^k = T_i^k + WT_i^k + s_i, \qquad i \in V, k \in K \tag{3.12}$$

$$T_j^k = \sum_{i\in V} \sum_{j\in V, i\neq j} x_{ij}^k \left(T_i'^k + t_{ij}\right), \qquad k \in K \tag{3.13}$$

$$WT_i^k = max\left[0, \left(E_i - T_i^k\right)\right], \qquad i \in I \tag{3.14}$$

(4) Electric vehicle electric capacity constraint

By setting the electric capacity constraint, the electric vehicle can access the fast charging or battery-swapping station before the power is insufficient to complete the following mobile service. It should be noted that the residual power should be able to supply the electric vehicle to go the nearest fast charging or battery-swapping station. The specific constraints are (3.15) and (3.16).

$$0 \leq b_j^k \leq B - A \cdot d_{ij} \cdot x_{ij}^k, i \in F \cup I_0, j \in I \cup I_{n+1} \cup F, k \in K, i \neq j \tag{3.15}$$

$$0 \leq b_j^k \leq b_j^k - A \cdot d_{ij} \cdot x_{ij}^k + B\left(1 - x_{ij}^k\right), i \in I, j \in I \cup I_{n+1} \cup F, k \in K, i \neq j \tag{3.16}$$

3.2.4. Mathematical model

The most significant difference between the electric vehicle routing problem and the traditional vehicle routing problem is whether there is an electric quantity constraint. Schneider has studied the electric vehicle routing problem. He adopted the power constraint method based on the linear relationship between the power consumed by the electric vehicle and the driving mileage. This thesis refers to the power consumption constraint and expands the model. Based on the above objective functions and constraints, the following mixed integer programming model is proposed:

The objective function (3.17) represents the total cost of minimizing operations

$$minZ \tag{3.17}$$

Subeject to

Constraint (3.18) means that each shared e-bike parking point must be served by an electric vehicle once.

$$\sum_{k \in K} \sum_{j \in I \cup I_{n+1} \cup F, i \neq j} x_{ij}^{k} = 1, \;\; i \in I \tag{3.18}$$

Constraint (3.19) means that electric vehicles may skip charging stations and battery-swapping stations.

$$\sum_{k \in K} \sum_{j \in I \cup I_{n+1} \cup F, i \neq j} x_{ij}^{k} \leq 1, \;\; i \in F \tag{3.19}$$

Constraint (3.20) represents the same number of vehicles arriving at and leaving any node.

$$\sum_{k \in K} \sum_{i,j \in V, i \neq j} x_{ij}^{k} = \sum_{k \in K} \sum_{i,j \in V, i \neq j} x_{ji}^{k} \tag{3.20}$$

Constraint (3.21) means that any electric vehicle is not allowed to pass two charging stations or battery-swapping stations in succession.

$$\sum_{k \in K} \sum_{i,j \in F} x_{ij}^{k} = 0 \tag{3.21}$$

Constraint (3.22) means that the load of the electric vehicle shall not exceed its maximum capacity.

$$0 \leq \sum_{j \in I, i \neq j} q_j \sum_{i \in I_0 \cup I \cup F} x_{ij}^{k} \leq Q, \qquad k \in K \tag{3.22}$$

Constraint (3.23) means that the time leaving i is the sum of the time arriving at i, waiting time at i, and service time at i.

$$T_i'^{k} = T_i^{k} + WT_i^{k} + s_i, \qquad i \in V, k \in K \tag{3.23}$$

Constraint (3.24) is the sum of the departure time from i and the travelling time of arc (i,j).

$$T_j^k \sum_{i\in V} \sum_{j\in V, i\neq j} x_{ij}^k \left(T_i'^k + t_{ij}\right), \quad k \in K \tag{3.24}$$

Constraint (3.25) represents the waiting time of electric vehicle at the shared e-bike parking point.

$$WT_i^k = max\left[0, \left(E_i - T_i^k\right)\right], \qquad i \in I \tag{3.25}$$

Constraint (3.26) means electric energy constraints of the electric vehicle from charging and battery-swapping station i or from the shared e-bike battery warehouse to reach j

$$0 \leq b_j^k \leq B - A \cdot d_{ij} \cdot x_{ij}^k, i \in F \cup I_0, j \in I \cup I_{n+1} \cup F, k \in K, i \neq j \tag{3.26}$$

Constraint (3.27) means electric energy constraint that from shared e-bike parking point i to j when the electric vehicle is not charged. And The constraints (3.26) and (3.27) ensure that SOC of electric vehicle will not fall below zero along the service routing

$$0 \leq b_j^k \leq b_j^k - A \cdot d_{ij} \cdot x_{ij}^k + B\left(1 - x_{ij}^k\right), i \in I, j \in I \cup I_{n+1} \cup F, k \in K, i \neq j \tag{3.27}$$

Constraints (3.28) and (3.29) are expressed as binary decision variables.

$$x_{ij}^k \in \{0, 1\}, \qquad i, j \in V, k \in K, i \neq j \tag{3.28}$$

$$y_{ij}^k \in \{0, 1\}, \qquad i \in I, j \in F, k \in K \tag{3.29}$$

3.3. Summary of this chapter

This chapter aims to build the EVRPTW-FC/BS model, which mainly includes two parts. The first part describes the problem of EVRPTW-FC/BS, and puts forward the assumptions of the problem in turn; The second part sets up the final model from three aspects: the definition of variables and parameters, the objective function, and the constraint conditions.

4 Algorithm design of EVRPSTW-FC/BS

EVRPSTW-FC/BS is typical of the NP-hardness problem, which is highly nonlinear and discrete. This problem is challenging to be solved by classical precise programming algorithms, so this chapter adopts the genetic algorithm, particle swarm optimization, and chaotic particle swarm optimization to solve EVRPSTW-FC/BS.

4.1. Genetic algorithm

4.1.1. Principles of genetic algorithm

Genetic algorithms refer to the survival of the fittest to find the best path results. The basic idea of the genetic algorithm is to randomly generate a set of variables as the initial solution and map it into a chromosome composed of several genes according to specific rules. Each initial chromosome is an individual, and several individuals comprise a population. The individual fitness of all individuals in the population is calculated respectively. Then the next generation population is obtained by genetic operations such as selection, crossover, and mutation according to the fitness. After several iterations, the fitness of individuals within the population becomes higher and higher, and the result is obtained when the convergence condition is finally reached.

Genetic algorithms give a new role[20][21] to the technical terminology of genetics. The general summary of related genetic terms is shown in Table 4.1.

Table 4. 1: Terminology of genetic algorithm

terminology	**application of genetic algorithm**
chromosome	the coding of solution
	common methods: binary coding, floating point coding and symbol coding
individual	the feasible solution

fitness	the fitness function is transformed from the objective function
	common methods: linear scaling and exponential scaling
population size	by selecting a set of chromosomes according to the fitness function, which can be generally taken as 20-100
selection	the individual is selected from the species with a certain probability to be the parent chromatids according to the principle of "best wins bad tide"
	common methods: roulette selection, random race selection and best retention selection
crossover	the new set of solutions is generated by crossing primitives
	common methods: single-point crossing, multi-point crossing and uniform crossing
mutation	the process by which a portion of a code changes,
	common methods: basic bit mutation, uniform mutation and boundary mutation

4.1.2. Encoding and decoding methods

According to the characteristics of EVRPSTW-FC/BS model, the genetic algorithm in this thesis adopts the way of natural number coding. The length of each chromosome in the population is m+n+k+1. The shared e-bike battery warehouse is number 0. There are charging and battery-swapping station with the quantity of m. There are electric vehicles with the quantity of k. And the electric vehicle offer battery replacement service for shared electric bike parking points 1,2,3 $\dots, n$ until the electric vehicle returns to the shared e-bike battery warehouse. The charging and battery-swapping stations are represented by $n+1, n+2, \dots, n+m$.

Assume that two electric vehicles provide battery replacement service for five shared e-bike parking points, whose numbers are $(1,2,3,4,5)$. This area has two charging stations or battery-swapping stations, numbered $(6,7)$. The chromosome code $(0,1,5,0,2,3,7,4,0)$ indicates that two electric vehicles depart from the shared e-bike battery warehouse to provide replacement battery service for the five shared e-bike parking points. The service route of electric vehicle 1 is $0-1-5-0$, which means that electric vehicles start from shared e-bike battery warehouse and provide battery replacement service for shared e-bike parking points numbered 1 and 5. Finally, return to the shared e-bike battery warehouse. The service route of electric vehicle 2 is $0-2-3-7-4-0$, which means that electric vehicles start from shared e-bike battery warehouse and provide battery replacement service for shared e-bike parking points numbered 2 and 3 in turn. Then it enters the charging station numbered 7 or battery-swapping station to supplement the electric energy and provides battery replacement service for the shared e-bike parking point numbered 4. Finally, electric vehicle 2 returns to the shared e-bike battery warehouse.

4.2.2. Process of genetic algorithm

The process of genetic algorithm is shown in Figure 4.1.

