Research on safety risk monitoring of urban rail transit operation based on blockchain

Tingting Liu

Jilin Vocational and Technical College of Transportation, Jilin, China

Abstract. The rapid urbanization-driven expansion of urban rail transit underscores the criticality of operational safety. Conventional centralized risk monitoring systems face limitations in data integrity and response latency. This study introduces a blockchain-based operational safety risk monitoring system, structured around 28 indicators spanning four dimensions: equipment failure, environmental factors, human operations, and structural safety. Leveraging blockchain technology, the proposed distributed architecture integrates data cleaning, feature engineering, standardization, and random forest algorithms for risk analysis. Empirical validation using Wuhan Metro Line 6 demonstrates superior performance over traditional systems in data tampering detection time, fault response speed, and false alarm rate. Future work includes expanding multi-source data fusion and optimizing smart contract triggers, while cross-regional consortium chains enhance operational management capabilities.

Keywords: Urban rail transit, Operation safety risk monitoring, Blockchain technology, Risk index system, Random forest algorithm.

1. Introduction

The introduction of blockchain technology in urban rail transit has innovated and broken through traditional operational safety risk monitoring models[1]. The integration and development of the urban rail transit industry with emerging technologies also cannot do without it. The overall technical level and competitiveness of the industry have been enhanced through its use, while laying the foundation for the future development of smart transportation. This is not just a technological innovation; under the impetus of technology, the industry's development will integrate with emerging technologies, and its overall competitiveness and technical level will also be inseparable from it.

2. Urban rail transit operation safety risk index system

2.1 Classification of risk indicators

To comprehensively and systematically monitor the operational safety risks of urban rail transit, it is essential to establish a scientifically sound risk indicator system[2]. This study specifically categorizes the operational safety risks of urban rail transit into four major categories: equipment failure risk, environmental risk, human operation risk, and structural safety risk. The specific indicators and data sources are shown in Table 1.

Table 1. Three Scheme comparing.

Risk type	Specific indicators	Data sources
Equipment failure risk	Signal system failure rate, track structure crack rate	Sensors, inspection records
Environmental risks	The frequency of extreme weather impact and the rate of geological subsidence	Meteorological stations, geological monitoring
Operational risk due to human error	Driver error rate, emergency response delay time	Operation log and drill record
Structural safety risk	Bridge inclination, tunnel seepage	BIM model, monitoring equipment

2.2 Risk classification criteria

In order to accurately assess the severity of urban rail transit operation safety risks and formulate reasonable countermeasures, it is necessary to classify the risks into different levels[3]. This study adopts the risk matrix method to comprehensively consider the two factors of risk occurrence probability and consequence severity, and divides them into four levels: extremely high, high, medium and low. The specific classification criteria are presented in Table 2.

Table 2. Three Scheme comparing.

Risk grade	Probability of occurrence (per year)	The severity of the consequences	Risk matrix coding
Polar altitude	> 1 time/year	Major casualties	R1
Tall	0.5-1 times/year	The man was seriously injured	R2
Centre	0.1-0.5 times/year	property loss	R3
Low	<0.1 times/year	Minor effects	R4

When the probability of a risk occurring exceeds once per year and the severity of its consequences reaches major casualties, it is classified as an extremely high-risk level[4].

3. Data monitoring and analysis methods

To ensure the quality and availability of monitoring data, raw data collected needs to undergo preprocessing. The steps include data cleaning, feature engineering, and standardization[5]. Data cleaning involves handling incomplete and irrelevant data; feature engineering focuses on generating and processing features; standardization deals with data volume reduction and simplification. The specific process is shown in table3.

Table 3. Three Scheme comparing.

Step	Operate the content	Technical method
Data cleaning	Remove outliers (such as sensor fault data)	Statistical analysis based methods, such as the 3σ principle
Feature engineering	Extract key indicators (such as the standard deviation of track irregularity)	Methods based on signal processing and machine learning, such as Fourier transform and principal component analysis
Standardization	Heterogeneous data are processed by Z-score method	Formula: $(x- \mu) / \sigma$, where x is the original data, μ is the mean, and σ is the standard deviation

During the data cleaning phase, when using the 3σ principle based on statistical analysis, data points with deviations from the mean exceeding three times the standard deviation are identified as outliers and removed. For instance, in monitoring track structure crack rate data points, if a certain point shows significant deviation from other data, it is judged as an outlier according to the 3σ principle[6]. The logic behind this can be interpreted as sensor failure or data transmission error. After removing these abnormal data points, the accuracy of the data improves. When processing signals, converting them into frequency domain features is also part of feature engineering. By leveraging Fourier transform, time-domain signals are converted to extract frequency-related features and complete the calculation of the standard deviation for track irregularity. Principal component analysis reduces the dimensionality of multi-dimensional raw data, extracting key indicators. During the normalization stage, formula $(x-\mu) / \sigma$ is used to process heterogeneous data, converting data of different scales into Z-Score values for uniform comparison. The horizontal force and vertical acceleration components of the track have different scales; after normalization, the scale differences are eliminated, enhancing data comparability and aiding subsequent analysis and modeling.

