DETECTION OF LUBRICATION STARVATION IN BALL BEARINGS AND PRELOAD EFFECTS.

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Abstract: Detection of lubricant starvation in ball bearings is essential to maximize their lifetime. The lack of lubrication introduces impulses in the vibration signal related to fundamental train and ball spin frequencies. The phenomenon is attributed to the lack of a damping to dissipate the impacts of the balls when entering to the load zone together with the gap increase between bearing components, previously filled by lubricant. This work presents an experimental vibration analysis to study the effect of preload as a mean to decrease the extra clearance in dry conditions and eliminate the source of impulses that characterize lubrication starvation. Furthermore comparison between RMS, Crest Factor and Kurtosis reveals that an increase in preload indeed reduces the signal impulsivity and kurtosis proves to be an effective method to detect lubricant starvation. Finally, the application of fast-kurtogram algorithm is used as a pre-processing method to improve the performance of kurtosis in detecting of lubrication starvation.

Key words: Ball bearing; crest factor; fast-kurtogram; kurtosis; lubrication starvation, RMS.

Introduction: Bearings is the most common failure mode for electric motors and pumps [1], therefore condition monitoring of ball bearings is fundamental for good preventive maintenance program for these type of systems. Bearing lifetime has increased with the advanced manufacturing technologies, but eventually all bearings fail due to fatigue which cause spalling on the surfaces in contact [2]. Current technology can detect the initial stages of spalling months in advance, but most bearings have premature failures due to improper lubrication (contaminants, starvation, and wrong selection) [3] and 90% never reach their expected lifetime [4]. The early detection and diagnosis of improper lubrication could maximize bearing lifetime and avoid downtime problems. The benefits of lubrication are not only to decrease friction between components but also to dissipate high temperatures, avoid corrosion and prevent contamination with foreign debris. Additionally, the lubricant could be modeled as a spring-damper system for vibration analysis, this was studied by Wijnant et al. [5].

The process of condition monitoring is classified by some authors in three stages [6], the first stage is to detect the presence of a fault in the system (fault detection or screening). Based on the impulsive nature of bearing faults, some of the most common screening indicators are Crest Factor (CF), high frequency RMS, and Kurtosis [7]. Pachaud [8] shows that kurtosis is a more sensitive indicator than crest factor but also is highly sensitive to noise, which requires a pre-treating process. Once a fault has been found, the next stage is to determine the cause of the fault (fault diagnosis), in this stage is important to isolate the signal of interest and relate it to a known characteristic fault signature. Diagnosis of ball bearing faults is mainly based on the characteristic signatures for bearings presented by Tandon and Choudhury [9]. These signatures are used to identify mainly localized cracks or spalls in the raceways, rollers, or defects in the cage. The finally stage, called prognosis, is to predict the time of failure of the specific damaged component or system.

Efforts have been made to address the problem of lubrication starvation. Singh and Kazzas [10] found an increase of RMS value of wavelet components related to dry bearing conditions proving that it is possible to isolate the frequencies associated with lubrication starvation. Using a more complex analysis, Boškoski et al. [11], found an increment in ball spin (BSF) and fundamental cage frequencies (FTF) by using spectral coherence analysis and fast-kurtogram to identify the frequency band affected by impacts, and envelope analysis to the selected band. Boškoski proposed that fault signature on FTF and BSF is caused due the lack of movement restriction of the cage, created by the absence of lubricant filling the gaps between components.

Besides the use of lubricant, one method to reduce clearance of bearing components is to apply a certain preload. Based on the experimental results of Tallian and Gustafsson, that proves ball pass frequency (BPF) amplitude is proportional to clearance, Akturk et al. [12] studied the effect of different preload on ball bearings and results showed the BPF could be reduced by selecting an adequate preload. The disadvantage of increasing preload is the friction increase and consequently the temperature rises, which is an accelerating factor for bearing degradation [13], [14].

