Editorial

Fault Diagnosis and Prognosis of Railway Vehicle System

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Railway vehicles are essential for modern urban transportation systems. With the rapid global expansion of high-speed rail networks, ensuring running safety has become increasingly important. Railway vehicles face potential risks from both the health of railway infrastructure and the key components of the vehicles themselves. Fault diagnosis and prognosis play a critical role in monitoring the condition of railway vehicles and assessing potential risks during the running of railway vehicle systems. Through the output results, maintenance engineers or departments may create further effective strategies to avoid accidents. To achieve these purposes, the main task is to collect monitoring data from railway vehicle systems and extract valuable information through data analysis. Relevant methodologies and technologies include measurement and data collection, condition monitoring, fault diagnosis, health assessment, and prognosis. These areas are key topics in the field and serve as the foundation for improving safety and reliability in railway operations. The purpose of this special issue is to disseminate the advanced research and its applications in fault diagnosis and prognosis of railway lines and key components of vehicles. It is expected to provide series of solutions to the difficulties in safety assurance of railway vehicle systems. This special issue in Measurement Science and Technology was open for submission from 6 June 2023 to 31 January 2024 and contains 36 outstanding papers in relevant topics.

The paper by Peng et al [1] presents a wayside detection method for evaluating railway vehicle hunting stability by monitoring wheelset lateral motion. Through installing 20 eddy current sensors along the track, lateral displacement data is gathered to detect vehicle instability. Analysis of these measurements provides insight into hunting instability levels, wheel wear, and wheel/rail contact conicity, thus offering a reliable basis for vehicle safety assessments. The proposed approach and monitoring index also offer valuable references for developing similar wayside hunting instability monitoring systems.

The paper by Peng et al. [2] introduces an adaptive Capon method with diagonal loading for Lamb wave-based damage imaging in railway vehicle plate-like structures. This method addresses the sensitivity of the conventional Capon method to modeling errors by adapting the diagonal loading based on waveform correlations, which are determined using virtual time reversal. Validation on an aluminum plate demonstrates that the proposed method improves imaging quality, reduces artifacts, and suppresses noise, enhancing the effectiveness of structural health monitoring for railway applications.

The paper by Han et al [3] introduces the transient-extracting wavelet transform, a time-frequency analysis technique designed to enhance characterization of impulsive-like signals by filtering out noise and irrelevant components. The method selects relevant time-frequency coefficients to reconstruct signals and includes a transient feature extraction approach to accurately identify impulse timing, aiding in fault type identification. Results indicate this approach is effective for analyzing impulsive signals and detecting bearing defects.

The paper by Chen et al. [4] proposes an interpretable health indicator (HI) construction method for bearing monitoring using semi-supervised autoencoder latent space variance maximization (SSALSVM). This approach uses a deep convolutional neural network as the encoding layer to focus on degradation features, and a variance maximization constraint in latent space to enhance sensitivity to anomalies. An auxiliary layer helps capture early degradation points. Experiments on two datasets confirm the effectiveness of the method in detecting bearing health and degradation states.

The paper by Li et al. [5] proposes an enhanced deep reinforcement learning approach for rolling bearing fault diagnosis, addressing limitations in training efficiency and stability found in conventional deep Q-networks (DQN). The method integrates a dual network cyclic update scheme to improve training stability and a novel experience playback system to enhance efficiency and reduce overfitting. Experimental results show that these improvements lead to higher training efficiency, stability, and diagnostic accuracy, contributing valuable insights to rotating machinery fault diagnosis.

The paper by Xie et al. [6] proposes a fusion-driven fault diagnosis method for axle box bearings in high-speed trains, addressing the challenge of limited fault samples in actual operations. By constructing a bearing dynamics model for simulated fault data and validating it with experimental data, the study combines simulated fault samples with normal test samples to pre-train deep learning models. A parameter transfer strategy is then applied to fine-tune the model with minimal test fault samples. Real-train experiments demonstrate the method's improved generalization and diagnostic accuracy in small sample scenarios.

