Signal pre-processing techniques for fault signature enhancement in a bearing health monitoring system used in the automotive industry

Ehsan Jafarzadeh[1], Sara Rahimifard[1], Paola Sant Anna[2], Yu Cao[1], Frances Tenney[1], Hossein Sadjadi[1]
[1]*General Motors Technical Center, Markham, ON, L3R 4H8, Canada*
ehsan.jafarzadeh@gm.com
sarasadat.rahimifard@gm.com
hossein.sadjadi@gm.com
yu.cao@gm.com
frances.1.tenney@gm.com
[2]*General Motors Global Technical Center - Cole Engineering Center, Warren, MI, 48092, US*
paola.santanna@gm.com

ABSTRACT

Traditional internal combustion engine vehicles have low transmission bearing failure rates in their lifespans. However, the prolonged lifespan of electric and autonomous vehicles can surpass the reliable life of bearing designs, which poses a risk of bearing failure and loss of propulsion. In comparison to replacing bearings on a fixed schedule to ensure reliability, a bearing health monitoring system has proven to be a more cost-effective solution. Despite extensive research on bearing condition monitoring, implementing well-known methods such as vibration spectrum analysis in vehicles can be challenging due to vibrations from vehicle components and the road. This paper explores and compares the effect of various pre-processing techniques on the spectrum of a faulty drive unit's bearing with various fault levels. To achieve this objective, three faults with different width sizes of 0.1 mm (mild), 0.5 mm (moderate) and 2 mm (severe) were injected into the inner race of a ball bearing. A bench setup was then used to capture the vibrations of multiple vehicle components including the faulty ball bearing under various speed/load conditions. Phase domain transform, envelope and Fourier transform were used as the core signal processing steps, and advanced signal processing methods for removing discrete frequencies from other components and enhancing the fault signature were explored. A health indicator was then developed from the spectrum of the vibration signals and calculated for the captured data. Next, for each fault level, the area under Receiver Operating Characteristic (ROC) curve was calculated and used as a metric to compare the performance of the health monitoring system for classification of faulty and healthy bearings. The health indicator results show that applying minimum entropy deconvolution, and spectral kurtosis-based band pass filtering increases the ROC area from 0.40, 0.99, 1.0 to 0.84, 1.0 and 1.0 for the mild, moderate, and severe inner race faults, respectively. This implies that although applying only phase domain transform, envelope and Fourier transform might be enough for moderate and severe faults, advanced signal processing is needed to enhance the fault signature for early detection of mild faults.

1. INTRODUCTION AND BACKGROUND

1.1. Introduction

Bearing failure, which is a common cause of machine breakdown (Randall & Antoni, 2011), has been extensively addressed in industries like manufacturing and power generation. A number of effective methods have been presented for bearing fault diagnosis in early stages, which could prevent costly downtime (Nabhan, Ghazaly, Samy, and Mousa, 2015). However, bearing health monitoring has not been extensively studied in the automotive industry as the bearing failure rate is relatively low over the lifespan of Internal Combustion Engine (ICE) powered vehicles (Garner G D. S., 2021) (Rao SS, 1994). Additionally, it is typically assumed that a driver is able to detect any abnormal noise associated with bearing failure, allowing the fault to be identified before it reaches a critical safety level.

The vehicle market is anticipated to face a significant shift toward Electric Vehicles (EVs) in the near future. Prominent vehicle manufactures have made announcements indicating their plan to either exclusively manufacture Electric Vehicles (EVs) or significantly increase their production compared to ICE-powered vehicles (Weiss, 2021). This shift reflects the growing trend toward electrification and the increasing recognition of EVs as the future of transportation. The acceleration of this transition is being propelled by global regulations that aim to restrict CO_2 emissions, continuous technological advancements, and the rapid expansion of charging infrastructure (Weiss, 2019) (Haram MH, 2021).

Electric Autonomous Vehicles (EAVs) are also rapidly emerging (Pan S, 2021). It is expected that by 2040, EAVs could represent approximately half of all new vehicle sales.

The autonomous taxi sector is expected to dominate the EAV market with companies that investing heavily in these advancements like Cruise, Waymo, and Zoox (Deloitte University Press, 2016).

Battery technology advancements have facilitated the development of EVs and EAVs with extended lifespans reaching millions of miles (Motavalli, 2020). Consequently, the durability of current bearing designs is surpassed over the course of a vehicle's life, that significantly raise the probability of bearing failure and potentially vehicle failure in EVs compared to ICE-powered vehicles (Garner G S. P., 2021). The chance of bearing failure in autonomous taxi fleets could even be higher than EVs. This is primarily because the passengers in autonomous vehicles may not be able to recognize any abnormal sounds and indications of bearing failures that a human driver would typically identify.

