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RESEARCH ARTICLE

Low-Carbon Cold-Chain Logistics Path Optimization Problem Considering the Influence of Road Impedance

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ABSTRACT An improved road impedance function in conformity with Chinese city road traffic is designed for calculating the actual transportation time based on real-time traffic information and the complex road environment in the city. The objective function minimizes the total distribution cost, including fixed cost, transportation cost, damage cost, energy cost, penalty cost, and carbon emission cost. A mathematical model is constructed for cold-chain logistics distribution path optimization considering the influence of road impedance. The model is solved using three particle swarm optimization algorithms with improved weights. The experimental results show that the self-adaptive weighted particle swarm optimization algorithm is more efficient in solving this model. Experimental results obtained from the cold-chain logistics path optimization model considering road impedance compared to those of the model without road impedance indicate that the former are closer to the actual situation. Based on the changes in carbon emission and total cost under different carbon taxes, we analyze the critical carbon tax value and the optimal carbon tax value range to improve the economic and environmental benefits in the distribution process. This study should prove to be of great practical significance and application value for logistics enterprises to conduct rational planning of path problems.

INDEX TERMS Real-time traffic, road impedance function, particle swarm optimization algorithm, cold-chain logistics, critical carbon tax value.

I. INTRODUCTION

With the improvement of social living standards, consumers have higher requirements for the freshness of fresh and other cold-chain foods. This also imposes serious challenges to cold-chain logistics in distribution issues. Unlike ordinary logistics products, cold-chain logistics products are perishable. Therefore, the distribution process of cold-chain logistics can result in a loss of goods, increasing the cost of logistics operation. Data show that spoilage rates in China for fruits and vegetables, meat, and fish can reach 30%, 12%, and 15%, respectively, while annual losses for fruits and vegetables exceed \$12.5 billion, accounting for >30% of the value of the entire industry [1]. Related research indicates that reasonable path optimization for cold-chain logistics distribution can reduce transportation costs, cargo damage costs, and energy consumption in the distribution process, further improving transportation efficiency and lowering enterprise loss costs [2].

According to statistics, the transport sector will account for 23% of global CO_2 emissions in 2020. Transport delays caused by traffic congestion can be addressed by avoiding predictable traffic congestion in vehicle routing plans [3]. In cold-chain transportation, various studies have shown that traffic congestion and changes in the speed of delivery vehicles can affect carbon emissions [4], [5]. Nowadays, city roads are becoming more and more congested because of the increasing number of vehicles in various countries. Real-life

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road impedance and traffic congestion are already common. Road impedance will result in the increase of transportation time in the process of cold-chain logistics distribution. This affects carbon emissions, cargo freshness, etc. Therefore, in this study, we propose a road impedance function model suitable for city traffic in China and apply it to the cold-chain logistics path optimization problem.

The road impedance function model (referred to as the road resistance function) is expressed as the relationship between the travel time and traffic load of a road section. Currently, there is no unified road impedance function calculation method in China. Most of the calculations directly quote the traditional road impedance function calculation model. The Bureau of Public Roads (BPR) function is the traditional model for calculating the impedance function of a road section. It reflects the relationship between travel time and traffic flow on a freeway. Because traditional road impedance functions are mostly used for intercity road calculations, which differs from the mixed traffic situation in Chinese cities, there is a large error in their practical application. In this study, a road impedance function to meet the actual road conditions in China's city traffic is designed. The vehicle route optimization problem (VRP) was first proposed by Ramse and Dantzig [6]. The problem is an NP-hard problem. Numerous studies have demonstrated that intelligent optimization algorithms achieve better results in solving such problems. In this study, we will use the particle swarm optimization (PSO) algorithm with improved weights for solving the objective function model.

In this study, the influence of road impedance is considered and a mathematical model for cold-chain logistics path optimization is constructed with the objective of minimizing total cost. The improved PSO algorithm is used to solve the case. The research results obtained here are of practical significance and of important value.

II. RELATED WORK

In this section, research related to cold-chain logistics path optimization considering road traffic and carbon emissions is discussed.

A. ROAD TRAFFIC

Many scholars have considered the impact of road traffic conditions on cold-chain logistics. Some study the impact of traffic congestion on logistics transportation. Chen et al. [7] explored the impact of traffic congestion on cold-chain logistics in former warehouses and quantified the level of traffic congestion using the congestion index. Qi et al. [8] employed the congestion index provided by Baidu Maps to describe the actual traffic situation. They divided traffic into multiple time periods to calculate the transport time and applying their method to emergency cold-chain logistics scheduling problems. Xu et al. [9] used the Davidson road impedance function to calculate the transport time. For solving the fresh-food cold-chain logistics path optimization problem, Barth [5] embedded highway performance measurement systems into loop detectors on California freeways to collect real-time traffic data. The impact of traffic conditions on carbon emissions was described by means of a computational function of traffic density and volume. Figliozzi [10] collected data from highway sensors and related cases, using them to analyze the impact of traffic congestion on the carbon emissions generated by logistics transportation.

Nowadays, there are many scholars studying the acquisition of real-time road condition information. For example, Chen [11] used big-data cloud computing technology to obtain real-time road traffic information in logistics transportation through a unified access interface. Guo et al. [12] collected driving data from a large number of vehicles in the city and constructed a vehicle fuel consumption and carbon emission measurement model coupled with a dynamic traffic network. Xu et al. [13] acquired the actual traffic conditions of the road by GPS and analyzed the spatio-temporal knowledge to plan an effective route. There are also many scholars who have considered the impact of variable speeds on cold-chain logistics distribution. Li et al. [4] investigated the effect of vehicle speed on the total cost of cold-chain logistics distribution. The relationship between the deterioration rate and optimal speed was obtained from the case study. Liu et al. [3] designed a computational model for the variation of vehicle speed with time and proposed a method to avoid traffic congestion and temporary traffic congestion. Zhao et al. [14] considered the effects of time-varying road network traffic volumes and road types. Constructing a model for the path optimization problem of electric vehicles, Heni et al. [15] investigated the dynamic path of traffic and the instantaneous speed of traffic networks. Poonthalir et al. [16] proposed a computational model for the effect of triangularly distributed variable speeds on fuel consumption. Their results revealed that traffic moving at variable speeds leads to less fuel consumption than constant-speed traffic.

