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A SIMULATION-DRIVEN DEEP LEARNING APPROACH FOR CONDITION MONITORING OF HYDRODYNAMIC JOURNAL BEARINGS. PART I: DIAGNOSTICS OF WEAR FAULTS

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Abstract. *Early diagnostics of wear faults in hydrodynamic bearings using advanced condition monitoring is essential to avoid sudden failures during operation of rotating machines. Although an increasing number of data-driven condition monitoring approaches for rotating machines have been proposed in the past decade, they are mainly focused on rolling element bearings and rely on the collection of large amounts of training data from physical experiments or from the field. This paper presents the outcomes of the first part our research project which proposes a simulation-driven framework based on a deep learning algorithm to automatically extract features and classify wear faults in hydrodynamic journal bearings using simulated vibrations signals. A model to calculate the dynamic response of a hydrodynamic journal bearing system considering the existence of localized wear in the bearing walls was developed. A large database of simulated vibration signals for several bearing operation conditions, wear severities and artificially added noise levels was created. A deep convolutional neural network algorithm (CNN) was developed to classify the bearing wear severity using the simulated vibration signal database as training/testing data. The obtained classification results confirm the potential capability of using simulated data to train machine learning algorithms to be later used on real applications to predictions faults in rotating machinery.*

Keywords: *hydrodynamic journal bearings, condition monitoring, wear fault, simulation-driven deep learning*

1. INTRODUCTION

The study of rotating machines is of interest to many researchers in the field of machines and structures in view of the significant amount of typical phenomena associated with their operation. Such rotating systems represent the largest and most important class of machinery, used in the areas of transportation, manufacturing, power generation, naval and aeronautical propulsion, among many other applications. The existence of rotating components supported on bearings creates several problems found in most of the rotating machines: compressors, pumps, motors, turbines of large and small size. As such equipment is often an integral part of production plants or power generation plants, an unforeseen shutdown can result in major financial losses. Analysis of rotating systems involve many parameters and must include the rotor interaction with journal bearings, which are important elements being responsible for machine support and force transmission between the rotor and the foundation. Journal bearings are also subject to a great variety of failures. Hence, a critical issue in rotor dynamics is the evaluation of the conditions of the bearings, which directly affects the dynamic behavior and stability of the rotating system. Failures associated with the presence of wear in the hydrodynamic bearing wall are one of the most common causes of rotating machinery shutdowns. Several works have been done in order to model and evaluate the wear conditions in hydrodynamic bearings (Bouyer et al., 2007; Wu et al., 2008; Gertzos et al., 2011; Chasalevris et al., 2013; Machado and Cavalca, 2016). The major focus of these works, however, has been on the wear characterization rather than on wear detection based on the modeling of the bearing dynamic response. It is well-known that the presence of wear in the bearing walls can affect its dynamic response, which can accelerate the wear damage process leading to the ultimate failure of the component. Therefore, early diagnostics of wear faults in hydrodynamic bearings using advanced condition monitoring is essential to avoid sudden failures during operation of rotating machines (Gioia et al., 2018; Techane et al., 2018).

Among the existing diagnostics techniques applied to rotating machines, vibration analysis is the most popular in the industry due to its excellent capability in detecting hidden fault signatures related to machine performance. In these methods, bearing faults are detected through the application of signal processing techniques on measured vibration signals. However, these condition monitoring technologies are mostly developed for applications on rolling element bearings and gears in which specific frequencies triggered by faulty elements can be detected. For journal bearings, on the other hand, it is less clear how contact, lubrication, and wear scenarios influence the frequency range of the measured vibration data (Moder et al., 2018). Several vibration-based diagnostics methods have been proposed using traditional machine learning algorithms, such as K-nearest Neighbors and Artificial Neural Networks (Moosavian et al., 2013), and deep learning algorithms (Oh et al., 2018) in order to identify faults in journal bearings. However, these approaches mostly rely on the collection of large amounts of training data from physical experiments or from the field, which is often associated with high costs in test-rig building and instrumentation (Gecgel, Ekwaro-Osire, Dias, Nispel, et al., 2019; Gecgel, Ekwaro-Osire, Dias, Serwadda, et al., 2019). The use of dynamic models to simulate the vibration response of journal bearings under many faulty conditions can be a viable alternative to the expensive collection of data from experiments or field measurements. Even using models, the generation of large training datasets is challenging due to computational power limitations to run a large number of simulations for all relevant operating condition scenarios. This issue can be solved through data augmentation of the original training dataset, which corresponds to the generation of additional new training data by applying specific deformation techniques to the original training dataset. This technique has been successfully applied in deep learning classification problems involving recognition of sounds and images (Salamon and Bello, 2017; Wang and Perez, 2017) and can be useful on problems related to fault classification in rotating machines.

