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OPTIMIZATION OF CONTAINER TRANSPORT LOADING FOR CHINA–EUROPE FREIGHT TRAINS BASED ON RFID TECHNOLOGY

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Abstract:

With the rapid development of the global economy, international trade plays a crucial role in the economic growth and resource allocation of various countries. As an important logistics channel connecting China and Europe, the China-Europe Railway Express has significantly contributed to supporting the "Belt and Road" initiative and promoting regional economic cooperation. However, the efficiency of container transportation directly affects the quality of transport and operational costs, thus improving the loading efficiency of container transport has become an urgent issue in modern logistics management. Most existing container transport methods rely on traditional scheduling and loading strategies, which often fail to meet the real-time demands posed by dynamic market changes. This paper proposes a new real-time loading optimization framework based on Radio Frequency Identification (RFID) technology to address the container transport optimization problem for the China-Europe Railway Express. This framework manages real-time cargo requests through task queues and dynamically invokes the Iterative Heuristic Tree Search (IHTS) algorithm by the core decision-making component to generate loading plans and pass them to the execution component. By constructing a data generation model based on a normal distribution, this paper simulates the recognition probability of RFID tags to enhance decision-making accuracy. Experimental results show that the proposed method completed 45 tasks within 60 minutes, which is 50.00% higher than the improved Q-learning algorithm and 28.57% higher than the genetic algorithm based on the Metropolis criterion. In terms of path optimization, the length of the path in this method is 108 meters, significantly shorter than the 125 meters of the improved genetic algorithm and the 141 meters of the Q-learning algorithm. In addition, the total transportation cost of the proposed loading optimization method is 608.28 yuan. This cost integrates the vehicle transportation distance cost, the delay penalty caused by failure to load on time, and other operational losses. Experimental results demonstrate that this real-time loading optimization framework not only significantly enhances container loading efficiency but also effectively reduces operational costs, showing promising application prospects and practical value.

Keywords: *RFID; Container; Loading optimization; Q-learning algorithm; GA*

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1. Introduction

In the context of globalization, international trade has developed rapidly and become an important driving force for the economic growth of various countries. As the world's second largest economy, China is actively committed to promoting the growth of international trade, especially through the Belt and Road Initiative, connecting China with European markets (Casella et al., 2022). This initiative has led to the rapid development of the China-Europe Express, which has become an important logistics channel for regional economic cooperation between the two places. By transporting containers, the China-Europe freight train has reduced the time and cost of traditional sea transportation and provided a new solution for promoting trade facilitation. However, with the continuous growth of container transportation demand, how to improve the efficiency of container loading, improve the quality of transportation services, in order to reduce operating costs, has become an important challenge faced by modern logistics management (Zhang et al., 2022). At present, the traditional container transportation scheduling and loading strategies mostly rely on experience and static modes, which are powerless in the face of market dynamic changes. The research shows that the traditional scheduling method often cannot realize real-time monitoring and dynamic response, which leads to resource waste, low loading efficiency and transportation delay. In addition, the container transport environment is complex and changeable, not only facing a high frequency of cargo request changes, but also need to deal with a variety of constraints, such as transport path, time requirements (Groumpos, 2023). Therefore, developing an efficient and flexible container load optimization strategy to cope with these changes has become a key issue that the logistics industry needs to solve. The real-time loading optimization framework based on Radio frequency identification (RFID) technology is studied to solve the problem of container transportation optimization of China-Europe freight trains. Through the timely acquisition of real-time data and intelligent decision making, the research aims to improve container loading efficiency and reduce operating costs. The research methods include constructing a data generation model based on normal distribution, simulating the RFID tag identification probability, and using dynamic scheduling algorithm to optimize the cargo loading order to quickly respond to changes in market demand. The innovation of the research is mainly reflected in three aspects. Firstly, a new real-time loading optimization framework is proposed, which systematically applies RFID technology to container loading optimization, and improves decision-making accuracy and response speed through real-time data collection and processing. Secondly, an optimization solution based on dynamic scheduling algorithm is developed so that container loading can flexibly adapt to real-time changes in cargo requests and transportation conditions. Finally, by comparing with the traditional Q learning algorithm and the improved genetic algorithm, the significant advantages of this method in task completion efficiency, route optimization and transportation cost control are verified, and its potential in improving the efficiency of container transportation between China and Europe is demonstrated. Through the in-depth analysis of the research, it will provide an effective scheme for promoting the efficiency of container transportation of China-Europe freight trains, which has important practical significance for improving the flexibility and efficiency of modern logistics management.

2. Related Work

Currently, many domestic and foreign scholars have conducted in-depth research on logistics scheduling and the application of RFID technology. To improve the overall warehouse logistics scheduling process, Li (2023) used Q-learning technology to create a method model based on random forest, which was modeled as a Markov decision process, and further strengthened the proposed model using fuzzy control methods. Through experiments, the model achieved excellent performance compared to existing methods. Hou and Zhang (2024) focused on the balancing of assembly workshops and assembly lines, as well as multi-guided vehicle scheduling problems. They comprehensively considered various factors to maximize the objective function value while meeting production requirements, and proposed a scheduling rule selection method based on neural networks and knowledge bases. The proposed method's feasibility and efficacy were validated by a simulation analysis of an assembly workshop scenario, which was conducted in order to address the issues of assembly line balancing and multi-guided vehicle scheduling. This approach not only enhanced manufacturing efficiency but also bolstered the resilience of the workshop. Alzahrani and Irshad (2023) proposed a new 5G enabled secure RFID authentication scheme to address the trust and security issues faced by intelligent logistics in supply chain management. The results showed that this scheme supported more security features compared to other contemporary schemes. Meanwhile, the efficacy evaluation findings demonstrated a series of excellent performances of this scheme compared to other studies. Trebuna et al. (2023) proposed a mobile and autonomous RFID system using RFID technology to address the issue of inventory management using RFID robots in logistics management. This method achieved efficient inventory counting by using active and passive RFID chips embedded in the goods, combined with RFID robots for 2D spatial item positioning. The results showed that the inventory accuracy using RFID robots reached 95-99%.

