Fault injection method and ground-truth state of health development for a low-cost bearing fault monitoring system in the automotive industry

Ehsan Jafarzadeh[1], Dezhi Li[1], Sara Rahimifard[1], Paola Sant Anna[3], Yu Cao[2], , Hossein Sadjadi[1]
[1]*General Motors Technical Center, Markham, ON, L3R 4H8, Canada*
ehsan.jafarzadeh@gm.com
dezhi.li@gm.com
sarasadat.rahimifard@gm.com
hossein.sadjadi@gm.com
[2]*General Motors ATW Technology, Oshawa, ON, L1J 1N6, Canada*
yu.cao@gm.com
[3]*General Motors Global Technical Center - Cole Engineering Center, Warren, MI, 48092, US*
paola.santanna@gm.com

ABSTRACT

Bearing condition monitoring is a widely studied field, but applications to the automotive industry have received little attention as the bearing failure rates are typically low in traditional internal combustion engine vehicles with 200 – 300k mile lifespans. The rapid advancement of electric and autonomous vehicles enables vehicles with million-mile lifespans. This implies that the reliable life of existing bearing designs is exceeded throughout the vehicle life, which can potentially lead to vehicle failure. To enable the development of a bearing fault detection and prognostics system, healthy and faulty bearing data must be collected, and the ground-truth states of the health of bearings need to be determined for algorithm refinement and validation. This work explores the fault injecting options, and ground-truthing together with their limitations. Two methods based on precision machining and seeded spalling are developed and used to inject inner race faults in a ball bearing. A non-invasive ground-truthing method is proposed to quantify the state of health of the fault injected bearings in which bench test data is collected under various speed and load conditions. The vibration signals from the bench tests are used to calculate the root-square of the area under the acceleration Power Spectral Density curve (known as GRMS) for each speed and load condition. To remove the dependency of the results on load and speed conditions, a speed-load-GRMS plot is generated, and a plane is fitted to the data for each fault level. Next, the volume under the plot is calculated, yielding a single cumulative GRMS value for each fault level. This value is used as the ground-truth health of bearing for each fault level. For the bearing with the faults injected using precision machining fault injection, the obtained ground-truth values are 1.56, 3.68, and 4.36 times larger than the same figure for the healthy bearing for the faults with the widths of 0.1 mm, 0.5 mm, and 2 mm, respectively. The observed correlation between the fault sizes and the calculated ground-truth values validates the proposed method which can provide a good separation among different health states of a bearing.

1. INTRODUCTION AND BACKGROUND

1.1. Introduction

Bearing failure is known as one of the most frequent reasons for machine breakdown (Randall & Antoni, 2011). In industries such as manufacturing and power generation, powerful bearing fault diagnosis methods have been established to detect bearing failure at the incipient stage and avoid costly downtime (Nabhan, Ghazaly, Samy, and Mousa, 2015). However, in the automotive industry, bearing failure has not been widely studied. For Internal Combustion Engine (ICE) powered vehicles, bearings are designed so that their lifespan exceeds the vehicle's life (Garner, Drame, Du, and Sadjadi, 2021). Therefore, low bearing failure rates have been reported in these vehicles (Garner et al., 2021) (Rao & Tjandra, 1994). Even in the case of bearings failure, it is expected that the driver can notice an unusual noise and the fault can be detected before it becomes safety critical. Due to the lack of business cases, bearing health monitoring has received little attention in the ICE-powered vehicle industry.

Electric Vehicles (EVs) are expected to dominate the vehicle market soon as leading vehicle manufacturers such as General Motors (GM), Volkswagen, Honda, Ford, Volvo, and Nissan have announced that they will either manufacture Electric Vehicles (EVs) only or in significantly larger number than ICE soon (Weiss, 2021). Global regulations aiming to limit CO2 emissions, the rapid growth of charging infrastructure, technological advancements, and falling prices are accelerating this process (Weiss, 2019). It is estimated that there will be 85 million EVs on the roads by 2030 (Haram, Lee, Ramasamy, Ngu, Thiagarajah, & Lee, 2021).

