

Health Condition Monitoring of Ball Bearings Test Bench Under Running Conditions Using A Mems Accelerometer

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ABSTRACT

Background: Rolling-bearing faults are best caught while the machine is running, yet instruments that do this are costly. This experiment work reports the condition monitoring of ball bearings under running conditions with a low-cost ADXL335 MEMS accelerometer, and an indigenous impulse-excitation test bench for checking bearings at rest.

Methods: In the running-condition tests, a 6300-series bearing was run in five health states (healthy, inner-race fault, outer-race fault, combined inner-outer fault and combined cage-ball fault) at 1000, 1250 and 1500 RPM under 15, 30 and 60 kg applied load; 30 tests of 7 min each gave 200 samples.

Results: The calculated fault frequencies range up to 107 Hz at 1500 RPM and it lie inside the sensor bandwidth. The test bench, which strikes the inner race with a solenoid-driven rubber-tipped plunger and processes the response in LabVIEW through a PSoC interface, was validated with impact measurements on four new, defect-free 6201 bearings (50 impacts each); the coefficient of variation of the impact amplitude within a bearing was 0.4–3.7 %.

Conclusion: The combined cage-ball fault was the most readily detected condition, and the low-cost MEMS chain separated healthy and faulty bearings in the time domain.

Keywords: bearing condition monitoring; running condition; MEMS accelerometer; ADXL335; impulse excitation; kurtosis; crest factor; CUSUM chart.

Introduction

Rolling-element bearings support loads and maintain the operational accuracy of rotating machinery. As bearing degradation progresses, vibration levels may increase before noticeable performance deterioration occurs, making vibration-based condition monitoring an effective approach for early fault detection and condition-based maintenance scheduling [1, 3]. Existing diagnostic methodologies have evolved from basic time-domain statistical indicators to spectral analysis, envelope analysis, time-frequency techniques, and machine learning-based fault diagnosis [4, 9, 10]. Time-domain features, including root mean square (RMS), standard deviation, kurtosis, and crest factor, remain practical for small-scale industrial applications because they can be computed using low-cost hardware without requiring detailed bearing geometry information [3, 5, 11]. Statistical process monitoring techniques, particularly cumulative-sum (CUSUM) control charts, provide systematic mechanisms for identifying changes in monitored features and distinguishing persistent deviations from normal variation [6, 7]. However, the cost of laboratory-grade sensors and vibration analysers remains a significant barrier to widespread implementation. Furthermore, bearing inspection under stationary conditions, such as during goods receipt or after maintenance, can be affected by variations in impact force and striking angle when conventional hand-held hammer testing is employed [5, 8]. To address these challenges, this study investigates an economical microelectromechanical systems (MEMS)-based instrumentation approach using an ADXL335 accelerometer [8], supported by established vibration-based diagnostic principles and intelligent industrial monitoring concepts [2, 12]. The objectives are: (i) to quantify, through a 30-test experimental programme, the responses of RMS, standard deviation, kurtosis, and crest factor across five bearing health states, different shaft speeds, and applied loads; (ii) to verify whether the sensor bandwidth adequately captures the characteristic bearing fault frequencies, including BPFO, BPFI, BSF, and FTF; and (iii) to develop and validate an indigenous solenoid-based impulse-excitation test bench integrating a PSoC interface and a LabVIEW virtual instrument, thereby reducing the variability associated with manual hammer testing. The broader objective is to establish a practical, cost-effective bearing diagnostic solution that supports reliable industrial condition monitoring and maintenance decision-making [13, 14, 15].

Theoretical Foundations

Time-domain features

For a vibration record of N samples x_i with mean $\bar{x}$, the features used in this study are (Eq 1 to 4):

$$\text{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2} \quad (1)$$

$$\sigma = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (x_i - \bar{x})^2} \quad (2)$$

$$K = \frac{\frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^4}{\left[\frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^2 \right]^2} \quad (3)$$

$$C_f = \frac{x_{\text{peak}}}{\text{RMS}} \quad (4)$$

RMS is the amount of energy in the signal and increases as the general level of the vibration increases. The standard deviation (σ) is a measure of variation around the mean value. Kurtosis (K) is a measure of how impulsive the signal is, and it is known that a Gaussian signal has a K value of 3; a healthy bearing will have a value near 3, and impacts of the defect will cause this to increase. The crest factor (Cf) is the ratio of the peak value to the RMS value, and it shows the severity of the peaks; the RMS is in the denominator, so when the overall level of the vibration increases, the Cf can decrease, even if the peaks don't change.

Characteristic bearing frequencies

The localised defect gives rise to a periodic stream of impacts, with the frequency determined by the geometry. The outer-race (BPFO), inner-race (BPFI), ball-spin (BSF) and cage (FTF) frequencies for a bearing with Z balls, ball diameter d, pitch diameter D, contact angle α and shaft rotation frequency f_r are [Eq 5 -8]:

$$\text{BPFO} = \frac{Z}{2} (1 - \frac{d}{D} \cos \alpha) f_r \quad (5)$$

$$\text{BPFI} = \frac{Z}{2} (1 + \frac{d}{D} \cos \alpha) f_r \quad (6)$$

$$\text{BSF} = \frac{D}{2d} [1 - (\frac{d}{D} \cos \alpha)^2] f_r \quad (7)$$

$$\text{FTF} = \frac{1}{2} (1 - \frac{d}{D} \cos \alpha) f_r \quad (8)$$

CUSUM control chart

The tabular CUSUM chart adds deviations of a feature from a target μ_0 which are greater than an allowance k, with an upper sum S_H and a lower sum S_L resetting to zero whenever they become negative [Eq 9 to 11]:

$$S_H(i) = \max[0, x_i - (\mu_0 + k) + S_H(i-1)] \quad (9)$$

$$S_L(i) = \max[0, (\mu_0 - k) - x_i + S_L(i-1)] \quad (10)$$

$$k = 0.5\sigma, \quad \text{UCL} = +h\sigma, \quad \text{LCL} = -h\sigma, \quad h = 5 \quad (11)$$

The process is declared out of control when either sum crosses the decision limits. Shewhart-type charts are able to detect large changes, while CUSUM charts are able to detect small persistent changes and thus are more appropriate to use in the initial phase of a fault [5]. Here $k = 0.5\sigma$ and $h = 5$, within the range $h = 4-5$ commonly used.

