Machine-Learning Based Fault Diagnosis for a Rotordynamic System Using Multibody Simulations

YU-HUNG PAI, PETRI T. PIIROINEN, SHIVESH KUMAR and HAKAN JOHANSSON

ABSTRACT

Machine-learning based fault diagnosis plays an important role in condition monitoring for rotating machinery to prevent systems from catastrophic faults. It is important to note that the performance of data-driven methods relies highly on a large quantity of training fault data. Since rotating machinery operates under normal condition most of the time, collecting sufficient fault data from experiments takes a huge amount of time and expense, and under various operating conditions. To overcome the fault data insufficiency, building a virtual testbed for generating fault data is a promising way in bridging the gap between data requirement and prediction accuracy.

Many simplified dynamic models have been proposed to generate a single fault on some rotordynamic systems. These methods, however, cannot reflect complex operation conditions such as variant rotation speed or multi-faults. To better reveal vibration responses of local defects, this research aims to establish a multibody dynamics (MBD) model that can simultaneously analyze complete dynamic behavior and simulate a wider range of fault scenarios.

In this research, a simulation-driven fault diagnosis method is proposed to generate the simulation fault data. Firstly, a rigid-flexible hybrid model of a single-rotor-bearing system is established using MSC ADAMS, which is based on MBD and finite element analysis. Different fault conditions are simulated including outer race bearing faults, inner race bearing faults, and rolling element faults. After generating fault data, a time-frequency feature extraction method is developed based on Hilbert envelope and wavelet packet decomposition, extracting a large amount of features from the original signals. In addition, an autoencoder model is built to highlight the critical features, enhancing the performance of the classifier. This feature extraction is made to obtain fault-related features, which train the machine learning classifiers for discriminating the fault categories.

Yu-Hung Pai, Ph.D. student, Department of Mechanics and Maritime Sciences, Chalmers University of Technology, Goteborg, Sweden. Email: paiy@chalmers.se. Petri T. Piiroinen, Associate Professor, Department of Mechanics and Maritime Sciences, Chalmers University of Technology, Goteborg, Sweden. Hakan Johansson, Professor, Department of Mechanics and Maritime Sciences, Chalmers University of Technology, Goteborg, Sweden. Shivesh Kumar, Assistant Professor, Department of Mechanics and Maritime Sciences, Chalmers University of Technology, Goteborg, Sweden. Robotics Innovation Center, German Research Center for Artificial Intelligence, Bremen, Germany

To validate the simulation results, the Case Western Reserve University (CWRU) bearing dataset that has been widely accepted as a standard reference is introduced. A comparison of bearing fault frequencies between simulations and the CWRU dataset is then conducted. Meanwhile, a transfer learning method is applied using the CWRU dataset to fine tune the fault diagnosis classifier. This research lays a solid foundation for future development of a digital twin and simulation-driven transfer learning for fault diagnosis of rotating machines.

INTRODUCTION

Rotordynamic system, a key component in most industrial sectors, is prone to various defects during operations such as bearing faults, misalignment and unbalance. When a local fault grows to a critical level, it often leads to a long downtime, and in severe cases causing damage to the entire machine. Therefore, accurately diagnosing faults at an early stage is necessary for rotating machines.

Machine-learning-based fault diagnosis integrating traditional signal processing and machine learning methods serves as a predictive maintenance technique to identify the anomalies from monitoring data. However, a major obstacle in developing machine-learning models for rotating machines is the insufficiency of fault data [1]. Since most rotating machines operate under normal conditions for most of their lifespan, it is challenging to obtain sufficient fault data from physical systems. To solve the problem with missing fault samples, building a virtual counterpart of a rotating machinery plays an important role to generate various simulated fault data.

