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Optimization of Cold Chain Logistics Distribution Using ACO Algorithms

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Abstract: To address the high energy consumption and emissions of Cold Chain Logistics (CCL), this study proposes a distribution path optimization model based on an improved ant colony optimization algorithm. The model considers transportation, vehicle usage, energy, and carbon emission costs to achieve a balance between cost, carbon reduction, and distribution efficiency. Results indicated that the enhanced algorithm reduces the mean square error and computation time by 48.39% and 14.73%, respectively. The optimal path was found to lower cargo damage by 31.82% and improve customer satisfaction by 7.52%. Additionally, the model decreases the transportation, vehicle, energy, and carbon emission costs by 14.53%, 12.99%, 13.85%, and 17.41%, respectively. The results demonstrate that the proposed CCL distribut ion optimization model effectively balances route connectivity, low-carbon objectives, and customer satisfaction. It provides quantitative evidence to help governments establish green logistics subsidy standards and enables enterprises to fulfill their carbon reduction responsibilities. These findings are of practical significance for advancing policy implementation and promoting sustainable development within the CCL industry.

Keywords: Algorithms, carbon emission, cold chain, logistics, optimization.

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1. Introduction

CCL is an essential link for ensuring the quality of temperature-sensitive goods such as food and medicine; its efficiency and reliability directly impact supply chain stability, consumer health, and safety. In recent years, with the rising demand for fresh e-commerce and pharmaceutical cold chains, the CCL industry faces unprecedented opportunities and challenges (Wu et al., 2022; Zhang et al., 2024). The traditional CCL distribution model is inadequate for addressing issues such as high costs, dynamic demand fluctuations, and carbon emission pressures. In this context, China's "dual carbon" strategic goals and policies, such as the "14th Five-Year Plan" for CCL development, have established clear requirements for the industry's green and low-carbon transformation. Therefore, optimizing delivery routes to achieve a win-win scenario of economic and environmental benefits is not only an inherent need for enterprises to reduce costs and increase efficiency, but also an external necessity to respond to national policies and fulfill social responsibilities (Liu et al., 2023). At the technical level, traditional optimization algorithms such as the genetic algorithm have been widely used in path planning (He, 2023). However, these algorithms have limitations when dealing with the multi-objective and constrained nature of CCL distribution. They often focus on local improvements and lack comprehensive coordination of vehicle scheduling, cooling parameters, and route connectivity. Additionally, dynamic factors like traffic conditions and fluctuating customer demand require higher adaptability and robustness from algorithms. Conventional methods are less effective in managing these dynamic challenges (Fan et al., 2024; Lim et al., 2022). To address these issues, a CCL distribution optimization model based on an Improved Ant Colony Optimization (IACO) algorithm is proposed to enable efficient, low-carbon, and cost-effective operations. This was achieved by developing a multi-objective collaborative logistics distribution model that considers constraints such as vehicle capacity, delivery time windows, route connectivity, temperature control, and emissions, thereby forming a comprehensive optimization framework. Furthermore, strategies such as dynamic pheromone updating, hybrid heuristic functions, and a two-level optimization architecture are implemented to enhance the search capability and effectiveness of the Ant Colony Optimization (ACO) algorithm.

The core innovation of this research is its paradigm shift from "path search" to "policy generation," establishing a collaborative optimization framework featuring dual closed-loop systems for decision-making and execution. Unlike hybrid ACO models that merely enhance search efficiency, this framework drives algorithms to autonomously converge toward the Pareto frontier by internalizing policy metrics, such as carbon emissions, Time Windows (TWs), and service indicators into its pheromone mechanisms. Its innovative two-tier architecture systematically coordinates macro-level pathways with micro-level energy consumption at the algorithmic level, resolving the core challenge of linking carbon source from transportation and refrigeration at the algorithmic level. Ultimately, the model generates auditable carbon accounting data, providing a direct interface for corporate carbon compliance and precision government policy-making. This elevates the algorithm from a back-end tool to a cutting-edge decision support system, thereby advancing the knowledge frontier of sustainable logistics.

2. Related Works

In cross-domain optimization scenarios, the combined application of the ACO algorithm shows broad potential. To address fog computing resource scheduling issues in Internet of Things, Yin et al. (2024) proposed a model that integrates an improved genetic algorithm with ACO, significantly reducing time, cost, and overall expenses, while enhancing load balancing. For river flow prediction, Aghelpour et al. (2023) developed a metaheuristic model based on an adaptive neural fuzzy inference system combined with ACO. Using daily flow delay as an input, their model improved prediction accuracy and efficiency. To improve the path planning adaptability of inspection robots, Wang et al. (2023) designed a novel method that combines an advanced ACO algorithm with a cutting-edge artificial potential field algorithm. Their integration of pheromone adjustment coefficients and an enhanced global pheromone update method led to significant gains in operational efficiency, convergence speed, and overall optimization capabilities. To address long convergence times and susceptibility to local optima in the traveling salesman problem, Liu et al. (2023) introduced a dynamic adaptive ACO algorithm. By dynamically adjusting the number of ants and employing a mixed local selection strategy, their algorithm improved the diversity of initial solutions and the quality of optimization. To reduce workflow scheduling and execution costs with deadline constraints in cloud computing, Shobeiri et al. (2024) proposed a partial critical path ACO algorithm. Combining a partial critical path heuristic with metaheuristic ACO resulted in faster convergence and more efficient resource allocation.

In CCL optimization research, the multi-faceted application of intelligent algorithms has become a key path to overcoming industry bottlenecks. To optimize CCL management and distribution routes, Zhao (2024) proposed an enhanced fireworks-artificial bee colony (ABC) algorithm. By improving the ABC through neighborhood search and using the fireworks explosion operator to search for the optimal solution, the optimal path planning for economic and social benefits was achieved. To optimize the CCL distribution path problem, Liu et al. (2024) proposed an improved genetic algorithm. By introducing natural number encoding, an elite preservation strategy, and an adaptive crossover and mutation strategy, the total distribution cost was effectively reduced, providing valuable optimization tools for the CCL industry. To address the challenges of temperature monitoring in CCL, Pajic et al. (2024) proposed a comprehensive framework for integrating intelligent transportation using Internet of Things technology. Through the inspection of temperature monitoring equipment and standardized protocols and practices, real-time and accurate monitoring of temperature sensitive goods has been achieved. To balance the cost of CCL with consumer satisfaction, Li and Zhang (2024) designed a multi-objective cold chain vehicle routing problem model. By improving algorithm convergence and non-dominated solution quality, fuel consumption and carbon emissions were effectively reduced. To enhance customer satisfaction in the CCL of fresh agricultural products, Zhang and Ding (2023) proposed a multi-objective path optimization model that considers customer satisfaction. By using an enhanced elite non-dominated sorting genetic algorithm, an effective balance between customer satisfaction and cost was achieved.