In this work a preload was applied to bearings in dry conditions in order to reduce the impulsivity of the signal based on the hypothesis that extra clearance and gap between the cage and bearing balls are the cause of the characteristic signature of lubrication starvation. Besides the preload test, experiments with minimum levels of lubrication (5%) were done to determine a detection methodology useful not only for dry conditions, but for minimum level of lubrications. Kurtosis, CF, and RMS indicators performance were compared for each experiment to assess advantages and disadvantages of lubrication starvation indicators. The algorithm of fast-kurtogram was used to identify the band frequency most affected by the impacts. The band frequency was filtered to improve the performance of kurtosis indicator.

Experimental Setup: The test bench is shown in
Figure 1. The bearings used for the experiments are the standard series 6204-2RS-10. Bearing #2 is used for all experiments since it shows lower frequency perturbations from the variable frequency drive (VFD) and motor than bearing #1. The signal is sampled at 60

kHz, analog filtered at 20 kHz, and acquired for 4 seconds to achieve a frequency resolution (d) of 0.25. The rotational speed was set at 1680 rpm. A triaxial accelerometer is used but only the Y-Axis is acquired. To measure the shaft-speed a torque meter with a speed analog output is used.

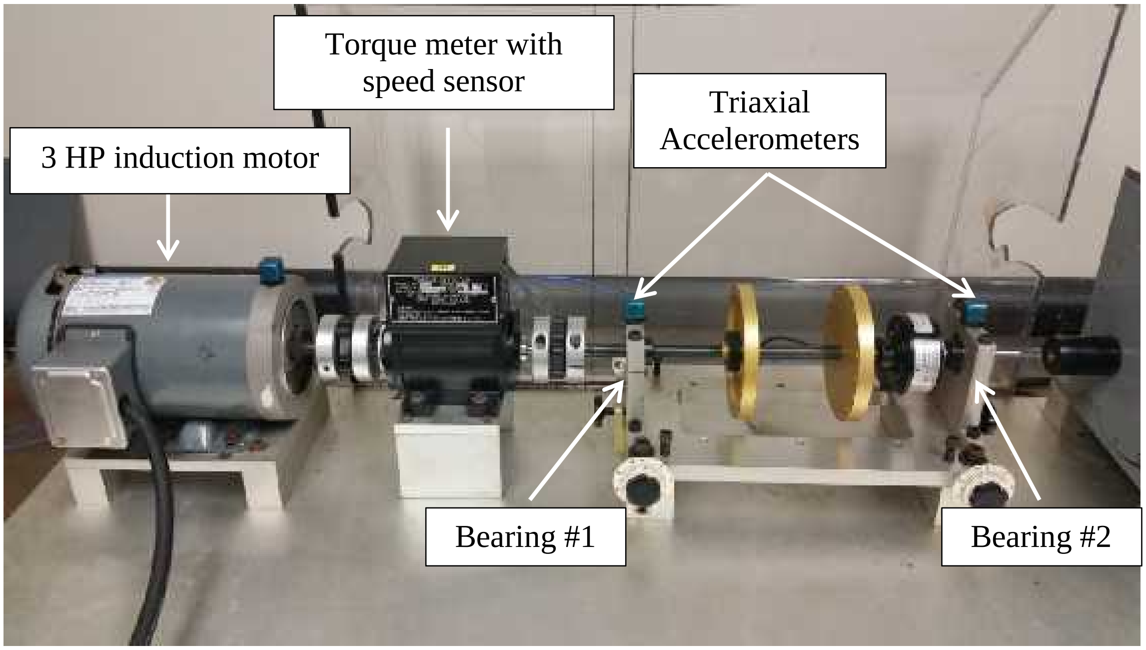

Figure 1: Test Bench Used for Experimentation.

A total of six experiments were conducted and each experiment consisted of four tests on a new bearing. The first test was realized under dry conditions, a careful and systematic procedure was done during the preparation of the bearings; mineral spirit was used to remove the lubricant and completely clean the bearings, special attention was made to avoid any foreign particles from entering the bearing and affecting the experiments. The bearing was temperature-mounted on the shaft. To mount the rotor on the bearing housings all screws were tightened to 15 lb-ft with the objective to control the preload on all tests.

Once the test with dry conditions was completed, the test was repeated but with a preloaded bearing, the preload was increased by reducing the housing diameter using a shim of .001". For the final two tests, the shim was removed from the bearing and two levels of lubricant were tested (5% level and 100%) to evaluate the efficiency of the methods on detecting dry, low, and fully lubricated conditions. Grease LGMT/2 was added to the bearing using a syringe, distributing even quantities around all rollers. The total amount of grease (1.2 g) was determined previously by weighting five bearings before and after removing the lubricant.

