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Intelligent Logistics Resource Scheduling Based on Hybrid Parameter Ant Colony Algorithm and Reinforcement Learning

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To solve the problem of low efficiency in logistics resource scheduling, research proposes an intelligent scheduling technology. A logistics resource task scheduling model is constructed by analyzing logistics tasks. To solve the scheduling model, a mixed-parameter improved ant colony algorithm is introduced to solve the problem. The ant colony traversal is used to search for the objective function, and the information is used to modify the parameter adjustment algorithm. In addition, the study introduced reinforcement learning to optimize the pheromone problem of the ant colony algorithm and improved the performance of the algorithm. In the experimental analysis, task execution time, execution efficiency and task cost were introduced as indicators. In the task operation time comparison, the improved hybrid parameter ant colony model could converge in the shortest time. The shortest packing operation time was 16052 s, which was shorter than other models. In the cost comparison of logistics resource scheduling task, the cost of the improved hybrid parameter ant colony optimization model in the purchasing task was 29865 yuan, which was lower than other models. In the comparison of the resource execution rate of the order taking task, when the number of resources was 5000, the resource execution rate of the improved hybrid parameter ant colony model was 95.65%, which was significantly better than the other models. In addition, comparing the cost reduction rate of different models in scheduling arrangement, the cost reduction rate of genetic algorithm and particle swarm algorithm was 3.54% and 6.45% respectively. While the improved hybrid parameter ant colony model was 9.54%, the research model had significantly better cost control. This indicates that the research model has better application in logistics scheduling. The research content will provide technical reference for the transformation of information technology in logistics industry and optimization of logistics resource scheduling.

Povzetek: Analizirana je inteligentna tehnologija razporejanja za reševanje problema nizke učinkovitosti pri razporejanju logističnih virov, ki temelji na izboljšanem algoritmu mravljinčje kolonije z mešanimi parametri.

1 Introduction

With the rapid development of global economy, logistics industry has become an important pillar industry of Chinese economy. In the field of logistics, logistics resource scheduling is one of the core issues in logistics management, which will directly affect the transportation management efficiency and user satisfaction of logistics enterprises, and has an important impact on the cost control and resource management of enterprises. Therefore, enterprises need to improve the effectiveness of logistics resource scheduling in the development process to accelerate their competitive advantage in the market. At present, in the field of resource scheduling, heuristic algorithms have a wide range of applications, including moth search algorithms, differential algorithms, genetic algorithm (GA), ant colony algorithm, etc. [1]. A large number of studies on learning algorithms related to resource scheduling are conducted by related scholars.

Devi et al. conducted a study on resource scheduling techniques for cloud base with the aim of improving the management efficiency of resource scheduling. Thus, coded chromosome-based GA was used to dynamically adjust the resources through which the number of physical machines required by the system is estimated. Finally, the technique was applied to a cloud computing platform, which could effectively reduce the cost of central cloud rental virtual machines and improve the effectiveness of resource scheduling [2]. In recent years, Prata et al. focused on the consumption and maintenance of scarce resources in standalone machines, aiming to improve the effect of resource scheduling in standalone systems and reduce the waste of resources. In this regard, an integer linear programming model was proposed by considering two crating formulas with crating constraints to ensure that the objective function completes the content in the shortest possible time. In addition, a simulated annealing algorithm was introduced to solve the modeling problem. Finally, experimental analysis demonstrated that the proposed resource scheduling management technique had a good application effect and improves the system computational efficiency [3]. Hamid et al. studied the existing data resource management system platform which needs to solve the system resource scheduling problem by studying the database, network as well as storage centers. Therefore, to improve the efficiency of data resource management task processing, a resource scheduling optimization model was proposed on the basis of time minimization. Moreover, the system scheduling effect was tested by increasing the number of virtual machines in Workflowsim environment. In the specific analysis of system resource scheduling, research techniques have demonstrated notable advancements in resource scheduling time and resource utilization efficiency. However, the computational cost remains a significant challenge. In special scenarios, model parameter problems need to be improved. The next research will also improve similar technical parameter problems [4].

Currently, heuristic algorithms have a wide range of applications in the logistics resource scheduling industry, which significantly improves the transportation efficiency of the logistics industry. Lei et al. conducted a study on the existing logistics industry, the logistics industry in the information technology era need to develop in the direction of intelligence. To solve the problem of traditional logistics management efficiency was too low, the research based on intelligent heuristic algorithm proposed an intelligent logistics distribution model. The model was based on intelligent logistics, through the real-time data analysis of each logistics warehouse, real-time distribution scheduling strategy, so as to ensure that the goods in the shortest time, the shortest path to reach the target point. The experimental results displayed that the research technology had a scheduling optimization effect, with significant improvements in execution efficiency and transportation costs. However, this technology still faced efficiency problems for complex processes and was a key focus of future technology research [5]. Zheng et al. conducted a study on the current cold chain logistics and found that cold chain logistics faces inefficiency in cold chain cross-docking truck scheduling. To solve this problem, the study proposed a mixed integer linear programming model. It aimed to optimize the cold chain transportation process so that the cold chain transportation cost was minimum and met the cold chain transportation conditions. Among them, considering the strong polynomial time processing problem (non-deterministic polynomial, NP) in the optimization of cold chain logistics scheduling, it was divided into two processes: the arrival time of inbound trucks and the departure time of outbound trucks and the processing time of the products. Moreover, it solved the optimization problem through the heuristic algorithms in multiple stages. Finally, through the cold chain scheduling experiments, this technology could effectively improve the efficiency of logistics and transportation and reduce the operating costs of enterprises [6]. Abosuliman et al. found that the logistics and transportation industry faced the challenge of timeliness, how to improve the efficiency of logistics and transportation in the shortest time and optimize the cost of logistics operations is a problem that companies need to solve. To solve the above problems, the study proposed an intelligent logistics resource scheduling framework based on Internet of Things. By constructing a logistics multi-scenario scheduling model, the study introduced a heuristic algorithm solution to realize the scheduling management of logistics resources. It was shown through experiments that the proposed technology can effectively improve the efficiency of logistics transportation and reduce the operating costs of enterprises, so as to improve the competitive advantage of enterprises in the market [7]. The summary list of related work is shown in Table 1.

Through the above research, it can be found that the traditional logistics industry faces the problems of timeliness and high cost in resource scheduling management, which can't meet the demand of logistics and transportation industry. At present, the swarm intelligence-inspired algorithm has excellent application advantages in resource scheduling problem, so the research can find the optimal solution through the transmission and updating of information elements. Therefore, in order to solve the logistics resource scheduling problem, the study proposes a hybrid parameter ant colony optimization (ACO) to construct a logistics resource scheduling model to realize the logistics resource scheduling efficiency and cost advantages. This research presents two innovations. The first is the proposal of an intelligent scheduling method based on hybrid parameter ACO. The method combines the characteristics of hybrid parameter and the advantages of ACO, and optimizes ACO through parameter load factor and information correction parameters, thereby enhancing the efficiency and quality of logistics resource scheduling. Secondly, to enhance the algorithm's initial search capability, the research incorporates a reinforcement learning algorithm to optimize the pheromone during the initial stage. This approach improves the algorithm's search efficiency and convergence speed. The research content will serve as a technical reference for the informationization transformation of traditional logistics enterprises and logistics scheduling management.