To generate fault signals, many simplified bearing models have been proposed [2] [3]. However, these models often fail to reflect the complete dynamic behavior of the rotating system and are limited in replicating certain fault types-particularly faults on rolling elements, which have been rarely discussed in the previous research. To overcome these limitations, multi-body dynamics (MBD) simulations are used in this work to reveal the realistic operating conditions and to model a wider range of fault scenarios in rotating machines. Recent work by [4] has demonstrated the effectiveness of optimal MBD simulations in condition monitoring, highlighting their potential for broader applications.

This work aims to develop a simulation-data-driven method to tackle the insufficiency of fault data in condition monitoring of rotordynamic system. First, a tunable simulation for the rotor-bearing system is developed to generate different bearing fault data. Second, several feature extraction techniques is presented to capture the fault-related features, which are used to build the fault diagnosis classifier. Third, the experimental datasets is used to validate the MBD model and fine tune the classifier. By combining simulation data and experimental data, the transfer-learning method bridges the gap between a virtual system and a real machine.

The proposed framework allows simulation data to build a fault diagnosis pre-trained classifier and only require a small portion of real data to fine tune the classifier, reinforcing the performance and increasing robustness of condition monitoring systems.

FRAMEWORK OF TRANSFER LEARNING METHOD

The typical transfer learning approach involves initially constructing a pre-trained model using data from a source domain, followed by refining this model with data from a target domain. The framework in this study is depicted in the Figure 1. Here, the source domain comprises simulated bearing fault data from the multibody dynamics (MBD) model, whereas the target domain contains experimental bearing data from the Case Western Reserve University (CWRU) dataset [5]. Initially, feature extraction techniques are applied to the source domain to effectively capture fault-related features while preserving their physical interpretations. After implementing signal processing methods and an autoencoder neural network to highlight these fault-related features, a pre-trained classifier is established based on the extracted source domain features. Subsequently, the parameters of the feature extraction process are frozen, and the classifier parameters are fine-tuned using the target domain dataset, allowing the model to adapt effectively to real data and improving its classification accuracy.

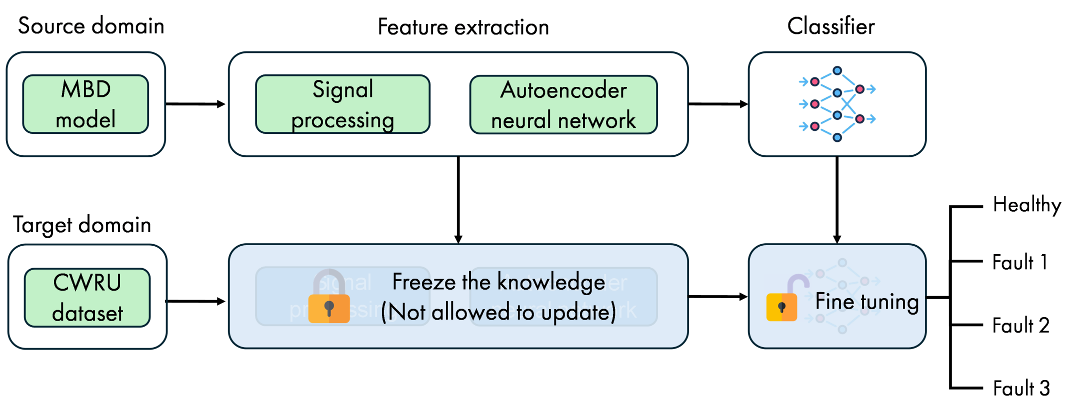

Figure 1. Framework of the proposed fault diagnosis method.

MULTIBODY DYNAMICS SIMULATION

In this work, the single-rotor-bearing model is built using the MBD analysis software, MSC ADAMS [6]. For a rigid-flexible hybrid MBD system, the equations of motion is described in the following general form [4]:

$$\begin{cases} M\ddot{q} + \Phi_q^T \lambda + F_q = Q(q) \\ \Phi(q,t) = 0 \end{cases} \tag{1}$$

where M is the system mass matrix, Φ_q is the derivative matrix of constraint equations with respect to the system generalized coordinates q, λ is the vector of Lagrangian multipliers associated with the constraints, $F(q)$ is the system elastic force vector, $Q(q)$ is the system external generalized forces, $\Phi(q,t)$ is the vector containing the system constraint equations and t is the time. The dynamic behaviors of each component can be calculated at each moment under the forces and torques applied.