In summary, although significant progress has been made in the fields of intelligent algorithms and MOO, there are still research gaps in dynamic demand response, path redundancy elimination, and the collaborative control of carbon emissions in complex CCL scenarios. Therefore, the proposed CCL distribution model, which is based on an optimized ACO algorithm, integrates dynamic pheromone updates, heuristic functions, and a two-layer optimization structure. This framework unifies carbon emission intensity, temperature control stability, and customer demand fluctuations into a comprehensive decision-making model. As a result, it reduces transportation costs and cargo damage rates while achieving precise control of carbon emissions, offering a solution that combines theoretical innovation with practical value for the industry’s green transformation.

3. Methods and Materials

3.1. Construction of Optimization Model for CCL Distribution

CCL mainly serves fresh food, pharmaceuticals, and other temperature-sensitive items, ensuring they are maintained at a suitable ambient temperature during transportation to reduce cargo damage and improve delivery efficiency (Bai et al., 2022). Currently, optimizing delivery routes to reduce operating costs, minimize carbon emissions, and enhance delivery efficiency is a key research focus. To clarify the optimization objectives, the study first analyzes the CCL implementation process, as shown in Fig. 1.

Fig. 1 presents the full implementation process of CCL, from procurement and production to final delivery to customers. After procurement and production, the product undergoes pre-cooling and sorting to ensure it reaches the right temperature before transportation. Next, the goods are refrigerated, packaged, classified, and stored in a cold chain warehouse. During the delivery process, goods are transported through the cold chain to the designated location, with temperature monitoring and data collection to make sure the entire process meets temperature control standards (Zhang et al., 2024). When it arrives at the distribution center, the goods are delivered to the customer, ensuring efficient and safe CCL transportation. To keep the CCL system running smoothly and reliably, various key factors are considered during optimization, as shown in Fig. 2.

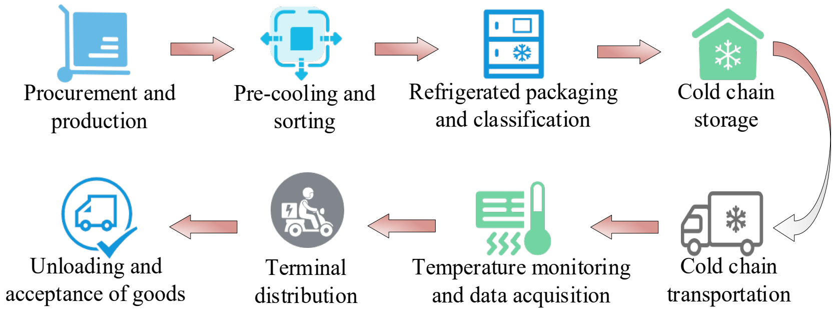

Fig. 1. Flow chart of CCL implementation

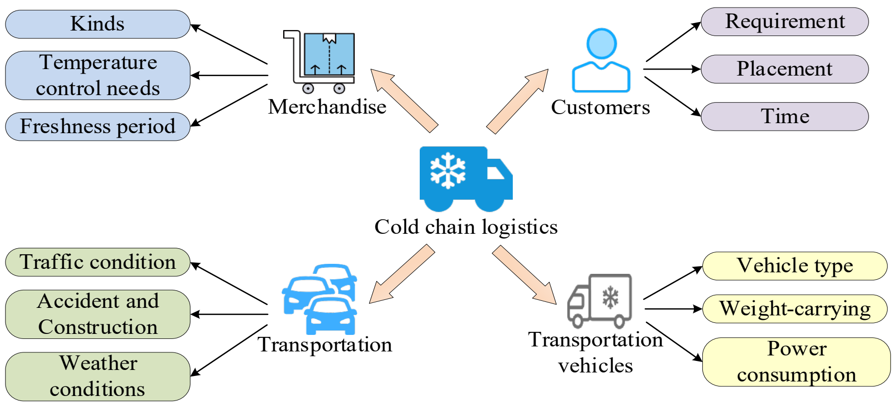

Fig. 2. Factors of CCL distribution path planning

In Fig. 2, the optimization of CCL is affected by various factors, including fluctuations in customer demand, choice of transportation vehicles, restrictions on cargo characteristics, and changes in traffic conditions. Customer demand influences the rationality of delivery routes, while the capacity, energy use, and carbon emissions of transportation vehicles impact transportation costs and environmental goals. Simultaneously, storage temperature, shelf life, and compatibility of goods impose strict requirements on the delivery process (Gebremedhin et al., 2024). Additionally, real-time traffic conditions, road restrictions, and weather factors also influence the delivery routes. Therefore, considering these factors scientifically is essential for optimizing CCL. Based on this, the research treats the CCL distribution path optimization as a low-carbon vehicle route optimization problem with time window constraints. An MOO model is developed under the premise of meeting delivery needs and cold chain environment constraints, as shown in Fig. 3.

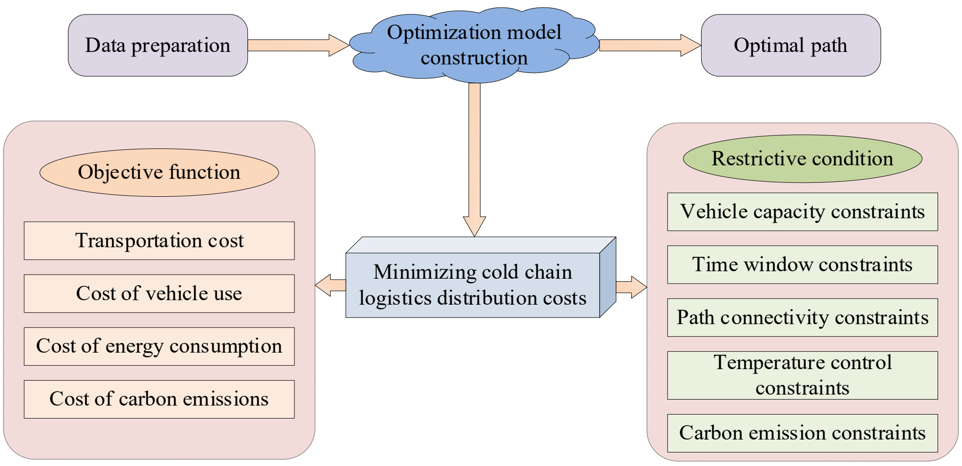

Fig. 3. CCL distribution optimization model based on minimizing the total transportation cost