Impulse excitation

In impulse excitation a short mechanical impact is applied to the specimen and the transient vibration that follows is recorded. In the gryndosonic approach used on the bench, the transient is examined in both the time domain (amplitude plot) and the frequency domain (power spectrum). A defect-free bearing is expected to give a smooth spectrum dominated by the excitation frequency, whereas damage adds energy at other frequencies and sidebands.

Experimental Work

Test programme

Two sets of measurements were made (Table 1). The running-condition tests are the main study; the impulse-excitation tests validate the bench on new bearings at rest. Counts are stated per measurement type so that they are not confused: the running tests produced 6000 samples from 30 tests, and the bench validation produced 200 impact measurements from four bearings.

Table 1. Summary of the two test sets.

	A. Running-condition tests	B. Impulse-excitation bench
Purpose	Effect of health state, speed and load on time-domain features	Repeatability of the bench on defect-free bearings
Bearings	6300-series ball bearing in five health states	Four new 6201 ball bearings
Condition	Running: 1000, 1250, 1500 RPM; 15, 30, 60 kg load	At rest; solenoid impacts on the inner race
Measurements	30 tests × 7 min; 200 samples per test	4 bearings × 50 impacts
Total	6000 samples (210 min)	200 impact measurements

Measurement system and processing stages

Vibration was measured with an Analog Devices ADXL335, a tri-axial MEMS accelerometer with an analog output, mounted on the bearing. Its main characteristics, from the manufacturer's data sheet [6], are listed in Table 2 with their relevance to this work. The signal is digitised by a PSoC embedded interface and processed in a LabVIEW virtual instrument.

Table 2. ADXL335 accelerometer characteristics (manufacturer data sheet [9]).

Parameter	Value	Relevance to this work
Measurement range	±3 g (minimum)	Covers the RMS levels measured (0.13–0.43 g)
Sensitivity	300 mV/g typical ($V_s = 3$ V)	Ratiometric: scales with supply voltage
Bandwidth	0.5–1600 Hz (X, Y); 0.5–550 Hz (Z)	Set by external capacitors; covers fault frequencies (Section 4.3)
Supply	1.8–3.6 V, 350 μ A typical	Low power; powered from the interface board
Noise density	150 μ g/√Hz (X, Y); 300 μ g/√Hz (Z)	Adequate for the amplitudes observed
Package	4 × 4 × 1.45 mm	Negligible mass loading on the bearing

The running-condition data are processed in the following stages: the record is segmented into samples (200 samples per test), RMS, standard deviation, kurtosis and crest factor are calculated for each sample, the features are compared with the running-condition limits of the healthy bearing at the same load, and a CUSUM chart tests for persistent shift in a feature (Fig 1).

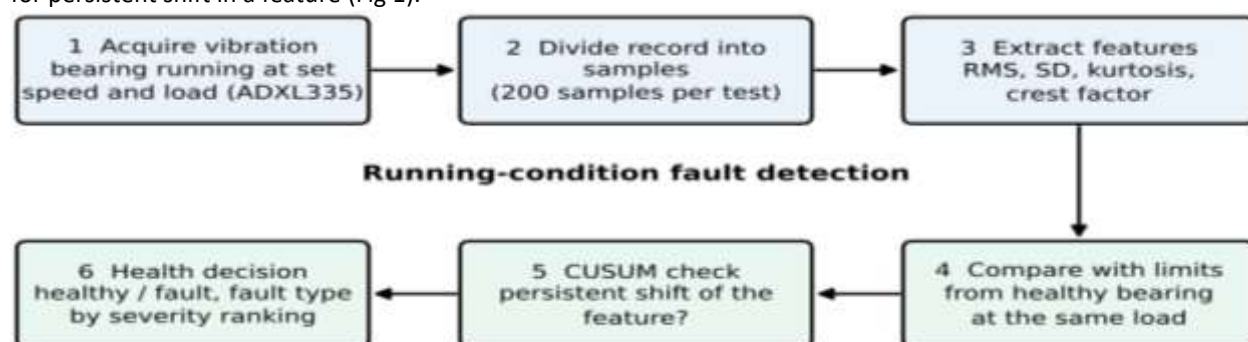


Fig 1. Stages of running-condition fault detection

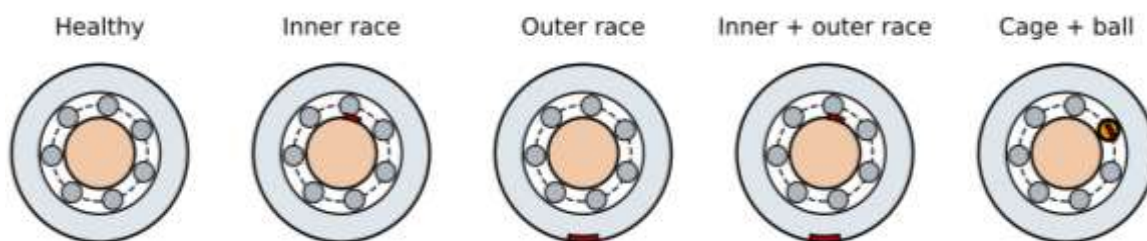
Bearings health Condition

The running tests were conducted using a 6300-series deep-groove ball bearing, with the following five health states: healthy, inner-race fault, outer-race fault, combined inner-race fault and combined outer-race fault, and combined cage fault and ball fault (as illustrated in Fig 2). The geometry of the bearings is shown in table 3. For the bench validation, four new 6201 deep-groove ball bearings (nominal 12 × 32 × 10 mm) were used as received.

Table 3. Geometry of the 6300-series test bearing.

Parameter	Value	Unit
Number of rolling elements, Z	7	–
Bore diameter	20	mm
Outer diameter	52	mm
Width	15	mm
Ball diameter, d	7.94	mm
Pitch diameter, D	36	mm
Contact angle, α	0	deg
Ratio d/D (calculated)	0.221	–

Designated 6300-N in the dataset; the 20 × 52 × 15 mm envelope is that of a 6304-size bearing.