Electric Autonomous Vehicles (EAVs) are also emerging quickly in the automotive industry due to the rapid decline in costs of some key components such as light detection and ranging (LiDAR) (Pan, Fulton, Roy, Jung, Choi, and Gao, 2021). (The Deloitte University Press, 2016) boldly predicted that EAVs may account for half of the new vehicle sales by 2040. Most of the EAV market will be taken by autonomous taxi fleets soon as companies such as Cruise, Waymo, and Zoox are now investing in such developments.

The rapid advancements in battery technology are enabling EVs and EAVs with million-mile lifespans (Motavalli, 2020). This implies that the reliable life of existing bearing designs is exceeded throughout the vehicle life (Garner, Santanna, and Sadjadi, 2021), and the likelihood of a bearing failure (and potentially a vehicle failure because of that) increases drastically in EVs compared to ICE vehicles in case the bearings are not redesigned. For autonomous taxi fleets, it is expected that the bearing failure rate would be even higher than EVs because of the following reason: In these vehicles, in addition to exceeding the bearing reliable lifespan associated with EVs, the bearing failures that could be detectable by a human driver are not avoidable as the passengers are unfamiliar with the vehicle and any possible usual sounds.

Replacing the bearings on a fixed schedule to maintain reliability can be considered the simplest solution to the above-mentioned problems. However, it wouldn't be cost-effective (Garner, Santanna, and Sadjadi, 2021), especially for EAV fleet companies. Instead, an automated bearing health monitoring system can be developed to detect and isolate bearing faults. The development of such a system can extend bearings' reliable range, reduce the maintenance cost, and mitigate safety concerns.

1.2. Background: Bearing Fault Detection

As the roller elements pass a local fault on the outer or inner race of a bearing, broadband vibration bursts are excited (Smith & Randall, 2015). The frequencies at which these vibration bursts occur (called bearing critical frequencies) can be calculated under a no-slip assumption for inner race and outer race faults using the formulas provided in (Randall & Antoni, 2011). Experimental variations of 1-2% from the ideal critical frequency formulas are expected (Randall & Antoni, 2011). Most bearing condition monitoring algorithms consume the signals of an accelerometer to capture those vibrations. If a peak at critical frequencies (known as fault signature) is found in the vibration spectrum, the bearing is detected as faulty (Randall & Antoni, 2011).

In the literature, various signal processing techniques have been studied to enhance the fault signature and reduce background noise, such as the envelope spectrum (Darlow, Badgley, and Hogg, 1974), bandpass filtering based on spectral kurtosis (SK) (Antoni, 2006), unsupervised noise cancellation (Antoni & Randall, 2004) and minimum entropy deconvolution (Sawalhi, Randall, and Endo, 2007). A detailed review of these techniques is available in (Randall & Antoni, 2011).

In (Garner, Santanna, and Sadjadi, 2021), it was concluded that the current simulation capabilities are not sufficient for developing a high-fidelity bearing fault detection algorithm in the automotive industry. Bench test data can be used to develop the algorithm, and vehicle data is required for refinement and verification. To enable bench test and vehicle data collection, bearings with various health states must be available. Therefore, a bearing fault injection method must be developed and implemented. Then, the state of health must be quantified.

This paper, which is the first in a series of research efforts to develop a fault detection algorithm for automotive bearings, lays the groundwork for developing an automated bearing fault detection system. Section 2 investigates the bearing failure modes in the automotive industry, proposes two fault injection methods to create faults similar to those from fatigue failure, and outlines the pros and cons of the proposed methods. Section 3 develops a method to quantify the ground-truth health state of a bearing and presents the results.

2. Bearing Failure Modes and Fault Injection

2.1. Bearing Failure Modes in Automotive Industry

Based on ISO 15243, there are 14 bearing failure modes in general. These failure modes are mainly categorized into fatigue, wear, fracture and cracking, corrosion, electrical erosion, and plastic deformation. Each mode can be divided into sub-modes: Fatigue includes subsurface and surface-initiated fatigue. There could be two sorts of wear such as adhesive and abrasive. Fracture and cracking can be divided into three sub-modes referred as forced and fatigue fracture and thermal cracking. Moisture and frictional are two kinds of corrosion where the latest one is divided into sub-modes including fretting corrosion and false brinelling. Electrical erosion is classified into excessive current erosion and current leakage erosion. The latest failure mode is categorized into overload deformation and indentation from debris (SKF, 2014). A detailed description of these failure modes is provided in (SKF, 2014).