In Fig. 3, the optimization objectives of the model include transportation costs, Vehicle Usage Costs (VUCs), Energy Consumption Costs (ECCs), and Carbon Emission Costs (CECs), to achieve an optimization strategy that balances economy and environmental protection. At the same time, the model sets multiple constraint conditions, such as vehicle capacity to ensure reasonable load allocation, TW to ensure delivery timeliness, path connectivity to ensure that all customer points are covered, temperature control to maintain a stable cold chain environment, and carbon emission constraints to limit the overall impact of delivery on the environment. These conditions ensure the feasibility and standardization of the delivery process in practical operation. In addition, distribution network modeling includes distribution centers, customer nodes, and connection paths, defining the demand and TWs of each node, the load and energy consumption characteristics of vehicles, as well as the driving distance, time, cost, and carbon emission coefficient of the path. Finally, the optimal distribution path is obtained through this optimization model, achieving systematic optimization of the CCL distribution system, improving transportation efficiency, and reducing operating costs. The objective function is denoted in Eq. (1).

$$\begin{cases} min\, Z_T = \sum\limits_{i,j\in O}\sum\limits_{k\in K} c_{ij}d_{ij}x_{ijk} \\ min\, Z_V = \sum\limits_{k\in K} F_k y_k \\ min\, Z_E = \sum\limits_{k\in K}\sum\limits_{i\in O} P_e t_{ik} \\ min\, Z_C = \sum\limits_{k\in K}\left(\lambda_1 E_k^{\text{trans}} + \lambda_2 E_k^{\text{refri}}\right) \end{cases} \tag{1}$$

In Eq. (1), Z_T, Z_V, Z_E, and Z_C represent transportation costs, VUCs, ECCs, and CECs, respectively; c_{ij} means the unit distance transportation cost of vehicles; d_{ij} means transportation distance; $x_{ijk} \in \{0,1\}$ denotes whether vehicle k is traveling from node i to node j (1=Yes, 0=No); K means a collection of vehicles; O means the set of all nodes; F_k represents the fixed operating cost of vehicle k; $y_k \in \{0,1\}$ means whether the vehicle k has been called (1=Yes, 0=No); P_e represents the unit time ECC of refrigeration equipment; t_{ik} means the dwell time of vehicle k at node i; λ_1 and λ_2 represent the conversion coefficients of CECs per unit time for transportation and refrigeration equipment, respectively; E_k^{trans} and E_k^{refri} respectively represent the CECs of transportation and refrigeration. The expression for the vehicle capacity constraint is shown in Eq. (2).

$$\sum_{i\in O} q_i \sum_{j\in O} x_{ijk} \le Q_k y_k,\ \forall k \in K \tag{2}$$

In Eq. (2), q_i denotes the demand of customer i; Q_k represents the max load capacity of vehicle k. The expression for the TW constraint is denoted in Eq. (3).

$$a_i \le T_i \le b_i,\ \forall i \in O_c \tag{3}$$

In Eq. (3), a_i and b_i denotes the lower and upper limits of the TW for customer point i, respectively; T_i denotes the time when the vehicle arrives at the customer point i; O_c denotes a collection of customer points. The expression for path connectivity constraint is shown in Eq. (4).

$$\begin{cases} \sum\limits_{k\in K}\sum\limits_{j\in O} x_{ijk} = 1, \forall i \in O_c \\ \sum\limits_{j\in O} x_{0jk} = \sum\limits_{j\in O} x_{j0k} = y_k, \forall k \in K \\ \sum\limits_{i\in O} x_{ihk} = \sum\limits_{j\in O} x_{hjk}, \forall h \in O_c, k \in K \end{cases} \tag{4}$$

In Eq. (4), x_{0jk} represents the path variable of vehicle k from distribution center 0 to node j; x_{j0k} represents the path variable for vehicle k to return from node j to the distribution center; x_{ihk} means the path variable of vehicle k from customer node h to node i; x_{hjk} represents the path variable for vehicle k to return from node i to customer node h. The expression for temperature control constraints is shown in Eq. (5).

$$T_{\min} \le \tau_{ik} \le T_{\max},\quad \forall i \in O_c, k \in K \tag{5}$$

In Eq. (5), τ_{ik} represents the temperature of the cargo box of vehicle k when serving customer point i; T_{min} and T_{max} respectively represent the minimum and maximum temperatures allowed for the goods. The expression for carbon emission constraints is denoted in Eq. (6).

$$\sum_{k\in K}\left(E_k^{\text{trans}} + E_k^{refri}\right) \le E_{max} \tag{6}$$

In Eq. (6)upload E_{max} represents the maximum allowable total carbon emissions for the delivery task. By systematically modeling the objective function and constraints mentioned above, a collaborative optimization framework that balances economic and environmental benefits is formed, achieving the construction of a multi-objective low-carbon CCL distribution optimization model.

3.2. IACO Algorithm for Solving Optimization Strategies

The research adopts the IACO algorithm to solve the high-dimensional, strong constraint, and low-carbon demand characteristics of the multi-objective path optimization model for CCL transportation. ACO is an optimization algorithm based on the behavior of ants when foraging. It is suitable for solving optimization problems, such as the travelling salesman issues and vehicle routing challenges. The basic principle of the ACO algorithm is shown in Fig. 4.

From Fig. 4, ants release pheromones along the path when searching for food, and other ants tend to choose paths with higher concentrations of pheromones. The ACO algorithm simulates this process by continuously releasing pheromones on different paths through ants, gradually forming an optimal route. The path with a higher concentration of pheromones has a greater chance of being selected. At the same time, pheromones evaporate over time to prevent premature convergence of the algorithm. Through continuous exploration by ants and the updating of pheromones, the optimal path is ultimately identified. Although the ACO algorithm performs well in path optimization, it has drawbacks in convergence speed, solution set diversity, and multi-objective processing ability due to the complexity of multi-objective path optimization problems in CCL. Therefore, it is necessary to improve solving efficiency and optimize delivery routes. The optimization strategy proposed in the study is shown in Fig. 5.

