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RESEARCH ARTICLE

Research on Urban Cold Chain Logistics Path Optimization Considering Multi-Center and Time-Varying Road Networks

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ABSTRACT This paper aims to address the time-dependent multi-depot vehicle routing problem with time windows (MDVRPTW) in urban cold chain logistics under a dynamic road network. The study considers the impact of carbon emissions and traffic congestion on urban cold chain logistics distribution activities. It proposes a cross-period road segment travel time calculation method, constructs a multi-objective optimization model that minimizes total costs encompassing comprehensive transportation costs, carbon emission costs, time penalty costs, cargo damage costs, and refrigeration costs. An adaptive large neighborhood search ant colony optimization algorithm (ALNS_ACO) is designed, which combines the exploration capability of ant colony optimization algorithm (ACO) with the local search capability of adaptive large neighborhood search algorithm (ALNS) to optimize and solve the model. Finally, the model is optimized and solved through simulation using six sets of C-type, R-type, and RC-type instances from the Solomon test database. The results indicate that: 1) The planned routes can reasonably avoid peak congestion periods in the morning and evening. Compared to the single-center scenario, the multi-center approach achieves superior solutions in terms of the total cost, carbon emissions, and total travel time in urban cold chain logistics distribution; 2) The exacerbation of traffic congestion leads to increased costs, and different optimization objectives have a significant impact on the model solutions; 3) Finally, through multidimensional comparisons of simulation performance with ACO and GA algorithms, the effectiveness of the proposed optimization algorithm is validated.

INDEX TERMS Multi-depot, time-varying speeds, urban cold chain logistics, multi-objective optimization, ALNS_ACO algorithm.

I. INTRODUCTION

As China accelerates its pace towards carbon neutrality, low-carbonization has become a common pursuit across society. The introduction of the important goals of ''peak carbon emissions by 2030 and carbon neutrality by 2060'' signifies the continuous and steady advancement of China's energy towards green and low-carbon transformation. This entails the continued promotion of optimization and upgrading of industrial structures, coordinated efforts towards carbon reduction, pollution control, expansion of green areas, and growth enhancement. The dual goals of carbon reduction and pollution control are increasingly becoming the green engine driving China's high-quality economic development. The achievement of carbon neutrality targets requires actions across various sectors. As an essential, strategic, and leading industry supporting the development of the national economy, the logistics industry must undergo low-carbon reforms. Cold chain logistics, as an important branch of the logistics sector, plays a crucial role in ensuring the quality and safety of fresh and perishable products in cities. Effectively planning cold chain logistics routes can not only reduce energy consumption and carbon emissions but also improve logistics efficiency and distribution quality, further meeting

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consumers' demands for product quality and safety. Therefore, with the increasing prominence of cold chain logistics in urban life, enhancing its service quality and safety level in logistics activities, considering the realistic distribution scenarios of urban cold chain logistics, and reducing uncertainties such as cargo damage and transportation risks have become particularly important. Thus, researching the effects of urban road network variability, multiple distribution centers, and other factors on urban cold chain logistics route planning is imperative for current development needs.

The optimization of distribution routes for urban cold chain logistics can be effectively summarized as a Vehicle Routing Problem (VRP), a topic that has garnered widespread attention in academia since its proposal in 1959 [1]. The optimization research on the Multi-depot Vehicle Routing Problem with Time Window (MDVRPTW) for urban cold chain logistics with time-varying road networks aims to establish mathematical models that better fit the distribution scenarios of urban cold chain logistics. It seeks efficient heuristic optimization algorithms or methods [2], [3], [4], [5], with the objectives of minimizing distance, time, or total cost to enhance the efficiency of logistics distribution. This process requires comprehensive consideration of factors such as temperature and humidity requirements in cold chain logistics, as well as the impacts of dynamic factors such as traffic congestion, road construction, and weather on route selection in time-varying road networks. Time window constraints can be classified as soft or hard time window requirements, and the consideration of multiple distribution centers accounts for the practical scenarios of urban cold chain distribution activities. The effective planning of urban cold chain logistics distribution routes has become an urgent issue in the development of cold chain logistics, aiming to adapt the planned routes to the dynamic changes in urban traffic environments and ensure the quality and safety of cold chain products. From the perspective of model optimization in cold chain logistics path optimization problems, the focus has gradually shifted towards multi-objective [6], multi-depot [7], multi-constraint, dynamic programming models, etc., with increasing difficulty and complexity, approaching practical applications more closely. This paper addresses the optimization problem of MDVRPTW for urban cold chain logistics under time-varying road networks by proposing a cross-period road segment time calculation method and designing a path planning algorithm based on an adaptive large neighborhood search ant colony algorithm. This aims to tackle the challenges of cold chain logistics transportation brought about by multiple distribution centers and the time-varying nature of road networks. By analyzing the various optimization objectives and constraints of urban cold chain logistics and integrating optimization theory and algorithm design, the paper endeavors to provide more reliable and efficient path planning solutions for urban cold chain logistics, promoting the development of urban cold chain logistics and safeguarding food safety and the sustainable development of supply chains.

II. LITERATURE REVIEW

A. MULTI-DEPOT VEHICLE ROUTING PROBLEM OPTIMIZATION

To improve the efficiency and service level of logistics distribution systems, many e-commerce companies typically establish multiple warehousing and distribution centers. Thus, optimizing logistics distribution paths for multi-depot operations holds significant practical value. The optimization of the multi-depot vehicle routing problem (MDVRP) has been the subject of several successful studies carried out in recent years by both domestic and international researchers. Gillett et al. [8] first proposed the multi-vehicle routing problem in 1976, which subsequently attracted widespread attention from scholars at home and abroad. Renaud et al. [9] proposed the MDVRP model with vehicle capacity and mileage constraints and solved it with a taboo search algorithm to minimize costs. Kuo and Wang [10] designed a three-stage variable neighborhood search algorithm to solve the MDVRP problem while considering loading costs. Alinaghian and Shokouhi [11] constructed an MDVRP model with both capacity and delivery distance constraints, and proposed a hybrid algorithm that combines adaptive large neighborhood search with variable neighborhood search. In order to maximize fuel consumption and driving distance, Li et al. [12] constructed a bi-objective MDVRP model with capacity and vehicle number limitations. They then combined an adaptive local search with a hybrid genetic algorithm. A genetic algorithm was utilized by Zhang et al. [13] to solve a multi-objective MDVRP model with capacity restrictions that sought to reduce carbon emissions, journey time, and overall expenditures. Zhou et al. [14] designed an improved ant colony method with a minimum total cost objective for the green vehicle routing problem by measuring the effect variables of vehicle fuel consumption and carbon emissions function and assigning clients to different depots using K-means clustering. To reduce carbon emission costs, driving time, and maximize profits, Li et al. [15] built a multi-objective MDVRP model with capacity and vehicle number limits. They also suggested an improved ant colony optimization algorithm. Jabir et al. [16] constructed an MDVRP model with capacity constraints, aiming to minimize carbon emission costs, variable vehicle usage costs (including fuel consumption costs), and fixed costs, and proposed a hybrid algorithm that combines ant colony algorithm with variable neighborhood search.

B. PATH OPTIMIZATION PROBLEM IN TIME-VARYING ROAD NETWORKS

The current optimization problem of cold chain logistics paths mainly revolves around static road networks. However, in actual distribution processes, road network data often exhibits time-varying characteristics. To attain path optimization, it is therefore required to take into account dynamic and time-varying road conditions during various times, such as morning and evening rush hours, student commuting times, and off-peak hours, in urban cold chain logistics distribution. Lan et al. [17] proposed that road conditions have an impact on logistics time and established a cold chain logistics model using a genetic algorithm combined with 2-opt local optimization. Fan et al. [18] designed an adaptive genetic large neighborhood search algorithm to solve the time-dependent mixed time window VRP problem. Additionally, Fan et al. [19] comprehensively considered factors such as multiple types of vehicles and dynamic customer demands to minimize total costs and constructed a dynamic VRP model under time-varying road network conditions. Zhou et al. [20] considered carbon emissions and established a time-dependent green VRP objective optimization model, which was solved using an improved ant colony algorithm. Liu et al. [21] designed a road segment travel time calculation method based on time intervals and introduced a carbon emission calculation function integrating multiple factors, including a traffic congestion index. They created a mathematical model for the time-varying vehicle routing problem in low-carbon logistics with the goal of minimizing carbon emissions. Meneghetti and Ceschia [22] considered the variation in vehicle speed caused by traffic congestion and reduced load capacity during the delivery process. They established a corresponding mathematical model to minimize fuel costs.

C. PATH OPTIMIZATION FOR COLD CHAIN LOGISTICS

Due to the need for temperature control in cold chain logistics to maintain product quality, more fuel is consumed for insulation during transportation, leading to increased carbon emissions. Therefore, many scholars consider the impact of carbon emissions on path optimization for cold chain logistics. Jabir et al. [23] were the first to incorporate carbon dioxide emissions into the vehicle routing problem model and successfully resolved the contradiction between cost and carbon reduction goals, thereby suppressing the rise in economic costs. A cost-minimizing green and low-carbon optimization model for cold chain logistics distribution channels was created by Wang et al. [24], who also suggested using a cyclic evolutionary genetic algorithm (CEGA) to solve the problem. Chen et al. [25] focused on vaccine distribution in cold chain logistics and proposed a vehicle routing optimization model with the objective of minimizing distribution costs. They combined the balanced optimizer algorithm with simulated annealing to improve the algorithm's ability for global search and local optimization. In order to minimize production costs, Wang et al. [26] established an optimal distribution route model for fresh agricultural products that takes carbon emissions into consideration and accounts for variations in energy consumption during transportation and unloading caused by opening cold storage doors. Chen et al. [27] presented a multi-vendor vehicle routing problem with time windows (MCVRPTW) in the context of fresh food e-commerce. They developed a total cost model that includes carbon emission costs. Other researchers have considered the personalized demand characteristics of fresh cold chain logistics in the objective function and proposed optimizing customer satisfaction as the goal. A multi-objective model incorporating cold chain distribution costs, carbon emissions, and customer satisfaction was examined by Zhao et al. [6]. Ghannadpour et al. [28] used a multi-objective dynamic truck routing problem with fuzzy travel durations and customer satisfaction to investigate the effects of carbon taxes on carbon emissions in cold chain distribution systems. A cold chain distribution planning model that considers the deterioration in food quality with time was developed by Hsiao et al. [29]. Their goal is to satisfy consumer demands for a variety of goods while keeping distribution costs to a minimum by offering companies distribution agreements.

