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Half-open time-dependent multi-depot electric vehicle routing problem considering battery recharging and swapping

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A B S T R A C T

In order to promote green and sustainable development of the transportation industry, an increasing number of logistics companies have begun to deploy electric vehicles (EVs) to provide urban distribution services. This paper studies a Half-Open Time-Dependent Multi-Depot Electric Vehicle Routing Problem Considering Battery Recharging and Swapping (HOTDMDEVRPBRS) in last-mile delivery. Based on the calculation functions of EV energy consumption, travel time, and carbon emissions under the time-dependent road network, a mixed integer programming model is formulated. The goal of the model is to minimize the economic cost and environmental cost of logistics companies. Given the complexity of the problem, this paper designs a multi-objective simulated annealing algorithm (SAA). Finally, this paper carries out comprehensive computational experiments to verify and evaluate the performance of the proposed model and method and examines the economic and environmental benefits brought by the Half-Open Joint Distribution Mode (HOJDM). According to the results, SAA shows good performance and provides a high-quality solution. Meanwhile, the HOJDM significantly reduces the total cost and carbon emissions of logistics enterprises and provides valuable suggestions for enterprise managers and government decision-makers.

1. Introduction

Nowadays, Green House Gas (GHG) emission has become a severe issue endangering human life. The transportation industry is one of the significant contributors to GHG emissions. In the United States of America and the European Union, the transportation industry generates 29% (USEPA, 2019), and 24% (GGES 2016) of GHG emissions, respectively. As a result, extensive research has started to shift toward greener transportation in both industry and academia. In this case, applying EVs to logistics distribution may be a promising solution (Huang et al., 2019). In addition to lowering air pollution, EVs also can ease traffic congestion and reduce noise in residential areas while decreasing fossil fuel consumption (Xiao et al., 2021). Various countries have issued relevant policies to promote the electrification of transportation. Italy will phase out diesel vehicles completely in Milan from 2027. Five cities in France provide free or discounted parking for EVs – Aix-en-Provence, Lyon, Marseille, Nice, and Paris. The Netherlands requires the 30–40 largest municipalities to introduce "zero-emission zones" for freight by 2025, meaning that only EVs will be permitted to drive through the zone.

However, some challenges restrict the EVs' application in city freight transportation, the most prominent of which is the limited mileage of EVs (Basso et al., 2019). Therefore, if EVs are applied to urban distribution, it is necessary to plan EVs' battery energy supplement needs reasonably. Currently, the mainstream way for EVs to replenish energy is to charge at the charging station (CS). With the gradual improvement of energy replenishment infrastructure, the ways of replenishing energy

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for EVs will be more diversified. EVs can not only go to the CS to charge but also to the battery swapping station (BSS) to replace the battery. Different ways of replenishing energy will affect the distribution cost and efficiency of logistics enterprises. In this regard, it is of great practical significance to study the electric vehicle routing problem (EVRP) considering both recharging and battery swapping operations.

Moreover, in today's fiercely competitive market, enterprises are under tremendous pressure to boost efficiency by reducing operational costs. Since distribution cost constitutes a significant portion of a company's operational expenditures, one effective strategy to help achieve this goal is to make full use of multiple depots of logistics enterprises to carry out joint distribution (Gansterer & Hartl, 2018). In addition to evident economic benefits, the joint distribution also can reduce the energy consumption of EVs, with certain environmental benefits. Currently, the electricity source of EVs mainly depends on thermal power generation, so there are still some GHG emissions in the use of EVs (Teixeira and Sodré 2018). Reducing the energy consumption of EVs means reducing carbon emissions. However, studies have rarely applied both EV carbon emissions and joint distribution mode to EVRP.

In the meantime, the traffic conditions of the urban road network have time-varying characteristics, and vehicles may travel at different speeds in different time periods. Speed is one of the main factors affecting travel time and EV energy consumption. Time-dependent speed makes it arduous to directly calculate travel time and EV energy consumption, leading to certain difficulties in EV distribution route planning (Zhang et al., 2020). If an EV runs out of power during delivery, the solution will be far more complex than a fuel vehicle (FV). Because FVs are usually equipped with backup fuel, but EV batteries are expensive (Andwari et al., 2017), general logistics companies cannot be equipped with backup batteries. This means that time-dependent speed is a crucial factor for the route planning of EVs.

Due to the necessity of reducing EV energy consumption and considering the significant benefits of the joint distribution, in this paper, we integrate practical factors such as multiple depots, half-open joint distribution mode (HOJDM), time-dependent speeds, hybrid energy replenishment mode (HERM) and EV carbon emissions into the EVRP. Aiming to minimize economic cost and environmental cost, we explore a more comprehensive Half-Open Time-Dependent Multi-Depot Electric Vehicle Routing Problem Considering Battery Recharging and Swapping (HOTDMDEVRPBRS). Moreover, in contrast to many studies in the literature that calculate electrical energy consumption only based on the travel distance, this paper considers the EV weight, speed, travel distance, acceleration, and other factors related to the energy consumption, and then designs the calculation methods of EV energy consumption, travel time and carbon emissions under the time-varying road network. Furthermore, other assumptions are regarded, including the times of recharging and battery swapping, customer demand and service time. Eventually, due to the high complexity of the problem, a multi-objective simulated annealing algorithm is devised to solve the problem. The main contributions of this study can be summarized as follows,

- Simultaneously considering two ways of replenishing energy in the EVRP, which is forward-looking in line with future development,
- EVRP research that takes time-dependent speed into account is more realistic,
- Creating flexible energy replenishment plans to fulfil the actual distribution requirements of enterprises,
- Providing an extensive computational experiment to evaluate the performance of the proposed model and approach and examine the economic and environmental benefits of HOJDM.

The rest of this paper is organized as follows. In Section 2, the studies on the VRP related to recharging and battery swapping, HOJDM, carbon emissions and time-dependent speed are reviewed, and the innovation of this article is explained. Section 3 provides a description of the problem. In Section 4, the Calculation method of EV energy consumption, travel time and carbon emissions under time-dependent speed is developed, and the mixed integer programming model of HOTDMDEVRPBRS is formulated. In Section 5, a simulated annealing algorithm based on multi-objective is designed. The validation and rationality of the proposed approach are investigated in Section 6. Meanwhile, we put forward reasonable operation suggestions for logistics enterprises. Finally, the conclusion and prospects for future research are provided in Section 7.

2. Literature review

The Vehicle Routing Problem (VRP), one of the most studied topics in logistics management, concerns finding optimal sets of routes to deliver packages from depots to customers according to an objective function like minimizing the total transportation distance or cost (Tao et al., 2021). Dantzig and Ramser (1959) initially introduced this issue. Since then, scholars have developed many extensions of the VRP to incorporate real-world assumptions and make more practical models. As one of the variants of VRP, EVRP was first proposed by Conrad et al. (2011). In this section, we focus on the research works that are most relevant to this paper.

The charging strategy has always been one of the research hotspots of EVRP, aiming to solve the problem of EV distribution mileage limitation. Many scholars have conducted research on different charging strategies. Mauricio et al. (2020) studied EVRP with backhauls under full charging strategies, and designed an iterated local search algorithm to solve it. Zhou et al. (2021) studied a new variant of the EVRP that considers partial recharge. To solve the problem, they developed a hybrid metaheuristic by integrating a modified greedy algorithm with the variable neighborhood search. David et al. (2019) constructed an iterated local search metaheuristic framework and a variable neighborhood descent algorithm to solve EVRP under partial charging strategies, and proposed to make reasonable use of charging time, such as delivering packages to customers close to the CS by walking. Keskin et al. (2018) conducted a comparative experiment with three recharging configurations which can be referred to as normal, fast and super-fast recharges in the process of EV distribution. Shen et al. (2021) assumed that each CS has three charging types (slow, regular and fast charging), and formulated EVRP mathematical models of multiple charging types with the goal of minimizing the total cost. Karakatič (2021) studied the multi-depot EVRP with nonlinear recharging times, and designed a two-layer genetic algorithm to solve the problem. With the development of science and technology, EVs can replenish energy by swapping the battery. Zhou et al. (2022) investigated the EVRP with battery swapping. The mathematical model aims to minimize the total distribution cost and maximize the average utilization of batteries simultaneously, and a multi-objective whale optimization algorithm is developed to solve the problem. Raeesi and Zografos (2020) presented an EVRP with synchronised mobile battery swapping. They assumed that a battery swapping van would replace the depleted battery on an EV with a fully charged one at a designated time and location. Jie et al. (2019) proposed a two-echelon capacitated electric vehicle routing problem with battery swapping stations and designed a hybrid algorithm that combines a column generation and an adaptive large neighborhood search to solve the problem. The above literature provides a theoretical basis and method reference for EVRP under different energy replenishment strategies.