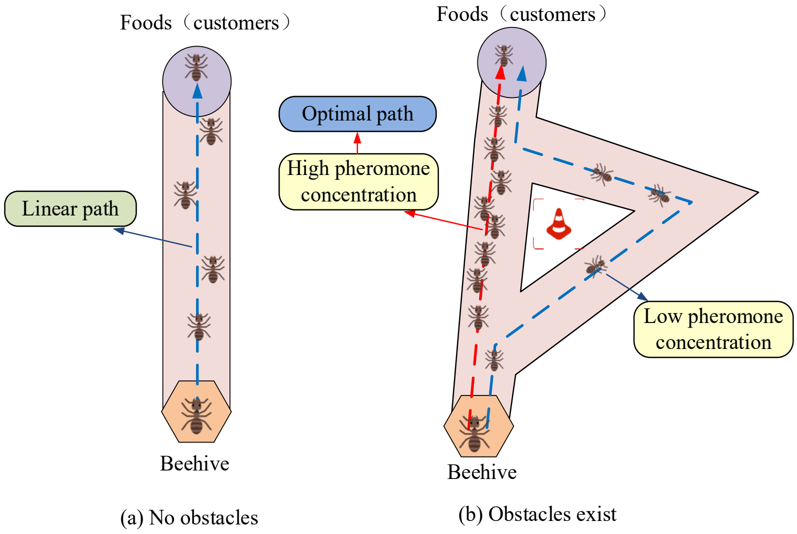

Fig. 4. Schematics of path optimization using the ACO algorithm

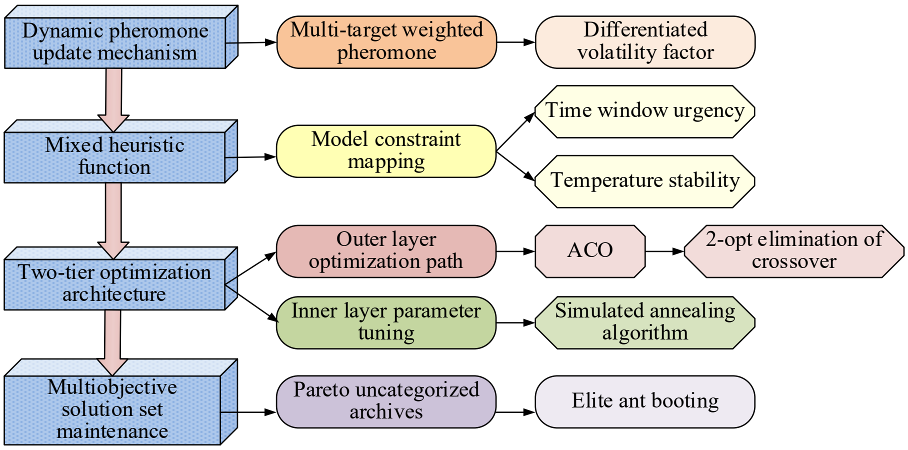

Fig. 5. The ACO algorithm optimization strategy

As shown in Fig. 5, the study first develops a dynamic pheromone update that considers factors such as intensity of carbon emissions, time window satisfaction rate, and elements in pheromone weight calculation. By differentiating these volatile factors, it speeds up the removal of high-pollution paths and enhances the algorithm's low-carbon focus. Next, a hybrid heuristic function is created to support multi-constraint collaborative decision-making in cold chain scenarios by integrating inter-node distance, time window urgency, and temperature stability factors. Additionally, the study introduces a two-level optimization architecture: the outer layer generates initial paths using the ACO algorithm and checks basic constraints like load capacity and connectivity. To improve convergence speed and solution quality, a local search strategy combining two-element optimization (2-optimization, 2-opt) is employed, reducing unnecessary detours and improving path connectivity by swapping two edges. The inner layer uses a simulated annealing mechanism to dynamically optimize vehicle speed and cooling temperature parameters, thereby lowering transportation energy use and carbon emissions. Lastly, a Pareto frontier solution set maintenance strategy is implemented to balance diversity and convergence of solutions through non-dominated sorting and crowding degree calculation. The pheromone update rule is shown in Eq. (7).

$$\Delta\tau_{ij} = \frac{\omega_1}{Z_C} + \frac{\omega_2}{T_{\text{Violation}}} + \frac{\omega_3}{L_{\text{total}}} \tag{7}$$

In Eq. (7), $\Delta\tau_{ij}$ represents the increment of pheromones; ω_1, ω_2 , and ω_3 represent the weight coefficients of carbon emission intensity, TW satisfaction rate, and cargo damage rate, respectively; $T_{\text{Violation}}$ represents the duration of TW violation; L_{total} represents the total cargo damage rate. The final IACO algorithm is obtained through the above optimization strategy, and the basic process of using IACO to solve the optimal path of CCL transportation is denoted in Fig. 6.

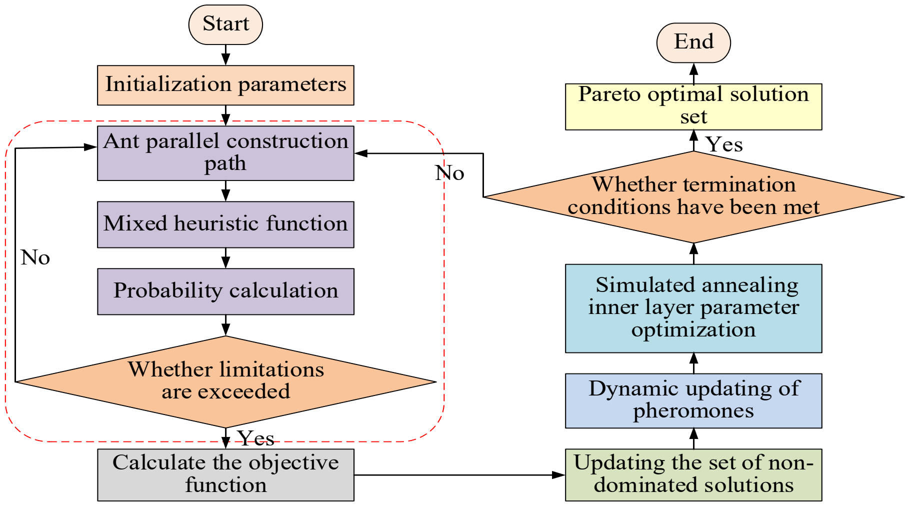

Fig. 6. The process of solving the optimal path with IACO algorithm

According to Fig. 6, when using the IACO algorithm to address the optimal path, the algorithm parameters are first initialized and a mixed heuristic function that integrates multidimensional decision factors is constructed. Ants start from the distribution center, select the next node based on dynamic pheromone distribution and heuristic function values, and prioritizes accessing customer points that are closer, have a wide TW, and stable temperature. During the process, real-time detection of load exceeding limits and time delay risks is carried out. After each iteration, a comprehensive evaluation is conducted on the generated paths to select a set of high-quality paths that meet both low cost and low carbon emissions requirements. Diversity maintenance strategies are used to avoid convergence of solution sets. Subsequently, the pheromone network is dynamically updated to enhance the guidance signal of efficient and low-carbon paths, and combined with a two-layer optimization architecture, the feasible paths generated by the outer layer are fine tuned for vehicle speed and cooling parameters. A progressive annealing strategy is adopted to balance local exploration and global convergence. The final algorithm terminates after a preset number of iterations or stable solution set, and outputs multiple sets of differentiated path schemes to provide decision-makers with optimal solutions that balance economic and environmental benefits. Through biomimetic search and multi-constraint coupling mechanism, this algorithm can systematically solve the complex challenges of path optimization and resource coordination in CCL.