D. OPTIMIZATION ALGORITHMS

The optimization model for cold chain logistics path is a complex and difficult problem, belonging to the NP-hard problem category. Therefore, improved heuristic algorithms are commonly used to solve it. In order to prevent the influence of irrational parameter selection on algorithm performance, Zhang et al. [30] integrated RNA computation with the ant colony optimization algorithm and incorporated the notion of low-carbon economics into the optimization model for cold chain logistics path. In order to minimize carbon emissions and overall distribution costs, Ning et al. [31] developed a mathematical model. They also suggested an enhanced quantum ant colony method based on adaptive rotation angle, which was used in simulation instances. A multi-objective simulated annealing-ant colony optimization (MOSA-ACO) technique was created by Wang et al. [32] to solve the periodic vehicle routing problem with time windows and service choices. A multi-objective optimization model based on cost, carbon emissions, and customer satisfaction was presented by Zhao et al. [6] for cold chain logistics distribution. To find more Pareto optimal solutions, they created an enhanced version of the ant colony algorithm, ACOMO, featuring a multi-objective heuristic function. In addition, Ren et al. [33] studied the optimization model for minimizing total cost in cold chain logistics distribution paths using an ant colony algorithm that incorporates taboo search and dynamic probability selection. Chen et al. [34] considered cost, freshness, and environmental pollution in fixing the cold chain logistics vehicle routing issue. They developed an LCFD-VRP solution algorithm based on IACA and TS and constructed an LCFD-VRP model based on carbon emissions. Galarcio-Noguera et al. [35] aimed to minimize freshness loss by increasing perishable products and improving customer satisfaction during delivery, and proposed a hybrid PSO-TS-PSO algorithm to solve the model.

Analyzing the current research status of urban cold chain logistics by domestic and international scholars, it can be observed that the research on cold chain logistics is still a relatively new field. To effectively increase the application study on the comprehensive distribution efficiency of cold chain logistics, more investigation into its research material is required. Achieving low-carbon development in urban cold chain logistics has gained significant importance with the advent of the low-carbon age. The current cold chain logistics path optimization mostly considers costs related to fixed expenses, transportation, cargo damage, refrigeration, carbon emissions, etc., as optimization objectives. However, it fails to consider the variation in vehicle speed over time due to road congestion during urban distribution processes. Furthermore, the current optimization of cold chain logistics paths mostly focuses on the optimization of single distribution centers, while the optimization of multiple distribution centers is given less attention. At the same time, with the rise of swarm intelligence algorithms, the application of optimized intelligent algorithms in the process of optimizing urban cold chain logistics paths has not been fully explored, which could lead to comprehensive improvement in the efficiency of cold chain logistics enterprises.

As previously indicated, the case of many distribution centers and the characteristics of time-varying road network speeds were not taken into account in prior research on the optimization model of urban cold chain logistics paths. This paper presents a thorough optimization model for cold chain logistics called MDVRPTW (Multiple Depot Vehicle Routing Problem with Time Windows), which accounts for the costs of comprehensive transportation, carbon emissions, time penalties, cargo damage, and refrigeration. The model was developed in response to the limitations of earlier research. Additionally, a cross-time period method for calculating segment travel time is proposed to address the changing speeds of urban road networks. To solve the optimization model, an improved self-adaptive large neighborhood search ant colony algorithm is designed by combining the exploration ability of ant colony optimization algorithm and the local search ability of the adaptive large neighborhood search algorithm.

III. MODEL ESTABLISHMENT

A. PROBLEM DESCRIPTION

A number of cold chain logistics distribution centers are established based on the real growth conditions in China, taking into account the necessity for low-carbon transformation in urban cold chain logistics. There is a set amount of vehicles at each distribution center. After leaving the distribution center to satisfy every customer's request, the distribution vehicles return to the original location. The distribution centers' locations and the cars' capabilities are known. The customer quantities, locations, demand volumes, time windows, and service times are known as well. The vehicle speeds during peak congestion periods and normal driving periods are considered. The objective is to optimize the vehicle routes for urban cold chain logistics, minimizing comprehensive costs while satisfying constraints such as vehicle capacity, vehicle load, time-varying road network, customer time windows, and meeting the demands of all customers. The following presumptions are made in order to aid in analysis and research:

(1) The path optimization problem covers multiple distribution centers, each of which can provide cold chain services to multiple customers.

(2) The load and capacity limitations for every vehicle are similar and known, as are the fixed numbers of vehicles that can be dispatched from each distribution center.

(3) Cars travel at both regular and congested speeds, and they instantly return to the distribution center after the delivery is finished.

(4) Customer demand points' demand volume, location, time window, and service time are all known. Every demand point is met once, and the demand volume for a single order cannot be greater than the delivery vehicle's maximum carrying capacity.

(5) All roads are interconnected and are bidirectional drivable roads.

(6) There is a soft time window for customer service. Penalty costs apply if the vehicle arrives at the client location before the earliest permitted service time or after the latest permissible service time.

B. PARAMETER SYMBOL AND VARIABLE DEFINITION

In this section, we provide the definitions of variables, sets, and decision variables used in our study:

Set:

C : Represents the set of customer locations, $C = \{1, 2, 3 \ldots\ldots n\}$, where n is the total number of customers.

D : Represents the set of distribution centers, $D = \{n+1, n+2 \ldots\ldots n+m\}$, where C is the total number of distribution centers.

N : Represents the set of node indices, $N = \{1, 2, 3 \ldots\ldots n+m\}$, namely $A = C \cup D$;

K : Represents the set of vehicles available at each distribution center.

T : Represents the set of time intervals within a day.

Parameter:

L : Represents the maximum travel distance allowed for each vehicle.

Q : Represents the maximum capacity or load limit of each vehicle.

q_i : Represents the demand quantity of customer location i.

$[ET_i, LT_i]$: Represents the time window requirements for customer location i.

$[EET_i, LLT_i]$: Represents the acceptable time window constraints for customer location i.

d_{ij} : Represents the distance from customer location i to customer location j.

v_s : Represents the driving speed when the road is uncongested.

v_j : Represents the driving speed during congested periods on the road segment.

v_{ijt} : Represents the driving speed on the road segment (i, j) within a time interval t.

T_{ijtk} : Represents the driving time of a vehicle k on the road segment (i, j) within a time interval t.

T_{mk} : Represents the departure time of a vehicle k from the distribution center m.

T_{ik} : Represents the arrival time of a vehicle k at the customer location i.

TL_{ik} : Represents the departure time of a vehicle k from the customer location i.

TS_{ik} : Represents the service time of a vehicle k at the customer location i.

Decision variables:

x_{ij}^{mk} : Represents the selected driving route for a vehicle k departing from the distribution center $m_{\text{andmovefrom}}$ the node i to the node j.

y_i^{mk} : Represents whether a vehicle k departing from the distribution center m_{and} serves customer location i.

z_{ijt}^{mk} : Represents the travel from node i to node j by a vehicle k departing from the distribution center m within a specific time interval t.

C. OBJECTIVE FUNCTION

This paper builds an optimal mathematical model for the city cold chain logistics MDVRPTW problem under time-varying road networks based on the model description and parameter settings given above. The model's goal is to reduce the whole cost of the city's cold chain logistics distribution channels. This includes the costs associated with carbon emissions, comprehensive transportation, fines for missing deadlines, damage to perishable goods, and refrigeration.

1) COMPREHENSIVE TRANSPORTATION COSTS

Three components make up comprehensive transportation expenses: fuel consumption costs, variable costs, and fixed costs. Fixed costs, such as vehicle depreciation and startup fees, are directly correlated with the total number of cars. Variable costs mainly include driver labor costs. Fuel consumption costs represent the expenses incurred during vehicle operation due to fuel consumption. Based on the above analysis, the formula for calculating the comprehensive transportation costs of cold chain logistics can be expressed as:

$$C_1 = f_0 \sum_{i\in N}\sum_{j\in N}\sum_{m\in D}\sum_{k\in K} x_{ij}^{mk} + f_k \sum_{i\in N}\sum_{j\in N}\sum_{m\in D}\sum_{k\in K} x_{ij}^{mk} d_{ij} + \phi \sum_{i\in N}\sum_{j\in N}\sum_{m\in D}\sum_{k\in K}\sum_{t\in T} FC_{ijtk} Z_{ijt}^{mk} d_{ij} \tag{1}$$

where:

f_0 : Represents the fixed cost per vehicle (including vehicle rental fees, vehicle insurance fees, vehicle maintenance fees, etc.).

f_k : Represents the variable cost per vehicle (including driver labor costs and other variable costs).

ϕ : Represents the cost per unit of fuel consumption.

