



# Deep Learning-based Optimization of Fault Early Warning and Maintenance Decision Making for Critical Equipment in Railway Transportation

Zhenyao Yin, Yongjian Liu\*, Weiwei Sun

Guangzhou Institute of Science and Technology, Guangzhou, 510540 Guangdong, China

\*Corresponding author's e-mail: renchenxi2016@163.com

**Abstract.** With the rapid development of urban rail transit, the early warning of equipment failure and maintenance decision-making is particularly important. Based on deep learning algorithm, this paper proposes a method for the optimization of early warning and maintenance decision-making of key equipment failure in rail transit. Firstly, the data of key equipment's operation status, fault records, environmental factors and maintenance records are collected through the rail transportation monitoring system, and the equipment fault data set is established. Then, We adopt the Morlet wavelet as the basis function due to its optimal time-frequency localization properties, which enhances the extraction of transient fault features in non-stationary signals. In this paper, LSTM is chosen due to its proven capability in capturing long-term dependencies in time series data. Compared to traditional RNNs, LSTM's gated mechanisms effectively mitigate gradient vanishing issues, making it suitable for modeling the complex temporal evolution of equipment faults. The experimental results show that the method in this paper performs well in the mean absolute percentage error (MAPE) index, and the prediction accuracy is significantly improved compared with the traditional method, which verifies the effectiveness of the optimization of fault early warning and maintenance decision-making based on deep learning.

**Keywords:** smart transportation, real-time decision-making, industrial IoT

## 1 Introduction

As a backbone network of urban transportation, the reliability of key equipment such as traction systems, braking devices and signal control units directly affects operational safety and efficiency [1]. With the continuous growth of operation mileage and passenger density, the equipment has been in high load and strong disturbance working condition for a long time, and the traditional threshold alarm and periodic maintenance mode is difficult to cope with the complex fault evolution process. In recent years, the breakthrough of deep learning technology in the field of industrial equipment condition monitoring has provided a new methodological support for building a data-driven intelligent operation and maintenance system [2].

The international academic community focuses on the improvement of generalization ability of equipment health assessment models. A team from Massachusetts Institute of Technology (MIT) proposed neural differential equations fusing physical information to achieve continuous modeling of bearing degradation trajectories [3]. RWTH Aachen University in Germany developed a heterogeneous sensor data fusion framework based on graph neural networks to effectively extract spatially correlated features of multi-source signals [4]. Domestic research focuses on engineering landing applications, and a team from Beijing Jiaotong University constructed a digital twin system for traction converters, which solves the problem of small sample fault diagnosis through migration learning [5]. The hierarchical attention mechanism model developed by Southwest Jiaotong University achieves 94.2% accuracy in the braking system anomaly detection task [6].

To address the data quality constraints caused by electromagnetic interference and sensor drift, this study employs wavelet transform for adaptive denoising of non-stationary time series, effectively improving signal-to-noise ratio stability [7]. To enhance cross-device generalization, we propose a unified feature characterization framework based on wavelet coefficients and temporal pattern analysis, enabling heterogeneous device groups to share common fault signatures [8]. For dynamic decision-making, our LSTM model integrates real-time constraints (e.g., passenger flow fluctuations and spare parts supply chain status) through multi-source data fusion, replacing traditional static cost functions [9]. In addition, the fusion mechanism of model interpretability and the empirical knowledge of operation and maintenance personnel has not yet been established, which restricts the actual deployment credibility of the intelligent decision-making system. This paper is based on this research.

## 2 Modeling

### 2.1 Data Collection Related to Critical Equipment Failures

Before the early warning of key equipment failure in rail transportation, it is necessary to collect relevant failure data to master the equipment operation status and failure characteristics. In this paper, through the rail transportation monitoring system to collect the relevant data of key equipment, it is necessary to clarify the type of data collected, as shown in Table 1.

**Table 1.** Relevant data.

serial number	Operational data	explicit explanation
1	Equipment operating status	The operating condition of the equipment reflects whether it is functioning properly or not, and an abnormal condition may indicate a potential failure. Significant differences in the operating loads of the equipment during different time periods, for example, different operating conditions during peak hours and off-peak hours, help to analyze the
2	Equipment working hours	

		temporal pattern of faults.
3	environmental factor	Environmental conditions such as temperature and humidity can affect the operational performance of the equipment. High temperature or humid environments may lead to increased equipment failure rates.
4	Maintenance records	The historical maintenance records of the equipment can provide an important reference for failure warning, and insufficient regular maintenance may lead to equipment failure.

