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Cold Chain Logistics Path Optimization via Improved Multi-Objective Ant Colony Algorithm

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ABSTRACT In order to improve the performance and change the current situation of the cost minimization model widely used in the cold chain logistics distribution process, a multi-objective optimization model based on cost, carbon emissions and customer satisfaction is proposed. Considering the characteristic of this proposed optimization model, we design an improved ant colony algorithm with a multi-objective heuristic function to solve it, termed as ACOMO. Experimental results show that the proposed ACOMO can effectively solve the vehicle routing problem of the multi-objective optimization model, and outperforms the classic ant colony algorithms, resulting in more Pareto optimal solutions. It offers an environmentally friendly distribution solution for the problem. Specifically, the distribution path obtained by the improved ant colony algorithm manages to achieve the above multiple goals, including reduction of distribution costs and carbon emissions, and improvement of customer satisfaction. In addition, compared with a single-target model that only provides one single distribution route to cost minimization, multi-objective optimization can provide a variety of distribution route options for logistics companies in practice. Finally, through the sensitivity analysis of temperature changes and cargo damage coefficients, the proposed system successfully provides reference for the optimization of the path of cold chain logistics enterprises, and promotes logistics enterprises to effectively arrange their work and to be more socially responsible.

INDEX TERMS Cold chain logistics, path optimization, multi-objective optimization, carbon constraints, customer satisfaction.

I. INTRODUCTION

With the improvement in the living standards of consumers and the change of consuming ideas, the cold chain logistics of the fresh products has developed rapidly in recent years, which brings higher requirements for the distribution process to the logistics companies. To ensure the freshness of the perishable foods, low-temperature control is required throughout the distribution process, which is also the most remarkable feature of cold chain logistics that differs from traditional logistics. The cold chain logistics causes the carbon emissions to increase since two factors contribute to this issue, which are called the vehicle itself causing carbon emission due to the delivery process and the refrigeration equipment leading higher energy consumption to keep the product at lower degrees. However, the issues relating to environmental protection, energy conservation, and emission reduction have been highly considered by the international community. The carbon tax as a useful policy tool and an essential criterion for environmental protection has been introduced for energy conservation and emission reduction, which increases the distribution costs of the logistics companies. Therefore, ensuring the freshness of the products while reducing environmental pollution and achieving low-carbon green transportation is a problem that should be addressed in the distribution of the cold chain logistics in real life.

In December 2009, the World Climate Conference in Copenhagen focused on energy conservation and emission reduction. The concept of low-carbon life such that "low energy consumption, low pollution, and low emissions" has received increasing attention. Global statistics on carbon emission show that the carbon emissions of the transportation industry account for 14% of the total emissions. The carbon emissions of road traffic account for more than 70% of the

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entire transportation industry [1]. The EU started to increase carbon taxes in 2012. China also proposed that by 2020 CO_2 emissions will be reduced by 40% - 45% compared with that of 2005 [2]. At the same time, the cold chain transportation, as an industry that satisfies the needs of residents for multiple varieties of food, grows at a rate of more than 10% per year, and its logistics costs are 40% - 60% higher than the costs of ordinary logistics. The cold chain is responsible for storing and transporting perishable food in an appropriate temperature range. If the temperature is much higher or lower than the product's optimal specific temperature range, it will cause a certain of cargo damage and unnecessary waste of resources, and even endanger food safety [3]. The cold chain logistics distribution vehicle is equipped with a freezing chamber and a cold storage chamber, which can keep the product at a low temperature [4]. However, refrigeration requires a certain amount of electric consumption, which in turn leads to the increasement of distribution costs [5]. Also, fuel consumption and carbon emissions will make an impact on the environment [6]. Recently, low-carbon logistics is attracting more and more attention from enterprises and professionals. Reducing energy consumption and carbon emissions have become an inevitable trend in the development of the logistics industry [7], [8]. In view of these factors that need to be considered in cold chain logistics distribution, this paper proposes a multi-objective optimization model. It aims to improve the customer satisfaction while reducing costs and carbon emissions during the distribution process. The sensitivity analysis to the temperature control and the cargo damage coefficient is carried out to explore the deep impact of temperature difference and changes of cargo damage coefficient on carbon emissions and distribution costs.

The remaining of this paper is organized as follows: Section II briefly reviews some representative works in the field. Section III explains the proposed multi-objective model in detail, including problem descriptions, symbols, and model formulas. Solutions of the improved ant colony algorithm are introduced in Section IV. Finally, Section V compares and experimentally analyzes the proposed method, while Section VI concludes the work.

II. RELATED WORK

A. MULTI-OBJECTIVE OPTIMIZATION

It is often difficult to judge the quality of a plan by only one indicator. Multiple measurements are thus needed for evaluation, i.e., multi-objective goals. However, those multi-objective goals are sometimes not coordinated or even contradictory. Multi-objective optimization is thereby a complex mathematical process that aims to find a best trade-off for a given problem by satisfying all constraints [9]. As a consequence, multi-objective planning has increasingly gained research attention:

Paksoy *et al.* [10] developed a fuzzy multi-objective linear programming model for discussing the optimization of the production distribution network for edible vegetable oil manufacturers. Sahar *et al.* [11] proposed a multi-objective optimization model for a two-tier dairy product supply chain, which aimed at minimizing the carbon dioxide emissions during transportation and the total product distribution costs. Teimoury *et al.* [12] presented a multi-objective model for determining the optimal import quota policy of the supply chain of fruit and vegetables. Liu *et al.* [13] solved the problems in global supply chain production, distribution and capacity planning, and developed a multi-objective mixed integer linear programming method to optimize the three goals of the total cost, circulation time and sales loss. Özceylan *et al.* [14] adopted the fuzzy multi-objective linear programming method to solve the designing problem of the fuzzy dual-objective reverse logistics network, which considers two goals, i.e., minimizing the total cost of the system and the total delivery time. Bortolini *et al.* [15] proposed a three-objective distribution planner to solve the tactical optimization problem of fresh food distribution network, involving the operation cost, carbon footprint and delivery time objectives into consideration. Finally, Wang [16] *et al.* introduced a green vehicle routing problem with multiple warehouses. It also proposes a dual-target model to minimize total carbon emissions and operating costs, and implement staged fines for advancement and delay to reduce waiting time and increase customer satisfaction. The above are typical applications of multi-objective optimization.

B. CARGO DAMAGE AND CARBON EMISSIONS

How to reduce the carbon emissions in the distribution process of the cold chain logistics has become a hot topic in current research, and there exist some works [17], [18] targeting on it. Generally, the distribution models of cold chain logistics need to take into account many factors. Here, we briefly review some example works. Hsu [19] proposed an SVRPTW model for the randomness of the distribution process of the perishable food by taking into account the effect of temperature changes. Ji [20] proposed a VRPSDP optimization model for multiple customer nodes in a single distribution center by minimizing the total cost of the cold chain logistics and combining the distribution and the pick-up operations of the cold chain logistics. Mehdi [21] conducted a comprehensive study of the factors that affect fuel consumption in the time-varying path selection for vehicles, where these factors include load, vehicle speed, road slope, and urban traffic and so on.

There is another problem that needs to be studied. For example, perishable foods may lose their values in the distribution process. Chen *et al.* [22] proposed a nonlinear mathematical model for production scheduling and vehicle routing, regarding the time window for the freshness of the perishable foods. Neder-Mead method and heuristic algorithm were also studied for the same type of problem. Osvald [23] proposed a fresh vegetable allocation algorithm with perishability as the key factor. This algorithm calculated the impact of perishability as part of the overall distribution cost, where a specific problem expressed as the vehicle routing problem of VRPTWTD was addressed. Amorim [24] split the tow concepts of minimization of distribution costs and maximization of product freshness, and studied the tradeoffs between distribution scenarios and cost-freshness, showing the conflict between the two goals of cost and freshness.

In addition to freshness, there are also some works conducted research on reduction of carbon emissions and impact of the carbon tax policies. For example, Zhang [25] presented a path optimization model of the cold chain logistics which involved into the cost of carbon emissions. It combined the ribonucleic acid calculation and the ant colony algorithm to reduce the total cost of logistics and the carbon emissions. Govindan *et al.* [26] formulated a two-level location routing problem with time windows (2E-LRPTW) for the sustainable design and optimization of the economic environment in the supply chain of the perishable food. Zhan [27] proposed a decision model for the cold chain logistics system using a two-level planning method, pointing out that as the demand for low-carbon cold chain logistics continues to grow, corresponding subsidy policies and carbon emissions trading policies are needed to guide cold chain logistics enterprises to conduct cold storage. The transformations pertinent to energy-saving and emission reduction provide a scientific basis for the decisions of governments and enterprises. It can be seen that the re-examinations of the impact of the cold chain logistics on the environment and society are aimed at reducing the carbon footprint of the entire network and the costs caused by greenhouse gas emissions.

C. CUSTOMER SATISFACTION

Customer satisfaction is the subjective feelings of customers about the goods or services that they buy or use. Therefore, understanding customer satisfaction has an important role in improving the quality of products and the service levels of enterprises. To improve the customer satisfaction in the distribution service, higher demands are made to the organization and coordination of the cold chain enterprises. Specifically, Wang [28] suggested that customer satisfaction was mainly reflected in freshness. Due to the great losses in the distribution process of the cold chain enterprises, the complexity of the vehicle routing problem increases. Therefore, it is very important to devise an effective distribution route to minimize the total cost and maximize the freshness of the distributed products. To this end, Song [29] proposed a nonlinear mathematical model and a heuristic algorithm to find efficient vehicle routes. Its goal is to maximize customer satisfaction. Shi [30] proposed a satisfaction function based on the service time window by conducting a simulation model under the time-varying conditions and devised a minimum envelope cluster analysis method and a hybrid genetic algorithm to solve it.

D. ROUTE OPTIMIZATION

The traditional path planning methods mainly include artificial potential field methods [31], Dijkstra algorithm [32], A * algorithm [33], and so on. Path planning is an NP-hard problem. Hence, many heuristic algorithms such as particle swarm optimization [34]–[36], genetic algorithm [37], [38], artificial bee colony algorithm [39], [40], fruit fly optimization algorithm [41], [42], Tabu search algorithm [43], [44], ant colony algorithm are used to solve the problem. Among all of them, the ant colony algorithm was first proposed by Dorigo [45], and its characteristics can be defined as positive feedback and a heuristic random search. It simulates the foraging of biological groups and has some advantages such as better robustness, strong global search capability, and convenient expression of environmental constraints. As a result, the ant colony algorithm has been applied to data mining area [46]–[48] and to solve VRP derivative problems such as two-dimensional loading VRP problem [49], and multi-distribution center problem [50], [51] dynamic vehicle routing problem [52], weighted vehicles Routing problem [53], time-varying vehicle routing problem [54], etc.