**Fig 2.** Health states tested (schematic, red marks indicate the simulated defect location)

Running-condition test matrix

Thirty tests were run at three shaft speeds (1000, 1250 and 1500 RPM) and three applied loads (15, 30 and 60 kg), each for 7 min with 200 samples. Each health state was tested six times and each speed ten times, but the matrix is not fully crossed (Fig 3, Table 4): the healthy bearing was run once at 15 kg, twice at 30 kg and three times at 60 kg, and the combined cage–ball fault four times at 60 kg but once at each lower load. The feature tables of Section 4.1 also include a 0 kg point that does not appear in the test list.

	15 kg			30 kg			60 kg		
Healthy		#1		#11		#21	#16	#6	#26
Inner Race	#12	#2		#17		#22		#7	#27
Outer Race	#13	#3			#8	#23	#18		#28
Combined (I-O)		#4	#24	#14	#9		#19		#29
Combined (C-B)		#5		#15			#20	#10	#25
	1000	1250	1500	1000	1250	1500	1000	1250	1500

Speed (RPM) within applied load

Fig 3. Coverage of the 30-test matrix. Filled cells show the test number run at each combination of health state, applied load and speed; grey cells were not run**Table 4.** Number of running tests per health state and applied load.

Health state	15 kg	30 kg	60 kg	Total
Healthy	1	2	3	6
Inner Race	2	2	2	6
Outer Race	2	2	2	6
Combined (I-O)	2	2	2	6
Combined (C-B)	1	1	4	6
All states	8	9	13	30

Impulse-excitation test bench

The bench workflow is displayed in (Fig 4). The start command is passed through the LabVIEW front panel to the PSoC hardware, which controls the powering of a solenoid that has its rubber-bushed head mounted at an angle to gently touch the inside race at a constant speed. The impact is exciting the bearing, the outer race of which is

instrumented with the ADXL335, and taking this measurement, the PSoC digitises it, while LabVIEW creates the amplitude plot and the power-spectrum plot using its spectrum palette. A mechanical device keeps the bearing fixed and away from the outside vibrations, and a movable clamp is used for bearings of various sizes (Fig 5). The solenoid takes the place of the hammer of traditional impulse testing, eliminating any force or angle variation from strike to strike, while the soft rubber tip reduces any high-frequency noise at contact.

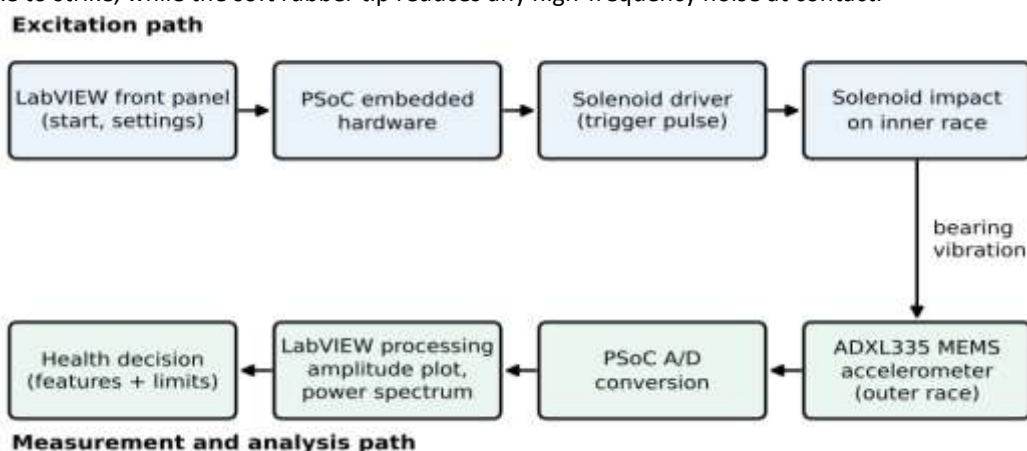


Fig 4. Workflow of the impulse-excitation bearing test bench



Fig 5. Experiment test bench: solenoid-driven, rubber-tipped plunger striking the inner race, ADXL335 accelerometer on the outer race, and the PSoC–LabVIEW acquisition system

Results and Discussion

Effect of load on the time-domain features (running condition)

Table 5 and Fig 6 give the RMS, standard deviation and kurtosis of the healthy, inner-race-fault and outer-race-fault bearings against applied load, and Table 6 gives the crest factor for all five states.

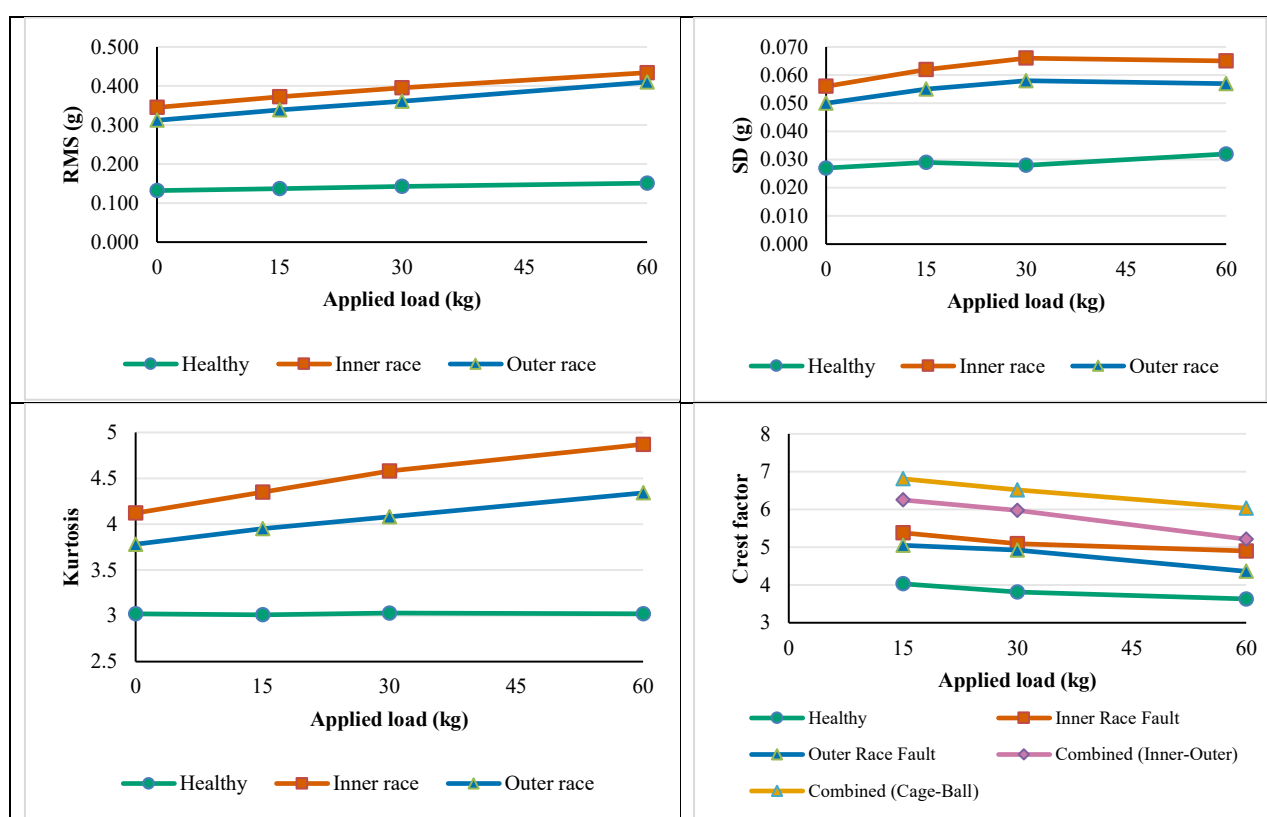
Table 5. RMS, standard deviation and kurtosis against applied load.