The paper by Yan et al. [7] presents a novel bearing fault diagnosis approach utilizing an attention mechanism-guided residual convolutional variational autoencoder (AM-RCVAE) to address the challenges of nonlinear and non-stationary characteristics in vibration signals, as well as noise interference. The method improves generalization performance and robustness by incorporating an adaptive batch normalization layer in an enhanced residual module. The AM-RCVAE model leverages convolutional block attention to automatically learn fault features from raw data. Experimental results demonstrate that this approach significantly enhances recognition accuracy and diagnostic performance compared to several conventional methods.

The paper by Wang et al. [8] presents a fault detection system for subway sliding plug doors, enhancing operational reliability through adaptive empirical mode decomposition (AEMD). The system includes a custom hardware acquisition device and analysis software to collect motor current signals. The AEMD method effectively denoises signals by reconstructing intrinsic mode functions using an adaptive Hausdorff distance threshold. Additionally, it classifies 12 fault types using machine learning techniques, achieving an identification accuracy of 98.96%. The results demonstrate the method's effectiveness and robustness through various experimental validations.

The paper by Chang et al. [9] presents a novel electromagnetic acoustic emission-based peak-to-peak (EMAE-PTP) method for detecting ferromagnetic rail defects, complemented by a dedicated confidence probability indicator (CPI). A simulation model integrating Lorentz forces and magnetostrictive effects is developed, demonstrating the EMAE-PTP method's theoretical feasibility. The CPI serves as a defect evaluation threshold, defining peak-to-peak amplitude ranges with a confidence level of 96%, facilitating effective defect signal segregation. The study also identifies optimal excitation conditions for electromagnetic acoustic emission applications, confirming the method's efficacy through comprehensive theoretical and experimental validation.

The paper by Li et al. [10] presents a lithium battery life prediction model that combines an attention mechanism-convolutional neural network (ACNN), a Mogrifier long short-term memory network (LSTM), and maximum mean discrepancy (MMD) for enhanced safety and reliability in lithium battery operations. The model utilizes historical capacity degradation data, optimized through the whale optimization algorithm, to identify intrinsic mode functions (IMFs). Features extracted from these IMFs inform the Mogrifier LSTM for estimating remaining useful life (RUL). The method demonstrates superior accuracy, with prediction errors for the B5 and B6 batteries below 6% and 10% MAPE, respectively, showcasing its robustness and practicality.

The paper by Huo et al. [11] presents a novel network for cross-domain unsupervised fault diagnosis of rolling bearings, addressing challenges posed by imbalanced data and frequent operating condition switches. The method includes a multiscale parallel feature extraction technique that effectively captures high-level representations of various fault types. It incorporates a squeeze-and-excitation attention mechanism to enhance relevant features and suppress redundancies. Additionally, a new loss function is introduced to optimize model performance by accurately classifying imbalanced source domains and aligning related subdomains. Experimental results demonstrate the method's stable generalization performance and robust capabilities across multiple diagnostic tasks on two bearing datasets.

The paper by Li et al. [12] presents a novel health indicator (HI) for rolling bearing degradation assessment, aiming to detect early faults and improve maintenance strategies. The proposed HI utilizes nonlinear characterization of enhanced Hjorth's feature space based on extended probability entropy. It enhances original signal characteristics through time-frequency spectral modulation and combines new generalized Hjorth parameter features to construct a high-dimensional feature space. The method calculates distances in a low-dimensional subspace, demonstrating superior sensitivity in identifying initial defects compared to existing HIs, as validated by experimental results.

The paper by Liu et al. [13] presents a novel method for rolling bearing fault identification based on the Hindmarsh-Rose (HR) model and its period-doubling bifurcation characteristics. The authors analyze the bifurcation properties of the HR model to identify suitable oscillators for fault detection and use multiplicative period bifurcation points to distinguish different fault types. Vibration signals are decomposed with the Hilbert-Huang transform, and amplitude characteristics are calculated for the HR detection oscillator input. The method demonstrates a new approach to employing nonlinear oscillators in bearing fault diagnosis, validated through comparative analysis with the empirical wavelet transform.

