Innovation and Application of IoT and AI in the Logistics Measurement System of Alumina Production

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Abstract

With the rapid development of modern industrial technologies, the application of logistics measurement and detection systems in alumina production has become a key means to enhance production efficiency and management levels. This paper comprehensively explores the innovation and application of multiple key measurement systems. Traditional systems, such as truck scales, rail scales, and instrument monitoring and management systems, face numerous limitations, including difficulties in detecting extreme conditions for truck scales, low measurement accuracy, poor anti-interference capability and high risks associated with manual data entry for rail scales, and inefficient instrument monitoring. To address these challenges, a series of innovative technologies and upgrade measures have emerged.

Keywords: Flow limit warning system, Logistics measurement system, IoT + AI, Precise measurement and efficient operation, Remote centralized control.

1. Introduction

As a critical measuring device in the railway freight system, rail scales play a central role in monitoring truckload weights, with their measurement accuracy directly linked to transportation safety efficiency, logistics resource allocation optimization, and full lifecycle cost control. Traditional rail scale systems, primarily utilizing mechanical sensors and linear basic algorithms, face significant challenges under complex working conditions: Firstly, mechanical sensing units are susceptible to environmental interference such as temperature and humidity fluctuations and track vibrations, leading to zero drift (empirical data shows error increases of up to 0.8 % in winter low-temperature environments) in long-term operation; secondly, manual operations involve risks of truck number misrecording and data tampering, with a certain railway bureau's 2022 audit report indicating annual settlement disputes exceeding 12 million RMB (1.68 MUSD approx.) due to such issues.

In recent years, breakthroughs in artificial intelligence technologies have provided a new pathway for the paradigm upgrade of weighbridge systems. Through the deep integration of deep learning algorithms and multi-source sensing data, the new generation of intelligent rail scales has achieved three major innovations: At the technical architecture level, a "terminal-edge-cloud" collaborative computing model has been constructed, enabling millisecond-level data preprocessing through edge gateways; at the algorithm optimization level, an improved YOLOv8 model has been adopted to achieve carriage positioning under complex lighting conditions (recall rate > 98 %), combined with LSTM (Long Short-Term Memory) time series networks to predict sensor abnormal states; at the application scenario level, expansion to high-risk areas such as port bulk cargo loading and chemical hazardous materials monitoring has been realized. This paper will systematically discuss dimensions such as heterogeneous data fusion mechanisms, anti-interference weighing algorithm design, and full-process trustworthy measurement systems, and explore the empowerment direction of future weighbridge intelligence development through 5G and digital twin technologies.

2. Research Background and Feasibility Analysis

2.1 Research Background

Alumina, as a core raw material in the metallurgical industry, relies heavily on the accuracy and efficiency of logistics measurement in its production process. Taking a typical production line with an annual output of 1.5 million tonnes of alumina as an example, every 0.5 % increase in raw material warehousing errors will lead to an annual increase in soda consumption costs of approximately 6 million RMB, highlighting the necessity of high-precision measurement. However, traditional measurement systems face the following key bottlenecks:

1. Technical Limitations: Truck scales, due to mechanical limit detection blind spots (empirical error fluctuations of ±1.5 %), struggle to meet the ±0.3 % error threshold required for raw material slurry blending;
2. Dynamic Adaptability Insufficiency: During peak railway transportation periods, dynamic weighing of 200 trains per day is required, but traditional rail scales exhibit a high out-of-tolerance rate of 7.2 % when train speeds exceed 20 km/h (data source: 2023 operation and maintenance report of a large aluminium enterprise);
3. Environmental Tolerance Defects: High temperatures (> 90 °C) of red mud slurry and highly corrosive medium ($NaOH$ concentration > 30 %) shorten sensor lifespans to 40 % of normal operating conditions, with annual replacement costs exceeding 800 kRMB (112 kUSD approx.).

These challenges necessitate the industry to explore the deep integration of IoT and AI technologies to construct a new generation of logistics measurement systems that are both robust and intelligent.

2.2 Current Situation Analysis (Existing Problems)

2.2.1 Technical Bottlenecks of Traditional Rail Scales

Traditional rail scales, based on mechanical levers and analogic sensing technologies, have their inherent defects significantly amplified under complex working conditions:

Efficiency-Precision Imbalance: Static weighing requires interruption of transportation flows, with a single weighing taking ≥ 18 minutes, unable to adapt to high-density freight demands; In dynamic mode, non-linear increases in weighing errors occur with fluctuations in train speeds: errors rise from 0.4 % to 1.8 % as speeds increase from 10 km/h to 25 km/h.

Low Mechanical Reliability: Lever-type sensor arrays have annual maintenance costs accounting for 35 % of total equipment investment, with zero drift frequencies due to rusting reaching 1.2 times per month; track installation accuracy requirements are stringent (horizontal error ≤ 0.15 mm/m), with actual operation and maintenance compliance rate of less than 55 %, requiring frequent manual calibration.

High Environmental Sensitivity: for every 10 °C change in temperature, analogic sensors exhibit a temperature drift coefficient of 0.06 % FS, with cumulative errors exceeding 2.1 % under extreme cold conditions in Northeast China; data anomaly events caused by track dust accumulation or icing occur 4.3 times per day on average, accounting for 68 % of total faults.

Lack of Complex Vehicle Condition Adaptability: Non-standard axle-base tankers (axle base > 2.5 m) exhibit weighing deviations 2.8 times greater than standard vehicle models; during dynamic weighing of multi-carriage formations, coupling vibrations between carriages cause data fluctuation amplitudes exceeding ±3 %.

Data Intelligence Shortcomings: 99 % of traditional rail scales only support basic data storage, lacking abnormal load identification functions and relying on manual reviews, taking an average of 3.5 hours per day.

2.2.2 Efficiency Bottlenecks in Measurement Instrument Monitoring Systems

High Sampling Rates and Massive Data Pressure: Modern sensors can achieve sampling frequencies up to the kilohertz range. When multiple nodes operate simultaneously, the data volume grows exponentially, exceeding the carrying capacity of traditional communication protocols (e.g., RS485, 4–20 mA), leading to transmission delays or packet loss.

Asynchronous and Synchronous Issues:
1. Timestamp Asynchrony Across Multiple Sensors (especially with heterogeneous devices): Additional algorithms are required to align time axes, increasing processing complexity; Wireless transmissions (e.g., LoRa, NB-IoT) are prone to interference, and retransmission mechanisms further reduce efficiency.
2. Inadequate Data Processing and Analysis Capabilities:
   Limited Edge Computing Resources: Embedded devices (e.g., PLCs, edge gateways) have constrained computing power, unable to execute complex algorithms (e.g., Fourier transforms, machine learning models) in real-time, resulting in processing delays.

