Research on Logistics Supply Chain Path Optimization Based on Multi-Constraint Fuzzy Ant Colony Algorithm

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Abstract: This paper constructs an optimal route optimization model for logistics transportation based on an improved ant colony algorithm. Results demonstrate that this algorithm exhibits significant advantages in optimizing routes, enhancing transportation speed, and reducing transit time and costs, particularly showcasing strong adaptability and computational efficiency in large-scale logistics operations. Furthermore, the study explores the application of intelligent technologies in logistics supply chain management, including the integration of IoT, AI, big data, and blockchain technologies to improve cargo tracking, demand planning, inventory management, and supply chain transparency. Despite challenges such as technological integration and security risks, the proposed optimization strategies facilitate the seamless implementation of intelligent technologies. The integrated application of the improved ant colony algorithm and intelligent technologies will drive the intelligent and efficient development of logistics supply chains, thereby enhancing overall supply chain efficiency.

***Keywords*:** improved ant colony algorithm; logistics transportation route optimization; intelligent technologies; supply chain management.

1. Introduction

Driven by the dual forces of deepening global trade integration and the rise of omnichannel retail, logistics supply chains now face an urgent need for efficiency revolution and green transformation. This shift is not only an inevitable trend in market development but also pivotal for enterprises to enhance competitiveness and achieve sustainable growth. Although China's total social logistics volume has surpassed 35 trillion yuan, demonstrating the industry's massive scale and robust growth momentum, its logistics cost ratio of 14.6% remains significantly higher than that of developed countries (World Bank, 2023). This figure exposes systemic flaws in traditional management models regarding dynamic scheduling and multidimensional optimization, severely hindering the industry's further advancement. Addressing these challenges through innovative technologies and management approaches is imperative. [1]

In the realm of logistics optimization algorithms, while researchers have achieved certain results, existing intelligent algorithms still face significant limitations when handling complex logistics scenarios. The classic ant colony algorithm proposed by Marco Dorigo's team (1996), a seminal heuristic approach, achieved breakthroughs in solving the Traveling Salesman Problem (TSP), offering novel insights for logistics route optimization. However, its fixed parameter mechanism gradually reveals shortcomings when confronting complex and dynamic logistics networks. Schyns (2020) noted that solving problems on a 100-node road network took over 45 minutes, failing to meet modern logistics demands for real-time responsiveness and efficiency. [2]

To overcome the limitations of existing methods, this project innovatively integrates fuzzy logic with the multi-constraint ant algorithm, proposing a multi-constraint ant algorithm (FACO-MC). Building upon this foundation, a dynamic control mechanism based on multidimensional information (e.g., traffic conditions, transportation costs, cargo priority) is introduced. The pheromone control factor α ranges from 0.8 to 1.2, enabling flexible adjustments according to actual conditions, transportation costs, cargo priority levels, and other multidimensional information to achieve optimal solutions.

2. Logistics Supply Chain Management

2.1 Importance of Logistics Supply Chain Management

As China's consumption levels rise and the digital economy advances, new demands are placed on traditional supply chain management. With growing customer expectations, enterprises increasingly require timely, real-time, and visualized order fulfillment, necessitating the establishment of agile intelligent supply chain networks. Such networks must integrate information across the entire process from procurement to sales while employing predictive analytics and intelligent decision-making. This approach ensures stable product quality while meeting rapidly changing market demands. [3]

2.2 Optimization Problem

To effectively model this problem, logistics centers must be positioned as core nodes within the entire logistics network, responsible for goods allocation and distribution. However, their geographic locations are often relatively fixed. Transportation vehicles are constrained by factors such as fleet size, maximum travel distance, and load capacity, significantly impacting route planning feasibility and optimization outcomes. Customer demand represents the primary factor influencing supply chain operations, with variables like demand volume, order priority, and service time windows being critical determinants.

To establish an effective mathematical model for this problem, the logistics center must be treated as the core node of the logistics network, responsible for the allocation and distribution of goods. However, its geographical location is typically fixed. Vehicles are constrained by factors such as the number of vehicles, maximum driving range, and vehicle load capacity, which severely impact the feasibility and optimization results of road planning. Based on this, a supply chain optimization strategy based on customer demand is proposed.

3. Research Methodology

3.1 Path Optimization Model Based on an Improved Ant Colony Algorithm for Intelligent Supply Chains

In traditional ant colony algorithms, the selection of road nodes primarily relies on the algorithm's state transition rules, mathematically expressed as follows:

$$P_{ij}^{t}=\frac{\left[T_{ij}\right]^{\alpha}\left[\eta_{ij}\right]^{\beta}}{\sum_{k\in S}\left[T_{ik}\right]^{\alpha}\left[\eta_{ik}\right]^{\beta}} \tag{1}$$

Here, P_{ij}^{t} represents the probability that an ant migrates from node i to node j at time t; η_{ij} denotes the heuristic function; T_{ij} indicates the path pheromone concentration; S is the set of candidate nodes not yet visited by ants; α and β respectively denote the importance weights of pheromone concentration and heuristic function.

