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Advances in fault diagnosis for high-speed railway: A review

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Abstract—The high speed railway (HSR) is a complex system with many subsystems and components. The reliability of its core subsystems is a key consideration in ensuring the safety and operation efficiency of the whole system. As the service time increases, the degradation of these subsystems and components may lead to a range of faults and deteriorate the whole system performance. To ensure the operation safety and to develop reasonable maintenance strategies, fault detection and isolation is an indispensable functionality in high speed railway systems. In this paper, the traction power supply system, bogie system, civil infrastructure system, and control and signaling system of HSR are briefly summarized, and then different fault diagnosis methods for these subsystems are comprehensively reviewed. Finally, some future research topics are discussed.

Keywords- High-speed railway (HSR); fault diagnosis; traction power supply system (TPSS); bogie system

I. INTRODUCTION

Since the first high-speed train (HST) started to operate in 1964, this comfortable and efficient transportation means has been deployed across a number of countries worldwide, including Japan, Spain, Germany, China and France [1], to just name a few. With the rapid development of high-speed railway (HSR), its safety and reliability has become an increasingly important issue. The traction power supply system (TPSS), bogie system, civil infrastructure system, and control and signaling system are important subsystems in HSRs. As illustrated in Figure 1, the TPSS transmits reliable electric power to the train, the bogie system guides the train running along the rail. Both motor and bogies are under the control of the train control and signaling system. While the rail is supported by supporting structures. To ensure the safety and reliable operation, performance monitoring and fault diagnosis of these critical HSR subsystems are vital.

In HSR, the fault diagnosis methods can generally be classified into visual-based methods and signal-based methods according to the data source type. The visual-based use image processing and pattern recognition techniques to extract information from images, and the signal-based methods detect faults by analyzing various electrical signals collected by for example current, voltage and vibration sensors. Meanwhile, the diagnosis algorithms can be

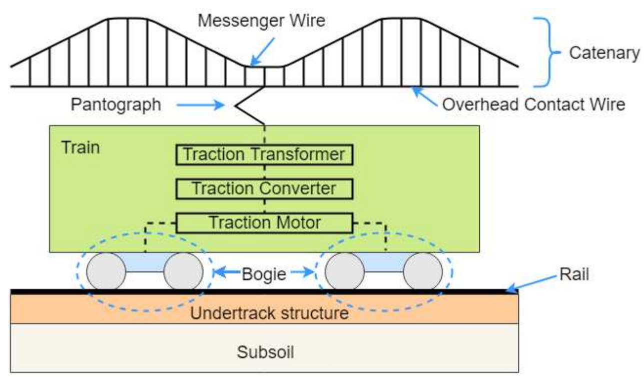

Figure 1. High speed railway system

classified into three categories, namely model-based, signal processing-based and knowledge-based. The model-based approaches are based on the development of accurate system models. Observers, filters and bond graph are among useful model-based fault diagnosis tools. The signal processing-based approaches extract features from the measured signals to diagnose faults. The most commonly used signal processing-based fault diagnosis approaches are time-domain features analysis, frequency spectrum analysis, and time-frequency analysis. The knowledge-based fault diagnosis approaches require neither a system model nor signal patterns, they diagnose faults by analyzing a large volume of historic data [2]. The commonly used knowledge-based approaches include the principal component analysis (PCA), partial least squares, support vector machines (SVMs), and artificial neural networks (ANNs), etc. These three type of approaches and their variants including hybrid approaches are widely used in HSR.

This paper presents a comprehensive review of methods applied to the HSR subsystems. The remainder of this paper is organized as follows. Sections 2 to 5 give a brief summary of the main components and structures of HSR, namely the TPSS, bogie system, civil infrastructure, and control and signaling system, respectively, and the fault diagnosis methods for these subsystems are reviewed. Section 6 concludes the paper.

II. TRACTION POWER SUPPLY SYSTEM AND ITS FAULT DIAGNOSIS

The traction power supply system (TPSS) is one of the core subsystems in HSR, and it directly impacts the safe, quick, and efficient operation of the train. It is a complex electromechanical coupling system that mainly consists of pantograph-catenary system, traction transformers, traction converters (include AC/DC rectifiers, traction inverters, etc.), and traction motors. Generally, mechanical, electrical and sensor faults are three main types of TPSS faults. The fault diagnosis for the TPSS is of great significance for the operation and maintenance of HST. The degradation of components in TPSS will directly lead to a whole performance degradation of the traction systems.

A. Pantograph Catenary System Fault Diagnosis

Pantograph catenary (PAC) system transmits electric power from the catenary to the train via the pantograph mounted on the roof of a train. The improper contact force between the pantograph head and contact wire can lead to frequent faults occurring in the PAC system, which degrades the quality of the contact and reduces the reliability of HSR operations. To maintain the PAC system in a good condition and ensure the power transmission quality, the timely detection and diagnosis of faults in the PAC system are required. Many diagnosis methods have been developed for the PAC systems, which are largely classified into two types, one is the current–voltage processing-based approach and the other is the image processing-based approach [3].

