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Physical Delivery Network Optimization Based on Ant Colony Optimization Neural Network Algorithm

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ABSTRACT

The development of modern logistics chains is not just simple cargo transportation, it has become a cross-integrated industry that integrates many emerging technologies such as IoT technology, intelligent transportation, cloud computing and mobile Internet. Based on the ant colony algorithm (ACA), this paper optimizes the physical delivery network of the optimized neural network algorithm, establishes a mathematical model for the constraints and optimization objectives in the optimization of the physical delivery path, and proposes some improvements to the ACA to improve the convergence of the algorithm. speed and global search ability, so as to use the improved algorithm to solve the physical delivery path optimization problem. Experiments show that the optimal distance of physical delivery path planning calculated by traditional ACA is 207.8544km, while the optimal distance of improved ACA path planning is 197.9879km. The performance of the improved ACA is improved by analyzing the results of solving typical examples.

KEYWORDS

ACA, Logistics and Distribution, Neural Network

The development level of a country's logistics chains can objectively reflect the country's comprehensive national strength and enterprise competitiveness. Modern logistics and distribution widely exist in daily life and enterprise management, connecting production and consumption to meet the increasing demand of human beings. Social consumption demand and systematic and rational logistics management will create considerable economic profits for the country and society. Logistics started late in China, but developed rapidly, and has become one of the pillar industries of the national economy. The rapid development of the logistics chains is of great significance to promoting economic growth, changing the mode of development and improving the competitiveness of the national economy (Zhao et al., 2020). The development of modern logistics chains is not only a simple cargo transportation, but also a cross-integrated industry that integrates a variety of emerging technologies such as Internet of things (IoT), intelligent transportation, cloud computing, and mobile internet (Afra & Behnamian, 2021). Therefore, the systematization of logistics and distribution has become a top priority (Mavrovouniotis & Yang, 2015). Modern logistics covers many industries

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of the national economy. It is not only the product of economic development, but also the pillar of economic development. It is not only a value-added economic activity, but also an economic activity that affects the ecological environment (Geng & Wang, 2014). Because of the importance of logistics in the modern economy, how to save logistics costs and create higher profits has become a research hotspot. Developing the logistics chains and reducing the total logistics cost will become a new economic growth point in China (B. Wang et al., 2020). For enterprises, in the face of increasingly fierce competition, how to reduce the total logistics cost has become an urgent problem to be solved.

Optimizing logistics algorithms can not only realize scientific logistics, but also improve the economic benefits of logistics. The ant colony algorithm (ACA) has only been put forward for a few decades, and it is still in the simulation stage. No one can give a mathematical explanation yet. Although the research time is not long, it has shown great advantages in solving complex optimization problems, indicating that its application prospect is still very bright (Chen et al., 2020). In a word, although the ACA is in the development stage, it is an algorithm with very broad development space and great development potential, reflecting its great theoretical research value (Lei et al., 2019). The main research content of this paper is the ACA and physical delivery network optimization. First, the ACA and physical delivery optimization problem are understood in detail. Second, the mathematical model of constraints and optimization objectives in physical delivery route optimization is established. By improving the convergence speed and global search ability of the algorithm, the physical delivery path optimization problem can be solved, and the shortest path can be solved.

Through in-depth research by scholars, it is found that the use of bionic optimization algorithms can better solve such combinatorial optimization problems. In this regard, the ACA has shown significant advantages in solving complex optimization problems, so it can be better applied to solve the physical delivery path optimization problem (Y. Wang et al., 2017). At present, the search method based on physical delivery can no longer meet the needs of actual physical delivery, and the planning based on optimal physical delivery not only requires finding the shortest physical delivery path, but also requires strict real-time performance (Sakai et al., 2016). In the process of physical delivery planning, from the application point of view, it is particularly important to plan the route reasonably and improve the calculation response speed (Q. Liu, 2020). A large number of experts and scholars have conducted in-depth research on physical delivery route planning. How to plan a reasonable physical delivery in time has a very practical significance for the research problem. The grid method is used to model the transportation environment of physical delivery, the ACA is applied to the physical delivery planning, and the results show that the ACA can solve the physical delivery planning problem well (Singh et al., 2019). Applying the operators in the genetic algorithm to improve the performance of the ACA, the genetic algorithm and the ACA are found to be very similar in some characteristics. For example, they are both methods of simulating biological evolution. The ACA uses swarm intelligence to find the optimal solution. The genetic algorithm uses population evolution to find the optimal solution, and the genetic algorithm is a relatively mature optimization algorithm, which is widely used to solve combinatorial optimization problems. To a certain extent, the time efficiency is improved (Droździel et al., 2017). The physical delivery network optimization technology based on the ant colony optimization neural network algorithm has the following advantages:

1. This paper conducts further research and improvement on the basis of the existing ACA and then applies it to the issue of optimization of flow distribution path in order to obtain higher economic benefits and to manage logistics scientifically.
2. This paper uses the operators in the genetic algorithm to improve the performance of the ACA to reduce the execution cost of the algorithm. At the same time, the genetic algorithm searches for the optimal solution faster, which can improve the time efficiency to a certain extent.

This paper studies the optimization problem of a physical delivery network based on an ant colony optimization neural network algorithm. The architecture is as follows: The first section is the introduction part. This part mainly expounds the research background and research significance of physical delivery network optimization based on the ant colony optimization neural network algorithm and puts forward the research purpose, method, and innovation of this paper. The second section mainly summarizes the relevant literature, summarizes the advantages and disadvantages, and proposes the research ideas of this paper. The third section is the method part, which focuses on the optimization of the physical delivery network combining the ACA and neural network algorithm and establishes a mathematical model for it. The fourth section is the experimental analysis part. This part is experimentally verified on the data set to analyze the performance of the model. Section 5 includes conclusions and outlook. This part mainly reviews the main content and results of this research, summarizes the research conclusions, and points out the direction of further research.