Table 1: Summary of related work

Rreferences	Research objective	Result
Reference [2]	Devi K L et al. conducted research on resource scheduling techniques for cloud infrastructure to improve resource management efficiency	Research technology can significantly improve scheduling efficiency and reduce execution time.
Reference [3]	Prata B A et al. aim to improve the resource scheduling efficiency of standalone systems and reduce resource waste	The system has a high computational load, resulting in improved execution efficiency.
Reference [4]	Hamid L et al. conducted research on existing data resource management system platforms to address system resource scheduling issues	Significant improvement in resource utilization efficiency and execution time effectiveness
Reference [5]	Lei N et al. conducted research on the existing logistics scheduling process to address the issue of logistics scheduling efficiency	Research technology has scheduling optimization effects, with significant improvements in execution efficiency and transportation costs
Reference [6]	Zheng F et al. optimized and improved the current cold chain logistics to solve the problem of low scheduling efficiency	Research skills significantly improve vehicle scheduling effectiveness, reduce transportation time, and lower economic costs
Reference [7]	Abosuliman S et al. found that logistics transportation faces the decision problem of improving logistics transportation efficiency in the shortest possible time, and therefore optimized its scheduling decision	The proposed technology can effectively improve logistics transportation efficiency, reduce enterprise operating costs, significantly reduce execution time, and improve scheduling efficiency

2 Second section

2.1 Materials

Laboratory equipment: Foton Omak S3 logistics and distribution truck provided by BAIC Foton. JM-504 stopwatch is provided by Shanghai Star Diamond Stopwatch. Yuchai Guo San YC6j175-T302 logistics forklift truck is offered by Guangxi Yuchai Machinery.

Parameters of the software system tools: The hybrid parameter ACO is proposed by Gambardella and Dorigo. The experimental environment is Pytorch development platform (version 3.7) provided by Facebook, USA. The processor is INTL i7 13700 provided by INTEL. The graphics card is Asus RTX3070 provided by Asus Taiwan. The experimental system is WINDOWS 10 provided by Microsoft, USA.

2.2 Logistics resource scheduling based on hybrid parameter ant colony algorithm

2.2.1 Logistics resource task scheduling model construction

In logistics resource scheduling, a complete logistics scheduling task is composed of multiple subtasks. The running order of different subtasks will affect the final completion efficiency of the task, thus affecting the management effect of logistics resource scheduling. In order to improve the efficiency of logistics resource scheduling, the logistics resource scheduling process will be modeled. The logistics resource scheduling process is shown in Figure 1 [8].

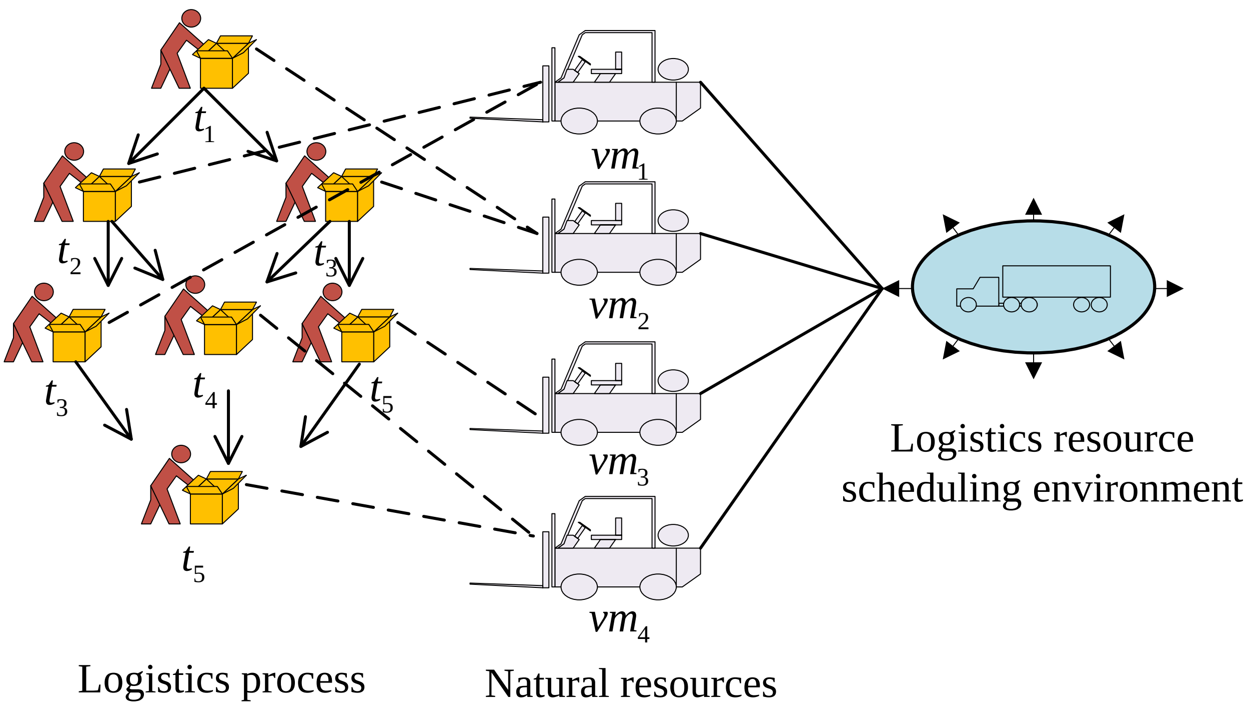


Figure 1: Logistics resource scheduling task process

In Figure 1, in a logistics resource scheduling task, it consists of multiple t1 to tn subtasks. Each subtask corresponds to a corresponding resource task, thus constituting a complete logistics resource scheduling process. In the actual logistics resource scheduling, t1 tasks need to be completed before t2 tasks can be completed. There is a dependency relationship between the two, but there is no dependency relationship between some tasks. For example, between t2 and t3, the tasks that do not have dependencies can be processed in parallel in the actual task, thus improving the efficiency of subtask execution [9].

In the study, the DAG process is used to describe the task process, and the four-dimensional $G(T, Vm, D, ET)$ is used to describe the process, and the set of tasks is shown in Equation (1).

$$T = \{t_1, t_2, t_3, \cdots, t_n \mid n \in N\} \quad (1)$$

In Equation (1), n represents the number of subtasks, and the set of resources corresponding to the tasks is shown in Equation (2).

$$Vm = \{vm_1, vm_2, vm_3, \cdots, vm_m \mid m \in N\} \quad (2)$$

In Equation (2), m denotes the number of resources corresponding to subtasks. Describing the inter-task dependencies is shown in Equation (3).

$$D_{ij} = \{(t_i, t_j) \mid t_i t_j \in T, i \neq j\} \quad (3)$$

In Equation (3), D_{ij} indicates that there is a dependency between task t_i and t_j, which needs to prioritize the execution of t_i in order to continue the execution of t_j.

