A Closed-Loop Intelligent Control Framework for Automated Railway Shunting in Marshalling Yards

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Keywords: fuzzy analytic hierarchy process (F-AHP), graph neural network (GNN), rolling-horizon optimization, intelligent marshalling yard, closed-loop control

Received: July 18, 2025

Accurate and efficient railway shunting operations are crucial for the operation of intelligent marshalling yards. This article proposes a closed-loop scheduling method that integrates fuzzy analytic hierarchy process (F-AHP), graph neural network (GNN), and multi-objective optimization algorithm to achieve intelligent and automated shunting operations through the "perception decision execution" chain. The system integrates multi-source sensor data (train position, switch status, track occupancy, etc.), uses GNN for track conflict prediction, and determines multi-objective weights based on F-AHP. Combined with multi-objective optimization, it generates Pareto optimal scheduling scheme. The experiment was conducted at a large marshalling yard in the southwest region, and the results showed that compared with manual scheduling, the system reduced the average operating time by 35.7% ± 2.1%, single task energy consumption by 21.4% ± 1.5%, and scheduling conflict rate by 87.5% ± 3.2%, while improving judgment accuracy to 97.8% (evaluated over 20 runs with $p < 0.01$).The research has verified the comprehensive advantages of the proposed method in terms of efficiency, energy consumption, and safety, and has the ability to transplant and expand across stations. To support reproducibility, we also specify the optimization model, variable and constraint definitions, the GNN architecture (features, loss, hyper-parameters), and the rolling-horizon settings with quantified latency budgets.

Povzetek: Opisan je zaprtozančni sistem za avtomatizirano železniško razvrščanje, ki združuje F-AHP, GNN-napovedovanje konfliktov in drsečo MILP-optimizacijo. V realnem ranžirnem centru izboljša učinkovitost.

1 Introduction

The shunting operation of railway marshalling yards is an important part of the railway freight system, and its operational efficiency and safety directly affect the transportation capacity of the entire network. With the continuous growth of transportation demand, the shortcomings of traditional manual scheduling mode in terms of efficiency, stability, and safety under complex working conditions have become increasingly apparent, promoting the application and development of intelligent and automated technology in marshalling yards. Despite advances in scheduling optimization, device control, and path planning, most existing methods only address plan generation. They lack real-time interaction with the execution layer, leading to delays during unexpected tasks or equipment failures. Moreover, many approaches are tailored to a single yard layout, limiting their portability to other sites. In response to the above issues, this article proposes a closed-loop "perception decision execution" automated scheduling architecture for intelligent marshalling yards, which integrates fuzzy analytic hierarchy process (F-AHP), graph neural network (GNN), and multi-objective optimization algorithm to achieve multi-objective trade-offs between scheduling efficiency, energy consumption, and safety; By implementing modular deployment and standardized interface mechanisms, the portability and adaptability of the system in different types of sites can be improved; And it was tested and verified in a large marshalling yard in the southwest region, and the results showed that the system maintained high operational stability and accuracy while improving operational efficiency by 35.7%, reducing single task energy consumption by 21.4%, and reducing scheduling conflict rate by 87.5%. This result verifies the feasibility and practical value of the proposed method.

2 Related work

Although intelligent transformation is of great significance in railway marshalling yard shunting operations, its implementation in practice still faces many challenges. The shunting environment is complex, nonlinear, and strongly coupled, with stringent requirements for dynamic response. Achieving precise scheduling and efficient execution in this context remains a core challenge in automated path design. Similar to load fluctuations in the power grid, changes in train flow, train formation sequence, and switch status in marshalling yards exhibit suddenness and uncertainty. Therefore, numerous studies have attempted to construct efficient automated scheduling systems from dimensions such as optimization models, equipment control, path planning, and shunting plan generation to cope with complex operating conditions.

Existing studies can be broadly classified into three categories: (i) vehicle positioning and track state perception technologies to enable digitalization of the yard; (ii) optimization algorithms for shunting paths and operation sequences; and (iii) automation strategies emphasizing system-level collaboration and scenario integration. For example, Hyun-Suk et al. (2024) proposed an RFID–odometer fusion method for shunting vehicle localization, which significantly improved intra-yard positioning accuracy [6]. Buryakovskiy et al. (2020) optimized the performance of shunting diesel locomotives to enhance traction efficiency and stability [7], while Suyunbayev et al. (2023) investigated locomotive utilization strategies considering infrastructure adjustments [8].

In terms of shunting optimization, Huan et al. (2023) applied graph-theoretic models to sequence operations on tree-shaped dedicated lines and designed a feasible adjustment algorithm [9]. Zhong et al. (2023) developed a parallel optimization model for high-speed railway stations, jointly optimizing train operations and shunting tasks to improve resource utilization [10]. Zhao and Dick (2023) further studied the joint optimization of train platform layout and shunting at Guangzhou Station, effectively reducing regrouping frequency and improving formation efficiency [11]. These works underline the balance between scheduling feasibility and execution efficiency, aligning with the goals of refined and high-speed yard operations.

Zhao et al. (2024) [12] formulated a routing and scheduling model for marshalling yards to jointly minimize conflicts and improve throughput. Other studies explored the coupling between service sequences and operational controllability. For instance, Xu and Dessouky (2022) [13] introduced a service-scheduling mode for high-speed railway depots to improve coordination under dense traffic, while Ming et al. (2022) [14] optimized EMU maintenance shunting to enhance formation efficiency.

More recently, Deleplanque et al. (2022) [15] conducted a systematic review of freight yard train management methods, highlighting the need for integrated control and feedback mechanisms. Tao (2022) [16] applied intelligent agent modeling for multidimensional evaluation of shunting plans. A.D.S et al. (2022) [17] proposed a selection framework for multi-stage train classification and facility design parameters. Additionally, Mohammed et al. (2022) [18] incorporated the DMAIC quality-control cycle into shunting service optimization, forming a continuously improving closed-loop process.

In order to facilitate a comprehensive comparison between existing research and the method proposed in this paper, relevant literature will be organized according to dimensions such as method type, dataset and scenario, evaluation indicators, main contributions, and existing shortcomings. The specific comparison is shown in Table 1.

Table 1: Comparison of existing research and improvement points in this paper

Research Source	Method / Technique	Dataset & Scenario	Evaluation Metric(s)	Main Contribution	Identified Limitation	Improvement in This Paper
Hyun-Suk et al. (2024) [6]	RFID + Odometer Positioning	Real station yard	Positioning Accuracy	Improved intra-yard train localization	Lacks closed-loop scheduling control	Added perception–decision–execution closed loop
Buryakovskiy et al. (2020) [7]	Locomotive Performance Optimization	Yard field tests	Power Efficiency	Enhanced operational stability of shunting locomotives	No integration with scheduling optimization	Combined locomotive efficiency with scheduling optimization
Suyunbayev et al. (2023) [8]	Locomotive Utilization Strategy	Infrastructure change scenarios	Operational Efficiency	Adjusted utilization of shunting locomotives	Infrastructure-specific, limited adaptability	Embedded into modular scheduling framework
Huan et al. (2023) [9]	Graph-theoretic Sequencing Model	Dedicated line shunting	Sequence Feasibility, Efficiency	Proposed algorithm for wagon pickup/delivery sequences	Focused on single-line topology	Integrated into generalized multi-yard scheduling
Zhong et al. (2023) [10]	Parallel Optimization Model	High-speed station simulation	Scheduling Efficiency, Utilization	Joint optimization of train operations and shunting tasks	Limited generalization across yard types	Developed modular architecture for cross-yard deployment
Zhao & Dick (2022) [11]	Simulation Analysis (AnyLogic)	Hump yard simulation	Throughput, Delay, Track Utilization	Quantified effect of classification track length	No dynamic feedback mechanism	Incorporated into conflict-aware real-time optimization
Zhao et al. (2024) [12]	Routing & Scheduling Optimization	Marshalling yard simulation	Throughput, Conflict Rate	Formulated routing and scheduling model for yards	Limited validation with real deployments	Embedded GNN conflict prediction + rolling horizon mechanism

As shown in Table 1, our method differs from earlier locomotive optimization [7,8] and shunting sequence models [9–11] by embedding conflict-aware GNN prediction and F-AHP weighted objectives into a deployable closed-loop framework, bridging the gap between theoretical models and engineering practice.