RELATED WORK

Hou et al. (2017) successfully applied the self-organizing innuendo network to the route planning problem and the solution of the vehicle distribution area problem, using a one-dimensional ring network topology to solve the vehicle routing problem. Du et al. (2018) discussed two types of demand paths and adopted the simulated annealing algorithm, which saved the computational complexity of the algorithm and improved the applicability of the two-stage simulated annealing algorithm. Li et al. (2016) transformed the traditional free annealing algorithm into a directional annealing with direction orientation, transformed the traditional free annealing algorithm into a directional annealing algorithm by providing some commonsense knowledge for the search program, and proved that the algorithm improved the efficiency with an example. Safeer et al. (2014) studied the vehicle routing optimization problem considering the uncertainty of vehicle travel time and customer service time, proposed an incomplete undirected graph representation of the physical delivery network composed of two types of nodes, the distribution center and the customer, and established a physical delivery network, a fuzzy programming model for vehicle path optimization, which solves the problem by embedding the Floyd algorithm in the predator search algorithm. He (2020) transformed the traditional free annealing algorithm into directional annealing with direction orientation, transformed the traditional free annealing algorithm into a directional annealing algorithm by providing some common-sense knowledge for the search procedure, and proved that the algorithm improved the efficiency with an example. Moncayo–Martínez et al. (2016) proposed an ACA with the characteristic of mutation in the genetic algorithm, so as to change the problem of the slow convergence speed of the. Utamima et al. (2019) deeply studied the ant colony system model for optimization problems in continuous space. S. Q. Liu et al. (2012) proposed a model that solves the assignment problem and can be used to solve the graph coloring problem. Ting et al. (2013) analyzed and studied the transportation route optimization problem of distribution centers from the perspectives of direct delivery and distribution transportation. Considering the shortest distribution route and the minimum cost, a vehicle route optimization model was established, and the ACA was used to solve the problem. Feng (2020) also introduced a genetic algorithm into the ACA and adopted a new coding method: coding the distance between the distribution center and the customer, constructing a fitness function, and designing a new improved ACA. C. Qi (2013) used the activity-based costing method to improve the model of the vehicle routing optimization problem to study the book routing problem and used the ACA to solve the model.

The research of these methods has not fully integrated the characteristics of the actual distribution and transportation network. Most researchers regard the distribution and transportation network as a fully connected graph, that is, the basis for thinking that any two points can be directly reached. The model and algorithm design are carried out on the above, the physical delivery path optimization problem is not combined with the connectivity of the distribution and transportation network, and the solution to the optimal result may be one-sided to a certain extent. In the physical delivery problem, at present, the application research of ACA is gradually emerging. ACA has strong potential in the problem of combinatorial optimization, and it is worthy of in-depth study in the optimization of the physical delivery problem. The improvement and application of the ACA can be divided into three main aspects: First is to improve the structure and rules of the existing ACA to improve the performance of the algorithm; second is to integrate other algorithms and combine the advantages of various algorithms, establishing a hybrid intelligent algorithm; third is to expand the application field of ACA. This subject is mainly to improve the ACA and apply it to an actual physical delivery model.

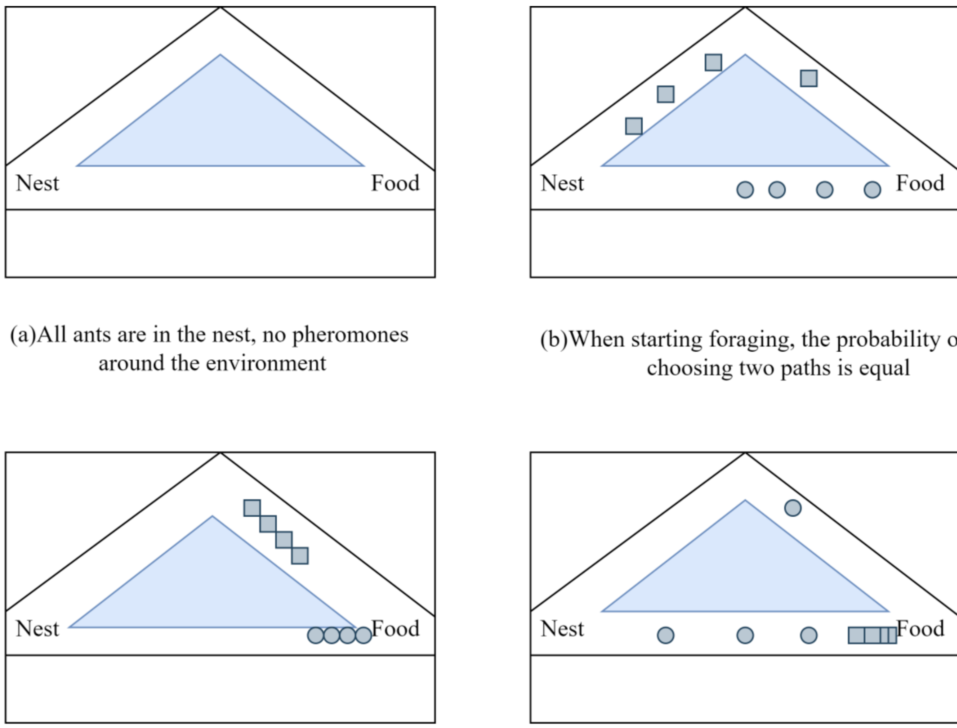
METHODOLOGY

Principle of ACA and Its Application in Physical Delivery Network Optimization

Both the logistics transportation network and the physical delivery network are line activities. According to whether the spatial position of the item moves, logistics activities can be divided into line activities and node activities, where line activities refer to the movement caused by the position of objects. Numerous phenomena and behaviors in nature are an important source of human innovation: Many biological groups and natural systems are capable of self-evolution, and this evolution can often solve seemingly complex and intractable problems effectively. Usually, distribution refers to the logistics activities of distributing goods at the logistics base, according to the customer's ordering requirements, and delivering the allocated goods to the customer in time to ensure the smooth progress of the logistics process and optimize the allocation of resources. The transportation activity is the activity of transporting items to the designated place on the transportation route by means of transportation, and it is a kind of route activity. An ant colony is a typical biological group. Scientists have found through long-term observation and research on the behavior of ant colonies that the intelligence level of individual ants is very low, but they can work in coordination with each other and perfectly perform behaviors such as foraging, building ant colonies, and multiplying offspring such that the ant colony as a whole shows extraordinary wisdom. Distribution is a process in which the distribution department connects production and consumption and generates benefits in time and space. Therefore, improving the operational efficiency of distribution is of great significance for reducing distribution costs. In this paper, a topology model of a physical delivery path network based on graph theory is designed, and a distribution path planning scheme is constructed based on an improved ACA.