In summary, most of the existing studies on traditional vehicle routing problems employ a single-objective model that minimizes only the cost. Although there are some works have taken into account the factors such as carbon emissions and customer satisfaction, they just merge the cost of product freshness loss and the cost of vehicle carbon emissions and regard them as one objective. When the subject is considered under the title of cost accounting, the diversity of objectives is ignored. This paper proposes a multi-objective optimization model that minimizes the transportation costs and carbon emissions costs and meanwhile maximizes customer satisfaction. In particular, we design an improved ant colony algorithm, which dynamically improves the pheromone concentration, limits the pheromone concentration range, and sets the number of periodic loop iterations to update the global pheromone. Besides, we redesign the heuristic function so that the ants not only take into account the distance factor when moving to the next node but also consider the time limit. It also sets the parameters of the selection rule of the pseudo-random proportional action so that the ants can choose the optimal path with a higher probability. This operation can also accelerate the convergence. Hence, the optimal solution can be obtained in a relatively shorter time. As a result, a Pareto solution set based on the proposed multi-objective optimization is achieved. Finally, the effectiveness of the model and the algorithm is demonstrated by using the Solomon test set.

III. PROBLEM FORMULATION

The path optimization problem in the cold chain logistics that takes into account carbon emissions has three components as follows: (1) a distribution center serving multiple customers; (2) multiple refrigerated trucks starting the process from the distribution center; and (3) traversing each customer to complete the delivery service and then returning to the distribution center. A customer can only be served by one refrigerated truck, and the freshness of goods has to be within certain time limits. On the other hand, the delivery vehicle should meet the time window requirements. A specific penalty cost should be given for early or late arrivals to improve customer satisfaction. The penalty cost for late arrival is higher than that of early arrival. When such a delivery is a concern, we need to take into account several factors such as carbon emissions, customer satisfaction, and minimization of the costs to find the optimal distribution path besides the requirements of goods, refrigerated vehicle weight, and time window.

Since the problem is related to a distribution of path, we need to explain some of the notations that will be used in the method. Let $G = (V, A)$ be a fully directed graph, representing the network of the cold chain distribution. Specifically, $V = \{0, 1, 2, \ldots, n\}$ is a set of all nodes, where 0 represents the distribution center and $1, 2, 3, \ldots, n$ represents the customer points. $A = \{(i, j) : i, j \in N, i \neq j\}$ denotes the routes. Assuming that the distribution center, customer location, and demand are all known in advance. The Euclidean distance between two customers (i, j) is defined as follows: $d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$.

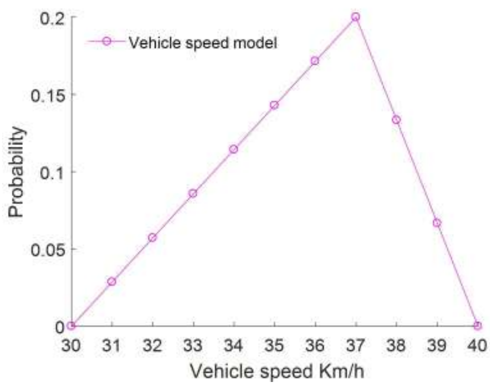

FIGURE 1. Speed model.

A. COST MODEL

1) FIXED COSTS

The fixed cost mainly composes of the vehicle wear, the maintenance, the depreciation expense, and the salary of the driver. Let f_k indicate the used vehicle k. x_{ij}^k is a 0-1 decision variable, where $x_{ij}^k = 1$ denotes that the vehicle k departs from the distribution center to the customer i and j, and otherwise, $x_{ij}^k = 0$. Thus, the fixed cost, C_1, can be computed as:

$$C_1 = \sum_{k=1}^{K} \sum_{i=1}^{n} \sum_{j=1}^{n} x_{ij}^k f_k \tag{1}$$

2) TRANSPORTATION COSTS

The customer's demand could be utilized to calculate the distribution cost of the refrigerated truck. t_c represents the freight price per unit weight and d_{ij} is the distance between the customer i and j. q^i denotes the cargo demand of the customer i. The transportation cost of the cold chain truck is denoted by C_2.

$$C2 = \sum_{\mathrm{k}=1}^{K} \sum_{i=1}^{n} \sum_{j=1}^{n} x_{ij}^k t_c d_{ij} q^i \tag{2}$$

3) COST OF CARGO DAMAGE

The fresh products are perishable. In existing works, they compute the cost of cargo damage from the timestamp that the vehicle leaves the distribution center. However, the fresh products are delivered to the customer within a preset time window requirements. In other words, the cargo damage occurred within that time window would be accepted by customers. Hence, the time start point in the cost computation should be the first time window exceeding the time acceptance. Moreover, The relationship between the distance and the damage coefficient is exponential. Supposing that δ is the decline coefficient of the freshness of the product, t_i is the actual time to reach the customer i and t_0 is the latest time window required by the customer, we have the cost of cargo damage, C_3, as following:

$$C_3 = \sum_{\mathrm{k}=1}^{\mathrm{K}} \sum_{i=1}^{n} \sum_{j=1}^{n} x_{ij}^k t_c d_{ij} q^i (1 - e^{-\delta_1 (t_i - t_0)}) \tag{3}$$

B. CUSTOMER SATISFACTION

Satisfaction is defined as the measure of the time that the distribution center responds to the needs of the customer. If it is in the expected time of the customer, the satisfaction index will be higher. The expected period of the customer is denoted by an interval $[e_i, l_i]$, the arrival time of the delivery vehicle is denoted by A_i and the number of customers is denoted by n. Besides, the total customer satisfaction is 100 for a delivery. The time penalty factor is ε. We have the early delivery penalty factor ε_1 and the late delivery ε_2, where $\varepsilon_1 < \varepsilon_2$. The satisfaction G_i of a single customer i is defined by:

$$G_i = \begin{cases} \dfrac{100}{n} - \varepsilon_1 \dfrac{e_i - A_i}{e_i}, & if\ e_i > A_i \\ \dfrac{100}{n}, & if\ e_i < A_i < l_i \\ \dfrac{100}{n} - \varepsilon_2 \dfrac{A_i - l_i}{l_i}, & if\ l_i < A_i \end{cases} \tag{4}$$

When the refrigerated truck arrives out of the expected time of the customer, the penalty coefficient is utilized to generate the penalty cost of the distribution (C_4) as:

$$C_4 = 5\varepsilon_1 \frac{e_i - A_i}{e_i} + 10\varepsilon_2 \frac{A_i - l_i}{l_i} \tag{5}$$

C. MEASUREMENT OF CARBON EMISSIONS

According to the green logistics requirements, the carbon emissions of the cold chain logistics vehicles mainly induces from two sources. The first one is related to the fuel emissions during the driving, while the second one is the additional carbon emissions generated by the refrigeration equipment at low temperatures. Carbon emissions from refrigeration maintenance are due to the heat transfer during the delivery of refrigerated vehicles and the heat exchange when the doors are open at the customer service point. The classic automobile energy consumption model proposed by Barth *et al.* [55] is employed to construct the energy consumption model of the refrigerated truck distribution as:

$$\begin{cases} CA = \sum_{k=1}^{k}\sum_{i=0}^{n}\sum_{j=0}^{n} x_{ij}^{k}\frac{d_{ij}}{v_{ij}}Rh, \\ R = \delta(\phi TV_s + P)/\mu, \\ P = P_t/\eta + P_c, \\ P_t = (M_q av + M_q gv\sin\theta + \frac{p}{2}C_d Av^2 + M_q gvC_r\cos\theta)/1000, \\ P_c = \gamma\Delta T\sqrt{SwSv} + (0.54n + 3.22)(\Delta T)\lambda, \end{cases} \tag{6}$$

The parameters in (6) are described as follows:

CA: Carbon emissions generated during vehicle distribution (unit: kg).

R: Fuel consumption rate per unit time (unit: g/s).

h: Conversion factor of fuel consumption and carbon emissions.

δ: Fuel-air mixture ratio.

ϕ: Engine friction factor.

T: Engine speed of the refrigerated truck.

V_s: Exhaust capacity of a refrigerated truck.

P: Power of refrigerated truck (unit: W).

P_t and P_c represent the normal power in the distribution process of the refrigerated truck and the additional power generated by the refrigeration equipment, respectively.

η: Transmission effective power.

μ: Energy consumption constant.

M_q: Refrigerated vehicle weight (unit: kg).

a: Vehicle driving acceleration.

v: Vehicle speed (unit: m/s).

g: Gravity acceleration.

p: Air-Density.

A: Frontal area of the vehicle (unit: m^2).

C_d: Traction coefficient.

C_r: Rolling resistance coefficient.

θ: Road gradient.

γ: Heat transfer derivative of the refrigerated truck ($W_m^{-2}K$).

ΔT: The temperature difference between the refrigerated truck and the outside environment.

S_v, S_w: Internal and external surface area of refrigerated truck (unit: m^2).

λ: Frequency of door opening.

n: Number of customers.

After obtaining the carbon emissions, i.e., CA, of the distribution vehicles by equation (6), the carbon emission cost of the cold chain distribution C_5 can be calculated as:

$$C_5 = \sum_{k=1}^{k}\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij}^{k}\frac{d_{ij}}{v_{ij}}RhY \tag{7}$$

where Y represents the carbon tax.

D. AVERAGE SPEED MODEL

According to the speed model proposed by Poonthalir [56], it is assumed that the vehicle speed fluctuates between 30 km/h and 40 km/h. The average expected speed of the vehicle during travel is calculated according to its expected speed. The initial speed limit is chosen as 30km/h. The maximum speed limit and the maximum speed limit before the acceleration reduction are considered as 40 km/h, and 37 km/h, respectively. The acceleration is equal to $a = 0$ when the vehicle speed increases to 40 km/h. The distribution of the expected speed is shown by the triangular distribution FIGURE 1.

