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INVESTIGATION INTO THE OPTIMISATION OF COLD CHAIN LOGISTICS DISTRIBUTION PATHS USING THE HYBRID ANT COLONY METHOD

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Abstract. China's cold chain logistics market has been growing quickly in recent years. Cold chain logistics helps minimize food loss and waste during transit in addition to meeting people's need for fresh food. As the idea of "green logistics" has gained traction, we created a better ant colony algorithm with a multi-objective heuristic function to address the issue. Specifically, we combined the A^* algorithm with the ACO algorithm to address the issue of insufficient pheromone in the early stages of the ACO algorithm, and the resulting improved multi-objective ACO algorithm was able to solve the vehicle path distribution problem with a multi-objective optimisation model more successfully than the traditional ACO algorithm, yielding more Pareto efficient solutions. Ultimately, simulation studies demonstrate that the distribution paths produced by the multi-objective model and algorithm presented in this paper can concurrently optimize for lowering distribution costs, cutting carbon emissions, and raising customer satisfaction, ultimately resulting in a more ecologically friendly and greener distribution solution.

Key words: vehicle path problem; cold chain logistics; energy saving and emission reduction; hybrid ant colony algorithm

1. Introduction. With the continuous improvement of the quality of life, people's demand for fresh green fresh products is also increasing [1]. In order to meet the market demand and promote the development of enterprises, cold chain logistics enterprises have invested a large number of vehicles in the transport link, but because the fuel consumption and carbon emissions generated in the process of cold chain logistics and distribution are far more than that of ordinary logistics, the pressure on enterprises to reduce the operating costs and the negative impact of automobile exhaust on the environment is also increasing. According to the survey of China Logistics and Purchasing, nearly half of the logistics enterprises' fuel expenses account for more than 40% of the transport costs [2]. According to the statistics of the World Resources Institute, the carbon emissions of the transport industry account for 20% of the total global emissions [3]. Facing the double pressure of economy and environment, energy saving and emission reduction is especially important for cold chain transport enterprises [4]. By promoting energy saving and emission reduction and controlling the amount of fuel consumption, enterprises not only compress the cost of fuel consumption on the one hand, but also, with the government of China continuously accelerating the full implementation of the carbon emissions trading system [5], it is likely to reduce the operating cost of carbon trading for the enterprise in the near future and increase the profit of the enterprise, which is conducive to the development of the enterprise. On the other hand, because carbon emissions depend on the amount of fuel consumption, while reducing the use of fuel resources also reduces the carbon pollution caused by the environment, in line with the concept of green logistics development [6]. Therefore, it is very important to add energy saving and emission reduction into the cold chain logistics vehicle path problem in order to seek a win-win situation between economy and environment for the rapid development of cold chain logistics enterprises.

Environment-friendly society is a social system that consists of environment-friendly technologies, products, enterprises, industries, schools, communities, etc., aiming at man and nature, based on environmental carrying capacity, following the law of nature as the core, and at the same time advocating environmental culture and ecological civilisation, and pursuing the coordinated development of economy, society and environment [7]. Environment-friendly society emphasizes the pursuit of harmony between man and nature as the goal, based on the carrying capacity of the environment, to follow the laws of nature as the core, to achieve the environment and the economic and social comprehensive and coordinated sustainable development of social relations, and

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to achieve the transformation of the industrial civilization from predatory, conquering and polluting to a co-ordinated, restorative and constructive ecological civilization[8]. Economic benefits frequently take precedence over energy consumption and environmental effects in conventional logistics and distribution channel design [9]. Green logistics calls on us to incorporate energy conservation, emission reduction, and other environmental protection components into the path optimization issue in order to minimize the adverse effects on the environment while maintaining economic advantages [10]. As a result, researching path optimization in cold chain logistics has a lot of application and aids businesses in developing green logistics in a sustainable manner.

There are two main issues: 1) In order to reduce the overall distribution cost, some scholars have focused the cold chain logistics route optimisation problem on vehicle path optimisation under static networks [11]. 2) The ACO algorithm is widely used and has strong parallelism and robustness [12].