   Unfiltered Redundant Data: Raw data contains significant noise or invalid information (e.g., repeated values under steady-state conditions). Without pre-filtering at the acquisition end, it occupies transmission bandwidth and increases backend processing burdens. Communication protocol differences among manufacturers (e.g., Modbus, Profibus) make data integration difficult, with time-consuming format conversions reducing overall efficiency.

Physical Limitations of Hardware and Environment:
1. Sensor Response Latency: Some instruments (e.g., electrochemical sensors) have inherent response delays (seconds to minutes), unable to meet rapid monitoring requirements (e.g., chemical process control).
2. Harsh Environmental Impacts: High temperatures, humidity, and vibrations can cause signal distortions, necessitating redundant checks or filtering processes that sacrifice real-time performance for reliability.

2.2.3 Data Risks and Management Costs Due to Human Dependence

As the core measuring device for railway freight, the accuracy of rail scale data directly affects cargo settlement, overload prevention, and logistics safety. Faced with three major challenges – manual entry risks, low monitoring efficiency, and fraud risks – technical upgrades and management optimizations are essential to achieve full-chain credible, real-time, and automated data.

Traditional rail scales require manual transcription of truck numbers and cargo weights, followed by system entry, leading to errors such as incorrect numbers (e.g., transcribing "3675" as "3657"), unit confusion (tonnes vs. kilograms), or duplicate entries. These errors can result in cargo settlement disputes (e.g., undercharging freight) or loading safety hazards (e.g., undetected overloads).

Incomplete truck weighing (partially on the scale) or adding counterweight lead blocks to artificially reduce weights and evade freight charges.

Low Monitoring Efficiency: From passive response to intelligent collaboration.

Time-Consuming Manual Inspections: Maintenance personnel must frequently check weighbridge sensor statuses (e.g., icing affecting accuracy in winter).

Delayed Data Flow: Paper records require multiple handoffs for summarization, leading to delayed fault responses (e.g., weighing deviations detected only the next day).

2.3 Research Background and Feasibility Analysis

2.3.1 IoT-Based Automated Data Acquisition

Smart Rail scale Transformation:
1. Incorporate weight sensors, RFID readers, and cameras. As trains pass, automatically collect:
2. Weight Data: Directly transmitted from sensors to the system, eliminating manual recording.
3. Truck Numbers: Automatically identified via RFID tags on trucks (replacing manual visual checks).
4. Image Evidence: Cameras automatically capture truck numbers and cargo statuses for later audits.
5. Edge-End Data Fusion: Deploy edge computing gateways to correlate truck numbers, weights, and timestamps in real-time, eliminating manual splicing errors.

Redundancy Verification Mechanisms:
1. Data Cross-Comparison: Automatically compare pre-declared cargo weights and truck numbers from the logistics system with measured values, triggering anomaly alerts (e.g., automatic interception for discrepancies exceeding 5 %).
2. Blockchain Storing: Generate blockchain hash values for each batch of data (e.g., using Hyperledger) to ensure immutability, enabling traceability to original records during third-party audits.

2.3.2 Economic Value of Monitoring Efficiency Optimization

Fully Automated Weighing and Real-Time Monitoring:
1. When the truck passes the track scale, the system automatically completes weight collection, number identification, and data association, generating electronic records and pushing them to the logistics management platform, reducing processing time from minutes to seconds.
2. The fully automated system reduces single-train processing time from 3 minutes to 8 seconds, increasing daily throughput by 22 times. The AI video recognition module (YOLOv8 + CRNN) maintains 98.7 % accuracy in truck number identification under rainy or snowy conditions, reducing manual review needs by 90 %.

Cost-Benefit Analysis:
After the renovation, the average annual failure frequency of the rail scale dropped from 15 times to 2 times, and the operation and maintenance costs were reduced by 78 %; The use of electronic weighbills with blockchain-based evidence storage shortened the financial reconciliation cycle from 5 days to 2 hours, enhancing the capital turnover efficiency by 12 times.

3. Related Technologies

3.1 Equipment Selection

Table 1. Equipment Selection List

Serial Number	Equipment Name	Specifications	Quantity	Unit
1	Serial Port Server		2	pieces
2	Digital Input Acquisition Unit	Equipped with relays	2	sets
3	Voice System	Amplifier/Speaker Column/Intercom System	2	sets
4	Infrared Beam Detector		4	pairs
5	Large Screen	3-layer outdoor waterproof	2	pieces
6	Electric Bell	24 V	2	pieces
7	Industrial Control Computer	I5/16/1T (including keyboard and mouse set)	2	units
8	Office Computer	i5/16/1T (including keyboard and mouse set)	2	units
9	Monitor	24-inch monitor	4	pieces
10	Monitoring Special Box		6	pieces
11	Hard Disk Video Recorder	4To hard disk	2	units
12	Indoor Dome Camera		2	units
13	Bullet Camera		4	units
14	Panoramic Camera	Hikvision dome model	2	units
15	High-Speed Camera	≥ 5 million pixels	4	sets
16	Constant-On Fill Light		4	sets
17	Fill Light		6	sets
18	POE Switch	16-port	2	sets
19	Special Camera Poles	0.5-meter/3-meter	4	sets
20	Special AI Camera Poles	3.0-meter with cross arm	2	sets
21	Video Image Computing Server		2	sets
22	Control Cabinet	1.2-meter	2	sets
23	AI Vehicle Number Video Image Processing Software	Customized	2	sets
24	Local Measurement Software for Track Scales on Tracks 10/11 at the West of the Factory	Customized	2	sets

Serial Number	Equipment Name	Specifications	Quantity	Unit
25	Remote Centralized Measurement Management System for Track Scales		1	set
26	RF Vehicle Number Identification System		1	set
27	Measurement Instrument	T800	1	set
28	CAN Card		1	set
29	UPS Power Supply	Santak	1	set
30	Dynamic and Static Track Scale Verification Fee		1	unit
31	Auxiliary Materials (Cables, Network Cables)		1	item

3.2 Technology Selection

Relevant technologies involved in the system implementation process:

3.2.1 Technology Selection for Rail scale Weighing System

Technical Versions and Technical Architecture are shown in Table 2 and Figure 1, respectively.