With the rapid development of urban logistics, many logistics companies have multiple depots. In the long-term logistics practice process, it is found that the independent distribution mode is arduous to share logistics resources, easily leading to roundabout transportation. The joint distribution mode can effectively reduce travel distance, decrease distribution cost and improve distribution efficiency. Therefore, the joint distribution mode has gradually become one of the hotspots in VRP research. Liu et al. (2020) studied the joint distribution mode of cold chain logistics companies and established an optimization model for the multi-depot vehicle routing problem (MDVRP) with the goal of minimizing total distribution cost and carbon emission cost. Brandão (2020) built an open MDVRP mathematical model for the joint distribution problem and designed an iterated local search algorithm to solve it. Wang et al. (2019) formulated an MDVRP model with shared transportation resources, and they designed a hybrid heuristic algorithm combining the saving algorithm, the sweep algorithm and the multi-objective particle swarm optimization algorithm to solve the problem. Zhang et al. (2022) proposed a heterogeneous multi-depot collaborative vehicle routing problem, considering the joint distribution of multi-category products, and developed a Benders-based branch-and-cut algorithm to solve the problem. In order to compare the differences between shared and non-shared resources in multiple depots during the distribution process, Li et al. (2018) conducted a comparative study. Likewise, Behdin et al. (2022) made a comparative study on the joint distribution and non-joint distribution of EVs. The above literature provides a theoretical basis and method reference for EVRP under the HOJDM.

Whether an EV is really clean depends on the cleanliness of its charge. EVs obtain electrical energy from the CS, and the electrical energy of the CS is provided by the power grid, which is converted from primary energy processing. In fact, most countries still supply electricity mainly through thermal power generation, so using EVs for urban distribution still has unavoidable carbon emissions. This issue has attracted the attention of a few scholars, who have considered carbon emissions in EVRP and conducted research from different perspectives. Zhu et al. (2020) addressed a multi-depot capacitated EVRP where client demand is composed of two-dimensional weighted items. Based on the data of Bloomberg New Energy Finance (BNEF), the carbon emissions of EVs and FVs in the distribution process are compared and analyzed. Li et al. (2020) thought that EV carbon emissions are related to energy consumption and put forward a measurement function of EV carbon emissions, which is applied to an EVRP considering battery life and battery swapping strategy. In the context of sharing economy, Li et al. (2020) studied the EVRP considering carbon taxes and time-of-use electricity prices and proposed an optimization model of the EVRP in view of sharing economy. Liao et al. (2019) studied the VRP with the consideration of carbon trading policies, and both the EV routing model and the traditional FV routing model are constructed to minimize the total costs. Finally, they concluded that carbon price plays an essential role in the transformation of logistics companies. The above literature provides a theoretical basis and method reference for the study of EVRP considering carbon emissions.

The traffic conditions of the urban road network have time-varying characteristics, and vehicles may travel at different speeds during different time periods. The time-dependent speed has a great impact on the distribution time cost of urban logistics. Scholars have studied the time-dependent vehicle routing problem (TDVRP) from different perspectives. Sun et al. (2018) introduced the TDVRP with time windows and precedence constraints and proposed a tailored labeling algorithm to solve this problem. Poonthalir and Nadarajan (2018) built a bi-objective TDVRP model with the goal of minimizing both route cost and fuel consumption and solved it by particle swarm optimization with greedy mutation operator and time varying acceleration coefficient. Xu et al. (2019) built a TDVRP planning model with the goal of minimizing carbon emissions and maximizing customer satisfaction and designed an improved non-dominated sorting genetic algorithm to solve it. Gmira et al. (2021) considered that paths between any two customers at different times of the day might be different and proposed a new variant of TDVRP with time window, then designed a tabu search algorithm to solve it. Some scholars have also studied the time-dependent electric vehicle routing problem (TDEVRP). Lu et al. (2020) comprehensively considered the constraints of EV energy consumption, time windows, charging decisions, etc., and built a TDEVRP model with the goal of minimizing the total distribution cost. To solve the problem, they designed an iterated variable neighborhood search algorithm. Wang et al. (2020) studied TDEVRP with time windows and path flexibility. With the goal of minimizing the total travel distance and the electrical energy consumption, a mixed integer programming model was established, and an improved variable neighborhood search algorithm was designed to solve it. The above literature considers the time-varying characteristics of urban traffic conditions, which is more in line with the actual situation of urban logistics distribution, and provides a reference for the application of EVs to urban distribution.

The existing research has laid a good foundation for the in-depth study of EVRP in urban environments, but there are still research gaps that can be further explored: (1) Most of the existing literature stipulates that EVs only replenish energy in the CS during the distribution, but in fact, there are many ways to replenish energy for EVs. As the country with the largest number of EVs in the world, China clearly proposed "accelerate the construction of battery swapping infrastructure" in its "New Energy Vehicle Industry Development Plan (2021-2035)", fully explaining that the EVRP considering recharging and battery swapping has broad application prospects. For a long time in the future, swapping batteries will become one of the mainstream energy supplementation methods for EVs. Although some scholars have studied EVRP based on battery swapping mode, EVRP research that simultaneously considers the hybrid energy replenishment mode of recharging and battery swapping is scarce. (2) Although much literature considers the time-varying characteristics of the urban road network, few studies integrate the time-dependent speed into EVRP. The time-dependent speed will affect EV travel time and energy consumption. If the distribution optimization scheme based on constant vehicle speed is applied to the actual traffic network, it will likely cause the EV to break down on the way of distribution, making it challenging to complete the task. (3) HOJDM can share logistics resources, shorten vehicle travel distance, and reduce energy consumption. At present, the electricity of many countries mainly relies on thermal power generation, so using EVs still has unavoidable carbon emissions. Reducing EV energy consumption means reducing carbon emissions. Therefore, the HOJDM will generate not only economic benefits but also environmental benefits. However, few EVRP studies comprehensively consider multiple depots, HOJDM and carbon emissions. (4) It takes a long time to charge, which affects the distribution efficiency. Therefore, most existing literature assumes that EVs are only charged once during distribution. However, the single-charge strategy limits the distance of EVs, and it is difficult to use EV capacity fully. By swapping the battery to replenish energy, each operation only takes a few minutes, which basically does not affect the total distribution time. Therefore, based on the energy replenishment strategy of single recharging and multiple battery swapping, when the task of EVs is heavy, this strategy can ensure the delivery timeliness and make full use of EV capacity; when the task of EVs is light, this strategy can also save distribution cost. This strategy is more in line with the actual needs of the enterprise. In summary, this paper studies HOTDMDEVRPBRS in last-mile delivery, considering factors such as multiple depots, HOJDM, customer coordinates, demand, EV capacity, carbon emissions, time-dependent speed, HERM, single-recharging and multiple-battery-swapping strategies. We formulate a mathematical optimization model with the goal of minimizing economic cost and environmental cost, and a simulated annealing algorithm is designed to solve it. This paper offers a more reasonable and scientific EV distribution-charging/swapping route planning scheme for urban logistics and provides references for the green development of urban logistics.

3. Description of the problem

This research addresses the HOTDMDEVRPBRS for last-mile delivery. In contrast to most of the literature, we assume that EVs carrying packages depart from multiple depots, and they do not have to return to the original depots after completing all distribution tasks, but can park at any depot nearby. In the distribution process, when the electrical energy of EVs is insufficient to continue the distribution, the EV needs to go to the CS or BSS to replenish energy. After the energy replenishment is completed, EVs continue to deliver the remaining packages to customers. In this problem, the EV capacity, battery capacity, customer coordinates, demand, and service time are all known (Fig.1).

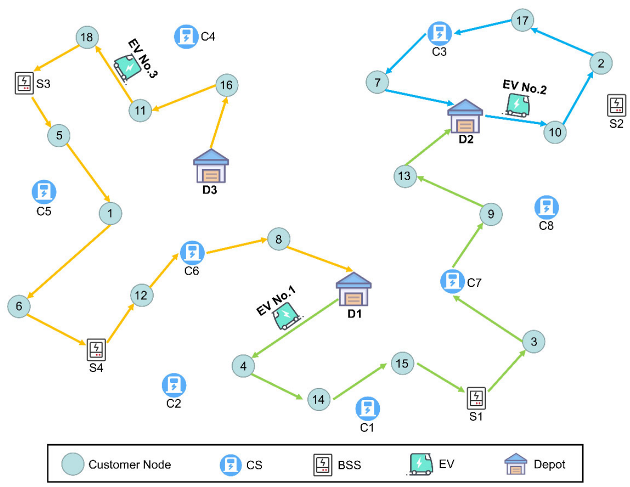

Fig.1. Schematic of the HOTDMDEVRPBRS

To clarify the application scope of the HOTDMDEVRPBRS, we make the following assumptions: (1) Each EV can be used at most once, each customer can be served only once, and each customer's demand is less than the EV capacity; (2) Affected by the time-varying characteristics of the urban road network, EVs travel at different speeds in different time periods. (3) The influencing factors of EV energy consumption include EV self-weight, actual load, travel speed and travel distance; (4) The coordinates of the CS and the BSS are known, and EVs do not need to wait after entering the CS or BSS, can replenish energy directly; (5) During the distribution process, EVs can be charged at most once, the times of battery swapping is unlimited.

