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Improved Fault Prediction Algorithm of High-Speed EMUs based on PHM Technology

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Abstract: *The essence of PHM technology is to process the collected information with the help of the system information collected by sensors, using information fusion, artificial intelligence, big data, reasoning algorithms and other technologies, and realize the monitoring management, status evaluation and fault prediction functions of the target system. PHM is an important part of the intelligent equipment detection and maintenance system. Its application and realization in the railway field is the key link of the intelligent operation and maintenance of multiple units, and is an important means to realize the shift from planned preventive maintenance to digital and accurate condition maintenance. It is of great significance for China's high-speed railway to maintain the world's advanced level and move towards higher quality, efficiency and efficiency. With the improvement of operation speed and the growth of application scale of High-Speed Electric Multiple Units in China, hereinafter referred to as EMU, the technical challenges of operation safety and security of EMUs are increasingly prominent. As a kind of equipment health management technology, PHM can realize equipment status monitoring, abnormal prediction, fault diagnosis, maintenance prediction and maintenance decision-making. In order to improve the safety assurance capability of high-speed EMU, reduce the maintenance cost and improve the maintenance efficiency, this paper deeply integrates big data technology, algorithm model and PHM technology, and explores the theory and method of intelligent fault prediction of key components of high-speed EMU based on PHM technology. Focus on the research of EMU condition monitoring and fault diagnosis technology based on HSMM and DBN algorithms, as well as the component maintenance prediction and maintenance decision-making technology based on fixed repair schedule prevention, so as to transfer the theoretical basis and technical support for the maintenance mode of EMU from "planned repair" to "planned repair predictive maintenance".*

Keywords: High speed EMU; Prognostics and Health Management; Traction Motor; Neural Network; Model

1. Introduction

In recent years, China's high-speed railway technology has developed rapidly and made world-renowned achievements, and the driving speed of high-speed trainsets has constantly set new world records. The Medium- and Long-term Railway Network Planning of China plans the operational mileage of high-speed railway in China, which will reach 40,000 km by 2035, marking the important position of high-speed railway in the infrastructure and transportation facilities of China. By the end of August 2022, China has more than 3,000 trains, and the number of high-speed trains is close to 2,000. With the rapid growth of domestic trains, the increase in the variety of models in service and large-scale operations, the trainset equipment industry has shifted from the large-scale manufacturing stage to the whole life cycle of operation and maintenance stage, and the high failure rate, low on-line rate and high maintenance cost of trainsets are many The problems are constantly exposed. How to ensure safety, improve passenger comfort, reduce maintenance costs, reduce or minimize the occurrence of failures is of great significance to the future development of China's high-speed rolling stock industry [1-4].

At present, China has carried out extensive research on fault diagnosis, prediction and health management in the fields of transportation, aerospace, shipbuilding industry, energy and power. Most of the research subjects are universities and scientific research institutions. The main research content is focused on the PHM architecture and intelligent diagnosis and prediction algorithm research. Although some achievements have been made, the overall scale and level of application research is still relatively backward, and basic theoretical research lacks application background support and experimental verification and other fatal defects. In particular, the following difficulties still exist in the field of fault prediction and health management of high-speed EMUs in China [5-7].

The fault diagnosis of key systems and components of high-speed EMU adopts post-fault processing method, which can not be predicted in advance before the fault occurs, which will cause system component damage, train delay and other problems affecting the operation order and safety. At the same time, the fault handling after the fault also needs a lot of manpower and material resources to prevent the expansion of the fault scope and the deterioration of the fault degree, which will not only increase the maintenance cost, but also significantly affect the safe operation and service quality of the EMU [8-10].

The structured, semi-structured and unstructured data generated during the development, design, production and manufacturing stages, operation and maintenance stages of the EMU are owned by different companies. For example, the production and manufacturing data of trains are in the manufacturing company, and the operation data of trains are in the national operation department. The detection data of the user's daily maintenance of the maintenance department under the train is stored in the user's specific system. The PHM technology of high-speed EMU is to study the overall state of the whole life cycle of the train. Data in different formats, data from different sources and interface interconnection need to be urgently solved [11-15].

The high-speed EMU includes nine core systems, such as traction, power supply, braking, network, car body, bogie, and more than 200000 parts, as well as more than 1000 monitoring sensors, including speed, acceleration, stress, pressure, voltage, current, temperature, etc. Each train will produce about 10GB of data every day (the relevant operation and maintenance data collected by a domestic main engine factory only around the high-speed EMU will reach PB level within two years), These data are not only huge in quantity but also various in types and structures. If traditional data processing methods are used, it is not only unable to deal with the real-time processing of large quantities of data, but also unable to excavate the intrinsic relevance value of data. Therefore, what technology to use to analyze the massive heterogeneous data generated by the train is also a problem that has to be considered [16].