Table 2. Detailed Technical Version List

Technology	Version
Spring Boot	2.0
Redis	4.0
SQL Server	2012
Lay-UI	4.0+

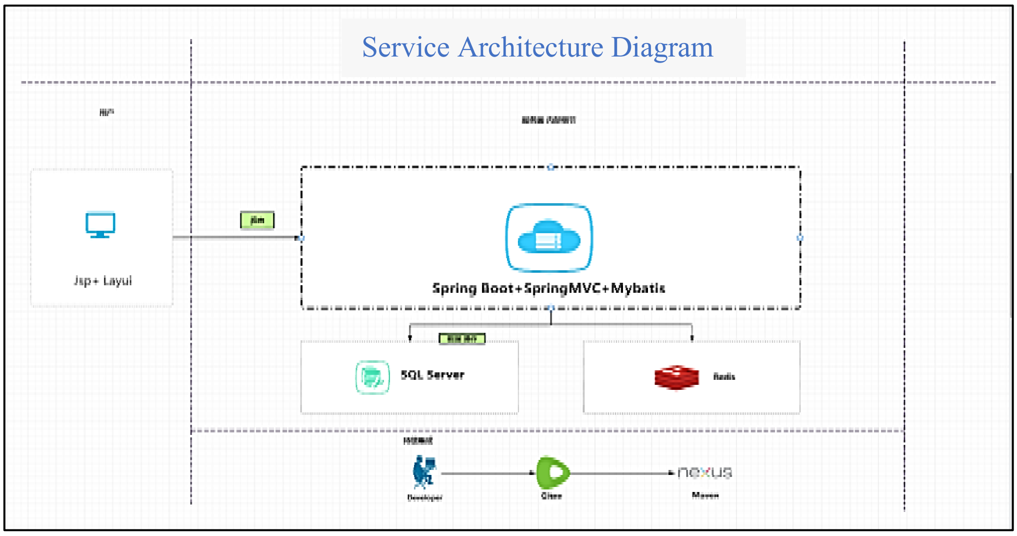


Figure 1. Technical Architecture Diagram

Our system's technical architecture is built upon Spring Boot 2.0 as the primary backend framework, leveraging its simplified configuration and efficient development capabilities to handle business logic and data access. Concurrently, we utilize Redis 4.0 as the caching database to enhance system read performance and response speed, while also serving roles such as message queuing or distributed locking. SQL Server functions as the persistent storage database, responsible for storing business data including user information and product details. On the frontend, Lay-UI is selected as the main framework to manage user interface rendering and interaction logic, facilitating data exchange with the backend via APIs. Maven is employed as the project management tool to handle dependency libraries, compilation, and packaging for Java projects, streamlining the build process. Finally, Git, a distributed version control system, is used to manage code versions and collaborative development, ensuring code security and traceability. By integrating these technologies, we have constructed a comprehensive system technical architecture aimed at fulfilling functional requirements and optimizing performance.

4. System Innovation Design and Technical Implementation

4.1 Installation Design

The installation is designed according to the unattended on-site and remote intelligent weighing mode, based on the company's actual business processes.

4.2 AI Video Terminal Design

Multi-view Camera System
License Plate Capture Camera: A 4K resolution camera with fill light (e.g., 2-megapixel, frame rate ≥ 25 fps) is deployed at a height of 3.5 meters on both sides of the track, tilted at 30° to capture the side of the carriage.
Panoramic Surveillance Lens: A fisheye camera covers the overall status of the carriage (e.g., detecting abnormal cargo loading).
Edge Computing Terminal: Equipped with NVIDIA Jetson AGX Orin for real-time video stream processing (≤ 50 ms delay).

Algorithm Flow
1. Video stream input → 2. Carriage localization (YOLOv8 segmentation model) → 3. ROI cropping of the license plate area → 4. Character segmentation (projection method/CNN) → 5. Character recognition (CRNN + CTC) → 6. Result verification (compared with RFID)

Core Optimization Points

1. Extreme Condition Adaptation
   Low Light/Reflection: HDR imaging + adaptive histogram equalization (CLAHE) to enhance contrast.
   Rain, Snow, and Stains: Embedded image restoration module (GAN network to complete occluded characters).
2. Multimodal Fusion
   Parallel verification of RFID tag reading results with video recognition results (triggers manual review when confidence < 95 %).
3. Continuous Learning Mechanism
   Establish a misrecognition sample library (e.g., blurred license plates, special fonts) and iterate the model monthly.
4. Federated Learning Mode
   Multi-site sharing of data features (non-raw data) to improve generalization ability.

4.3 Weighing Terminal Design

The weighing terminal, as the core execution unit of the logistics weighing system, adopts a B/S (Browser/Server) architecture to achieve integrated functions of data collection, weight analysis, and remote control through collaborative design between the browser and server sides. The following sections discuss the technical architecture, data collection mechanism, and functional implementation.

4.3.1 B/S Architecture Design and Technology Selection

Front-end Design
Framework Selection: Built with Vue3 + Element Plus for a responsive interface supporting multiple terminals (PC/mobile), enabling real-time visualization of weight data (dynamic refresh rate ≤ 500 ms);
Core Modules:
Real-time Monitoring Panel: Displays dynamic weighing curves of the track scale and sensor status (e.g., zero-drift alarms);
Historical Data Query: Supports multi-dimensional retrieval by time, license plate number, and cargo type, with data loading delay < 1 s. Exception Alarm Center: Pushes over-difference and cheating events via WebSocket protocol, triggering pop-up and SMS notifications.

Back-end Design
Microservice Architecture: Utilizes the Spring Cloud Alibaba framework, split into data collection, AI analysis, and permission management services to ensure stability under high concurrency (single node supports 1000+ concurrent requests).

Database Optimization
Time-series Database (InfluxDB): Stores high-frequency sensor data (sampling rate 1 kHz) with a compression rate of up to 80 %.
Relational Database (MySQL): Stores business data (license plate numbers, cargo information), supporting billions of data entries through sharding strategies.

Communication Protocols
Industrial Protocol Compatibility: Integrates OPC UA and MQTT protocols, compatible with traditional devices like Modbus and Profibus, with protocol conversion time < 50 ms.

Data Encryption: Uses TLS 1.3 for encrypted transmission, combined with the SM4 algorithm for end-to-end encryption of sensitive data (e.g., license plate numbers, weights).

4.3.2 Data Collection and Weight Analysis

Sensor Network Deployment
High-precision Digital Sensors: HBM PW15C sensors (accuracy 0.01 % FS, overload capacity 200 %) are deployed at key stress points of the track scale;
Redundancy Design: Each weighing node is equipped with dual sensors, triggering automatic switching and fault alarms when data differences exceed 0.1 %.

