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Optimization Technology for Loading and Unloading Operation Organization Planning in Railway Logistics Park

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Abstract: Railway logistics parks have a crucial part in the modern logistics system, and their efficient operation is of great significance for reducing logistics costs and increasing efficiency, promoting high-quality regional economic development, and implementing the dual carbon strategy. However, traditional methods for organizing and planning loading and unloading operations often struggle to achieve optimal resource allocation and efficient collaboration in complex, dynamic logistics environments, resulting in inefficient equipment utilization and poor path planning. To optimize the organization and planning of loading and unloading operations in railway logistics parks and improve operational efficiency, research optimizes the configuration of loading and unloading equipment in railway logistics parks based on queuing theory, and constructs an optimization model for loading and unloading operation organization based on a genetic algorithm. By simulating the mechanism of biological evolution, efficient scheduling of equipment, task timing, and path planning can be achieved through rapid optimization. The experimental findings denote that the optimized model improves accuracy to 96.52%, achieves an F1 score of 0.93, and reduces inference time to 1.43 seconds. Compared with traditional loading and unloading organization planning methods, the research method shows significant advantages in loading and unloading efficiency, cost control, and path optimization. The findings indicate that the proposed method for optimizing the organization of loading and unloading operations in railway logistics parks, based on queuing theory and a genetic algorithm, can effectively improve efficiency, reduce costs, and optimize transportation routes. The research method is of great significance for promoting the efficient operation of railway logistics parks and advancing the development of modern logistics systems.

Keywords: Railway logistics park; loading and unloading operations; loading and unloading equipment; queuing theory; genetic algorithm.

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1. Introduction

As modern logistics systems rapidly develop, railway logistics parks, as important logistics nodes, play a significant role in reducing logistics costs, improving regional economic quality, and achieving the dual carbon goals through efficient operations (Wei and Li, 2024). The railway logistics park not only provides basic functions of cargo transportation, warehousing, loading, and unloading, but also gradually offers additional services such as packaging, circulation processing, and distribution, becoming a key force in promoting the upgrading of the modern logistics system. At present, research on the organization and planning of loading and unloading operations in railway logistics parks has made certain progress. However, traditional methods for organizing and planning loading and unloading operations often struggle to achieve optimal resource allocation and efficient collaboration among operational processes in complex, ever-changing logistics environments (Wang, 2025). In addition, existing research still has shortcomings in dynamic resource scheduling and path optimization, making it difficult to fully meet the efficient operation needs of railway logistics parks. Queuing theory mainly studies the arrival process and service time of service objects, evaluates system performance using mathematical models, balances customer retention losses and service costs, and constructs an efficient and economical operating mechanism. Genetic Algorithms (GAs) can quickly optimize under complex constraints by simulating biological evolution mechanisms, achieving efficient matching of device scheduling, task timing, and path planning (Espitia-Mesa et al., 2025). Based on the above, a significant research gap exists in traditional methods for planning loading and unloading operations in railway logistics parks, which often suffer from insufficient global optimization, slow convergence, and ineffective dynamic scheduling and path planning in complex environments. To address this, this study aims to systematically improve operational efficiency, reduce costs, and optimize resource utilization through the following objectives. (1) Establishing a queuing theory-based model to optimize equipment configuration and reduce waiting times and congestion. (2) Constructing a GA-based model to enhance equipment scheduling, task sequencing, and path planning. (3) Validating the integrated model experimentally to demonstrate its advantages in accuracy, efficiency, and cost-effectiveness over traditional methods. Therefore, an innovative method for optimizing the organization of loading and unloading operations in railway logistics parks based on queuing theory and GA has been proposed, aiming to configure Loading and Unloading Equipment (LUE) to improve operational efficiency and service quality.

2. Related Works

Optimization of loading and unloading operations in railway logistics parks has garnered widespread attention, with existing research primarily focusing on operational safety, equipment scheduling, process automation, and system resilience. This analysis examines the shortcomings of existing studies through the lenses of safety and efficiency optimization of loading/unloading operations. The application of queuing theory in logistics systems. The solution to complex scheduling problems using GAs, and the development and limitations of integrated optimization methods. This serves to clarify the necessity and innovation of adopting a combined queuing theory and GA approach in this research.

As a core link in railway logistics parks, the safety and efficiency of loading and unloading operations directly impact overall operational performance. Meng et al. (2025) pointed out that the safety of these operations is often overlooked, and clarifying work safety categories while establishing strict operating procedures can effectively reduce accident rates. In terms of efficiency improvement, Zhang et al. (2024) proposed a mixed-integer linear programming model for automated container terminals, achieving efficient scheduling of LUE. In the field of hazardous goods handling, Claussner and Ustolin (2024) constructed a resilience assessment framework for liquid hydrogen terminal systems, significantly enhancing the safety of loading/unloading processes by analyzing accident databases and establishing safety barriers. Regarding automation, Mi et al. (2022) integrated deep learning with physical motion models to develop a real-time 3D pose measurement method, improving the safety performance of automated container handling. The synchronized loading/unloading yard crane scheduling method proposed by Gao et al. (2022, 2023), by optimizing equipment movement paths, effectively reduced crane idle time and container waiting time, enhancing the operational efficiency of underground container logistics systems.

As an effective tool for analyzing the operational efficiency of service systems, queuing theory has been widely applied in logistics and transportation. Wu and Geistefeldt (2024) developed a novel speed-flow model based on queuing theory that can more accurately describe the dynamic characteristics of highway traffic flow. In airport operations, Hu et al. (2023) established a multi-modal ground access queuing model, significantly improving passenger evacuation efficiency. In the field of port logistics, Xu et al. (2022) combined queuing theory with GAs to achieve integrated optimization of berth allocation and quay crane scheduling, effectively reducing vessel port time. These studies provide a theoretical basis and methodological framework for applying queuing theory to optimize equipment configuration in railway logistics parks.

GAs, by virtue of their powerful global search capabilities, have demonstrated excellent performance in solving complex constrained scheduling and path-planning problems. The hybrid GA proposed by Zhou et al. (2022) planned economically safe shipping routes for vessels under complex sea conditions, significantly reducing navigation time and fuel consumption. Torbi et al. (2025) used a method combining mixed-integer linear programming and GAs to optimize the scheduling of stackers and reclaimers in dry bulk terminals, improving resource utilization efficiency. The studies by Rahardji et al. (2024) and Zhu et al. (2024) further validated the effectiveness of GAs through mechanisms such as adaptive crossover operators and segmented integer encoding in solving combinatorial optimization problems, including equipment allocation and task sequencing.