B. CARBON EMISSIONS

The issue of carbon emissions has been an important research topic under continuous improvement. Zhang et al. [17] analyzed the key factors affecting the development of green logistics and explored the priority and hierarchy of the influencing factors. There are many scholars who have designed relevant carbon emission calculation models. Some scholars have also studied carbon emissions under carbon tax or carbon cap policies. Wang et al. [18] used a linear function of unit fuel consumption to calculate carbon emissions. Liu et al. [19] showed that a joint distribution is less costly than a single distribution in terms of carbon emissions and that the total cost is positively related to the cost of carbon emissions. Hu et al. [20] first used the cycle evaluation method and the input–output method to calculate the range of carbon emissions during each stage of cold-chain logistics. To develop a mathematical model for carbon footprint optimization, Ning et al. [21] developed a quantitative analysis of the carbon tax mechanism. Using carbon tax cost as a decision variable in an improved quantum bacterial foraging optimization algorithm, Wang et al. [22] established a logistics path optimization model including carbon emission costs. They analyzed critical carbon tax values for carbon emissions and allocation costs in the example results. Li [23] proposed a mathematical model to calculate the cost of carbon emissions and applied it to the cold-chain logistics distribution path optimization problem. Gong et al. [24] developed a mathematical model for simultaneous multi-vehicle distribution based on consideration of carbon emissions and time windows. With the goal of minimizing driver wages and carbon emission costs, Anna et al. [25] constructed time-dependent path optimization problems.

C. VRP SOLUTION METHOD

With the innovation of planning models and the increase in the size of nodes, traditional intelligent optimization algorithms have some shortcomings in solving VRPs. Therefore, many scholars have focused on the in-depth study of intelligent optimization algorithms. Many improved optimization algorithms and hybrid optimization algorithms have been designed to solve the objective model. Zhao et al. [26] studied a multi-objective path optimization model based on cost, carbon emission, and customer satisfaction and designed an improved ant colony algorithm solution model using a multi-objective heuristic function. Zhang et al. [27] designed an optimization algorithm combining RNA computation and an ant colony algorithm to solve the VRP. Qin et al. [28] established a cold-chain path optimization model with the objective of minimizing the cost of customer satisfaction and proposed a circular evolutionary genetic algorithm to compute the model. Ren et al. [29] constructed a multi-distribution-center cold-chain logistics path optimization model considering soft time window constraints and adopted the hybrid algorithm of an artificial fish swarm and an ant colony to solve the model. Song et al. [30] designed a special coding method to improve the artificial fish swarming algorithm by considering the characteristics of different car models. Zhu et al. [31] constructed a cold-chain logistics path optimization model with a minimum total cost based on consideration of fuel consumption and traffic congestion. A hybrid genetic–ant colony algorithm based on response surface methodology was proposed to solve the model. Wang et al. [32] proposed an adaptive genetic algorithm to solve the low-carbon cold-chain logistics distribution path problem. Chen et al. [33] analyzed the powerful global search capability of the improved ant colony algorithm and the good local search capability of the forbidden search algorithm. A hybrid optimization algorithm was designed to solve the VRP.

In summary, research on considering road traffic aspects in VRPs mostly focus of the impact of traffic congestion or speed and real-time road condition data on vehicle path optimization. However, few studies have considered road impedance. Road impedance directly affects the actual transportation time and indirectly affects the cost of each distribution of vehicle transportation. Therefore, we believe that it is important to consider the effect of road impedance on the VRP. At the same time, the analysis from the above study shows that cold-chain logistics will produce more carbon emissions than ordinary logistics. In the context of green logistics, it is essential to study low-carbon cold chains. Therefore, here we construct a low-carbon cold-chain logistics path optimization problem model with the objective of minimizing the total cost based on the influence of road impedance. The effectiveness of intelligent optimization algorithms in solving VRPs is also found. A PSO algorithm with improved weights is then designed to solve the target model.

III. ROAD IMPEDANCE FUNCTION ANALYSIS AND IMPROVEMENT

The Bureau of Public Roads (BPR) function is the traditional model for calculating the impedance function of a road section. It reflects the relationship between travel time and traffic flow on a roadway. It is one of the most widely used functional models in China. Of course, the BPR function also has some shortcomings. First, when the traffic volume of the traffic section is greater than the traffic capacity of the section, it does not reflect the actual situation of road impedance. Second, when the traffic volume on the road section is less than the traffic capacity of the section and the parameter value is larger, this leads to a travel time infinitely close to the free-flow time. The travel time on the road is given by

$$t = t_0\left(1+\alpha\left(\frac{Q}{C}\right)^{\beta}\right) \tag{1}$$

where t_0 is the free passage time during zero flow on the road segment, Q is the traffic volume on the road segment, C is the traffic capacity on the road segment, and α and β are parameters to be calibrated. The values recommended by the U.S. Highway Department are $\alpha = 0.15$ and $\beta = 4.0$.

The urban road impedance function consists of two parts: roadway impedance and intersection impedance. The actual travel time of urban road impedance is given by

$$T = T_1 + T_2 \tag{2}$$

where T_1 is the travel time of roadway impedance and T_2 is the travel time of intersection impedance.

The road section travel time impedance function in this study is based on the BPR function. In the BPR function model, it does not reflect the fact that the traffic flow on the road section increases and then decreases as the traffic flow density increases. To solve this problem, so that the traffic flow is not limited by traffic capacity, we use Wang's [34] idea of improving the BPR function.

By deriving the relationship among the three urban-road parameters (speed, density, and traffic volume), the variation between density and traffic volume can be derived. Their linear expression is given by

$$Q = VK \tag{3}$$

The linear relationship between velocity V and density in the Greenshield model can be expressed as

$$V = V_f\left(1 - \frac{K}{K_j}\right) \tag{4}$$

where V_f is the speed of free travel, K is the traffic density, and K_j is the density of road blockage at a vehicle speed of zero.