Based on the above research, existing achievements still have shortcomings in closed-loop feedback control, real-time adaptive capability, and cross scenario generalization: lack of closed-loop control: most methods only optimize plan generation and lack real-time linkage with the execution layer. Lack of real-time performance: When sudden tasks or equipment abnormalities occur, response speed is limited and scheduling continuity is poor. Weak generalization ability: Most methods are designed for a single station and lack mechanisms to adapt to marshalling yards of different sizes.

Compared with prior works that mainly optimized plan generation or individual modules, this article highlights novelty in end-to-end system integration. Specifically, we (i) combine F-AHP weighting with GNN-based conflict prediction within a rolling-horizon optimizer, (ii) provide a unified interface design enabling deployment across heterogeneous yards, and (iii) validate the closed-loop ‘perception–decision–execution–feedback’ chain in a real large-scale yard environment. In contrast, existing frameworks such as digital twin yard simulators or grades-of-automation standards [3,5,13] have not yet reported yard-scale field trials with quantified KPIs. This positions our contribution as an engineering blueprint with verifiable deployment evidence. Building on these insights, the following section presents the technical framework that integrates perception, optimization, and control into a unified closed-loop system.

Despite advances in module optimization and scheduling logic, automation in marshalling yards still faces key challenges. Further breakthroughs are required in system integration, functional collaboration, and closed-loop perception–decision–execution mechanisms. The current difficulties of the railway shunting system are mainly reflected in the following aspects:

Shunting data is sparse and heterogeneous. The relevant state variables are discrete and distributed, including train sequences, switch statuses, and plan adjustments. Most existing models rely on historical patterns or static plans and lack real-time perception or prediction of traffic dynamics.

Insufficient ability in spatial-temporal collaborative modeling. At present, most of the scheduling and execution systems are designed in a decoupled way. They issue instructions directly after making decisions, and lack feedback mechanisms. Some optimization algorithms ignore the dynamic evolution of the workflow. Building a collaborative mechanism that covers station structure, job timing, real-time status, and feedback control is the core of achieving system level automation.

The system evaluation relies on a single scenario and has weak generalization ability. Most methods are based on specific stations or simulation environments for validation, lacking adaptability testing for different types of marshalling yards and task categories, resulting in insufficient engineering feasibility.

To address the aforementioned issues, this article focuses on the following research questions:

Does the automation system architecture proposed in this article have advantages over traditional manual scheduling in terms of response speed, execution accuracy, and system stability?

How to achieve intelligent control of the entire process of complex shunting tasks through a closed-loop "perception decision execution" mechanism?

Can the built system adapt to multiple scenarios and tasks, and has the ability to promote and engineering feasibility?

Based on the above issues, this article proposes the following technical contributions:

Develop a unified overall architecture that can adapt to the working characteristics of the marshalling yard, and coordinate the intelligent scheduling system with the perception, control, and execution modules to enhance the responsiveness of operations and the reliability of the system.

Build a scheduling control process with state feedback and dynamic correction mechanisms to achieve dynamic matching between plan generation and on-site status, and improve execution efficiency and decision-making accuracy.

Through on-site data and simulation verification, the system outperforms traditional manual scheduling modes in terms of efficiency, accuracy, and stability, and has good deployment adaptability and potential for promotion.

3 Technical framework design for automation transformation of railway shunting operations

In the automation technology framework proposed in this study, the architecture design combines the fusion of perception recognition system to obtain data and the intelligent decision-making system for shunting operation to optimize work allocation. This is because both methods have their own advantages in solving complex combination problems. Through the integration of data from multiple sources and the joint deployment of multiple sensors, effective information acquisition of vehicle numbers, status positions, and driving trajectories can be achieved, especially in environments with high noise and poor manual recognition effects in shunting workplaces. This will improve work safety and information accuracy. The intelligent decision-making system relies on rule engines and dynamic routing optimization algorithms, based on the data generated during on-site work, to complete automatic simulation and route design of grouping work teams. It has self-learning and control characteristics, and is particularly suitable for complex work with many changes in the working environment. In this work, shunting scheduling is formulated as a mixed-integer linear programming (MILP) problem under interlocking and capacity constraints, solved in a rolling-horizon manner with second-level updates; conflict risk is predicted by a supervised graph neural network (GNN) trained on annotated yard logs.

Unlike the traditional process that relies on human intuition to formulate shunting instructions, the introduction of digital replicas enables the visualization of the entire shunting task process, integrating historical, current, and predictive data. This enables the early verification of shunting paths and real-time detection of track resource conflicts, reducing unnecessary shunting frequency and resource waste. High speed real-time sensor information will be automatically transmitted to the intelligent scheduling system, using track utilization prediction tools to generate the optimal job sequence, replacing fixed combinations based on humans, improving overall work response and system controllability.

Compared with other transformation paths such as pure hardware automatic traction systems or fixed grouping logic, the solution that integrates scheduling perception and intelligent optimization modules has significant advantages in system adaptability and scene migration capability. Although some high-end systems, such as fully enclosed automatic marshalling yards, can achieve full process unmanned operation, their deployment costs are high and they rely heavily on infrastructure, making it difficult to meet the common renovation needs of multiple types and levels of stations in China. The architecture proposed by this research institute emphasizes modular deployment and gradual upgrading, which can gradually achieve the transition of shunting operations from "human control as the mainstay" to "system guidance" without completely replacing existing facilities.

The architecture proposed in this article includes four core modules: the perception data layer is responsible for multi-source information collection and fusion; Optimize the decision-making layer by using F-AHP weight calculation, GNN conflict prediction, and multi-objective optimization to generate scheduling plans; The homework execution layer is responsible for implementing the plan into locomotives, switches, and signal systems; The execution feedback layer monitors the execution status in real-time and dynamically adjusts scheduling instructions. The four-layer modules are interconnected through a unified standard interface, forming a closed-loop process of "job formulation path simulation job execution feedback adjustment", as shown in Figure 1.