The machine was warmed up for two minutes before starting to acquire data, and ten continuous acquisitions were taken for each test. In all analysis, a 95% confidence interval was used to obtain the uncertainty of the ten measurements. All acquired signals were processed with a digital filter to remove a VFD perturbation at 15 kHz and band-passed between 1 kHz to 20 kHz, in order to keep only high frequency content and remove any residuals of the analogue filter.

Indicators Performance Comparison: RMS is one of the most common vibration indicators, it corresponds to the square root of the average of square values in a given signal.

Figure 2 compares RMS values at the different conditions for all experiments, for each experiment the value on dry conditions is higher than at lubricated conditions, but the range is different for each bearing, thus, it is not possible to establish a limit to detect lubrication starvation for all bearings without compromising the indicator with false alarms or missed faults. Besides, the indicator increases under preload even if the impulsivity of the signal decreases as shown further by the other indicators. The problem associated with preload is the change of resonance frequencies due a change in stiffness, and the possible excitation of the bearing housing due the increase in dry friction, which is random excitation generated from surface roughness. Hence, even if the impulsivity of the signal decreases the RMS cannot detect the change when a preload is applied.

Figure 3 shows a cascade comparison for experiment #2, where it is observed a switch of frequency due increase of stiffness from 4 to 6 kHz (frequency range associated with the rotor-assembly resonance frequency), and an increase in activity at 11 kHz (vertical resonance of house bearing).

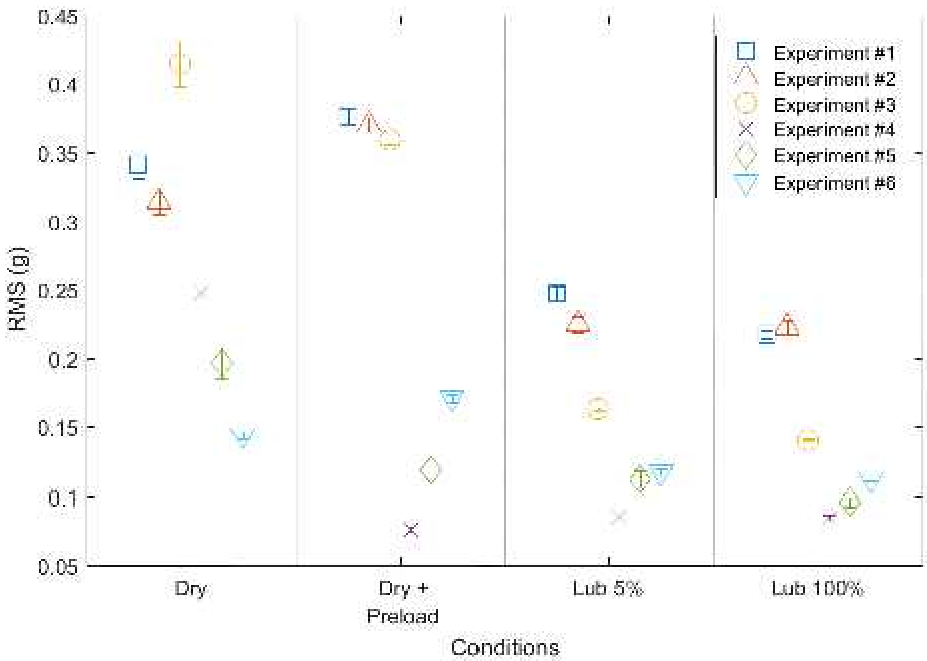

Figure 2: RMS Performance Comparison for Experimental Conditions.

Crest Factor is the ratio between the absolute-maximum peak value and the RMS value of a given waveform, the value for a sinusoidal signal is 1.414. When applied to detection of bearing starvation, it is a better indicator than RMS since is more related to impulsivity. The problem is the similarity between lubricated and dry conditions, as shown in

Figure 4, if a severity level is established based on dry condition results, some of the full lubricated results may trigger a false alarm. An advantage of CF is the high sensitivity for low lubrication levels.