Here, the most common failure modes in the automotive industry are classified into three main categories: contamination ingress, brinelling failure, and fatigue.

At high mileages, bearing sealing may become damaged. A damaged seal will allow water and contaminant ingress into the bearing. When water penetrates a bearing's seal, either through splashing or submergence, it can degrade the lubrication and lead to corrosion of the bearing raceways and rolling elements. When contaminants in the form of hard particles enter the bearing, the rolling elements over-roll the particles, which creates indentations in the raceways, especially when the particles have sharp edges.

Bearing brinelling occurs when the bearing experiences a heavy impact load, usually because of abuse events such as striking a curb or pothole and vehicle collision. This heavy stress can result in permanent indentations, known as Brinell marks, on the bearing raceway. In (Garner, Santanna, and Sadjadi, 2021), a fault injection method was developed to create bearing faults similar to those developed in a real scenario of a vehicle striking a curb or pothole. That required a fault injection mechanism that resembles the forces of a curb strike. They proposed a static load test fault injection method to stress the bearings and generate Brinell dents.

Indentation due to contaminant ingress or brinelling can lead to fatigue failure. The area around the indentation is subject to cyclic stress due to normal over-rolling by the rolling elements. Due to this cyclic stress, surface fatigue is initiated, and the metal will start to break away from the raceway, which is called spalling. Spalling damage can propagate until the bearing fails, which can even create safety concerns (SKF, 2014) (Upadhyay, Kumaraswamidhas, and Azam, 2013). Therefore, spalling damage due to fatigue failure can be considered as a crucial failure mode which should be detected by employing bearing health monitoring systems before the faulty bearing degrades significantly. The focus of this paper is on fatigue bearing failure.

2.2. Bearing Fault Injection Methods

In this section, two fault injection methods (seeded spalling, and precision machining) are proposed to create faults similar to spalling. The pros and cons of the proposed methods are also presented.

2.2.1. Seeded spalling

First, a small indent is created on the inner/outer raceway. Brinell dent fault injection method introduced in (Garner, Santanna, and Sadjadi, 2021) can be used to apply a heavy load on the bearing and create this indent. Alternatively, the load can be directly applied to a rolling element (as shown in Figure 1a) and pressed to the inner/outer raceway until the dent with the desired dimension is created. The latter approach is used and a dent is created with a diameter of 0.175 mm on the inner race of a ball bearing, which is shown in Figure 1b.

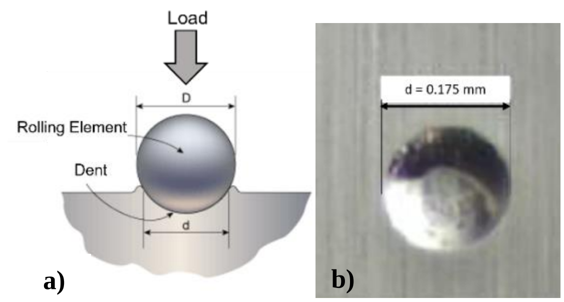

Figure 1. (a) Schematic of the indent creation process (b) The created indent on the inner race of a ball bearing.

After the fault is injected, the bearing is assembled and installed on a bearing bench test setup with a schematic shown in Figure 2. The bearing is run under load continuously so that the rolling elements can over-roll the injected defect in the previous step, the fault can propagate due to this cyclic load, and vibrations are generated. An accelerometer is attached to the setup and the vibration level is monitored using a computer connected to the accelerometer. As soon as the vibration reaches a certain level, the test is stopped, and the faulty bearing with a spalling defect is ready to use for algorithm development/ refinement or validation. The threshold can be selected as a certain ratio of root mean square (RMS) of the vibrations in the time domain for the faulty bearing to the same figure for a healthy bearing. More severe spalling faults can be injected if a higher threshold is set.