Scholars have categorized the VehicleRouting issue (VRP) as an NP-hard issue, meaning that solving this kind of problem with precise mathematical analytical techniques is challenging [13]. A number of academics have successfully solved VRP issues using heuristic methods [14]. This work uses the ant colony method to solve the model since it is resilient, parallel, and commonly utilized to tackle VRP issues [15]. The absence of a route pheromone in the early stages of the ant colony algorithm can easily result in blind search, which raises the number of convergence excessively high [16]. In order to tackle this issue, the model in this paper is proposed to be solved using a hybrid ACO algorithm in conjunction with the A^* algorithm. The route information is initialized to minimize the number of convergence times and decrease the convergence time of the ACO algorithm based on the optimal solution found by the A^* algorithm. In addition, the heuristic factor and transfer probability are enhanced in accordance with the research findings in this work, making the hybrid ant colony algorithm better suited to the issues this article will be studying.

2. Problem description. Researchers both domestically and internationally have been delving deeply into the topic of cold chain logistics in recent years. The influence of the number of delivery vehicles, client demand, and delivery time on the overall cost of cold chain distribution was investigated in study [17], which also used a genetic algorithm to solve the cold chain distribution route optimization model with tight time window limitation. Improved results were obtained by using a heuristic approach to solve a dynamic multi-objective vehicle route optimization model, as investigated in study [18].

The logistics route issue with time windows was investigated in study [19]. The ant colony algorithm was enhanced by modifying the pheromone for model solution, and the method's efficacy was confirmed by case analysis and comparison. Research [21] employed the enhanced simulated annealing approach to analyze the variation in distribution costs while taking into account the scenario of heterogeneous fleet based on the conventional route model.

When building a cold chain logistics path model, research [22] takes into account the variety of client demand types. An ant colony algorithm and clustering techniques are used to solve the model. Study [23] established a mathematical model under the constraints of vehicle load and customer demand, took into account the cost of cargo damage in the distribution process in relation to the perishability of fresh products, designed a traditional genetic algorithm in accordance with the model, and solved the model with an improved genetic algorithm. Some academics have focused on the study of low-carbon cold chain logistics as a result of the government's increasing demands for environmental preservation and sustainable development as well as people's growing awareness of energy conservation and emission reduction. In order to create a cold chain inventory model, study [25] considers carbon emission as a cost element. It then investigates the best inventory option given the limitations of cost and carbon emission, and it creates a precise algorithm to solve the model. Research [26] converted carbon emissions into economic costs to create a path optimisation model with fuzzy time; to improve results, the model was solved using an ant colony algorithm; research [27] created a path optimisation model that took into account both carbon emissions and customer time windows simultaneously, and it was solved using a heuristic algorithm.

In this work, we address the optimization problem of cold chain logistics paths for a single distribution center, where trucks originate from one center and return there upon fulfilling the delivery task of each customer's fresh goods. In actuality, cold chain logistics companies don't construct a lot of distribution centers because of budgetary constraints.

This paper's primary goal is to create a distribution strategy for a distribution center based on the resources at hand, accounting for variables like product demand, access time, and maximum transportation capacity. The aim of this initiative is to reduce the overall expenses incurred by the vehicle in relation to "wasteful," "green," "indirect," "indirect," "road damage," and "soft" costs related to incarceration, all while fulfilling the necessary requirements for product distribution between customs points and the district center. From the standpoint of reducing emissions and conserving energy, this is done.

Below are the particular presumptions:

- The distribution center has a enough number of identically equipped refrigerated trucks to fulfill consumer demand for fresh produce delivery; also, the vehicles are capacity-limited, meaning that demand at each customer site won't surpass the vehicle's maximum capacity;
- Every customer point's location, the need for fresh goods, the amount of time needed for servicing, and the window for delivery are all known;
- A single reefer can transport goods to several locations, but it can only depart from and arrive at each location once; only one reefer truck is scheduled to deliver to the same customer location and can ensure that the service meets the needs of the customer location;
- A fine shall be paid by the business to the refrigerated truck operator if the vehicle carrying fresh product to a customer site is not delivered within the window of time that was arranged with the customer site;
- During the delivery service for a customer point, the refrigerated truck does not load or unload any items; instead, it just loads and unloads recently acquired items that come from the service for the client point; it does not accept other delivery services. The refrigerated truck returns to the distribution center when the distribution task is finished;
- The drivers employed in cold chain distribution are all subjected to the same rigorous training and technical experience, and subjective variables do not affect the fuel usage.