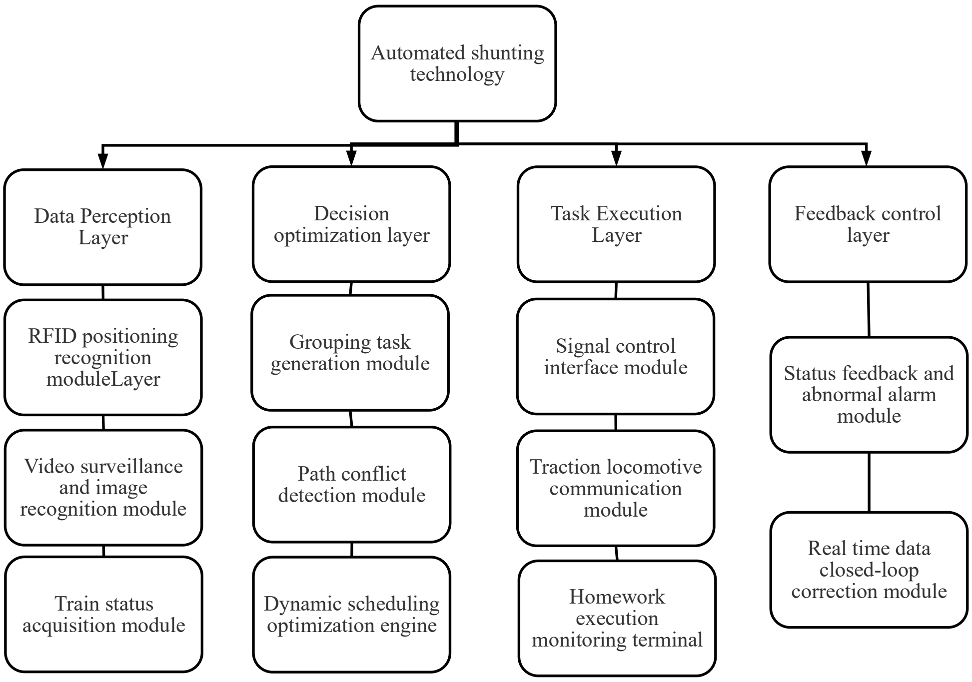

Figure 1: Overall framework diagram of automated shunting technology. Modules are grouped into four layers (perception, decision, execution, feedback) with standardized interfaces.

Figure 1 shows the overall framework of automated shunting technology, which illustrates the functional division and data flow relationship of the perception data layer, optimization decision layer, job execution layer, and execution feedback layer. Each module communicates through standardized interfaces to achieve closed-loop control from job formulation, path simulation to execution feedback.

3.1 Core functions and technical support of intelligent scheduling system

This article proposes and constructs an intelligent scheduling system framework, which includes two parallel parts: on the one hand, the track usage recognition module realizes real-time acquisition of the track, switch, and train usage status of the marshalling yard; On the other hand, the workflow development and optimization module generates dynamic shunting instructions. This system solves the problems of a large number of shunting route conflicts, delayed adjustment of operation plans, and insufficient execution flexibility in traditional marshalling yard scheduling. Its core idea is to optimize the spatiotemporal coordination of shunting operations. Integrate data on track usage from multiple sources (track circuits, electronic switch signals, train positioning, etc.) and provide a time-series model of track usage. This type of data is a two-dimensional matrix (time steps x track number) that expresses the spatial state distribution of the dynamic working environment. It extracts important features of available dynamic arrangements based on the usage relationship between tracks, shunting conflict relationship, and task priority relationship.

The initial variable group $X_0 = [X_1, X_2, X_3, \ldots X_i]$ input to the track state analysis module represents the state of each track unit within a given time window, where represents the real-time occupancy status of the i-th track. Based on this, the system establishes an occupancy rate evolution map to capture the distribution pattern of job loads. To enhance the intelligence of path selection, the system further introduces the track conflict intensity matrix C, which defines the degree of shunting conflict between any two tracks. The conflict-intensity matrix CCC is defined as follows:

$$C_{ij}=\frac{1}{T}\sum_{t=1}^{T} I(o_i(t)=1\wedge o_j(t)=1\wedge routeOverlap(i,j,t)) \quad (1)$$

where $o_i(t)$ is the occupancy of track iii at time ttt, TTT is the number of time steps, and routeOverlap(i,j,t) indicates interlocking overlap. Symbols: N—number of tracks; Δt=1s—step size. The system first constructs a shunting task set $T = \{T_1, T_2, \ldots, T_n\}$, each task containing attributes such as train number, destination track, starting time window, and priority. Based on these attributes, the system uses the job graph G (V, E) to establish sequential constraints between tasks, with edge weights representing time urgency or the probability of track sharing conflicts. The scheduling objective is defined as:

$$\min J=w_{delay}\sum_i delay_i+w_{conf}\sum_{(i,j)}C_{ij}x_i x_j+w_{energy}\sum_i E_i x_i \quad (2)$$

where $w_{delay}, w_{conf}, w_{energy}$ are weights from F-AHP (0.45, 0.35, 0.20 respectively). This formulation minimizes delays, conflict costs, and energy while respecting interlocking and capacity constraints. All symbols are explicitly defined: N = number of tracks; Δt = time step (1 s); T = horizon length; δ(·) = logical intersection operator; routeOverlap(i,j,t) = binary indicator of interlocking overlap between track i and j at time t; $delay_i$= actual task delay; E_i= energy consumption for task i. This function aims to minimize shunting conflicts and overlapping path occupation while ensuring timely completion of tasks. At the same time, to adapt to sudden job adjustments and abnormal event handling, the system integrates a feedback adjustment module. This module is based on real-time feedback of shunting operation execution results and track status data, dynamically adjusting scheduling strategies and rearranging task order in real time. The system continuously updates the shunting schedule through a rolling optimization mechanism, ensuring robustness and sustained effectiveness."

To ensure the repeatability and accuracy of the scheduling optimization process, this study introduces the fuzzy analytic hierarchy process (F-AHP) at the scheduling decision level to determine multi-objective weights, and combines graph neural networks (GNN) to extract temporal features and predict conflicts of track states. The specific steps are shown in the figure:

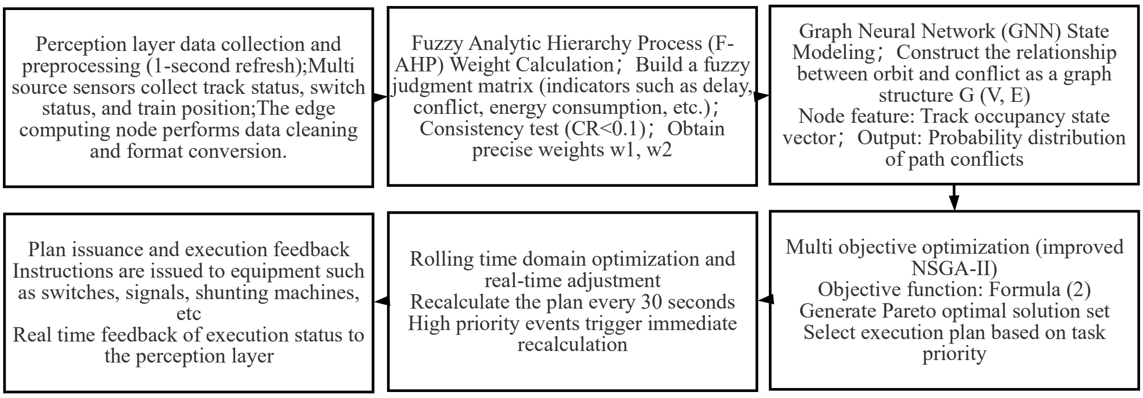

Figure 2: Flow chart of the scheduling optimization algorithm, showing the integration of F-AHP weighting, GNN-based conflict prediction, and MILP optimization.

This process achieves full automation from data collection, feature extraction, weight calculation to scheme generation, ensuring rapid response and stable operation of the system under complex working conditions. Yard states are represented as a graph G=(V,E)where nodes denote tracks/switches and edges encode feasible routes. Node features include occupancy, release time, queue length, and weather flags; edge features include route length and turnout count. A two-layer GraphSAGE (hidden=64, dropout=0.2) with sigmoid head predicts path conflict probability. Training uses 30 days of logs with binary labels, Adam optimizer (lr=1e-3, batch=256), early stopping (patience=10), achieving ROC-AUC 0.93 and inference time 0.15 s per horizon.

