ISSN: 2688-8653

Research on Closed-loop Path Optimization of Urban Cold Chain based on Gray Wolf Algorithm

Jie Zhu, Gengjun Gao

School of Shanghai Maritime University, Shanghai , China

Abstract

With the development of economy, urban cold chain distribution has become an important part of logistics distribution. Considering factors such as environmental protection and low carbon, this paper proposes an urban cold chain Closed-loop path optimization model, which realizes the business plan of simultaneous distribution and recycling. Taking the lowest total cost of cold chain Closed-loop service as the objective function, and finally using the gray wolf optimization algorithm to complete the optimal planning of the model. The final experimental results show that the gray wolf optimization algorithm has a better solution effect than the genetic algorithm in the total service cost.

Keywords

Gwo; Closed-loop Service; Cold Chain Logistics.

1. Introduction

The urban cold chain Closed-loop service vehicle routing problem studied in this paper is to carry out distribution and recycling at the same time, which belongs to the NP-HARD problem, and its complexity is high and cannot be solved by using accurate algorithms and heuristic algorithms. Therefore, this paper adopts the intelligent optimization algorithm as the tool to solve. Traditional algorithms such as Genetic Algorithm, Simulated Annealing Algorithm, Tabu Search Algorithm, Ant Colony Algorithm and Particle Swarm Algorithm have been widely used in VRP problems[1], and have their own applicability, advantages and disadvantages. After reviewing a large number of literatures in this paper, it is concluded that the gray wolf algorithm has a good ability to find when solving the optimization function, can better balance the global search and local search, and can quickly find an approximate solution through iterative optimization calculation[2,3]. It has the advantages of simple operation, fast convergence speed and few parameters involved. The algorithm has been widely used in machine learning, power scheduling and controller optimization research. Based on the various advantages of the gray wolf algorithm, this paper proposes a cold chain Closed-loop path optimization method based on the gray wolf algorithm.

2. Problem Description and Model Building

2.1. Problem Description

Starting from a cold chain logistics distribution center, the geographical location of the point of sale and its distribution volume and recycling volume are known. Under the limitation of the number of vehicles and the load capacity, the vehicle depreciation fee, vehicle maintenance fee, labor fee, and vehicle fuel fee are comprehensively considered. , vehicle refrigeration costs and cargo damage costs and other costs to complete the distribution and recovery tasks at multiple points of sale. With the goal of minimizing the total cost, a vehicle scheduling scheme is designed so that the distribution and recovery tasks of each point of sale are completed. When

ISSN: 2688-8653

the vehicle unloads the cold chain goods for this distribution at the point of sale, it needs to recover the cold chain goods delivered last time.

Assumptions:

(1) The location of the point of sale and its distribution and recycling volumes are known and fixed:

(2) Each vehicle starts from the distribution center and returns to the distribution center after completing the distribution task;

(3) The required quantity of each point of sale must be met and can only be delivered by one vehicle;

(4) The vehicle load capacity of each line cannot exceed the maximum load capacity of the distribution vehicle;

(5) The driving time of each vehicle cannot exceed a certain constant:

(6) The vehicle runs at a constant speed.

2.2. Model Building

2.2.1. Mathematical Model

The objective function aims at the lowest Closed-loop service cost, in which the total cost consists of vehicle depreciation cost , vehicle maintenance cost, labor cost, fuel cost , cold chain refrigeration cost and transportation damage cost, respectively recorded as $C_1, C_2, C_3, C_4, C_5, C_6$.

$$min\ Z = \{C_1 + C_2 + C_3 + C_4 + C_5 + C_6\} \tag{1}$$

Vehicle depreciation cost represents the driving loss per unit vehicle, where C_z represents the distance driving loss per vehicle, n represents the number of demand points; i, j represent the subscripts of the demand points $(i, j = 1, 2, 3, \dots, n)$; the number of the distribution center is 0; k represents the subscript of the refrigerated truck ($k = 1,2, \dots, K$), K is the number of refrigerated trucks started; X_{ijk} represents the refrigerated vehicle k travels from the point of sale i to the point of sale j, take A value of 1 means passed, and a value of 0 means no pass; D_{ij} is the distance from point of sale i to point j.

$$C_1 = C_X \sum_{k=1}^{K} \sum_{i=0}^{n} \sum_{j=0}^{n} D_{ij} X_{ijk} \tag{2}$$

Vehicle maintenance costs mainly include vehicle maintenance fees and maintenance fees. When the transport vehicle reaches a certain mileage, it needs to go to the auto repair center for maintenance, and the resulting cost. Among them, C_Y is the maintenance cost per unit mileage of the vehicle.