Data Preprocessing Flow
Dynamic Filtering Algorithm: Uses Kalman Filter to eliminate mechanical vibration noise, improving signal-to-noise ratio by 40 %.
Outlier Removal: Adopts a sliding window Z-Score algorithm (window size 1000 points, threshold $\pm 3\ \sigma$) to filter transient interference in real-time.
Weight Calculation Model and Dynamic Compensation Algorithm

Speed Compensation: Dynamically adjusts weight coefficients based on speed (5–30 km/h), reducing error from 1.2 % to 0.3 %.
Temperature Compensation: Real-time calibration via PT100 temperature sensors, with temperature drift error ≤ 0.005 %/°C.
Multi-carriage Coupling Correction:
Uses an LSTM network to predict vibration transfer effects between carriages, correcting multi-carriage weighing deviations.

4.3.3 Functional Implementation and Interaction Design

Weight Collection Process

Automatic Mode:
When a vehicle passes the scale, the system automatically triggers sensor data collection, preprocesses the data via an edge gateway (NVIDIA Jetson Nano), uploads it to the cloud, and matches license plate numbers with weights using the AI engine to generate electronic weight slips synchronized with the logistics management system.

Manual Intervention Mode:
Supports manual correction of license plate numbers and weights under abnormal conditions, with operation logs stored on a blockchain (Hyperledger Fabric).

Remote Control Functions
Remote Calibration: Sends calibration instructions via the browser for automatic zero calibration and span calibration of the track scale (duration < 2 minutes).

Data Visualization Examples
Real-time Curves: Dynamically displays weighing waveforms, speed, and temperature trends (see Figure 4.3.4).
Heatmap Analysis: Statistics on weighing error distributions across different time periods and vehicle types to aid operational decision-making.

4.3.4 Performance Verification and Optimization

Pressure Testing
Simulates 100 trains passing continuously (speed 20 km/h), with system processing delay stabilized at ≤ 120 ms and no data packet loss;
Database read/write performance: Time-series data write rate > 100 000 entries/second, query response time < 50 ms.

AI Model Optimization
Federated Learning Framework: Shares model parameters (non-raw data) across sites, reducing LSTM prediction error by 22 %.
Edge Model Lightweighting: Accelerates inference via TensorRT, reducing time from 120 to 35 ms.

4.4 Track Scale Weighing System Design

4.4.1 System Login

The system is deployed on the enterprise intranet. Open a browser and enter http://192.168.88.246:8080 to access the system (see Figure 2). Metering personnel can log in by entering their personal accounts.

4.4.2 System Homepage

Figure 2. System Interface

After successful login, the homepage defaults to the power plant dynamic track scale processing interface.

4.4.3 Homepage Design

1. In the top-left corner, the logged-in user's name is displayed. Clicking on it with the mouse will show options to enter the system backend or log out of the backend.
2. The central area displays weighing apparatus information, with controls for the weighing method located at the rear.
3. In the upper-middle left position, the dynamic weighing apparatus displays information on each sensor and zero-point data; the static weighing apparatus displays zero-point information and AI camera-recognized wheel position information. The weighing point position can be switched to control different weighing apparatuses.
4. In the lower-middle left position, real-time vehicle passage information is displayed.
5. The right-middle position displays real-time monitoring footage of the current weighing apparatus.
6. Weighing data is presented below.

4.4.4 Dynamic Weighing

1. Single Weighing Mode: The train passes the scale for gross weight without returning for tare weight. The system uses AI-recognized self-weight or a fixed self-weight from the tare library based on the license plate number.
2. Double Weighing Mode: The train passes the scale for gross weight, and AI recognizes the license plate number. After gross weighing, the train returns for tare weight.
3. Calibration Mode: The train passes the scale for gross weight without returning for tare weight. The system uses AI-recognized self-weight or a fixed self-weight from the tare library based on the license plate number.

Dynamic Weighing Operation:
Before the train passes the scale, a weighing notice is received from the railway department. Based on the situation, the corresponding weighing method is enabled at the corresponding scale point. For example, in double mode:

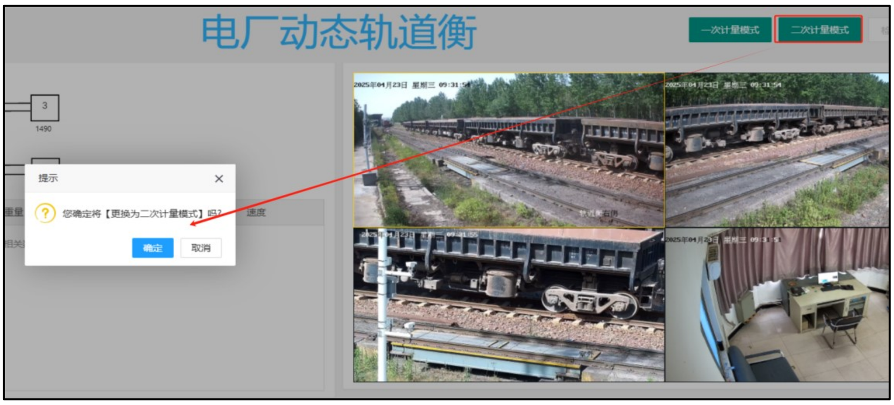


Figure 3. Confirmation for Mode Switching

电厂动态轨道衡	Power Plant Dynamic Rail Scale
一次计量模式	Single Weighing Mode
二次计量模式	Double Weighing Mode
提示	Prompt
您确定将【更换为二次计量模式】吗？	Are you sure you want to switch to [Double Weighing Mode]?
确定	Confirm
取消	Cancel

At the end of dynamic weighing, a prompt for manual completion appears. If no action is taken within 12 seconds, it automatically completes.

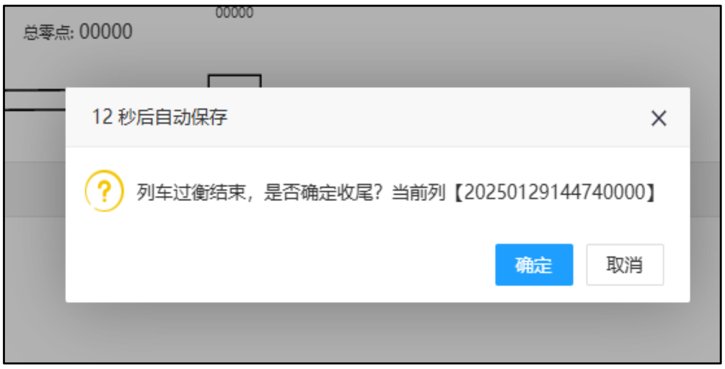


Figure 4. Automatic Completion Prompt

<table>
<tr><td>12秒后自动保存</td><td>Auto-save in 12 seconds</td></tr>
<tr><td>列车过衡结束，是否确定收尾？当前列【20250129144740000】</td><td>The train weighing is completed. Are you sure to conclude? Current train 【20250129144740000】</td></tr>
<tr><td>确定 | 取消</td><td>Confirm | Cancel</td></tr>
</table>

During train passage, buttons are disabled to prevent mis-operation.
After successful completion, in single weighing mode, data is directly saved to the "matched" column. In double weighing mode, the first weighing is saved to the "unmatched" column, and the second weighing (tare) is saved to the "matched" data. If the license plate number is lost, the system prompts and displays the issue in the exception information.