Load (kg)	RMS H	RMS IR	RMS OR	SD H	SD IR	SD OR	K H	K IR	K OR
0	0.132	0.345	0.312	0.027	0.056	0.050	3.02	4.12	3.78
15	0.137	0.372	0.339	0.029	0.062	0.055	3.01	4.35	3.95
30	0.143	0.395	0.361	0.028	0.066	0.058	3.03	4.58	4.08
60	0.151	0.434	0.410	0.032	0.065	0.057	3.02	4.87	4.34

H = healthy, IR = inner-race fault, OR = outer-race fault. RMS and SD in g

Table 6. Crest factor against applied load.

Health state	15 kg	30 kg	60 kg
Healthy	4.03	3.81	3.63
Inner Race Fault	5.38	5.09	4.90
Outer Race Fault	5.05	4.92	4.36
Combined (Inner-Outer)	6.25	5.97	5.21
Combined (Cage-Ball)	6.81	6.52	6.03

**Fig 6.** Variation of (a) RMS, (b) standard deviation, (c) kurtosis and (d) crest factor with applied load

RMS. The RMS of the healthy bearing is low and rises slowly with load, from 0.132 to 0.151 g (+14.4 %) between 0 and 60 kg. The faulty bearings start much higher and are more load-sensitive: the inner-race fault rises from 0.345 to 0.434 g (+25.8 %) and the outer-race fault from 0.312 to 0.410 g (+31.4 %). A fault therefore raises the energy content of the signal, and the increase grows with load.

Standard deviation. The standard deviation is 0.027–0.032 g for the healthy bearing and 0.056–0.066 g (inner race) and 0.050–0.058 g (outer race) for the faulty bearings. It increases with load up to 30 kg and is nearly flat between 30 and 60 kg for the two faults, so it is less sensitive to load than RMS.

Kurtosis. The kurtosis of the healthy bearing is 3.01–3.03 at every load, as expected for a defect-free bearing, and does not depend on load. The faulty bearings are well above this value and increase with load: 4.12 to 4.87 for the

inner race and 3.78 to 4.34 for the outer race. A defect therefore makes the signal markedly impulsive, and the effect becomes stronger at higher load.

Crest factor. Crest factor orders the health states identically at 15, 30 and 60 kg: healthy < outer race < inner race < combined inner–outer < combined cage–ball. At 15 kg it is 4.03 for the healthy bearing and 6.81 for the combined cage–ball fault, 1.69 times higher. In contrast to the other features, crest factor decreases with load in every state (by 8.9 % for the inner-race fault to 16.6 % for the combined inner–outer fault), because RMS grows faster than the peaks, as noted in Section 2.1.

Sensitivity to faults

Fig 7 shows the ratio of each feature in the faulty bearing to its value in the healthy bearing. RMS gives the largest separation (2.4–2.9 times), followed by the standard deviation (1.8–2.4 times) and kurtosis (1.25–1.61 times). The inner-race fault gives a larger ratio than the outer-race fault in every case, consistent with the inner-race defect rotating with the shaft and striking the balls continuously. The RMS ratio increases with load, whereas the standard-deviation ratio is largest at 30 kg.