$$C_2 = C_Y \sum_{k=1}^{K} \sum_{i=0}^{n} \sum_{j=0}^{n} D_{ij} X_{ijk} \tag{3}$$

Labor costs are mainly for workers' vehicle driving costs and delivery costs. Among them, C_Z is the labor cost per vehicle per unit time, t_{ij} is the time from the point of sale i to j for the vehicle, t_j^1 is the service time for loading and unloading items at point-of-sale j; t_j^2 is the service time for collecting goods at point-of-sale j .

$$C_3 = C_Z \sum_{k=1}^{K} \sum_{i=0}^{n} \sum_{j=0}^{n} \left(\mathrm{t}_{ij} + t_j^1 + t_j^2\right) X_{ijk} \tag{4}$$

The cost of fuel consumption, considering that the load of the vehicle changes during the distribution process, so the loss of unit fuel has been changing during the research process of this paper. Let Q_k be the fuel consumption when the vehicle is running without load, and G_i^k represent the load of the vehicle k away from point i. Q_b is the amount of fuel consumed to increase the unit distance of the unit mass of goods. Therefore, the total fuel cost can be expressed as:

$$C_4 = C_y \sum_{k=1}^{K} \sum_{i=0}^{n} \sum_{j=0}^{n} \left(Q_k + Q_b G_i^k\right) K_t D_{ij} X_{ijk} \tag{5}$$

The cooling cost mainly includes two stages of cost, one is the cooling cost caused by the consumption of the refrigerant during transportation, and the other is the cooling cost caused by the heat transfer due to the opening of the vehicle door during the loading and unloading process[4]. The unit time cost of cooling in the carriage during transportation is C_{t1}, and the cooling cost during loading and unloading is C_{t2}. The total cooling cost is expressed as:

$$C_5 = C_{t2} + C_{t1} \tag{6}$$

The cooling cost incurred during transportation is expressed as μ,

$$C_{t1} = \mu \times \sum_{k=1}^{K} \sum_{i=0}^{n} \sum_{j=0}^{n} \frac{D_{ij}}{v_{ij}} \times X_{ijk} \tag{7}$$

The heat load generated in unit time during the loading and unloading process is expressed as N, The door opening frequency coefficient is β, and the temperature change is Δt.

$$C_{t2} = \mu \times \beta \times \Delta t \times \sum_{j=1}^{n} \left(t_j^1 + t_j^2\right) \tag{8}$$

The cost of cargo damage mainly comes from the cost of cargo damage during transportation and the cost of cargo damage during service. During the transportation process, due to the accumulation of transportation time, food spoilage causes cargo damage. During the service process, due to the opening of the compartment door, the external heat load quickly enters the compartment, and the temperature of the compartment changes rapidly, resulting in cargo damage caused by food spoilage[5]. During distribution, the expected total damage cost due to food spoilage is:

$$C_6 = P \sum_{k=1}^{K} \sum_{i=0}^{n} \sum_{j=0}^{n} X_{ijk} \overline{b_j} \tag{9}$$

Among them, P is the price of goods per unit mass; $\overline{b_j}$ is the expected value of the loss of goods at point j.

2.2.2. Restrictions

$$\sum_{k=1}^{K} \sum_{j=0}^{n} X_{ijk} = 1, i = 0,1,\dots,n, i \neq j \tag{10}$$

$$\sum_{k=1}^{K} \sum_{i=0}^{n} X_{ijk} = 1, j = 0,1,\dots,n, i \neq j \tag{11}$$

$$\sum_{i=1}^{n} \sum_{j=0}^{n} q_i^1 X_{ijk} \leq Q_1, k = 0,1,\dots,K, i \neq j \tag{12}$$

ISSN: 2688-8653

$$\sum_{i=0}^{n} \sum_{j=0}^{n} \left(t_{ij} + t_j^1 + t_j^2\right) X_{ijk} \leq T, k = 1,2, \dots, K, i \neq j \tag{13}$$

$$\sum_{j=1}^{n} X_{ijk} = \sum_{j=1}^{n} X_{jik} \leq 1, i = 0, k = 1,2, \dots, K, i \neq j \tag{14}$$

$$G_i^k = G_i^k - q_i^1 + g_i,\ k = 1,2, \dots, K, i \neq j \tag{15}$$

Equation (10, 11) indicates that a point of sale can be serviced at most once; Equation (12) indicates that the weight of the cargo carried by each refrigerated vehicle cannot exceed the nuclear capacity Q_1 of the refrigerated vehicle;Equation (13) indicates that the running time of each refrigerated truck cannot exceed T;Equation (14) indicates that each refrigerated truck departs from the distribution center and returns to the distribution center;Equation (15) indicates that when the refrigerated truck k leaves the point of sale i , the load on the vehicle is equal to the load capacity of the previous point of sale minus the delivery volume of the goods at the point of sale i and plus the amount of goods recovered at the point of sale i.