1.2. Failure Modes in the Automotive Industry

There are various bearing failure modes that could mainly be categorized into fatigue, wear, fracture and cracking, corrosion, electrical erosion, and plastic deformation. In the automotive sector, the most frequent failure modes are typically divided into three categories including contamination ingress, brinelling failure, and fatigue (SKF, 2014).

As the mileage increases, the integrity of bearing sealing can be compromised which creates a pathway for water and contaminants to enter the bearing. This could deteriorate lubrication and initiate corrosion on the bearing elements. The next failure mode is bearing brinelling which may occur under a substantial impact load, typically resulting from abusive incidents such as being involved in a vehicle collision. This intense pressure could lead to permanent indentations called brinell marks (Upadhyay RK, 2013).

The presence of indentations caused by contamination ingress and brinelling failure has the potential to result in fatigue failure. This failure leads to the gradual degradation of the metal's surface, resulting in the formation of spalling marks. The spalling can propagate and grow in size if left undetected, leading to more severe damage to the bearing and potentially creates safety concerns. Therefore, it is crucial to detect a spalling originated from the fatigue mode in its early stages before failure and loss of functionality. In (Jafarzadeh, 2022), two fault injection methods were proposed to mimic fatigue failure mode and facilitate development of a bearing fault detection system for that common failure mode.

1.3. Bearing Fault Detection

Implementing a predetermined replacement schedule for bearings could be the most straightforward approach to ensure reliability and to address the failure modes. However, this method may not be cost effective for EVs, and in particular EAVs with an extended lifespan (Garner G S. P., 2021) (Jafarzadeh, 2022). On the other hand, an automated bearing health monitoring system offers a reliable solution for identifying and isolating the bearing faults. This method could expand the replacement interval and minimize the maintenance expenses while it also eliminates the risk of loss of propulsion and the associated safety concerns (Garner G S. P., 2021) (Jafarzadeh, 2022).

In general, electrical signature analysis, acoustic analysis, and vibration analysis have been studied as bearing health monitoring systems in the literature (Tandon, 1999)-(Smith WA, 2015). Electrical signature analysis involves monitoring the electrical signals such as current, voltage, and power. This method focuses on detecting abnormal electrical patterns or changes that can indicate bearing faults. Acoustic analysis focuses on analyzing the sound and noise generated by the bearing while operating. Vibration analysis involves using vibration sensors to measure vibration patterns of a bearing. Vibration analysis is often preferred over acoustic and electrical signature analysis due to its ability to capture detailed mechanical irregularities. Vibration analysis directly reflects the dynamic behaviors of the bearing and offers insights into localized faults, and load variations which might be challenging to capture through acoustic or electrical signature analysis, that might be influenced by additional factors like environmental noise or complex electrical systems. Vibration analysis can potentially detect bearing degradation at its early stages due to its sensitivity (Tandon, 1999)-(Smith WA, 2015).

In the presence of a local fault on either the outer or inner race of a bearing, the roller elements generate wideband vibration impulse (Smith WA, 2015). These vibration bursts occur at specific frequencies known as the bearing critical frequencies. It is expected to have an experimental variation of up to 2% from the ideal critical frequency formulation due to bearing slippage (Randall & Antoni, 2011). Therefore, a bearing fault is characterized by peaks at critical frequencies (Randall & Antoni, 2011).

To develop a bearing health monitoring system based on the vibration signals, it is required to enhance the fault signatures and remove noise. To achieve this purpose, various signal processing techniques have been investigated in the literature including envelope spectrum (Darlow, Badgley, & Hogg, 1974), minimum entropy deconvolution (Sawalhi, Randall, & Endo, 2007), unsupervised noise cancellation (Antoni & Randall, 2004), and bandpass filtering based on spectral kurtosis (Antoni J. , 2006). In (Randall & Antoni, 2011), a comprehensive review of these methods is provided.

In (Jafarzadeh, 2022), a bearing fault injection method along with a ground-truthing method were presented to enable development of a bearing health monitoring system in the automotive industry. This paper extends the findings and methodologies introduced in (Jafarzadeh, 2022). In this paper, an on-vehicle bearing health monitoring algorithm for EV's drive unit is presented and then compared the effect of various pre-processing techniques on the spectrum of a faulty drive unit bearing for different fault levels. Section 2 introduces the experimental setup and the proposed algorithm including the preprocessing steps. Section 3 presents the results for three bearing fault levels (mild, moderate, and severe).