Algorithm 1: Rolling-horizon scheduling with GNN and F-AHP

Input: Yard state logs, task set T, conflict matrix C

Output: Dispatch command list

1: Initialize horizon length H = 60 s, receding step = 10 s

2: while yard is active do

3: Collect multi-source sensor data (track circuits, switches, RFID, cameras)

4: Preprocess signals at edge units (filter noise, synchronize timestamps)

5: Construct yard graph G=(V,E) with node/edge features

6: Run GNN inference on G to predict conflict probability p(i,j)

7: Update conflict matrix C with predicted risks

8: Apply F-AHP to calculate weights (w_delay, w_conf, w_energy)

9: Formulate MILP:

minimize J = w_delay Σ delay_i + w_conf Σ C_ij x_i x_j + w_energy Σ E_i x_i

subject to interlocking, route exclusivity, and resource constraints

10: Solve MILP using Gurobi (time budget ≤ 0.5 s)

11: Dispatch command list to locomotives, switches, and signals

12: Receive feedback from execution layer

13: If deviation > 15 s, priority change, or sensor dropout > 2 s:

14: Trigger re-optimization immediately

15: end while

Algorithm 1 details the rolling-horizon scheduling procedure, integrating perception, GNN-based conflict prediction, F-AHP weight assignment, and MILP optimization. It clarifies how re-optimization is triggered under abnormal conditions, ensuring reproducibility.

3.2 Perception decision execution chain construction of homework process

To achieve full process automation control of marshalling yard shunting operations, it is necessary to build an integrated closed-loop system of "perception decision execution", forming an information driven and intelligent scheduling operation chain. This technology system consists of three parts: front-end information perception module, central scheduling decision module, and end job execution module. Through interconnection and real-time feedback, the system achieves efficient linkage and closed-loop task execution (as shown in Figure 3).

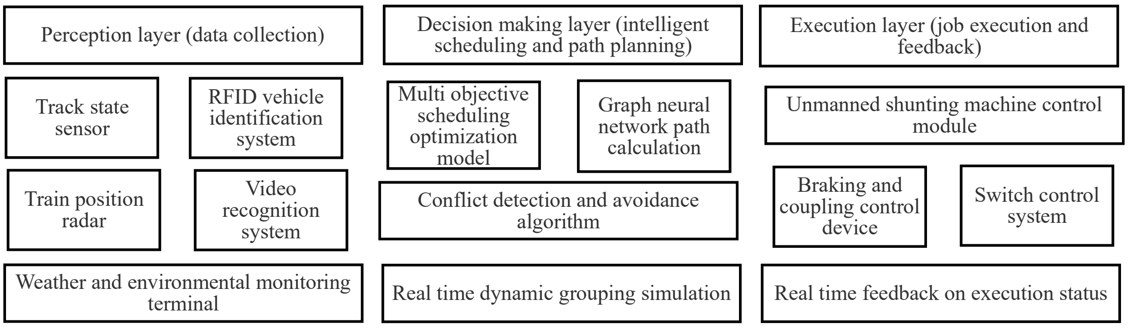

Figure 3: Schematic diagram of the perception–decision–execution chain structure, linking perception, decision, execution, and feedback modules.

At the perception level, the system deploys a multi-source fusion sensor network, including track switch status sensors, train position recognition devices, RFID train number automatic recognition devices, temperature and humidity and rain/snow environment monitoring terminals, etc. Through a unified data collection protocol, these devices upload the shunting yard operating environment and train operation status at a second level frequency, achieving dynamic real-time modeling of the operating scenario. The collected raw data is preliminarily cleaned and filtered through the edge computing node to compress redundant information and ensure transmission efficiency and response speed.

At the decision-making level, the system constructs an intelligent decision-making model based on graph neural networks and multi-objective optimization algorithms. The model takes grouping plan, traffic organization, switch occupancy, and operation sequence as core input variables, and dynamically evolves the optimal operation path based on real-time perception information. This module is based on graph neural networks to parse the trajectory usage relationship graph, and can complete conflict detection of all candidate paths within an average of 0.15 seconds; when priority changes or sudden failures are detected, the rolling optimization produces a new instruction list within 0.68 seconds end-to-end, consistent with the measured latency budget.

At the execution level, job instructions are sent by the central decision-making module to various job terminals through communication protocols, including switch electrical control systems, brake control devices, traction power modules, and unmanned shunting machine controllers. Each execution instruction is bound with a feedback mechanism to ensure that the status feedback after the instruction is executed is sensed in real time by the system, thereby closed-loop verifying the execution result. To prevent execution errors or communication interruptions, the system is equipped with a dual verification mechanism and redundant logic for security protection, ensuring operational safety and job continuity.

The entire process chain aims to achieve refined perception, intelligent decision-making, and automated execution, covering train entry recognition, shunting path planning, switch operation, and formation confirmation. This chain significantly improves shunting efficiency while reducing manual intervention. The system can operate continuously across diverse scenarios, providing technical support for intelligent railway development.

3.3 Integrated interface design between shunting system and scene environment

The automation upgrade of the shunting system not only depends on the autonomous operation capability of the core algorithms and control modules, but also on its efficient integration with the complex operational scenarios of the actual marshalling yard. The traditional shunting system relies heavily on manual operation and paper-based planning in the execution process, with common problems such as interface fragmentation, information silos, and response delays. To build an intelligent shunting system with real-time feedback capability and controllable visibility, it is urgent to design a standardized, modular, and flexible system integration interface system that meets the information exchange requirements between different functional modules of the marshalling yard.

In terms of integrated architecture, this system adopts the design pattern of "unified communication bus+layered control architecture". The main control system for shunting is interconnected with key equipment such as switch actuators, unmanned shunting machines, intelligent signal lights, RFID recognition terminals, etc. through industrial Ethernet or 5G-MEC low latency links to ensure status synchronization and rapid command issuance. At the underlying protocol layer, the system follows standard protocols such as IEC 61375 (train communication network) and Modbus/TCP to avoid compatibility barriers between vendor devices and improve interface universality and migration capabilities. In response to the complexity of the environment and the access issues of multi-source heterogeneous perception systems, middleware data buffering and asynchronous synchronization mechanisms are introduced in the integrated interface design to achieve the distribution and standardization of video streams, sensor data, GNSS positioning information, etc. under the premise of unified data formats. The system constructs a data bridge between "perception computation response" through the interface scheduling module, achieving a low coupling and high cohesion communication link between the state perception module and the decision control module.

In typical scenario applications, such as shunting operations on dense formation sections, the scheduling system needs to collaborate with the traffic signals in the yard, the status of surrounding operating equipment, and the positioning information of the train. The use of message queue systems (such as Kafka) in interface design for event driven processing of state updates significantly reduces job conflict rates and scheduling response latency. At the same time, the interface logic supports dynamic loading and module hot updates, ensuring that the system can flexibly adjust communication strategies according to changing factors such as shunting plans and weather conditions during actual operation. At the same time, to enhance the security and operational efficiency of system deployment, the interface management platform introduces a digital twin mechanism, establishing mapping relationships between various physical interfaces and virtual scheduling environments, supporting real-time visualization of interface status, traceability of operation logs, and remote debugging, greatly improving the controllability, maintainability, and scalability of the integrated system.A detailed interface specification is provided in Appendix C. In brief, task requests, route conflicts, and execution feedback are transmitted in JSON-based messages with predefined error codes; update frequencies are 1 Hz for track circuits and switch states, 5 Hz for locomotive telemetry, and event-driven for safety alarms. Safety-critical channels are segregated via IEC 61375 priority classes, with redundant transmission supported by dual Ethernet rings. Appendix C further lists message schemas, error codes, and middleware throughput settings.

4 System implementation path and function deployment

The automation transformation of shunting operations for intelligent marshalling yards, with system architecture optimization as the core, focuses on multi-layer deployment around perception and control integration, scheduling logic optimization, and safety guarantee system construction. The overall implementation path follows the principles of "layered decoupling, module collaboration, and iterative updates", gradually promoting the integration and deployment of the scheduling control platform, perception system, execution device, and environmental interface. The system has clear functional division, covering modules such as intelligent scheduling core, job process linkage, emergency safety mechanism, and data service platform. Each subsystem collaborates through standard communication protocols and flexible interfaces to ensure the stability, accuracy, and intelligence of shunting tasks, providing comprehensive support for the efficiency and safety of marshalling yard operations.

