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Multi-Compartment Electric Vehicle Routing Problem for Perishable Products

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ABSTRACT

The study first proposes a heterogeneous fleet, multi-compartment electric vehicle routing problem for perishable products (MCEVRP-PP). We capture a lot of practical demands and constraints of the MCEVRP-PP, such as multiple temperature zones, the hard time window, charging more than once during delivery, various power consumption per unit of refrigeration, etc. We model the MCEVRP-PP as a mixed integer program and aim to optimize the total cost including vehicle fixed cost, power cost, and cooling cost. A hybrid ant colony optimization (HACO) is developed to solve the problem. In the transfer rule, the time window is introduced to improve flexibility in route construction. According to the features of multi-compartment electric vehicles, the capacity constraint judgment algorithm is developed in route construction. Six local search strategies are designed with time windows, recharging stations, etc. Experiments based on various instances validate that HACO solves MCEVRP-PP more effectively than the ant colony optimization (ACO). Compared with fuel vehicles and single-compartment vehicles, electric vehicles and multi-compartment electric vehicles can save the total cost and mileage, and increase utilization of vehicles.

KEYWORDS

multiple compartments; electric vehicle; cold chain logistics; heterogeneous fleet; vehicle routing problem; hybrid ant colony optimization

Perishable products, such as flowers, meats, and breads, tend to deteriorate in production and delivery. The distribution center (DC) of the retailer needs to deliver various perishable product segments to grocery stores. Each product segment requires a specified temperature requirement. Retailers define multiple temperature zones for various perishable products according to their temperature requirements. For example, fruits, vegetables, and milk are suitable for storage at 2 to 10 ℃; Aquatic products and raw meat are suitable for storage at −2 to 2 ℃; Frozen dumplings, frozen meat, and ice cream are suitable for storage at −20 to −18 ℃. To keep the perishable products from deteriorating, temperature conditions are necessary to be met during their transport and distribution. In the past, retailers only used single-compartment vehicles (SCVs). Since products requiring different temperature zones (e.g., frozen and chilled) cannot be mixed, an SCV can only satisfies one temperature requirement. Therefore, if a grocery store orders multiple product segments that each belongs to one special temperature zone, it has to be visited several times and receiving one product segment at a time[1,2]. Nowadays retailers have the alternative of multi-compartment vehicles (MCVs). The carriage of a vehicle is split into separate compartments. Each compartment with a separate refrigeration system can be set to a different temperature. Therefore, a vehicle can transport products in multiple temperature zones at once[3]. This makes vehicle route planning and order allocation more flexible.

In the past, retailers mainly used fuel vehicles (FVs) to transport perishable products. As we know, fuel vehicle is one of the major contributors to greenhouse gas (GHG) emissions. Perishable products require cold facilities (refrigeration) to maintain freshness and usability during transportation. Refrigeration consumes a large amount of energy. Therefore, the FVs have more significant environmental impacts[4,5]. With the rapid development of electric vehicles (EVs) technology in recent years, retailers now can choose to use EVs. EVs are among the cleanest means of transport because they can be powered by sustainable and renewable energy sources. They have no local GHG emissions and produce only minimal noise. The latter two aspects are especially important in urban areas with frequent traffic congestion[6]. Moreover, EVs defined to be zero-emission are able to meet the emission targets. Therefore, it is a general trend to use EVs for urban distribution.

Although the power battery technology of EVs has developed rapidly in recent years, due to the battery attenuation caused by low temperatures, the driving range will be further reduced, especially in winter. Thus, the available range is potentially not sufficient to perform the typical delivery tour of a logistics service provider in one run. Because reducing the number of deliveries performed by one vehicle is not a profitable option, visits to public recharging stations along the routes are required. It is necessary to consider the recharging in route planning to avoid inefficient vehicle routes with long detours, especially if the number of available recharging stations is scarce.

In this paper, we first propose a heterogeneous fleet, multi-compartment electric vehicle routing problem for perishable products (MCEVRP-PP). There is no existing research on electric vehicle routing problem (EVRP) with multiple compartments and a heterogeneous fleet, especially for perishable products. In the MCEVRP-PP, the energy consumption rate of EVs has a linear relationship with the weight of EVs. Each store has a hard time window, which means the service start time at each store cannot be later than its time window. Since a cooling system is installed in

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each compartment, the temperature of each compartment can be adjusted. Each compartment can be dedicated to any temperature zone. The EVs can visit the charging station as many times as needed while travelling. A mixed integer programming model is developed for the MCEVRP-PP, which aims to minimize the total distribution cost, including vehicle fixed cost, power cost, and refrigeration cost. Considering the NP-hard of the proposed problem, a hybrid ant colony optimization (HACO) is developed to solve the MCEVRP-PP.

The contributions of this study can be summarized as follows:

(1) We introduce electric vehicles with multiple compartments to the vehicle routing problem (VRP) for perishable products. We propose the MCEVRP-PP which considers multiple temperature zones, a heterogeneous fleet, multi-compartment EVs, hard time windows, charging during delivery, energy consumption rate linearly related to the load, etc. The mathematical programming model of MCEVRP-PP is developed.

(2) The HACO is developed to solve the MCEVRP-PP. We introduce six local search strategies in algorithm proposed to solve the more complex problem structure of VRPs.

(3) We validate the performance of the HACO using two newly designed MCEVRP-PP instance sets. In further experiments, we show that EVs with multi-compartment are always better than FVs with multi-compartments or EVs with single-compartment with respect to the total cost.

The remainder of this paper is organized as follows: Section 1 presents an overview of the existing work related to this research. Section 2 presents a formal definition and a mathematical model for the MCEVRP-PP. The algorithm design process is introduced in Section 3. The algorithm is tested using extensive numerical experiments. The experimental design and the corresponding results are presented in Section 4. Finally, the main findings are summarized in Section 5.

1 Related Work

1.1 VRP for perishable products

When using vehicles without refrigeration equipment to distribute groceries such as perishable products, there is a phenomenon of decay and deterioration, so stores have higher requirements on the timeliness of perishable products distribution and often set strict time windows. Osvald and Stirn[1], Amorim et al.[7], and Govindan et al.[2] established the vehicle routing problem with time window (VRPTW) model for perishable products, which considers the loss caused by product decay. Wang et al.[8] considered a VRPTW model with multiple objectives to consider the cost-freshness trade-off. The loss of freshness is calculated using a nonlinear freshness factor. Some literature considered the relationship between road conditions, vibration, and mechanical damage in perishable food. Li et al.[9] considered road conditions and their influence on the deterioration and bruising in the distribution of fresh fruits and vegetables. Al Theeb et al.[10] presented a comprehensive mixed integer optimization model for the cold supply chain that combined the inventory allocation problem with the vehicle routing problem. To solve the model, Al Theeb et al.[10] designed a multi-phase approach. Babagolzadeh et al.[5] studied the inventory-route problem for the cold supply chain under a carbon tax supervision mechanism based on uncertain demand. The goal is to minimize total costs comprising storage cost, transportation cost, lost sale cost, and carbon emissions costs. However, although the article claims to use refrigerated vehicles, it does not consider the fuel consumption cost and carbon emission caused by vehicle refrigeration during transportation.

