Hybrid GA-ACO Algorithm for Optimizing Transportation Path of Port Container Cargo

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With the advancement of port transportation, optimizing the transportation path of container cargo has become a crucial consideration for logistics transportation companies. In this paper, a path optimization model was established for transporting container cargo from the yard to the customer, considering the customer's time window and aiming to minimize the total cost. A genetic algorithm-ant colony optimization (GA-ACO) algorithm was then devised to solve the model, and a case was analyzed to verify the effectiveness of this approach. It was found that the total cost of the path obtained by the GA-ACO algorithm was significantly lower than that of the GA and ACO individually (8.63% and 12.96%), reaching 7,458,268 yuan. Moreover, it used fewer vehicles. It suggested that the GA-ACO algorithm yielded a more efficient result. An analysis of different task quantities revealed that as the number of tasks increased, logistics transportation enterprises achieved higher vehicle utilization rates and better economic efficiency in completing container cargo transportation. These findings validate the reliability of the GA-ACO algorithm, affirming its applicability in real-world optimization of port container cargo transportation paths.

Povzetek: Hibridni algoritem GA-ACO združuje genetski algoritem (GA) in optimizacijo z mravljinčno kolonijo (ACO) za optimizacijo poti transporta kontejnerjev v pristanišču. Uporaba tega algoritma je pokazala zmanjšanje skupnih stroškov transporta ter optimizirano izrabo vozil.

1 Introduction

Under the influence of economic development, ports have gained significant importance in logistics transportation [1]. More and more goods are transported by sea [2], leading to a year-on-year increase in the throughput of containerized cargo at ports [3]. Containers offer a cost-effective and efficient mode of transportation, serving as a link between sea and land transportation. Upon port arrival, goods are unloaded from ships, stacked in yards, and transported to customers. With the continuous growth of container throughput, optimizing the transportation path of containerized goods has become essential in meeting the demands of logistics transportation [4]. Table 1 is the summary table of relevant research on port logistics.

Table 1. A summary of relevant works

	The used method	Main findings	Limitation
Chatterjee and Cho [5]	Machine learning and meta-heuristic algorithms	Artificial intelligence and machine learning are necessary for port management, as they have applicability in berth scheduling and terminal allocation.	Only simulation experiments were conducted, lacking analysis on actual data.
Bisevac et al. [6]	A linear integer programming model was established for the integration of the dock worker assignment problem and the quay crane allocation problem, and an integrated approach was used to solve it.	The method could reduce the total cost of dock workers. The average improvement rate of the objective function value of the obtained solution was 26.43%.	The issue of scheduling dock cranes was not taken into consideration.

Bavar et al. [7]	Genetic meta-heuristic algorithm	The method was highly efficient in solving the time and problem's answer.	The impact of quantity and quality of goods was not taken into account.
Zweers et al. [8]	Integer linear programming and heuristic methods	Compared to the methods currently used in practice, there was a cost reduction of approximately 20%.	Only include the import flow of containers.

Currently, research on transportation path optimization in port logistics transportation primarily focuses on the routing from the terminal to the port shore bridge. In contrast, research on transportation from the port yard to the customer's warehouse still needs to be completed. In today's fiercely competitive market, customer expectations regarding the timeliness of container cargo transportation have increased significantly. This paper established a time-window-based optimization model for the container cargo transportation path between the stockyard and the customer's warehouse to address this challenge. A hybrid approach, comprising a genetic algorithm (GA) and an ant colony optimization (ACO) algorithm, was developed to solve the model, and it was proven effective in optimizing container cargo transportation paths in ports through experimental analysis. This paper provides a new approach for path optimization in logistics transportation. Furthermore, it offers theoretical support for ports to enhance transportation efficiency, increase container cargo throughput, and meet customer demands.

2 Optimization model for transportation paths of port container cargo

2.1 Transportation of port container cargo

A container is a large unit used for the transportation of goods without the need to remove the contents during transit. Container logistics transportation offers several advantages, including excellent sealing, low damage rates, high efficiency, and cost-effectiveness. It is a scalable and streamlined mode of transportation that ensures the safety and efficiency of cargo transport. As a result, container logistics transportation finds extensive applications in logistics transportation [9].

Container cargo transportation ensures the efficient movement of goods from the port to the customer. This process can be divided into two main stages: firstly, the transportation of goods from the port to the yard, and secondly, from the yard to the customer's warehouse. These operations can be further categorized based on import and export activities.

