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An extended PSO algorithm for cold-chain vehicle routing problem with independent loading and minimum fuel volume

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A B S T R A C T

With the increasing complexity of the distribution environment, customers usually propose higher requirements, such as independent loading of local and foreign cold-chain items in the event of an emergency. Moreover, minimum fuel volume plays an important role in the process of transportation with different speeds and different kinds of vehicles. In this paper, we present a new mathematical model to characterize cold-chain vehicle routing optimization with independent loading of local and foreign items and minimum fuel volume. To address the above mathematical model, an extended particle swarm optimization (PSO) algorithm is proposed by combining original PSO with 2-opt optimization to improve diversity and reduce convergence speed. Six sets of experiments are set to verify the practical performance and stability of the extended PSO algorithm based on three standard datasets of C201, R201, and RC201 from Solomon.

1. Introduction

Vehicle routing problem (VRP) is a classic optimization problem for logistic companies to deliver the items with minimum total cost. Although the logistics companies only focus on the minimum total cost in VRP optimization, the customers will propose some requirements in cold-chain VRP, such as lower refrigerated cost with travel time and freshness of perishable foods. Therefore, it is important to meet the customers' requirements and improve customer satisfaction. However, those customers' requirements usually increase the distribution cost for logistics companies in the process of VRP optimization. Some scholars focus on the VRP optimization with minimum total cost and maximum consumers' satisfaction (Liang et al., 2023; Ahmadi-Javid et al., 2023; Li & Li, 2022).

Recently, the customers proposed higher requirements with the increasing complexity of the environment, such as pandemic and environmental pollution. For example, at the beginning of pandemic, customers are usually not willing to mix loading of cold items from local and foreign, because there exist risks to mix loading of the polluted items and clean items in the process of cold-chain logistic distribution. Moreover, environmental pollution is another important factor to impact the customers' satisfaction. If the cold-chain logistic companies would like to meet the customers' requirements of independent loading, the companies need to allocate more vehicles. As a result, vehicle space will be wasted a lot, and the operational cost of vehicle allocation will be increased significantly in cold-chain distribution. Furthermore, traffic congestion will also increase fuel consumption cost in the process of VRP optimization. Therefore, it is important to consider the customers' requirements regarding local and foreign independent loading when facing the environment of pandemic. However, to meet the independent loading, it will be increasing the distribution cost in cold-chain VRP optimization because of needing more distributed vehicles and disinfection fees. How to keep the safety environment with the minimum total cost is difficult for the logistics company

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to solve when facing the environment of a pandemic. Furthermore, fuel volume has a great influence on the distribution cost in cold-chain VRP optimization. Fuel volume is closely related to the traffic condition, vehicle speed, and different types of vehicles. Therefore, independent loading and fuel volume are two important factors in cold-chain VRP optimization.

Prior literature has been focusing on the VRP optimization with different customers' satisfaction. For example, Elgharably et al. (2022) considered green logistic distribution with a stochastic multi-objective vehicle routing model, including economic, environmental, and social aspects. They proposed a new hybrid search algorithm to solve it. Similarly, Yin (2022) explored a multi-objective optimization model in low-carbon VRP solved by Multifactorial Evolutionary Algorithm and Non-dominated Sorting Genetic Algorithm (NSGA-II). Talouki et al. (2021) investigated a dynamic VRP optimization with minimum environmental influences and maximum customer satisfaction. Zhou et al. (2022) considered a novel collaborative multi-heterogeneous-depot electric VRP with battery swapping and time windows. The optimization problem is solved by an extended NSGA-II with a new coding scheme and initial population generation. Sarbijan and Behnamian (2022) explored real-time collaborative feeder VRP with flexible time windows solved by multi-objective PSO with variable neighborhood search. Huang et al. (2022) considered the VRP with drones considering customers' assignment to drone-truck pairs and the number of dispatching drone-truck units. Liang et al. (2023) investigated perishable goods distribution in a multiple-time-period planning horizon considering transportation cost and customer satisfaction. Furthermore, some literature has been researching the cold-chain VRP with customers' satisfaction. For example, Wang and Wen (2022) considered low-carbon two-echelon heterogeneous-fleet cold chain VRP with mixed time window. Zhao et al. (202) explored a multi-objective cold chain VRP optimization considering cost, carbon emissions, and customer satisfaction. Moreover, Wang et al. (2016) demonstrated that customer satisfaction was closely related to freshness in perishable food distribution of multi-objective VRP optimization. Additionally, some scholars (Xu et al., 2023; Rajaei et al., 2022; Vincent et al., 2021) investigated multi-companies or multi-vehicle cooperation in VRP optimization.