FC_{ijtk} : Represents the amount of fuel consumed by vehicle k on the road segment (i, j) within a specific time interval t.

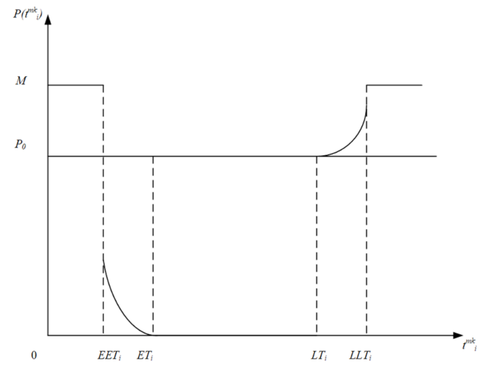

FIGURE 1. Improved customer time window penalty cost function.

2) CARBON EMISSION COSTS

This study considers carbon emissions originating from two main sources. Firstly, carbon emissions arise from vehicle transportation processes, primarily stemming from fuel and refrigerant consumption during transportation. Secondly, carbon emissions occur during unloading processes, primarily resulting from refrigerant consumption in this process. The carbon emission costs associated with the distribution process of cold chain logistics can be represented as follows, based on the previously indicated analysis:

$$C_2 = \sum_{i\in N}\sum_{j\in N}\sum_{m\in D}\sum_{k\in K}\sum_{t\in T} EC_{ijtk} C_e Z_{ijt}^{mk} + \sum_{i\in N}\sum_{k\in K} EC'_{ik} C_e TS_{ik} \tag{2}$$

C_e : Represents the cost per unit of carbon emissions.

EC_{ijtk} : Represents the carbon emissions of a vehicle k on the road segment (i, j) within a specific time interval t.

EC'_{ik} : Represents the carbon emissions of a vehicle k during its service at customer points i.

3) TIME PENALTY COSTS

Based on the level of acceptability by customers for delivery vehicles violating time window constraints, time window constraints in logistics path optimization problems are generally classified into three types: hard time windows, soft time windows, and hybrid time windows. Time penalty costs represent the additional costs incurred by vehicles due to their inability to meet customer time window requirements. In accordance with the specific characteristics of customer demands in actual cold chain logistics distribution processes, this paper designs a piecewise function that varies with time for penalty costs, as shown in the figure 1:

As can be seen from the above, under the time-varying road network, the penalty cost calculation method for urban cold chain logistics distribution that violates the time window constraint is as follows:

$$C_3(i)=\begin{cases} M, & 0<t_i^{mk}\le EET_i \\ P_t(t_i^{mk}-ET_i)^2, & EET_i<t_i^{mk}\le ET_i \\ 0, & ET_i<t_i^{mk}\le LT_i \\ P_0+P_t(t_i^{mk}-LT_i)^2, & LT_i<t_i^{mk}\le LLT_i \\ M, & t_i^{mk}>LLT_i \end{cases} \tag{3}$$

t_i^{mk} : Represents the time it takes for a vehicle k to reach a customer point i from the distribution center m.

P_t : Represents the unit time penalty cost for arriving early or late.

P_0 : Represents the fixed penalty cost incurred due to the opportunity cost loss resulting from late delivery within an acceptable time window.

$$C_3=P_t\sum_{i\in N}\sum_{k\in K}\sum_{m\in D}\max\left\{(t_i^{mk}-ET_i)^2,0\right\} + \sum_{i\in N}\sum_{k\in K}\sum_{m\in D}\left[P_0+P_t\max\left\{(t_i^{mk}-LT_i)^2,0\right\}\right] \tag{4}$$

4) LOSS COST

Perishable goods are vulnerable to several elements during the cold chain transit process, including temperature, humidity, and oxygen concentration in the storage environment. These factors might lead to specific losses over time. Considering the distribution process of perishable products, the loss cost primarily originates from two aspects. Firstly, it is caused by the gradual loss of goods during transportation due to the passage of time and cumulative handling of goods. Secondly, it arises from the loss of goods during unloading due to factors such as surrounding oxygen content, air circulation, and temperature changes. The loss cost in the cold chain logistics distribution process can be shown as follows based on the analysis above:

$$C_4=\sum_{i\in N}\sum_{j\in N}\sum_{m\in D}\sum_{k\in K}Pq_ix_{ij}^{mk}[1-e^{-\xi_1(T_{ik}-T_{mk})}] + \sum_{i\in N}\sum_{k\in K}\sum_{m\in D}PQ_iy_i^{mk}(1-e^{-\xi_2TS_{ik}}) \tag{5}$$

P : Represents the unit price of fresh products.

Q_i : Represents the remaining quantity of fresh products after serving customers point i by a vehicle k.

ξ_1 : Represents the freshness decay coefficient of fresh products during vehicle transportation;

ξ_2 : Represents the freshness decay coefficient of fresh products during unloading process.

5) REFRIGERATION COST

In contrast to the general VRP problem, the cold chain logistics path optimization problem must account for the cost of refrigeration incurred in order to preserve fresh goods. This cost is typically represented by the amount of refrigerant used to keep the vehicle compartment at a constant temperature. The cost of refrigerant generated by opening refrigeration equipment during shipping and the cost of refrigerant generated by opening refrigeration equipment during the unloading process comprise the majority of the refrigeration cost in the cold chain logistics distribution process. The precise formula for refrigeration cost in the cold chain logistics distribution process can be stated as follows, based on the analysis presented above:

$$C_5=\sum_{i\in N}\sum_{j\in N}\sum_{t\in T}\sum_{k\in K}\sum_{m\in D}P_1x_{ij}^{mk}T_{ijtk} + \sum_{i\in N}\sum_{k\in K}\sum_{m\in D}P_2TS_{ik}y_i^{mk} \tag{6}$$

P_1 : Represents the unit refrigeration cost during transportation;

P_2 : Represents the unit refrigeration cost during unloading process.

D. CALCULATION OF TIME SPAN FOR ROAD SEGMENTS

Vehicle travel speed is connected with both the departure time and the level of traffic congestion in the context of urban cold chain logistics distribution. Refrigerated vehicles adopt different travel speeds during different time periods within a day. Therefore, for road segments (i,j), the measurement of travel time across different time spans becomes a research focus in this context. The Ichoua model (2003) [36] considers that within a sufficiently short time span, the vehicle travel speed can be regarded as constant. The urban road network is split into peak and off-peak times based on this. A method for calculating vehicle journey time is presented in this study. The following are the precise steps:

1)Assuming that the vehicle remains in motion throughout, except during customer service at delivery points where it remains stationary, and no vehicle stops or waits occur during other operational stages. Let T_R denote a fixed time interval for speed segmentation, $T_R=\{T_0,T_1,T_2,T_3,T_4\ldots\ldots\}$ .t_{ijk}^R represents the travel time of the vehicle k on the road segment (i,j) within the time interval T_R, v_{ijk}^R represents the travel speed of the vehicle k on the road segment (i,j) within the time interval T_R, d_{ij} represents the distance of the road segment (i,j), and s_{ijk}^R represents the traveled distance of the vehicle k on the road segment (i,j) within the time interval T_R.

2)The starting time for the vehicle to enter i is denoted as t_i^{mk}, t_{ij}^k representing the total time from the customer point i to point j. Assuming that within a day, only peak and off-peak periods are distinguished, and peak periods occur only in the early morning and evening stages. Let v_j denote the travel speed during congested periods and v_s denote the travel speed during normal periods. If the vehicle arrives i during a congested period, then $t_{ij}^k=(T_{R+1}-t_i^{mk})+[d_{ij}-(T_{R+1}-t_i^{mk})v_j]/v_s$.

3)Assuming that the time period T_R vehicle enters i during a normal period, the subsequent delivery period can be divided into normal and congested periods. If only normal periods exist, then $t_{ij}^k=d_{ij}/v_s$. If there is a congested period, it can be further divided into congestion during intermediate deliveries and congestion at the final node. If congestion occurs during intermediate deliveries, then $t_{ij}^k = T_R + (d_{ij} - v_j T_R)/v_s$. If congestion occurs at the final node, then $t_{ij}^k = [\frac{d_{ij}}{v_s}] + (d_{ij} - v_s[\frac{d_{ij}}{v_s}])/v_j$. (Here, [ ] denotes rounding.)

E. MATHEMATICAL MODEL

In conclusion, this paper is designed to minimize the total cost, which includes comprehensive transportation costs, carbon emission costs, time penalty costs, cargo damage costs, and refrigeration costs, as the optimization objective. The following time-dependent urban cold chain logistics MDVRPTW model is constructed:

$$MINZ = C_1 + C_2 + C_3 + C_4 + C_5 \tag{7}$$

where:

$$\sum_{m\in D}\sum_{k\in K} y_i^{mk} = 1 \tag{8}$$

$$\sum_{i\in N} x_{ij}^{mk} - \sum_{j\in N} x_{ij}^{mk} = 0 \tag{9}$$

$$\sum_{j\in N} x_{ij}^{mk} \le 1 \tag{10}$$

$$T_{ik} + TS_{ik} \le TL_{ik} \tag{11}$$

$$\sum_{k\in K}\sum_{m\in D} x_{ij}^{mk} \le K \tag{12}$$

$$\sum_{i\in N} q_i y_i^{mk} \le Q \tag{13}$$

$$\sum_{i\in N}\sum_{j\in N} d_{ij} x_{ij}^{mk} \le L \tag{14}$$

$$x_{ij}^{mk} \in \{0, 1\},\ y_i^{mk} \in \{0, 1\},\ z_{ijt}^{mk} \in \{0, 1\} \tag{15}$$

where, equation (8) indicates that each customer point must be serviced exactly once; equation (9) represents the fact that vehicles arrive and depart from the same node; equation (10) signifies that each vehicle at any distribution center is used exactly once; equation (11) denotes the time window constraints for customer points; equation (12) stipulates that the number of vehicles used by a single distribution center must be less than the total number of vehicles; equation (13) constrains the vehicle capacity; equation (14) sets the distance traveled by vehicles; and equation (15) outlines the constraints on the decision variable values.