In the logistics, a task needs to be processed resource consuming time is defined as ET, then the task consuming time is shown in Equation (4).

$$ET_{ij} = length_i / mips_j \quad (4)$$

In Equation (4), $length_i$ denotes the length of this logistics task. $mips_j$ denotes the ability to handle the logistics task. Define the time taken to process the logistics resource vm_j as $EFT_{ij}(t_i)$, which is expressed as shown in Equation (5).

$$EFT_{ij}(t_i) = ET_{ij} + EST_{ij} \quad (5)$$

In Equation (5), EST_{ij} represents t_i in resource vm_j processing elapsed time. In the actual logistics resource scheduling, the process corresponding to the subtasks would include various subtask links such as goods inspection, packaging, transportation, etc., but ultimately the goal of logistics resource scheduling is to minimize the time of executing tasks [10]. If the logistics takes too long, it will affect the user logistics experience. In order to optimize the scheduling, it will be necessary to allocate the entire logistics task time to the execution resource task queue to optimize each subtask scheduling process, as shown in Equation (6).

$$EFT = EFT_{ij}(t_{exit}) \quad (6)$$

In Equation (6), t_{exit} denotes the logistics queue export task. In logistics resource scheduling, the scheduling effect needs to be reflected by task resource execution efficiency. If there is irrational task scheduling, the problem of long execution time of subtasks will occur and resources are wasted [11]. The total busy process resource processing time is defined as $VmTime$, and the expression is shown in Equation (7).

$$VmTime = \max\left\{CT_j \mid j = 1, 2, \cdots, m\right\} \quad (7)$$

In Equation (7), CT_j represents the total processing time on resource vm_j. Next, the average resource utilization is used to reflect the task scheduling effect, as shown in Equation (8).

$$AvgU = \sum_{j=1}^{m} U(vm_j) / m \quad (8)$$

In Equation (8), $U(vm_j)$ represents the individual resource utilization rate with $U(vm_j) = CT_j / VmTime$. Finally, the final objective function is obtained based on the relationship between the resource utilization rate and the physical tasks, as shown in Equation (9).

$$f = EFT / AvgU \quad (9)$$

2.2.2 Logistics resource scheduling model construction based on hybrid parameter ACO

In logistics resource scheduling task, the difficulty of individual subtasks and resource execution time need to be fully considered to make the logistics task execution time the shortest. In order to solve the logistics resource scheduling problem, an improved ACO algorithm based on hybrid parameter optimization is proposed to solve the logistics scheduling problem [12]. The principle is that the ant colony will enter from the subtask node, traverse all subtasks to match the best resources, and obtain the final objective function through continuous iteration. Ant colony scheduling is shown in Figure 2 [13].

In Figure 2, the phenomenon of matching multiple optimal solutions may occur after the ants traverse all the tasks, which makes a task execute multiple resources while some resources are idle. Therefore, the ant colony needs to follow the principle of matching one resource for one task when executing tasks to guarantee the efficiency of task execution [14]. At the same time, the ant colony on the optimal resource path selection depends on the path information concentration, which determines the ant colony's probabilistic selection of resources, using state transfer for resource selection, as shown in Equation (10).

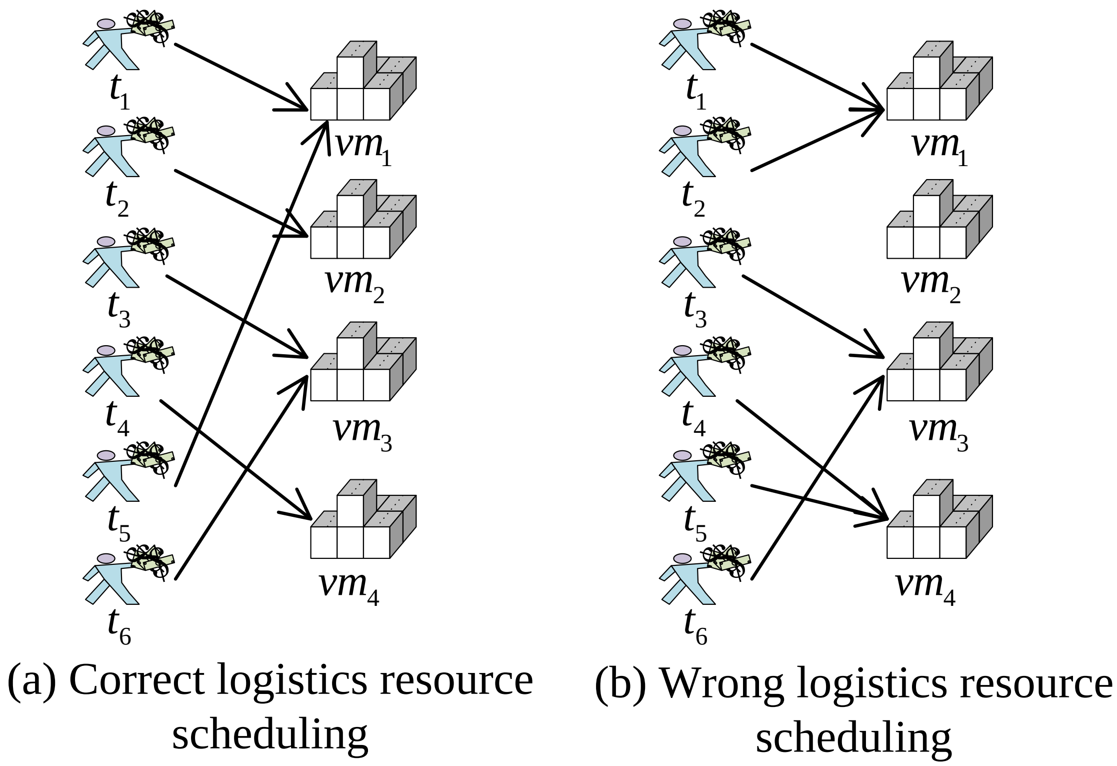


Figure 2: Ant colony scheduling

$$P_{ij}^{k}(i)=\begin{cases}\dfrac{[\tau_{ij}(t)][\eta_{ij}(t)]}{\sum_{s\subset allowed_k}[\tau_{is}(t)][\eta_{is}(t)]}, & j\subset allowed_k\\ 0 & \end{cases} \quad (10)$$

In Equation (10), $P_{ij}^{k}(i)$ denotes the probability that the ant colony matches resource vm_j for task t_i. $\tau_{ij}(t)$ denotes the information concentration corresponding to resource vm_j, and $\tau_{is}(t)$ denotes the total information concentration. $\eta_{ij}(t)$ denotes the heuristic function corresponding to resource vm_j. $\eta_{is}(t)$ denotes the heuristic function corresponding to the total resource. The traditional ACO algorithm relies heavily on the calculation of resource information concentration when matching resources at the initial stage, which makes the computationally weak resources ignored and the scheduling resources overloaded or idle. To solve this problem, parametric load factor is used to improve the efficiency of resource utilization [15]. In addition, the irregular updating of resource information in logistics scheduling leads to the residual information is not completely dissipated, which will have an impact on the updating and feedback of the subsequent ant colony information. In this regard, the information correction parameter is introduced to release the information concentration on the high matching resources, to ensure the effective feedback of the ant colony information, and to avoid the algorithm falling into convergence prematurely [16]. Define the parameter load factor as θ_j and use it to represent the execution state of the resource as shown in Equation (11).