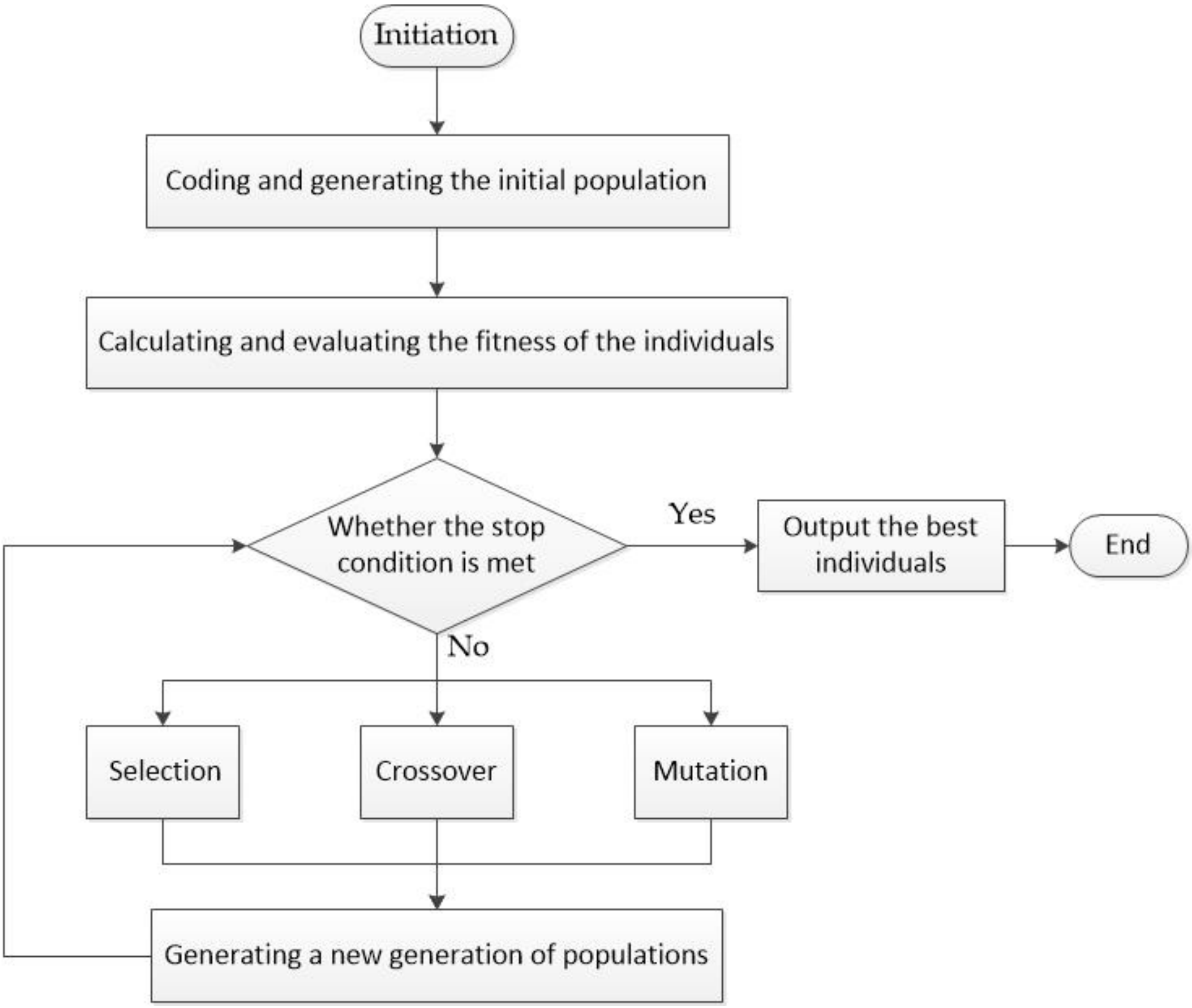

Figure 4. 1: The process of genetic algorithm

The specific steps can be described as follows:

***Step* 1**Before the search, it is necessary to encode the data into the chromosome according to specific rules through the problem analysis.

***Step* 2** Randomly generating M initial individuals according to the form of solving the question, and all individuals form a population. The population will be used as the beginning point of the genetic algorithm to start the evolutionary operation.

***Step* 3** Calculating the fitness of individuals in the species group and determine whether the fitness of individuals conforms to the optimization criteria according to the strategy. If it does, the best individuals and their optimal solutions are input, and the bundling iteration process is concluded. If not, go to the next step.

***Step* 4** The selection of parents' chromosomes is completed according to the fitness criteria. Individuals with higher fitness were more likely to be selected, while individuals with lower fitness are eliminated.

***Step* 5** Cross the chromosome of the parents according to a specific method to produce offspring.

***Step* 6** Mutating the chromosome of the offspring.

Step* 7** A new population is generated by crossover and mutation, then going back to ***step 3 until the optimal solution is generated.

4.2. Particle swarm optimization

4.2.1. Principle of particle swarm optimization

Particle swarm optimization is derived from the real-world behavior of birds flying in search of food. In particle swarm optimization, an individual in a crowd is regarded as a particle without mass and volume in a multidimensional space. Each particle with velocity and position represents a feasible solution to the problem. Particles are dynamically adjusted according to the flight experience of themselves and their companions. Each particle constantly corrects its position and speed by tracking its own optimal and group optimal and evaluates the merits and disadvantages of particles with the fitness function value corresponding to the particle position.

Suppose a group of n particles searches the q-dimensional space (the number of dimensions per particle). Each particle is denoted as $X_i = (x_{i1}, x_{i2}, \dots, x_{iQ})$and the velocity corresponding to each particle is denoted as $V_i + (v_{i1}, v_{i2}, \dots, v_{iQ})$. The optimal position searched by the particle i in iteration k is $P_i = (p_{i1}, p_{i2}, \dots, p_{id})$, which is the individual extremum $pbest$.

The optimal global position searched by the entire particle swarm is $P_j = (p_{j1}, p_{j2}, \dots, p_{jd})$, which is the global extremum $gbest$. The update formulas of the d-dimensional velocity v_{id}^{k+1} and position x_{id}^{k+1} of the particle i in the iteration k are Formula (4.1) and (4.2), respectively.

$$v_{id}^{k+1} = wv_{id}^{k} + c_1 \cdot c_2\left(pbest - x_{id}^{k}\right) + c_1 \cdot c_2\left(pbest - x_{id}^{k}\right) \tag{4.1}$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{4.2}$$

w is the inertia weight, the coefficient that keeps the original velocity. c_1 and c_2 are acceleration factors which respectively expressed as the weight coefficient of the particle tracking its optimal historical value and the weight coefficient of the group's optimal value. Appropriate c_1 and c_2 can accelerate the convergence rate and avoid easily falling into the local optimal. Generally, $c_1 = c_2 = 1.2$. r_1 and r_1 are independent random numbers in the interval $[0, 1]$.

4.2.2. Encoding and decoding methods

(1) Encoding method

This section constructs a $2n$-dimension space according to the number of shared e-bike parking points n. The $2n$ -dimensional vector Z corresponding to each shared e-bike parking point i is composed of two n-dimensional vectors, Z_{ix} and Z_{iy}. Z_{ix} refers to the number of an electric vehicle that provides a replacement battery service for the shared e-bike parking point i. Z_{iy} is the execution order of this electric vehicle in the service routing.[24][25]

(2) Decoding method

***Step* 1** As for the code of the electric vehicle, integer int (Z_{ix}) is taken for the vector Z_{ix} of particle i, and electric vehicle j assigned to the shared e-bike parking point i from the shared e-bike battery warehouse.

***Step* 2** The routing order of vehicle j can be determined according to the size order of vector Z_{iy} element. Firstly, find the shared e-bike parking point i of vehicle j to complete the mobile service. Then, according to the size of Z_{iy} corresponding to i, it is numbered in order from small to large, finally determining the path order of vehicle j.

Assume that three electric vehicles provide battery replacement services for five shared e-bike parking points, whose numbers are (1, 2, 3, 4, 5). This area has two charging and battery-swapping stations, numbered (6,7). The vector Z of particle i is shown in Table 4.2.

Table 4. 2: The 2n vector of particle i before decoding

	1	2	3	4	5	6	7
Z_{ix}	1.3	2.8	2.6	3.3	3.6	1.7	2.4
Z_{iy}	0.8	2.6	3.5	1.9	2.9	4.7	2.0

After ***step 1***, the situation of three electric vehicles at each location can be shown in Table 4.3

Table 4. 3: The 2n vector of particle *i* after decoding

	1	2	3	4	5	6	7
$int(Z_{ix})$	**1**	**2**	**2**	**3**	**3**	**1**	**2**
Z_{iy}	**0.8**	**2.6**	**3.5**	**1.9**	**2.9**	**4.7**	**2.0**

Then the routing of each vehicle corresponding to the particle is (0 represents shared e-bike battery warehouse) :

1) Electric vehicle 1: $0-1-6-0$

2) Electric vehicle 2: $0-7-2-3-0$

3) Electric vehicle 3: $0-4-5-0$

4.2.3. The process of particle swarm optimization

***Step* 1** Randomly initialize the velocity and position of each particle and set corresponding parameters.

***Step* 2** Calculating the fitness value of each particle in the population to start the evolution of this generation.

***Step* 3** Evaluating the fitness value of each particle in the population and compare each particle's current generation fitness value with its historical optimal fitness value. If the current fitness value is better, update the particle's position.

***Step* 4** Comparing the fitness value of the current optimal position of each particle with that of the optimal global position. If the current fitness value of any particle is better, update it to the optimal global position of the population.

***Step* 5** Using Formula (4.1) and Formula (4.2) to update the velocity and position of particles in the population; Step6 Determine whether the stop conditions are met. If not, go back to Step2. If yes, stop. The flow chart of particle swarm optimization is shown in Figure 4.2.

