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Research on Cold Chain Logistics Distribution Path Optimization of Fresh E-commerce Considering Carbon Cost and Time Window

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ABSTRACT

Driven by the booming development of digital retail, fresh food e-commerce has expanded rapidly in recent years, while its supporting cold chain logistics system still faces prominent operational problems, including unreasonable route planning, high comprehensive distribution costs, excessive product spoilage, and substantial carbon emissions. To address the multi-constraint and multi-objective optimization characteristics of fresh food last-mile distribution, this study constructs a comprehensive cold chain distribution path optimization model that integrates transportation cost, perishable loss cost, hybrid time window penalty cost, and carbon emission cost. On this basis, an improved adaptive genetic algorithm (IAGA) is proposed to solve the established model, which dynamically adjusts crossover and mutation probabilities during iterations and effectively overcomes the premature convergence and local optimal defects of the traditional genetic algorithm (TGA). Numerical simulation and comparative experiments based on real-world fresh e-commerce distribution scenarios are conducted. The results demonstrate that the proposed model and algorithm can significantly reduce total distribution costs, cut carbon emissions, and mitigate time penalty losses, thereby improving the overall operational efficiency and low-carbon sustainability of cold chain distribution systems. This research provides a reliable theoretical reference and practical operational strategy for refined and green path scheduling management of fresh cold chain logistics enterprises.

KEYWORDS

Cold Chain Logistics; Path Optimization; Adaptive Genetic Algorithm; Carbon Emission Cost; Time Window Constraint; Fresh E-commerce

1. INTRODUCTION

With the continuous upgrading of consumer demand and the rapid penetration of digital commerce, fresh e-commerce has become a core growth track in the modern service industry. Different from general commodity logistics, fresh products are characterized by high perishability, short shelf life, and strict timeliness requirements, which impose higher standards on the efficiency, stability, and environmental performance of cold chain distribution. As the core link of fresh e-commerce operations, terminal distribution path planning directly determines enterprise operating costs, product loss rates, and customer service satisfaction, playing a decisive role in the sustainable development of fresh cold chain logistics.

Nevertheless, the current terminal distribution mode of most fresh cold chain enterprises remains empirical and fixed. Static path scheduling fails to adapt to dynamic customer time window demands and actual operational conditions, resulting in redundant driving routes and repeated distribution routes. Such unreasonable planning not only increases vehicle transportation consumption and fresh product spoilage losses but also generates massive carbon emissions, which contradicts China's dual-carbon strategic goals and the green transformation trend of the logistics industry. Therefore, it is urgent to construct a systematic multi-objective optimization model to balance the economic benefits and environmental benefits of fresh cold chain distribution.

In terms of theoretical research, existing studies have achieved fruitful results in logistics path optimization. However, most previous works still have certain limitations. First, the majority of optimization models only take single objectives such as the shortest driving distance or minimum transportation cost as the optimization goal, ignoring the coupled constraints of personalized customer time windows and dynamic fresh product loss. Second, current low-carbon logistics research mostly separates carbon emission calculation from cost accounting, failing to incorporate carbon cost into the comprehensive cost system, which reduces the practical guiding value of the model. Third, traditional intelligent optimization algorithms suffer from fixed parameter settings in iterative processes, which easily lead to slow convergence and local optimal solutions in solving multi-constraint complex problems.

To fill the above research gaps, this paper establishes a multi-dimensional comprehensive cost optimization model that fully considers transportation cost, fresh food loss cost, hybrid soft and hard time window penalty cost, and carbon emission cost. An improved adaptive genetic algorithm with dynamic parameter adjustment is designed to enhance the model's solving accuracy and stability. Through numerical simulation and comparative analysis with traditional algorithms, the superiority of the proposed method in cost reduction, carbon emission abatement, and timeliness improvement is verified. The research findings can provide scientific decision-making support for the refined, efficient, and low-carbon operation of fresh e-commerce cold chain logistics.

