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Optimisation Methods for Cold Chain Logistics Path Considering Carbon Emission Costs in Time-Varying Networks

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ABSTRACT

With the escalating global climate change, the cost of carbon emissions has become a crucial metric for evaluating the sustainability of logistics systems. This study addresses the optimisation of cold chain logistics routes in a time-varying network environment, considering the carbon emission cost factor, and proposes an enhanced particle swarm optimisation algorithm to solve this optimisation problem. Firstly, we establish a cold chain logistics optimisation model that incorporates the time-varying network, integrating logistics route planning with carbon emission costs. Subsequently, we design an improved particle swarm optimisation algorithm suitable for time-varying networks. This algorithm optimises vehicle routes and adjusts delivery times to minimise the total cost incurred during distribution. Finally, through simulation experiments, we analyse the impact of vehicle speeds and carbon trading mechanisms on optimisation outcomes. The results demonstrate that this method effectively optimises cold chain logistics routes, considering real network conditions and environmental factors, thereby reducing delivery costs and carbon emissions.

KEYWORDS

time-varying networks; carbon emission costs; cold chain logistics; path optimisation; improved particle swarm algorithm.

1. INTRODUCTION

The global logistics industry is continually evolving but is also facing increasingly serious environmental challenges. The carbon emissions generated during logistics activities have become a prominent issue of concern. Specifically, in the field of cold chain logistics, where transportation requires strict temperature and humidity controls and involves relatively high energy consumption, the issue of carbon emissions becomes more pronounced. According to a survey by "China Logistics and Purchasing", the cost of cold chain transportation is at least 80% higher than regular transportation, with cold chain costs accounting for 40% of the total costs. Additionally, the carbon emissions from cold chain transportation vehicles are at least 20% higher than those from regular transportation vehicles. These high costs and increased carbon emissions not only add to the operating expenses of logistics enterprises but also create significant pressure on environmental protection efforts [1].

With the increasing demands for environmental protection and sustainable development in society, governments and businesses are imposing stricter regulations on carbon emissions. Therefore, there is an urgent need to integrate carbon emission costs into logistics path planning optimisation. Zhu et al. [2] proposed a time-dependent green vehicle routing model that allows vehicles to wait at nodes to choose appropriate departure times to avoid congestion. This optimisation of transportation routes and departure times aims to reduce transportation costs and environmental pollution. Guo et al. [3] addressed the time-dependent effects of traffic congestion by establishing a green vehicle routing optimisation model for cold chain logistics with time windows. Ren et al. [4] considered customer satisfaction in cold chain distribution and developed a carbon emission minimisation model for vehicle routing optimisation. Chen [5] et al. introduced a practical energy consumption model incorporating factors such as comprehensive distance, load capacity and speed. They minimised the sum of fixed costs, energy costs and carbon trading costs as the optimisation objective, constructing a mixed integer programming model. Zhang et al. [6] proposed a multi-objective low-carbon multimodal transportation planning problem with fuzzy demands and fuzzy time, aiming to minimise costs and time while incorporating mandatory carbon emissions, carbon taxes, carbon trading and carbon offset policies. Chen et al. [7] studied cold chain logistics with pre-positioned warehouses, proposing a time-based green vehicle routing problem from the perspective of a low-carbon economy and introducing a hybrid simulated annealing and tabu search algorithm (HSATA) as a solution. Li et al. [8] proposed an integrated location-routing-inventory problem (LRIP) model considering carbon trading mechanisms, optimising costs related to locations, transportation, inventory and carbon trading, and improving the non-dominated sorting genetic algorithm II (NSGA-II) to solve the model. These studies investigate various approaches to low-carbon optimisation in cold chain logistics, including time-dependent green vehicle routing, carbon emission reduction and hybrid algorithm applications, to minimise transportation costs and environmental impact. The research offers innovative solutions and highlights the significance of optimising logistics routes within a low-carbon economy. However, these studies may not fully account for real-world traffic conditions and market dynamics, nor do they adequately address the impact of the latest carbon emission policies on logistics distribution strategies.

Research on the vehicle routing problem in cold chain logistics has attracted considerable attention from numerous scholars. Many researchers focus on hot topics such as cold chain technologies, delivery time windows and carbon emissions in cold chain logistics. Their studies concentrate on various logistics processes, including cold storage site selection, inventory management and cold chain transportation. Wu [9] and others, considering the high demand for service time from customers, introduced the concept of time tolerance and its quantification method. They developed a multi-objective optimisation model for cold chain logistics distribution paths with the goals of maximising customer time tolerance and minimising costs for cold chain logistics enterprises. Ren [10] incorporated customer satisfaction and road congestion into a mathematical model for cold chain vehicle routing optimisation aimed at minimising total costs, and they designed a new knowledge-based ant colony algorithm for solving it. Lian J [11] addressed the complexity of cold chain logistics networks by establishing a multi-objective optimisation model for cross-docking scheduling of cold chain logistics vehicle routes with fuzzy time windows. Li [12], considering customer satisfaction, constructed a multi-objective distribution path optimisation model aiming to minimise comprehensive distribution costs including cargo damage costs and penalty costs. Golman et al. [13] developed a nonlinear multi-objective model that simultaneously optimises warehouse facility locations and vehicle routes to maximise operational efficiency, reduce costs, improve risk management and enhance product quality, ultimately ensuring the optimal delivery of temperature-sensitive goods. Zhang [14], using a demand-user equilibrium model, considered logistics users' demands when selecting new and existing cold chain distribution centres to minimise costs for each logistics user, and then used a cloud particle swarm optimisation algorithm to solve this model. Overall, these research findings have played a crucial role in enhancing the environmental and economic efficiency of cold chain logistics systems. The studies emphasise diverse methodologies for optimising cold chain logistics, highlighting the integration of customer satisfaction, time constraints and operational efficiency. Each study offers profound insights into the complexities of cold chain logistics and proposes innovative solutions to address these challenges. However, they generally overlook the socio-economic impacts and the dynamic nature of environmental policies, as well as fail to adequately consider real-world traffic conditions and the impact of evolving carbon emission regulations on cold chain logistics.