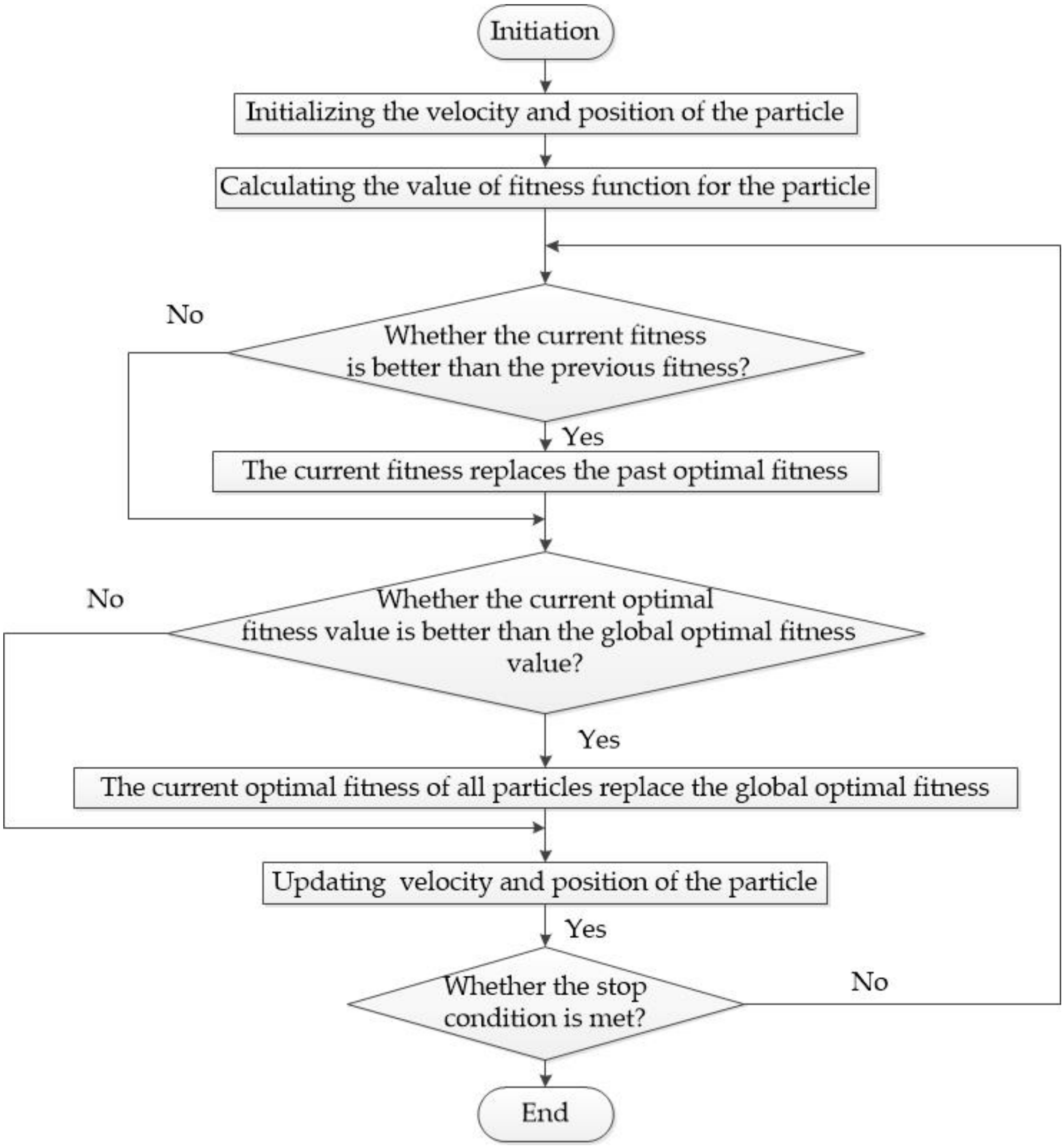

Figure 4. 2: The flow chart of particle swarm optimization

4.3. Chaotic particle swarm optimization

4.3.1. Principle of chaotic particle swarm optimization

In particle swarm optimization, each particle updates its velocity and position by individual extremum $pbest$ and global extremum $gbest$. If particle searches for an optimal local solution, all particles are attracted by the optimal solution and tend to gather around it quickly, resulting in premature convergence of the algorithm and falling into the optimal local solution. [22][23]

Chaos is a common phenomenon in the nonlinear system. [26][27] Its behavior is complex and random. The basic idea of the chaos optimization algorithm is first to generate a set of chaotic variables with the same number of optimization variables, enlarge the ergodic range of chaotic motion to the value range of optimized variables, and then directly use the randomness and ergodic properties of chaotic variables to search. Because the chaotic search algorithm is sensitive to the initial conditions, it is easy to jump out of the local minimum, and the search speed is fast. The search technology based on chaos is superior to other searches.

In order to overcome the precocious defects of the particle swarm optimization, the chaos idea is introduced into it. In each iteration, the chaotic disturbance of $gbest$ is used as the updated particle position, which can avoid the particle position convergence to a certain extent and strengthen the local search around the current global optimal position. [28][29]

The Logistic mapping expression in this section is expressed as shown Formula (4.3). Z_n is the chaos variable. Z_0 is the initial value of the chaos variable, and its slight difference will lead to the significant difference over a long time. Therefore, chaos can traverse all states of the search space according to its own laws without repeating.

$$Z_{n+1} = 4Z_n(1 - Z_n), \qquad 0 \le Z_0 \le 1 \tag{4.3}$$

According to the principle of chaos, chaos disturbance can be added according to Formula (4.4). Z is the chaos vector corresponding to the perturbation. Z_k is the chaotic vector with iteration k. Z^* is the chaotic vector formed after the current optimal solution is mapped to the interval $(0,1)$. For additional disturbance intensity, $\alpha \in (0, 1)$.

$$Z_k' = (1 - \alpha)Z^* + \alpha Z_k \tag{4.4}$$

Generally, at the initial stage of the search, a larger α is selected to strengthen the perturbation of the solution vector. As the search goes deeper and approaches the optimal solution, a smaller α should be selected for careful search in the region of the optimal solution. Generally, Formula (4.5) is used to determine α. And n is an integer which depends on the situation.

$$\alpha(k) = 1 - \left(\frac{k-1}{k}\right)^n \tag{4.5}$$

4.3.2. The process of chaotic particle swarm optimization

The specific steps can be described as follows:

***Step* 1** Randomly initializing the velocity and position of population particles and setting corresponding parameters, namely inertia weight factor, learning factor, and the maximum number of iterations.

***Step* 2** Initializing the particle population. Randomly generating D n-dimensional vectors according to Formula (4.3). By taking advantage of the sensitivity of chaos to the initial value, the population containing n initial particles can be obtained by assigning D initial values with slight differences.

***Step* 3** Inversely mapping chaos variable $Z_j = (Z_{j1}, Z_{j2}, \dots, Z_{jn})$ to the value interval of mobile service $[1, K]$.

***Step* 4** Decoding the particles to generate the service routing of electric vehicles and calculating the value of the fitness function of each particle, namely the total operating cost.

***Step* 5** Comparing the fitness value of the current generation of each particle with its historical optimal fitness value. If the current fitness value is better than the individual extreme value $pbest$, update the particle's position.

***Step* 6** Comparing the fitness value of the current optimal position of each particle with the fitness value of the optimal global position. If the current fitness value of any particle is better than the global extreme value $gbest$, it is updated to the optimal global position of the population

***Step* 7** Carrying out chaos optimization for $gbest$, the global optimal extreme value of particles. Firstly, the global optimal extreme value gbest is mapped to the definition domain of the equation [0,1], and then the series of n chaotic variables are iterated according to Formula (4.3). Finally, the series of these chaotic variables are returned to the value interval of the optimization variable $[1, K]$ by inverse mapping, n particles are obtained, and the fitness function value of each particle is calculated. The optimal solution $gbest'$ is obtained, and $gbest'$ is used to replace the position of the particles in the current population.

***Step* 8** Determining whether the particle swarm convergence is precocious. If the particle swarm convergence is precocious, chaos optimization is carried out for some better particles; otherwise, the particle swarm optimization algorithm is continued. There are two main signs of precocious convergence: one is the severe aggregation of particle swarm; Secondly, the optimal particle has no change or little change after many iterations.

***Step* 9** Chaos optimization is carried out for the partial optimal particle swarm. The method is the same as selecting the global optimal extreme value $gbest$. Because some particles have higher fitness and are closer to the optimal global solution, it is easy to obtain the new optimal particles by conducting the chaotic search on them.

***Step* 10** Checking whether the stop condition is met. If not, go to ***Step*4.** If yes, stop.

4.3. Summary of this chapter

In this chapter, according to the characteristics of EVRPSTW-FC/BS, genetic algorithm and particle swarm optimization are applied to solve the problem. Moreover, chaos is introduced, and the chaotic particle swarm optimization is designed to solve the shortcomings of particle swarm optimization, which is easy to converge prematurely and fall into the optimal local solution. This chapter introduces the principles and processes of the three algorithms in detail, which provides the methodology for the subsequent research.

5. Analysis of simulation instance

5.1 Description of data sources

Due to the short development time of shared electric bikes, there is very little research on the path planning of replacing the batteries of shared electric bikes. Many scholars have studied and used Solomon's VRPTW benchmark problems since Solomon put it forward in 1988.[30] Solomon benchmark is used as the test data in this paper, which is often used to study the vehicle routing problem with the time window.

Solomon's VRPTW benchmark problems include 56 instances, which can be divided into $C1, C2, R1, R2, RC1$ and $RC2$ according to the time window size and spatial distribution type.

In general, Class C is cluster data whose node distribution is clustered according to geographical location.

The demand nodes in class R are randomly distributed.

Class RC is a mixture of C and R characteristics. The geographic location of some customers in RC class is clustered, and the geographic location of some customers is random.

Type 1 has a short scheduling range, with fewer customers served on each route.

Type 2 has a long scheduling range, allowing the logistics vehicle to serve many customers.

The six characteristics of the Solomon benchmark are shown in Table (5.1) with the maximum vehicle load, time base, service time of each customer point, characteristics of the distribution of nodes, and time window size.

