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An optimised vehicle routing model for minimising distribution costs in cold-chain logistics

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Abstract: As economies and technology evolve, cold-chain logistics has emerged as a critical component in enhancing life quality and ensuring food safety. However, challenges remain due to incomplete technology and uneven customer distribution. This study proposes a routing model that integrates external temperature fluctuations into the cost calculations for simultaneous delivery and pick-up in cold-chain logistics. The model focuses solely on external temperature and examines its impact on distribution costs by analysing transportation, cargo damage, and refrigeration costs. To address the complexities of vehicle routing for simultaneous delivery and pick-up under variable external temperatures, this study enhances ant colony optimisation and genetic algorithms. Experimental results, based on multiple iterations, demonstrate that the improved model achieves lower overall distribution costs compared to traditional models, particularly in reducing cargo loss during transport and at customer nodes. These findings offer cold-chain logistics enterprises a more efficient, cost-effective strategy to reduce losses and boost efficiency.

Keywords: cold-chain logistics; vehicle routing problem with simultaneous delivery and pick-up; ant colony optimisation; ACO; genetic algorithm; GA.

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1 Introduction

The vehicle routing problem is a classical challenge in combinatorial optimisation with extensive applications in computer science, transportation engineering, communication engineering, systems engineering, operations research, information theory, and cybernetics (Sankul et al., 2024). In recent years, there has been a growing need to address the vehicle routing problem in a more realistic context, particularly with the emergence of simultaneous delivery and pick-up scenarios. This new variant, involving customer nodes with both delivery and pick-up demands, better reflects the actual requirements of modern logistics and transportation systems (Ning et al., 2021).

Numerous studies have been conducted to tackle the vehicle routing problem with simultaneous delivery and pick-up. Min (1989) was among the first to propose the extension of this problem, while Tao et al. (2021) developed a two-stage perturbation management method based on customer demand changes. Other researchers, such as Liu and Jiang (2022), Madankumar and Rajendran (2019), and Hou et al. (2021), have explored various aspects of the problem, including time window constraints, multiple distribution centres, and low-carbon optimisation. Furthermore, the rise of cold-chain logistics has introduced additional considerations in this field. Ji et al. (2015) examined costs in cold-chain logistics, including fixed, driving, loss, and refrigeration costs. Sujaree and Samattapapong (2021) focused on transporting vaccines under epidemic conditions, ensuring temperature range adherence during transport. Similarly, Khan and AlArjani (2021) incorporated product quality as a driving factor in cold-chain logistics vehicle path planning. To address the temperature limitations in cold-chain logistics distribution, Chen and Hsu (2015) introduced the concept of dividing cold-chain logistics vehicles into multiple temperature zones to accommodate different temperature requirements. Additionally, multiple objective optimisation models have been developed to simultaneously consider logistics cost, carbon emissions, cargo freshness, and customer satisfaction (Leng et al., 2020).

This study explores the under-examined influence of outside temperature fluctuations on the distribution costs within cold-chain logistics. It advances the discourse in the vehicle routing problem with simultaneous delivery and pick-up by intricately mapping out and integrating three novel dimensions.

- 1 A holistic approach to addressing the dual necessities of delivery and pick-up at customer nodes.
- 2 A nuanced differentiation of service times for the vehicles based on the distinct requirements of delivery versus pick-up activities.
- 3 A groundbreaking investigation into the previously overlooked outside temperature variations and their direct correlation with the overall distribution expenses in cold-chain logistics.

This innovative angle promises unprecedented insights into optimising cold-chain distribution efficiency and cost-effectiveness.

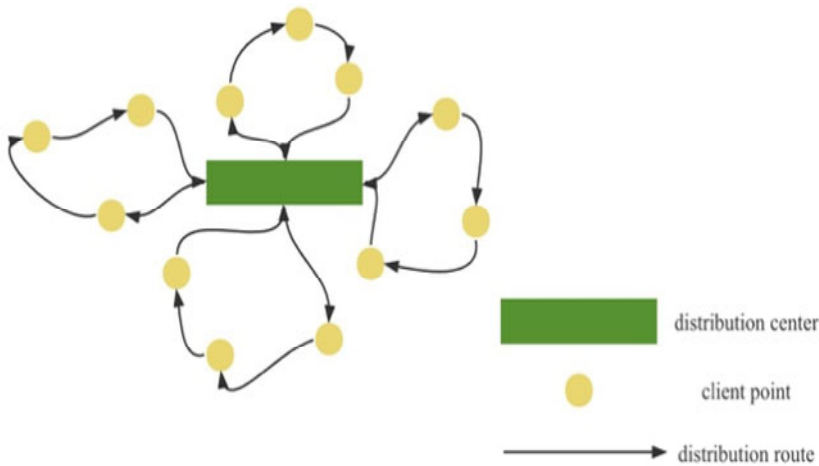
The remaining parts of this study are organised as follows. Section 2 outlines the problem under investigation. Section 3 details the formulation of the model, while Section 4 discusses the solution approach, which incorporates both ant colony optimisation (ACO) and genetic algorithms (GA) for model optimisation. Section 5 describes the detailed computational experiments conducted to demonstrate the proposed

model's validity and the effectiveness of the algorithm. Section 6 contains the conclusion and future work.

2 Problem description

The investigation centres on the vehicle routing problem with both delivery and pick-up tasks being handled simultaneously, applying it to cold-chain logistics distribution. The cold-chain logistics system comprises a distribution centre and multiple customer nodes (Simsir and Ekmekci, 2019). Figure 1 illustrates the customer nodes, depicted as solid yellow points, along with the distribution centre represented by a green rectangle, and the black solid lines are the distribution routes.