$$\theta_j=\frac{1}{M_j} \quad (11)$$

In Equation (11), M_j represents the average value of resource utilization of the T_j task set executing on resource vm_j. Among them, the smaller vm_j is, the higher is the value of M_j. By dividing the tasks to vm_j, the mean value of resource utilization M_j at this moment is shown in Equation (12).

$$M_j = \frac{1}{m}\sum_{j=1}^{m}\frac{C_j}{\max\left\{C_j \mid j=1,2,\ldots m\right\}} \quad (12)$$

In Equation (12), C_j denotes the busy time of executing vm_j resources. Next, the heuristic function is improved by expressing the heuristic function in terms of task execution capacity as shown in Equation (13).

$$\eta_{ij}(t) = \frac{1}{\theta_j * ET_{ij}} \quad (13)$$

In ACO algorithm optimization, the update of resource information concentration is the key to ensure the optimization of ACO. When the ant colony ends an iterative update, the resource information concentration matched by the optimal value of the ant colony objective function will also be updated, and the pheromone value at this moment is shown in Equation (14) [17].

$$\tau_{ij} = (1-\rho)\tau_{ij} + \sum_{k=1}^{n}\Delta\tau_{ij}^{k} \quad (14)$$

In Equation (14), τ_{ij} represents the ant colony pheromone value of the task corresponding to vm_j resources, and $\Delta\tau_{ij}^{k}$ represents the change pheromone value. In the early stage, due to the lack of pheromone value to guide the ant colony, it mainly selects the resource with larger target value f by heuristic algorithm, while updating the pheromone at the resource. While the excessive pheromone concentration makes the later ant colony unable to judge accurately, which leads the algorithm to fall into extreme value convergence when it seeks the best path [18]. Therefore, in order to avoid this problem, the information correction parameter is introduced in the larger target value f resources for concentration update adjustment, the expression is shown in Equation (15).

$$\Delta x_{ij}^{k} = \begin{cases} (1+\lambda)\dfrac{B}{f_k}, f_k \le f_{\min} \\ (1-\lambda)\dfrac{B}{f_k}, f_k > f_{\min} \end{cases} \quad (15)$$

In Equation (15), $f_{\min}$ denotes the minimum objective function value. k denotes the traversal ant. λ denotes the information correction parameter. Introducing the information correction parameter to adjust the pheromone in the allocation data will attract more ants to choose this allocation path. If ants select the final solution corresponding to the target value f_k is lower than all traversal target values, it will be adjusted according to the information correction parameter $1+\lambda$. If the target value f_k corresponding to the final solution selected by ants is higher than all the traversed target values, it will be adjusted according to the information correction parameter $1-\lambda$.

2.2.3 Construction of logistics resource scheduling model improved by reinforcement learning

The hybrid parameter-enhanced ACO algorithm has been demonstrated to be capable of more accurate logistics resource scheduling than its predecessor. However, the initial order phase path optimization of the improved ACO algorithm is not as informative as it could be due to the pheromone complementation that occurs during the initialization phase. In addition, the existence of unstable characteristics of pheromone release on resources in the preliminary stage also leads to the fact that the improved ACO algorithm requires more computational time in the iteration, resulting in a decrease in the convergence effect of the algorithm [19]. With the continuous accumulation of ant colony on resource pheromone, its pheromone feedback will also be improved, and gradually improve the path finding optimization effect. Therefore, the ant colony satisfies the evolutionary characteristics, and its evolutionary process is shown in Figure 3 [20].

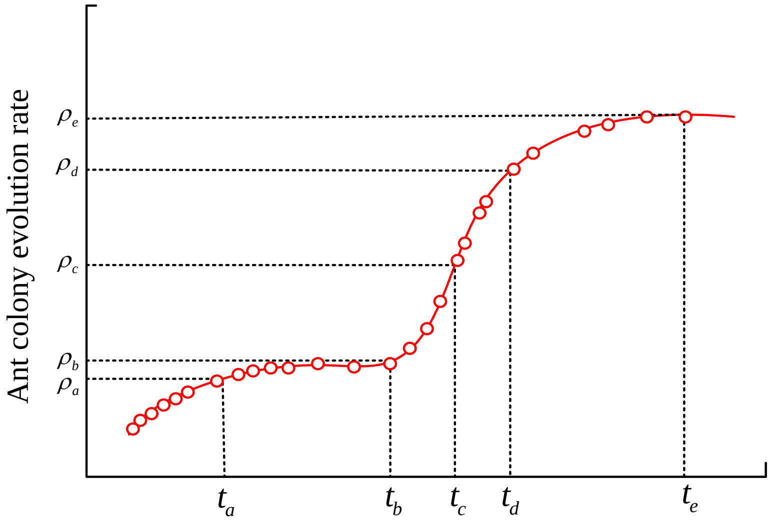


Figure 3: Evolution rate pattern of ant colony

According to the colony evolution law graph in Figure 3, it is easy to observe that in the initial process from ta to tb, the ant colony has a very low evolution rate at that time. However, with the increase of iteration period, its evolution process is accelerated, such as arriving at the te stage when the ant colony reaches the highest level of evolution rate [21]. It can be observed that it is difficult to have a better breakthrough in the solution by only optimizing the parameters of the ACO, therefore, the incorporation of reinforcement learning algorithm (Q-Learning) in the improved ACO algorithm is considered to improve the solution. Its advantage lies in the fact that it does not require knowledge of all possible states of the environment. Through the interaction of ant colony individuals, the complex environment of all possible states can be understood. This can dynamically adjust the search range of the ant colony and improve the target search [22-23]. The specific process is shown in Figure 4.

In the study, Q-Learning is used to obtain resource pheromones in the improved ACO algorithm. In the process, Q-Learning is used to solve and obtain the Q-function, which is then used as the pheromone value parameter in the initial stage of ACO. Based on the final information data obtained, the ant colony search area can be dynamically adjusted to improve the target search performance. The ant colony optional path process in logistics resource scheduling is shown in Figure 5.

The Q-Learning algorithm is used to improve the initial stage pheromone of the ant colony, then the improved initial stage pheromone expression is shown in Equation (16).

$$\tau_{ij}(0) = Q(s_i, a_i) \tag{16}$$

In Equation (16), s_i denotes the state of step i and a_i denotes the action of step i. Then the improved hybrid parameter ACO process is shown in Figure 6.