Table 5. 1: Characteristics of Solomon benchmark

type	quantity of instance	maximum capacity	timebase	service time	distribution	time window size
R1	12	200	230	10	random	small
R2	11	1000	1000	10	random	big
C1	9	200	1236	90	cluster	small
C2	8	700	3390	90	cluster	big
RC1	8	200	240	10	mixture	small
RC2	8	1000	960	10	mixture	big

The base hypothesis in the Solomon benchmark is as follows:

(1) There are 100 customers in each instance, and each customer's information is included: customer number, customer X, Y coordinate position, customer demand, the earliest and latest service time acceptable to the customer, and service time.

(2) All customers are distributed in the interzone plane coordinates of $(0, 100)$.

(3) There is only one distribution center to provide distribution services for

customers.

(4) The vehicle's load capacity is finite and the same.

(5) The distance of distribution is calculated by the Euclidean distance formula.

Considering the characteristics of solid mobility, distribution of parking points, and high battery replacement frequency of shared electric bikes in cities, this chapter selects C101 of Solomon Class C as the data set to verify the model and algorithm of EVRPSTW-FC/BS. Part of the original data is shown in Table 5.2.

Table 5. 2: First ten customer data of Salomon instance C101

customer no.	x coord.	y coord.	demand quantity	ready time	due time	service time
1	45	68	10	912	967	90
2	42	66	10	65	146	90
3	42	68	10	727	782	90
4	42	65	10	15	67	90
5	40	69	20	621	702	90
6	38	68	20	255	324	90
7	35	66	10	357	410	90
8	35	69	10	448	505	90
9	25	85	20	652	721	90
10	22	75	30	30	92	90

According to EVRPSTW-FC/BS, the usage of raw data C101 in this chapter is described as follows:

(1) Take distribution center 0 as the e-bike battery warehouse.

(2) The random formula of Excel is used to select 60, 8, and 4 points from 100 customer points of C101 as e-bike parking points, fast charging and battery-swapping stations for electric vehicles, respectively.

(3) Since electric vehicles replace batteries for shared electric bikes, unloading batteries with insufficient power in the e-bike battery warehouse and loading usable batteries in the e-bike battery warehouse are manual operations. Manual operations are affected by weather, time, and physical factors. There may be a decrease in operational efficiency, which will bring difficulties to the research process and increase the complexity of the model. In addition, this thesis focuses on the study of vehicle routing, so the manual operation process is somewhat simplified. The service time of the shared electric bike replacement, the time for unloading and loading the battery at the e-bike battery warehouse are set to constant. Considering that the average battery demand of 60 e-bike parking points is about 18, and the manual operation time for changing the battery of an e-bike is one to two minutes, the service time required for each e-bike parking point is revised to 30 minutes.

(4) The raw data of C101 included 12 vehicles with the same load capacity. The number of vehicles needs to be adjusted for analysis purposes. Scaled equally according to the number of customer points, a fleet of 8 pure electric logistics vehicles is set up in this chapter. Moreover, the structure of the fleet is explained in more detail in the following sections.

(5) Since the transportation distance is calculated by the Euclidean distance formula, the default unit of path distance in this chapter is km to facilitate cost calculation.

The data of some modified e-bike parking points are shown in Table (5.3).

Table 5. 3: First ten customer data for EVRPSTW-FC/BS

node no.	x coord.	y coord.	demand quantity	ready time	due time	service time
1	45	68	10	912	967	30
2	42	66	10	65	146	30
3	42	68	10	727	782	30
4	42	65	10	15	67	30
5	40	69	20	621	702	30
6	38	68	20	255	324	30

7	35	66	10	357	410	30
8	35	69	10	448	505	30
9	25	85	20	652	721	30
10	22	75	30	30	92	30

The selected fast charging station information is shown in Table (5.4).

Table 5. 4: The fast charging station information for EVRPSTW-FC/BS

node no.	x coord.	y coord.	demand quantity	ready time	due time	service time
62	45	70	0	0	1236	0
63	20	80	0	0	1236	0
64	15	75	0	0	1236	0
65	15	80	0	0	1236	0
66	20	50	0	0	1236	0
67	10	35	0	0	1236	0
68	30	30	0	0	1236	0
69	50	35	0	0	1236	0

The selected battery-swapping station information is shown in Table (5.5).

Table 5. 5: The charging station information for EVRPSTW-FC/BS

node no.	x coord.	y coord.	demand quantity	ready time	due time	service time

70	35	30	0	0	1236	0
71	38	15	0	0	1236	0
72	48	40	0	0	1236	0
73	62	80	0	0	1236	0

The distribution of nodes for EVRPSTW-FC/BS is shown in Figure (5.1). Green points represent shared e-bike parking points, red point represents e-bike battery warehouse, pink points represent charging stations, and blue points represent the battery-swapping stations. Shared e-bike parking points generated by C101 are distributed in clusters, and each cluster can be regarded as a commercial center, residential area, or public transport station. Within a cluster, different points can be regarded as shared e-bike parking points, fast charging and battery-swapping stations set by operators around a specific urban functional area. That fits well with shared electric bikes and electric logistics vehicles in real.

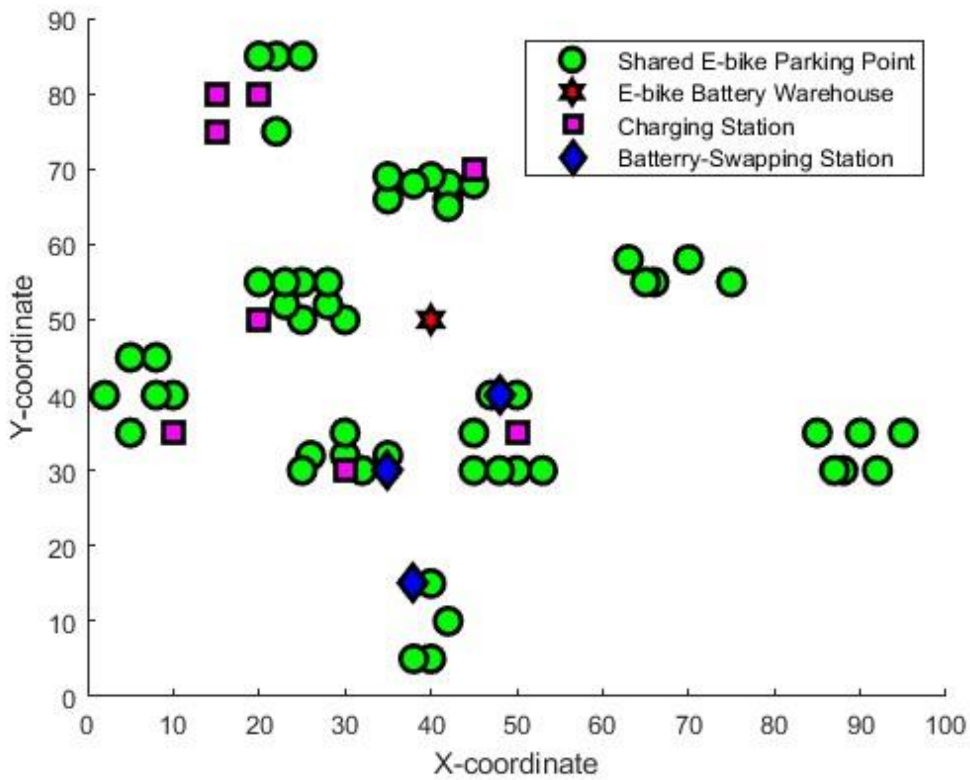

Figure 5. 1: The distribution of nodes for EVRPSTW-FC/BS

5.2. Explanation of relevant parameters

5.2.1. Electric vehicle parameters

Green development is one of China's essential development concepts. At present, driven by national economic growth and accelerated urbanization, China's logistics industry has got significant development. Electric logistics vehicles are entering the urban scenario at an unprecedented trend.

The biggest problem in the practical application of electric logistics vehicles is their driving range. Although the driving range of electric logistics vehicles has increased significantly in recent years, the driving range of most electric logistics vehicles has increased from 100km in the past to more than 300km now. Nevertheless, this is only the range that vehicle manufacturers say it can reach, which can only be achieved under ideal conditions.

The electric vehicle runs at a constant speed on a well-paved road with no load, which is difficult to achieve in the real world, where batteries are replaced for shared bikes.

Since most EVRPSTW-FC/BS scenarios studied in this thesis are short-distance routes and relatively fixed, the mileage of logistics vehicles is set as 150km in this paper to better match the actual situation.

According to Section 5.1, eight logistics vehicles provide replacement battery services for shared e-bikes with a maximum carrying capacity of 200 e-bike batteries. The electric vehicle starting from the e-bike battery warehouse is in full charge, excluding charging/ battery-swapping time and charging/ battery-swapping fee.

During the delivery process, the constant speed of the electric vehicle is 45km/h in the urban area, and it takes 0.5h (30 min) to replace the battery at each e-bike parking point.

When it is low, the vehicle must go to the fast charging or battery-swapping station. The time of each charge is constant at 0.5 h (30 min), and the time of each battery change is constant at 0.1h (6 min).

In this thesis, an electric vehicle's transport cost per kilometer (variable cost) is 11 yuan. The variable cost is proportional to the transport distance of the electric vehicle, which can be regarded as the expense of road use.

Operators must pay a fixed cost for each electric vehicle used, equivalent to depreciation expense. The fixed cost of electric vehicles with fast charging is 200 yuan a day, and the fixed cost of electric vehicles with battery swapping mode is 400 yuan a day.