The average speed is calculated as follows:

$$\begin{aligned} V(x) &= \int_a^b xf(x)dx \\ &= \int_{30}^{40} xf(x)dx \\ &= \int_{30}^{37} x\frac{2(x-30)}{(40-30)(37-30)}dx \\ &\quad + \int_{37}^{40} x\frac{2(40-x)}{(40-30)(40-37)}dx \\ &= 35.6667 \end{aligned} \tag{8}$$

E. MULTI-OBJECTIVE OPTIMIZATION MODEL

Considering the factors of distribution such as cost, customer satisfaction, and carbon emissions, the final path optimization model of the cold chain distribution can be descripted as follows (9)–(11), as shown at the bottom of the next page.

Eqs. (12) and (13), as shown at the bottom of the next page: customers can only be served by one refrigerated truck, which means that each customer has only one delivery vehicle service. Eq. (14), as shown at the bottom of the next page: all delivery vehicles depart from the distribution center to deliver the goods and then return to the distribution center. Eq. (15), as shown at the bottom of the next page: the sum of the weights of the goods required by customers on each distribution route cannot exceed the maximum load of the vehicle. Eq. (16), as shown at the bottom of the next page: the number of refrigerated trucks in the distribution center is limited. Eq. (17), as shown at the bottom of the next page: the time relationship between refrigerated trucks k from customer i to customer $i+1$. Eq. (18), as shown at the bottom of the next page: after giving service to the customer i, the weight of the refrigerated vehicle is reduced by q^i. Eq. (19), as shown at the bottom of the next page: the vehicle departing from the distribution center is the same vehicle of returning to the distribution center. Eq. (20), as shown at the bottom of the next page: the demand cannot be negative. Eq. (21), as shown at the bottom of the next page: the value of the decision variable takes 0-1. Eq. (22), as shown at the bottom of the next page: time window requirements. Eqs. (23) and (24), as shown at the bottom of the next page: the delivery vehicle arrives early or late.

IV. ALGORITHMIC SOLUTION

Strong global search ability, positive feedback mechanism, distributed computing, and strong robustness are the main characteristics of the ant colony algorithm. The distributed computer system of the ant colony algorithm constitutes a distributed multi-agent system, which enhances the reliability and search ability of the algorithm. The algorithm does not depend on the initial solution selection, i.e., the initial solution does not have any considerable impact on the solution. It adaptively adjusts the optimization route during the entire process with strong adaptability and stability. The traditional ant colony algorithm calculates the transition probabilities according to the pheromone concentration $\tau_{ij}(t)$ and the distance between the paths n_{ij}. Although the positive feedback mechanism facilitates the continuous convergence of the ant colony algorithm during the search process, it increases the possibility of falling into the local minimum. The proposed method in this paper dynamically improves the pheromone concentration in the algorithm design, limits the range of pheromone concentration, and updates the global pheromone in 20 iterations. Besides, the heuristic function is redesigned such that the ants no longer only consider the distance factor when moving to the next node, but also the time limit. The rule parameters are selected using Pseudo-random proportional action to increase the probability of finding the optimal path and approximating the optimal solution. Accordingly, the Pareto solution set of multi-objective optimization is obtained.

A. ALGORITHM PRESENTATION

$$p_{ij}^{k} = \begin{cases} \dfrac{[\tau_{ij}(t)]^{a}[n_{ij}]^{\beta}}{\sum\limits_{j \in allowd_{ik}} [\tau_{ij}(t)]^{a}[n_{ij}]^{\beta}}, & j \in allowed_{ik}; \\ 0, & \text{else.} \end{cases} \tag{25}$$

$$\begin{aligned} MinC = C_1 + C_2 + C_3 + C_4 + C_5 &= \sum_{k=1}^{K}\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij}^{k} f_k + \sum_{\mathrm{k}=1}^{\mathrm{K}}\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij}^{k} t_c d_{ij} q^{i} + \sum_{\mathrm{k}=1}^{\mathrm{K}}\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij}^{k} t_c d_{ij} q^{i} (1 - e^{-\delta_1 \blacklozenge t_i - t_0)}) \\ &+ \sum_{k=1}^{k}\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij}^{k} \frac{d_{ij}}{v_{ij}} (\delta(\phi T V_s + (M_q a v + M_q g v \sin\theta + \frac{p}{2} C_d A v^2 + M_q g v C_r \cos\theta)/1000/\eta \\ &+ \gamma \Delta T \sqrt{SwSv} + (0.54n + 3.22)(\Delta T)\lambda)/\mu) h Y + 5\varepsilon_1 \frac{e_i - A_i}{e_i} + 10\varepsilon_2 \frac{A_i - l_i}{l_i} \end{aligned} \tag{9}$$

$$MinT = \sum_{k=1}^{k}\sum_{i=0}^{n}\sum_{j=0}^{n} x_{ij}^{k} \frac{d_{ij}}{v_{ij}} (\delta(\phi T V_s + P_t/\eta + P_c)/\mu) h \tag{10}$$

$$MaxG = (\frac{100}{n} - \varepsilon_1 \frac{e_i - A_i}{e_i}) + \frac{100}{n} + (\frac{100}{n} - \varepsilon_2 \frac{A_i - l_i}{l_i}) \tag{11}$$

$$st. \sum_{i=1, j=1}^{n} \sum_{k=1}^{K} x_{ij}^{k} = 1, \tag{12}$$

$$\sum_{i=1}^{n}\sum_{k=1}^{K} x_{im}^{k} - \sum_{j=1}^{n}\sum_{k=1}^{K} x_{mj}^{k} = 0, \quad m \in n, \tag{13}$$

$$\sum_{i=1}^{n}\sum_{k=1}^{K} x_{io}^{k} = \sum_{j=1}^{n}\sum_{k=1}^{K} x_{oj}^{k} = K, \quad \forall i, j \in V,\ k \in K, \tag{14}$$

$$\sum_{i=1}^{n} x_{i}^{kr} q^{i} \le Q_{k}^{r}, \quad \forall k \in K,\ r \in R_k, \tag{15}$$

$$\sum_{k=1}^{K}\sum_{j=1}^{n} x_{j}^{k} \le K, \quad \forall k \in K, \tag{16}$$

$$t_{ok(i+1)} = t_{oki} + s_{ik} + t_{i(i+1)k}, \quad \forall k \in K,\ i \in V, \tag{17}$$

$$\sum_{j=0}^{n} (Q_{ji}^{p} - Q_{ij}^{p}) = q^{i}, \quad \forall (i, j) \in V, \tag{18}$$

$$\sum_{k=1}^{K}\sum_{i,j=0}^{n} x_{ij}^{k} = \sum_{k=1}^{K}\sum_{i,j=0}^{n} x_{ji}^{k}, \quad \forall i,\ j \in V,\ k \in K, \tag{19}$$

$$q_i \ge 0, \quad \forall i \in V, \tag{20}$$

$$x_{ij}^{k}(1 - x_{ij}^{k}) = 0, \quad \forall i,\ j \in V,\ k \in K, \tag{21}$$

$$e_i \le A_i \le l_i, \quad i \in n, \tag{22}$$

$$e_i - \mathrm{A}_i > 0, \quad \forall i \in V, \tag{23}$$

$$l_i - \mathrm{A}_i < 0, \quad \forall i \in V. \tag{24}$$

We will provide the meanings of some notations used in the algorithm.

p_{ij}^{k}: The k ant chooses the state transition probability of the next node. $\tau_{ij}(t)$: The pheromone concentration of (i, j) sections. n_{ij}: Heuristic function value, which is set according to the specific problem. α and β are the weight parameters of $\tau_{ij}(t)$ and n_{ij}, respectively. The ant colony Algorithm will be a random greedy algorithm with multiple starting points when $\alpha = 0$. The bigger α is, the more likely it is to choose a path with more pheromones. β plays a role in expanding the solution space of the optimization problem in a positive feedback search. $allowed_{ik}$: The k ant is located at i, it can be transferred to the next node-set. $allowed_{ik}$ is equal to $allowed_{i}$ that has removed the visited node.

n_{ij} is a heuristic function, and generally $n_{ij} = 1/d_{ij}$. When calculating the probability of moving to the next node, the basic ant colony algorithm only takes into account the distance factor. Differently, our method also considers cargo demand, distance, and time window constraints. Q_j is the demand for cargo at the node j, d_j is the distance to the node j, and l_j is the expected arrival time.

$$n_{ij}=3-\frac{Q_j-MinQ_{ij}}{MaxQ_{ij}-MinQ_{ij}}-\frac{d_j-Mind_{ij}}{Maxd_{ij}-Mind_{ij}}-\frac{l_j-Minl_{ij}}{Maxl_{ij}-Minl_{ij}} \tag{26}$$

In the process of moving from node i to node j, the ant k calculates the probability of moving to the next node P_{ij}^{k} according to the action selection rule. The ant selects the next node by playing roulette:

$$p = \frac{p_{ij}^{k}}{\sum\limits_{j\in allowd_{ik}} p_{ij}^{k}}, \quad j \in allowed_{ik}. \tag{27}$$

The significance of the roulette method is that it allows ants to choose the optimal path with a greater probability. When the transfer probability which is calculated according to the parameters of the selection rule of action is relatively larger, the possibility of being selected by roulette is greater. However, this strategy cannot guarantee that the optimal path is selected. Therefore, we set the parameter of the selection rule of the pseudo-random proportional action as p^f. When the optimal node transfer probability $p_{ij}^{k} < p^f$, the optimal node j is directly selected for transfer. When $p_{ij}^{k} > p^f$, the state transition probability is selected based on the roulette. In summary, by setting a fixed threshold value of p^f, we realize the unity of random search and deterministic search to increase the search space for a better solution. Thus, it is avoided being trapped into the local optimum by expanding the search range.

In the single-target ACS(ant-cycle system) pheromone incremental model, only the path distance needs to be considered. While multi-objective optimization considers cost C, carbon emissions T, and customer satisfaction G as shown in Eq. (28), as shown at the bottom of the next page, where w_1, w_2 and w_3 represents the weighting factors of the optimization goal. C_{local}, T_{local}, and G_{local} represent that each ant runs the full distribution cost, carbon emissions, and satisfaction. During this iteration, $MinC_{local}$ and $MaxC_{local}$ represent the minimum and maximum distribution costs, respectively. It is the same to carbon emissions T and customer satisfaction G. As expressed in Eq. (28), the pheromone increment is related to the overall search path, so that it can be regarded as a global information update.