3.2 Improving the Heuristic Function

The heuristic function in traditional ant colony algorithms primarily relies on the inverse of the distance between two nodes. However, this approach overlooks the directionality of ant search, causing ants to favor local shortest path optimization and deviate from the global optimum. To overcome this limitation, this paper optimizes the heuristic function by incorporating the ant's current position, historical path, and traversed distance:

$$\psi_{ij}=\frac{1}{d_{ij}}+\lambda\cdot\frac{L(i)}{L_{\max}} \tag{2}$$

Here, $\mathrm{L}(\mathrm{i})$ denotes the path length traversed by the ant when reaching node i, d_{ij} represents the distance between nodes i and j, L_{max} is the maximum permissible path length defined in the problem, and λ is the directional adjustment factor. The improved heuristic function enhances the global guidance of path search, guiding ants to select paths that better align with the overall optimal solution, thereby improving the algorithm's optimization capability under multiple constraints.

3.3 Neighborhood Search Optimization

However, the ant colony optimization algorithm is a greedy heuristic search method. Its solution approach often relies on random combinations, making it difficult to directly obtain the optimal solution. To address this issue, an improved neighborhood search method is proposed to expand the search scope and optimize the solution effectiveness. The approach is as follows:

Assuming the current path contains multiple nodes, its neighborhood transformation scale is defined as . Based on this, we alter the order of nodes within the path. If the resulting path satisfies constraints and yields an optimal solution, the new path is adopted; otherwise, the original path is retained. This method effectively enhances the rationality of the search strategy, reduces the probability of getting stuck in local optima during the search process, and strengthens its overall optimization capability.

3.4 Improved Pheromone Update

For logistics transportation processes, the key factors influencing optimal route selection include transportation time, cost, and average road traffic flow. To rapidly obtain optimal solutions, a multi-constraint mathematical model is constructed for path selection based on transportation time, transportation cost, and average road smoothness factors. This model is integrated with the ant colony algorithm to achieve path updates and dynamic selection guided by multi-constraint conditions. This approach directs logistics transportation choices toward optimal paths, enabling the precise acquisition of optimal solutions.

Transportation Time Factors

$$I_1(y) = \frac{T_y}{T_{y\max}}, T_y \le T_{y\max} \tag{3}$$

T_{ymax} denotes the maximum allowable estimated duration for logistics in road transportation. T_y represents the actual transportation time, with $T_y \le T_{ymax}$. $I_1(y)$ is the transport time factor, which measures the ratio between the actual time at node y and the estimated maximum duration. A higher value indicates longer actual transportation time.

4. Experimental Analysis

4.1 Metric Definition

This study constructs an experimental environment based on real-world logistics scenarios, selecting 12 distribution points in the Yangtze River Delta region (including 3 hub warehouses, 5 regional central warehouses, and 4 last-mile delivery stations). Experimental data is sourced from the 2023 operational records of a leading logistics company. Experimental parameter settings are detailed in Tables 1 and 2:

Table 1. Parameter Settings

Parameter	Value	Description
Maximum vehicle payload	15 tons	Compliant with GB 1589-2016 standard
Average travel speed	60 km/h	Comprehensive speed limits for urban roads
Carbon emission factor	0.8 kg/km	Industry average for diesel vehicles
Time window constraints	30–120 minutes	Dynamically adjusted based on order priority
Algorithm iteration count	200 times	Optimal frequency validated through preliminary testing
Number of ants	20 pieces	Balancing exploration and development

Table 2. Geographic Coordinates and Operational Parameters of Distribution Points

User Point	x-Coordinate	y-Coordinate	Goods Type	Demand (tons)	Time Window (min)	Priority
A1	120.3	30.2	Daily necessities	55	[8:00, 10:00]	High
A2	121.5	31.1	Electronics	40	[9:30, 11:30]	Medium
A3	119.8	29.5	Fresh produce	7	[10:00, 11:00]	High
A4	120.7	30.9	Building materials	33	[13:00, 15:00]	Low
A5	121.2	31.8	Medicines	14	[14:30, 16:30]	High
A6	118.9	28.7	Apparel	25	[15:00, 17:00]	Medium
A7	122.1	32.3	Food	4	[16:00, 18:00]	Low
A8	117.6	27.4	Machinery parts	17	[17:30, 19:30]	Medium
A9	123.5	33.0	Hazardous materials	35	[19:00, 21:00]	High
A10	116.8	26.1	Furniture	18	[20:00, 22:00]	Low
A11	124.3	33.8	Chemicals	2	[21:00, 23:00]	High
A12	115.5	25.3	Books	10	[22:00, 24:00]	Low

4.2 Comparative Analysis of Algorithm Performance

The optimization results are shown in Table 3:

