Optimization on Perishables Vehicle Routing Considering Cold Storage Multi-temperature Joint Distribution of Simultaneous Pickup-delivery

Meng Yuan, Haibo Mu, Yuchen Li, Xu Huang, Huo Chai

***Abstract*—Aiming at the Perishables Vehicle Routing Problem of Cold Storage Multi-temperature Joint Distribution with Simultaneous Pickup-Delivery (PVRPCSMTJDSPD), a customer satisfaction function with comprehensive evaluation of time satisfaction and quality satisfaction is established, a multi-objective optimization model with minimization of the sum of total distribution cost and maximization of the comprehensive customer satisfaction is constructed, and an Improved Adaptive Non-dominated Sorting Genetic Algorithm (IANSGA-II) has been developed for solving the model. In the algorithm solving session, Adaptive Large Neighborhood Search (ALNS) is introduced to improve NSGA-II algorithm, and large-scale neighborhood search is carried out by destroying and repairing operators, which effectively improves the algorithm's ability to find the optimal. The performance of the algorithm is tested by selecting the test data set cases, and the results show that: ①the multi-objective model developed in this paper demonstrates superior ability in striking a finer equilibrium between overall costs and customer satisfaction in contrast to the single-objective model; ②the IANSGA-II algorithm developed in this paper achieves the minimum total cost, maximum customer satisfaction, and the number of vehicles are 1883.31, 0.80, and 5., respectively, while the traditional NSGA-II algorithm yields 1971.74, 0.79, and 6, respectively. In comparison, the IANSGA-II algorithm has certain advantages in saving cost and improving customer satisfaction.**

***Index Terms*—Vehicle routing problem, Cold Storage MTJD, Simultaneous pickup-delivery, IANSGA-II algorithm**

I. INTRODUCTION

As people's requirements for the quality of perishables continue to improve, the distribution of perishables continues to highlight the problem of its short shelf life and easy to wear and tear of the characteristics of the distribution link requires a higher timeliness. However, the traditional refrigerated vehicle distribution model exhibits significant limitations, including high vehicle specificity, low utilization rates, and frequent order splitting. To address these challenges, the cold storage Multi-temperature Joint Distribution (MTJD) model has emerged in cold chain logistics. Unlike conventional refrigerated vehicles that rely on engines and compressors to maintain compartment temperatures, the cold storage MTJD system utilizes ordinary vehicles equipped with temperature-controlled insulated containers to facilitate the joint distribution of goods across different temperature zones [1]. This approach represents a more advanced and flexible distribution model in modern cold chain logistics [2].

The Vehicle Routing Problem (VRP) was first introduced by Dantzig, G.B. et al. [3] and has since evolved into various extensions. The Perishable Vehicle Routing Problem (PVRP) differs from the traditional VRP in that it requires stringent temperature control during transportation. Early research on PVRP primarily focused on single-temperature perishable goods [4-9]. Building on this, Ji, Y. et al. [10] extended the vehicle scheduling problem by incorporating simultaneous pickup-delivery constraints for single-temperature cold-chain products. Deng, F. et al. [11] further expanded this framework to optimize routing for multiple cold-chain products with simultaneous pickup and delivery, thereby extending PVRP to multi-vehicle, multi-temperature perishable distribution. The emergence of the MTJD model has driven research on the co-distribution of perishables across multiple temperature zones. Cho, Y.J. et al. [12] confirmed the feasibility of the cold storage MTJD mode. Hsu, C.J. et al. [13] and Wang, S.Y. et al. [14] demonstrated its economic and social benefits compared to conventional refrigerated vehicle distribution. Wang, S. et al. [15] found that the cold storage MTJD mode can reduce energy consumption by over 40% relative to traditional refrigerated vehicle distribution. Dai, X. et al. [16] further explored scheduling strategies for multi-temperature cargo demands, showing that the cold storage MTJD model significantly lowers distribution costs compared to mechanical refrigeration-based distribution.

As the research continues, a single PVRP variant of the problem is no longer sufficient to meet the demand, and thus it is gradually expanding to form many multi-variant fusion problems. Li, W. et al. [17] studied the vehicle path problem under low carbon conditions; Zhang, S. et al. [18] invstigated the vehicle path problem in a low-carbon context and stochastic demand; Wei Hu et al. [19] examined traditional mechanical multi-temperature joint distribution with simultaneous pickup and delivery, proposed a single-objective model that minimizes total cost and

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designing a genetic algorithm (GA) to solve it; Xiaofang Yang et al. [20] constructed a multi-objective model by considering factors such as the freshness of perishables, and used the main objective method to transform the multi-objective into a single-objective for solving; Qiulei Ding et al. [21] considered the impact of time and order completion rate on customer satisfaction, then constructed a multi-objective optimization model, and used GA to transform multi-objective into single-objective solution; Haoran Gao et al. [9] developed a PVRP model with the combined effect of time and perishable product quality, then transformed customer satisfaction into a minimum satisfaction constraint, and designed Improved Adaptive Genetic Algorithms (IAGA) to solve the problem; Qian Li et al. [22] introduced the fuzzy time window factor to evaluate customer satisfaction, constructed a multi-objective model and designed NSGA-II to solve the problem; Shuyun Wang et al. [23] constructed a multi-objective comparison model between mechanical MTJD and cooling-storage MTJD considering the freshness factor of cold chain goods, solved using NSGA-II and compared the results. For solving the multi-objective vehicle path problem for general cargo, Xiancheng Zhou et al. [24] and Xintong Qie [25] designed the hybrid algorithm based on NSGA-II and LNS to solve the multi-objective model; and Jian An [26] used the ALNS algorithm to solve the multi-objective problem.

