

Remote Diagnosis and Analysis of Rail Vehicle Status Based on Train Control Management System Data

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Abstract: This article focuses on the remote diagnosis and analysis of rail vehicle status based on the data of the Train Control Management System (TCMS). It first expounds on the importance of train diagnostic analysis and designs a unified TCMS data frame transmission format. Subsequently, a remote data transmission link using 4G signals and data processing methods is introduced. The advantages of remote diagnosis are analyzed, and common methods such as correlation analysis, fault diagnosis, and fault prediction are explained in detail. Then, challenges such as data security and the balance between diagnostic accuracy and real-time performance are discussed, along with development prospects in technological innovation, algorithm optimization, and application promotion. This research provides ideas for remote analysis and diagnosis based on TCMS data, contributing to the safe and efficient operation of rail vehicles.

Keywords: Rail vehicle; TCMS data; Remote diagnosis; Data processing; Fault prediction

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1. Train diagnostic analysis overview

Train diagnostic analysis is a crucial step in ensuring the safe and efficient operation of trains, covering multiple aspects and methods. The main content of train fault diagnosis includes monitoring, diagnosis, and judgment of faults. When there are signs of a train malfunction, the diagnostic system needs to quickly detect and make judgments. This usually involves multiple steps, including collecting fault information, analyzing possible causes of faults, determining the most likely fault point, and so on. The modern train fault diagnosis system utilizes TCMS data and analyzes it to achieve rapid and accurate diagnosis and early warning of vehicle faults. These systems can monitor the operating parameters of trains in real time, such as speed, current, temperature, pressure, etc., and based on the real-time changes of these parameters, diagnose the cause of faults through preset fault models and issue warning information^[1]. The computing performance of equipment in each train will have bottlenecks, and remote train diagnostic analysis can fully leverage the advantages of ground server clusters, providing a large amount of resources and computing power to meet the needs of multiple scenarios and big data^[2,3].

2. TCMS data content

In order to unify the TCMS data transmission format, this article designs a standard data frame transmission format for reference in other projects in the future ^[3]. The data frame content is based on hexadecimal, and the overall structure is shown in **Table 1**.

Table 1. Data frame structure

MessageHeader	Type	MessageID	Content	ReservedFields	MessageTail
3 bytes	1 byte	4 bytes	N bytes	2 bytes	3 bytes

- (1) Message header: Fixed padding bytes 0xAA, 0xAB, and 0xAC represent;
- (2) Type: Fixed use 0x01;
- (3) Message ID: Indicates the number of the message, starting from 0. For each new message sent, the message number is incremented by 1 and continues to accumulate until it reaches its maximum value before cycling;
- (4) Data area: Loaded with status and fault data of vehicle TCMS;
- (5) Reserved fields: fixed use of 0x00, 0x00;
- (6) Message tail: Fixed padding bytes 0xBA, 0xBB, 0xBC. The specific message format is shown in **Table 2**.

Table 2. Wireless transmission message format

Byte No.	Content							Remarks	
	0	1	2	3	4	5	6		7
0				Message header 0xAA					
1				Message header 0xAB					
2				Message header 0xAC					
3				Message type 0x01					
4–7				Message ID					
8				0x02					
9				0x10					
10–13				Data Length					
14				0x01					
15				Line ID					
16–17				Train ID					
18				0x01					Equipment ID
19				Date (year)					
20				Date (month)					
21				Date (day)					
22				Date (hour)					
23				Date (minute)					
24				Date (second)					

Table 2 (Continued)

Byte No.	Content							Remarks
	0	1	2	3	4	5	6	7
25–26	Time (ms)							
27–34	Reserved							
35–35+N-1	Vehicle operation data area, N bytes							Data area
35+N	Reserved							
35+N+1	Reserved							
35+N+2	Message tail 0xBA							
35+N+3	Message tail 0xBB							
35+N+1	Message tail 0xBC							

The data filling principle is based on variable filling (classified by navigation on all HMI status pages), and strives to continuously fill in data from unified subsystems, generally including traction system, auxiliary system, braking system, communication status, door system, air conditioning system, emergency communication unit, smoke and fire system, train operation parameters, axle temperature system, bypass status, and other important operational analysis variable data. The uploaded status data content should at least include the requirement to meet all status display variables of the display, for the purpose of reproducing the display interface on the ground. The uploaded fault data content should at least include all integrated subsystems and fault variables of each level in the onboard TCMS display unit ^[4].