Although existing research has begun to explore the integration of multiple methods, such as Xu et al. (2022), who successfully combined queuing theory and GAs for port optimization, significant shortcomings remain in addressing the complex operational scenarios of railway logistics parks. On the one hand, traditional planning methods struggle to coordinate dynamic resource scheduling and operational processes for optimization. On the other hand, most algorithms still have limitations in global search capability, convergence speed, and handling multidimensional constraints. Therefore, based on the complementary advantages of queuing theory and GAs, this research constructs an optimization method for the organization of loading/unloading operations in railway logistics parks. This approach both addresses the deficiencies of existing research and provides a new technical path to improve the operational efficiency of logistics parks.

In summary, although existing research has made progress in optimizing loading/unloading operations, a systematic optimization method tailored to the specific complexity of railway logistics parks has not yet been formed. To address this, this study proposes an innovative loading/unloading operation optimization scheme based on queuing theory and GAs, aiming to enhance the organization and planning efficiency of these operations within railway logistics parks. This research method not only enriches the theoretical system for organizing and planning loading/unloading operations in railway logistics parks but also provides effective technical support for practical applications, holding significant innovative value for promoting the development of modern logistics systems.

3. Methods and Materials

3.1. Optimization of Loading and Unloading Equipment Configuration in Railway Logistics Parks Based on Queuing Theory

Railroad consolidation and transportation play a crucial role in modern logistics. Its efficient operation is not only the core engine for reducing logistics costs and improving logistics efficiency, but also an important foundation for promoting the high-quality development of the regional economy and for implementing the dual-carbon strategy (Wu et al. 2023). The functional positioning of railway logistics parks should be based on a multidimensional condition analysis framework that integrates core elements such as strategic orientation, location characteristics, and the economic environment to develop a scientific functional planning scheme. The basic functional structure of the railway logistics park is denoted in Fig. 1.

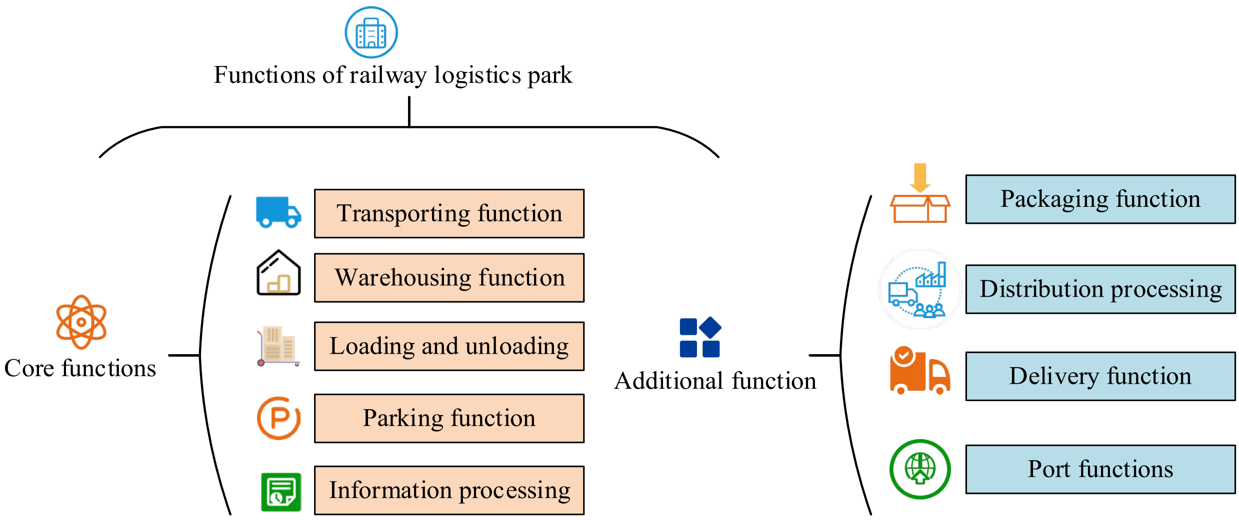


Fig. 1. Functional structure diagram of railway logistics park

As shown in Fig. 1, the functional system of the railway logistics park is divided into three levels: the basic functional level includes mainline transportation, material storage and distribution, standardized cargo loading and unloading, parking configuration, and intelligent scheduling. The extended functional layer includes industrial packaging, pre-processing in the supply chain, end-of-pipe distribution, and customs clearance services. The innovative service layer has developed high-end services, including supply chain finance and customized logistics solutions. Queuing theory can quantitatively analyze the characteristics of system queues and optimize service resource allocation by establishing a probability model of customer arrival and service duration (Johnston et al., 2022; Mas et al., 2022). Therefore, the study adopts queuing theory to optimize the loading and unloading process. The queuing model for loading and unloading operations in the railway logistics park is shown in Fig. 2.

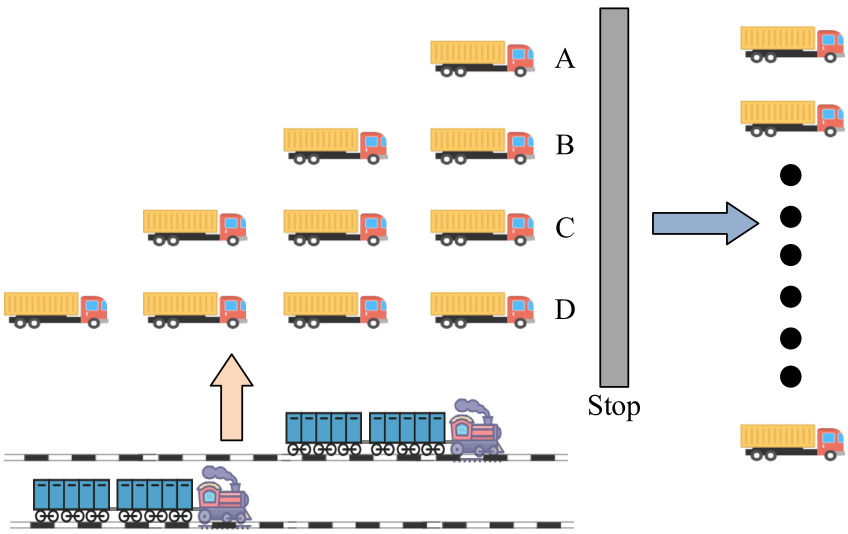


Fig. 2. Railway logistics loading and unloading queuing model

In Fig. 2, the model adopts a four-level priority queue scheduling mechanism, dividing vehicles into four queues, A, B, C, and D, according to their service levels. To ensure priority passage for high-priority vehicles, vehicles of the same level will pass on a first-come, first-served basis. The high-priority queue in the model has absolute service priority, and the model will schedule the next-level queue only when all higher-priority queues are empty. The symbolic expression of the queuing model for loading and unloading operations in railway logistics centers is shown in Eq. (1).