1.2 VRP for multiple compartments vehicles

All the above studies used SCVs. Due to technological advances, MCVs can be used to deliver perishable products. The use of MCVs allows retailers to transport products with multiple temperature zones in one vehicle, which would otherwise need to be transported in multiple shipments. This will reduce the number of visits to a store and enable more flexible route planning and order allocation. Besides perishable products, multi-compartment vehicle routing problem (MCVRP) is widely applied in fuel delivery, classified collection of waste, etc.[11–15] In these applications, MCVs are capable of transporting goods that cannot be mixed at one time. There have been many scholars discussing MCVRP in different scenarios. Fallahi et al.[16] discussed a basic MCVRP in which the type of product in each compartment is fixed, and the demand of a store for a product is not allowed to be split. Mendoza et al.[17] solved MCVRP with random demand by constructive heuristics. Alinaghian and Shokouhi[18] discussed a multi-depot MCVRP and developed a hybrid adaptive large neighborhood search. Eshtehadi et al.[19] proposed an MCVRP based on realistic urban logistics. The study considered hard time windows and divided stores into three groups based on order arrival time and delivery service preference. Chen and Shi[20] presented a hybrid particle swarm optimization with simulated annealing to solve the MCVRP.

Gas stations sell a variety of fuel products, which need to be delivered by oil tankers with multi-compartment. Coelho and Laporte[11] defined and discussed the differences in four multi-compartment distribution problems for fuel delivery. Some accurate algorithms are designed for the above four multi-compartment delivery problems[14]. Avella et al.[21] discussed the fuel delivery network of one depot and a heterogeneous fleet with compartments. They proposed a set partition formula, and employed the branch pricing method to solve the problem of 6 trucks and 25 stores. Cornillier et al.[22–24] conducted a series of studies on the MCVRP for fuel delivery. First, they developed an accurate algorithm for MCVRP with a single depot and heterogeneous fleet[22], then further considered MCVRP[23] with the limited number of vehicles, and then discussed MCVRP with time window, and proposed two heuristic algorithms[24]. In 2012, Cornillier et al.[25] further studied a more practical MCVRP for fuel delivery in which they consider multiple depots, heterogeneous fleet, the limited number of vehicles, hard time window, multi-trips, unsplit compartments, unsplit tanks, and the gas station that can only be visited once by a vehicle. Wang et al.[12] described a model for the fuel replenishment problem (FRP), which considers multi-compartments trucks, a heterogeneous fleet, multiple trips of each truck, and hard time window. The goal of FRP is to compute schedules of minimum duration. Efthymiadis et al.[26] developed an optimization model to solve a heterogeneous fleet MCVRP for a medium size gasoline delivery company.

Chen et al.[27] considered multi-compartment vehicles with a single fleet for cold chain logistics based on the practical situation, and proposed a large neighborhood search (LNS) algorithm. The experimental results showed that LNS solved MCVRP effectively. Ostermeier and Hübner[3] discussed the vehicle routing and selection problem of single- and multi-compartment vehicles for grocery distribution. The LNS was presented to solve the corresponding problem. Experiments showed that a mixed fleet is always better than an exclusive fleet of single-compartment vehicles or multi-compartment vehicles, which can reduce costs by up to 30%. Martins et al.[28] proposed the adaptive large neighborhood search (ALNS) algorithm for MCVRP with product-oriented time windows assignment and validated the effectiveness with basic instances. In addition, the experiments by simulating data from retail practices showed that a consistent MCV distribution leads to a better overall solution comparison with daily planned ex-post time window assignment and facilitated more on-time deliveries.

1.3 VRP for electric vehicles

EVRP is a variant of VRP. Making a viable distribution plan for electric vehicles requires considering the electric vehicle features, such as, endurance, recharging, and so on. Bruglieri et al.[29] modeled the EVRP with the objectives of shortest mileage, shortest charging time as well as the fewest vehicles. A branching variable neighborhood search algorithm was designed to solve the problem. One of the main features of electric vehicles is that the power source is electrical energy. The charging strategy affects the EVRP solutions. In the study of Keskin and Çatay[30], the recharging station determines the charging amount based on the charging strategy. Erdem and Koç[31] also considered the charging state. Erdelić et al.[32] proposed the strategies that mixed the single charging strategy and multiple charging strategies for the EVRPTW problem. As far as charging speed is concerned, three charging strategies are available: fast, normal, and slow charging[33]. In terms of charging degree, there are two strategies: full charging and partial charging[30]. Linear function and nonlinear function are two relationships of charging quantity and charging time[34–36]. From the aspect of allowable charging times, it can be divided into single charging and multiple charging[32]. In this study, the EVs are allowed to charge on the way for one time, and it is assumed that each charge will be filled at a constant rate under the fast strategy. Furthermore, Verma[37] considered both recharging and battery swapping in the EVRPTW and assumed that the available stations are both recharging stations and battery swapping stations. The driving range of EVs is shorter than that of fuel vehicles. Therefore, energy consumption is a current research hot topic in EVRP. Most studies assumed a linear correlation between energy consumption of EVs and mileage. However, other factors such as acceleration, load, and speed are also relevant to energy consumption[38]. In Goeke and Schneider's[39] research on the EVRP, the effect of loads on energy consumption has received attention, while Zhang et al.[40] considered the stochastic and unoptimized speed, slope, and other factors. Xiao et al.[41] introduced energy consumption rate (ECR) into the EVRPTW, and ECR was considered as a joint nonlinear function of the speed and load.

1.4 Summary

There is no literature on the application of multi-compartment electric vehicles with a heterogeneous fleet to VRP for perishable products so far. In this study, heterogeneous electric vehicles with multiple compartments are applied to perishable products distribution for the first time. The fuel VRP for perishable products frequently considers decay losses and carbon emissions. While in our MCEVRP-PP, it is not necessary to consider product deterioration and carbon emissions, but to consider such requirements as refrigeration energy consumption and charging at public recharging stations during distribution. These requirements significantly increase the complexity of problem-solving.

2 Problem Description and Formulation

The DC is responsible for delivering various perishable product segments to grocery stores. We defined the set of grocery stores $C=\{1,2,\dots,n\}$. 0 and $n+1$ are the DC. 0 and $n+1$ represent that an EV departs from the DC and an EV returns to the DC, respectively. In practice, an EV may visit the same charging station several times during a trip. In the mathematical model, we introduce virtual charging stations, which are the copies of real charging stations. It is ensured that the charging station is visited at most once during a trip. We defined the set of real and virtual recharging stations $F=\{1,2,\dots,l\}$. $V=C\cup F\cup\{0\}\cup\{n+1\}$. The problem is defined on a complete directed graph $G=(V,E)$ with the set of arcs $E=\{(i,j)\,|\,i,j\in V, i\neq j\}$. Each arc is associated with a non-negative distance d_{ij}, and a travel time t_{ij}.