4. Results

4.1. Comparison of Experimental Environment and Path Planning Effects

To prove the effect of the CCL distribution optimization model based on the IACO algorithm, simulation experiments were designed and studied. The experiment used MATLAB 2022a as the simulation platform, running on the Windows 11 operating system, and combined with Gurobi mathematical optimization solver as the benchmark comparison tool. The experimental dataset was based on the Solomon Vehicle Routing Problem with Time Windows (VRPTW) standard library, extended and modified according to the characteristics of cold chain scenarios. It covers core fields such as customer node coordinates, cargo demand, hard TW constraints, and temperature control intervals. At the same time, it simulated the correlation data between refrigeration energy consumption and load capacity in real-time cold chain transportation. The parameter settings are denoted in Table 1.

Table 1. Experimental parameter setting

Algorithm Parameters	Value	Model Parameters	Value
Number of ants	50	Unit transportation costs (RMB / km)	1.2
Pheromone weight	1.0	Vehicle fixed cost (RMB / session)	100
Heuristic function weight	3.0	Refrigeration energy costs (RMB / h)	15
Basic volatilization factor	0.1	Transportation carbon emission factor (CO_2/km·kg)	0.12
Dynamic volatilization factor	0.05	Refrigeration carbon emission factor (kg CO_2/h)	0.8
2-opt local search probability	0.3	Carbon emission conversion factor (RMB/kg CO_2)	0.5
Low-carbon orientation weight	1.2	Time window width(h)	[0.5, 2]
Time window satisfaction rate weight	0.8	Temperature control range (°C)	[-18, -15]
Cargo loss ratio weight	1.0	Cargo damage rate threshold (%)	5

Based on the above experimental parameter settings, the study first verified the path optimization effect of the proposed IACO algorithm. Three common solving algorithms: Improved ACO based on simulated annealing algorithm (SA-ACO), Improved ACO based on genetic algorithm (GA-ACO), and Improved ACO algorithm based on particle swarm optimization (PSO-ACO) were introduced for comparison. Taking 20 customer nodes, 1 distribution center, and 4 delivery vehicles selected from a certain location as an example for analysis, the path optimization results of the four algorithms are denoted in Fig. 7.

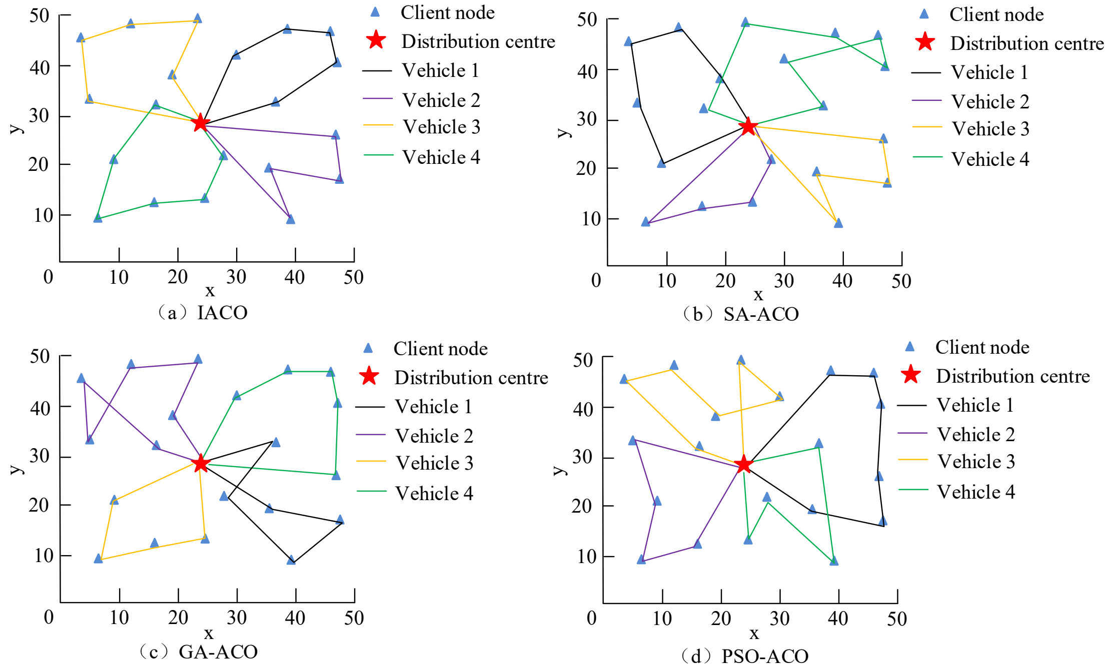

Fig. 7. Comparison of the optimal path planning maps for the different algorithms

Comparing the optimal path planning diagrams of the four algorithms in Fig. 7, the IACO algorithm proposed in the study significantly outperformed the other three algorithms in solving the CCL distribution path. The path planned by the IACO algorithm was relatively compact, and the vehicle travel routes were more concentrated, reducing unnecessary detours and intersections. This indicates that the dynamic pheromone mechanism strengthened the low-carbon path guidance of the algorithm, and the introduction of the 2-opt strategy effectively reduced path redundancy. In contrast, the path planned by GA-ACO algorithm had multiple turns and intersections, which violates the vehicle path connectivity constraint. This may be due to the synergistic conflict between the crossover mutation operation of the genetic algorithm and the ACO pheromone mechanism. To further verify the path planning capability of IACO, the optimal path mileage and Mean Absolute Error (MAE) solved by four algorithms were compared, and the results are shown in Fig. 8.