2. PHM Technology Architecture

The typical architecture of fault prediction and health management is OSA-CBM(open system architecture for condition-based maintenance) system architecture, which is an important reference in this field. It is a single dimensional seven module functional architecture oriented to general objects. OSA-CBM architecture divides the functions of PHM into seven levels, mainly including data acquisition, feature extraction, condition monitoring, health assessment, fault prediction, maintenance decision-making and human-computer interaction interface, as shown in Figure 1.

The PHM system is composed of seven functional modules. The data flow between each functional module basically follows the above sequence. Any one of the functional modules has the ability to obtain the required data from the other six modules. The functions of each module are as follows:

- Data acquisition: collect the required monitoring data by installing corresponding sensors at appropriate locations, including temperature, speed, strain gauge, infrared sensor, etc., and store them according to the defined data format.
- Feature extraction: processing the acquired signals and data, mainly using filtering, linear judgment, spectrum analysis and dimension reduction processing, in order to obtain information that can characterize the performance of the monitored object.
- Condition monitoring: it mainly uses threshold judgment, fuzzy logic and other methods to compare the processed features and data with the working condition data signals under different operating conditions, and generates alarm signals for features beyond the threshold range.
- Health assessment: judge the current health status of the equipment by monitoring the operating status, load condition and monitoring data of the equipment. This requires that the degradation status be

specifically divided in the whole life cycle of the equipment according to the actual operating conditions. If degradation occurs, new monitoring conditions and thresholds are required.

- Fault prediction: the most important role of fault prediction is to predict the degradation at a certain time in the future based on the current health state of the equipment, according to historical data and future operation data, or predict the remaining life of the equipment within a certain confidence interval.
- Operation and maintenance decision: according to the information provided by condition monitoring, health assessment and fault prediction, multi-objective optimization, allocation algorithm and dynamic planning are used to optimize the maintenance time and space, taking the operating conditions, maintenance history, degradation status of key components and current task curve as constraints, and taking the minimum time and cost for task completion as the solution goal, so as to scientifically and reasonably formulate maintenance decisions Maintenance plan and replacement support requirements.

Human machine interface: it studies the relationship between human and machine. The main functions of this module are information exchange, feedback control and visual output of data. It has the function of adjusting control parameters after health assessment, and the ability to control the monitored object to stop after alarm is generated. This module usually has data interfaces with other modules of PHM, so as to facilitate the information transmission between various modules.