M denotes the set of product segments. Perishable products requiring the same temperature can be transported in the same compartment and they constitute a product segment. The set $K=\{1,2,\dots,N\}$ denotes a heterogeneous fleet of EVs, which transport perishable products for stores in C. Each EV consists of multiple compartments, and the number of compartments of different vehicles is the same. D is the set of compartments of a vehicle. Each compartment is dedicated to only one product segment. Since a cooling system is installed in each compartment, the compartment can be dedicated to any product segment. It means that different compartments in a vehicle can carry the same product segment. The capacity of compartment d of vehicle k is p_{kd} (kg). The battery capacity of each EV is G_k (kW·h). An EV departs from the DC with fully-charged batteries and returns to the DC. When the vehicle is low on power during transport, it can be recharged several times at the recharging station and fully charge the battery each time. We assumed the charging rate is v (kW) and it is constant. The fixed cost of using a vehicle k is f_k (RMB). The unit power consumption cost is h (RMB/(kW·h)). All stores need to be visited by a vehicle with some orders. For each store i, the hard time window is denoted by $[e_i,l_i]$. s_i (h) denotes the service time in the store i. The orders of each store for various product segments are known. Let O_{im} denotes the order for product segment m of store i, and q_{im} denotes the quantity of O_{im}. The order O_{im} can be met by any compartment of any vehicle. $q_{im}\leqslant p_{kd}$ for any $k\in K, d\in D$. Each order cannot be split, and can only be delivered by one compartment. Moreover, the store can order part of product segments. When $q_{im}=0$, it means that the store i has no order for the product segment m.

Every travelled arc consumes battery charge. Firstly, trams are powered by electricity. Assuming that the vehicle speed is constant and ignoring the factors such as slope and road surface, the power consumption per unit mileage of the vehicle has a linear relationship with the vehicle weight. Therefore, the power consumption per kilometer of EV h_k can be expressed by the following formula $h_k=a_kQ+b_k$, where a_k and b_k are parameters, Q denotes the load on the vehicle k. As the vehicle load will be gradually reduced due to order delivery in the distribution process, the unit power consumption of vehicles in each arc of the route will also be gradually reduced. Secondly, electric energy refrigeration is needed to keep the product segment at its corresponding temperature. Assuming that the external ambient temperature is fixed, the electric energy consumed by refrigeration per unit time in a compartment is related to the temperature zone and space size of the compartment. The lower the temperature zone and the larger the space, the higher the electric energy consumed by refrigeration per unit time. Let c_{kdm} denote electric energy consumption per hour in compartment d of vehicle k for the product segment m. Since the size of a compartment is fixed, c_{kdm} is constant and known. The cost of refrigeration is related to the time of refrigeration, which is incurred during transport, unloading, charging, and waiting. It should be noted that, whenever the compartment is empty during the distribution, it is unnecessary to refrigerate. The sets, parameters, and variables of MCEVRP-PP are shown in Tables 1 and 2.

We model the MCEVRP-PP as a mathematical program as follows:

(1) Objective function

The objective is to minimize the total cost which consists of three terms. The first term is the fixed cost related to each vehicle used; the second term is the vehicle power cost; and the third term is the refrigeration cost. Equations (1)–(4) are the objective functions.

Table 1 Set/parameter and description of MCEVRP-PP.

Set/parameter	Description
C	Set of store points, $C=\{1,2,\dots,n\}$
K	Set of EVs, $K=\{1,2,\dots,N\}$
F	Set of recharging station, $F=\{1,2,\dots,l\}$
$0,\ n+1$	Distribution center
V	Set of stores, recharging stations, and DC, $V=C\cup F\cup\{0\}\cup\{n+1\}$
M	Set of product segments
D	Set of EV compartments
f_k	Fixed cost of EV, $k\in K$, (RMB)
h	Unit power consumption cost, (RMB/(kW·h))
d_{ij}	Distance between nodes i and j, $\text{arc}(i,j)\in E$, (km)
t_{ij}	Travel time between nodes i and j, $\text{arc}(i,j)\in E$, (h)
L	A large number
v	Charging rate, (kW)
$[e_i,l_i]$	Time window of node $i\in V$
p_{kd}	Capacity of the compartment $d\in D$ of EV, $k\in K$, (kg)
O_{im}	Order for product segment $m\in M$ of store $i\in C$
q_{im}	Demand of product segment $m\in M$ in store $i\in C$, (kg)
G_k	Battery capacity of EV, $k\in K$, (kW·h)
s_i	Loading time in store $i\in C$, (h)
a_k,b_k	Parameters of electric energy consumption per kilometer of vehicle $k\in K$
c_{kdm}	Refrigeration electric energy consumption per hour in the compartment $d\in D$ of vehicle $k\in K$ for the product segment $m\in M$, (kW)

$$\min Z=\sum_{i=1} Z_i \tag{1}$$

$$Z_1=\sum_{i\in C\cup F}\sum_{k\in K} x_{0ik} f_k \tag{2}$$

$$Z_2=h\sum_{i\in V\backslash N+1}\sum_{j\in V\backslash 0, i\neq j}\sum_{k\in K} x_{ijk} d_{ij}\Big(a_k\sum_{d\in D}\sum_{m\in M} g_{ikdm}+b_k\Big) \tag{3}$$

$$Z_3=h\sum_{k\in K}\sum_{d\in D} T_{kd}\sum_{m\in M} z_{kdm} c_{kdm} \tag{4}$$

(2) Vehicle route constraint

Constraint (5) ensures that each store can only be visited once. Constraint (6) ensures the continuity of the route. Constraint (7) guarantees that each vehicle leaves DC and returns to DC. There is one trip per vehicle at most. Constraint (8) guarantees that not all recharging visit vertices must be used.

$$\sum_{i\in V\backslash N+1, i\neq j}\sum_{k\in K} x_{ijk}=1, \forall j\in C \tag{5}$$

$$\sum_{i\in V\backslash N+1, i\neq j} x_{ijk}-\sum_{i\in V\backslash 0, i\neq j} x_{jik}=0, \forall j\in C\cup F, \forall k\in K \tag{6}$$

$$\sum_{i\in C\cup F} x_{0ik}=\sum_{j\in C\cup F} x_{j,N+1,k}\leqslant 1, \forall k\in K \tag{7}$$

$$\sum_{i\in F, j\in V\backslash 0} x_{ijk}\leqslant 1, \forall k\in K \tag{8}$$

(3) Vehicle loading constraint

Constraints (9) and (10) ensure that the sum of products in the compartment does not exceed the compartment capacity. Constraints (11) and (12) keep track of the remaining load in the compartment and guarantee that demand of all stores is satisfied.

$$\sum_{i\in C}\sum_{m\in M} y_{ikdm} q_{im}\leqslant p_{kd}, \forall k\in K, d\in D \tag{9}$$

$$\sum_{m\in M} g_{ikdm}\leqslant p_{kd}, \forall i\in V\backslash N+1, k\in K, d\in D \tag{10}$$

$$\begin{gathered} g_{jkdm}+y_{jkdm}q_{jm}x_{ijk}-p_{kd}\left(1-x_{ijk}\right)\leqslant g_{ikdm}, \\ \forall i\in V\backslash\{N+1\}, j\in C, i\neq j, k\in K, d\in D, m\in M \end{gathered} \tag{11}$$

$$\begin{gathered} g_{jkdm}-p_{kd}\left(1-x_{ijk}\right)\leqslant g_{ikdm}, \forall i\in V\backslash\{N+1\}, \\ j\in F, i\neq j, k\in K, d\in D, m\in M \end{gathered} \tag{12}$$

Table 2 Decision variable.

