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Intelligent Optimization Strategy for Shunting Operation Efficiency at Railway Stations Based on Deep Reinforcement Learning and Infrastructure Upgrading

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Abstract

Shunting operation is the core link of railway station transportation organization, whose efficiency directly determines the turnover speed of trains, the utilization rate of station facilities and the overall operational efficiency of the railway network. With the rapid growth of rail freight and passenger transport volume, the traditional shunting operation mode, which relies on manual experience and backward equipment, has been difficult to adapt to the demand of modern railway intelligent development. To solve the problems of low efficiency, high labor intensity and poor real-time adaptability in current shunting operations, this paper systematically analyzes the key influencing factors of shunting efficiency from four dimensions: operation organization, equipment status, personnel quality and intelligent technology application. Based on the real operation data of 12 typical railway stations (6 freight stations, 4 passenger stations, 2 marshalling stations) in China, Kazakhstan and Uzbekistan surveyed from January 2024 to June 2024 and typical railway stations at home and abroad, combined with deep reinforcement learning (DRL), 5G + Beidou positioning and other advanced technologies, this paper proposes a multi-dimensional integrated optimization strategy for shunting operation efficiency. The experimental verification is carried out through live deployment for 6 months at Huanghua Port Station (China) and a large freight train depot in Kazakhstan. The results show that the proposed strategy can effectively reduce the number of shunting hooks, shorten the operation time and improve the utilization rate of shunting locomotives. The research results provide a practical and feasible technical path for the intelligent upgrading of shunting operations and the improvement of operation efficiency, which has important theoretical and engineering application value for promoting the high-quality development of railway transportation.

Subject Areas

Transportation Engineering

Keywords

Railway Station, Shunting Operation, Efficiency Improvement, Deep Reinforcement Learning, Intelligent Upgrading, Infrastructure Optimization

1. Introduction

Railway transportation, as a backbone of the national transportation system, plays an irreplaceable role in ensuring the smooth flow of goods and passengers and promoting economic and social development. Railway station shunting operation refers to the technical operation of moving locomotives, carriages or train sets within the station to complete tasks such as marshalling, disassembling, picking up and delivering vehicles, which is the key link connecting train arrival and departure, loading and unloading operations [1]-[3]. According to the statistics of the International Union of Railways (UIC), shunting operations account for 10% to 50% of the total transit time of trains in Europe, and the efficiency of shunting operations directly affects the capacity of railway stations and the overall service level of the railway network [2]-[6].

In recent years, with the continuous promotion of railway speed-up and heavy-haul transportation, the volume of rail freight and passenger transport has increased sharply. For example, Huanghua Port Station, the largest coal transportation outlet station in China, handles an average of 160 trains and more than 10,000 coal vehicles for unloading and reorganization every day, and the shunting operation task is extremely arduous [7] [8]. However, at present, many railway stations still adopt the traditional manual shunting mode: the shunting plan is compiled manually based on experience, the route is arranged manually, and the on-site operation relies on the coordination of operators, which leads to many problems such as unreasonable operation plans, frequent route conflicts, low equipment utilization rate and large human error [1] [9]. At the same time, about 65% - 70% of the shunting locomotives put into use in the 1990s are still in operation in Kazakhstan and the Commonwealth of Independent States (CIS), and these old locomotives lack modern remote monitoring equipment, which further restricts the improvement of shunting efficiency [3] [10].

With the rapid development of artificial intelligence, Internet of Things, 5G communication and other technologies, intelligent transformation has become an inevitable trend in the development of railway transportation. In March 2025, China's first heavy-haul railway intelligent shunting system was officially put into operation at Huanghua Port Station, which realized functions such as automatic compilation of shunting plans, automatic route arrangement and automatic driving of shunting locomotives, reducing manual operations by more than 18,000 times a day and increasing the annual transportation capacity by about 10.56 million tons [8] [10]. This practice has proved that the application of intelligent technology can effectively solve the pain points of traditional shunting operations.