Recent advancements in optimisation algorithms have significantly contributed to improving logistics systems across various dimensions. Huang et al. [15] developed a multi-factor constrained logistics centre location model and compared the results of layout optimisation using particle swarm optimisation and immune genetic algorithms. The findings indicate that the distribution of logistics centre locations and the coverage of freight demand obtained using the particle swarm optimisation algorithm is more balanced compared to those derived from other algorithms. Lu et al. [16] improved the grey wolf optimisation algorithm by incorporating superior point sets, dynamic adaptive inertia weights and memory-guided location update equations to solve a green transportation model considering carbon emission costs. The results indicate that the involvement of new energy logistics vehicles in long-distance transportation can reduce both costs and pollution. Md. et al. [17] proposed a novel hybrid metaheuristic algorithm that combines PSO with neighbourhood search to address the mixed fleet green clustered logistics problem under CO_2 emission caps. The results demonstrate that the proposed hybrid PSO outperforms the state-of-the-art algorithms available in the literature. Miao et al. [18] optimised the traditional ant colony algorithm by replacing the pheromone increment update function and proposed a time-window-constrained path optimisation model. This model offers new technical support for the path optimisation of cold chain distribution for perishable agricultural products. Collectively, these studies highlight the ongoing innovation and effectiveness of advanced optimisation techniques in addressing various challenges in logistics systems. However, further research is needed to explore the practical limitations, real-world applicability and potential integration issues of these algorithms in diverse logistical scenarios.

Dynamic networks can better reflect the dynamic changes in actual logistics networks, aligning more closely with the characteristics of real logistics transportation. However, in-depth research on optimising cold chain logistics paths considering carbon emission costs in dynamic networks is relatively limited. Addressing how to achieve path planning to minimise carbon emissions costs in dynamic networks and adapt to continually changing environmental conditions are urgent issues that need to be addressed. Therefore, this study aims to explore more environmentally friendly and economically efficient path planning solutions in the cold chain logistics industry, in response to increasingly stringent environmental regulations and societal demands for green logistics. Building upon previous research, this study makes the following contributions:

1) To reduce cold chain logistics distribution costs and carbon emissions, the study establishes a path optimisation model tailored for dynamic networks, considering carbon emission costs as one of the optimisation objectives. This model not only solves logistics path optimisation problems but also takes into account environmental protection and sustainable development considerations, providing new theoretical support for the green development of the logistics industry.
2) The study utilises a logistic chaos model and adaptive strategy to optimise the PSO algorithm, making it more suitable for handling dynamic problems. Introducing the logistic chaos model enhances the randomness and diversity of the algorithm, while the adaptive strategy dynamically adjusts algorithm parameters based on problem characteristics, thus improving algorithm convergence and robustness.
3) The proposed optimisation model is validated through case studies, demonstrating its feasibility and practicality in real cold chain logistics scenarios. Additionally, sensitivity analysis on multiple key parameters reveals the impact of different parameters on logistics distribution path selection, providing specific decision-making bases and optimisation recommendations for cold chain logistics management.

The structure of this paper is organised as follows. The first section provides a comprehensive review of the relevant literature, with a focus on the methodologies and frameworks used in previous studies and identifies their limitations. The second section defines the time-varying network and provides a detailed description of the research problem addressed in this study. The third section develops a path optimisation model incorporating carbon emission costs to better reflect practical routing scenarios. The fourth section presents improvements to the particle swarm optimisation algorithm to enhance its suitability for addressing the research problem. The fifth section presents the research results and validates the effectiveness of the proposed methods. The sixth section performs an effectiveness analysis, discussing the impact of various factors on the research outcomes and providing corresponding optimisation recommendations for enterprises. Finally, the seventh section summarises the main findings of the paper and suggests potential directions for future research.

2. PROBLEM DESCRIPTION AND ASSUMPTIONS

In cold chain logistics, optimising delivery routes under a time-varying network while considering carbon emission costs is particularly complex. The cold chain logistics system involves the transportation of temperature-sensitive goods, which requires maintaining specific environmental conditions throughout the supply chain. Variations in traffic patterns and congestion levels significantly impact the efficiency and cost-effectiveness of route planning. Additionally, incorporating carbon emission costs into the optimisation process further complicates the problem, as it necessitates balancing operational efficiency with environmental considerations. This section aims to detail the complexity of the problem, define the scope and objectives of the optimisation model, and highlight the key factors influencing decision-making in the given context.

2.1 Problem description

By incorporating unique characteristics of cold chain logistics into the classic vehicle routing problem (VRP) model, we consider factors such as carbon emissions from vehicle fuel consumption during transport, as well as node emissions generated when vehicles load and unload goods at each demand point. Given the perishable nature of fresh food in cold chain logistics, we also account for costs associated with product loss due to freshness degradation during transportation. Furthermore, we introduce penalty costs for early or late deliveries based on customer-expected delivery times. Customer satisfaction is deemed a critical metric, closely linked to delivery timing.

In this model, the demand volume and geographical coordinates of each customer point are known. Parameters such as vehicle maximum load capacity and fuel consumption per unit distance when fully loaded or empty are also provided. Our optimisation objective is to devise an optimal transportation plan that minimises costs while maximising customer satisfaction, considering delivery time constraints and other specified factors.

This article focuses on the situation of time-varying networks and divides time into w intervals based on the changing speed patterns caused by actual urban traffic congestion. Each time interval corresponds to a different speed, and the vehicle maintains a constant speed within each interval, as shown in *Figure 1*.