The specific data filling situation of the data area needs to be compiled into a data list and submitted to the ground system, which will analyze the data based on the data list. The data list in the status area should include: variable name, variable code, byte offset, bit offset, data type, conversion expression, system, parsing rules, units, and other information. The fault area data list should include: fault name, fault code, fault code, byte offset, bit offset, data type, conversion expression, system, fault level, carriage number, fault cause, fault description, solution measures, etc.

3. Remote diagnosis and analysis with TCMS data

3.1. Data link

In order to use TCMS data as a data source to empower vehicle operation management, it is necessary to transmit the TCMS data of vehicles to the ground, and utilize the computing resources and capabilities of ground reconstruction to achieve data statistics, analysis, calculation, storage, mining, etc. A data transmission link based on 4G signal transmission was designed for this purpose ^[5,6]. The overall link is shown in **Figure 1**.

**Figure 1.** Vehicle analysis system data link

The data on the TCMS bus is transmitted to the server's public IP through the onboard wireless module and 4G channel. After passing through the server's firewall, the data is received, parsed, stored, counted, analyzed, and displayed by the server^[7-9]. To prevent signal interruption during data transmission, a breakpoint continuation function is added on the onboard equipment side. When the train briefly reaches a section without 4G signals, the onboard equipment will briefly record the data that has not been sent out and wait for 4G to recover before retransmitting the data. The network layer uses TCP connections instead of unstable UDP, and the scheduled sending frequency of data packets is set to 1 second.

3.2. TCMS data processing

3.2.1. Missing value handling

- (1) Delete: Delete samples (rows) or features (columns) with missing information attribute values to obtain a complete data table.

Advantages: Simple and easy to implement, very effective in situations where an object has multiple missing values for attributes, and deleted objects with missing values have a relatively small amount of data compared to the initial dataset.

Disadvantages: When the proportion of missing data is large, especially when the missing data is not randomly distributed, this method may lead to data deviation and lead to incorrect conclusions.

- (2) Interpolation: Average value filling: If the null value is numerical, fill in the missing attribute value based on the average value of the attribute's values in all other objects; If the null value is non-numeric, use the mode of the attribute to fill in the missing attribute value.

3.2.2. Data normalization/standardization

Normalization and standardization of data are methods of feature scaling and key steps in data preprocessing. Different evaluation indicators often have different dimensions and units, which can affect the results of data analysis. In order to eliminate the dimensional influence between indicators, data normalization/standardization processing is needed to ensure comparability between data indicators.

- (1) Normalization: Normalization is generally the process of mapping data to a specified range, used to remove the dimensions and units of data from different dimensions. The common mapping ranges are $[0,1]$ and $[-1,1]$, and the most common normalization method is Min Max normalization.
- (2) Standardization: Standardization is processing data according to the columns of the feature matrix. There are various methods for data standardization, such as linear methods (such as extreme value method, standard deviation method), folded line methods (such as three line method), and curved methods (such as semi-normal distribution). Different standardization methods will have different impacts on the evaluation results of the system. Among them, the most commonly used is Z-score standardization. Z-score normalization provides the mean and standard deviation of the original data for data normalization. The processed data conforms to the standard normal distribution, with a mean of 0 and a standard deviation of 1.

3.2.3. Data denoising

- (1) Wavelet transform: The widely used method for time series denoising is nonlinear threshold processing, which is based on the principle that the energy of useful signals is concentrated on a few wavelet coefficients after wavelet transform, while white noise is still dispersed on a large number of wavelet

coefficients in the wavelet transform domain. Therefore, relatively speaking, the wavelet coefficients of useful signals are inevitably larger than those of noise with dispersed energy and smaller amplitudes. Therefore, from the amplitude of the spectrum, useful signals and noise can be separated.