In summary, the research results in the literature on PVRP are remarkable, laying a foundation for further optimization of its model and algorithm, although there are also several shortcomings. Existing research on PVRP primarily focuses on the distribution and simultaneous pickup-delivery of single-temperature perishables, with limited attention given to the simultaneous pickup-delivery of multiple perishable goods. Furthermore, few studies have explored the simultaneous pickup-delivery of multi-temperature perishable goods combined with cold storage MTJD constraints. Additionally, when solving the multi-objective model of MTJD with cold storage, most existing research converts the multi-objective problem into a single-objective one, which leads to limited results. To address these gaps, this paper investigates multiple PVRPs, proposing a multi-objective optimization model that minimizes total cost and maximizes customer time satisfaction and merchandise freshness, while considering the demand for cold-storage MTJD and simultaneous pickup-delivery. The model is solved using the IANSGA-II algorithm to optimize vehicle routing.

II. Problem Description And Model Establishment

A. Problem Description

Assumed that a supplier sets up a distribution center with k identical ordinary vehicles to Simultaneous deliver and pick up h perishable products of different temperatures to n retailers using cooling-storage multi-temperature co-distribution. The Distribution centers have no storage capacity. The Retailers are not allowed to run out of stock. The vehicles are required to start from the distribution center, complete the pickup and delivery services in a certain order at a constant speed, and finally return to the original distribution center. The optimization objective is to find the optimal path that minimizes the pickup-delivery costs and maximizes customer satisfaction.

The basic assumptions of the model are as follows:

1) The cold storage insulation boxes can meet the temperature requirements of perishable goods. The distribution and retrieval of goods can be mixed, and the deterioration rate of different types of goods is equal.

2) Cargo size is not considered, and vehicle loading is not allowed to be overweight.

3) Each retailer's pickup of each type of goods is less than the demand, and each retailer is delivered only once during an order cycle.

B. Related Parameters

The symbols and decision variables in the text are represented as shown in Table I.

TABLE I MEANING OF SYMBOLS AND VARIABLES

Notation	Interpretation
H	A collection of perishable species categories, $H=\{1,2,...,h\}$
N	All nodes, $N=\{0,1,2,...,n\}$, 0 for distribution centers, $\{1,2,...,n\}$ for each retailer
K	Distribution vehicle pooling, $K=\{1,2,...,k\}$
D_{hi}	Retailer i's orders for class h goods
$D_{hi}^{'}$	Distribution center's shipments for Retailer i for class h goods
θ	Rate of loss of perishable goods in transit
δ	Perishable goods loss rate at retailer's inventory stage
c_b	Unit inventory holding cost
c_d	Unit cost of goods loss
c_k	Common vehicle fixed costs
c_f	Transportation costs per unit distance for ordinary vehicles
v	Average speed of ordinary vehicles
d_{ij}	Distance from retailer i to retailer j, with $i=0$ indicating the distance from the distribution center to each retailer
g	Fixed cost of cold storage and holding tanks
c_h	Refrigeration costs incurred for storing goods of type h per unit of cold-storage container
q	Volume of goods that can be loaded per unit of cold storage insulation box
N_h^k	Integer variable indicating the total number of cold storage insulation tanks required for category h cargo loaded in vehicle k (1 tank if less than 1 tank).
Q	Maximum number of cold holding tanks that can be loaded per vehicle
Q_n	Maximum loading capacity of ordinary vehicles
q_{hi}	Retailer i's demand for deliveries of goods in category h
p_{hi}	Retailer i's pickup demand for goods of category h
g_i^k	Service time of vehicle k at retailer i
t_{ij}^k	Travel time of vehicle k from retailer i to retailer j
t_i^k	Time of arrival of vehicle k at retailer i
$[e_i,l_i]$	Retailer i's desired time window
$[E_i,L_i]$	Retailer i's maximum tolerable time window
x_{ij}^k	0-1 variable with a value of 1 when vehicle k travels from retailer i to retailer j; 0 otherwise
y_i^k	0-1 variable with a value of 1 when vehicle k serves retailer i; 0 otherwise

C.Model Establishment

The biggest difference between cold chain distribution of perishable goods and ordinary goods distribution is that the cold chain distribution needs to strictly control the temperature, which makes the cost of cold chain logistics much higher than ordinary logistics. Therefore, effective cost analysis and control of cold chain distribution is conducive to enhancing the core competitiveness of cold chain logistics enterprises.

1. Relationship between shipments, orders and demand for perishables

Considering the use of cold storage tanks, the temperature stability of perishables can be effectively ensured both in transit and in the retailer's inventory stage. Therefore, it is considered to be a constant deterioration process, and the loss rate in transit and in the retailer's inventory stage are θ and δ, respectively. Considering the in-transit loss, the shipment quantity $D_{hi}^{'}$ of the category h perishable product from the distribution center to retailer i is larger than its order quantity D_{hi}. Considering the loss in the inventory stage of retailer i, the order quantity D_{hi} is larger than its demand quantity q_{hi}. The following relation is obtained [27]:

The relationship between shipments and orders is:

$$D_{hi}^{'}\left(1-\theta\right)=D_{hi} \tag{1}$$

The relationship between orders and demand is:

$$D_{hi}\left(1-\delta\right)=q_{hi} \tag{2}$$

2. Retailer Inventory Cost Analysis

1) Inventory holding costs

Since retailer i's demand and optimal order quantity for product h during the cycle are q_{hi} and D_{hi}. Then the retailer i's inventory cost is $c_b\left(D_{hi}-q_{hi}\right)$.

So, the cost of inventory at the retailer is expressed as:

$$TC_1=\sum_{h=1}^{H}\sum_{i=1}^{N}c_b\left(D_{hi}-q_{hi}\right) \tag{3}$$

2) Inventory damage costs

Since the retailer is not allowed to run out of stock, excess inventory is created, and as inventory is held for longer periods of time, losses are incurred.