Low contact force or disconnection between pantograph and contact wire may cause an arc to form. Arcing occurrence overheats the contact region, ablates the pantograph slide and contact wire, and generates harmonic and electromagnetic interference affecting the signaling and communication system. It is therefore one of the most commonly observed faults in HSR systems. The current-voltage processing-based methods, which mainly include advanced signal processing techniques and knowledge-based techniques, are applied to detect the arc condition [4]. In addition, a number of image processing-based methods have been developed to detect arc or contact point in HST PAC systems.

The wear and other mechanical damages of the PAC system were studied in [5], and the modelling and simulation approaches used to describe the pantograph and catenary interaction were reviewed. The irregularity of contact wire is a major anomaly of the HSR catenary system. It can directly change the dynamic contact force and even cause severe damages to the PAC systems. Thus, the contact wire condition should be closely monitored and its irregularity should be detected timely. The wavelet packet entropy [6] and quadratic time-frequency representation [7] were employed to detect the wire irregularity. Apart from the current-voltage processing-based methods for the PAC mechanical fault detection, the image processing and vision technology based approaches are becoming widely used in the PAC systems due to a number of merits, such as anti-interference, minimal invasiveness, and good generality. To improve the detection accuracy, the deep learning techniques and real-time detection algorithms are often adopted [8].

B. Traction Transformer Fault Diagnosis

Traction transformers are essential components in the HSR traction power supply systems that provide a reliable source of power to the traction rectifiers. A traction transformer mainly consists of inlet-outlet line, winding and iron core, and it is prone to failure due to its structure and operation environment. Accurate and fast fault diagnosis for transformers is a key to ensure the normal operation of the traction system in HST.

The disconnection fault, short circuit fault and ground fault are among the main electrical fault types of a traction transformer. Model-based methods were developed to identify the faulty element as well as the fault type of the transformer [9]. In [10], a signal processing-based fault diagnosis method was proposed to detect the transformer internal short-circuit fault. The aging problem of the insulation paper in a transformer leads to interturn short circuit in the secondary windings of current transformers, and sometimes may lead to unexpected dangers for a TPSS. To estimate the insulation status of the insulation paper, the dissolved gas analysis (DGA), Furfural analysis, and the frequency domain dielectric spectroscopy (FDS) are among the most commonly used approaches. Knowledge-based methods are also used to detect transformer internal faults. Based on the DGA, the kernel principal component analysis (KPCA) combined with random forest was applied to diagnose the traction transformer thermal and electrical faults, which achieved higher diagnosis accuracy than some traditional methods and show good anti-jamming performance [11]. The FDS is also shown to be an effective approach to diagnose the status of the oil-paper with non-uniform aging [12].

C. Traction Converter Fault Diagnosis

A traction converter consists of a rectifier, a DC-link circuit and a inverter, and it is widely used in HSR TPSS. Up to date, only a few reports can be found on HST traction converter fault diagnosis.

In [13], a mixed logical dynamic based model was proposed to detect open-switch fault in single-phase pulse width modulated (PWM) rectifier of the HST traction system, the faulty switch is detected based on the difference between the model output and the actual operation conditions. [14] studied the fault modes and effects of the DC-link circuit in the HST traction converter, and proposed a fault diagnosis method based on notch filter, and a frequency compensation based fault tolerant control method was successfully applied. While [15] proposed a multi-mode KPCA based fault diagnosis approach for PWM inverter of CRH5, and it is shown to be able to diagnose both incipient faults and short-circuit faults of insulated-gate bipolar transistors (IGBT).

D. Fault Diagnosis of Traction Motors

Traction motors are the core power equipment in HSR traction system that convert electric energy into mechanical energy. The timely diagnosis of faults occurring in HST traction motors has a great impact on improving the reliability of the traction system and reducing the cost of system operation and maintenance. So far, only a few reports can be found in the literature with a focus on the HST traction motor fault diagnosis, for which the model-based methods are commonly applied.

In [16], an interval sliding mode observer (SMO) was proposed to model the fault dynamics of traction motors with uncertainties, based on which a robust residual and threshold were generated for the detection of the stator-winding incipient turn-to-turn faults of the traction motor. While in [17], based on a traction motor model built by the Takagi-Sugeno fuzzy modelling strategy, the incipient actuator faults can then be detected and isolated by combining SMO with the total measurable fault information residual (ToMFIR) theory. Finally, in [18] based on the traction motor model, a robust observer was applied to detect incipient stator/rotor winding fault for traction motors of HST.