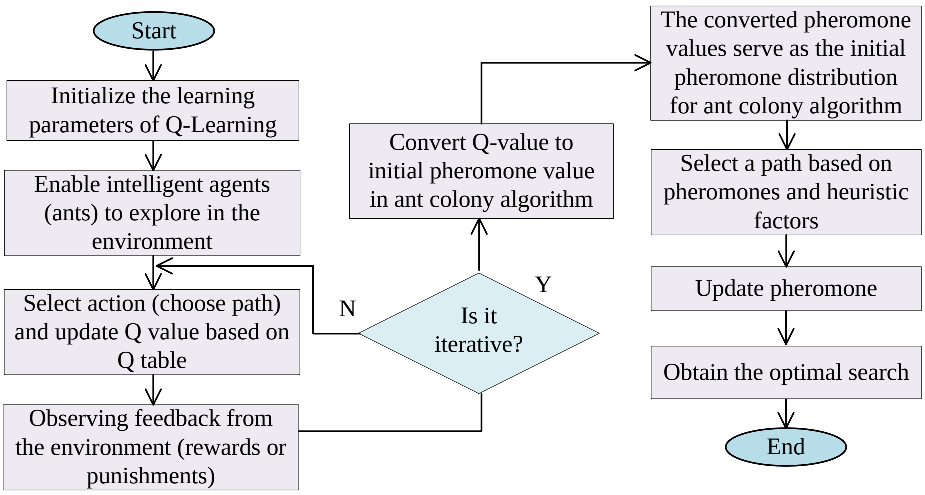


Figure 4: Q-Learning to obtain resource pheromone flow in improved ACO algorithm

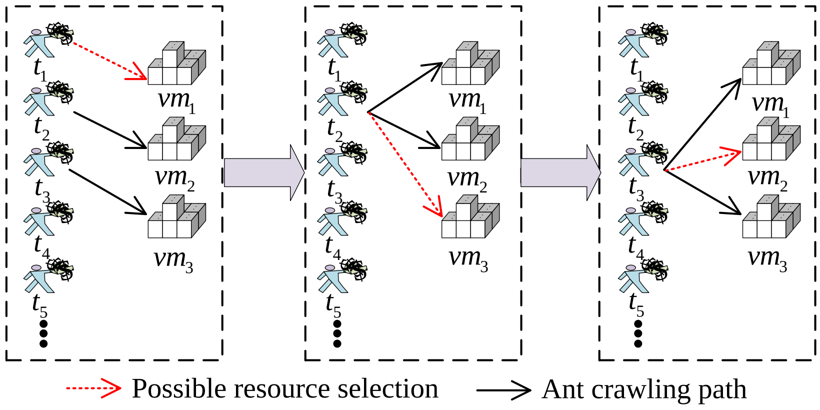


Figure 5: Ant colony path selection process

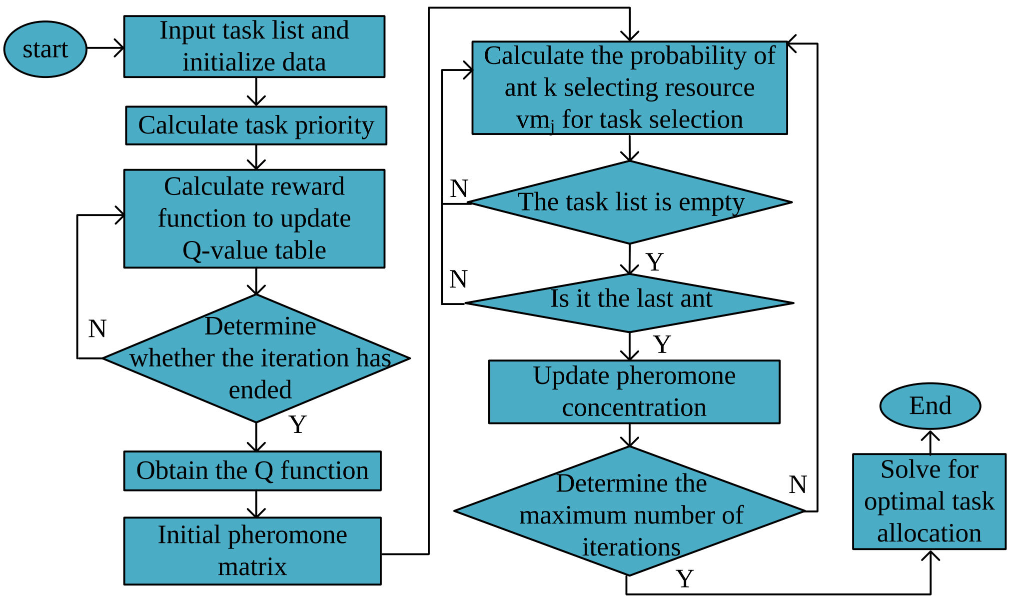


Figure 6: Flow chart of improved hybrid parameter ant colony algorithm

Table 2: Experimental parameter settings for research models

Ant colony optimization (ACO)		Q-Learning	
Parameter	Numerical value	Parameter	Numerical value
Population	100	Learning rate	0.75
Iterations	100	Discount factor	0.75
Pheromone factor	1	State space	Random initialization
Information constant	100	-	-
Genetic algorithm (GA)		Particle swarm optimization (PSO)	
Parameter	Numerical value	Parameter	Numerical value
Population size	100	Particle number	200
Iterations	100	Learning factor	2
Mutation rate	0.1	Particle dimension	2

Table 3: Logistics resource scheduling task information

Task number	Task type	Number of tasks	Number of resources

1	Receiving orders	12	15653
2	Procure	8	9562
3	Pack	14	5465
4	Scheduling arrangements	15	256
5	Vehicle transportation	6	205
6	Track	8	11628

Figure 6 shows the improved hybrid parameter ACO process. In solving the logistics resource scheduling task, the ACO algorithm and Q-Learning algorithm need to be initialized first. In the initial stage, the Q-function is updated according to the reward function and the updated Q-function is used as the pheromone in the initial stage of ACO solving. Next, it is iteratively updated according to ACO to obtain the optimal scheduling allocation scheme.

3 Results

3.1 Experimental environment setup

To test the effectiveness of the proposed improved hybrid parameter ACO in logistics resource scheduling in the study, logistics resource scheduling experiments will be carried out using a logistics operation and management center as a case study. In this case, the algorithmic environment is Python 3.7, the processor is INTEL I7 13700, and the running system is WINDOWS 10. In addition, this study selects GA and particle swarm optimization (PSO) algorithm as testing benchmarks. The hyperparameter settings for different test benchmarks are mainly obtained by empirical settings, trial and error methods, or optimization processes. The hyperparameters of ant colony algorithm include the number of ants, the importance of pheromones, etc. The hyperparameters of GAs, such as population size, crossover probability, and mutation probability, are also determined through multiple experiments and tuning. The specific parameter settings are shown in Table 2.

In the logistics resource scheduling experiment, it includes the process of order taking, purchasing, packing, call scheduling, vehicle transportation, tracking, feedback, and so on. Different tasks will correspond to different execution resources, and subtasks have priority characteristics. At the same time, a single task contains multiple sub-tasks, such as packing includes goods inspection, packing boxes, posting the single number, arranging the priority of goods and arranging the packing boxes. Therefore, multiple logistics scheduling tasks will be set up in the logistics scheduling experiment, as shown in Table 3.

In Table 3, there are total 6 main tasks in logistics scheduling, while different tasks correspond to multiple subtasks as well as the number of resources. At the same time, different tasks have priority characteristics, and the previous task determines the next task scheduling, but the existence of different tasks can be processed in parallel.