The CS adopts a partial charging strategy, and the charging rate is constant. The BSS adopts the strategy of swapping the fully charged battery, and the battery swapping time is fixed; (6) The EV has both economic cost and environmental cost. Economic cost includes fixed usage cost, travel time cost, charging cost, battery swapping cost, and customer service time cost. Environmental cost mainly is carbon emission cost. Given the aforementioned characteristics of the problem, the objective of the HOTDMDEVRPBRS is to minimize the sum of the economic cost and environmental cost of all EVs.

4. Mathematical models

4.1 EV energy consumption model

Referring to the energy consumption calculation methods proposed by Bektaş et al. (2011) and Goeke et al. (2015), the average speed of EVs in a very short time period is taken as the travel speed of EVs in period R, so the energy consumption e_{ijk}^R of EV k traveling on arc (i,j) in period R is:

$$e_{ijk}^R = \alpha_{ij}(L+l)F_{ijk}^R + \beta(v_{ijk}^R)^2 F_{ijk}^R \tag{1}$$

where α_{ij} is a parameter related to the road section, $\alpha_{ij} = a + \sin\theta_{ij} g + C_r \cos\theta_{ij} g$, a represents EV acceleration, g represents the gravity constant, θ_{ij} represents the road angle, and C_r represents the rolling resistance coefficient. L denotes the weight of an empty EV; l denotes the actual load of an EV; v_{ijk}^R and F_{ijk}^R are the travel speed and distance of EV k on arc (i,j) in period R, respectively. β represents the coefficient related to EVs, $\beta = 0.5 C_d A\rho$, C_d represents the traction coefficient, A represents the windward area of the EV, and ρ represents the air density. This paper's approach for calculating EV energy consumption can fully account for the influence of critical variables like EV speed, load, and travel distance, making EV energy consumption more accurate and consistent with its practical applications.

4.2 EV travel time and energy consumption under the time-dependent speed

Referring to the method proposed by Liu et al. (2020), a day is divided into multiple period sets T according to a fixed time length U, $T = \{T_0, T_1, ..., T_L\}$, and $[T_{R-1}, T_R]$ represents the R-th period. d_{ij} is the length of arc (i,j). Let t_{ijk}^R be the travel time of EV k on arc (i,j) in period R. Let d_{ijk}^R be the distance that EV k still needs to travel on arc (i,j) after period R, and R_k is the time that EV k can travel in period R. Assume that time t_{ik}^l at which EV k leaves node i is within period R, i.e., $t_{ik}^l \in [T_{R-1}, T_R]$, $R_k = T_R - t_{ik}^l$. So the calculation steps of travel time T_{ijk} and energy consumption E_{ijk} required for EV k from node i to j are as follows:

Procedure 1: The calculation method of travel time and energy consumption of EV k on arc (i,j) in the first period R. $F_{ijk}^R = v_{ijk}^R R_k$. If $F_{ijk}^R \geq d_{ij}$, then $t_{ijk}^R = d_{ij} / v_{ijk}^R$, $e_{ijk}^R = \alpha_{ij}(L+l)d_{ij} + \beta(v_{ijk}^R)^2 d_{ij}$, go to Procedure 3; Otherwise, $d_{ijk}^R = d_{ij} - F_{ijk}^R$, $t_{ijk}^R = R_k$, $e_{ijk}^R = \alpha_{ij}(L+l)F_{ijk}^R + \beta(v_{ijk}^R)^2 F_{ijk}^R$, go to Procedure 2.

Procedure 2: The calculation method of travel time and energy consumption of EV k on arc (i,j) in each subsequent period. Step1: Let $\xi = 1$. Step2: $F_{ijk}^{R+\xi} = v_{ijk}^{R+\xi} \cdot U$, if $F_{ijk}^{R+\xi} < d_{ijk}^{R+\xi-1}$, then $t_{ijk}^{R+\xi} = U$, $d_{ijk}^{R+\xi} = d_{ijk}^{R+\xi-1} - F_{ijk}^{R+\xi}$, $e_{ijk}^{R+\xi} = \alpha_{ij}(L+l)F_{ijk}^{R+\xi} + \beta(v_{ijk}^{R+\xi})^2 F_{ijk}^{R+\xi}$, $\xi = \xi + 1$, go to Step2; Otherwise, $t_{ijk}^{R+\xi} = d_{ijk}^{R+\xi-1} / v_{ijk}^{R+\xi}$, $e_{ijk}^{R+\xi} = \alpha_{ij}(L+l)d_{ij}^{R+\xi-1} + \beta(v_{ijk}^{R+\xi})^2 d_{ij}^{R+\xi-1}$, go to Procedure 3.

Procedure 3: Calculate the travel time and energy consumption of EV k for the entire arc (i,j), $T_{ijk} = \sum_{R\in T} t_{ijk}^R$, $E_{ijk} = \sum_{R\in T} e_{ijk}^R$, and the calculation ends.

4.3 EV carbon emission measurement function under the time-dependent speed

The EV carbon emissions are related to the energy consumption on arc (i,j) and carbon emission factor h. Referring to the measurement method proposed by Li et al. (2020), the carbon emissions of EV k traveling from node i to j is given as follows:

$$H_{ijk} = h \cdot E_{ijk} \tag{1}$$

where the EV carbon emission factor h is the carbon dioxide emission per unit of electrical energy consumption. This factor is related to the type of EVs and energy generation and is a constant in a specific logistics distribution. Here, according to the study by Feng et al. (2013) and Hickman et al. (1999), we set it to $h = 0.69kg / kWh$.

4.4 Notations and variables

(1) Set

C denotes the set of customers; G_1 denotes the set of charging stations; G_2 denotes the set of battery swapping stations; M is the set of depots; V denotes the set of all nodes in the logistics system, $V = C \cup G_1 \cup G_2 \cup M$; K denotes the set of all EVs, $K = \{1, 2, ..., k\}$; C^k denotes the set of customers who still need to be served after EV k has visited the charging station.

(2) Parameter

W denotes the capacity of an EV; Q denotes the battery capacity of an EV; d_{ij} denotes the distance between node i and node j ; s_i denotes the service time required by customer i ; D_i denotes the demand of customer i ; q_{ik} denotes the charging amount of EV k at charging station i ; t_{ik}^l denotes the time when EV k leaves node i ; t_{ik}^a denotes the time when EV k arrives at node i ; S_{ik}^l denotes the remaining energy of EV k when it leaves node i ; S_{ik}^a denotes the remaining energy of EV k when it arrives at node i ; u_{ik}^l denotes the load of EV k when it leaves node i ; u_{ik}^a denotes the load of EV k when it arrives at node i ; σ_{ik} denotes the charging time of EV k at charging station i ; φ denotes the battery swapping time of EV k at the battery swapping station, which is a fixed constant; c_1 denotes the travel cost of the EV in unit time; c_2 denotes the fixed usage cost to be paid for dispatching one EV; c_3 denotes the unit time cost of serving customers; c_4 denotes the charging cost per unit time; c_5 denotes the cost per battery swapping; c_6 denotes the carbon emission cost per unit energy consumption of EVs; η denotes the charging efficiency of the EV; p_e denotes the power of the charging interface.

(3) Decision variables

x_{ijk} is a 0-1 variable, 1 if EV k travels from node i to j , 0 otherwise; y_{ijkR} is a 0-1 variable, 1 if EV k travels from node i to j in period R , 0 otherwise; w_{ik} is a 0-1 variable, 1 if EV k visits customer i , 0 otherwise; z_{ik} is a 0-1 variable, 1 if EV k visits charging station i , 0 otherwise; r_{ik} is a 0-1 variable, 1 if EV k visits battery swapping station i , 0 otherwise.

4.5 Cost analysis

$$P_1 = c_1 \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} T_{ijk} x_{ijk} \tag{3}$$

$$P_2 = c_2 \sum_{i \in M} \sum_{j \in C} \sum_{k \in K} x_{ijk} \tag{4}$$

$$P_3 = c_3 \sum_{i \in C} \sum_{k \in K} s_i w_{ik} \tag{5}$$

$$P_4 = c_4 \sum_{i \in G_1} \sum_{k \in K} \sigma_{ik} z_{ik} \tag{6}$$

$$P_5 = c_5 \sum_{i \in G_2} \sum_{k \in K} r_{ik} \tag{7}$$

$$P_6 = c_6 \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} H_{ijk} x_{ijk} \tag{8}$$

P_1 is the total travel time cost; P_2 is the total fixed usage cost of EVs; P_3 is the total customer service time cost; P_4 is the total charging cost; P_5 is the total battery swapping cost; P_6 is the total carbon emission cost.