The ACA is a natural simulation evolutionary algorithm inspired by the foraging behavior of ants in nature. The general process of ants looking for food sources from the ant nest is as follows: At the beginning, the ants choose the path randomly, but later the ants in the selection of the path will adaptively search for new paths as the process of finding food continues. The researchers found that the group foraging behavior of ants has two typical characteristics: (a) ants can instinctively release pheromones, and each pheromone is volatile and will gradually decrease with time; (b) ants can detect some situations in a small area, such as judging whether there is food or other similar pheromone tracks around the area. The main reason for this is that ants in the ant colony will release chemicals called pheromones in the places they pass to maintain indirect asynchronous contact when they are looking for food or on their way back to the nest and, with the information on the path and the passage of time, the pheromones will gradually decrease according to a certain proportion. At the same time, the concentration of pheromones is also related to the length of the path. The shorter the path, the greater is the concentration of pheromones. The more or stronger the accumulated pheromone concentration, the greater the possibility of being selected by other ants the next time, and this cycle will form a positive feedback effect until all ants take the shortest path. It should be noted that it is not that the ants following will definitely choose the path with high pheromone concentration, but the probability of choosing the path with high concentration is relatively high, which provides the possibility for the ants to expand the search range. In nature, the process of an ant colony finding food is a positive feedback process, and the optimization algorithm of an artificial ant colony is the process of simulating it. The specific foraging behavior diagram of ants is shown in Figure 1.

Figure 1. Foraging Behavior of Ants



(a)All ants are in the nest, no pheromones around the environment

(b)When starting foraging, the probability of ants choosing two paths is equal

(c)Ants that choose a shorter path arrive at the food source in advance. Therefore, when ants return, because there are more pheromones on the shorter path, the probability of ants choosing a shorter path is greater than that of ants choosing a longer path.

(d)The pheromone on the shorter path is strengthened, and the probability of all ants choosing the shorter path is greater than that of choosing the longer path. Finally, ants will concentrate around the shorter path to find the shortest path.

The Solving Model of Basic ACA

Dorigo et al. proposed an ant system model: Let $b_i(t)$ be the number of ants at customer point i at time t, there are n customers in total, and the total number of ants in the ant colony is m, then allow for Equations (1) and (2).

$$m = \sum_{i=1}^{n} b_i(t) \tag{1}$$

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{\left[\tau_{ij}(t)\right]^{\alpha} * \left[\eta_{ij}(t)\right]^{\beta}}{\sum\limits_{s \subset allowed_k} \left[\tau_{is}(t)\right]^{\alpha} * \left[\eta_{is}(t)\right]^{\beta}} \\ 0 \end{cases} \tag{2}$$

In Equations (1) and (2), the amount of information on the path (i,j) between customer points i and j at time $\tau_{ij}(t)$. In the process of path search and optimization, the ants mainly calculate the amount of information on each path and the heuristic information on the path. The state transition probability, and p_{ij}^{k} represents the state transition probability of the ant from customer point i to j at t time, $\eta_{ij} = 1/d_{ij}$ is the heuristic function, d_{ij} is the distance between customer points i and j, and α is the information heuristic factor, indicating the relative travel trajectory. Importance; β is the expectation heuristic factor, indicating the importance of the heuristic information displayed by the ants when choosing a path. $tabu_k$ is the taboo table used to record the customers who have completed the delivery task for each ant at present, and $allowed_k = \{C - tabu_k\}$ represents the customers that the ant k can choose in the next step. Ants will leave pheromones during the entire journey, and, at the same time, they will leave more pheromones on the shorter path. After each round of movement, all the pheromones on the entire path will evaporate. Then, all ants will release pheromones around the current route according to the length of the path constructed by themselves, thus obtaining the update rule of pheromone, as shown in Equations (3) and (4).

$$\tau_{ij}(t+n) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}(t) \tag{3}$$

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t) \tag{4}$$

In Equations (3) and (4), ρ is the pheromone volatilization coefficient, $0 \leq \rho < 1$ and c$1-\rho$ are the pheromone residual coefficients; $\Delta\tau_{ij}$ is the pheromone increment of (i,j) on the path in this iteration process, and the initial value is $\Delta\tau_{ij} = 0$; $\Delta\tau_{ij}^{k}(t)$ is the kth ant in this iteration. The amount of information left on path (i,j) in the loop. From this, the basic model of the ACA is obtained, as shown in Equation (5).

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} Q/L_k \\ 0 \end{cases} \tag{5}$$

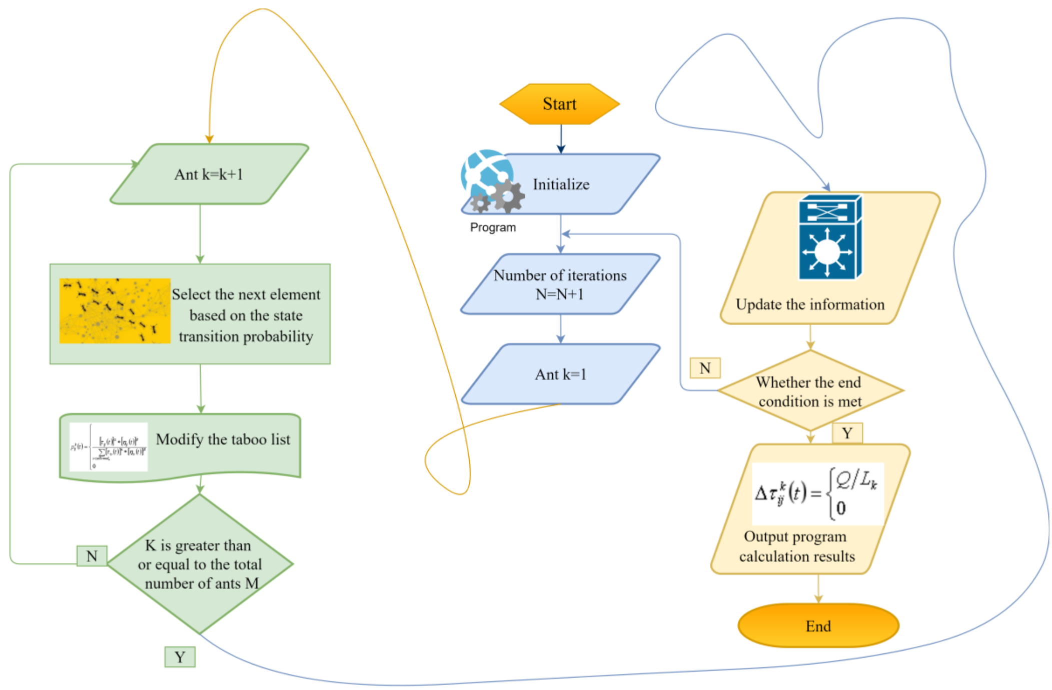
In Equation (5), Q is the pheromone intensity, which will affect the convergence speed of the algorithm to a certain extent; L_k is the total length of the path that the k ant traveled in this cycle. The flow chart of the running program of the ACA is shown in Figure 2.