The prior literature focused on minimum total cost of cold-chain VRP optimization with meeting the customers' requirements, such as delivering in time window. They still ignored that independent loading of customers' satisfaction with minimum travelling cost, as well as fuel consumption cost related to traffic congestion and different types of vehicles. To solve the above mentioned challenges, the customers' requirements of independent loading regarding local and domestic should be considered into traditional VRP optimization. Fuel volume calculation is related to lots of factors and also needs to be included in the mathematical model. Thus, a novel mathematical model is proposed to characterize the cold chain VRP with independent loading requirements (CC-VRP-ILR). Specifically, we consider three types of customers with different requirements regarding mixed loading from local and foreign products. As the different customers' requirements, different vehicles are used to improve the loading rate and reduce the cost with a smaller number of vehicles in logistic distribution. Furthermore, fuel consumption cost is considered with different loading weight, travelling speeds, and traffic conditions. The cold-chain VRP with the requirement of independent loading is an NP-hard problem. In this paper, we employ an extended particle swarm optimization (PSO) algorithm to solve the CC-VRP-ILR problem. PSO algorithm (Eberhart & Kennedy, 1995) is a population-based algorithm to simulate birding foraging behavior to find the optimal food with continually updating its speed and location. However, the original PSO algorithm is easily trapped into local optimization. Therefore, we combine the original PSO algorithm with 2-opt optimization (Wang et al., 2020) to improve the performance and stability in solving CC-VRP-ILR problem. We design six sets of experiments to verify the practicality, performance, stability of the extended PSO algorithm by comparing with the original one based on three standard datasets of C201, R201 and RC201 in Solomon's library. The results demonstrate that the proposed PSO algorithm has better performance and stability than the traditional PSO algorithm in solving the CC-VRP-ILR.

The contributions of this paper are summarized as follows. First, a novel cold-chain VRP model is proposed to meet the customers' requirements of independent loading from local and foreign. Furthermore, we comprehensively consider the various important factors in cold-chain logistic distribution, including the cost of fuel consumption related to traveling speed and traffic condition, the costs of refrigeration and carbon emissions. Moreover, we propose an extended PSO algorithm combined with a 2-opt optimization algorithm to improve the local and global search performance in solving the cold-chain VRP.

The remaining organization of this paper is shown as follows. Problem description and model framework are presented in Sections 2 and 3, respectively. Section 4 is to demonstrate the extended PSO algorithm, and then we design and discuss the six sets of experiments results in Section 5. Section 6 is about the conclusion and future work.

2. Model framework

2.1. Problem Description

According to the requirements of independent loading from customers, this paper divides into three kinds of customers, including only delivering foreign frozen goods (Customers A), only independent loading with local items (Customers B), and approval of mixed loading (Customers C), as shown in Fig. 1.

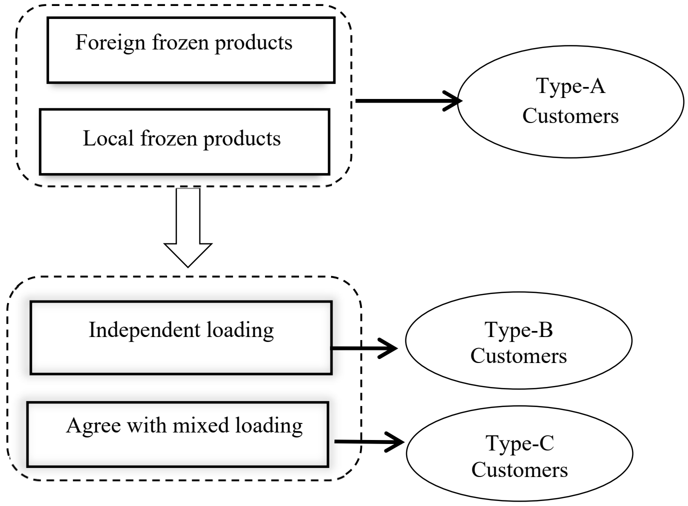


Fig. 1. Classification of customers based on different requirements.

The distribution company will deliver the frozen goods from the distribution center to the end customer according to the three types of customers and their order quantities, as shown in Fig. 2. There are two types of vehicles A and B used for distribution. Vehicle A can be chosen to deliver frozen goods to two customers B and C1 and vehicle B can be chosen to deliver customers A, C2, and C3. Therefore, it is important to select the appropriate vehicles and optimize suitable distribution routing with minimum total cost.

The assumptions are set as follows:

1. Customers' demand and locations are transparent;
2. Only one distribution center provides delivering services to customers;
3. Different kinds of vehicle attributes (load capacity, fuel consumption coefficient, refrigerated emission coefficient) are transparent;
4. Each customer can be distributed by only one vehicle;
5. All vehicles are delivering with uniform speeds in one period;
6. The service times for loading and unloading are the same in one customer point;
7. The vehicle will depart from the distribution center and return back to the distribution center after completing the delivering service.

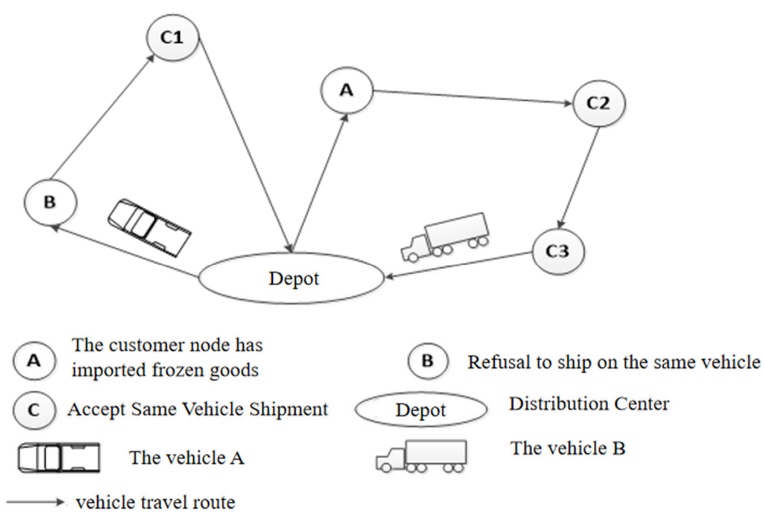


Fig. 2. Distribution network of frozen products.