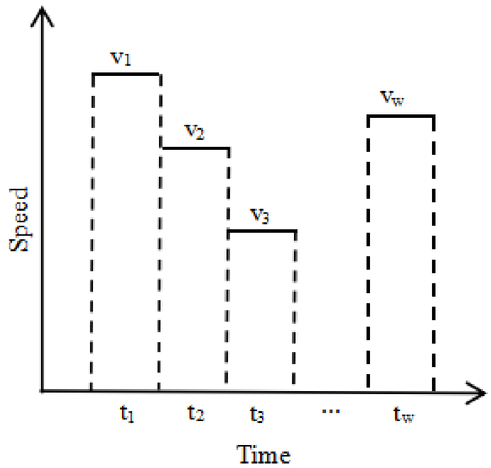

Figure 1 – Diagram of speed time variation

Due to varying distances between any two nodes, three scenarios may arise during deliveries:

1) Completing delivery tasks within a single time period.
The delivery task between two nodes within a single time period is considered fulfilled if the vehicle k has enough remaining time during that period to travel a distance greater than or equal to the actual distance between node i and node j. In this case, the delivery time for that route segment is expressed as *Equation 1*.

$$t_{ij} = \frac{d_{ij}}{v_w} \tag{1}$$

2) Completing a delivery task across two time periods.
To complete a delivery task spanning two time periods, the vehicle k must have remaining travel time within a specific time period such that the distance travelled is less than the actual distance between node i and node j. Additionally, in the next time period, the vehicle k must travel a distance greater than or equal to the remaining distance between node i and node j. The delivery time for this route segment is expressed as *Equation 2*.

$$t_{ij} = t_w - t_i + \frac{d_{ij} - v_w(t_w - t_i)}{v_{w+1}} \tag{2}$$

3) Complete delivery tasks across two or more time periods.
If vehicle k in a certain time period has remaining travel time such that the distance travelled is less than the actual distance between node i and node j, and in the next time period the distance travelled by vehicle k is also less than the remaining distance between node i and node j, then vehicle k needs to continue into a new time period repeatedly until the maximum distance travelled by vehicle k within the new time period is greater than or equal to the remaining distance between node i and node j. During this process, the

delivery time for this route segment is calculated based on the total time taken across these multiple time periods until the vehicle can successfully cover the remaining distance between node i and node j. At this time, the delivery time for this section is expressed as *Equation 3*.

$$t_{ij} = t_w - t_i + t_a(n-2) + \frac{d_{ij} - \sum_{r=1}^{n-1} t_a v_{w+r} - v_w(t_w - t_i)}{v_{w+n}} \quad (3)$$

2.2 Problem assumptions

1) Cold chain delivery vehicles *K* depart from a central distribution centre I_0 and must return to I_0 after completing assigned tasks within specified delivery time windows.
2) All refrigerated vehicles *K* from the distribution centre I_0 are of the same model with identical carrying capacities and refrigeration capabilities to maintain the required temperatures for goods.
3) All customer demands q are fulfilled by a single distribution centre I_0, which has sufficient inventory to meet the needs of all customers.
4) Each customer can only be served by one vehicle at a time, and vehicles must fully satisfy all customer demands during each service.
5) The total demand of customers on each distribution route is less than the rated load capacity of the refrigerated vehicles.
6) The distribution network consists of a single known distribution centre I_0 with adequate supply capacity.
7) The locations, service time windows and static demand volumes of all customer points are known in advance.
8) All customer points have specified time windows $[e_t, l_t]$ and $[E_t, L_t]$, and any arrival of delivery vehicles outside of these expected time windows incurs penalty costs f_1 or f_2.
9) The model accounts only for variations in travel speed over time due to changing traffic conditions and time-dependent road network dynamics, without considering other incidental events such as extreme weather, road construction or accidents.

3. COLD CHAIN LOGISTICS PATH OPTIMISATION MODEL

The definitions and explanations of the model symbols based on the problem descriptions are listed in *Table 1*.

Table 1 – Symbols variables definitions and explanations in the model

Symbols	Meanings
$I=\{0,1,2,...,n\}$, $i,j \in I$	Collection of distribution centres and customer points
$K=\{0,1,2,...,m\}$	Collection of delivery vehicles
C_0	Fixed cost of vehicles
E_{fue}	Fuel consumption of the vehicle at v_t
E_{bas}	Ideal fuel consumption of vehicles at optimal fuel efficiency
v_t	The actual driving speed of the vehicle at *t*
v_{bas}	Ideal speed of the vehicle at optimal fuel efficiency
d_{ij}	The distance from *i* to *j*
t_{ij}	Time required from *i* to *j*
P_{fue}	Fuel price
q_i	The demand for customer *i*
p0	Unit price of cold chain goods
$[e_t, l_t]$	Customer's expected delivery time

$[E_t, L_t]$	Acceptable delivery time for customers
f_1	The waiting cost per unit time for vehicles arriving early
f_2	The delay cost per unit time of delayed vehicle arrival
α	Carbon emissions per unit cooling time
β	Carbon emissions per unit of fuel consumption
a	Speed impact parameter
c	Cost per kilogram of carbon emissions
λ	Quality decline rate
Q	The maximum payload capacity of the refrigerated vehicles

The total fixed cost associated with dispatching each delivery vehicle includes one-time usage expenses such as vehicle acquisition costs, routine maintenance fees and driver wages, which remain constant and are independent of the vehicle's travel time or distance. The overall fixed cost can be calculated by multiplying the number of delivery vehicles by the fixed cost per vehicle. Therefore, the total fixed cost can be expressed as *Equation 4*.

$$C_1 = \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=1}^{m} C_0 \cdot x_{ijk} \tag{4}$$

In the context of a dynamic network, the transportation costs associated with refrigerated trucks primarily consist of fuel consumption, which is positively correlated with the vehicle's travel time, travel speed and travel distance. This paper focuses on studying the variation in vehicle speeds within a dynamic network. The fuel consumption model in a dynamic network is expressed as *Equation 5*.

$$E_{fue} = E_{bas} \cdot (1 + a(v_t - v_{bas})^2) \tag{5}$$

The total transportation cost can be represented as *Equation 6*.

$$C_2 = \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=1}^{m} d_{ij} \cdot E_{fue} \cdot P_{fue} \cdot x_{ijk} \tag{6}$$

In cold chain logistics transportation, product freshness deteriorates over time. Therefore, this study introduces a quality function to represent the freshness level of the products.

$$Q_t = Q_0 \cdot e^{-\lambda t} \tag{7}$$

In this context, Q_t represents the value of cold chain products at t, which decreases as time progresses. Q_0 represents the initial value of the product and also the quality decay rate. λ is reflecting the product's sensitivity to time.