This paper presents the outcomes of the first part our research project, which proposes a simulation-driven framework based on a deep learning algorithm to automatically extract features and classify wear faults in hydrodynamic journal bearings using simulated vibrations signals. First, a model to calculate the dynamic response of a hydrodynamic journal bearing system considering the existence of localized wear in the bearing walls was developed. The dynamic model was used to create a large database of simulated bearing vibration signals for several operation conditions and wear severities. Furthermore, the training datasets were augmented through the addition of Gaussian white noise to the original simulated datasets. Lastly, a deep convolutional neural network (CNN) algorithm was developed to classify the bearing wear severity using the simulated vibration signal database as training/testing data.

2. METHODOLOGY

2.1 Numerical Model of Worn Hydrodynamic Bearing

The rotor is modeled using the finite element method employing Timoshenko's beam elements with 4 degrees-of-freedom per node, namely, two translational and two angular (lateral vibration) motions (Nelson, 1980). The resulting equation of motion is given by,

$$\mathbf{M}\ddot{\mathbf{q}} + (\mathbf{C} + \Omega\mathbf{G})\dot{\mathbf{q}} + \mathbf{K}\mathbf{q} = \mathbf{F}, \quad (1)$$

where \mathbf{M} , \mathbf{C} , \mathbf{K} , and \mathbf{G} are the global mass, damping, stiffness and gyroscopic matrices, respectively. Ω represents the rotating speed of the system, \mathbf{q} is the vector with the system's degrees of freedom and \mathbf{F} contains the external forces, for this case, the unbalance force. The \mathbf{C} matrix, which represents the shaft equivalent structural damping, is modeled as a proportion of the stiffness matrix:

$$\mathbf{C} = \beta\mathbf{K}. \quad (2)$$

The Reynolds equation, which is numerically solved by the finite volumes method, provides the pressure distribution in the fluid given by,

$$\frac{\partial}{\partial\theta}\left(h^3\frac{\partial p}{\partial\theta}\right) + \frac{\partial}{\partial x}\left(h^3\frac{\partial p}{\partial x}\right) = 6\mu U\frac{\partial h}{\partial\theta} + 12\mu\frac{\partial h}{\partial t}, \quad (3)$$

where p is the pressure, μ is the dynamic viscosity of the oil, U is the shaft's linear velocity, h is the oil film thickness, t is the time, and (θ, x) are the spatial coordinates of the bearing domain. The pressure distribution is integrated to obtain the supporting hydrodynamic forces and the equivalent stiffness and damping coefficients of the bearing, as schematically illustrated in Figure 1(a). The dynamic coefficients are inserted into the stiffness and damping matrices of the system, \mathbf{C} and \mathbf{K} in Eq. (1), in the respective positions of the bearings, in order to represent the inherent flexibility and dissipation of this type of bearing.

The fault model used in this work considers that the wear (an abrasive assumption) in the bearing wall has variable depth in the circumferential direction and uniform thickness in the axial direction (Machado and Cavalca, 2016). In this model, the wear can be located in any region of the bearing bore, which is essentially different from the well-known wear

model proposed by (Dufrane et al., 1983) where the wear is fixed to only one region of the bearing bore. The wear model introduces an additional oil film layer with thickness $\delta_h(\theta)$, as indicated in Figure 1(b) and the lubricating film thickness in the presence of wear becomes:

$$h(\theta) = h_0 + \delta_h(\theta), \quad (4)$$

$$\delta_h(\theta) = d_o + C_r(1 - \cos(\theta - \pi/2)), \quad (5)$$

where C_r is the radial clearance and d_o is the maximum wear depth. Outside the wear region between $\theta = \theta_s$ and $\theta = \theta_f$, the depth $\delta_h(\theta)$ is null. Consequently, the extreme points of the wear are given by,

$$\cos(\theta - \pi/2) = \frac{d_o}{C_r} - 1. \quad (6)$$

As the cosine function in Eq. (6) has two identical solutions in the trigonometric arc, and including the angular displacement γ , we get,

$$\theta_s = \frac{\pi}{2} + \cos^{-1}\left(\frac{d_o}{C_r} - 1\right) + \gamma, \quad (7)$$

$$\theta_f = \frac{\pi}{2} - \cos^{-1}\left(\frac{d_o}{C_r} - 1\right) + \gamma.$$

Finally, the film thickness can be rewritten as follows:

$$h(\theta) = \begin{cases} h_0 & 0 \leq \theta \leq \theta_s \text{ and } \theta_f \leq \theta \leq 2\pi. \\ h_0 + \delta_h(\theta) & \theta_s < \theta < \theta_f. \end{cases} \quad (8)$$

Equation (8) is added to the Reynolds equation and solved by finite volumes method (Patankar, 1980). For the time response, a non-linear Newmark scheme is used along with the Newton-Raphson method in order to find the position, velocity, and acceleration values for each time step (Bathe, 2014). As shown in Figure 1(c) the finite element model of the rotor consists of 16 beam elements, one disk element (node 11) and two hydrodynamic bearings (nodes 4 and 15). The following properties were considered for the rotor: elastic modulus (2×10^{11} N/m²), density (7,850 kg/m³), Poisson's ratio (0.3), shear modulus (0.796×10^{11} N/m²), and the coefficient of the stiffness proportional damping matrix (1.5×10^{-5}). In addition, the main geometric and operational parameters of the bearing are presented in Table 1. The viscosity is considered as a function of temperature, using Roelands' model (Larsson et al., 2000). A complete model for the rotating system was implemented and Figure 2 presents a flowchart of the main inputs and outputs of the algorithm.

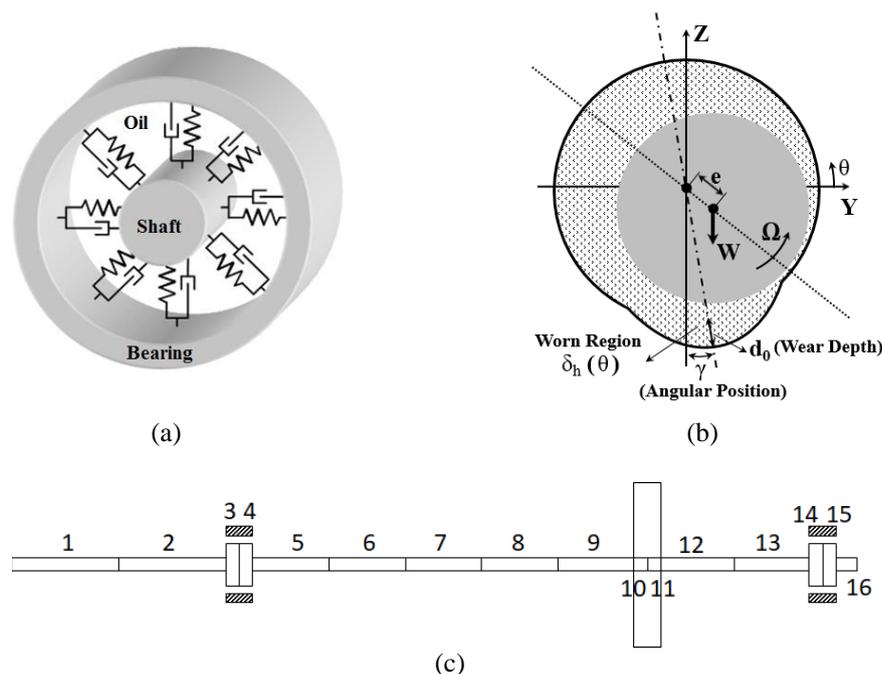


Figure 1. Hydrodynamic bearing system: a) dynamic model, b) wear model, c) finite element model.