Notation	Description
x_{ijk}	$x_{ijk}=1$, if $\text{arc}(i,j)\in E$ is traversed by EV $k\in K$; 0, otherwise
y_{ikdm}	$y_{ikdm}=1$, if order O_{im} is delivered by compartment $m\in M$ of EV $k\in K$; 0, otherwise
z_{kdm}	$z_{kdm}=1$, if compartment $d\in D$ of EV $k\in K$ is dedicated to product segment $m\in M$; 0, otherwise
w_{ikd}	$w_{ikd}=1$, if compartment $d\in D$ of EV $k\in K$ is not empty when leaving store $i\in C$; 0, otherwise
u_{ik}	Remaining energy of EV $k\in K$ when arriving at store $i\in C$, $u_{0k}=G_k$
t_{ik}	Arrival time at store $i\in C$ for EV $k\in K$
t_{ik}^{+}	Depart time at store $i\in C$ for EV $k\in K$
g_{ikdm}	Remaining quantity of product segment $m\in M$ in compartment $d\in D$ of EV $k\in K$ when leaving store $i\in C$, (kg)
T_{ikd}	Equals departure time from store $i\in C$, if compartment $d\in D$ of EV is emptied for the store $i\in C$; 0, otherwise. $T_{ikd}=0$, when $i\in F$ or $\{0\}$
T_{kd}	Time when compartment $d\in D$ of EV $k\in K$ is emptied

(4) Time constraint

Formulas (13) and (14) determine the time when compartment d of vehicle k is emptied. Constraint (15) denotes the time relationship between nodes i and j on arc(i,j) when i is store, DC, recharging station respectively. Simultaneously, Constraint (16) denotes the time relationship when i is the recharging stations. Equation (17) determines the departure time of vehicle k from store i. Constraint (18) ensures the arrival time is earlier than l_i of time window.

$$T_{ikd}=\begin{cases} t_{ik}^{+}, & \text{if } \sum_{m\in M} g_{ikdm}=0 \text{ and } \sum_{m\in M} Y_{ikdm}=1; \\ 0, & \text{else}; \end{cases} \quad \forall i\in V\setminus\{N+1\}, k\in K, d\in D, m\in M \tag{13}$$

$$T_{kd}=\max\{T_{ikd}\}, \forall i\in V\setminus\{N+1\} \tag{14}$$

$$\max\{e_i, t_{ik}\}+(s_i+t_{ij})x_{ijk}-L(1-x_{ijk})\leqslant t_{jk}, \quad \forall i\in C\cup 0, \forall j\in V\setminus\{0\}, i\neq j, \forall k\in K \tag{15}$$

$$t_{ik}+(t_{ij}+(G_k-u_{ik})/v_i)x_{ijk}-L(1-x_{ijk})\leqslant t_{jk}, \quad \forall i\in F, \forall j\in V\setminus\{0\}, i\neq j, \forall k\in K \tag{16}$$

$$t_{ik}^{+}=\max\{e_i, t_{ik}\}+s_i, \forall i\in C, \forall k\in K \tag{17}$$

$$0\leqslant t_{ik}\leqslant l_i, \forall i\in V, \forall k\in K \tag{18}$$

(5) Vehicle power constraint

Constraints (19)–(21) ensure that the vehicle power remaining is never negative in arc(i,j) when i is store, DC, recharging station, respectively.

$$u_{jk}\leqslant u_{ik}-\left[d_{ij}\left(a_k\sum_{d\in D}\sum_{m\in M} g_{ikdm}+b_k\right)+(t_{ij}+s_i+\max\{e_i-t_{ik},0\})\sum_{d\in D}\left(w_{ikd}\sum_{m\in M} c_{kdm}z_{kdm}\right)\right]x_{ijk}+G_k(1-x_{ijk}), \forall i\in C, \forall j\in V\setminus 0, \forall k\in K, i\neq j \tag{19}$$

$$u_{jk}\leqslant G_k-\left[d_{ij}\left(a_k\sum_{d\in D}\sum_{m\in M} g_{ikdm}+b_k\right)+t_{ij}\sum_{d\in D}\left(w_{ikd}\sum_{m\in M} c_{kdm}z_{kdm}\right)\right]x_{ijk}+G_k(1-x_{ijk}), \forall i\in F\cup 0, \forall j\in V\setminus 0, \forall k\in K, i\neq j \tag{20}$$

$$0\leqslant u_{ik}\leqslant G_k, \forall i\in V, \forall k\in K \tag{21}$$

(6) Decision variable

Constraint (22) ensures that each order is delivered only by one compartment. Constraints (23) and (24) represent the relationship between variables. Constraint (25) guarantees that each compartment is loaded with at most one product segment. The compartment is allowed to be empty. Equation (26) is the range constraint on the decision variable.

$$\sum_{k\in K}\sum_{d\in D} y_{ikdm}\leqslant 1, \forall i\in C, m\in M \tag{22}$$

$$w_{ikd}=\begin{cases} 1, & \text{if } \sum_{m\in M} g_{ikdm}>0; \\ 0, & \text{else}; \end{cases} \quad \forall i\in V\setminus\{N+1\}, k\in K, d\in D, m\in M \tag{23}$$

$$z_{kdm}=\begin{cases} 1, & \text{if } \sum_{i\in C} y_{ikdm}\geqslant 1; \\ 0, & \text{else}; \end{cases} \quad \forall k\in K, d\in D, m\in M \tag{24}$$

$$\sum_{m\in M} z_{kdm}\leqslant 1, \forall k\in K, d\in D \tag{25}$$

$$x_{ijk}\in\{0,1\}, y_{ikdm}\in\{0,1\}, \forall i\in V\setminus N+1, j\in V\setminus 0, i\neq j, k\in K, d\in D, m\in M \tag{26}$$

3 Hybrid Ant Colony Optimization for MCEVRP-PP

MCEVRP-PP is NP-hard. An exact algorithm can be used to find the exact solution for small-scale MCEVRP-PP. As the increase in the number of stores and recharging stations, the solution space increases exponentially and cannot be solved by an exact algorithm. Therefore, heuristic methods or metaheuristic methods are generally used to solve the problem. Ant colony optimization (ACO), Tabu search, variable neighborhood search, and ALNS are effective for solving VRPs.