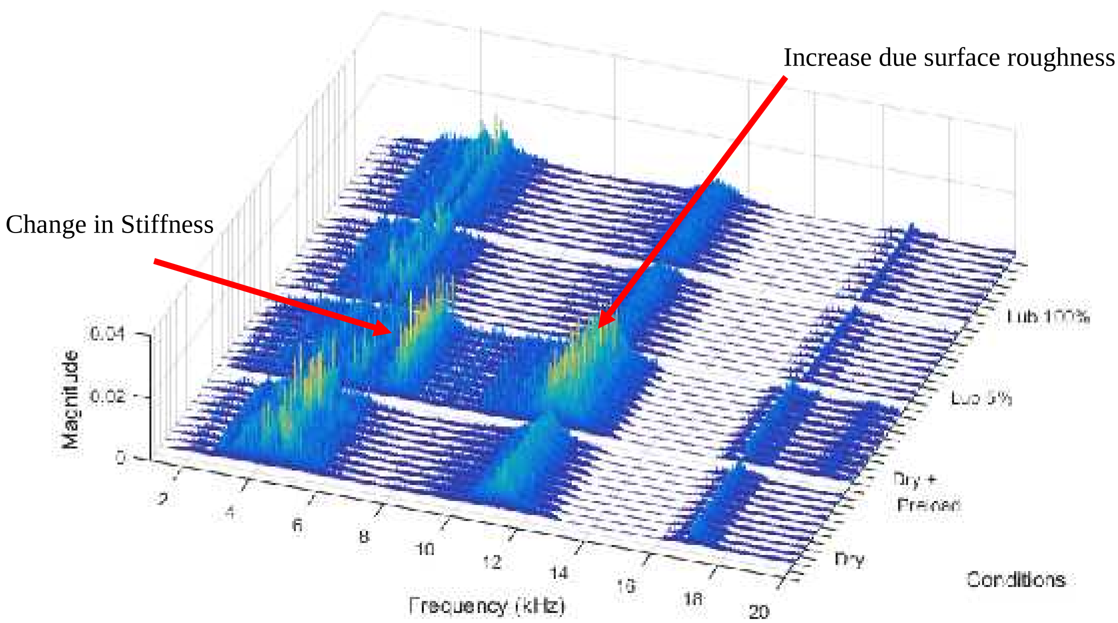

Figure 3: Cascade Comparison and Preload Effects on Experiment #2.

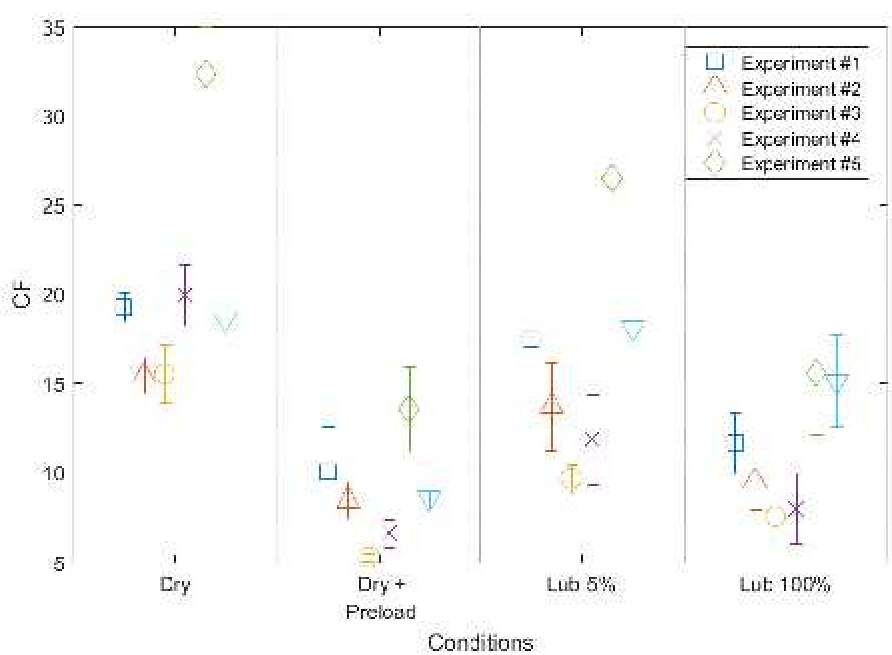

Figure 4: Crest Factor Performance Comparison for Experimental Conditions.