The cost of inventory loss at retail stage is denoted as:

$$TC_2=\sum_{h=1}^{H}\sum_{i=1}^{N}c_d\delta D_{hi} \tag{4}$$

3. Transportation cost analysis

1) Fixed costs of vehicles and cold storage insulation box

In this model, the fixed cost of vehicles mainly includes the purchase cost of vehicles, vehicle depreciation, wear and tear costs and maintenance costs, etc.; the fixed cost of the cold storage box consists of the depreciation costs of the cold storage box and maintenance costs and so on. Therefore, the total fixed cost can be expressed as:

$$TC_3=\sum_{k=1}^{K}c_k+g\sum_{k=1}^{K}\sum_{h=1}^{H}N_h^k \tag{5}$$

2) Fuel cost of the vehicle

Assuming that the vehicle fuel cost is a function related to the distance traveled by the vehicle. So it can be expressed as:

$$TC_4=c_f\sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=1}^{K}d_{ij}x_{ij}^k \tag{6}$$

3) Refrigeration costs of cold storage insulation box

Cold storage tanks must be cold storage before use, this step will consume energy and generate a large amount of power consumption costs (refrigeration costs). In the cold storage multi-temperature co-distribution model, the loading and unloading of the cargo will be loaded and unloaded together with the cold storage box, which leads to no need to consider the refrigeration cost during transportation of the vehicle as well as opening and closing of the door. Thus the refrigeration cost of the cold storage insulation box can be expressed as:

$$TC_5=\sum_{k=1}^{K}\sum_{h=1}^{H}c_hN_h^k \tag{7}$$

4) Cost of transportation loss

The temperature is stable during the distribution process using the cold storage and holding box, so only the loss caused by the accumulation of time in the distribution and pickup process needs to be considered, The cost of cargo loss in the distribution and pickup process is as follows:

$$TC_6=\sum_{h=1}^{H}\sum_{i=1}^{N}c_d\left[(D_{hi}^{'}-D_{hi})+\theta p_{hi}\right] \tag{8}$$

4. Comprehensive Customer Satisfaction Measurement

1) Time satisfaction

Comparing the vehicle arrival time to the customer with the delivery time window of the customer's demand, customer satisfaction is measured by the degree of deviation from the delivery time window. The fuzzy affiliation function of time satisfaction is expressed as:

$$f_1\left(t_i\right)=\begin{cases}0 & t_i\in\left[0,E_i\right]\\ \dfrac{t_i-E_i}{e_i-E_i} & t_i\in\left[E_i,e_i\right]\\ 1 & t_i\in\left[e_i,l_i\right]\\ \dfrac{L_i-t_i}{L_i-l_i} & t_i\in\left[l_i,L_i\right]\\ 0 & t_i\in\left[L_i,+\infty\right]\end{cases} \tag{9}$$

The meaning of the above equation is that $[e_i,l_i]$ is the desired time window of customer i, if the goods arrive within this range, the customer satisfaction is 1; $[E_i,L_i]$ is the tolerable time window of customer i, if the goods arrive at $[E_i,e_i]$ or $[l_i,L_i]$, the customer is acceptable but the satisfaction decreases linearly; if the delivery is made at other times, the customer refuses to accept the goods and the satisfaction is 0.

2) Quality satisfaction

Perishables will gradually deteriorate during transportation, and the deterioration rate is θ. The earlier the goods are delivered, the better the quality, and the more satisfied the customer is. Therefore, it can be described as a function:

$$f_2\left(t_i\right)=1-\theta t_i \tag{10}$$

3）Comprehensive customer satisfaction

Assuming that $w_a = (a_1, a_2)$ is a weight vector measuring the importance of time satisfaction and quality satisfaction, the satisfaction function of customer i can be expressed as:

$$F_i = a_1 f_1(t_i) + a_2 f_2(t_i) \tag{11}$$

On the basis of obtaining the satisfaction level of each customer, assuming that $w_b = (b_1, b_2, \cdots, b_n)$ is a vector of weights measuring the importance of different customers, the overall satisfaction level of customers is as follows:

$$F_2 = \sum_{i=1}^{n} b_i \cdot F_i \tag{12}$$

Objective function:

$$\begin{aligned} \min F_1 &= TC_1 + TC_2 + TC_3 + TC_4 + TC_5 + TC_6 \\ &= \sum_{h=1}^{H}\sum_{i=1}^{N} c_b \left(D_{hi} - q_{hi}\right) + \sum_{h=1}^{H}\sum_{i=1}^{N} c_d \delta D_{hi} + \\ &\sum_{k=1}^{K} c_k + g\sum_{k=1}^{K}\sum_{h=1}^{H} N_h^k + c_f \sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=1}^{K} d_{ij} x_{ij}^k + \\ &\sum_{k=1}^{K}\sum_{h=1}^{H} c_h N_h^k + \sum_{h=1}^{H}\sum_{i=1}^{N} c_d \left[(D'_{hi} - D_{hi}) + \theta p_{hi} \right] \end{aligned} \tag{13}$$

$$\max F_2 = \max(\sum_{i=1}^{n} b_i \cdot F_i) \tag{14}$$

Constraints:

$$\sum_{i=0}^{N}\sum_{k=1}^{K} x_{ij}^k = 1, \forall j \in N \setminus \{0\}, i \neq j \tag{15}$$

$$\sum_{i=0}^{N} x_{ir}^k = \sum_{j=0}^{N} x_{rj}^k, \forall r \in N \setminus \{0\}, k \in K \tag{16}$$

$$\sum_{h=1}^{H} N_h^k \leq Q, \forall k \in K \tag{17}$$

$$\sum_{h=1}^{H}\sum_{i=1}^{N} D'_{hi} \cdot y_i^k \leq q \cdot Q, \forall k \in K \tag{18}$$

$$\sum_{i=0}^{N}\sum_{j=0}^{N} D'_{hi} \cdot x_{ij}^k \leq q \cdot N_h^k, \forall h \in H, k \in K, i \neq j \tag{19}$$

$$\sum_{i=0}^{N}\sum_{j=0}^{N} p_{hi} \cdot x_{ij}^k \leq q \cdot N_h^k, \forall h \in H, k \in K, i \neq j \tag{20}$$

$$\sum_{i=1}^{S}\sum_{j=1}^{S} x_{ij}^k \leq |S| - 1, \forall k \in K, S \subset N \setminus \{0\} \tag{21}$$

$$E_i \leq t_i^k \leq T_i, \forall i \in N, i \neq 0 \tag{22}$$

$$\sum_{k=1}^{K}\sum_{i=1}^{N} x_{ij}^k \left(t_i^k + g_i^k + t_{ij}^k \right) = t_j^k, \forall j \in N, i \neq j \tag{23}$$