5.2.2 Cost of fast charging or battery-swapping

At present, there are few commercial applications for battery swapping. There are two main charging modes for charging stations: fast charging and slow charging. Fast charging time is 0.5 h to 1 h, and slow charging time is 6 h to 8 h. Since timeliness is crucial for EVRPSTW-FC/BS, this thesis uses fast charging and battery-swapping mode to improve the efficiency of the mobile service.

Battery capacity, electricity price, and charging efficiency are the main factors affecting electric logistics vehicles' electricity cost.

The battery capacity of electric vehicles varies depending on the brand, origin, and other factors, generally ranging from 15 to 80kWh. For example, BYD T4 pure electric logistics vehicle has a battery capacity of 63kWh and a driving range of 160km.

The current electricity price is determined according to the type of user, the voltage level, the amount of electricity used, and the time of use in China. In general, the price of electricity per kilowatt-hour increases step by step with the increase in the amount of electricity consumed per capita. Setting electricity prices by time segment can realize differentiated pricing of market segments, improve electricity efficiency, and save energy. Voltage levels mainly determine industrial and commercial electricity prices. Electricity prices for citizens are generally between 0.4 and 0.6 yuan per kWh. State Grid DC charging stations are generally between 0.4 yuan and 0.9 yuan per kWh. And third-party AC charging stations is generally between 1.2 yuan and 1.8 yuan per kilowatt-hour.

As for charging efficiency, the average AC charging station is 88% efficient, and DC is about 93% efficient.

For the convenience of calculation in this section, the price of the fast charge is defined as 100 yuan an hour. According to Section 5.1., it can be seen that the time for the electric vehicle to complete a fast charging is 0.5h, so the fast charge cost of each electric vehicle is 50 yuan. The battery-swapping price is 1000 yuan per hour, according to Section 5.1. It can be seen that the time for an electric vehicle to complete one battery-swapping is 0.1h, so the cost of each electric vehicle is 100 yuan once at a time.

In addition, electric vehicles must wait 30 minutes and 6 minutes, respectively, for fast charging and battery-swapping. The time taken by electric vehicles to supplement electric energy will have a specific impact on the subsequent distribution route and the choice of customer points. Therefore, this thesis sets the time cost of electric vehicles caused by supplementing electric energy as 0.5 yuan per minute.

5.2.3 Cost of service time

Due to the many users of shared e-bikes, timely replacement of batteries is necessary to ensure the smooth operation of the shared e-bike system. Considering the distribution characteristics and the actual situation in EVRPSTW-FC/BS, the time cost is set. The objective function of EVRPSTW-FC/BS model is the minimum operating cost, and its unit is yuan, so the time cost needs to be quantified.

Each e-bike parking point has a time window. Electric vehicles must arrive before the latest time required by the e-bike parking point. If they arrive late, they will have to pay the penalty cost of the customer waiting, which is set at 20 yuan a minute. If the electric vehicle arrives before the earliest time required by the e-bike parking point, it needs to pay the cost of waiting for the e-bike parking point, which is set at 10 yuan a minute.

5.2.4. Summary of the instance parameters

Combined with the above basic data description and related parameters of electric vehicles, the model parameters of EVRPSTW-FC/BS are summarized in Table 5.6.

Table 5. 6: Summary of the instance parameters

parameter	definition	quantitative value
$\boldsymbol{Speed}$	speed of electric vehicle	45km/h
$\boldsymbol{s_i}$	battery replacement time at e-bike parking point	0.5 h
$\boldsymbol{Q}$	maximum load capacity of electric vehicle	200
$\boldsymbol{v}$	variable cost	11 yuan/km
$\boldsymbol{w_1}$	fixed cost of fast charging mode	200 yuan/day
$\boldsymbol{w_2}$	fixed cost of battery swapping mode	400 yuan/day

π	The time cost of replenishing electricity	0.5 yuan/min
π_1	the time cost of arriving early	10 yuan/min
π_2	the time cost of being late	20 yuan/min
P_f	the cost of fast charging	100 yuan/h
t_f	the time of fast charging	0.5 h
P_s	the cost of battery-swapping	1000 yuan/h
t_s	the cost of battery-swapping	0.1 h

5.3. The analysis of the algorithm performance

To evaluate the algorithm's effectiveness, a fleet of 8 electric vehicles with the same capacity is constructed that provide battery replacement services for 60 e-bike parking points. Their numbering and replenishment modes are shown in Table (5.7). By loading data and parameter setting, the maximum number of iterations is set to 50. The objective function values are solved by genetic algorithm (GA), particle swarm optimization (PSO), and chaotic particle swarm optimization (CPSO), respectively.

Table 5. 7: Structure of the electric vehicle fleet

EV no.	mode
1	fast charging
2	fast charging
3	fast charging
4	fast charging
5	battery-swapping

6	battery-swapping
7	battery-swapping
8	battery-swapping

The results are shown in Figure (5.2), where the horizontal axis represents the number of iterations, and the vertical axis represents the optimal objective function value, namely the lowest total operating cost. Chaotic particle swarm optimization has the lowest total operating cost.

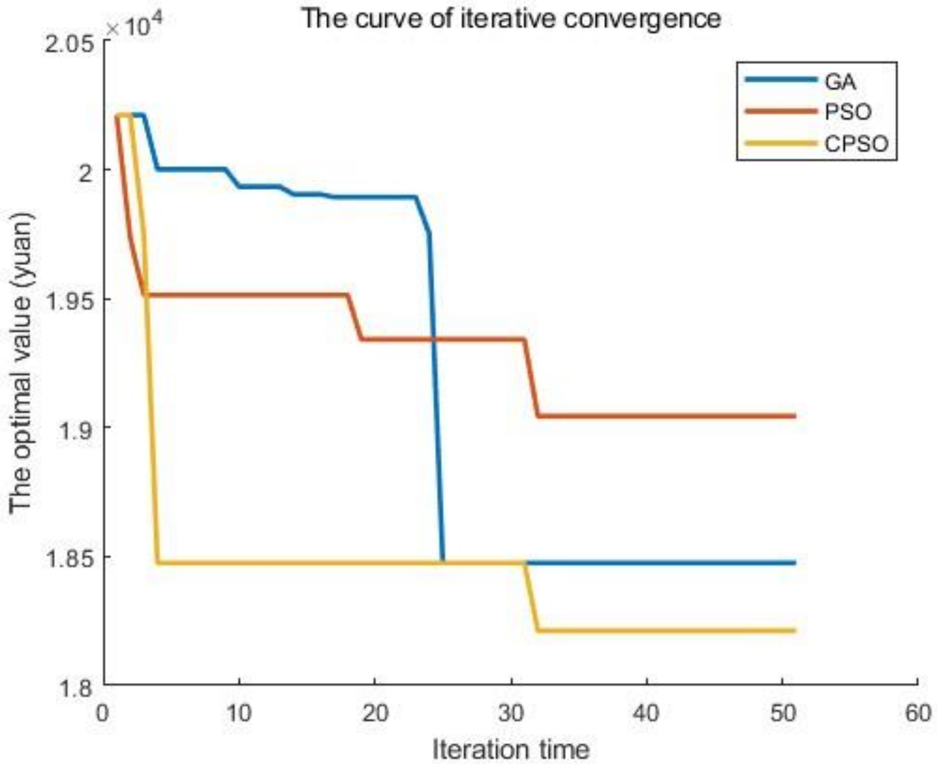

Figure 5. 2 The curve of iterative convergence

As seen from Table (5.8), although the genetic algorithm is the earliest to achieve algorithm convergence, only 30 iterations are needed. However, from the optimization results, the solution obtained by chaotic particle swarm optimization is only 18212.2 yuan,

The optimal value of chaotic particle swarm optimization is 262.7 yuan less than that of the genetic algorithm, and the algorithm performance is improved by 1.42%. Particle swarm optimization has the worst performance. Compared with chaotic particle swarm optimization, the optimal value of particle swarm is more 831.8 yuan than CPSO, and its algorithm performance is reduced by 4.36%.

Table 5. 8: Recording of the optimal value of GA, PSO and CPSO

Times	GA	PSO	CPSO
10	19934.1	19513.7	18474.9
20	19893.5	19342	18474.9
30	18474.9	19342	18474.9
40	18474.9	19044	18212.2
50	18474.9	19044	18212.2

5.4. The analysis of the carbon emission

After 50 iterations using genetic algorithm, as shown in Figure (5.3), each shared e-bike parking point can be served by only one electric logistics vehicle. The path of each electric logistics vehicle is shown in Table (5.9), and the driving range of all electric logistics vehicles is 762.41 km. The No. 3 electric logistics vehicle has the most extended driving range at 176.41 km. In order to complete the mobile service, it goes through the fast charging station 62 and 68 for fast charging. The No. 8 electric vehicle has a driving range of 0, which means it is not started, which means only seven electric vehicles are participating in the mobile battery replacement service.

Under the same conditions, the optimal path planning results obtained by particle swarm optimization are shown in Figure (5.4) and Table (5.10). The range of all electric logistics vehicles is 757.77 km.