4.6 HOTDMDEVRPBRS model

According to the problem description, model assumption and above analysis, the mathematical model of HOTDMDEVRPBRS is described as follows:

$$f = \min\left(P_1 + P_2 + P_3 + P_4 + P_5 + P_6\right) \tag{9}$$

$$\sum_{i\in M}\sum_{j\in C} x_{ijk} \le 1, \forall k \in K, i \ne j \tag{10}$$

$$\sum_{i\in C} w_{ik} = 1, \forall k \in K \tag{11}$$

$$\sum_{i\in V} x_{ijk} = \sum_{l\in V} x_{jlk}, \forall j \in \{V \setminus M\}, \forall k \in K \tag{12}$$

$$\sum_{i\in M}\sum_{j\in C} x_{ijk} = \sum_{j\in C}\sum_{l\in M} x_{jlk}, \forall k \in K \tag{13}$$

$$\sum_{i\in C} D_i w_{ik} \le W, \forall k \in K \tag{14}$$

$$u_{ik}^{l} = u_{ik}^{a} - D_i, \forall i \in C, \forall k \in K \tag{15}$$

$$S_{ik}^{l} = Q, \forall i \in M, \forall k \in K \tag{16}$$

$$S_{ik}^{l} = S_{ik}^{a}, \forall i \in C, \forall k \in K \tag{17}$$

$$E_{ijk} = \sum_{R\in T} e_{ijk}^{R} y_{ijkR}, \forall i, j \in V, \forall k \in K \tag{18}$$

$$S_{jk}^{a} \le \left(S_{ik}^{l} - E_{ijk}\right) x_{ijk} + Q(1 - x_{ijk}), \forall i, j \in V, \forall k \in K \tag{19}$$

$$S_{ik}^{l} \ge \begin{cases} E_{ijk} + E_{jlk}, & if\ j \in C, l \in G_1 \bigcup G_2, k \in K \\ E_{ijk}, & if\ j \in G_1 \bigcup G_2 \bigcup M, k \in K \end{cases} \tag{20}$$

$$S_{ik}^{a} \ge 0, \forall i \in V, \forall k \in K \tag{21}$$

$$q_{ik} \le Q - S_{ik}^{a}, \forall i \in G_1, \forall k \in K \tag{22}$$

$$q_{ik} = \min(Q - S_{ik}^{a},\ E_{ijk}x_{ijk} + \sum_{j\in C^k}\sum_{l\in C^k \bigcup M} E_{jlk}x_{jlk}),\ \forall i \in G_1, \forall k \in K \tag{23}$$

$$S_{ik}^{l} = Q \cdot r_{ik}, \forall i \in G_2, \forall k \in K \tag{24}$$

$$t_{ik}^{l} = (t_{ik}^{a} + s_i) w_{ik}, \forall i \in C, \forall k \in K \tag{25}$$

$$T_{ijk} = \sum_{R\in T} t_{ijk}^{R} y_{ijkR}, \forall i, j \in V, \forall k \in K \tag{26}$$

$$t_{jk}^{a} \le \left(t_{ik}^{l} + T_{ijk}\right) x_{ijk} + (1 - x_{ijk}) T_L, \forall i, j \in V, \forall k \in K \tag{27}$$

$$\sigma_{ik} = 60 \cdot \frac{q_{ik}}{\eta \cdot p_e} \tag{28}$$

$$t_{ik}^{l} = t_{ik}^{a} + \sigma_{ik} \cdot z_{ik} + \varphi \cdot r_{ik}, \forall i \in G_1 \bigcup G_2, \forall k \in K \tag{29}$$

$$x_{ijk}, y_{ijkR}, w_{ik}, z_{ik}, r_{ik} \in \{0,1\} \tag{30}$$

Objective function (9) minimizes the total cost, including the economic cost and environmental cost of using EVs. Constraint (10) ensures that each EV can be enabled at most once in the distribution task. Constraint (11) guarantees that each customer must be served by one EV only once. Constraint (12) guarantees the flow balance of customer location, CS, and BSS. Constraint (13) ensures that each EV can return to any nearby depot after completing its distribution task. Constraint (14) forces the EV capacity feasibility, i.e., the total demand of customers served by each EV cannot exceed its capacity. Constraint (15) controls the arrival loads and departure loads of EV k at customer i . Constraint (16) stipulates that the battery of each EV is fully charged while the EV departs from the depot. Constraint (17) shows that the remaining energy of EV k does not change when serving customer i . Constraint (18) denotes a formula for the energy consumption of EV k traveling from node i to j. Constraint (19) ensures that the remaining energy of each EV arriving at node j is the energy while it departs from node i minus the energy consumption between arc (i, j). Constraint (20) is a requirement for the remaining energy when the EV leaves its current location. That is, if the next node is a customer node, the current energy of the EV must be sufficient to travel from the current location to the next customer location, and then from the next customer location traveling to the nearest CS or BSS; if the next node belongs to a CS or a BSS or a depot, the current energy of the EV must be sufficient to travel from the current node to the nearest CS or BSS or depot. Constraint (21) guarantees that the remaining energy of the EV must be nonnegative when it arrives at any node. Constraint (22) specifies the charging amount limit of the EV at the CS. Constraint (23) represents a formula for calculating the charging amount of EV k at CS i . Constraint (24) determines the energy of EV k when it leaves the BSS. Constraint (25) states that the time when EV k departs from customer i is equal to the time when it arrives at customer i plus the customer service time. Constraint (26) represents a formula for calculating the total time of EV k traveling from node i to node j. The EV arrival time at node j is the sum of the EV departure time from node i and the travel time between arc (i, j), as given by constraint (27). Constraint (28) denotes the calculation formula of charging time of EV k at CS i . Constraint (29) indicates the time relationship between arriving and leaving any CS or BSS. In addition, the binary variables are specified by constraint (30).

5 Algorithm design

VRP has been proved to be an NP-hard problem, and it is usually challenging to find the optimal solution, so we can only use heuristic algorithms to obtain a satisfactory solution. The constraint condition of HOTDMDEVRPBRS is more complex than that of VRP, and it is more difficult to solve. Simulated annealing algorithm (SAA) is a general heuristic algorithm (Osman 1993) [44], which was first proposed by Metropolis et al., in 1953. It uses the similarity between the annealing process of solid matter in physics and the general combinatorial optimization problem to realize simulated annealing, so as to provide an effective solution for problems with Non-deterministic Polynomial complexity and overcome the dependence on local and initial values in other optimization processes. It has the characteristics of strong robustness, flexible search, global search and easy to implement. Therefore, according to the characteristics of the problem and model, the SAA is used to solve the HOTDMDEVRPBRS (Fig.2).

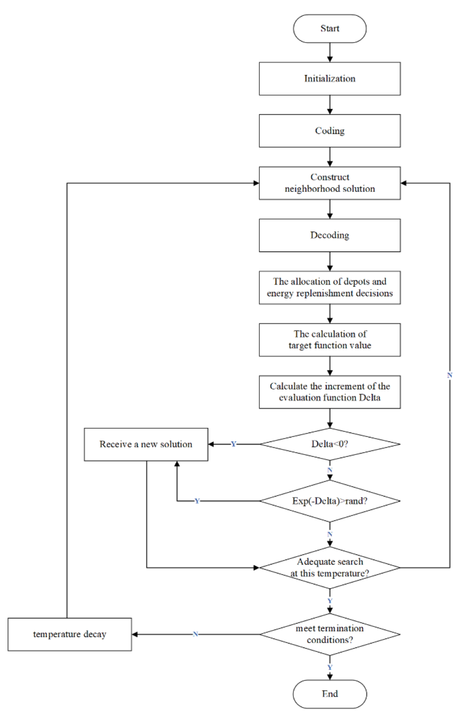

Fig. 2. Flowchart of Simulated Annealing Algorithm

The specific solving steps are as follows:

Procedure 1: Parameter initialization. Let $totalCost$ be the optimal total cost, $totalCost = +\infty$. Let $bestSol$ be the optimal solution, sol be the current solution, N be the maximum number of EVs used, and C be the number of customers. Let L be the length of Markov chain, $L=50$. Let K be the temperature decay coefficient, $K=0.98$. Let T_0 be the initial temperature, $T_0=100$, and T be the current temperature, $T = T_0$. $maxIter$ denotes the maximum iterations, $maxIter=600$. $iter$ denotes the current iterations, $iter = 1$. $iter2$ denotes the times of searches at the current temperature, $iter2 = 1$.

Procedure 2: Coding. According to real number coding, the real number sequence of $1 \sim C + N - 1$ is randomly generated as the current solution.

Procedure 3: The construction of neighborhood solution. A neighborhood solution $newSol$ is constructed by performing neighborhood search on current solution sol through the swap, insert, and flip operators.

Procedure 4: Decoding. Find real number subscript $splitLoc$ whose value is greater than C (the number of customers) in the solution sequence, then divide the solution sequence into multiple distribution routes $paths$ by $splitLoc$.

Procedure 5: The allocation of depots and energy replenishment decisions. The specific process of depot allocation and energy replenishment decision for a single distribution route $path$ is as follows: Step 1: Initialization. Enter the initial route $path$ of the EV, and let $newPath$ be the distribution route after adding depots and energy replenishment infrastructure (CS and BSS). Step2: The allocation of depots. Using the greedy strategy, we select depot M_i closest to first customer $path_{first}$ on the EV distribution route as the starting point, and select depot M_j closest to last customer $path_{end}$ on the EV distribution route as the return point, then $newPath = [M_i, path, M_j]$. Step3: The energy replenishment decision of the EV. It is judged whether the EV satisfies the remaining energy condition for traveling from the current node i to next node j during the distribution process (Constraint 20). If it is satisfied, the EV travels to node j; otherwise, the EV needs to select energy replenishing station G closest to node i , and insert G into $newPath$.