Vehicle scheduling plays a key role in logistics operations and has a direct impact on efficiency, cost control and customer satisfaction throughout the supply chain. In recent years, with the progress of technology, especially the development of information technology and algorithms, the research on vehicle scheduling in academia and industry has gradually deepened. The following are some aspects of expansion and enrichment. In modern logistics, the demand for dynamic scheduling is increasing, especially in the face of uncertain market demand and traffic conditions. The application of genetic algorithms in supply chain allocation scheduling mentioned by Zhang (2022) highlights the advantages of using bio-inspired algorithms to solve complex problems. By simulating natural selection and genetic variation, the algorithm can quickly find a near-optimal solution in a large solution space. The case study shows that this method not only performs well in reducing operational costs, but also shows good performance in dealing with the real-time adjustment ability of complex logistics networks. In addition, the parallel processing capability and adaptability of the algorithm enable it to maintain high efficiency in dynamic environments. The heterogeneous UAV scheduling study proposed by Yuan et al. (2021) solves a complex challenge in urban environments, namely the cooperative scheduling of multiple types of UAVs. Their genetic algorithm framework introduces specialized genetic manipulation and weight-based loading methods, which not only improve the drone's load efficiency, but also optimize the flight path and reduce energy consumption. In the urban environment, taking into account the impact of buildings and the requirements of air traffic management, their research provides innovative solutions for UAV logistics distribution and shows the research direction of future urban logistics. Bansal et al. (2022) collaborative system concept combines the advantages of ground vehicles and drones to minimize delivery times and increase service efficiency. The clustering analysis in their method not only considers the spatial distribution, but also combines the delivery time window to make dynamic decisions through a heuristic algorithm, showing a higher efficiency than the traditional truck-drone model. The implementation of this collaborative framework will help reduce delivery costs and improve customer satisfaction at the same time, marking an important development direction for future multi-mode distribution systems. Guo et al. (2024) proposed a novel logistics scheduling model in response to the problems of logistics scheduling and routing efficiency brought about by the rapid development of e-commerce, and utilized radio frequency identification technology to optimize vehicle routing. The adaptive tabu search algorithm and the nearest neighbor algorithm are used to solve random customer demands and service times. Experiments have proved that this method is superior to other methods in completing tasks and reducing queuing time. Case studies show that the optimized routes recommended by this model can reduce transportation costs by more than 25% compared to using RFID technology alone, highlighting the potential of this technology to enhance logistics efficiency. Begić et al. (2024) proposed an active Building Information Modeling (BIM) system based on Internet of Things (IoT) support for the ready-mixed concrete distribution problem (RMCDP), to achieve the optimized distribution of ready-mixed concrete for multiple projects. This system generates the best distribution plan through dynamic and automatic input/output exchange, using data supported by real-time maps, including concrete volume, supply volume, the best route and the lowest cost, and can be dynamically adjusted to cope with real-time data changes.

Although the above methods have achieved certain results in logistics scheduling, most of the research is conducted in specific environments. For container transportation, which is a more complex and everchanging logistics environment, specific models may not be able to adapt to changes in demand in different contexts. Therefore, a real-time loading optimization framework based on RFID has been designed to improve the efficiency of container transportation on China Europe freight trains and provide a flexible solution to meet dynamic demands. The research innovation lies in proposing a novel real-time loading optimization framework, which improves the responsiveness of container transportation through dynamic scheduling algorithms. RFID technology is systematically applied to container loading optimization of China Europe freight trains, achieving automatic collection and processing of real-time data.

3. Methods and materials

3.1. Construction of container transport loading model based on RFID technology

A real-time loading optimization framework grounded on RFID technology is proposed for the container transportation optimization problem of China Europe freight trains. In this framework, the decision-making component and loading optimization solver are at the core, combined with the current loading situation of the China Europe freight train and real-time cargo requests, to make reasonable loading arrangements and achieve efficient response to demand (Al-Shboul, 2023; Chiu and Shih, 2023; Flanagan and McGovern, 2023). The real-time loading optimization framework mainly contains five parts, namely task request component, real-time data management component, decision component, loading optimization solver, and execution component. The task request component comprises two main elements: a request generator and a task queue. The purpose of these elements is to simulate the generation of real-time cargo requests and to temporarily store these requests. The real-time data management component comprises two key elements: an RFID data generator and an RFID data management component (Abdullahi et al., 2024; Wang et al., 2025). The former is used to simulate the generation of real-time RFID data, while the latter is employed to manage the data, thereby facilitating the decision-making process. The decision-making component consists of two parts: the decision maker and the real-time loading algorithm. The function of this component is to ascertain whether the existing loading capacity of the China Europe freight train is sufficient to accommodate the real-time cargo requests. It then prioritises these requests in the task queue, passes the processed task results to the execution component and finally transmits the tasks to be loaded to the loading optimisation solver. The execution component comprises two elements: performance evaluation and execution display. The former is applied to assess the performance of loading results, while the latter displays the final loading plan (Rajesh and Rahuman, 2025; He et al., 2025). The RFID-based container transportation loading optimization framework is shown in Figure 1.

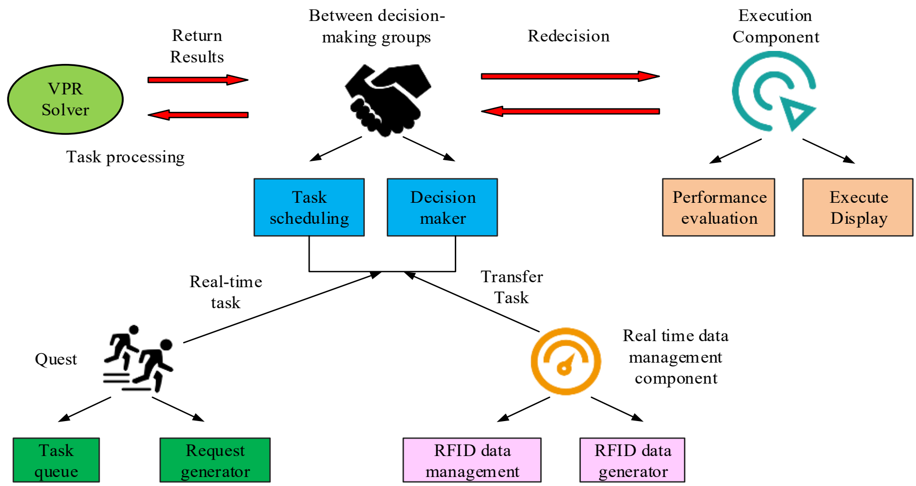


Fig. 1. Optimization framework for container transport loading based on RFID

In Figure 1, the RFID data generator and decision maker are important modules for achieving efficient loading in the research on container transportation optimization of China Europe freight trains based on RFID technology. The RFID data generator is mainly responsible for generating real-time data related to containers, including cargo information, loading status, and location information. The effective distance is a key parameter of the RFID system, which determines the range within which the RFID tag is recognized by the reader/writer. To maximize the probability of reading, it is necessary to set a suitable effective distance [20-21]. When the limiting factors decrease, the effective reading range of the tag will increase, thereby improving the probability of the tag being recognized by the reader/writer. To simulate and calculate the reading probability of labels, a data generator model based on normal distribution is studied and constructed. This model can consider various influencing factors, such as the effective placement of containers, environmental stability, and the performance of RFID devices, as shown in formula (1) [22].

$$P = P_{self} \cdot P_{location} \tag{1}$$

In formula (1), P represents the probability of label reading and writing, P_{self} represents the probability of self influence, and $P_{location}$ represents the probability of location. Among them, the calculation of $P_{location}$ is shown in formula (2).

$$P_{location} = f(distance)/f(0) \tag{2}$$

In formula (2), $distance$ means the distance between the tag and the reader/writer, Unit: Meter (m). f means the probability or validity of the tag being recognized by the reader/writer at a specific distance, and $f(0)$ means the recognition probability of the tag at a distance of zero, which is the ideal situation. The calculation formula for function f is shown in formula (3).

$$min\, f(x) = \frac{1}{r\sqrt{\pi}} e^{-\frac{x^2}{2r^2}}, 0 \le x < \infty \tag{3}$$

In formula (3), r represents the effective distance, Unit: Meter (m), and x represents the input value of distance. The calculation of $distance$ is shown in formula (4).

$$distance = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 (z_1 - z_2)^2} \tag{4}$$

In formula (4), (x_1, y_1, z_1) means the reader/writer coordinates, and (x_2, y_2, z_2) means the label coordinates, Unit: Meter (m). By using the above formula, it can achieve real-time monitoring and analysis of the reading probability of RFID tags, optimize the decision-making accuracy of the decision-making component, ensure that the container loading process can adapt to constantly changing cargo demands, and raise the efficiency and flexibility of the entire logistics system. Usually, there is a certain interval between each decision action of the research model decision maker. The interval time is mainly used for data collection and processing to ensure that decisions are based on reliable information. In addition, it can smooth real-time data fluctuations, reduce the risk of misjudgment, and provide time for model self optimization and adjustment. This interval allows the system to respond to external changes in a timely manner, allocate resources reasonably, and optimize the supply chain process, thereby raising the efficiency and flexibility of the entire logistics system under dynamic demand. The specific decision-making process is denoted in Figure 2.