Table 1. Bearing parameters

Diameter (D)	31mm
Length (L)	20mm
Radial clearance (C_R)	90 μ m
Lubricant Oil	ISO VG32
Bearings loads	B1@11.31N; B2@15.94N

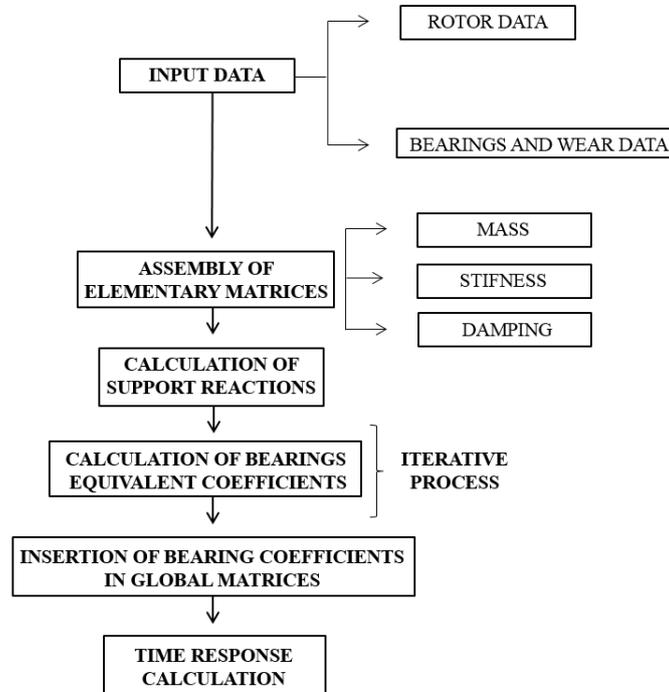


Figure 2. Flowchart of the algorithm developed for the rotating system

2.2 Fault Classification Model

In total, 45 simulated signals for Bearing 1 and Bearing 2 were generated using 3 different operating lubricant temperatures (21.5, 26.5, and 31.5°C), 3 different operating rotational speeds (42.5, 63.75, and 85 Hz), and 5 different rotating imbalances (3.28×10^{-5} , 4.54×10^{-5} , 5.80×10^{-5} , 7.06×10^{-5} , and 8.33×10^{-5} kg.m). Each set of 45 simulation signals for Bearing 1 and Bearing 2 was repeated for 7 different wear conditions (classes) as shown in

Table 2. As it is well known, deep learning algorithms perform better as the sample size increases. There are many data augmentation techniques that are used to improve the results of deep learning. In order to analyze the impact of the size of the dataset, the original dataset was augmented by adding Gaussian white noise with 5 different signal-to-noise ratios (SNR) levels to the original dataset (with 10, 12, 14, 16, and 18 SNR) as shown in Figure 3. A MatLab built-in function called *awgn* was used to add the noise to the original signal with the corresponding power according to the SNR value. All the signals were labeled according to the conditions and combined together. As a result, a dataset with 270 signals per condition was obtained which makes 1890 signals in total.

Table 2 shows the dataset size of the original dataset and augmented dataset, as well as the wear fault parameters for each condition.

Table 2. Wear conditions (classes) considered in the deep learning classification problem.

Wear Condition	Depth (μ m)	Angle ($^\circ$)	Original Dataset Size	Augmented Dataset Size
C1	22.5	0	45	270
C2	22.5	20	45	270
C3	30.0	0	45	270
C4	30.0	20	45	270
C5	45.0	0	45	270
C6	45.0	20	45	270
C7	0.0	-	45	270
Total number of signals			315	1890

The classification model used in this work is based on CNN. Figure 3 shows the general framework used in the study. After the original and augmented datasets were generated, all datasets were split into 80% and 20% for training and testing purpose, respectively. Each signal with its corresponding label was fed to the CNN model that consists of 3 consecutive layers of convolutional, activation and pooling, which are followed with 3 fully connected layers. After each activation layer, drop out layers were used to avoid overfitting. The testing data was fed to the trained CNN model and then for each signal, the probability of each class was calculated. The fault prediction was determined according to the highest probability class as shown in Figure 3.