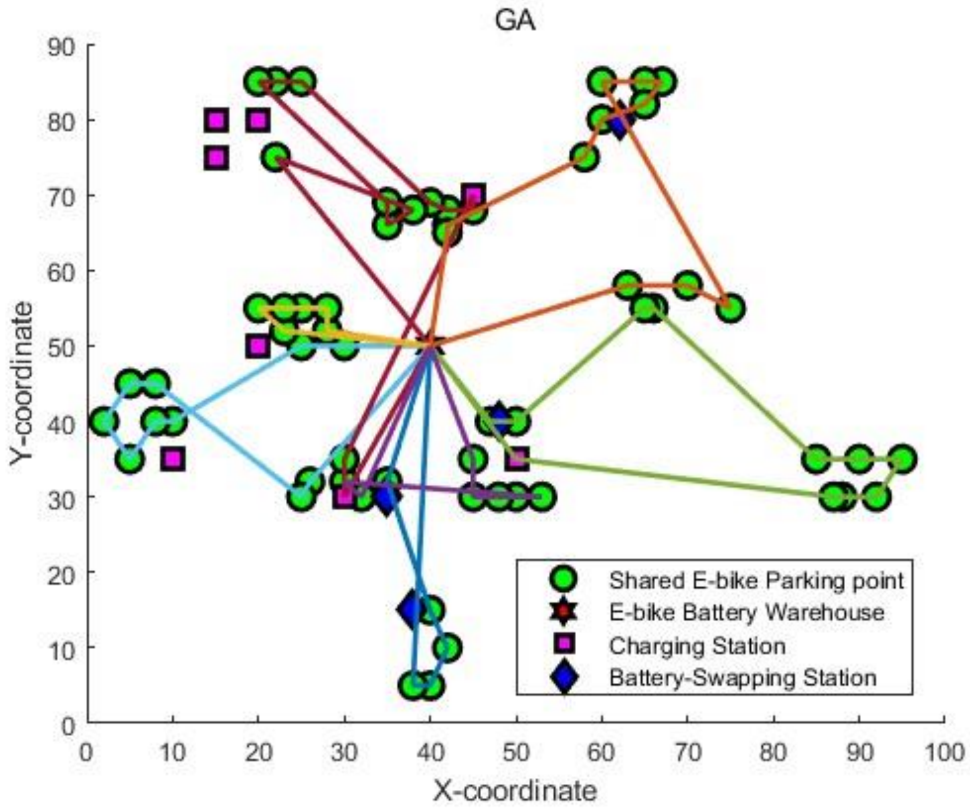

Figure 5. 3: The schematic diagram of optimal path of genetic algorithm

Table 5. 9: The path of the optimal solution of genetic algorithm

EV no.	mileage (km)	optimal path of GA
1	141.20	0 40 38 53 52 49 46 43 45 47 48 69 0
2	103.23	0 13 16 21 22 24 26 25 23 32 31 0
3	176.41	0 10 6 7 8 12 11 9 5 3 1 62 30 68 0
4	94.21	0 27 35 33 34 36 0
5	126.58	0 4 2 60 58 57 55 56 59 50 51 54 0
6	44.52	0 18 20 19 17 15 14 0
7	76.26	0 28 29 44 37 39 41 42 0
8	0	0

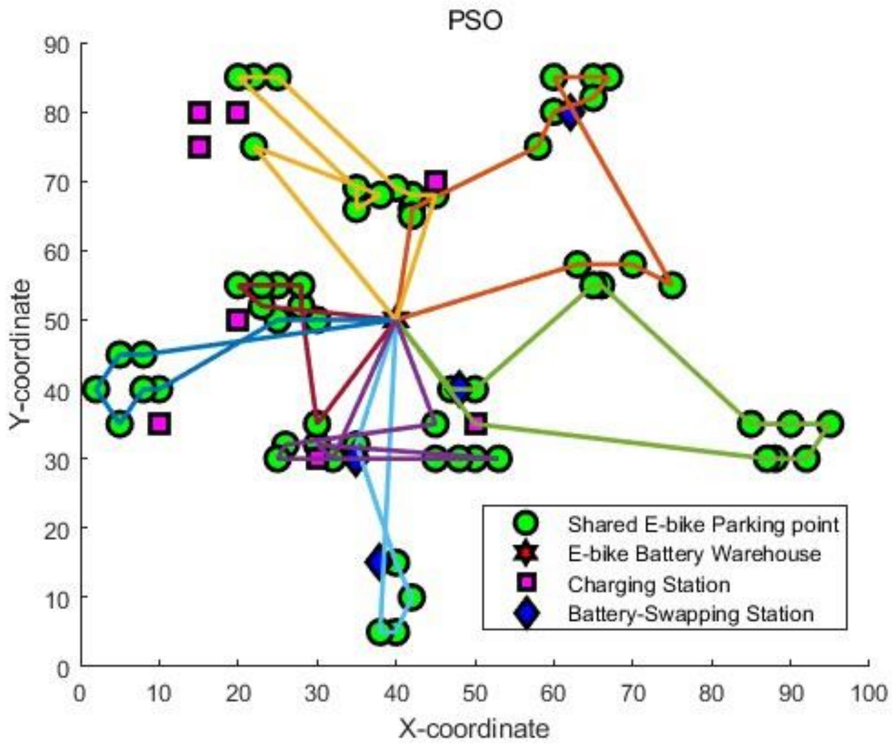

Figure 5. 4: The schematic diagram of optimal path of particle swarm optimization

Table 5. 10: The path of the optimal solution of particle swarm optimization

EV no.	mileage(km)	optimal path of PSO
1	141.2	0 40 38 53 52 49 46 43 45 47 48 69 0
2	94.21	0 27 35 33 34 36 0
3	67.5	0 18 20 19 17 15 14 30 0
4	0	0
5	87.9	0 13 16 21 22 24 26 25 23 0
6	126.58	0 4 2 60 58 57 55 56 59 50 51 54 0
7	127.65	0 10 6 7 8 12 11 9 5 3 1 0
8	112.73	0 28 29 44 37 39 41 32 31 42 0

The optimal path planning results obtained using chaotic particle swarm optimization are shown in Figure (5.5) and Table (5.11). The total driving distance of chaotic particle swarm optimization is the shortest among the three algorithms, which is 738.53 km. Similar to the results of genetic algorithm and particle swarm optimization, the optimal chaotic particle swarm optimization solution showed that seven electric logistics vehicles are started. This shows that the three algorithms demonstrate that seven electric logistics vehicles are the optimal solution.

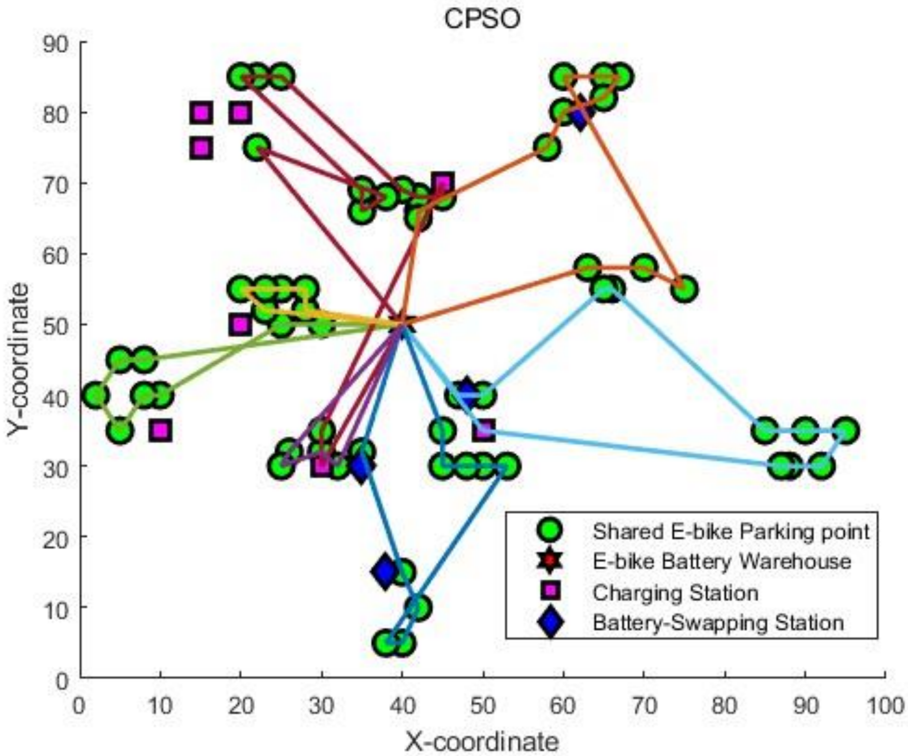

Figure 5. 5: The schematic diagram of optimal path of chaotic particle swarm optimization

Table 5. 11: The path of the optimal solution of chaotic particle swarm optimization

EV no.	mileage /km	optimal path of CPSO
1	87.9	0 13 16 21 22 24 26 25 23 0
2	141.2	0 40 38 53 52 49 46 43 45 47 48 69 0
3	176.41	0 10 6 7 8 12 11 9 5 3 1 62 30 68 0
4	107.13	0 27 35 33 34 36 44 37 39 41 42 0

5	126.58	0 4 2 60 58 57 55 56 59 50 51 54 0
6	44.52	0 18 20 19 17 15 14 0
7	54.79	0 28 29 32 31 0
8	0	0

Electric logistics vehicles do not produce exhaust gas in the driving process, so the greenhouse gas emissions of electric logistics vehicles are mainly determined by upstream power generation. Calculating CO_2 emissions from electric logistics vehicles is usually a complex process.

This thesis refers to Peng Mei-chun's [31] calculation model of carbon emissions of the electric logistics vehicle and determines the carbon emissions per kilometer of electric vehicle in EVRPSTW-FC/BS as 34.55 kg.

As shown in Figure (5.6), the optimal chaotic particle swarm optimization solution has the least carbon dioxide emission. The optimal solution of chaotic particle swarm optimization reduces greenhouse gas emissions by 3.13% compared with the optimal genetic algorithm solution. Meanwhile, it reduces greenhouse gas emissions by 2.53% compared with particle swarm optimization.