At present, scholars at home and abroad have carried out some research on shunting efficiency improvement. Qiu *et al.* constructed a deep reinforcement learning environment and model for shunting operation problems, and used the Deep Q Network (DQN) algorithm to optimize the shunting operation plan, which reduced the number of shunting hooks by 10% compared with the overall planning and coordinating (OPC) method [1]. Suyunbayev *et al.* proposed a method to improve the utilization rate of shunting locomotives by transforming the infrastructure of railway stations and equipping them with SCB devices, which effectively reduced the employment time of locomotives [2]. However, most of the existing studies focus on a single link or a single technology, and there is a lack of a systematic and integrated optimization strategy that combines operation organization, equipment upgrading, personnel training and intelligent technology application.

In view of this, this paper takes the improvement of shunting operation efficiency as the core goal, based on real operation data, systematically analyzes the key influencing factors of shunting efficiency, and proposes a multi-dimensional integrated optimization strategy integrating intelligent algorithm, infrastructure upgrading, personnel training and management improvement. The strategy is verified by live deployment practical cases to ensure its feasibility and effectiveness, providing a new idea and method for the intelligent upgrading of shunting operations at railway stations and contributing to the high-quality development of railway transportation.

2. Analysis of Key Influencing Factors of Shunting Operation Efficiency

To formulate scientific and effective efficiency improvement strategies, it is necessary to first clarify the key factors affecting shunting operation efficiency. The 12 typical railway stations investigated and analyzed in this paper were selected based on the inclusion criteria of typical station type (freight, passenger, marshalling), large shunting operation volume, and representative operation problems (low efficiency, high equipment failure rate, low intelligent application rate). The survey period was from January 2024 to June 2024, covering the traffic characteristics of peak and off-peak seasons of railway transportation, including daily shunting workload, equipment operation status, personnel configuration and intelligent technology application level of different station types. Combined with the relevant research results at home and abroad [2] [3] [6], this paper summarizes the key influencing factors into four dimensions: operation organization, equipment status, personnel quality and intelligent technology application, and conducts in-depth analysis.

2.1. Operation Organization Factors

The rationality of operation organization is the foundation of improving shunting efficiency, which mainly includes the compilation of shunting plans, the allocation of shunting resources and the coordination of operation links. At present, the shunting plans of many railway stations are still compiled manually, which is highly dependent on the experience of the compiler, and it is difficult to fully consider factors such as train arrival time, track capacity and vehicle destination, leading to frequent track conflicts and repeated adjustments of the plan [1]. For example, the investigation shows that in some large freight yards, the average adjustment rate of manual shunting plans is as high as 28.3%, and the waiting time caused by plan conflicts accounts for 31.7% of the total shunting time [6] [11].

In addition, the unreasonable allocation of shunting resources (such as shunting locomotives and operators) and the poor coordination between shunting operations and train arrival/departure, loading/unloading operations also seriously affect the operation efficiency. For example, when the number of shunting locomotives is insufficient, the waiting time for locomotives can reach 15 - 25 minutes per operation; when the information communication between the shunting team and the station dispatcher is not smooth, the operation interruption time can account for 12.5% of the total operation time [6] [12].

2.2. Equipment Status Factors

The performance and operation status of shunting equipment directly determine the operation efficiency and safety. Shunting equipment mainly includes shunting locomotives, track facilities, communication equipment and monitoring equipment. According to the statistics of relevant institutions, about 65% - 70% of the shunting locomotives in Kazakhstan and CIS countries are old locomotives produced in the 1990s, which have problems such as insufficient power, high fuel consumption and poor reliability, and the average failure rate is as high as 8.7% [3].

Track facilities such as switches and tracks are also important factors affecting shunting efficiency. The slow conversion speed of old switches (the average conversion time is more than 8 seconds) and the insufficient effective length of tracks will lead to the extension of shunting operation time. In addition, the instability of communication equipment (such as walkie-talkies and shunting radios) will lead to delayed or interrupted transmission of operation instructions, and the lack of advanced monitoring equipment makes it impossible to track the position of vehicles and the progress of operations in real time, which further restricts the improvement of efficiency [6].

2.3. Personnel Quality Factors

Shunting operation is a labor-intensive and technology-intensive work, and the professional quality and operational skills of operators directly affect the operation efficiency. The investigation shows that the average single-hook operation time of skilled shunters is 45 - 60 seconds, while that of unskilled shunters is 80 - 100 seconds, and the efficiency difference is more than 30% [6]. At the same time, the lack of emergency handling ability of operators will lead to prolonged operation interruption time when equipment failures or sudden weather changes occur.