Substituting Eq. (4) into Eq. (3) yields

$$Q = V_f K - \frac{V_f}{K_j}K^2 \tag{5}$$

Let $dQ/dK = 0$. Then, when $V = 0.5V_f$, $K = 0.5K_j.Q$ has a maximum value of $0.25V_f K_j$,The traffic volume at this point is the traffic capacity of the roadway. that is $C = 0.25V_f K_j$.

Substituting Eqs. (5) and $C = 0.25V_f K_j$ into Eq. (1) yields

$$t = t_0\left(1 + \alpha\left(1 - \left(1 - \frac{K}{K_j}\right)^2\right)^\beta\right) \quad K \in \left[0, 2K_j\right] \tag{6}$$

From the above, the degree of saturation Q/C is replaced by the density formula. Letting $x = Q/C$, we have

$$x = 1 - \left(1 - \frac{K}{K_j}\right)^2 \tag{7}$$

We used the road impedance function model proposed by SPIESS [35]:

$$T_1 = t_0\left(2 + \sqrt{\beta^2\left(1-x\right)^2 + \gamma^2} - \beta\left(1-x\right) - \gamma\right) \tag{8}$$

where $\gamma = \frac{2\beta-1}{2\beta-2}$, $\alpha > 0$, $\beta > 1$, and the degree of saturation is $x = 1 - \left(1 - K/K_j\right)^2$.

In China's urban road intersections, which have different forms, to facilitate the calculation, we assumed that the signal intersection for a type. Among them, the Webster model is a well-known model for calculating road signal intersection delays [36]:

$$T_2 = \frac{c(1-\lambda)^2}{2(1-\lambda x)} + \frac{x^2}{2Q(1-x)} - 0.65\left(\frac{c}{Q^2}\right)^{\frac{1}{3}}x^{(2+5x)} \tag{9}$$

where Z_2 is the time impedance of vehicles (i.e., vehicle delays), c is the signal cycle, x is the saturation level of the road, λ is the ratio of green lights to signal lights, and Q is the traffic flow arriving at the intersection. The first part of this equation is the basic delay term resulting from vehicles arriving at the intersection and stopping or queuing. The second part is the random delay term. The third part is the correction term for the random delay term. Webster's later study revealed that the third component was less weighted in the overall model. Therefore, the equation can be simplified as

$$T_2 = \frac{9}{10}\left[\frac{c(1-\lambda)^2}{2(1-\lambda x)} + \frac{x^2}{2Q(1-x)}\right] \tag{10}$$

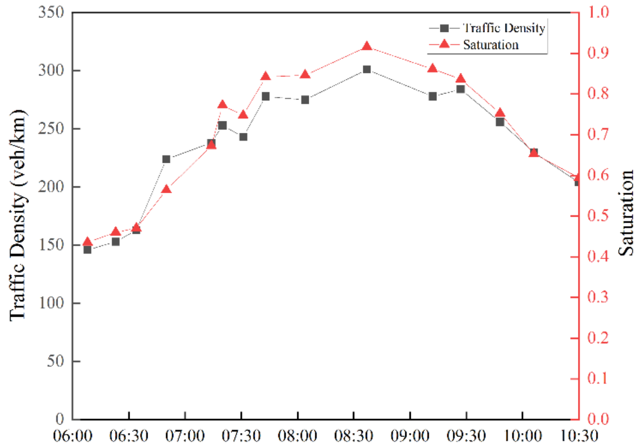

FIGURE 1. Change of saturation and traffic density.

Therefore, the urban road impedance function is a function of the traffic density K:

$$\begin{aligned} T &= T_1 + T_2 \\ &= t_0\left(2 + \sqrt{\beta^2\left(1-x\right)^2 + \gamma^2} - \beta\left(1-x\right) - \gamma\right) \\ &\quad + \frac{9}{10}\left[\frac{c(1-\lambda)^2}{2(1-\lambda x)} + \frac{x^2}{2Q(1-x)}\right] \end{aligned} \tag{11}$$

where $x = 1-\left(1 - K/K_j\right)^2$, $\gamma = 2\beta-1/2\beta-2$, and α and β are parameters to be calibrated. In this study, we used the U.S. Highway Department recommended values of $\alpha = 0.15$ and $\beta = 4.0$.

A. DATA COLLECTION

The section between the subway entrance of Central Street and the Shenyang University of Technology in the Tiexi District, Shenyang, was selected for an example analysis. The data acquisition methods commonly used were the photographic method and the access method. Because the survey road section is not obscured by shelters, the photographic method was used to obtain relevant data such as road traffic density.

We collected traffic data from 06:00 to 21:00 on this road section. In Figs. 1 and 2, the curves represent the trends in traffic density and saturation from 06:00 to 11:00 and from 17:00 to 21:00, respectively. The trends of traffic density and saturation from 6:00 to 11:00 and from 17:00 to 21:00 show that the traffic density varies with saturation.

B. MODEL COMPARISON AND VALIDATION

Roadway data collected at 18:00 were taken as an example. We obtained the traffic density of each road section K, and intersection traffic volumes Q using a road blockage density of K_j =125vehicles/km and parameters $\alpha = 0.15$ and $\beta = 4.0$.

The travel time of the road section from 06:00 to 21:00 was calculated using the BPR road impedance function model, the improved road impedance function equation of Wang [34], and the improved road impedance function model of this