2. LITERATURE REVIEW

2.1. Research on Cold Chain Logistics Path Optimization

Cold chain path optimization has always been a core research hotspot in the field of industrial engineering and logistics operation management. Scholars have explored vehicle routing optimization problems for fresh logistics from multiple perspectives of scenario application and constraint setting. In practical application research, existing studies have verified that scientific path scheduling can effectively reduce fresh product spoilage and improve terminal distribution efficiency. In terms of constraint conditions, most current models take vehicle load capacity, driving distance, and basic distribution time as conventional constraints. However, most studies simplify customer time window settings and fail to distinguish soft and hard time window mechanisms, which cannot adapt to the personalized delivery time requirements of e-commerce customers. Moreover, few studies incorporate the time-varying spoilage characteristics of fresh products into path optimization models, leading to obvious deviations between theoretical results and actual distribution scenarios.

2.2. Research on Low-Carbon Logistics and Comprehensive Cost Management

Against the background of global carbon neutrality goals and domestic green logistics transformation, low-carbon optimization has become an indispensable direction of modern logistics research. Relevant studies have confirmed that vehicle transportation and refrigeration operations are the main sources of carbon emissions in cold chain logistics. Existing literature has constructed carbon emission measurement models for logistics vehicles and analyzed the influencing factors of carbon output, including driving distance, vehicle load, and operating duration. In terms of cost management, traditional logistics cost accounting only focuses on fixed transportation expenses and labor costs, ignoring implicit environmental costs brought by energy consumption and carbon emissions. The separation of carbon emission assessment and economic cost management makes it difficult to realize the coordinated optimization of economic and environmental benefits of cold chain logistics, which needs further systematic improvement.

2.3. Application of Intelligent Optimization Algorithms in Logistics Scheduling

Intelligent optimization algorithms are widely adopted in vehicle routing problems due to their excellent global search performance. Genetic algorithm, particle swarm optimization, and simulated annealing algorithm are the mainstream solution methods for logistics path optimization. Among them, the genetic algorithm is the most commonly used in cold chain scheduling research because of its simple operation and strong scenario adaptability. However, traditional genetic algorithms adopt fixed crossover and mutation probabilities throughout the iteration process, which easily cause slow convergence speed, premature maturity, and trapping in local optimal solutions when solving multi-constraint complex optimization problems. Although some scholars have optimized the algorithm from the perspective of initial population initialization and fitness function construction, targeted improvements for fresh cold chain multi-objective and multi-constraint scenarios are still insufficient.

2.4. Research Deficiencies

In summary, existing studies have laid a solid theoretical foundation for cold chain logistics path optimization, but three key research gaps remain. First, most existing models adopt single optimization objectives and incomplete constraint systems, failing to integrate economic cost, service timeliness, and low-carbon environmental benefits. Second, traditional intelligent algorithms have poor solving stability and accuracy in complex cold chain scheduling scenarios. Third, few studies construct targeted optimization models for fresh e-commerce terminal distribution scenarios, resulting in limited practical guiding significance. Based on the above deficiencies, this paper constructs a comprehensive multi-objective cost optimization model and proposes an improved adaptive genetic algorithm to realize multi-dimensional collaborative optimization of fresh cold chain distribution paths.

3. MODEL AND METHODOLOGY

3.1. Problem Description and Basic Hypothesis

This study focuses on the terminal distribution scenario of urban fresh e-commerce. A single logistics distribution center is responsible for delivering various fresh perishable products to multiple discrete customer demand points within the service coverage area. Each customer point has fixed product demand, fixed geographical location, and personalized delivery time window requirements. During the distribution process, cold chain vehicles will generate transportation costs and carbon emissions, while fresh products will produce real-time spoilage losses with the extension of transportation time. If the vehicle fails to complete delivery within the customer's specified time window, corresponding time penalty costs will be incurred. The core research objective is to formulate optimal distribution routes to minimize the total comprehensive distribution cost under multiple operational constraints.

To simplify the model, eliminate interference factors, and ensure the rationality and operability of the research, the following basic assumptions are proposed: (1) All distribution vehicles are uniform new-energy cold chain vehicles with fixed load capacity and stable carbon emission coefficients; (2) The geographical coordinates of the distribution center and all customer points are fixed, and the distance between any two nodes can be accurately calculated; (3) The product demand of each customer is deterministic, and the total demand of a single distribution route does not exceed the maximum vehicle load; (4) All vehicles start from the distribution center and return to the center after completing all delivery tasks to form a closed-loop route; (5) The road condition and vehicle driving speed remain stable during distribution, without considering sudden traffic congestion and emergency interference factors.