ACA Combined With Neural Network Technology to Analyze Physical Delivery Problems

The general physical delivery path problem is described as follows: It is known that there are M customer points, and the demand volume and location of each customer point are also known. There are N vehicles from the distribution center to each demand point, and it is stipulated that the completion of after the distribution task, return to the logistics center, and the load capacity of each car is certain. It is required that the transport distance of the driving route of the delivery vehicle must be the shortest.

Figure 3 is a simple example of a specific physical delivery route, assuming that there is one logistics center, six distribution points, and three vehicles. The distribution tasks of the three customer points on the left go through distribution route one; the one customer point on the bottom and the two customer points on the right go through route two and route three, respectively; three delivery vehicles depart from the distribution center to deliver items, in order to traverse the customer points on the specified route and, finally, return to the distribution center.

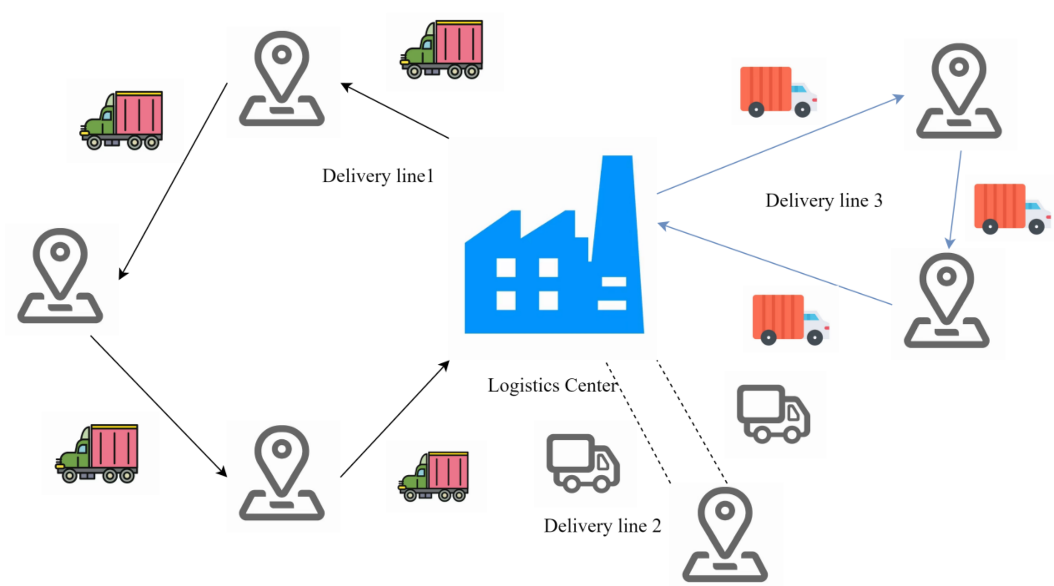
Figure 2. Flow Chart of the Running Program of ACA



The Establishment of Distribution Mathematical Model

Suppose there are Q_k vehicles in the distribution center, the load capacity of each vehicle is D_k, and the maximum driving distance of a vehicle distribution is C. A total of $q_i(1, 2, 3\cdots, C)$ customers

Figure 3. Example of Physical Delivery



are delivered goods. The demand for customer points i is j. The distance is d_{ij}, when $i,j = 0$ represents the distribution center, that is, d_{01} represents the distance from the distribution center to customer point 1, and i represents the distance from customer point 3 to the distribution center. Let d_{30} be the total number of customers delivered by vehicle n_k, and when k, it means that vehicle $n_k = 0$ has not been delivered, among which, $k = 1, 2, \cdots K$. R_k is used to represent the set of customer points delivered by the vehicle k, and the element k in this set indicates that the order of the delivery path of the vehicle r_k^i to the customer is i. From the physical delivery path problem described above, and according to the set mathematical symbols, plus the constraints that need to be considered for the problem, we can get:

The sum of the demand for customer points on each route does not exceed the car's load capacity, as shown in Equation (6).

$$\sum_{i=1}^{n_k} q_{r_k^i} \leq Q_k, n_k \neq 0 \tag{6}$$

The total length of each delivery route does not exceed the maximum travel distance for one delivery by car, as shown in Equation (7).

$$\sum_{i=1}^{n_k} d_{r_k^{i-1} r_k^i} + d_{r_k^{n_k} 0} \leq D_k, n_k \neq 0 \tag{7}$$

Only one car is allowed to pass a certain customer point, as shown in Equation (8).

$$R_{k1} \cap R_{k2} = \varnothing, k_1 \neq k_2 \tag{8}$$

All customer points complete the delivery, as shown in Equations (9)–(11).

$$\bigcup_{k=1}^{k} R_k = \{1, 2 \ldots, C\} \tag{9}$$

$$0 \leq n_k \leq C \tag{10}$$

$$\sum_{k=1}^{k} n_k = C \tag{11}$$

Therefore, the optimization goal to be achieved by the physical delivery path problem, as shown in Equations (12) and (13).

$$\min S = \sum_{k=1}^{k} \left[\sum_{i=1}^{n_k} d_{r_k^{i-1} r_k^i} + d_{r_k^{n_k} 0}\, sng(n_k) \right] \tag{12}$$

$$sng(n_k) = \begin{cases} 1, n_k \geq 1 \\ 0, else \end{cases} \tag{13}$$

The ACA is a probabilistic algorithm used to find optimal paths, which originates from the research on the problem of ants searching for food. The algorithm is not only an adaptive distributed algorithm, but also a random search algorithm. Ants communicate and cooperate through chemical substances left on their paths during foraging, called pheromones. The stronger the pheromone, the shorter is the corresponding path distance. When the concentration of path pheromone is high, the probability of ants discovering the path is greater and, at the same time, other ants passing through the path will also release a certain amount of pheromone to enhance the concentration of the path pheromone, thus forming a kind of learning information and positive feedback phenomenon. With this positive feedback, the ant colony will eventually find the best path from the nest to the food source. However, biologists found that the concentration of the pheromone along the path would gradually decay over time. The basic steps of the ACA to solve the optimization problem are: The ant walking path is regarded as the feasible solution of the optimization problem, and the ant colonies on all paths constitute the solution space of the optimization problem. Pheromones are released more in the short path and, as time goes by, the accumulation of pheromone in the short path gradually increases, and more and more ants will choose these short paths. Eventually, the ants will focus on the best path under the action of positive feedback.