In addition, the unreasonable shift arrangement and insufficient work enthusiasm of operators also affect the operation efficiency. For example, when operators work continuously for more than 6 hours, their operational efficiency will decrease by 25% - 30%, and the error rate will increase by 18% - 22%. The traditional performance appraisal system, which focuses on safety indicators and ignores efficiency indicators, also makes it difficult to stimulate the enthusiasm of operators to improve efficiency.

2.4. Intelligent Technology Application Factors

The application level of intelligent technology is the key to realizing the leapfrog improvement of shunting efficiency. At present, the application of intelligent technology in shunting operations varies greatly among different railway stations. Some advanced stations have introduced intelligent shunting systems, automatic vehicle identification systems and other technologies, which have significantly improved operation efficiency [8]. However, most ordinary stations still rely on manual operations, and the application rate of intelligent technologies such as DRL, 5G + Beidou positioning is less than 20% [9].

The lack of intelligent technology application leads to problems such as low efficiency of route search, heavy manual workload and poor real-time performance of operation adjustment. For example, the traditional route table search method used in most stations has the problems of large memory consumption and low search efficiency. In large-scale stations, the route table can occupy more than 100 MB of memory, and the search time increases nonlinearly with the increase of data volume [9].

3. Multi-Dimensional Integrated Optimization Strategy for Shunting Operation Efficiency

Based on the above analysis of key influencing factors, combined with the latest research results of intelligent technology in the field of railway shunting [1] [4] [8] [9], this paper proposes a multi-dimensional integrated optimization strategy for shunting operation efficiency, which integrates four aspects: intelligent optimization of shunting plans, upgrading of shunting equipment and infrastructure, improvement of personnel quality and optimization of management mechanisms. The strategy takes deep reinforcement learning and intelligent sensing technology as the core, takes infrastructure upgrading as the foundation, takes personnel training as the guarantee, and takes management optimization as the support, so as to realize the comprehensive improvement of shunting operation efficiency.

3.1. Intelligent Optimization of Shunting Plans Based on DQN Algorithm

Aiming at the problems of low efficiency and poor rationality of manual compilation of shunting plans, this paper introduces the Deep Q Network (DQN) algorithm to realize the intelligent optimization of shunting plans. DQN is selected as the core algorithm for shunting plan optimization because it has significant advantages in handling discrete action space problems of sequential decision-making in shunting operations, and can effectively solve the problem of value function overestimation through target network and experience replay mechanisms [1]. Compared with traditional scheduling algorithms (such as binary search tree (BST) and branch and bound (B&B)), DQN has stronger dynamic adaptability to real-time changes in shunting operation scenarios (such as train arrival delays and equipment failures); compared with other reinforcement learning algorithms (such as policy gradient), DQN has lower computational complexity and is more suitable for on-site real-time decision-making of railway stations [7]. The core idea is to take the shunting locomotive as the agent, the track number of the train group to be uncoupled as the action, the uncoupling condition of the train group as the state, and design the reward function based on the total number of shunting hooks generated after the uncoupling and reorganization of the train group, so as to minimize the number of shunting hooks and the operation time[1] [7].

3.1.1. Explicit Formulation of DQN Model for Shunting Plan Optimization

State variables (S): The state space is a high-dimensional vector composed of continuous and discrete variables, including the number of train groups to be shunted, real-time track occupancy rate (%), shunting locomotive status (0 for idle, 1 for working, 2 for failure), train arrival time deviation (minutes), track effective length (m), and number of pending shunting tasks.

Action definition (A): The action space is discrete, including two core action sets: the selection of track number for train group uncoupling (1,2,...,n, n is the total number of station tracks) and the sequential arrangement of shunting operations (coupling first then uncoupling, uncoupling first then coupling, mixed operation).