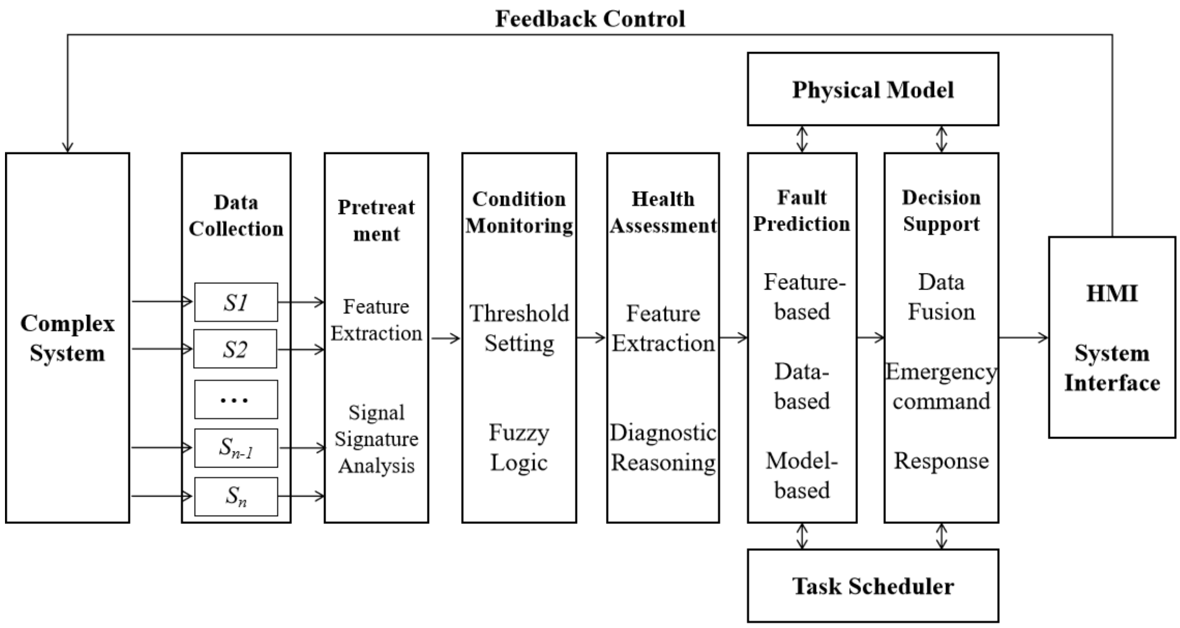

Figure 1. PHM technology architecture

3. Problems Encountered in Fault Prediction of High-speed EMU at Present

Reliability engineering is a field of modern engineering equipment that uses the viewpoint and methodology of system engineering to carry out a series of tasks such as reliability design, reliability prediction, reliability analysis, reliability test, and reliability maintenance of equipment components or systems. Reducing the probability of equipment failure and improving the engineering technology of equipment reliability. Reliability engineering runs through the entire life cycle of equipment. Since the 1980s, reliability engineering has been widely used in the fields of electronics, electric power, nuclear energy, transportation, and light industry. With the continuous development and improvement of the theory, it gradually branched out into disciplines such as maintainability engineering and test engineering, and formed performance indicators and requirements for comprehensive evaluation of product reliability, usability, maintainability and safety , that is, RAMS technology.

3.1 RAMS Technical Composition

RAMS is a general term for product reliability, usability, maintainability and safety. It is a technology that studies failure rules, analyzes failure consequences, establishes RAMS indicators, and continuously optimizes product comprehensive performance during the entire life cycle of a product.

Reliability and safety: Reliability refers to the ability of equipment to work normally during its life cycle, and safety is derived from reliability, which refers to the ability to avoid unacceptable risk accidents. Reliability and safety are inherent attributes formed in the process of product development, technology and processing. Reasonable maintenance in product use can only ensure that this attribute does not decline or slow down the rate of decline, and cannot improve or improve its reliability and safety. . Improvements in product inherent reliability can only be achieved through improved design and improved manufacturing. For EMUs, the design process and source quality problems in the manufacturing process will directly affect the reliability and safety of EMUs. Therefore, the source quality control of EMUs has always been a key work at the head office level. An important link in reliability engineering.

Availability: Refers to the ability of a product to be available at any random moment. Availability is a comprehensive measure of product reliability, maintainability and maintenance support, which directly reflects the degree of product availability. The probability measure is availability, and the commonly used evaluation indexes of availability are: inherent availability, reachable availability, and usage availability. The impact of component failure on operation quality and transportation order will reduce the availability of EMUs, while the safety redundancy of components can effectively improve the availability of EMUs.

Maintainability: refers to the ability to maintain or restore its specified state within the specified time, according to the specified procedures and methods, that is, the maintenance of EMUs, including advanced maintenance and operational maintenance. The purpose of maintenance is to prevent the consequences of the failure rather than the failure itself. The severity of the consequences of the failure is the starting point for determining whether to do preventive maintenance. Through comprehensive weighing, usually only for important products with safety, mission and serious economic consequences, preventive maintenance work is required.

4. PHM Platform Design of High-speed EMU

The fault abnormal state of high-speed EMU often involves multiple levels such as train cluster, system cluster and component cluster. The state characteristics of each level are interrelated, which makes fault prediction and location extremely complex. Therefore, to carry out the research on intelligent diagnosis and fault prediction of high-speed EMU, it is necessary to extract and preprocess the real-time status data, dig deeply into the historical data accumulated by train operation, establish the mathematical model of fault prediction of the system, and monitor and logically deduce the feature data and correlation at the train, system and component levels. The fault prediction and health management platform for high-speed EMU is mainly composed of four elements: On-board PHM system, vehicle ground data transmission and communication system, ground information perception system and ground PHM system. The system architecture is shown in Figure 2.