Figure 5. Weighing Information Editing Page

动态过衡数据编辑	Dynamic Weighing Data Editing
发货单位	Shipping Unit
请输入文字或者拼音字母	Please enter text or pinyin letters
收货单位	Receiving Unit
产品名称	Product Name
进出厂类别	In/Out Factory Category
扣除厢重	Deduct Container Weight
是 | 否	Yes | No
备注	Remarks
保存 | 取消	Save | Cancel

Unmatched data can have information such as receiving unit, shipping unit, and inbound/outbound details pre-entered. Check the corresponding data and batch edit it. Matched Data Handling example ca be found in Figure 6.

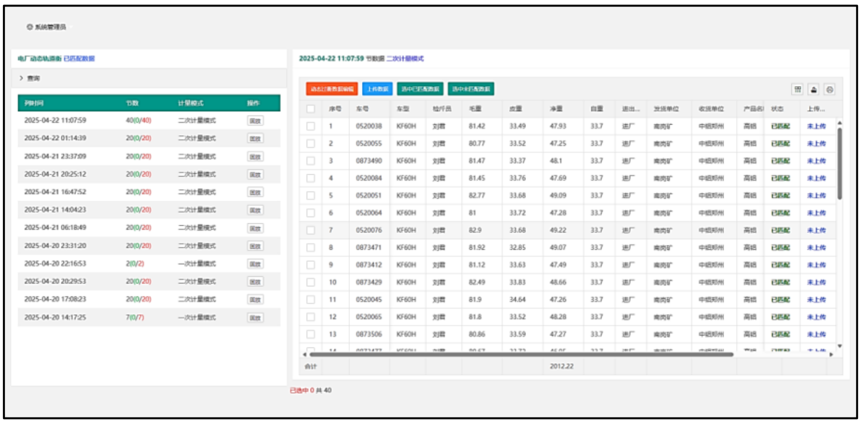


Figure 6. Processed Data Matching

After editing the data, check the corresponding data and click "Upload Data" to send it to the upstream scale system in one click. In single weighing mode, if there is carriage weighing, support for deducting carriage weight is available.

Exception Handling

If manual completion is required after the train has passed, it indicates a license plate number exception. Exception data is displayed below, and the data can be voided for re-weighing. Click "View" to enter the exception handling interface.


异常数据

保存数据 查看回放

1.车号丢失,双击车号,车型进行编辑。

2.车号疑似识别错误,先左侧查询上次过衡数据,双击车号,车型对照进行编辑,如果方向一直从上往下编辑,方向不一致从下往上编辑。

车号	车型	重量	自重	速度	异常信息	过衡时间	方向	列id
	KF60H	20	33.7	3.6	车号为空	2025-04-25 15:43:25	L	20250425144740...
0520585	KF60H	20	33.7	3.9	0520585,车号疑似存在识别错误，未匹配到毛重。	2025-04-25 15:43:37	L	20250425144740...
0520595	KF60H	20	33.7	3.6	正常	2025-04-25 15:43:50	L	20250425144740...
0520647	KF60H	10	33.7	3.3	正常	2025-04-25 15:44:04	L	20250425144740...
0520650	KF60H	20	33.7	3.6	正常	2025-04-25 15:44:17	L	20250425144740...

Figure 7. Data Anomaly Handling Interface 1

The right table highlights rows with license plate exceptions (lost or unmatched). Double-click the license plate cell to manually enter the lost number. In double weighing mode, the left table can query previously uploaded license plate numbers for reference. The entered number is compared with the left list and cannot be saved if it does not exist. After entering the correct number, click "Save Data" to simulate re-weighing and save the data.

Video Playback

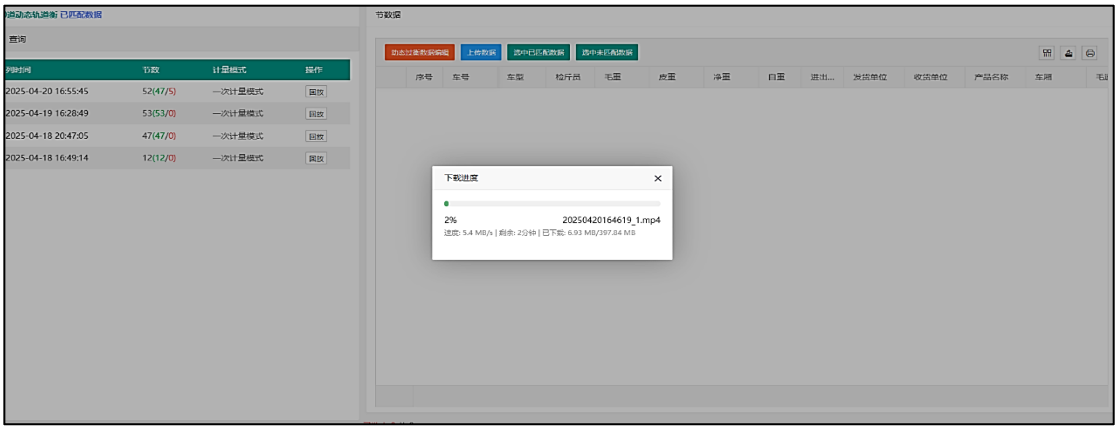


Figure 8. Weighing Video Download

Click "Playback" on the left to view the weighing video.

4.4.5 Static Weighing

Standard Weighing Mode: The train passes the scale for single-car weighing. AI recognizes the license plate number, first for tare weight, then for gross weight. For vehicles with deductible weight, the system automatically deducts the package weight based on the load.

Tare Weighing Mode: The train passes the scale, and AI recognizes the license plate number, using the historical tare weight for that number to directly weigh the gross weight.

Static scales support remote zeroing. If the scale does not return to zero, click "Remote Zero" to reset it.