The total cost of goods damage is expressed as *Equation 8.*

$$C_3 = \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=1}^{m} p_0 \cdot q_i \cdot \left(1 - e^{-\lambda t_{ij}}\right) \cdot y_{ik} \tag{8}$$

Due to the high timeliness requirement in cold chain logistics, customers typically schedule a specific time window for receiving their goods. In this study, a soft time window is defined, and if the delivery time falls outside of the acceptable service window for the customer, penalty costs will be incurred as exemplified in *Equation 9*.

$$C_5 = f_1 \sum_{i=1}^{n} max[(e_t - t_i), 0] + f_2 \sum_{i=1}^{n} max[(t_i - l_t), 0] \tag{9}$$

Logistics carbon emission costs refer to the costs associated with the carbon dioxide emissions generated by logistics companies during transportation activities. For cold chain logistics, carbon emission costs primarily consist of two parts: first, the carbon emissions produced during vehicle transportation, and second, the carbon emissions generated during refrigeration in the vehicle during transportation.

Emission cost of driving is expressed as *Equation 10*.

$$C_6 = \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{k=1}^{m} d_{ij} \cdot E_{ful} \cdot c \cdot \beta \cdot x_{ijk} \tag{10}$$

Refrigeration carbon emission cost is expressed as *Equation 11*.

$$C_7 = \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{k=1}^{m} \alpha \cdot t_{ij} \cdot c \cdot x_{ijk} \tag{11}$$

The cold chain logistics route optimisation model is as follows.

$$minC = C_1 + C_2 + C_3 + C_4 + C_5 + C_6 + C_7 \tag{12}$$

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

$$\sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{k=1}^{m} x_{ijk} \leq m \tag{14}$$

$$\sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{k=1}^{m} x_{ijk} = \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{k=1}^{m} x_{jik} \tag{15}$$

$$\sum_{i=0}^{n} \sum_{k=1}^{m} q_i y_{ik} \leq Q \tag{16}$$

$$E_t \leq t_i \leq L_t \tag{17}$$

$$x_{ijk} \begin{cases} 1, vehicle\ from\ customer\ i\ to\ j \\ 0,\ \text{otherwise} \end{cases} \tag{18}$$

$$y_{ik} \begin{cases} 1, \text{Vehicle } k \text{ serves customer } i \\ 0,\ \text{otherwise} \end{cases} \tag{19}$$

Equation 12 represents the total delivery cost. *Equation 13* indicates that each customer can only be served by one vehicle. *Equation 14* states that the total number of participating vehicles in the delivery process cannot exceed the total number of vehicles available. *Equation 15* specifies that vehicles depart from and return to the distribution centre. *Equation 16* ensures that the total demand of customers on each route does not exceed the maximum load capacity of the vehicles. *Equation 17* ensures that each vehicle arrives at customers' locations within their acceptable time windows. *Equations 18* and *Equations 19* represent the summation constraints for two binary decision variables.

4. ALGORITHM DESIGN

Particle swarm optimisation (PSO) algorithm possesses several advantages when applied to logistics route optimisation problems, including strong global search capability, dynamic adjustment strategies, suitability for multi-objective optimisation, simplicity in implementation and robust adaptability [19].

The formula for updating particle velocity and position is as exemplified in *Equation 20* and *Equation 21*.

$$v_{i,j}^{t+1} = \omega^t v_{i,j}^t + c_1 r_1 (p_{i,j}^t - x_{i,j}^t) + c_2 r_2 (g_{i,j}^t - x_{i,j}^t) \tag{20}$$

$$x_{i,j}^{t+1} = x_{i,j}^{t} + v_{i,j}^{t+1} \tag{21}$$

$v_{i,j}^{t}$ is the velocity of the i-th particle in the t-th generation at the j-th dimension, and $x_{i,j}^{t}$ is the position of the i-th particle in the t-th generation at the j-th dimension, $r_1$and $r_2$are two random numbers between [0,1], ω^t is the inertia weight, c_1 and c_2 are learning factors, $p_{i,j}^t$ and $g_{i,j}^t$ best represent the j-th dimension of the personal best solution of the i-th particle in the t-th generation and the global best solution, respectively.

PSO algorithm's performance heavily relies on the values of parameters such as inertia weight and learning factor, which play crucial roles in its convergence behaviour. Researchers typically use conventional values for these parameters, but this can potentially affect the algorithm's convergence and convergence speed. Similarly, the initialisation process also significantly impacts the accuracy and speed of the algorithm. Non-uniform distribution of the solution space often leads to falling into local optima [20].

4.1 Chaos initialisation

Traditional particle swarm algorithms generally use random initialisation to determine the initial distribution of positions for the population. This involves generating random numbers using a computer and then randomly generating the initial positions of each particle according to *Equation 22*.

$$Posituins = rand \cdot (ub - lb) + lb \tag{22}$$

Positions representative particle positions generated; *rand* representative generated random numbers, values within the range [0, 1]; *ub, lb* respectively representing the upper and lower bounds of the solution space.

Typically, random initialisation can generate different initial populations each time, making it convenient to use. However, this method has a drawback: the initial particles are unevenly distributed in the solution space, resulting in some regions being too densely populated while others are too sparse. This uneven distribution harms early convergence in optimisation algorithms, particularly swarm algorithms prone to local optima, potentially decreasing convergence speed or causing failure to converge.

In contrast, chaotic initialisation can effectively avoid these problems. Chaotic initialisation exhibits randomness, thoroughness and regularity. It traverses the search space according to its own rules within a certain range, thus generating initial populations that show significant improvements in solution accuracy and convergence speed.