2. EXPERIMENTAL SETUP AND METHODS

2.1. Fault Injection and Experimental Setup

A Precision machining method (described in (Jafarzadeh, 2022)) is used for fault injection. The experimental setup for fault injection is depicted in Figure 1. The figure illustrates the placement of the bearing within the lathe spindle chuck, allowing the motion controller to maneuver the cutting tool mounted on the tool holder, and inject the fault. The bearing is disassembled for placement in the presented setup and fault injection. The size, shape, and location of the defect can be controlled by this method. Using this method, a fault with 3 levels were injected (with width sizes of 0.1mm, 0.5 mm, and 2mm) into the inner race of a ball bearing, shown in Figure 2. Figure 3 shows the assembled faulty ball bearing with width of 2mm.

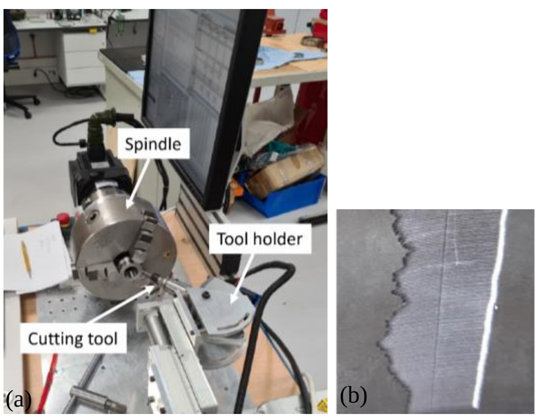

Figure 1. (a) Experimental setup for fault injection, (b) an example of the injected fault under a microscope.

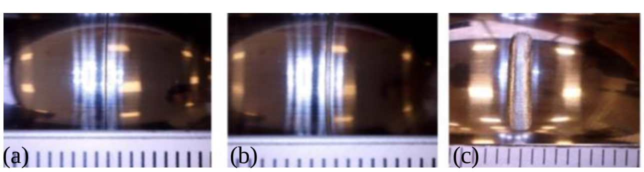

Figure 2. Injected fault into the inner race of a ball bearing with the size of (a) 0.1mm, (b) 0.5 mm, and (c) 2mm.

Figure 3. Injected fault into the inner race of a ball bearing.

A method based on volume under the Power Spectral Density curve of the vibrations (known as GRMS) versus load and speed is considered here for ground-truthing state of health, which was introduced in (Jafarzadeh, 2022). Table 1 provides the calculated ground-truth values for the injected faults.

Table 1. Ground-truth values for different fault level of the bearings.

	Volume ($N.m^2/s^2$) × 10^4	**Volume (faulty) / Volume (healthy)**
Healthy	2.39	1
Faulty –0.1 mm	3.75	1.56
Faulty –0.5 mm	8.80	3.68
Faulty –2 mm	10.42	4.36

The faulty bearing is then assembled on the motor shaft of an EV drive unit which has other shafts, ball bearings, roller bearings and gear pairs. The drive unit is then installed on a dynamometer to be able to capture the data under various loads and speeds. This is to ensure that the developed fault detection method is robust to the load and speed and can monitor the health of the bearings in the vehicle under various condition use. An accelerometer sensor is attached to the external surface of the drive unit casing afterwards, and vibration data (with the healthy and faulty bearings) is captured under a wide range of load (20- 400 Nm.) and speed (1000-6000 rpm) to cover the operating range of an EV drive unit.

2.2. Methods

In the proposed method, signal processing steps are applied on the captured vibrations. The processed signals are then transformed to the frequency domain and are used to define a health indicator for fault detection. The signal processing steps are divided into the core algorithm and optional steps as shown in Figure 4.

For a vehicle, the speed varies during a trip while the fault signature can be seen at the critical frequencies of raw vibrations only if the bearing's shaft rotates with a constant speed. Order tracking is needed to remove this speed variation and allow the usage of frequency domain approaches (Randall & Antoni, 2011). Therefore, raw vibrations are transformed from the time domain to the phase domain as the first step. It is shown that applying an envelope filter is necessary to attenuate high frequency components, isolate transients and enhance the fault signature (Randall & Antoni, 2011) before transforming the phase domain signals to the frequency domain. To transform the processed signal to the frequency domain, the signal is broken into small overlapping segments, a window (such as Hanning or hamming) is applied on the small segments to reduce the frequency domain artifacts, and then a Fast Fourier transform (FFT) is employed on each windowed segment. These processing steps including phase domain, envelope filter and FFT are called the core algorithm.