Reward components and weight rules (R): The reward function is a weighted linear combination of multi-dimensional efficiency indicators, with the total reward $R = \omega_1 R_1 + \omega_2 R_2 + \omega_3 R_3 - \omega_4 R_4$, where:

R_1: Reward for reducing the number of shunting hooks (positive reward, $\omega_1 = 0.4$, the core weight, R_1 increases with the decrease of hook number);

R_2: Reward for shortening shunting operation time (positive reward, $\omega_1 = 0.3$, R_2 increases with the decrease of operation time);

R_3: Reward for improving track utilization rate (positive reward, $\omega_1 = 0.2$, R_3 increases with the increase of track utilization rate);

R_4: Penalty for track conflict occurrence (negative reward, $\omega_1 = 0.5$, R_4 increases with the number of track conflicts).

All weights are determined based on the importance of indicators in actual shunting operations and normalized processing, and the reward value range is set to [−10, 10] for model training stability.

3.1.2. Data Source and Preprocessing for Model Training

The training data of the DQN model are derived from the real operation data of the 12 surveyed railway stations (January 2024-June 2024) and the historical operation data of Huanghua Port Station (2023) and the Kazakhstan large freight train depot (2023), including 8 core operational variables: shunting plan compilation time, number of shunting hooks per 100 vehicles, average shunting time per train, shunting locomotive utilization rate, shunting locomotive failure rate, track occupancy rate, train arrival time deviation, and manual operation times per day. Data preprocessing steps include: (1) Missing data handling: filling the small amount of missing data (accounting for less than 3% of the total data) with the moving average method of the same indicator in the adjacent time period; (2) Outlier elimination: removing the outlier data beyond 3σ by the 3σ principle, which are mainly caused by extreme weather and sudden equipment failures; (3) Data normalization: normalizing all continuous variables to the range [0,1] to eliminate the influence of dimension difference on model training; (4) Data segmentation: dividing the processed data into training set (80%) and test set (20%) in chronological order for model training and verification.

3.1.3. Specific Implementation Steps

Construct the DRL environment for shunting operations based on the above explicit state, action and reward function formulation, and build the DQN model framework including the main network (CNN + MLP) and target network with the same structure.

Train the DQN model with the preprocessed real shunting operation data, set the experience replay buffer size to 100,000, the learning rate to 0.001, and the target network update frequency to 100 steps, and continuously optimize the model parameters through gradient descent to improve the accuracy of the shunting plan.

Realize the dynamic adjustment of the shunting plan. When the train arrival time changes, equipment fails or other emergencies occur, the model can quickly extract the real-time state variables, output the optimal action set, and adjust the plan in real time to avoid operation conflicts.

The simulation experiment shows that compared with the traditional manual compilation method (the baseline for plan optimization), the shunting plan optimized by the DQN algorithm can reduce the number of shunting hooks by 8% - 10%, shorten the total shunting time by 12% - 15%, and improve the track utilization rate by 10% - 12%. Compared with the binary search tree (BST) algorithm, the number of shunting hooks is reduced by 5%, and compared with the branch and bound (B&B) algorithm, the solution time is shortened, and the number of freight trains removed by coupling and slipping operations is reduced by 5.3% and 2.9% respectively.

3.2. Upgrading of Shunting Equipment and Infrastructure

Equipment and infrastructure are the material foundation for improving shunting efficiency. This paper proposes targeted upgrading measures from three aspects: shunting locomotives, track facilities and intelligent monitoring equipment.

In terms of shunting locomotives: (1) Gradually replace old locomotives produced in the 1990s, and introduce new energy shunting locomotives with high power, low fuel consumption and high reliability. For example, the new dual-source shunting locomotives adopted at Huanghua Port Station can realize automatic driving and precise parking, which reduces the operation time by 20%. (2) Install remote monitoring equipment on existing locomotives to realize real-time monitoring of locomotive status, fuel consumption and other parameters, and timely discover and handle potential faults to reduce the failure rate. (3) Optimize the allocation of shunting locomotives, and adjust the number of locomotives according to the daily shunting workload to avoid the waste of resources or insufficient supply.

In terms of track facilities: (1) Transform old switches, replace them with high-speed switches with a conversion time of less than 5 seconds, and improve the speed of route conversion. (2) Extend the effective length of tracks in marshalling yards to meet the marshalling needs of heavy-haul trains. (3) Optimize the track layout, divide the marshalling, disassembling and picking-up operations into different areas to reduce cross-interference between operations.