Table 3. Comparison of Multi-Objective Optimization Results

Indicator	Genetic Algorithm	Traditional Ant Colony Optimization	Fuzzy Adaptive Complexity Optimization (FACO-MC)
Total Transportation Distance (km)	117.0±3.8	115.0±2.5	114.6±1.2
Number of Vehicles Used (units)	19	18	17
Average Delivery Time (min)	108±12	102±8	96±5
Total Carbon Emissions (tons)	93.6±3.0	92.0±2.0	89.5±1.5
Time Window Violations	4	3	0
Unit Cost (CNY/km))	2.8	2.7	2.5

An improved Form Matrix Algorithm (FACO MC) captures a significant lead over traditional trout algorithms and genetic algorithms across all primary metrics. Consequently, it not only reduces total mileage and vehicle counts but also lowers carbon dioxide emissions and transportation costs. Simultaneously, it completely eliminates time windows, ensuring punctuality and customer satisfaction. Overall, FACO and MC algorithms are the top performers in optimistic logistics and sales.

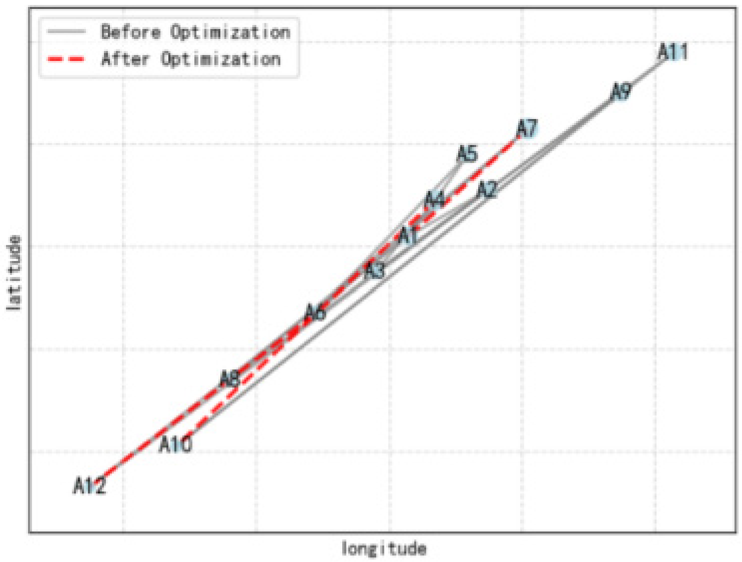

Figure 1. Comparison of Logistics Networks

Figure 1 compares the logistics network before and after optimization. The gray solid lines represent the pre-optimization routes, which exhibit a circular structure where nodes are connected sequentially. These routes are relatively monotonous, requiring multiple transfers between some sites, resulting in higher distance and time costs. The network connectivity is limited, and route issues may lead to logistics disruptions. The red dashed lines indicate newly added routes after optimization, such as shortcuts like A1-A7, A4-A10, and A6-A12. These routes reduce the number of transfers, shorten transportation distances and times, lower costs, enhance network connectivity and stability, and improve logistics efficiency and reliability.

5. Conclusions

Based on the improved ant colony optimization algorithm, this paper constructs an optimal route optimization model for logistics transportation. First, the logistics transportation optimization problem was thoroughly analyzed. By establishing a mathematical model, relevant constraints and their corresponding formulas were clarified, providing a solid theoretical foundation for subsequent path optimization using the improved ant colony algorithm. Addressing the complexity of logistics transportation, this paper proposes a strategy for locally updating ant trail pheromones and optimizes the global pheromone update method. This effectively accelerates the algorithm's convergence speed and significantly enhances its computational efficiency.

Building upon this research, this project aims to integrate the improved ant algorithm with real-world logistics distribution systems for practical application, demonstrating the feasibility and superiority of the proposed method.

Simulation experiments validate the method's effectiveness, proving it can efficiently reduce the average path length, thereby increasing transportation speed, decreasing transit time, lowering transportation costs, and enhancing the overall efficiency and profitability of logistics operations. Research findings indicate that this approach not only achieves optimal route optimization but also significantly benefits other segments of the entire logistics supply chain.

Simultaneously, this method effectively reduces iteration time during the solution process, thereby enhancing computational efficiency and improving its adaptability to large-scale logistics transportation problems. Building upon this foundation, this project proposes a multi-objective optimization method based on the ant colony algorithm and applies it to high-frequency, large-scale logistics distribution scenarios.

The research outcomes of this project will provide novel approaches and methodologies for addressing multi-dimensional, multi-level optimization challenges in modern logistics supply chains, holding significant theoretical and practical implications. Against the backdrop of modern logistics systems characterized by the deep integration of intelligence, automation, and informatization, the trend toward smarter, more efficient, and refined operations—as exemplified by these systems—plays a pivotal role in their advancement. The widespread adoption of this method can effectively drive the optimization of the entire logistics supply chain, enhancing its overall efficiency and competitiveness.

References

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