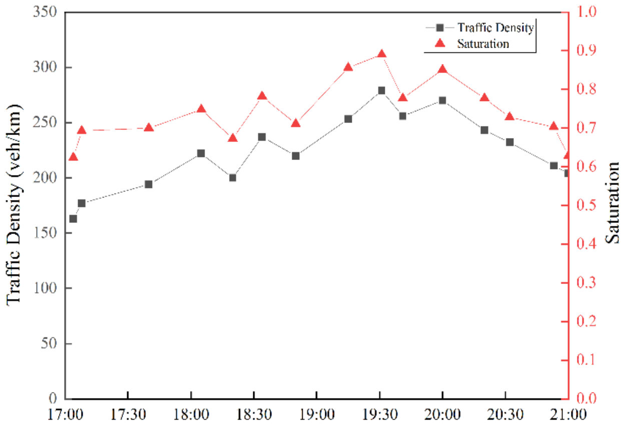

FIGURE 2. **Change of saturation and traffic density.**

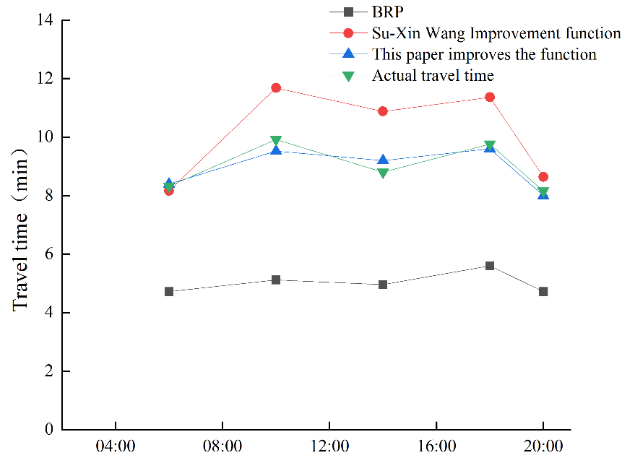

FIGURE 3. **Comparison of travel times.**

study, respectively. The results obtained from the three road impedance functions were further compared and verified with the actual driving time. The comparison graph shows that the whole driving time calculated by using the BPR function is significantly lower than the actual value. This is because the principle of the BPR road impedance function does not account for road node impedance. While the travel time calculated using the improved road impedance function model of Wang is greater than the actual value, the calculation results of the improved road impedance function model in this study are closer to the actual driving time, being significantly better than those of other road impedance functions.

In the following sections, the actual travel time T under road impedance conditions will be used as the actual transport time of the vehicle.

IV. PROBLEM FORMULATION

A single distribution center problem was considered in which the actual transportation time in the cost function was calculated for the above improved road impedance function. The detailed assumptions of this study are as follows: (1) The refrigerated truck is the same model, and the vehicle cannot be overloaded. (2) The maximum distribution distance on each distribution path shall not exceed the maximum distance the vehicle can travel. (3) The amounts of cold-chain goods in distribution centers are adequate. The vehicle departs from the distribution center and has to return to the distribution center after the distribution is completed. (4) Each demand point can only be delivered by one vehicle and only delivered once. (5) The delivery time window of each customer demand point, the demand quantity, and the geographical location are all known. (6) The density of road blockage during vehicle transportation is known.

A. SYMBOLS AND DECISION VARIABLES

We set the following relevant parameters according to the need for building the model:

m : number of vehicles ($k = 1, 2, \cdots, m$);

n : number of customers ($i = 1, 2, \cdots, n; j = 1, 2, \cdots, n$);

Q_0 : weight of the refrigerator truck itself;

Q : maximum load capacity of a refrigerator truck;

D : furthest delivery distance for refrigerated trucks;

P_1 : fixed costs per refrigerated truck;

P_2 : cost of transportation per unit of time;

P_3 : price per unit of product quality;

P_4 : cost per unit of refrigerant;

P_6 : unit cost of carbon emissions;

t_{ijk} : actual transport time of refrigerated truck k in section i, j;

t_{jk} : service time when refrigerator truck k is unloading for customer point j;

T_{ijk} : time for refrigerated truck k to complete the whole distribution process from customer point i to customer point j;

t_i : time of arrival of goods at customer point i;

q_j : demand for customer point j;

α_1 : rate of cargo damage per hour of transport process;

α_2 : rate of cargo damage per hour of unloading process;

Q_1 : heat load generated by heat inside and outside the carriage;

Q_2 : heat load generated by heat leakage from the carriage compartment;

β : heat leakage coefficient, usually taking on value in the range of [0.1,0.3];

Q_3 : heat load generated by opening doors during unloading;

μ : frequency factor of door opening;

V : refrigerated truck compartment volume;

$[E_i, L_i]$: time window for delivery of goods requested by customer i;

θ_1 : cost factor for damage to goods delivered by distribution vehicles earlier than the time specified in the time window;

θ_2 : penalty cost factor for delivery vehicles exceeding the time specified in the time window for delivery;

t_i : time of arrival of goods at customer point i;

ρ_0 : fuel consumption per unit distance at no load;

ρ_m : fuel consumption per unit distance at full load;

ε : carbon emission factor;

σ : carbon emission factor in the refrigeration process;

q_{ij} : refrigerator truck load when transporting between customer i and customer j;

$\rho(x)$: fuel consumption per unit distance;

a : constant factor;

b : constant value;

x_{ij}^k : 0-1 variable (when refrigerator truck k is transported on route i, j, $x_{ij}^k = 1$; otherwise, $x_{ij}^k = 0$);

y_i^k : 0-1 variable (when the refrigerator truck k is the distribution for customer point j, $y_i^k = 1$; otherwise, $y_i^k = 0$).

B. MODEL BUILDING

1) FIXED COSTS

The fixed costs in cold-chain logistics distribution mainly include the wages of vehicle drivers, maintenance costs for the loss or depreciation of refrigerated vehicles, and the usual vehicle preservation costs. Therefore, fixed cost C_1 is expressed as follows:

$$C_1 = mP_1 \tag{12}$$

2) TRANSPORTATION COSTS

In this study, the actual transportation time obtained from the road impedance function was used to calculate the transportation cost as follows:

$$C_2 = P_2 \sum_{k=1}^{m} \sum_{i=0}^{n} \sum_{j=0}^{n} t_{ijk} x_{ij}^k \tag{13}$$

3) COST OF CARGO DAMAGE

The cost of cargo loss in the cold-chain logistics distribution optimization model is determined by two main aspects. One is the actual transit time in the distribution, which is calculated from the road impedance function in the previous chapter. The second is the service time to unload the car door at the customer's point of arrival. Then the cost of goods damage is calculated using

$$C_3 = P_3\alpha_1 \sum_{k=1}^{m} \sum_{i=0}^{n} \sum_{j=0}^{n} x_{ij}^k \alpha_1 t_{ijk} q_j + P_3\alpha_2 \sum_{j=1}^{n} \sum_{k=1}^{m} y_j^k q_j t_{jk} \tag{14}$$

4) ENERGY CONSUMPTION COSTS

The cost of energy consumption is divided into the cost of cooling in transit and the cost of refrigerant consumed when opening the door during unloading. The heat load in the model is calculated using the empirical formula; that is, the heat load generated by the heat exchange inside and outside the refrigerated room is $Q_1 = RS\Delta T$ [27], where R is the heat transfer coefficient of the compartment, S is the average irradiated surface area of the compartment, and ΔT is the temperature difference between the inside and outside of the compartment. In addition to this, the heat load generated by the heat leakage from the compartment is $Q_2 = \beta Q_1$, where β is the heat leakage coefficient, usually taking on values in the range of $[0.1, 0.3]$.