(1) Import operations: In this scenario, vehicles transport containerized cargo from the yard to the customer's warehouse and return to the empty yard.

(2) Export operations: Vehicles depart from the yard empty and travel to the customer's warehouse. At the warehouse, cargo is loaded into containers, after which the vehicles return to the yard.

Additionally, container cargo transportation can be classified based on the nature of the goods in the containers.

(1) Full container load: goods in containers solely belong to a single customer.

(2) Less than container load: goods in containers belong to various customers.

It is assumed that all containerized cargo transportation is limited to full container transportation (e.g., in situations where clients have a high demand for a single cargo). Furthermore, it is assumed that goods transported from the port are temporarily stored in the yard before onward transportation.

2.2 Yard-customer transportation path optimization model

Timeliness is crucial in container cargo transportation and strongly correlates with customer satisfaction. Amid intense market competition, logistics transportation companies must strive to meet delivery deadlines and enhance customer satisfaction. By doing so, they can earn customer trust and loyalty, leading to increased profitability. Therefore, this paper incorporates time windows into container cargo transportation. The research problem is to minimize the total cost of completing transportation tasks from the yard to customer warehouses by optimizing routes, while meeting time window requirements. The following assumptions are made:

(1) vehicles depart from the yard and return to the yard after completing their tasks;

(2) each task is assigned to one and only one vehicle;

(3) fixed startup costs and unit driving costs for each vehicle are known;

(4) the one-way travel distance and time between the yard and the customer's location are known;

(5) the loading and unloading time for each task are known;

(6) vehicles must operate within the earliest and latest timeframes specified by the customer for accepting the service.

The symbols involved in the yard-customer transportation path optimization model are listed in Table 2.

Table 2: Symbols involved in the model and their implications.

Symbol	Implication
$A = \{1,2,\cdots,n\}$	A task set
$B = \{1,2,\cdots,k\}$	A set of vehicles available to logistics transportation companies

x_{ij}	If $x_{ij} = 1$, it indicates the cargo transportation task for customer i is accomplished by vehicle j; otherwise, it is not.
y_j	If $y_j = 1$, it means that vehicle j is accomplishing the transportation task; otherwise, it means that it is not.
s_i	One-way travel distance from yard to customer i
t_i	One-way travel time from yard to customer i
T_i	The cargo handling time for customer i
J	The vehicle fixed startup cost
L	The vehicle unit driving cost
$[a, b]$	Vehicle time window, i.e., each vehicle starts transportation no earlier than a'o clock and returns to the yard by no later than b'o clock.
$[ET_i, LT_i]$	Clients i' most satisfied service period
E_i	The earliest time that a vehicle reaches customer i
L_i	The latest time that a vehicle reaches customer i
o_i	The time that a vehicle reaches customer i
P_1	Penalty factor when a vehicle reaches within $[E_i, ET_i]$
P_2	Penalty factor when a vehicle reaches within $[LT_i, L_i]$

The final model for yard-customer transportation path optimization is:

$$minC = \sum_{i=1}^{n} L \times 2\, s_i + \sum_{i=1}^{n} p_i + J \times \sum_{j=1}^{k} y_i.$$

The constraints of the model are as follows.

(1) Each task is completed by one and only one vehicle: $\sum_{j=1}^{k} x_{ij} = 1$.

(2) Vehicle j's total transportation time cannot exceed its maximum working hours: $\sum_{i=1}^{n}(T_i + 2t_i + w_i) \times x_{ij} \le y_i \times (a - b)$.

(3) The earliest departure time for each task shall be later than the earliest departure time for the vehicle: $o_i - t_i \ge a$.

(4) The latest end time for each task shall be earlier than the latest closing time for the vehicle: $o_i + w_i + t_i \le b$.

(5) The time that vehicle j reaches customer i must be within the customer's time window: $E_i \le o_i \le L_i$.

(6) Penalty costs for vehicles arriving early or late:

$$p_i = \begin{cases} P_1 \times (ET_i - o_i),\ E_i \le o_i \le ET_i \\ 0, ET_i \le o_i \le LT_i \\ P_2 \times (o_i - LT_i), LT_i \le o_i \le L_i \end{cases}.$$

(7) Waiting time of the vehicle at the customer's place: $w_i = \begin{cases} (ET_i - o_i),\ E_i \le o_i \le ET_i \\ 0,\ o_i \ge ET_i \end{cases}.$

3 Solution algorithm based on GA and ACO

In the field of transportation path optimization, various methods have been applied, including GA [10] and simulated annealing algorithms [11]. However, for complex problems, it is often difficult to obtain good results using only one algorithm. Combining different algorithms effectively can significantly enhance the solving ability [12].