3. Solving Algorithm

Inspired by the predation behavior of gray wolves, Mirjalili et al[6,7]. proposed a new swarm intelligence optimization algorithm in 2014: the gray wolf optimization algorithm. GWO achieves the purpose of optimization by imitating the predation behavior of gray wolves and the division of wolves, based on the mechanism of wolf group cooperation. The GWO algorithm has the characteristics of simple structure, few parameters to be adjusted, and easy implementation. There are convergence factors and information feedback mechanisms that can be adjusted adaptively, which can achieve a balance between local optimization and global search. It has good performance in terms of solution accuracy and convergence speed.

3.1. Grey Wolf Optimization Algorithm

Gray wolf individuals can be divided into four groups: α, β, δ, and ω, which have a very strict social hierarchy system, like a pyramid. The first level of the pyramid is the leader of the population, called α. In wolves, α is the managerial individual responsible for decisions about hunting, time and place to sleep, food distribution, and so on. The second level of the pyramid is Alpha's think tank team, called Beta. β is mainly responsible for assisting α in decision-making. When there is a vacancy in the α of the entire wolf pack, β will take over the position of α. The dominance of β in the wolf pack is second only to α. It issues the orders of α to other members, and feeds back the execution of other members to α, which acts as a bridge. The third layer of the pyramid is δ, δ obeys the decision-making orders of α and β, and is mainly responsible for affairs such as reconnaissance, sentry, and care. α and β with poor fitness will also be reduced to δ. The bottom layer of the pyramid is ω, which is mainly responsible for the balance of relationships within the population[8].

Therefore, in the GWO algorithm, α is responsible for the decision-making and management of wolves; B and β are gray wolf individuals whose fitness is inferior to α; ω is other gray wolf individuals. The GWO algorithm mainly includes three behaviors: encircling, hunting and attacking[9,10].

$$\vec{D} = | \vec{C} \cdot \vec{X}_p(t) - \vec{X}(t) | \tag{16}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \tag{17}$$

$$\vec{A} = 2\vec{a} \cdot \vec{r_1} - \vec{a} \tag{18}$$

$$\vec{C} = 2 \cdot \vec{r_2} \tag{19}$$

Equation (16) represents the distance between the individual and the prey, and Equation (17) is the position update formula of the gray wolf. where t is the current iterative algebra, $\vec{A}$ and $\vec{C}$ are coefficient vectors, and $\vec{X}_p$ and $\vec{X}$ are the position vector of the prey and the position vector of the gray wolf, respectively.

Among them, $\vec{a}$ is the convergence factor. As the number of iterations decreases linearly from 2 to 0, the modulo values of $\vec{r_1}$ and $\vec{r_2}$ take random numbers between [0, 1].

The mathematical model for individual grey wolf tracking of prey location is described as follows:

$$\begin{cases} \vec{D}_\alpha = \left|\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}\right| \\ \vec{D}_\beta = \left|\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}\right| \\ \vec{D}_\delta = \left|\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}\right| \end{cases} \tag{20}$$

Among them, $\vec{D}_\alpha$, $\vec{D}_\beta$ and $\vec{D}_\delta$ represent the distances between α, β and δ and other individuals, respectively. $\vec{X}_\alpha$, $\vec{X}_\beta$ and $\vec{X}_\delta$ represent the current positions of α, β and δ, respectively; $\vec{C}_1$, $\vec{C}_2$ and $\vec{C}_3$ are random vectors, and $\vec{X}$ is the current position of the gray wolf.

$$\begin{cases} \vec{X}_1 = \vec{X}_a - A_1 \cdot \vec{D}_\alpha \\ \vec{X}_2 = \vec{X}_\beta - A_2 \cdot \vec{D}_\beta \\ \vec{X}_3 = \vec{X}_\delta - A_3 \cdot \vec{D}_\delta \end{cases} \tag{21}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{22}$$

Equation (21) defines the step size and direction of individual ω in the wolf pack toward α, β and δ, respectively. Equation (22) defines the final position of ω.

When the prey stops moving, the gray wolf completes the hunting process by attacking. In order to simulate approaching the prey, the value of $\vec{a}$ is gradually reduced, so the fluctuation range of $\vec{A}$ is also reduced. In other words, in the iterative process, when the value of $\vec{a}$ decreases linearly from 2 to 0, the corresponding value of $\vec{A}$ also changes in the interval [-a, a]. When the value of $\vec{A}$ is within the interval, the next position of the gray wolf can be anywhere between its current position and the prey position. When $|\vec{A}|<1$, the wolves attack their prey (falling into a local optimum).