- (2) Variational mode decomposition: Variational mode decomposition is an adaptive, completely non-recursive method for modal variation and signal processing. This technology has the advantage of determining the number of modal decompositions, and its adaptability is manifested in determining the number of modal decompositions for a given sequence based on actual conditions. During the subsequent search and solution process, it can adaptively match the optimal center frequency and finite bandwidth of each modality, and can effectively separate the intrinsic mode components (IMF), divide the signal into frequency domains, and obtain the effective decomposition components of the given signal, ultimately obtaining the optimal solution of the variational problem. It has a solid mathematical theoretical foundation, which can reduce the high complexity and strong nonlinearity of time series non-stationarity, decompose to obtain subsequences containing multiple different frequency scales, and is relatively stable, suitable for non-stationary sequences.

3.3. Advantages of remote diagnostic analysis

- (1) Resource sharing and collaboration: The remote fault diagnosis system can achieve the sharing of fault diagnosis data for multiple subway lines, and multiple diagnostic systems can work together to improve the stability and accuracy of fault diagnosis. This means that a wider range of professional knowledge and resources can be fully utilized to jointly solve complex fault problems.
- (2) Reduce labor and material costs: Remote fault diagnosis does not require technical personnel to personally go to the fault site, and only requires a remote connection to the equipment for troubleshooting. This greatly reduces labor costs and avoids additional expenses such as travel expenses. At the same time, it reduces the need for on-site operations and reduces the risk of equipment damage and maintenance.

3.4. Remote diagnostic analysis method

3.4.1. Correlation analysis

Correlation analysis can analyze which characteristic variables have a linear correlation with faults, including the fault itself and state data.

- (1) Cross correlation: The correlation coefficient ranges from $[-1,1]$, where -1 represents absolute negative correlation and 1 represents absolute positive correlation.
- (2) Autocorrelation: To measure the correlation between current and historical failures, we need to use autocorrelation and partial autocorrelation functions. Autocorrelation is the cross-correlation of itself, representing the degree of correlation between different moments of the same sequence. At a delay of k , the autocorrelation function (ACF) is the correlation between sequence values separated by k time intervals, while the partial autocorrelation function (PACF) also considers values between intervals.

3.4.2. Fault diagnosis

- (1) Fault decision tree: The decision tree method has a wide range of applications in fields such as classification, prediction, and rule extraction^[10]. A decision tree is a tree-like structure where each leaf node corresponds to a classification, while non-leaf nodes correspond to partitions on a certain attribute.

Based on the different values of the sample on that attribute, it is divided into several subsets ^[11–13].

Fault decision trees require a lot of experience accumulation, and each type of fault needs to be sorted out as clearly as possible, and then diagnosed based on real-time data corresponding to the decision tree. As shown in **Figure 2**, determine the cause of the fault based on different judgment conditions.