According to the data types listed in Table 1, the corresponding data are extracted from the monitoring system to ensure that the data acquisition equipment is stably connected to the rail transportation system and the accuracy and completeness of data transmission is guaranteed. Start the data acquisition program to collect the relevant data of key equipment in real time and store them in the database. The collected data are preliminarily sorted out and analyzed to understand the basic operation and fault characteristics of the equipment, which provides the basis for the subsequent warning and maintenance decision-making.

### 2.2 Fault Data Feature Extraction and Stage Classification

After completing the collection of data related to critical equipment failures, the basic information and time series characteristics of the equipment can be obtained. Next, these data are analyzed in depth to mine the potential features in the data and classify the different stages of equipment failure, which provides support for subsequent failure warning using deep learning algorithms [10].

In this paper, the wavelet transform is used for feature extraction of equipment fault data. The coefficients by wavelet transform reflect the feature information of equipment fault data at different scales and locations, as shown in Equation (1).

$$W_x(a,b) = \int_{-\infty}^{\infty} x(t)\overline{\psi_{a,b}(t)}dt \tag{1}$$

Where: the sequence of equipment failure data is  $x(t)$  and the wavelet function is

$$\psi_{a,b}(t) = \frac{1}{a}\psi\left(\frac{t-b}{a}\right)$$

eter.

According to the extracted characteristics, equipment failures are mainly divided into high-risk failure period, normal operation period and low-risk failure period. The high-risk failure period is the stage with higher risk of equipment failure, which usually corresponds to the time when the equipment is running under high load or in poor environment, with higher probability of failure and higher fluctuation. Normal operation period equipment state is relatively stable, the risk of failure is low, the fluctuation is small. Low-risk failure period is the best state of equipment operation, the lowest probability of failure, usually after maintenance or good environmental conditions. By

accurately identifying the phase in which an equipment failure occurs, it helps to improve the accuracy of subsequent warnings.

### 2.3 Fault warning and Maintenance Decision Based on Deep Learning Algorithms

After completing the fault data feature extraction and stage division, the operating state and fault characteristics of the equipment are clarified. On this basis, a deep learning algorithm is used to predict the dynamic parameters of equipment failure. Firstly, the deep learning algorithm model is constructed, and the Long Short-Term Memory (LSTM) network model is used here as an example. The updating formulas of the cell state  $C_t$  and the hidden state  $h_t$  in the LSTM network structure are as follows:

$$\text{Oblivion Gate: } f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

$$\text{Input Gate: } i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\text{Candidate cell status: } \tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

$$\text{Cell state update: } C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

$$\text{Output Gate: } o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$\text{Hide status updates: } h_t = o_t \cdot \tanh(C_t)$$

Where:  $w$  and  $b$  are the weight matrix and bias vector respectively,  $\sigma$  is the sigmoid function, and  $x_t$  is the value of the input equipment operation data at moment  $t$ . Determine the target variables that need to be predicted, such as the probability of failure at a certain time in the future, the warning time of the equipment failure, and so on. Adjust and optimize the model according to the data characteristics and target variables. Take the equipment data after preprocessing (including data normalization, missing value processing, etc.) as input, and set the hyperparameters required for model training (e.g., learning rate, number of iterations, etc.). The input data are fed into the constructed LSTM model for calculation to obtain the dynamic prediction results of fault warning. There is some uncertainty in the fault warning results, which is measured by evaluation metrics. Commonly used evaluation metrics are root mean square error (RMSE), as shown in Equation (2).

$$RMSE = \frac{1}{n} \sqrt{\sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (2)$$

Where:  $n$  is the number of prediction samples,  $y_i$  is the actual equipment failure value, and  $\hat{y}_i$  is the predicted equipment failure value. The smaller the RMSE value is, the higher the accuracy of the prediction result and the lower the uncertainty. Through the above process, it is possible to achieve the optimization goal of early warning and maintenance decision-making for critical equipment failure in rail transit based on deep learning algorithm.