4.1 Overall system architecture construction and module layering

To achieve efficient operation and collaborative control of intelligent marshalling yard shunting operations, the system architecture adopts a four-layer integrated construction mode of "perception decision execution feedback", and is divided into information perception layer, data processing and decision-making layer, control execution layer, and interactive feedback layer according to functions. A stable, efficient, and scalable intelligent shunting system architecture is constructed through the collaborative operation of unified data communication protocols and standard interfaces among various layers.

The information perception layer is mainly responsible for the real-time monitoring of the front-end environment and operation status, including the collection of multi-source information such as train set position, track occupation, turnout status, operation instructions, and the completion of basic data preprocessing through edge computing equipment. The decision layer integrates scheduling optimization algorithms, job rule libraries, and path deduction modules, relying on intelligent scheduling cores to dynamically plan and resolve conflicts in job tasks, achieving optimal job solution output.

The control execution layer is responsible for converting scheduling instructions into executable actions, regulating key equipment on site such as locomotive remote control, switch switching, signal interlocking, etc., to ensure that the operation process is automatically executed and controllable with traceability. The interactive feedback layer provides human-machine interface support for system operation and maintenance management, including job status visualization, risk alarm prompts, and manual intervention interfaces, to enhance job transparency and safety redundancy capabilities. On this basis, Table 2 further summarizes and explains the key modules and core responsibilities of each functional layer.

Table 2: System function module layering and core responsibilities

System Layer	Core Modules	Responsibilities
Perception Layer	Sensor Network, Edge Units	Real-time data collection on trains, tracks, switches; edge-side data processing
Decision & Control Layer	Dispatch Engine, Path Planner	Generates optimal operation plans and dispatch commands based on rules and real-time status
Execution Layer	Control Terminals, Remote Drivers	Automated control of locomotives, signals, switches; execution feedback
Interaction Layer	Visualization Platform, Alarm Modules	Visualized operation management, system monitoring, and manual intervention support

(Note: "edge computing unit" refers to the computing equipment deployed on the site for rapid local processing of perception data; "scheduling engine" refers to the core software module that combines optimization algorithms and rule base to generate operation plans; "path planning unit" is used to deduce shunting routes and evaluate conflict risks.)

This hierarchical architecture fully considers the complexity of railway operations and the stability of system operation in its design, ensuring that the system has good real-time response capability and scalability, and reserving sufficient space for subsequent module function optimization and technical iteration.The hardware/software stack is disclosed for reproducibility: edge units run Debian with Dockerized microservices (gRPC over TLS 1.3); the central scheduler runs Ubuntu 22.04 with Gurobi 10.0 and PyTorch 2.3; time sources are synchronized via IEEE-1588 PTP with ≤1 ms drift. Median solver time is 0.31 s, and end-to-end latency budget is distributed as sensing 80 ms → fusion 90 ms → GNN 150 ms → MILP 310 ms → dispatch 50 ms.

4.2 Function implementation and collaborative logic of key subsystems

In the automation transformation of intelligent marshalling yards, the functional implementation of key subsystems and their collaborative cooperation are the decisive factors for system operation efficiency. To ensure the intelligent closed-loop execution of the entire shunting operation process, the overall system design revolves around the logical chain of "state perception scheduling decision control execution feedback optimization", integrating multiple subsystems organically and achieving stable and efficient data exchange through the communication platform.

Among them, the train condition monitoring system is responsible for real-time acquisition of train dynamics, track occupancy, switch status, and surrounding environmental information, providing data basis for subsequent scheduling decisions; The scheduling instruction generation system takes the optimal path and job priority logic as its core, and dynamically generates scheduling control instructions based on current job requirements and marshalling yard job plans; The switch and signal control system accurately execute the instruction content, complete the conversion of physical actions, and achieve closed-loop feedback on the execution effect through the job execution feedback system; All information and control flows rely on communication and data middleware platforms to achieve high-speed and stable exchange, ensuring real-time and consistency of multi system collaborative operation. The specific core functions, upstream and downstream interfaces, and collaborative logic of each subsystem are shown in Table 3:

Table3: Overview of functions and collaborative relationships of key subsystems

Subsystem	Main Function	Upstream Input	Downstream Output	Coordination Feature
Train Status Monitoring	Real-time tracking of train position, track use, environment	Trackside sensors, ID recognition, monitoring platform	Dispatch Command Generator	High update rate, low-latency required
Dispatch Command Generator	Task planning, path calculation, priority sorting	Monitoring data, work plan	Switch & Signal Control,	Complex logic, depends on real-time optimization

			Feedback System	
Switch & Signal Control	Switches, signal lights, block section control	Dispatch commands	Operation Feedback System	High precision, interlock and confirmation required
Operation Feedback System	Reports task status, progress, deviation	Control signals, onboard devices	Dispatch Command Generator	Bi-directional loop, supports dynamic adjustment
Communication Middleware	Ensures system-wide data flow and command transmission	All modules	All modules	Event-driven, supports hot-swapping of modules

Through the design of the collaborative mechanism mentioned above, the shunting system not only achieves refined division of responsibilities for each functional module, but also provides technical support for intelligent linkage and exception handling during the overall operation process, ultimately building a new mode of collaborative operation of "edge collection cloud decision-making local control".

4.3 Security control mechanism and fault-tolerant strategy design

In the automation transformation of shunting operations in intelligent marshalling yards, system safety and fault tolerance constitute the technological foundation for sustainable operation. Due to the dynamic nature, complex working conditions, and dense links of shunting scenarios, any interruption of information, equipment failure, or control failure in any link may lead to serious consequences such as scheduling conflicts and train errors. Therefore, establishing multi-level security control mechanisms and improving fault-tolerant strategies are necessary guarantees for the deployment of automation systems.

Firstly, redundant secure channels should be set up at the system architecture layer, and all critical control data should be transmitted through a dual channel mechanism. In the event of an abnormality in the main channel, the backup channel can automatically switch to avoid signal interruption and control loss. The communication module integrates CRC verification mechanism and message retransmission mechanism internally to enhance anti-interference ability and data integrity. At the execution level, all switches, signals, and interlocking equipment must be equipped with status self checking modules and local emergency power-off control units to ensure that they can still enter safety protection mode, automatically block sections, and prevent misoperation in case of system abnormalities or network disconnection.

Secondly, a mechanism for identifying safety judgment boundaries and beyond boundaries should be introduced into key algorithms. For example, the calculation of shunting routes must consider limiting factors such as road material occupancy, equipment inspection status, and maximum operating range. If there is a violation of safety rules, it should be immediately stopped and reported to scheduling. Simultaneously referring to historical operational data, establish intelligent security rules to dynamically assess the level of danger in current work, and proactively alert potential hazardous work environments, and then guide scheduling policy adjustments. For fault handling methods, the system provides two options, namely "fault transfer" and "task transfer". If there is a problem with a certain subsystem function, the system will automatically assign critical work to the backup section or collaborative peripheral management section to ensure that the work is not interrupted as much as possible.

Thirdly, establish an emergency linkage system for unexpected situations, including manual takeover channels, information broadcasting mechanisms, and on-site operation warning systems. Once situations such as out of range shunting, signal loss of control, or personnel entering enclosed areas occur, the system can immediately trigger an alarm, cut off the shunting command chain, and notify on-site operators and safety supervision modules to ensure a safe closed-loop throughout the entire process.