2.2. Model

In this section, we focus on the transportation time and fuel volume of vehicles, and then consider the total cost with multiple vehicles distribution, including fixed cost, transportation cost, carbon emission cost, etc.

2.2.1. Transportation time calculation based on vehicle variable speed

The fuel consumption of each vehicle has a close relationship with the vehicle speed (Bektaş & Laporte, 2011) and transportation time, especially in the period of traffic jams (Li et al., 2023). In this paper, a new segmentation function is employed to characterize transportation time based on different vehicle speeds, as shown in Fig. 3. The vehicle speed will depend on the traffic conditions; thus vehicles will travel at different speeds in different periods. We consider three cases: in case A, vehicles *i* and *j* are travelling with the same speed in one period and the transportation time of case A is shown in Eq. (1.1); in case B, vehicles *i* and *j* are travelling in the adjacent periods with corresponding different speeds and the transportation time of case A is shown in Eq. (1.2); in case C, vehicles *i* and *j* are travelling in the two periods with multiple intervals, as shown in Eq. (1.3). Therefore, the equation of transportation time from customer *i* to customer *j* is shown in Eq. (1), where t_i means departure time from customer *i*; T_a represents start time in the period of a when vehicles are travelling with the same constant speed of v_a and u means the number of multiple intervals between two periods.

$$t_{ij} = \begin{cases} \dfrac{d_{ij}}{v_a}, & \text{if} \quad T_a \le t_i \le T_{a+1} - \dfrac{d_{ij}}{v_a} \quad (1.1) \\ (T_{a+1} - t_i) + \dfrac{d_{ij} - (T_{a+1} - t_i)v_a}{v_{a+1}}, & \text{if} \quad T_{a+1} - \dfrac{d_{ij} - (T_{a+2} - T_{a+1})v_{a+1}}{v_a} \le t_i \le T_{a+1} \quad (1.2) \\ (T_{a+u} - t_i) + \dfrac{d_{ij} - (T_{a+1} - t_i)v_a - \sum_{u=a+1}^{U+a}(T_{u+1} - T_u)v_u}{v_{a+u}}, & \text{if} \quad T_{a+1} - \dfrac{d_{ij} - \sum_{u=a+1}^{U+a}(T_{u+1} - T_u)v_u}{v_a} \le t_i \le T_{a+1} \quad (1.3) \end{cases} \tag{1}$$

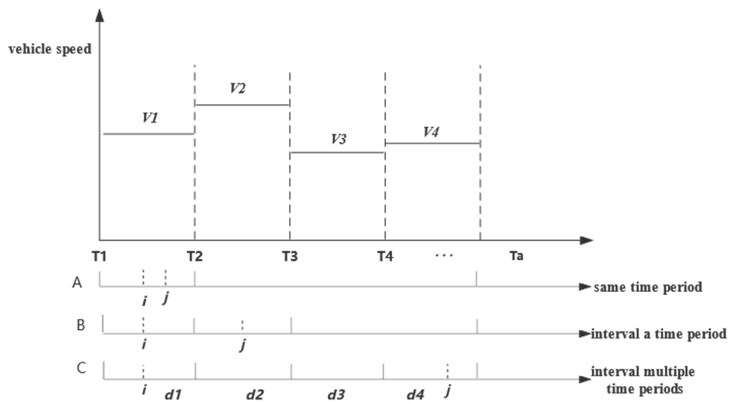


Fig. 3. Vehicle speed in different periods

2.2.2. Fuel volume of multi-vehicle vehicle

The transportation time is closely related to different vehicle speeds. The fuel volume is not only related to vehicle speed, but also related to the load volume, travelling distance, different types of vehicles and ground slope. The calculation of fuel volume of vehicle distribution is based on the model of integrated fuel consumption and the formula is shown as (Bektaş & Laporte, 2011; Li et al., 2011; Baldacci et al., 2008):

$$FC_{ij} = \left[\alpha_{ij}\left(Q_{p0} + f_{ij}\right)d_{ij} + \beta v_{ij}^2 d_{ij}\right]/q \tag{2}$$

The first term of Eq. (2) represents fuel consumption of vehicles with unloaded weight Q_{p0} of vehicle type *p* and loading weight f_{ij} of products from customers *i* to *j*; the second term of Eq. (2) means the fuel consumption based on vehicle speed and distance between customers *i* and *j*. The parameters and variables settings in this paper are shown in Table 1.

2.2.3. Objective function of CC-VRP-ILR

This paper considers a new VRP problem with multi-type vehicle and different customers' requirement of mixed loading of imported and domestic cold-chain. The aim of the distribution company is to minimize the total cost, including vehicle fixed cost, transportation cost, refrigeration cost, cargo disinfection cost, and carbon emission cost. The decision variable is whether *k*th vehicle with *p*-type will choose the routing from consumers *i* to *j*, i.e., $x_{ijpk} = \{1,0\}$. The constraint conditions include vehicle capacity, transportation distance, disinfection protection time and customer requirement of accept or reject mixed loading. The objective function of mathematical model is characterized as follows:

$$\min C = \sum_{p=1}^{p}\sum_{k=1}^{k}\sum_{j=1}^{n} x_{0jpk}F_p + \sum_{p=1}^{p}\sum_{k=1}^{k}\sum_{i=0}^{n}\sum_{j=1}^{n} x_{ijpk}\, C_f FC_{ij} \quad + \sum_{p=1}^{p}\sum_{k=1}^{k}\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ijpk} R_1 t_{ij} + \\ + \sum_{p=1}^{p}\sum_{k=1}^{k}\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ijpk} R_2 t_s + \sum_{i=1}^{n} q_i C_D + \sum_{p=1}^{p}\sum_{k=1}^{k}\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ijpk} C_E * \theta * FC_{ij} \tag{3}$$

subject to

$$\sum_{p=1}^{p}\sum_{k=1}^{k}\sum_{j=0}^{n}x_{ijpk}=1 \tag{4}$$
$$\sum_{p=1}^{p}\sum_{k=1}^{k}\sum_{i=0}^{n}x_{ijpk}=1 \quad \forall j \tag{5}$$
$$\sum_{j=0}^{n}f_{jipk}-\sum_{h=0}^{n}f_{ihpk}=q_i \quad \forall i,p,k \tag{6}$$
$$\sum_{i=1}^{n}\sum_{j=0}^{n}x_{ijpk}\le |S|-1 \quad S\subset N\backslash\{0\}\ S\ne\phi\ \forall p,k \tag{7}$$
$$q_j x_{ijp}\le f_{ijpk}\le (Q_p-q_i)x_{ijpk} \quad \forall i,j,p,k \tag{8}$$
$$\sum_{p=1}^{p}\sum_{k=1}^{k}\sum_{j=1}^{n}x_{ijpk}d_{ij}\le L_p\ ;\forall i \tag{9}$$
$$\sum_{i}^{n}\sum_{j}^{n}x_{ijpk}t_{ij}+\sum_{i}^{n}\sum_{j}^{n}x_{ijpk}t_s\le T_{max};\forall p,k \tag{10}$$
$$\left(\beta_i\sum_{p=1}^{p}\sum_{k=1}^{k}x_{ijpk}\right)\left(q_i^*\sum_{i=1}^{n}\sum_{p=1}^{p}\sum_{k=1}^{k}x_{ijpk}\right)=0 \quad \forall j \tag{11}$$
$$x_{ijpk}\in\{0,1\} \quad \forall i,j(i\ne j),p,k \tag{12}$$

Table 1
Parameters and variables.

Notation	Definition	Notation	Definition
$G=\{N,E\}$	set of distribution networks for cold chain foods	T_{max}	disinfection and protection time
$N=\{0,1,2,3,..,n\}$	set of all nodes, 0 is the index of the depot	F_p	the fixed cost of the vehicle type p
$E=\{(i,j)\|i,j\in N,i\ne j\}$	set of arc(i,j) refers to the vehicle routes	C_f	unit fuel price/litre
$P=\{1,2,3,...,p\}$	set of delivery vehicle types，p is vehicle type，$p\in P$	R_1	cost of refrigerated agents for transportation
$M=\{1,2,3,...,m\}$	set of logistics vehicles,k is the number of vehicles used ，$k\in M$	R_2	cost of refrigerated agent for loading and unloading
q_i	the demand of customer i	C_D	cost of disinfection of goods
Q_{P0}	unloaded weightof vehicle type p	C_E	unit carbon emission cost
Q_p	loading capacity of vehicle p	θ	carbon emission conversion factor
d_{ij}	the distance bewteen customer i and j	$q_i^*=\{1，0\}$	$q_i^*=1$if the customer delivers goods from an epidemic area; otherwise q_i^* =0
L_p	maximum transportation distance of vehicle p	$\beta_i=\{1，0\}$	$\beta_i=1$if the customer refuses to load the goods together; otherwise β_i =0
v	vehicle speed	$x_{ijpk}=\{1,0\}$	Binary variable denoting the k-th vehicle in the travel route of vehicle type p，x_{ijpk}=1 if it goes from nodei to j; otherwise x_{ijpk}=0
t_s	service time for vehicle unloading		

The objective function Eq. (3) regarding the total cost of distribution is consisting of five terms: the first term is the fixed cost of operating vehicles with maintenance cost; the second term is the cost of fuel consumption, the product of the amount of fuel and the unit price of fuel obtained by the approximate formula for calculating the amount of fuel; the third part is the cost of refrigeration, represents as the sum of vehicle transportation refrigeration cost and loading and unloading refrigeration cost, because considering that the vehicle speed is non-uniform under traffic congestion, the vehicle travel time is also variable, and the refrigerated cost is expressed by the product of refrigerant unit cost and transportation time during the travel process, similar to the loading and unloading process still generates refrigerated cost; the fourth part is the cost of disinfection of goods, considering that the secondary disinfection of goods will be increased before providing distribution during the epidemic, so it is the disinfection cost of the goods multiplied by the quantity of the goods. The fifth part is fuel carbon emissions, according to the current logistics industry to promote energy saving and emission reduction measures, the carbon emissions generated by the vehicle to the environment environmental pollution, this article uses the product of carbon emission conversion coefficient, carbon emission unit price, and fuel quantity to represent.

Constraints (4) and (5) indicate that each demand node has a car for service and is visited exactly once. Constraint (6) indicates the flow balance constraint. Constraint (7) indicates the elimination of path sub-loop. Constraint (8) indicates that the weight of the goods does not exceed the maximum capacity of the delivery vehicle. Constraint (9) indicates that the vehicle transportation distance does not exceed its maximum transportation distance. Affected by the pandemic, the disinfection frequency of distribution vehicles will increase, which will restrict the delivery time of vehicles, constraint (10) indicates that the vehicle in the delivery time cannot exceed the vehicle disinfection protection time. Constraint (11) indicates that the vehicle loaded with goods from the epidemic area will not be able to dispatch customers who exclude goods from the epidemic area, i.e., independent constraint. Constraint (12) is a decision variable taking the value of 0 or 1, indicating whether there is a distribution path between two nodes.