Figure 1 Diagram of cold-chain logistics vehicle routing problem (see online version for colours)



This research studies the cold-chain logistics path planning, explicitly focusing on the influence of outside temperature on the overall distribution cost. To address this issue, this study proposes an optimisation model for vehicle routing planning that simultaneously considers delivery and pick-up while accounting for outside temperature variations. The optimised model aims to minimise total distribution costs, including transport, cargo damage, and refrigeration costs (Yeasmin et al., 2024). This model optimises the route planning by providing distribution services from the distribution centre to each customer node. In addition, the study outlines several assumptions critical to optimising simultaneous delivery and pick-up route in cold-chain logistics, especially considering outside temperature changes (Wu et al., 2019).

- 1 This research analyses the distribution problem of a specific cargo type, permitting a mix of deliveries and pick-ups at customer nodes.
- 2 Vehicle capacity is limited, and the total amount of cargo delivery and pick-up per distribution must not exceed this capacity.
- 3 Each customer node is exclusively serviced by a single vehicle, which can serve multiple customer nodes.

- 4 Distribution is restricted to intra-city transport to minimise losses incurred during transportation.
- 5 The vehicle initiates its task from the distribution centre to a customer node. Subsequently, it returns to the distribution centre after completing all tasks.
- 6 Each customer node may have both delivery and pick-up requirements.
- 7 The distribution centre's location, the customer node positions, and their respective demands are provided.
- 8 The distance between each customer node and the distribution centre is known, along with the corresponding service time for each customer node.
- 9 The process of cargo loss follows a uniform distribution throughout the distribution service.

3 Model formulation

Following the characteristics of cold-chain logistics distribution, this research proposes to divide the distribution cost into three parts, which are the transport cost of vehicles in performing distribution services, the cost of cargo damage occurring during the driving process and at customer nodes, and the cost of refrigeration (Zhao et al., 2020). Transportation costs are influenced by the fixed cost per kilometre for each vehicle and the distance it travels. Cargo damage costs encompass two aspects, one being the loss of cargo due to the extended distribution time and the other being the hot air entering the vehicle compartment during door operations at customer nodes. Two factors contribute to refrigeration costs.

- 1 The refrigerant consumption resulting from the temperature difference between the vehicle's interior and exterior during transport.
- 2 Additional costs incurred when the doors are opened during loading and unloading at customer nodes.

This study considers changes in external temperature when calculating cargo damage and refrigeration cost for the vehicle, rather than treating external temperature as a constant. The impact of external temperature changes on cold-chain logistics distribution costs was also examined (Al Theeb et al., 2020).

This study on a simultaneous delivery and pick-up cold-chain logistics vehicle routing planning model based on outside temperature involves several parameter symbols, and it is necessary to uniformly define these symbolic variables before constructing the optimisation model (Kumar and Kumar, 2018). The various symbolic parameters for the outside temperature based simultaneous delivery and pick-up cold-chain logistics vehicle routing optimisation model are shown in Table 1.

Most cold-chain logistics vehicles do not adjust their setting temperature during transportation, so they are already set before the distribution task is carried out. However, since external temperature continuously changes, the setting temperature of the vehicle compartment needs to be adjusted during the distribution process to reduce the total cost of distribution and reduce the consumption of resources. Thus, this study formulates a

vehicle routing model that integrates simultaneous delivery and pick-up, taking into account external temperature conditions (Liu and Zhang, 2021).

Table 1 Definition of symbols

Type	Symbol	Unit	Meaning
Set	n	-	Set of customer nodes
	K	-	Set of vehicles
Parameter	Q	piece	Maximum capacity of vehicles
	a	km/¥	Transport cost per km travelled by vehicle
	d_{ij}	km	Distance travelled from customer node i to j
	c	¥/piece	Value per piece of cargo
	β_1	%	The loss rate per piece of cargo per unit time during distribution
	β_2	%	The loss rate per piece of cargo per unit time during service in customer nodes
	t_{ij}	min	Travel time from customer node i to j
	T_j	min	Service time at customer node j
	α	%	Depreciation of vehicles
	W_1	-	Heat transfer coefficient of the vehicle
	W_2	-	Heat transfer coefficient of air
	S_1	cm ²	External surface area of the vehicle
	S_2	cm ²	Area of the vehicle when it is opened
	q_j	piece	Delivery demand of customer node j
	p_j	piece	Pick-up demand of customer node j
	δ	¥	Unit price of refrigerant
	H_0		Temperature demand of cargo transported
	t_k	-	Time for vehicle k to complete the distribution task
	t_{k0}	-	Time for vehicle k to start the distribution task
	$ n $	unit	Number of customer nodes
	0	-	Distribution centre
Variable	$\Delta H(t)$	-	Temperature difference between inside and outside the vehicle during transport
	$H(t)$	-	Change in temperature over time t during the day
Decision variable	x_{ijk}	-	When $x_{ijk} = 1$, vehicle k drives from customer node i to j , else $x_{ijk} = 0$
	y_{ik}	piece	The loading of the vehicle after completing the task at customer node i

3.1 Transport cost

The transport cost is fixed, including fuel consumption incurred in the distribution process by the vehicles. The transport cost of a vehicle is proportional to its mileage, which is calculated as the product of the transportation distance and the transport cost per kilometre, and its mathematical expression is shown in equation (1).

$$C_1 = \sum_{i \in n} \sum_{j \in n} \sum_{k \in K} ad_{ij} x_{ijk} \quad (1)$$

3.2 Cargo damage cost

The cargo damage cost in cold-chain logistics services during distribution and at customer nodes is primarily due to the accumulation of distribution time and the temperature difference between the inside and outside of the vehicle (Takanokura et al., 2019). One is cargo loss due to the extended distribution time and the fluctuating outside temperatures while serving customer nodes. The other type of cargo loss cost occurs when the vehicle door opens during loading and unloading at customer nodes, allowing hot air to enter the compartment. This can cause the temperature to exceed the threshold set for the transported cargo. The specific costing formula for cargo loss is shown in equation (2).

$$C_2 = c \left[\beta_1 \sum_{i \in n} \sum_{j \in n} \sum_{k \in K} t_{ij} y_{ik} + \beta_2 \sum_{j \in n} \sum_{k \in K} T_j y_{jk} \right] \quad (2)$$

3.3 Refrigeration cost

External temperatures fluctuate significantly throughout the day and are not constant. Let's consider the temperature as a time-dependent function, $H(t)$. The temperature difference between the vehicle's interior and the outside is $\Delta H(t)$, with the required temperature for the cold-chain cargo being H_0 . Hence, $\Delta H(t) = H(t) - H_0$.