GA is an algorithm based on the principles of biological evolution, which obtains approximate optimal solutions through generations of evolution. It is particularly suitable for large-scale searches and has a relatively high search speed. GA mainly includes the following content.

(1) Encoding: The parameters of the problem that need to be solved are converted into a gene string structure, known as a chromosome, which can be processed by GA. Methods such as binary encoding and ordered string encoding can be used.

(2) Population initialization: As a population-based search method, before genetic operations, an initial population is generally generated using random methods. Each initial individual represents an initial solution.

(3) Fitness: GA uses fitness to evaluate the quality of individuals and selects individuals based on their fitness to ensure that individuals with better fitness can produce more offspring in the next generation.

(4) Genetic operations: it includes selection, crossover, and mutation. Selection involves choosing individuals from the parent population to pass on to the next generation. Crossover is a process of exchanging parts of genes in chromosomes in a certain way to create new individuals and ensure diversity in the new population. Mutation is also a way to generate new individuals by replacing gene values at certain loci in the coding string, maintaining population diversity.

(5) Termination condition: GA generally uses convergence and accuracy as termination criteria. Setting the maximum iteration count is the most commonly used method. If the maximum iteration count is reached, then the algorithm terminates; otherwise, it continues searching.

The ACO algorithm is a random search algorithm based on the foraging mechanism of ants. During the foraging process, ants release pheromones to find paths. Higher concentrations of pheromones indicate a greater probability of being chosen by subsequent ants. Based on this, the optimal path can be found. As a positive feedback algorithm, the ACO algorithm has good robustness and parallelism and is easy to combine with other algorithms. Currently, it has been widely applied in problems such as path planning and vehicle scheduling.

GA is known for its robust global search capability but may encounter issues such as premature convergence [13]. The ACO algorithm excels in local optimization but may require longer search times. To address these challenges, a hybrid algorithm that combines GA and ACO has been successfully applied in various domains, such as parameter optimization and task scheduling [14]. This paper uses both GA and ACO to solve the optimization model established in the previous section. Initially, the ACO algorithm is utilized to obtain an initial solution. Subsequently, GA is employed to search for the optimal solution, leading to higher-quality solutions and improved convergence speed [15].

The natural number coding method [16] is used in the coding process. 0 represents the port yard. For example, it is assumed that a logistics transportation company uses three vehicles to transport containerized goods to seven customers. The order in which each vehicle serves the customers represents a path. All paths form a chromosome code, for example, 01502603470. It means that vehicle 1's transportation route is 0-1-5-0, vehicle 2's transportation route is 0-2-6-0, and vehicle 1's transportation route is 0-3-4-7-0.

The population initialization is based on the ACO algorithm. Let the quantity of nodes be n, the quantity of ants be m, and the distance between nodes be d_{ij}, the pheromone concentration be τ_{ij} , and the intimate concentration be ϑ_{ij}, $\vartheta_{ij} = 1/d_{ij}$. The probability of ant k transfering from node i to node j is written as:

$$p_{ij}^k = \begin{cases} \frac{\tau_{ij}^{\alpha}(t)\vartheta_{ij}^{\beta}(t)}{\sum_{j\in allowed_k}\tau_{ij}^{\alpha}(t)\vartheta_{ij}^{\beta}(t)}, j \in allowed_k \\ 0, otherwise \end{cases},$$

where α is an information heuristic factor that reflects the impact of the amount of information on each path on ant's choice of paths, β is an expectation heuristic factor that reflects the impact of heuristic information on ant path selection, and $allowed_k$ is a set of nodes that ant k can access.

The initial visit point for each ant is generated randomly. The beginning of each chromosome is the port yard (0), and a random number point is selected for visiting. Then, according to the state transition rules, the next visit point is generated and added to the taboo list. The operation repeats until traversal ends.

To avoid prematurity, a combination of deterministic and random selection is used. Variable q_0 is introduced; the ants are selected in the following way:

$$S = \begin{cases} argmax(p_{ij}^k), q < q_0 \\ rand(allowed_k), otherwise \end{cases},$$

where q is a random variable, $q \in (0,1)$. According to the above equation, if $q < q_0$, then the node with p_{ij}^k is visited; otherwise, a random accessible node is visited.