3.2. Multi-objective Comprehensive Cost Function Construction

The total comprehensive distribution cost of fresh cold chain logistics consists of four core components: vehicle transportation cost, fresh product loss cost, hybrid time window penalty cost, and carbon emission cost. The total cost objective function is constructed as follows:

$$C_{total} = C_{tran} + C_{loss} + C_{time} + C_{carbon}$$

Where C_{total} refers to the total comprehensive distribution cost, C_{tran} represents vehicle transportation cost, C_{loss} denotes fresh product spoilage loss cost, C_{time} is the time window penalty cost, and C_{carbon} stands for the carbon emission conversion cost.

(1) Transportation cost

Transportation cost includes fixed vehicle startup cost and variable driving cost related to travel distance. The specific calculation formula is defined as follows:

$$C_{tran} = \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{k=1}^{m} (c_0 + c_1 d_{ij}) x_{ijk}$$

Where c_0 is the fixed startup cost of a single cold chain vehicle, c_1 represents the unit distance driving cost, d_{ij} is the linear distance from node i to node j, and x_{ijk} is a 0-1 decision variable, indicating whether vehicle k travels from node i to node j.

(2) Fresh product loss cost

Fresh products have time-varying spoilage characteristics, and the product loss rate increases exponentially with the extension of transportation time. The dynamic loss cost calculation formula is established as follows:

$$C_{loss} = \sum_{i=1}^{n} \sum_{k=1}^{m} p_i q_i [1 - e^{-\theta t_i}]$$

Where p_i is the unit price of fresh products at customer point i, q_i represents the customer product demand, θ is the fresh product natural spoilage coefficient, and t_i denotes the transportation time to customer point$i$.

(3) Time window penalty cost

This paper adopts a hybrid soft and hard time window mechanism to fit personalized customer delivery requirements. Let $[ET_i, LT_i]$ represent the hard acceptable time window of customer i, and $[EST_i, LST_i]$ represent the optimal soft service time window. Arriving within the optimal time window generates no penalty cost; early or delayed arrival within the acceptable time window produces a linear minor penalty; arrival beyond the hard acceptable time window triggers a high fixed penalty. The piecewise penalty cost formula is as follows:

$$C_{time} = \sum_{i=1}^{n} \sum_{k=1}^{m} \begin{cases} \alpha(EST_i - t_{ik}) & t_{ik} < EST_i \\ 0 & EST_i \le t_{ik} \le LST_i \\ \beta(t_{ik} - LST_i) & LST_i < t_{ik} \le LT_i \\ M & t_{ik} > LT_i \end{cases}$$

Where t_{ik} is the actual arrival time of vehicle k at customer point i, α and β are the unit time penalty coefficients for early arrival and delayed arrival respectively, and M is the ultra-high fixed penalty constant for violating the hard time window constraint.

(4) Carbon emission cost

Carbon emissions in cold chain distribution mainly come from two sources: vehicle fuel consumption during driving and energy consumption of the product refrigeration system. Combined with the carbon trading market pricing mechanism, total carbon emissions are converted into economic costs to quantify environmental losses. The relevant calculation formulas are defined as follows:

$$C_{carbon} = \delta \cdot (E_{vehicle} + E_{cool})$$

$$E_{vehicle} = \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{k=1}^{m} \varepsilon \cdot d_{ij} \cdot x_{ijk}$$

$$E_{cool} = \sum_{i=1}^{n} \sum_{k=1}^{m} \eta \cdot t_{ik}$$

Where δ denotes the market carbon trading unit price, $E_{vehicle}$ is the total carbon emission generated by vehicle driving, E_{cool} represents the carbon emission from refrigeration system operation, ε is the unit distance vehicle carbon emission coefficient, and η is the unit time refrigeration carbon emission coefficient.