There are challenges associated with the on-vehicle health monitoring of drive unit's bearings. The bearing fault signature may be buried in frequency content from other components of the vehicle and in particular other components of the drive unit such as other bearings, shafts, and gears. So, it is essential to remove vibrations generated from other components. To remove the vibrations from other components including shafts and gears as well as other bearings (not on the same shaft as the bearing of interest), it is suggested to use discrete frequency removal (DFR) techniques including Autoregressive (AR) Linear prediction, Self-Adaptive Noise Cancellation (SANC), and Time Synchronous Averaging (TSA) (Randall & Antoni, 2011) (Sawalhi N. R., 2005). The SANC method can enhance the visibility of fault by removing the unwanted noise, however it can be sensitive to the choice of parameters and therefore requires careful tunning. The TSA is useful for extracting synchronous components; however, it may not work well if there is significant variation in the repetition rate (Randall R. B., 2011). The AR is considered in this paper due to its ability to capture temporal relationships, adapt to changing patterns, and providing effective fault isolation from noise. AR predicts the deterministic part of a signal (for example signals from shafts and gears in this case) based on a certain number of samples in the past so that this part can be subtracted from the measured signal.

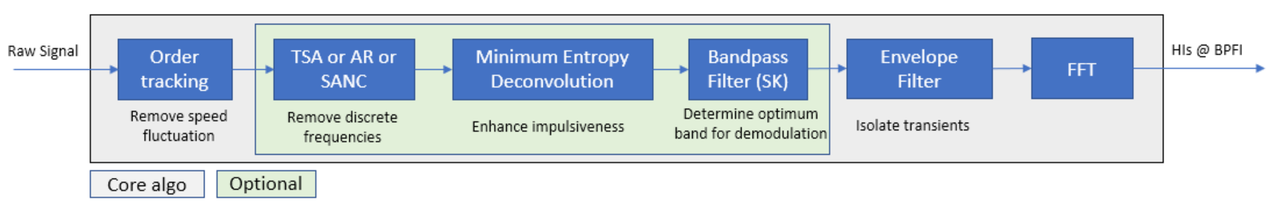

Figure 4. Signal processing steps for bearing fault detection algorithm.

Further to the removal of vibration from other components, it is expected that signal-to-noise ratio (SNR) is lower for on-vehicle health monitoring compared to fault detection using a controlled environment and bench setup and the fault signature might be buried in noise. It is known that pulses originated from the fault are impulsive (Randall & Antoni, 2011). Therefore, enhancing the impulsiveness leads to fault signature enhancement. Two methods are employed here to improve the signal impulsiveness: Minimum entropy deconvolution (MED) and band pass filtering based on the spectral Kurtosis (Wiggins, 1978) (Sawalhi N. R., 2005).

MED is an iterative filter which is automatically tuned to maximize the Kurtosis of a signal. Bandpass filtering finds and isolates the frequency range in which the Kurtosis is maximum. Using these two methods, the impulsiveness and consequently the fault signature can be enhanced. The AR, MED and band pass filtering are considered as the optional steps in this paper.

3. Results

In this section, the mentioned signal processing steps are applied and then compared on the captured vibrations for the injected faults to a ball bearing located on the motor shaft of an EV's drive unit (it is called BB11 in this paper). As the injected faults are at the inner race, peaks at the ball pass frequency inner race (BPFI) are for the faulty bearings.

Firstly, the core signal processing steps are applied (phase domain, envelope filter and FFT) to the vibrations from different fault levels. As an example, Figure 5 shows the vibration spectrum for the severe (2 mm) and mild (0.1 mm) faults at 91 Nm. and 1000 rpm (motor shaft). It is indicated that after applying the envelope filter, peaks can be observed at BPFI harmonics of the bearing with the severe fault. However, for a fault with 0.1 mm size, more advanced processing steps are required as the fault signature cannot be seen in this figure.

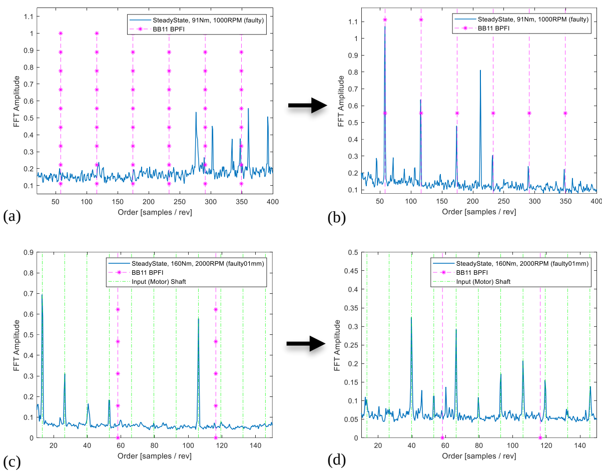

Figure 5. Core processing for severe and mild faults, a) raw spectrum of a faulty bearing (severe) b) spectrum of a faulty bearing (severe) with applying the envelope, c) raw spectrum of a faulty bearing (mild), d) spectrum of a faulty bearing (mild) with applying the envelope.