The fitness function is based on the objective function established in the previous section. For individual i, there is an evaluation function:

$$f_i = C'/C,$$

where C' stands for the cost of the optimal chromosome in each chromosome population and C stands for the optimal total cost.

The fitness function of individual i is:

$$F_i = \frac{f_i}{\sum_{i=1}^{n} f_i},$$

The crossover operator uses the partial matching crossover (PMX) method [17]. For example, for two parents,

A: 125684937,

B: 325716849,

the cross symbol "|" is randomly generated:

A: 12|5684|937,

B: 32|5716|849.

The selected substring "5684" in A is placed at the beginning, and the genes in B are compared with "5684" in turn. The final result is obtained after deleting the same gene:

A1: 5684 325716849 → A1: 568432719,

B1: 5716 125684937 → B1: 571628493.

In the transportation path optimization model, each chromosome contains "0" representing the yard. However, there may be instances where the offspring generated through the PMX operation do not meet the criteria. Therefore, in each PMX operation, it is necessary to check whether the first and last genes of the offspring are "0". If they are not, any "0" gene in the middle of the offspring is exchanged with either the first or last gene to obtain a qualified offspring.

The mutation algorithm uses reverse order mutation to randomly generate mutation points and do reverse order mutation on selected substrings, for example:

before reverse order mutation: 526|4891|37,

after reverse order mutation: 526|1984|37.

After completing the path assignment for all ants, the pheromone is updated:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij},$$

$$\Delta\tau_{ij} = \sum_{k=1}^{K} \Delta\tau_{ij}^k,$$

$$\Delta\tau_{ij}^k = \begin{cases} Q/L_k, if\ the\ k-th\ and\ passes\ route(,j) \\ 0, otherwise \end{cases},$$

where $\tau_{ij}(t+1)$ refers to the total amount of pheromone after the $t+1$-th iteration, ρ refers to the pheromone volatilization factor ($0 \le \rho < 1$), $\Delta\tau_{ij}$ is the pheromone concentration of all ants between i and j, $\Delta\tau_{ij}^k$ is the pheromone concentration released by the k-th ant between i and j (initial value = 0), Q is a constant, which represents the total amount of pheromone released by an ant after traversing once, and L_k is the distance passed by the k-th ant.

The process of the based solution algorithm is described below.

(1) Based on the ACO algorithm, the population is initialized.

(2) The fitness value is calculated. A new generation of populations is generated through crossover and mutation operations.

(3) The pheromone on the path is updated.

(4) Whether the termination condition is reached is determined. The optimal solution is obtained. The path numbers are converted to customer points to get the optimized transportation path.

4 Results and analysis

4.1 Experimental setup

The experiment was carried out in a computer with a Windows 10 system, Intel Core i7-6500U CPU, 2.5 GHz, and 8 GB memory. MATLAB R2017b was used as the simulation platform. The settings of parameters involved in the GA-ACO algorithm are presented in Table 3. The parameter values were determined based on existing literature and a large number of experiments.

Table 3: GA-ACO parameter settings

Parameter	Value
Colony size	50
α	1
β	5
q_0	0.5
ρ	0.1
Q	50
Crossover probability	0.9
Mutation probability	0.1
Maximum number of iterations	100

In the yard-customer transportation path optimization model, it was assumed that the logistics transportation enterprise had 86 vehicles for completing the transportation service for 250 customers, and Table 4 shows the settings of relevant parameters in the model.

Table 4: Model parameter settings

Symbol	Hidden meaning	Value
J	The vehicle fixed startup cost	200 yuan/vehicle
L	The vehicle unit running cost	20 yuan/km
$[a, b]$	Vehicle time window, i.e., each vehicle starts transportation no earlier than a 'o clock and returns to the yard by no later than b 'o clock.	[6,24]
P_1	Penalty factor when a vehicle reaches within $[E_i, ET_i]$	20 yuan/hour
P_2	Penalty factor when a vehicle reaches within $[LT_i, L_i]$	40 yuan/hour

The customer's distance from the yard, the service time window, and the loading and unloading time were known. The data for some of the customers are shown in Table 5.

