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Research on the Construction and Application of AI-Based Failure Prediction Model for Rail Transportation Equipment

Tao Lin

Tongfang Technovator Int. (Beijing) Co., Ltd., Beijing, China
gongzuo1232024@126.com

ABSTRACT

In order to improve the intelligent operation and maintenance level of rail transit systems in smart cities, the application of artificial intelligence (AI)-based fault prediction models in rail transit equipment maintenance is studied. A fault prediction model with strong predictive ability and adaptability is constructed by fusing multi-source data, including equipment operation status, environmental factors and city dynamic information. The results show that the model has significant advantages in reducing operation interruptions, lowering maintenance costs, optimizing resource scheduling, and improving the reliability and efficiency of rail transit systems. Through multi-system collaboration and intelligent operation and maintenance, the model helps to promote the intelligent upgrading of rail transit and improve the response speed and service quality of urban transportation systems.

KEYWORDS

Rail transportation; Fault prediction; Artificial intelligence; Smart city

1. INTRODUCTION

1.1. Background of the Study

As the core infrastructure in the smart city, rail transportation bears the main task of large-scale public travel in the city, which directly affects the efficiency of urban transportation and the convenience of residents' daily travel. However, the negative impact on the transportation network caused by frequent failures of rail transportation equipment should not be ignored. Failures not only increase the risk of operational disruptions, but also aggravate the maintenance costs, affecting the operational efficiency of the entire city. The traditional "one-size-fits-all" maintenance model cannot respond to the dynamic changes in equipment status in a timely manner, resulting in lagging or redundant resource allocation, which cannot effectively match the efficient and flexible needs of smart cities. This contradiction makes the current operation and maintenance mode unable to meet the needs of urban intelligent management, and it is urgent to introduce more accurate and intelligent fault prediction and management technology.

1.2. Significance of the Study

The application of AI-based fault prediction model in rail transportation has significant practical value. By accurately predicting equipment failures, the model effectively reduces operational disruptions and guarantees the continuity and efficiency of the transportation network. In addition, the introduction of the AI model significantly reduces the high costs under the traditional operation and maintenance model, improves resource utilization, and enhances scheduling flexibility, making transportation management more responsive and refined. In terms of promoting intelligent upgrading of the industry, fault prediction technology not only promotes the intelligent level of urban transportation, but also optimizes the dynamic allocation of urban resources, strengthens the responsiveness of public services, and thus improves the comprehensive management effectiveness and service quality of the city, providing technical support for the construction of smart cities.

1.3. Current Status of Domestic and International Research

Under the background of smart city construction, intelligent and refined management of rail transit system has become a hot spot of research. Relevant researches at home and abroad have made some progress in rail transit equipment fault prediction, but still face problems such as data processing, model generalization ability and multi-system synergy. Foreign studies such as the AI-based rail transit equipment fault prediction model proposed by Sun and Dai (2024) have initially realized equipment condition monitoring and predictive maintenance [1]. Zeng et al. (2022), on the other hand, realized track break prediction through imbalance service data, which further advances the accuracy of equipment fault identification [2]. In addition, Daniyan et al. (2022) investigated the application of AI in operations and maintenance in the rail industry, exploring an AI-based maintenance operation model [3].

However, most of the existing methods focus on localized equipment failure prediction and lack consideration of multi-source data fusion and multi-system synergy in the complex environment of smart cities. Domestic studies such as the failure prediction based on ARIMA-SVR model proposed by Wang Yuelong et al. (2025) have made some progress in predicting the number of equipment overhaul and occasional replacement parts, but the versatility and adaptability of their models are still insufficient to fully meet the demand for efficient, real-time, and collaborative operation and maintenance in smart cities [4]. Most of the current research at home and abroad relies on traditional data processing methods, which lacks a comprehensive perception and analysis of the dynamic state of equipment, and is difficult to support collaborative decision-making and resource optimization across fields.