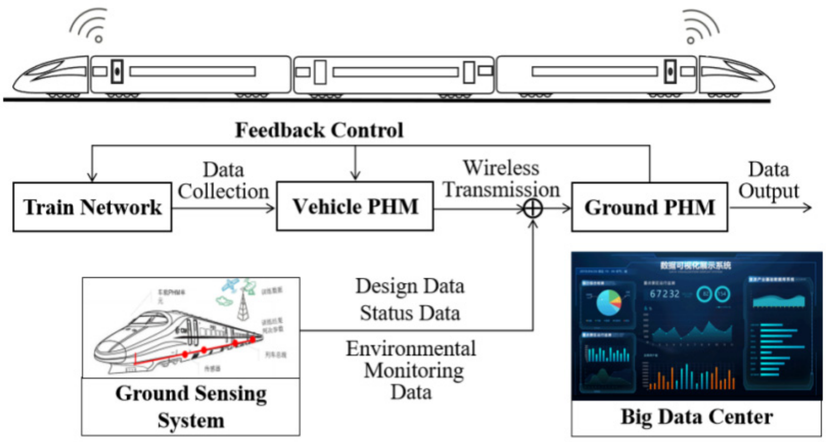

Figure 2. PHM system architecture

4.1 On Board PHM System

The on-board PHM system is used to collect vehicle data in real time and identify the abnormal state of the vehicle in advance through the on-board fault warning model. The system preprocesses the real-time vehicle data, places the early warning model with high real-time requirements and small calculation amount on the vehicle side, and transmits the calculation results to the ground server, so as to improve the real-time calculation efficiency of vehicle data. The on-board PHM system is composed of component level PHM and train level PHM. By adding a component level PHM unit in the control host of traction, braking, axle temperature and other subsystems, the collected internal data can be used for fault warning, prediction and self diagnosis of system status, so as to complete the component level PHM analysis; And use the train network to send the original data, status information and fault information of the components to the on-board PHM host, so as to complete the self diagnosis of the train. The train intelligent display screen displays the diagnosis information and transmits the data to the ground PHM system through the on-board wireless transmission device WTD (wireless transmission device).

Taking the status monitoring of train traction motor as an example, the structure of on-board PHM system is shown in Figure 3. The on-board PHM system monitors the operation data of the traction motor in the bogie through the train's own network system, performs real-time calculation and Analysis on the component level characteristic data such as axle temperature, vibration frequency, voltage, current, acceleration and vehicle level data of the traction motor, and transmits the processed warning information and status characteristics to the main processing unit of the train network, and then transmits them to the WTD of the train. Finally, it is sent to the big data platform receiving server of the ground PHM system through the vehicle ground data transmission communication system.

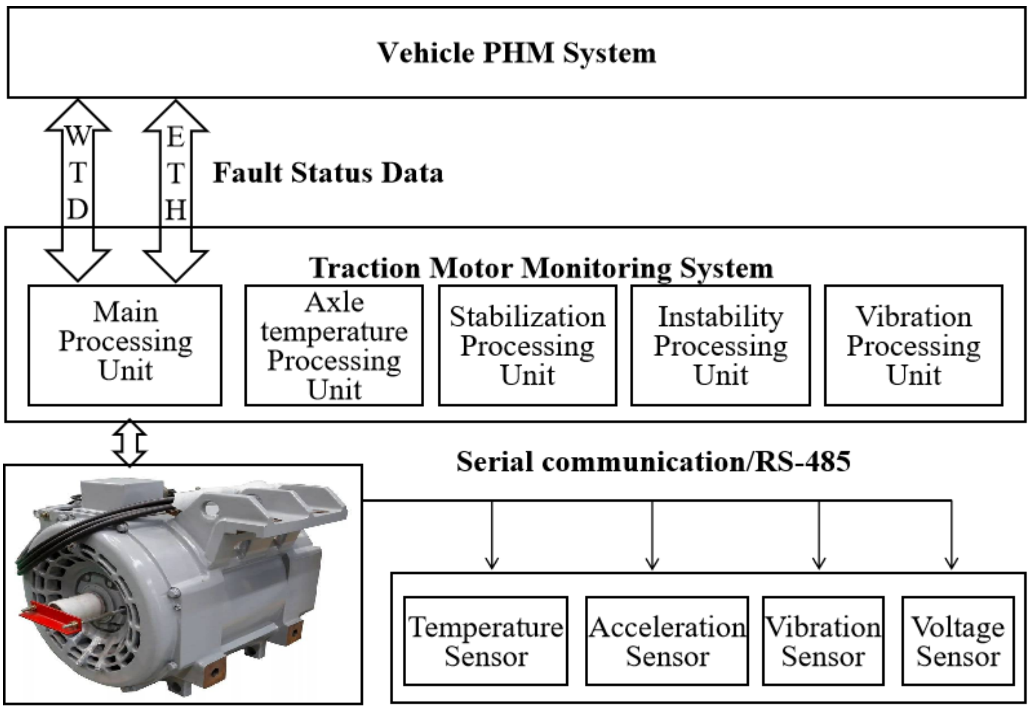

Figure 3. PHM1 model of traction motor

4.2 Train Ground Data Transmission Communication System

The data generated by the on-board PHM system is compressed by the vehicle ground data transmission and communication system, and the data is sent to the ground server in real time through the specified communication protocol by satellite or 4G, 5G equipment and antenna for centralized storage and processing, and then transmitted to all users through the dedicated network for use by the ground PHM system. In the whole data transmission process, data, information and network security technology are required. For non real-time data, the data transmission between the on-board PHM system and the ground PHM system can be carried out through WiFi, optical fiber and other Internet methods, including the fault data maintained by the on-board maintenance workers and the data reported in other ways.