It is assumed that the pheromone concentration on the initial path is zero, and the pheromone concentration on the path should be readjusted after completing each iteration. Let p be the pheromone volatility coefficient on the path and $\Delta\tau_{\mathrm{ij}} = \sum\limits_{k=1}^{m} \Delta\tau_{ij}^{k}$ being the incremental pheromone released during the transfer process of the ant. Then, after all ants completing a path search, the total amount of pheromones on the path can be adjusted as follows:

$$\tau_{\mathrm{ij}}(t+1) = (1-p) * \tau_{ij}(t) + \Delta\tau_{ij} \tag{29}$$

When there are a lot of pheromones left in the path, the possibility of searching the previously selected path increases, and the ants would eventually concentrate on the same path, which thus affects the random performance of the algorithm. Especially, when dealing with the problems of large-scale nodes, it is not easy to find paths that have never been searched. Thus, the randomness of the search process is weakened, leading to reduce the feasible solution space and the algorithm's global search ability. Although small pheromone concentration can improve the random performance and global search ability of the algorithm, it will affect the convergence rate of the algorithm to a certain extent. Therefore, the total amount of pheromones on the path needs to be constrained to maintain the total amount of pheromones between $\tau_{\max}$ and $\tau_{\min}$. When $\tau_{\mathrm{ij}}(t+1) > \tau_{\max}$ constrain $\tau_{\mathrm{ij}}(t+1) = \tau_{\max}$; $\tau_{\mathrm{ij}}(t+1) < \tau_{\min}$, $\tau_{\mathrm{ij}}(t+1) = \tau_{\min}$, where

$$\tau_{\mathrm{ij}}(t+1)=\begin{cases}\tau_{\max} & \tau_{\mathrm{ij}}(t+1) > \tau_{\max},\\ (1-p)*\tau_{ij}(t)+\Delta\tau_{ij}, & \tau_{\min} < \tau_{\mathrm{ij}}(t+1) < \tau_{\max},\\ \tau_{\min} & \tau_{\mathrm{ij}}(t+1) < \tau_{\min}.\end{cases} \tag{30}$$

The node is saved by constructing a local *L_Tab* tabu list where *L_Tab* is an empty list at the beginning of each iteration. It has a restrictive effect on the ants of the current iteration, and only records the optimal path that occurs during one iteration. According to the probability of a random search algorithm, the iterative search process may cause the loss of the optimal solution that has been found, that is, it does not appear in the next iteration due to the volatilization effect of the pheromone on the path. If the lost optimal path is not found, its pheromone will gradually decrease, which is not conducive to the convergence of the algorithm. In the iterative process, the searched optimal path needs to be saved. In each iteration, the optimal path searched by the ant is compared with the historical optimal path and it save the historical optimal path.

B. IMPLEMENTATION OF THE IMPROVED ANT COLONY ALGORITHM

Step1: Initialization of algorithm parameters. Parameters of the algorithm mainly include the number of ants m, the maximum number of iterations $N\_{\max}$, the number of renewed pheromone iterations R_n, the weights of the pheromone concentration and the heuristic function α and β, the volatility coefficient ρ, the parameter of the selection rule of the pseudo-random proportional action q^f, and the maximum and minimum values of the pheromone $\tau_{\max}$ and $\tau_{\min}$.

Step2: Randomly placing m ants on different nodes, initializing the path pheromone concentration, and selecting the next available node based on the current node.

Step3: Updating the pheromone concentration and restricting it between $\tau_{\max}$ and $\tau_{\min}$. According to Eqs. (26) and (28), the state transition probability of the ant p_{ij}^k is obtained, and the passed nodes are added to the Tabu list L_Tab until all the ants have completed the visit of all nodes.

Step4: Calculating the distribution cost C, carbon emissions T, and satisfaction G. If C and T are smaller and meanwhile G is larger than theirs previous results, we add them into the Pareto matrix table $\{C_i, T_i, G_i\}$.

Step5: Letting $N = N + 1$, adding the optimized solution obtained in this iteration into the Pareto matrix table, and updating it. When N reaches R_n, the pheromone concentration is re-initialized.

Step6: If $N < N\_{\max}$, going to Step2, otherwise, finishing the iteration and outputting the Pareto optimization set and the optimal distribution path.

C. PARETO OPTIMAL VALUE

The number of multi-objective Pareto optimization solution sets is not unique, so it is necessary to determine the optimal solution for the optimal distribution path. In this work, we assign weights of 1/3 to each of the factors, which are called cost, carbon emissions, and customer satisfaction $\{C_i, T_i, G_i\}$, respectively. Then, we calculated the final score for the optimized solution set S_i separately. Cost and carbon emissions are the goals of minimization, and customer satisfaction is the goal of maximization. Eqs. (31) and (32) are the minimization and the maximization, respectively. $Meanx_i$ is the average.

$$MinX_i = \sum_{i=1}^{n} \frac{Meanx_i}{x_i} \tag{31}$$

$$MaxX_i = \sum_{i=1}^{n} \frac{x_i}{Meanx_i} \tag{32}$$

$$Si = \frac{1}{3}MinC_i + \frac{1}{3}MinT_i + \frac{1}{3}MaxG_i \tag{33}$$

The largest S_i is the optimal value in the Pareto optimal solution set.

V. CASE ANALYSIS

A. DATA SELECTION

We take the Solomon standard test set c101as an example for analysis, where 0 represents the distribution center and the numbers from 1 to 100 are the customer indexes. Specific information includes location coordinates, customer demand, service time, time window constraints, as shown in Table 1.

B. THE PARAMETER SETTING

In this work, Dongfeng-Xiaobawang refrigerator car is selected as the delivery vehicle. Some of the parameters are pre-determined as follows: the gravitational acceleration g is 9.81 kg/m^2; the air density P is 1.225 kg/m^3; the gradient θ is 0; the temperature difference between the refrigerator car and the outside environment, ΔT, is 20°C; the frequency of opening the door, λ, is 0.6; the transportation price of per unit weight of goods, t_c, is 1; the decline coefficient of the product freshness, δ, is 0.01; the early arrival time penalty coefficient, ε_1, is 0.6; the late arrival time penalty coefficient, ε_2, is 0.8; the vehicle maximum load is 200; the refrigerator vehicle fixed cost is 200; the soft time window is set to 20; the carbon tax is 20. Table 2 lists other specific parameters related to refrigerator vehicles.

As shown above, the parameters of the improved ant colony algorithm are set as follows: the number of iterations of pheromone renewal, R_n, is 20; the weight α of pheromone concentration and the weight β of heuristic function are set to 1 and 3 respectively; the volatility coefficient ρ is 0.8; the parameter of the selection rule of Pseudo-random proportional action q^f is 0.9; the maximum value $\tau_{\max}$ and the minimum value $\tau_{\min}$ of pheromone are set to 10 and 0.001 respectively; the weights w_1, w_2, and w_3 of the optimization objectives are all $1/3$. The method is implemented by using Python 3.7.3 and the visual studio code editor is running on a computer with Intel Core I5,2.60 GHz, 4.00 GB RAM,and Windows 10 operating system.

The number of ants has an important influence on the optimization of the model. Firstly, to verify the influence of ant numbers, we conduct an experiment by setting different ant numbers. Fig.2 shows the optimal costs of 500 iterations with different ant numbers. The optimal costs are 3392.42,3373.9,3406.72,3393.63 and 3387 corresponding to $m = \{10, 20, 30, 40, 50\}$. We cannot find a very positive correlation between the number of ants and the optimal cost. Therefore, the number of ants m with the lowest cost of 3373.9 is 20. When the iteration is around 250, the cost is stable and near to the optimal one. As a result, we set the maximum iteration number $N_{-\max}$ as 250.

$$\Delta\tau_{ij}(t) = \frac{(w_1 + w_2 + w_3) - w_1 * \frac{(C_{local} - MinC_{local})}{MaxC_{local} - MinC_{local}} - w_2 * \frac{(T_{local} - MinT_{local})}{MaxT_{local} - MinT_{local}} - w_3 * \frac{(G_{local} - MinG_{local})}{MaxG_{local} - MinG_{local}}}{w_1 + w_2 + w_3} \tag{28}$$

TABLE 1. Distribution center and customer information.

Serial number	Abscissa	Ordinate	Demand quantity	Earliest window	Latest window	Service hours	Serial number	Abscissa	Ordinate	Demand quantity	Earliest window	Latest window	Service hours
0	40	50	0	0	1236	0	**51**	25	30	10	725	786	90
1	45	68	10	912	967	90	**52**	25	35	10	912	969	90
2	45	70	30	825	870	90	**53**	44	5	20	286	347	90
3	42	66	10	65	146	90	**54**	42	10	40	186	257	90
4	42	68	10	727	782	90	**55**	42	15	10	95	158	90
5	42	65	10	15	67	90	**56**	40	5	30	385	436	90
6	40	69	20	621	702	90	**57**	40	15	40	35	87	90
7	40	66	20	170	225	90	**58**	38	5	30	471	534	90
8	38	68	20	255	324	90	**59**	38	15	10	651	740	90
9	38	70	10	534	605	90	**60**	35	5	20	562	629	90
10	35	66	10	357	410	90	**61**	50	30	10	531	610	90
11	35	69	10	448	505	90	**62**	50	35	20	262	317	90
12	25	85	20	652	721	90	**63**	50	40	50	171	218	90
13	22	75	30	30	92	90	**64**	48	30	10	632	693	90
14	22	85	10	567	620	90	**65**	48	40	10	76	129	90
15	20	80	40	384	429	90	**66**	47	35	10	826	875	90
16	20	85	40	475	528	90	**67**	47	40	10	12	77	90
17	18	75	20	99	148	90	**68**	45	30	10	734	777	90
18	15	75	20	179	254	90	**69**	45	35	10	916	969	90
19	15	80	10	278	345	90	**70**	95	30	30	387	456	90
20	30	50	10	10	73	90	**71**	95	35	20	293	360	90
21	30	52	20	914	965	90	**72**	53	30	10	450	505	90
22	28	52	20	812	883	90	**73**	92	30	10	478	551	90
23	28	55	10	732	777	90	**74**	53	35	50	353	412	90
24	25	50	10	65	144	90	**75**	45	65	20	997	1068	90
25	25	52	40	169	224	90	**76**	90	35	10	203	260	90
26	25	55	10	622	701	90	**77**	88	30	10	574	643	90
27	23	52	10	261	316	90	**78**	88	35	20	109	170	90
28	23	55	20	546	593	90	**79**	87	30	10	668	731	90
29	20	50	10	358	405	90	**80**	85	25	10	769	820	90
30	20	55	10	449	504	90	**81**	85	35	30	47	124	90
31	10	35	20	200	237	90	**82**	75	55	20	369	420	90
32	10	40	30	31	100	90	**83**	72	55	10	265	338	90
33	8	40	40	87	158	90	**84**	70	58	20	458	523	90
34	8	45	20	751	816	90	**85**	68	60	30	555	612	90
35	5	35	10	283	344	90	**86**	66	55	10	173	238	90
36	5	45	10	665	716	90	**87**	65	55	20	85	144	90
37	2	40	20	383	434	90	**88**	65	60	30	645	708	90
38	0	40	30	479	522	90	**89**	63	58	10	737	802	90
39	0	45	20	567	624	90	**90**	60	55	10	20	84	90
40	35	30	10	264	321	90	**91**	60	60	10	836	889	90
41	35	32	10	166	235	90	**92**	67	85	20	368	441	90
42	33	32	20	68	149	90	**93**	65	85	40	475	518	90
43	33	35	10	16	80	90	**94**	65	82	10	285	336	90
44	32	30	10	359	412	90	**95**	62	80	30	196	239	90
45	30	30	10	541	600	90	**96**	60	80	10	95	156	90
46	30	32	30	448	509	90	**97**	60	85	30	561	622	90
47	30	35	10	1054	1127	90	**98**	58	75	20	30	84	90
48	28	30	10	632	693	90	**99**	55	80	10	743	820	90
49	28	35	10	1001	1066	90	**100**	55	85	20	647	726	90
50	26	32	10	815	880	90							