$$x_{ij}^k = \{0,1\}, \forall i, j \in N, k \in K \tag{24}$$

$$y_i^k = \{1,0\} \tag{25}$$

In the above model, The formula (13) is the minimum total cost; The formula (14) is the maximum customer satisfaction; The formula (15) is for each customer to be served only once by one vehicle; The formula (16) is a flow balance constraint that ensures that the vehicle returns to the distribution center after departing from the distribution center, enters the retailer to complete the service, and then exits to the other retailers, i.e., the outgoing degree is equal to the incoming degree at each point; The formula (17) is a constraint on the number of cold storage containers, i.e., it ensures that the number of cold storage containers loaded on each vehicle does not exceed the maximum capacity of the vehicle; The formula (18) is the total number of shipments per distribution route not to exceed the maximum capacity of the vehicle; The formula (19) and (20) are load capacity constraints, which ensure that the total number of forward shipments and the total number of reverse pickups of single-temperature-layer goods on each distribution route does not exceed the maximum load capacity of the vehicle's corresponding temperature-layer insulated box; The formula (21) is the sub-loop elimination constraint, eliminating redundant and superfluous paths and ensuring that all paths start and end at the distribution center; The formula (22) is the time to reach the retailer must be within its maximum tolerable time window; The formula (23) shows that the time to reach Retailer j is the sum of the time to reach the previous Retailer i, the time served at Retailer i, and the travel time from Retailer i to Retailer j; In the formula (24) and (25), x_{ij}^k and y_i^k are decision variables.

III. Algorithm Design

The PVRPCSMTJDSPD multi-objective model studied in this paper contains multiple VRP variants of the problem, which is challenging to solve. NSGA-II, as a classical multi-objective solution algorithm, has the advantages of good robustness, global search and parallelism [28]. Still, its local search ability is poor, while the ALNS algorithm, through destruction and repair operations, can search in different neighborhood spaces to avoid falling into local optimal solutions and significantly enhancing the diversity and global optimization ability of the solution process. Therefore, NSGA-II is selected as the core algorithm in this paper. At the same time, to obtain high-quality new solutions and improve the algorithm's ability to find the optimal solution, the ALNS algorithm is further introduced to improve NSGA-II, and an IANSGA-II algorithm is proposed for the solution. The flow chart of the algorithm is shown in Fig. 1 (placed at the end of the article).

A. Encoding and decoding

The chromosome in this paper adopts the real number coding method, as shown in Fig. 2. If there is a distribution center, N customer points, and K vehicles. The length of the chromosome is N+K-1, the customer points are numbered as 1, 2, ..., N, and the distribution vehicles are numbered as N+1, N+2, ..., N+K. In the decoding process, the full arrangement of the customer points is randomly generated according to the maximum tolerance window of each customer. Then the vehicle load constraints are checked, and the K vehicles are inserted into the customer sequence in order, with the remaining empty vehicles arranged at the end.

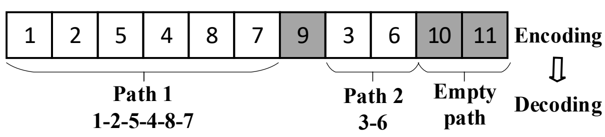

Fig. 2. N=8, K=3 Chromosome Coding and Decoding Example

B.Adaptation function

The fitness of individuals in the population can reflect the viability of the chromosome. The larger the fitness function value, the more viable the chromosome is, and the closer it is to the optimal solution of the problem to be solved. Since the objective function of the model in this paper is to minimize the total cost and maximize customer satisfaction, the fitness function is formulated as:

$$f_i = F_1 + \frac{1}{F_2} \tag{26}$$

C.Crossover and mutation operations

The NSGA-II algorithm is used as the basis for non-dominated sorting, selection, crossover and mutation operations on the initialized population. Partial Mapping Crossover (PMX) is used in the crossover operation, and the principle is shown in Fig. 3. Two crossover points a and b are randomly selected in the paternal parents 1 and 2 to form two crossover segments, which are interchanged and mapping relationships are established. Then conflict detection is done, and the conflicting genes are eliminated through the mapping relationships to ensure that the new pair of offspring genes formed are conflict-free. PMX crossover operation can effectively improve the quality of the Pareto deconvolution set. The chromosomes after crossover are judged to determine whether they need to be mutated according to the mutation probability. The swap mutation method is chosen for the chromosome that needs to be mutated. Two gene variants are randomly selected from the parent generation to be swapped to obtain the mutated individual, and the shortest path is found by continuously randomizing the mutation. The solution that does not satisfy the load constraint after crossover mutation is reinitialized to generate a new individual for replacement.

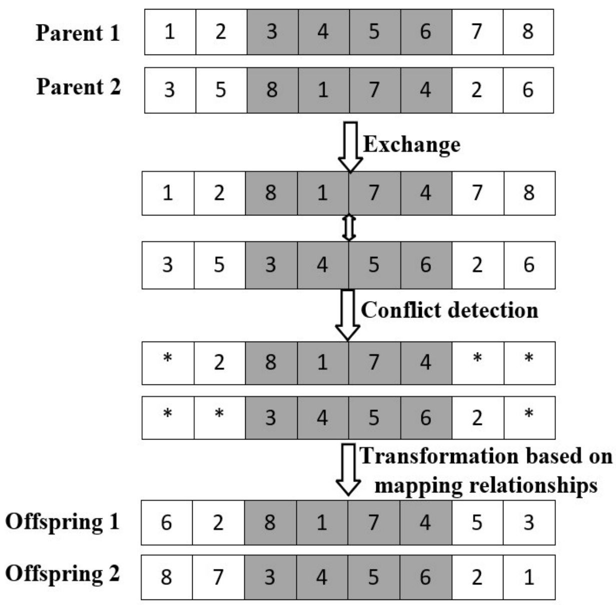

Fig. 3. PMX Schematic

D.Adaptive large-scale neighborhood search operations

Based on the objectives of minimizing total distribution cost and maximizing customer satisfaction, the ALNS algorithm considers various factors such as path length, vehicle loading, time window, etc., and designs multiple destruction operators and multiple repair operators to search the solution space to form new solutions, which enhances the ability of exploring the solution space. The weights of the destruction and repair operators are adaptively updated according to the advantages and disadvantages of the new solutions, which makes the ALNS algorithm applicable to the whole iteration cycle. The destructive operators include stochastic destructive operator, correlation destructive operator, and minimum destructive operator for vehicle service customers. The repair operators include the stochastic repair operator, the optimal greedy repair operator, and the shortest distance repair operator.