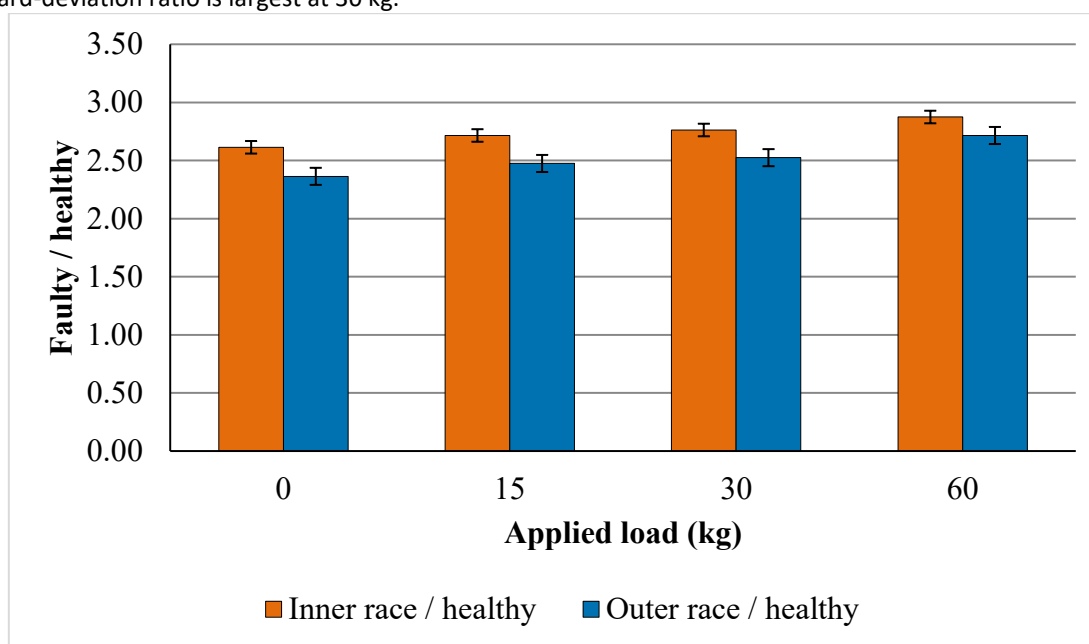


Fig 7 (a) – RMS ratio

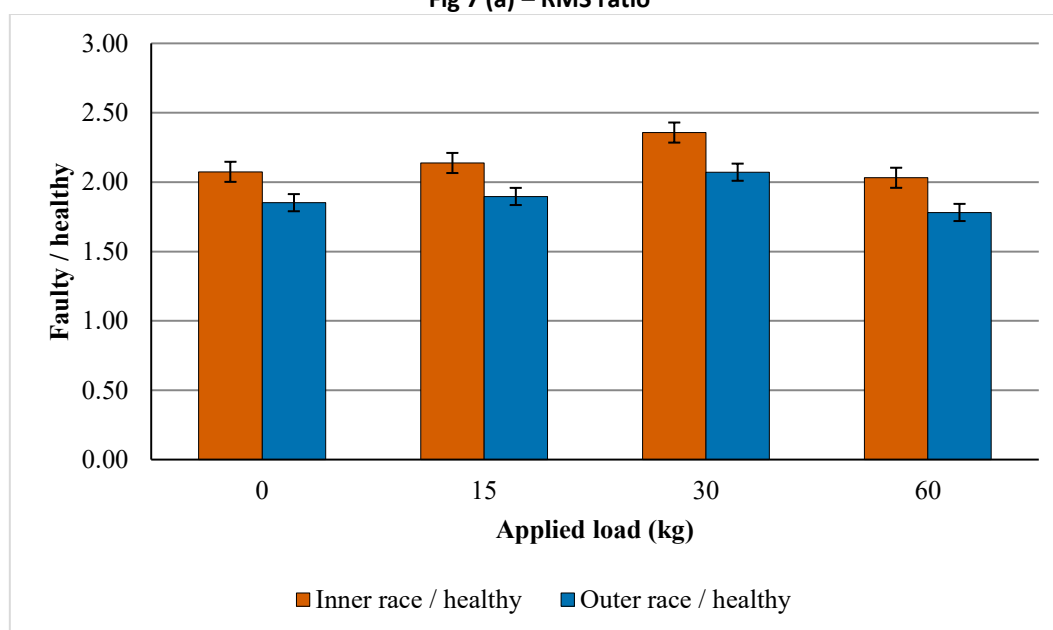


Fig 7 (b) – SD ratio

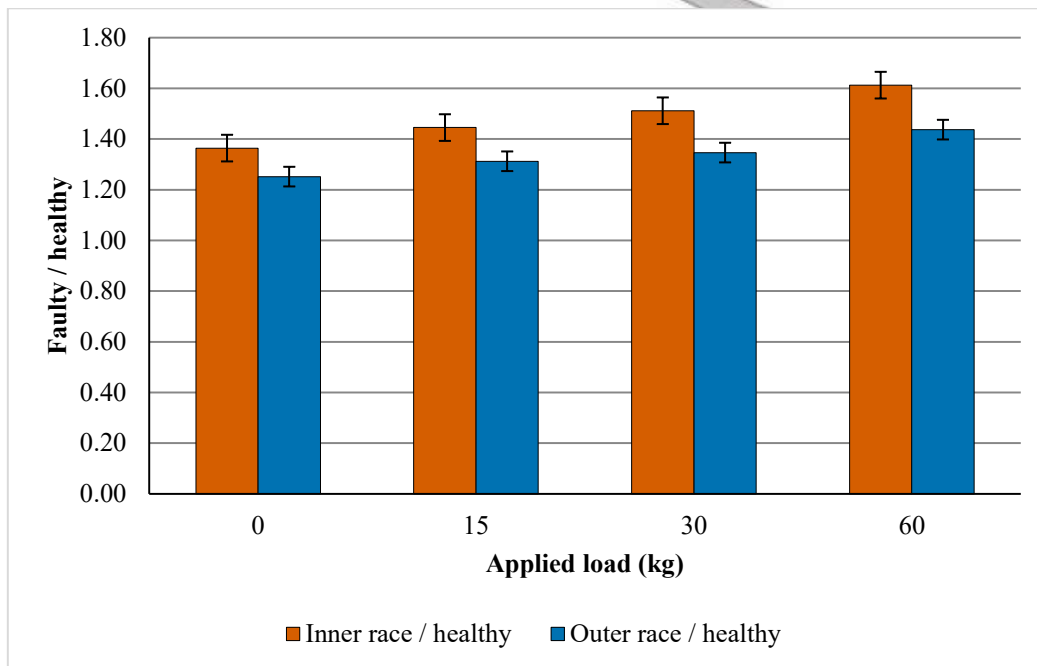


Fig 7 (c) – Kurtosis ratio
Fig 7. Ratio of faulty to healthy feature value against applied load

For the combined faults only the crest factor is available. Relative to the healthy bearing it is 1.44–1.57 times higher for the combined inner–outer fault and 1.66–1.71 times higher for the combined cage–ball fault, against 1.20–1.35 times for the single faults. The combined cage–ball fault is therefore the most readily detected condition in this dataset.

The data also allow decision limits to be placed (Table 7). At all loads tested, every healthy value is below every single-fault value, so any limit inside the gap separates the classes in the present data. Because the healthy values come from a single bearing, the limits are provisional and should be confirmed on additional healthy bearings. Kurtosis has the practical advantage that its healthy value is fixed by theory (3) and does not move with load.

Table 7. Gap between the highest healthy value and the lowest single-fault value (all loads).