In this study, a risk assessment model based on the random forest algorithm of machine learning is constructed. The structure and parameter setting of the model are shown in table4.

Table 4. Three Scheme comparing.

Model name	Structural description	Parameter setting
Random forest	It is composed of multiple decision trees and the final result is determined by voting mechanism	Number of decision trees: 100, maximum depth: 5, minimum sample segmentation number: 2

4. Empirical analysis

4.1 Case Background

This study selects Wuhan Metro Line 6 as the case for empirical analysis. This line is an inter-town rail transit backbone that spans the Han River, connecting Hankou and Hanyang. It connects areas such as the Sports Center, Expo Center, Hanyang Commercial Center, Hankou Commercial Center, the northern residential area, Changqing Garden, and Jin Yin Lake. It serves as the main channel for passenger flow between Dounkou Economic Development Zone, Hanyang District, Hankou District, and Dongxihu District, positioned as a high-capacity line. The total length of the line is 42.95 kilometers, all of which are underground stations with 32 stops. The daily average passenger volume is significant, and the operating environment is complex, making it typical and representative.

The monitoring cycle runs from January to December 2024. During this period, sensors, IoT devices, and various monitoring instruments installed in systems such as vehicles, tracks, signaling, and power supply collect 1.2 million data points. These data include equipment operation, environmental conditions, personnel operations, train running status, track structure, signal system parameters, power system indicators, weather information, and driver operation records. Subsequent analysis and validation can be supported by this rich dataset.

4.2 Comparison of application effects

A comparative analysis of the application effectiveness between the blockchain-based monitoring system and conventional monitoring systems in Wuhan Metro Line 6 is presented in Table 5.

Table 5. Three Scheme comparing.

metric	Traditional systems	Blockchain system	The extent of the increase
Data tampering detection time	48 hours	actual time	100%
Fault response speed	35 minutes	12 minutes	65.7%
Risk false alarm rate	18.2%	5.3%	70.9%
Metric	Traditional systems	Blockchain system	The extent of the increase

In terms of data tamper detection, traditional systems store data centrally, requiring manual periodic checks and comparisons to detect tampering, with an average discovery time of 48 hours. Blockchain systems leverage the decentralized and immutable nature, where each node maintains a complete copy of the data. Any changes are immediately monitored by other nodes, and once anomalies are detected, alerts are triggered instantly, achieving real-time detection with a 100% improvement in accuracy.

Traditional systems have the drawback of overly lengthy processes for handling equipment failures. After an incident occurs, information must be reported and data transmitted through multiple layers before maintenance procedures can be initiated, with an average response time of 35 minutes. In contrast, the use of smart contracts and real-time data sharing in blockchain systems enables proactive alerts when equipment fails. Fault information is then sent to maintenance personnel and managers in real time, allowing them to quickly obtain specific fault details and take action. This reduces the average response time to 12 minutes, increasing response speed by 65.7%.

Traditional systems have flaws in data processing and analysis capabilities, with significant impacts from noise data and interference factors, leading to a high risk misreporting rate of 18.2%. In contrast, the blockchain system, through the integration of machine learning algorithms and the use of high-quality monitoring data, offers more accurate security risk identification and assessment capabilities, with a false positive rate of only 5.3%, a reduction of 70.9%. The comparative data demonstrates that the blockchain monitoring system has notable advantages in data security, response speed, and the accuracy of risk assessment, effectively enhancing the ability to monitor related safety risks in urban rail transit operations.

5. Conclusion and outlook

This study has established a comprehensive urban rail transit operation safety risk monitoring system. The design scientifically includes four major risk dimensions: equipment failure, environment, human operations, and structural safety. Specifically, it can be divided into 28 indicators, providing a systematic framework for related monitoring tasks. With the support of blockchain technology, a distributed architecture system has been designed, with key modules covering encryption mechanisms, smart contracts, consensus algorithms, and distributed ledgers. The monitoring data processing is automated, and its credibility and security requirements are ensured through real-time sharing and non-tamperable features. The real-time nature and effectiveness of the data are also enhanced and guaranteed through technology in the monitoring process.

Relying on advanced data monitoring and analysis methods, preprocessing of multi-source heterogeneous data, risk assessment, and visual presentation are achieved to realize real-time monitoring and precise early warning of urban rail transit operation safety risks. In the empirical analysis of Wuhan Metro Line 6, the blockchain-based monitoring system shows significant advantages over traditional systems in terms of data tamper detection time, fault response speed, and false alarm rate. The monitoring system enhances the level of urban rail transit operation safety risk monitoring and validates the results of relevant data analysis.

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