The cooling costs incurred by the vehicle during transportation are as follows:

$$C_{41} = P_4 \sum_{k=1}^{m} \sum_{i=0}^{n} \sum_{j=0}^{n} x_{ij}^k (Q_1 + Q_2) t_{ijk} \tag{15}$$

The cooling costs incurred for unloading are

$$C_{42} = P_4 \sum_{k=1}^{m} \sum_{j=1}^{n} y_j^k Q_3 t_{jk} \tag{16}$$

In summary, the cooling costs for the entire distribution process are

$$C_4 = P_4 \sum_{k=1}^{m} \sum_{i=0}^{n} \sum_{j=0}^{n} x_{ij}^k (Q_1 + Q_2) t_{ijk} + P_4 \sum_{k=1}^{m} \sum_{j=1}^{n} y_j^k Q_3 t_{jk} \tag{17}$$

5) PENALTY COSTS

Because the freshness of cold-chain products is very demanding in terms of time. In terms of delivery, customers generally have certain restrictions on delivery time. There is a soft time window and a hard time window. This model selects soft time windows for calculation according to the actual situation of urban distribution. That is, the customer requires delivery within $[E_i, L_i]$ to describe the time window range. If delivered early, waiting costs are incurred. Penalty costs will be incurred if delivery is overdue. Therefore, the time penalty cost of this model is

$$C_5 = \theta_1 \sum_{i=1}^{n} \max(E_i - t_i, 0) + \theta_2 \sum_{i=1}^{n} \max(t_i - L_i, 0) \tag{18}$$

6) COST OF CARBON EMISSIONS

The cost of carbon emissions is mainly generated by the fuel consumption of refrigerator trucks on the transport road and vehicle cooling. In the transport process, fuel consumption is not only related to the transport distance but is also influenced by the amount of cargo carried. We selected the following approximate linear function between fuel consumption per unit distance and cargo capacity from the literature [37]:

$$\rho(x) = a(Q_0 + x) + b \tag{19}$$

By assuming that the maximum cargo capacity of the refrigerator truck is Q, the fuel consumption per unit distance when the refrigerator truck is empty and fully loaded, respectively, is given by

$$\rho_0 = a \times Q_0 + b \tag{20}$$

$$\rho_m = a(Q_0 + Q) + b \tag{21}$$

From Eqs. (20) and (21), we can see that $a = (\rho_m - \rho_0)/Q$ and $b = \rho_0 - aQ_0$. Substituting into Eq. (19) yields the formula for calculating fuel consumption per unit distance:

$$\rho(x) = \frac{\rho_m - \rho_0}{Q} x + \rho_0 \tag{22}$$

When the load transported between customer points i and j is $x = q_{ij}$, the fuel consumption per unit distance is

$$\rho(q_{ij}) = \frac{\rho_m - \rho_0}{Q} q_{ij} + \rho_0 \tag{23}$$

The carbon emissions in transit can be expressed as the product of fuel consumption per unit distance and a carbon emission factor as follows:

$$C_{61} = \varepsilon \rho(q_{ij}) d_{ij} \tag{24}$$

Carbon emissions from refrigeration equipment are linearly related to transport distance and cargo capacity [22]. The carbon emissions from refrigeration during the distribution process are given by

$$C_{62} = \sigma q_{ij} d_{ij} \tag{25}$$

In summary, the total carbon emission cost of the cold-chain logistics distribution process is:

$$C_6 = P_6 \sum_{k=1}^{m} \sum_{i=0}^{n} \sum_{j=0}^{n} x_{ij}^k \left(\varepsilon \rho(q_{ij}) + \sigma q_{ij}\right) d_{ij} \tag{26}$$

C. PATH OPTIMIZATION MODEL

By considering the impact of road impedance on the actual transportation time, the cold-chain logistics path optimization model with the objective of minimizing the total cost can be established as (27), shown at the bottom of the page.

The constraints that should be satisfied by this model are as (28)–(33), shown at the bottom of the page.

Equation (28) specifies that the number of distribution refrigerated trucks is equal to or greater than the number of distribution routes. Equation (29) specifies that each distribution refrigerator departs from the distribution center and must return to the distribution center after performing the distribution task. Equation (30) specifies that each customer can be served by only one refrigerated truck and only once. Equation (31) specifies that the total demand of customer points in each distribution path must not exceed the maximum

$$\begin{aligned}
\min C &= C_1 + C_2 + C_3 + C_4 + C_5 + C_6 \\
&= P_1 m + P_2 \sum_{k=1}^{m} \sum_{i=0}^{n} \sum_{j=0}^{n} t_{ij}^k x_{ij}^k + P_3 \alpha_1 \sum_{k=1}^{m} \sum_{i=0}^{n} \sum_{j=0}^{n} x_{ij}^k \alpha_1 t_{ij}^k q_j \\
&\quad + P_3 \alpha_2 \sum_{j=1}^{n} \sum_{k=1}^{m} y_j^k q_j t_j^k + P_4 \sum_{k=1}^{m} \sum_{i=0}^{n} \sum_{j=0}^{n} x_{ij}^k (Q_1 + Q_2) t_{ij}^k + P_4 \sum_{k=1}^{m} \sum_{j=1}^{n} y_j^k Q_3 t_j^k \\
&\quad + \theta_1 \sum_{i=1}^{n} \max(E_i - t_i, 0) + \theta_2 \sum_{i=1}^{n} \max(t_i - L_i, 0) \\
&\quad + P_6 \sum_{k=1}^{m} \sum_{i=0}^{n} \sum_{j=0}^{n} x_{ij}^k \left(\varepsilon \rho(q_{ij}) + \sigma q_{ij}\right) d_{ij}
\end{aligned} \tag{27}$$