In previous studies, the external temperature was often ignored and assumed to be constant. Therefore, the calculation of refrigeration costs used a fixed external temperature coefficient. Under this assumption, the $\Delta H(t)$ is a constant coefficient, and the refrigeration cost calculation formula is equation (3).

$$C_3 = (1 + \alpha) W_1 S_1 \delta \sum_{i \in n} \sum_{j \in n} \sum_{k \in K} t_{ij} x_{ijk} \Delta H(t) + W_2 S_2 \delta \sum_{i \in n} \sum_{j \in n} \sum_{k \in K} x_{ijk} T_j \Delta H(t) \quad (3)$$

However, the outside temperature is not constant, it is a changing process. Therefore, the outside temperature needs to be taken into account when calculating the cost of refrigeration. The refrigeration cost consists of two main aspects. The first aspect involves heat transfer, which occurs due to the difference in temperature between the inside and outside of the vehicle throughout the distribution process. To account for this, an integral is used to calculate the cost due to the temperature difference from the beginning of the distribution to the end of the distribution process. The second factor is heat exchange, which results from air movement during cargo loading and unloading at customer nodes (Zhang and Chen, 2014). Refrigeration costs are calculated based on refrigerant consumption and encompass the costs associated with refrigeration throughout the distribution process as well as those incurred during loading and unloading, as specified in equation (4).

$$C_4 = (1 + \alpha) W_1 S_1 \sum_{i \in n} \sum_{j \in n} \sum_{k \in K} x_{ijk} \int_{t_{k0}}^{t_k} \Delta H(t) dt + W_2 S_2 \sum_{i \in n} \sum_{j \in n} \sum_{k \in K} x_{ijk} T_j \Delta H(t) \quad (4)$$

3.4 Model formulation

This study is based on the traditional vehicle path problem and integrates a cold-chain logistics vehicle routing planning model that considers some customer nodes with delivery and pick-up requirements. In addition, this study considers the case of a single distribution centre serving multiple customer nodes (Hsu and Chen, 2014). The routing planning optimisation model for simultaneous delivery and pick-up in cold-chain logistics aims to minimise the total distribution cost. This total cost includes the transport cost incurred by the cold-chain logistics vehicle during delivery tasks to customer nodes, as well as the cargo damage and refrigeration costs incurred during delivery, pick-up, and loading/unloading services at customer nodes. In this study, the objective function is represented by equation (5) if changes in external temperature are not considered. Conversely, the objective function that incorporates the impact of changes in the external temperature on the total distribution cost of cold-chain logistics vehicles is represented by equation (6).

$$\min F'(x_{ijk}) = C_1 + C_2 + C_3 \quad (5)$$

$$\min F^*(x_{ijk}) = C_1 + C_2 + C_4 \quad (6)$$

s.t.

$$\sum_{i \in n} \sum_{j \in n} \sum_{k \in K} x_{ijk} = |n| + k \quad (7)$$

$$\sum_{i \in n} \sum_{k \in K} x_{ijk} = 1, \forall j \in n; i \neq j \quad (8)$$

$$\sum_{j \in n} \sum_{k \in K} x_{ijk} = 1, \forall i \in n; i \neq j \quad (9)$$

$$\sum_{i \in n} x_{0ik} = \begin{cases} 1 & \text{If } i \text{ is the first customer node of a route} \\ 0 & \text{other} \end{cases} \quad (10)$$

$$\sum_{j \in n} x_{j0k} = \begin{cases} 1 & \text{If } j \text{ is the last customer node of a route} \\ 0 & \text{other} \end{cases} \quad (11)$$

$$0 \leq y_{ik} \leq Q, \forall i \in n; k \in K \quad (12)$$

$$y_{0k} \leq Q, \forall k \in K \quad (13)$$

$$y_{jk} = \sum_{i \in n} x_{ijk} (y_{ik} - q_j + p_j), \forall j \in n; k \in K \quad (14)$$