In Figure 2 (a), the decision system is divided into three parts: the representation layer, the action layer, and the data layer. Among them, the decision-making process belongs to the key link in the action layer. It can be seen that in addition to the decision maker, the action layer also includes optimization algorithms, which have a great influence on the decision maker's decisions. In Figure 2 (b), when implementing loading optimization, the design of real-time loading optimization algorithm needs to consider the following core factors: loading priority. The algorithm must be able to allocate the loading sequence of containers reasonably based on factors such as the urgency of goods and destination distance, to maximize efficiency under limited transportation resources. Real-time data mean that algorithms need to adapt to the real-time data input brought by RFID technology, quickly respond to changes in actual loading conditions, and thus quickly process and adjust dynamic requests.

Considering obstacles and limiting factors, the algorithm should be able to identify and handle potential obstacles, limiting factors, and changing external environments that may occur during the loading process, ensuring smooth loading operations.

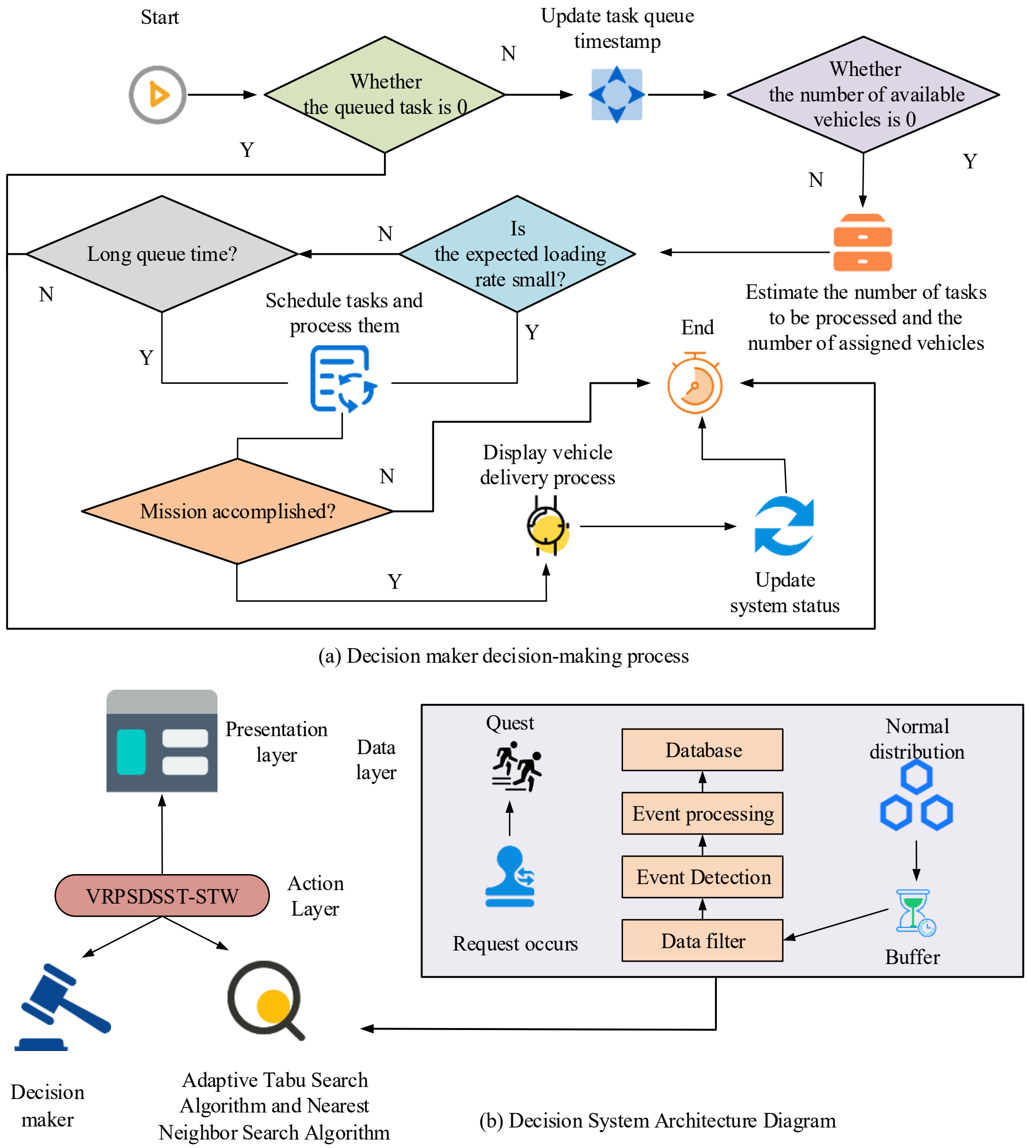


Fig. 2. Decision process structure of decision maker

The container transportation loading optimization model studied is based on the following core assumptions:
Hypothesis 1: Each container task has a strict time window. Vehicles arriving before the time window need to wait. If it is reached after the time window, it will be regarded as a delay and a corresponding penalty will be imposed.
Hypothesis Two: Each transport vehicle has a fixed maximum load capacity and volume. In route planning, the cumulative loading capacity of any vehicle at any node must not exceed its capacity upper limit.
Hypothesis Three: The actual demand for containers is unknown until the vehicle arrives at the loading location, but its probability distribution is known.
Hypothesis Four: Cargo requests arrive at the task queue in real time in the form of a Poisson process, and the optimization system needs to respond dynamically to these new requests.

3.2. Optimization analysis of container transportation loading based on RFID technology

In the container transportation loading optimization model grounded on RFID technology, the actual demand and loading time of containers are unknown, and the delivery time of containers also has specific customer requirements (Dardouri et al., 2023; Pereira et al., 2023; Cammarano et al., 2023). Although transport vehicles can arrive outside of the customer's designated time, they will face certain penalties for breach of contract. To better address this challenge, the research set that the actual demand for containers can only be displayed when the container loading vehicle arrives at the loading location (Pereira et al., 2024). The loading time of a container is directly related to its demand, and the larger the demand, the corresponding increase in loading time required. Therefore, when designing container transportation routes, it is necessary to consider the range of changes in container demand and adjustments to loading time. Therefore, the function for optimizing container loading is represented by formula (5).