E. Sensor Fault Diagnosis in Traction Systems

Sensor fault is a fault type that often occurs in the HST traction systems. A number of sensors are mounted on the traction system, such as on the traction transformer, traction converter and traction motor. These sensors provide signals to the train for monitoring and control [19]. To ensure continuous monitoring and safe and reliable control, the sensor signals must be accurate and reliable. A faulty sensor not only leads to inaccurate even wrong measurements, thus degraded traction system performance, it may even cause catastrophic failure of the whole system. Therefore, it is vital to diagnose sensor faults.

Sliding mode observer (SMO) is a common model-based fault diagnosis and isolation approach for sensor fault diagnosis due to its robustness under parameter uncertainties and measurement noises [20]. Knowledge-based diagnosis methods, such as PCA have been proposed for incipient sensor fault detection and diagnosis in recent years.

III. BOGIE SYSTEM FAULT DIAGNOSIS

Bogies are important components of the HST that connect the train body and the track through suspensions and wheel sets, their mechanical behavior seriously impact the safety and reliability of the HSR system. The deterioration of the bogie will increase vibration and instability of the train, and even cause derailment and rollover. Therefore, it is necessary to rapidly and accurately estimate the bogie's current operation condition according to the features extracted from the vibration signals, and to identify faults in bogie system.

Classification methods are commonly used fault diagnosis methods in HST bogies. The common classifiers employed in HST bogie fault diagnosis are SVMs, ANNs, and K-Nearest Neighbor (KNN), etc. SVM is a powerful knowledge-based fault diagnosis approach that has been successfully used in HST bogie fault detection [21]. Wavelet entropy, which combines the advantage of Wavelet Transform and entropy, was used in HST for vibration signal feature selection [22], and the SVM was then used to recognize the bogie fault.

The deep learning methods are new tools for HST bogie fault recognition, which can provide higher diagnosis accuracy and cost less time than that of the traditional neural networks. In [23], the deep neural network (DNN) was built for single fault detection of a HST bogie. A deep belief network (DBN) hierarchical ensemble was presented to automatically learn the hierarchical features of the bogie vibration signals by combining the deep learning with classification ensemble technology [24]. For time series prediction problems, the long-short-term memory (LSTM) neural network shows superior performance, and a LSTM-based bogie fault prediction method was studied in [25], where the spatial and temporal correlation of fault features can be learned from the original time series signals without any prior knowledge. In [26], a convolutional recurrent neural network (CRNN) was proposed for the HST bogie fault diagnosis, which can simultaneously achieve high accuracy and save time as it inherits the advantages of CNN and Simple Recurrent Unit.

IV. FAULT DIAGNOSIS OF HST CIVIL INFRASTRUCTURE

The HSR civil infrastructure system that spans over large distance is complex by nature. It contains quite a number of railway track components, considerable supporting structures and facilities and very large structural layers to provide safe and reliable services for passengers. Routine monitoring and maintenance of the HSR civil infrastructure system is a vital task to ensure the reliability and longevity of infrastructures, and guarantee the running safety of HSTs.

A. Track Components Fault Diagnosis

Conventional ballasted tracks and ballastless tracks are two main categories of the track types. Both tracks have two parts, i.e. superstructure (or permanent way) and substructure (or formation). As shown in Figure 2, the main components of the ballasted track superstructure are the rails, fasteners, sleepers, and ballast beds. And the substructure mainly consists of protection layers and subgrades. For ballastless track, the rails, fasteners, rail pads, concrete slabs, and cement-emulsified asphalt mortar are main superstructure components, the frost protection layers and subgrades are main components of the substructure. To maintain safety and reliability operation of HSRs, fault diagnosis of track components should be performed periodically.

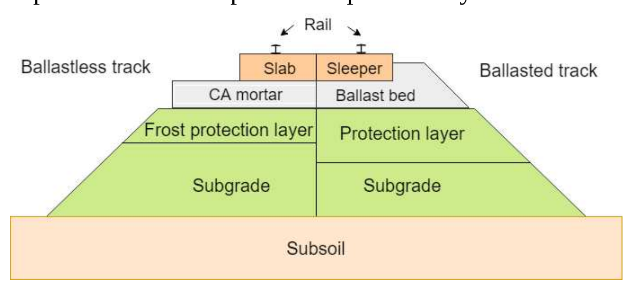

Figure 2. Ballastless/Ballasted Track structure of HSR

Railway tracks are subjected to intense bending and shear stresses, plastic deformation and wear, leading to degradation of their structure integrity with time. The geometry of tracks directly affects the operation safety and comfortability of HSTs. Therefore, various nondestructive evaluation (NDE) methods were developed for HSR track defect inspection to achieve reliable operation and improve the maintenance efficiency. [27] summarized the NDE techniques used for rail track defects detection, among all the techniques surveyed, the automated visual inspection technique is popular for HSR systems, which can detect track corrugation, missing part and defective ballast. [28] developed an image processing method to detect track defects based on the scanned track surface image. In [29], an acoustic emission (AE) technology-based NDE method was proposed for HSR track defect detection, and the Kalman filter was applied to denoise the AE signals.