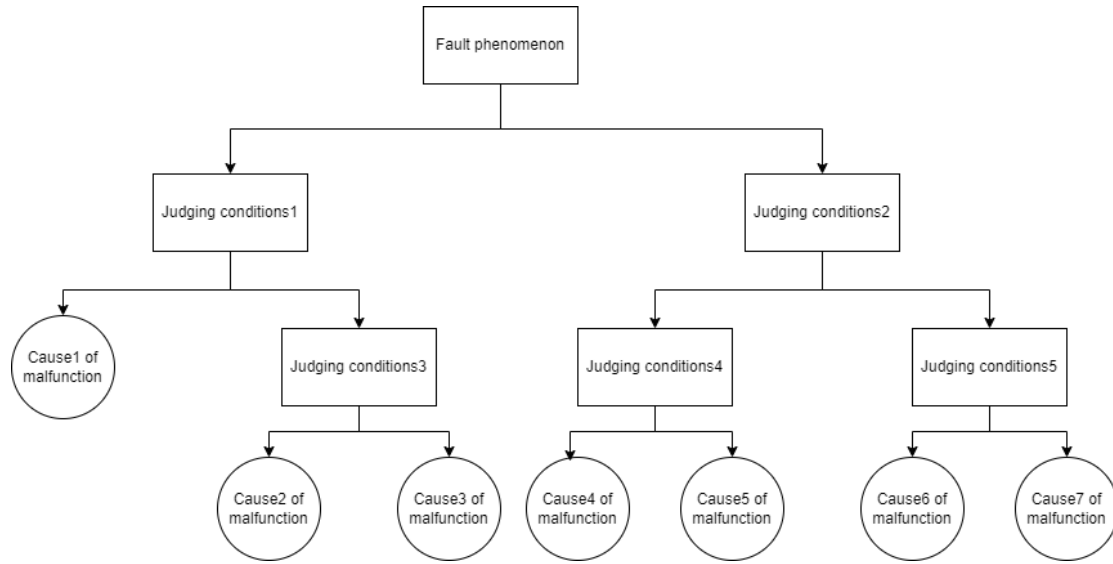


Figure 2. Fault decision tree

(2) Neural network classification: Use neural networks to classify each data. As shown in **Figure 3**, X represents each input data, which consists of fault codes and corresponding state feature data ^[14,15]. Z corresponds to each type of fault cause, and fault diagnosis is achieved by mapping the fault to the fault cause through a neural network.

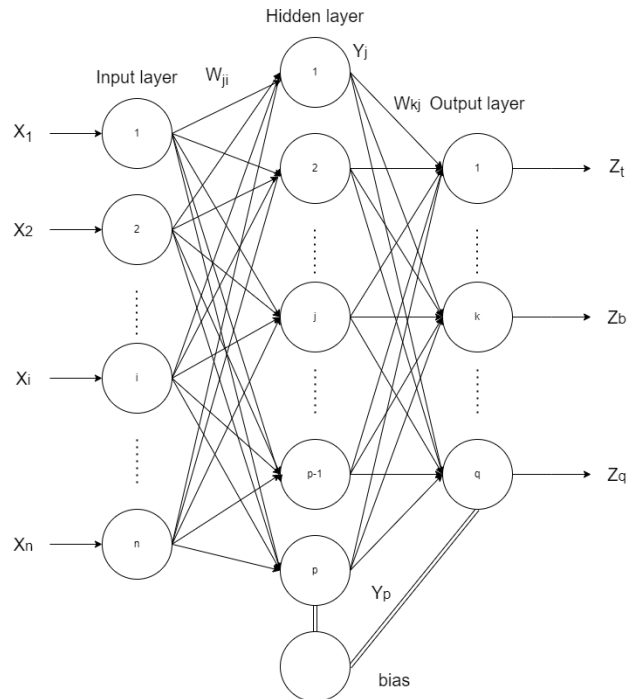


Figure 3. Principles of neural network classification

3.4.3. Fault prediction

Faults usually occur over time, and this type of data that describes one or more features that change over time is called time series data ^[16–18]. The use of historical data to predict the future is called a time series prediction algorithm. The general formula can be written as:

$$F(x_1, x_2, x_3, \dots, x_n, Y') = \hat{Y}$$

Among them, x_n represents state characteristic data such as vehicle speed and network voltage, Y' represents the historical fault dataset, and $\hat{Y}$ represents the predicted fault dataset. The fitting of prediction functions can be achieved through deep learning methods, thereby achieving fault prediction.

(1) Using LSTM prediction

Long short-term memory (LSTM) is a special type of recursive neural network. In order to solve the gradient problem during the training process of recurrent neural networks and the problem of information loss caused by excessive time, the LSTM network was developed ^[19,20]. The LSTM network is composed of multiple unit modules connected, each of which contains feedback-connected neurons and multiplication units. The unit modules include input gates, output gates, forget gates, and an internal memory unit. The structure of the LSTM network is shown in **Figure 4**.