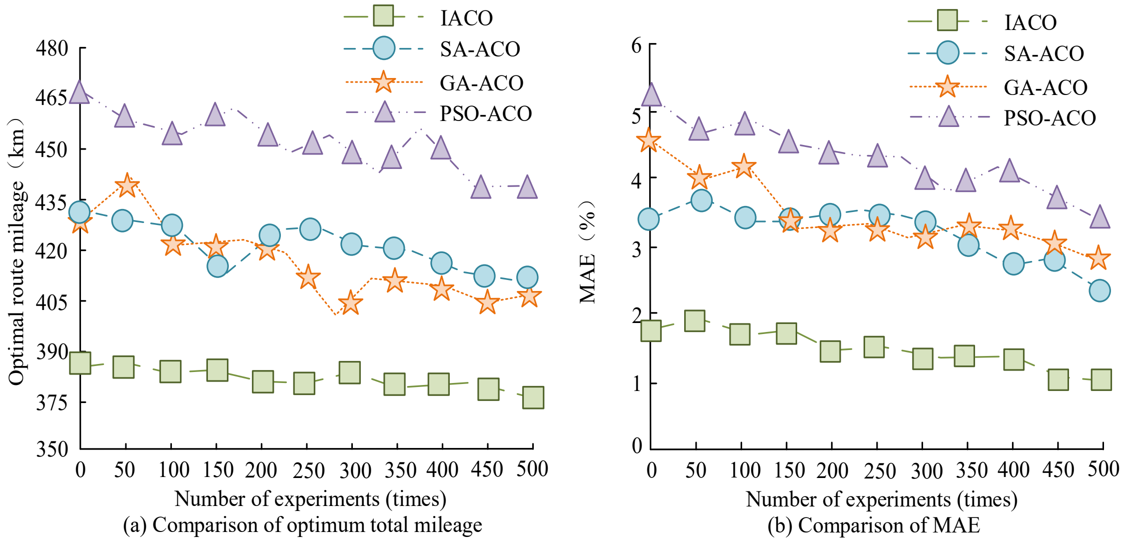

Fig. 8. Optimal path mileage and MAE comparison for different algorithms

According to Fig. 8(a), as the number of experiments increased, the optimal path mileage of the IACO algorithm remained at the lowest level. This indicated that the IACO algorithm could more accurately balance path length, TW constraints, and low-carbon goals through dynamic pheromone updates and mixed heuristic functions, thereby effectively searching for shorter paths. Fig. 8(b) shows the MAE comparison of different algorithms. The MAE variation of the IACO algorithm was relatively stable and significantly lower than other algorithms. When the number of experiments was 200, the MAE value of the IACO algorithm was about 1.57%, which was an average decrease of 48.39% compared to other algorithms. This indicated that the IACO algorithm had great advantages in the accuracy of optimization results. Through a bipolar optimization architecture and diverse maintenance strategies, it could reduce unnecessary detours and delays, thereby improving the connectivity and effectiveness of the path, and ultimately reducing errors.

4.2. Verification of Optimization Effect of CCL Distribution based on IACO

After verifying the effectiveness of CCL distribution path planning further testing of the IACO algorithm was found effective. The iterative convergence effect and computational efficiency were used as the test indicators, and the findings are expressed in Fig. 9.

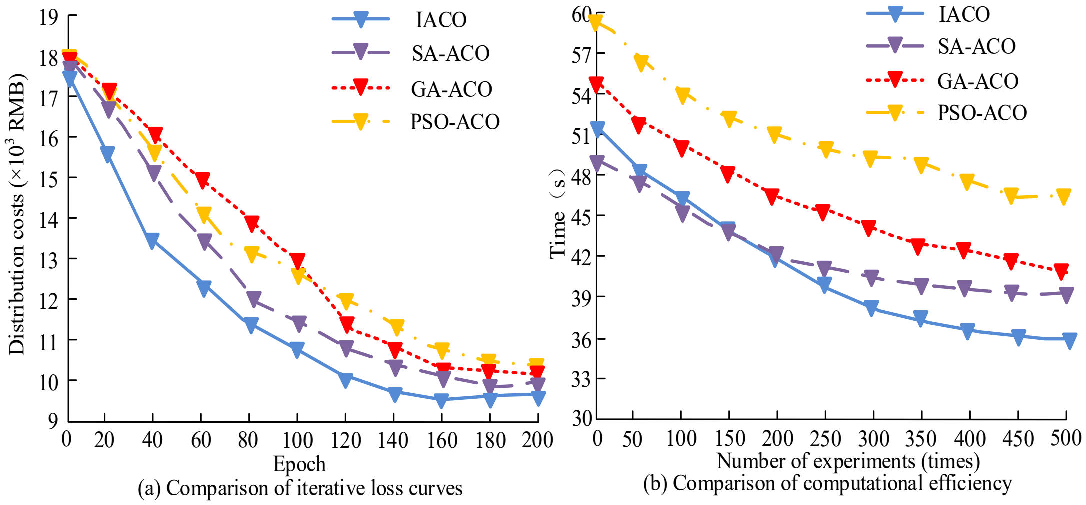

Fig. 9. Comparison of the iterative optimization effect and computational efficiency of different algorithms

Fig. 9(a) shows the iterative loss curves of different algorithms in CCL distribution. With the increase of iteration times, the delivery cost of the IACO algorithm decreased significantly, showing fast convergence speed and good optimization effects. This indicates that optimization strategies such as the dynamic pheromone update mechanism and the simulated annealing mechanism effectively avoided local optima and improved the efficiency and stability of the IACO algorithm in optimizing distribution costs. The comparison of computation time for different algorithms is shown in Fig. 9(b). In the early stages of the experiment, the IACO algorithm took slightly longer to compute than the SA-ACO algorithm. However, the computational efficiency of the IACO algorithm increased significantly when the number of experiments reached 200. When the total number of experiments was 500, the computation time of the IACO algorithm was reduced by about 14.73% compared to other algorithms. This indicates that the IACO algorithm had significant advantages in computational efficiency. For this reason, the IACO algorithm, through a 2-opt local search strategy and a two-level optimization architecture, quickly filters out high-quality paths, reduces unnecessary computational steps, and improves computational efficiency. Furthermore, the study compared the number of vehicles used and cargo damage rates under different customer node sizes, as seen in Fig. 10.

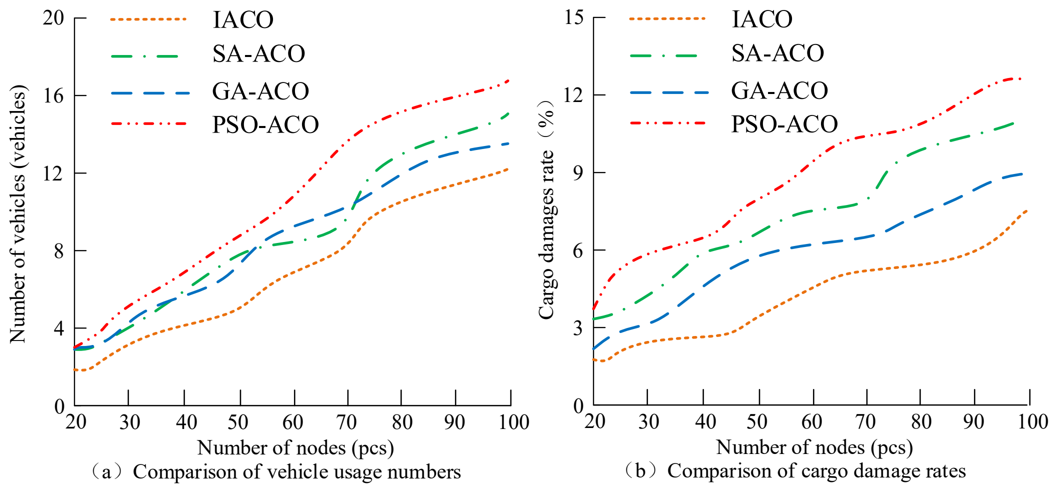

Fig. 10. Comparison of the number of vehicles use and cargo loss rate of different algorithms

