Editorial for IJPHM special issue on data-driven diagnostics in rotating machines

Letter from the Guest Editors

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Rotating machines are essential in numerous sectors, including railways, energy, and robotics. These machines exhibit unique degradation patterns and critical components that require monitoring. Despite the existence of various fault detection and diagnostic methods in current literature, only few techniques that effectively consider the different data sources and variable operating conditions are published. Furthermore, a generalized approach for consistent monitoring across different systems remains challenging. Thus, this special issue aims to enhance the generalization and application of these methods to diverse systems, emphasizing their robustness.

This special issue is dedicated to addressing the challenge of developing robust and generic Prognostics and Health Management (PHM) algorithms for rotating machines. It particularly focuses on condition monitoring, fault detection and diagnostics, as well as prognostics under various operating conditions and with heterogeneous data sources.

To promote innovative methods in the field of rotating machine's fault detection and diagnostics, this special issue It presents new research in fault detection, diagnostics, and prognostics, underlining the need for robust, scalable monitoring systems for industrial users.

The first paper entitled "A Fault Diagnosis in Non-Stationary Systems via Interval Observers" proposed a fault diagnostic method of servo actuator. They addressed non-stationary linear dynamic equations under unmatched disturbances and measurement noise. To do so, authors proposed an observer insensitive to changes in system conditions by generating two residual bounds. (upper and lower) residuals such that if zero is between these residuals, then the faults in the system are absent; if zero is out of these residuals, one concludes that a fault has occurred. The interval observer consists of two subsystems: the first one generates the lower residual, the second one the upper residual. The relations describing both subsystems are given. Theoretical results are illustrated by practical example of the electric servo-actuator for which the fault diagnosis problem is solved.

Recent research increasingly focuses on generalizing solutions using machine learning techniques. However, these techniques often act as black-box tools. In the second paper *"Evaluating the Influence of Time-Domain Feature Distributions on Estimating Rolling Bearing Flaking Size with Explainability"* focuced on the explainability of extracted features rather than the machine learning model itself. Because of conventional rule-based methods estimate the magnitude of flaking by analyzing the time interval of feature vibrations, this method requires trial-and-error adjustments by experts, limiting its applicability to a wide range of rotating machines. To overcome this limitation, they developed a deep learning-based estimation model and demonstrated that its performance depends on the distribution of time-domain features in the training data, which are associated with flaking damage. They analyzed then the manner in which these feature distributions impose limitations on the estimation accuracy of the model. Finally, they incorporated explainability using Grad-CAM to verify that the extracted features were aligned with the physical phenomena of flaking damage, thereby confirming the link between the feature vibrations and estimation results. The test on experiments under various training–test split conditions indicated that time-domain shifts of these features affect the model's performance, providing insight into how feature distributions constrain the estimation of the flaking size.

Besides, the third paper "*DiffLIME: Enhancing Explainability with a Diffusion-Based LIME Algorithm for Fault Diagnosis"* introduces a novel explainable AI algorithm that extends the well-known Local Interpretable Model-Agnostic Explanations (LIME). Actually, deep learning models are often considered "black boxes" due to their opaque decision-making processes, making it challenging to explain their outputs to industrial equipment experts. The complexity and vast number of parameters in these models further complicate understanding their predictions. This paper introduced a novel Explainable AI (XAI) algorithm, an extension of the well-known Local Interpretable Model-agnostic Explanations (LIME). The authors used a conditioned Probabilistic Diffusion Model to generate altered samples in the neighborhood of the original sample studied. They validated the method using various rotating machinery diagnosis datasets, and they compared their approach with state-of-the-art XAI methods, employing nine metrics to evaluate the desirable properties of any XAI method.

The fourth paper *"Predicting Remaining Useful Life During the Healthy Stage in Rolling Bearings"* highlighted the lack of methodologies to predict the remaining life up to the first spalling event using vibration signals alone. In fact, quantitative predictions of the time before the spall initiation phase (origination of the first spall) in pristine ball bearings running under an applied load is of great industrial relevance, especially for systems that require high running accuracy and/or high-speed performance. They pointed out the fact that less available methodologies exit to predict the remaining life until the first spalling event exclusively from vibration signals. For this purpose, they presented an end-to-end approach, based on deep learning (one dimensional convolutional layers combined with long short-term memory units), that is able to quantify the time before the origination of the first spall in ball bearings, having as sole input vibration measurements. The method has been validated on a set of bearings run to failure on independent but identical test-rigs which had not been considered during training.

The fifth paper *"Towards a Universal Vibration Analysis Dataset: A Framework for Transfer Learning in Predictive Maintenance and Structural Health Monitoring"*, presented a perspective paper that addressed the lack of a comparable large-scale, annotated dataset to support transfer learning. In visual computing, ImageNet has established itself as an indispensable resource for transfer learning (TL), enabling the development of highly effective models with reduced training time and data requirements. However, the domain of vibration analysis, which is critical in fields such as predictive maintenance, structural health monitoring, and fault diagnosis, lacks a comparable large-scale, annotated dataset to facilitate similar advancements. To address this gap, they proposed a dataset framework that begins with a focus on bearing vibration data as an initial step towards creating a universal dataset for vibration-based spectrogram analysis for all machinery. The initial phase featured a curated collection of bearing vibration signals, designed to represent a wide array of real-world scenarios, including vibration data of various public bearing datasets. Then, in future iterations, this proposal will evolve to encompass a broader range of vibration signals from multiple types of machinery and sensors, with an emphasis on generating spectrogram-based representations of the data. Multi-sensor data, including signals from accelerometers, microphones, and other devices should be used, ensuring versatility for both domain-specific and generalized applications. They will be incorporated to create a more holistic and comprehensive dataset, enabling the application of advanced sensor fusion techniques in vibration analysis. Each sample will be labeled with detailed metadata, such as machinery type, operational status, and the presence or type of faults, ensuring its utility for supervised and unsupervised learning tasks. This extension will position this work as a universal resource for various industries, enhancing the ability of researchers and practitioners to apply TL to diverse vibration analysis problems. In addition to the dataset, a comprehensive framework for data preprocessing, feature extraction, and model training specific to vibration data should be developed. This framework will standardize methodologies across the research community, fostering collaboration and accelerating progress in predictive maintenance, structural health monitoring, and related fields.

This special issue presents a variety of applications in fault detection, diagnosis, and prognosis. A distinguishing feature of the presented research is the use of multiple scenarios and abundant data to enhance the generalizability and applicability of the proposed approaches.

We would like to sincerely thank the authors, reviewers, and the editorial team of the journal for their hard work and dedication in bringing this special issue to fruition. We hope that this collection will serve as a valuable resource for researchers and practitioners in the PHM community.

We are also sincerely grateful to Dr. Marcos Orchard Editor-in-Chief at the International Journal of Prognostics and Health Management, for his constant help and guidance. This special joint issue would not have been possible without the able assistance of the colleagues Dr Khanh T. P. Nguyen, Prof Kamal Medjaher, Prof Guy Clerc and Prof Hubert Razik for their support in preparing this special issue.

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