E.Adaptive mechanisms

To improve the adaptive adjustment ability of the ALNS algorithm, this paper assigns a weight ω_η to each kind of operator, π_η denotes the weight of operator η, and m denotes the number of operators. Based on the change of the value of ω_η to change the size of the probability that the operator is selected. The weight ω_η of each operator is calculated as:

$$\omega_\eta = \frac{\pi_\eta}{\sum_{j=1}^{m} \pi_j}, \eta = 1, ..., m \tag{27}$$

In the initial phase, each operator has the same weight value1. Based on the roulette idea, adjusting operator weights during iteration relies on an adaptive process. The adaptive process relies on the scoring of the operators, and the higher the score, the better the performance of the operator and the higher the probability of being selected in the next round. In this paper, we set three scoring scores for the algorithm: σ_1, σ_2 and σ_3 ($\sigma_1 > \sigma_2 > \sigma_3$), and the scoring rules are: 1) if the new solution is a new global optimum, the score is increased by σ_1; 2) if the new solution is better than the current solution, the score is increased by σ_2; 3) if the new solution is worse than the current solution but still accepted by the algorithm, the score is increased by σ_3.To prevent the operator from converging too fast and falling into local optimization, this paper adds an operator weight updating coefficient ψ in the process of operator weight π_η updating to improve the diversity of the operator search process and the ability to jump out of local optimization. The operator weight update formula is as follows [29]:

$$\pi_\eta = \begin{cases} \pi_\eta, f_\eta = 0 \\ \psi(\frac{s_\eta}{f_\eta}) + (1-\psi)\pi_\eta, f_\eta \neq 0 \end{cases} \tag{28}$$

In the above equation, π_η is the weight of the operator, s_η is the cumulative score, and f_η is the cumulative number of uses.

IV.EXAMPLE ANALYSIS

A.Calculated example solution and analysis

This paper has taken the data of R109 in Solomon's standard arithmetic as an example, choosing node 0 as the distribution center, nodes 1-20 as retailer points. Three kinds of perishable goods are distributed at the same time, $h=1$ is room temperature goods, $h=2$ is refrigerated goods, and $h=3$ is frozen goods. The information of the time window, service time, and demand quantity is shown in Table II. (placed at the end of the article), and the data is obtained from the literature [30]. The values of the model parameters are shown in Table III. Adjust the above test data as follows: the customer distribution demand is q_{hi}, and there is no pickup demand in the original sample, so the pickup demand is determined as 10% of the distribution demand. To simplify the calculation, the distance between customer nodes adopts the Euclidean distance: $d_{ij}=\sqrt{(x_2-x_1)^2+(y_2-y_1)^2}$

TABLE III. MODEL PARAMETER VALUES

Notation	Parameter Value
Q_n	600kg
H	3 types
θ	0.2%
δ	0.3%
c_b	5 Yuan/kg
c_d	5 Yuan /kg
c_k	100 Yuan /vehicle
c_f	1 Yuan/km
v	1 km/min
g	2 Yuan/pc
c_1	0 Yuan
c_2	0.24 Yuan
c_3	0.72 Yuan
q	10 kg
Q	60 cases
w_a	(0.7,0.3)
w_b	(0.3,0.05,0.05,0.05,0.1,0.05,0.1,0.05,0.05,0.05, 0.05,0.1,0.05,0.05,0.1,0.05,0.1,0.05,0.05,0.05)

The IANSGA-II algorithm is used to solve this example. maxgen = 50, popsize = 800, Pc = 0.5, and Pm = 0.05. The solution is run by using MATLAB R2018b. The Pareto solution set is shown in Table IV., and K denotes the number of vehicles in use (unit: Vehicles). The Pareto frontier is shown in Fig. 4.

TABLE IV. IANSGA-II ALGORITHM PARETO SOLUTION SET TABLE

Pareto Frontier	$F1$	$F2$	K
1	1883.31	0.80	5
2	1890.42	0.81	5
3	1892.69	0.82	5
4	1896.30	0.83	5
5	1897.68	0.83	5
6	1898.78	0.84	5
7	1899.95	0.84	5
8	1902.39	0.85	5
9	1903.77	0.86	5
10	1904.66	0.86	5
11	1906.04	0.87	5
12	1916.26	0.87	5
13	1918.70	0.88	5
14	1920.07	0.89	5
15	1922.35	0.90	5

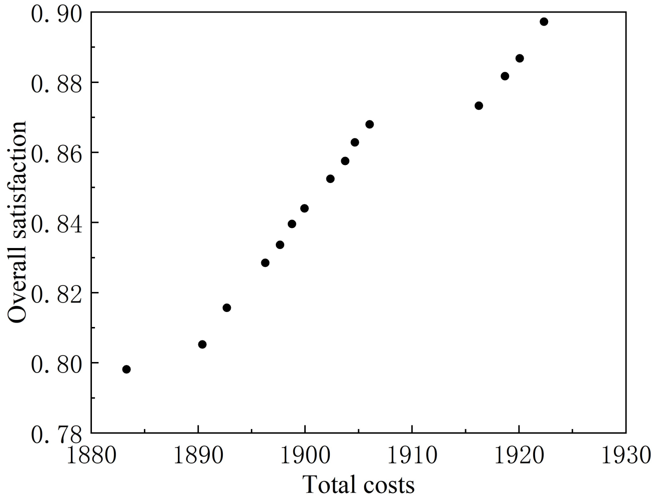

Fig. 4. IANSGA-II Algorithm Pareto Frontier Map

As can be seen from Table IV. and Fig. 4., there are 15 path combination schemes in the Pareto solution set, and the following conclusions are obtained from the analysis: 1) frontier point 15 has the optimal but the smallest customer satisfaction, in which the total cost is 1883.31, and the customer satisfaction is 0.80. On the contrary, frontier point 15 has the optimal customer satisfaction but the largest total cost, with the total cost being 1922.35 and customer satisfaction being 0.90; 2) the total cost and customer satisfaction between the two objectives are negatively correlated, which cannot be optimized at the same time. The total cost reduction often leads to a decline in customer satisfaction, and vice versa; 3) when choosing the optimal distribution plan, the decision maker needs to make trade-offs according to the different preferences for total cost and customer satisfaction.