3. Examining the Model's Known Parameters and Variables. The traditional ant colony algorithm uses a positive feedback mechanism to continuously converge during the search process by calculating the transfer probability based on the distance between paths and the concentration of pheromones. However, this algorithm has the drawback of prematurely settling into the local optimum.This work limits the range of pheromone concentration, performs global pheromone updating with a cycle of 20 iterations in the algorithm design, and dynamically increases pheromone concentration in order to prevent the ant colony algorithm from entering a state of local optimality and enhance the accuracy of the solution. The time restriction is now taken into account by the ants in addition to distance when they move to the next node, thanks to a revision of the heuristic algorithm. The multi-objective optimization of the Pareto solution set is realized by setting the parameter of the pseudo-random proportional action selection rule such that the ants have a high chance of selecting the best path and ultimately approaching the optimal solution.

3.1. Recognized parameters. The cold chain logistics path optimization model that is the subject of this paper's study has the following known parameters.

N: Every client that the distribution center must service;

K: The total amount of cars at the district center that are needed for distribution;

f_k: The one-time fee for utilizing a refrigerated car k;

$fuel$: the quantity of fuel produced during the distribution of vehicles;

a: The distribution vehicles' refrigerant usage component during the transportation phase;

b: Distribution vehicles' refrigerant consumption coefficient throughout the loading and unloading process;

q_i: The level of fresh product demand at consumer point i;

p: The cost per unit of fresh product that the delivery vehicle transports;

∂_1: The freshness degradation coefficient of fresh goods while the delivery truck is in motion;

∂_2: The rate at which fresh goods loses freshness while being loaded and unloaded from the distribution vehicle;

t_i^k: The moment at which delivery vehicle k reaches client location i;

t_o^k: The moment at which delivery vehicle k leaves the distribution facility;

T_i: The duration of service for the distribution vehicle at customer point i;

Q_{ij}: The weight must move in order to get straight from customer point i to customer point j;

Q: The vehicle's maximum load capacity;

ε_1: A penalization element in case the delivery vehicle reaches the client's address prior to the mutually agreed-upon maximum time range;

ε_2: The penalty factor in case the delivery vehicle reaches the customer's location beyond the prearranged time window's lower bound.

3.2. Variable analysis.

3.2.1. Analysis of decision variables. In order to make the model analysis easier, the client point is represented by the letters i, j ,$i, j = 1, 2, 3, ..., (N)$ as well as the distribution facility receiving the number 0.

The following values are accepted for the decision variable x_{ijk}.

In the event that vehicle k travels directly along path i from customer point i to customer point j, j equals 1, otherwise x_{ijk} equals 0.

When car k fulfills i 's delivery order and delivers the products at customer point i, the response is 1, while in the other case, it is 0.

3.2.2. Cost Variable Analysis.

(1) Fixed expenses during the distribution of cars (C_1). A certain fixed cost, usually related to the number of activated refrigerated vehicles, is needed to activate the refrigerated vehicles that are used to provide distribution services to each customer point from the distribution center. These costs include vehicle depreciation, maintenance, and driver compensation. This is demonstrated by Eq.3.1:

$$C_1 = \sum_{k=1}^{K} \sum_{j=1}^{N} x_{0jk} f \tag{3.1}$$

where the value is 0 otherwise and 1 when the distribution center turns on the refrigerated truck K.

(2) The deployment of vehicles involves green costs (C_2).. The fuel costs incurred by the business for the fuel used in the transportation of refrigerated vehicles and the environmental costs incurred for the carbon emissions produced during transportation that lead to contamination of the environment are considered the "green costs" in this study.

The vehicle load and fuel consumption rate have a specific linear relationship. The typical driving unit distance fuel consumption rate of a reefer truck is ρ_0 when the truck is empty; once the vehicle is completely loaded, the normal driving unit distance fuel consumption rate is ρ_* . Eq.3.2 illustrates the typical driving unit distance fuel usage when the reefer truck is carrying goods weighing M .

$$\rho(M) = \rho_0 + \frac{\rho_* - \rho_0}{Q} M \tag{3.2}$$

where Q is the vehicle's maximum load capacity.

Fuel consumption from client location i to client location j is shown in Eq.3.3.

$$\rho\left(Q_{ij}\right) d_{ij} \tag{3.3}$$

Eq.3.4 can be used to calculate the fuel usage during the entire distribution process once the truck has finished serving every consumer point.

$$fuel = \sum_{k=0}^{K} \sum_{i=1}^{N} \sum_{j=1}^{N} x_{ijk} \rho\left(Q_{ij}\right) d_{ij} \tag{3.4}$$

Eq.3.5 illustrates the cost of fuel used during the entire distribution process.

$$C_{21} = cfuel \tag{3.5}$$

where c is the oil price.