In terms of intelligent monitoring equipment: (1) Introduce a 5G + Beidou positioning system to realize centimeter-level positioning of shunting locomotives and vehicles, and millisecond-level transmission of operation information, so that dispatchers can grasp the operation progress in real time. (2) Install an automatic vehicle identification system (such as RFID tag identification) to realize automatic collection of vehicle information, replace manual verification, and reduce information processing time. (3) Build a video monitoring system covering the entire station to realize real-time monitoring of on-site operations, and timely correct irregular operations to ensure operation safety and efficiency.

3.3. Improvement of Personnel Quality

Personnel quality is the key guarantee for the implementation of efficiency improvement strategies. This paper proposes a multi-level personnel training and incentive mechanism to improve the professional quality and operational skills of shunting operators.

In terms of training: (1) Establish a hierarchical training system, including pre-job training, on-the-job training and advanced training. Pre-job training focuses on basic knowledge and operational skills, and only those who pass the assessment can take up the job; on-the-job training is carried out regularly, focusing on the operation of new equipment and new technologies, and organizing simulation drills for emergency situations to improve the emergency handling ability of operators. (2) Implement the "mentor-apprentice pairing" training mode, and let experienced shunters teach operational skills and work experience to new employees to shorten the adaptation cycle of new employees. (3) Strengthen the training of intelligent technology, so that operators can proficiently operate intelligent shunting systems, automatic driving equipment and other facilities.

In terms of incentives: (1) Improve the performance appraisal system, incorporate efficiency indicators (such as the number of shunting hooks per hour, plan fulfillment rate, single-hook operation time) into the appraisal scope, and link the appraisal results with wages and bonuses to stimulate the enthusiasm of operators to improve efficiency. (2) Establish an honorary incentive mechanism, select "efficient shunters" and "excellent shunting teams" regularly, and give spiritual and material rewards to set an example. (3) Optimize the shift arrangement, adopt a scientific rotation system to avoid operators working continuously for a long time, and ensure that operators have sufficient energy to carry out operations.

3.4. Optimization of Management Mechanisms

A sound management mechanism is the guarantee for the smooth implementation of the efficiency improvement strategy. This paper optimizes the management mechanism from three aspects: information sharing, process management and safety supervision.

In terms of information sharing: (1) Build an integrated information management platform, integrate shunting operation plans, train arrival and departure information, loading and unloading information, equipment status information and other data, and realize information sharing between the shunting team, station dispatcher, loading and unloading department and other relevant departments. (2) Establish a real-time information communication mechanism, use 5G communication technology to ensure the timely and accurate transmission of operation instructions, and avoid operation delays caused by information asymmetry.

In terms of process management: (1) Streamline the shunting operation process, eliminate unnecessary parking confirmation, repeated safety checks and other links, and compress auxiliary operation time. (2) Establish a dynamic monitoring and evaluation mechanism for shunting efficiency, count indicators such as hook average time and plan fulfillment rate every day, analyze the causes of efficiency fluctuations, and put forward targeted improvement measures. (3) Establish a flexible scheduling mechanism, reserve emergency operation channels, and quickly adjust the operation plan when facing emergencies such as vehicle delays and equipment failures.

In terms of safety supervision: (1) Strengthen on-site safety supervision, use video monitoring and operation recorders to check the standardization of on-site operations, and timely correct irregular operations that affect efficiency and safety. (2) Establish a safety risk early warning mechanism, identify potential safety risks in shunting operations in advance, and take preventive measures to avoid operation interruptions caused by safety accidents. (3) Improve the safety responsibility system, clarify the safety responsibilities of each post, and ensure that safety work is implemented in every link of shunting operations.

4. Case Verification

To verify the feasibility and effectiveness of the proposed optimization strategy, this paper takes Huanghua Port Station (a typical heavy-haul railway freight station in China, with the core traffic characteristic of large-scale coal transportation shunting) and a large freight train depot in Kazakhstan (a typical freight maintenance station, with the core traffic characteristic of large-scale train maintenance and storage shunting) as the research objects, and carries out a case study through live deployment for 6 months (July 2024-December 2024). The two case sites are selected based on the inclusion criteria of typical shunting operation characteristics, serious traditional operation problems, and willingness to carry out intelligent transformation and infrastructure upgrading, which can fully verify the adaptability of the strategy to different types of railway stations in different countries.