$$x_{ijk} \in \{0, 1\}, \forall i, j \in n; k \in K \quad (15)$$

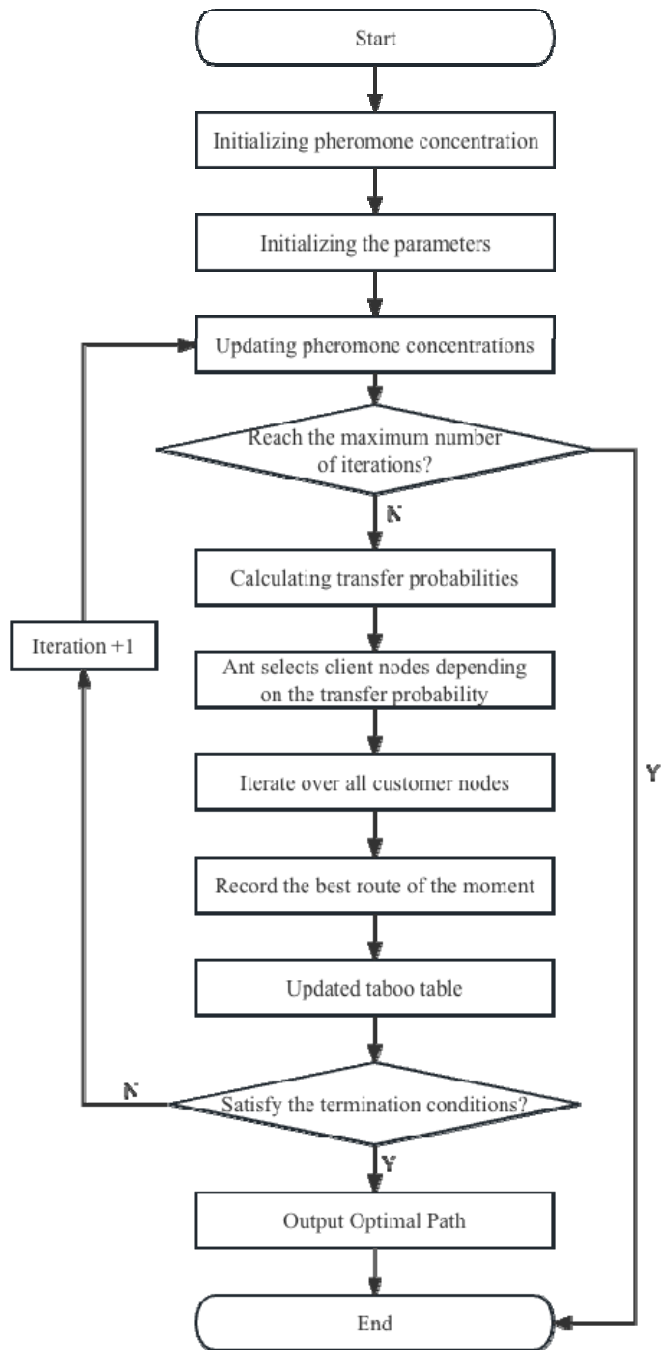
The objective function is represented by equations (5) and (6), meaning the minimisation of the total distribution cost, including transport, cargo damage, and refrigeration costs.

Equations (7) to (15) are the constraints, respectively. Equation (7) ensures that all customer nodes are delivered and picked up, i.e., the cold-chain logistics vehicle needs to travel to all customer nodes. Equations (8) and (9) are designed to constrain that only one cold-chain logistics vehicle can delivery and pick-up from a customer node. Only one cold-chain logistics vehicle can arrive and depart from a customer node. Equations (10) and (11) illustrate that the vehicle begins its distribution task by leaving the distribution centre and makes its way back to the centre after the task is done. Equations (12) and (13) demonstrate that during the distribution process and at the distribution centre, the cargo load in any cold-chain logistics vehicle does not exceed the vehicle's maximum capacity. Finally, equation (14) constrains the cold-chain logistics vehicle's current load capacity to equal the load quantity after serving a customer node plus the pick-up quantity.

4 Ant colony optimisation and genetic algorithm for the optimised model

This study addresses the simultaneous delivery and pick-up vehicle routing problem under external temperature fluctuations, which is categorised as an NP-hard problem. Given the complexity of this type of problem, exact algorithms such as branch-and-bound or dynamic programming often become computationally infeasible for large-scale instances. As a result, heuristic and metaheuristic algorithms are widely applied to achieve near-optimal solutions within reasonable time constraints. Several advanced algorithms, such as particle swarm optimisation (PSO), simulated annealing (SA), Tabu search (TS), and variable neighbourhood search (VNS), have been successfully applied to vehicle routing problems (VRP). Each of these methods has its strengths; for example, PSO is known for its fast convergence, while TS effectively avoids local optima through memory-based strategies. Despite the effectiveness of these algorithms, they also come with limitations, such as susceptibility to premature convergence or difficulty in fine-tuning parameters.

In this study, we focus on two widely used metaheuristic algorithms: ACO and GA. The decision to select ACO and GA stems from their complementary strengths (Babagolzadeh et al., 2020). ACO is particularly suited for VRP due to its robust local search capabilities and its pheromone-based mechanism, which dynamically updates solution paths based on iterative feedback. This enables ACO to efficiently handle complex routing problems. GA, on the other hand, is chosen for its global search capabilities, leveraging evolutionary processes such as selection, crossover, and mutation. GA is versatile in exploring diverse solution spaces, making it highly effective for VRP problems (Zhang et al., 2022). While other algorithms could also be applied, the selection of ACO and GA in this study is based on their demonstrated ability to balance exploration and exploitation in solving NP-hard problems like VRP, and their adaptability to the model-specific characteristics of cold-chain logistics under varying external temperatures. These two algorithms offer an effective compromise between solution quality and computational efficiency, making them ideal candidates for the problem addressed in this research.

Figure 2 Flowchart of the improved ACO

4.1 Ant colony optimisation

The bionic algorithm based on the tendency of ants to choose shorter paths in their search for food is known as ACO. The characteristic of the ACO is that the ants are not only able to leave pheromones on the paths they walk, but they are also able to sense the pheromone concentration in the external environment and use this as a basis for calculating the probability function and then selecting the next customer node based on some selection strategy. In general, ants tend to choose paths with higher pheromone concentration, i.e., shorter paths, based on the roulette selection strategy, and they choose paths with shorter total distances based on the positive feedback of pheromone concentration (Zhang et al., 2021). The flow of the improved ACO algorithm designed in this study is shown in Figure 2.

Transfer probability. Each ant will choose the next customer node when it starts from the starting point and maintains a stock of pheromones for the path between that starting point and the next point, which stores the pheromones that the ant passes through at a time. The ants select the next customer node according to a certain probability, which is the core of the ACO. In previous studies, the expected degree of transition probability from i to j for ants often used fixed parameters, such as the distance between two points. Thus, the transition probability is given by equation (16). However, in this study, the transportation cost between two points is used as the expected degree, making it a calculation process that needs to consider the vehicle's load capacity. Under this scenario, the transition probability is given by equation (17).

$$P_{ij}^h(z) = \begin{cases} \frac{[\tau_{ij}(z)]^{\alpha} [d_{ij}(z)]^{\beta}}{\sum_{s \in j_h(i)} [\tau_{is}(z)]^{\alpha} [d_{is}(z)]^{\beta}}, & j \in j_h(i) \\ 0 & j \notin j_h(i) \end{cases} \quad (16)$$