The impact of optional processing steps on the spectrum of the 0.1 mm fault can be seen for the examples shown in Figure 6 - 8. Figure 6 shows that applying MED enhances fault signature at BPFI while attenuating the other peaks in the spectrum. Adding band pass filtering can add more enhancement to the fault signature compared to other peaks in the spectrum as illustrated in Figure 7. Figure 8 demonstrates that applying AR attenuates the shaft frequency (as a discrete frequency) which also results in the enhancement of the fault signature.

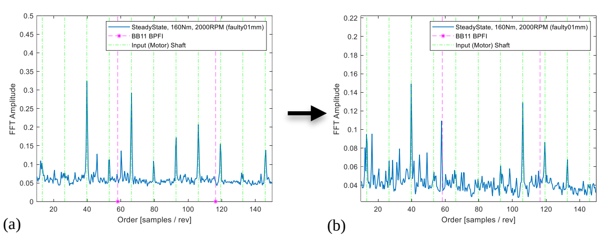

Figure 6. Effect of MED on a mild fault a) spectrum of a faulty bearing with core preprocessing steps, b) spectrum of a faulty bearing with core preprocessing steps and MED

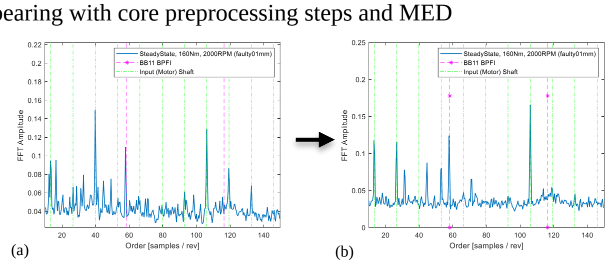

Figure 7. Effect of bandpass filtering on a mild fault a) spectrum of a faulty bearing with core preprocessing steps, b) spectrum of a faulty bearing with core preprocessing steps, MED, and bandpass filtering.

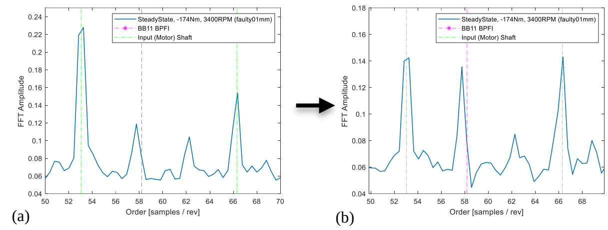

Figure 8. Effect of AR on a mild fault a) spectrum of a faulty bearing with core preprocessing steps, b) spectrum of a faulty bearing with core preprocessing steps, MED, and bandpass filtering.

The suggested signal processing steps in Figure 4 can significantly improve the fault signature. Figure 9 displays the spectrum of the faulty bearing with fault level 2 mm with applying only phase domain and FFT in comparison to phase domain, AR, MED, band pass filter (bpf), envelope and FFT. It is evident that the fault signature, which is the peak at BPFI, is strengthened, and frequency content of other components and noise have been removed.

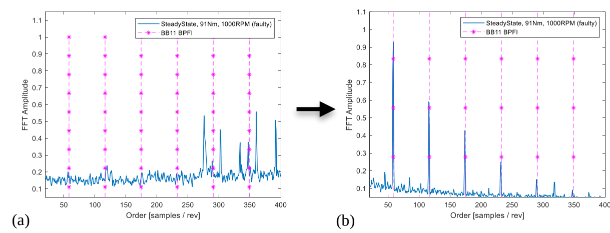

Figure 9. Spectrum of a faulty bearing (severe fault) a) before and b) after applying the suggested preprocessing steps.

The effect of signal processing steps is compared quantitatively after defining and calculating a health indicator (HI). In general, HI extracts the features that are most informative and relevant to health condition monitoring. In the proposed method, a peak height in a small window centered at the first harmonic of the critical frequency (BPFI) is used as the HI for each segment after normalizing by the median of the FFT amplitude of a window centered at BPFI. The selection of window size serves as a calibration parameter. An optimal window size should effectively encompass the critical frequency information while mitigating the interference of unrelated frequencies. Figure 10 visualizes the small and large windows around BPFI that are considered for HI calculation. The introduced HI is defined as,

$$\boldsymbol{HI} = \frac{\textbf{max(FFT amplitudes in a small window centred at the BPFI)}}{\textbf{median (FFT amplitudes in a larger window centred at the BPFI)}} \quad (1)$$

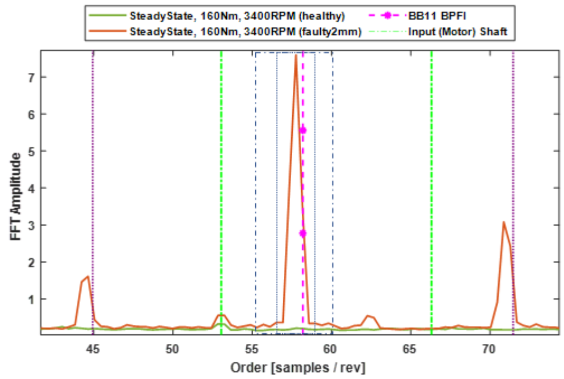

Figure 10. Spectrum of a healthy bearing compared to a faulty bearing together with the window used in HI calculation.