$$(A/B/C):(d/e/f) \tag{1}$$

In Eq. (1), A means the distribution of operating hours for loading and unloading machinery; B is the distribution of arrival intervals for freight trains. C is the number of loading and unloading machinery. d is a source restriction for freight trains. e is the limit for loading and unloading operations in railway logistics centers. f is the operating rule for LUE. The probability of all LUE being idle is shown in Eq. (2).

$$P_0 = \left[\sum_{k=0}^{C-1} \frac{\lambda^k}{\mu^k k!} + \frac{1}{C!}\left(\frac{\lambda}{\mu}\right)^C \left(\frac{1}{1-\rho}\right)\right]^{-1} \tag{2}$$

In Eq. (2), k represents the number of trains in the system. C represents the total number of LUE that can work simultaneously. P_0 represents the probability of all LUE being idle. $C!$ represents the total number of LUE that can work simultaneously. λ is the number of trains arriving per unit time. μ is the number of trains that have completed loading and unloading in a unit of time. ρ is the system utilization rate. The probability of having n Freight trains in the logistics center are shown in Eq. (3).

$$P_n = \begin{cases} \dfrac{\lambda^n}{\mu^n n!} P_0, & 1 \le n < C \\ \\ \dfrac{\lambda^n}{\mu^n C! C^{n-C}} P_0, & C \le n < \infty \end{cases} \tag{3}$$

In Eq. (3), P_n represents the probability of having exactly n freight trains in the logistics center. P_0 represents the probability that all LUE is idle. The calculation of the number of trains waiting for loading and unloading is shown in Eq. (4).

$$L_q = \sum_{n=0}^{\infty} n P_{n+C} = \frac{\rho \lambda^C}{\mu^C C! (1-\rho)^2} P_0 \tag{4}$$

The average waiting time for all incoming freight trains is calculated as denoted in Eq. (5).

$$W_q = \frac{L_q}{\lambda} = \frac{\rho \lambda^{C-1}}{\mu^C C! (1-\rho)^2} P_0 \tag{5}$$

In Eq. (5), W_q represents the average waiting time for all incoming freight trains. L_q represents the number of trains waiting for loading and unloading. The average dwell time of freight trains is shown in Eq. (6).

$$W_s = \frac{L_s}{\lambda} = \frac{L_q}{\lambda} + \frac{1}{\mu} = \frac{\rho \lambda^{C-1}}{\mu^C C! (1-\rho)^2} P_0 + \frac{1}{\mu} \tag{6}$$

In Eq. (6), W_s represents the average dwell time of freight trains in the system. L_s is the sum of the amount of loading and unloading trains and the number of trains to be loaded and unloaded. When the arrival volume of trains exceeds the railway logistics system's processing capacity, it causes operational congestion. The congestion probability is shown in Eq. (7).

$$P(n > N) = \sum_{n=N+1}^{\infty} \frac{1}{C! C^{n-C}} \left(\frac{\lambda}{\mu}\right)^n P_0 \tag{7}$$

In Eq. (7), $P(n > N)$ is the congestion probability. N is the maximum number of trains allowed to enter the railway logistics center. As the core hub of the logistics network, optimizing LUE configuration in railway logistics parks has a profound impact on overall operational efficiency, cost control, and service quality. Optimizing LUE configuration can reduce overall costs, avoid train waiting and cargo backlogs, and prevent resource waste from idle equipment. Large loading and unloading machinery usually adopts a fixed layout mode, and their installation positions strictly correspond to the loading and unloading lines of each functional area. On small mobile devices, when scattered, they can occupy a lot of space and affect equipment maintenance and management (Hayden et al., 2025). Therefore, small mobile devices are placed centrally. The operation process of the railway collection park is mainly divided into three parts: sending, arrival, and entry and exit. The operation process of the railway logistics park is shown in Fig. 3.