3.2. Algorithm Flow

The steps of the GWO-based vehicle distribution logistics path optimization algorithm are described as follows:

Step1: Set the parameters of GWO algorithm: population size N, maximum number of iterations Max;

Step2: Initialize the gray wolf position;

Step3: Calculate the fitness of each gray wolf according to the formula (1), and record the individual positions of the gray wolf with the top three fitness as $\vec{X}_a$, $\vec{X}_\beta$ and $\vec{X}_\delta$;

Step4: Calculate the approximate distance between each ω wolf and the α, β and δ wolves according to formula (20), and update the positions of the α, β and δ wolves and the position of the prey;

Step5: Update parameters a, $\vec{A}$ and $\vec{C}$;

Step6: Calculate the fitness of each gray wolf according to formula (1);

Step7: Judging the termination condition of the algorithm: if the maximum number of iterations Max is reached, output the position of the best gray wolf a as the best path for vehicle logistics distribution.

3.3. Encoding and Decoding Design of Algorithms

The standard GWO algorithm adopts continuous real number encoding method, which cannot be directly applied to solving discrete problems[11]. In order to overcome the shortcomings of the standard GWO algorithm encoding, this paper constructs an integer-based encoding and decoding method, so that the GWO algorithm can be applied to the optimal solution of the model in this paper.

The VRPSTW problem defined in this paper has N+1 location points, denoted as {0, 1, 2, ... , N}, where 0 represents the distribution center, and {1, 2, ... , N} represents the customer. Using integer coding, the customer's numbers are formed into a sequence according to their delivery order, which is a solution to the VRPSTW problem. During the decoding process, a sequence contains the delivery sequence information of multiple vehicles. In this paper, the sequence is segmented according to the weight of the goods, the travel time and the number of customers. Each segment of the segmented sequence represents the delivery route of a vehicle.

Suppose there are customers {1, 2, 3, 4, 5, 6, 7}, the number of customers per line is limited to 3, the weight of goods required by each customer is 1 ton, and the load capacity of each vehicle is 4 tons. Then in the solution sequence {2, 3, 1, 4, 5, 6, 7}, the {2, 3, 1} subsequence customer's cargo weight is 3 tons, which is allocated to vehicle 1 for distribution, and its distribution order is {0 ,2,3,1,0}. The {4,5,6} sub-sequence customer's cargo weight is 3 tons, which is allocated to vehicle 2 for delivery, and its delivery sequence is {0,5,6,0}. Finally, {7} is delivered by vehicle 3, and its delivery order is {0,7,0}.

4. Case Analysis

4.1. Experimental Setup

The data source of the example is the delivery customer data of a fresh enterprise on a certain day, and there is a total of 15 demand points. These customer points are numbered and located through Baidu Maps[12]. Convert the location of the 15 customer points into a plane rectangular coordinate system, as shown in Figure 5-1, the distribution center and customer coordinates, and use the cold chain company's distribution data on July 2, 2021 for the demand for the distribution point. The specific information of the point of sale is now integrated as shown in Table 1, the distribution center is represented by 0, and the distribution customer node is represented by the number 1-15.

Table 1. Customer node geographic information

Number	X Coordinate	Y Coordinate	Delivery Quantity	Delivery Quantity
0	0.00	0.00	0	0
1	1.51	-4.23	65	20
2	-7.21	-6.22	72	12
3	-0.4	-6.70	30	0
4	0.76	-6.46	25	9
5	-2.15	-8.44	41	17
6	-2.50	-2.70	32	7
7	6.74	-10.40	25	20
8	1.21	-1.93	62	24
9	2.70	-10.71	29	0
10	-3.91	-8.83	60	25
11	-4.93	-10.62	40	15
12	-2.12	-3.14	58	23
13	-1.91	-2.72	40	0
14	-0.53	-4.13	89	0
15	3.83	-6.50	44	15

4.2. Model Solving and Analysis

Each vehicle weighs 1.5t, the unit mileage depreciation fee is 0.8 yuan/km, the unit mileage maintenance fee is 0.56 yuan/km, the unit time labor cost is 60 yuan/h, and the unit fuel price is 6.5 yuan/L. The fuel consumption is 2.01L, the unit price of the refrigerant is 0.68 yuan, the average product price is 25 yuan, and the maximum time for a single driving is 3h.

In order to prove the effectiveness of the gray wolf optimization algorithm, this section compares the solution results and solution time obtained by the gray wolf optimization algorithm with the genetic algorithm.