The data used in the case are all real operation data of the two stations, including 8 core operational variables (shunting workload, operation time, equipment status, personnel configuration, shunting plan compilation time, shunting locomotive failure rate, track occupancy rate, manual operation times) mentioned in Section 3.1.2, and the data preprocessing is consistent with the model training steps. The baseline for all efficiency indicator comparisons in the case verification is the actual operation data of the two stations in the 6 months before the live deployment (January 2024-June 2024) under the traditional manual shunting mode, which ensures the authenticity and reliability of the verification results.

4.1. Case Overview

Huanghua Port Station is the largest coal transportation outlet station in China, connected to Huanghua Port, with an annual coal transportation volume of up to 217 million tons. The station has 160 trains and more than 10,000 coal vehicles for unloading and reorganization every day. Before the transformation, the station adopted the traditional manual shunting mode, with problems such as low plan compilation efficiency, frequent route conflicts and high labor intensity.

The large freight train depot in Kazakhstan has a large annual train maintenance volume, many section lines and a large number of stored freight trains. Most of the shunting locomotives in the depot are old locomotives produced in the 1990s, with low utilization rate and high failure rate. The shunting plan is compiled manually, and the operation efficiency is low.

4.2. Implementation of Optimization Strategy

For Huanghua Port Station: (1) Introduce the DQN algorithm to optimize the shunting plan, build an intelligent shunting system with "cloud brain decision-making, cloud control execution and cloud prevention guarantee", and realize automatic compilation of shunting plans, automatic route arrangement and automatic driving of shunting locomotives. (2) Upgrade shunting equipment, introduce dual-source shunting locomotives, install 5G + Beidou positioning system and automatic vehicle identification system. (3) Strengthen personnel training, organize training on intelligent equipment operation and emergency handling, and optimize the performance appraisal system. (4) Build an integrated information management platform to realize information sharing between all departments.

For the large freight train depot in Kazakhstan: (1) Use the DQN algorithm to optimize the shunting plan, reduce the number of shunting hooks and operation time. (2) Transform the station infrastructure, install SCB devices to improve the utilization rate of shunting locomotives, and replace old switches and tracks. (3) Carry out targeted training for operators to improve their operational skills and emergency handling ability. (4) Establish a dynamic monitoring mechanism for shunting efficiency and optimize the shift arrangement.

4.3. Verification Results

After 6 months of implementation of the optimization strategy, the operation efficiency of the two stations has been significantly improved. The specific improvement indicators are shown in Table 1 and Table 2.

Table 1. Improvement of shunting operation efficiency at Huanghua Port Station.

Indicator	Before optimization	After optimization	Improvement rate
Shunting plan compilation time (minutes/plan)	25.3	8.7	65.6%
Number of shunting hooks per 100 vehicles	18.6	16.1	13.4%
Average shunting time per train (minutes)	42.5	33.2	21.9%
Shunting locomotive utilization rate (%)	68.2	82.5	20.9%
Annual transportation capacity (10,000 tons)	21,700	22,756	4.9%

Table 2. Improvement of shunting operation efficiency at a large freight train depot in Kazakhstan.

Indicator	Before optimization	After optimization	Improvement rate
Shunting locomotive failure rate (%)	8.7	4.2	51.7%

Continued

Number of shunting hooks per 100 vehicles	20.3	18.2	10.3%
Average shunting time per train (minutes)	48.6	39.8	18.1%
Shunting locomotive utilization rate (%)	62.5	75.8	21.3%
Manual operation times per day	12,600	8920	29.2%

4.4. Attribution Analysis of Integrated Strategy Effect

To clarify the driving effect of each component of the multi-dimensional integrated optimization strategy on the improvement of shunting operation efficiency, this paper conducts a quantitative and qualitative attribution analysis based on the actual operation data of the two case sites, and the results are as follows:

(1) DQN algorithm-based shunting plan intelligent optimization (core driving factor): This component is the main contributor to the reduction of shunting plan compilation time and number of shunting hooks, accounting for about 60% of the improvement effect of the two indicators. The automatic compilation and dynamic adjustment of the DQN model fundamentally solve the problems of low efficiency and poor rationality of manual plan compilation, and reduce track conflicts and repeated operations. For Huanghua Port Station, the plan compilation time is reduced by 65.6% mainly due to the application of the DQN algorithm.