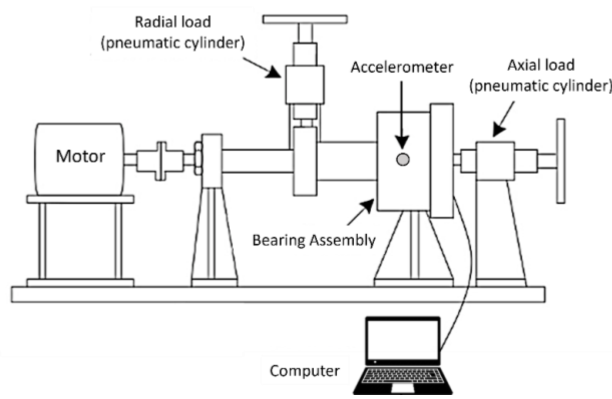

Figure 2. Schematic of a bearing bench test setup.

Figure 3a shows a ball bearing for which the spalling fault was injected into its inner race using the proposed method. It started from the 0.175 mm dent shown in Figure 1b, the vibrations increased as the fault progressed and reached to 1.6g (g=9.8 m/s^2) after about 240 hours of running the bearing on the bench test. It yielded a spalling fault with a width of 6 mm shown in Figure 3b.

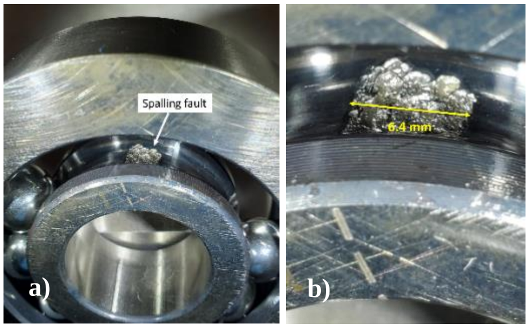

Figure 3. (a) A faulty ball bearing after implementing the proposed seeded spalling method, (b) Spalling defect created on the inner race of a faulty bearing.

The main advantage of this method is that it is very realistic as a similar process happens for dent creation and spalling propagation in the vehicle. However, the method is time-consuming and might need a few hours to a few days of running depending on the severity of the desired fault. Therefore, it can be considered a relatively expensive method. Also, the fault size, shape, and location are difficult to control. Therefore, it is almost impossible to replicate the fault injection. In addition, in case the fault dimensions need to be measured, the bearing is required to be disassembled and assembled again, which can damage the bearing. These advantages and disadvantages are listed in Table 1.

Table 1. Comparison between proposed methods for spalling fault injection.

	Seeded Spalling	Precision Machining
Realistic	High	Low
Control of the fault size	Moderate	High
Control of the fault shape	Low	High
Control of the fault location	Moderate	High
Difficulty in measuring the fault size	Moderate	Low
Time	Very High	low
Cost	High	moderate

2.2.2. Precision machining

In this method, a machine tool is used to create the fault. Figure 4a shows the experimental setup used to inject the fault. As can be seen in this figure, the bearing is placed in the chuck of a lathe spindle, a motion controller can move the cutting tool mounted on the tool holder, and the fault can be machined on the bearing. In this method, the bearing requires to be disassembled for fault injection (Figure 4b shows a fault being injected into the inner race of a bearing). After fault injection, the bearing is assembled. The size and shape of the cutting tool can be selected based on the shape and size of the defect. The tool shown in Figure 4c is used in this paper. Figure 4d shows an example of an injected fault using this method and this tool under a microscope. As can be seen in this figure, the injected fault is similar to a spalling defect in terms of the appearance although it is different from a spalling in its essence.

The disadvantage of this method is that a fault similar to Figure 4d might be considered too neat to replicate the damage in the real application. However, using this method, we can control the size, location, and shape of the defect. Also, we can ensure that the defect covers the entire width of the race so that contact between the rolling elements and the fault will be guaranteed. In this method, the injected fault can be measured after the fault injection, the fault injection process is quick and consequently cost-effective. These advantages and disadvantages are listed in Table 1 and compared to the seeded spalling method.