4.3 Ground Information Perception System

The information sensing system is mainly used to collect ground facilities, vehicle status, environmental climate and other data and send them to the ground PHM system. It mainly includes: 1) physical information reflecting the status of parts, such as the temperature, vibration frequency of bearings and the voltage, current and other physical quantities of traction motors. 2) Reflect the performance of the train state, such as the physical information of smoothness and comfort, and the position and environment information of the train. 3) It reflects the information of some ground equipment, such as the physical information of the track, the contact power grid and the surrounding environment of the track. 4) Data reflecting relevant parameters during vehicle design, test or maintenance.

4.4 Ground PHM System

The ground PHM system receives the vehicle status data, operation and maintenance environment data, design and manufacturing data, etc. from the information perception system. After cleaning, conversion and storage, it processes the real-time data stream based on the built analysis model to achieve accurate fault prediction and health management from the train cluster to key components. At the same time, knowledge mining is carried out on non real-time data through big data analysis as the basis for optimizing PHM model. The ground PHM application platform includes visual display and decision support, which can timely realize information interaction with the operation management level, feed back the analysis results of the ground PHM system to the on-board PHM system, and guide the design improvement, intelligent manufacturing and maintenance of trains.

5. Research on Fault Prediction Method of High-speed EMU

The primary task of fault prediction technology is to track and monitor the fault evolution law and degradation state of equipment, use intelligent algorithms to process the information in the whole life cycle of equipment, and achieve the goal of accurate prediction according to the fault evolution law and failure mechanism. The intelligent diagnosis and fault prediction model of the whole vehicle, subsystem or component of high-speed EMU is a prediction model established by abstracting the mathematical method according to its own inherent attribute parameters, logic and functions. Regarding the classification of fault prediction algorithms , different research institutions and organizations have different references at present. The overall classification of fault prediction algorithms is shown in Figure 4. As for the current mainstream fault prediction methods, as shown in Figure 4. This paper studies the accuracy of prediction, capital cost investment and application universality.

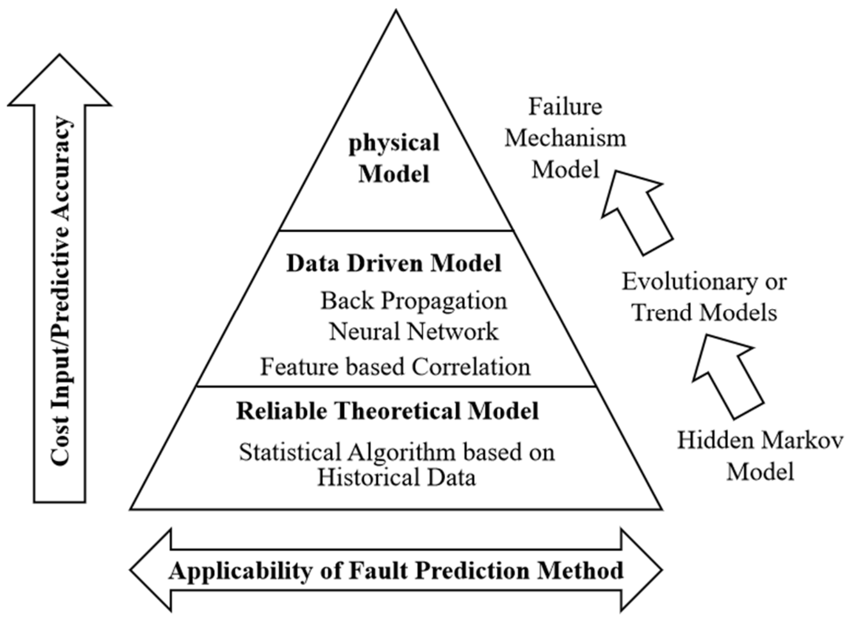

Figure 4. Algorithms of fault prediction

5.1 Model based fault prediction technology

Model-based fault prediction refers to the prediction method using dynamic models or processes. Physical model methods, Kalman filters, particle filters, hidden Markov models, and methods based on expert experience can all be classified as model-based fault prediction techniques.

5.2 Data Driven Fault Prediction Technology

For complex equipment, it is difficult to establish physical model due to its complex structure, many constituent systems and various failure forms. However, it is easy to collect information in the whole life cycle through monitoring system and sensors. Therefore, data-driven method is usually used to predict the fault of complex equipment. By collecting and processing the information in the whole life cycle of the equipment, the method uses machine learning to build the mapping relationship between data input and output to achieve the fault prediction of the equipment. Typical data-driven fault prediction methods include artificial neural network(ANN), time series, decision tree(DT), support vector machine(SVM) and other intelligent prediction methods.

Compared with the regression analysis and time series analysis methods in the traditional statistical category, neural network is one of the most widely used methods in fault prediction methods and application research. It can learn from samples and try to capture the intrinsic functional relationship between sample data. In particular, BP neural network has strong nonlinear mapping ability, which can better perform nonlinear classification. Moreover, BP neural network has high speed in processing information, high fault tolerance rate, and can associate and remember external information. It is a very effective fault prediction algorithm. This is also an important reason why this paper chooses BP neural network as the fault prediction of traction motor of high-speed EMU.