The paper by Wei et al. [14] presents a novel fusion non-convex group sparsity difference (FNC-GSD) method for bearing fault diagnosis, addressing the challenge of extracting periodic transient signals from strong noise. Traditional denoising methods often lose important features and underestimate amplitude. The FNC-GSD method leverages group sparsity in the difference domain to enhance feature selection while introducing L1-norm regularization to preserve impulse components in the time domain. A non-convex penalty function prevents amplitude underestimation. The solution employs a majorization-minimization algorithm, and experiments demonstrate that the FNC-GSD method significantly outperforms existing techniques in fault feature extraction.

The paper by Zhang et al. [15] proposes a time-frequency ridge extraction diagnosis method based on multisynchrosqueezing transform (MSST) to address the challenges of extracting weak fault characteristics in gearboxes where bearing and gear faults interact. The MSST enhances compound fault features, particularly the amplitude modulation components of gear faults. The method employs time-frequency ridge extraction to distinguish between gear fault amplitude modulation and bearing fault impact pulse components. Additionally, it incorporates time shifting and verifies the independence of the harmonic zero hypothesis for accuracy in fault component identification. The approach's effectiveness is validated through simulations and practical applications.

The paper by Zhang et al. [16] introduces a novel dual attention mechanism network (DAMN) for rolling bearing fault diagnosis, addressing the limitations of classical deep learning models that utilize a single attention mechanism. The DAMN employs a self-attention (SA) mechanism to capture global relationships between input features and fault types, while a frequency channel attention (FCA) mechanism focuses on local information across different input channels. An ablation study demonstrates that combining multiple frequency components enhances diagnostic accuracy. Experiments reveal that DAMN outperforms existing fault diagnosis models in both accuracy and convergence speed, confirming that its dual attention framework is more effective than single attention approaches.

This paper by He et al. [17] presents a Bayesian convolutional neural network (CNN)-based fusion framework to improve the identification of sensor errors in high-speed trains, where distinguishing faults from mechanical components and sensor issues is challenging. The framework extracts abnormal features using wavelet time–frequency maps and employs a Bayesian CNN for spatial feature acquisition from individual sensors. It then integrates multi-source features with a bidirectional long short-term memory network and enhances these features using an attention mechanism to filter out irrelevant information. The proposed method achieves a 95.4% accuracy, outperforming single-source feature extraction methods by 7.8%.

The paper by Chen et al. [18] presents an enhanced perception health state assessment method for subway sliding plug door transmission systems, addressing the challenges posed by varying acceleration and weight. The method involves calculating the equivalent resistance force from current and rotational speed data using mechanical dynamics. Sensitive features distinguishing normal and abnormal states are extracted from an enhanced dataset comprising current, rotational speed, and equivalent resistance force data. An integrated learning algorithm is employed to assess the health state of the transmission system. The method demonstrates higher accuracy across four classifiers and a broader applicability under varying conditions, as validated by benchmark experimental data.

The paper by Xie et al. [19] presents a framework called the domain-specific invariant adversarial network for bearing fault diagnosis, addressing data distribution offsets and unlabelled data in multi-domain conditions. This framework integrates domain-invariant representation learning and feature de-entanglement, using domain-specific information as auxiliary training to adapt labelled source domain data to target domains. Through this approach, the model uncovers hidden information components, enhancing pattern recognition. Experimental analysis on four fault datasets demonstrates the method’s robust diagnostic capabilities.

The paper by Lei et al. [20] presents a novel data augmentation method, variational autoencoding generative adversarial networks with self-attention, to address data imbalance issues. This method integrates an encoding-decoding process to inform the generator's sampling, accelerating convergence and enhancing sample quality. A self-attention module in the discriminator captures global data information, aiding the generator. Experimental results on public and engineering datasets show the method’s effectiveness in generating high-quality samples and improving data balance, generalization, and robustness compared to other algorithms.

The paper by Yan et al. [21] presents a robust intelligent fault diagnosis method for rolling bearings under noisy conditions, combining sparsity-assisted parameter adjustable variational mode decomposition (VMD) with a whale optimization algorithm-optimized least-squares support vector machine (WOA-LSSVM). An improved Gini index optimizes VMD parameters, enhancing decomposition and feature extraction. The proposed method constructs a multi-dimensional feature vector set, fed into WOA-LSSVM for accurate fault detection. Experimental validation demonstrates the method's superior fault recognition accuracy and robustness compared to similar techniques, offering a new perspective for noise-resistant diagnostic solutions.