Procedure 6: The calculation of target function value. Take the sum $cost_{newSol}$ of the economic cost and environmental cost of each distribution route as the target value, if $cost_{newSol} \le totalCost$, then $totalCost = cost_{newSol}$, $bestSol = newSol$.

Procedure 7: Acceptance criteria for the new solution. Calculate the value of Δ , $\Delta = cost_{newSol} - cost_{sol}$. If $\Delta \le 0$, then receive the current solution, $sol = newSol$, $cost_{sol} = cost_{newSol}$; otherwise, calculate the value of p , $p = exp(-\frac{\Delta}{T})$. If $p \ge rand$, then receive the current solution with a certain probability, $sol = newSol$, $cost_{sol} = cost_{newSol}$.

Procedure 8: The judgment of algorithm termination. If $iter > maxIter$, the algorithm ends; otherwise, further judge whether $iter2 \le L$, if $iter2 \le L$, then $iter2 = iter2 + 1$, go to Procedure 3; otherwise, $iter = iter + 1$, $T = T * K$, $iter2 = 1$, go to Procedure 3.

6 Computational experiments

6.1 Experimental setup

Currently, there is no standard test instance about HOTDMDEVRPBRS, and most literature generates test instances based on Solomon instances. For example, Schneider et al. (2014) used the Solomon instance as a benchmark instance, and generated 21 charging stations (code S0-S20) in each benchmark instance to construct a new experimental instance. Therefore, in this paper, we use the test instance constructed by Schneider as the benchmark instance, and some CS nodes in the instance are converted into depot and BSS nodes, so the HOTDMDEVRPBRS test instance is built. In each test instance, there are 100 customers, 6 depots, 7 charging stations and 8 battery swapping stations. The data of each test instance specifically includes depot coordinates, CS coordinates, BSS coordinates, customer coordinates, demand, and service time.

In order to meet the requirements of the algorithm test in this paper, the following data are supplemented: (1) According to the update time of the traffic congestion index in Beijing, we set $U = 15$ minutes, and the whole day is divided into 96 periods. (2) We set the earliest working time of the depot to be 6:00 in the morning, the morning and evening traffic peak time periods are 7:00-9:00 and 17:00-19:00, respectively. We set the speed $v_{ijk}^R = 20$ during the congestion period. (3) Using the remainder function $\lambda = \text{mod}(R,3)$, when λ takes the value [1, 2, 0], it corresponds to the three time-dependent travel speeds $[v(1\text{-}\varpi), v(1\text{+}2\varpi), v(1\text{-}3\varpi)]$ of the EV in the ordinary period, where $\varpi = 0.1$, $v = 60$ km/h. (4) The futures price of carbon emissions in Europe in 2021 has been fluctuating within the range of 50-90 Euros/ton, that is, 345-621 yuan/ton (converted at the exchange rate of EUR/RMB at 1:6.9). Therefore, this paper sets the unit carbon emission price c_6 of logistics enterprises to 500 yuan/ton, that is, 0.5 yuan/kg. (5) Referring to the data of Liu et al. (2020) and market price standards. The experimental parameter settings are shown in Table 1.

Table 1
The settings of model variables and algorithm parameters

Parameters	**Value**	**Parameters**	**Value**
L	3000 kg	W	1000 kg
Q	55 kWh	a	0 m/s^2
g	9.8 m/s^2	θ_{ij}	0°
C_r	0	C_d	0.7
A	6.710 m^2	ρ	1.29 kg/m^3
η	90%	p_e	60 kW
φ	10 min	c_1	0.5 yuan/min
c_2	200 yuan/car	c_3	0.3 yuan/min
c_4	0.5 yuan/min	c_5	50 yuan/time
L	50	$maxIter$	600
K	0.98	T_0	100

The proposed SAA was implemented in MATLAB 2020a. All experiments were performed on a computer with an 11th Gen Intel(R) Core(TM) i5-1135G7 @ 2.40 GHz processor and 16 GB RAM.

6.2 Experimental results analysis

6.2.1 Result analysis of HOTDMDEVRPBRS in different instances

To verify the rationality and effectiveness of the HOTDMDEVRPBRS, the experiments were carried out with test instances of different customer coordinate distributions. The experimental results are shown in Table 2. IN represents the instance name, TC represents the total cost (unit: yuan), TT represents the total distribution time (unit: minute), FC represents the total fixed usage cost of EVs (unit: yuan), DC represents the travel time cost (unit: yuan) , AC represents the customer service time cost (unit: yuan), SC represents the battery swapping and charging cost of EVs (unit: yuan), CC represents the carbon emission cost (unit: yuan), SS represents the times of charging and battery swapping, CN represents the number of EVs used, RT represents the program runtime (unit: seconds), and AVE represents the average value.

Table 2
The experimental results of HOTDMDEVRPBRS for different instances

IN	**TC**	**TT**	**FC**	**DC**	**AC**	**SC**	**CC**	**SS**	**CN**	**RT**
C101	1294.81	2070.13	400.00	475.39	300.00	59.68	59.74	2	2	126.58
C102	1241.07	1803.74	400.00	391.87	300.00	100.00	49.20	2	2	123.82
R101	1360.13	2186.73	400.00	533.49	300.00	59.88	66.76	3	2	136.87
R102	1458.43	2197.78	400.00	558.62	300.00	130.27	69.54	3	2	130.06
RC101	1432.22	2150.84	400.00	535.35	300.00	130.07	66.80	3	2	140.87
RC102	1463.55	2203.43	400.00	563.27	300.00	128.45	71.83	3	2	145.75
C201	1395.78	2163.65	400.00	546.73	300.00	80.10	68.95	2	2	124.59
C202	1311.19	2016.17	400.00	472.76	300.00	80.32	58.11	2	2	120.77
R201	1420.83	2216.68	400.00	543.67	300.00	109.67	67.49	3	2	129.82
R202	1471.07	2222.70	400.00	571.72	300.00	129.63	69.72	3	2	130.64
RC201	1546.95	2352.06	400.00	636.44	300.00	129.59	80.92	3	2	139.33
RC202	1473.73	2219.87	400.00	571.37	300.00	128.56	73.80	3	2	140.16
AVE	1405.82	2150.32	400.00	533.39	300.00	105.52	66.90	3	2	132.44

It can be seen from the results in Table 2: (1) According to the values of TC, FC, DC, AC, SC and CC, the fixed usage cost, travel time cost, customer service time cost, battery charging and swapping cost and carbon emission cost of EVs account for 28.45%, 37.94%, 7.51%, 21.34% and 4.76% of the total cost, respectively. It shows that the fixed usage cost of EVs, the travel time cost and the customer service time cost are the main factors that affect the total cost of logistics distribution. Logistics enterprises should use large-capacity EVs for distribution as much as possible to reduce the number of EVs used; at the same time, enterprise managers must consider the influence of time-dependent speed on the travel time of EVs in the actual operation planning, avoid traffic congestion period as far as possible to carry out distribution, shorten the EV travel time and reduce the cost of logistics distribution. (2) According to the experimental results of TT, DC, SS, and CN, two EVs are enabled for distribution in each type of test instance, where two EVs in type C instances can complete the distribution task by respectively replenishing energy at most once on the way, but in type R and type RC instances, one of the EVs needs to replenish energy twice on the way to complete the distribution task. Because the customer coordinates of type C are relatively concentrated and the distance between customer locations is short, so the EVs can complete the distribution task as long as traveling a shorter distance; the customer coordinates of type R and type RC instances are relatively scattered and the distance between customer locations is long, so the EVs need to travel a longer distance to complete the distribution task. If the EVs are only allowed to replenish energy once during the distribution, more EVs will be enabled to carry out tasks, making it difficult to use the EV capacity fully, and the logistics cost will be increased. In actual logistics planning, the EV energy replenishment times should be arranged reasonably according to the EV capacity, customer coordinates and demand. (3) According to the value of RT, the algorithm's runtime is 145.75 seconds at the maximum, 120.77 seconds at the minimum, and 132.44 seconds on average. It shows that the SAA in this paper can give a planning scheme that meets the decision-making objective in a reasonable time, which is efficient, feasible and practical.