Intelligent prediction models combining multi-source data, especially the dynamic operation and maintenance system oriented to the comprehensive management needs of smart cities, have become a key issue to be solved. In this study, the AI-based rail transit fault prediction model aims to break through the limitations of the existing methods, improve the prediction accuracy, and achieve more efficient resource deployment and multi-system synergy, providing theoretical and technical support for the intelligent operation and maintenance of rail transit in smart cities.

2. ANALYSIS OF RAIL TRANSPORTATION EQUIPMENT OPERATION AND MAINTENANCE DEMAND IN THE CONTEXT OF SMART CITY

2.1. Requirements of Smart Cities for Rail Transportation

Under the background of smart city construction, rail transit not only undertakes the basic commuting function, but is also endowed with the new mission of system intelligence, efficient collaboration and precise service. The operation and maintenance level needs to have the ability to sense the real-time state of the equipment and support predictive maintenance and dynamic scheduling management driven by multi-source data to ensure the continuity and safety of the transportation system. This demand essentially requires that the operation and maintenance model has a stronger perception, calculation and response capabilities, rather than relying on the traditional time-cycle-oriented static maintenance system. The disconnection between equipment operating status and external city operating conditions in the traditional model leads to lagging or redundant maintenance resource allocation, which not only reduces efficiency, but also makes it difficult to support the rapid response and optimized scheduling needs of city-level transportation systems [5]. What the smart city needs is a data-driven, service-capable intelligent operation and maintenance system that can realize the fine-grained, real-time and collaborative control of the operation status of the urban transportation system.

2.2. Gap Between The Existing Operation and Maintenance Model and the Needs of Smart Cities

Currently, the operation and maintenance of rail transportation equipment is still dominated by regular maintenance and aftermath maintenance, which lacks continuous perception and dynamic analysis of equipment operation status, resulting in low data utilization and unable to support accurate operation and maintenance management for the whole life cycle. Under the background of insufficient data processing capacity, equipment anomalies are often identified only after a failure occurs, and the response lags behind, making it difficult to meet the requirements of urban transportation systems for high availability and real-time scheduling. The existing O&M system mostly operates as an independent system and lacks a linkage mechanism with the urban transportation management platform, which hinders the information synergy and risk linkage disposal among different transportation subsystems [6]. Compared with the real-time sensing, intelligent diagnosis and system coordination requirements put forward by smart cities for rail transit, the traditional O&M model has essential gaps in technical architecture, management mechanism and data-driven capability, and it is urgent to realize system reconstruction through the introduction of intelligent means.

3. AI-BASED RAIL TRANSPORTATION EQUIPMENT FAULT PREDICTION MODEL CONSTRUCTION

3.1. Data Fusion and Processing

Data fusion and processing, as the basic link for model accuracy improvement, need to take into account the multidimensional integration of city-level macro data and equipment-level micro data. In this study, a hierarchical data fusion mechanism is designed, whereby rail equipment operation logs (e.g., vibration, current, voltage, and other time-series data) and maintenance records (including overhaul time, repair type, and fault description) are aligned with the primary key, and initial synchronization is achieved through feature coding and label standardization; subsequently, environmental data (temperature and humidity, settlement value, and structural stress in subway tunnels) are introduced to cross-domain fusion with dynamic information of the smart city (urban Traffic flow, population density, and special event labels) are fused across domains, and a graph structure modeling method based on Graph Attention Network (GAT) is used to establish semantic edge connections between device nodes and urban environmental factors, forming a dynamic graph representation for subsequent model inputs (Fig. 1). During the data cleaning process, sliding window outlier detection and self-encoder-based noise reconstruction algorithm are introduced to ensure data continuity and physical consistency. The fused data finally constructs a feature engineering table (Table 1) to provide a unified interface for multi-model structure.