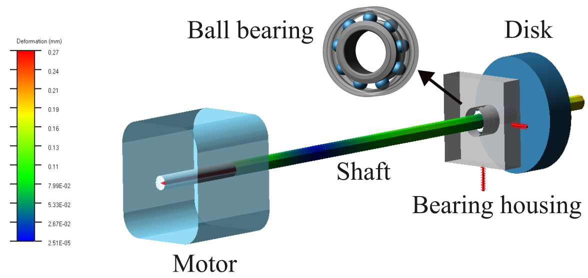

Figure 2. The single-rotor-bearing MBD model.

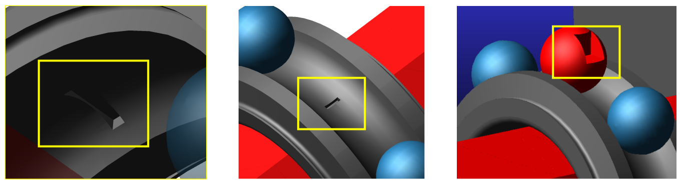

Figure 3. (left) Fault on the outer ring; (middle) fault on the inner ring and (right) fault on the ball.

This model comprises a motor, a shaft, a ball bearing, a bearing housing and a disk as shown in Figure 2. The shaft is modelled as a flexible body, while other components are simulated as rigid bodies. Initially, allowing the simulation to be validated by the CWRU dataset, the SKF 6205-2RS deep groove ball bearing is chosen. The bearing faults are shown in Figure 3. In this bearing model, the 3D CAD geometry of the bearing is obtained from the SKF official website [7]. Since the roller elements from the CAD file are unified as one rigid body, they are replaced with the sphere bodies in MSC ADAMS that can be tuned separately. The bearing model contains 18 contacts, 9 of which are defined between the roller elements and the inner race and 9 of which are defined between the roller elements and the outer race. The parameters of the contacts are demonstrated in [8]. All the intervals of adjacent rolling elements are confined, and the rolling elements can only rotate along with the longitudinal axis during rotation. Subsequently, the shaft is connected to the motor, the inner race of the bearing and the disk, allowing the rotation around the longitudinal axis and the radial translation confined by the bearing. The outer race of the bearing is fixed on the bearing housing, and the constrains between the housing and the ground are 3 rotational and 3 translational springs. Vertical acceleration responses are measured from the bearing housing to enable comparison with the CWRU dataset.

METHODS OF FAULT DIAGNOSIS

Based on the geometry parameters and rotating speed of the bearing, the bearing fault frequencies associated with the inner race, outer race and rolling element are ball passing frequency of inner race (BPFI), ball passing frequency of outer race (BPFO), and ball spin frequency (BSF). The theoretical fault frequencies are defined as follows:

$$\mathrm{BPFI} = \left[\frac{nf_r}{2}(1 + \frac{d}{D}\cos(\alpha))\right] \tag{2}$$

$$\text{BPFO} = \left[\frac{nf_r}{2}(1 - \frac{d}{D}\cos(\alpha))\right] \tag{3}$$

$$\text{BSF} = \left[\frac{Df_r}{d}(1 - (\frac{d}{D}\cos(\alpha))^2)\right] \tag{4}$$

where n is the number of the rolling elements, f_r is the rotating speed of the inner ring, d is the diameter of the rolling elements, D is the pitch diameter of the bearing and α is the contact angle.