Next, the HI is calculated for all load and speed variations as well as all combinations of the proposed processing steps including the raw signals. As an example, Figure 11 shows the HI values versus load and speed for which AR is applied to the vibration signal in addition to the core preprocessing steps for the healthy and faulty bearings. Figure 12 shows boxplots of the calculated HIs under all conditions for the healthy and faulty bearings using the core processing steps, and AR. Both figures indicate a good separation between healthy and faulty bearing, especially for fault size of 2mm and 0.5mm.

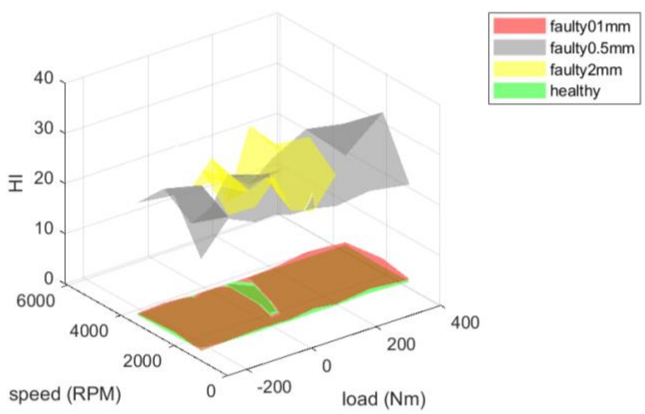

Figure 11. Health indicator values for faulty and healthy bearings as a function of load and speed.

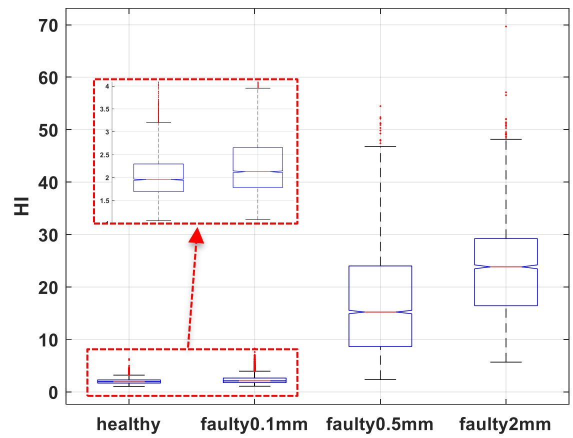

Figure 12. Boxplot of HI values for faulty and healthy bearings under all load and speed conditions.

To improve the fault detection performance, a moving average with the window size of 200 segments is applied to the HIs calculated for each segment. These matured HIs are used for fault detection. The area under the Receiver Operating Characteristic (ROC) curve (True Positive Rate (TPR) versus False Positive Rate (FPR)) is commonly used to evaluate the performance of a fault detection algorithm. This curve is shown for the case presented in Figure 13, where the core processing steps, and AR are applied. The figure illustrates a trade-off between the TPR and FPR, where a curve closer to the top-left corner indicates that the model is capable of achieving higher TPR while keeping the FPR low. The presented curves show that the model outcome for the severe and moderate faults have a high performance. ROC values of 1, 1, and 0.84 are obtained for the separation of the healthy to the severe, moderate and mild faults, respectively.

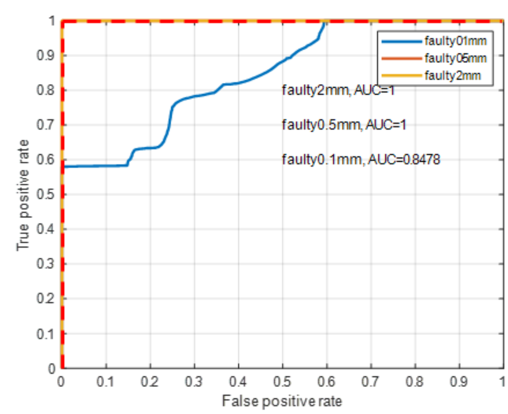

Figure 13. ROC curve for different bearing fault levels after applying the core processing steps and AR.