Kurtosis is a statistical analysis called “fourth moment” that represents the deviation of signal's amplitude from a Gaussian distribution and is useful to detect impulsiveness in a signal, e.g. faults in ball bearings. From a statistic point of view, it is a measure of the sharpness of the tail in a frequency-distribution curve. Kurtosis results, presented in Figure 5, show a better performance than RMS and CF to detect lubrication starvation, the consistency between experiments allow proposal of severity levels: 0-3 good, 3-7 satisfactory, 7-10 unsatisfactory, 10- unacceptable.

The main disadvantage is the variability between acquisitions of the same experiment, therefore more than one acquisition is recommended for an effective evaluation, which could be a problem when a large number of machines must be assessed. In both CF and Kurtosis indicators it is possible to observe a decrease in impulsivity of the signal when a preload is applied, as explained by Sawalhi and Randall [15], the impulsivity could be attributed to each time a ball enters the load zone and a small impact is produced, generally these excitation are small and quickly damped by the lubricant which also acts as an isolation mechanism between the balls and the bearing structure, but with the absence of lubricant and the increase in clearance, the impact amplitude increases and the wave is propagated to the bearing housing, hence the increase in FTF and BSF. When a sufficient preload is applied, the clearance between the balls, train, and the races is reduced as an effect of load deformation and in the case of light loads the deformation due preload dominates over the deformation due to dynamic or static load, therefore the ball never enters or leaves the “load zone”. Both factors reduce the source of impacts that characterize the lack of lubrication.

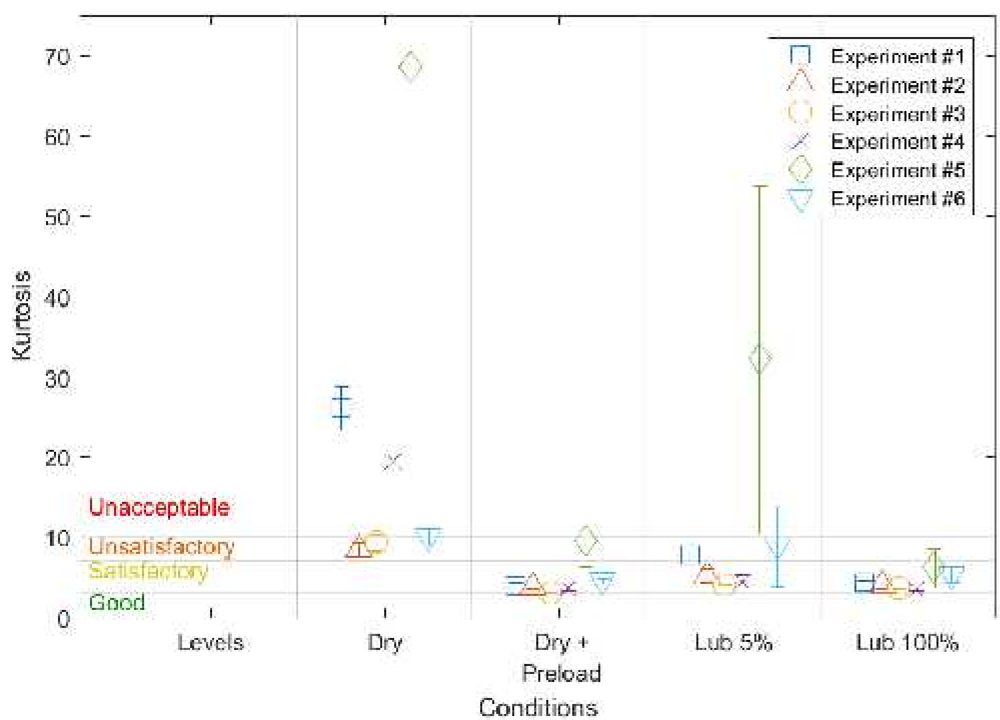

Figure 5: Kurtosis Performance Comparison for Experimental Conditions with Severity Levels.