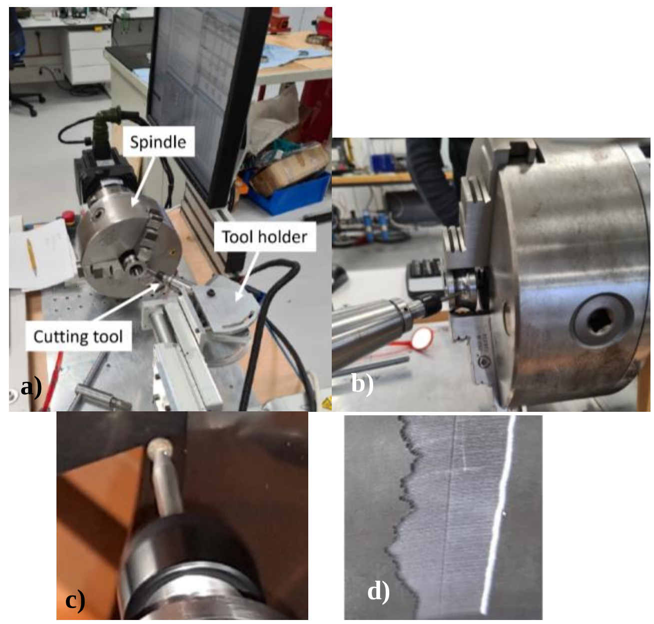

Figure 4. (a) Experimental setup used for fault injection using the precision machining method. (b) A fault is injected into the inner race of a bearing. (c) The used cutting tool. (d) An example of the injected fault under a microscope.

This method is used to inject 0.1, 0.5-, and 2-mm faults into the inner race of a ball bearing. The faults are shown in Figure 5 before re-assembling the bearing. Figure 6 shows the ball bearing for which the 2 mm fault is injected after assembly.

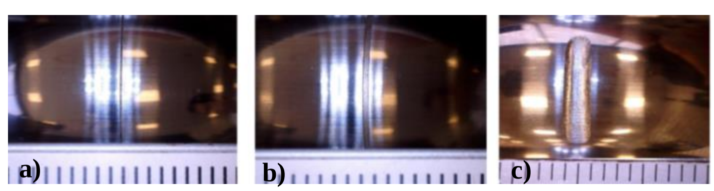

Figure 5. Injected faults on the inner race of a ball bearing with the width of (a) 0.1 mm, (b) 0.5 mm and (c) 2 mm.

Figure 6. Injected fault using the precision machining method into the inner race of a ball bearing.

3. The Ground-truth State of Health

3.1. Method

To use the fault injected bearings for fault detection algorithm development, refinement, or verification, the injected faults must be quantified, and the ground-truth state of health of each experimental bearing must be known. The simplest method for this ground-truthing is to measure the dimensions of the defect and use it to quantify the defect. For fatigue failure, in (Lybeck, Marble, and Morton, 2007), spall length was used as the ground truth and a good correlation was found between the spall length and severity of the fault. The benefit of this method is that it directly quantifies the physical damage to the bearing. However, this method has two major drawbacks: 1- Measuring the defect size requires disassembling the bearing. In many cases, it damages the bearing. 2- Dimension measurement is difficult and might be inaccurate for spalling defects as they are usually small with irregular shapes. Also, considering only one dimension (spall length) may be a poor metric of the overall bearing state of health as the effect of other dimensions (spall width, and spall depth) are ignored. Therefore, a more comprehensive metric which includes the effect of all contributing factors is required to characterize the state of health of the defect.

An alternative approach for ground-truthing is to quantify the effect of the physical damage instead of measuring it directly. Noise (sound) and vibrations are considered as two main effects of the bearing faults (Park, Kim, Choi, and Lee, 2021). However, noise can be easily contaminated with environmental noise. It is noted that the algorithm should be ideally developed based on the vehicle data to incorporate various noise factors while the ground truth is to quantify the state of health of a component, and it is better to be developed in a controlled environment such as bench tests. Moreover, a different approach to the main fault detection algorithm requires to be used for ground truthing. Otherwise, it cannot be used to evaluate or validate the performance of the developed algorithm. As mentioned in section 1.2, most of the bearing fault detection algorithms are based on the fault signature (peak at critical frequencies) in the frequency domain of the vibrations.