The procedure for feature extraction is illustrated in Figure 4, which aims to identify and isolate fault-related characteristics within various frequency bands. Both bearing-fault and healthy data are generated from MBD model. Ensemble Empirical Mode Decomposition (EEMD) is applied for signal denoising, with the first intrinsic mode function (IMF) being selected for further analysis [9]. Subsequently, the Hilbert envelope method is used to demodulate the signals and to extract the fault frequencies and their harmonics. Even though the simulated acceleration signals do not perfectly replicate the CWRU dataset, their envelope spectrums consistently exhibit similar patterns of fault frequencies [1]. Next, wavelet packet decomposition (WPD) decomposes the envelope signals into different frequency bands, allowing computation of the energy distribution and root means square values across all bands [10]. These extracted features indicate that notably higher energy responses in frequency bands associate with fault frequencies. Finally, the extracted features are processed through an autoencoder neural network to identify critical features, which are then used to train a classifier capable of effectively distinguishing among various fault conditions.

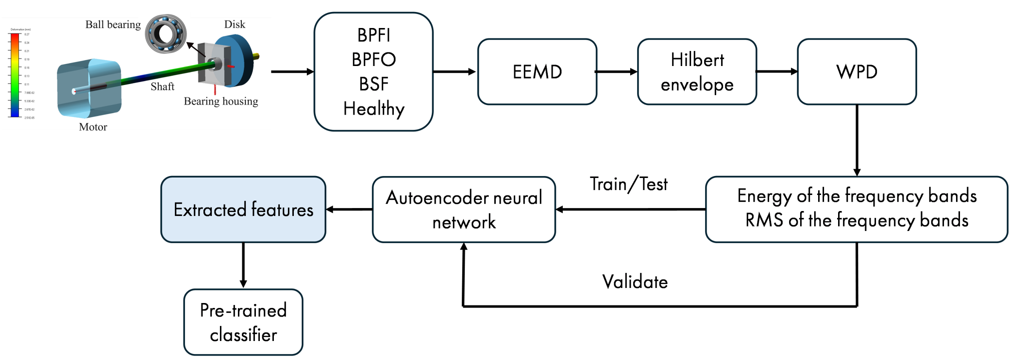

Figure 4. Procedure of feature extraction.

DISCUSSION AND COMPARISON

The rotating speed and sampling rate in the MBD model are set to 1797 rpm and 12000 Hz respectively, which are identical to the CWRU setup. Each case is simulated for 19 s, with data sampled every 0.5 s, leading to 152 ($38 \cdot 4$) samples in total. In contrast, each case in the CWRU dataset spans 10 s and is sampled at the same 0.5 s, resulting in 80 ($20 \cdot 4$) samples in total. Figure 5 presents a comparison of the envelope spectrums between the simulated data and the CWRU data for different bearing faults. Although the numerical model introduces additional noise, the MBD model still successfully captures the characteristic fault frequencies. TABLE I demonstrates that

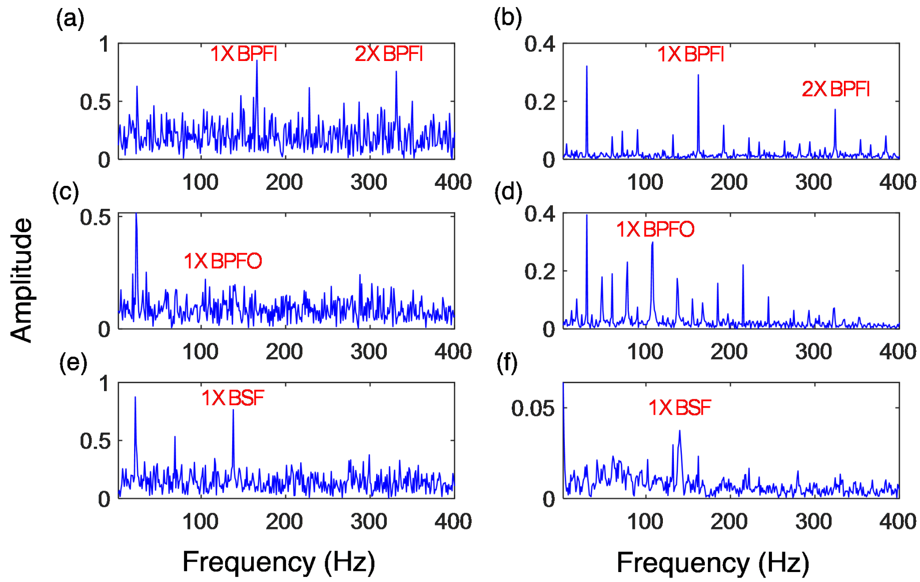

Figure 5. (left (a)(c)(e)) Envelope spectrums from simulated dataset and (right (b)(d)(f)) envelope spectrums from CWRU dataset.