2.2.4. An extended PSO algorithm

There are two kinds of algorithms used to solve VRP problems, including exact algorithms (Baldacci et al., 2021) and heuristic algorithms (Pasha et al., 2022; Ahn and Kim, 2022; Gao et al., 2023). Exact algorithms can obtain the accurate solution, but only suitable for small-scale problems. Heuristic algorithm is based on observation and accumulation of experience. It is widely used in solving VRP because it has the advantages of high efficiency and practicality in the process of practical problem processing by generating feasible solutions under relevant constraints. Particle swarm optimization (PSO) is one of heuristic algorithms, with the advantages of easy implementation and fast convergence. However, the traditional PSO algorithm is easily trapped into local optimization. Therefore, an extended PSO is proposed to effectively learn from better individuals and balance global search and local improvement by combining a 2-opt neighborhood search algorithm. Fitness value is an important factor of heuristic algorithms to measure the survival advantage of an individual in the population. In this paper, Eq. (3) is considered as the fitness function to evaluate the performance of individuals in the population. The fitness function is closely related to fuel consumption of vehicles and various costs. The extended PSO algorithm is used to solve new VRP problem with multi-type vehicle and customers' requirements regarding mixed loading, the specific sets are shown as the follows:

Step 1: Individual encoding. Each individual particle consists of the No. of customers visited in order.

Step 2: Initialization phase. The starting customer node is randomly generated by the greedy algorithm. Then, the next node will be added based on the distance matrix and the previous location of the customer. The vehicle routing problem should meet the requirements of customers about independent loading of cold chains. The frequency of vehicle disinfection should be increased to satisfy timeliness of vehicle protection and ensure safety, and thus the customers are divided into different vehicles, consisting of the initial solution.

Step 3: Set up the fitness function. The fitness function represents the minimization of distribution cost of CC-VRP-ILR. That is to minimize the sum of fixed cost, transportation cost, loading and unloading refrigeration cost, and the cost of disinfection of goods.

Step 4: Introduce 2-opt optimization algorithm (Croes, 1958). The 2-opt optimization algorithm is employed to improve the local search with higher speed. The principle of the 2-opt optimization algorithm is to randomly select two points in the solution and overturn the ranking of the routing solution between the two points. As shown in Fig. 4, the original solution is 0-1-5-8-6-0, and 1 and 6 are selected to overturn between these two customers points by employing a 2-opt optimization algorithm. Thus, 5-8 will become 8-5 and the new solution can be obtained as 0-1-8-5-6-0.

Step 5: Fitness function. The individual best value and the group best value are identified based on the fitness function.

Step 6: Introduce crossover operators. The roulette strategy is employed to select parents' candidate solutions for crossover operator, the probabilities of particle selection are $\omega/(c1 + c2 + \omega)$, $c1/(c1 + c2 + \omega)$, and $c2/(c1 + c2 + \omega)$ for reverse order, the current optimal solution, and the global optimal solution, respectively.

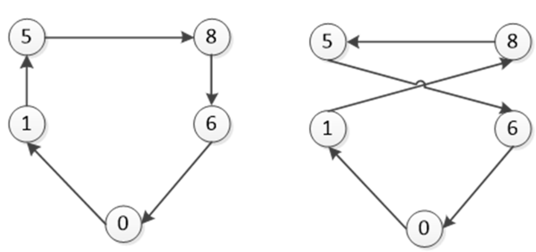


Fig. 4. 2-opt optimization.

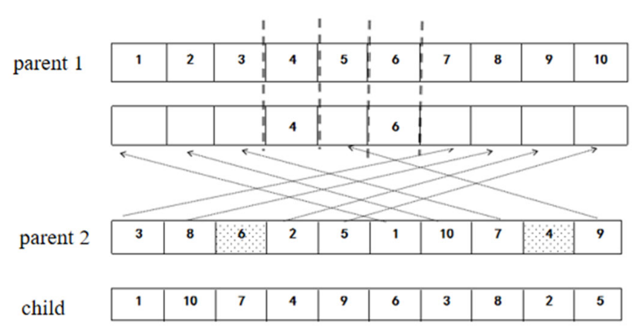


Fig. 5. Crossover operator of particles

Step 7: Update the local optimal solution. The fitness values of the new and previous individuals will be calculated, and then compare the two fitness values of the two particles. If the fitness value of the new particle is better than that of the previous individual, the previous particle will be replaced by the new one.

Step 8: Update the global optimal solution. If the fitness value of the current particle is better than the global optimal fitness value, the customer point distribution order corresponding to the current particle will be replaced by the global best customer point distribution order.

Step 9: After running the algorithm until terminal iteration times, the loop will be jumped and output the near-optimal solution. Fig. 6 shows the flow chart of the improved PSO algorithm.