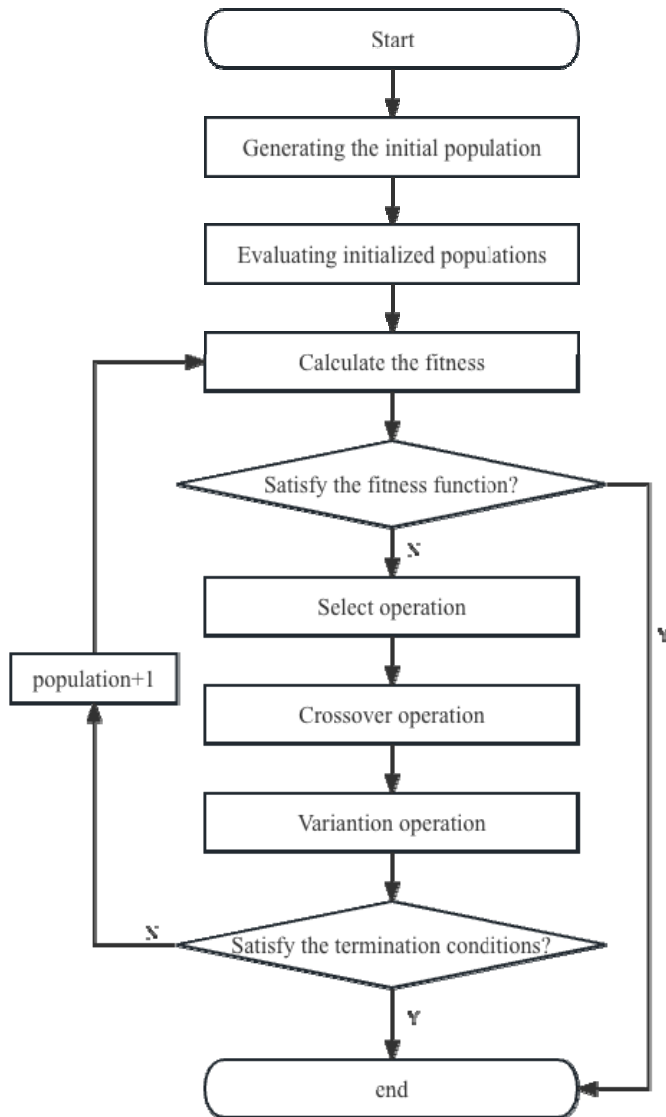
$$P_{ij}^h(z) = \begin{cases} \frac{[\tau_{ij}(z)]^{\alpha} [F_{ij}(z)]^{\beta}}{\sum_{s \in j_h(i)} [\tau_{is}(z)]^{\alpha} [F_{is}(z)]^{\beta}}, & j \in j_h(i) \\ 0 & j \notin j_h(i) \end{cases} \quad (17)$$

where

- $P_{ij}^h(z)$ is the probability that the h^{th} ant in the z^{th} generation of ants chooses i to j
- $\tau_{ij}(z)$ is the pheromone concentration from customer node i to j
- $d_{ij}(z)$ is the distance from customer node i to j
- $F_{ij}(z)$ is the cost from customer node i to j
- α represents the importance of pheromone
- β represents the importance of the heuristic factor
- $j_h(i)$ represents the set of customer nodes that ant h can currently choose in customer node i .

Pheromone update. When all ants complete a generation of iterations, that is, each ant has traversed all customer nodes, then because the ants leave pheromones during the walking process, the pheromones on all feasible paths also change. Therefore, it is necessary to update the pheromone on each path in time so that the child ants can find the path according to the pheromone left by the parent ants. For the pheromone of the first generation of ants to find the path, it is necessary to pre-set the initial pheromone concentration to update the pheromone matrix.

Figure 3 Flowchart of the improved GA



4.2 Genetic algorithm

This study uses the GA to solve the vehicle routing problem with simultaneous delivery and pick-up in cold-chain logistics. GA is usually implemented using computer simulations that chromosomally encode the solution to the optimisation problem to be solved, generating a certain number of feasible solutions that evolve toward the optimal distribution solution. The evolutionary process of the GA starts with a population of completely random individuals, after which the optimal distribution route solution is obtained through continuous iteration and evolution of the child. The child evaluates the fitness of the entire population utilising a particular evaluation system, selects several individuals at random from the current population according to the fitness values of the chromosomes, and then generates a new population by natural selection, crossover, and mutation, which is called the current population in the next iteration, and so on until the optimal solution to the problem is generated or the termination condition of the algorithm is reached (Hsiao et al., 2018). Figure 3 illustrates the process of the improved GA developed in this study.

Coding of chromosomes. This study uses the natural number encoding method to encode its chromosomes to solve an optimised model. The permutations from the natural numbers 1 to $|n|$ are generated to form a certain number of chromosomes, with the natural numbers representing the customer node numbers. The distribution centre 0 is inserted into the chromosome to complete the distribution route. For instance, 729638145 represents a complete permutation of natural numbers. By inserting the number 0, which symbolises the distribution centre, the sequence becomes 0729063801450, resulting in three delivery routes: 729, 638, and 145. The chromosome encoding method of the GA is shown in Figure 4.

Figure 4 Coding of chromosome

3	4	5	2	1	6	9	8	7
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0	3	4	5	0	2	1	6	0	9	8	7	0
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Initial population. The initial population is structured as a $|n| \times L$ matrix, with $|n|$ being the count of customer nodes and L being the predetermined population size. The matrix is generated at random, with each gene string representing a possible solution. The size of the population has an impact on the convergence speed and the range of solutions.

The fitness function. In the GA, the degree of merit of the cold-chain logistics vehicle route is evaluated during the search process based on the fitness value. The research utilises the inverse of the objective function for the fitness function. Initially, the fitness function was defined as $F_{it}(x_{ijk}) = F(x_{ijk})$. However, the proposed improvement defines the fitness function as $F_{it}(x_{ijk}) = \frac{1}{F(x_{ijk})}$, refining the evaluation process.