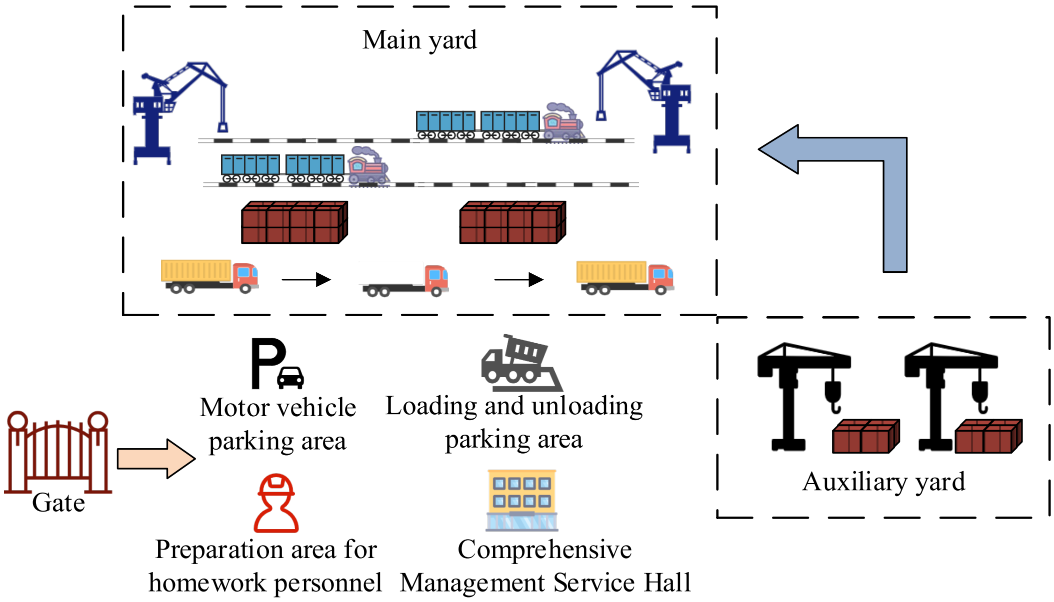


Fig. 3. Operation process of railway logistics park

As shown in Fig. 3, the logistics park includes a main yard, an auxiliary yard, a motor vehicle parking area, a loading and unloading machinery parking area, a waiting area for cargo loading operators, and a comprehensive management hall. The goods are transported by railway to the park, and then unloaded, inspected for quality, and classified. Qualified goods are temporarily stored in designated yards or storage areas. After the order is confirmed, they are sorted and loaded onto corresponding trains or other transportation vehicles according to the scheduling plan, and finally sent to the destination.

3.2. Optimization of Loading and Unloading Operation Organization Design in Railway Logistics Park Based on GA

By optimizing LUE configuration in railway logistics parks, operational efficiency has improved, operating costs have been reduced, and resource-intensive utilization has been achieved. To further achieve efficient matching between dynamic resource scheduling and job processes, a GA-based optimization model for the organization of loading and unloading operations is developed. GA simulates the biological evolution mechanism, quickly seeks optimization under complex constraints such as equipment scheduling, task timing, path planning, and coordinates the relationship between equipment utilization and operational processes, and ultimately achieves the globally optimal solution of efficiency, cost, and resource balance, and promotes the systematic upgrading of railroad logistics parks from static resource allocation to dynamic organization and management (Rahardja et al., 2024; Zhu et al.; 2024). The layout of the loading and unloading process in the railway logistics park is shown in Fig. 4.

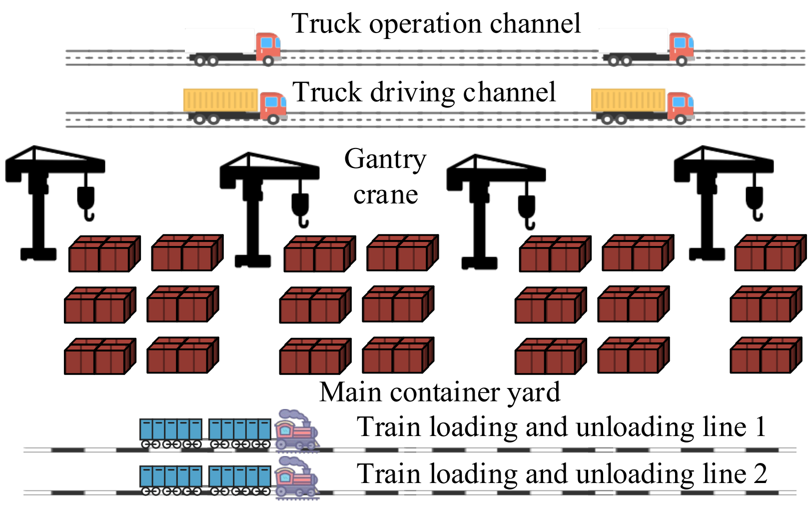


Fig. 4. Layout of railway logistics loading and unloading operation area

In Fig. 4, multiple loading and unloading areas are distributed along the railway line in the railway logistics park. Each loading and unloading area is equipped with multiple devices to ensure the safe transfer of goods from trains to trucks in the shortest possible time. The train is transported to the work area and unloaded into the main container yard. These six types are transported by train to the work area and loaded by truck. During loading and unloading operations, the delay time for rail gantry cranes and truck operations is shown in Eq. (8).

$$\begin{cases} F_1 = \min \max_{c \in C} T_c \\ F_2 = \min \mathrm{T}_i \end{cases} \tag{8}$$

In Eq. (8), F_1 means the objective function for delay time optimization. F_2 means the simplified objective function for delay time; T_i means the response lag time for emergency freight tasks. The peak hourly throughput of the gantry crane can be defined as T_c. The objective function of the optimization model is denoted in Eq. (9).

$$F = a_1 \min \max_{c \in C} \mathrm{T}_c + a_2 \min T_i \tag{9}$$

In Eq. (9), F represents the overall objective function. The a_1 and a_2 represent weight coefficients. The constraint condition that any loading and unloading operation unit must and can only be independently completed by one track-mounted gantry crane is denoted in Eq. (10).

$$\sum_{i \in I} \sum_{c \in C} x_i^c = 1 \quad \forall i, j \in I, c \in C \tag{10}$$

In Eq. (10), I represents the collection of all tasks that need to be performed in the railway logistics park. x_i^c represents a binary decision variable. Any two adjacent work tasks on the same gantry crane must satisfy a strict time-series relationship: the two consecutive operations of each gantry crane can only start after the previous task is completely completed. The constraint conditions are shown in Eq. (11).

$$st_j^c + M(1 - z_{ij}^c) \geq et_i^c + t_{ij}^c \quad \forall i, j \in I, c \in C \tag{11}$$

In Eq. (11), st_j^c represents the start time of the operation on the gantry crane. et_i^c represents the end time of the homework on the gantry crane. t_{ij}^c represents the time required for crane c to move from the location of task i to the location of task j. z_{ij}^c represents the binary sequence variable. M represents a sufficiently large constant. The constraint condition that rail gantry cranes cannot cross each other is shown in Eq. (12).

$$(i - j)(\sum_{c \in C} x_i^c \cdot c - \sum_{c' \in C} x_j^{c'} \cdot c') \geq 1 - M(z_{ij}^c + z_{ji}^c) \quad \forall i, j \in I, c, c' \in C \tag{12}$$

In Eq. (12), z_{ij}^c and z_{ji}^c represent the sequential relationship of tasks on the gantry crane and are binary sequential variables. To more effectively address the optimization problem of organizing container loading and unloading, a segmented integer coding mechanism is used to construct a scheduling solution. The chromosome is divided into two functional segments. The front segment is the task sequence coding area, and the back segment is the equipment mapping coding area (the gene value represents the door crane number assigned to the corresponding position task). The two genes establish a strict one-to-one mapping relationship through position indexing. This dual-segment encoding design not only ensures the feasibility of arranging and combining job sequences but also enables the precise allocation of equipment resources, which conforms to the GA encoding specification for solving combinatorial optimization problems. An example of chromosome-encoded decoding is shown in Fig. 5.