In the study, an HACO that combines local optimization with ACO is developed for solving the MCEVRP-PP. Based on traditional ACO, we introduce time window factor in the transfer rules. The max-min strategy is proposed for the pheromone update. The pseudo-code of HACO is shown in Algorithm 1. “it” represents the number of current iterations. L_{iter} is the maximum number of iterations. “anti” is the i-th ant. anti$_{\max}$ denotes the total number of ants.

3.1 Route construction

At the initial state, tabu$_k$ denotes the set of nodes that have been visited. All the ants locate in the DC when tabu$_k=\varphi$. An ant denoting an EV departs from the DC. It needs to visit as many stores as possible until there is no more to visit, subject to constraints of the power, time window, and capacity of each compartment. After visiting the last store, the ant then returns to DC. Then the ant denoting another EV departs from the DC to visit as many remaining stores as possible until there is no store to visit. When all stores have been visited, the multiple routes formed by the current ant form a solution. During route construction process, the current ant may be in one of three states: (1) at the

Algorithm 1 Pseudo-code of HACO

Initialize: it $\leftarrow 1$, anti $\leftarrow 1$
Repeat
  For each ant k **do**
    Repeat
      Construct a feasible solution S
      Local search procedure
      anti $\leftarrow$ anti $+1$
    Until anti $>$ anti$_{\max}$
  End for
  Pheromone update procedure
  it $\leftarrow$ it $+1$
Until it $> L_{\text{iter}}$
Output the best solution S^*

DC; (2) at the store; (3) at the recharging station. For different types of nodes i, the nodes j that can be selected to visit to are different. Therefore, the route construction process for the ants in these three states is shown in Algorithm 2. The set of accessible stores is denoted by allowed_k, and the accessible stores need to satisfy the following three constraints:

(1) **Capacity constraint.** The capacity constraint judgement algorithm that shown in Section 3.2 is used to determine whether the demand of the transferred node j can be loaded in the vehicle. Any store satisfies this constraint when the ant locates in the DC.

(2) **Time window constraint.** The ant departs from the DC during $[e_0, l_0]$, and reaches the store j before l_j.

(3) **Electricity constraint.** It should be ensured that there is enough power to return to the DC or the nearest charging station when it has visited node j.

During the route construction process, the ant tries multiple types of vehicles and keeps the model that results in the lowest cost.

In the route construction process, the ant k selects the nearest public recharging stations. When the route is constructed, there may be public recharging stations that make the total cost smaller. To avoid routes with long detours, we propose the local recharging station insertion operator. Firstly, we delete the original public recharging stations for the tour containing public recharging stations. Insert the remaining public recharging stations in turn and calculate the distance travelled by ant k. Insert the public recharging station with the shortest distance.

Algorithm 2 Pseudo-code of the route construction process of HACO

Initialize: $\text{tabu}_k \leftarrow \alpha, u_{0k} \leftarrow G, p_{kd} \leftarrow 0$
Repeat
Ant k simulates a new EV k
If k in DC
  Move k to node j by transition probability, $j \in \text{allowed}_k$
Else if // k in C
  If $\text{allowed}_k = \varnothing$
    If the nearest station f^* meets power constraint && a store point meet capacity and time window constraints or not enough power to return to the DC
      Move k to f^*
    Else
      Move k to DC
    End if
  Else // $\text{allowed}_k \neq \varnothing$
      Move k to point j by transition probability, $j \in \text{allowed}_k$
  End if
Else // k in F
  If $\text{allowed}_k = \varnothing$
    Move k to DC
  Else
    Move k to point j by transition probability, $j \in \text{allowed}_k$
  End if
End if
Until all store points are visited
Return route_k
End procedure

3.2 Capacity constraint judgement algorithm

We assume that the number of all product segments is M, which is equal to the number of compartments. The number of product segments that store i demands is up to M. The correspondence between compartments and product segments is not fixed. Each compartment can be set to any temperature zone. When the vehicle visits store i, the compartments can form a clear correspondence with each product segment. When determining the set of candidate nodes for the next visit, the correspondence can be adjusted to enable all product segments. The process of capacity constraint judgement algorithm is as follows:

(1) If the vehicle k is in node i, and visits store j next. The vehicle k needs to carry the products of all stores on the route from the DC to store j. The number of product segments is $W\,(W \leqslant M)$. Sort products by the amount of each product segment in descending order $\{E_1, \dots, E_w, \dots, E_W\}$.

(2) If $W < M$, the compartments can be combined so that the product segments and the number of compartments are equal. List all combinations of compartments for the number of product segments.

(3) Sort compartments by capacity in descending order, $\{p_{k1}, \dots, p_{kw}, \dots, p_{kW}\}$.

(4) For one combination of compartments, if $p_{kw} \geqslant E_w$, $w = 1, 2, \dots, W$, store j meets the capacity constraint. Otherwise, vehicle k cannot visit store j next.

3.3 Transfer rule

The heuristic information includes pheromone concentrations and distance in ACO. We introduce the distance saving and time window to the transition probability.

Attraction value of node j to node i is calculated by Eq. (27). η_{ij} is defined as the inverse of the distance from node j to node i. τ_{ij} denotes the amount of pheromone on the route between the current node i and possible node j. μ_{ij} denotes the distance saving of node i to node j. TM_{ij} is the match of time window between node i and node j. The notations of α, β, γ, and δ denote the relative influence of the distance values, the pheromone trails, distance saving, and time window, respectively.

$$\xi_{ij} = \left[\eta_{ij}\right]^{\alpha} \left[\tau_{ij}\right]^{\beta} \left[\mu_{ij}\right]^{\gamma} \left[\text{TM}_{ij}\right]^{\delta} \tag{27}$$

The match of time window is defined as Eq. (28). E_i and L_i denote the actual earliest and latest arrival time to node i for ant k, respectively. $E_i = \max\{e_0 + t_0, e_i\}$, $L_i = \min\{l_0 - t_{0i} - s_i, l_i\}$. T_i is the service time in node i for ant k and is a constant. $\tilde{L}_{ij}$ represents the overlapping duration of time windows between nodes i and j.

$$\text{TM}_{ij} = \begin{cases} \dfrac{\tilde{L}_{ij}}{L_i - E_i} + \text{tm}_0, & \text{if } [E_i + T_i + t_{ij}, L_i + T_i + t_{ij}] \cap [e_j, l_j] \neq \varnothing; \\ \text{tm}_0, & \text{if } L_i + T_i + t_{ij} < e_j \end{cases} \tag{28}$$

$$\tilde{L}_{ij} = \begin{cases} \min\{L_i + T_i + t_{ij}, l_j\} - \max\{E_i + T_i + t_{ij}, e_j\}, \\ \quad \text{if } [E_i + T_i + t_{ij}, L_i + T_i + t_{ij}] \cap [e_j, l_j] \neq \varnothing; \\ 0, \ \text{if } L_i + T_i + t_{ij} < e_j \end{cases} \tag{29}$$

Equation (29) indicates that the larger the overlap between $[E_i + T_i + t_{ij}, L_i + T_i + t_{ij}]$ and $[e_j, l_j]$, the more flexible from node i to node j for ant k. It is beneficial to visit more stores.