Feature	Highest healthy	Lowest single fault	Gap
RMS (g)	0.151	0.312	0.161
Kurtosis	3.03	3.78	0.75
Crest factor	4.03	4.36	0.33

Fault frequencies and sensor bandwidth

The characteristic frequencies of the 6300-series bearing were calculated from Equations 5–8 with the geometry of Table 8 (Fig 8).

Table 8. Calculated characteristic frequencies (Hz) of the 6300-series bearing ($\alpha = 0^\circ$).

Speed (RPM)	Shaft	FTF	BSF	BPFO	BPFI
1000	16.7	6.5	35.9	45.5	71.2
1250	20.8	8.1	44.9	56.8	89.0
1500	25.0	9.7	53.9	68.2	106.8

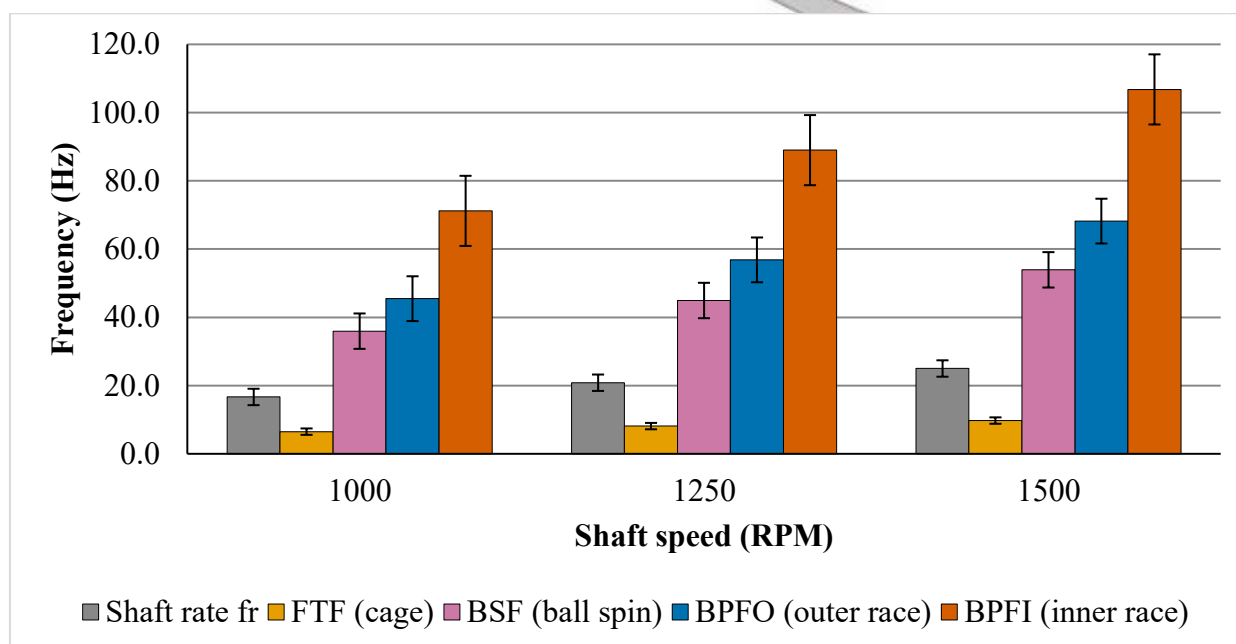


Fig 8. Calculated characteristic frequencies against shaft speed

The inner-race frequency (1500 RPM, 106.8 Hz) is the highest fundamental. Its fifth harmonic (~534 Hz) is still below the 550 Hz bandwidth of the ADXL335 Z axis and its X and Y axes go up to 1600 Hz, so the sensor could in principle be able to resolve the fault frequencies and their low order harmonics. Structural resonances excited by an impact are generally at higher frequencies and would be suppressed if the bandwidth is defined by the external capacitors; the value of the capacitors should be designed to fit the resonances of interest.

Bench validation with 200 impact measurements

Validation is the procedure that checks to see if the impulse-excitation bench responds in the same way when the bearing being tested is not defective. Fig 9 gives the amplitude of each of the 50 impacts for the four new 6201 bearings and Table 9 give the summarised statistics. Within each bearing the amplitude is tightly clustered: the coefficient of variation is 0.4 % for Bearing 3 and 0.5 % for Bearing 4, and 2.4 % and 3.7 % for Bearings 2 and 1. The larger values are caused by isolated outliers (416, 350 and 300 counts for Bearing 1; 313 counts for Bearing 2); the impacts lie within ± 3 % of the median in 90 %, 98 %, 100 % and 100 % of cases for Bearings 1 to 4.

Table 9. Bench validation on four new 6201 bearings (50 impacts each, 200 in total).

Bearing	Mean amplitude	SD	CV (%)	Amplitude range	Median amplitude	Median power spectrum	Max power spectrum
Bearing 1	378.7	13.9	3.7	300–416	380	0.138	3.031
Bearing 2	370.4	8.9	2.4	313–378	370	0.132	1.636
Bearing 3	396.9	1.5	0.4	387–398	397	0.054	2.512
Bearing 4	394.0	1.9	0.5	385–402	394	0.058	2.054