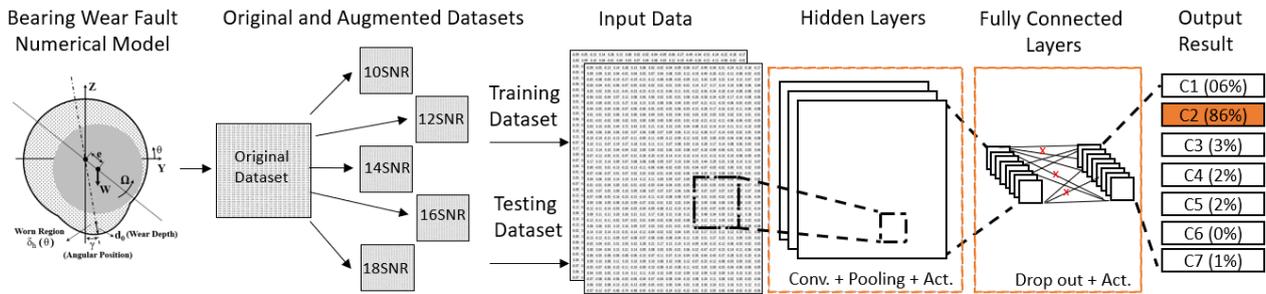


Figure 3. Wear fault diagnostics framework with convolutional neural network

3. RESULTS AND DISCUSSION

Figure 4(a) shows the simulated accelerations of the original dataset for the 7 conditions whereas Figure 4(b) shows the respective accelerations of the augmented dataset with 10 SNR noise level. For the sake of clarity in the analysis of the results, the transient part of the responses was not included in the results presented here. The original accelerations have constant amplitudes and a very regular pattern, which are not realistic according to experimental observations. In real-life situations, acceleration signals present random components due to noise, which should be taken into account in the bearing dynamic modeling. Moreover, the random nature of the added noise creates slight variations of the original signal which augmented dataset size. Thus, the performance of the deep learning algorithm was improved.

The original dataset with 315 samples and the augmented dataset with 1,890 samples for both Bearing 1 and Bearing 2 were used as inputs to the CNN algorithm. The accuracy of the proposed classification framework was assessed by running the CNN algorithm 25 times consecutively with the random selection of the training and testing datasets to check the consistency and the variation of the results. Figure 5 presents the results for the mean accuracies obtained from the 25 runs and the standard deviation (represented by error bars) for both the original and augmented datasets of Bearing 1 and Bearing 2. From this figure, it can be seen that the data augmentation improved the accuracy results of both datasets for both bearings significantly. While the classification accuracy of Bearing 1 went from 61% to 90%, the mean accuracy of Bearing 2 went from 78% to 95%. As it can be seen from the error bars with the augmented datasets, accuracy results get more consistent and standard deviation decreases drastically. This proves that data augmentation technique results in remarkable improvement for the classification results. However, Bearing 1 has a higher improvement in accuracy than Bearing 2 results. This shows that data augmentation technique has a higher impact on more challenging datasets. Since a lower static load was applied to Bearing 1, the wear in this bearing is more difficult to detect. On the other hand, Bearing 2 has experienced a higher static load and the wear is more perceptible due to the reduction in the lubricant film thickness compared to Bearing 1.

Confusion matrices for the wear fault classification of Bearing 1 and Bearing 2 with the augmented datasets are presented in Figure 6. These matrices show the detailed condition classification and misclassification obtained with the proposed framework. The vertical axis represents the actual label of the wear condition in terms of its depth and angular position, and the horizontal axis shows the predicted label. The diagonal of the confusion matrix (from top left to bottom right) represents the classification accuracy of each condition. A diagonal value lower than unity indicates that the classifier has confused certain wear condition with a different one. For instance, in Figure 6(a) 98% of the C6 condition was predicted correctly, 1% was misclassified as C3 and 1% was misclassified as C4. In both bearings, most of the misclassification was observed in lower levels of wear depth. The classification accuracy increases as the wear level increases due to the stronger fault signatures. As aforementioned, the overall accuracy of Bearing 2 is higher due to the higher load. But, when individual accuracy scores of each class are investigated, it can be seen that at 45 μ m (condition C5 and C6) wear depth level, the results of Bearing 1 and Bearing 2 are almost same, unlike lower wear depths. Thus, it can be concluded that the applied load has no effect on the accuracy result as the fault size increases.