Selection operation. This study used roulette selection to choose individuals from the parent generation, favouring those with higher fitness levels to form a new population. Additionally, a fixed percentage of the top solutions is preserved in each iteration, ensuring that the best individuals are carried over to the next generation.

Crossover operation. This study employed partially matching crossover to create crossover operators. Given that some data is lost during selection, adjustments to gene

positions in the chromosomes are necessary based on specific probabilities, leading to variation operators.

Variation operation. The improved GA may lose some vital information in the crossover process, so this study needs to introduce a moderate amount of variation to ensure the accuracy of the improved GA. Variation in improved GA is achieved by changing the gene positions of the feasible solutions in this study.

4.3 Comparison of the original and improved algorithm

This study's relevant customer node data comprises coordinated location, delivery and pickup volume, and service time. Table 2 shows the basic information of distribution centre and 15 customer nodes. In addition, the parameter settings of the model are also given in Table 3.

Table 2 Information on distribution centre and customer nodes

Node no.	Coordinates (X, Y)	Delivery (piece)	Pick-up (piece)	Service time (min)
0	(35, 35)	0	0	0
1	(45, 49)	10	25	15
2	(35, 17)	7	15	20
3	(55, 45)	13	0	15
4	(55, 20)	19	35	17
5	(15, 20)	26	0	22
6	(15, 30)	3	24	16
8	(20, 50)	5	17	18
9	(10, 43)	9	0	20
10	(55, 60)	16	18	25
11	(20, 65)	12	20	16
12	(50, 35)	19	0	15
13	(30, 25)	23	20	21
14	(15, 10)	20	0	14
15	(30, 5)	8	17	16

Table 3 Parameter settings in the model

Parameters	a	c	β_1	β_2	α	W_1	W_2	δ
Values	0.25	100	0.0015	0.025	0.08	0.5	0.54	0.2

This study improves two types of heuristic algorithms to solve the optimised model. The optimal distribution routes of cold-chain logistics vehicles are planned in the ACO by improving the pheromone matrix, and the optimal distribution routes are explored in the GA by improving the fitness function. To verify the effectiveness of the improved algorithm, this study compares and analyses it.

For the comparison between the original and the improved ACO, this study uses a maximum number of 500 iterations and 50 ants to analyse the experimental results of the optimised model. Since the ACO is not an exact algorithm, several iterations are needed to obtain experimental results to compare the original and improved ACO. The

parameters for the comparison experiments between the original and the improved ACO are shown in Table 4.

Table 4 Parameters between the original and improved ACO

<i>Parameters</i>	<i>Explanation</i>	<i>Value</i>
m	Colony size	50
alpha	The importance of pheromone	1
beta	The importance of the heuristic factor	1
Rho	Level of pheromone dilution	0.15
A	The total amount of pheromones in an ant	130
Max-iteration	Maximum number of iterations	500

For the comparative analysis of the original and the improved GA, this study evaluates the results obtained from the optimised model, which was tested with an initial population of 50 and a maximum of 500 iterations. The parameters were calibrated for the original and the improved GA comparison experiments, as shown in Table 5.

Table 5 Parameters between the original and improved GA

<i>Parameters</i>	<i>Explanation</i>	<i>Value</i>
NP	Initial population	50
Pc	Probability of crossover	0.9
Pm	Probability of mutation	0.1
Max-iteration	Maximum number of iterations	500

Table 6 presents the results from 10 experimental repetitions of the optimisation model, utilising both the original and improved versions of ACO and GA, respectively. This study compares the total distribution cost, the number of iterations until the first convergence to the optimal solution, and the algorithm's computation time. These factors are critical for evaluating the performance of the algorithms. Firstly, cost is the most intuitive and critical factor, as the objective function of the model aims to minimise the total distribution cost. Comparing the computation time of the algorithms provides insight into their efficiency, which is crucial for practical applications where time is a significant constraint. Lastly, the number of iterations until the first convergence indicates the algorithm's convergence speed and stability. Evaluating these aspects together allows for a balanced assessment of the algorithms' effectiveness and efficiency.

The results in Table 6 indicate no significant difference between the original and improved ACO in terms of the number of convergence iterations required to obtain the optimal distribution route (175 iterations for the original and 234 iterations for the improved). However, the improved ACO demonstrates superiority over the original version in both the total distribution cost and computation time. Specifically, the total cost is reduced from 723 to 644. The improvement in cost demonstrates that enhancing the pheromone matrix leads to more efficient routing solutions.

Similarly, the improved GA outperforms the original version in terms of total delivery cost, the number of iterations to first convergence, and algorithm runtime. The total delivery cost is reduced from 729 to 627, the number of iterations to first convergence drops from 297 to 141, and the computation time remains almost constant

(14 seconds for the original and 15 seconds for the improved). Consequently, the improved fitness function proves to be more effective in solving the routing planning problem for simultaneous delivery and pick-up vehicles under external temperature conditions.

Table 6 Comparison of the original and improved algorithms

	<i>Original algorithm</i>			<i>Improved algorithm</i>		
	<i>Cost</i>	<i>Computing time</i>	<i>Convergence</i>	<i>Cost</i>	<i>Computing time</i>	<i>Convergence</i>
ACO	723	215	175	644	234	317
GA	729	14	297	627	15	141

5 Results

In the process of transportation services, cold-chain logistics enterprises can improve customer satisfaction and ensure the quality and safety of their transported cargo, and reduce the distribution cost and resource consumption of the vehicles in distribution centres by reasonably planning the distribution routes of the vehicles. Through several experiments, this study explores the distribution route planning of the vehicles considering the external temperature. It uses improved ACO and GA to solve the distribution route planning of vehicles with delivery and pick-up needs of customer nodes. This study focuses on reducing cold-chain logistics costs, preventing cargo loss and damage, and increasing the efficiency of the logistics operations. For the original model, the route planning is based on fixed external temperatures, without accounting for any temperature fluctuations. In contrast, the improved model uses expected external temperature values to ensure the optimal route is determined before departure. It should be noted that the temperature input for the improved model is based on expected values rather than real-time measurements. This allows for a more accurate estimation of refrigeration costs during the planning phase, without needing to adjust the route once the vehicle has left the distribution centre.