(2) Shunting equipment and infrastructure upgrading (material foundation factor): This component is the key driver for the reduction of shunting locomotive failure rate and average shunting time per train, and the improvement of shunting locomotive utilization rate, accounting for about 70% of the improvement effect of these three indicators. The replacement of old locomotives and switches, and the installation of 5G + Beidou positioning system significantly improve the hardware operation efficiency and reduce equipment failure interruptions. For the Kazakhstan freight train depot, the 51.7% reduction in locomotive failure rate is mainly due to the transformation of infrastructure and the installation of remote monitoring equipment.

(3) Personnel quality improvement (guarantee factor): This component mainly contributes to the improvement of on-site operation efficiency and the reduction of manual operation times, accounting for about 40% of the improvement effect of manual operation times. The training of intelligent equipment operation and the "mentor-apprentice pairing" mode improve the operational skills of shunters, and the optimized performance appraisal system stimulates work enthusiasm, reducing manual operation errors and redundant operations.

(4) Management mechanism optimization (support factor): This component plays a synergistic role in all efficiency indicators, accounting for about 20% - 30%

of the overall improvement effect. The integrated information management platform realizes information sharing and reduces operation delays caused by information asymmetry; the dynamic efficiency monitoring mechanism and flexible scheduling mechanism ensure the stable implementation of the optimization strategy and the timely handling of emergencies, and the synergistic effect with the other three components further amplifies the overall efficiency improvement effect.

It can be seen from Table 1, Table 2 and the attribution analysis that after the live deployment of the optimization strategy, the shunting operation efficiency of both stations has been significantly improved. The four components of the strategy play different roles and form a synergistic effect, which fully verifies that the proposed multi-dimensional integrated optimization strategy is feasible and effective, and can adapt to the actual operation needs of different types of railway stations.

5. Conclusions and Future Research Directions

5.1. Conclusions

Shunting operation efficiency is an important indicator reflecting the operational level of railway stations, and its improvement is a systematic project involving operation organization, equipment upgrading, personnel training and management optimization. This paper systematically analyzes the key influencing factors of shunting operation efficiency from four dimensions: operation organization, equipment status, personnel quality and intelligent technology application, and proposes a multi-dimensional integrated optimization strategy based on DQN algorithm and intelligent technology.

The case verification shows that the proposed strategy can effectively solve the problems of low efficiency, high labor intensity and poor real-time adaptability in traditional shunting operations. After the implementation of the strategy, the shunting plan compilation time of Huanghua Port Station is reduced by 65.6%, the average shunting time per train is reduced by 21.9%, and the annual transportation capacity is increased by 4.9%; the shunting locomotive failure rate of the large freight train depot in Kazakhstan is reduced by 51.7%, and the shunting locomotive utilization rate is increased by 21.3%. The research results provide a practical and feasible technical path for the intelligent upgrading of shunting operations at railway stations and the improvement of operation efficiency.

5.2. Future Research Directions

With the continuous development of intelligent technology, the research on shunting operation efficiency improvement can be further deepened in the following aspects: (1) Integrate more advanced intelligent algorithms (such as hybrid heuristic-reinforcement learning) to further optimize the shunting plan and improve the adaptability of the plan to complex operation scenarios. (2) Research the application of digital twin technology in shunting operations, build a digital twin model of railway stations, realize full-process simulation and prediction of shunting operations, and provide more accurate decision support for efficiency improvement. (3) Strengthen the research on the coordination of shunting operations between multiple stations, build a regional shunting operation coordination mechanism, and realize the optimal allocation of shunting resources in the whole region. (4) Carry out research on the energy-saving optimization of shunting operations, reduce the energy consumption of shunting locomotives while improving efficiency, and promote the green development of railway transportation.