IV. ALGORITHM DESIGN

The aforementioned MDVRPTW problem is a typical NP-hard problem. When the scale of nodes is small, an exact solution can be obtained using mathematical programming methods. However, as the scale of nodes increases, the solution space grows exponentially, making it infeasible to achieve precise solutions using mathematical programming methods. Therefore, heuristic methods or metaheuristic methods are commonly employed for solving such problems. Adaptive Large Neighborhood Search (ALNS), Tabu Search, Genetic Algorithm, Particle Swarm Optimization, and Ant Colony Optimization are the most popular algorithms among academics, according to a statistical analysis of metaheuristic algorithms for solving VRP problems done by Elshaer and Awad [37]. The Ant Colony Optimization algorithm, characterized by its systematic, self-organizing, positive feedback, and distributed computing features, possesses excellent global search capabilities and is easily integrated with other algorithms, making it widely applicable in combinatorial optimization, communication network path selection, automatic control, and systems engineering (2022) [38]. On the other hand, the ALNS algorithm demonstrates precise local optimization capabilities, with a high probability of exploring better solutions, but this also increases the risk of the algorithm getting trapped in local optima (2021) [39]. Thus, this work presents an algorithm for Adaptive Large Neighborhood Search Ant Colony Optimization (ALNS_ACO) and discusses the features of the urban cold chain logistics MDVRPTW problem. This approach improves the program's capacity for global optimization by fusing the exploration powers of Ant Colony Optimization (ACO) with the local search powers of Adaptive Large Neighborhood Search (ALNS). Initially, the algorithm constructs initial solutions using the Ant Colony Optimization algorithm, then disrupts and repairs parts of existing solutions, changing the majority of solutions at each iteration (2019) [40], and ultimately obtains the optimal solution based on an adaptive mechanism.

A. CONSTRUCTION OF INITIAL SOLUTIONS

The ALNS algorithm's following optimization phase is heavily influenced by the quality of the initial solution, and a better initial solution will raise the probability of obtaining satisfactory answers (2023) [41]. Considering the characteristics of the MDVRPTW problem, this study adopts the Ant Colony Algorithm to obtain improved initial solutions (2023) [42]. Initially, all ants are allocated to various distribution centers, with each ant initializing a route. BThe ants employ a roulette wheel selection method based on the transition probability formula to choose which customer nodes to visit. The customer nodes that are selected are added to the current route one after the other until the ant is no longer eligible to visit customers. Subsequently, the ant is reset to the initial distribution center and recommences its visiting process. This process is repeated until the ant has visited all customers.

1) STATE TRANSITION PROBABILITY SETTING

$$P_{ij}^m(t) = \begin{cases} \dfrac{\tau_{ij}(t)^\alpha \eta_{ij}^\beta}{\sum_{j\in unvisit_m} \tau_{ij}(t)^\alpha \eta_{ij}^\beta} & , if\ j \in unvisit_m \\ 0 \quad if\ j \in visited_m \end{cases} \tag{16}$$

where, $P_{ij}^m(t)$ represents the probability that ant m transfers from customer point i to customer point j at time t. $unvisit_m$ represents the set of possible destination points (customers) for ant k(vehicle) at time t. In the algorithm, each ant (vehicle) is assigned a taboo list $tabu_m(m = 1, 2\ldots\ldots)$ to record the set of visited destination points (customers). $unvisit_m = \{1, 2, 3\ldots\ldots n\} - tabu_m$ represents the set of cities that ant m is allowed to choose for the next step. When an ant (vehicle) completes a tour (route), its taboo list is cleared. When all cities are included in the taboo list $tabu_m$, ant m completes a full traversal, and the path followed by ant m corresponds to a workable fix for the issue.

α represents the important factor of pheromone concentration (carbon emissions) during the ants' (vehicles') movement, while β represents the relative importance of the expected heuristic factor (road conditions) in the ants' (vehicles') path selection. Here, the higher the concentration and importance, the larger the corresponding parameter values.

2) PHEROMONE UPDATE STRATEGY

$$\tau_{ij}^{new} = \tau_{ij}^{old}(1-\rho) + \sum_{m=1}^{M} \Delta\tau_{ij}^{m} \tag{17}$$

$$\Delta\tau_{ij}^{m} = \begin{cases} f/Dis\tan ce_m, & if\ ant\ m\ passes\ by\ ij\ at\ timet \\ & and\ t+1 \\ 0, & otherwise \end{cases} \tag{18}$$

where, τ_{ij}^{new} represents the pheromone update formula, where τ_{ij}^{old} is the pheromone concentration before the update, and τ_{ij}^{new} is the pheromone concentration after the update. $\rho(0 < \rho < 1)$ represents the coefficient of pheromone evaporation on the path, while $1-\rho$ represents the persistence coefficient of pheromone. $\Delta\tau_{ij}^{m}$ represents the increment of pheromone on arc (i, j) for ant m. f is a constant that represents the amount of pheromone secreted by ants in each trip. $Dis\tan ce_m$ is the total distance traveled by ant m.

3) SPECIFIC IMPLEMENTATION STEPS OF ANT COLONY ALGORITHM

Step 1: Setting up a parameter. Enter the required test data, such as vehicle capacity, maximum trip distance, client demand, service time windows, vehicle coordinates, fixed and variable vehicle costs, unit carbon emissions cost, and vehicle speed in a time-varying road network. Here, $Iter_{ant}$ represents the current iteration count, $\max Iter_{ant}$ represents the maximum number of iterations, $\min Len$ represents the shortest distance traveled by all ants, $antNum$ represents the number of ants, and $initialRoute$ represents the initial best travel route.

Step 2: Determine $Iter_{ant}$ if the condition $Iter_{ant} \leq \max Iter_{ant}$ is satisfied. If satisfied, assign a value to ant m such that $m = 1$, and check if m satisfies the condition $m \leq antNum$. If satisfied, proceed to the next step; if not satisfied, proceed to Step 5. (Here, $tabu_m$ is the taboo list of ant m. $tabu_m = 0$) Otherwise, proceed to Step 7.

Step 3: Place ant m at different distribution centers and allocate the maximum allowable capacity and travel distance for it. Using the state transition probability calculation, choose customer nodes that meet the constraint constraints and incorporate them into the existing solution. Then, remove that node from the set $unvisit_m$ of ant m and place it into the set $tabu_m$ of ant m. Repeat the above operations until ant m no longer satisfies the conditions for visiting any remaining customer nodes.

Step 4: Relocate ant m to the initial distribution center and reset its maximum capacity. Determine $unvisit_m$ if it is an empty set. If $unvisit_m \neq 0$, return to Step 3; otherwise, save the total distance $antLen_m$ traveled by ant m into a set $iterLen_{iter}$, and save the travel route $antSol_m$ of ant m into a set $iterSol_{iter}$, then proceed to Step 5.

Step 5: Set $m = m + 1$, clear the taboo list $tabu_m$, reset the $unvisit_m$ settings, and continue with Step 3. Analyze all the traveled distances in the set $iterLen_{iter}$ to derive the best traveled distance $bestLen_{iter}$ and the best travel route $bestRoute_{iter}$. If $bestLen_{iter} = \min Len$, set $\min Len = bestLen_{iter}$ and update the global optimal route to $initialRoute = bestRoute_{iter}$. Conversely, if $bestLen_{iter} > \min Len$, set $bestLen_{iter} = \min Len$ and $bestRoute_{iter} = initialRoute$. Then, before proceeding to the next step, update the route according to the pheromone updating formula.

Step 6: Set $Iter_{ant} = Iter_{ant} + 1$ and return to Step 2.

Step 7: Following the greedy principle, based on the time-varying conditions of vehicles and multiple vehicle constraint conditions, insert the uninserted customer demand points into the optimal initial path $initialRoute$ until all customer points and distribution centers are included in the feasible route. Through this process, a tailored initial solution $initialSol$ is designed for ALNS.

B. DESIGN OF ADAPTIVE LARGE NEIGHBORHOOD SEARCH OPERATORS

The optimization objective of this paper is mainly closely related to travel time, which in turn is related to vehicle speed and distance. In addition, the problem also includes customer time window requirements. Therefore, the large neighborhood operators proposed in this paper are mainly designed around these characteristics. In addition, relevance operators, random operators, greedy operators, and regret criterion operators are all efficient search operators in general adaptive large neighborhood search algorithms and have also been considered. Furthermore, when performing repair operations, it is necessary to ensure that the repaired solution is feasible, that is, it satisfies the basic constraints of the vehicle. Based on this, this paper uses 5 destruction operators and 3 repair operators, and designs an adaptive weight updating formula based on historical performance to adjust the operator weights.

(a) Removal Operators

Removal operations often disrupt the structure of the current solution, which is beneficial for escaping local optima. In existing VRP-related literature, demand removal primarily follows the following principles: (1) randomly selecting parts to remove to ensure retrieval diversity; (2) removing the worst-performing parts; (3) choosing comparable units to be eliminated, like points with comparable numbers, time periods, and spatial placements. The following five destruction operators are used in this study based on these three concepts; each removal operator doesn't stop working until every customer has been gone.

(1) Random removal: Randomly select r customer nodes and delete them directly from the current solution, while updating the paths.