Fast-Kurtogram: The use of kurtosis is maximized when the resonance frequency excited by bearing impulses is isolated from other excitations. Introduced by Dywer in 1983 [16], Spectral Kurtosis (SK) is a time-frequency plot used to obtain a kurtosis value of a specific frequency band in the time direction and is useful to detect frequency bands with more content of impulsive signals. The main issue with SK is the selection of an optimum value for the bandpass filter bandwidth and the center frequency. A map can be used where the kurtosis value is calculated for each frequency in Time-Frequency analysis and a range of bandwidths. This map is called a "Kurtogram". The disadvantage of this method is computation time; is expensive for online systems. One solution for this problem is called "Fast-Kurtogram" (FK) and was presented by Antoni in 2007 [17]. The technique is based on a series of digital filters instead of time-frequency analysis and the decomposition of the signals is based in a dyadic decomposition similar to the discrete wavelet packet transform. The FK creates a map where one of the axes is a progressive split of the frequency range in bands and the other axis is the center frequency of the band. A typical recommended to do it with a 1/3-binary tree where the division is a sequence of 1/2, 1/3, 1/4, 1/6, 1/8, and so on.

The results of FK exhibit a predominant central frequency (f_c) at 17.8 kHz with a bandwidth (B) of 1.8 kHz (level 4), the region is associated with a resonance frequency of the bearing housing.
Figure 6 shows the results for dry conditions of experiment #1, these parameters could be used to filter all signals and apply an envelope analysis to find the origin of the impulses and how the amplitude reduces. This work presents the advantages of using FK analysis to improve kurtosis as a fault detection method for lubrication starvation.
Figure 7 compares the results of kurtosis before and after using FK. The mayor improvement is the sensitivity to detect low levels of lubricant where the kurtosis of the entire high frequency spectrum does not differs from full to low lubrication. Moreover, a decrease of impulses on the signal is corroborated on these results as well.

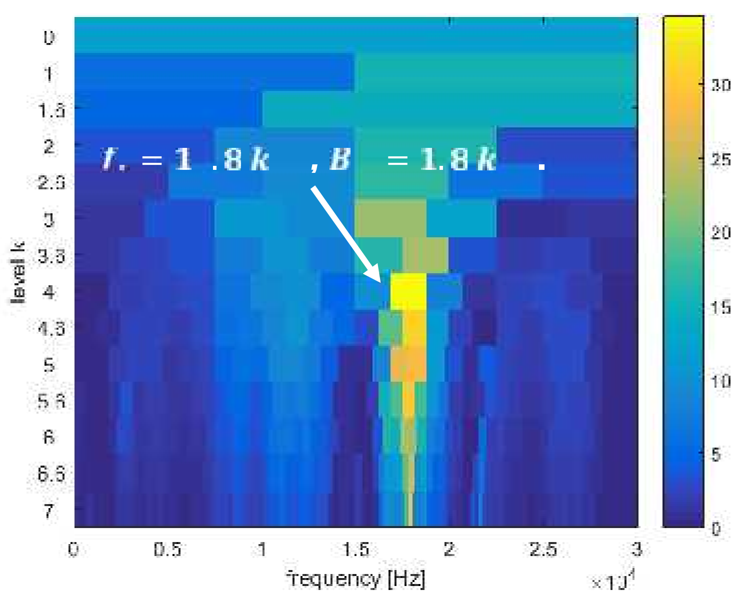

Figure 6: Fast Kurtogram for Experiment #1 on Dry Conditions.

The levels proposed for the kurtosis of high frequency spectrum were also used in the kurtogram results. Experiments 1,2,5, and 6, detected low lubrication as an unacceptable fault. For condition monitoring it is important to minimize false alarms without compromising the sensitivity of the method to detect a problem which, as in this case, is low levels of lubrication.