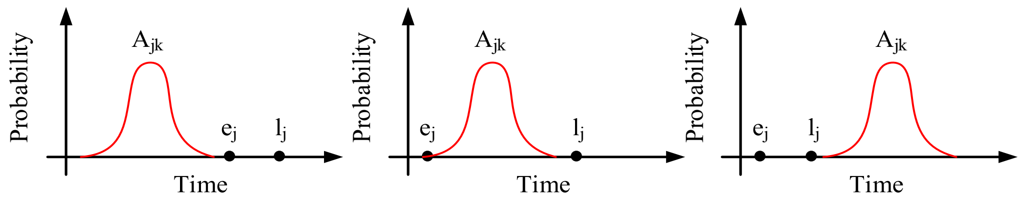
$$\begin{aligned} min\, f(x) = \textstyle\sum_{i,j\in A} \sum_{k\in K} c_{ij} x_{ijk} + \\ + \textstyle\sum_{j\in N} \sum_{k\in K} \lambda_{jk} E(D_{jk}) + g(x) \end{aligned} \quad (5)$$

In formula (5), $f(x)$ represents the objective function, the total cost to be minimized, including transportation cost, delay penalty and other costs. x is a decision variable vector, usually representing path selection or loading plan. K represents a collection of vehicles and is used to distinguish different transportation resources. c_{ij} represents the transportation cost from node i to node j, which may include fuel cost, time cost or distance cost. x_{ijk} is a binary decision variable indicating whether vehicle k travels from node i to node j (if it is 1, it indicates choosing this path; otherwise, it is 0). N represents a collection of nodes, such as all customer points or loading and unloading points. λ_{jk} is the penalty coefficient, which is used for the delay of vehicle k at node j and reflects the cost incurred due to failure to arrive on time. E means the expected value of container loading delay time, D_{jk} represents container loading delay time, and $g(x)$ represents the corrected value of loading cost. There are three relationships between container loading time and expected time, as shown in Figure 3.
In Figure 3, e_j means the left boundary of the container loading time interval, which is the completion time ahead of schedule; l_j means the right boundary of the container loading time interval, which is the delayed completion time. There are three scenarios for container loading time and expected time, namely early completion, completion within the time window, and delayed completion. Among them, early completion requires setting a certain period of time to complete the loading and unloading services, which may lead to inefficient utilization of resources as vehicles do not complete specific tasks during the waiting period. Completing this within the time window is an ideal situation, and any scheduling system should prioritize such situations to ensure service quality. Delayed completion can still provide services, but certain penalties need to be imposed for delayed tasks, which may affect the future development of business. For the function proposed in formula (5), the study will use an Iterative Heuristic Tree Search (IHTS) algorithm to solve it. In the IHTS algorithm, the width of the time window and the transportation distance are used as criteria for node selection. On this basis, the algorithm adjusts important parameters such as taboo length and domain structure, and introduces adaptive penalty coefficients to cope with possible additional costs and breach penalties during transportation. To generate initial solutions, the study introduces the Nearest Neighbor Heuristic (NNH) algorithm for path construction. When constructing the initial container

transportation path, the initial node is selected to depart from the distribution center, and the selection of subsequent nodes is based on minimizing the Shipping Cost (SC) of the cargo location. The expression for this selection process is shown in formula (6).

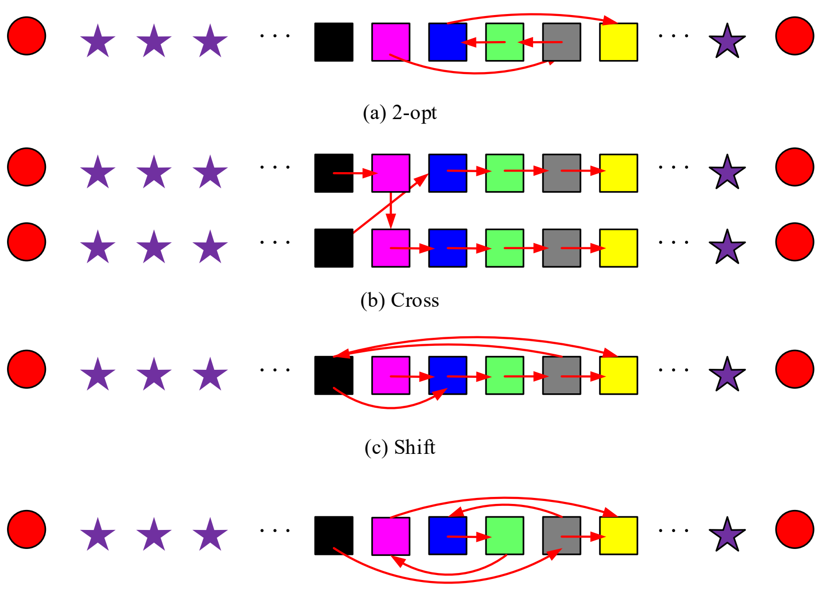
$$SC = B(l_j - e_j) - c_{ij} \tag{6}$$

In formula (6), SC represents the selection cost, which is used to evaluate the priority of node j. The smaller the value, the more priority the node is selected. B means the weight of the container loading time difference. l_j is the loading time or the last allowed time of the node j, indicating the deadline for completing the loading. e_j is the expected time or earliest time of the node j, indicating the ideal time to start loading. c_{ij} represents the transportation cost from node i to node j. To prevent getting stuck in local optima during the process of solving formula (5), an adaptive taboo length strategy is adopted in the study. This method can dynamically adjust with the search process of the algorithm. In finding the best solution, if the current solution is better than the previous solution, the taboo length will be increased. If the current solution is inferior to the previous solution, it will reduce the taboo length. At the same time, four general neighborhood strategies are used for alternating search, as shown in Figure 4.



(a) Arrive early (b) Reached within the time window (c) Delay in reaching

Fig. 3. Distribution of container loading time and expected time



(a) 2-opt

(b) Cross

(c) Shift

(d) Exchange

Fig. 4. Alternating search using neighborhood strategy

In Figure 4, the 2-opt neighborhood is mainly used to improve the order of paths or loops. The strategy of Cross neighborhood involves crossing customers from different paths to form new paths. The Shift neighborhood strategy involves moving a customer from their original position to another position in the path. Two different clients in the Exchange neighborhood are selected and their positions in the current solution are exchanged to generate a new solution. By obtaining the model solution values from the above, the quality of the solution values can be shown in formula (7).

$$f(s) = c(s) + \alpha * q(s) + \beta * t(s) \tag{7}$$

In formula (7), $f(s)$ represents the objective function value of solution s, representing the total cost (including fines). The smaller the value, the better the solution. $c(s)$ indicates the loading cost of the solution s, including direct costs such as transportation and handling. α stands for the penalty coefficient for capacity constraints, which is used to punish violations of container capacity limits. The larger the value, the more severe the penalty. $q(s)$ is the constraint value of the capacity constraint, indicating the extent to which solution s violates the container capacity limit. β is a time-constrained fine coefficient used to punish behaviors that violate the time window. The larger the value, the more severe the penalty. $t(s)$ is the constraint value of the time constraint, indicating the extent to which the solution s violates the time window limit. If there is no conflict with the capacity constraint value or time window constraint value during the solving process, the value of the penalty coefficient is shown in formula (8).

$$\begin{cases} \alpha = (\alpha - 1)/(1 + \xi) \\ \beta = (\beta - 1)/(1 + \xi) \end{cases} \tag{8}$$

In formula (8), ξ means a random variable that satisfies a uniform distribution. Based on the above solution, the solution process using NNH and IHTS in the RFID-based container transportation loading framework is shown in Figure 5.
In Figure 5, the first step is the deployment of RFID tags, which are deployed at key locations and items on the containers and their transportation paths that need to be tracked and monitored. Next is the configuration of the RFID reader, which emits radio frequency signals to the surrounding area. When the RF signal encounters a container with an RFID tag installed, the tag will immediately respond and return a unique serial number. After receiving the response from the tag, the RFID reader will read the data stored in the tag. These data may include information such as the current location, loading status, and transportation progress of the container. Next is data transmission.