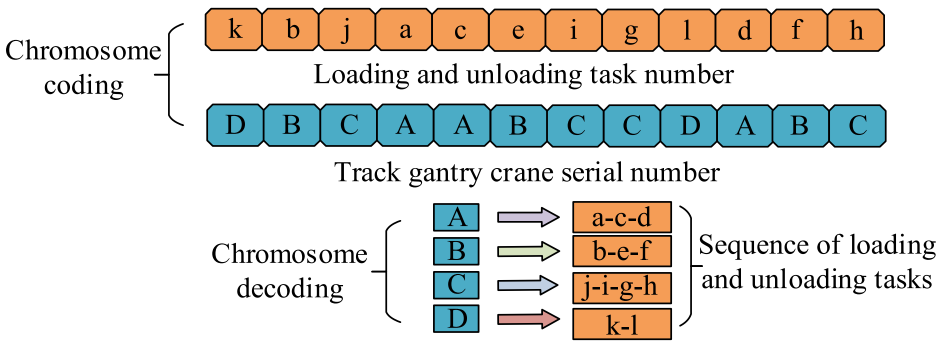


Fig. 5. Schematic diagram of chromosome encoding and decoding

According to Fig. 5, completing twelve container loading and unloading tasks requires the use of four gantry cranes. The A-track gantry crane executes task numbers A, C, and D in sequence. The B-track gantry crane executes task numbers b, e, and f in sequence. The C-track gantry crane executes task numbers j, i, g, and h in sequence. The D-track gantry crane executes task numbers k and l in sequence. In GAs, the fitness function is utilized to determine the quality of chromosomes in the GA population, and the corresponding fitness function is selected as shown in Eq. (13).

$$fit(i) = \frac{1}{F(i) + \mu} \tag{13}$$

In Eq. (13), $fit(i)$ represents the fitness of chromosome i, i represents the total cost function value of chromosome i, and μ denotes a positive real number within the $(0,1)$ interval. In the strategy selection section, the study constructs a probability function for elimination based on individual fitness size, as shown in Eq. (14).

$$P_x = \frac{1 - f_x}{\sum \tilde{n}_{x=1} f_x} \tag{14}$$

In Eq. (14), P_x represents the probability of being selected. $\tilde{n}$ represents the population size. f_x represents individual fitness. The crossover operator randomly determines exchange sites in its gene sequence, exchanges fragment genes according to preset recombination rules, and generates new individuals with parental characteristics. To facilitate the automated adjustment of the processing method, processing order, processing parameters, boundary conditions, and constraint conditions based on data characteristics during processing and analysis, with the objective of adapting to the statistical distribution characteristics and structural features of the processed data (Choudhuri et al., 2023), a crossover operator is introduced to calculate the crossover probability adaptively, as demonstrated in Eq. (15).

$$\begin{cases} \vec{P}_x = \vec{P}_{x1} - \dfrac{(\vec{P}_{x1} - \vec{P}_{x2})\left(\underset{x}{f\leftarrow} - \overline{f}_x\right)}{f_{max} - \overline{f}_x} \\ \underset{x}{f\leftarrow} \geq \overline{f}_x \\ \vec{P}_{x2} \\ \underset{x}{f\leftarrow} < \overline{f}_x \end{cases} \tag{15}$$

In Eq. (15), $\vec{P}_x$ represents the crossover probability of the current two parent individuals. $\vec{P}_{x1}$ and $\vec{P}_{x2}$ represent the preset maximum and minimum crossover probabilities. $\underset{x}{f\leftarrow}$ indicates the fitness value of the individual with higher fitness among the two parent individuals. $\underset{x}{f\leftarrow}$ indicates the max fitness value. $\overline{f}_x$ indicates the average fitness value. The specific process of GA is shown in Fig. 6.