Fuel usage × carbon dioxide emission factor = carbon emissions, according to Ottmar's analysis. These two variables have a particular linear relationship. Eq.3.6 illustrates the environmental cost of the entire distribution process:

$$C_{22} = wfuel \tag{3.6}$$

for which the coefficient of carbon emissions is w .

Eq.3.7 illustrates the green cost associated with transporting chilled vehicles, as fuel costs and environmental costs follow a particular linear relationship with fuel usage.

$$C_2 = C_{21} + C_{22} = (c + \downarrow \omega)fuel = \gamma fuel \tag{3.7}$$

where the coefficient of green costs is γ .

(3) The price of refrigeration for vehicles being distributed (C_3). The price of the refrigerant used to keep the temperature inside the car compartment is typically what is considered the refrigeration cost during the distribution process of refrigerated vehicles. This calculation does not account for the fuel used for refrigeration because the fuel used for refrigeration is already included in the green cost. The heat load that the car experiences while it is traveling, the degree of vehicle cracking, the heat transfer rate, the area of the compartment that receives solar radiation. The cost of refrigeration during vehicle transportation can be roughly estimated as positively correlated with the vehicle operating time because, according to assumption Eq.3.1, the distribution center's vehicles are all of the same type, have similar compartment parameters and levels of deterioration, and have relatively stable internal and external environments during driving. With the equipment already unloaded and disposed of, the distribution service can be fulfilled by simply opening the premises, i.e., the deployment costs and the demobilization phase of idling can be assumed to be positively correlated with time.This information is based on the distribution of each customer point in time and the assumptions Eq.3.2. Eq.3.8 can thus be used to illustrate the cost of refrigeration during the vehicle transport process:

$$C_3 = \sum_{k=1}^{K} \sum_{i=0}^{N} \sum_{j=0}^{N} \left(at_{ij}^{k} x_{ijk} + bT_i y_{ik} \right) \tag{3.8}$$

T_i is the vehicle's servicing time from customer point .

(4) Price of fresh product cargo loss during vehicle distribution (C_4). Cargo loss is typically associated with the fresh products themselves, as well as distribution collisions, distribution timing, distribution methods, etc. Cold chain distribution, on the other hand, only takes into account cargo loss as a result of the fresh products themselves and the lapse in distribution time because it uses refrigerated vehicles to preserve the products in an atmosphere that is suited for their protection. The two primary factors that contribute to cargo loss are as follows: first, there is cargo loss throughout the distribution process as a result of time and items building up. The other is because of product loading and unloading, which results in environmental changes like temperature and oxygen content variations brought on by the depletion of fresh goods.

This study introduces the freshness decay function of fresh goods:

$$\theta(t) = \theta_0 e^{-\partial t} \tag{3.9}$$

The product's proportion of decay at a given temperature is shown in Eq.3.9. θ_0 represents the freshness of the product, for the product during vehicle transportation, ∂_1 stands for the freshness attenuation coefficient, and ∂_2 represents the freshness attenuation coefficient of the product during vehicle loading and unloading. Due to the loading and unloading process of the carriage door being open to make the temperature in the carriage, oxygen content, and other significant changes in the freshness of the product attenuation rate faster, there is $\partial_2 > \partial_1$. Freshness attenuation coefficient is typically related to the temperature and oxygen content around the goods. In conclusion, the following is an expression of the vehicle distribution process for fresh products during the cost of goods loss:

$$C_{41} = \sum_{k=0}^{K} \sum_{i=1}^{N} y_{ik} P q_i \left(e^{-\partial_1 \left(t_i^k - t_0^k \right)} \right) \tag{3.10}$$

$$C_{42} = \sum_{k=1}^{K} \sum_{i=0}^{N} y_{ik} P Q_{in} \left(1 - e^{-\partial_2 T_i}\right) \tag{3.11}$$

$$C_4 = \sum_{k=0}^{K} \sum_{i=1}^{N} y_{ik} P \left[q_i \left(e^{-\partial_1 \left(t_i^k - t_0^k\right)}\right) + Q_{in} \left(1 - e^{-\partial_2 T_i}\right)\right] \tag{3.12}$$

where Q_{in} is the weight of the goods still on board the vehicle as it departs the customer's point i.