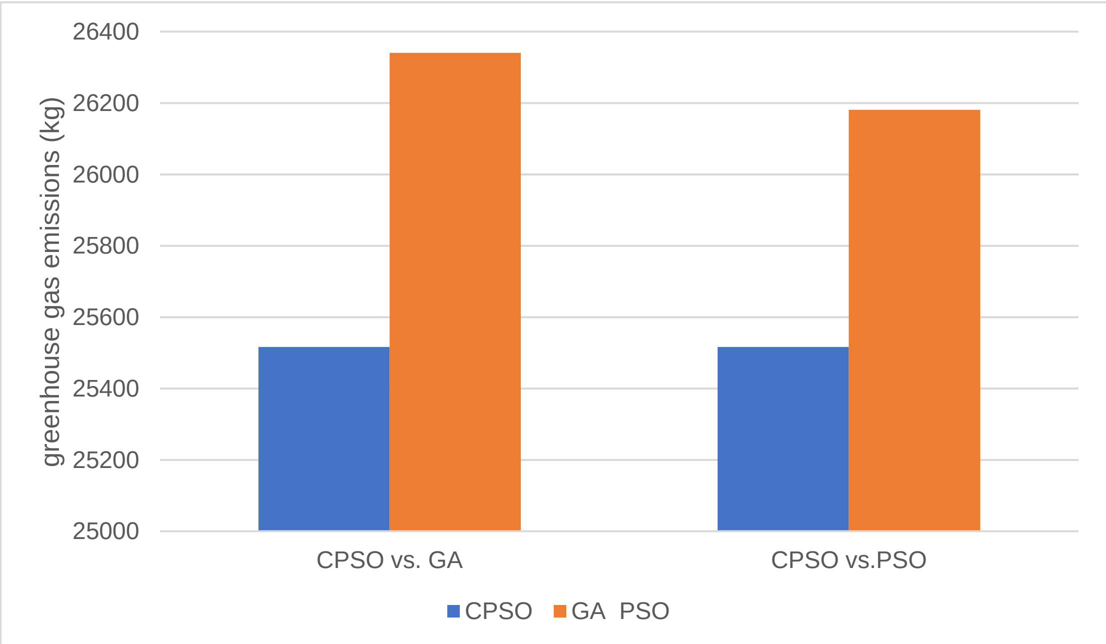

Figure 5. 6: Carbon emission comparison of optimal solutions of GA, PSO and PSO

5.5. The sensitivity analysis

In this section, sensitivity analysis is carried out from three aspects: the maximum load of the electric logistics vehicle, the battery capacity of the electric logistics vehicle, and the structure of the electric logistics fleet.

5.5.1. Load capacity of electric logistics vehicle

It is known maximum load of electric logistics vehicles is 200 e-bike batteries. In order to conduct sensitivity analysis, the maximum load of electric logistics vehicles is increased from 200 to 300 and then solved EVRPSTW-FC/BS. As seen from Figure (5.7), generally, within a specific range, the shared e-bike' battery replacement operation system is more inclined to choose a larger electric logistics vehicle load.

However, the operating system has a different sensitivity to the maximum load under different algorithms. A larger electric logistics vehicle load for GA does not reduce operating costs. However, the optimal solutions of particle swarm optimization and chaotic particle swarm optimization show that increasing the maximum load of electric logistics vehicles within a specific range will reduce the operating cost. When the maximum load is 250, the optimal solution of particle swarm optimization reduces the operating cost by 3.49% compared to the maximum load of 200. At the same time, when the maximum load is 275-300, the chaos particle swarm optimal solution reduces the operating cost by 0.72%.

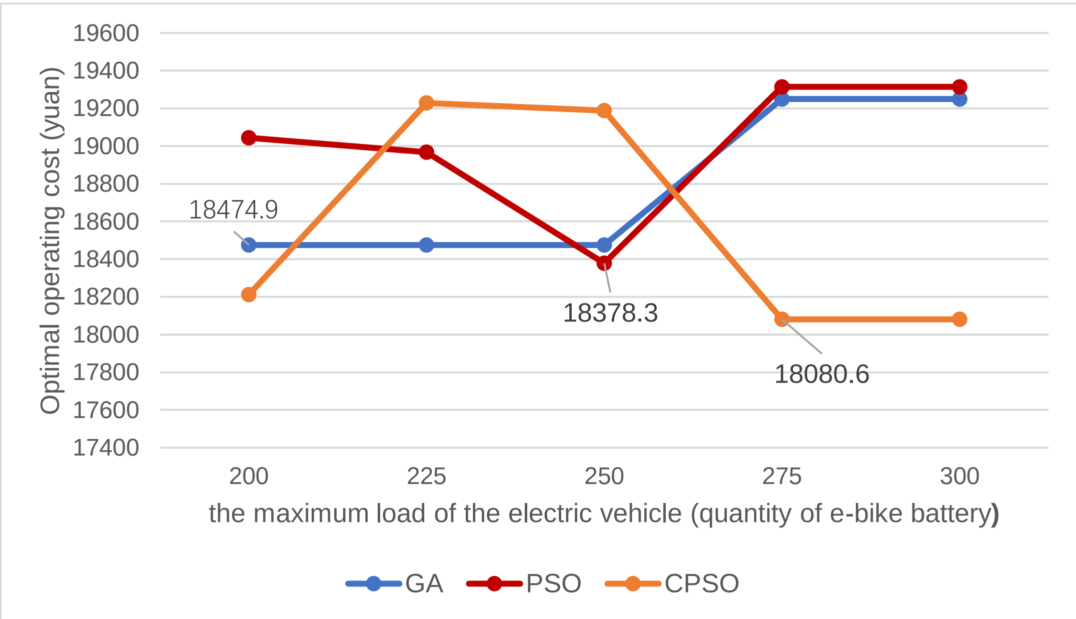

Figure 5. 7: The sensitivity analysis for load capacity

5.4.2. Battery capacity of electric logistics vehicle

It is known that the mileage of the electric logistics vehicle in this thesis is 150 km. In order to conduct sensitivity analysis, the range of the electric logistics vehicle is increased from 150 km to 250 km and then solved EVRPSTW-FC/BS. As seen in Figure (5.8), generally, the battery replacement operation system of shared electric bicycles prefers the battery capacity of larger electric logistics vehicles within a specific range.

When the range is 175 km, the optimal solutions of particle swarm optimization and chaotic particle swarm optimization reduce the operating cost by 2.64% and 1.06%, respectively, compared with the range of 150 km. When the range is between 225-250km, the optimal GA solution reduces the operating cost by 1.99%.

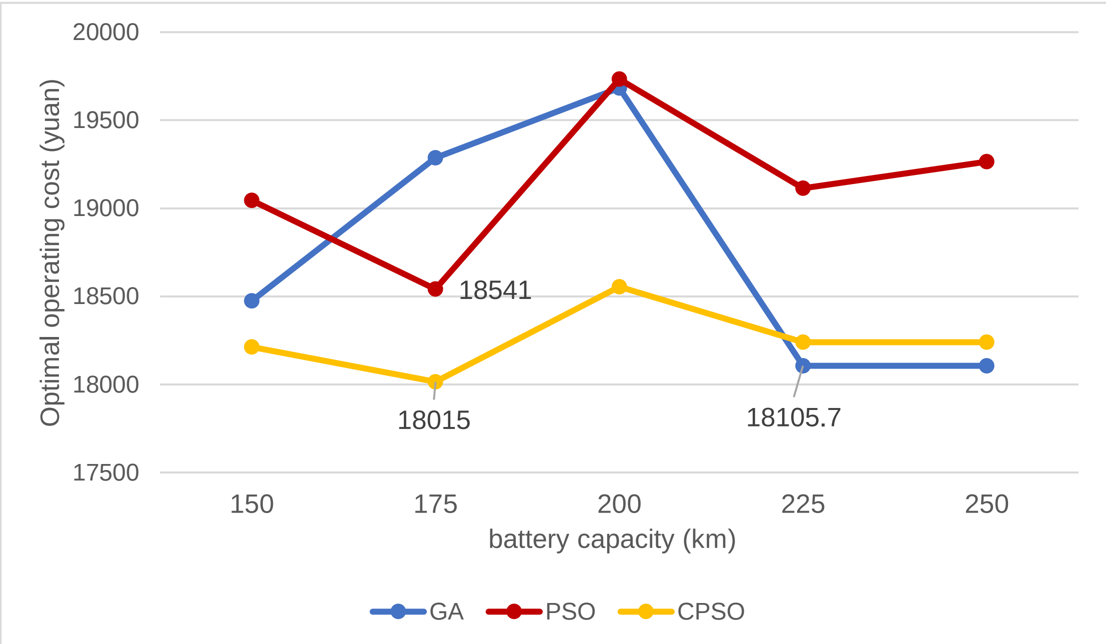

Figure 5. 8: The sensitivity analysis for battery capacity of electric logistics vehicle

5.4.3. Structure of the fleet

It is known that the fleet consists of four fast charging mode and four battery-swapping mode electric logistics vehicles. The fleet structure is numbered as (E_f, E_s) for sensitivity analysis and solved. E_f represents the number of electric logistics vehicles in fast charging mode, and E_s represents the number of electric logistics vehicles in battery-swapping mode. For example, (0,8) indicates eight battery-swapping mode EV logistics vehicles but no fast charging mode.

It can be seen from Figure (5.9) that the battery replacement operation system of shared e-bikes is more inclined to choose electric logistics vehicles with fast charging mode. Compared with the fleet structure (4,4), when the fleet structure is (7, 1), the optimal solutions of GA and PSO reduce the operating cost by 2.01% and 5%, respectively. When the fleet structure is (8, 0), the optimal chaotic particle swarm optimization solution reduces the operating cost by 2.9%.