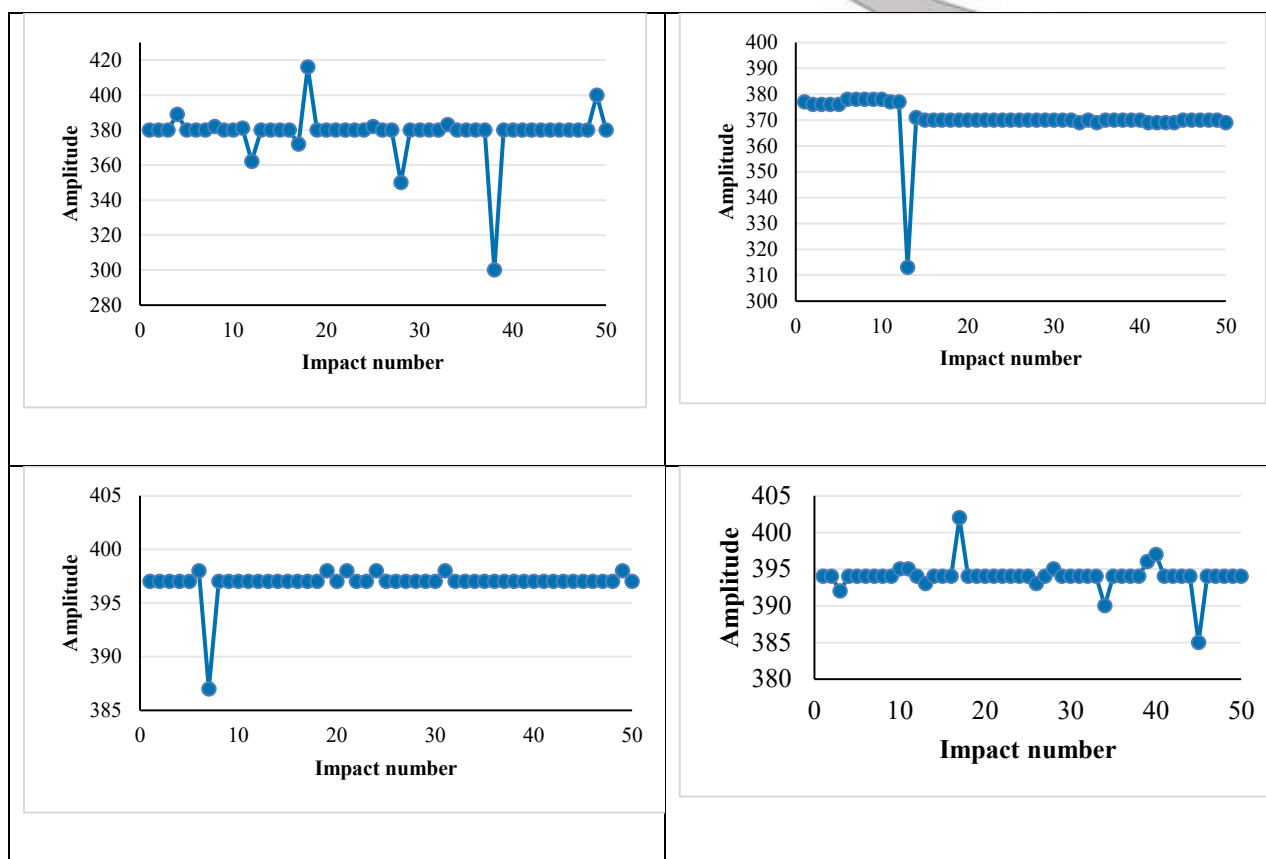


Fig 9. Amplitude of each impact for four new 6201 bearings. Dashed line: median; labelled points deviate by more than 20 counts from the median

Two features of Fig 9 deserve comment. First, the baseline differs between bearings (median 370–397; pooled mean 385.0 over 200 impacts, a span of about 7 %), so an amplitude limit must be set for each bearing and mounting rather than taken from a single reference. Second, bearing 2, which has an outlier at impact 13, 376-378 counts, has a step of ~7 counts, from 376-378 counts to 369-371 counts, immediately after the outlier, possibly because the bearing settled in the clamp after an early impact. This is a hypothesis and was not tested.

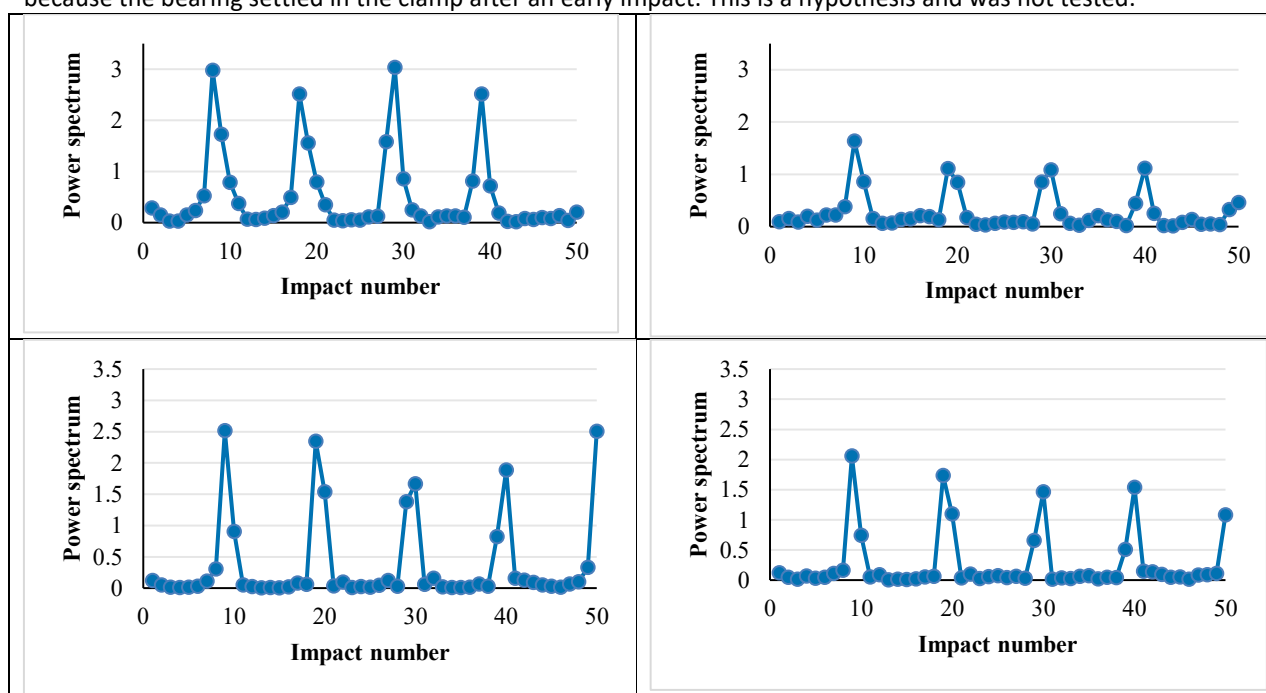


Fig 10. Power-spectrum value of each impact for four new 6201 bearings

The power-spectrum values (Fig 10) are low for most impacts: the median is 0.13 for Bearings 1 and 2 and 0.05–0.06 for Bearings 3 and 4, and 58–82 % of the impacts are below 0.2. The authors' spectrum displays for these bearings showed a smooth spectrum with minimal amplitude and no sidebands, the expected signature of a defect-free bearing in which only the excitation frequency is present. The values do, however, show a recurring burst of up to 3.0 (Bearing 1) and 1.6–2.5 (Bearings 2–4) at approximately every tenth impact (impacts 8–9, 18–19, 28–30, 39–40, and also 50 for Bearings 3 and 4). Because the same pattern appears in four different bearings, it is more likely to originate in the acquisition or averaging cycle of the instrument than in the bearings, and it should be checked before the power-spectrum value is used as a fault indicator.