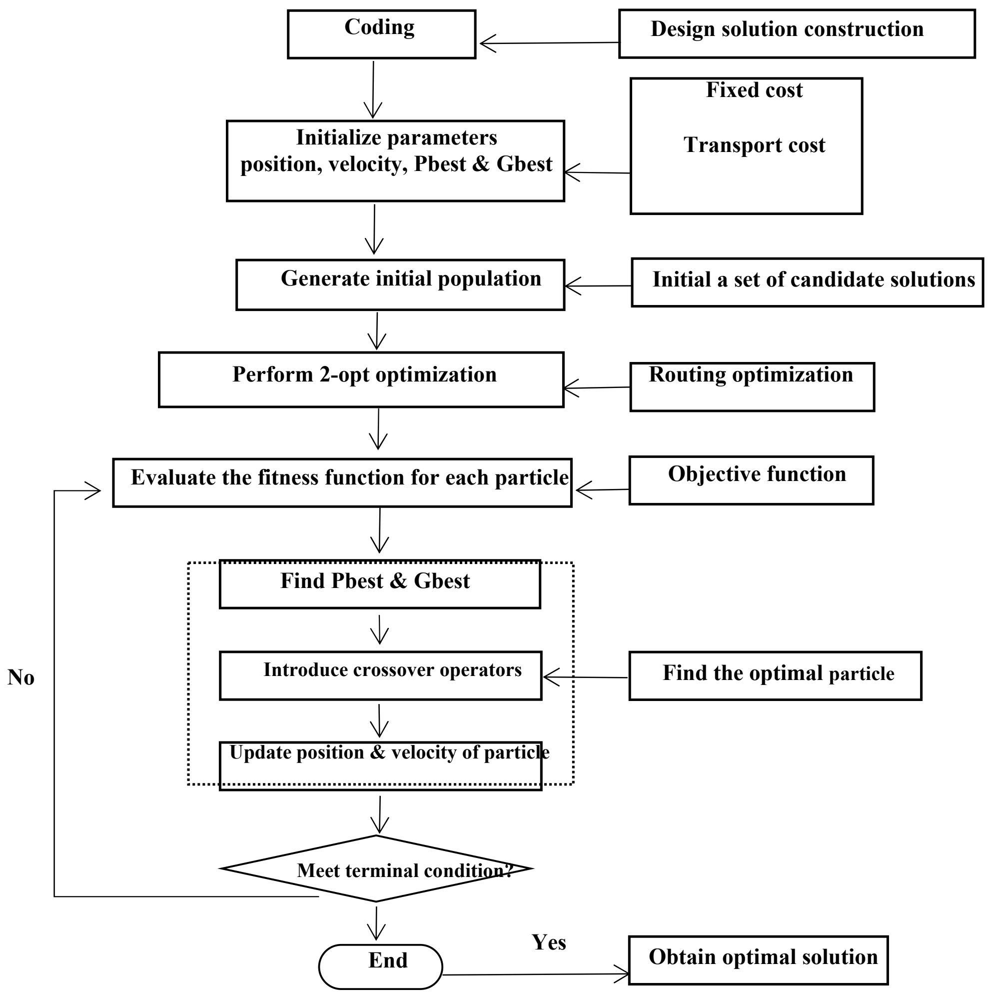


Fig. 6. An extended PSO algorithm.

3. Results

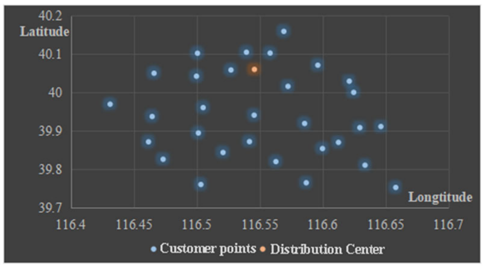
3.1. Data description

In this study, the feasibility of the model is verified with one distribution center and 30 customers. There are three types of vehicles, marketed as a, b, and c. However, this case still lacks data about three types of customer nodes. Therefore, we randomly generate three types of customer nodes: A, B and C. There are six customers of type A, including 2, 4, 8, 11, 14, 25, respectively; five customers of type B, including 1, 3, 7, 19, 23, respectively; and 19 customers of type C. Fig. 7 shows the locations of the 30 customers. Table 2 shows the parameters related to vehicle cost and algorithm.

In this paper, the dynamic vehicle speeds of vehicles are considered because of traffic congestion, assumed as follows.

1. The working time of the distribution center is 8:00 and the ending time is 22:00.

2. The analysis of the variable driving speed is based on one-hour increments, and the working time will be divided into 14 periods.
3. According to the traffic situation, 7:00 to 9:00 and 17:00 to 19:00 will be set as the morning and evening peak operation time, respectively. The vehicles will be driving 20km/h in peak time. The rest of the time is the normal time period.
4. The vehicle speed will be within [40km/h-70km/h] in normal time, and randomly generated as shown in Fig. 8.



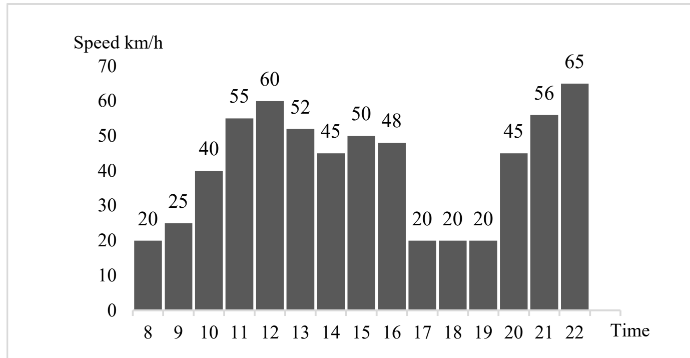


Fig. 7. Scatter diagram of customers locations

Fig. 8. Running speeds in different periods

3.2. Experimental Results

In this section, a single distribution center is used to deliver cold-chain products to 30 customer points, and an extended PSO algorithm is used to combine with the 2-opt local search algorithm to solve the optimal solution. The VRP problem is solved by the extended PSO algorithm in Fig. 9.