Due to the difficulty in obtaining actual customer nodes and their associated delivery and pick-up requirements, the random generation method was used to generate two-dimensional coordinates for 1 distribution centre and 100 customer nodes for the simulation experiments in this study. The random generation method was also adopted for the primary data, such as delivery, pick-up volume, and service time for the customer nodes. Table 7 shows the basic information about the distribution centre (node No. 0) and some customer nodes (nodes No.1–100).

For the improved ACO, this study determines the design of the relevant parameters through several experiments to increase the fitness of the improved algorithm to the optimisation model. For the improved ACO, the focus is on improving the design of the heuristic factors in the ACO. In previous research, for the ACO to solve the vehicle path planning problem, the heuristic factors were designed using the inverse of the distance matrix. They needed to be updated during each generation of ants to find the optimal path. To reduce the total delivery cost, the optimised vehicle routing model for simultaneous delivery and pick-up influences costs by performing both delivery and pick-up operations at customer nodes. The heuristic factor matrix is updated by

combining the cost matrix with the current load at each node. Pheromones are deposited by each generation of ants to assist subsequent generations in selecting better paths.

Table 7 Information distribution centre and customer nodes

<i>Node no.</i>	<i>Coordinates (X, Y)</i>	<i>Deliveries (piece)</i>	<i>Pick-up (piece)</i>	<i>Service time(min)</i>
0	(35, 35)	0	0	0
1	(45, 49)	10	25	15
2	(35, 17)	7	15	20
3	(55, 45)	13	0	15
4	(55, 20)	19	35	17
5	(15, 20)	26	0	22
6	(15, 30)	3	24	16
8	(20, 50)	5	17	18
9	(10, 43)	9	0	20
10	(55, 60)	16	18	25
...	...	...	...	...
100	(45, 20)	20	11	16

Table 8 Experimental results of the improved ACO

<i>Iterations</i>	<i>Items</i>	$F'(x_{ijk})$	$F^*(x_{ijk})$	<i>Difference</i>
30	Cost	4,812	4,298	514
	Computing time	573	646	-73
	Convergence	20	19	1
50	Cost	4,796	4,274	522
	Computing time	977	1,179	-202
	Convergence	32	32	0
100	Cost	4,764	4,257	507
	Computing time	2,414	2,529	-115
	Convergence	45	66	-21

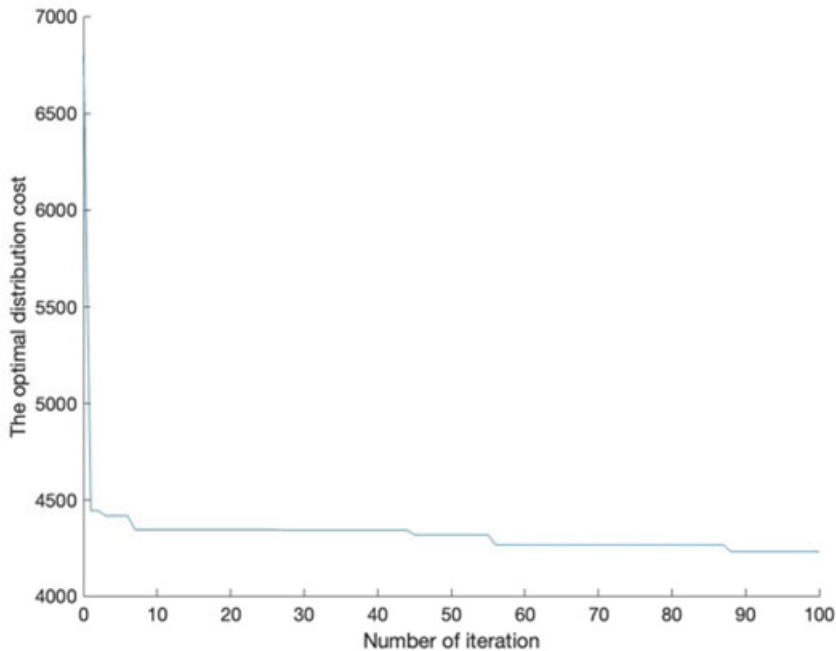
For the improved ACO, 20 ants are used to address the delivery service requirements for 100 customer nodes from the distribution centre. Given the heuristic nature of the improved ACO, each experiment's results vary, necessitating 10 repetitions to average the results for analysis. This study sets different maximum iterations of 30, 50, and 100 for both the original model $F'(x_{ijk})$ and the optimised model $F^*(x_{ijk})$ to explore the optimal distribution route. The study compares the total cost of the distribution solution, the number of convergence iterations to achieve the optimal distribution route for the first time, and the algorithm's running time. Table 8 presents the experimental results of the improved ACO.

From the experimental results, it is evident that the optimised model significantly reduces the total distribution cost across all iteration counts. Although the computation time increases, the cost savings achieved justify this increase. The differences in convergence iterations between the two models are minimal, and as the number of iterations increases, the difference in convergence iterations continuously shrinks.

Overall, the optimised model $F^*(x_{ijk})$ outperforms the original model $F(x_{ijk})$ by significantly reducing total distribution costs and maintaining algorithm efficiency despite a slight increase in computation time. This demonstrates the clear superiority of the optimised model over the original.