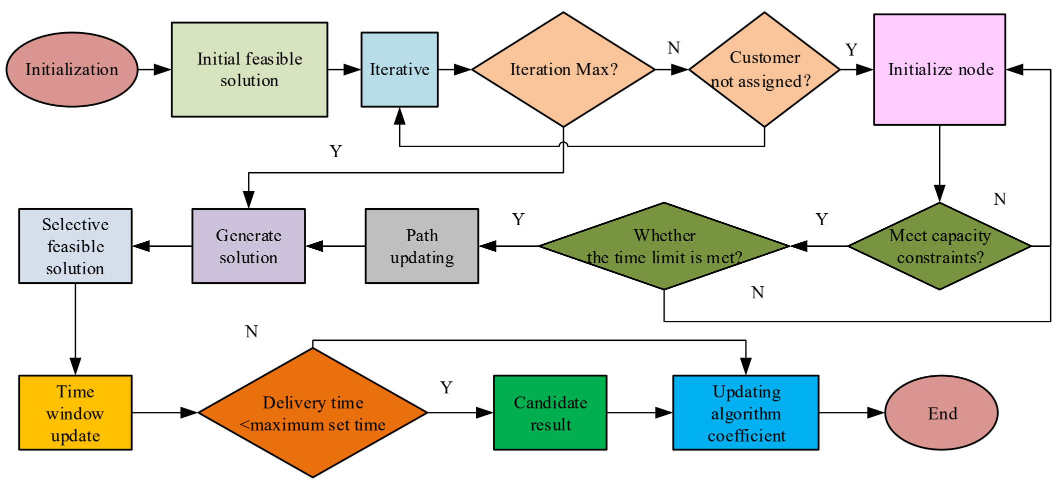


Fig. 5. RFID-based container transportation loading model

After successfully reading the data, the RFID reader will transmit the data in real-time to the main database or logistics management system application through the network. This process ensures the immediacy and accuracy of information, providing a reliable data foundation for subsequent decision-making. Finally, there is real-time tracking and scheduling. Through the system's integrated RFID technology, logistics managers can track the dynamic location of containers in real time and effectively schedule and optimize the transportation process. This real-time data update helps management to finely manage container transportation, thereby reducing delays, optimizing loading plans, and improving operational efficiency. After the above introduction, the pseudo-code of the proposed method in the research is specifically shown in Table 1.

4. Results

4.1. Performance analysis of container transportation loading optimization model based on RFID technology

To verify the optimization effect of RFID technology in container transportation loading, simulation experiments were conducted to analyze it. The specific experimental environment settings were as follows: the processor was AMD Ryzen 7, the memory was 32GB, the storage was 1T solid-state drive, the graphics card was NVIDIA GTX 1660, the operating system was Windows 10, and the simulation software was MATLAB and its toolbox. The input data of the experiment is constructed and extended based on the Solomon benchmark dataset of the classic vehicle routing problem (VRP) to fit the container loading scenario of the China-Europe Railway Express. To conduct a fair comparison, the study selected two meta-heuristic algorithms widely used in the field of logistics scheduling as performance benchmarks: the improved Q-learning algorithm and the Metropolis standards-based genetic algorithm (Metropolis-GA) for comparative analysis. Among them, the improved Q-learning algorithm models the loading scheduling problem as a Markov decision process, explores it using the ε-greedy strategy, sets the learning rate at 0.1 and the discount factor at 0.9. Metropolis-ga adopts roulette selection, two-point crossover and single-point mutation operations. The population size is 100, the number of iterations is 500, and the Metropolis criterion is introduced to accept inferior solutions with a certain probability to avoid premature convergence. All algorithm parameters were determined through pre-experiments. The core parameters of the IHTS algorithm are shown in Table 2.

The main computational overhead of the IHTS algorithm lies in the generation and evaluation of neighborhood solutions. Each iteration generates 100 candidate solutions. It takes O(n) time to evaluate the cost of one solution s, where n is the number of scheduled tasks. In the worst-case scenario, the algorithm complexity is O (Max_Iterations * N_size * n), which is a polynomial time complexity related to the problem size. By setting Max_Iterations and N_size, the computing time can be effectively controlled to meet the requirements of real-time scheduling.

The research adopts three standardized indicators, namely task completion efficiency, path optimization rate and total operating cost, to comprehensively evaluate the performance of the algorithm. The number of completed tasks: It refers to the total number of container transportation tasks successfully arranged and completed by the algorithm within the simulation time window. This indicator directly reflects the throughput and efficiency of the system. Path length: It refers to the total distance actually traveled by the AGV during the execution of its tasks, with the unit being meters (m). This indicator is used to evaluate the optimization degree of algorithm path planning and directly affects energy consumption and time cost. Global total cost: This indicator is a core measure of the system's comprehensive performance, with the unit being monetary units (such as the yuan, RMB). The calculation formula is as follows: Total cost = Fixed operating cost + Σ (transportation cost × path length) + Σ penalty cost. Among them, fixed operating cost includes equipment depreciation, labor, etc. Transportation cost refers to the driving cost per unit distance. The penalty costs mainly include two types: (1) Time window penalty: If a task is not completed within its specified time window, a linear or double penalty will be imposed based on the duration of the timeout. (2) Damage cost: The cost of goods damage caused by improper operation or bumpy roads is calculated as a certain proportion of the value of the goods. The results are shown in Figure 6.

Figure 6 (a) showcases the outcomes of the algorithm in solving the amount of tasks, where Q-learning completed 30 tasks at 60 minutes. Metropolis-

GA completed 35 tasks. The research method completed 45 tasks. Compared to Q-learning and Metropolis-GA, the research method increased the completion rate by 50.00% and 28.57%, respectively. Figure 6 (b) shows the outcomes of the algorithm in terms of the amount of queued tasks, where Q-learning, Metropolis-GA, and the research method had task queues of 41, 34, and 20 at 60 minutes, respectively.

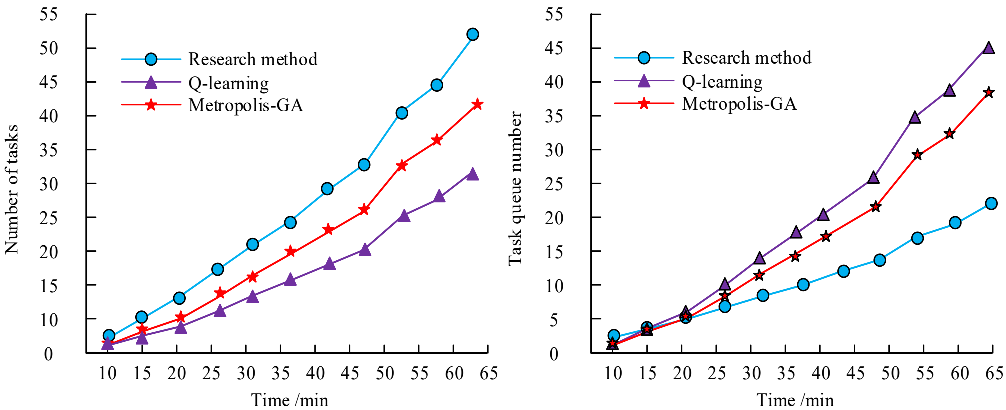
Table 1 Iterative Heuristic Tree Search (IHTS) for Container Loading