B.Analysis of model validity

To verify the validity of the model in this paper, the single-objective models of minimizing the total cost and maximizing the overall customer satisfaction are constructed, respectively. The LNS algorithm improves GA, and the IAGA is designed to solve the two single-objective models. Compare the results with Table IV. See Table V.

TABLE V. OPTIMAL SOLUTION RESULTS FOR SINGLE-OBJECTIVE MODELS

Optimization Models	Optimization Goals	F_1	F_2
Multi-objective model	Pareto frontier 1	1883.31	0.80
	Pareto frontier 15	1922.35	0.90
Single-objective model	Minimal total cost	1530.80	0.80
	Maximum customer satisfaction	2698.77	0.93

As can be seen from Table V., when the decision maker prefers total cost, comparing the single-objective result with the minimum total cost with frontier point 1 in Table IV., the total cost is 18.72% lower and customer satisfaction is equal; when the decision maker prefers customer satisfaction, comparing the single-objective result with the maximum customer satisfaction with frontier point 15, the satisfaction is 3.33% higher. Still, the total cost is 40.39% higher. Comparison shows that the multi-objective model constructed in this paper reduces the total cost while ensuring that customer satisfaction achieves a non-inferior solution, and the results are balanced between the two objectives.

C.Algorithm Performance Analysis

To evaluate the performance of the IANSGA-II algorithm proposed in this paper, a comparison with the traditional NSGA-II algorithm is conducted. Using the base data provided in the arithmetic example, with the parameters kept constant, the IANSGA-II and NSGA-II algorithms are run 10 times to calculate the average value. The optimization objectives are presented in Table VI., and the comparison of the Pareto frontiers for the two algorithms is shown in Fig. 5. Additionally, the evolution iterations of the two algorithms are depicted in Fig. 6 and Fig. 7, respectively.

TABLE VI. COMPARISON OF RESULTS BETWEEN IANSGA-II AND NSGA-II

Algorithm	Total Cost		Customer Satisfaction	
	Optimum Value	Average Value	Optimum Value	Average Value
NSGA-II	1973.72	2036.85	0.87	0.81
IANSGA-II	1858.60	1946.15	0.91	0.84

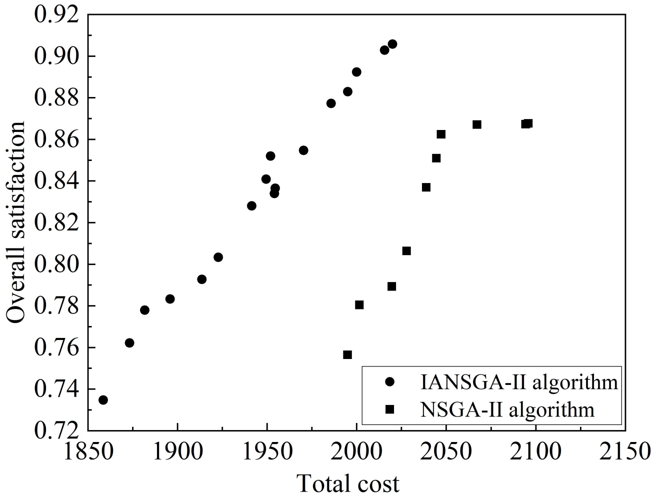

Fig. 5. Pareto Frontier Comparison between IANSGA-II and NSGA-II

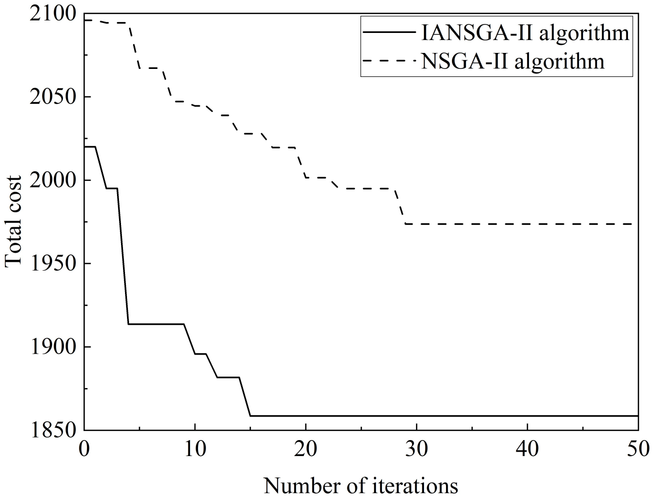

Fig. 6. Comparison of Total Cost Iterations between IANSGA-II and NSGA-II

As shown in Table VI., the solution quality of the IANSGA-II algorithm outperforms that of the NSGA-II algorithm in both total cost and customer satisfaction. The comparison in Fig. 5 reveals that the IANSGA-II algorithm produces a wider range and a more evenly distributed set of Pareto frontier solutions, dominating the Pareto frontier solutions of NSGA-II. This indicates that IANSGA-II has a larger search space and a stronger ability to identify optimal solutions.