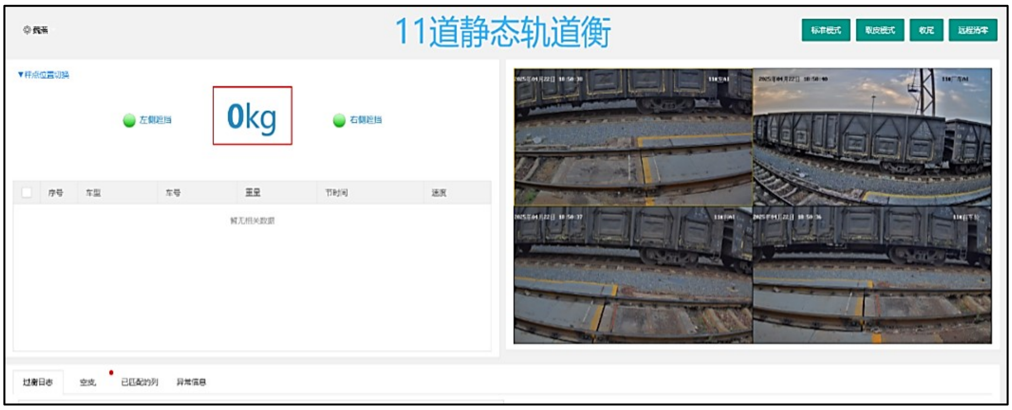


Figure 9. Static Weighing Page

11道静态轨道衡	Track 11 Static Rail Scale

Static Weighing Operation
Similar to dynamic weighing, a weighing notice is received, and the corresponding weighing method is enabled, such as standard mode:

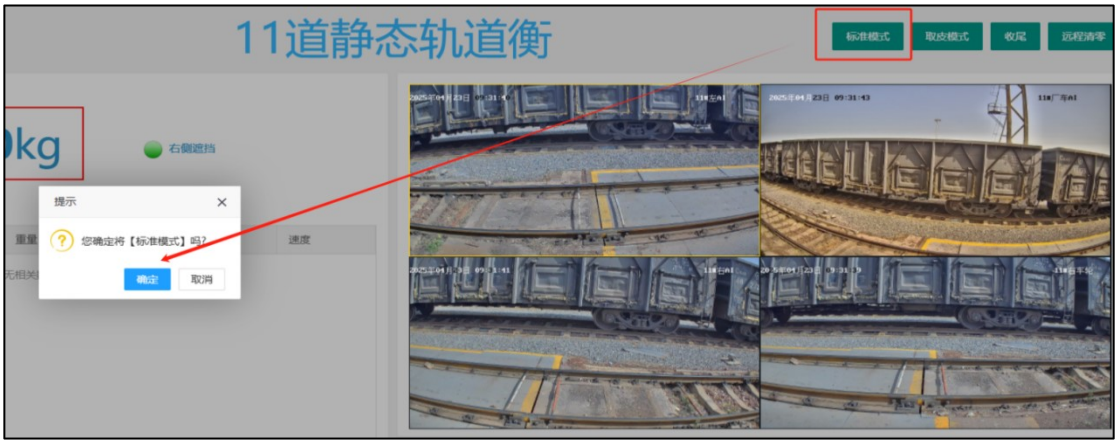


Figure 10. Switching to Standard Weighing Mode

11道静态轨道衡	Track 11 Static Rail Scale
您确定将【标准模式】吗？	Are you sure to set [Standard Mode]?

Static weighing differs from dynamic weighing in that weights are automatically matched. After the entire train has passed, completion is required to finalize the weighing.

Static Weighing Precautions:
1. Observe the "left occlusion" and "right occlusion" indicators. If "left occlusion" turns red, notify the site via voice communication to adjust the vehicle to the right, and vice versa.
2. Alternatively, observe the weighing log at the bottom of the page for real-time vehicle information. Green indicates normal, and red indicates exceptions.
3. Upon successful weighing, a real-time prompt indicates that the vehicle data has been saved.

Matched Data Handling

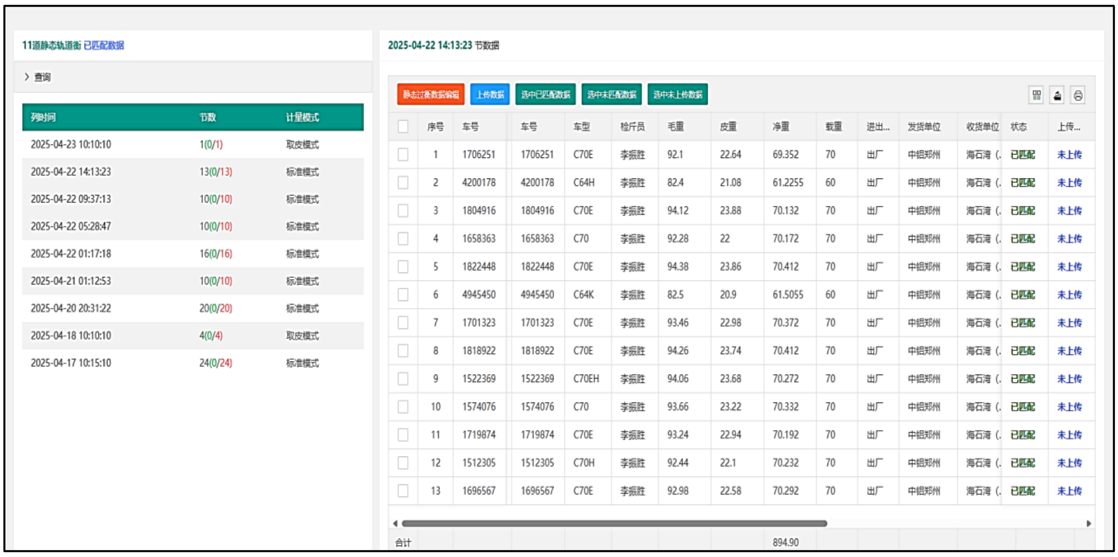


Figure 11. Processed Data Matching

For gross weight, the system matches tare weights from different columns based on the license plate number to form a new gross weight column without disrupting the order. Handling is similar to dynamic weighing: select the corresponding gross weight column for editing.

If a ticket number is required, enter the starting ticket number, and the system will automatically append numbers for other vehicles (enter digits only). Then, enter the corresponding shipping unit, receiving unit, product name, and inbound/outbound type. The package weight defaults to "No." If "Yes" is selected, the system automatically deducts the corresponding number of packages and weight based on the load (e.g., a load of 70 with a package weight of 40 deducts 40 bags; a load of 60 deducts 35 bags). Custom package numbers and weights can also be entered. Support is also provided for deducting tarpaulin weight, moisture (percentage), and miscellaneous weight.