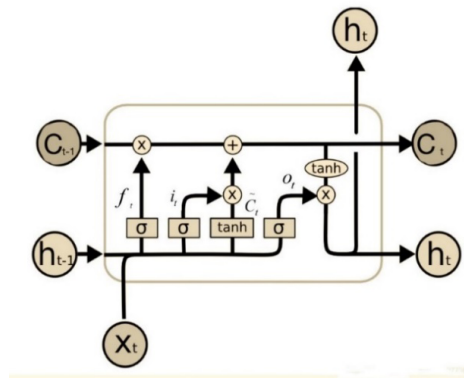


Figure 4. LSTM structure diagram

Use RNN models such as LSTM for autoregressive prediction, in order to predict the values of data in the future and achieve prediction of faults or other operational data. But single-point prediction can only represent the trend of data and cannot accurately predict the value of data, as shown in the following **Figure 5**.

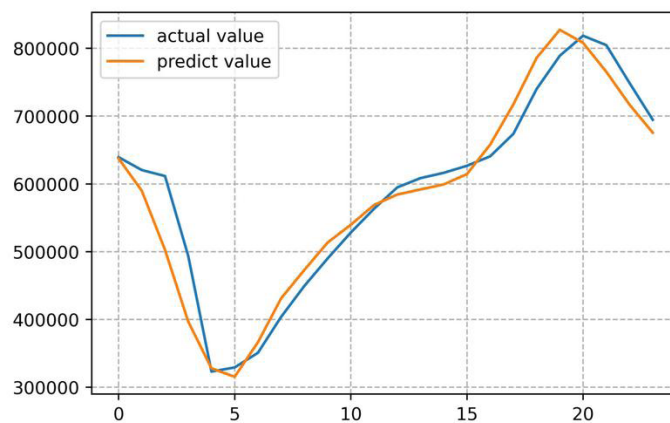


Figure 5. Schematic diagram of LSTM prediction

(2) Using DeepAR prediction

DeepAR is a prediction algorithm proposed by Amazon for unified modeling of a large number of related time series. DeepAR can generate probability predictions, with the goal of simulating conditional probability distributions $P(\mathbf{z}_{i,t_0:T} | \mathbf{z}_{i,t_0-1}, \mathbf{x}_{i,1:T})$, that is, modeling future sequences $\mathbf{z}_{i,t_0:T}$ using past time series $\mathbf{z}_{i,t_0-1}$ and covariates $\mathbf{x}_{i,1:T}$. Among them, t_0 is the time division point, $Z_{i,t}$ representing the value of the time series i in time t . Its overall structure is shown in **Figure 6**.

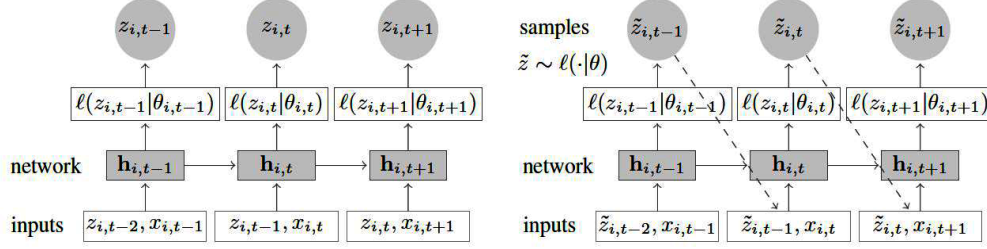


Figure 6. DeepAR structure diagram

If it is assumed that the data is approximately normally distributed, probability prediction can be used to obtain the probability distribution of the predicted results in different confidence intervals. From **Figure 7** below, it can be seen that predicting future data with different confidence intervals based on historical data is more effective in production environments than single-point prediction.