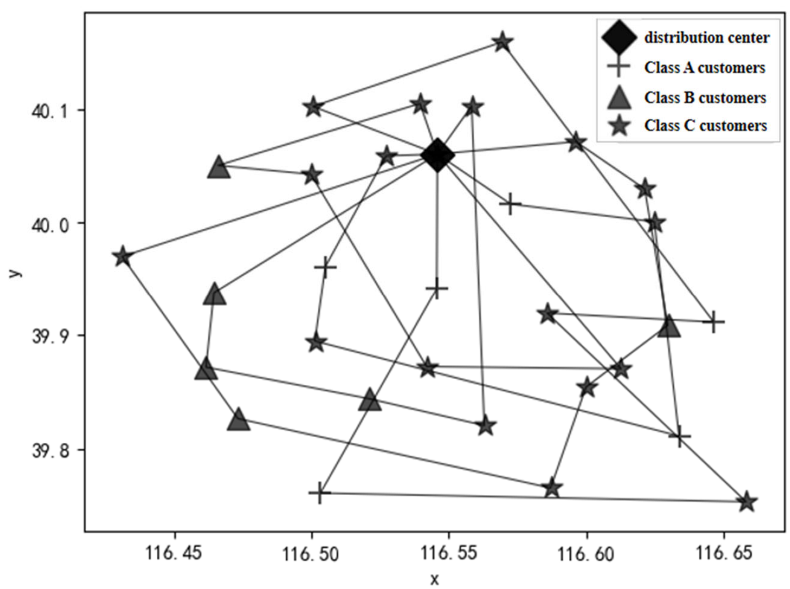


Fig. 9. Routing optimization of minimum cost based on 30 customers.

4. Discussion

To investigate the impact of different optimization objectives on distribution cost and related costs, the optimization goal is to minimize the total delivery cost and the shortest traveling length. As shown in Table 3, the solution R1 is solved based on the minimum transportation distance, and the solution R2 is solved based on the minimum distribution cost. In terms of vehicle traveling distance, the total traveling distance of solution R2 is 21.01% longer than that of solution R1. There exist different types of vehicles between solutions R1 and R2. Specifically, solution R1 employed three vehicles with a, b, c types each. Solution R2 employed three b-type vehicles and two a-type vehicles. However, the average loading rate of solution R2 is higher than that of solution R1. Specifically, the average loading rate of solution R1 is 91.88%, and the average loading rate of solution R2 is 93.14%. From the cost analysis in Table 4, the fuel consumption cost and carbon emission cost of solution R1 are 28.75% and 28.74% higher than those of solution R2, respectively. The result may be influenced by the different types of vehicles, loading, and travelling speed. The vehicle investment cost of solution R1 is 0.7% higher than that of solution R2, and total delivery cost of solution R1 is 5.29% and higher than that of solution R1.

Table 3
Solutions R1 and R2 route optimization

Solution	Objective	Fixed cost (yuan)	Refrigeration cost (yuan)	Fuel consumption cost (yuan)	Carbon emission cost (yuan)	Disinfection cost (yuan)
R1	Minimum distance	1360	84.81	306.69	19.08	15.32
	Total	1801.24				
R2	Minimum cost	1350	92.38	238.19	14.82	15.32
	Total	1710.71				

Table 4
Cost analysis of solutions R1 and R2

Solution	Objective	Sub-route	The vehicle type	Demand	Loading rate(%)	Distance
R1	Minimum distance	0-24-23-21-17-29-18-27-0	a	2.31	92.4	55.46
		0-30-15-8-22-28-0	b	1.86	93	56.41
		0-1-7-5-20-3-19-0	a	2.45	98	65.93
		0-14-12-9-6-11-26-16-2-0	a	2.4	96	101.55
		0-4-25-10-13-0	c	1.2	80	47.07
	Total		5	10.22	91.88	326.42
R2	Minimum cost	0-8-15-11-20-4-17- 0	b	2	100	65.84
		0-19-3-7-6-18- 0	b	1.92	96	69.18
		0-25-2-16-10-14-28-22-0	a	2.23	89.2	114.51
		0-24-1-26-9-13-30-27-0	a	2.3	92	81.67
		0-12-5-21-23-29-0	b	1.77	88.5	63.83
	Total		5	10.22	93.14	395.03

According to the above results analysis, the managerial insights for the logistics enterprise in distribution include: (1) it is not a wise decision for the enterprise to only focus on the shortest distribution distance when delivering the cold-chain products. In fact, the total cost will be influenced by the fixed vehicle cost, refrigeration costs, fuel consumption and other factors. Thus, it should consider the various costs when developing vehicle distribution solutions. The choice of vehicle type also has a great influence on costs of fuel consumption and carbon emission. With the increasing attention on sustainability, economic and environment-friendly vehicles are important to be considered in distribution. As a result, energy consumption and emissions can be effectively reduced to improve the economic and environmental benefits of enterprises. To verify the effectiveness and stability of the algorithm, the extended PSO algorithm and original PSO algorithm are compared to solve the VRP problems with running 10 times. As shown in Figure 10, according to the aim of the minimized total cost, most of the solutions solved by the extended PSO algorithm are better than those solved by the original PSO algorithm. Furthermore, the fluctuating range of the solutions solved by the original PSO algorithm is obviously higher than that of the solutions solved by the extended PSO algorithm. Therefore, from the perspective of effectiveness and stability, the proposed PSO algorithm is better than the original PSO algorithm in solving the VRP problem.