In Fig. 10(a), as the number of nodes increases, the vehicle usage of the IACO algorithm consistently remains at the lowest level. When the node count reached 100, the SA-ACO, GA-ACO, and PSO-ACO models used 13, 15, and 17 vehicles, respectively, whereas the proposed model required only 12, resulting in an average reduction of 20.00%. This shows that the IACO algorithm has significant advantages in vehicle resource allocation and can reduce vehicle usage by optimizing paths, thus lowering operating costs. Based on Fig. 10(b), the cargo damage rate of the IACO algorithm remained the lowest. When the node number was 100, the optimal path cargo damage rate achieved by the IACO algorithm was approximately 6.89%, which is an average decrease of 31.82% compared to other algorithms. This means that fresh food and pharmaceutical products reach consumers in a safe condition. Not only does this reduce resource waste, but ensures cold chain integrity, it also effectively lowers public health risks stemming from food spoilage or drug degradation. This holds profound significance for safeguarding consumer rights and maintaining social stability. By optimizing the path and temperature control parameters, this model could effectively reduce delays and temperature fluctuations during transportation, thereby reducing the rate of cargo damage. Finally, the study introduced CCL distribution optimization models proposed by studies for comparison, while also benchmarking the research findings against industry standards. The "industry average" was compiled from the China Cold Chain Logistics Development Report and relevant corporate financial reports, while the "standard TMS software" data was simulated and estimated based on publicly available optimization capability case studies from mainstream commercial transportation management systems. The comparison results are shown in Table 2.

Table 2. Comparison of the effects of different CCL distribution optimization models

Model	Transportation costs (RMB)	Vehicle usage costs (RMB)	Energy consumption costs (RMB)	Carbon emission costs (RMB)	Optimal path mileage (km)	Calculation efficiency (s)	Customer satisfaction (%)
This Text	2652.27	720.12	1223.48	782.10	390.80	32.04	96.32
Reference (Zhao, 2024)	3200.98	856.26	1481.38	985.62	452.55	59.20	85.39
Reference (Liu and Li, 2024)	2950.47	805.82	1350.05	907.28	425.71	45.83	93.28
Reference (Li and Zhang, 2024)	3158.30	820.69	1429.29	948.03	438.90	51.29	90.07
Industry average	3450.00	950.00	1650.00	1250.00	510.00	-	82.50
Standard TMS software	3050.00	850.00	1450.00	1050.00	440.00	25.00	88.00

Table 2 compares the effectiveness of different CCL distribution optimization models. The CCL distribution optimization model based on the IACO algorithm proposed by the research had significantly lower distribution costs than other models. Its transportation cost, VUC, ECC, and CEC were 2652.27 yuan, 720.12 yuan, 1223.48 yuan, and 782.10 yuan, respectively, with an average reduction of 14.53%, 12.99%, 13.85%, and 17.41%, respectively. This study demonstrated that by utilizing vehicle scheduling and considering energy and carbon emission constraints, delivery costs were reduced. Furthermore, carbon emission intensity was integrated into pheromone weight calculation, and unit time carbon emissions were reduced through dynamic adjustment of refrigeration parameters. In addition, the optimal path planned by the model proposed in this research was 390.80 km, with a computation time of 32.04 s. These values represent a reduction of 10.99% and 38.51%, respectively, compared to other models, further demonstrating the superiority of this method in balancing optimization effectiveness and computational speed. In terms of customer satisfaction, the model proposed in the study improved by an average of 7.52% compared to other models, indicating that it performed better by ensuring on-time delivery, reducing cargo damage, and improving the customer experience. Compared with existing industry practices, the model reduced total transportation costs by 23.12% relative to the industry average, with CECs showing a particularly significant reduction of 25.51%. Simultaneously, the optimal route mileage was shortened by 23.37%, and customer satisfaction increased by 16.75%. This demonstrates the model's significant potential in driving industry cost reduction, efficiency improvement, and green transformation. Compared to standard TMS software, the IACO model maintained a 9.45% lead in customer satisfaction while achieving further optimizations of 13.04% in total cost and 25.51% in CEC. This demonstrates that the customized algorithm developed in this research outperforms generic commercial optimization tools in addressing the multi-objective, strongly constrained problems unique to CCL. Although standard TMS may be faster in individual computational steps, the research model delivers significantly higher-quality global optimization solutions within acceptable timeframes, achieving a better balance between optimization effectiveness and computational efficiency.

5. Discussion

This study constructs an e-commerce CCL route optimization model based on an IACO algorithm, achieving multi-objective coordination optimization of transportation costs, energy consumption, and carbon emissions. Findings demonstrate that the model exhibits great merits in route planning efficiency and carbon reduction. These findings provide quantitative evidence for policy formulation and industry regulation. For instance, regulatory bodies can reference the model's carbon accounting methodology to establish more precise CCL carbon footprint benchmarks, thereby designing differentiated carbon tax or emissions trading mechanisms. For enterprises, the model can be integrated into decision support systems as a technical solution for applying green subsidies or meeting compliance requirements, incentivizing widespread industry adoption of low-carbon delivery models. Furthermore, optimized CCL routes yield positive socioeconomic impacts. Reduced cargo damage rates and enhanced temperature control stability effectively minimize food waste and pharmaceutical damage, elevating food safety and public health standards, while cost optimization and low-carbon route planning bolster corporate competitiveness, mitigate operational risks, and propel the CCL sector toward efficient, green development. Moreover, the IACO model not only holds technical optimization significance but also provides a feasible pathway for industry collaboration. Logistics enterprises can embed the model into their transportation management systems to achieve dynamic order-vehicle dispatching. Retailers can leverage model outputs to forecast delivery delays and temperature control risks, thereby optimizing inventory planning; governments can reference the model's carbon emissions accounting methodology to establish cold chain carbon footprint benchmarks and differentiated carbon tax policies, fostering a green logistics ecosystem that integrates enterprises, retailers, and regulators. Simultaneously, implementing optimization strategies may stimulate demand for new roles in logistics informatization, temperature-control equipment maintenance, and intelligent transportation management, creating employment opportunities in sustainable logistics and achieving dual improvements in economic and social benefits.

From a practical application perspective, while the model demonstrates excellent performance under experimental conditions, it faces unpredictable factors such as road congestion, weather changes, and equipment failures in large-scale cold chain networks. Future research could integrate real-time traffic information and dynamic scheduling mechanisms, incorporate reinforcement learning for adaptive optimization, and leverage cloud computing platforms to support multi-node parallel processing, thereby enhancing the model's robustness and scalability.