Iterative Heuristic Tree Search (IHTS) for Container Loading

```
Input:
Task queue Q
Set of vehicles K
Real-time RFID data stream
Maximum iterations Max_Iterations
Initial tabu tenure tabu_tenure_initial
Output:
Optimal scheduling solution s_best
// Initialization Phase
Generate initial solution s_current using Nearest Neighbor Heuristic (NNH);
s_best ← s_current;
Initialize tabu list T as empty;
tabu_tenure ← tabu_tenure_initial;
// Main Optimization Loop
for iteration = 1 to Max_Iterations do

    // Neighborhood Generation
    Generate neighborhood set N(s_current) by applying four operators:
        - 2-opt operator
        - Crossover operator
        - Displacement operator
        - Exchange operator

    // Candidate Selection
    Filter N(s_current) to remove solutions violating tabu conditions;
    Select best candidate solution s_candidate from remaining neighborhood;

    // Solution Evaluation and Update
    if f(s_candidate) < f(s_best) then   // f(s) is objective function from Eq. (7)
        s_best ← s_candidate;
        // Adaptive tabu tenure: increase when improving
        tabu_tenure ← tabu_tenure × 1.1;
    else
        // Adaptive tabu tenure: decrease when not improving
        tabu_tenure ← tabu_tenure × 0.9;
    end if

    // Tabu List Management
    Update tabu list T:
        - Add reverse move of current solution to T
        - Set tenure for this move to current tabu_tenure
        - Remove expired moves from T

    s_current ← s_candidate;

end for

return s_best;
```

Table 2 Core Parameter Table of the IHTS Algorithm

Parameter	Symbol	Value/range	Explanation
Stop standard	Max_Iterations	500	Maximum number of iterations
	Max_Time	300 s	Maximum running time
	No_Improve_Iter	50	The number of consecutive iterations without improvement
Initial taboo length	tabu_tenure_init	10	The initial duration of the taboos list
Adaptive update rules	tabu_tenure	tabu_tenure * 1.1 or * 0.9	If a better solution is found, increase by 10%; otherwise, decrease by 10%. The upper and lower limits are [5, 30].
Neighborhood size	N_size	100	The number of candidate solutions generated in each iteration
Penalty coefficient update	α*, β*	The initial α=100, β=150	For every 10 iterations, if the solution is feasible, multiply the coefficient by 0.95; if not, multiply it by 1.05.

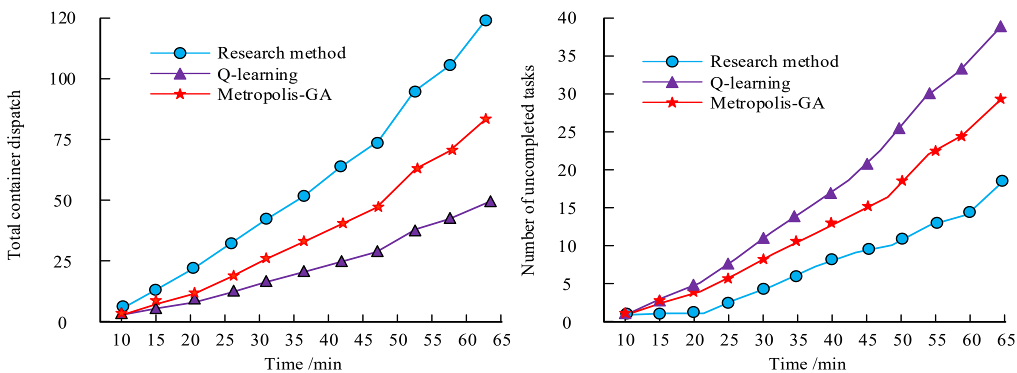


(a) Task completion result (b) Task queue result

Fig. 6. Comparison results of algorithm efficiency and performance

Compared to Q-learning and Metropolis-GA, the research method reduced the number of task queues by 51.22% and 41.18%, respectively. The outcomes denote that the research method performs better in processing efficiency, can complete tasks faster, and thus reduce queues. The study continued to validate the model from multiple perspectives, evaluating the total amount of containers scheduled by the model and the amount of unfinished ones. The results are shown in Figure 7.

Figure 7 (a) showcases the total amount of containers scheduled by the algorithm, where the total scheduling results of Q-learning, Metropolis-GA, and the research method at 60 minutes were 48, 75, and 110, respectively. The findings reflected the excellent performance of the research method in scheduling capability and efficiency, with improvements of 46.67% and 129.17% compared to Metropolis-GA and Q-learning. Figure 7 (b) showcases the amount of unfinished tasks for the algorithm. At the 60 minute time point, there were 15 unfinished tasks for the research method, 25 unfinished tasks for Metropolis-GA, and 33 unfinished tasks for Q-learning. The results demonstrated the advantages of the research method in terms of efficiency and capability in scheduling tasks, with higher total scheduling numbers and lower number of unfinished tasks indicating the effectiveness of the method in algorithmic scheduling scenarios. The results of container scheduling path length for different algorithms are shown in Figure 8.



(a) Total number of tasks result (b)Number of uncompleted tasks result

Fig. 7. Comparison of total container scheduling and unfinished number in the model

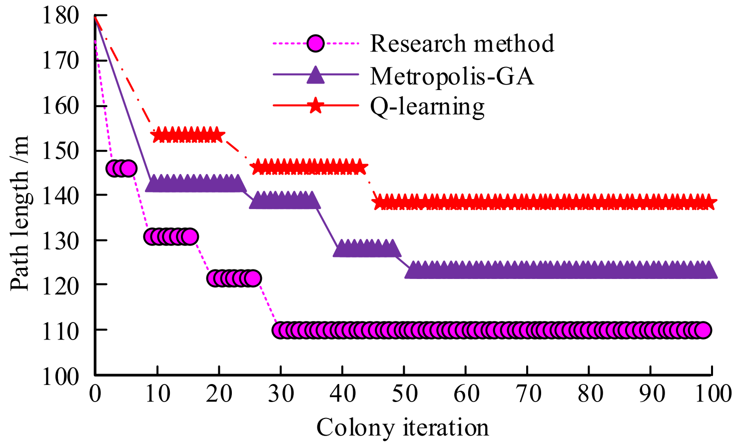


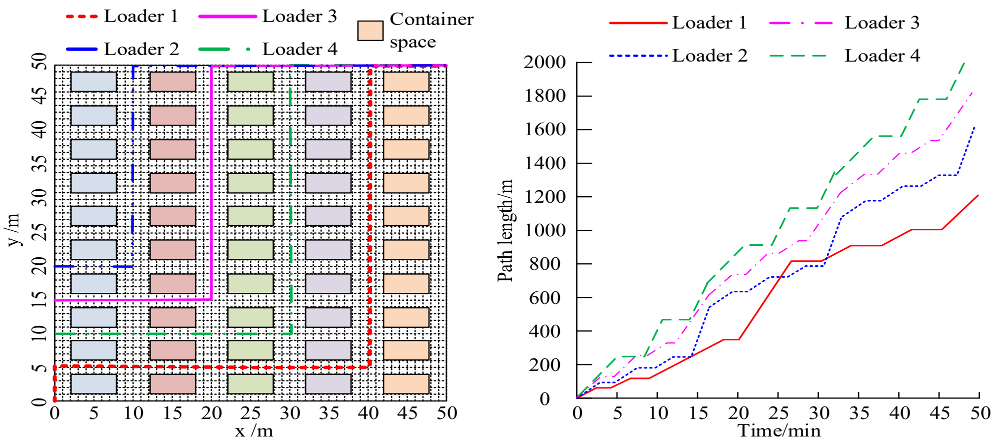
Fig. 8. Comparison of container scheduling path length for different algorithms

Figure 8 shows how different algorithms evaluate the path planning performance of each algorithm at the granularity of a single loading task. In this scenario, the performance metric is the complete path length from the starting point to the destination point planned by the algorithm for a single transport vehicle. The Metropolis-GA began to converge at the 50th iteration, and the final convergence value of container scheduling path length was 125m. The Q-learning algorithm converged at the 42nd iteration, but the path length converged to 141m. The research method converged at the 30th iteration, with a path convergence length of 108m. The results indicated that the research method not only improved the convergence speed, but also achieved a shorter total path length in path planning, which means it can improve scheduling efficiency and reduce operating costs.