After editing the data, check the corresponding data and click "Upload Data" to send it to the upstream scale system in one click.
Exception Handling

If the license plate number is lost during static weighing, the data also appears in the exception information. Click "View" to enter the exception handling page.

Figure 12. Vehicle Number AI Recognition

修改车号	Modify Vehicle Number
过车图片：	Vehicle Image:
双击放大/缩小图片	Double-click to zoom in/out the image
输入车号：	Enter Vehicle Number:
请输入车号	Please enter the vehicle number
提交	Submit
取消	Cancel

Displays the captured license plate number. Enter the corresponding number and click "Submit" to simulate re-weighing. To re-weigh or void the data, click "Delete License Plate" at the top left.

4.5 System Management

4.5.1 User Management

Examples are found in Figure 13.

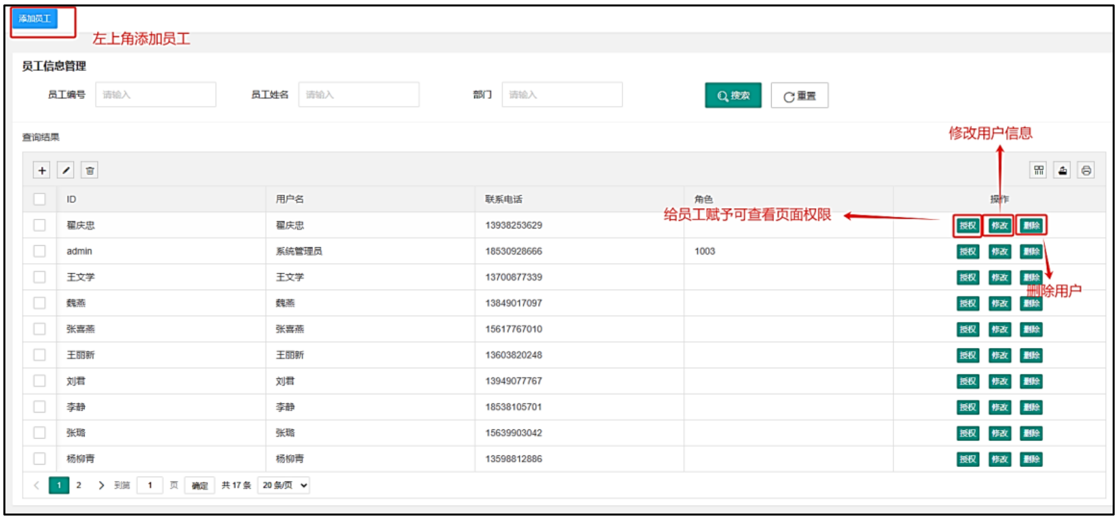
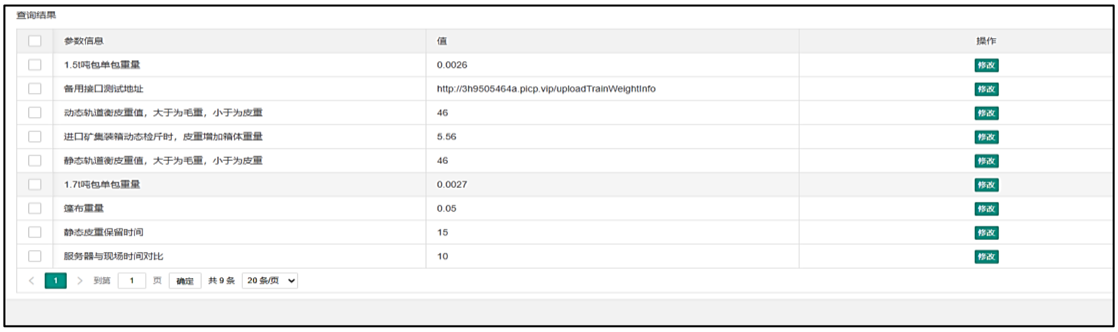


Figure 13. User Management

左上角添加员工	Add Employee in the Top-Left Corner
员工信息管理	Employee Information Management
员工编号	Employee ID
员工姓名	Employee Name
部门	Department
查询	Search
重置	Reset
查询结果	Search Results
修改用户信息	M odify User Information
给员工赋予可查看页面权限	Grant employees the permission to view pages
删除用户	Delete User

Enables user management functions such as adding, deleting, modifying, and authorizing users.

4.5.2 Parameter Management



查询结果

参数信息	值	操作
1.5t吨包单包重量	0.0026	修改
备用接口测试地址	http://3h9505464a.picp.vip/uploadTrainWeightInfo	修改
动态轨道衡皮重值，大于为毛重，小于为皮重	46	修改
进口矿集装箱动态检斤时，皮重增加箱体重量	5.56	修改
静态轨道衡皮重值，大于为毛重，小于为皮重	46	修改
1.7t吨包单包重量	0.0027	修改
篷布重量	0.05	修改
静态皮重保留时间	15	修改
服务器与现场时间对比	10	修改

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Figure 14. Parameter Settings

Used to modify dynamic parameters such as package weight.

4.5.3 Track Scale Business Management

Static Historical Tare Weight Query
Supports setting tare weights as permanent in-plant transfer weights, marking as unmatched, voiding, or permanent deletion.

Dynamic Track Scale Weighing Data Query
Queries dynamic weighing data.

Static Track Scale Weighing Data Query
Supports custom queries by checking shipping unit, receiving unit, and product name. Combines dynamic and static data.

4.6 Information Maintenance

Enables management of receiving units, shipping units, product information, and inbound/outbound information.

5. Effectiveness Evaluation and Industry Promotion Value

5.1 Technical Indicator Verification

Through actual deployment and continuous 6-month operational testing, the system has achieved significant breakthroughs in key performance indicators:

Weighing Accuracy Improvement
Dynamic weighing error: Reduced from ±1.2 % in traditional systems to ±0.25 % (speed ≤ 30 km/h), meeting the ±0.3 % process requirement for alumina production;

Temperature adaptability: Sensor temperature drift error ≤ 0.005 %/°C in the -30 to 50 °C range, a 10-fold improvement over traditional analog sensors (0.05 %/°C).

Efficiency Optimization
Unattended weighing efficiency: Single train processing time reduced from 5 minutes in manual mode to 30 seconds, with a 10-fold increase in daily throughput.

AI recognition accuracy: License plate recognition accuracy ≥ 99.5 % (≥ 97 % in extreme rain/snow conditions), vehicle type classification accuracy ≥ 98.3 %.

Anti-cheating Capability
Exception interception rate: The interception rate of fraudulent behaviors increased from 68 % to 99.8 % through AI video analysis (e.g., carriage edge detection, counterweight lead block identification);

Data credibility: Blockchain-based data coverage for 100 % of weighing data, reducing tampering risk to near-zero and audit disputes by 92 %.