4. Create an optimization model for the cold chain distribution path. This study created a mathematical model, represented by Equation Eq.4.1. The concept aims to reduce the overall expenses related to the distribution of cold chain logistics vehicles, including fixed costs, greasing costs, cold storage costs, fresh product loss, and fines for going beyond the time window that was mutually agreed upon.

$$\min Z = C_1 + C_2 + C_3 + C_4 + C_5 \tag{4.1}$$

$$\sum_{k=1}^{K} y_{ik} = 1, \forall i \tag{4.2}$$

$$\sum_{k=1}^{K} \sum_{j=0}^{N} x_{0jk} = \sum_{k=1}^{K} \sum_{j=0}^{N} x_{j0k} \tag{4.3}$$

$$\sum_{i=0}^{N} x_{ijk} = y_{jk}, \forall j, k \tag{4.4}$$

$$\sum_{j=0}^{N} x_{ijk} = y_{ik}, \forall i, k \tag{4.5}$$

$$\sum_{i,j \in S \times S}^{j} x_{ijk}, S \subseteq \{1, 2 \cdots N\} \tag{4.6}$$

$$t_j = t_i + T_i + t_{ij}, \forall i, j \tag{4.7}$$

Eq.4.2 and Eq.4.7 state that no vehicle's load can exceed the vehicle's maximum load; they also state that a vehicle can only visit each customer point once; they also state that the vehicle must exit the distribution center and return there; they also state that a vehicle may only be permitted to set out and arrive at any one of the customer points once; they are constraints; they seek to eliminate sub-circuits; and they state that the distribution must continue.

5. Sample analyses and solutions. The algorithm's efficacy is tested using Matlab 2018b coding, with the AMD Ryzen 3700x4.2 GHz(16 GB RAM) machine and Win10 as the operating system. The delivery distance of the case is determined by taking the straight line distance from the demand location for the sake of ease in the research.Python is used to scrape the Gaode map and determine the driving time, distance traveled between 66 spots, and real-time road speed using a speed algorithm. The distribution locations of the experiment are sixty-six neighborhoods located 20 km from a cold chain firm in city C. The distribution center is chosen to be the cold chain center in order to ascertain the planar rectangular coordinates of the experiment.

Table 5.1: Examples of medium-scale real data.

No.	Coordinate	Demand	Household Service Time Window	No.	Coordinate	Demand	Household Service Time Window
1	(185.59,89.67)	/	0	18	(140.85,120.80)	2	[3/6,1+30/60]
2	(155.78,78.99)	2.2	[5/6,1+4/6]	19	(137.47,74.87)	1.9	[1/6,1+50/60]
3	(163.22,93.01)	1.8	[15/60,1+2/6]	20	(242.38,100.88)	2.2	[2/6,1+1/6]
4	(153.44,96.65)	1.8	[2/6,50/60]	21	(144.17,140.32)	2.0	[20/60,1+2/6]
5	(142.75,59.32)	2.1	[4/6,1+20/60]	22	(210.55,125.33)	2.4	[5/6,1+20/60]
6	(134.20,62.83)	2.3	[30/60,1+10/60]	23	(138.67,123.44)	2.0	[1+5/6,3]
7	(158.99,157.24)	2.2	[1+2/6,2+3/6]	24	(158.30,98.10)	1.8	[2/6,1+2/6]
8	(141.76,123.11)	2.5	[3/6,1+4/6]	25	(188.95,103.99)	1.7	[3/6,50/60]
9	(130.39,119.72)	2.3	[1+2/6,3]	26	(124.55,78.22)	1.5	[2/6,2+1/6]
10	(189.05,139.33)	1.7	[20/60,1+30/60]	27	(133.47,111.58)	1.9	[1,3]
11	(204.52,72.15)	1.9	[1,1+2/6]	28	(192.33,98.67)	2.2	[2/6,40/60]
12	(136.33,69.55)	1.9	[4/6,2+2/6]	29	(159.84,112.33)	2.4	[1+2/6,2+50/60]
13	(144.88,136.13)	2.8	[1+5/6,3+1/6]	30	(172.68,98.38)	1.8	[4/6,1]
14	(223.17,141.79)	1.6	[40/60,1+4/6]	31	(203.12,115.72)	1.7	[1/6,1+2/6]
15	(216.75,74.92)	1.7	[5/6,50/60]	32	(186.40,100.19)	1.8	[2/6,1+55/60]
16	(152.03,96.87)	2.0	[2/6,1+20/60]	33	(122.45,149.99)	2.5	[1+10/60,3+1/6]
17	(129.82,54.55)	2.5	[1+2/6,2+2/6]	34	(170.87,100.30)	2.2	[40/25/60]

Table 5.2: Initialized pheromone comparison results.