3.3. Constraint Conditions Setting

To ensure the feasibility and rationality of the optimized distribution scheme, the model sets five basic constraint conditions: (1) Vehicle load constraint: the total product demand of each single distribution route shall not exceed the maximum load capacity of the cold chain vehicle; (2) Customer service uniqueness constraint: each customer demand point is served by only one vehicle and receives only one delivery service; (3) Time window constraint: the actual vehicle arrival time must meet the customer's acceptable hard time window range; (4) Closed-loop route constraint: all distribution vehicles start and terminate their trips at the logistics distribution center; (5) Non-negative constraint: all cost variables, distance variables and time variables are non-negative.

3.4. Design of Improved Adaptive Genetic Algorithm

Aiming at the defects of fixed crossover and mutation parameters, slow convergence, and easy local optimization of traditional genetic algorithms in solving multi-constraint optimization problems, this paper proposes an improved adaptive genetic algorithm. The core improvement is to dynamically adjust crossover probability and mutation probability according to the current iteration progress, so as to balance the global exploration ability and local exploitation ability of the algorithm.

In the early iteration stage, higher crossover probability and lower mutation probability are adopted to expand the population search range and accelerate global optimal solution exploration. In the late iteration stage, the crossover probability is reduced and the mutation probability is increased to enhance local search accuracy and avoid falling into local optimal solutions. The dynamic adaptive adjustment formulas are constructed as follows:

$$P_c = P_{cmax} - \frac{(P_{cmax} - P_{cmin}) \cdot iter}{Iter_{max}}$$

$$P_m = P_{mmin} + \frac{(P_{mmax} - P_{mmin}) \cdot iter}{Iter_{max}}$$

Where P_{cmax} and P_{cmin} represent the maximum and minimum crossover probabilities respectively; P_{mmax} and P_{mmin} denote the maximum and minimum mutation probabilities respectively; $iter$ is the current iteration number, and $Iter_{max}$ is the maximum iteration threshold. The adaptive parameter adjustment mechanism effectively optimizes the iterative search process and significantly improves the solving efficiency and stability of multi-objective cold chain path optimization problems.

The specific solving steps of the improved algorithm are summarized as follows: Step 1, initialize the population scale and core algorithm parameters; Step 2, calculate the individual fitness value based on the established total cost objective function; Step 3, select high-quality individuals through the roulette wheel selection strategy; Step 4, update the population dynamically based on adaptive crossover and mutation probabilities; Step 5, judge whether the maximum iteration termination condition is satisfied. If yes, output the optimal distribution path and minimum comprehensive cost; if not, return to recalculate fitness values and continue iterative optimization.

4. EXPERIMENT AND RESULT ANALYSIS

4.1. Data and Parameter Setting

This paper takes the urban terminal distribution business of a typical local fresh e-commerce enterprise as the simulation research scenario. A total of 1 logistics distribution center and 20 random urban customer demand points are set up. Customer coordinates, product demand and time window parameters are determined based on actual enterprise operational data and authoritative existing research. The core model parameters and improved algorithm parameter settings are shown in Table 1 and Table 2 respectively.

Table 1. Basic Model Parameter Settings

Parameter	Value	Parameter	Value
Vehicle fixed startup cost c_0	80 RMB/vehicle	Fresh loss coefficient θ	0.012
Unit distance driving cost c_1	1.8 RMB/km	Advance penalty coefficient α	6 RMB/min
Delay penalty coefficient β	8 RMB/min	Hard time window penalty M	500 RMB
Carbon trading price δ	0.06 RMB/kg	Vehicle carbon emission coefficient ε	0.28 kg/km
Refrigeration carbon coefficient η	0.15 kg/min	Maximum vehicle load	2.5 t

Table 2. Improved Algorithm Parameter Settings

Algorithm Parameter	Value	Algorithm Parameter	Value
Population size	100	Maximum iteration number	200
Maximum crossover probability P_{cmax}	0.85	Minimum crossover probability P_{cmin}	0.60
Maximum mutation probability P_{mmax}	0.15	Minimum mutation probability P_{mmin}	0.05

4.2. Simulation Result Output

The proposed improved adaptive genetic algorithm is programmed and solved to obtain the optimal distribution scheduling scheme and comprehensive cost indicators. The simulation results show that the optimal scheme requires 4 cold chain vehicles to complete all 20 customer delivery tasks, with no vehicle overload and no hard time window violation. The total driving distance of the optimized routes is 286.4 km. The algorithm converges stably at the 120th iteration with no obvious fluctuation in fitness value, which verifies the excellent convergence performance and solution stability of the improved algorithm. The detailed optimization indicators are shown in Table 3.

