Research and Application of Train Online Health Status Detection Based on Feedforward Neural Network

Jianyong Zuo*, Furen Feng and Yixin He
Institute of Rail Transit, Tongji University, Shanghai, China
*Email: zuojy@tongji.edu.cn

Abstract. A large amount of data is generated during train operation. By using PHM technology, we can analyse the health status of train systems and equipment which guide train operation and maintenance scientifically and effectively. Based on the feedforward neural network, the paper introduces some research of train on health status, such as remaining life prediction. To better verify the method, an online health analysis equipment suitable for train CAN bus is designed. The method and equipment are tested based on the data of a real train braking system, and the results show that the remaining predicted mileage of the brake system decreased by 1.1%, and the remaining predicted maintenance time decreased by 2.3% because of the impact of fault injection technology on brake cylinder performance. The result proved the effectiveness of the method and equipment for the online health status analysis of trains.

1. Introduction
With the rapid development of the rail transit industry, it is essential to realize the intelligent overhaul and maintenance of train safety. The traditional method is to formulate a strict maintenance cycle, which maintains a large redundancy and is likely to cause great waste. It is hard to understand the changing trend of the equipment health status through system data by which the train can be maintained more scientifically. The PHM technology, which analyses equipment status through data monitoring, provides a solution to this problem and has broad development prospects [1-3]. Specifically, in the field of rail transit, Jianying Liang [4] and others used the axle temperature data collected by the on-board PHM system to model the reliability of train bearings, and realized the pre-processing and location of potential faults. Relied on Boruta algorithm and CBC algorithm Wei Wang [5] has completed fault diagnosis, health evaluation and fault trend analysis model. However, there are few cases of applying neural network prediction model to rail transit vehicle online health status detection. Therefore, this paper analyses and researches on-line health status detection of rail transit trains based on feedforward neural network. First, it introduces the method of using feedforward neural network prediction model to analyse train health status, and then designs an intelligent equipment to verify the method, which can obtain data from the train bus, and send the information to the cloud platform after pre-processing and calculation. The user can view the train health status analysed by the cloud platform neural network through the web page, and finally based on a certain train braking system with CAN bus the method and equipment are tested by using fault injection technology.

2. Train Health Analysis Method Based on Feedforward Neural Network
The feedforward neural network consists of an input layer, an output layer and hidden layers. Each layer of neurons can receive the signals transmitted by the upper layer of neurons and transmit it to the next layer. As shown in Figure 1, Neural network has strong learning ability and self-adaptive ability, and is widely used in signal detection, data early warning and other fields [6-9].

Figure 1. Feedforward neural network structure diagram.

This paper uses feedforward neural networks to predict train system status and equipment parameters, that is, a time series is understood as a deterministic system, assuming that the current time of the system is \( t \) and the state variable of the system is \( X \), then the state variable at the next moment of the system is \( X_{i+1} \), and as shown in equation (1),

\[
X_{i+1} = R(t + 1, a_{i+1}, b_{i+1} \ldots)
\]

where \( a_{i+1} \), \( b_{i+1} \) et al. are the state parameters related to \( X_{i+1} \) at time \( t+1 \) [10-11], and equation (2) can be obtained from the Sobolev imbedding theorems,

\[
X_{i+1} = f(x_i, x_{i-1}, \ldots, x_{i-n+1})
\]

where \( n \) is the embedding dimension, the current value of the variable \( X_t \) and \( t-1 \) past response values \( X_{t-1}, X_{t-2}, X_{t-n+1} \) can be used to predict the future response value of the system \( X_{i+1}^F \) [12], and as shown in equation (3),

\[
X_{i+1}^F = f_1(x_i, x_{i-1}, \ldots, x_{i-n+1})
\]

where \( f_1 \) is the approximate mapping of \( f \). After the value at time \( t+1 \) is predicted, the value can be calculated iteratively, or the predicted value of the system's T step \( (X_{i+1}^F, X_{i+T}^F) \).

The predicted value of the train state parameters reflects the change trend of the train state. Actually the rail transit train is an extremely complex electromechanical system, which includes multiple subsystems such as traction system, braking system, air supply system, auxiliary system, etc., the key analysis objects in each subsystem are different. Therefore, separate analysis is required for different subsystems or devices. In summary, we should proceed from the perspective of the degree of influence on the system, take the sensitivity of system parameters as a reference index, and comprehensively consider its overall influence on the system for appropriate state variables. Then the feedforward neural network works to predict these variables.

Generally speaking, there are relatively clear definitions and delimitations for determining the value range of a variable. If it exceeds a certain range, it is considered that the device corresponding to the variable has lost its designed function. Therefore, if the predicted value is very different from the
ideal value obtained based on expert experience, it needs to be analysed. Figure 2 shows two abnormal

trends.

![Figure 2. Ideal range and two abnormal trends.](image)

Based on the previous time series data, the data changes after t time are predicted. Abnormal trend 1 shows that the future data will continue to decline and more data falls outside the ideal zone. Abnormal trend 2 shows data fluctuations and has a greater probability of falling outside the ideal zone. Both of these situations require early warning because of potential health risks.

Many equipment’s performance shows good consistency and stability, which cannot meet the requirements just due to long-term service performance degradation [13]. And their life or health status can be predicted by the method in this paper, as shown in Figure 3.