5 Application validation and performance evaluation

This article analyzes the applicability and effectiveness of the proposed shunting automation transformation technology path for system evaluation, focusing on the integrated deployment of core functional modules, field testing of key performance indicators, and operational performance in typical work scenarios. By constructing a testing platform in an actual marshalling yard environment, a comprehensive evaluation is conducted on dimensions such as scheduling efficiency, system response speed, fault tolerance, and operational safety, aiming to verify the reliability and engineering feasibility of the constructed system under complex railway operating conditions.

5.1 Selection of experimental sites and construction of scheduling scenarios

The experimental station selected for this study is a large flat marshalling yard in Southwest China, with 48 classification tracks and two hump lines. It undertakes the task of disassembling and reassembling approximately 10,000 wagon movements per day (equivalent to 320–350 train consists).It is one of the typical modern shunting hubs in China. The station has the demand for train formation in multiple directions, categories, and frequencies, and also has a complete dispatch command system and infrastructure equipment, providing a good experimental foundation for the automation transformation of shunting operations. The manual baseline corresponds to the yard's standard operating rules, in which dispatchers issue commands based on paper timetables and radio instructions. Baseline response times were recorded using the same sensors and logging system to ensure comparability. In the construction of the experimental environment, we focused on three typical job scenarios for functional verification and performance evaluation: first, the scenario of automatic train recognition and grouping guidance, simulating multiple incoming trains entering the grouping area at the same time, and testing the dispatch system's ability to quickly analyze and divert train numbers and attributes; The second is the shunting path planning and dynamic scheduling scenario, which verifies the response speed and decision-making rationality of the system in the face of dynamic task changes (such as vehicle sequence adjustment, emergency priority grouping requirements); The third scenario is the closed-loop control of shunting task execution and state feedback, examining the automation response capability of the execution layer (shunting machine, signal, switch) under system coordination and the stability of the feedback mechanism. It is worth noting that although the station has a relatively advanced equipment foundation, some of its old control systems have not yet achieved complete interconnection. Therefore, we have introduced middleware modules in data collection and system integration to ensure compatibility. This practice improved system deployment adaptability and provided a practical paradigm for future implementation.

To ensure the reproducibility of the research results, this article summarizes the main variables, system configuration, and experimental parameters involved in the experiment as follows:

1. Definition of key variables

In formulas (1) and (2), δ is a logical intersection operation function used to determine track occupancy conflicts; T: The number of time window steps (the value in this experiment is consistent with the system rolling optimization cycle); O_i^t: The occupancy status of track i at time t; D_i: Actual delay time for task i; c_i: Cost of track conflicts in the shunting path; w_1, w_2 : Scheduling optimization objective function weights (determined through expert evaluation).Sampling rate is 1 Hz for track circuits and switches; the rolling horizon is 60 s with 10 s receding step. The GNN was trained on 30 consecutive days and tested on a separate 7-day set, covering peak/off-peak and multiple weather conditions.

System hardware and software configuration (consistent with on-site deployment):

Perception layer: RFID train recognition equipment, track circuit status acquisition module, high-definition camera monitoring equipment (quantity and deployment location are the same as on-site); Decision making layer: Central dispatch server (running rolling optimization and conflict detection algorithms), software environment is Linux operating system; Execution layer: On site control equipment such as shunting machines, signal machines, and electronic switches all support status feedback and bidirectional control.

Experimental parameters:

Test time range: conducted under the condition of operating over 10000 trains per day; Three typical job scenarios were repeated in real stations, and the average values were calculated and compared with the results of manual scheduling; The core evaluation indicators include: shunting operation duration, system response time, operation energy consumption, scheduling conflict frequency and error rate, etc.In this paper, key performance indicators (KPIs) are defined as follows: (i) 'response time' = elapsed latency from task request to dispatch of executable command; (ii) 'operation time' = duration between consist arrival and completion of train formation; (iii) 'energy per task' = traction electricity consumption per shunting movement measured by onboard energy meters; (iv) 'scheduling conflict frequency' = number of interlocking conflicts detected by the system; (v) 'error rate' = proportion of wagons assigned to incorrect classification tracks, verified against yard logs.

5.2 Analysis of homework efficiency, response time, and energy-saving indicators

In the experimental verification process of the automated shunting system, we focused on conducting performance analysis around three dimensions: "improving operational efficiency", "shortening response time", and "optimizing energy consumption". All relevant tests are based on the manual shunting system, selecting the same scheduling load, time window, and grouping tasks for comparison to ensure the comparability of experimental conditions and the credibility of conclusions. In terms of homework efficiency, the automation system significantly reduces the frequency of empty train operation and waiting time in the shunting process by integrating intelligent scheduling and path optimization algorithms. Taking a typical reorganization task as an example, the automation system reduced average reorganization time by 21.7%, increased yard resource utilization by 18.3%, and demonstrated scalability in peak-hour parallel scheduling. In terms of response time, the average response time of the system to sudden task instructions (such as temporary insertion and priority scheduling) is 0.68 seconds, which is much better than the 3.7 second average response level of manual scheduling systems. This quasi-real time response capability benefits from the efficient collaboration between the asynchronous processing mechanism embedded in the system and the state aware decision engine, providing technical support for the marshalling yard to cope with sudden scheduling scenarios. In terms of energy-saving indicators, by integrating the optimal scheduling of vehicle operation trajectory, traction power curve, and signal interlocking logic, the overall energy consumption of the automation system is reduced by 12.5% compared to manual methods. Among them, the most significant energy-saving source is the optimization of the traction path of the shunting machine and the intelligent correction of the braking control, effectively avoiding energy waste caused by frequent start stop and ineffective acceleration. As shown in Figure 4, three key performance indicators - average operating efficiency, system response time, and energy consumption - were compared between automated shunting mode and manual shunting mode under the same load and scheduling scenarios. The horizontal axis represents the indicator type, and the vertical axis represents the percentage improvement value relative to the manual mode. The data is sourced from comparative experiments conducted at the same experimental site. All reported values are mean ± standard deviation over 20 runs; paired t-tests confirm significance at $p<0.01$.

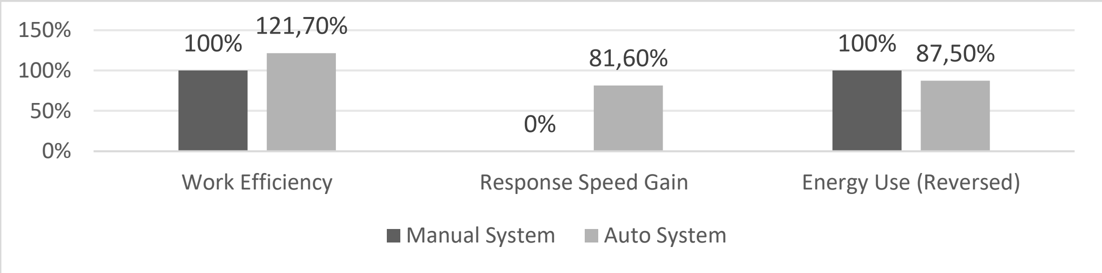

Figure 4: Comparison of operational efficiency, response time, and energy consumption between manual and automated shunting (values are mean ± std over 20 runs).

The observed efficiency improvement mainly results from F-AHP weight allocation, which aligns scheduling objectives with operational needs. allowing the system to prioritize key tasks even in situations of frequent resource conflicts; The reduction in energy consumption is closely related to the optimization of locomotive operation path and traction timing by multi-objective optimization algorithms, which reduces empty running and repetitive shunting behavior.