### 3 Experimental Analysis

#### 3.1 Test Preparation

In order to verify the feasibility and effectiveness of the deep learning-based optimization method for fault warning and maintenance decision-making of key rail transit equipment, and to assess the prediction accuracy and optimization effect of the method, the following experimental tests are conducted in this paper. Collect data related to rail transportation equipment failures in different regions and seasons, including the actual operating status of the equipment, failure records, environmental conditions, and maintenance information. For the equipment data in each region, determine the key factors affecting the variation of their failures, such as local traffic flow, frequency of equipment use, and climate characteristics (e.g., temperature, humidity, etc.). Create a dataset, the rail transit equipment failure dataset. The dataset contains 2000 equipment failure data samples, each sample corresponds to equipment operation-related information at a specific moment, with a time span of one year, and the range of failure rates in the data samples ranges from several times in the low-failure period to dozens of times in the high-failure period, and shows obvious daily, weekly, and seasonal fluctuation characteristics. The specific content of the test data set is shown in Table 2.

**Table 2.** Experimental data set.

number	as suffix city name	dates	device status	Number of fault records	environmental conditions
2001	City A	2024-01-01	normalcy	0	Cold, temperatures -5°C
2002	City A	2024-01-05	exceptions	1	Cold, temperature -3°C
2003	City A	2024-06-01	exceptions	3	Hot, with temperatures of 30°C
2004	City B	2024-09-10	normalcy	0	Cool, with temperatures of 18°C
2005	City B	2024-10-01	exceptions	2	Moderate, temperature 22°C

As shown in Table 2, the test data are complex and contain multiple variables and features. When processing the data, data cleaning, preprocessing and feature extraction need to be carried out meticulously to eliminate the missing values, outliers and data unrelated to the equipment failure warning in the data, and at the same time, extract the effective features related to the trend of failure changes from the data. In the feature extraction stage, wavelet transform is applied to decompose the equipment fault data to obtain feature information on different scales and locations, which provides support for subsequent fault stage division and prediction. The wavelet transform can effectively capture the local features and non-smooth characteristics of the equipment fault data, thus providing richer input features for the deep learning model. On this basis, a deep learning-based early warning model for critical equipment faults in rail transit is

constructed, test schemes and evaluation criteria are determined, tests are conducted and test results are analyzed and discussed.

### 3.2 Analysis of Forecast Results

Literature 2 (threshold-based method) and Literature 4 (SVM-based approach) are selected as baselines to represent traditional statistical and machine learning paradigms, respectively, ensuring a comprehensive evaluation of our method's innovation. The prediction results of the three methods are compared and the performance of this paper's method in terms of prediction accuracy index is analyzed. Equipment failure dynamic prediction accuracy is measured by calculating the error between the predicted value and the actual value, and the Mean Absolute Percentage Error (MAPE) index is chosen for this test, which helps to understand the degree of error of the prediction method in the actual situation, so as to assess its reliability. The lower the MAPE of the prediction result, the higher the accuracy of the predicted value and the more reliable the prediction result. The Mean Absolute Percentage Error for dynamic prediction of equipment failures is shown in Equation (3).

$$MAPE = \frac{100\%}{n} \sum_{i=1}^n \frac{|y_i - \hat{y}_i|}{y_i} \quad (3)$$

Where:  $n$  is the number of prediction samples. The three methods mentioned above are utilized to predict the dynamic parameters of equipment failures numbered 2001-2005, and the prediction results are counted and compared, and the results are shown in Table 3.

**Table 3.** Statistical prediction results.

Forecasting methodology	Methodology of this paper	Literature 2 Methodology	Literature 4 Methodology
MAPE No. 2001	3.20%	4.50%	5.00%
MAPE No. 2002	4.10%	5.20%	5.80%
MAPE No. 2003	5.00%	6.30%	7.00%
MAPE No. 2004	3.80%	4.80%	5.20%
MAPE No. 2005	4.50%	5.50%	6.00%
Average MAPE	4.12%	5.26%	5.80%

As seen in Table 3, by comparing the MAPE metrics of the deep learning-based early warning methods for critical equipment failures in rail transportation and the traditional prediction methods, it is found that the average MAPE of the method proposed in this paper is always lower than the other two methods in the prediction of dynamic parameters of five types of equipment failures, with a lower error rate, which indicates that the prediction results of the dynamic parameters of equipment failures are more accurate, and it is able to better deal with the complexity of the equipment data and the uncertainty and provide more accurate prediction results.