The paper by Yu et al. [22] presents a simulation-driven transfer learning model, called the clustering multi-stage training transfer learning framework (CMSTL), for rolling bearing fault diagnosis. CMSTL uses simulation data as a substitute for labeled real-world data, applying clustering and multistage training to capture domain-independent, fault-specific features. The clustering strategy enhances category differentiation by aligning samples with clustering centers, while multistage training improves pseudo-label accuracy for real data. Validated on experimental datasets, CMSTL achieves a minimum 2.2% improvement in fault diagnosis accuracy and enhances clustering capability over other transfer learning methods.

The paper by Zhang et al. [23] presents an advanced dynamic model for rolling bearing vibration analysis, addressing multiple influencing factors such as cage flexibility, time-varying displacement excitations, and elastohydrodynamic (EHD) lubrication. This model offers a detailed examination of force states and vibration responses, particularly under fault conditions. Key findings include identifying contact force as the primary excitation source and establishing a mapping mechanism between force states and vibration responses. This work enhances understanding of bearing dynamics, supporting improved health monitoring and vibration control for machinery.

The paper by Yao et al. [24] presents a novel fault diagnosis method for rolling bearings, tackling data inconsistency in variable conditions using dynamic convolution and dual-channel feature fusion. A dual-channel convolutional structure captures high- and low-frequency information in shallow layers, while an enhanced GhostNetV2 bottleneck layer leverages dynamic convolution and attention mechanisms in deeper layers. Validation on the Case Western Reserve University and DDS datasets demonstrates the model's effectiveness in accurately detecting faults across diverse operational scenarios.

The paper by Hu et al. [25] presents a tacholess order tracking (TLOT) method to address gearbox fault diagnosis under rapidly varying speeds in urban rail trains. This method uses a time-frequency Gini coefficient to determine optimal search points, extracting time-varying meshing frequencies from non-stationary signals. By transforming unstable signals into stable angular domain signals, TLOT enhances energy aggregation and mitigates resonance band interference. Simulation and experimental results validate its superior extraction of weak harmonic components, enabling effective fault diagnosis in unstable gearbox conditions.

The paper by Zhong et al. [26] presents an improved metrics-based meta-learning approach for few-shot cross-domain fault diagnosis of traction motor bearings in subway trains. This method addresses complex bearing conditions and limited fault data by introducing a 1D-signal channel attention mechanism for feature extraction and the Adabound algorithm for enhanced classification. Case studies validate the method's superior diagnostic accuracy and performance compared to other approaches, showcasing its effectiveness in intelligent train bearing diagnosis.

The paper by Cui et al. [27] presents a rolling bearing fault diagnosis method that combines fast Fourier transform (FFT) image coding with a lightweight CNN (L-CNN) to enhance diagnostic accuracy and speed. The method first denoises and reconstructs signals, then extracts and fuses frequency and phase spectra features via FFT. These features are encoded into heat maps and classified by an improved L-CNN. Tested on two datasets, the approach achieved diagnostic accuracies of 98.75% and 99%, demonstrating fast, accurate, and generalizable fault classification.

The paper by Ma et al. [28] presents a novel approach for pantograph fault diagnosis using a graph neural network (GNN) with a unique graph construction method. The method converts 1D load signals from pantographs into 2D images in the time and frequency domains through Gramian angular field, Markov transition field, and recurrence plot techniques. Pixel values in these images serve as vertex features, creating graphs through neighboring connections. The constructed graphs then train the GNN for fault diagnosis. Laboratory results show the proposed method's superior diagnostic performance compared to conventional techniques.

The paper by Lin et al. [29] presents an intelligent identification method for axle fatigue cracks using acoustic emission signals based on deep belief networks (DBNs). The proposed method constructs a DBN model trained on acoustic emission data obtained from a custom experimental setup, enabling accurate identification of axle fatigue cracks. This approach eliminates the need for manual feature extraction and screening, fully utilizing the information in fault data. Experimental results demonstrate the method's effectiveness in identifying fatigue cracks at various stages, indicating its promise for improving axle fatigue crack detection in railway applications.