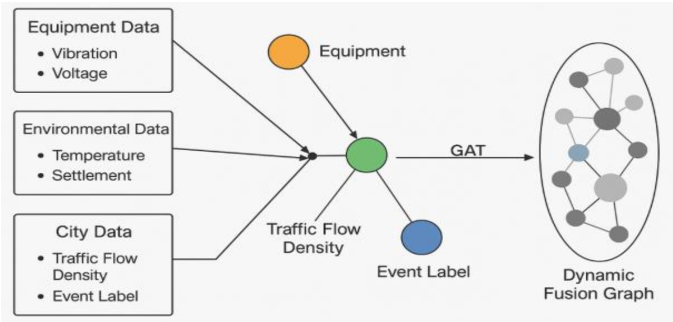

Figure 1. Structure of data fusion based on graph attention mechanism

Table 1. Characteristics of data for rail transit equipment failure prediction models

characteristic category	Specific field names	data type	Data sources	Treatment
Operational data	Current, Voltage, Temperature	continuous	Device Sensors	Sliding window mean + standardization
Maintaining data	Downtime, type of repair	categorical	Maintenance record system	One-hot coding
Environmental data	Tunnel settlement, surface temperature and humidity	continuous	Geographical monitoring system	Missing value filling + Z-score normalization
Urban data	Population density, traffic flow index	time series (math.)	Urban Transportation Big Data Platform	hysteresis eigenstructure
event tag	Major events, weather warnings	binary	Urban Incident Dispatch System	Time Alignment + Tag Expansion

3.2. Model Architecture Design

In order to adapt to the complex and changing transportation operation environment in smart cities, a multimodal failure prediction model architecture integrating structural engineering monitoring and artificial intelligence algorithms is designed (Fig. 2). The model as a whole adopts a dual-pathway structure: on one side, a time-series prediction module with LSTM as the core is constructed to process the operational parameters (e.g., vibration, current, and operating temperature) from the rail transportation equipment; on the other side, a hybrid CNN-GRU structure is introduced, which is specifically used to resolve the data features of civil engineering dimensions, including low-frequency but strong correlation such as tunnel deformation, track settlement rate, and geologic disturbance frequency, and so on. structural parameters. The two pathway features are realized in the back-end through the attention fusion layer for feature weighting and dynamic selection, and finally output to the prediction layer for anomaly trend fitting. In order to improve the adaptivity of the architecture, a structural response function [7] is introduced in the design:

$$R(t) = \alpha \cdot D_s(t) + \beta \cdot \Delta\theta(t)$$

Where Ds(t) denotes the settling rate and Δθ(t) denotes the change in lateral offset angle, which is used as a weighting parameter for the environmental channel characteristics.

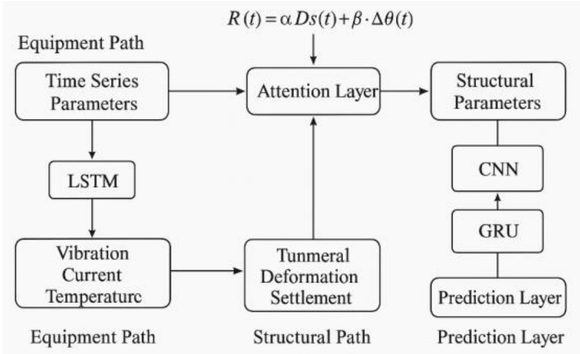

Figure 2. Model dual pathway fusion architecture diagram

3.3. Model Training and Optimization

In the model training and optimization process, a training dataset generation mechanism for smart city multi-scenario features is constructed by combining the dual-pathway fusion architecture. In order to simulate the complexity of the real operating environment, the training samples cover multiple scenarios such as peak and trough traffic hours, extreme meteorological conditions (e.g., persistent rainfall, high temperature) and major events in the city (e.g., traffic disturbances in holidays), etc., and the model's semantic recognition ability is enhanced by constructing a weighted label set. In the training process, device data sequences are batch-inputted using a sliding window, and the AdamW optimizer is used to enhance the robustness of the model under unstable input conditions; the gradient trimming strategy with memory gating is introduced into the structural pathway to avoid the gradient explosion problem caused by deep CNN-GRU fusion. In terms of loss function design, a weighted combined loss function is used to double constrain the model performance [8]:

$$L_{total} = \lambda_1 \cdot L_{MSE} + \lambda_2 \cdot L_{GIoU}$$

Among them, L_{MSE} is used to measure the numerical error between the predicted value and the real value, L_{GIoU} is introduced to calculate the geometric overlap of the spatial trend, which is used to control the model's localization accuracy of the trend boundary of the faulty region; λ1 and λ2 are the weight coefficients of the loss term, which are used to dynamically adjust the optimization priority of numerical accuracy and spatial consistency. The training phase also combines the distributed parallel framework to construct a cross-GPU data parallel flow graph, which improves the convergence speed and generalization ability under large-scale multi-source data.

4. APPLICATION SCENARIOS AND VALUE EMBODIMENT OF MODELS IN SMART CITIES

4.1. Intelligent Operation and Maintenance Management

In the smart city rail transit system, the AI-based equipment failure prediction model realizes the joint modeling of equipment operation state and structural environment response by introducing multi-source data fusion and dual-pathway deep learning structure to provide predictable and quantifiable decision-making basis for the intelligent operation and maintenance management. The system design interfaces the model output signal with the equipment O&M platform, and after the prediction threshold is triggered, the optimal allocation of maintenance resources is realized through the scheduling optimization function by combining the dimensions of equipment type, fault level, and geographic location [9]:

$$\min \sum_{i=1}^{n} \left(C_i \cdot T_i + R_i \cdot D_i \right)$$

Where Ci is the single maintenance cost of the ith type of equipment, Ti is the predicted maintenance cycle, Ri is the cost factor of urban resource deployment, and Di denotes the scheduling distance or interference weight. This mechanism significantly changes the time-cycle-based "scheduled inspection + emergency repair" mode, so that resources are tilted to potentially high-risk nodes, to achieve the key parts of the "on-demand pre-maintenance". Through interoperability with the urban transportation management system, the platform maps the forecast information to the capacity deployment module, avoiding line interruption or traffic congestion caused by equipment abnormalities in advance, and improving the overall efficiency and density of urban public service resources.

4.2. Cooperative Transportation Scheduling

In the smart city rail transit system, the AI-based equipment failure prediction model provides accurate scheduling information for traffic management by predicting the time and location of potential equipment failures. The model assists dispatchers in optimizing train operation plans by monitoring the status of equipment in real time and identifying high failure periods in advance. At the train scheduling level, the system adjusts the frequency and interval of train operations based on the prediction results, avoiding delays and service interruptions caused by equipment failures and improving overall operational efficiency. The model shares data with city bus systems and road traffic management platforms to form a multi-level linkage mechanism. When rail transit equipment fails, the model automatically calculates and recommends scheduling optimization plans for bus lines and roads, and mitigates the impact of rail transit shutdowns on other modes of transportation in the city by dynamically adjusting the frequency of bus departures or road traffic flow. Through this cooperative optimization, the overall traffic flow is balanced, and urban traffic congestion can be alleviated. This prediction-based scheduling cooperative scheme can not only improve the flexibility of the transportation system, but also enhance the overall traffic mobility of the city and improve the efficiency of the use of public resources.

4.3. Urban Safety and Security

AI-based rail transportation equipment failure prediction model plays a crucial role in urban safety and security in smart cities. Through real-time monitoring and failure warning of rail equipment, the model is able to identify potential risks in advance of equipment failures and provide timely feedback of early warning information to the transportation management system. This early warning mechanism enables managers to quickly dispatch backup plans, such as adjusting the frequency of train operation, enabling alternative transportation, etc., to avoid the risk of local traffic paralysis and crowd congregation in the city triggered by rail transit shutdowns. By dynamically evaluating different failure modes, the model not only provides an accurate time window for equipment maintenance, but also links with the urban emergency management platform to optimize the deployment of urban resources, preventing large-scale traffic congestion or crowd gathering due to emergencies, and enhancing the city's emergency response capability [10]. The continuous optimization of the model can also enhance the resilience of the urban transportation system, reduce the systematic risk due to equipment failure, and effectively guarantee the safe and stable operation of urban transportation.