The ROC calculation is repeated for all combinations of the preprocessing steps. The results are shown in Figure 14. Comparing the results for the core signal processing steps (indicated as HI_raw_env in the figure) to the ones which include optional preprocessing steps shows that optional preprocessing steps can increase the ROC values from 0.40 to 0.84 for the mild fault. It implies that detection of this fault is possible only if the optional processing steps are employed. On the other hand, the increase of 0.99 to 1 in the ROC value for the moderate fault and unchanged value of 1 for the severe fault shows that for moderate to severe faults, the core preprocessing steps might be adequate. It should also be noted that results in Figure 14 confirms that envelope filter offers superior results.

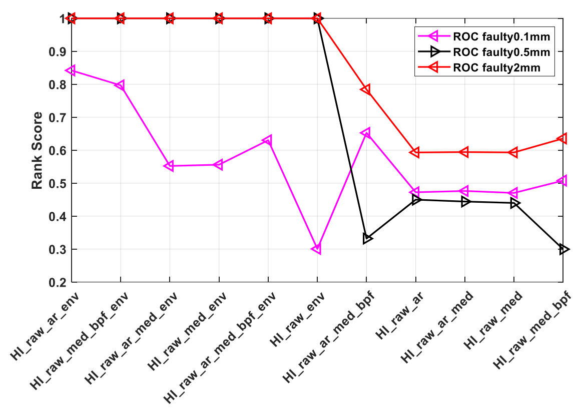

Figure 14. Ranking of preprocessing combinations for the faulty bearings.

4. Conclusion

This paper presents a method that demonstrates an early-stage fault detection capability, thus representing a predictive maintenance approach. The impact of various signal processing techniques on the frequency representation of the vibration signals of faulty bearings is investigated in this paper. A health indicator is then proposed and calculated. ROC values are used as a metric to compare the signal processing steps for classification of healthy and faulty bearings. The results show that although applying only phase domain transform, envelope and Fourier transform might be enough for moderate and severe faults, advanced signal processing including AR, MED, and band pass filtering is needed to enhance the fault signature for early detection of mild faults.

For future work, the estimation of the remaining useful life (RUL) can also be added to the developed health monitoring algorithm as an output. In addition, the presented algorithcan be refined and verified using vehicle-level test data. Further insights on the effectiveness of the presented algorithm can be achieved by expanding the method to other bearing types such as roller bearings.

Acknowledgement

The authors of this paper would like to acknowledge SKF USA Inc. for their contributions and assistance in implementing the fault injection method.

References

Antoni, J. (2006). The spectral kurtosis: a useful tool for characterising non-stationary signals. *Mechanical Systems and Signal Processing, 20*(2), 282-307.

Antoni, J., & Randall, R. B. (2004). Unsupervised noise cancellation for vibration signals: part I—evaluation of adaptive algorithms. *Mechanical Systems and Signal Processing, 18*(1), 89-101.

Darlow, M. S., Badgley, R. H., & Hogg, G. W. (1974). Application of High-Freuqency Resonance Techniques for Bearing Diagnostics in Helicopter Gearboxes. *Army Air Mobility Research and Development Laboratory*, 74-77.

Deloitte University Press. (2016). *Gearing for Change: Preparing for transformation in the automotive ecosystem.* Deloitte University Press.

Garner G, D. S. (2021). Brinell Fault Injection to Enable Development of a Wheel Bearing Fault Monitoring System for Automobiles. *Annual Conference of the PHM Society* .

Garner G, S. P. (2021). Modeling the Business Value of a Predictive Maintenance System using Monte Carlo Simulation. *Annual Conference of the PHM Society.*

Haram MH, L. J. (2021). Feasibility of utilising second life EV batteries: Applications, lifespan, economics, environmental impact, assessment, and challenges. *Alexandria Engineering Journal, 60*(5), 4517-36.

Jafarzadeh, E. L. (2022). Fault injection method and ground-truth state of health development for a low-cost bearing fault monitoring system in the automotive industry. *Annual Conference of the Prognostics and Health Management Society.*

Lybeck N, M. S. (2007). Validating prognostic algorithms: a case study using comprehensive bearing fault data. *2007 IEEE Aerospace Conference* .

Motavalli, J. (2020, 11 12). *Million-Mile Batteries? They're Coming.* (AutoWeek) Retrieved 02 24, 2021, from https://www.autoweek.com/news/a34620676/million-mile-batteries-theyre-coming/

Nabhan A, G. N. (2015). bearing fault detection techniques - a review. *Turkish Journal of Engineering, Science and Technology, 3*(2), 1-8.

P, W. (2019). Charger collaborations power global electric vehicle expansion. *Engineering, 5*(6), 991-2.