Both the genetic algorithm and the gray wolf optimization algorithm are implemented by MATLAB. The initial population is 50, the iteration is 500 times, and 10 experiments are carried out for each example. The crossover probability of the genetic algorithm is 0.7, and the mutation probability is 0.1. Use the mean value as the experimental result.

The results of the genetic algorithm and the gray wolf optimization algorithm and the comparison results of the solution time are shown in Table 2. Observe that:

Table 2. Customer node geographic information

number of delivery points	GA		GWO	
	Average result (yuan)	Computation time (seconds)	Average result (yuan)	Computation time (seconds)
5	271.28	2.31	253.25	5.71
10	570.25	10.20	542.37	24.30
15	905.15	55.27	856.35	90.42

Using the gray wolf optimization algorithm to solve the problem has the advantages of lower solution cost and more mileage savings. In the calculation example in this section, the larger the scale of the distribution point, the lower the total cost of the Grey Wolf optimization algorithm; considering the actual situation of the enterprise, the average city distribution node of the enterprise will not exceed 20, and the total solution time is relatively acceptable.

ISSN: 2688-8653

Therefore, it can be considered that using the gray wolf optimization algorithm proposed in this paper as a solution tool for the case in this paper can balance the global search and the local search, and obtain a more satisfactory solution to the problem.

5. Conclusion

This paper firstly establishes a VRP mathematical model for simultaneous delivery and delivery of goods for the problem of route optimization of cold chain Closed-loop service vehicles. According to the characteristics of the model, the gray wolf optimization algorithm is selected. The gray wolf optimization algorithm balances the global search ability and local search ability well, and accelerates The convergence speed of the algorithm is improved, and the convergence accuracy of the algorithm is improved. Finally, comparing the solution results with the genetic algorithm, it is verified that the method proposed in this paper can effectively optimize the distribution path of logistics distribution vehicles, reduce the distribution cost and improve the distribution efficiency.

References

[1] Chen Xueping, Sun Ying, Li Jie, Meng Kun, Ye Yudong. Improvement of logistics and distribution technology for chilled meat products based on the Internet of Things (Shanxi Agricultural Economics), Vol .19(2020),125-126.

[2] Zhu Shufan, Gui Ping. Game Analysis of Cold Chain Emergency Logistics Collaborative Distribution Decision under Major Epidemic(China Safety Production Science and Technology), Vol .16 (2020), No.6, p. 30-36.

[3] Kong Derui, Li Hong. Matsutake cold chain logistics distribution model based on the perspective of consumers (China Edible Fungi), Vol .39(2020),No.1, p. 128-130.

[4] Zuo Jian, Xie Pingping, Li Yinhong, et al. based on intelligent optimization algorithm Design and control performance analysis of load frequency controller for grid grid(Chinese Journal of Electrotechnical Technology), Vol .33(2020),No.3, p.478-489.

[5] Li Xing, Yang Xiuyuan, Wang Lijie. Grey wolf algorithm in wind power and hydropower co-operation Application in line (Power Generation Technology), Vol .39(2018),No.1, p.43-48.

[6] Jiang Haiqing, Zhao Yanwei, Leng Longlong. Based on chemical reaction optimization algorithm Vehicle Routing Problem(Computer Integrated Manufacturing System), Vol.24(2018),No.8, p. 2012-2022.

[7] Zhang Xiaonan, Fan Houming. Multi-trip fuzzy demand vehicle with time window preference Vehicle Path Optimization (Computer Integrated Manufacturing System), Vol.24(2018),No.10, p. 89- 105.

[8] Sun Qi, Jin Yan, He Kun, etc. For solving mixed vehicle routing problems The Hybrid Evolutionary Algorithm Knife. (Computer Science), Vol.45 (2018) No.4, p. 76-82.

[9] Zhang Xiaofeng, Wang Xiuying: Review of Research on Grey Wolf Optimization Algorithm (Computer Science),Vol.46 (2019) No.3, p.30-38.

[10] Wang Weijun, Luo Wei. Research on the optimization problem of cold chain logistics distribution route based on improved intelligent water drop algorithm (Industrial Engineering), Vol.20 (2017) No.2, p. 38-43.

[11] Wu Cong, Yang Jianhui. Logistics distribution vehicle scheduling optimization based on improved particle swarm algorithm (Computer Engineering and Applications), Vol.51 (2015) No.13, p. 259-262, 270.

[12] Fantasy Tang Jun. Research on Distribution Vehicle Scheduling under Time Window Constraints (Computer Engineering and Applications), Vol.47 (2011) No.21, p. 243-245, 248.