5. APPLICATION CASE ANALYSIS BASED ON SMART CITY SCENARIOS

5.1. Application Scenario Selection

In order to verify the adaptability and generalization ability of the constructed fault prediction model in multiple urban traffic environments, this paper selects three types of representative smart cities as application cases: densely populated mega-cities, cities with frequent geological disturbances, and cities with seasonal tourist peaks. These three types of scenarios show a high degree of heterogeneity in terms of data flow density, equipment operation complexity and external disturbance factors, which can fully reflect the stability and adaptability of the model in the dimensions of data fusion and structure identification. In the case selection process, based on the classification standards for the digitalization level of the transportation system and the intelligent perception capability of urban infrastructure in the National Smart City Development Assessment Indicator System (2023), and combined with the density of urban rail transit lines (per unit area/km^2), the average daily peak passenger flow, and the regional geologic disaster risk level, a multi-indicator quantitative scoring system is set up (Table 2) to ensure the structural completeness and technical testing value of the case. structural completeness and technical testing value.

Table 2. Case City Application Scenario Screening Indicator Table

Urban category	Peak average daily passenger flow (10,000 passengers)	Track line density (km/km^2)	Frequency of geologic disturbance events per year	Annual Peak Tourism Fluctuation Coefficient (CV)	Intelligent Sensing Coverage of Transportation Systems
City A (densely populated)	920	2.4	Low (<5 times)	Low (0.14)	High (≥90%)
Urban B (geological risks)	330	1.6	High (>20 times)	Medium (0.32)	Medium (75-85%)
City C (tourist city)	410	1.1	Medium (10-15 times)	High (0.58)	High (≥90%)

5.2. Model Implementation Process

In practical application, the deployment process of the AI-based rail transportation equipment failure prediction model includes several links to ensure its deep integration with the smart city traffic management system. First of all, the model realizes data docking with the traffic management platform of each city through APIs to obtain real-time traffic flow, equipment status and environmental changes and other information. During this process, the data is transmitted through an encrypted channel to ensure the security and real-time information. Then, the model starts to run, first processing historical equipment operation data and real-time sensor data, and utilizing preprocessing algorithms for noise filtering and feature extraction. The model generates predictions by combining equipment status with external environmental factors through time series analysis and graph network algorithms. The key to this process is an efficient collaborative mechanism, where the model works closely with other urban intelligent systems such as emergency dispatch platforms, weather warning systems, and urban traffic flow management systems to form a multi-level linkage network. When the model predicts that a section of track is likely to fail, it delivers early warning information to the dispatch center, automatically adjusts the train operation plan, and triggers the activation of backup equipment.

5.3. Assessment of Application Effectiveness

According to the three selected smart city scenarios, the application effect of the AI-based rail transportation equipment failure prediction model is significantly reflected in multiple dimensions. As shown in Figure 3, in terms of the improvement of city traffic efficiency, the model can accurately predict the time and location of equipment failure, effectively avoiding train delays caused by equipment failure. Taking city A as an example, after the model is applied, the average delay time of urban traffic flow is reduced by about 15%, and the transportation capacity during peak hours is improved by 18%. In terms of O&M costs, the model's intelligent warning mechanism significantly reduces unnecessary periodic maintenance and unexpected repair costs in the traditional O&M model. In City B, O&M costs dropped by about 12% based on intelligent scheduling and resource allocation predicted by the model. Residents' travel satisfaction was also improved, with waiting time during peak hours reduced by 20% through fault prediction and dispatch optimization. The introduction of the model makes the overall system more efficient, flexible and responsive, especially in the face of the complex and changing urban transportation environment, which significantly improves the availability of urban public transportation and the travel experience of residents.