In the process of fault prediction, we use sigmoid activation function to complete the nonlinear transformation of data and solve the problem of insufficient expression and classification ability of linear models. The formula is as follows.

$$S(\mathrm{x}) = \frac{1}{1+e^{-x}} \quad (1)$$

In order to optimize the parameters of the neural network model, we use the loss function. The function of the loss function is to calculate the difference between the forward calculation result of each iteration of the neural network and the real value, so as to guide the next training in the right direction. The smaller the value of the loss function, the closer the predicted value of the model is to the true value. The loss function is obtained in the forward propagation calculation and is also the starting point of the backward propagation. The formula is as follows.

$$E = \frac{1}{2N}(T - Y)^2 = \frac{1}{2N}\sum_{i=1}^{N}(t_i - y_i)^2 \quad (2)$$

The matrix can be represented by capital letters, where T represents the real label, Y represents the network output, i represents the i-th data, and N represents the number of training samples.

5.3 Prediction Method Based on Traditional Reliability Theory

Hidden Markov Model (HMM) is one of the commonly used models for state recognition. Once this model was proposed, it was improved and perfected by scholars such as Lawearnce R. Rabiner and applied to speech recognition for the first time, and has achieved great results. success. In recent years, with the development of theory and the improvement of algorithms, HMM has been widely used in the field of pattern recognition such as speech recognition, performance degradation recognition, degradation state prediction, handwriting recognition and fault diagnosis of mechanical equipment. The reason why HMM can be widely used is because of its successful application in speech recognition, and another important reason is that it has a strong mathematical theoretical basis for support.

Neural Network (Artificial Neural Network , ANN) calculates by simulating the working principle of the human brain, and has the characteristics of strong prediction performance for large-scale data. It consists of an input layer, a hidden layer and an output layer, and each layer consists of several basic components - neurons. Neural networks learn by iteratively adjusting weights. The neurons in the network are similar to the neurons of the human brain. The input data is obtained from several neurons in the front layer, multiplied by the corresponding weights and summed, and added to the corresponding bias of the neuron to obtain the total value of the neuron.

6. Fault Warning and Temperature Prediction Model of Traction Motor

The traction motor of high-speed EMU is the core component of the power system of EMU. It will generate heat loss during operation. If the temperature of the motor rises sharply and exceeds the maximum temperature it can bear due to changes in internal resistance and poor heat dissipation, it will cause equipment failure and lead to train delay or stop. This paper takes the traction motor of CR400AF high-speed EMU as an example to illustrate the idea of building the fault warning and temperature prediction model of key components of the EMU.

6.1 Establish Real-time Temperature Warning Sub Model

First of all, starting from the working principle of traction motor, the core judging index of motor state - motor stator temperature and its influencing factors are analyzed, and the range of characteristic variables is defined. The judgment index shall cover not only the number of characteristic variables directly related to temperature, such as motor current, train speed, traction level, weather conditions (temperature, rain and snow), but also indirect influence variables, such as the ramp and curve radius of the line section, which will affect the traction power of the motor and thus the motor temperature. The high-speed EMU transmission system test bench can perform run-in and cleaning tests on the gearboxes or axle boxes of high-speed EMUs or ordinary trains, and can be applied to the oil washing and running-in of axle gearboxes of different models Automatic control is complete. It has basic functions such as automatic measurement, analysis, storage, alarm, report and record query of the temperature, vibration, noise, speed, torque and other signals of the gearbox and axle box.

The second step is to extract the operation data of each EMU for two days in a natural month by sampling, and to cover different lines as much as possible. Arrange the sampling data in time order and hide the train number and car information. 1000 groups of data were randomly selected, and the correlation between each variable and motor stator temperature was verified by Pearson analysis through SPSS software. Select data indicators with correlation greater than 0.2 and significance (two sides) less than 0.01 to build the model. See Table 1 for eligible data indicators.