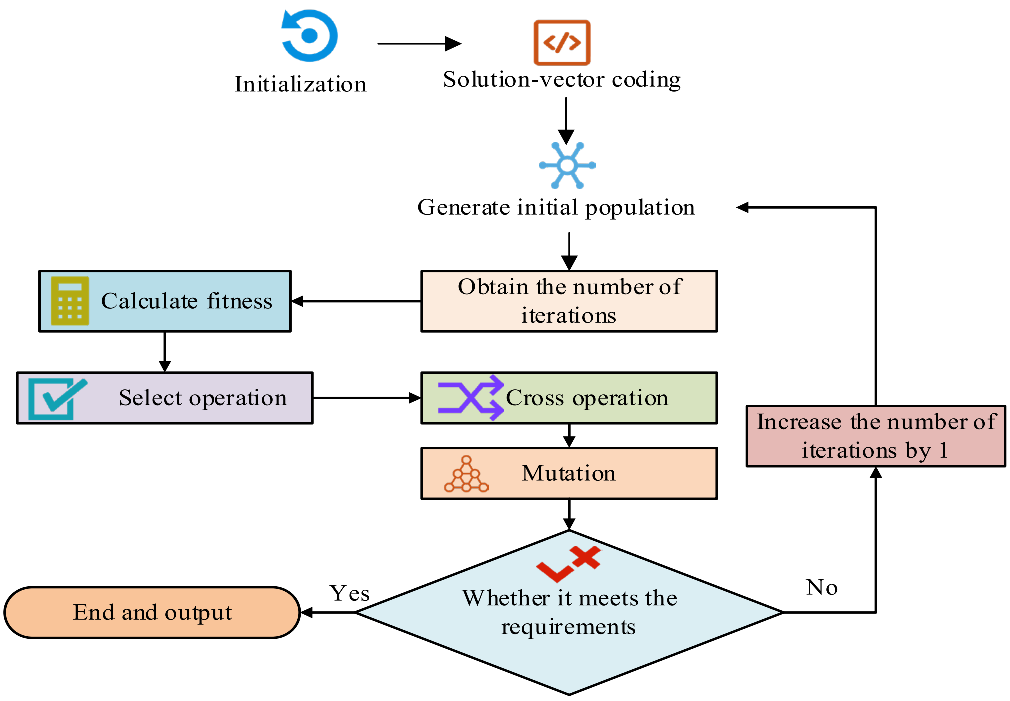


Fig. 6. Specific process of GA

As illustrated in Fig. 6, the GA performs iterative computations based on an initial population generated by encoding, with initialization achieved by randomly generating chromosome strings. The algorithm operates through the following sequential steps: initialization, in which the population size and genetic parameters are set, and the initial population is randomly generated. Encoding, which employs the segmented integer encoding mechanism to construct chromosomes comprising task sequence and equipment mapping segments. Fitness evaluation, which calculates the quality of each chromosome using the defined fitness function. Selection, which chooses individuals for reproduction based on their fitness, employs an elite-preservation strategy. Crossover, which recombines parent genes with an adaptive probability to generate new offspring; mutation, which introduces random variation to maintain population diversity, and termination check, which halts the algorithm upon reaching convergence criteria or the maximum number of generations, and outputs the optimal loading and unloading plan. This process essentially constructs a closed-loop optimization mechanism of "generation-evaluation-evolution," whose core lies in efficiently approximating the global optimum within the solution space through the directed search capability of genetic operators.

4. Results

4.1. Performance Testing of Loading and Unloading Operation Organization Planning Model in Railway Logistics Park

To test the research method, the experimental environment used a CPU (Intel Core i9-11900K), GPU (NVIDIA RTX 3090), 64GB DDR4 3200MHz memory, and Ubuntu 20.04 LTS operating system. The development framework was based on Python 3.8. The core logic of the algorithm was implemented through NumPy and SciPy. Path optimization parallel computing was completed by PyTorch. Ablation experiments were conducted to test the design method. In the design of ablation experiments, the study compared performance changes as improved modules were gradually added. The baseline model used traditional loading and unloading organization planning techniques. +Queuing theory refers to the incorporation of queuing theory techniques; +GA refers to the incorporation of GAs; Finally, the full model integrated all the improved modules to evaluate the overall performance improvement. The evaluation results are denoted in Table 1.

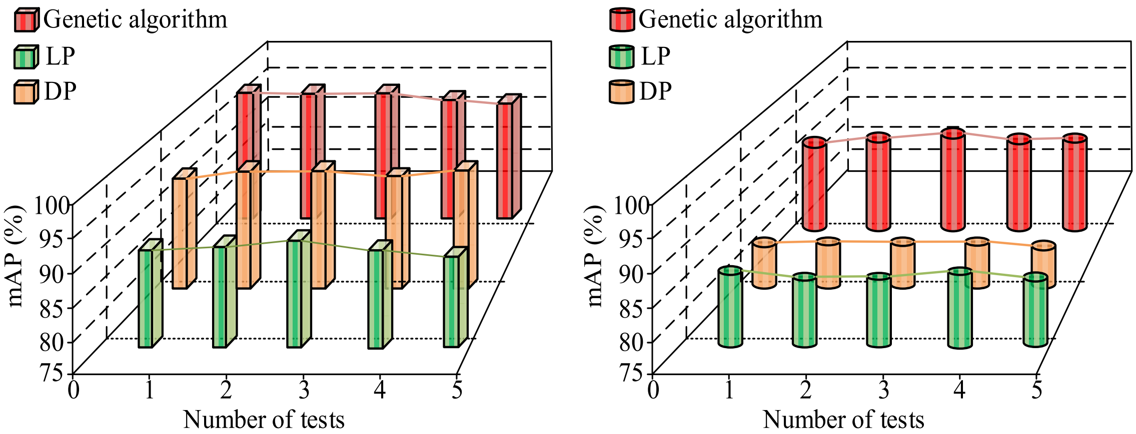
Table 1. Results of ablation experiment

Algorithm	Accuracy (%)	F1 score	Inference time (s)	*p*-value (vs. Traditional)
Traditional loading and unloading organization planning techniques	91.23	0.87	1.75	/
+Queuing theory	93.56	0.89	1.72	< 0.05
+GA	94.23	0.91	1.49	< 0.01
Full-model	96.52	0.93	1.43	< 0.001

According to Table 1, from the baseline model to the full model, accuracy showed a continuous improvement trend, gradually increasing from the initial 91.23% to 96.52%, fully demonstrating that the research method can effectively improve the efficiency and accuracy of the organization planning for loading and unloading operations in railway logistics parks. The accuracy of the traditional loading and unloading organization planning method was 91.23%, the F1 score was 0.87, and the inference time was 1.75 seconds. After introducing queuing theory on this basis, the accuracy increased to 93.56%, the F1 score increased to 0.89, and the inference time was slightly reduced to 1.72 seconds. When further combined with GA, the accuracy reached 94.23%, the F1 score was 0.91, and the inference time was significantly reduced to 1.49 seconds. The final full model performed the best with an accuracy of 96.52%, an F1 score of 0.93, and the shortest inference time. The study evaluated the performance of GAs, LP, and Dynamic Programming (DP) methods using Mean Average Precision (mAP) as an indicator, as shown in Fig. 7.

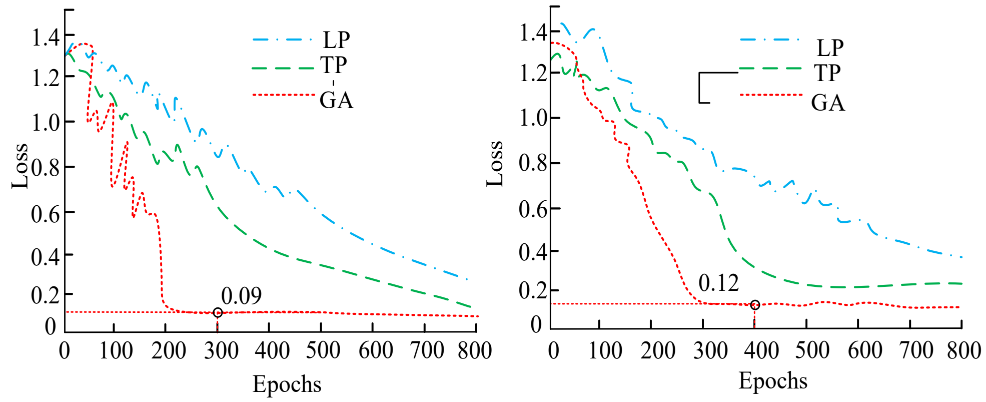
According to Fig. 7(a), during the daytime, the GA achieved a maximum of 96.89% on the mAP, significantly better than DP's 93.23% and LP's 88.93%. This indicates that the method can more comprehensively plan loading and unloading operations and reduce errors. From Fig. 7(b), at night, the highest mAP planned by the GA was 91.68%, which was also better than DP and LP, proving that the research method has strong generalization ability. The study compared changes in loss values across different methods for optimizing the organization of loading and unloading operations, as shown in Fig. 8.