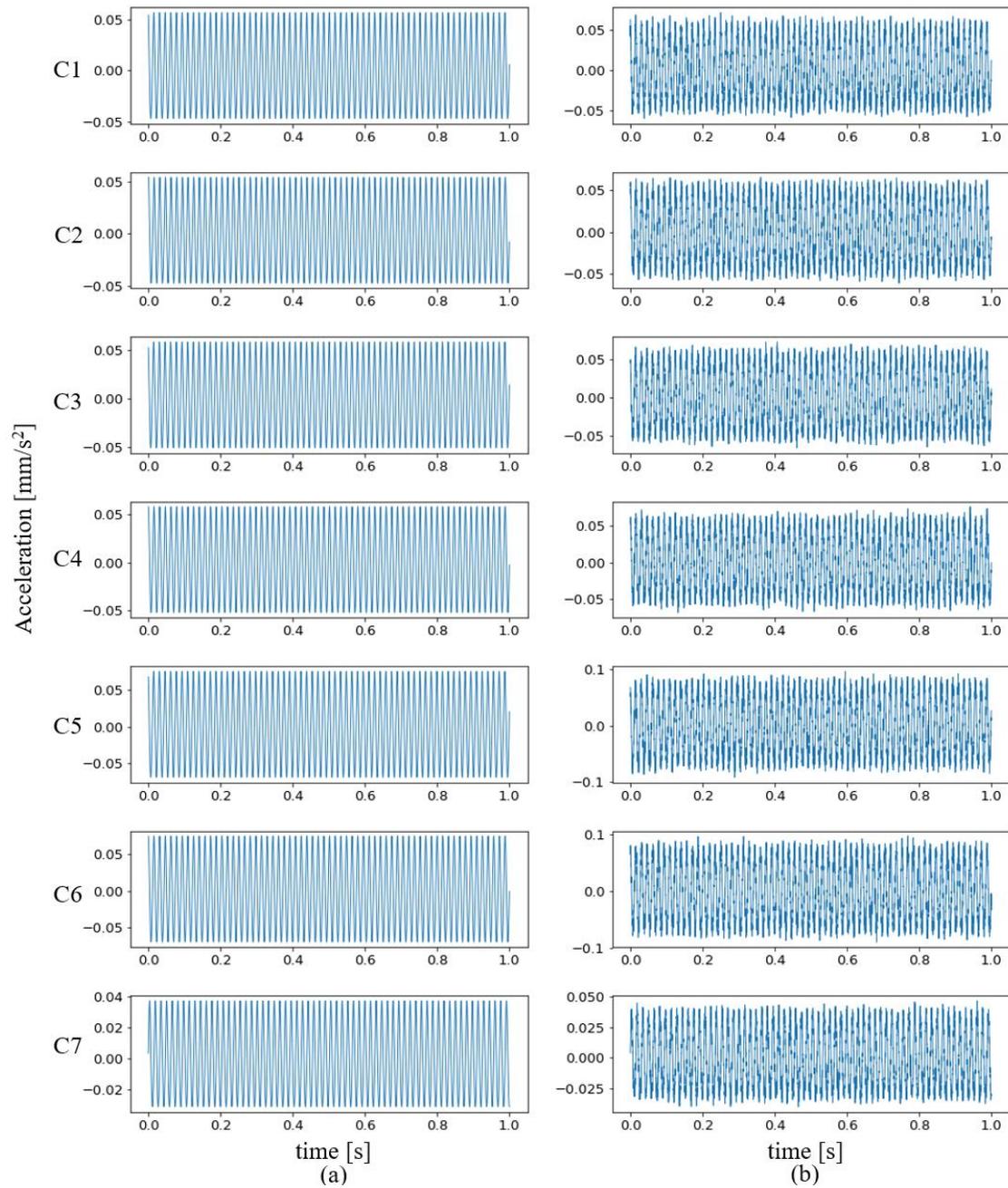


Figure 4. Simulated accelerations for the 7 conditions: (a) without added white Gaussian noise and (b) with added white Gaussian noise (10 SNR)