With the popularization and development of the ACA in recent years, although it shows excellent performance and strong development potential for solving many complex optimization problems, at the same time, the ACA also has a large amount of calculation and a slightly longer search time. It is easy to fall into the local optimal solution, and there are shortcomings such as stagnation. In view of the possible shortcomings of the ACA, this paper makes corresponding improvements to the algorithm, thereby accelerating the convergence speed, improving the local optimal search ability, and improving the global search ability. At the same time, the adaptive ability of the algorithm is also slightly improved, along with the efficiency of the algorithm.

The local pheromone of each ant is updated as shown in Equation (14).

$$\tau_{ij}(t+1) = (1-\lambda)\tau_{ij}(t) + \lambda\Delta\tau_{ij}^{k}(t,t+1) \tag{14}$$

In Equation (14), $\lambda \in [0,1]$, $\Delta\tau_{ij}^{k}(t,t+1)$ is the pheromone increment of the ant k on the path (i,j) in this cycle, which is expressed as shown in Equation (15).

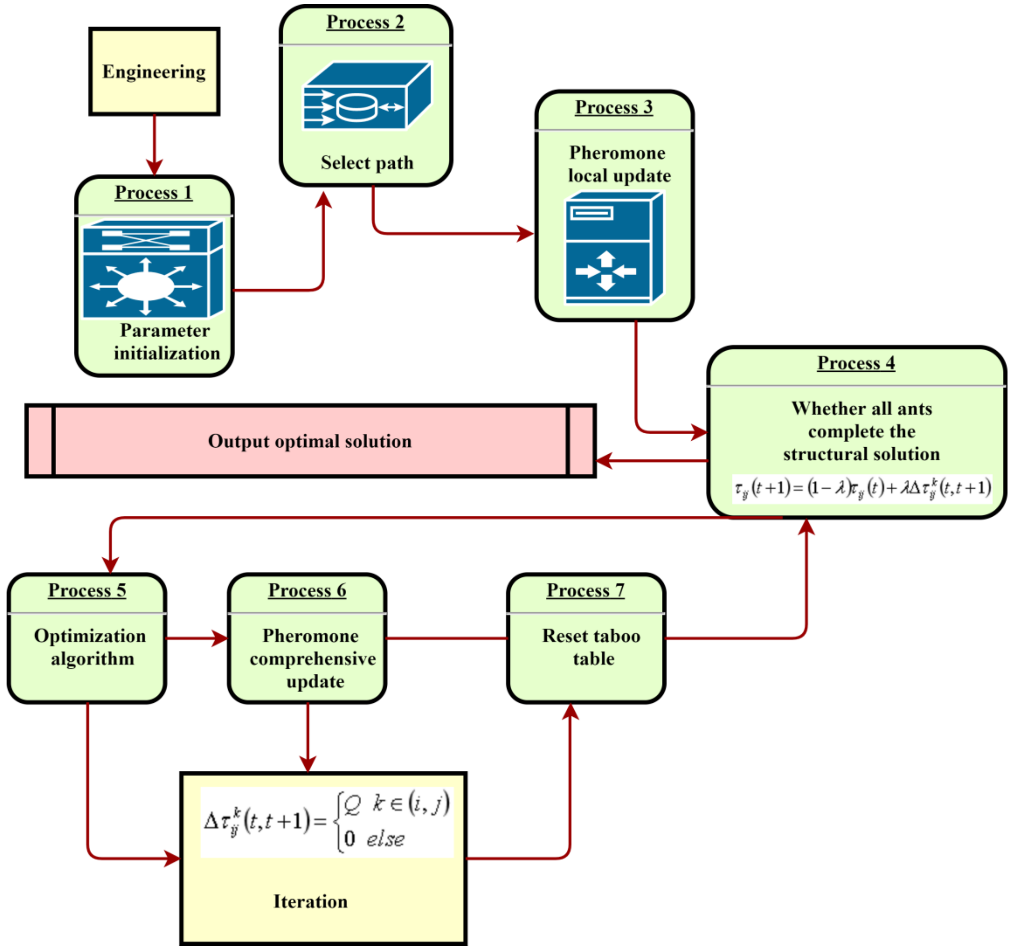
$$\Delta\tau_{ij}^{k}(t,t+1) = \begin{cases} Q & k \in (i,j) \\ 0 & else \end{cases} \tag{15}$$

Through the local optimization of the ACA, the solution of each iteration process is further improved, thereby shortening the length of the optimal solution and improving the convergence speed of the improved algorithm.

The global update of pheromone is only implemented for the ants that have obtained the shortest path. When all ants have completed a cycle, the update of pheromone adopts the following principles, $\rho \in (0,1)$ is the pheromone volatility coefficient, $1-\rho$ is the residual degree of pheromone; $\Delta\tau_{ij}^{k}$ $(t,t+1)$ is the increment of pheromone on the path dd (i,j), that is m is the sum of the pheromones left by the ants on the path (i,j) during this iteration. The main reason to improve the global search ability is to avoid the stagnation of the local optimal solution in the process of ant optimization. The main reason is the influence of pheromone accumulation and transmission on ants.

The improved ACA adopts the strategy of combining local and global pheromone updates, and further improves the information residual factor of global pheromone update, so as to ensure the optimal solution and speed up the convergence. The flowchart of the improved ACA is shown in Figure 4.

Figure 4. Improved ACA Process



RESULTS ANALYSIS AND DISCUSSION

In the Matlab programming environment, this paper compares the impact of different values of various parameters on the performance of the improved ACA iterative calculation path planning. Before comparing the different values of the parameters, we fix the values of other parameters and keep them constant, so as to determine the calculation process of the improved ACA one by one in parameter optimization. In the Matlab programming environment, the performance analysis of the physical delivery path planning results of the improved ACA and the traditional ACA is carried out, and the path planning results are generated respectively to verify the effectiveness of the improved algorithm proposed in this paper.