(2) Worst removal: This operator aims to remove points that have the greatest impact on the cost of the entire path, intuitively reducing the total cost. Calculate the difference in the objective function before and after removing each customer point, and select the customer point with the largest difference for removal, while updating the paths. Repeat the removal operation until r customers are removed. This strategy was proposed by Hemmelmayr et al. [43].

(3) Association Removal. This method was initially proposed by Shaw [44] in 1998, which involves splitting two highly correlated customers to generate new solutions and explore a larger solution space (2023) [45]. First, a customer node (i) is assigned to set $C_{unvisit}$ after being arbitrarily chosen for removal. The similarity between each customer point in the current solution and the deleted customer point is then determined using a similarity function. To be removed and added to set $C_{unvisit}$ is the customer node that has the most similarity in the current solution. Subsequently, a customer node is randomly chosen from the set $C_{unvisit}$, and the process of similarity calculation is repeated to remove the node with the highest similarity. This step is repeated until r customer nodes have been removed. The association between customer i and customer j is represented by $R(i, j)$, and the expression is as follows:

$$\begin{aligned} R(i,j) &= \psi_1 d_{ij} + \psi_2(\left|T_{ik} - T_{jk}\right| + \left|TL_{ik} - TL_{jk}\right|) + \psi_3(\left|q_i - q_j\right|) \\ &\quad + \psi_4 x_{ij}^{mk} \end{aligned} \tag{19}$$

Here, $\psi_1, \psi_2, \psi_3, \psi_4$ represent the weight coefficients for distance, time window, demand, and path, respectively. A smaller value of $R(i, j)$ indicates a higher association between two nodes, and it is desired to minimize the overall association among all removed nodes. If customer i and j are on the same path, it is represented x_{ij}^{mk} as 1; otherwise, it is represented as 0. The next customer to be deleted is chosen based on the ascending order of association values, and this process is repeated until r customers have been eliminated from the set.

(4) Farthest Time Window Removal. This essay addresses time penalty costs, which necessitate that the car arrive as close to the customer's requested time window as feasible. The customer node that arrived at the time that was farthest from the customer's required time window gets eliminated. If the vehicle's arrival time satisfies the time window of customer i, $\Delta t_i = 0$, otherwise:

$$\Delta t_i = \min\left\{\lambda \left|t_i^{mk} - T_{ik}\right|, \left|t_i^{mk} - TL_{ik}\right|\right\} \tag{20}$$

Here, λ represents the multiplicative relationship between the penalty for arriving early and the penalty for arriving late. Based on $i = \arg\max\{\Delta t_i\}$, r customers are selected for removal.

(5) Maximum Velocity Difference Removal. This method was proposed by Franceschetti et al. [46] in 2017. The basic idea is to remove the customer with the maximum difference in velocities before and after the vehicle's arrival at the customer's location. This study considers the time-varying factors in urban cold chain distribution. If the difference in velocities before and after the customer's location is Δv_j, Nr customers are selected for removal based on $j = \arg\max\left\{\Delta v_j\right\}$.

(b) Repair Operators

The clients who were removed are gradually reinserted by the repair operators into the existing partial solution. This study designs three repair operators to search for feasible solutions: random insertion, best greedy insertion, and regret criterion insertion.

(1) Random insertion

A random customer is chosen from the set $C_{unvisit}$ of deleted customers, and all permitted insertion locations are established in accordance with vehicle capacity and journey distance limitations. The customer is then inserted into a randomly chosen position. Until all r clients have been reintegrated into the solution, this process is repeated.

(2) Best Greedy Insertion

The best greedy insertion method selects the position with the minimum impact on the objective function value for insertion. A random point is chosen, and the increase in the total cost of the path after inserting the point at each position is evaluated. The position corresponding to the lowest increase value is selected for insertion. Until every removed customer has been reintegrated into the solution, this process is repeated.

(3) Regret Criterion Insertion

First, determine every location where the r removed consumers may be inserted, taking into account the fundamental limitations of the cars. Subsequently, determine the regret value of every eliminated point and arrange the points in order of greatest regret value being inserted into the position with the least amount of overall cost increase. The total of the discrepancy in distance increments between the top i ideal insertion positions and the best position for every customer is used to compute the regret value. Continue doing this until all r clients have been added back into the system.

(c) Adaptive Weight Adjustment

The adaptive adjustment of operator weights based on past performance is the fundamental idea behind the ALNS algorithm. In this study, the initial operator weight is set to 10 and the initial operator score is set to 0. All operators are initially allocated the same weight and score. To increase the diversity of operator selection, the roulette wheel rule is used to guide the selection of removal and insertion operators in each search phase throughout the algorithm's iteration. A stepwise scoring system is then utilized to score the various performances of operators, with higher scores denoting greater performance, based on the quality of the solution(*updateSol*) updated after each iteration. The operator weights change when the number of iterations crosses a predetermined threshold.

In this study, the score of operator i in stage j is defined as ε_{ij}, and a four-level scoring system has been established. The update rule for ε_{ij} is as follows:

$$\varepsilon_{ij} = \varepsilon_{ij(j-1)} + \begin{cases} 30, & \textit{if bestSol} \leq \textit{updateSol} \\ 10, & \textit{if currentSol} < \textit{updateSol} < \textit{bestSol} \\ 6, & \textit{if currentSol} < \textit{updateSol}, \textit{ and} \\ & \textit{updateSol is accepted} \\ 0, & \textit{otherwise} \end{cases} \tag{21}$$

According to the scoring system, the corresponding operators for destruction and repair receive points based on how well the updated solution compares to the current and global best solutions. More specifically, the participating operator will gain 30 extra points if the modified neighborhood solution outperforms the global best solution. The operator gets 10 points if the updated neighborhood solution still outperforms the current solution but falls short of the global best solution. The operator gets six points if the revised neighborhood solution is still approved even though it is inferior to the current global best answer. Lastly, no point is awarded to the relevant destruction and repair operators if the updated solution does not improve upon the current solution nor is accepted.

During the algorithm iteration process, the probability of an operator being selected after the $j-th$ iteration is updated using the following operator weight update formula: $\omega_{i(j+1)} = (1-\theta)\omega_{ij} + \theta\pi_{ij}/\varepsilon_{ij}$, where $\omega_{i(j+1)}$ represents the weight value of operator i in stage $j+1$, assuming an initial operator weight of 10, θ is the weight adjustment coefficient, and π_{ij} denotes the number of times operator i is selected during during the N_b iterations in stage j. If operator i is not used during the current stage j, its weight remains unchanged in subsequent stages. After the weight update, both ε_{ij} and π_{ij} are reset to zero.

C. DESIGN OF ALNS_ACO ALGORITHM

Adulyasak et al. developed the simulated annealing approach, which was utilized as the acceptance rule for solutions in this work [47]. If updated solution *updateSol* performs better than current solution *currentSol* during the iteration process, the new solution is retained. If not, there's a chance that the revised solution will remain in place. The initial temperature is set to $TEMP_{min} = 1000$ and follows the cooling schedule $TEMP_n = TEMP_{n-1} \times H$, where the cooling rate is set to $H = 0.995$. If the maximum iteration limit is reached, the entire search process ends.

V. SIMULATION AND RESULTS ANALYSIS

A. EXPERIMENTAL SETUP

In light of the characteristics of the MDVRPTW problem, this study uses test cases from the Solomon benchmark dataset(1987) [48] as the experimental dataset. The dataset consists of cluster distribution test set (C-type), random distribution test set (R-type), and random cluster distribution test set (RC-type). The first coordinate of each test case represents the depot, and three additional locations at coordinates (10, 30), (50, 75), and (70, 20) are added as depots, forming the simulation instances for this study. The new instances consist of four depots and 100 customer points. The earliest departure time for refrigerated vehicles from the four depots is set at 6:00 (defined as time zero), and the latest arrival time back at the depots is set at 22:00, resulting in a total service time of 16 hours. Based on the traffic patterns in urban areas, the time periods from 7:00 to 9:00 and 18:00 to 20:00 are designated as congestion periods (morning and evening rush hours), during which vehicles travel at congested speeds v_j. During non-congestion periods, vehicles travel at normal speeds v_s. The speeds v_s and v_j are set to 40 km/h and 20 km/h, respectively. For ease of analysis, the straight-line distance is used as the shortest distance between customer locations. The algorithm is implemented using Matlab 2021a and executed on a computer with a CPU speed of 2.50 GHz and 16 GB of memory.

B. PARAMETER OPTIMIZATION

The model and algorithm in this study involve various parameters, including parameters specific to the MDVRPTW problem and parameters specific to the algorithm. For the parameters specific to the problem, some are set based on relevant literature, such as fixed costs of vehicles, carbon emission costs per unit, fuel consumption costs per unit, freshness decay coefficient, etc., while others are set by the author based on real-world circumstances. For the parameters specific to the algorithm, some are set based on relevant literature, such as weights for time window constraints, distance constraints, and demand constraints, pheromone evaporation coefficient, initial temperature for simulated annealing, etc., with the numerical values directly referenced from the cited literature. Some parameters are optimized through experimentation, such as the number of iterations for the ALNS algorithm, increment of operator scores, and adjustment coefficient for operator weights, primarily following the recommendations from the classical ALNS paper [49]. The remaining parameters are set by the author, as detailed in Table 1.

C. SIMULATION RESULTS ANALYSIS

1) VEHICLE ROUTING AND DISTRIBUTION TIME DISTRIBUTION

To verify the effectiveness of the model constructed and the algorithm proposed, Solomon simulation cases C201, C202, Pseudocode of ALNS_ACO algorithm is shown below:

Input: *initialSol*: Use ant colony algorithm to form initial solution; $TEMP_{\min}$: Initial temperature; H: Cooling rate;H:Cooling rate;

Input: RO: Set of destruction operators, including removal operators that remove customer points; IO: Set of insertion operators, including insertion operators that insert customer points.