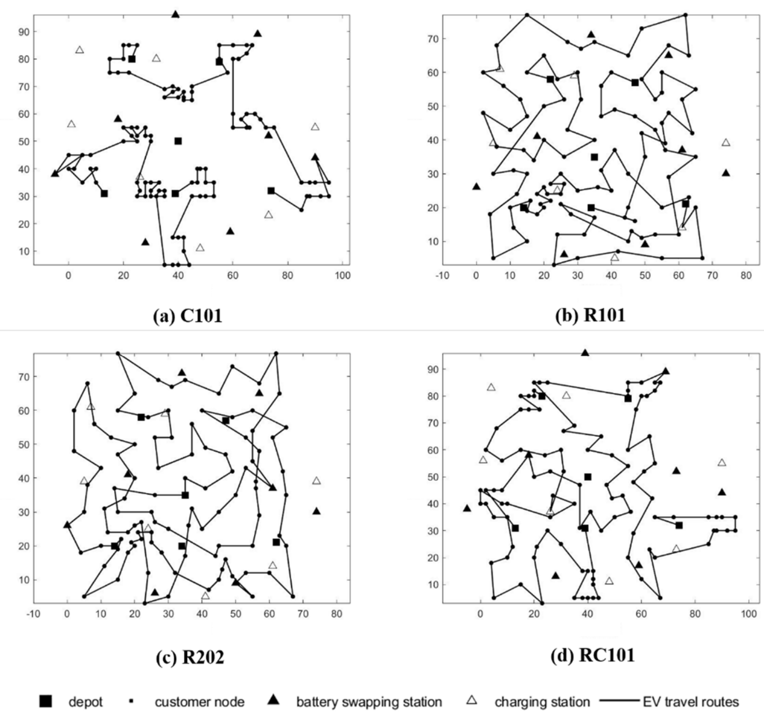

Fig. 3. The planning schemes of HOTDMDEVRPBRS in different instances

The planning schemes of HOTDMDEVRPBRS in instance C101, R101, R202 and RC101 are shown in Fig.3(a), 3(b), 3(c) and 3(d), respectively.

It can be seen from Fig. 3: (1) The customer coordinates of the type C instance (Fig.3(a)) are centralized distribution, customers are concentrated in several areas, and adjacent customers in each area are served by the same EV, which has a short travel distance. (2) The customer coordinates of the type R instance (Fig.3(b) and Fig.3(c)) are random distribution, customers are randomly distributed in each area, and customers in similar locations are served by the same EV, which has a long travel distance. (3) The customer coordinates of the type RC instance (Fig.3(d)) are mixed distribution, customer distribution has the characteristics of a combination of centralized distribution and random distribution, and adjacent customers in each area are served by the same EV, which has a relatively long travel distance. (4) The distribution routes of each instance are clear, seldom circuitous and crossed. It shows that the algorithm in this paper can scientifically plan the joint distribution route of EVs according to various factors such as EV capacity, customer coordinates, demand, and the coordinates of CS and BSS, which is feasible and reasonable.

6.2.2 Comparative analysis of different energy replenishment modes

On the premise that the other parameters remain unchanged, a comparative experiment is carried out between pure battery swapping mode (PBSM) (all energy supplement facilities are only BSSs), pure charging mode (PCM) (all energy supplement facilities are only CSs) and hybrid energy replenishment mode (HERM) (energy supplement facilities include both CSs and BSSs). The experimental results are shown in Table 3.

Table 3
Comparative results of different energy replenishment modes

IN	HERM			PBSM			PCM		
	TC	TT	SC	TC	TT	SC	TC	TT	SC
C103	1249.97	1904.67	80.43	1270.43	1855.93	100.00	1229.75	1954.28	59.92
R103	1340.99	2072.43	80.40	1361.86	2024.78	100.00	1320.11	2120.20	60.63
RC103	1606.00	2290.17	200.00	1606.00	2290.17	200.00	1486.77	2415.11	86.46
C203	1318.49	1940.36	100.00	1318.49	1940.36	100.00	1278.38	2041.10	57.46
R203	1368.48	2117.11	79.43	1390.13	2070.76	100.00	1348.51	2167.86	58.00
RC203	1496.59	2347.87	110.86	1518.15	2216.03	150.00	1456.45	2361.59	91.29
AVE	1396.75	2112.10	108.52	1410.84	2066.34	125.00	1353.33	2176.69	68.96

It can be seen from the results in Table 3: (1) Considering the values of TC, TT and SC, in each test instance, the total distribution time based on the PBSM is generally less than that of other energy supplementation modes. The average total distribution time of the HERM and the PCM is 2.21% and 5.34% longer than that of the PBSM, respectively. However, the total cost and energy replenishment cost of the PBSM are higher than other energy replenishment modes. In terms of the total cost, the PBSM is 1.01% and 4.25% higher on average than the HERM and the PCM, respectively; in terms of energy replenishment cost, the PBSM is 15.19% and 81.26% higher on average than the HERM and the PCM, respectively. The total cost and energy replenishment cost of the PCM are both the lowest, but its total distribution time is the longest. It shows that the PBSM for EVs can effectively shorten the energy replenishment time, but it will result in higher energy replenishment cost, which is suitable for logistics distribution scenarios with high urgency of customer demand or strong timeliness of packages; using PCM can effectively reduce the energy replenishment cost, but requires a longer charging time, which is suitable for logistics distribution scenarios with weak timeliness requirements. Using the HERM has strong flexibility, EVs can swap the battery to replenish energy in a situation with tight time and heavy tasks and choose partial charging to replenish energy in a situation with low timeliness requirements and lighter tasks. (2) According to the experimental results of TC and TT, although both the total cost and total distribution time of the HERM cannot achieve the optimum, the average total cost of the HERM is only 3.11% more than that of the PCM. The average total distribution time of HERM is only 2.16% more than that of the PBSM. It shows that the HERM can balance both total distribution cost and distribution efficiency at the same time.

6.2.3 Comparative analysis between HOJDM and closed distribution mode

On the premise that the other parameters remain unchanged, multi-type instances are applied to compare the HOJDM with the closed distribution mode (CDM). The experimental results are shown in Table 4, where TD represents the total travel distance (unit: km), PU represents the total energy consumption (unit: kWh), TCSR represents the total cost saving ratio between HOJDM and CDM (unit: %), TTSR represents the total distribution time saving ratio between HOJDM and CDM (unit: %). CCSR represents the carbon emission saving ratio between HOJDM and CDM (unit: %), and the meaning of the remaining notations is shown in Table 2.

Table 4
Comparative results of HOJDM and CDM

IN	HOJDM					CDM					TCSR	TTSR	CCSR
	TC	TT	TD	PU	CC	TC	TT	TD	PU	CC			
C104	1443.08	2252.17	856.07	208.7	72.00	1486.47	2328.79	917.88	223.42	77.08	3.01%	3.40%	7.05%
R104	1442.26	2167.49	823.44	198.61	68.52	1477.44	2229.65	873.39	210.47	72.61	2.44%	2.87%	5.97%
RC104	1550.51	2361.68	965.09	230.9	79.66	1606.94	2461.36	1045.47	250.06	86.27	3.64%	4.22%	8.30%
C204	1331.68	2135.6	761.65	185.15	63.88	1409.24	2272.54	872.18	211.51	72.97	5.82%	6.41%	14.24%
R204	1406.50	2192.07	793.34	189.75	65.46	1446.03	2261.92	849.48	203.08	70.06	2.81%	3.19%	7.03%
RC204	1469.79	2215.35	859.64	209.02	72.11	1524.94	2312.6	938.45	227.94	78.64	3.75%	4.39%	9.05%
AVE	1440.63	2220.73	843.21	203.69	70.27	1491.84	2311.14	916.14	221.08	76.27	3.55%	4.08%	8.54%

It can be seen from the results in Table 4: (1) According to the values of TC and TT in each test instance, both the total cost and total distribution time of the HOJDM are less than that of the CDM. Among them, the total cost can be saved by 5.82% at the highest, 2.44% at the lowest, and 3.55% on average; the total distribution time can be saved by 6.41% at the highest, 2.87% at the lowest, and 4.08% on average. This is because after completing the distribution task, the EV based on the HOJDM does not have to return to the original depot, but can choose to park in the nearest depot, shortening the EV travel time and reducing the distribution cost to a certain extent. Therefore, when an enterprise decides to set up a new depot, the collaboration between the depots should be considered. (2) According to the results of TD and PU, the travel distance and energy consumption of the HOJDM are significantly lower than that of the CDM, with an average saving of 8.65% and 8.54%, respectively. It shows that applying the HOJDM gives the planning scheme a greater space for route optimization, effectively shortening the EV travel distance and reducing the EV energy consumption, which is scientific, rational and feasible. Enterprises should promote the use of this model in the actual logistics distribution. (3) According to the result of CC, the

HOJDM significantly reduces the EV carbon emissions compared with the CDM, the highest carbon emission reduction is 14.24%, the lowest carbon emission reduction is 5.97%, and the average carbon emission reduction is 8.54%. It shows that the HOJDM can effectively promote the energy saving and emission reduction of logistics distribution, which is of great significance for promoting the green development of urban logistics. Government decision-makers should encourage urban logistics enterprises to consider the possibility of joint distribution when building multiple depots.