In the proposed method of this paper, a test bench with an accelerometer (similar to the one shown in Figure 2) is used to capture the bearing vibrations under various load and rotational speed combinations. It is noted that torque load is calculated from the axial and radial loads and used as one single load value in the N.m unit. For each load- speed combination, the Power Spectral Density (PSD) of the acceleration signals is found. The frequency range of interest is identified, and then, the area under the PSD vs. frequency curve is calculated for the specified interval. The root-square of this area is referred as GRMS (Sutherlin, 2017) (Simmons, 1997). From these individual measurements and calculation, the speed-load-log (GRMS) curve is plotted, and a plane is fitted to each fault level data. Log operation is used to compress the values for ease of visualization. Then, the overall bearing health ground-truth is calculated as the volume under the speed-load-log(GRMS) fitted plane. The proposed method can be considered a robust method as it uses a wide range of load and speed so that it addresses the challenge of the dependence of bearing vibration on rotational speed and load. The detrimental effect of outliers is also greatly reduced by fitting a plane to the speed-load-GRMS results.

To implement the proposed method, the vibrations of the healthy and three faulty bearings described in section 2.2 were recorded for 10 seconds over a wide range of torque load and speed. The speed and torque ranges considered in this study are 1000 rpm <speed<6100 rpm and $21\ N.m < torque\ load < 390\ N.m$, respectively. Considering 7 levels of speed and 9 levels of torque load in the specified range, 17 test cases have been considered to test the healthy and three severity levels of fault. These 68 generated test cases are then used to validate the proposed method in this paper. The GRMS is then calculated in the frequency range between $1/10$ ball pass frequency inner race (BPFI) and the $10th$ BPFI.

3.2. Results

In this section, the proposed method is implemented for the precision machined fault injected bearings as the defect dimensions can be controlled and measured. This allows a comparison of the results with the actual width of the defects for validation. The validated method proposed in this paper, then can be used to quantify the state of health for any bearings with fatigue failure including seeded spalling without measuring the physical damage.

Figure 7a. shows 1 second of the vibrations for the fault levels of 0.1, 0.5, and 2 mm in the time domain under the nominal speed of 3400 rpm and the torque load of 91 N.m. Figure 7b. shows the PSD of these vibrations. The GRMS is calculated using the area under this figure. GRMS values of 1.97 was obtained for the healthy bearing, and 3.81, 18.95, and 37.22 m/s^2 were calculated for the faulty bearings with the fault levels of 0.1, 0.5 and 2 mm, respectively. A well-known health indicator known as BPFI peak is commonly considered for fault detection algorithm. Here, this fault signature (BPFI) and its higher-order harmonics can be seen clearly, especially for the 0.5- and 2-mm defects, if an envelope is applied before the frequency domain transform (shown in Figure 7c.). The developed ground-truth method can be used to evaluate fault detection algorithms including BPFI based method.

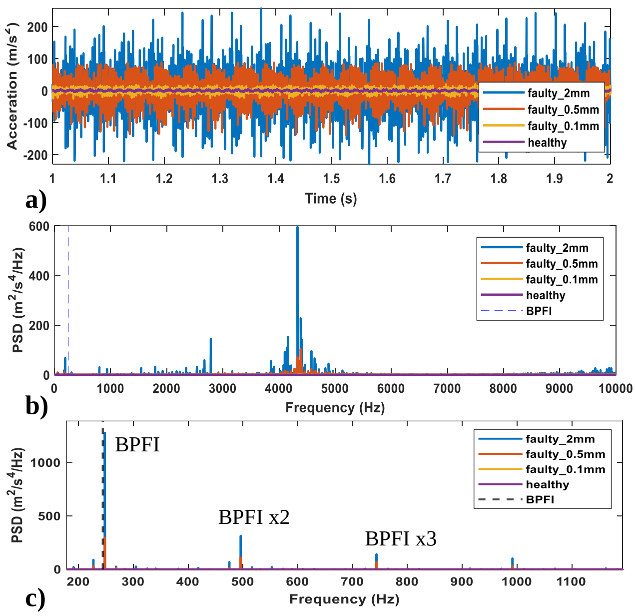

Figure 7. vibrations for the fault levels of 0.1, 0.5, and 2 mm under the nominal speed of 3400 rpm and torque load of 91 N.m in the (a) time-domain (b) frequency domain (c) frequency domain after applying an envelope.