The standard datasets of C201, R201 and RC201 in Solomon's library are employed to verify the performance of the extended PSO algorithm in solving VRP different scales of customers. Each example of data consists of three different numbers of customers, including 25, 50, 100. However, the types of customers are still missing in the database. Thus, we randomly generate three different categories A, B and C. Specifically, the size of 25 customers is divided into three type-A, five type-B, and 17 type-C customers. Similarly, the size of 50 customers is divided into four type-A, five type-B, and 41 type-C customers. The size of 100 customers is divided into six type-A, 10 type-B and 88 type-C customers. To compare the performance of the extended PSO and original PSO algorithms, the solutions of the proposed VRP model are calculated based on those three datasets (i.e., C201, R201, and RC201). The comparison results are shown in Table 5.

Fig. 10. Comparison results of near-optimal solutions with 10 running times.

Table 5
Comparison results of minimum total cost of route optimization based on standard examples

Customer size	The standard arithmetic cases	The original PSO	The improved PSO
C201	25	1652.7	1608.8
	50	3180.4	3120.7
	100	7270.9	6810.3
R201	25	1377	1340.1
	50	2700.3	2826.9
	100	5874.2	5703.5
RC201	25	2119	2213.7
	50	4014.7	4339.0
	100	7319.8	7092.7

According to Fig. 11, the solutions of VRP with independent loading solved by the extended PSO algorithm have a significant advantage of cost-saving than those solved by the original PSO algorithm. As the example of 100 customer nodes from the databases C201, R201, and RC201, the cost-savings of those solutions solved by extended PSO algorithm can be well saved 6.76%, 2.99%, and 3.2%, respectively. Similarly, for 25 customer nodes from the databases C201 and R201, the total cost saving of the solutions solved by extended PSO algorithm can be reduced 2.73% and 2.75%, respectively. Furthermore, the solutions of VRP based on the dataset C201 solved by the extended PSO algorithm can always obtain positive cost savings, compared with those solved by the original algorithm. However, for the database of RC201 with 25 and 50 customer nodes, the solutions solved by the extended PSO are slightly inferior to those solved by the original PSO algorithm. In sum, the extended PSO algorithm has better performance than the original PSO algorithm in solving VRP with independent loading constraints.

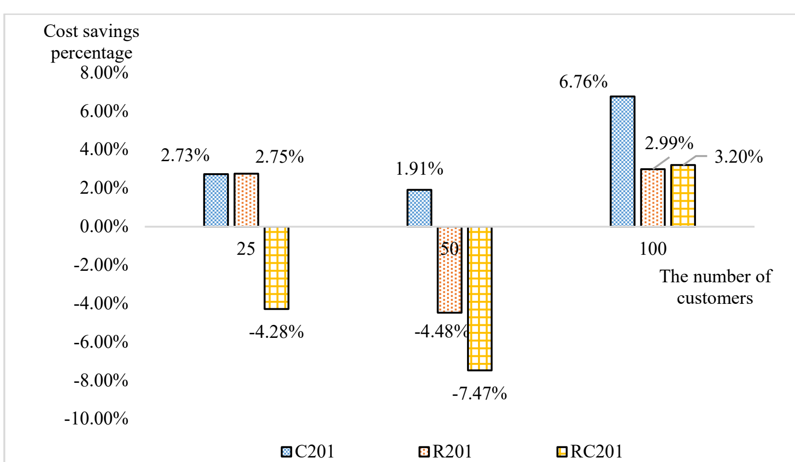


Fig. 11. Results of routing cost savings.

5. Conclusions

In this paper, we have considered customers' requirements about the independent loading of imported and domestic cold chain food in the context of the epidemic. To characterize the different requirements of the customers in distribution service, we have proposed a new VRP problem with three different kinds of customers and multiple vehicles, as well as considering various costs, including vehicle fixed cost, transportation cost, refrigeration cost, cargo disinfection cost, and carbon emission cost. To solve this VRP problem, an extended PSO algorithm is proposed to obtain the solutions by combining the 2-opt optimization. According to the results of experimental analysis based on three datasets, the extended PSO algorithm has better performance and stability than the original PSO algorithm in solving the VRP problem with independent loading.

The contribution of this study can be summarized as follows: (1) A new mathematical model has been proposed to characterize the VRP with the customer requirements regarding mixed-load distribution under the environment of pandemic. Furthermore, we have considered fuel consumption related to different traffic conditions. (2) We have also proposed an extended PSO algorithm to solve the new VRP problem with independent loading. The extended PSO algorithm is based on the original PSO algorithm to combine with 2-opt optimization to effectively learn from better individuals and balance global search and local improvement.

There are some limitations that need to be further improved. For example, if sudden traffic congestion or disruptions events appear in the process of distribution, how to provide an optimal solution of the VRP. Furthermore, different kinds of customers' satisfaction with time window and safety of cold-chain products are an important factor to be considered in the pandemic environment.

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Data Availability Statement

Not applicable.

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Conflicts of Interest

The authors declare no conflict of interest.

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