In Fig. 8(a), during the daytime, the GA used in the study exhibited the fastest convergence rate, with a rapid decrease in loss and stabilization at 0.09 after 300 training sessions. In contrast, the loss value of the LP method decreased slowly and eventually stabilized at a slightly higher level than the research method. The decrease rate of TP loss value was between the two, and the final loss value was lower than LP but higher than GA. According to Fig. 8(b), at night, the GA used in the study still exhibited the fastest convergence rate, with a rapid decrease in loss and stabilization at 0.12 after 400 training sessions. In contrast, the loss value of the LP method decreased slowly and eventually stabilized at a slightly higher level than the research method. The decrease rate of TP loss value was between the two, and the final loss value was lower than LP but higher than GA. In summary, the research designed loading and unloading operation organization planning model is significantly superior to other methods, further verifying its robustness. This indicates that the model can maintain high positioning accuracy during both daytime and nighttime.



(a) In the day (b) At night

Fig. 7. Performance comparison of different algorithms

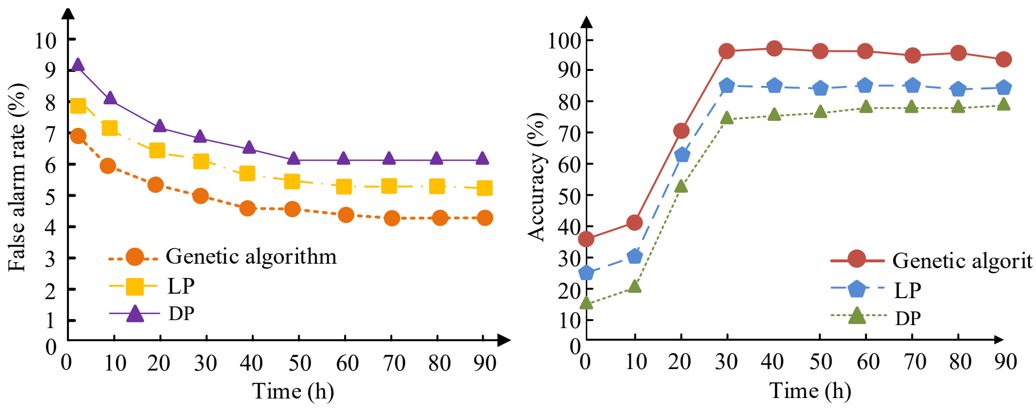


(a) In the day (b) At night

Fig. 8. Changes in loss value

4.2. Practical Application Testing of Loading and Unloading Operation Organization Planning Model in Railway Logistics Park

To verify the effectiveness of the designed loading and unloading operation organization planning model in practical applications, the loading and unloading data of a railway logistics park were selected for research and analysis. The accuracy and loading/unloading organization planning repetition rate within 90 hours obtained by comparing the GA used with LP and DP are shown in Fig. 9.



(a) Planning repetition rate (b) Detection accuracy

Fig. 9. Accuracy and repeatability of loading and unloading planning

In Fig. 9(a), the planning repetition rate of the research method rapidly decreased from the initial 6.82% to 4.57% after 40 hours and remained stable thereafter. The planned repetition rate of LP rapidly decreased in the early stages of testing, dropping to 7% after 20 hours, then gradually stabilized at 5.31%. The false alarm rate of DP gradually decreased from the initial 9.14% to 6.51% after 50 hours, then stabilized. According to Fig. 9(b), the planning accuracy of the research method increased rapidly from the initial 42.54% to 96.84% around 30 hours, and remained stable thereafter. The planning accuracy of LP rapidly increased in the early stages of testing, reaching around 80.81% within 30 hours, and gradually stabilized thereafter. The planning accuracy of DP increased slowly in the early stages of testing, reaching 74.32% in 30 hours and stabilizing. The research method is highly feasible and effective. The comparison of loading and unloading weight and efficiency between traditional planning methods and four LUE using the research method shown in Fig. 10.

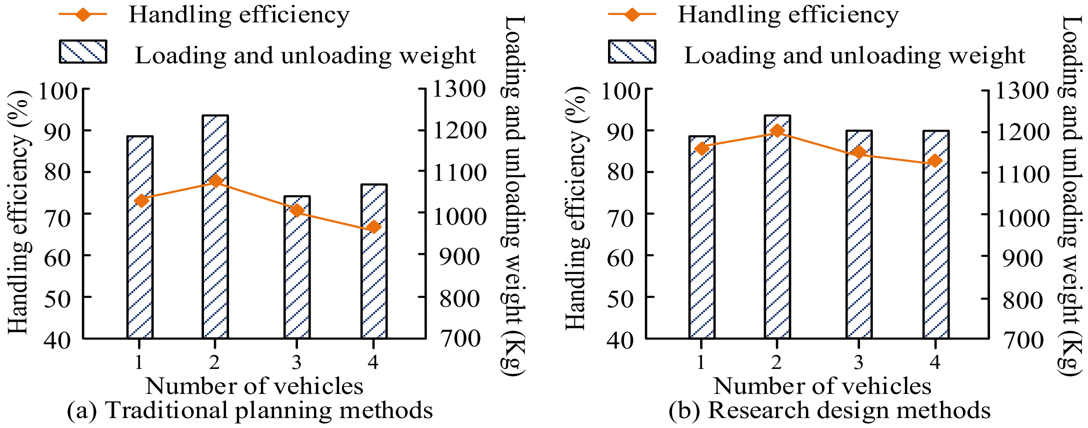


Fig. 10. Comparison of loading and unloading weight and efficiency

In Fig. 10(a), when using traditional planning methods, the loading and unloading weights of the four LUE were 1195 kg, 1249 kg, 1050 kg, and 1080 kg, respectively, with loading and unloading efficiencies of 72.5%, 75.8%, 71.3%, and 69.7%, respectively. In Fig. 10(b), when using the research design planning method, the loading and unloading weights of the LUE were 1195 kg, 1249 kg, 1200 kg, and 1190 kg, respectively. The loading and unloading weights of the LUE were 86.5%, 91.3%, 86.2%, and 83.8%, respectively. It can be seen that the research design planning method can effectively improve loading and unloading efficiency and reduce costs. The comparison between the original loading and unloading operation transportation path and the optimal transportation path using the research model is shown in Fig. 11.