Chaotic initialisation significantly enhances PSO by providing a well-distributed initial population, improving global search capabilities, accelerating convergence, optimising search space coverage, increasing robustness and maintaining solution diversity. By incorporating chaotic sequences, PSO algorithms can achieve more reliable and efficient optimisation, especially for complex and high-dimensional problems. This approach ensures that the algorithm is better equipped to handle a variety of optimisation challenges, leading to improved performance and more accurate solutions [21].

This article uses the logistic chaotic model for initialisation. The formula for the logistic chaotic model is represented in *Equation 23*.

$$x_{k+1} = \lambda \times x_k(1 - x_k), \lambda \in (0,4) \tag{23}$$

The parameter $\boldsymbol{\lambda}$ in the chaotic model mapping represents the control parameter. If $\boldsymbol{\lambda}$ is in the range [3.57,4], then the system is in a chaotic state; if $\boldsymbol{\lambda}$ =4, the system is in a fully chaotic state. Typically, $\boldsymbol{\lambda}$ is commonly set to 4.

4.2 Adaptive inertia weight

The impact of the inertia weight factor on PSO performance is significant. When the inertia weight factor is large, it benefits global exploration, helping the algorithm to discover potential optimal solutions. Conversely, when the inertia weight factor is small, it accelerates the convergence of the algorithm, promoting detailed local optimisation and aiding in finding more precise optimal solutions.

To balance the global search capability and local refinement ability of PSO, researchers have proposed the use of nonlinear dynamic inertia weight coefficient formulas [22]. These formulas dynamically adjust the value of the inertia weight based on the current state of the algorithm, allowing for a better balance between global exploration and local optimisation needs at different stages.

Specifically, nonlinear dynamic inertia weight coefficient formulas adjust the inertia weight based on iteration count or other algorithmic variables, adapting to optimisation needs at different stages.

Adaptive strategies significantly enhance the performance of PSO by dynamically adjusting parameters, improving convergence speed, enhancing both global and local search capabilities, increasing robustness, maintaining solution diversity and improving algorithm adaptability. By effectively applying adaptive strategies, PSO can better tackle complex optimisation problems, find high-quality solutions and maintain stable performance across different problems and environments.

The expression for this dynamic inertia weight coefficient formula is *Equation 24*.

$$\omega = \begin{cases} \omega_{min} - \dfrac{(\omega_{max} - \omega_{min}) \cdot (f - f_{min})}{f_{avg} - f_{min}} \\ \omega_{max}, f > f_{avg} \end{cases} \tag{24}$$

In the formula above, f represents the real-time objective function value of a particle, f_{avg} represents the current average objective value of all particles and f_{min} represents the current minimum objective value among all particles, ω_{max} is maximum inertia weight, ω_{min} is minimum inertia weight, and it can be seen that the inertia weight changes with the variation in the particle's objective function value.

4.3 Dynamic learning factors

In the standard particle swarm optimisation (PSO) algorithm, the learning factors c_1 and c_2 are key parameters that represent the individual cognitive and social learning characteristics of the particles in the swarm. Specifically, the learning factor c_1 signifies a particle's focus on its own historical best position, reflecting the component where a particle learns from its own experience. On the other hand, the learning factor c_2 indicates the extent to which a particle learns towards the global best position, reflecting the degree of learning from the overall swarm's experience towards the global optimum.

During the execution of the particle swarm algorithm, to achieve a broad exploration of the solution space and increase the diversity of particles at the beginning stage, it is advisable to set a larger value for c_1 and a smaller value for c_2. This encourages particles to focus more on local exploration, thereby aiding in exploring the overall search space.

However, as the algorithm progresses to ensure that particles converge rapidly and accurately towards the global optimum, it is necessary to adjust the values of the learning factors. Therefore, typically in the later stages of the algorithm, c_1 should be set to a smaller value while c_2 should be set to a larger value. This encourages particles to actively converge towards the global best position, speeding up the convergence rate and improving precision.

To implement this dynamic adjustment strategy, a strategy is adopted where c_1 is set as a monotonically decreasing function, while c_2 is set as a monotonically increasing function. This design enables learning factors to adapt with iteration count, balancing exploration and exploitation capabilities and thus improving the performance and convergence of the particle swarm algorithm.

$$c_1 = 2sin^2\left[\frac{\pi}{2}\left(1 - \frac{t}{T_{max}}\right)\right] \tag{25}$$

$$c_2 = 2sin^2\left(\frac{\pi t}{2T_{max}}\right) \tag{26}$$

t represents the current iteration number and T_{max} is the maximum number of iterations for the particle swarm. By dynamically adjusting learning factor values, the algorithm facilitates rapid exploration towards optimal values in the early stages and enables quick, accurate convergence to the optimal solution in later stages.

The steps for improving the particle swarm algorithm are shown in *Figure 2*.