Figure 5 is an iterative convergence diagram of the improved ACO. Initially, due to the lack of initial information, the cost of the route planning graph obtained in the first iteration of the ACO is very high. It requires a certain number of iterations to achieve a more optimal cost route planning graph. This is due to the strong search capabilities of the ACO algorithm, which allows it to quickly obtain a better-cost route planning graph after a certain number of iterations. Figure 5 illustrates the convergence curve process of the improved ACO over a maximum of 100 iterations. The graph demonstrates that the convergence effect of the improved ACO in solving the cold-chain logistics simultaneous delivery and pick-up vehicle routing problem is likely superior. The improved ACO shows a rapid decrease in cost after a few iterations, indicating its enhanced efficiency in finding an optimal solution.

Figure 5 The convergence process of the improved ACO (see online version for colours)

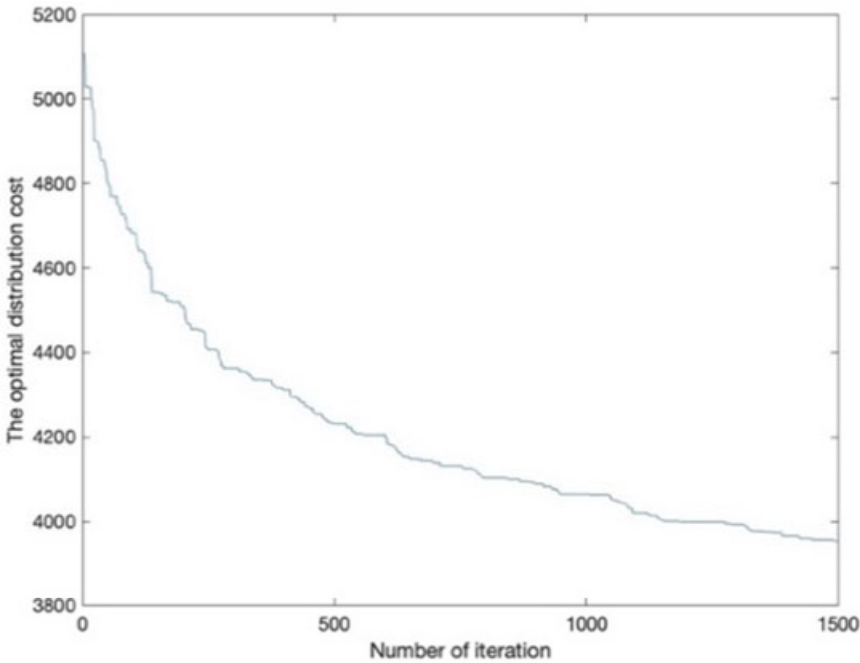


To further validate the optimised model, this research employed the GA for solving the distribution path problem. This study plans a distribution path for the optimised model to minimise the total distribution cost, using an initial population size of 50 and a maximum number of iterations of 500. Since the GA is a heuristic algorithm, the results vary for each iteration, so the average results after 10 repetitions of the experiment are used for the analysis. Table 9 shows the experimental results of the improved GA for the cases of 500, 1,000, and 1,500 maximum iterations, respectively.

Table 9 Experimental results of the improved GA

<i>Iterations</i>	<i>Items</i>	$F'(x_{ijk})$	$F''(x_{ijk})$	<i>Difference</i>
500	Cost	4,958	4,224	734
	Computing time	18	18	0
	Convergence	492	482	10
1,000	Cost	4,705	4,022	683
	Computing time	37	64	-27
	Convergence	973	959	14
1,500	Cost	4,625	3,901	724
	Computing time	59	101	-42
	Convergence	1,478	1,479	-1

Figure 6 The convergence process of the improved GA (see online version for colours)



The experimental results show that both the original and the optimised model can reduce the delivery cost of vehicles by increasing the maximum number of iterations of the improved GA. However, there is also a corresponding increase in computation time. The comparison between the original model and the optimised model shows that the optimised model still outperforms the original model in terms of cost after the maximum number of iterations is increased. However, the advantages regarding the convergence curve and computation time are less pronounced. Despite this, cold-chain logistics enterprises are primarily concerned with cost reduction, so the optimisation model retains a significant advantage.

Figure 6 illustrates that the improved GA, when applied to the optimised model, demonstrates a noteworthy capacity for cost reduction. Specifically, the distribution cost exhibits a diminishing trend with an escalating number of iterations. This improved GA shows that, compared to the improved ACO, the initial costs are relatively lower, which can be attributed to the higher quality of initial solutions generated by the GA. Additionally, the cost consistently decreases with further iterations, without any premature convergence.

The study compares the performance of the improved ACO and GA in solving the problem, each with different maximum iterations. The results show that the optimised model using the improved GA consistently achieves lower distribution costs than the improved ACO, for both the original and optimised models. Additionally, the improved GA significantly outperforms the improved ACO in terms of computation time. Given that the vehicle routing problem is NP-hard, and exact solutions are impractical, the improved GA is preferred for achieving the optimised model efficiently.

6 Conclusions and future work

This study tackled inefficiencies in cold-chain logistics by developing a simultaneous delivery and pick-up vehicle routing model that integrates external temperature into the cost calculations. By addressing transport, cargo damage, and refrigeration costs, this model provides a more accurate reflection of the challenges faced in real-world distribution processes. Two heuristic algorithms, an improved ACO and GA, were employed to solve the model efficiently. The experimental results demonstrated that both algorithms are highly effective in reducing total distribution costs, especially in scenarios with fluctuating external temperatures. While the improved ACO and GA both show significant potential for optimising cold-chain logistics routes, the GA outperforms ACO in terms of convergence speed and overall cost reduction. These findings suggest that the proposed model can be a valuable tool for improving resource allocation and reducing operational costs in cold-chain logistics.

However, there are areas for further improvement. To begin with, the weight coefficients used in calculating the total distribution costs should be more refined to account for the varying impact of different costs on the overall total. Next, the computational speed of the improved ACO can be enhanced. Finally, the convergence curve of the improved GA needs optimisation by combining it with an exact algorithm for finding the initial population and subsequently using the improved GA to explore optimal distribution solutions.

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