![Figure 3. Health status prediction and status details at each stage.](image)

The consistency of the health data is obvious, that is, the data is gathered within the ideal value range. As the health status declines, on the one hand, taking a certain period of time as an analysis point, it can be seen that the centre of mass of the data has a certain deviation from the ideal value, and the data has large fluctuations and uncertainties. In this way, the health status evaluation index is established, and the life trend of the product can be better predicted through the mining of the accumulated data characteristics.
3. Design of Train Online Health Status Equipment Based on Train Bus
The key to online train health status analysis is to obtain the required train operation data in real time, and use data mining methods to comprehensively analyse train status information from multiple dimensions. In order to verify the practical application of feedforward neural network in train online health status analysis, a rail transit train health status equipment based on train bus is designed. The equipment is shown in Figure 4.

![Figure 4. Equipment and internal structure.](image)

The equipment is mainly composed of mini PC for data calculation, DTU for remote data transmission and peripheral circuits. Its built-in CAN bus board can read the required data from the bus network according to the data protocol and perform pre-processing, and send the results through the 4G network. It uses DB9 interface to connect with the train bus, as a node in the topological structure, and its installation position is shown in Figure 5.

![Figure 5. Train bus control structure and equipment installation location.](image)

The train bus is the key system of modern rail train control system. In the traditional industrial environment, it is necessary to place sensors to monitor a certain state value. The placement of sensors is limited by the motion state of the device under test, the power supply mode, installation conditions and the degree of damage, etc., and the dense and complex sensor network has many restrictions. However, adding nodes on the bus can realize adaptive configuration, that means the equipment plugs and plays, which greatly simplifies the difficulty of data acquisition.

The equipment uses the 4G network to upload the pre-processed results to the cloud server. On the one hand, the server stores these data and starts to use the feedforward neural network to perform related calculations and predictions. The user can interact with the server using a mobile phone, according to need to analyse the train's health status. And the process is described in Figure 6.
same time, in order to ensure the validity and integrity of data transmission, a verification mechanism has been added to the equipment software to avoid poor 4G network in the orbital operating environment \cite{14}.

4. Experiment and Method Validation
Train health analysis is a long-lasting process. Algorithm optimization and analysis on actual lines are time-consuming and difficult. Therefore, the method is verified by combining existing vehicle test data and fault injection. That is, the equipment is connected to a real CAN network train bus, the data is saved as a file, and then the train CAN bus is simulated by the combination of software and hardware in the laboratory environment. Then the previously saved data is formatted in the network protocol format using the host computer (data centre) and sent to the bus, and the equipment is used as a node to receive data. The rest is exactly the same as the train test. The simulation is shown in Figure 7. The advantage of this method is that it can artificially modify the sending frequency of bus data and shorten the waiting time of the algorithm. On the other hand, it can inject faults into the simulated sent data, so as to perform targeted simulation tests on the status degradation and fault occurrence of the train system.

The paper takes the train air brake system as an example for analysis. Figure 8 shows the AMESim model and principle diagram of the train air brake system. The air is braked from the air compressor to the main air pipe to the EP valve to the relay valve to the brake cylinder. Therefore, the brake cylinder is the end of the braking system, and its pressure directly acts on the basic braking device, and its
parameter characteristics also directly affect the strength of the braking ability. The industry generally selects the brake cylinder pressure rise time ($0.1P$ to $0.9P$) and the steady-state pressure ($P$) of the brake cylinder as the evaluation index of the braking ability.

![AMESim model and principle diagram of the train air brake system](image)

**Figure 8.** AMESim model and principle diagram of the train air brake system.

Regarding the braking system as a black box system, the two characteristics of brake cylinder pressure will also change significantly as the performance of the internal equipment of the braking system deteriorates. Therefore, for the train brake cylinder pressure data injection failure, the model is trained with different calculation time sections to predict the change trend of its brake cylinder pressure characteristics. The data of ten braking processes is used as a record point, and the reference runs The trend of mileage, braking mileage and brake cylinder pressure characteristics, combined with the actual maintenance strategy, the test results are shown in Figure 9.

![Remaining status dashboard](image)

**Figure 9.** Prediction of brake cylinder pressure characteristic change and remaining status dashboard.

It can be seen from the results that injecting faults in a short-term range actually has little effect on the result of the characteristic value change with the data within 1 month as the analysis unit, and it is more indicative of performance degradation. However, when the data within 3 hours is used as the analysis unit, the abnormal fluctuation is more obvious, and this feature can be used to warn the online mutation abnormality. The performance degradation will inevitably lead to a reduction in its expected service life, that is, the remaining mileage will drop by 1.1% (including the mileage calculated for 100 braking operations in this analysis time) and the remaining maintenance time will drop by 2.3%. The determination of these parameters needs to be corrected based on the actual maintenance requirements,
while adjusting the number of neural network layers, accuracy and the length of the data prediction period to better meet the actual engineering needs.

5. Conclusions
This paper has done relevant research on the theoretical application of neural network prediction models in train health analysis. Aiming at the online health status of rail trains, an intelligent equipment based on the train bus is designed to implement the theoretical method of this paper in the field of application. This article uses real train data and fault injection technology to simulate the train online operation environment in a laboratory environment, thereby verifying the method and equipment in this paper. The number of layers, accuracy and prediction range of the neural network need to be adjusted according to actual maintenance requirements to meet the requirements of real-time and accuracy.

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