The improved hybrid ACA in this paper is implemented by language programming. In order to show the effectiveness and rationality of the algorithm, a lot of adjustments and improvements have been made to the improved hybrid ACA, which is completed by solving the physical delivery path optimization problem. For the test of the algorithm in this paper, the shortest path results obtained by the test are compared with the experimental results of several other algorithms. The algorithm in this section is tested on a part of the data set, and the minimum number of iterations before and after the improvement of the algorithm is compared. The test results are shown in Table 1.

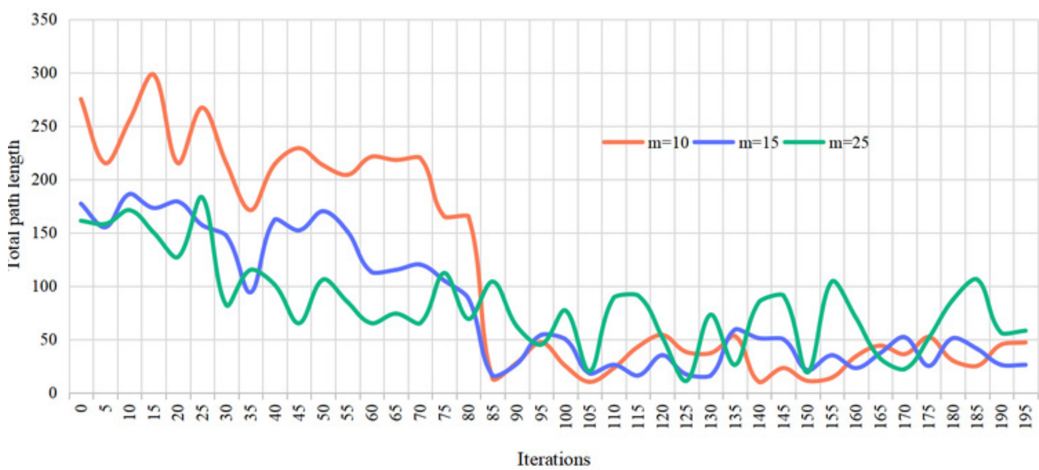
Table 1. Comparison Results of the Minimum Number of Iterations Before and After Improvement of ACA

Problem	DL	Best length	Traditional	Improved
Oliver30	426.71	426.71	110	31
Att48	33527.9	33527.9	65	19
Eil51	436	436	98	34
St70	668	668	150	122

Table 2. Performance Comparison of ACA Before and After Improvement

Arithmetic example	Optimal solution	Optimal solution after improvement	Before improvement	After improvement
Oliver30	411.56	411.56	144.22	111.5
Att48	32111.39	32111.39	883.2	662.3
Eil51	437.5	437.5	22.5	11.2
St70	666	666	111.5	85.2

Figure 5. Effect When the Number of Ants is 10, 15, or 25



In the specific implementation, it is found that when the routing path search is performed under the local and global update pheromone strategy, the convergence speed of its search rate algorithm is not good. Therefore, through further analysis of the ACA, a part of the data set is tested. The test results are shown in Table 2.

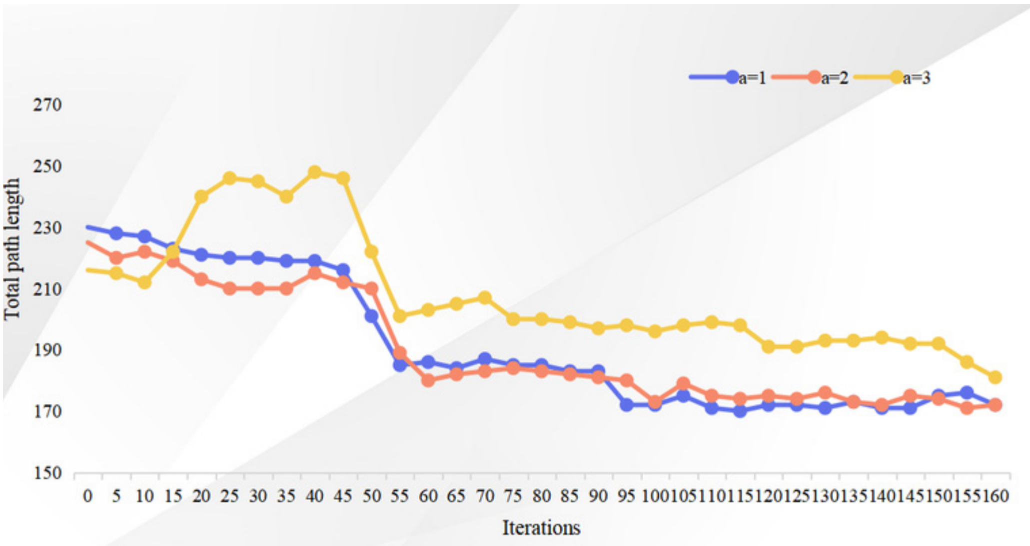
It can be seen from Table 2 that under the new pheromone update strategy, the traditional ACA problem can be solved while the local optimal solution is trapped, and the convergence performance of the algorithm can be improved.

Parametric Analysis

The Effect of the Number of Ants on the Path

In order to discuss the influence of the number of ants on the optimal path of logistics, this paper analyzes six groups of different ant numbers. Figure 5 shows that when the number of ants (m) is selected as 10, 15, or 25, the shortest path will gradually decrease as the number of ants increases.

Figure 6. Effects of Pheromone Concentration Factors on Pathways



The algorithm calculates the number of times, that is, the path with the most travel times is set as the optimal path. This process simulates the foraging process of ants. As shown in Figure 5, as the number of ants increases, the planned shortest path will gradually increase. Therefore, when m = 15, the proposed improved ACA can make the result of each running of the improved hybrid ACA as small as possible, and the result can be kept as stable as possible.

Effects of Pheromone Concentration Factors on Pathways

In order to discuss the influence of pheromone concentration factors on the optimal path of logistics, different groups of pheromone concentration factors are set for comparative analysis, as shown in Figure 6.

