Anomaly Detection of Rotating and Oscillating Bearings using Autoencoder

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Summary:
This paper explores the effectiveness of Autoencoders (AE) in detecting anomalies in both Fully Rotating Bearing (FRB) and Oscillating Bearing (OB) data, with an emphasis on early degradation detection. AE demonstrate greater sensitivity and precision in anomaly detection compared to Principal Component Analysis, a traditional statistical Predictive Maintenance method. The study utilizes a comprehensive and well-studied Kaggle dataset for FRB, along with a dataset from the German Aerospace Center for OB. AE built on these datasets enable the capture of degradation patterns for both operating modes.

Keywords: Machine Learning, Anomaly Detection, Autoencoder, Predictive Maintenance, Rolling Bearings, Oscillating Bearings

Introduction
In technical applications like wind turbine pitch actuators and aerospace control mechanisms, rolling bearings undergoing small oscillatory movements are essential but vulnerable to wear and tear, risking operational disruptions. Predictive maintenance is thus crucial in these applications for minimizing downtime and enhancing efficiency. While publicly available datasets for fully rotating bearings exist, such as the well-studied NASA Bearing Database of the University of Cincinnati [1], there is a lack of similar datasets for oscillating bearings. This paper contributes to this field of research by applying a data-driven model, which works well on Fully Rotating Bearing (FRB), to Oscillating Bearing (OB). We adopt an Autoencoder (AE) approach, following Ahmad et al.’s method for rotating machinery [2] and adapt it for both FRB and OB, focusing on deep feature extraction and reconstructive techniques. This study compares the AE’s performance against traditional methods like Principal Component Analysis (PCA) in anomaly detection, using acceleration data from the NASA dataset for FRB [1] and a German Aerospace Center (DLR) dataset for OB [3]. Both datasets capture degradation patterns across the bearings’ lifecycle, underscoring the AE’s effectiveness in early degradation detection.

Methodology
In this section, we offer an overview of the datasets used in our study and elaborate on the machine learning based AE algorithm implemented.

The NASA dataset includes multiple test runs for FRB, where each bearing was subjected to a constant rotational speed of 2000 RPM and a radial load of 26.7 kN. In each test run 4 Rexnord ZA-2115 double row bearings have been used. During these tests, acceleration data were collected every 10 minutes, with each data point representing a 1-second sample recorded at a 20 kHz sampling rate. The DLR test bench, shown in figure 1, is designed for performance degradation tests for OB. In the current setup, only the motor-driven shaft was operated to avoid slip effects in oscillatory motion which might occur in the depicted set-up which uses a belt. The housing contains two spaced SKF Explorer 3209 A bearings, with axial force applied via disc springs adjusted by front cover screws. Axial force and shaft angular position are measured by a load cell and a rotary encoder, respectively. Four acceleration sensors are mounted on the housing, with three directly screwed onto it and one glued via an intermediate part. Additionally, two temperature sensors are embedded in the housing, and a third outside which measures...
the ambient temperature. Note that in this study only the acceleration measurement of one sensor is used to test the AE. The data used in this study are collected during a 120-hour life cycle assessment. The shaft rotates and applies a reference signal with constant amplitude oscillations of 20° as a sequence of alternating trapezoidal and sinusoidal trajectories with a period of 1 second under constant axial load. Data was recorded every 2 minutes. For consistency in analysis between OB and FRB, the data was downsampled to use data points from every 10 minutes. As of this publication, we have completed one full test run for a single OB under these conditions. In order to conduct anomaly detection, we employ an AE, a type of artificial neural network suited for unsupervised learning. An AE consists of two primary components: the encoder and the decoder. The encoder compresses input data into a lower-dimensional representation, and the decoder reconstructs the original input from this compressed form, as illustrated in figure 3. Both encoder and decoder are trained simultaneously using data from normal operating conditions, aiming to minimize the reconstruction error using the mean-squared-error function. This approach is based on the premise that the lower-dimensional representation should capture key features of the input data. Under normal operating conditions, the AE is expected to reconstruct acceleration data with minimal error. However, anomalies, such as the onset of bearing degradation, will likely result in higher reconstruction errors. We use an AE that uses a sample of 5120 datapoints and scales it down to a bottleneck of 160 features using layers of (5120, 2560, 1280, 320, 160, 320, 1280, 2560, 5120) neurons and a ReLu activation function. To identify these anomalies, we have devised a specific criterion: if the reconstruction error remains outside a 3 · σ-environment around the data measured under nominal conditions for five consecutive data points, it is flagged as an anomaly. This method indicates the likely beginning of degradation. For comparison, we use PCA as a fault diagnosis method, following Gu et al. (2018). This method is well understood and suitable for fault diagnosis of rolling bearings. [4] PCA transforms the data into principal components (PCs), ordered by the variance they capture. The first PC, which accounts for the most variance, is used to assess adherence to normal operating conditions. The same anomaly criterion as for the AE is applied.

**Training and Reference Process**

**Data Preparation**

While the AE is trained on the raw acceleration data, the PCA is trained on a pre-selection of 10 statistical features. The AE is able to learn the most important features of the data autonomously. For the PCA 10 time domain features are extracted for each data sample, namely the mean value, the root mean square, the kurtosis, the skewness, the peak-to-peak value, the variance, the entropy, the crest factor, the impulse factor and the margin factor. These features are chosen as proposed by Guo et al. (2017) [5] as time-domain features with high informative value about the status of the bearing.