C. ANALYSIS OF THE RESULTS

The efficient solution of the multi-objective programming problem is also called the Pareto optimal solution. The set of Pareto solutions is called the Pareto front. Commonly, improving any objective function based on a dominant solution is subject to weaken at least one of the other objective

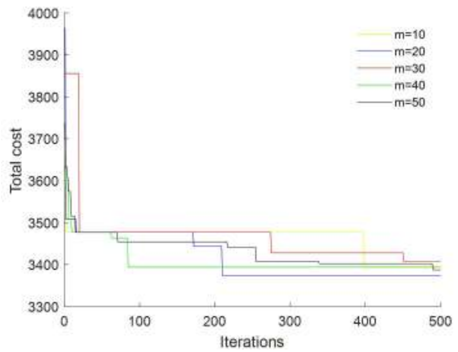

FIGURE 2. Parametric experimental iteration.

TABLE 2. Refrigerated vehicle parameter table.

Parameters	Implications	Take Value
R	Fuel consumption per unit time（g/s）	22.37
h	Fuel consumption and carbon emission conversion factor L/kg	1/2.7
δ	Fuel-air ratio	1
φ	Engine friction factor	0.2
T	Engine speed of refrigerated truck(r/min)	2000
V_s	Air Displacement(L)	1.051
η	Effective power transmission	0.45
μ	Energy consumption constant	44
M_q	Refrigerated truck weight(kg)	1510
A	Windward area of vehicle(m^2)	3.96
C_d	Coefficient traction	0.4
C_r	Coefficient of rolling resistance	0.01
γ	Heat transfer coefficient refrigerated truck	0.4
S_w	External surface area of refrigerated truck(m^2)	43.36
S_v	Interior surface area of refrigerated truck(m^2)	22.32

functions. Since all solutions in the Pareto front are not dominated by solutions outside it (and other solutions within the Pareto front curve), these non-dominated solutions have the fewest objective conflicts than the other ones. This feature provides a superior choice space for the decision-maker. In this paper, multi-objective optimization of the cost, the carbon emission, and customer satisfaction is considered, whose solution is expressed as a Pareto optimal solution. To attain a more practical situation, multiple experiments and analyses are performed on distribution centers for different numbers of customers.

1) RESULTS WITH 25 CUSTOMERS

FIGURE.3 is the Pareto optimal solution set and multi-dimensional linear interpolation of the c101 (25) test table. There are 15 Pareto optimal solutions. As shown in this figure, smaller values (blue part of the indicator) represents the better the quality of the Pareto optimal solution, while larger values (yellow part of the indicator) means that its quality needs to be further improved.. In the Pareto solution set, the blue part represents that the optimal solution possesses low costs, low carbon emissions, and high customer satisfaction. In contrast, the yellow part shows results with high cost, high carbon emissions and low customer satisfaction. Among the Pareto optimal solutions, the lowest cost is 3392.42, the lowest carbon emission is 19.73, and the five optimal solutions have the highest customer satisfaction, reaching 98.40. In calculating the score, the cost, carbon emissions and customer satisfaction of the optimal solution are: 3481.3, 19.73, and 98.40, respectively. The distribution vehicle path is shown in FIGURE.4: It can be seen that the distribution center needs 5 refrigerated trucks to serve it, and the vehicle travel path is: (0,20, 25, 23, 22, 21, 0); (0, 5, 3, 7, 10, 11, 9, 4, 2, 1, 0); (0, 24, 8, 6, 0); (0, 17, 19, 14, 12, 0); (0, 13, 18, 15, 16, 0). The refrigerated truck departs from the distribution center and returns to the departure position after serving all customers.

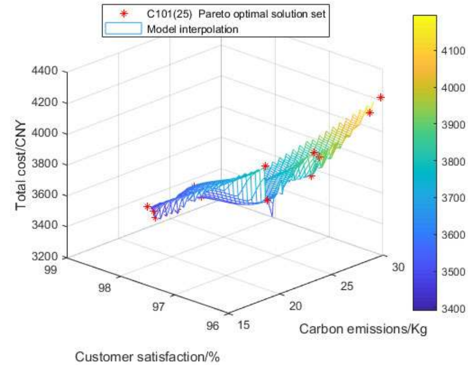

FIGURE 3. C101(25) Pareto optimal solution set and its multi-dimensional interpolation.

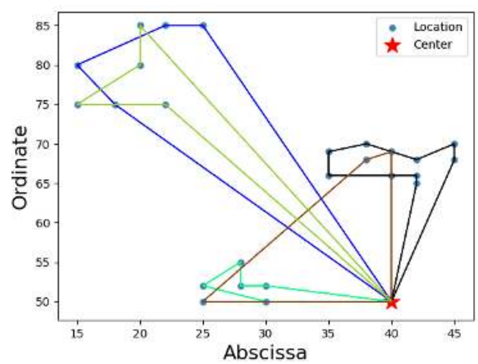

FIGURE 4. C101(25) vehicle distribution route.

2) RESULTS WITH 50 CUSTOMERS

FIGURE.5 shows the obtained Pareto optimal solution and its multidimensional linear interpolation by using the c101 (50) test table with 50 customers. There are 6 Pareto optimal solutions in the figure. The number of optimal solutions is less than the one with the test set having 25 customers. Generally, the fewer the optimal solutions there are, the fewer distribution plans the distribution center can choose. From this figure, we can find that the ones with the lowest cost,

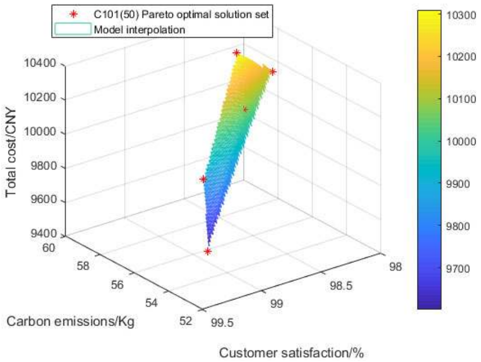

FIGURE 5. C101(50) Pareto optimal solution set and its multi-dimensional interpolation.

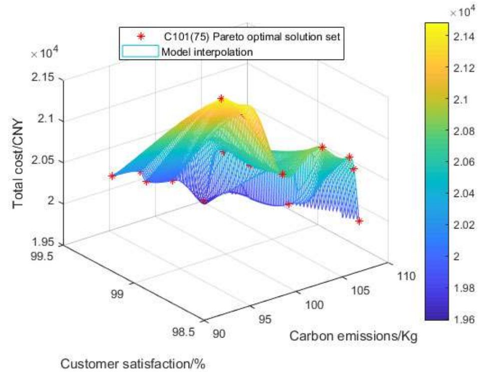

FIGURE 7. C101(75) Pareto optimal solution set and its multi-dimensional interpolation.

the lowest carbon emissions and the highest customer satisfaction are shown at the bottom of the interpolation graph, which means they are the optimal solutions. In this work, the optimal solution denotes the optimal distribution plan. The distribution center needs 11 refrigerated trucks to serve it. The optimal distribution path is: (0, 20, 24, 27, 29, 30, 26, 23, 22, 21, 49, 0), (0, 5, 3, 7, 10, 11, 9, 6, 2, 1, 47,0),(0, 43, 41, 40, 44, 45, 48, 50, 0),(0, 42, 35, 37, 39, 36, 34, 0), (0, 8, 4, 0,), (0, 17, 19, 14, 12, 0), (0, 28, 0, 31, 38, 0), (0, 25, 46, 0), (0, 13, 18, 15, 16, 0), (0,32, 33, 0). The specific vehicle path is shown in FIGURE. 6. Compared with the test set with 25 customers, when the number of customers reaches 50, it means that the distribution center needs more refrigerated vehicles to serve it.

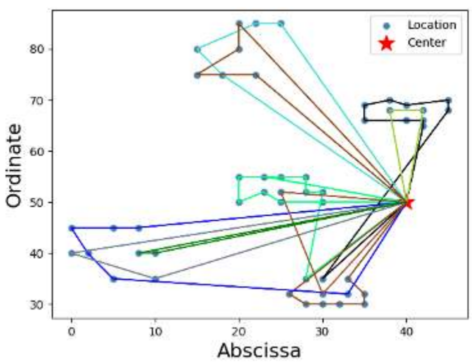

FIGURE 6. C101(50) vehicle distribution route.