Ants can produce special chemicals called pheromones, which are volatile. According to research, in the ant colony system, the communication between ants and between ants and the environment depends on pheromones. Figure 6 shows that when the pheromone concentration factor $\alpha=3$, the change of the total length of the path planning is obvious, when the pheromone concentration factor $\alpha=1$ or 2, the change of the total length of the path planning is not obvious, but when $\alpha=1$, the convergence rate of path planning is significantly faster than $\alpha=2$, so $\alpha=1$ is finally selected as the pheromone concentration factor parameter.

The Effect of the Path Expectation Factors on the Path

In order to discuss the influence of the route expectation factors on the optimal logistics route, different groups of route expectation factors are set for comparative analysis, as shown in Figure 7.

Figure 7 shows that when the path expectation factor $\beta=1$, the result of path planning fluctuates greatly. On the contrary, when the path expectation factor $\beta=2$, the path planning result is more stable. Therefore, this paper chooses $\beta=2$ as the path expectation factor, which can obtain a more stable and more realistic path planning effect than other path expectation factors during the experiment.

Effects of Pheromone Volatile Factors on Pathways

The effect of pheromone volatile factors on the pathway is shown in Figure 8.

Figure 7. Influence of Path Expectation Factors on Path

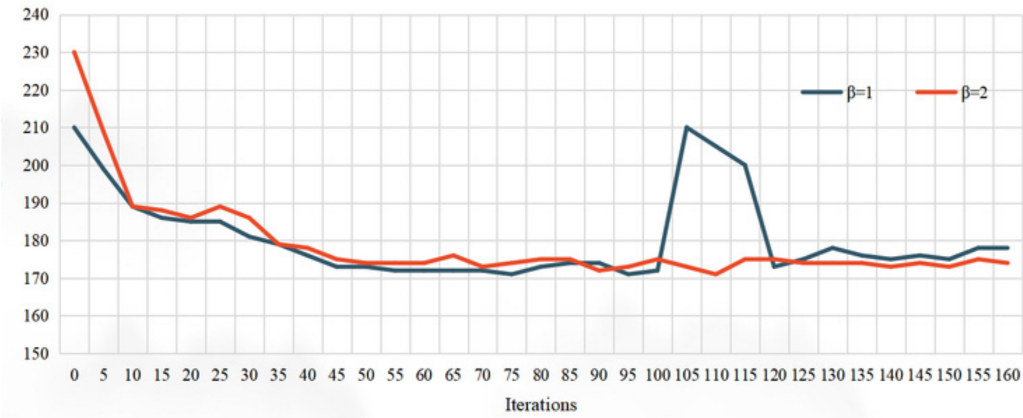
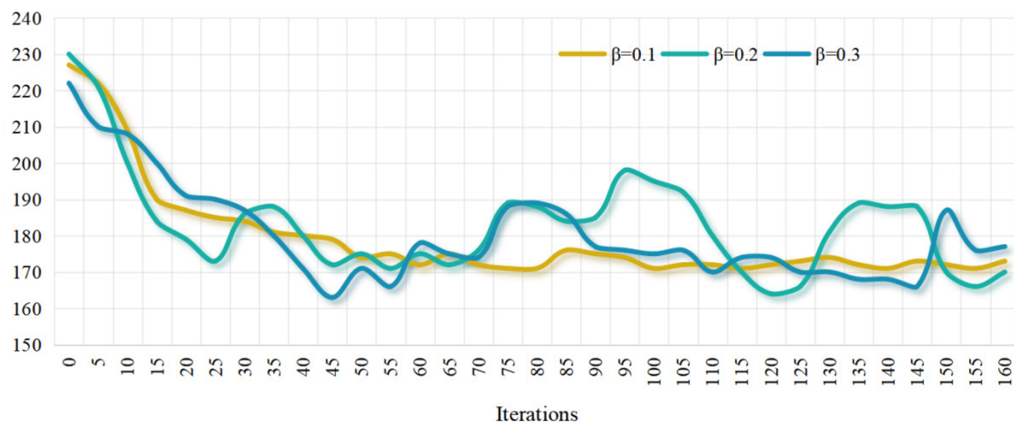


Figure 8. Effects of Pheromone Volatile Factors on Pathways



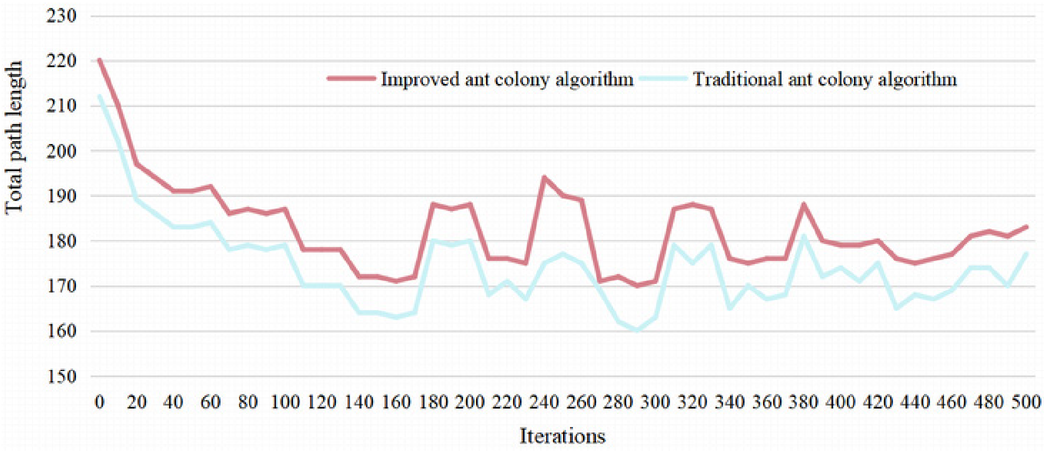
If the pheromone volatilization factor is set too large, the pheromone volatilizes quickly, and the pheromone content on each path varies greatly, which increases the search range of ants. If the pheromone volatilization factor is set too small, the pheromone volatilization is slow, and the difference in pheromone content on each path is small, which is conducive to finding the global optimal solution, but will slow down the convergence speed of the algorithm. In order to control the convergence speed of the algorithm and avoid the algorithm falling into the local optimal solution, the pheromone volatility factor should be set reasonably. Figure 8 shows that when the pheromone volatility factor ρ=0.1, the shortest path gradually converges with the increase of the number of iterations, and when ρ=0.2 or 0.3, the path planning result fluctuates greatly with the increase of the number of iterations. Therefore, it is more reasonable to choose ρ=0.1 in this paper.