$bestSol \leftarrow initialSol$, $TEMP \leftarrow TEMP_{\min}$
while the stopping condition is not met do
$updateSol \leftarrow initialSol$
Use roulette wheel selection method to select a removal operator $d \in RO$ based on the weights of operators in RO
if the selected removal operator is a customer point removal operator then
if the resulting route is infeasible after removal then
    Select an insertion operator from IO to repair the route by inserting customer nodes
$updateSol = r(d(x))$
else
    Select an insertion operator from IO to repair the route directly
end if
if $f(bestSol) \leq f(updateSol)$ then
$bestSol \leftarrow currentSol \leftarrow updateSol$, Increase the scores of all applied neighborhood operators ε_1
else if $f(currentSol) < f(updateSol) < f(bestSol)$ then
$currentSol \leftarrow updateSol$, Increase the scores of all applied neighborhood operators ε_2
else if $f(updateSol) \geq f(currentSol)$, *updateSol* is accepted by the simulated annealing criterion is accepted then
$currentSol \leftarrow updateSol$, Increase the scores of all applied neighborhood operators ε_3
else if, increase the scores of all applied neighborhood operators ε_4
end if
$TEMP \leftarrow TEMP \times H$
if $TEMP < TEMP_{min}$ then
$TEMP \leftarrow TEMP_{min}$
end if
Update the weights of each operator in RO and IO using the operator weight update formula
end while

TABLE 1. Summary of model and algorithm parameter settings.

Parameter symbol	Numerical value	Parameter symbol	Numerical value
L	600km	ξ_2	0.003
Q	3000kg	P_1	5yuan/h
f_0	200200 yuan/car	P_2	12yuan/h
f_k	30 yuan /h	α	1
φ	6.5yuan/L	β	3
C_e	0.0528yuan/kg	$\rho(0<\rho<1)$	0.7
P_t	6yuan/min	$antNum$	30
P_0	2yuan/min	$\max Iter_{ant}$	400
P	18yuan/kg	θ	0.3
ξ_1	0.002	$\psi_1,\psi_2,\psi_3,\psi_4$	0.2、0.5、0.2、0.1

R201, R202, RC201, and RC202 were used for simulation analysis. The program runtimes were 83.06s, 86.98s, 116.67s, 132.66s, 135.3s, and 113.23s, respectively. The optimal vehicle routing schemes generated by the program are shown in Figure 2, where the square represents the distribution center.

For the convenience of presentation, this paper specifically provides the optimal travel path and time distribution of case

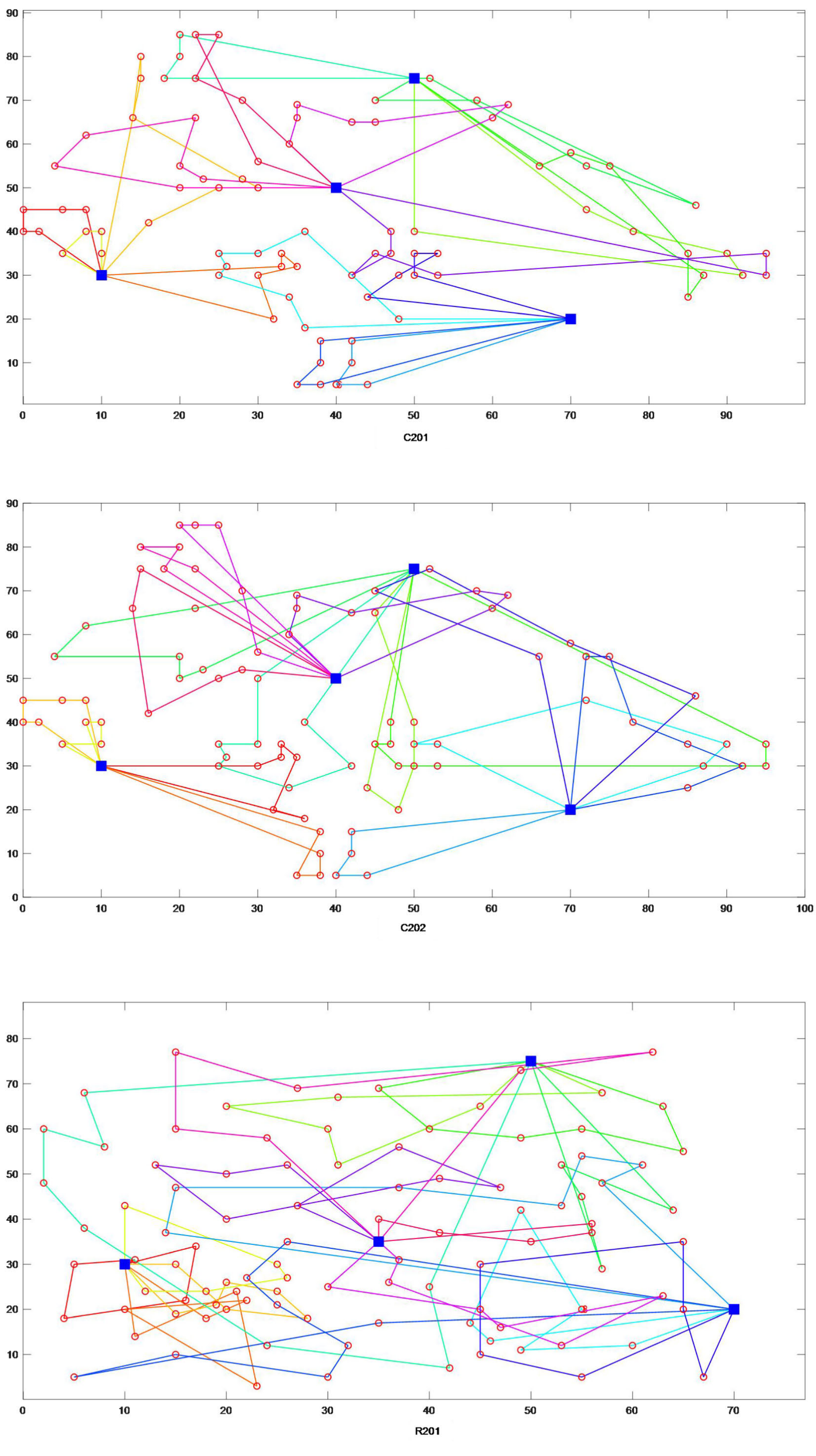

FIGURE 2. Optimal vehicle routing results of simulation cases.

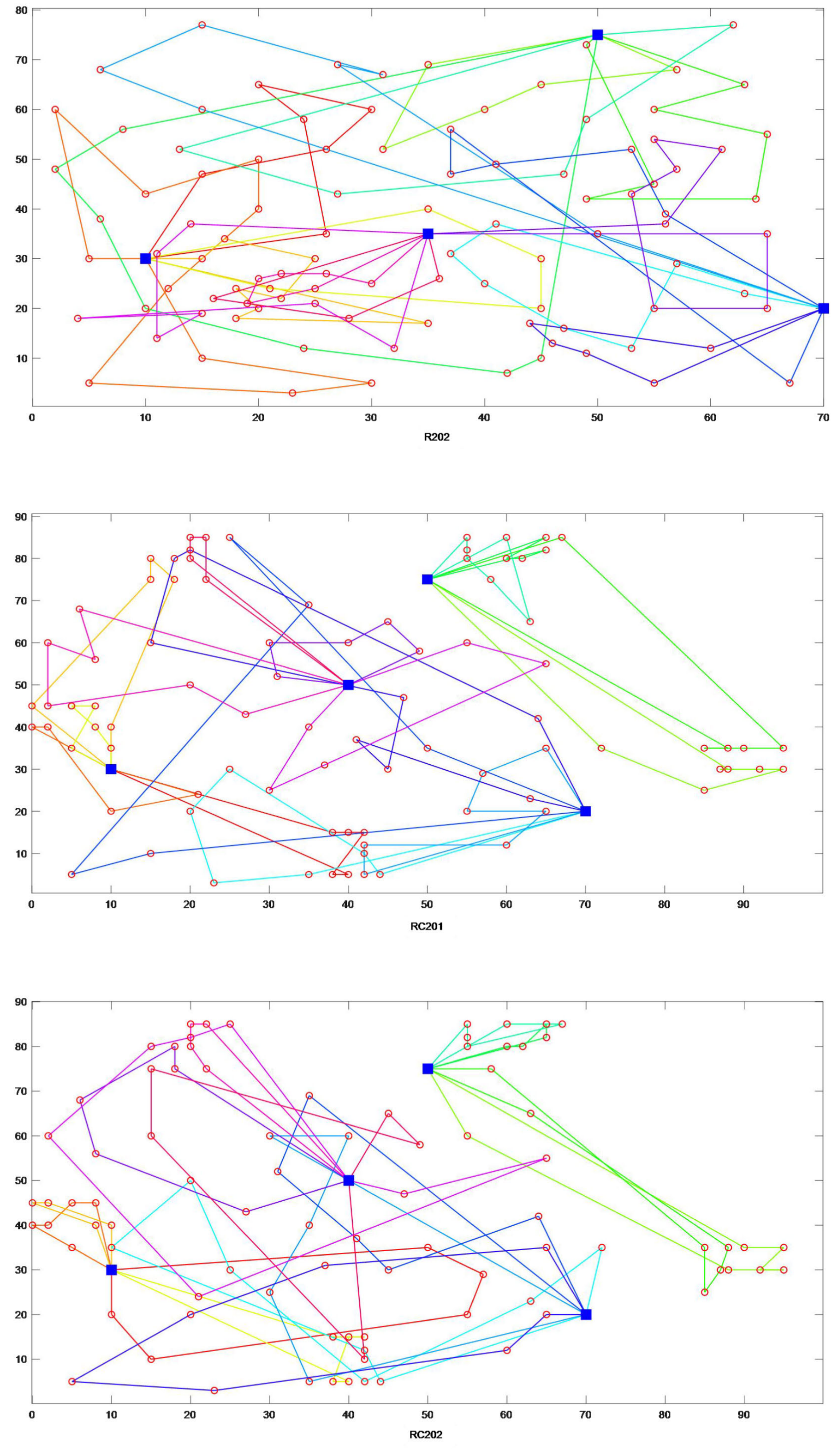

FIGURE 2. ***(Continued.)*** **Optimal vehicle routing results of simulation cases.**

RC201, as shown in Table 2. Where: DN represents the depot number, SN represents the vehicle number, VR represents the vehicle travel path, and VAT represents the time at which the vehicle arrives at each node.