$$\sum_{k=1}^{m} \sum_{i=1}^{n} x_{ij}^k \le m, \ i = 0 \tag{28}$$

$$\sum_{k=1}^{m} \sum_{j=1}^{n} x_{ij}^k = \sum_{k=1}^{m} \sum_{j=1}^{n} x_{ji}^k, \quad i = 0, k = 1, 2, \cdots, m \tag{29}$$

$$\sum_{k=1}^{m} y_i^k = 1, \quad i = 1, 2, \cdots, n \tag{30}$$

$$\sum_{i=1}^{n} q_i y_i^k \le Q, \mathrm{i} \ne j, \quad k = 1, 2, \cdots, m \tag{31}$$

$$\sum_{i=0}^{n} \sum_{j=0}^{n} d_{ij} x_{ij}^k \le D, \mathrm{i} \ne j, \quad k = 1, 2, \cdots, m \tag{32}$$

$$T_{ijk} = t_{ijk} + t_{jk} \tag{33}$$

TABLE 1. PSO specific steps.

Step	Motion	Specific practices
1	Initialization	Set the relevant parameters. Generate random positions and velocities of vehicle number particles and task order particles in *D*-dimensional space.
2	Evaluation of particles	According to the objective function, the objective value is calculated to find the optimal value of the particle population (Gbest) and the optimal value of each particle (Pbest).
3	Update optimal	(1) Compare the fitness of the particle with the optimal value of Pbest of each particle. If it is better than Pbest, then the position of Pbest is the current position of the particle. (2) Compare the fitness of the particle with the population optimum Gbest. If it is better than Gbest, then the position of Gbest is the current position of the particle.
4	Update particles	The velocity and position of the particle are updated according to Eq. (34)
5	Stop conditions	If the set maximum number of iterations is reached, the algorithm ends; otherwise, it returns to Step 2 for updating iterations.

carrying capacity of the refrigerator truck. Equation (32) specifies that the total distribution distance of each distribution path shall not exceed the refrigerator truck's maximum distribution distance.

Equation (33) specifies that the distribution process of each refrigerator truck is continuous.

V. ALGORITHM RESEARCH

A. PSO ALGORITHM

The PSO algorithm is straightforward and easy to implement. It converges quickly and has group search and cooperative search features. Consequently, it is widely used in solving VRPs. The specific steps of the PSO algorithm used to solve the logistics distribution path optimization problem are given in Table 1.

The standard PSO algorithm for updating the velocity and position of particles is formulated as

$$\begin{aligned} v_i(n+1) &= wv_i(n) + c_1 r_1 (p_i - x_i(n)) \\ &\quad + c_2 r_2 (p_g - x_i(n)) \\ x_i(n+1) &= x_i(n) + v_i(n) \end{aligned} \tag{34}$$

B. WEIGHT IMPROVEMENT OF THE PSO ALGORITHM

Although the standard PSO algorithm is an efficient and intelligent optimization algorithm, its development time has been short and there are still many aspects that need to be improved. The inertia weight w is the most important adjustable parameter in the PSO algorithm. A larger w can improve the global search capability, while a smaller w can enhance the local search capability. The weight improvement methods for linear decreasing weight PSO (LINWPSO), adaptive weight PSO (SAPSO), and random weight PSO (RANDWPSO) are described in the following.

1) LINWPSO

If the PSO falls into local convergence early on or generates oscillatory situations near the global optimal solution later on, LINWPSO can be used to solve this. The w-improved equation is

$$w = w_{\max} - t\frac{w_{\max} - w_{\min}}{t_{\max}} \tag{35}$$

2) SAPSO

The SAPSP formula can also be used to balance the local and global search capabilities of the algorithm as follows:

$$\begin{cases} w_{\min} - \dfrac{(w_{\max} - w_{\min})(f - f_{\min})}{f_{avg} - f_{\min}}, & f \le f_{avg} \\ w_{\max}, & f > f_{avg} \end{cases} \tag{36}$$

3) RANDWSPO

Setting random weights w obeying some random distribution of random numbers can overcome the deficiency caused by the linear decrease of w. The formulas are

$$\begin{cases} w = \mu + \sigma N(0,1) \\ \mu = \mu_{\min} + (\mu_{\max} - \mu_{\min}) rand(0,1) \end{cases} \tag{37}$$

VI. EXAMPLE ANALYSIS

A. DATA AND PARAMETER SETTINGS

The data for this study were obtained from the Dongpu Fresh Food Distribution Center and 20 Xindagang fresh food supermarket chains in the Tiexi District, Shenyang. First, the latitude and longitude coordinates and location information of the distribution center and the 20 fresh food supermarkets were obtained through the coordinate picker of Baidu Map [37]. Each fresh produce supermarket was further selected to collect and obtain demand information such as the specified time window, maximum daily fresh produce demand, and unloading service time in May. The relevant location and demand information is given in Table 2. In the first column of the table, 0 represents the distribution center, and 1–20 represents the fresh supermarket.

TABLE 2. Demand information of distribution centers and points.

Number	X coordinate (km)	*Y* coordinate (km)	Demand (kg)	Time windows	Service time (min)
0	123.322033	41.775686	0	4:00–14:00	0
1	123.530775	41.81187	479	5:00–8:00	24
2	123.429079	41.957566	480	5:00–8:00	25
3	123.413367	41.925223	488	5:00–8:00	24
4	123.468726	41.776575	481	5:00–8:00	25
5	123.368586	41.874804	490	5:00–8:00	24
6	123.368586	41.874804	466	5:00–8:00	25
7	123.396874	41.874563	489	5:00–8:00	25
8	123.433251	41.91999	477	5:00–8:00	25
9	123.411889	41.889406	493	5:00–8:00	24
10	123.494016	41.744811	486	5:00–8:00	24
11	123.437908	41.92918	484	5:00–8:00	25
12	123.246551	41.768033	490	5:00–8:00	24
13	123.404718	41.922767	475	5:00–8:00	24
14	123.439192	41.949909	483	5:00–8:00	25
15	123.38327	41.878438	482	5:00–8:00	25
16	123.412219	41.910454	493	5:00–8:00	24
17	123.412219	41.910454	476	5:00–8:00	25
18	123.412219	41.910454	482	5:00–8:00	24
19	123.407199	41.9502	481	5:00–8:00	24
20	123.595603	41.926237	487	5:00–8:00	24

In this study, the parameters related to the target model were obtained from other literature reports and based on practical assumptions. The data are given in Table 3.