3) RESULTS WITH 75 CUSTOMERS

Let we take c101 (75) as a test table with 75 customers, and use the proposed algorithm to get the Pareto optimized solution set. As shown in FIGURE. 7, the solution set contains 21 optimized solutions. Through multi-dimensional linear interpolation, it can be seen that the more optimal solutions there are, the more space it takes up, which means that the distribution center has more choices of distribution solutions. Among all the optimal solutions, the minimum cost is 19598.69 and the maximum cost is 21472.29; the minimum carbon emission is 94.87 and the maximum one is 109.41; and customer satisfaction is consistently high. By ranking these scores, values of the cost, carbon emissions and customer satisfaction in the highest ranked optimal solution are 20195.27, 94.87 and 99.47, respectively. By contrast, the three values in the lowest ranked solution are 20688.05, 108.31 and 98.67, respectively. The distribution center needs 17 refrigerated trucks to deliver to customers. The optimal routes is: (0, 20, 24, 27, 29, 30, 26, 23, 22, 21, 49, 0); (0, 67, 41, 40, 46, 45, 48, 51, 50, 52, 47,0); (0, 5, 3, 7, 10, 11, 9, 4, 2, 1, 75, 0); (0, 65, 62, 72, 61, 64, 68, 66, 69, 0); (0, 43, 42, 44, 59, 0); (0, 55, 53, 56, 60, 34, 0); (0, 8, 6, 0); (0, 17, 19, 14, 12, 0); (0, 35, 37, 36, 0); (0,31, 39, 0); (0, 13, 18, 28, 0); (0,32, 33, 38, 0); (0, 25, 15, 16, 0); (0,63, 74, 73, 0);(0, 71, 0); (0, 70, 0); (0,57, 54, 58, 0). The specific vehicle path is shown in FIGURE. 8:

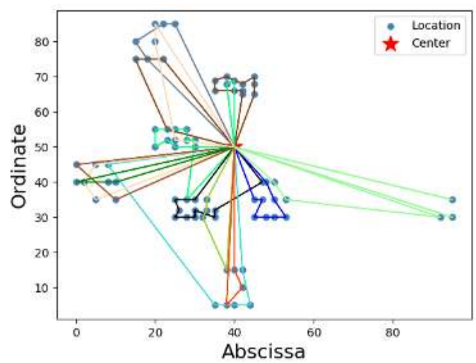

FIGURE 8. C101(75) vehicle distribution route.

4) RESULTS WITH 100 CUSTOMERS

The Pareto optimized solution set shown in FIGURE.9 is obtained from the experiment using the c101 table with 100 customers. There are a total of 12 optimized solutions in the solution set. Compared with the solution set which have 21 optimal solutions in the test set with 75 clients, we can find that the increase in the number of clients does not show an increase in the number of optimal solutions. Particularly, among all the optimal solutions, the smallest cost

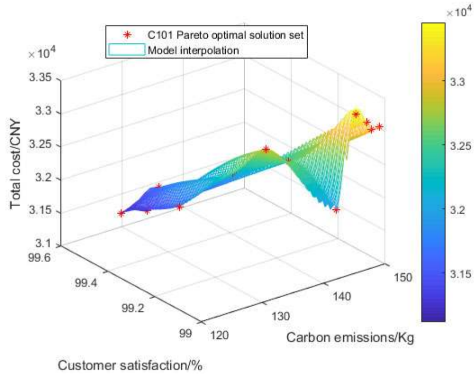

FIGURE 9. C101(100) Pareto optimal solution set and its multi-dimensional interpolation.

is 31116.35 and the largest one is 33232.30; the smallest carbon emission is 129.87 and the largest one is 149.48. The darkest blue area shows the highest ranked optimized solution. The distribution center needs 23 refrigerated trucks to deliver to customers. The specific routes are: (0, 55, 40, 44, 45, 48, 51, 50, 52, 49, 47, 0); (0, 90, 86, 83, 82, 84, 89, 91, 69, 0); (0, 20, 24, 27, 29, 30, 26, 23, 22, 21, 75, 0); (0,67, 65, 41, 53, 72, 61, 64, 66, 1, 0); (0, 5, 3, 7, 10, 11, 9, 4, 2, 0); (0, 43, 42, 35, 37, 36, 34, 0); (0, 96, 94, 92, 99, 0); (0, 87, 76, 73, 77, 79, 80, 0); (0,62, 68, 0); (0, 8, 6, 0); (0,98, 95, 100, 0); (0, 12, 0); (0, 17, 19, 14, 0); (0, 31, 39, 0); (0, 81, 78, 71, 70, 59, 0); (0, 13, 18, 28, 0); (0, 32, 33, 38, 88, 0); (0, 25,46, 60, 0) ;(0, 63, 74, 85, 0); (0, 57, 54, 56, 58, 0); (0, 97, 0); (0, 93, 0);(0, 15, 16, 0);. The detailed vehicle path is shown in FIGURE.10:

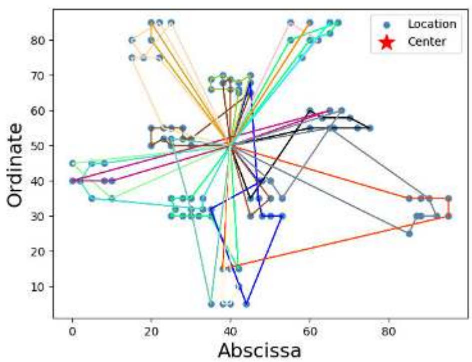

FIGURE 10. C101(100) vehicle distribution route.

5) COMPARISON WITH DIFFERENT ALGORITHMS

As shown in TABLE. 3, the improved ant colony algorithm shows significant advantages over the ant colony algorithm in terms of the used evaluation metrics. More specifically, the improved ant colony algorithm obtains more Pareto optimal solutions than the ordinary ant colony algorithm. For example, the number of the optimal solutions obtained by ACOMO ranges from 6 to 21, while the largest number of the optimal solutions of ACO is only 7, especially in the result with the table of 25 customers where the number is only 2. In practice, the number of Pareto optimal solutions has an important influence on the choice of decision-making options. That is, the more optimal solutions there are, the more options decision-makers can select. In addition to the number of optimal solutions, ACOMO also has advantages in cost, carbon emissions, and customer satisfaction. Except for the test set with 25 customers, when the number of customers reaches 50 and 75, the cost of ACOMO is reduced by 3.44% and 5.73% respectively compared to the classic ant colony algorithm. Specifically, when there are 100 customers, the cost of improved ant colony algorithm is reduced by 2.89%. In terms of carbon emissions, the improved ant colony algorithm possesses consistently less carbon emissions than those classic ant colony algorithms, with an average reduction of around 6.17%. Meanwhile, customer satisfaction has also been improved. Generally, customer satisfaction of the classic ant colony algorithm has been in a higher position, while the improved ant colony algorithm further increases it by 0.71%. In summary, the improved ant colony algorithm indeed outperforms the classic ant colony algorithms.

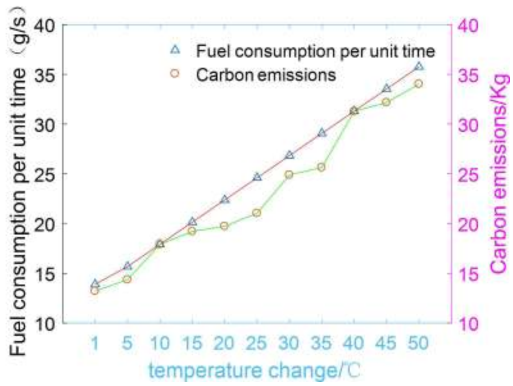

FIGURE 11. Relationship between temperature and carbon emissions.

6) SENSITIVITY ANALYSIS OF TEMPERATURE CHANGES

As an important factor in cold chain logistics, temperature control plays an active role in cold chain logistics distribution. The strict temperature control can effectively reduce the impact of temperature fluctuations on cargo in cold chain transportation. To a certain extent, refrigeration equipment has caused an increase in carbon emissions. Figure. 11 shows a sensitivity analysis of temperature changes and the relationship between temperature changes and the amount of carbon emissions generated by distribution vehicles during the cold chain logistics distribution process. It can be seen that the temperature difference changes have an absolute linear correlation with the fuel consumption rate and carbon emissions. When the temperature difference between the external environment and the refrigerated truck increases, carbon emissions also increase. For example, when the temperature difference is 1°C, the fuel consumption rate per unit time is 13.89g/s and the carbon emission is 13.22Kg;

TABLE 3. Comparison of performance using ACOMO and ACO methods.

	ACOMO				ACO			
	Costs /CNY	Carbon Emissions /Kg	Customer Satisfaction /%	Pareto Number	Costs /CNY	Carbon Emissions /Kg	Customer Satisfaction /%	Pareto Number
C10125	3481.31	19.73	98.4	15	3393.63	20.48	98.4	2
C10150	9583.70	53.75	99.2	6	9913.25	54.63	98.4	3
C10175	20195.27	94.87	99.47	21	21351.56	112.06	98.5	7
C101	31202.27	129.87	99.6	12	32103.39	135.4	98.58	6

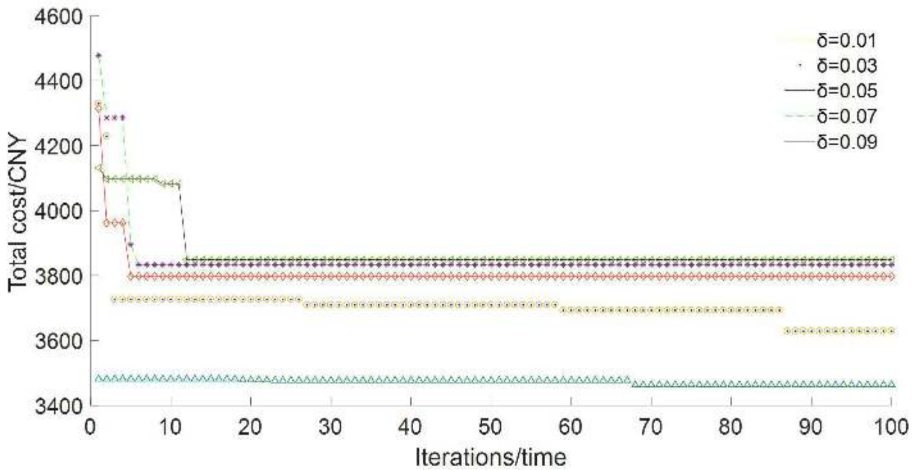

FIGURE 12. Cost iterations with different cargo damage factors.

when the temperature difference becomes to 50°C, the fuel consumption rate reaches up to 35.76g/s and the carbon emission increases to 34.01Kg. In general, when the temperature difference increases by 5°C, carbon emissions will increase by 10.19%. In this case, refrigerated trucks should have good thermal insulation to prevent extra carbon emissions caused by external environmental factors.