Results Analysis

In this paper, the optimal calculation parameters are selected for physical delivery path planning. Figure 9 shows the performance comparison between the improved ACA and the traditional ACA.

In this paper, the optimal calculation parameters are selected to plan the physical delivery route: The number of ants is $m = 15$, the pheromone concentration factor is $\alpha = 1$, the route expectation factor

Figure 9. Performance Comparison Between the Improved ACA and Traditional ACA



is β = 2, the pheromone volatilization factor is ρ = 0.1, and the number of iterations is 500. Figure 9 shows that the improved ACA has a convergence effect more than the traditional ACA. And the optimal distance of physical delivery path planning calculated by the traditional ACA is 207.8544km, while the optimal distance of the improved ACA path planning is 197.9879km. It can be seen from the analysis of the above results that a better optimization scheme can be obtained by using the improved ACA and neural network algorithm to solve the physical delivery network optimization problem.

In order to ensure the good performance of the improved ant colony algorithm in the logistics delivery path, the improved ant colony algorithm is compared with the genetic algorithm. Although the genetic algorithm is good at finding the global optimal solution by exploring a large search space and converging to the optimal solution, the calculation cost of genetic algorithm may be high, especially for complex problems with a large number of variables. And it may take a long time to converge to the best solution, especially for the problem of rugged terrain. The improved ACA algorithm is designed to be more efficient and faster than traditional algorithms in terms of convergence speed and solution quality. The ACA algorithm incorporates local search techniques to exploit the neighborhood of solutions, leading to better exploitation of the search space. The algorithm can adapt dynamically to changes in the environment or problem landscape, making it more robust in dynamic optimization scenarios.

The improved ACA has emerged as a powerful tool for optimizing a wide range of complex optimization problems, particularly in the realm of logistics networks. Its adaptability and effectiveness make it a promising solution for enhancing efficiency in medium to larger-scale logistics operations. However, when considering its application in diverse geographical contexts, several key factors must be carefully considered to maximize its utility and effectiveness.

Adaptation to Different Geographical Contexts

1. Topology: Tailoring the ACA algorithm to accommodate the unique topological characteristics of various logistics networks is essential. By customizing the algorithm to account for the specific layout of roads, warehouses, and distribution centers in different geographic settings, organizations can enhance the accuracy and efficacy of route planning and resource allocation.
2. Distance calculation: Integrating geographic information such as distance metrics, traffic patterns, and terrain data into the algorithm enables more precise and efficient route optimization. By

factoring in these variables, the ACA algorithm can generate optimal solutions that account for real-world conditions and constraints.

3. Climate and environmental factors: In regions where climate and environmental considerations significantly impact logistics operations, adjusting the ACA algorithm to incorporate these factors is crucial. By accounting for variables like weather conditions, ecological constraints, and sustainability goals, organizations can improve operational efficiency while minimizing environmental impact.

In conclusion, the enhanced ACA algorithm presents a valuable opportunity for optimizing medium and larger-scale logistics networks across diverse geographical contexts. By tailoring the algorithm to address specific logistical challenges, mitigating scalability issues, and leveraging its benefits in route optimization and resource allocation, organizations can unlock significant operational improvements and competitive advantages. However, successful implementation of the ACA algorithm requires careful consideration of challenges such as scalability, real-time updates, and data integration to ensure its seamless integration into diverse logistics settings.

CONCLUSION

The rapid development of the global economy has made logistics chains an important part of the modern economy. Optimizing physical delivery can not only save resources and time, but also reduce environmental pollution, which is of great significance to the future development of the country and enterprises. This paper consults many domestic and foreign literatures, summarizes the research status and future development trend of the vehicle routing problem, classifies its solving algorithms, conducts in-depth research on the operation mechanism of ACA, and designs an improved ACA. According to the characteristics of physical delivery in small areas, a mathematical model of physical delivery in line with the actual situation is established, and the improved ACA is used to optimize the solution.

In conclusion, this study meticulously examines the operational principles of ACA along with three distinct ACA models, emphasizing the ant colony's pathfinding process, pheromone updating mechanisms, and the advantages and drawbacks of ACA. The pivotal tasks within ACA encompass pheromone updates and pathfinding. By scrutinizing ACA, a blend of local and global pheromones is leveraged for pheromone updates, with half of the ant-constructed solutions incorporating local search to enhance solution quality and efficiency.

In the quest to optimize the algorithm, a function has been integrated into the global update formula to expedite algorithm convergence while retaining optimal solutions. Experimental results reveal that while the traditional ant colony swarm algorithm yields an optimal distance of 207.8544km for physical delivery path planning, the enhanced ACA path planning achieves 197.9879km. The incorporation of this function reduces the number of cycles needed to attain the optimal solution, and dynamic adjustments to the pheromone volatilization degree coefficient during the ACA iteration process further enhance performance.

Upon evaluating the outcomes from typical examples, the improved ACA demonstrates enhanced performance in optimizing physical delivery paths. However, it is crucial to acknowledge potential shortcomings such as the sensitivity of the algorithm to parameter settings and the need for robust validation across diverse scenarios to ensure its applicability in real-world settings. While the improved ACA exhibits promising efficiency in solving physical delivery path problems and identifying optimal solutions promptly, further research is warranted to address these potential limitations and enhance the algorithm's robustness.

In essence, the findings presented in this paper offer practical insights and valuable references for optimizing physical delivery routes. By acknowledging both the feasibility of the improved ACA and potential areas for refinement, future advancements in this research area can be guided toward more effective and reliable solutions.

In order to improve the relevance and applicability of the research results, this study puts forward specific implementation suggestions to integrate the research results into the real-world logistics operation.

We can cooperate with logistics companies to test the improved ACA algorithm in their delivery operations, or we can develop a software tool or module and use the improved ACA for route optimization. This tool can be integrated into the existing logistics management system used by enterprises, providing a practical and user-friendly implementation for the research results. A case study is compiled to show the successful implementation of the improved ACA in optimizing the physical delivery route and to emphasize the best practices and lessons learned from these cases to guide other enterprises to adopt similar strategies.

DATA AVAILABILITY

The figures and tables used to support the findings of this study are included in the article.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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