λ	Average distribution cost	Average number of convergences
$\lambda = 1$	1359.8	34.7
$\lambda = 1.5$	1248.6	23.4
$\lambda = 1.8$	1209.5	21.1

The novel knowledge-based ACO algorithm was evaluated and processed on 66 distribution sites to verify its efficacy under varying data quantities.

Table 5.1 displays 34 examples of the demand points, which are set to be l_i (i= 2, 3,...,n) and the distribution center, which is set to be l_1. Based on the obtained real examples, the 33 demand points in medium scale are randomly re-generated according to the probability P by adopting the random offset principle, which produces 30 sets of simulated data for the upcoming analysis and comparison experiments. This process aims to confirm the efficacy of the constructed algorithm and demonstrate its applicability in various scenarios.

5.1. Results analysis. The model is solved using the sample data and the algorithm presented in this work. The model is solved using MATLAB programming; the ideal distribution strategy, which has been executed ten times on a personal computer, is displayed in Fig. 5.1.The number of ants is set to 10,$\alpha = 1, \beta = 3, \rho = 0.5, N_{\max} = 5, \lambda = 1.8, \eta = 0.99$; the total amount of pheromone is 100.

Fig. 5.1 illustrates how effective the study's model algorithm is. Currently, the distribution strategy consists of three vehicles leaving the distribution center: the first vehicle serves the 8th, 13th, 11th, 10th, 12th, 6th, and 15th customer points in that order; the second vehicle serves the 1st, 4th, 5th, 2nd, and 9th customer points; and the third vehicle serves the 3rd, 7th, and 14th customer points. Afterwards, the three vehicles return to the distribution center. Using this technique, the total cost of distribution comes to$1,159.

5.2. Examining the differences between the ACO algorithm. After executing the algorithm ten times at random with the aforementioned parameters, the ACO algorithm with initialized pheromone is compared with the ACO method with uninitialized pheromone. Table 5.2 presents the comparative findings.

Table 5.2 illustrates how the ant colony algorithm's number of convergences is decreased and its speed of convergence is increased when it is initialized with pheromones. Additionally, by combining the A*and ant

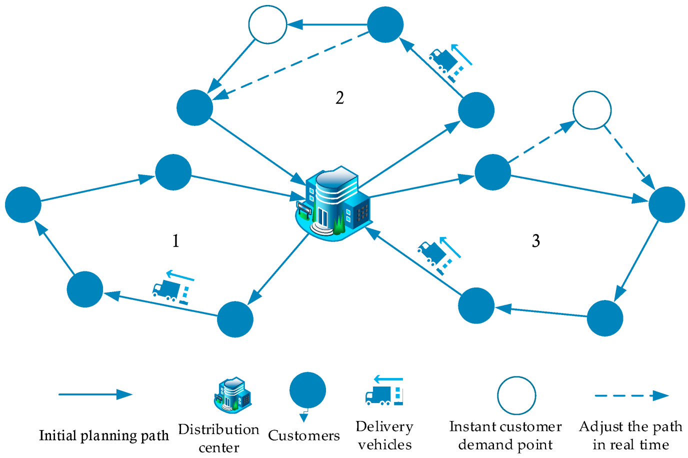

Fig. 5.1: Roadmap for vehicle distribution.

Table 5.3: Results of the experimental comparison.

Experimental	Algorithm	Total Cost	Experimental	Algorithm	Total Cost
1	A	1360	4	A	1360
1	B	1288	4	B	1255
1	C	1217	4	C	1198
2	A	1360	5	A	1360
2	B	1303	5	B	1303
2	C	1240	5	C	1240
3	A	1360	6	A	1360
3	B	1152	6	B	1217
3	C	1130	6	C	1183

Table 5.4: Corresponding optimal distribution techniques for every algorithm.

Algorithm	Minimum Distribution Costs	Distribution Strategy
A	1360	0-6-10-7-12-0
B	1155	0-9-12-13-11-12-6-15-0
C	1130	0-9-12-13-11-12-6-15-0

colony algorithms, the operation's outcomes are optimized, the enterprise's revenue is increased, its distribution costs are decreased, and the enterprise's growth is promoted.