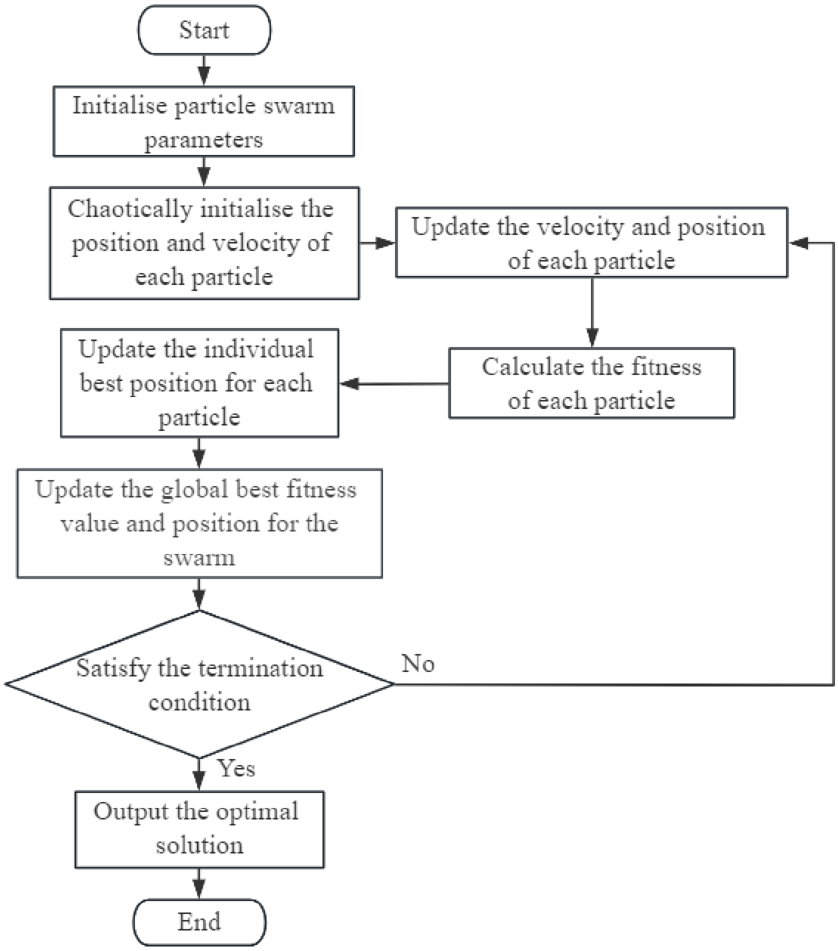

Figure 2 – Steps to improve particle swarm optimisation algorithm

5. CASE ANALYSIS

5.1 Case background introduction

To validate the applicability of the model and algorithm, we simulated a city distribution scenario consisting of 1 distribution centre and 100 customers. The data for the distribution centre, customers and vehicle information were obtained from the C109 test dataset provided by Solomon, which is known for its absence of significant congestion. However, the original dataset used hard time windows, whereas our study required consideration of soft time windows. Therefore, we scaled up the time windows in the dataset by a factor of 1.2 to simulate the setting of hard time windows [23]. This setting provides additional time beyond the strict hard time window requirements to accommodate potential delays while maintaining flexibility and control over deliveries. Such a configuration is commonly used and reasonable, as it helps to efficiently manage deliveries while mitigating potential issues caused by unpredictable factors.

To simulate road congestion conditions, we referenced the daily city road congestion index released by AMAP and converted it into average speeds for different time intervals. The formula is as follows.

$$V_{instant} = \theta \cdot V_{free} \tag{27}$$

$V_{instant}$ represents the actual driving speed, θ is the traffic congestion index and V_{free} is the free flow speed.

In this study, Shanghai was selected as a sample for road congestion variation, focusing on the time period from 6:00 AM to 12:00 PM on 6 September 2023, divided into 30-minute time intervals. The data of road average speeds are shown in *Figure 2*. This simulated environment provides a better reflection of real-world time constraints and road congestion in urban distribution scenarios, further validating the applicability and effectiveness of our proposed model and algorithm in practical applications. The average speed data are shown in *Figure 3*.

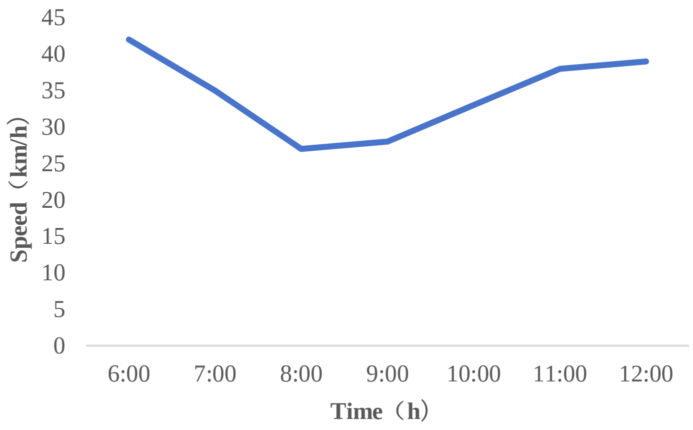

Figure 3 – The vehicle driving speeds from 6:00 AM to 12:00 PM

The delivery centre vehicles depart every morning at 7:00 AM. Assuming that the refrigerated distribution vehicles are fully loaded at departure, we consulted current carbon trading data from China's 9 major pilot carbon markets and the national carbon market. We have decided to set the carbon emission cost at 0.1 yuan per kilogram. The default carbon emission quota is set to zero. Relevant parameters are shown in *Table 2*.

Table 2 – The values of the relevant parameters

Symbols	Values	Units
C_0	400	¥
E_{bas}	0.15	L/km
V_{Bas}	90	km/h
α	0.3	kg/h
β	2.7	kg/L
c	0.1	¥/kg
P_{fue}	7.65	¥/L
Q	5	t
f_1	20	¥/h
f_2	30	¥/h
p_0	5000	¥/t
λ	0.2	/

5.2 Optimisation results

Using the above case study, we conducted simulations and optimisations using PSO and improved PSO with the assistance of MATLAB 2021a. The algorithm parameters were set as follows: number of particles N=50, ω_{max}=0.9, ω_{min}=0.4 and maximum iterations T=500.

The optimised delivery routes using improved PSO are shown in *Figure 4*, while those using PSO are shown in *Figure 5*. The vehicle distribution plans optimised using improved PSO are presented in *Table 3*, and those using PSO are shown in *Table 4*. A comparison of the optimisation results of both algorithms is summarised in *Table 5*. The improved PSO algorithm required 263.76 seconds to complete, while the PSO algorithm took 326.83 seconds.