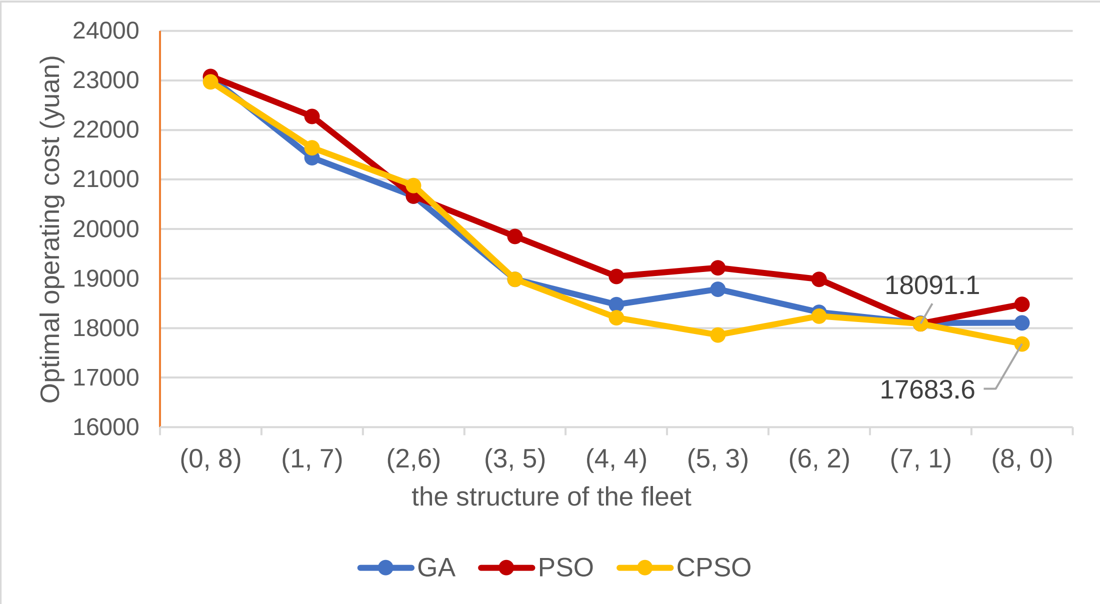

Figure 5. 9: The sensitivity analysis for the structure of fleet

5.4.4. The summary of sensitivity analysis

As shown in Figure (5.10), The battery capacity and maximum load of electric logistics vehicles will have an impact on operating costs. And the battery replacement operating system of shared electric bicycles is the most sensitive to the structure of the fleet, and the operating system prefers electric logistics vehicles in fast charging mode. In other words, the mode of electric logistics vehicles supplementing electric energy is an important factor affecting the operation.

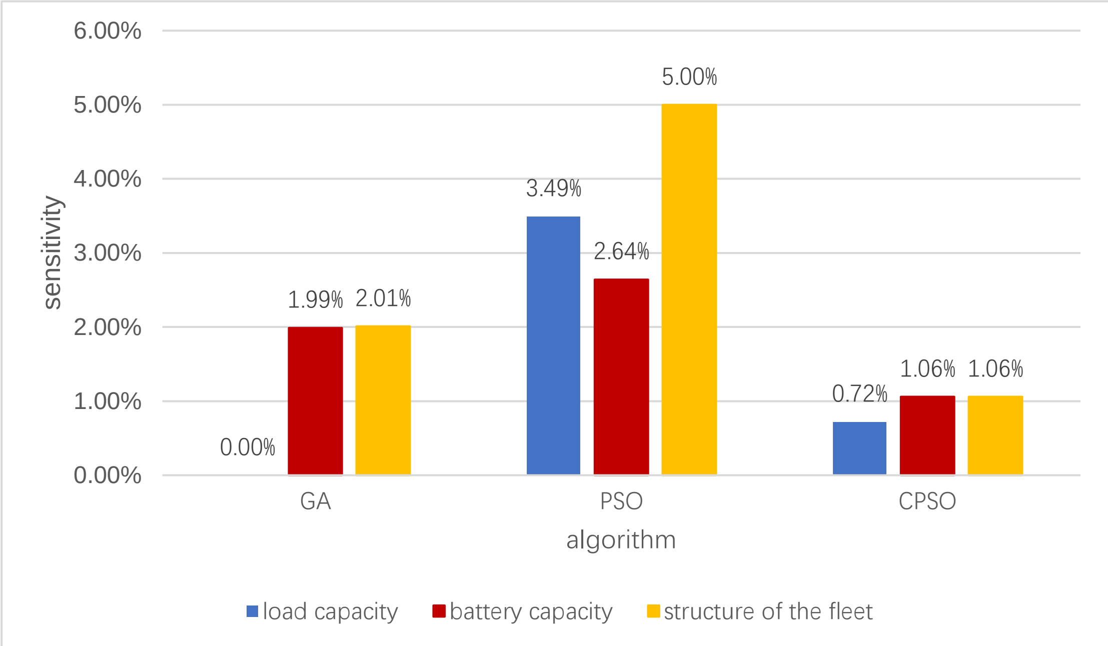

Figure 5. 10: The summary of sensitivity

6 Conclusion and outlook

Conclusion

Based on the electric logistics vehicle to replace the battery for shared e-bike, the routing optimization of the electric logistics vehicle is done by the following work:

(1) Review the development and current situation of shared electric bikes and logistics vehicles in China. Describing the charging mode of the e-bike, thus entering the topic of mobile service routing planning. The characteristics of the routing optimization problem and corresponding algorithm are analyzed. Lay a foundation for the subsequent model building and algorithm design.

(2) According to the characteristics of the operating system for battery replacement of shared e-bikes, this thesis established the Electric Vehicle Routing Problem with Soft Time Window-Fast Charging/Battery-Swapping (EVRPSTW-FC/BS). The model is designed to minimize operation costs, including transportation costs, fast charging/battery-swapping, and the cost of service time. A routing optimization strategy is proposed to solve this problem.

(3) Aiming at the characteristics of EVRPSTW-FC/BS for the logistics distribution of electric vehicles, this thesis applies genetic algorithm and particle swarm optimization to solve the problem. Considering the shortcomings of particle swarm optimization, which is easy to fall into sub-optimal solutions, the concept of chaos is introduced, and the EVRPSTW-FC/BS model is also solved by chaotic particle swarm optimization.

(4) There are few relevant studies on the battery replacement of shared electric bikes. Solomon C101 is selected as the data set for the simulation test, considering the distribution characteristics of shared electric bikes in cities. Screening 60, 1, 8, and 4 points in the raw data as shared e-bike parking points, e-bike battery warehouse, and fast charging stations/battery-swapping stations for the electric logistics vehicle, respectively. Three algorithms, genetic algorithm, particle swarm optimization, and chaotic particle swarm optimization, are respectively used for 50 iterations to solve the optimal mobile service path. According to the calculation results, the genetic algorithm can find the feasible solution quickly, but the chaotic particle swarm optimization can minimize the operating cost and the carbon emission. The effect of particle swarm optimization is somewhere in between.

(5) According to the equal scale of Solomon's instance, a fleet consisting of eight electric logistics vehicles is built. After the demonstration of the above three algorithms, the optimal solution is seven electric logistics vehicles. Load capacity, battery capacity of electric logistics, and fleet structure are used to analyze the sensitivity of shared e-bikes' battery replacement operating system. Test data shows that structure of the fleet occupies the greatest sensitivity which means the mode of electric logistics vehicles supplementing electric energy is a critical factor affecting the operation.

Outlook

As a new means of transportation, shared e-bikes have become an important choice for urban residents. With the improvement of policies and supervision, shared e-bikes still have great potential for development in the future.

However, electric logistics vehicles are still in the promotion stage, the layout of stations could be better in reality, and there are few quick charging stations and battery-swapping stations for industrial electricity. Therefore, the route optimization of electric logistics vehicles has broad application prospects.

Therefore, this paper puts forward the following prospects:

(1) A battery replacement operation network with great potential can be established for electric logistics vehicles combined with shared electric bikes. The friendly interaction between electric vehicles opens up endless possibilities for urban transportation.

(2) To speed up the construction of fast charging and battery-swapping stations, the amount of infrastructure involved will affect the efficiency of performing tasks of electric logistics vehicles in the city.

(3) The business models of fast charging and battery-swapping need to be developed. Reasonable pricing will help promote the application of electric logistics vehicles.

(4) In the future, relying on the platform of big data and cloud computing, shared electric bikes and electric logistics vehicles will become essential in the construction of intelligent transportation and smart city.

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parameter delimiter	parameter definition
I_0, I_{n+1}	shared e-bike battery warehouse (starting point), virtual end point
I	the set of shared e-bike parking points
F	the set of fast charging or battery-swapping stations
K	the set of electric vehicles
V	the set of above four type parameters
E_i	the earliest service time which e-bike parking point can accept
L_i	the latest service time which e-bike parking point can accept
S_i	the time for EV to replace the battery at e-bike parking point i
T_i^k	the time of electric vehicle k accesses to e-bike parking point i
T'^k_i	the time of electric vehicle k lefts from e-bike parking point i
WT_i^k	the waiting time of electric vehicle k at e-bike parking point i
q_i	the demand of battery of e-bike parking point i
t_{ij}	the time from i to j for electric vehicles
d_{ij}	The distance from i to j
b_i^k	SOC of electric vehicle k at e-bike parking point i
C_{ij}	the variable cost of electric vehicle k from i to j
Q	the max loading capacity of each electric vehicle
A	the power consumption rate of electric vehicles
B	the max electric capacity of each electric vehicle
v	the unit transport cost
w	the fixed cost of each electric vehicle operating
P_f, P_s	the cost of fast charging and battery-swapping
π_1, π_2	the punishment cost coefficient
x_{ij}^k	the routing decision variable of electric vehicle k from i to j
y_{ij}^k	the supplementary electricity decision variable of electric vehicle k from i to j