Therefore, in order to improve the scheduling efficiency of logistics resources, a scheduling model will be used to optimize the logistics task process and provide logistics scheduling. Meanwhile, PSO and GA are introduced as test benchmarks in the experiment. To facilitate the logistics scheduling experiments, the study defines the proposed hybrid parameter ACO as H-ACO and the improved hybrid parameter ACO as Q-ACO. The experimental evaluations are the metrics task execution time, resource execution rate, and task operation cost. Among them, task execution time refers to the total time required from the start of logistics task execution to task completion. This includes the time required to load, transport, and unload goods, as well as any waiting, transit, and other intermediate processes that may occur. Resource execution rate refers to the ratio of resources (such as vehicles, labor, etc.) actually used in the logistics scheduling process to the total available resources, reflecting the efficiency of resource utilization and the rationality of scheduling. Task operation cost refers to the total cost required to complete a logistics task, including transportation costs, labor costs, fuel costs, maintenance costs, and other costs directly related to task execution. It is used to evaluate the economic benefits of scheduling.

3.2 Logistics resource scheduling experiment based on hybrid parameter ant colony algorithm

Next, in order to validate the performance effect of the proposed logistics resource scheduling model, PSO algorithm and GA are introduced along with the proposed technique of the study for comparison. The comparison of operation time of different techniques in logistics packing and vehicle transportation process is shown in Figure 7.

In Figure 7, two tasks of logistics packing and vehicle transportation are selected for experiments to analyze the differences between different scheduling techniques. In the packing scheduling, all four scheduling models have different packing job times. The best performance is Q-ACO model, which can converge in the shortest time and has the shortest packing operation time of 16052 s. The Q-ACO algorithm combines Q-Learning global exploration with ACO collective optimization to optimize initial pheromones, dynamically adjust the search area, avoid premature convergence, and achieve short execution time, greatly improving execution efficiency. In contrast, H-ACO model performs the second best, with a time of 16650 s. The PSO model and GA model have a packing operation time of 18125 s and 17495 s, respectively. In the vehicle transportation task, it is still the Q-ACO model that reaches the fastest convergence and achieves the minimum operation time. The four scheduling models PSO, GA, H-ACO, and the Q-ACO proposed by the study take 30545 s, 30556 s, 30015 s, and 28516 s, respectively. It can be concluded that both the Q-ACO and H-ACO models have obvious advantages in job time optimization. Next, the cost of each process task of logistics resource scheduling is compared, as shown in Figure 8.

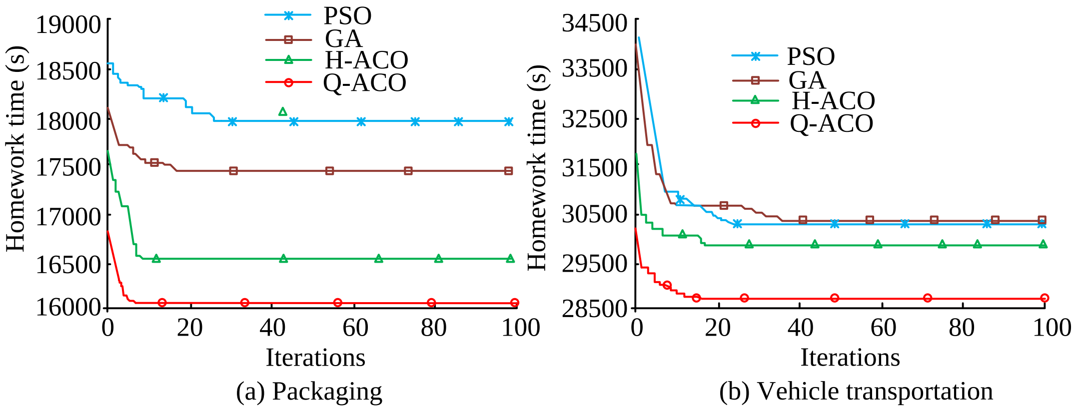


Figure 7: Comparison of packaging and vehicle transportation operation time

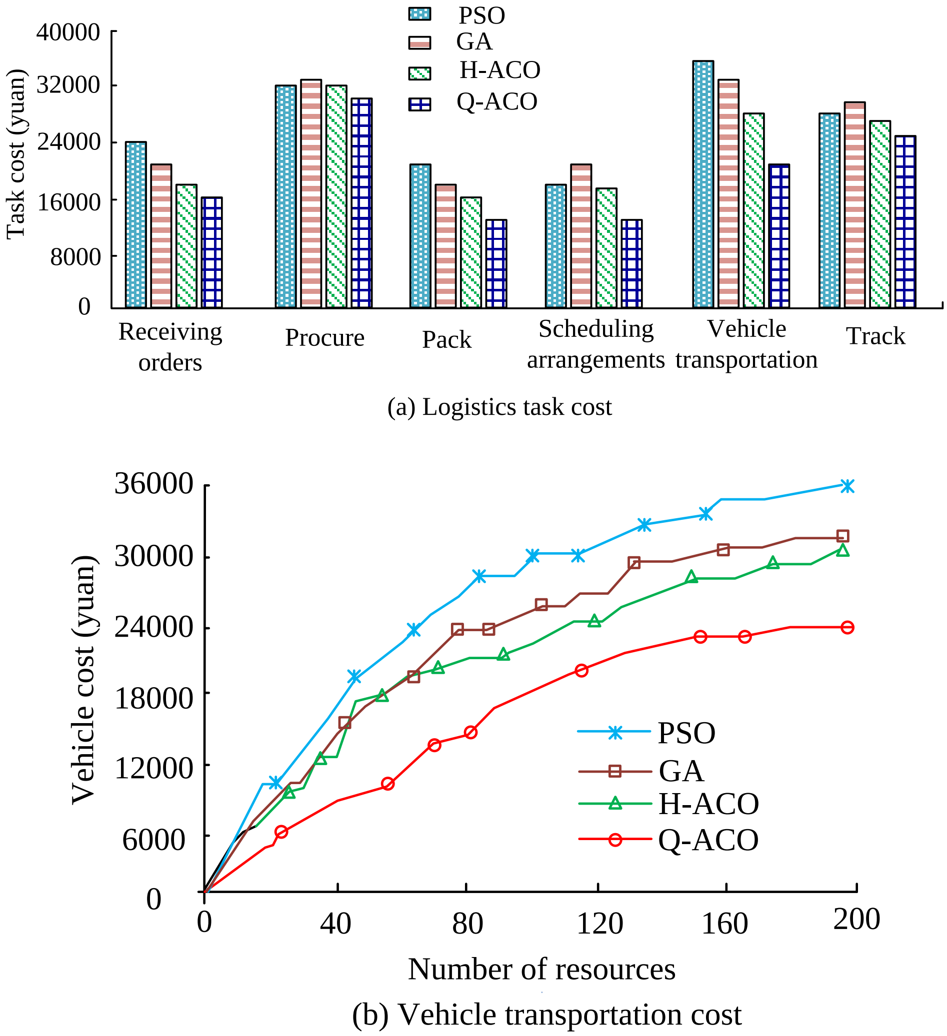


Figure 8: Comparison of logistics resource scheduling task costs.