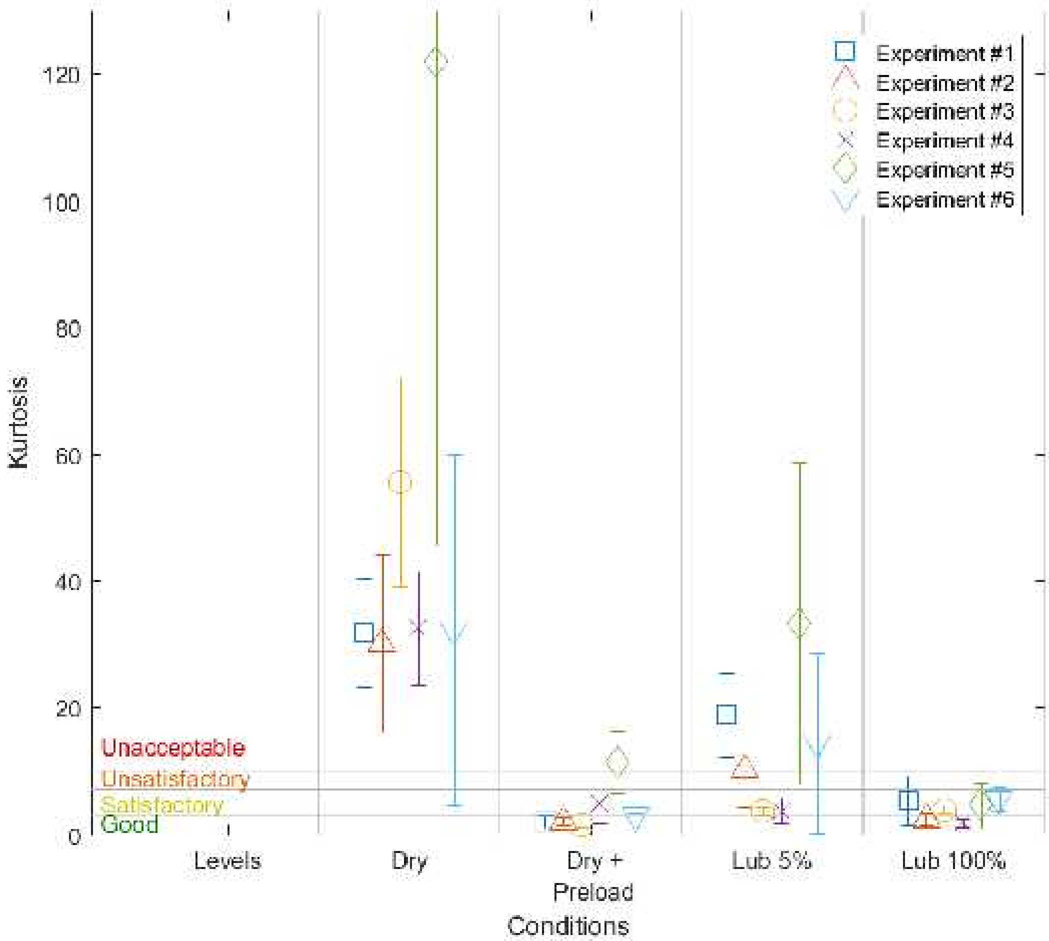

Figure 7: Kurtosis of Filtered Frequency Band Localized by Kurtogram.

Conclusions: Three main indicators, RMS, CF, and Kurtosis were evaluated to detect lubrication starvation in a ball bearing under light load. While RMS detects the presence of a fault in the system, it is not recommended to be used alone to isolate faults related to bearings. It must be used with an additional indicator, sensitive to impulsivity, such as kurtosis or CF. Kurtosis proves to be a more consistent indicator than CF to discriminate between lubricated and dry conditions.

Levels of severity are proposed for kurtosis, the levels are based on experimental results, but a formal methodology to select levels is needed. Instead of using fixed levels based only on kurtosis values a machine learning technique could be applied to include RMS and CF to improve the fault detection for lubrication starvation.

A Fast Kurtogram was used to improve the fault detection based on kurtosis. An increase in sensitivity to low lubrication levels and a better discrimination between dry and lubricated conditions are some of the benefits. In future work, determining if FTF value decreases with preload is important as it supports the idea that the characteristic signal of lubrication starvation is generated due to the increase of clearance gap between bearing components. This could be done by applying an envelope analysis to the predominant frequency detected by the fast-kurtogram as explained previously by Boškoski.

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