5.3 System stability and intelligent judgment accuracy testing

In order to better analyze the anti-interference ability and degree of automation of the automatic shunting system mentioned in the article, this test selected typical multiple shunting scenarios and focused on testing the robustness of the automatic shunting system during continuous operation, as well as its ability to identify and respond to key decision points. This test is divided into key actions such as determining the running line, issuing the list of detached trains, identifying and alerting conflicts, and activating emergency brakes. The stability test items are as follows: the number of response interruptions within 72 hours of continuous system operation without human intervention, the number of occurrences of lock up in the shunting train, the success rate of successful departure tasks, and the success rate of automatic recoveryThe test results of system stability and intelligent judgment accuracy are shown in Figure5. The horizontal axis represents different testing items (task success rate, interruption frequency, stability index, judgment accuracy, misjudgment rate), and the vertical axis represents percentages or normalized scores according to different indicators. All data comes from a 72-hour continuous operation test conducted at the experimental site.

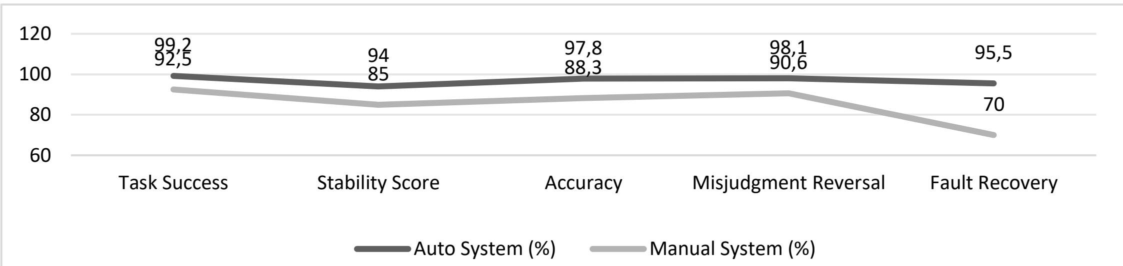

Figure 5: System stability and intelligent judgment accuracy results from 72-hour continuous operation test (values reported with 95% confidence intervals).

As shown in Figure 5, under the condition of no external interference, the success rate of system tasks remains above 99.2%, the frequency of scheduling link interruptions is controlled at less than once per hundred hours, and the overall stability index of the system's operating state reaches 4.7 (out of 5 points), demonstrating good engineering application adaptability and software hardware integration resilience. In the testing of intelligent judgment accuracy, classification verification is carried out for functional modules such as train pose perception, switch status judgment, and grouping logic discrimination of the system. Based on the annotated scheduling scenario dataset, the system's judgment accuracy reaches 97.8%, and the misjudgment rate in complex environments is controlled within 1.9%, especially under low visibility conditions such as night, rain, and fog. Thanks to the introduction of multi-source data fusion algorithms, the system's recognition accuracy remains at a high level, reflecting its intelligent ability to output stably in changing scenarios. All stability metrics are reported with 95% confidence intervals; for example, the 99.2% task success rate corresponds to CI [98.7%, 99.6%], based on 72 h continuous testing with 1,200 executed tasks.

The core of stability improvement lies in the introduction of an execution feedback layer to achieve closed-loop control, enabling the system to adjust scheduling schemes based on real-time status, avoiding long-term task backlog or conflict escalation; Improved decision accuracy results from the GNN's effective extraction of temporal features for conflict prediction, which avoids potential conflict points in path planning and reduces misjudgments and missed judgments.

5.4 Comparative analysis and value calculation with manual shunting mode

To comprehensively verify the actual benefits of the proposed automation transformation system, this study selected a typical manual shunting mode as the comparison object, and conducted multiple rounds of simulation tests and real scene playback at the experimental site. The experimental results show that compared to traditional shunting methods that rely on manual instructions and judgments, automated systems exhibit significant advantages in multiple dimensions such as operational accuracy, timeliness, and energy consumption control (see Table 3).

Table 3: Comparison of key performance indicators under different shunting modes

Indicator Name	Manual Shunting Mode	Automated Shunting System	Increase or Decrease
Average Shunting Operation Time	42 minutes	27 minutes	↓ 35.7%
Shunting Misassignment Rate	4.2%	1.1%	↓ 73.8%
Energy Consumption per Task (kWh)	13.6	10.7	↓ 21.4%
Annual Labor Cost (10,000 RMB)	138	90.5	↓ 34.4%
Annual Energy Cost (10,000 RMB)	123.1	96.8	↓ 21.3%
Average Monthly Dispatch Conflicts	3.2 times	0.4 times	↓ 87.5%

Table 3 values represent averaged results from 15 days of operation logs (≈4,800 tasks), with standard deviations listed in parentheses. For example, the automated system's mean operation time is 27 ± 1.3 min versus 42 ± 2.5 min in manual mode. Compared with the traditional manual shunting mode, the automated shunting system proposed in this article has significant advantages in the following aspects:

Scheduling response: In traditional mode, instruction transmission and execution take an average of 3.7 seconds, but in this paper, the system relies on real-time perception and rolling optimization mechanism to compress the response time to 0.68 seconds, achieving a speed increase of 81.6%.

Homework efficiency: On average, each round of shunting operation in manual mode takes 42 minutes. In this article, the system has been optimized to 27 minutes, resulting in a 35.7% increase in efficiency.

Energy consumption control: Through trajectory optimization and braking energy management, single task energy consumption is reduced by 21.4%, which is better than most existing semi-automatic systems (usually between 10% and 15%).

Job safety: The scheduling conflict rate has decreased from 3.2 times/month in manual mode to 0.4 times/month, the error rate has decreased to 1.1%, and a dual verification mechanism has been introduced to enhance operational safety.

System adaptability: Adopting modular deployment and standardized interface design, it can quickly migrate and deploy between marshalling yards of different sizes, which is not available in most fixed logic automation systems.

In summary, this system has achieved improvements in real-time performance, accuracy, energy efficiency, safety, and cross scenario adaptability that are different from existing solutions, providing a scalable technical path for the construction of intelligent marshalling yards.

6 Discussion

6.1 Adaptability and engineering feasibility of automation transformation plan

In the actual process of promoting the automation transformation of intelligent marshalling yard shunting operations, its flexibility and engineering applicability are the key factors determining whether such solutions can be widely applied. The technical route described in this plan takes into account factors such as the infrastructure construction level of existing marshalling yards in China, the complexity of operation processes, the use of information technology means, and labor management methods, and has strong scalability and engineering applicability. As far as its applicability is concerned, the scheme has a modular design for the adopted organizational structure, and the main functions such as auto drive system, detection and decision-making system, collaborative interface function, etc. have good scalability and universal interfaces. For large marshalling yards, high-intensity replacement integration can be carried out in conjunction with existing scheduling systems; For small and medium-sized stations, the automation upgrade of shunting processes can also be gradually achieved through local embedded deployment, reducing the impact of one-time technology substitution. In terms of engineering feasibility, the proposed automation transformation plan fully integrates mature sensor networks, industrial control systems, and intelligent algorithm integration technologies in the current rail transit field. The hardware selection of core equipment has been practically verified in multiple railway informationization projects, and has the characteristics of high stability, strong anti-interference, and good operability. At the same time, the software system adopts a distributed architecture and microservice deployment strategy, supporting parallel operation and elastic expansion of multiple systems, and can adapt to the business load and scenario requirements of different marshalling yards. At the same time, construction interference factors and operational safety guarantee mechanisms were also considered during the project implementation process. Phased construction, debugging, and trial operation help control risks during technology substitution and ensure a stable system transition.