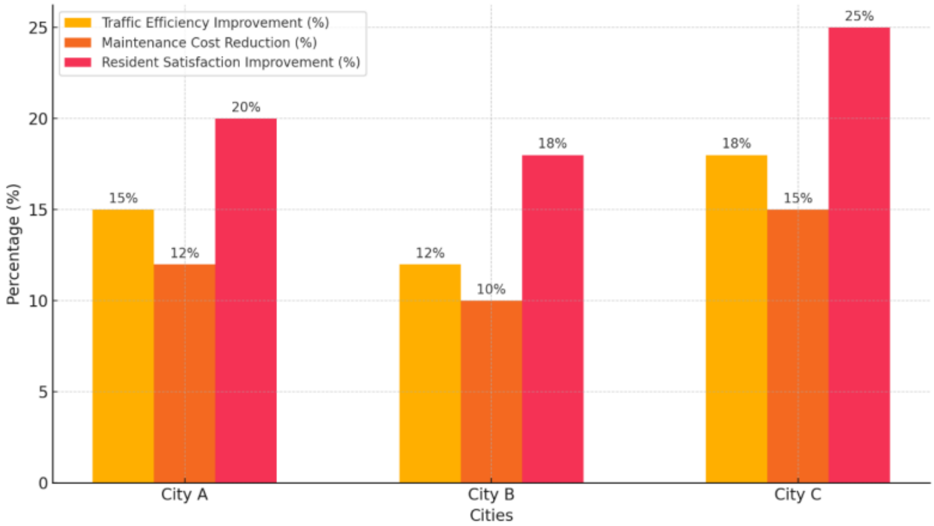

Figure 3. Comparison chart for evaluation of application effects

6. DIRECTIONS FOR MODEL IMPROVEMENT AND OPTIMIZATION

In order to improve the adaptability and generalization ability of the model in changing urban scenarios, it is necessary to further expand the data sources and realize multi-dimensional data coupling between rail transit and other urban infrastructure systems (e.g., electric power, drainage, and fire protection), so as to enhance the model's sensitivity to the environmental interference factors. The algorithm structure can introduce a reinforcement learning mechanism to dynamically adjust the prediction strategy, so that the model maintains the responsiveness and learning ability in the high incidence scenario of sudden failures. In order to break through the bottleneck of the current system linkage efficiency, a unified city-level data center should be constructed to realize the high-frequency synergy between the rail equipment prediction model and multiple systems such as traffic dispatching, emergency management, and meteorological warnings, and to improve the effectiveness of the overall fault early warning and the precision and timeliness of the system linkage disposal through the introduction of the heterogeneous information fusion mechanism.

7. CONCLUSIONS AND FUTURE PROSPECTS

The AI-based rail transit equipment failure prediction model constructed in this study has demonstrated significant application potential in the construction of smart cities, especially in the intelligent operation and maintenance of rail transit, collaborative management of urban transportation, and safety and security. By accurately predicting equipment failures, the model optimizes resource deployment and scheduling efficiency, reduces operating costs, and improves the availability and safety of urban public transportation. In the future, with the development of emerging technologies such as 5G and IoT, the model will be deeply integrated with these technologies to provide more powerful data support and real-time response capabilities for the comprehensive intelligence of urban transportation systems. In particular, the low-latency characteristics of 5G technology will greatly improve the response speed of the model to sudden failures, laying the foundation for the refined management and cross-system collaboration of rail transportation. In addition, with the further accumulation of data and the continuous optimization of algorithms, the model will be more accurately adapted to changing urban environments, promoting the process of intelligentization of the whole chain of smart cities, and further enhancing the resilience and sustainable development of urban transportation systems.

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