7) IMPACT OF CARGO DAMAGE FACTOR ON COST

This section simulates the relationship between the change in cargo loss coefficient and the distribution cost of cold chain logistics, as showed in FIGURE.12. It can be seen that with the increase of cargo loss coefficient, the distribution cost gradually increases. Specifically, when the cargo damage factor is 0.09, the distribution cost is 3848.6; when the cargo damage factor is reduced to 0.05, the distribution cost is down to 3797.8; when the cargo damage factor is 0.01, the distribution cost is 3463.26. Every time the cargo loss factor is reduced by 0.01, the distribution cost is reduced by 1.25%. In the process of reducing the cargo damage factor from 0.09 to 0.05, the distribution cost decreased by 0.33% for every 0.01 reduction of the cargo damage factor. While, when the freight loss coefficient is reduced by from 0.05 to 0.01, the delivery cost is reduced by 2.20% for every decrease of 0.01. Here, we can conclude that the distribution cost shows an exponential growth trend with the increase of the cargo loss coefficient. Therefore, in order to reduce costs, the

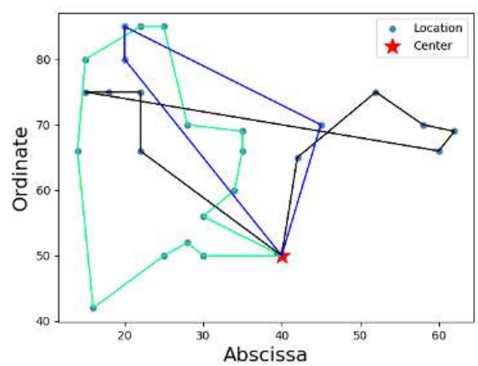

FIGURE 13. C201(25) distribution path.

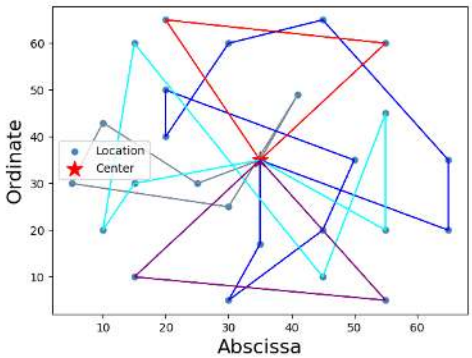

FIGURE 14. R201(25) distribution path.

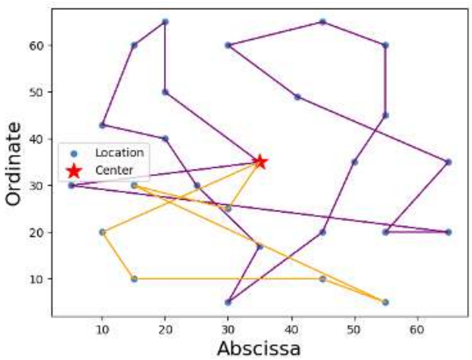

FIGURE 15. R211(25) distribution path.

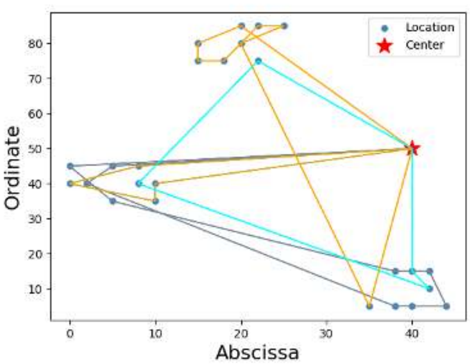

FIGURE 16. RC201(25) distribution path.

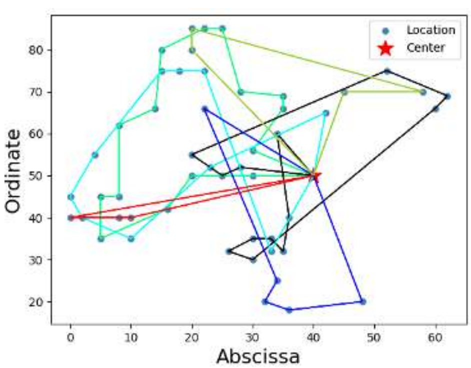

FIGURE 17. C201(50) distribution path.

refrigerated truck should strictly control the cargo loss and keep it in a low range during the distribution process.

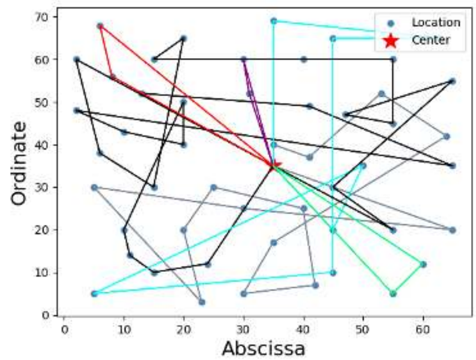

FIGURE 18. R201(50) distribution path.

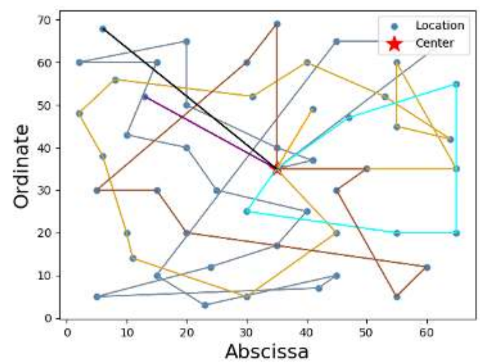

FIGURE 19. R211(50) distribution path.

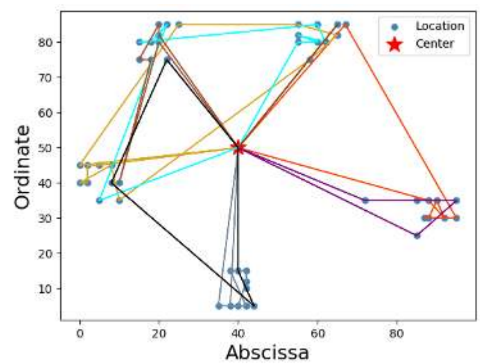

FIGURE 20. RC201(50) distribution path.

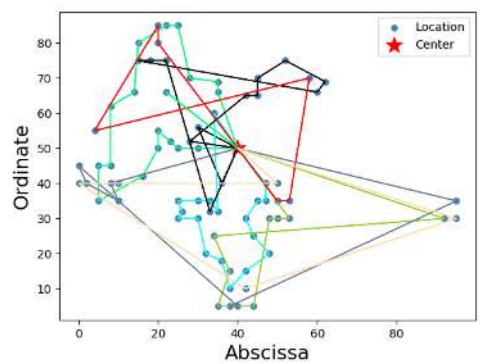

FIGURE 21. C201(75) distribution path.

8) RESULTS WITH VARIOUS TEST SETS

In addition to C101, we also conduct experiments on C201, R201, and R211, RC201 with 25, 50, 75, and 100 customers, respectively. As shown in the table, the maximum of Pareto

TABLE 4. Other test set results.

No.	Number of Pareto Solution Sets	Number of Vehicles	Costs	Carbon Emissions	Customer Satisfaction	Score
C201(25)	46	3	613.81	22.28	100	1.051
R201(25)	16	5	946.39	45.17	100	1.238
R211(25)	2	2	400.00	24.11	100	1.319
RC201(25)	12	4	847.18	31.43	100	1.208
C201(50)	9	6	1232.80	42.46	100	1.124
R201(50)	5	6	1404.82	69.75	100	1.212
R211(50)	7	7	600.00	44.87	100	1.307
RC201(50)	15	8	1554.47	80.00	100	1.207
C201(75)	11	9	2177.34	58.81	100	1.146
R201(75)	22	7	2482.75	98.40	100	1.099
R211(75)	22	7	873.41	72.94	100	1.166
RC201(75)	24	10	2186.50	121.39	100	1.157
C201	16	13	2221.71	99.08	100	1.145
R201	18	13	2931.63	111.02	100	1.142
R211	17	9	1080.64	84.49	100	1.226
RC201	25	11	2959.41	139.20	100	1.110

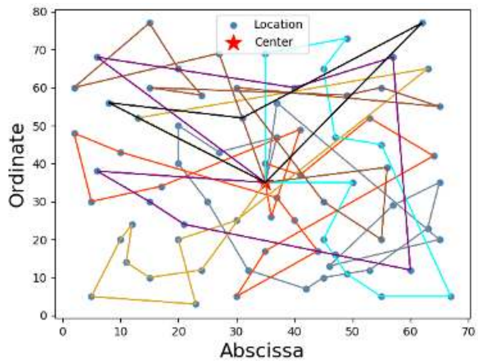

FIGURE 22. R201(75) distribution path.

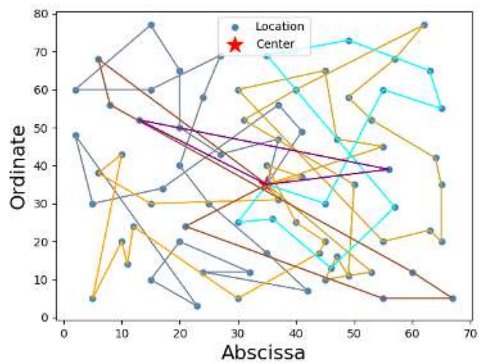

FIGURE 23. R211(75) distribution path.

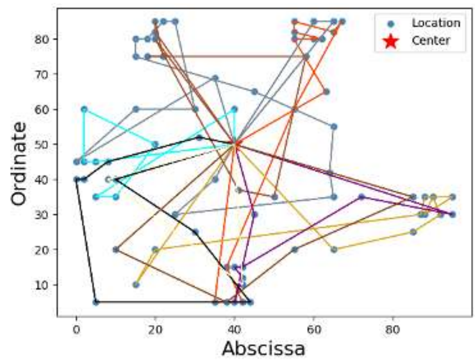

FIGURE 24. RC201(75) distribution path.