6.2.4 Comparative analysis on the times of energy replenishment

On the premise that the other parameters remain unchanged, a comparative experiment is carried out between the multiple-charging-and-swapping strategy (MCSS) and single-charging-and-swapping strategy (SCSS). The SCSS means that an EV can only be charged or swapped battery once on the road, while the MCSS allows an EV to be charged once and swapped battery unlimited. Several test instances of type C and type RC are applied to conduct experiments. The experimental results are shown in Table 5, where MTD represents the average travel distance of each EV (unit: km), MLD represents the average load of each EV (unit: kg), and the meanings of other notations are shown in Table 2.

Table 5
Comparative results of MCSS and SCSS

IN	MCSS				SCSS				TCSR
	TC	MTD	MLD	CN	TC	MTD	MLD	CN	
R104	1407.52	387.60	729.00	2	1826.49	215.17	364.50	4	29.77%
R105	1480.72	445.69	729.00	2	1805.07	208.69	364.50	4	21.91%
R204	1495.11	444.68	729.00	2	1753.74	196.52	364.50	4	17.30%
R205	1494.30	442.55	729.00	2	1791.25	206.31	364.50	4	19.87%
RC104	1595.37	497.10	862.00	2	1719.39	189.35	431.00	4	7.77%
RC105	1468.10	440.60	862.00	2	1855.89	212.65	431.00	4	26.41%
RC204	1379.23	399.32	862.00	2	1923.08	239.49	431.00	4	39.43%
RC205	1533.46	470.02	862.00	2	1845.91	224.57	431.00	4	20.38%
AVE	1481.73	440.94	795.50	2	1815.10	211.59	397.75	4	22.50%

It can be seen from the results in Table 5: (1) According to the values of TC and CN, in each test instance, the total cost of using MCSS is significantly lower than that of using SCSS, with a maximum saving of 39.43%, a minimum saving of 7.77%, and an average saving of 22.50%. Because the SCSS makes the working hours of the EV battery, the number of served customers and the distribution range limited, so it is necessary for logistics enterprises to enable more EVs to carry out distribution, increasing the EV fixed usage cost. (2) According to the values of MTD and MLD, in the test instances of type R and RC, using MCSS only needs to enable two EVs to complete the distribution task, and each EV serves a larger number of customers, travels a longer distance, which can effectively use the load capacity of each EV; while using SCSS requires four EVs to complete the distribution task, and each EV serves a relatively small number of customers, travels a relatively short distance. It is difficult to fully use EV load capacity, resulting in the waste of transportation capacity. The average travel distance and average load capacity of an EV under the MCSS are 108.39% and 100.00% higher than those under the SCSS, respectively. It shows that the MCSS can effectively expand the EV travel distance, improve the utilization rate of EV capacity, reduce the distribution cost, lift the distribution efficiency, and provide more optimization space for multi-depot EV half-open joint distribution route planning.

6.2.5 Sensitivity analysis

(1) Comparative experiment on different speeds of EVs

The experiment is conducted for analysis by a test instance of type R with the random distribution of customer coordinates (R206). On the premise that the other parameters remain unchanged, the travel speed of the EV during the normal period varies within the range of [40, 80] at a step of 10 km/h, and the travel speed during the congestion period varies within the range of [10, 30] at a step of 5 km/h. The specific speed combination and experimental results are shown in Table 6, where VC represents the travel speed of the EV in the normal period (unit: km/h), VF represents the travel speed of the EV in the congestion period (unit: km/h), and the meanings of the other notations are shown in Table 2.

Table 6
Experimental results on different speeds of EV

VC	VF	TC	TT	DC	PU	CC	SS
40	10	1542.31	2601.08	770.38	121.06	41.77	1
50	15	1450.44	2307.23	618.40	150.24	51.83	2
60	20	1370.77	2123.40	528.04	185.71	64.07	2
70	25	1372.88	2088.85	480.34	241.91	83.46	3
80	30	1474.72	2054.95	452.05	325.36	112.25	5

It can be seen from the results in Table 6: (1) According to the value of TC, the total cost decreases with EV speed increasing from 40 km/h to 60 km/h, while when the speed is greater than 60 km/h, the total cost increases with the increase of speed. (2) According to the values of TT and DC, both the total distribution time and the travel time cost show a decreasing trend as the EV speed increases, but when the EV speed increases from 40 km/h to 60 km/h, the total distribution time decreases by 22.50%, the total travel time decreases by 45.89%; when the EV speed increases from 60 km/h to 80 km/h, the total distribution time only decreases by 3.33%, the total travel time cost only decreases by 16.8%. It shows that the benefits brought by the increase of EV speed to the total distribution time and the total travel time cost are gradually decreasing. (3) According to the values of PU and SS, both the energy consumption and the times of charging and battery swapping show an increasing trend with the increase of EV speed. This is because the increase in the EV speed during normal and congestion periods can effectively shorten the distribution time and significantly reduce the EV travel time cost. However, the increase in speed will also increase the EV energy consumption, making EVs need to replenish energy more times on the distribution routes, which increases the charging and battery swapping time and cost. (4) According to the value of CC, although the increase in EV speed brings about a cost reduction, the EV carbon emissions will also increase due to the increase in energy consumption. Meanwhile, when the EV speed increases from 40 km/h to 60 km/h, the EV carbon emissions increase by 53.39%, but when the EV speed increases from 60 km/h to 80 km/h, the EV carbon emissions increase by 75.20%, indicating that the increase in EV speed will lead to an accelerated increase in carbon emissions, which is not conducive to the green development of logistics distribution. Therefore, EVs traveling too fast or too slow are both not conducive to the economic and environmental development of logistics distribution. In actual distribution, EV travel speed should be kept at 60-70 km/h during normal periods and 20-25 km/h during congestion periods, which is helpful in reducing distribution cost and improving distribution efficiency.

(2) Comparative experiment on different number of depots

The experiment is conducted for analysis by a test instance of type R with the random distribution of customer coordinates (R106). On the premise that the other parameters remain unchanged, the number of depots varies within the range of [1, 7] at a step of 2. The experimental results are shown in Table 7, where m represents the number of depots, and the meanings of the other notations are shown in Table 2.

Table 7
Experimental results on different number of depots

m	TC	TT	DC	PU	CC
1	1514.89	2298.98	609.20	218.50	75.38
3	1486.65	2246.40	582.93	212.94	73.46
5	1386.83	2236.20	557.13	199.21	68.73
7	1318.76	2113.86	495.96	179.21	61.83

It can be seen from the results in Table 7: (1) According to the result of TC, the total cost decreases continuously with the increase in the number of depots. When the number of depots is increased from 1 to 3, the total cost is reduced by 1.90%; when the number of depots is increased from 3 to 5, the total cost is reduced by 7.20%; when the number of depots is increased from 5 to 7, the total cost is reduced by 5.16%. It shows that although the increase in the number of depots reduces the operating cost of logistics companies, the benefits brought by it do not always show an upward trend. Meanwhile, this paper has not considered the cost of building and maintaining depots. Therefore, when a logistics enterprise plans to build a new depot, it should also comprehensively consider its business scale, the distribution of customer locations and the operation cost of the new depot, so as to avoid blind expansion of the depot. (2) According to the results of TT, DC, PU and CC, the total distribution time, travel time cost, EV energy consumption, and carbon emissions all decrease with the increase in the number of depots. Among them, the total distribution time is reduced by an average of 2.86%, the travel time cost is reduced by an average of 7.16%, and the energy consumption and carbon emissions are reduced by an average of 6.89%. This is because after increasing the number of depots, the depots where EVs choose to depart and return have more optimization space, thus effectively shortening the EV travel distance and travel time and reducing energy consumption. It shows that the multi-depot joint distribution is helpful for enterprises to reduce economic and environmental costs.

(3) Comparative experiment on different carbon prices.

Carbon prices in the current global trading market are not fixed and can rise or fall over time. In order to analyze the impact of carbon trading price on the enterprise and social environment, on the premise that the other parameters remain unchanged, the carbon price c_6 varies within the range of [0, 3] at a step of 0.5.

Table 8
Experimental results on different carbon prices

C_6	CC	CM	TC	CCP
0	0.00	131.41	1646.50	0.00%
0.5	65.09	130.18	1712.78	3.80%
1	127.14	127.14	1777.12	7.15%
1.5	186.90	124.60	1849.84	10.10%
2	240.32	120.16	1897.04	12.67%
2.5	300.40	120.16	1963.40	15.30%
3	360.48	120.16	2023.48	17.81%

The experiment is conducted for analysis by an instance of type R with the random distribution of customer coordinates (R106). The experimental results are shown in Table 8 and Fig.4, where CM represents the amount of carbon emission (unit: kg), and CCP represents the proportion of carbon emission cost in the total cost.