Fasteners are major parts that fix the tracks to the sleepers or concrete base, it is important to detect fasteners frequently and accurately to ensure safety operation of HSTs. Signal processing-based fault diagnosis methods, such as power spectral density analysis, EMD and time-frequency entropy can be applied to detect the state of rail fasteners. With the development of the image processing and pattern recognition technology, many image-based methods have been presented for the detection of fasteners on HSR tracks. In [30], a method was proposed to detect damaged and loose fasteners of HSR track by adopting decision tree classifier and a centerline extraction method. Based on the 3-D point clouds of HSR fasteners obtained from structure light sensors, the fault types of the fasteners were detected by the decision tree classifier, and the looseness of the fasteners was evaluated by extracting the centerline of the fastener's metal clip.

Due to the suffering of long-term dynamic loading during the operation of HSRs, the undertrack structure of the HSRs can be damaged and thus lead to geotechnical engineering problems such as unexpected settlement and bring potential risk to the operation safety. Therefore, detection methods, especially the NDE method should be studied to reveal the internal problems of the undertrack structure. Most of the approaches applied to detect the defect of undertrack structures are based on finite-element analysis (FEA) [31] and signal processing methods [32].

B. Fault Diagnosis of Supporting Structures and Facilities

Supporting structures and facilities can reduce settlement and increase the bearing capacity of subgrades and foundations. However, the post-construction settlement of the supporting system is also important factor that influences normal operation of a HSR, which need to be predicted and monitored accurately.

[33] proposed a simple settlement calculation method based on the Mesri creep model and the Mindlin-Geddes method. [34] proposed an improved three-dimensional composite analysis method to predict the long-term settlement of HSRs pile foundation. [35] investigated the characteristics of deep compression deformations below pile foundations by the field tests and FEA, and used single-point settlement gauges and strain gauges to monitor the compression deformation of pile shafts and subsoil layers.

V. FAULT DIAGNOSIS OF HST CONTROL AND SIGNALING SYSTEM

HST control and signaling system is the core component of the HSR, which controls the running speed and ensure operation safety and efficiency of the train. The probability theory, Bayesian Network (BN), text mining, and deep learning technology have been widely used for fault diagnosis of the control and signaling system in HST. In [36], a combination of Fault Tree Analysis and BN was adopted to evaluate the failure rate of the HST control system as well as its subsystems, and analyze the impact of any one or more subsystem failures on system failure. [37] proposed a text mining based fault diagnosis method for VOBE of HST, in this paper, the topic model was adopted to extract fault features from the maintenance data, and a BN was used to adapt the uncertainty and complexity of VOBE fault diagnosis. And [38] analyzed the faults of VOBE by a text-chain based text mining method. Considering the shortcomings of text mining methods, intelligent fault diagnosis and maintenance methods were put forward for VOBE. [39] proposed a prior Latent Dirichlet Allocation model for fault feature extraction, and then fed these features into a SVM-based hierarchical classifier with feature fusion for VOBE fault diagnosis. In [40], to diagnose the faults in VOBE of HSTs, a DBN was developed based on Restricted Boltzmann Machine, and the diagnostic results are better than that achieved by both KNN and ANN.

VI. CONCLUSION

In this paper, an overview of fault diagnosis methods applied in the HSR systems are reviewed. As an important passenger transportation infrastructure, HSR's running safety and reliability must be guaranteed. As surveyed in this paper, many fault detection and diagnosis methods have been developed to maintain the safe operation and cost-effective maintenance of HSRs, including model-based, signal processing-based and knowledge-based methods.

HSR is a complex system that contains many subsystems and components. Model-based fault diagnosis methods show limited applications in HSR due to the difficulty in establishing an accurate HSR system model. Therefore, signal processing-based and knowledge-based methods are more commonly used in HSR fault diagnosis. In addition, considering the characteristics of the system structure and fault form, visual-based diagnosis methods have been widely adopted to detect faults occurred in PAC system, track components and wheel sets.

Generally speaking, most of the diagnosis strategies currently applied in the HSR subsystems are simple, the massive data generated by the HSR operation and maintenance have not been fully utilized for HTR monitoring, detection and diagnosis. In recent years, with the rapid development of ICT technology and the AI technology, many new methods have been proposed for fault diagnosis problems, such as deep learning technology, which is regarded as a very promising approach for the future research. These advanced fault detection and diagnosis methods deserve more investigations to release their full potential in the HSR system to further improve the diagnosis ability and maintenance efficiency.

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