Table 1. Description of data

Motor stator temperature	Speed	Rotor Frequency	DC Voltage	Tap Position	Constant Speed state	Ambient Temperature	Route Slope
Pearson Correlation Coefficient	0.584	0.584	0.494	0.362	0.362	0.275	0.238
Significance (two-sided test)	0	0	0	0	0	0	0

The third step is to screen out the historical fault information of 7 traction motors of CR400AF EMU, all of which are common grounding faults caused by poor insulation of motor winding. According to the design principle and data analysis, the motor temperature changes greatly before and after such faults occur. Select the motor temperature within 0.5h before the fault and the related data in Table 1 as the fault samples, and select the normal historical data of 50 multiple units for a total of 100h as the normal samples to form a sample library with the fault samples. The current data collection cycle is 10s, so the sample library contains 37260 groups of data. Every 6 groups of data are recorded as a sample, and 6210 samples are generated, including 6000 normal samples and 210 fault samples. The sample data is randomly scrambled and divided into training set and test set according to the ratio of 7:3. There are 4347 samples in the training set, including 4200 normal samples and 147 fault samples; The test set includes 1863 samples, including 1800 normal samples and 63 fault samples. A three-layer traction motor temperature early warning neural network model is established by using BP neural network learning algorithm. The input neurons include the data index variables in Table 1, and the output neurons of the model are traction motor temperature early warning information. The schematic diagram of the model is shown in Figure 5.

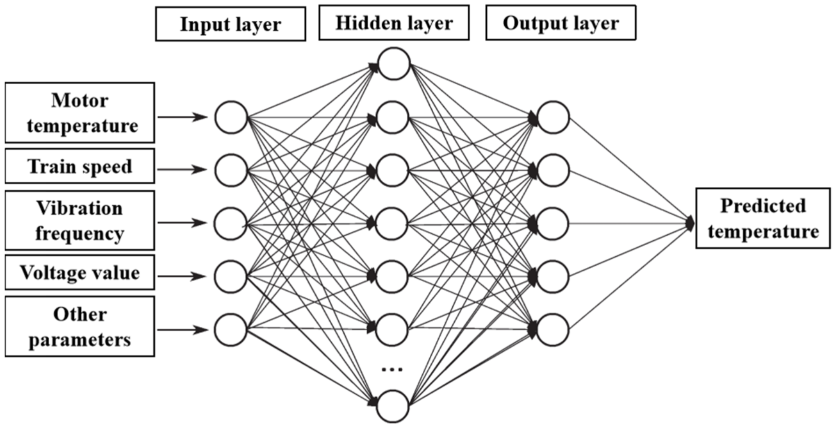

Figure 5. Schematic diagram of traction motor temperature BP neural network model

Finally, the model is trained with the training set sample data at a learning rate of 0.1, and the target relative error is 1×10-2, and the maximum number of iterations is 5000. After the training, the generalization ability is detected by using the test set data. When the generalization ability is no longer improved, the training is terminated to complete the construction of the real-time temperature warning model of the traction motor based on the neural network algorithm. The prediction results of the model test set are shown in Table 2. The accuracy rate of the model is 99.14%, and the recall rate is 93.65%.

Table 2. Description of data

Predictive Target	Forecast Results
TP(True Positive)	59
FN(False Negative)	4
FP(False Positive)	12
TN(True Negative)	1799
Accuracy=(TP+TN)/(TP+FN+FP+TN)	99.14%
Precision=TP/(TP+FP)	83.10%
Recall=TP/(TP+FN)	93.65%

6.2 Establish Temperature Trend Prediction Sub Model

The departure and arrival time of the same train and the maximum running speed of the line are completely the same, so the factors affecting the temperature of the traction motor such as the operation of the multiple units in the same section and the line slope are basically the same. Only the ambient temperature belongs to the unstable variable, which can be obtained from the weather forecast data along the line. Based on this, we can realize the temperature prediction of traction motor.

First of all, from the normal operation data of CR400AF multiple unit in the latest year, the 8 data index variables in Table 1 are sampled according to different seasons and lines, and the stator temperature of the traction motor is regressed to build a motor temperature prediction model.

Then, the latest normal operation state data of the EMU in the subsequent sections, including speed, rotor frequency, DC voltage, gear, constant speed state, line slope and electric current, are obtained through the correlation between the operation plan of the day, real-time GPS positioning information and historical data, and the weather forecast ambient temperature data along the line are obtained through the Internet. The acquisition cycle of all data association is 30min, and the temperature change trend of each traction motor in the following 30min under the normal working condition is predicted by the temperature prediction model.

In order to reflect the predicted motor temperature, the actual motor temperature of a certain EMU on a certain day is compared with the predicted motor temperature on that day, and the results are shown in Figure 6. From the data analysis results, the prediction effect is very good when the driving conditions of the EMU are relatively simple (such as in the state of constant speed and constant gear). When the driving conditions of multiple units are complex (such as repeated speed regulation and frequent traction braking switching), the prediction deviation increases. The reason for this is that under complex working conditions, the gear, motor current, voltage and other indicators related to the prediction model change dramatically, and the WTD vehicle ground data transmission cycle is long (10s), so it is impossible to completely record its change process.