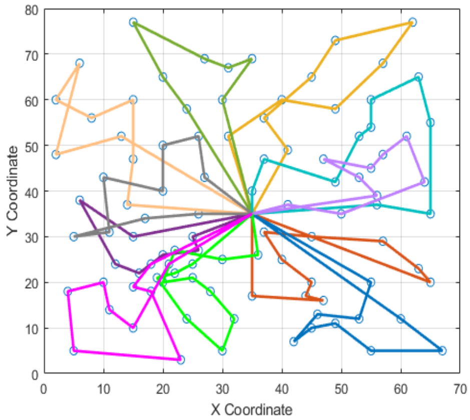

Figure 4 – Improved PSO optimisation results

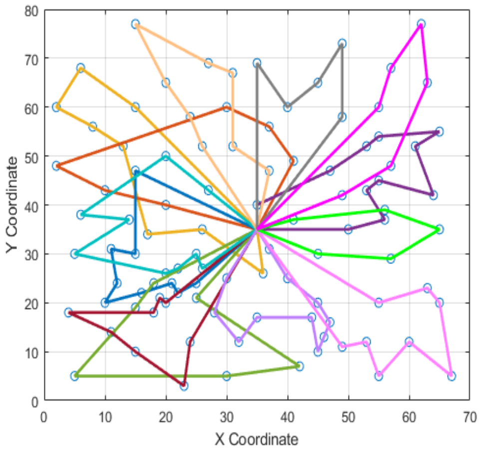

Figure 5 – PSO optimisation results

Table 3 – Optimised vehicle distribution routes using improved PSO

Vehicle	Path
1	0-1-70-20-66-65-71-51-30-31-0
2	0-2-72-73-21-40-53-26-54-55-25-0
3	0-4-56-74-41-22-75-23-67-39-0
4	0-5-45-61-85-99-94-6-0
5	0-10-32-90-63-64-11-62-0
6	0-27-69-76-33-81-9-35-34-24-80-0
7	0-28-12-29-78-79-3-50-77-68-0
8	0-48-46-49-36-47-19-82-83-0
9	0-52-88-7-18-8-84-17-60-89-0
10	0-58-13-96-37-97-87-57-15-42-98-92-95-0
11	0-59-14-44-16-86-38-43-100-91-93-0

Table 4 – Optimised vehicle distribution routes using PSO

Vehicle	Path
1	0-1-70-10-46-8-18-0
2	0-4-55-25-67-39-23-56-75-0
3	0-9-71-65-35-79-76-0
4	0-12-80-77-3-29-78-34-81-33-50-27-0
5	0-13-87-57-2-73-22-74-72-21-40-53-0
6	0-19-49-36-47-48-60-89-58-0
7	0-26-54-24-68-28-0
8	0-32-30-20-66-51-0
9	0-37-98-100-86-44-14-43-42-0
10	0-52-7-45-83-17-99-96-6-94-0
11	0-69-31-90-63-64-11-62-88-0
12	0-82-5-84-61-16-85-59-92-95-0
13	0-93-91-38-15-41-97-0

Table 5 – Comparison of algorithm optimisation costs

Algorithm	Fixed cost	Transportation cost	Goods damage cost	Carbon emission cost	Time window cost	Total cost
PSO	5200	3426.3	2362.9	398.5	3173.7	14561.4
Improved PSO	4400	3059.2	2128.8	360.1	2897.1	12845.2

The results from the figure demonstrate the significant advantages of the improved PSO algorithm in optimising distribution routes. Firstly, the algorithm effectively reduces the number of required vehicles, substantially minimising the utilisation of transportation resources. Moreover, the number of route intersections is significantly reduced, enhancing the overall rationality of route planning and mitigating potential risks of traffic congestion and delivery delays. Additionally, the total travel distance is further shortened, directly contributing to lower fuel consumption and transportation costs. Most importantly, the overall distribution efficiency is greatly improved, ensuring that delivery tasks are completed at a lower cost while meeting demand. These findings underscore the strong potential and practical value of the algorithm in logistics optimisation.

6. ANALYSIS OF MODEL EFFECTIVENESS

6.1 Impact of vehicle speed on delivery outcomes

To validate the necessity and effectiveness of considering time-varying networks in this study, while keeping all other model parameters constant, we compared and analysed the solution results of the model by adjusting the vehicle speeds. The vehicle speeds in the two static networks were assumed to be 30 km/h and 50 km/h, respectively. The solutions were then obtained based on these two static networks as well as the time-varying network, and the results are presented and compared in *Table 6* for analysis.

Table 6 – Solution results of the model in static and time-varying networks

Speed (km/h)	Number of vehicles	Delivery time (min)	Total cost
Time-varying speed	11	291	12845.2
30	11	354	14968.7
50	11	268	11238.4

Observing the table, it is evident that fixing the vehicle's travelling speed to a static value significantly affects the total delivery cost and mileage, without adjusting the number of vehicles. Specifically, when the vehicle's speed is set at 30 km/h, both the total delivery cost and mileage are lower compared to those in the time-varying network. However, when the vehicle's speed is increased to 50 km/h, the total mileage and cost of delivery exceed the corresponding values in the time-varying network.

This demonstrates that logistics companies can adopt flexible operational strategies when dealing with varying congestion levels across different cities or regions. For instance, in heavily congested urban areas, companies may opt for lower delivery speeds to mitigate the volatility caused by traffic conditions. Conversely, in regions with smoother traffic flow, higher speeds can be employed to capitalise on off-peak periods, thereby improving efficiency. Furthermore, companies could implement dynamic speed adjustments, leveraging real-time traffic data to optimise delivery routes, which would further reduce costs and enhance operational efficiency. By tailoring strategies to different congestion patterns, companies not only optimise their operations but also develop adaptive solutions aligned with specific urban traffic conditions, thereby enhancing their overall competitiveness.

6.2 Impact of carbon emission quotas on delivery outcomes

To study the impact of different carbon trading quotas held by enterprises on the objective function of the model, this paper assigns various carbon trading quotas to cold chain logistics distribution companies and investigates their influence on operational costs in cold chain logistics distribution. By conducting a sensitivity analysis on the total distribution costs under different carbon trading quotas, we get the results in *Figure 6*.