5.2 Economic Benefit Analysis

Based on the Life Cycle Cost (LCC) model, the system transformation yields significant comprehensive benefits
Labor Costs: On-site personnel reduced by 90 %, saving approximately 2.4 million yuan in annual labor expenses.
Operation and Maintenance Costs: Fault rate decreased by 85 % (average annual repairs reduced from 15 to 2 times), reducing annual maintenance costs by 1.2 million yuan.

Indirect Benefit Improvements
Production efficiency: Reduced soda consumption losses due to weighing errors by 600 tonnes/year, valued at approximately 2.8 million yuan;
Return on Investment: System transformation cost of approximately 2 million yuan, with an investment recovery period ≤ 1.8 years (traditional system transformation periods typically ≥ 3 years).

5.3 Industry Promotion Potential

The system's technical architecture and application model are universally adaptable across industries and scenarios, with promotion value manifested in the following aspects:

Technical Replicability
Modular design: Supports customization of functional modules (e.g., AI recognition, blockchain-based data storage) to meet the differentiated needs of industries such as coal, steel, and chemicals;
Protocol compatibility: Seamless integration with over 90 % of industrial equipment via OPC UA and MQTT protocols, reducing enterprise transformation costs.

Industry Pain Point Coverage
High-corrosion environments: Sensor protection rating upgraded to IP68 for wet metallurgy scenarios (e.g., copper smelting), extending lifespan by 3 times;
Hazardous material monitoring: Suitable for real-time weight monitoring of hazardous chemical transportation, with overload warning response time < 1 s.

Standardization Promotion
Data interface specifications: Participation in drafting the "Intelligent Track Scale Data Interaction Standard" (group standard draft) to promote industry-wide data interoperability.

Low-carbon Benefits
Unattended mode reduces on-site energy consumption by 30 %, aiding enterprises in achieving ESG (Environmental, Social, Governance) goals.

5.4 Typical Application Cases

Intra-aluminium Industry Promotion
Replicated across six alumina refineries under the China Aluminum Group, with dynamic weighing errors consistently within ±0.3 % and annual comprehensive benefits exceeding 50 million yuan.
An aluminium smelter introduced the system, improving anode carbon block weighing efficiency by 40 % and process stability by 15 %.

Cross-industry Expansion
Coal industry: Deployed at a Shanxi coal mine railway loading point, achieving ≥ 99 % accuracy in carriage full-load detection and reducing annual transportation waste by over 8 million yuan.

Port logistics:
Applied at Qingdao Port's bulk cargo terminal, reducing cargo mismatch rates from 1.5 to 0.2 % and improving loading/unloading efficiency by 25 %.

5.5 Future Technology Integration Directions

Deep Application of Digital Twins:
Construct a 3D digital twin of the track scale for real-time physical device state mapping, improving predictive maintenance accuracy to 95 %.
Combine with AR technology for remote expert collaborative maintenance (e.g., sensor fault location).

5G + Edge Computing:
Utilize 5G network slicing to ensure critical data (e.g., overload alarms) transmission delay < 10 ms; Lightweight edge AI models (TensorFlow Lite) support real-time reasoning on low-power devices.

6. Conclusion and Outlook

6.1 Conclusion

This study has constructed an intelligent logistics weighing system for alumina production through the deep integration of IoT and AI technologies, achieving unattended, remote intelligent, and data-trustworthy track scale weighing. This effectively addresses the efficiency bottlenecks and human risks of traditional weighing models. Key achievements are summarized as follows:

Technical Breakthroughs:
1. A YOLOv8 + CRNN-based multimodal AI recognition model achieves 99.7 % accuracy for license plate numbers and 98.5 % for vehicle types, maintaining > 95 % robustness in extreme weather;
2. Dynamic weighing algorithms reduce errors from ±1.2 % to ±0.25 % through LSTM vibration compensation and Kalman filter noise reduction, meeting the stringent ±0.3 % process requirement for alumina production;
3. Blockchain-based data storage and TLS + SM4 encryption technologies ensure full-link data tamper resistance, increasing annual cheating interception rates to 99.8 % and reducing audit disputes by 92 %.

Management Upgrades
1. Unattended mode reduces single train weighing time to 30 seconds, increasing daily processing capacity by 10 times and cutting labour costs by 90 %;

2. Electronic weight slips and cloud collaboration reduce financial reconciliation cycles from 5 days to 4 hours, improving capital turnover efficiency by 12 times.

Industry Value
Scalable application across six factories under the China Aluminum Group has yielded annual comprehensive benefits exceeding 50 million yuan, validating the technology's universality and economic viability.

6.2 Outlook

Despite the system's current success, future exploration should focus on the following directions:

Technology Fusion Innovation
1. Deep application of digital twins: Construct a 3D dynamic twin of the track scale for real-time device health state mapping, combined with AR technology for fault prediction and remote expert collaborative maintenance (e.g., intelligent diagnosis of bearing wear).
2. 5G + edge computing optimization: Utilize 5G network slicing to ensure critical data (e.g., overload alarms) transmission delay < 10 ms and deploy lightweight AI models (TensorFlow Lite) to edge devices, reducing inference time from 35to 15 ms.

Algorithm Capability Enhancement
1. Federated learning and incremental learning: Improve AI recognition generalization (e.g., special license plate fonts, new cheating methods) through collaborative model training across multiple sites while protecting data privacy.

Industry Ecosystem Expansion
1. Cross-industry standardization: Jointly develop the "General Specification for Intelligent Weighing Systems in Process Industries" with steel, coal, and chemical sectors to promote multi-industry data interoperability and equipment compatibility.
2. Low-carbon upgrades: Introduce photovoltaic power supply and low-power sensor designs to reduce overall system energy consumption by 40 %, aiding in "dual carbon" goal achievement.

Security System Strengthening
Zero-trust architecture: Implement dynamic identity verification and micro-segmentation to defend against APT (Advanced Persistent Threat) attacks on IoT nodes.

This system, with IoT as its foundation, AI as its core, and trustworthy security as its guarantee, has reshaped the technological paradigm for logistics weighing in process industries. Its successful practice not only provides reliable support for the efficient operation of alumina production but also opens new paths for digital transformation in process industries through modular design and standardized output. In the future, with the deep integration of cutting-edge technologies such as 5G and quantum sensing, intelligent logistics weighing systems will unlock greater industrial internet empowerment value across broader dimensions, driving the leapfrog upgrade from "manufacturing" to "intelligent manufacturing."

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