TABLE 2. Optimal travel path and time distribution of case RC201.

DN	SN	VR	VAT
1	1	1->24->22->20->23->21->1	590-645-679-701-754-819-851
	2	1->16->15->59->96->87->86->1	129-161-183-199-227-246-270-293
	3	1->17->7->8->6->10->1	59-89-124-182-197-215-244
	4	1->13->12->14->11->9->1	385-410-436-451-483-497-526
2	1	2->50->33->26->28->88->89->32->30->2	452-490-504-527-549-572-592-623-641-677
	2	2->31->34->29->95->98->104->27->35->2	29-48-66-81-104-137-167-194-241-277
	3	2->36->39->38->37->97->103->2	15-24-59-115-191-237-358-427
	4	2->40->72->41->42->44->43->2	28-42-76-124-156-197-241-293
3	1	3->25->77->74->102->52->19->18->3	216-237-259-287-315-337-384-402-527
	2	3->62->84->51->63->76->93->49->48->3	84-98-133-147-169-188-202-241-270-304
	3	3->56->70->92->99->75->58->3	151-179-199-231-274-312-352-715
	4	3->85->66->64->80->60->46->45->67->3	56-75-136-149-197-233-271-292-310-357
4	1	4->81->61->68->100->55->69->4	413-469-486-533-575-590-643-679
	2	4->65->57->83->90->91->71->54->4	240-259-273-288-319-364-427-463-624
	3	4->82->53->94->5->101->47->73->78->79->4	319-366-394-429-467-491-551-582-604-653-694

From Table 2, it can be observed that: (1) Based on the SN column, a total of 15 delivery vehicles are used for the four distribution centers. Specifically, distribution center 1 utilizes 4 vehicles, distribution center 2 utilizes 4 vehicles, distribution center 3 utilizes 4 vehicles, and distribution center 4 utilizes 3 vehicles. (2) The number of consumers served by various vehicles varies, as indicated by the VR column. There is a minimum of five customers served and a maximum of nine. This difference is primarily due to factors such as the location of the distribution centers, traffic congestion conditions, customer demand and service time windows, as well as vehicle capacity. (3) Based on the VAT column, vehicle 4 from distribution center 1, vehicle 1 from distribution center 2, and vehicles 1 and 2 from distribution center 4 entirely avoid the peak congestion periods in the morning and evening. The remaining vehicles only enter either the morning or evening peak congestion period separately This suggests that the strategy put out in this research can successfully avoid periods of heavy traffic, improve the effectiveness of vehicle distribution for cold chain logistics, and successfully lower total distribution costs.

2) ANALYSIS OF SIMULATION RESULTS FOR SINGLE DEPOT AND MULTIPLE DEPOTS AT DIFFERENT LOCATIONS

To compare the impact of single depot and multiple depots on different optimization objectives, simulations were conducted for various scenarios using single depots at different locations (Single Depot 1, Single Depot 2, Single Depot 3, Single Depot 4) and multiple depots. The simulation results are presented in Table 3. Herein, TC represents the total cost (in units of yuan), CC represents carbon emission cost (in units of yuan), and TT represents the total travel time of vehicles (in units of minutes).

According to Table 3, the following observations can be made: (1) The vehicle distribution costs of multiple distribution centers are much lower than those of a single distribution center. In terms of total distribution costs, compared to the vehicle distribution costs of Single Distribution Center 1, Single Distribution Center 2, Single Distribution Center 3, and Single Distribution Center 4, the vehicle distribution costs of multiple distribution centers have average reductions of 19.81%, 21.56%, 20.57%, and 23.18% respectively. In terms of carbon emission costs, multiple distribution centers also exhibit certain advantages, with average cost reductions of 12.33%, 10.5%, 11.36%, and 12.56% respectively. This indicates that the use of multiple distribution centers for vehicle distribution can effectively reduce both distribution costs and carbon emissions. (2) The total travel time of vehicles in multiple distribution centers is lower than that of a single distribution center. Compared to the vehicle distribution of Single Distribution Center 1, Single Distribution Center 2, Single Distribution Center 3, and Single Distribution Center 4, the average travel times of vehicles in multiple distribution centers are reduced by 12.8%, 13.62%, 14.77%, and 13.66% respectively. Therefore, through a comprehensive comparison of total distribution costs, carbon emission costs, and total travel time, it can be concluded that using multiple distribution centers for urban cold chain logistics delivery services results in lower distribution costs, less environmental pollution, and higher delivery efficiency.

3) ANALYSIS OF SIMULATION RESULTS FOR DIFFERENT CONGESTION SPEEDS

Under the constant model parameters and constraints, simulation experiments were conducted on various scenarios with congestion speeds of 15 km/h and 10 km/h, respectively. As indicated in Table 4, the outcomes were contrasted with the simulated results at a congestion speed of 20 km/h. In the table, TC represents the total cost (in units of yuan), CTC represents the comprehensive transportation cost (in units of yuan), and CC represents the carbon emission cost (in units of yuan).

From Table 4, it can be observed that as congestion speed decreases, total distribution costs, vehicle usage costs,

TABLE 3. Comparison of simulation results for different single depot and multiple depots.

Case Study	Single Distribution Depot 1			Single Distribution Depot 2			Single Distribution Depot 3			Single Distribution Depot 4			Multi-distribution Depot		
	TC	CC	TT	TC	CC	TT	TC	CC	TT	TC	CC	TT	TC	CC	TT
C201	58937	1628	25663	58746	1572	26373	58426	1521	26617	59237	1350	26137	47885	1406	23977
C202	48377	1798	21837	53277	1875	20713	51069	1739	21072	54172	1443	20155	45017	1649	20086
R201	21196	1791	7092	19856	1766	7714	19437	1935	7919	23329	2368	8103	14773	1733	5914
R202	18511	1989	6637	18852	1902	7026	18746	2037	7125	18035	1958	7039	13729	1781	4837
RC201	20682	2346	7320	20824	2257	7441	21649	2317	7473	20662	2589	7527	14662	1926	5733
RC202	19437	2457	7108	19754	2394	7113	19597	2331	7203	19913	2334	7452	14001	2037	5429
Avg	31190	2002	12610	31885	1961	12730	31487	1980	12902	32558	2007	12736	25011	1755	10996

TABLE 4. Comparison of simulation results for different congestion speeds.

Case Study	20			15			10		
	TC	CTC	CC	TC	CTC	CC	TC	CTC	CC
C201	49935	41087	1754	51027	42245	1774	52438	45331	1898
C202	47353	38992	1869	48391	39174	1893	49936	41472	1983
R201	16036	10733	1731	17855	10926	1860	18042	13633	2035
R202	14725	10818	1662	16253	10897	1704	17473	11279	1869
RC201	14359	10994	1597	14934	12527	1617	16375	12604	1954
RC202	13898	10735	1725	14437	11353	1793	15062	13472	1901
Avg	26051	20560	1723	27150	21187	1774	28221	22965	1940

and carbon emission costs gradually increase, indicating an inverse relationship between these costs and congestion speed. (1) Regarding total distribution costs, when the congestion speed decreases from 20 km/h to 15 km/h, the average total cost increases by 4.22%; when the congestion speed decreases from 20 km/h to 10 km/h, the average total cost increases by 8.33%. (2) In terms of vehicle usage costs, when the congestion speed decreases from 20 km/h to 15 km/h and 10 km/h, the vehicle usage costs increase by an average of 3.05% and 11.7%, respectively. (3) With respect to carbon emission costs, when the congestion speed decreases from 20 km/h to 15 km/h and 10 km/h, the carbon emission costs increase by an average of 2.96% and 12.59%, respectively. In summary, the analysis indicates that traffic congestion has varying degrees of impact on vehicle distribution costs, fuel consumption, and carbon emissions. Moreover, as the level of traffic congestion increases, vehicle distribution costs and carbon emission costs also increase.

4) SIMULATION RESULTS ANALYSIS FOR DIFFERENT OPTIMIZATION OBJECTIVES

Simulators were run under identical conditions, with the optimization goals of minimizing vehicle total trip time and minimizing vehicle total travel distance, respectively. Table 5 displays the comparison between the obtained findings and the simulation results of this work, where the optimization aim was total cost. Here, TC represents total cost (unit: yuan), TD represents total travel distance (unit: km), and TT represents total travel time (unit: min). CTC represents comprehensive transportation costs, CC represents carbon emission costs, TPC represents time penalty costs, CDC represents cargo damage costs, and RC represents refrigeration costs.