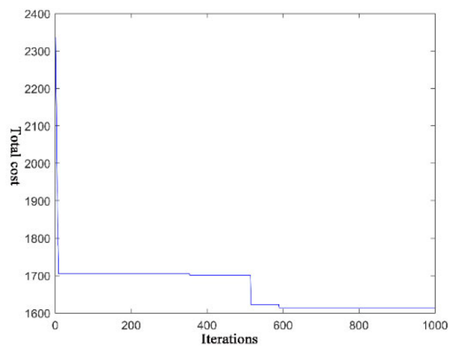

FIGURE 4. LINWPSO iteration diagram.

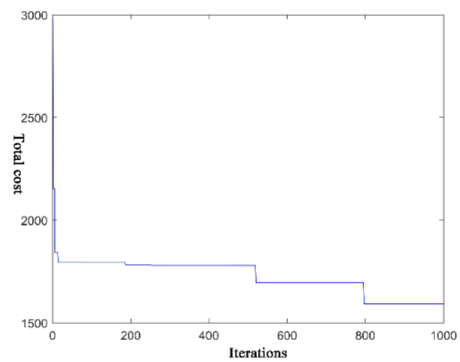

FIGURE 5. RANDWPSO iteration diagram.

In this study, the parameters related to the target model were obtained from other literature reports and based on practical assumptions. The data are given in Table 3.

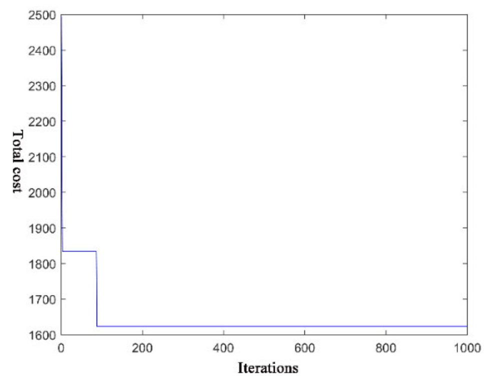

FIGURE 6. SAPSO iteration diagram.

B. ANALYSIS OF THE RESULTS

1) DIFFERENT PSO ALGORITHMS

The previous section introduced the basic principles of the PSO algorithm and improvements to the weight correlation. In this study, LINWPSO, RANDWPSO, and SAPSO were used. The above-established cold-chain logistics path optimization model considering the influence of road impedance was solved. The minimum total cost of the objective function was obtained by running the algorithm program for 1000 iterations separately through MATLAB software. The iterative plots of the total distribution cost for each algorithm are shown in Figs. 4–6. The LINWPSO algorithm can be seen in the iterative plots as the weights decrease linearly in the mid-iteration, leading to a decrease in the convergence rate. The iterative process of the RANDWPSO algorithm is not

TABLE 3. Objective-related parameters.

Parameter	Parameter value	Parameter	Parameter value
m	4veh	Q_1	280
n	20	Q_2	56
Q_0	5.3t	Q_3	129
Q	3 t	μ	0.5
D	400 km	V	4055×1940×1770 (mm)
P_1	100 yuan	θ_1	50 yuan/h
P_2	2 yuan/min	θ_2	90 yuan/h
P_3	5 yuan/kg	ε	2.61 kg/L
P_4	1.5 yuan/h	σ	2.61 kg/L
P_6	0.1 yuan/kg	K_j	125 vehicles/km
α_1	0.012	α_2	0.014

stable enough. Comprehensive comparison of the SAPSO algorithm's convergence speed and stability is better and thus more suitable for solving the target model of this study.

2) CONSIDERATION OF ROAD IMPEDANCE

For illustration purposes, the target model considering road impedance is considered as model A, and the target model not considering road impedance is considered as model B. According to the relevant data, the head distance was set at 2 m and the average length of the motor vehicle was set at 6 m. The theoretical blockage density K_j for a single lane was determined to be 125 vehicles/km through Baidu Map's real-time road development tool. By querying the nature of the roads between the stores of each Xindagang fresh supermarket in Shenyang, we derived average traffic density K values for different road properties. The actual transportation time between each customer point of model A was obtained from Eq. (11). The transportation time without the effect of road impedance was taken as the zero flow time; i.e., the actual transportation time of model B can be obtained by using the distance and speed between each customer point [37]. The optimal vehicle path and the minimum total cost of the two models were obtained by solving the SAPSO algorithm. The results are given in Tables 4 and 5.

A comparison between the costs of the two models in Tables 4 and 5 shows that Model A has higher transportation costs, damage costs, energy costs, and penalty costs relative to Model B. This is because the actual transport time calculated using the road impedance function is greater than the free transport time of model B. Moreover, all four costing methods of the target model in this study are related to transportation time. The carbon emission cost is mainly related to the load weight and transportation distance, so does not change much between the two models. However, the cost of carbon emissions accounts for a significant proportion of the total cost and therefore cannot be ignored in cold-chain logistics transportation.

The percentage difference between the total costs of model A and model B is 32.6%, which indicates that whether road impedance is considered in cold-chain logistics transportation has a great impact on the total cost. It is therefore necessary to consider the influence of road impedance on

TABLE 4. Optimal vehicle routing.

Vehicle number	Distribution route	
	Model A	Model B
1	0 → 1 → 16 → 10 → 0	0 → 1 → 18 → 0
2	0 → 20 → 19 → 12 → 18 → 8 → 0	0 → 3 → 9 → 14 → 0
3	0 → 9 → 15 → 17 → 13→ 0	0 → 20 → 11 → 4 → 10→ 0
4	0 → 6 → 7 → 14 → 2 → 3 → 11 → 0	0 → 6 → 17 → 5 → 2 → 13 → 12 → 0

TABLE 5. Optimal cost comparison.