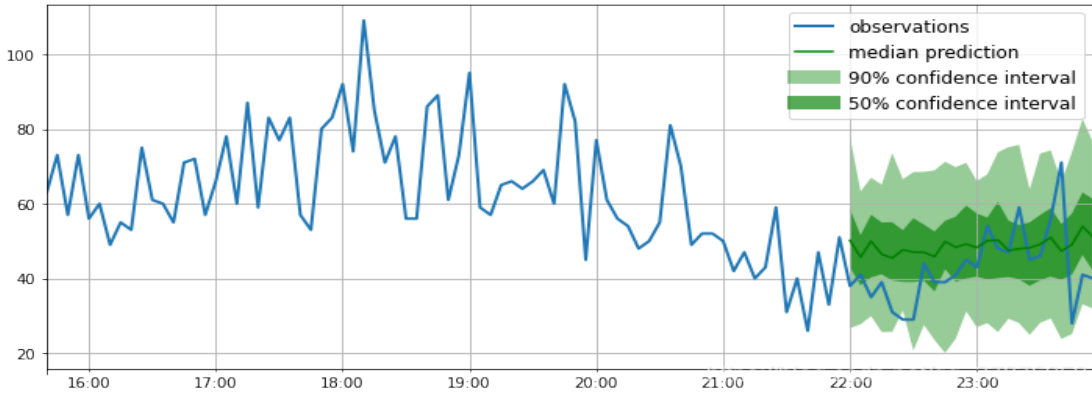


Figure 7. DeepAR prediction schematic diagram

4. Challenges and prospects of remote analysis and diagnosis of train status

4.1. Challenges faced

4.1.1. Data security assurance

- (1) Data encryption: For data during transmission and storage, advanced encryption algorithms such as AES (Advanced Encryption Standard) should be used for encryption. This can effectively prevent hackers or other unauthorized third parties from intercepting or stealing data. Meanwhile, for the distribution and management of keys, public key encryption algorithms such as RSA can be used to ensure secure transmission of keys.
- (2) Access control: Strict management and control of data access permissions, only authorized personnel

and institutions can access sensitive data. This can be achieved through the Role-Based Access Control (RBAC) model, which divides users into different roles and controls access based on their responsibilities and permissions. At the same time, two-factor authentication technology is adopted, such as the combination of a password and biometric information, to improve the security of the access system.

4.1.2. Balancing diagnostic accuracy and real-time performance

- (1) High-speed network connection: Utilize high-speed and stable network connections, such as 5G or dedicated networks, to ensure fast and reliable data transmission between trains and remote diagnostic centers.
- (2) Data compression and encoding: Adopting data compression technology to reduce data transmission volume, while adopting efficient data encoding methods to accelerate data processing speed.
- (3) Algorithm optimization: Based on the characteristics of train fault diagnosis, optimize the algorithm model, reduce computational complexity, and improve real-time response speed.

4.2. Development prospects

4.2.1. Technological innovation

- (1) Introducing new technologies: Introducing IoT technology to achieve a real-time connection between train equipment and remote diagnostic centers, improving data transmission efficiency and stability. Utilize cloud computing and big data technology to build a train fault data warehouse, providing powerful data support for fault analysis and prediction. Explore the use of artificial intelligence and machine learning technologies to achieve automatic fault identification and early warning, reducing errors and delays in human intervention.
- (2) Device intelligence: Develop intelligent train equipment that can monitor and report its own status in real-time, reducing the frequency and intensity of manual inspections. Optimize communication protocols and interfaces between devices to achieve fast and accurate information transmission, and improve diagnostic efficiency.

4.2.2. Algorithm optimization

- (1) Algorithm selection: Based on the characteristics and diagnostic needs of train faults, choose appropriate machine learning or deep learning algorithms, such as Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), etc. Develop customized algorithms to better meet the practical needs of train fault diagnosis.
- (2) Model training and optimization: Utilize a large amount of train fault data for model training to improve diagnostic accuracy and generalization ability. Using regularization, dropout, and other techniques to prevent model overfitting, while utilizing optimization algorithms to improve training speed.
- (3) Real-time diagnosis and prediction: Optimize the calculation speed and memory usage of algorithms to ensure fast response and accurate results during real-time diagnosis. Using methods such as time series analysis to predict train faults, develop maintenance plans in advance, and reduce the risk of faults occurring.

5. Conclusion

This article starts with an overview of remote diagnosis, followed by an introduction to the TCMS data structure and remote transmission link, explaining the advantages of remote diagnosis, and finally introducing the commonly used methods of correlation analysis, fault diagnosis, and fault prediction in remote diagnosis, providing a research approach for remote analysis and diagnosis based on TCMS data.

Disclosure statement

The authors declare no conflict of interest.

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