The transfer rule that ant k transfers from node i to node j is given by Eq. (30). P_{ij} denotes the transition probability from node i to node j for ant k. Ant k selects a node j from allowed_k to visit according to transition probability.

$$P_{ij} = \frac{\xi_{ij}}{\sum_{e \in \text{allowed}_k} \xi_{ie}}, j \in \text{allowed}_k \tag{30}$$

3.4 Local search phrase

Local search optimization can effectively improve the search capability of ACO. We design the following six local search strategies. These strategies are adapted from Eshtehad et al.[19] to reflect the features of MCEVRP-PP[22]. The new solution must satisfy the constraints and be with a lower total cost. The pseudo-code of the local search is shown in Algorithm 3.

(1) **Relocate.** Randomly select two nodes to swap in the current solution.

(2) **Reverse.** Select any circuit in current solution. Then randomly select the nodes segment and reverse the visit order of all nodes in this segment.

(3) **Exchange.** Randomly select two circuits in current solution, and then randomly select a node in each circuit. Exchange the positions of the two nodes.

(4) **TimeGreedy.** Remove customers with maximum time window period $[e_i, l_i]$ and then insert the removed nodes into the route by using the greedy algorithm.

(5) **Worst-Customer.** Remove the node with the largest increase in power consumption cost. Then the removed node is inserted into the location that minimizes the total cost increase.

(6) **2-opt.** Select a circuit with charging stations in current solution and remove the charging stations in the circuit selected. Then randomly select two nodes. And then the order of visits to all customer points between these two customer points is reversed.

When using the last 3 strategies, it is necessary to judge whether the route to insert the removed nodes needs recharging stations or not. If it does, the recharging station is inserted by the local optimization algorithm for recharging stations that proposed in Section 3.1.

3.5 Pheromone update

When all solutions have been improved by local search, we should update the global pheromone of the optimal solution. The global pheromone update strategy adapted from Reed et al.[13] is given in Eq. (31).

$$\tau_{ij}^{\text{new}} = (1-\rho)\,\tau_{ij}^{\text{old}} + \rho\Delta\tau_{ij}^{\text{bs}}, \quad \forall i,j \in T^{\text{bs}} \tag{31}$$

where τ_{ij}^{new} and τ_{ij}^{old} are the pheromone concentration $\text{arc}(i,j)$ after and before the updating, respectively. ρ is the rate of pheromone evaporation. $\Delta\tau_{ij}^{\text{bs}}$ is the increased pheromone on $\text{arc}(i,j)$ of the current best solution, and is calculated by Eq. (32). T^{bs} is the current best route. L^{bs} is the total cost of T^{bs}.

$$\Delta\tau_{ij}^{\text{bs}} = \frac{1}{L^{\text{bs}}} \tag{32}$$

The difference in pheromone concentration between arcs can be limited to avoid falling into local optima and improve the global search ability of the algorithm. In this study, the maximum and minimum values of pheromone concentration are set to ensure that the difference in pheromone concentration is reasonable.

Algorithm 3 Pseudo-code of the local search

```
For each solution S
  For each local search strategies r
    Repeat
      Current iterations it ← 1
        Optimize S, generate S'
        If the total cost z(S') < z(S), Then
          S ← S'
        End if
        it ← it + 1
     Until it > L_iter
   End for
 End for
 Output : all solutions S
```

4 Experimental Result

The instance sets in the experiment are adapted from the benchmark instances of Solomon for MCEVRP-PP. Three experiments are conducted to verify the effectiveness of HACO. Each small-scale instance includes 5, 10, and 15 stores, respectively. There are 12 instances for each store scale. There are 56 large-scale instances, and each instance includes 100 stores. The instances are divided into 3 types based on the characteristics of store distribution: Clustered (C), Random (R), and Random&&Clustered (RC) distribution.

Three experiments are conducted to verify the performance of HACO. In the first experiment, we respectively select 6 small-sale instances for 3 types, and 35 large-scale instances to verify the efficiency and correctness of HACO. And we compare the performance of each local search strategy for large-scale instances. In the second and third experiments, we compare FVs with EVs, and compare single-compartment vehicles with multi-compartment vehicles.

HACO is coded in Python 3.7, and is performed on a computer with Core i4-4210U, 4 GB RAM.

4.1 Parameter setting

In the experiments, the product segments are set as three kinds: ambient, chilled, and frozen. The number of vehicle compartments is the same as the number of product segments. The parameters of vehicle capacity and battery capacity are adapted from the experimental data of Solomon. The fleet consists of two models. For each model, the capacity of each compartment is the same, the parameters of electric energy consumption: $a_k = 0.055\ \text{kW}\cdot\text{h}/(\text{t}\cdot\text{km})$, $b_k = 0.5$. The unit power consumption cost $h = 1\ \text{RMB}/(\text{kW}\cdot\text{h})$, the travel speed $v_k = 60\ \text{km/h}$, and the charging rate $v = 50\ \text{kW}\cdot\text{h}$. For Model 1, $p_{kd} = 0.07t, \forall d = 1,2,3$, $f_k = 200\ \text{RMB}$, and $G_k = 60\ \text{kW}\cdot\text{h}$. For Model 2, $p_{kd} = 0.2t$, $\forall d = 1,2,3$, $f_k = 300\ \text{RMB}$, and $G_k = 76\ \text{kW}\cdot\text{h}$. Based on the actual scenario, for Model 1, we set c_{kdm} =0.5 kW, 1 kW, and 1.5 kW for ambient, chilled, and frozen, respectively. For Model 2, we set c_{kdm} =2 kW, 2.5 kW, and 3 kW, respectively. The related parameters of ACO are set based on the current research and are detailed in Table 3.

4.2 Study on small-scale instances

We solve MCEVRP-PP on 18 small-scale instances with ACO and HACO. ACO and HACO perform 10 runs for each instance respectively. The results are shown in Table 4. Column ACO and HACO are the total cost for the best solutions with the two algorithms, respectively. The cost reduction percentage of the HACO compared to ACO is shown in column Δ. Results show that HACO efficiently solve all MCEVRP-PP instances. For the instances of 5 and 10 stores, the ACO and HACO can find the

Table 3 Related parameters of ant colony optimization.