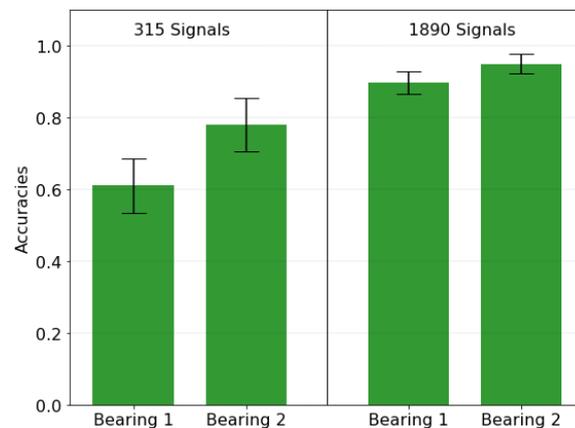


Figure 5. Accuracy results for the original and augmented datasets for Bearings 1 and 2

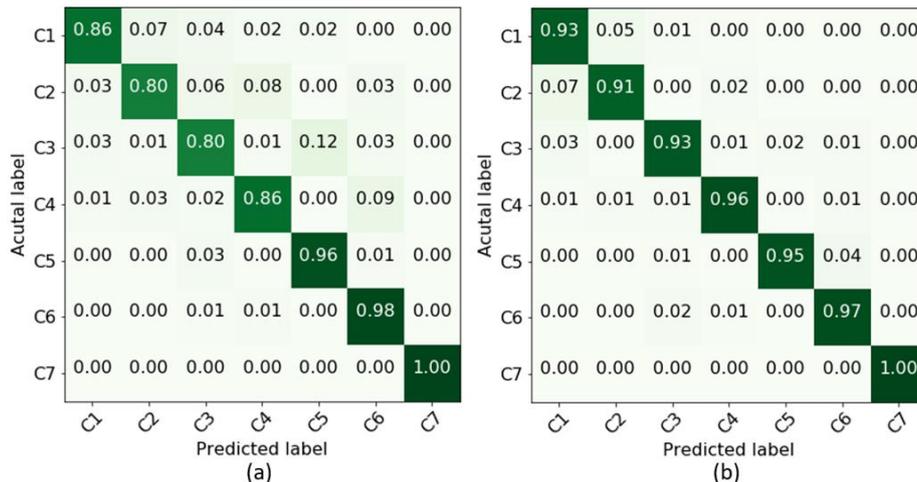


Figure 6. Confusion matrices for the wear fault detection for (a) Bearing 1 and (b) Bearing 2 augmented datasets

4. CONCLUDING REMARKS

In this paper, diagnostics of wear faults in hydrodynamic journal bearing have been predicted using a convolutional neural network (CNN) classification algorithm. Bearing acceleration data was generated using a numerical model based on a coupled solution of the Reynolds Equation for the pressure distribution in the lubricant film and a finite element method to determine the dynamic response of the rotor system. Seven conditions (one for the healthy condition and 6 different worn conditions) for 2 bearings with different static loads were simulated in order to create a baseline dataset for the fault classification. Furthermore, the baseline dataset was augmented with five different levels of Gaussian white noise in order to create a sufficiently large training dataset for the CNN algorithm. After the CNN model was trained, the testing dataset was fed to CNN and prediction accuracies were presented.

The results showed that CNN is a powerful tool to predict the wear faults in bearings. It was observed that as the wear depth gets smaller, it gets more difficult to obtain accurate results. This is basically due to the low severity faults having weaker signatures. It was also observed that as the load on the bearing increases, the fault signatures become stronger, which resulted in better predictions particularly for incipient faults in both bearings. Moreover, it was observed that adding different levels of Gaussian white noise to the dataset to augment the original dataset brought substantial improvements to the classification results. The obtained results demonstrate the feasibility of future applications of machine learning algorithms trained with simulated data for wear fault detection in real-life rotating machines.

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