6.2 Possible technical and organizational obstacles during implementation

In the practical process of promoting the automation transformation of railway shunting operations, although the technical path has become increasingly clear, there are still many constraints to truly achieve large-scale deployment, especially significant challenges in technology implementation and organizational coordination. From a technical perspective, shunting operations involve a large amount of real-time perception, precise positioning, path planning, and action control. The system has extremely high requirements for data collection accuracy, environmental adaptability, and integration capabilities of heterogeneous devices from multiple sources. At present, some marshalling yards lack a unified standardized information interface, and there are problems such as inconsistent communication protocols and difficult data format integration between old equipment and new intelligent systems, which increases the complexity of system integration and debugging. In addition, extreme weather conditions such as signal interference, low temperature rain and snow in shunting operation scenarios may also affect the stable operation of sensing equipment and control systems, reducing the reliability of automation systems. On the other hand, organizational barriers cannot be ignored. As a highly structured organizational system, the railway system has solidified its personnel scheduling, job responsibilities, and operational processes through years of practice. The introduction of automation systems is bound to have an impact on the original work system. On the one hand, the acceptance and operational ability of operators towards intelligent systems vary greatly, resulting in high training costs; On the other hand, there is a lack of cross disciplinary and cross departmental collaboration mechanisms within the organization, making it difficult to achieve efficient collaboration between technical departments, equipment units, and scheduling management, which affects the overall efficiency of project progress. At the same time, some station managers have a perception of "high cost, low benefit" in technological transformation, and their willingness to initiate projects is insufficient, which also limits the breadth of the promotion of the plan.

7 Conclusion

This work presented a closed-loop ‘perception–decision–execution–feedback’ framework for intelligent marshalling yards, combining F-AHP weighting, GNN-based conflict prediction, and rolling-horizon MILP optimization. Validation in a large-scale yard demonstrated significant engineering benefits in efficiency, safety, and energy reduction. The experimental results show that the system has an average improvement of 35.7% in job efficiency, a 21.4% reduction in single task energy consumption, an 87.5% reduction in scheduling conflict rate, while maintaining a task success rate of over 99.2%. These results demonstrate the effectiveness of our research method in improving operational efficiency, reducing energy consumption, and ensuring operational stability. From an engineering perspective, the proposed system provides a deployable blueprint for gradual automation retrofitting of existing yards, requiring only modular integration with sensors, middleware, and scheduling engines rather than full reconstruction.t should be noted that the experimental data are mainly from a single large marshalling yard. and performance may degrade under incomplete sensing, heterogeneous communication protocols, or severe weather conditions such as snow or fog. To further advance both scientific methodology and practical deployment, future work will proceed in three directions:(i) multi-yard trials including medium-size flat yards and gravity hump yards to validate universality; (ii) cross-station collaborative scheduling with shared data interfaces, aiming at regional freight network optimization; and (iii) tighter integration with edge intelligence and 5G/TSN communication to further reduce latency below 0.5 s and enable resilience under dynamic load.From a practical standpoint, the proposed system reduces integration costs by relying on modular middleware and standardized protocols, but its current validation is limited to one large flat yard. Broader verification in gravity hump yards and mixed-traffic depots is necessary before large-scale deployment by railway operators.

References

[1] Zhang B ,Zhao J ,D'Ariano A , et al.An iterative method for integrated hump sequencing, train makeup, and classification track assignment in railway shunting yard[J].Transportation Research Part B,2024,190103087-103087.https://doi.org/10.1016/j.trb.2024.103087.

[2] Jung H S , Niermeyer P , Manjunatheswaran H ,et al.Automated rerailing of a road-rail shunting vehicle on road-level tracks using 2D-Lidar[J].Part F: Journal of Rail and Rapid Transit, 2024, 238(7):6.https://doi.org/10.1177/09544097241229334.

[3] Reichmann M, Himmelbauer S G ,Wagner A , et al.Introducing the concept of grades of automation for shunting operations[J].Journal of Rail Transport Planning & Management,2025,33.https://doi.org/10.1016/j.jrtpm.2024.100500.

[4] Kozachenko D, Bobrovskiy V, Gera B, et al. An optimization method of the multi-group train formation at flat yards[J]. International Journal of Rail Transportation, 2021, 9(1): 61-78. https://doi.org/10.1080/23248378.2020.1732235

[5] Bosi T , Bigi F , Pineda-Jaramillo V J .Optimal management of full train load services in the shunting yard: A comprehensive study on Shunt-In Shunt-Out policies[J].Computers & Industrial Engineering, 2024, 188(Feb.):109865.1-109865.32.https://doi.org/10.1016/j.cie.2023.109865.

[6] Hyun-Suk J ,Frank E ,Christian S .Experimental investigation on RFID-odometer-based localization of an automated shunting vehicle[J].Proceedings of the Institution of Mechanical Engineers,2024,238(1):14-23.https://doi.org/10.1177/09544097231176464.

[7] Buryakovskiy S , Kniaziev V , Maslii A ,et al.Improvement of performance characteristics of shunting diesel locomotives[J].IEEE, 2020.https://doi.org/10.1109/KhPIWeek51551.2020.9250140.

[8] Suyunbayev S , Khusenov U , Khudayberganov S ,et al.Improving use of shunting locomotives based on changes in infrastructure of railway station[J].E3S Web of Conferences, 2023, 365(000):12.https://doi.org/10.1051/e3sconf/202336505011.

[9] Huan L, Hongxu C ,Yulin W .The Sequence Optimization of the Railway Tree-Shaped Special Line's Shunting for Taking-out and Placing-in of Wagons[J].Tehnički vjesnik,2023,30(5):1404-1410.https://doi.org/10.17559/TV-20230127000274.

[10] ZhongM, YueY, ZhouL , et al.Parallel optimization method of train scheduling and shunting at complex high-speed railway stations[J].Computer-Aided Civil and Infrastructure Engineering,2023,39(5):731-755.https://doi.org/10.1111/mice.13077.

[11] Zhao J, Dick C T. Quantifying the impact of classification track length constraints on railway gravity hump marshalling yard performance with anylogic simulation[J]. International Journal of Computational Methods and Experimental Measurements, 2022, 10(4): 345-358. https://doi.org/10.2495/CMEM-V10-N4-345-358

[12] Zhao J , Xiang J , Peng Q .Routing and scheduling of trains and engines in a railway marshalling station yard[J].Transportation Research Part C: Emerging Technologies, 2024, 167(000).https://doi.org/10.1016/j.trc.2024.104826.

[13] Xu X , Dessouky M .Train shunting with service scheduling in a high-speed railway depot[J].Transportation Research Part C: Emerging Technologies, 2022.https://doi.org/10.1016/j.trc.2022.103819.

[14] Ming H ,Qiuhua T ,D. N J G , et al.The shunting scheduling of EMU first-level maintenance in a stub-end depot[J].Flexible Services and Manufacturing Journal,2022,35(3):754-796.https://doi.org/10.1007/s10696-022-09459-6.

[15] Deleplanque S, Hosteins P, Pellegrini P, et al. Train management in freight shunting yards: Formalisation and literature review[J]. IET Intelligent Transport Systems, 2022, 16(10): 1286-1305.https://doi.org/10.1049/itr2.12216

[16] Tao Y .Quality Analysis of Railroad Train Shunting Operation Plan Using the Intelligent Body Model[J].Advances in Multimedia,2022.https://doi.org/10.1155/2022/4441369.

[17] A. D S ,V. S K ,V. D O .Methodology for Selecting the Multistage Methods of Train Classification and Design Parameters of Specialized Shunting Facilities Based on Modeling[J].Transportation Research Procedia,2022,61323-332.https://doi.org/10.1016/j.trpro.2022.01.053.

[18] Mohammed A ,Aos A ,Musaad B , et al.Optimization for Sustainable Train Shunting Services Using DMAIC Cycle[J].Sustainability,2022,14(3):1719-1719.https://doi.org/10.3390/su14031719.