Table 5: Selected customer data

Customer number	Distance to the yard/km	$[ET_i, LT_i]$	$[E_i, L_i]$	Loading and unloading time
1	71.26	[7:00-8:30]	[6:30-9:30]	15
2	25.31	[8:30-10:30]	[7:30-11:30]	20
3	15.69	[7:00-8:45]	[6:30-8:30]	10
4	54.26	[8:30-9:30]	[7:00-10:30]	5
5	51.96	[9:30-11:30]	[7:30-12:30]	12
......	......	......	......	......
250	26.95	[10:30-11:30]	[9:30-12:30]	20

4.2 Result analysis

The solution results of the GA, ACO, and GA-ACO algorithms for the yard-customer transportation path optimization model are displayed in Table 6.

Table 6: Solution results of different algorithms

Solution algorithm	Transportation path		Minimum total cost	Iteration times for optimal solution
GA	Path 1	0-1-3-55-67-84-91-0	8,162,543 yuan	99
	2	0-52-64-44-72-69-92-0		
	3	0-68-99-123-126-135-216-0		
	4	0-7-94-88-207-0		
	5	0-231-216-116-157-0		
	......	……		
	Path 85	0-245-233-158-92-0		
ACO	Path 1	0-26-33-46-91-0	8,569,258 yuan	87
	2	0-25-39-48-116-217-2-0		
	3	0-16-19-29-31-84-0		
	4	0-137-165-142-0		
	5	0-67-18-22-7-0		
	......	……		

	Path 86	0-111-105-187-219-233-0		
GA-ACO	Path 1	0-2-56-95-85-24-0	7,458,268 yuan	56
	2	0-3-5-91-45-6-84-16-0		
	3	0-22-19-25-33-37-0		
	4	0-1-57-61-38-201-116-112-0		
	5	0-24-34-59-68-231-168-0		
	......	……		
	Path 84	0-7-31-145-171-0		

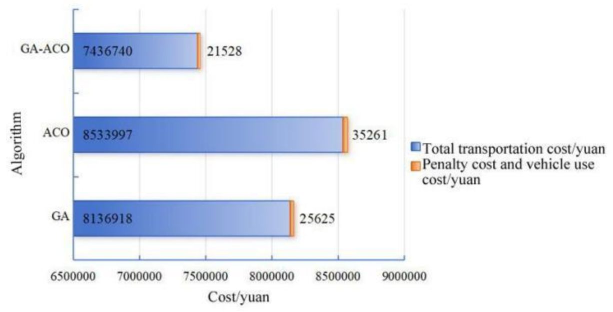

Figure 1: Cost analysis of optimal solutions of different algorithms

Based on the analysis of Table 6 and Figure 1, it was observed that the ACO solution yielded the highest total cost of 8,533,997 yuan, including penalty costs and vehicle usage costs (35,261 yuan). According to Table 6, the GA yielded 85 transportation paths, meaning that 85 vehicles were needed to complete the transportation task. In contrast, the ACO algorithm required 86 vehicles. The total cost of the paths obtained by the GA was slightly lower than that of the paths obtained by the ACO algorithm, indicating that the GA performed better than the ACO algorithm. The proposed GA-ACO hybrid method achieved the lowest total cost of 7,458,268 yuan, which was 8.63% and 12.96% lower than the costs from the GA and ACO algorithm, respectively. The total transportation cost was 7,436,740 yuan, with penalty and vehicle usage costs amounting to 21,528 yuan. This cost was lower than that of both ACO and GA algorithms. Moreover, only 84 vehicles were required to complete the container cargo transportation task for 250 customers. These findings demonstrated the reliability and effectiveness of the hybrid algorithm in solving the optimization model for yard-customer transportation paths. In terms of the number of iterations required for optimal solutions, the GA required 99 iterations, the ACO algorithm required 87 iterations, while the GA-ACO algorithm only needed 56 iterations, significantly fewer than either GA or ACO alone. This result demonstrated the superior optimization performance of the GA-ACO algorithm, i.e., its ability to achieve faster convergence.

To further demonstrate the reliability of the proposed method, it was compared with some existing hybrid solving methods (Table 7).