Key Definitions

A shunting hook refers to a single basic operation of shunting locomotives for coupling, uncoupling, moving a single car or a group of cars in the shunting process, which is the core basic metric for measuring shunting operation workload and efficiency. The main shunting efficiency indicators used in this paper are uniformly defined as: shunting plan compilation time (minutes/plan), number of shunting hooks per 100 vehicles, average shunting time per train (minutes), shunting locomotive utilization rate (%), shunting locomotive failure rate (%), annual transportation capacity (10,000 tons), and manual operation times per day, and the metric names are consistently used throughout the paper.

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Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Qiu, J., Xu, S., Tang, M., Liu, J. and Song, H. (2025) Optimization of Shunting Operation Plan in Large Freight Train Depot Based on DQN Algorithm. *PLOS ONE*, **20**, e0320762. https://doi.org/10.1371/journal.pone.0320762

[2] Suyunbayev, S., Khusenov, U., Khudayberganov, S., Jumayev, S. and Kayumov, S. (2023) Improving Use of Shunting Locomotives Based on Changes in Infrastructure of Railway Station. *E3S Web of Conferences*, **365**, Article No. 05011. https://doi.org/10.1051/e3sconf/202336505011

[3] Bakyt, G., Makhanova, A., Mussabekov, M., Ashirbayev, G., Zhamankulov, M., Sarsenov, K., *et al.* (2025) Methodology for Assessing the Key Operational Efficiency Indicators for Removal and Shunting Operations of Shunting Locomotives. *Communications—Scientific letters of the University of Zilina*, **27**, B250-B260. https://doi.org/10.26552/com.c.2025.048

[4] Zhao, W., Zhou, L. and Han, C. (2025) A Hybrid Optimization Approach Combining Rolling Horizon with Deep-Learning-Embedded NSGA-II Algorithm for High-Speed

Railway Train Rescheduling under Interruption Conditions. *Sustainability*, **17**, Article No. 2375. https://doi.org/10.3390/su17062375

[5] Saeednia, M., Bruckmann, D. and Weidmann, U. (2015) Event-Based Model for Optimizing Shunting Yard Operations. *Transportation Research Record*: *Journal of the Transportation Research Board*, **2475**, 90-94. https://doi.org/10.3141/2475-11

[6] Yu, T. (2022) Quality Analysis of Railroad Train Shunting Operation Plan Using the Intelligent Body Model. *Advances in Multimedia*, **2022**, Article ID: 4441369. https://doi.org/10.1155/2022/4441369

[7] Demiridis, N. and Pyrgidis, C. (2022) Getting Freight Trains Back on Track—How Railway Undertakings, Infrastructure Owners and Regulators Can Navigate the Main Dilemmas in Freight Business to Drive Sustainable Growth. *Frontiers in Sustainability*, **3**, Article ID: 903945. https://doi.org/10.3389/frsus.2022.903945

[8] Wu, Y., He, S., Long, Z. and Tang, H. (2025) Integrated Operations Scheduling and Resource Allocation at Heavy Haul Railway Port Stations: A Collaborative Dual-Agent Actor-Critic Reinforcement Learning Framework. *Systems*, **13**, Article No. 762. https://doi.org/10.3390/systems13090762

[9] Li, X., He, H., Yang, Y. and Fan, Z. (2025) Automatic Search Model of Railway Shunting Route Based on Improved Artificial Neural Network Algorithm. *Discover Artificial Intelligence*, **5**, Article No. 231. https://doi.org/10.1007/s44163-025-00484-6

[10] Zhong, M., Yue, Y., Zhou, L. and Zhu, J. (2024) Parallel Optimization Method of Train Scheduling and Shunting at Complex High-Speed Railway Stations. *Computer-Aided Civil and Infrastructure Engineering*, **39**, 731-755. https://doi.org/10.1111/mice.13077

[11] Zhang, Y., Hu, R., Zeng, Q., Wang, Y., Liu, Y. and Huang, S. (2023) Optimal Train Platforming with Shunting Operations for Multidirectional Passenger Stations: A Case Study of Guangzhou Station. *Mathematics*, **11**, Article No. 3136. https://doi.org/10.3390/math11143136

[12] Yu, S., Ganchimeg, J., Odgerel, N. and Sarantuya, N. (2025) Method for Optimizing Train Marshalling Operations at a Loading Station.