Cost type (yuan)	Model A	Model B	Difference (%)
Total	1651.46	1245.49	32.6
Fixed	400	400	0
Transportation	280.14	196.49	42.6
Cargo damage	247.25	110.77	123.2
Energy	196.06	96.95	102.2
Penalty	293.73	193.55	51.8
Carbon emission	234.28	247.73	5.7

TABLE 6. Carbon emissions and total costs under different carbon taxes.

Carbon tax (yuan/kg)	Cost of carbon emissions (yuan)	Total costs (yuan)	Carbon emissions (kg)
0.01	1.31	1892.85	131
0.03	3.92	1892.46	130.66
0.05	6.51	1893.21	130.2
0.07	9.11	1895.68	130.14
0.09	11.71	1990.31	130.11
0.1	12.96	1993.32	129.6
0.2	24.22	2003.45	121.1
0.4	46.62	2026.83	116.56
0.6	69.44	2041.92	115.74
0.8	91.38	2061.21	114.23
1	101.86	2080.23	112.46

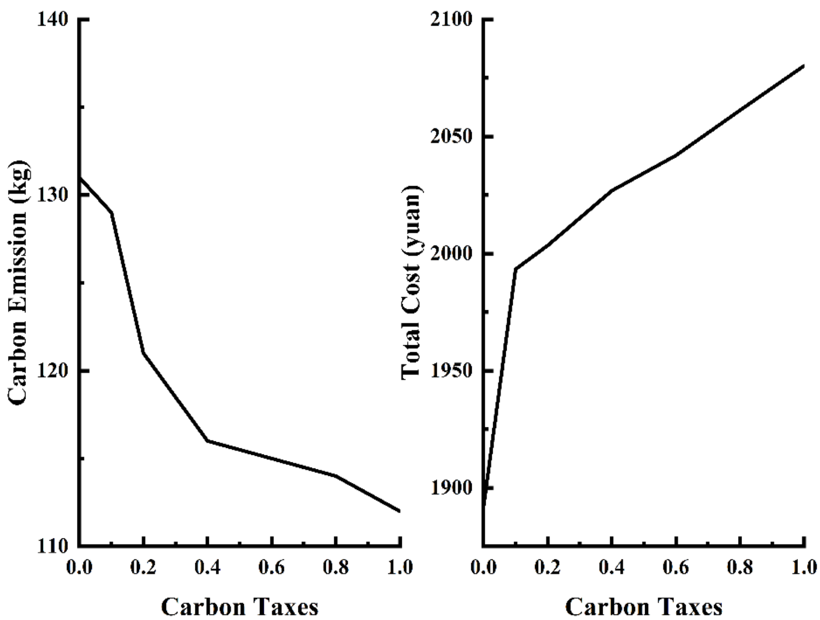

FIGURE 7. Trend of carbon emissions and total cost under different carbon taxes.

cold-chain transportation because it makes the transportation time more relevant to reality.

3) DIFFERENT CARBON TAXES

Different carbon tax values were selected in Model A. We separately solved for carbon emissions and associated costs. According to the current relevant policies and studies, the carbon tax value was selected in the range of [0.01,1]. The experimental results are given in Table 6. Figure 7 depicts the trend of carbon emission and total cost with carbon tax based on data analysis of the obtained results.

It can be seen from Table 6 that the cost of carbon emissions and the total cost both increase with the increase of carbon tax value, and carbon emissions decrease with the increase of carbon tax value. When the carbon tax value varies in the range of [0.01,0.1], the total cost increases slowly and the carbon emission reduction is not significant. Therefore, it has no control effect on energy saving and emission reduction in enterprise transportation. When the carbon tax value is taken in the range of [0.1,1], the total cost increase is greater and of similar magnitude. After the carbon tax value is >0.4, the carbon emission reduction rate is slow; therefore, 0.4 is considered the critical carbon tax value. That is, when the carbon tax value is in the range of [0.1, 0.4], enterprises need to pay attention to cost planning so that the economic and environmental benefits can be balanced and the sustainable development of green logistics can be promoted.

VII. CONCLUSION

With the increase of vehicle ownership in China, road traffic density in cities has increased, resulting in a greater impact of road transportation on cold-chain logistics and distribution. Therefore, the aim of this study is to improve the road impedance function and derive a road impedance function that is consistent with the current urban traffic environment. Toward that goal, we constructed an optimization model of the cold-chain logistics distribution path considering road impedance and compared it with the optimization model without considering the influence of road impedance. The results reveal that whether you consider road impedance has a strong influence on transportation costs, cargo damage costs, penalty costs, and energy costs. Therefore, the optimal distribution path planned by the objective model considering road impedance is closer to reality. It provides important guidance for cold-chain logistics and distribution enterprises. LINW-PSO, SAPSO, and RANDWPSO algorithms are adopted to solve the target model, respectively, and experimental results are analyzed to show that SAPSO is more suitable for the model. The experimental results under different carbon taxes are compared to analyze the range of carbon tax values for enterprises to control operating costs, save energy, and reduce emissions in environmental aspects of cold-chain logistics transportation.

Compared with existing studies, we considered the actual transportation time during the transportation process. An improved road impedance function was designed. In addition, we consider the cooling cost and carbon emission cost during transportation to make the model more reliable. We also take into account the time window constraint with penalty costs. The cold chain logistics path optimization model is constructed with the objective of minimizing the total cost. On this basis, the optimal cost under different carbon taxes is investigated. The carbon emissions and associated costs under different carbon taxes are solved separately. The trend in Figure 5 shows that when the carbon tax value is taken as [1, 0.1], the total cost increase is larger and of similar magnitude. After the carbon tax value is greater than 0.4, the reduction of carbon emissions is slow. Therefore, 0.4 is considered the critical carbon tax value. In view of the coordination between the current social economy and the environment, this paper uses the research on the scope of the carbon tax in path optimization to coordinate the balance between the cost and carbon emissions in logistics. It will maximize the attention of enterprises to cost planning and contribute to the sustainable development of logistics distribution. We produce that when the carbon tax value is in the range of [0.1, 0.4], which is the best range of carbon tax to advocate green logistics and can be used for reference by logistics enterprises.

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