Cyclic monitoring of the Remaining Useful Life RUL for the Bearing fault prognosis

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Abstract

Over the last decades, Prognostics has played a dominant role in preventive maintenance in manufacturing. It usually involves estimating the Remaining Useful Life (RUL) or the Time to Failure (TTF) of mechanical systems. In Prognosis, the analysis could often be purely data-driven (Trend Analysis). It requires a vast data set and offers the double benefit of being both applicable in many systems and being relatively precise. In this paper, we implemented the « Threshold Data » approach, considering the limited amount of run-to-failure data and the fact that the Bearings' features are suitable for a degradation model creation. Moreover, this study sheds light on Cyclic Prediction Method, intending to prove that cyclic monitoring could also estimate the RUL for the bearing fault with the integrity of data, and precisely track the degradation. Firstly, different filters are compared: Simple Moving Average (SMA), Cumulative Moving Average (CMA) and Exponential Moving Average (EMA). After that, both the Principal Component Analysis (PCA) and Model Fitting are deployed in order to construct a degradation model and fit the exponential function to the last n data. Finally, using the selected indicators, we managed to estimate the RUL of the bearing cyclically, thus exhibiting accurate predictions throughout each phase of its life till failure.

1 IMS Bearing Data

The data was generated by the NSF I/UCR Center for Intelligent Maintenance Systems (IMS – www.imscenter.net) with support from Rexnord Corp. in Milwaukee, WI. [2].

1.1 Test Rig Setup

The experimental setup consisted of installing four (4) Rexnord ZA-2115 double row bearings onto a shaft, as depicted in Figure 1. To ensure a constant rotation speed of 2000 RPM, an AC motor was connected to the shaft through rub belts. A spring mechanism was employed to apply a radial load of 6000 lbs to the shaft and bearings. Notably, all bearings were lubricated using force lubrication for optimal performance [1].

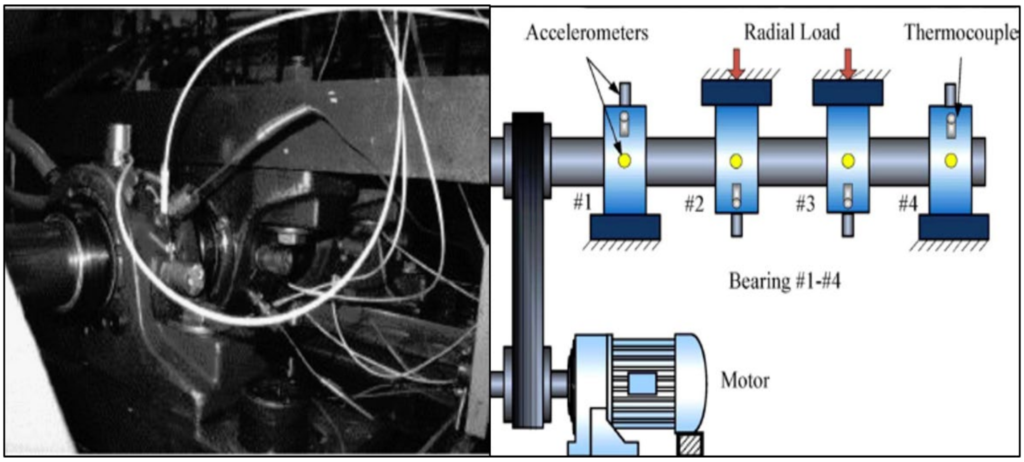

Figure 1: IMS test rig layout [1].

1.2 Data Description:

The data packet, IMS-Rexnord Bearing Data.zip, includes three (3) data sets that represent test-to-failure experiments. Each data set comprises multiple individual files containing 1-second vibration signal snapshots recorded at specific intervals. These files consist of 20,480 data points with a sampling rate of 20 kHz. The file names indicate the respective collection times. In the data files, each record (row) represents a data point. The data collection process utilized the NI DAQ Card 6062E. Notably, larger time intervals indicated in the file names signify the continuation of the experiment on the following working day [1].

Dataset	*Announced Damages at the End*	*Number of Files*	*Number of Channels*	*Endurance Duration*	*Duration of Recorded Signal*
1	Bearing 3: inner race Bearing 4: rolling element	2156	8	49680 min	34 days 12h 36 min
2	Bearing 1: outer race	984	4	9840 min	6 days 20h 16 min
3	Bearing 3: outer race	4448	4	44480 min	31 days 10h 74 min

Table1: Datasets description.

2 Methodology

2.1 Comparative Evaluation of Moving Average Filters

In this study, we have chosen to investigate a specific type of database defect with the objective of applying our cyclic estimation strategy for Remaining Useful Life‶RUL″. Our selection was focused on the bearing three (3) from Dataset 1, which exhibits an inner ring fault.

Upon performing an analysis of statistical features that have been extracted from the data, we have concluded that a comparative evaluation of three distinct iterations of the Moving Average filter is of considerable significance. This evaluation aims to determine the optimal filter that accurately captures the authentic dynamics inherent in the data. Notably, the Moving Average filter, encompassing the methodologies of Simple Moving Average (SMA), Cumulative Moving Average (CMA), and Exponential Moving Average (EMA), is employed to accomplish data smoothing within the temporal context.