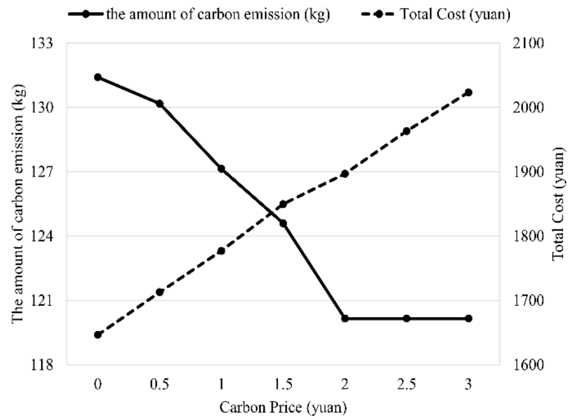

Fig. 4. Changes in carbon emissions and total costs under different carbon prices

Combining the results in Table 8 and Fig. 4, we can see that when the carbon price is between [0, 2], with the rise of carbon prices, the carbon emission of EVs gradually decreases from 131.41kg to 120.16kg, a decrease of 9.36%, the total cost of the enterprise at this time is on the rise, from 1646.50 yuan to 1897.04 yuan, an increase of 15.22%. When the carbon price is greater than 2 yuan/kg, even if the carbon price continues to increase, the carbon emissions of the enterprise basically remain unchanged. That is, due to the limitations of technology and optimization, the company can no longer continue to reduce emissions. It shows that the restraint effect of carbon prices on enterprises' carbon emission behavior is limited, and too high or too low carbon price is not conducive to promoting logistics enterprises' green development. In this instance, the carbon price in the range of [0.5,2] (unit: yuan/kg) is more reasonable. In this price range, logistics companies are more sensitive to the carbon price, and they will focus on the carbon emissions caused by the EV energy consumption when planning distribution routes to reduce the energy consumption as much as possible and control the cost. For government decision-makers, reasonable control of carbon trading prices and gradual improvement of the carbon trading mechanism are important means to promote energy conservation, emission reduction and green sustainable development in logistics distribution.

6.3 Comparative analysis of different algorithms

In order to verify the effectiveness of SAA, a genetic algorithm (GA) for solving HOTDMDEVRPBRS is compiled for comparative analysis. In the GA, the population size is set to 50, the crossover probability is set to 0.9, the mutation probability is set to 0.05, the genetic generation gap is set to 0.9, and the times of iterations is set to 600. Multi-type instance experiments are conducted to compare SAA and GA, and the experimental results are shown in Table 9.

Table 9
Experimental results on different optimization algorithms

IN	SAA				GA				TCSR	TTSR
	TC	TT	DC	RT	TC	TT	DC	RT		
C107	1229.17	1868.64	400.15	125.40	1319.03	2111.79	498.03	140.04	7.31%	13.01%
R107	1411.39	2112.37	541.19	119.44	1451.77	2265.35	573.67	158.69	2.86%	7.24%
RC107	1505.98	2282.11	601.1	127.46	1668.36	2478.96	701.02	139.88	10.78%	8.63%
C207	1424.59	2125.97	528.11	124.51	1480.43	2221.59	578.97	135.88	3.92%	4.50%
R207	1443.30	2256.08	564.61	119.52	1515.14	2381.22	629.13	139.24	4.98%	5.55%
RC207	1352.54	2174.43	529.02	125.17	1488.22	2334.09	605.91	136.43	10.03%	7.34%
AVE	1402.16	2136.60	527.36	123.58	1487.16	2298.83	597.79	141.69	6.06%	7.59%

It can be seen from the results in Table 9: (1) According to the values of TC, TT and RT, the total cost and total distribution time of each test instance solved by SAA are significantly less than those of GA, in which the maximum saving of total cost is 10.03%, the minimum saving is 2.86%, and the average saving is 6.06%; the maximum saving of total distribution time is 13.01%, the minimum saving is 4.50%, and the average saving is 7.59%. Moreover, the average runtime of SAA is 14.65% lower than GA's. It shows that SAA can solve the HOTDMDEVRPBRS quickly and efficiently, effectively reduce the distribution cost, shorten the distribution time, and improve distribution efficiency. (2) According to the value of DC, the average travel time cost of each instance solved by SAA is 13.36% less than that solved by GA. It shows that SAA can reasonably plan the multi-depot half-open joint distribution routes of EVs and effectively shorten the EV distribution distance, which is feasible, reasonable and practical.

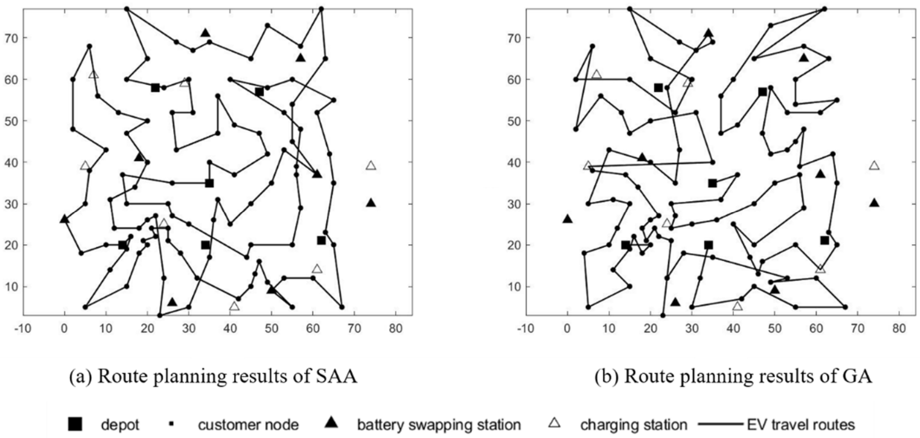

Fig. 5. Planning scheme of the HOTDMDEVRPBRS under different optimization algorithms

The planning scheme of the HOTDMDEVRPBRS for test instance R207 solved by SAA and GA is shown in Fig.5 (a) and Fig.5 (b), respectively.

According to Fig. 5, it can be seen that: (1) The EV distribution routes solved by SAA in Fig.5 (a) are clear, seldom crossed and circuitous, while distribution routes solved by GA in Fig.5 (b) overlap, existing the problem of roundabout distribution. (2) The energy replenishment facilities selected by EVs in Fig.5 (a) are all near the EV distribution routes, and the EVs only need to travel a short distance to replenish electricity; some of the energy replenishment facilities selected by EVs in Fig. 5 (b) are far away from the EV distribution routes, and the EVs need to travel a relatively long distance to replenish electricity, which delays the package delivery time of customers and reduces distribution efficiency. It shows that SAA can scientifically plan the distribution routes of HOTDMDEVRPBRS, shorten the travel distance and improve the distribution efficiency, which is reasonable, scientific and practical.

7. Conclusions and prospects

This paper studies HOTDMDEVRPBRS in last-mile delivery, the goal is to minimize the economic cost and environmental cost of logistics enterprises. Therefore, a mathematical optimization model is constructed and a multi-objective simulated annealing algorithm is designed according to the characteristics of the model. Extensive computational experiments are carried out with multi-type test instances, and the performance of the proposed model and method is evaluated. Finally, the experimental results show that: (1) The fixed usage cost and travel time cost of EVs are the main factors affecting the total operating cost of logistics enterprises. Large-capacity EVs should be used for distribution as much as possible to reduce the number of EVs used. At the same time, the influence of time-dependent speed on the travel time of EVs should be considered, and the distribution during the traffic congestion period should be avoided as far as possible, so as to shorten the EV travel time and reduce the logistics distribution cost. (2) By adopting the HOJDM, there is more optimization space for MDEVRP, which can effectively shorten the EV travel distance and reduce energy consumption and carbon emissions. Given the deteriorating urban environment, government decision-makers and logistics enterprise managers should vigorously popularize the HOJDM to promote the green sustainable development of urban distribution. (3) MCSS can effectively expand the travel distance of EVs, improve the utilization rate of EV capacity, reduce distribution cost and improve distribution efficiency. Logistics enterprises should actively collaborate with the charging and swapping station operators to establish a more rounded energy replenishment network to support the MCSS in the EV distribution task. (4) The EV travel speed and the number of depots will have a certain impact on logistics distribution. The increase in EV travel speed can significantly reduce the travel time cost, but it brings higher energy replenishment costs and carbon emissions, so logistics enterprises should require drivers to control the speed to maximize benefits when leasing EVs for distribution. The increasing number of depots has a certain optimization effect on reducing the total cost, total distribution time and EV travel time. However, when enterprises plan to increase a new depot, they also need to consider the construction cost and maintenance cost. They should comprehensively consider their business scale, the distribution of customer locations, the operating cost and other factors to avoid blind expansion of the depot. (5) Reasonable carbon prices can provide effective incentive signals for logistics enterprises to reduce carbon emissions. A too high or too low carbon price is not conducive to promoting the green development of logistics enterprises. If the carbon price is too low, it will dampen the enthusiasm of logistics enterprises to reduce emissions; if the carbon price is too high, it will also lead to a heavy burden on logistics enterprises. Therefore, the key for logistics enterprises is to correctly view the opportunities and challenges brought by carbon prices from the perspective of promoting the low-carbon transformation of the industry. The level of carbon prices is a market signal, enterprises should comply with the general trend of green and low-carbon transformation, deploy strategies such as the HOJDM, and seize favorable opportunities in development. Designing a faster and more efficient algorithm and considering the charging queuing phenomenon in the process of EV distribution will be the focus of subsequent research.

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