Figure 8 shows the cost comparison results of logistics resource scheduling. In Figure 8(a), compared with PSO, GA and H-ACO, the Q-ACO model has significantly lower costs in the six major logistics tasks. The main reason is that the Q-ACO algorithm provides an optimized initial pheromone distribution for ACO through Q-Learning. This allows ant colonies to focus on more promising paths in the early stages of search, reducing blind searches and ineffective iterations. In addition, by using the Q function as the initial pheromone, Q-ACO can dynamically adjust the ant colony's search area based on environmental feedback. This flexibility allows the algorithms to more quickly adapt to environmental changes and find better solutions. For example, in the procurement process, the Q-ACO task cost is 29,865 yuan, which is significantly lower than the other models. In addition, in the vehicle costs in Figure 8(b), the vehicle costs all increase significantly as the number of resources increases. The increase in vehicle cost slows down after the number of resources reaches a certain value. The reason for this is that the more resources are purchased, the vehicle transportation cost will be shared equally and the cost increase will decrease. Q-ACO still has the best cost control, when the number of resources is 200, the cost is 24,256 yuan, which is significantly lower than other models. Next, the efficiency of resource implementation of different models is analyzed, as shown in Figure 9.

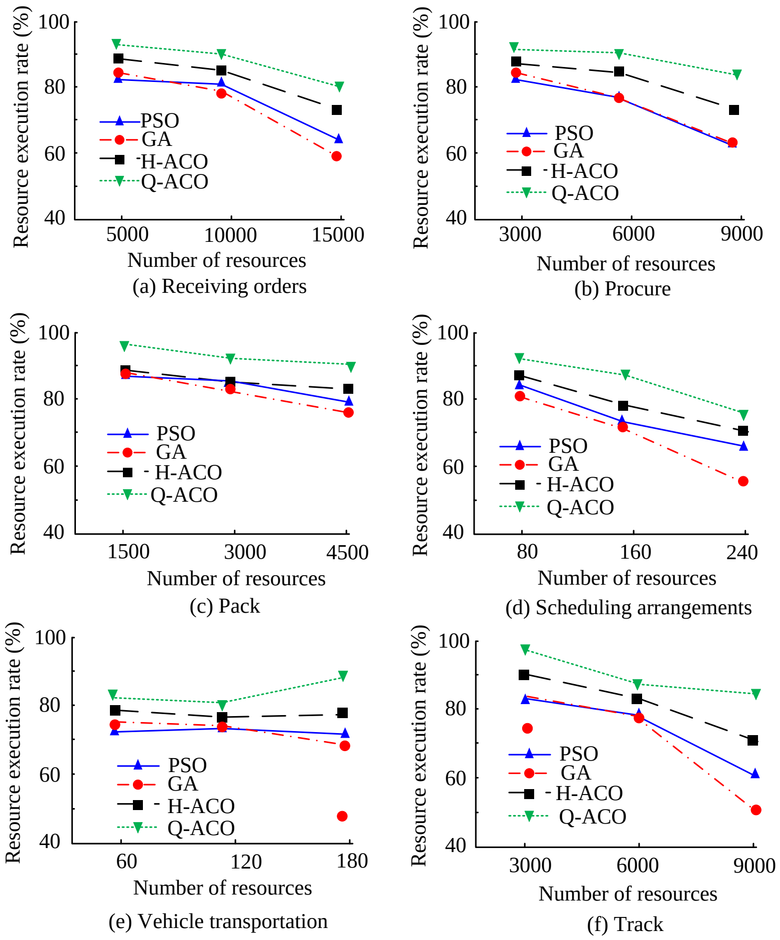
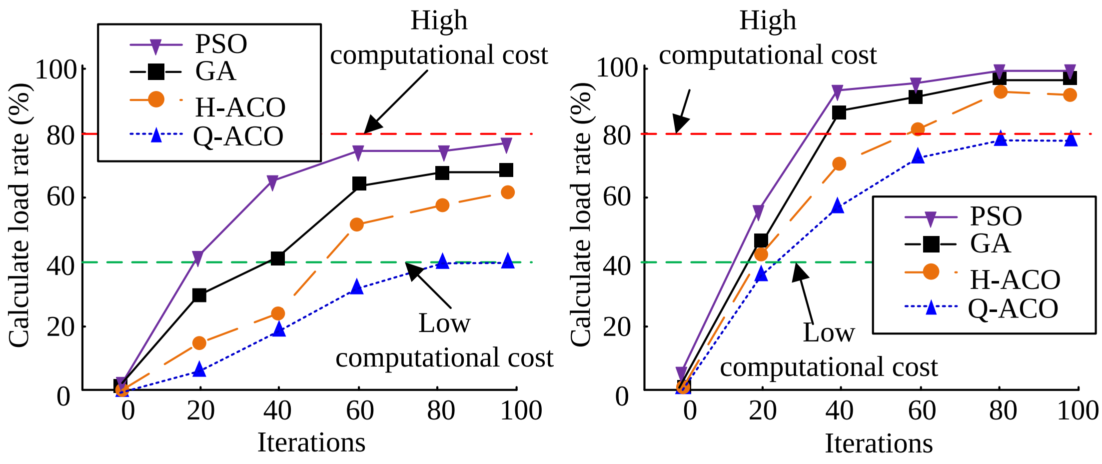


Figure 9: Comparison of execution efficiency of logistics scheduling resources

Figure 9 shows the resource execution efficiency of the six major processes of logistics resource scheduling. Most of the logistics subtasks show a decreasing trend in resource execution efficiency as the number of resources increases. However, in a comprehensive comparison, the resource execution rate of Q-ACO model is significantly better than other models. The main reason is that Q-ACO combines the global exploration capabilities of Q-Learning with the collective optimization properties of the ant colony algorithm. Although the PSO algorithm has a fast convergence speed, it tends to get stuck in local optima. The GA has strong global search capability, but it has high computational complexity and slow convergence speed. The H-ACO algorithm is susceptible to premature convergence due to the rapid updating of pheromones, which presents a challenge in achieving optimal results. In contrast, the Q-Learning ACO algorithm provides optimized initial pheromones for ACO through Q-Learning, dynamically adjusts the search range, avoids premature convergence, and achieves more efficient and accurate solutions in logistics resource scheduling. For example, in the order-taking task, when the number of resources is 5000, the resource execution rates of PSO, GA, H-ACO and Q-ACO are 88.02%, 89.32%, 90.01% and 95.65%, respectively. When the number of resources reaches 15000, the execution efficiency is 61.25%, 67.35%, 76.35%, and 83.65%, respectively. In addition, vehicle transportation resource scheduling is different from other tasks in that the vehicle execution efficiency is generally low when the resources are low. When the number of resources is high, the execution efficiency is higher, mainly because the vehicles need to wait for the resources to be loaded. Finally, the comprehensive effects of different models are compared using SPSS software for t-test, and there is a significant difference ($P<0.05$) between the data. The specific experimental results are shown in Table 4.