The data of the FRB of the NASA-dataset is pre-treated and do not have to be further processed. The data of the DLR test stand is recorded with sinusoidal and trapezoidal trajectories, as shown in figure 2. Therefore, only parts of increasing trapezoidal flanks have been used, as these ought to show the least amount of variance in the acceleration data.

**Training**

For each examined bearing an AE with the described topology is trained separately starting with random parameters and being subjected only to the data of this specific bearing. Each AE is initially trained on the first tenth of the particular dataset, a period where wear is presumed absent and the system is operating normally. To facilitate this, the data of each bearing is split into two sets: the training set, comprising the first tenth, and the testing set, containing the remainder. The training process involves optimizing the AE’s parameters to minimize reconstruction error for the training data. Anomalies in the testing data are identified by monitoring its reconstruction error. An anomaly is flagged when this error surpasses the 3 · σ threshold of the training data error for five consecutive data points.

**Comparison**

As a reference, a similar process is conducted with the PCA. The PCA is optimized on the training data and the first PC is monitored. The same criterion for an anomaly is applied as for the AE. As soon as the variance of the data in this component exceeds the 3 · σ-environment of the variance of the training data continuously for 5 data points, it is considered a
Results

Detection Efficacy in FRB

Our results demonstrate the robustness of the AE in early anomaly detection in FRB. Notably, the AE identified anomalies earlier than the PCA as it can be seen in table 1. This early detection capability is critical for predictive maintenance, allowing for timely intervention before significant bearing degradation. The detection of the start of bearing degradation is crucial for further remaining lifetime analysis.

Figure 4 illustrates the comparative anomaly detection timeline of the AE and PCA. The AE’s early detection is followed by a phase where both methods exhibit a similar pattern in identifying the progression of anomalies, which indicates that the AE detects an existing anomaly earlier than the PCA. The data of the PCA has more noise than the loss of the AE, which deviates only very little before the anomaly is detected. This reliability aids the AE in detecting anomalies early.

Performance in OB

In figure 5, the top and middle panels demonstrate that the AE successfully detects anomalies in OB, while the PCA only identifies single deviations. The comparison between the expected and actual trajectory data of the bearings shows that the bearing, as shown in figure 2, is subject to physical deformation. This results in an increasing friction torque and as a consequence reduced achievable maximum oscillation amplitude limited by the maximum available motor torque. Figure 4 shows clear indication of ongoing degradation. The declining maximum amplitude of the trajectory, as shown in the lower panel of figure 5, is a clear indicator of actual bearing degradation. This supports the identified anomaly by the AE. That the degradation starts sooner than in the case of FRB can be explained in the differences of the test stands and operation modes. Interestingly, towards the end of the test period, we observed a stagnation and even a decrease in the AE’s loss. This phenomenon might be explained by initial material chipping in

<table>
<thead>
<tr>
<th>Anomaly Detected by AE</th>
<th>Anomaly Detected by PCA</th>
<th>Bearing Failure</th>
</tr>
</thead>
<tbody>
<tr>
<td>NASA FRB Test 1 - Bearing 3</td>
<td>217 h</td>
<td>245 h</td>
</tr>
<tr>
<td>NASA FRB Test 1 - Bearing 4</td>
<td>178 h</td>
<td>209 h</td>
</tr>
<tr>
<td>NASA FRB Test 2 - Bearing 1</td>
<td>89 h</td>
<td>114 h</td>
</tr>
<tr>
<td>NASA FRB Test 3 - Bearing 3</td>
<td>987 h</td>
<td>1034 h</td>
</tr>
<tr>
<td>DLR OB</td>
<td>13 h</td>
<td>—</td>
</tr>
</tbody>
</table>

Tab. 1. Time of anomaly detection by AE and PCA for each bearing. It is only used for bearings that are known to be defective after the test run. The AE detects anomalies earlier than the PCA in all cases.

Conclusion

Our research indicates that the proposed Autoencoder (AE) based approach identifies indications of bearing degradation considerably sooner than the traditional Principal Component Analysis (PCA) method. The early detection of bearing degradation is crucial for implementing effective predictive maintenance strategies. By accurately identifying the onset of bearing deterioration, methods that estimate the remaining useful life of bearings can be employed. This enables the determination of the most opportune moment for bearing replacement, optimizing maintenance schedules and potentially reducing downtime. [6]

Our research highlights the versatility and potential for broader application of the AE method in anomaly detection. Despite the distinct operational characteristics of OB compared to FRB, the method is able to successfully detect anomalies in both types of bearings.

The research also suggest the importance of integrating additional physical metrics with AE analysis for a more comprehensive monitoring strategy. Such an approach can enhance the reliability of anomaly detection and degradation assessment in bearings.
In summary, our study provides an advancement in the field of predictive maintenance of OB. The data-driven AE method holds promise for widespread adoption in various industrial settings, leading to more efficient and cost-effective maintenance practices. Future work could explore the integration of additional predictive metrics and the application of this method to a broader range of mechanical systems. Additionally more data on OB needs to be collected to further validate the method.

References