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Editorial

Fault Diagnosis and Health Management of Power Machinery

Te Han [1,2,*], Ruonan Liu [3], Zhibin Zhao [4] and Pradeep Kundu [5]

1 Center for Energy and Environmental Policy Research, Beijing Institute of Technology, Beijing 100081, China
2 School of Management and Economics, Beijing Institute of Technology, Beijing 100081, China
3 College of Intelligence and Computing, Tianjin University, Tianjin 300072, China; ruonan.liu@tju.edu.cn
4 School of Mechanical Engineering, Xi'an Jiaotong University, Xi'an 710049, China; zhaozhibin@xjtu.edu.cn
5 Department of Mechanical Engineering, KU Leuven, 8200 Bruges, Belgium; pradeep.kundu@kuleuven.be
* Correspondence: hante@bit.edu.cn

Power-machinery systems are widely used in various industries, including manufacturing, energy production, transportation, and infrastructure. However, unexpected failures of these systems can cause significant economic losses and safety hazards. The development of a proactive program to effectively reduce unexpected failures and improve the reliability and safety of power machinery systems is of great significance. Real-time sensor monitoring techniques have brought tremendous opportunities to enhance the reliability and safety of power-machinery systems. The diagnosis process assists in the identification/classification of machinery faults in terms of severity and type. The knowledge from diagnosis is also utilized to quantify the machinery's health state and track the evolution of machinery performance degradation in support of its remaining useful life (RUL) prognosis.

In 2021, this Special Issue was initiated with a focus on exploring cutting-edge research in the field of fault diagnosis and health management of power machinery. It is worth noting that the Special Issue received an overwhelming response and numerous submissions. Through a rigorous peer-review process, 16 papers were carefully selected and included in this Special Issue.

In [1], Bryakin et al. developed a method for diagnosing oil aging in power transformers. It involves a high-frequency measuring loop using a dielcometric capacitor cell to compute the current resistances of oil and impurities. The proposed monitoring system identifies the moisture content, dielectric losses, and dissolved gas content in the oil, with a sensitivity threshold in the order of tenths of ppm.

In [2], Santiago-Perez et al. proposed Fourier-based adaptive signal decomposition (FBASD) for fault detection in induction motors. FBASD uses an adaptive band-pass filter and STFT to isolate nonstationary time-frequency components. FBASD effectively detects and classifies broken rotor bars using startup transient current.

In [3], Liu et al. proposed an impact feature extraction method using EMD and sparse decomposition. The impact dictionary is designed by identifying modal parameters from EMD and a transient impact component extracted by MP.

In [4], a model for analyzing the vibration responses of a bearing-rotor-gear system with a misaligned rotor is presented. The model is validated through experiments, and shows that vibration responses are affected by rotor and harmonic frequencies of bearings and gear pairs. As misalignment defects deepen, high-order harmonic responses are excited, and vibration intensity generated by gear pairs is attenuated.

In [5], Al-Ameri et al. investigated frequency response analysis (FRA) for detecting faults in three-phase induction motors. They found dissimilar signatures for normal and faulty windings, proposing statistical indicators to quantify deviations and identify faults in different frequency ranges based on winding parameters.

In [6], Stephen et al. proposed a new method to predict asset degradation in centrifugal pumps due to deviation from optimal operating criteria. The method captures the dependency between operating parameters, and partitions operating zones using an

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empirical distribution. The technique is demonstrated in a case study of civil nuclear generation feedwater pumps and could inform optimal plant configurations.

In [7], He et al. analyzed synchronous generator behavior under a dynamic stator inter-turn short circuit using finite element analysis. The study found that this condition leads to the increased amplitude of the odd-numbered harmonic components of the phase current, and to increased even-numbered harmonic components of the electromagnetic torque.

In [8], a study investigated the effect of fit clearance between the outer race and housing on the vibration characteristics of a cylindrical roller bearing with localized defects. The results showed that the RMS of housing acceleration decreases with increasing stiffness and damping, while increasing with clearance and friction coefficient. The study provides a theoretical foundation for condition monitoring of rotating machinery systems.

In [9], Li et al. proposed a fault diagnosis method for compressor valves using p-V diagram features. The 4D characteristic variables were extracted with principal component analysis (PCA) and linear discriminant analysis (LDA) to establish a diagnostic model. The method was validated on various levels of valve leakage and actual faults.

In [10], a few-shot reliability assessment approach was proposed, using morphological component analysis (MCA) to decompose vibration signals and estimate reliability with a mixture of Gaussian hidden and Markov models (MoG-HMM). Based on experiments on an aerospace bearing dataset, the method was effective and overcame dependence on historical failure data.

In [11], an incremental learning scheme based on the R-REMIND method for bearing fault diagnosis using deep learning was designed. The R-REMIND method can learn new information while retaining older information under various working conditions. The results show the continuous learning ability of the R-REMIND model.

In [12], a multi-resolution fusion generative adversarial network (MFGAN) is proposed for imbalanced fault diagnosis of rolling bearings. The generator model uses data augmentation to generate synthetic faulty data, while a multi-scale ensemble discriminator architecture learns multi-scale features. The experimental results show the superiority of the proposed framework.

In [13], Zong et al. developed a semi-supervised transfer learning method for bearing fault diagnosis in machinery systems. Their method overcomes data imbalance and limited labeled data using domain adversarial training and a semi-supervised framework based on uncertainty-aware pseudo-label selection. The experimental results demonstrate the method's effectiveness.

In [14], Duan et al. used adversarial discriminative domain adaptation to improve cross-domain remaining useful life prediction. Their method involves constructing an LSTM feature extraction network and adjusting the parameters using adversarial training to achieve domain-invariant feature mining. The proposed scheme achieved state-of-the-art performance.

In [15], Zhang et al. proposed a self-attention-based multi-task network (SMTN) for RUL prediction in the presence of missing values. The SMTN utilizes self-attention and LSTM for feature fusion, and a multi-task learning module for missing value imputation.

In [16], a transfer learning-based method for bearing RUL prediction using a two-stage transfer regression convolutional neural network was proposed. The proposed method was evaluated on real data collected from run-to-failure bearing experiments, and is shown to outperform existing state-of-the-art methods.

The research published in this Special Issue has been extensive, covering a wide range of techniques including signal processing, physical modeling, data-driven approaches, and more. Signal processing methods and physical model methods have been widely studied and utilized for feature extraction and fault detection [17–20]. Data-driven methods, particularly deep learning, have also gained significant attention for their ability to learn complex patterns and relationships within data [21–25]. In addition, emerging approaches such as deep transfer learning have shown great potential in improving the performance of fault diagnosis and health management systems [26–31]. As this field continues to evolve, further investigation into novel and advanced techniques is necessary to enhance the accuracy, reliability, and efficiency of power machinery systems. For instance, data-driven methods should focus on addressing the challenges of the out-of-distribution detection (OOD) problem in real-world scenarios [32]. Developing more effective approaches for OOD detection and trustworthy analysis will be crucial to improving the reliability and safety of intelligent models [33,34]. Moreover, integrating domain-specific knowledge and expertise in feature engineering could further enhance the compliance of machine learning models with real-world domain knowledge, thereby mitigating concerns over risk [35,36]. In addition, future research could leverage the power of deep learning to alleviate computational challenges in practical applications, leading to more efficient and accurate condition monitoring and decision-making.

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