Parameter	Description	Value
n_{ant}	Number of ants	50
L_{iter}	Maximum iterations	100
ρ	Rate of pheromone concentration	0.2
T_{max}	Maximum pheromone concentration	6
T_{min}	Minimum pheromone concentration	0.001
β	Influence of pheromone	1
α	Influence of distance	2
γ	Influence of distance saving	1
δ	Influence of time window	2

Table 4 Experimental results of small-scale instances.

Instance	Cost (RMB)		Δ (%)
	ACO	HACO	
C101c5	490.25	490.25	0.00
C103c5	306.76	306.76	0.00
R104c5	305.67	305.67	0.00
R202c5	424.17	424.17	0.00
RC105c5	445.42	445.42	0.00
RC105c5	493.80	493.80	0.00
C101c10	818.06	818.06	0.00
C202c10	581.23	571.37	**1.70**
R103c10	513.37	513.37	0.00
R203c10	579.54	579.54	0.00
RC102c10	741.89	741.89	0.00
RC205c10	712.60	740.85	−3.96
C103c15	849.85	847.66	**0.26**
C202c15	979.10	979.10	0.00
R105c15	998.82	998.82	0.00
R205c15	858.34	827.45	**3.60**
RC103c15	1029.11	979.24	**4.85**
RC204c15	747.07	747.07	0.00
Average	—	—	0.36

same optimal solutions. However, the increased stores cause high computational complexity. For the instances of 15 stores, the ACO is poor to search for better solutions and tends to stagnate. Local optimization can improve the solutions.

4.3 Study on large-scale instances

To verify the effectiveness of each local optimization strategy, we first randomly select six instances from the large-scale instances and solve with the ACO combining a local search strategy. We donate the algorithms with a different strategy by Relocate, Reverse, Exchange, TimeGreedy, Worst-Customer, and 2-opt. For each instance, each algorithm performs 10 runs. Figure 1 shows the results with the highest cost reduction. The column denotes the cost reduction percentage comparing with the ACO. The results show that Relocate, Reverse, Worst-Customer, and 2-opt solve the problem effectively for large-scale instances. 2-opt performs the best, as charging is important in delivery and the strategy related to public recharging stations can improve the

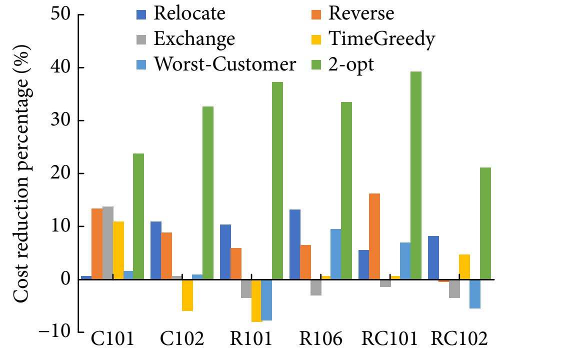

Fig. 1 Analysis of improvement rate of local optimization strategies.

solutions effectively. Exchange and TimeGreedy are poor to improve the solutions. Therefore, we note the algorithm that ACO combining four strategies that perform better, as HACO-I.

To analyze the performance of HACO-Ⅰ, ACO, Relocate, Reverse, Worst-Customer, 2-opt, and HACO-Ⅰ are performed for 10 runs on the remaining 29 large-scale instances. The average cost reduction percentage of each type of instances are shown in Fig. 2. And the detailed experimental results of ACO, 2-opt, and HACO-Ⅰ are shown in Table 5.

From the results, we find that five algorithms can improve the solutions for all types of instances. 2-opt and HACO-I improve all instances and are superior to Relocate, Reverse, and Worst-Customer. The average cost reduction percentage of 2-opt and HACO-I are 20.71% and 21.16%, respectively. The improvement of Relocate and Reverse is less effective. Worst-Customer performs the worst. We notice that 2-opt performs better than HACO-I for half of the instances. This indicates that the ACO that combined four local search strategies performed worse than the one combining the strategy of 2-opt in some instances. Possible causes of this situation may be as follows: (1) other strategies, especially Worst-Customer, interfere with the HACO-I; (2) the iteration times are not enough, and the advantages of the HACO-I are not fully reflected.

4.4 Comparison of EVs and FVs

In the experiment, we compare two fleets: EVs and FVs. There are two types of vehicles for EVs and FVs. For FVs, the number and capacity of a compartment are the same as EVs. For Model 1, the capacity of the fuel tank is 100 L, the capacity of the battery is 100 kW·h, and the fixed cost is 200 RMB. For Model 2, the capacity of the fuel tank is 120 L, the capacity of the battery is 120 kW·h, and the fixed cost is 300 RMB. Unit fuel consumption cost is 5.5 RMB/L.

We assume that the power fuel consumption is linearly related to the load. The refrigeration fuel consumption is related to the

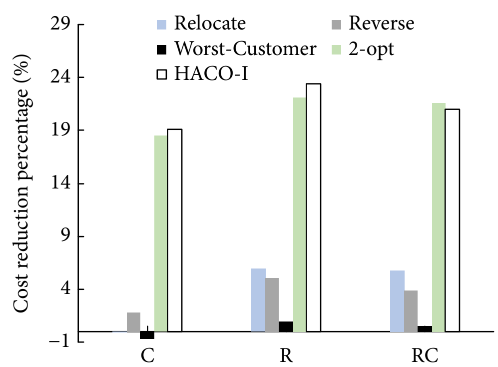

Fig. 2 Average improvement rate of different algorithms to cost.

Table 5 Experimental results of large-scale instances.

Instance	ACO	2-opt		HACO-I	
	Cost (RMB)	Cost (RMB)	Δ (%)	Cost (RMB)	Δ (%)
C101	4916.61	3744.39	**23.84**	3838.62	21.93
C102	6129.75	4124.78	**32.71**	4124.78	32.71
C105	4792.39	3984.09	**16.87**	4033.12	15.84
C107	5243.21	4255.25	18.84	4229.69	**19.33**
C108	4629.16	3968.78	14.27	3867.85	**16.45**
C109	4944.94	3718.01	24.81	3657.07	**26.04**
C201	5717.39	4427.54	22.56	4403.98	**22.97**
C202	4526.73	4209.97	7.00	3907.39	**13.68**
C203	4945.78	4286.84	**13.32**	4345.96	12.13
C205	4696.16	3592.82	**23.49**	3620.93	22.90
C206	5130.58	3941.50	**23.18**	4104.98	19.99
C207	4002.15	3961.47	1.02	3794.41	**5.19**
R101	8890.79	5573.59	37.31	5270.05	**40.72**
R102	8451.74	4924.28	**41.74**	5117.49	39.45
R106	6745.04	4488.90	33.45	4347.17	**35.55**
R107	6037.42	3946.74	**34.63**	4103.14	32.04
R109	5805.33	4298.46	**25.96**	4393.10	24.33
R110	5115.44	4018.97	21.43	3824.76	**25.23**
R201	5050.08	4249.33	15.86	4207.73	**16.68**
R205	4498.43	3993.05	11.23	3826.92	**14.93**
R206	4209.05	3901.47	7.31	3893.89	**7.49**
R207	4627.15	3946.88	14.70	3810.38	**17.65**
R209	4376.61	3972.52	9.23	3892.74	**11.06**
R210	4416.02	3875.60	12.24	3746.84	**15.15**
RC101	8267.34	5027.89	39.18	5050.60	38.91
RC102	6385.36	5034.82	21.15	4954.12	**22.41**
RC106	5357.34	4493.38	16.13	4303.21	**19.68**
RC107	5738.20	4023.49	**29.88**	4027.15	29.82
RC201	5665.15	5056.99	10.74	4870.61	**14.03**
RC202	5587.97	4873.51	**12.79**	4919.09	11.97
RC203	5596.85	4525.44	**19.14**	4573.16	18.29
RC205	5670.61	4529.44	**20.12**	4636.78	18.23
RC206	5637.22	4366.12	**22.55**	4375.22	22.39
RC207	5358.10	4109.35	**23.31**	4397.45	17.93
RC208	5366.16	4147.91	**22.70**	4431.95	17.41
Average	—	—	20.71	—	21.16