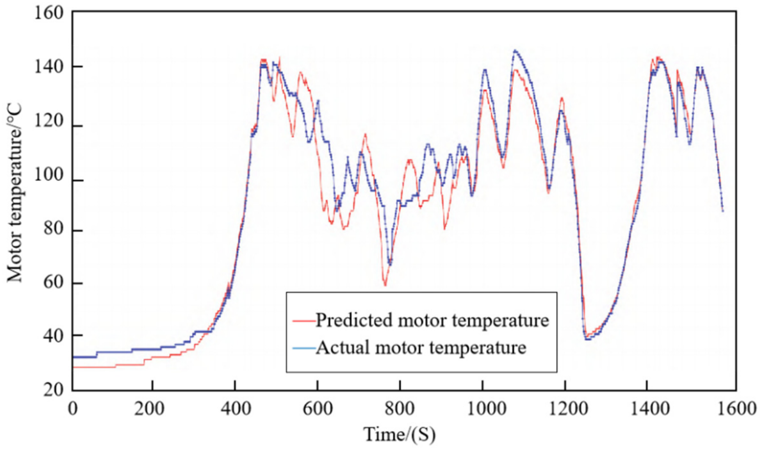

Figure 6. Comparison between actual traction motor temperature and model predicted temperature

To further evaluate the prediction effect, the predicted value of the model is fitted with the actual value for analysis, as shown in Fig. 7. It can be seen that the actual temperature is in good agreement with the predicted temperature trend, and the R2 value of the fitting coefficient is 0.97, which basically meets the expected requirements.

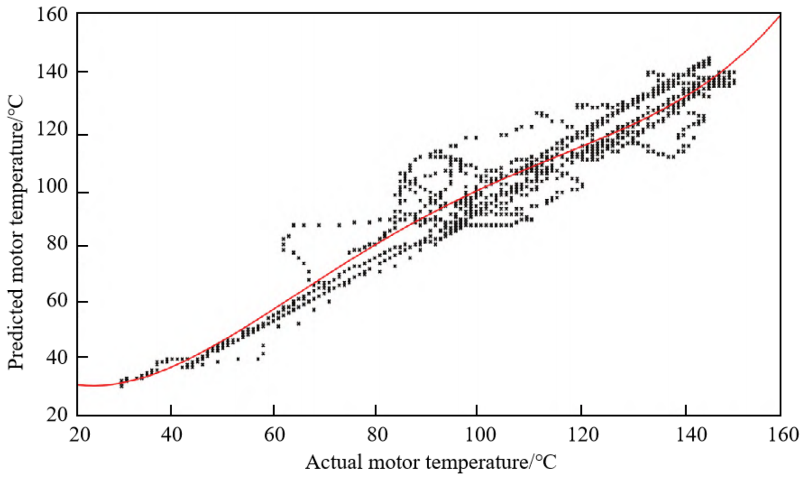

Figure 7. Fitting analysis between predicted values and actual values of traction motor stator temperature prediction sub model

So far, the stator temperature prediction model of the traction motor has been built. Its functions include two parts: one is to determine whether the traction motor works normally, so as to identify abnormalities and remind the emergency commander to intervene in time. The second is to obtain the temperature change trend information within 30 minutes after the motor is in normal working condition, and compare it with the real-time temperature after the motor fails, so that the emergency commander can intuitively understand the abnormal degree of the motor and provide data support for subsequent analysis and decision-making.

In order to realize component failure risk prediction and advanced prevention, and ensure the operation safety of EMUs and components, Chapter 4 conducts research on the early prediction algorithm for key components of high-speed EMUs . Considering that most of the key component replacement and maintenance work of the EMU is mainly based on the advanced maintenance and repair procedures, it is implemented through the advanced maintenance and maintenance project, and the EMU advanced maintenance plan stipulates when and what type of advanced maintenance and maintenance will be performed for the EMU Project, therefore , the advanced maintenance plan directly affects the maintenance time and maintenance category of key components. In order to support the maintenance decision-making of EMUs and key components, this chapter predicts the advanced maintenance plan of high-speed EMUs, and solves the problem of inaccurate prediction of advanced maintenance plans through the mileage prediction of EMUs.

7. Conclusions

On the basis of fault prediction and health management technology, this paper analyzes the current situation of fault prediction of high-speed EMU, and introduces the architecture of PHM platform of high-speed EMU. In the process of prediction method research, three commonly used prediction technologies are compared and analyzed, and a method based on the combination of component failure mechanism and BP neural network algorithm is used to explore and build a traction motor failure warning and temperature prediction model with the traction motor of high-speed EMU as an application case. It provides a theoretical basis and research ideas for the fault prediction technology of high-speed EMU, and has a good reference significance. The next step will be to study the application of big data technology and intelligent diagnosis technology in PHM and establish a new high-speed EMU Operation and maintenance system with multi-source data fusion, algorithm optimization and intelligent diagnosis.

Conflicts of Interest: The authors declare no conflict of interest.

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