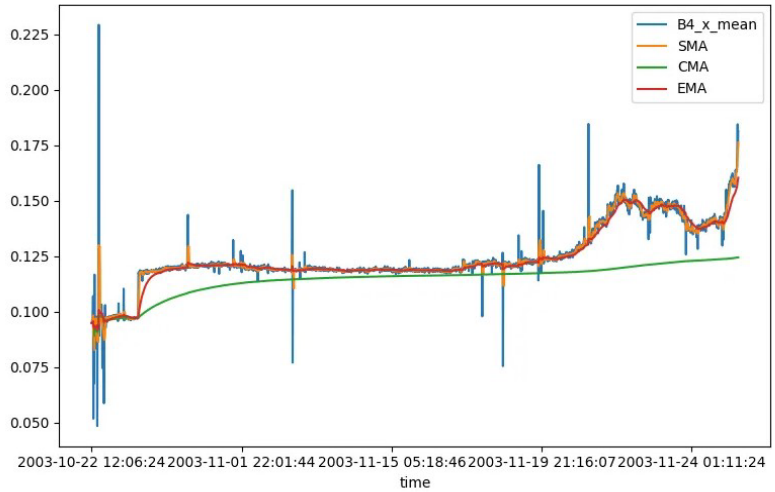

Figure 2: Moving average filters comparison

Following a thorough analysis of the graphical representations and comparative assessment, it can be concluded that the EMA emerges as the most viable choice for data filtering. This determination is rooted in its superior ability to accurately capture and mirror the actual moves observed in the real dataset.

2.2 RUL Prediction

a) Principal Component Analysis (PCA) is employed to construct a degradation model by extracting a representative feature that encapsulates the information contained within the base features. This technique identifies the principal component with the highest variance, which serves as a focal point for subsequent investigations. Through PCA, the dimensionality redundancy inherent in the data is effectively reduced, resulting in the acquisition of a primary feature that captures essential characteristics. We found that the explained variance of **Principal Component 1** amounts to **0.9955862512721826**, indicating its substantial contribution in representing the original dataset.

b) Model fitting: When it comes to time series prediction, it is commonly assumed that degradations follow an exponential pattern in numerous natural phenomena. Hence, a function representing an exponential model with a consistently positive slope is constructed and fitted using the scipy.optimize library. To ensure the inclusion of specific movements that could aid in forecasting future outcomes, the exponential model is not fitted to the entire available dataset. Rather, the exponential function is fitted specifically to the most recent "n" data points.

c) We applied our cyclic prediction assuming that the first 650 cycles are healthy. The figure below shows the cycles predictions.

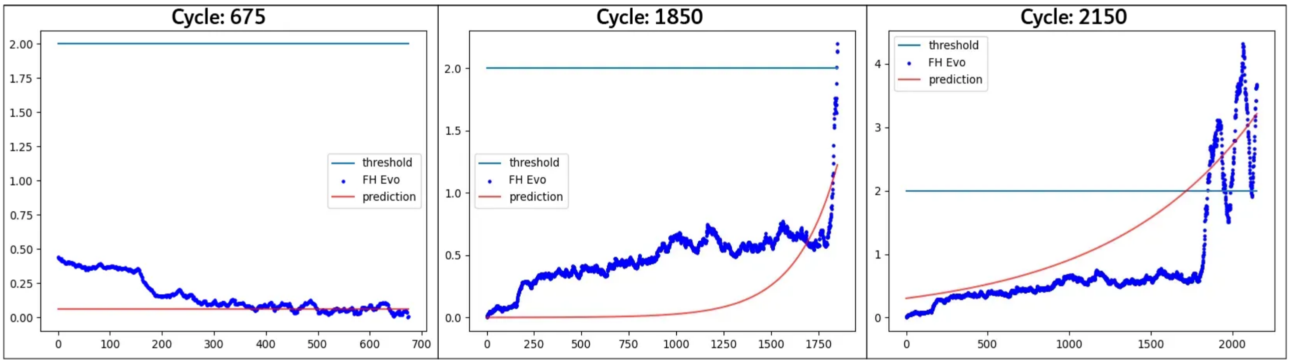

Figure 3: Cycles predictions (cycles: 675, 1850 and 2150)

We found that it failed at **1717.9009275180667.** This table summarizes the cyclic prediction of the bearing 03:

Cycle	*Time*	*Prediction*	*isvalid*	*real*
675	2003-11-09 00:51:44	6.218055e+10	False	normal
975	2003-11-15 01:08:46	7.432427e+11	False	normal
1350	2003-11-18 05:12:30	1.987825e+03	True	normal
1625	2003-11-21 01:24:03	5.951757e+10	False	normal
1775	2003-11-22 06:56:56	2.547281e+03	False	normal
1800	2003-11-22 11:06:56	2.567900e+03	False	suspect
1850	2003-11-22 19:26:56	1.959186e+03	True	**suspect**
1975	2003-11-23 21:01:24	1.895768e+03	True	suspect
2100	2003-11-24 20:57:32	1.804905e+03	True	suspect
2125	2003-11-25 11:47:32	1.659149e+03	True	Inner_race_failure
2150	**2003-11-25 15:57:32**	**1.717901e+03**	**True**	**Inner_race_failure**

Table2: Cyclic prediction

References

[1] D. Lixiang, F. Zhao, W. Jinjiang, W. Ning et Z. Jiwang, *An Integrated Cumulative Transformation and Feature Fusion Approach for Bearing Degradation Prognostics*, Hindawi, 2018.

[2] J. Lee, H. Qiu, G. Yu, J. Lin, and Rexnord Technical Services, IMS, "Bearing Data Set", NASA Prognostics Data Repository, NASA Ames Research Center, Moffett Field, CA, University of Cincinnati, 2007.

[3] Q. Hai, L. Jay, L. Jing, *Wavelet Filter-based Weak Signature Detection Method and its Application on Roller Bearing Prognostics*. Journal of Sound and Vibration, 2006, 289, pp.1066-1090.