Next, GRMS values are calculated for all load-speed combinations, shown in Figure 8a. To reduce the effect of outliers, a plane is fitted to the G-RMS results shown in figure 8b.

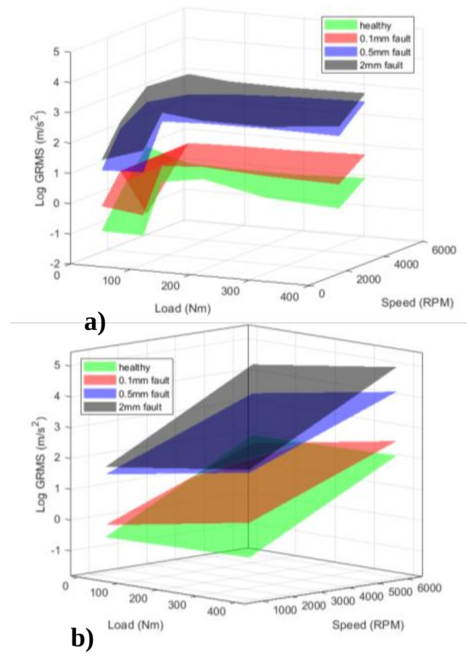

Figure 8. Calculated GRMS values for bearings with different fault levels under various load and speed conditions (a) before fitting a plane, (b) after fitting a plane.

Then, the volume under these planes is calculated and listed in table 2. As can be seen in this table, a good separation between healthy, and faulty results has been achived using the proposed method. These values (or the ratio of them to the same figure for the healthy bearing) can be used as the ground truth to quantify the state of health of the bearing in the bearing fault detection algorithm development, and refinement of validation.

Table 2. Ground-truth values obtained for the bearings with injected fault using the precision machining method.

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

4. CONCLUSION

This paper outlined two approaches to injecting spalling faults into automotive bearings: precision machining and seeded spalling. It was concluded that seeded spalling creates more realistic defects while it is almost impossible to replicate a fault. On the other hand, precision machining can be used when the ability to control the fault size, location, and shape as well as price are important factors. A method was also proposed to quantify the state of health of the fault injected bearings, which is a key step for fault detection algorithm development, refinement, and validation. In the proposed method, vibrations from bench tests are used to calculate the GRMS values. To remove the dependency of the results on load and speed conditions as well as any possible outliers, a speed-load-GRMS plot is generated, a plane is fitted to the data for each fault level and the volume under the plot is used as the ground truth. A good separation between healthy, and faulty results was achieved using this ground-truthing method.

From this point, the following steps are required to develop an algorithm:

- Collect vehicle-level test data with both healthy and faulty bearings.
- Develop a fault injection algorithm based on the vibration signals in the frequency domain.
- Assess the proposed fault detection algorithm for performance and robustness to noise factors using the ground truth.
- Validate the fault detection algorithm on a set of bearings that were not used in development.

These steps, the results of the development effort will be the subject of future publications in our work group. Also, other bearing types (e.g., roller bearing) can be used to study the ground-truthing candidates in the future.

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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 also served as a design league judge, award committee member and scholar reviewer at the University of Toronto, and SRI. He is now working at the Canadian Technical Center of General Motors, where he develops prognostics algorithms for electric vehicles.

Dezhi Li received his Ph.D. in Mechanical & Mechatronics Engineering from the University of Waterloo, Canada in 2015. He served as a mechatronics engineer at Magna Powertrain Inc., development engineer and CAE analyst at Litens Automotive Inc. He is now working at the Canadian Technical Center of General Motors, where he develops prognostics algorithms for vehicle hardware. His research interests include signal processing, machine learning, and artificial intelligence for automotive applications.

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 design release engineer for gears and shafts.

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.

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.