5.3. Comparison of algorithms. Six randomized trials with a total pheromone count of 100, an iteration count of 100, and an initialised pheromone multiplier of 1.8 were carried out for each instance in order to confirm the efficacy of the algorithm, $\eta = 0.99, \alpha = 1, \beta = 3, \rho = 0.4, q_0 = 0.6$, the number of iterations is 100, and the initialization pheromone multiplier is 1.8. Table 5.3- Table 5.5 present the optimal results. Each algorithm's minimum distribution cost and matching distribution method are listed in Table 5.4, and each algorithm's cost composition is provided in Table 5.5 under the minimum distribution cost.

The hybrid ACO algorithm reported in this work outperforms both the A* algorithm and the basic ACO method when energy savings and emission reduction are taken into consideration, according to the experimental results.When compared to the A* algorithm and the basic ACO method, the overall distribution cost is decreased by roughly 15.9% and 8%, respectively. Based on the optimal results' cost components, it is evident

Table 5.5: Algorithm cost components for each algorithm executing the best distribution plan.

Algorithm	Distribution Costs	Fixed Costs	Green Costs	Cargo Damage Costs	Cooling Costs	Penalty Costs
A *Algorithm	1360	445	228	442	38	197
Basic Ant Colony Algorithm	1155	445	193	252	32	222
Hybrid Ant Colony Algorithm	1130	445	188	255	35	209

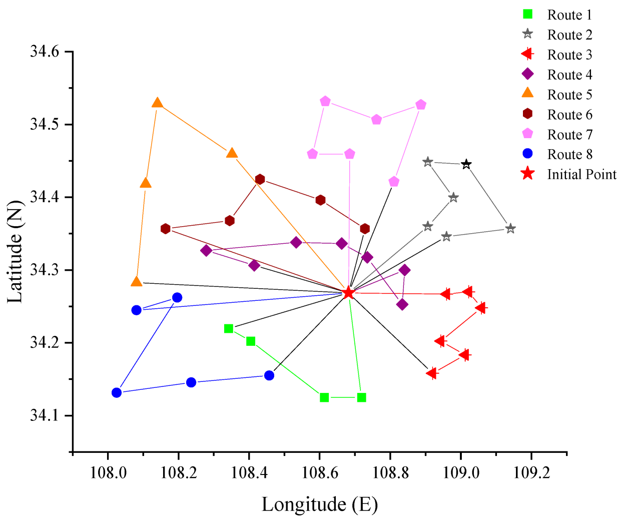

Fig. 5.2: Optimal route map.

that the hybrid ACO algorithm outperforms the original A* algorithm in terms of cost and enterprise operation. This is advantageous for the enterprise's growth as it leverages the ACO algorithm's parallelism and positive feedback to optimize resultsFurthermore, because the cost of green energy and cargo damage has been significantly reduced, it saves resources, safeguards the environment, and maintains product quality all at once. In contrast to the basic ACO algorithm, the hybrid algorithm yields lower green costs and penalty costs, saving resources, protecting the environment, and adhering to the concepts of sustainable development and green logistics. While the overall cost reduction is not as evident, the hybrid algorithm also results in lower carbon pollution and reduced use of environmental resources. Furthermore, the reduction of penalty costs associated with missing delivery windows increases the rate of on-time delivery, which enhances customer satisfaction, the final optimal different routes are shown in Fig. 5.2.

6. Conclusion. Green logistics has emerged as the trend for the future growth of the logistics sector as a result of the ongoing promotion of the idea of sustainable development. This paper presents an analysis of energy saving and emission reduction from the perspective of cost factors to be taken into account in the model. Under the constraints of time window, customer demand, and vehicle loading, a path optimization model is established with the minimum total cost of fixed cost, green cost, refrigeration cost, cost of cargo loss of fresh products, and penalty cost of violating the time window agreed upon with the customer. A hybrid ACO solution model is developed by integrating A^* algorithm to initialize the pheromone of ACO algorithm and reduce the ACO algorithm's convergence time, aiming at the problem of delayed convergence caused by blind search owing to inadequate pheromone at the beginning of ACO algorithm. Examples are used to simulate the algorithm and compare the algorithms in order to confirm the efficacy of both the model and the algorithm. The results demonstrate the effectiveness of both the model and the algorithm and can offer methodological support for the advancement of enterprise search and the application of the concept of green logistics.

Data Availability. The experimental data used to support the findings of this study are available from the corresponding author upon request.

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