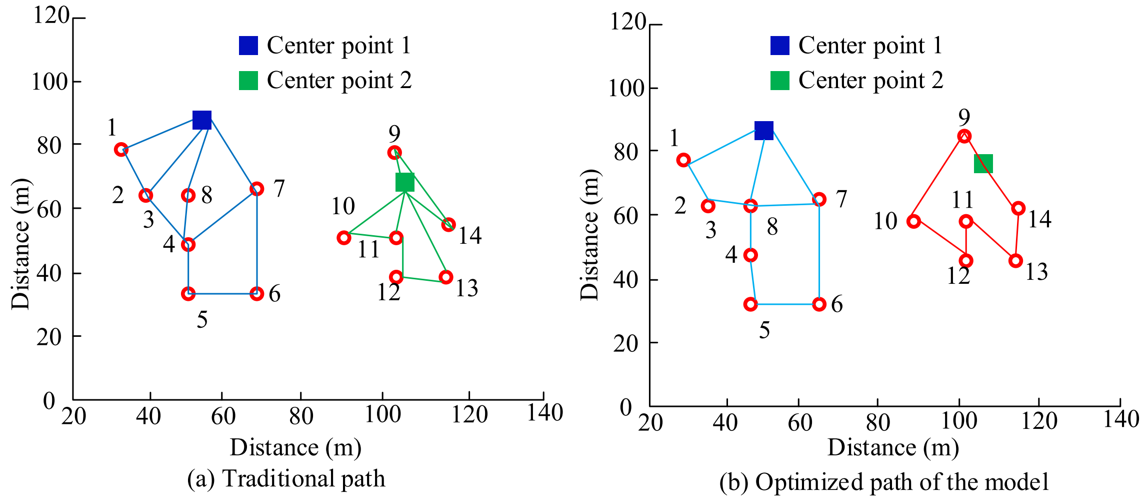


Fig. 11. Comparison diagram of original path and optimal path

As shown in Fig. 11(a), the original loading and unloading transportation route was more chaotic, with a more complex, varied path. There were many intersecting lines and unnecessary detours along the path. This path not only increased the total distance traveled but also led to longer transportation time and increased costs, making it clearly not the optimal transportation strategy. As shown in Fig. 11(b), the loading and unloading transportation paths generated by the research model were orderly, fully demonstrating the GA's excellent ability to optimize path problems. It is clear that the connections between service points are clean and direct, with almost no intersections or duplications, thereby greatly reducing travel distance and transportation time. Inefficient routes, such as backtracking, were effectively avoided, thereby maximizing overall transport efficiency. The findings indicate that the research model effectively optimizes the loading and unloading transportation path and can generate more concise and efficient loading and unloading transportation plans.

5. Conclusion

The research aimed to optimize the organization and planning of loading and unloading operations in railway logistics parks, improve operational efficiency, reduce costs, and promote the development of modern logistics systems. The study adopted a queuing theory-based optimization method for LUE configuration and a GA-based optimization model for the organization design of loading and unloading operations. The experimental results showed that by introducing queuing theory and GA, the accuracy of the organization planning for loading and unloading operations improved to 96.52%, the F1 score reached 0.93, and the inference time was shortened to 1.43 seconds. Compared with traditional loading and unloading organization planning methods, the optimized model showed significant advantages in loading and unloading efficiency, cost control, and path optimization. The planning repetition rate was reduced to 4.57%, and the average loading and unloading efficiency of LUE increased from 72.5% to 86.5%, effectively improving the overall efficiency of loading and unloading operations. In terms of transportation path optimization, the optimized path reduced unnecessary intersections and detours. The statistical significance of these improvements ($p < 0.001$) strongly validates the efficacy of the proposed method. Furthermore, the proposed model is designed for seamless integration with existing railway systems through standardized data interfaces, acting as a decision-support module within the current operational framework. It can connect to Railway Operation Management Systems (ROMS) or Terminal Operating Systems (TOS) via Application Programming Interfaces (APIs) to ingest real-time data on train schedules, yard inventory, and equipment status. A recommended phased deployment strategy, starting with a parallel “digital twin” mode for validation, progressing to a human-supervised decision-support role, and eventually achieving limited automation for specific tasks, ensuring smooth adoption without disrupting established workflows. This integration empowers dispatchers with optimized equipment schedules and transportation paths, directly resulting in reduced train turnaround times, lower operational costs, and enhanced asset utilization, thereby improving system efficiency without necessitating a complete infrastructure overhaul. Although significant achievements have been made in optimizing the organization of loading and unloading operations in railway logistics parks, there are still some shortcomings. The current testing data is concentrated in a single logistics park and does not account for complex interference factors, such as extreme weather and large-scale equipment failures. Future research should expand beyond multi-scenario verification to explore several promising directions. These include integrating the model with AI-based predictive maintenance systems to create a joint optimization framework that coordinates operational scheduling with equipment health management, thereby minimizing unexpected downtime. Furthermore, investigating real-time dynamic rescheduling capabilities in response to emergent disruptions, extending the model to coordinate multi-modal transportation networks beyond the railway park, and incorporating human-in-the-loop collaborative decision-making mechanisms represent critical steps towards building more resilient, adaptive, and comprehensive intelligent logistics systems.

Author Contributions

ChiMeihui Wang contributed to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision, project administration, and funding acquisition. Lina Guo contributed to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision, project administration, and funding acquisition.

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Institutional Review Board Statement

Not applicable.

Declaration of Artificial Intelligence (AI) Tools

The authors used AI tools solely for language editing and readability improvement. The authors reviewed and verified all content and take full responsibility for the accuracy and integrity of the manuscript.

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