The paper by Fang et al. [30] presents a rapid measurement method for key dimensions of train wheelsets using image processing algorithms. The study examines the system's framework, detailing the functions of its modules, including the optimization of the continuous line spot center extraction algorithm during tread measurement. A three-dimensional model is reconstructed from point cloud data, enabling accurate measurement and calculation of key dimensions. Comparative tests with traditional measurement methods validate the feasibility of this approach, demonstrating its effectiveness for daily train maintenance and ensuring safe operation.

The paper by Yao et al. [31] presents a real-time monitoring method for rail displacement using a camera system that is resilient to variations in ambient light intensity. The proposed system leverages a flexible field programmable gate array-based framework with parallel and pipelined architecture to enhance image data processing efficiency by 24.7%. It effectively locates and measures rail displacement in complex environments despite external light interference. Experimental validation demonstrates that the detection system achieves a precision of 0.07 mm and a detection accuracy of 95.2% under varying light conditions.

The paper by Zhou [32] presents a novel fault diagnosis method called Bayesian Graph Balanced Learning (BGBL) to tackle the challenges of imbalanced sample sizes and unlabeled data. The method employs a balancing strategy that assigns and optimizes weights for samples in imbalanced categories, utilizing graph theory to establish and update category beliefs from unlabeled data. Posterior estimates are derived within a Bayesian neural networks framework to train a fault diagnosis model. Experimental results on the planetary gearbox fault dataset demonstrate that BGBL improves diagnostic accuracy by over 26% compared to existing methods, showcasing its effectiveness in challenging scenarios.

The paper by Liu et al. [33] presents a novel approach for identifying rail corrugation damage from axle box acceleration data using an improved successive variational mode decomposition (SVMD) algorithm combined with a deep learning model. A numerical model of the vehicle-rail-track system is established, integrating indicator analysis into the SVMD for noise reduction and useful component extraction. The fast Continuous Wavelet Transform is applied to convert the data into two-dimensional images, which are then classified using the You Only Look Once (YOLO) model. Results indicate that the improved SVMD effectively extracts corrugation components, and the YOLO model achieves rapid identification with a recognition rate of 98% for different wavelengths, outperforming traditional methods in training time and recall rate.

The paper by Chen et al. [34] presents an adaptive remaining useful life (RUL) prediction method that effectively captures prediction uncertainty using deep learning and stochastic processes. It employs a stacked autoencoder (SAE) to extract deep features from monitoring signals, with principal component analysis (PCA) selecting significant inputs that reflect health status. A Generalized Wiener Process models health indicator evolution, with parameters estimated using Maximum Likelihood Estimation. An adaptive update based on Bayesian theory enhances the model, leading to an accurately derived Probability Density Function for RUL prediction. The proposed method improves prediction accuracy and reduces uncertainty, as validated by numerical simulations and experimental studies on bearing degradation data.

The paper by Sun et al. [35] presents a vibration-based diagnosis method for railway point machines (RPMs), addressing their high failure rates and the need for effective diagnostics. It introduces a novel feature called derivative multi-scale permutation entropy to better capture fault information in the signal derivatives. Additionally, a decision fusion strategy based on three feature sets is developed to enhance the accuracy of support vector machines, particularly in distinguishing normal and reverse directions. Experimental results from Xi'an Railway Signal Co., Ltd demonstrate the method's effectiveness, achieving diagnosis accuracies of 99.43% for reverse-normal and 100% for normal-reverse directions, confirming its superiority.

The paper by Hu et al. [36] presents a local depth estimation method for detecting rail surface anomalies, enhancing the safety of train operations. It addresses the limitations of manual detection methods and traditional models that struggle to assess the extent of damage accurately. The proposed method utilizes a point cloud of the rail surface reconstructed by PatchmatchNet, following a structured data collection protocol for generating a multi-view dataset. The approach estimates local anomaly depth based on the reconstructed point cloud, achieving a maximum estimation error of only 10% within a depth range of 0.35 mm compared to measurements from a structured light camera. This method provides a comprehensive three-dimensional representation of anomalies, offering richer information to distinguish true defects from surface irregularities, ultimately improving defect assessment precision and aiding in the development of precise repair strategies.

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