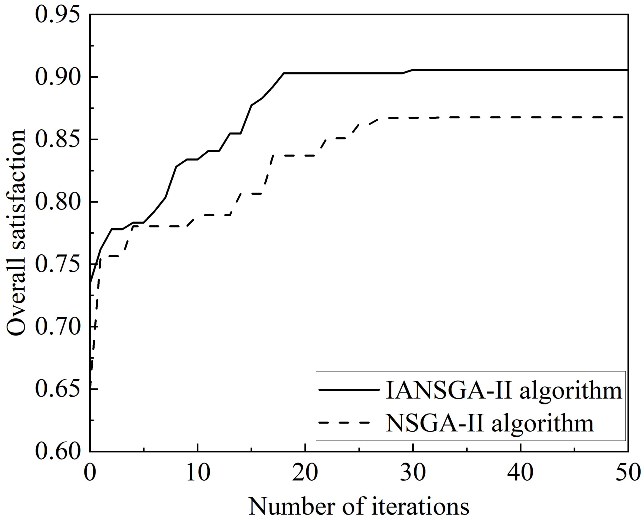

Fig. 7. Comparison of Overall Satisfaction Iterations between IANSGA-II and NSGA-II

The Figures 6 and 7 demonstrate that the IANSGA-II algorithm converges more quickly in terms of both total cost and customer satisfaction. In conclusion, the IANSGA-II algorithm proposed in this paper exhibits superior search performance and solution efficiency, making it more suitable for solving the model presented in this paper compared to the NSGA-II algorithm.

D.Algorithm sensitivity analysis

1. Population size sensitivity analysis

Ensure that other parameters remain unchanged and set the population size to 600, 700, 800, 900, and 1000, respectively, to compare the Pareto solutions for different population sizes under the IANSGA-II algorithm (see Fig. 8). From Fig. 8, it can be observed that when the population size is 900 or 1000, the cost for the same satisfaction level increases compared to other population sizes. Furthermore, when the population size is 600 or 700, the number of optimal solutions is lower, and some solutions are inferior compared to the population size of 800. With a population size of 800, the Pareto solutions are more uniformly distributed, and the total cost and overall satisfaction level are optimal compared to other population sizes. Therefore, a population size of 800 is more appropriate.

2. Iteration number sensitivity analysis

Ensure that the other parameters remain unchanged and set the maximum number of iterations to 30, 35, 40, 45, and 50, respectively, to obtain the Pareto comparison of the IANSGA-II algorithm with different numbers of iterations (see Fig. 9). From Fig. 9, it can be observed that when the number of iterations is 55, the total cost for the same level of satisfaction is higher, and the comprehensive satisfaction is lower for the same total cost compared to other iterations. Additionally, when the number of iterations is 45 or 60, the Pareto solution spans a narrower range of values and takes longer to run. When the number of iterations is 40, the distribution of the optimal solution set spans a wider range, but some solutions are inferior to others. Therefore, the maximum number of iterations is set to 50, which is more appropriate.

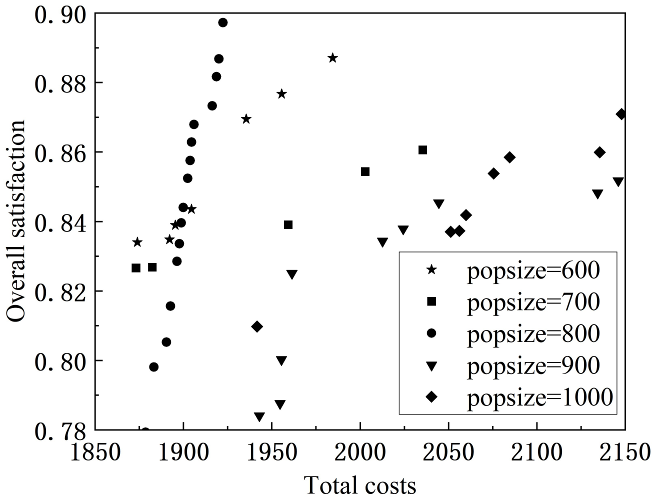

Fig. 8. Pareto optimal solution sets for different population sizes

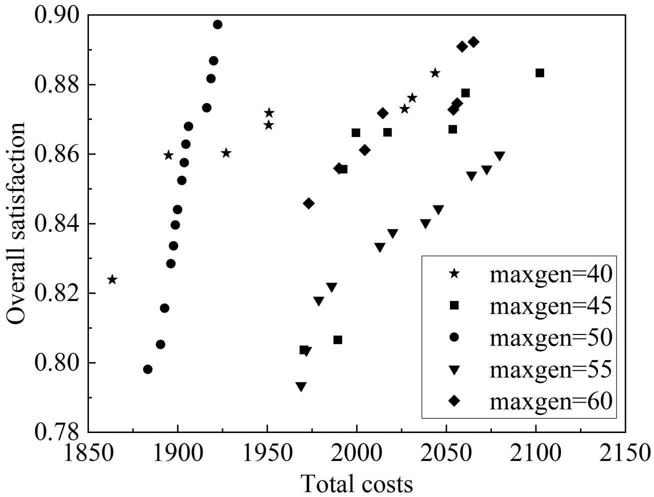

Fig. 9. Pareto optimal solution set for different number of iterations

In summary, when the population size and the number of iterations vary within a certain range, the results of the IANSGA-II algorithm vary greatly, and it is more appropriate to choose a population size of 800 and a maximum number of iterations of 50.

V. CONCLUSION

This paper aims to solve the problem of how to reduce the total cost and improve customer satisfaction by improving the distribution mode and rationally planning the route for perishables in the cold chain distribution link. According to the characteristics of perishables, this paper introduces the cold storage multi-temperature co-distribution mode which can better meet the distribution conditions of perishables, establishes the customer satisfaction function is established which is more in line with the distribution of perishables. A multi-objective model is constructed with the objectives of minimizing the total cost and maximizing the customer satisfaction, and the IANSGA-II algorithm is designed to solve the problem. The experimental results show that:

1) compared with the traditional customer satisfaction measure that only considers the time window, this paper comprehensively considers the time window and freshness, which more accurately describes the customer satisfaction and is closer to the actual situation.

2) the multi-objective model constructed in this paper can achieve a better balance between the total cost and customer satisfaction, and ensure that the total cost is optimal while obtaining the customer satisfaction of a non-inferior solution compared with the single-objective model.