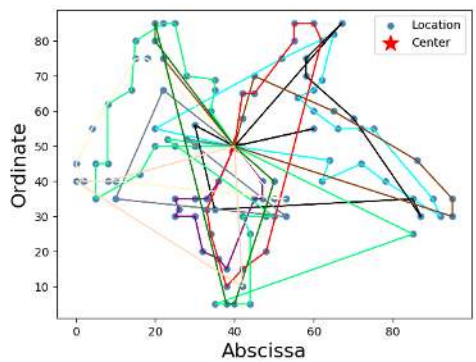

FIGURE 25. C201 distribution path.

solution sets is 46 on C201(25), and the minimum one is 2 on R211(25). It can be seen that the number of customers have no absolute relationship with the number of optimal solutions. Differently, there is a weak relationship between the number

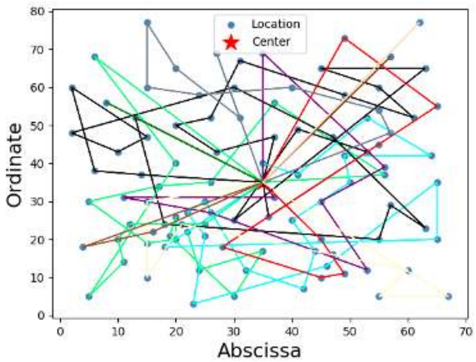

FIGURE 26. R201 distribution path.

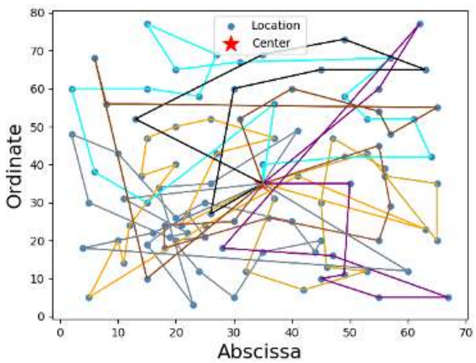

FIGURE 27. R211 distribution path.

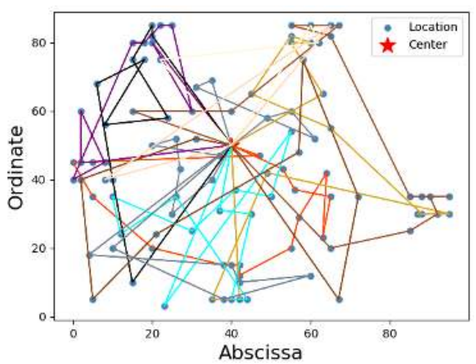

FIGURE 28. RC201 distribution path.

of distribution vehicles and the number of customers. That is, with the increment of distribution customers, the distribution center needs more refrigerated vehicles to serve. For example, in the result of R211(25) test table with 25 customers, it only needs two refrigerated trucks to complete the distribution task. While, it needs 13 refrigerated trucks in the C201 and R201 with 100 customers. Next, we will analyze the table in detail.The specific distribution routes are shown in the following FIGURES:

The Pareto optimal solution sets are obtained from the solutions of all multi-objective optimization problems that are pertinent to lower cost, lower carbon emission, and higher customer satisfaction. Then, their optimal solution is chosen by using the weights. The trends of the cost and the carbon emission can be seen from the test set optimizations. When the number of customers increases, both the cost and the carbon emissions increase significantly. There is a significant positive correlation between them. Hence, the enterprises should find the distribution of the optimal path by reducing the distribution cost and reducing the carbon emissions by assuming that the corresponding social responsibility is met.

As the number of customers is increased from 25 to 50, 50 to 75, and 75 to 100, carbon emissions are increased by 112%, 54%, and 30%, respectively. In other words, as the number of customers increases, the growth ratio of carbon emissions shows a downward trend. When customers reach a specific size, they can restrain the growth of carbon emissions to a certain extent. Hence, when multiple distribution centers deal with a smaller number of customers, they can reduce carbon emissions by integrating logistics distribution centers and increasing their capacity to deal with more distribution tasks.

VI. CONCLUSION

In this work, we have presented the relevant concepts of cold chain logistics path optimization, and established a multi-objective optimization model under the real application scenario. The presented model outperforms the widely adopted single-objective optimization model that focuses only on cost minimization, and achieves a breakthrough in the path optimization problem, from one-dimensional goal to multi-dimensional goals. Moreover, an improved ant colony algorithm is proposed to perform multi-objective optimization by considering cost, carbon emissions and customer satisfaction. Experimental results shows that the improved ant colony algorithm is superior to the classic ant colony algorithm. It can effectively avoid falling into local optimality and obtain more Pareto optimal solutions. The improved ant colony algorithm achieved the goals of reducing distribution costs and carbon emissions, and improving customer satisfaction. In addition, this paper also conducted a sensitivity analysis on temperature control and cargo damage coefficient. When the temperature difference between the refrigerated truck and the outside increases by 5°C, carbon emissions increase by 10.19% accordingly. Strict temperature control can thus minimize the impact of temperature fluctuations on cargo during cold chain transportation. Also, when the freight loss coefficient is in the range of 0 to 0.1, the distribution cost consistently decreases by 1.25% for every decrease of 0.01 in freight loss coefficient. The distribution cost shows an exponential growth trend with the increase of the cargo loss coefficient. In order to reduce the distribution cost, the cargo loss should be kept in a low range. This research has a certain of practical significance. Multi-objective optimization outputs multiple Pareto optimal solutions. That is, there will be a variety of distribution schemes for the distribution center to choose, which provides a reference for the distribution route to the relevant logistics company.

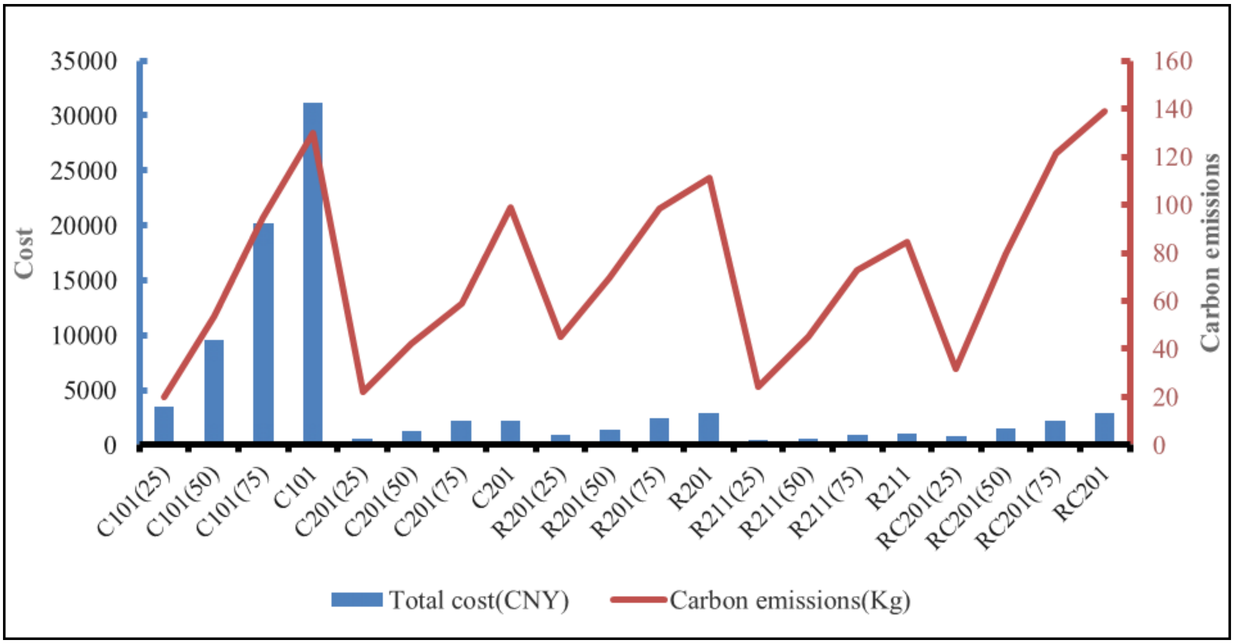

FIGURE 29. Trends in costs and carbon emissions.

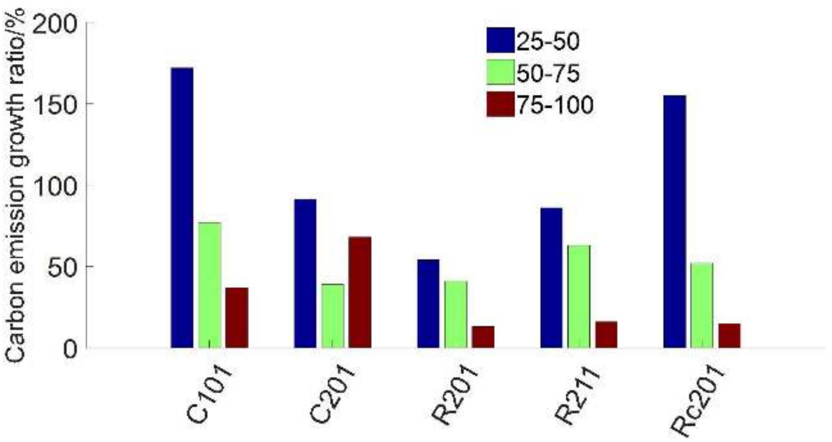

FIGURE 30. Ratio of increase in carbon emissions.

Future research directions mainly include the following:

1) Effective temperature control can minimize the deterioration rate of food during transportation. Different products such as fruit, vegetables, meat, and aquatic products require different temperature controls during cold chain transportation. In the future, the different temperature control adjustments of the same refrigerated truck will be considered as the entry point for in-depth research.

2) This article establishes a complex vehicle energy consumption model, and quantifies the carbon emissions from fuel consumption accurately. However, with the emergence of the concept of green logistics, electric vehicles with clean energy will become the mainstream of goods distribution in the future. The cold chain logistics distribution of electric vehicles with charging stations can be used as the new focus of future research.

3) The improved ant colony algorithm is used to solve the multi-objective optimization problem, and multiple Pareto optimal solutions are thus obtained. In the future, we will try to use other heuristic algorithms to improve the convergence of the optimal solution.

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