Table 4: Comprehensive comparison results of logistics resource scheduling

Task	Method	Average homework time (s)	Average resource execution rate	Cost reduction rate (%)	P
Receiving orders	PSO	25830	0.705	5.56	*(p<0.05)
	GA	25752	0.753	5.98	**(p<0.05)
	H-ACO	25520	0.825	7.56	*#(p<0.05)
	Q-ACO	24562	0.856	9.54	-
Procure	PSO	9542	0.724	3.56	*(p<0.05)
	GA	9575	0.785	2.54	**(p<0.05)
	H-ACO	8456	0.811	4.25	*#(p<0.05)
	Q-ACO	7568	0.865	5.68	-
Pack	PSO	18125	0.825	4.85	*(p<0.05)
	GA	17495	0.845	5.68	**(p<0.05)
	H-ACO	16650	0.904	6.45	*#(p<0.05)
	Q-ACO	16052	0.942	7.56	-
Scheduling arrangements	PSO	4562	0.715	6.45	*(p<0.05)
	GA	4358	0.768	3.54	**(p<0.05)
	H-ACO	4025	0.804	6.76	*#(p<0.05)
	Q-ACO	3854	0.865	9.54	-
Vehicle transportation	PSO	30545	0.761	4.41	*(p<0.05)
	GA	30556	0.756	5.45	**(p<0.05)
	H-ACO	30015	0.786	6.29	*#(p<0.05)
	Q-ACO	28516	0.876	8.54	-
Track	PSO	15682	0.689	4.58	*(p<0.05)
	GA	15001	0.725	3.25	**(p<0.05)
	H-ACO	14856	0.825	4.89	*#(p>0.05)
	Q-ACO	12354	0.895	5.48	-



(a) Small scale logistics scheduling (b) Large scale logistics scheduling

Figure 10: Cost calculation of logistics scheduling model

Annotations (in resource execution efficiency comparison: * representatives' comparison between PSO and Q-ACO, * * representatives comparison between GA and Q-ACO, * # representatives comparison between H-ACO and Q-ACO)

The results of the integrated scheduling of different models are presented in Table 4. The Q-ACO model proposed in the study has significant advantages in average operating time, average resource execution rate, and cost reduction rate. In the scheduling arrangement, the cost reduction rate of Q-ACO is 9.54%, while H-ACO, GA and PSO are 6.76%, 3.54%, and 6.45%, respectively. In addition, statistical analysis is conducted on resource execution efficiency in the study. According to the results, the Q-ACO model shows significantly better execution efficiency than the other three scheduling techniques in the vast majority of work task segments. Moreover, the comparison between the data is statistically significant ($P<0.05$). Furthermore, the study evaluates the computational costs of diverse algorithms across two scenarios: small-scale and large-scale. The system's detection of resource database occupancy served as the basis for determining resource costs. The results are shown in Figure 10.

In Figure 10, two scenarios, small-scale and large-scale, are selected to compare the resource consumption of the logistics scheduling models. In the small-scale test, all four techniques are able to complete scheduling with moderate computational overhead, especially the research model Q-ACO, which maintained a computational overhead rate of 40% to complete the task, showing the best overall performance. The reason may be related to the path simplification of Q-Learning, where Q-Learning optimizes the search path of the ACO during the learning process, reduces invalid iterations, and significantly reduces its computational cost. To prove this hypothesis, in large-scale logistics scheduling tests, the final iteration kept the cost of Q-ACO in the moderate cost range, while other scheduling techniques are at high cost. It can be concluded that the scheduling model proposed by the research has excellent application effects in logistics resource scheduling.

4 Discussion

In recent years, with the rapid development of e-commerce and industrial manufacturing, the logistics industry has also ushered in rapid development. In contrast to the conventional manufacturing sector, the logistics industry is a labor-intensive composite industry. It involves many work processes, and there is a priority or parallel relationship between different tasks. In the past nearly 20 years, the logistics industry has brought great development to China's economy. However, as the world enters the era of industrial intelligence, traditional logistics can no longer meet the needs of social and economic development. In light of the aforementioned considerations, the research proposes the implementation of an intelligent logistics resource scheduling technology, which is then applied to the logistics resource scheduling process.

In the context of actual logistics resource scheduling, the efficacy of the PSO algorithm, the GA, and the technology proposed by the research study is evaluated through a comparative analysis. The Q-ACO model has demonstrated superior performance in terms of task completion time, logistics task cost, and resource utilization efficiency. The primary objective is to optimize the parameter problem based on the ACO algorithm and introduce Q-Learning to provide an optimized initial pheromone distribution for ACO. In particular, Q-Learning obtains the initial pheromone through the Q function and dynamically adjusts the search area of the ant colony through environmental feedback, which can provide a more accurate search space for the ant colony algorithm and further improve its search performance. For example, in the order taking task comparison, compared with the other three models, the average job execution time of the Q-ACO model proposed by the research was shorter, which was 24562s, while PSO, GA, and H-ACO were 25830s, 25752s, and 25520s, respectively. Meanwhile, compared with the original task cost, the cost reduction rate of the Q-ACO model was 9.54%, which was significantly better than the other models. Furthermore, in the context of resource execution rate in vehicle transportation logistics, the Q-ACO model employs the Q-Learning algorithm to optimize the pheromone in the initial phase, thereby facilitating a more accurate identification of the optimal path in comparison to the conventional ACO approach. For example, when the number of resources was 60, the resource execution rate of Q-ACO was 83.65%, while that of H-ACO was 79.25%. In addition, with the powerful path-finding ability of the ACO algorithm, the H-ACO model can better optimize the vehicle paths and integrate the resources. It significantly improved the resource execution rate compared with other models. In addition, considering that the introduction of Q-Learning into the ACO algorithm may increase the computational cost of the model, different scales of logistics scheduling were selected for experiments. Moreover, the final result shows that Q-ACO has lower computational overhead compared to other scheduling techniques. The main reason is that Q-Learning optimizes the search area of the ant colony algorithm during training, and only searches the reward area, thereby reducing the model overhead.

In addition, the study also compared with the literature [4] as well as the techniques proposed in the literature [6]. The Q-ACO model of the research model was found to have a lower total logistic operation time control with an improvement of 5.35% compared to the heuristic algorithm of literature [4]. In comparison with literature [6], Q-ACO model also performed better in total logistics operation time control with 4.25% improvement. While in the overall logistics cost control, Q-ACO model has obvious advantages in vehicle transportation and scheduling arrangement. In particular, the Q-Learning algorithm was used to improve the pheromone in the initial phase of ACO, which significantly improved its path-seeking optimization effect in the initial phase. The Q-ACO model reduced its total logistics cost by 3.35% compared with literature [4]. Compared with the literature [6], its total logistics cost decreased by 4.26%. This showed that the proposed Q-ACO model had a better application compared to similar models.

5 Conclusion

In conclusion, the contemporary logistics industry is evolving in a manner that is increasingly characterized by the integration of information and intelligence. The intelligent industrial logistics system will manage the logistics task process in a more scientific manner, with an emphasis on task integration and resource execution efficiency. The experimental results demonstrated that the proposed scheduling technology for logistics resource scheduling exhibited an excellent application effect, particularly in comparison to similar technologies. It was evident that this technology possesses distinctive advantages. However, there were also some shortcomings in the research that need to be addressed, such as not considering more specific task scheduling processes, and not taking into account the impact of suppliers on logistics resources. In addition, this technology is mainly targeted at logistics scheduling scenarios and has not been used in industrial scheduling or cloud resource management scenarios. Therefore, in future work, it is necessary to analyze more influencing factors of logistics. At the same time, the technology should be extended to more areas to improve its application effectiveness in management and scheduling in various industries.

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