3) IANSGA-II algorithm has certain advantages in cost saving and customer satisfaction improvement compared with the traditional NSGA-II algorithm.

Overall, the research in this paper provides a certain reference for perishables enterprises to formulate a reasonable vehicle routing program in the cold chain distribution link. However, considering that the real-time demand of customer pickup and delivery in the actual distribution process is not limited to the simple determination of the demand, the inclusion of random demand in the scope of the study is the next stage of in-depth research.

TABLE II. RETAIL STORE NODE BASIC INFORMATION

Customer Number	Coordinate （X,Y）	Distribution Demand q_{hi}			Service Time /min	Tolerable Time Window	Expectation Time Window
		h=1	h=2	h=3			
0	(35,35)						
1	(41,49)	33	25	25	10	[88,243]	[133,198]
2	(35,17)	22	22	30	10	[0,142]	[22,87]
3	(55,45)	27	27	36	10	[64,177]	[98,143]
4	(55,20)	43	32	32	10	[74,233]	[123,184]
5	(15,30)	50	38	38	10	[0,138]	[20,93]
6	(25,30)	19	19	25	10	[39,168]	[76,131]
7	(20,50)	27	20	20	10	[24,147]	[61,110]
8	(10,43)	24	32	24	10	[37,162]	[75,124]
9	(55,60)	30	30	39	10	[39,164]	[74,129]
10	(30,60)	30	30	39	10	[68,189]	[107,150]
11	(20,65)	35	35	18	10	[0,153]	[42,101]
12	(50,35)	43	43	21	10	[0,141]	[38,97]
13	(30,25)	47	47	24	10	[76,251]	[131,196]
14	(15,10)	33	33	44	10	[0,171]	[32,114]
15	(30,5)	31	23	23	10	[0,139]	[35,96]
16	(10,20)	43	43	21	10	[11,148]	[52,10]
17	(5,30)	24	24	12	10	[67,246]	[124,189]
18	(20,40)	26	26	35	10	[29,154]	[69,114]
19	(15,60)	30	41	30	10	[13,148]	[52,109]
20	(45,65)	32	24	24	10	[61,200]	[105,156]

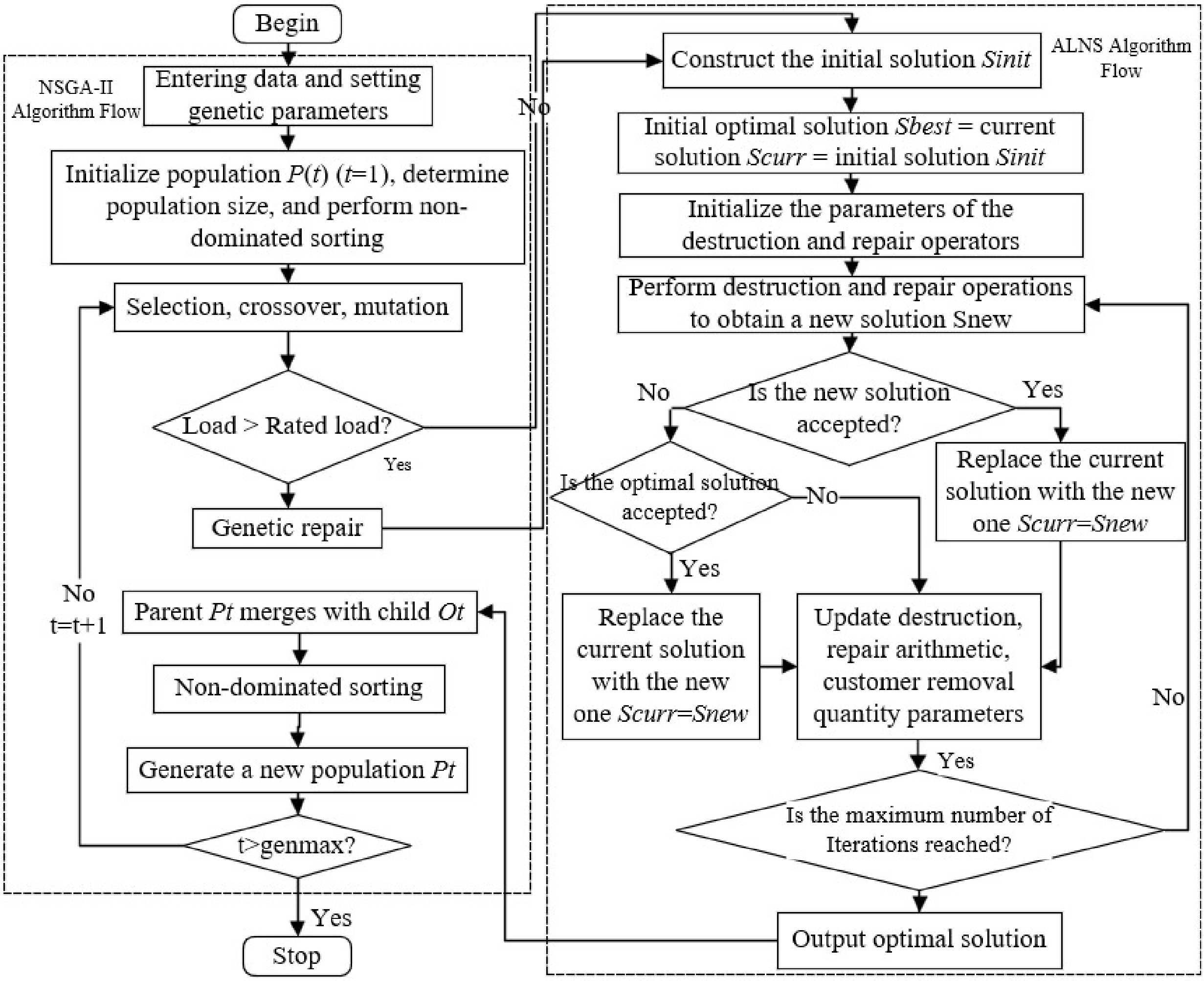

Fig. 1. IANSGA-II Algorithm Flowchart

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