Table 7: Comparisons with other hybrid solving algorithms

	Total cost/yuan	Number of vehicles/n	The average penalty cost and use cost per vehicle/yuan
The hybrid k-means GA [18]	7,885,621	85	23,154
Cross entropy genetic algorithm (CEGA) [19]	7,765,821	85	22,985
Cellular genetic algorithm (CGA) [20]	7,652,185	85	22,451
Quantum genetic algorithm [21]	7,598,658	84	21,986
Artificial bee colony (ABC) algorithm + GA [22]	7,514,526	84	21,853
Chicken swarm optimization algorithm + GA [23]	7,486,157	84	21,774
GA-ACO	7,458,268	84	21,528

From Table 7, it can be observed that compared to some existing hybrid solution methods, the GA-ACO algorithm possessed some advantages. The hybrid k-means GA), CEGA, and CGA all required 85 vehicles for transportation, resulting in relatively high total costs. Both the ABC+GA and CAO+GA algorithms required the same number of vehicles as the GA-ACO algorithm, which was 84 vehicles; however, the GA-ACO algorithm had a lower total cost, thus proving the reliability of combining the GA with the ACO algorithm.

Penalty cost refers to the cost of waiting after the vehicle arrives at the customer's point because it cannot be serviced in time. The total cost and penalty cost of the algorithms were compared under different numbers of tasks (Table 8).

Table 8: Relationship between penalty cost and the quantity of tasks

Number of tasks	Total cost/yuan	The quantity of vehicles/n	The average penalty cost and use cost of every vehicle/yuan
50	152,648	18	127.84
100	302,514	36	111.25
150	451,241	51	100.76
200	602,536	64	95.21
250	7,458,268	84	87.87
300	8,215,263	112	81.23

Based on Table 6, it is evident that as the number of customers to be served increased, the total cost produced in the yard-customer container cargo transportation process and the number of vehicles used by the logistics transportation company also increased. However, the average penalty cost and usage cost of every vehicle exhibited the average cost decreased as the number of tasks increased. For instance, when the cargos were transported to 50 customers, the company utilized 18 vehicles, resulting in an average cost of 127.84 yuan. When there were 300 customers, the company employed 112 vehicles, and the average cost decreased to 81.23 yuan, showing a reduction of 36.46% compared to that when there were 50 customers. These findings indicated that the logistics transportation company achieved better economic efficiency when the task became more extensive.

5 Discussion

With the continuous development of the port logistics industry, port logistics has become one of the hot research topics. Port logistics includes many aspects, such as optimizing the layout of import cargo yards, port berths, transportation routes for vehicles between ships and yards, and container collection and distribution in ports. Current research mainly focuses on transportation from docks to port bridges by vehicles, with limited studies on the optimization of transportation routes from yards to customers. Therefore, this paper established a model and designed the GA-ACO algorithm to solve this issue.

Through the analysis of experimental results on the simulation case, it can be observed that the GA-ACO algorithm achieved the best solution. It obtained a result with 84 vehicles and a total cost of 7,458,268 yuan in the case study. Compared to single GA and ACO algorithms, it scheduled fewer vehicles with a lower total cost and required fewer iterations. This result demonstrates the advantages of the hybrid algorithm over single algorithms in terms of solving speed and performance.

Hybrid algorithms can combine the advantages of different algorithms to achieve better results. The GA enables fast global search over a wide range but often needs more repetitive iterations, leading to low efficiency. On the other hand, the ACO algorithm employs a distributed and parallel approach for searching but requires a longer search time. By combining a GA and an ACO algorithm, their respective shortcomings can be overcome, achieving complementarity and obtaining optimal solutions while speeding up the solving process. In comparison with other hybrid solving algorithms (Table 7), the GA-ACO algorithm also achieved the best results. Compared with the ABC+GA and CSO+GA algorithms, which used the same number of vehicles (84), the GA-ACO algorithm reduced the total cost by 0.75% and 0.37%, respectively. This result further demonstrates the superiority of the GA-ACO algorithm in model solving.

In the study of optimizing transportation routes for container cargo in ports, this article has achieved some results. However, there are some limitations, such as making some assumptions during model establishment to facilitate research, which restricts the application of the model in practical scenarios. Additionally, only the minimization of total costs was considered, which is limiting. Therefore, in future research, efforts should be made to relax assumptions as much as possible and analyze real-life scenarios while considering the influence of more objective functions.

6 Conclusion

This paper proposed a yard-customer transportation path optimization model for port container cargo transportation. A GA-ACO algorithm was developed to address this model effectively. The case analysis indicated that both the model and problem-solving approach were found to be highly effective. The results indicated that the GA-ACO algorithm achieved a lower total transportation cost than the GA and ACO, showing better solving effects. It provides a lower-cost and more efficient method for vehicle dispatching in logistics transportation enterprises, which can be applied in practical logistics transportation enterprises.

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