4.2. Practical application analysis

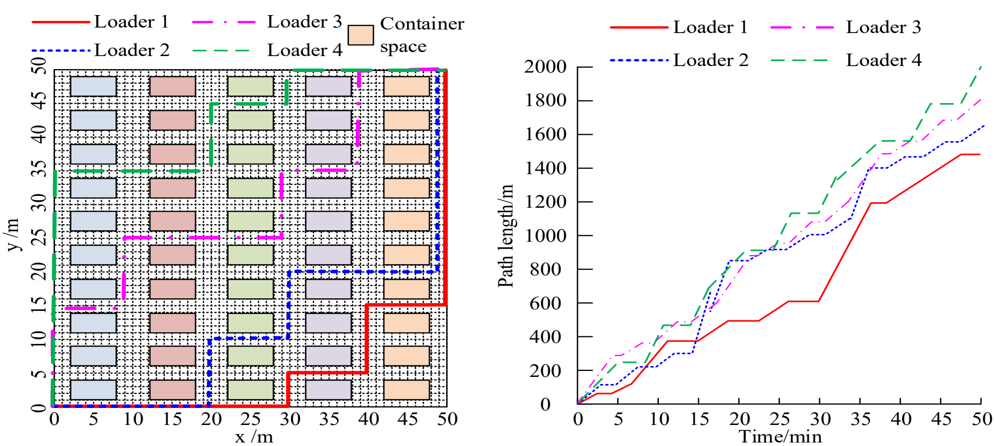
To further evaluate the robustness and efficiency of the algorithm in long-term operation, the study extended the simulation time to a standard 8-hour work shift and examined the total cumulative driving path of the vehicle during this period. This indicator can more comprehensively reflect the algorithm's comprehensive scheduling capability and its impact on energy consumption. Under this measurement, the total length of the path reaches the order of several kilometers, which is caused by the accumulation of dozens of transportation tasks carried out by vehicles within the shift system. The research sets up a working area for a container yard with a length and width of 50 meters each. To simplify the initial model and focus on the core performance of the path optimization algorithm, the following basic assumptions are made in the study: the containers are placed in a single layer and not vertically stacked. The position of the container in the yard is determined by the center coordinates of its bottom surface, forming a two-dimensional planar layout grid. Among them, the horizontal spacing of the containers is 4 meters and the vertical spacing is 2 meters. Four ground mobile loaders are used as loading and unloading equipment. This equipment model simulates the working mode of common straddles or reach cranes in ports, which move in a two-dimensional plane and perform loading and unloading operations. The study proposed a method for planning container loading of loaders, and the results are shown in Figure 9.

Figure 9 (a) showcases the research method for container loader path scheduling. The results showed that the loader path was distinct, with corresponding loaders responsible for different channels. There were no intersections on the route, and there were a total of 12 turning points in the path. Figure 9 (b) showcases the path length results of container loader scheduling. At the 50 minute time point, four loaders traveled 2000m, 1800m, 1600m, and 1200m respectively, for a total of 6600m. The container loading planning of Metropolis-GA is shown in Figure 10.



(a) The scheduling results of the research method (b) Length of container loading path

Fig. 9. Research method container loading planning results



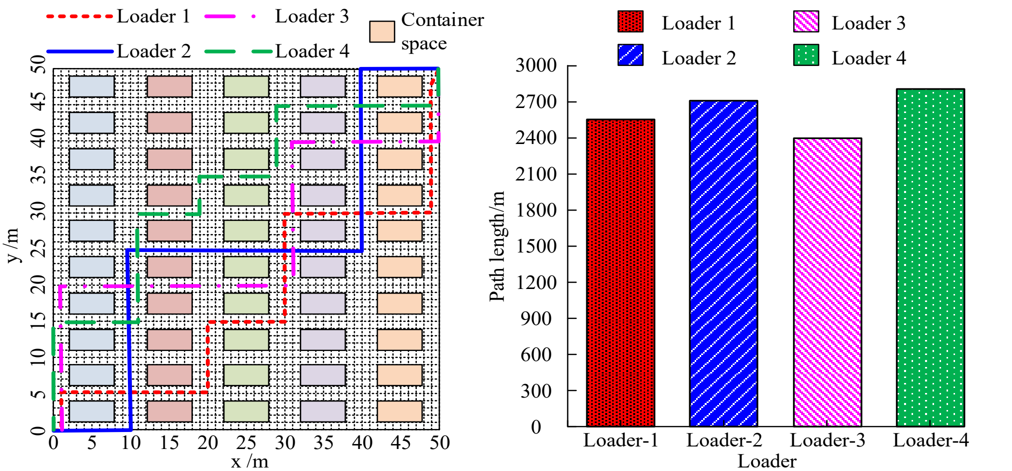
(a) The scheduling results of the research method (b) Length of container loading path

Fig. 10. Container loading planning results of Metropolis-GA

Figure 10 (a) shows the container loader path scheduling diagram of Metropolis-GA, which shows that the loader path was clear, but all channels and container cargo positions were not covered. Although there were no intersections on the route, there were a total of 21 turning points on the path. Figure 10 (b) shows the path length results of container loader scheduling. At the 50 minute time point, four loaders traveled 2000m, 1800m, 1700m, and 1500m respectively, for a total of 8000m. The container loading planning of Q-learning algorithm is shown in Figure 11.

Figure 11 (a) shows the path scheduling diagram of the container loader using the Q-learning algorithm. The outcomes showed that the loader paths intersected, and there were a total of 21 turning points in the path where most of the channels and container cargo positions were not covered. Figure 11 (b) shows the path length results of container loader scheduling. At the 50 minute time point, four loaders traveled 2450m, 2700m, 2400m, and 2800m respectively, for a total of 8350m. Comparing the results of Figures 9, 10, and 11 comprehensively, Metropolis-GA and Q-learning algorithms showed shortcomings in path coverage and efficiency, especially

Q-learning, which may result in poor path design due to the randomness in the policy learning process. The research method reduced the travel distance of the loader and improved the clarity of the path through reasonable path planning and scheduling strategies, reducing the time and efficiency losses caused by intersections. To gain a more intuitive understanding of the delivery situation, a study was conducted to compare the cost of container cargo location delivery. To ensure the statistical reliability and universality of the experimental results, each experimental scenario was independently repeated 30 times. All the result data reported below (including the values in the tables and figures) are the arithmetic mean of the results of 30 runs, with standard deviations attached. In addition, to evaluate the statistical significance of the performance differences of the algorithms, we used the paired sample t-test (when the data conformed to a normal distribution) or the Wilcoxon signed-rank test (when the data did not conform to a normal distribution), with the significance level set at $p < 0.05$. For specific results, please refer to Table 3.