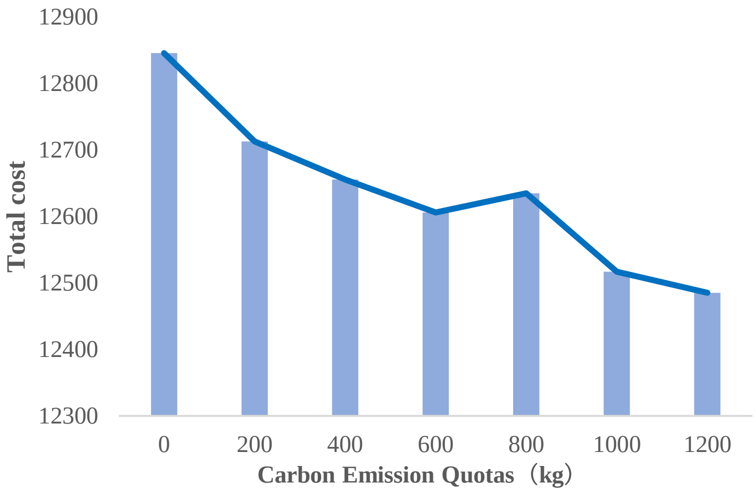

Figure 6 – Graph of total logistics costs variation under different carbon quotas

From the observations in the graph, it can be noted that as the carbon quota increases, the total cost of cold chain logistics exhibits an overall trend of gradual decrease despite fluctuations. Research findings indicate that the amount of carbon emission allowances a company obtains significantly influences the overall distribution costs.

When carbon emissions are relatively low, companies can adopt optimised transportation routes to shorten delivery times, thus achieving cost savings. Conversely, with a surplus of carbon quotas, companies can sell excess allowances on the carbon trading market to gain additional profits and offset costs, thereby reducing the total expenses of cold chain logistics. These findings provide crucial economic strategic directions for companies, enabling them to flexibly adjust distribution strategies based on varying carbon quota levels, optimising costs and securing additional profits.

6.3 Impact of carbon trading prices on distribution outcomes

To investigate the impact of carbon emission prices on distribution outcomes, the results under two different carbon trading prices of 0.5 ¥/kg and 1 ¥/kg are compared while keeping all other model parameters constant, as shown in *Table 7*.

Table 7 – Model solution results at different carbon emission prices

Unit carbon price	Number of vehicles	Carbon emission cost	Total cost
0.1	11	360.1	12845.2
0.5	11	1689.4	14157.4
1	11	3429.1	15894.7

The table shows that as the carbon price increases to 0.5 ¥/kg, the number of vehicles remains unchanged, while total costs rise by 10.22%. When the carbon price reaches 1 yuan/kg, the number of vehicles remains constant, but total costs increase by 23.74%. This trend is primarily due to the direct impact of rising carbon emission prices on overall transportation costs. For logistics companies, this indicates that operational costs will increase significantly with the rise in carbon prices, which could negatively affect profit margins and market competitiveness.

To address this challenge, logistics companies may adopt several strategies to mitigate the financial impact of rising carbon prices. Firstly, companies can improve transportation efficiency by optimising distribution routes, enhancing vehicle utilisation and reducing empty mileage, thereby lowering carbon emissions. Secondly, the gradual introduction of low-carbon or zero-carbon vehicles, such as electric or hydrogen fuel cell vehicles, could be a viable long-term solution, despite the higher initial investment. This would effectively reduce cost increases caused by higher carbon prices over time. Additionally, companies could engage in carbon trading markets or purchase carbon offset credits to alleviate the direct impact of rising carbon prices on operations. Lastly, fostering collaboration across the supply chain to promote green logistics and sustainability would not only help reduce emissions but also enhance brand image and market competitiveness.

In conclusion, while the rise in carbon prices presents new challenges to the cost structure of logistics companies, adopting appropriate strategies can not only help companies navigate these challenges but also offer long-term competitive advantages in the transition to a low-carbon economy.

7. CONCLUSION

This study establishes an optimisation model for cold chain logistics paths based on time-varying networks and carbon emission costs. The model employs an enhanced particle swarm optimisation (PSO) algorithm and investigates the impacts of vehicle speed and carbon trading mechanisms on optimisation outcomes. The results indicate that the improved PSO algorithm performs effectively in addressing cold chain logistics path optimisation considering carbon emission costs. Compared to traditional algorithms, our approach significantly reduces carbon emission costs, optimises delivery routes and enhances logistics efficiency. Vehicle speed notably influences delivery outcomes. Adjusting vehicle speed can further lower carbon emission costs while meeting time window and cargo requirements, making it an effective strategy for emission reduction. Additionally, carbon trading mechanisms significantly affect optimisation results by encouraging logistics companies to cut emissions and supporting sustainable development in the cold chain logistics sector.

In summary, this study proposes a time-varying network cold chain logistics path optimisation model based on an improved PSO algorithm. Analysis incorporating vehicle speed and carbon trading mechanisms provides new insights and methods for reducing carbon emission costs, optimising logistics routes and improving resource utilisation. Future research could explore more complex scenarios and constraints to improve the model's practicality and generalisability, thereby advancing the integration of carbon reduction and logistics efficiency.

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王泽宇，陈富坚，莫程程

时变网络下考虑碳排放成本的冷链物流路径优化方法研究

摘要

随着全球气候变化问题的日益严峻，碳排放成本已成为衡量物流系统可持续性的重要指标。本文针对时变网络环境下的冷链物流路径优化问题，提出了

一种基于碳排放成本的改进粒子群优化算法。首先，构建了一个综合考虑时变网络和碳排放成本的冷链物流优化模型，将物流路径规划与碳排放成本有效融合。随后，设计了一种适用于时变网络环境的改进粒子群优化算法，该算法通过优化车辆路径和调整配送时间，实现配送过程中的总成本最小化。最后，通过仿真实验，深入分析了车辆速度和碳交易机制对优化结果的影响。实验结果表明，该方法能够在真实网络条件和环境因素下，显著优化冷链物流路径，有效降低配送成本和碳排放。

关键词
时变网络；碳排放成本；冷链物流；路径优化；改进粒子群算法。