temperature of the compartment. The fuel consumption per mile is calculated with Eqs. (33) and (34).

$$F_1 = 0.03Q_{ij} + 0.09 \tag{33}$$

$$F_2 = 0.03Q_{ij} + 0.12 \tag{34}$$

where F_1 is the power fuel consumption per unit mile for Model 1. Q_{ij} is the quality of the product for vehicle from node i to j.

The refrigeration fuel consumption per hour is given in Eq. (35).

$$L_m = \begin{cases} 1.24, & m = 1; \\ 1.86, & m = 2; \\ 2.48, & m = 3 \end{cases} \tag{35}$$

where L_m (L/h) is the refrigeration fuel consumption per hour for the product segment m.

We use HACO to solve 9 instances for the MCEVRP-PP, which are randomly selected from the large-scale instance set. HACO runs 10 times for each instance. The results are shown in Table 6. For FVs, the average mileage is 1798.31 km, and the average total cost is 4499.31 RMB. For EVs, the average mileage is 2120.12 km, and the average total cost is 4135.78 RMB. The mileage of EVs is longer than FVs, as the continuity limit and demand for recharging increase the mileage. Nevertheless, the total cost of EVs is lower than FVs with a cost reduction percentage of about 8%. Using EVs for cold chain logistics can reduce the total cost.

4.5 Comparison of SCVs and MCVs

This experiment is conducted to verify the advantages of MCVs for the perishable products delivery. We assume that each vehicle is responsible for only one product segment in the mode of using SCVs. If a customer has orders for multiple product segments, multiple visits to the customer are required. Three large-scale instances of R, C, and RC are randomly selected. Other parameters remain unchanged. The experimental results are shown in Table 7. The column ΔC is the cost reduction percentage of the MCVs compared to SCVs. The column ΔM is the mileage reduction percentage.

Table 7 shows that MCV is superior to SCV in total cost and mileage for all instance. For total cost, the average total cost of SCVs is 12 311.59 RMB, while the average total cost of MCVs is only 4360.78 RMB, improved by 61.90%. For mileage, the average mileage of SCVs is 4148.93 km, while the average mileage of MCVs is 1345.96 km, improved by 67.74%. Therefore, in cold chain logistics, the use of MCVs can improve vehicle utilization, and reduce the distance traveled and the total cost compared with SCVs.

5 Conclusion

In this study, we propose a heterogeneous fleet, multi-compartment electric vehicle routing problem for perishable products, based on the practical needs of cold chain logistics,

Table 6 Comparison of travel distance and total cost between FVs and EVs.

Instance	Mileage (km)		Total cost (RMB)	
	FVs	EVs	FVs	EVs
C101	2607.25	2980.47	6598.21	5921.64
C107	1916.42	2566.94	5384.00	4940.85
C205	1574.53	1974.60	4001.22	3921.54
R109	1287.71	1406.07	4200.60	3972.71
R205	1580.23	1834.84	4079.33	3817.90
R207	1608.94	2186.30	4080.51	3640.89
RC101	1721.99	**1664.52**	3461.91	3142.91
RC107	1551.16	**1480.84**	3656.45	3384.48
RC201	2336.52	2986.48	5031.57	4479.10
Average	1798.31	2120.12	4499.31	4135.78

Table 7 Experimental comparison of SCVs and MCVs.

Instance	SCV		MCV		ΔC (%)	ΔM (%)
	Total cost (RMB)	Mileage (km)	Total cost (RMB)	Mileage (km)		
C101	11 196.00	3658.32	3838.62	1004.59	65.71	72.54
C105	11 121.60	3773.93	4124.78	1053.86	62.91	72.08
C201	9097.33	3212.48	4033.12	1059.09	55.67	67.03
R106	14 117.76	4381.25	4403.98	1321.72	68.81	69.83
R107	12 626.34	4048.48	5270.05	1280.63	58.26	68.37
R109	11 021.81	3746.88	5117.49	1248.28	53.57	66.68
RC102	15 390.89	5231.86	5050.60	1590.89	67.18	69.59
RC106	12 605.61	4587.23	4954.12	1530.04	60.70	66.65
RC201	13 627.02	4699.94	4870.61	2024.57	64.26	56.92
Average	12 311.59	4148.93	4360.78	1345.96	61.90	67.74

referred to as the MCEVRP-PP. We construct a mixed integer programming model to minimize the total cost. Each EV is allowed to be charged multiple times during delivery. The unfixed compartment temperature can be adjusted to meet any product segment. The power consumption per kilometer is linearly related to the load. The compartment is not refrigerated when it is empty. The above considerations make the research more realistic. HACO is designed to solve the problem. To improve the performance of the algorithm, we introduce a time window matching factor in the transfer rule, design a capacity-constrained algorithm based on the features of MCEVRP-PP, and propose six local search strategies in terms of time windows and charging stations. The algorithm is validated via various experiments, including small-scale instances and large-scale instances. To test the performance of each local search strategy, we compare the HACO with ACO, and ACO combined with a single strategy, respectively. The experimental results show that the HACO is superior to ACO, especially for large-scale instances. Finally, we compare EVs with FVs and compare MCVs with SCVs. The results show that EVs and MCVs can effectively lower the total cost, while the mileage of EVs is increasing.

We assume that each customer has the same time window for different product segments and that each customer can only be visited at most once in the research. But in fact, the customer may have different time window preferences for products in different temperature zones. For example, a supermarket may want to receive frozen food in the morning and other types of goods can be delivered later. Future research will consider customers' preferences for time window, and it belongs to a multiple time window problem. In addition, we assume that the number of compartments is the same as the number of product segments, and all vehicles are multi-compartment vehicles. Future research could consider a combination of single-compartment vehicles and multi-compartment vehicles for distribution.

Dates

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