(a) The scheduling results of the research method (b) Length of container loading path

Fig. 11 Container loading planning results of Q-learning algorithm

Table 3 Comparison of cost distribution across loaders and global total cost for different algorithms (Unit: RMB, Note: * indicates P<0.05 compared with IHTS)

Algorithm	Loader	Transportation cost (yuan)	Damage cost (yuan)	Proportion of damage cost (%)	Total cost of a single machine (yuan)
IHTS	Loader -1	100.23±5.1	22.71±1.8	0.185	122.94±6.2
	Loader -2	120.51±6.3	27.83±2.1	0.188	148.34±7.5
	Loader -3	135.75±7.0	31.56±2.5	0.189	167.31±8.1
	Loader -4	140.46±7.2	29.23±2.3	0.172	169.69±8.3
	Total/Average	496.95±21.5	111.33±7.2	0.183	608.28±26.8
Metropolis-GA	Loader -1	160.92±8.9	20.18±2.0	0.111	181.10±9.8
	Loader -2	110.33±6.8	32.50±2.7	0.227	142.83±8.1
	Loader -3	145.25±8.1	27.00±2.4	0.157	172.25±9.0
	Loader -4	125.67±7.5	30.00±2.6	0.193	155.67±8.7
	Total/Average	542.17±26.3	109.68±7.8	0.168	651.85±29.5*
Q Learning	Loader -1	155.44±9.5	30.98±2.9	0.166	186.42±10.8
	Loader -2	130.24±7.9	25.41±2.5	0.163	155.65±9.1
	Loader -3	170.20±10.1	28.52±2.7	0.144	198.72±11.3
	Loader -4	145.71±8.7	35.70±3.1	0.197	181.41±10.2
	Total/Average	601.59±31.2	120.61±9.1	0.167	722.20±35.8*

The results in Table 3 show that the IHTS algorithm proposed in the research demonstrates the best comprehensive performance in container loading scheduling, with a global total cost of only 608.28 yuan, which is lower than 651.85 yuan of the Metropolis-GA algorithm and 722.20 yuan of the Q-learning algorithm. Specifically, the IHTS algorithm performed outstandingly in transportation cost control, at 496.95 yuan, which was approximately 8.3% and 17.4% lower than Metropolis-GA and Q learning respectively. The damage cost was 111.33 yuan, although slightly higher than Metropolis-GA's 109.68 yuan. But it is far lower than the 120.61 yuan of QLearning. Furthermore, the proportion of damage costs in the total cost in IHTS is 18.3%, which is higher than the 16.8% and 16.7% of the other two algorithms. This indicates that IHTS effectively offsets the slightly higher damage risk by significantly reducing transportation costs, thereby minimizing the overall operating cost. The standard deviations of each cost item are relatively small, reflecting the stability of the results and verifying the reliability and superiority of this method.

5. Discussion

The research results indicated that the raised real-time loading optimization framework based on RFID could complete 45 tasks within 60 minutes, showing significant advantages compared to 30 tasks based on improved Q-learning and 35 tasks based on Metropolis-GA. This framework combined real-time data management components and decision-making components, enabling task requests and loading strategy adjustments to quickly reflect real-time changes and provide rapid response capabilities to dynamic requests. In terms of path length, the studied path length was 108 meters, lower than Metropolis-GA's 125 meters and Q-learning's 141 meters. In the cost analysis, the total delivery cost of the proposed method was 608.28 yuan, which reflects its significant advantage in cost control compared to Metropolis-GA at 651.85 yuan and Q-learning at 722.20 yuan. The model could adjust the loading plan based on real-time RFID data, allowing more containers to be scheduled and loaded in a timely manner. By combining adaptive taboo search strategy and neighborhood search strategy, the optimization of loading paths was effectively improved.
In the same type of research, Su et al. (2022) established a mathematical model for profit maximization dynamic scheduling that adapts to dynamic priority for logistics pickup and distribution problems, and solved it through GA, variable neighborhood search algorithm, and taboo search algorithm. The study compared their proposed method with the best solution of benchmark instances, and the results showed that their method could improve over 35% of the total distance and 30% of the vehicle situation. Zhong et al. (2023) proposed an optimal scheduling strategy for AGV based on a novel two-layer genetic algorithm to effectively integrate and schedule different equipment in automated container terminals. Simulation results showed that this method optimized the current scheduling strategy and reduced the path energy consumption of AGV. Although the above methods have certain effects, compared with research methods, they are difficult to quickly adapt to market changes and still have gaps in real-time updates and dynamic scheduling.
In actual container yards, after the introduction of vertical stacking, the problem space model needs to be expanded from two dimensions to three dimensions, and the optimization model needs to incorporate the complex constraints brought by stacking, especially the restrictions on loading and unloading sequence: before extracting the lower layer of containers, all the containers pressing on top need to be moved away, thereby generating a large amount of inefficient "mobile operations". The optimization objective thus shifts to a trade-off between "path optimization" and "reducing mobile operations", while also taking into account physical constraints such as stacking stability and load-bearing safety. Despite the challenges, the IHTS algorithm framework proposed in this study has the potential for expansion and can address such three-dimensional layout issues by redefining node states (including three-dimensional positions and stacking states) and introducing targeted "pre-occupation" operations.
On the other hand, if the operation equipment is changed from ground transport vehicles to rail-mounted overhead cranes, the optimization paradigm of the entire operation system will undergo a fundamental transformation. The overhead crane runs along a fixed track, and its operation range covers the area above the box. The optimization core has shifted from "planar path planning" to "three-dimensional fixed-point operation scheduling". At this point, the connotation of the "path length" indicator changes. The optimization objective is no longer the

planar movement distance, but the "estimated operation time" that includes actions such as the movement of the main vehicle, the movement of the small vehicle, and the lifting of the lifting gear. Although the problem of path intersection between devices no longer exists, multi-machine collaborative scheduling, job area avoidance and task allocation optimization have become key. Despite these differences, this study, based on the core framework of real-time data acquisition by RFID, dynamic processing of task queues through decision-making components, and generation of scheduling instructions using an optimization solver, still holds significant reference value and application potential in the overhead crane dispatching system, indicating that the proposed method has universal guiding significance at the conceptual level.

6. Conclusion

Against the backdrop of an increasingly complex global logistics network, the China Europe freight train, as an important trade channel connecting China and Europe, is receiving increasing attention to the optimization of container transportation loading. With the increasing demand for transportation efficiency and cost control, traditional loading strategies are facing the problem of being unable to respond to dynamic market demands in a timely manner. A novel real-time loading optimization framework was proposed to address the practical challenges of container transportation on the China Europe freight train. The framework effectively combined RFID technology with decision-making algorithms, aiming to enhance the flexibility and efficiency of container transportation. The research results indicated that the study not only improved the efficiency of container transportation on the China Europe freight train, but also proposed a feasible framework to raise the in-depth application of RFID technology in logistics management. By optimizing container loading strategies, not only could operating costs be reduced, but overall transportation quality could also be improved, enhancing the competitiveness of China Europe freight trains in the global logistics network. However, this study also has certain shortcomings. Firstly, the applicability and robustness of the model in extremely complex or uncertain environments still need further validation. Secondly, the model lacks analysis of dynamically changing goods. Future research directions can focus on improving the robustness of algorithms to cope with rapidly changing logistics environments, exploring more flexible real-time scheduling strategies to cope with larger and more complex transportation networks.

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