Regarding industry standards and benchmark comparisons, current research primarily contrasts with traditional algorithms, lacking alignment with cold chain industry best practices. Subsequent research should benchmark model outcomes against industry metrics such as energy consumption, temperature control compliance rates, and carbon emission intensity to validate the model's comprehensive advantages in energy conservation, emissions reduction, and operational efficiency. Establishing a unified evaluation system would enhance the model's industry applicability and provide technical support for standardizing cold chain optimization algorithms.

In summary, this research demonstrates significant comprehensive advantages in algorithm performance, policy application, and societal value. However, further refinement is needed in scalability verification, standardized evaluation, and cross-industry application. Future work could integrate technologies like IoT sensing, cloud-edge collaboration, and reinforcement learning to enhance the IACO model's dynamic decision-making and real-time optimization capabilities, providing sustained support for building a green, efficient, and intelligent CCL system.

6. Conclusion

CCL has been a significant obstacle to the industry's sustainable development, mainly due to the high costs, carbon emissions, and cargo damage rates inherent in the process. To cut operating expenses, reduce carbon emissions, and boost delivery efficiency, a low-carbon vehicle routing optimization model with time window constraints was developed and solved. By integrating a dynamic pheromone update mechanism, a dual-layer optimization architecture, and combining a hybrid heuristic function with a 2-opt local search strategy to improve path connectivity, global optimization of delivery paths was achieved. Experiments showed that the IAOC algorithm reduced the MAE by 48.39% compared to other algorithms, effectively minimizing path redundancy, while its computational efficiency increased by 14.73%. Additionally, the IACO-based model reduced transportation, VUC, ECC, and CEC costs by 14.53%, 12.99%, 13.85%, and 17.41%, respectively. The optimal path planned by this model was 390.80 km, with a calculation time of 32.04 seconds, demonstrating significant advantages. Furthermore, customer satisfaction reached 96.32%. The results indicated that the proposed optimization model and IACO algorithm effectively balance path length, temperature stability, and low-carbon goals, verifying the feasibility of multi-objective collaborative optimization.

Author Contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Wei Zi, Yan Zhang. The first draft of the manuscript was written by Wei Zi, manuscript review and revisions were performed by Yan Zhang, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Conflicts of interest

All authors declare that they have no conflicts of interest.

Declaration of Artificial Intelligence (AI) Tools

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References

Aghelpour, P., Graf, R., and Tomaszewski, E. (2023). Coupling ANFIS with ant colony optimization (ACO) algorithm for 1-, 2-, and 3-days ahead forecasting of daily streamflow: A case study in Poland. *Environmental Science and Pollution Research*, 30(19), 56440–56463.

Bai, Q., Yin, X., Lim, K., and Dong, C. (2022). Low-carbon VRP for cold chain logistics considering real-time traffic conditions in the road network. *Industrial Management & Data Systems*, 122(2), 521–543.

Fan, X., Zhang, Y., Xue, J., and Cao, Y. (2024). Exploring the path to the sustainable development of cold chain logistics for fresh agricultural products in China. *Environmental Impact Assessment Review*, 108(9), 1–12.

Gebremedhin, S., Shiferie, F., Tsegaye, A., Alemayehu, A., Wondie, T., Zeleke, S., and Biks, A. (2024). Perspectives on the performance of the Ethiopian vaccine supply chain and logistics system after the last mile delivery initiative: A phenomenological study. *The American Journal of Tropical Medicine and Hygiene*, 110(5), 1029–1038.

He, K. (2023). AP clustering algorithm for analysis of the impact of cold chain distribution center location on logistics costs. *Journal of Industrial and Production Engineering*, 40(8), 661–676.

Lim, M. K., Li, Y., Wang, C., and Tseng, L. (2022). Prediction of cold chain logistics temperature using a novel hybrid model based on the mayfly algorithm and extreme learning machine. *Industrial Management & Data Systems*, 122(3), 819–840.

Liu, H., Lee, A., Lee, W., and Guo, P. (2023). DAACO: Adaptive dynamic quantity of ant ACO algorithm to solve the traveling salesman problem. *Complex & Intelligent Systems*, 9(4), 4317–4330.

Liu, K., Sun, Y., and Yang, D. (2023). The administrative center or economic center: Which dominates the regional green development pattern? A case study of Shandong Peninsula urban agglomeration, China. *Green and Low-Carbon Economy*, 1(3), 110–120.

Liu, Z. and Li, X. (2024). Optimization model of cold chain logistics delivery path based on genetic algorithm. International *Journal of Industrial Engineering*, 31(1), 152–169.

Pajic, V., Andrejic, M., and Chatterjee, P. (2024). Enhancing cold chain logistics: A framework for advanced temperature monitoring in transportation and storage. *Mechatronics and Intelligent Transportation Systems*, 3(1), 16–30.

Shobeiri, P., Akbarian Rastaghi, M., Abrishami, S., and Shobiri, B. (2024). PCP–ACO: A hybrid deadline-constrained workflow scheduling algorithm for cloud environment. *The Journal of Supercomputing*, 80(6), 7750–7780.

Wang, W., Yin, X., Wang, S., Wang, J., and Wen, G. (2023). Robot path planning method combining enhanced APF and improved ACO algorithm for power emergency maintenance. *International Journal of Information Technologies and Systems Approach*, 16(3), 1–17.

Wu, J., Shi, L., Zhan, H., Lai, K., and Zhang, J. (2022). A buffer-based ant colony system approach for dynamic cold chain logistics scheduling. *IEEE Transactions on Emerging Topics in Computational Intelligence*, 6(6), 1438–1452.

Li, X. and Zhang, Z. (2024). Multi-objective low carbon vehicle routing for cold chain distribution with customer time loss aversion. *Journal of Systems Science and Information*, 12(5), 590–623.

Yin, C., Fang, Q., Li, H., Peng, Y., Xu, X., and Tang, D. (2024). An optimized resource scheduling algorithm based on GA and ACO algorithm in fog computing. *The Journal of Supercomputing*, 80(3), 4248–4285.

Zhang, J. and Ding, B. (2023). Multi-objective cold chain path optimization based on customer satisfaction. *Journal of Applied Mathematics and Physics*, 11(6), 1806–1815.

Zhang, L., Fu, M., Fei, T., Lim, K., and Tseng, L. (2024). A cold chain logistics distribution optimization model: Beijing–Tianjin–Hebei region low-carbon site selection. *Industrial Management & Data Systems*, 124(11), 3138–3163.

Zhang, X., Chen, H., Hao, Y., and Yuan, X. (2024). A low-carbon route optimization method for cold chain logistics considering traffic status in China. *Computers & Industrial Engineering*, 193(7), 1–15.

Zhao, M. (2024). Optimization of distribution paths in cold chain logistics management based on IFW-ABC algorithm. *Intelligent Decision Technologies*, 18(3), 1711–1726.

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