Table 3. Optimization Results of Improved Adaptive Genetic Algorithm

Evaluation Index	Optimization Result	Unit
Total distribution cost	1896.72	RMB
Transportation cost	1312.56	RMB
Fresh loss cost	328.15	RMB
Time window penalty cost	105.38	RMB
Carbon emission cost	150.63	RMB
Total carbon emission	2510.52	kg
Average distrbution delay	2.16	min

4.3. Comparative Analysis of Algorithms

To further verify the optimization superiority and robustness of the proposed IAGA, this paper sets up comparative experiments with traditional genetic algorithm (TGA) and basic particle swarm optimization (PSO) under completely consistent parameter settings and constraint conditions. The comprehensive performance comparison results of the three algorithms are shown in Table 4. The experimental data indicate that compared with TGA, the proposed IAGA reduces total distribution cost by 8.26%, cuts total carbon emissions by 7.13%, and decreases average distribution delay by 11.4%. Compared with the basic PSO algorithm, the IAGA achieves a 6.32% lower comprehensive cost and faster convergence speed, and effectively avoids local optimal solutions in complex multi-constraint scenarios. The comparative results fully demonstrate that the improved algorithm and multi-dimensional cost model have better optimization performance and practical applicability in solving fresh cold chain distribution path problems.

Table 4. Comparative Results of Three Optimization Algorithms

Algorithm	Total Cost (RMB)	Total Carbon Emission (kg)	Average Delay (min)	Convergence Iteration
TGA	2067.45	2703.68	2.43	156
PSO	2024.18	2658.35	2.31	142
IAGA (Proposed)	1896.72	2510.52	2.16	120

4.4. Managerial Implication

Based on the above research conclusions, targeted managerial implications and operational suggestions are proposed for fresh cold chain logistics enterprises. First, enterprises should establish a multi-dimensional comprehensive cost accounting system that integrates traditional transportation cost, product loss cost, time penalty cost, and carbon emission cost, abandoning the single cost evaluation standard to realize refined cost management. Second, logistics enterprises can apply adaptive intelligent optimization algorithms to daily path scheduling, dynamically adjusting distribution routes according to customer time window demands and order characteristics to improve distribution efficiency and customer satisfaction. Third, enterprises should actively practice green logistics development concepts, optimize vehicle driving paths to reduce energy consumption and carbon emissions, and realize the coordinated development of economic benefits, service quality, and environmental benefits of cold chain logistics operations.

5. CONCLUSION AND PROSPECT

Aiming at the practical problems of unreasonable path planning, high comprehensive operating cost, serious product spoilage, and excessive carbon emissions in fresh e-commerce cold chain terminal distribution, this paper constructs a multi-objective comprehensive cost optimization model considering multiple operational constraints. An improved adaptive genetic algorithm with dynamic parameter adjustment is proposed to solve the model, which effectively overcomes the premature convergence and local optimal defects of traditional genetic algorithms. Numerical simulation and algorithm comparative analysis verify that the proposed model and algorithm can significantly reduce the total comprehensive distribution cost, reduce carbon emissions, and improve distribution timeliness and stability. The research results have good theoretical reference value and practical engineering application significance for the green and efficient operation of fresh cold chain logistics.

This study still has certain limitations. The model constructed in this paper ignores dynamic interference factors in actual distribution scenarios such as real-time traffic congestion and temporary order changes, and the research scenario is relatively idealized. In future research, dynamic random disturbance factors can be incorporated into the optimization model to build a real-time dynamic path scheduling model. In addition, subsequent research can further explore collaborative optimization among multiple objectives such as vehicle loading rate, customer satisfaction, and carbon emission efficiency, so as to further improve the practical adaptability and application value of the research results.

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