According to Table 5: (1) The model presented in this study, which set total cost as the optimization goal, reduced comprehensive transportation expenses by an average of 18.24% and 21.78%, respectively, as compared to models that set out to minimize total journey time and total travel distance; (2) In terms of carbon emission costs, the proposed total cost minimization model achieved an average reduction of 19.49% and 16.8% compared to the models with minimizing total travel distance and minimizing total travel time, respectively; (3) In terms of time penalty costs, the proposed total cost minimization model achieved an average reduction of 28.65% and 16.31% compared to the models with minimizing total travel distance and minimizing total travel time, respectively; (4) In terms of cargo damage costs, the proposed total cost minimization model achieved an average reduction of 26.61% and 19.2% compared to the models with minimizing total travel distance and minimizing total travel time, respectively; (5) In terms of refrigeration costs, the proposed total cost minimization model achieved an average reduction of 22.28% and 17.39% compared to the models with minimizing total travel distance and minimizing total travel time, respectively.

In summary, the model proposed in this paper, which considers comprehensive transportation costs, carbon emission costs, time penalty costs, cargo damage costs, and refrigeration costs, with total cost as the optimization objective, is more effective in reducing the distribution costs of urban cold chain logistics and improving the economic benefits of logistics companies, compared to the optimization objectives of minimizing total travel distance and minimizing total travel time.

D. ANALYSIS OF SIMULATION RESULTS FOR DIFFERENT ALGORITHMS

To validate the effectiveness of the proposed ALNS_ACO algorithm, the algorithm is applied to the Solomon simulation examples of the six MDVRPTW problems and

TABLE 5. Comparison of simulation results for different optimization objectives.

Case Study	Minimization of total cost					Minimization of total travel distance					Minimization of total travel time				
	CTC	CC	TPC	CDC	RC	CTC	CC	TPC	CDC	RC	CTC	CC	TPC	CDC	RC
C201	29031	7463	4476	4398	2508	47794	12049	8066	7274	4083	39772	9357	6275	5612	3012
C202	27279	6575	4573	4173	2132	41045	9782	6381	5793	3091	35419	8088	5799	5233	2729
R201	9076	2027	1612	1424	716	14240	3159	1839	1965	1120	11885	2763	1635	1526	879
R202	8349	2360	1404	1196	687	12488	2785	1793	1775	1042	9216	2352	1875	1637	827
RC201	9151	2021	1667	1042	729	11169	2571	1941	1764	770	9536	2301	1374	1383	707
RC202	8728	2375	1790	1351	635	12796	3001	1734	1440	927	11291	2571	1587	1418	814
Avg	15269	3804	2587	2264	1235	18677	4725	3626	3085	1589	19520	4572	3091	2802	1495

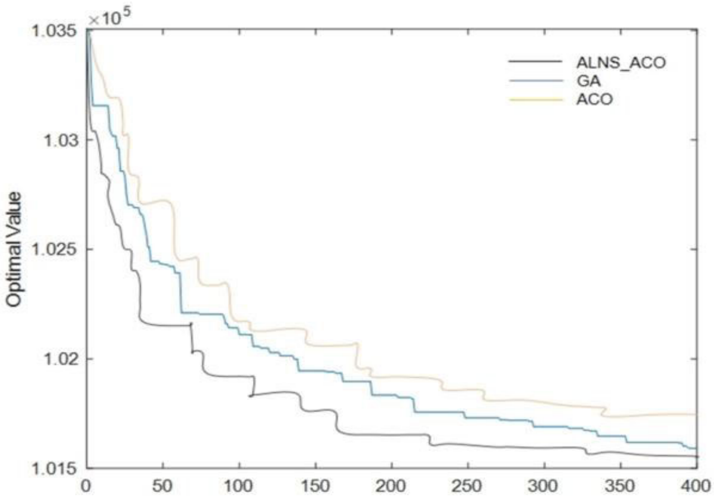

FIGURE 3. Comparison of iterative processes of different algorithms.

TABLE 6. Comparison of simulation performance for different optimization algorithms.

Case Study	ALNS_ACO			ACO			GA		
	TC	Convergence time/s	Calculation time/s	TC	Convergence time/s	Calculation time/s	TC	Convergence time/s	Calculation time/s
C201	48910	23.73	83.06	57159	59.88	161.25	56202	57.18	179.35
C202	46185	29.18	86.98	54803	65.34	167.54	51960	55.7	168.81
R201	15404	40.19	116.67	17946	73.71	209.53	16330	62.56	203.2
R202	14227	50.08	132.66	16949	81.37	231.24	16930	72.72	220.38
RC201	14510	47.06	135.3	17047	83.41	213.89	16277	66.15	206.52
RC201	13949	31.89	113.23	17157	87.22	223.65	16599	79.43	228.6
Avg	25530	37.02	111.32	30176	75.16	201.18	29049	65.62	201.14

compared with the Ant Colony Algorithm (ACO) and Genetic Algorithm (GA), all with the objective of minimizing total costs. The codes are implemented using Matlab 2021a, and the simulation results are presented in Table 6 and Figure 3. Table 6 provides the distribution total costs, convergence time, and simulation execution time for different optimization algorithms after 400 iterations on various standard test case sets. Figure 3 displays the convergence curve of the optimal solutions obtained by different optimization algorithms during the simulation process for the RC201 example.

According to Table 6: (1) In terms of total delivery costs, the ALNS_ACO algorithm achieves the optimal solution in all cases, with the lowest convergence time and computation time. Compared to the ACO and GA algorithms, the ALNS_ACO algorithm reduces the average delivery costs by 15.4% and 12.11% respectively. (2) In terms of convergence time, the ALNS_ACO algorithm reduces the average convergence time by 50.68% and 43.58% compared to the ACO and GA algorithms respectively. (3) In terms of computation time, the ALNS_ACO algorithm reduces the average computation time by 44.67% and 43.58% compared to the ACO and GA algorithms respectively. (4) As shown in Figure 3, the ALNS_ACO algorithm reaches convergence faster and obtains better solutions compared to the ACO and GA algorithms, indicating that the improved ALNS_ACO algorithm has higher solution accuracy and improves solution quality compared to conventional algorithms. Based on the above analysis, it can be concluded that the designed ALNS_ACO algorithm not only achieves better optimization results in model solving, but also demonstrates significant improvements in terms of iterative convergence and simulation efficiency compared to the single Ant Colony and Genetic Algorithms.

VI. CONCLUSION

Logistics and transportation are one of the main sources of carbon emissions, and in order to contribute to the overall goals of carbon neutrality and peak carbon emissions, this study focuses on the optimization of urban cold chain logistics routes considering multiple distribution centers, aiming to promote the green development of transportation and logistics distribution. Taking into account the characteristics of peak hours in urban transportation, the time-varying factors are incorporated into the model. A total cost minimization objective is designed, which includes comprehensive transportation costs, carbon emission costs, time penalty costs, cargo damage costs, and refrigeration costs. A city multi-distribution center cold chain logistics route optimization model under time-varying road networks is constructed. Based on the characteristics of the model, an ALNS_ACO algorithm is designed to solve the model. Finally, the feasibility of the model and algorithm is verified through numerical experiments using 6 test cases from the Solomon benchmark database. The main results are as follows:

(1) In the optimization of the urban cold chain logistics MDVRPTW problem model, the number of vehicles departing from each distribution center is maintained at 3-4, and there is a certain difference in the number of customers served by different vehicles. Meanwhile, some vehicles perfectly avoid the morning and evening peak periods, while others only avoid either the morning or evening peak period. This indicates that the route planning can reasonably avoid traffic congestion time periods and demonstrates the effectiveness of the model optimization.

(2) Combining the simulation results of the optimization solutions for multiple distribution centers and single distribution centers, it can be observed that multiple distribution centers have made significant improvements in terms of total delivery costs, carbon emission costs, and total travel time compared to single distribution centers. This demonstrates that using multiple distribution centers for urban cold chain logistics services can effectively reduce delivery costs, generate less environmental pollution, and improve overall delivery service efficiency.

(3) The changes in vehicle congestion speed will have a significant impact on total delivery costs, vehicle usage costs, and carbon emission costs. As congestion speed decreases, i.e., as traffic congestion worsens, it will gradually lead to an increase in total delivery costs, vehicle usage costs, and carbon emission costs.

(4) The changes in different optimization objectives will also have a significant impact on the optimization results of the model. The total cost minimization objective designed in this study, which includes comprehensive transportation costs, carbon emission costs, time penalty costs, cargo damage costs, and refrigeration costs, compared to the optimization objectives of minimizing total distance and total time, can effectively reduce the distribution costs of urban cold chain logistics and thus widely improve the economic benefits of logistics enterprises.

5) Through the performance comparison of different optimization algorithms, it is found that the ALNS_ACO algorithm has relatively better optimization effects in terms of total delivery costs, convergence time, and computational time compared to ACO and GA algorithms. This indicates that the improved optimization algorithm has made significant improvements compared to a single ant colony algorithm and genetic algorithm.

Based on the above research findings, some feasible suggestions for the low-carbon development of urban cold chain logistics can be proposed, especially for cold chain logistics enterprises. This paper provides some development insights and references on how to effectively reduce distribution costs and subsequently improve the quality of logistics services. However, this paper only explores and analyzes the urban cold chain logistics MDVRP problem in theory. In particular, in the empirical case study section, there is a lack of specific development examples for optimizing urban cold chain logistics routes. Furthermore, in future research, it will be important to further refine the time-varying factors, analyze the main influencing factors of carbon emissions, and design more scientifically effective optimization algorithms for logistics multi-distribution centers. These areas are worthy of in-depth exploration and investigation.

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