TABLE I. Comparison of the fault frequencies

	MBD model (Hz)	CWRU dataset (Hz)	Theoretical frequency (Hz)
BPFI	166	162	162.18
BPFO	105	108	107.36
BSF	138	140	141.17

the errors between the MBD model and the theoretical frequencies are all within 2.3%, highlighting the accuracy of the proposed MBD model.

In the transfer learning part, the simulated dataset is divided into two datasets, 50% for training and 50% for testing to develop the initial pre-trained classifier. Similarly, the CWRU dataset is divided into two datasets, 33% for classifier fine-tuning and 67% for testing the fine-tuned classifier. Figure 6 (left) shows that the classifier cannot distinguish between BPFO and BSF and also misidentifies a part of healthy samples as fault samples, leading to a relatively low classification accuracy of 74.26 %. This result indicates that the gap between the simulated data and the experimental data is still large. However, after the fine-tuning process using the CWRU data, the results demonstrate a substantial improvement in fault diagnosis, achieving an accuracy up to 98.15%, as shown in Figure 6 (right). This significant change clearly shows the classifier successfully adapts to the experimental dataset.

CONCLUDING REMARKS

This work aims to enrich the field of study for condition monitoring using MBD simulation as the source of training data for fault diagnosis. A MBD model is first built and validated by the CWRU bearing dataset, successfully capturing the bearing fault frequencies. The flexibility of the MBD model in simulating diverse conditions and

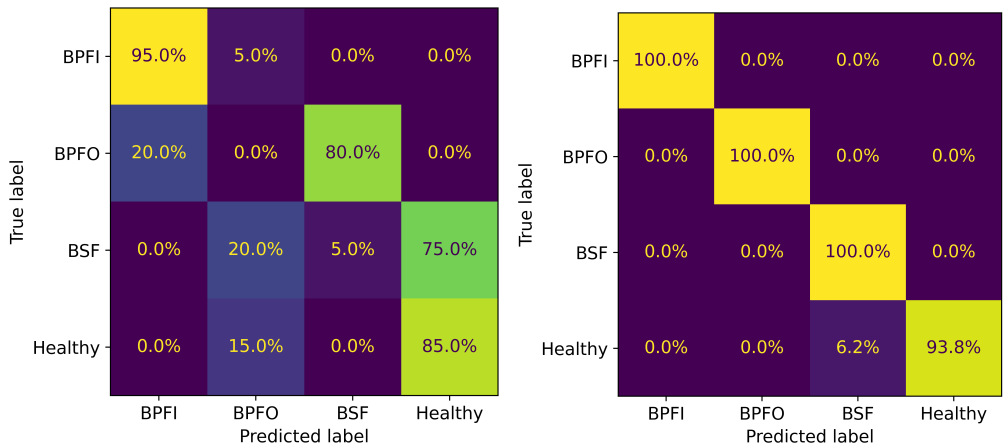

Figure 6. (left) Classification results before transfer learning and (right) classification results after transfer learning.

capturing realistic dynamic responses makes it a promising tool for advancing multi-fault diagnosis in future research.

To overcome the challenge of limited fault training data, a transfer learning strategy is presented, indicating a strong potential for enhancing model generalization. By fine-tuning the pre-trained classifier with a small portion of real data, the classification accuracy is significantly improved from 74.26% to 98.15%. This work lays a solid foundation for the integration of digital twin systems and transfer learning methods in advanced condition monitoring and structural health monitoring applications.

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