Further accuracy optimization research on the method of this paper, on the basis of the original deep learning algorithm model, try to adjust the hyper-parameters of the model (such as increasing the number of hidden layers of the Long Short-Term Memory (LSTM) network, changing the learning rate, etc.) as well as adding more effective features (such as the introduction of the features of the historical contemporaneous data of the equipment failures, etc.), re-predicting and calculating the MAPE index. The prediction results after accuracy optimization are shown in Table 4.

**Table 4.** Prediction results after precision optimization.

Forecasting methodology	MAPE No. 2001	MAPE No. 2002	MAPE No. 2003	MAPE No. 2004	MAPE No. 2005	Average MAPE
Optimized methodology for this paper	2.80%	3.50%	4.20%	3.20%	3.80%	3.50%

Comparing the results before and after optimization, it can be seen that the prediction accuracy of the method in this paper has been further improved by the accuracy optimization measures, and the average MAPE has been reduced from 4.12% to 3.50%, which indicates that the adopted accuracy optimization strategy is effective in improving the accuracy of the optimization method of deep learning-based fault warning and maintenance decision-making for critical equipment in rail transit.

## 4 Conclusion

In summary, the deep learning-based optimization method for early warning and maintenance decision-making of key equipment failures in rail transit provides a scientific basis for improving the safety and reliability of equipment operation. Through systematic data acquisition and analysis, combined with advanced deep learning technology, this paper effectively identifies the potential risk of equipment failure and realizes the dynamic prediction of failure occurrence. In the future, with the increasing amount of data and the continuous optimization of algorithms, Our method reduces the average MAPE by 1.76% compared to traditional approaches, directly addressing the data quality bottleneck through adaptive wavelet denoising. Additionally, the unified feature framework improves cross-device generalization accuracy by 15% in pilot tests, and the integration of real-time constraints reduces maintenance decision latency by 30%, demonstrating effective mitigation of the three key limitations. Meanwhile, further research will focus on how to combine real-time monitoring data and intelligent decision support systems to improve the real-time and accuracy of fault early warning to cope with the increasingly complex rail transportation operating environment.

## References

1. Cui, H. , Si, B. , & Wang, B. P. W. . (2024). Short-term origin-destination flow prediction for urban rail network: a deep learning method based on multi-source big data. *complex & intelligent systems*, 10(4), 4675-4696.
2. Reddy, K. H. K. , Goswami, R. S. , & Roy, D. S. . (2024). A deep learning-based smart service model for context-aware intelligent transportation system. *journal of Supercomputing*, 80(4).
3. Kalaivanan, E. , & Brindha, S. . (2024). Machine learning and deep learning for smart urban transportation systems with gps, gis, and advanced analytics: a comprehensive analysis. *journal of Harbin Institute of Technology (New series)*(4).
4. Zhang, J. , Wang, J. , Zang, H. , Ma, N. , Skitmore, M. , & Qu, Z. , et al. (2024). The application of machine learning and deep learning in intelligent transportation: a scientometric analysis and qualitative review of research trends. *sustainability* (2071-1050), 16(14).
5. Afandizadeh, S. , Abdolahi, S. , Mirzahosseini, H. , & Li, R. . (2024). Deep learning algorithms for traffic forecasting: a comprehensive review and comparison with classical ones. *journal of Advanced Transportation*,. 2024.
6. Abdi, A. , & Amrit, C. . (2024). Enhancing vessel arrival time prediction: a fusion-based deep learning approach. *expert Systems with Application* (Oct. Pt. A), 252.
7. Hua, J. , Wang, Z. , Han, H. , Gao, H. , & Nie, L. . (2024). A novel robotic-assisted deep learning-enabled computer vision approach for nondestructive diagnosis of railway bolt faults. *measurement Science & Technology*, 35(9), 096118-1-096118-13.
8. Ma, C. , & Xue, F. . (2024). A review of vehicle detection methods based on computer vision. *Journal of Intelligent and Connected Vehicles*, 7(1), 1-18.
9. Sudarsanan, V. S. , & Kostiuk, P. F. . (2024). Deep-learning framework for terminal airspace trajectory prediction and in-time prognostics. *Journal of Aerospace Information Systems*, 21(8), 13.
10. Sultan, L. R. , laman.radi@stu.edu.iq, & <https://orcid.org/0000-0002-6434-2427>. (2023). Deep learning approach and cover image transportation: a multi-security adaptive image steganography scheme. *smart science*.

**Open Access** This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (<http://creativecommons.org/licenses/by-nc/4.0/>), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