Pan S, F. L. (2021). Shared use of electric autonomous vehicles: Air quality and health impacts of future mobility in the United States. *Renewable and Sustainable Energy Reviews*.

Park J, K. S. (2021). Frequency energy shift method for bearing fault prognosis using microphone sensor. *Mechanical Systems and Signal Processing, 147*.

Randall, R. B. (2011). A comparison of methods for separation of deterministic and random signals. (pp. 11-19). International Journal of Condition Monitoring.

Randall, R. B., & Antoni, J. (2011). Rolling element bearing diagnostics - A tutorial. *Mechanical Systems and Signal Processing, 25*, 485-520.

Rao SS, T. M. (1994). Reliability-based design of automotive transmission systems. *Reliability Engineering & System Safety, 46*(2), 159-69.

Sawalhi, N. R. (2005). Spectral kurtosis optimization for rolling element bearings. *Proceedings of the Eighth International Symposium on Signal Processing and Its Applications*. Sydney, NSW, Australia: IEEE.

Sawalhi, N., Randall, R. B., & Endo, H. (2007). The enhancement of fault detection and diagnosis in rolling element bearings using minimum entropy deconvolution combined with spectral kurtosis. *Mechanical Systems and Signal Processing, 21*(6), 2616-2633.

Simmons, R. (1997, August). *Calculating G-RMS*. (NASA) Retrieved April 2020

SKF. (2014). *Bearing damage and failure analysis.* SKF Explorer.

Smith WA, R. R. (2015). Rolling element bearing diagnostics using the Case Western Reserve University data: A benchmark study. *Mechanical systems and signal processing, 1*(64), 100-31.

Sutherlin, R. G. (2017). Wheel Bearing Brinelling and a Vehicle Curb Impact DOE to Understand Factors Affecting Bearing Loads. *SAE International*.

Tandon, N. ,. (1999). A review of vibration and acoustic measurement methods for the detection of defects in rolling element bearings. *Tribology International 32*, 469–480.

Upadhyay RK, K. L. (2013). Rolling element bearing failure analysis: A case study. *Case studies in engineering failure analysis, 1*(1), 15-7.

Wiggins, R. A. (1978). Minimum entropy deconvolution. *Geoexploration*, 21-35.

Ehsan Jafarzadeh received his Ph.D. in Mechanical Engineering from the University of Toronto, Canada in 2020. His Ph.D. thesis focused on signal processing in ultrasound imaging. During his Ph.D., he worked closely with R&D of FUJIFILM VisualSonics Inc., a world leader in high frequency ultrasound imaging. After his Ph.D., he joined Sunnybrook Research Institute (SRI) and led a research team to develop a system and software for ultrafast ultrasound imaging. He joined General Motors in 2021, where he develops prognostics algorithms for electric vehicles.

Sara Rahimifard received her Ph.D. in Mechanical Engineering from McMaster University, Canada, in 2022, M.Sc. degree in electrical engineering from Amirkabir University of Technology, and B.Sc. degree in electrical engineering from Shiraz University, Iran. She is now working at General Motors, Canadian Technical Center, Markham, ON, where she develops prognostics algorithms for electric vehicles.

Paola Santanna works at General Motors, where she is a Global Technical Specialist Gears/Shafts Power Transfer.

Yu Cao received his Ph.D. degree in mechanical engineering from University of Saskatchewan, Canada, and M.Sc. and B.Sc. degrees in automotive engineering from Jilin University, China. He has been working at General Motors, Canadian Technical Center, Oshawa, ON, since 2016, and currently the senior advance technology engineer in Chassis. Before joining GM, he had different positions in mechatronics industries. His research interests include vehicle dynamics, control algorithm development and mechatronic system design. He has published several papers in the top-ranking journals in mechatronics.

Frances Tenney received her B.Sc. degree in Mechatronics Engineering from the University of Waterloo in 2022. She is now working at General Motors, Canadian Technical Center, Oshawa, ON, where she develops advanced technology chassis projects and supports the development of prognostics algorithms for electric vehicles.

Hossein Sadjadi received his Ph.D. degree in electrical engineering from Queen’s University, Canada, and M.Sc. degree in mechatronics and B.Sc. degree in electrical engineering from the American University of Sharjah, UAE. He has been working at General Motors, Canadian Technical Center, Markham, ON, since 2017, and is currently the Global Technical Specialist for Vehicle Health Management. He also has served as a postdoctoral medical robotic researcher at Queen’s university, senior automation engineer for industrial Siemens SCADA/DCS solutions, and senior mechatronics specialist at AUS mechatronics center. His research interests include autonomous systems and medical robotics. He has published numerous patents and articles in these areas, featured at IEEE transactions journals, and received several awards.