CUSUM chart on the healthy baselines

A CUSUM chart was applied to the impact amplitude of each new bearing, with the target and σ taken from the same 50 impacts and the limits of Section 2.3 (Fig 11). In the bearing four is in good condition in all the ways. The lower sum crossed the limit once for Bearing 1 (impact 38, the 300-count outlier), at impacts 13–14 for Bearing 2 (the 313-count outlier) and at impacts 7–9 for Bearing 3 (a single 387-count impact). In every case the signal arose from one isolated low impact, the alarm lasted only one to three impacts, and the sum then decayed back toward zero, that is, the excursions were transient rather than persistent. For Bearing 3 the within-bearing σ is only 1.5 counts, so a 10-count dip is more than six standard deviations and trips the chart. In monitoring practice, the decision rule should therefore require persistence (for example, several consecutive points beyond the limit) or use a σ estimated from several healthy bearings.

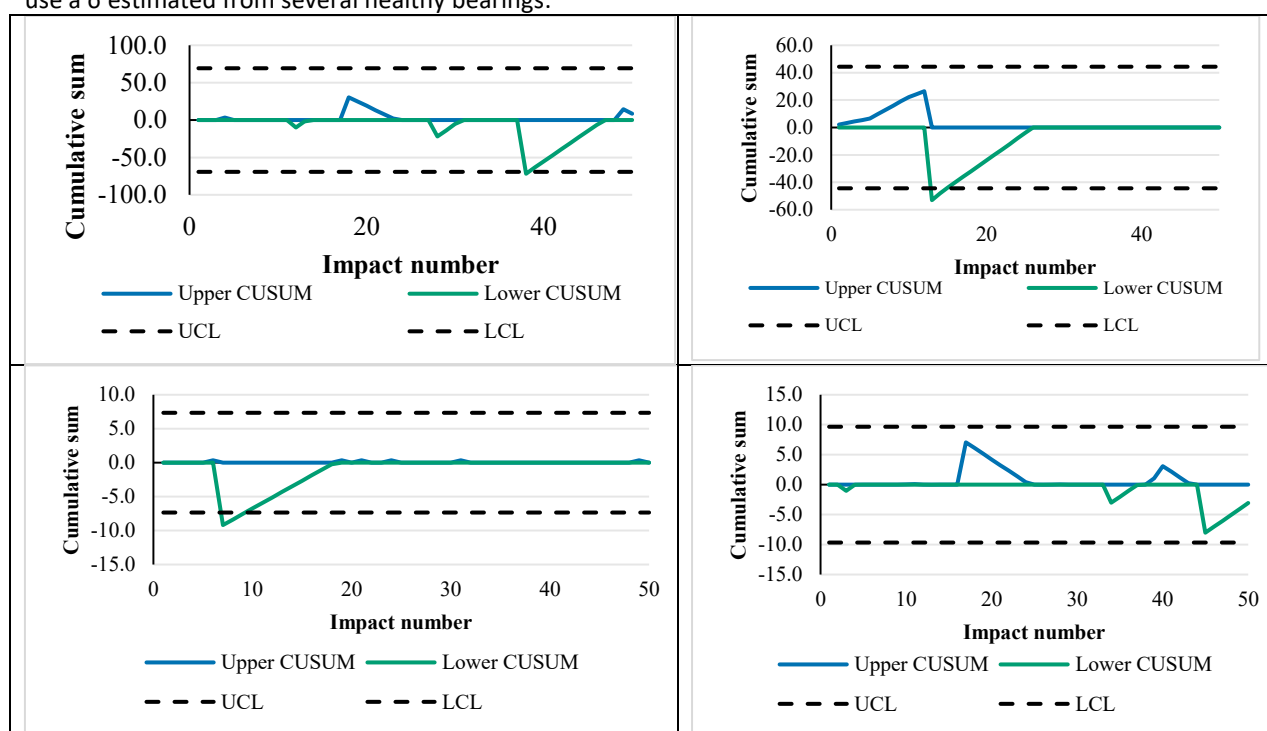


Fig 11. Tabular CUSUM charts of impact amplitude for the four new 6201 bearings

Limitations

The above tested bearing was small size general purpose using bearings. The 200 impacts and 6,000 samples is repeated testing by the running tests on one of the 6300-series bearing types in five health states, and by the bench validation on four new 6201 bearings. Conclusions are therefore drawn on the response of the features for this bearing type and test range and should be validated on a higher population before limiting to general values is carried out. Single bearing is used for the healthy reference in the running tests and the test matrix is unbalanced, causing the load and speed effects to be confounded with the number of repeats. The combined faults are characterised only by crest factor. It was not possible to test the CUSUM chart for its ability to detect the seeded faults, as only healthy baselines were used in this demonstration. A machine-learning classifier was not trained in this study, but with a larger labelled dataset supervised classification [11, 12] is a natural extension.

Conclusions

Under running conditions, ball bearings were monitored using a low cost ADXL335 MEMS accelerometer and a indigenous impulse-excitation bench was constructed and validated. The key results are:

1. In running tests at 1000–1500 RPM and 15–60 kg, single faults raise RMS by 2.4–2.9 times and standard deviation by 1.8–2.4 times relative to the healthy bearing, and kurtosis rises from about 3.0 to 3.8–4.9; the effect grows with load for RMS and kurtosis.
2. Crest factor ranks the health states in the same order at every load (healthy < outer race < inner race < combined inner–outer < combined cage–ball) and decreases with load. The combined cage–ball fault gives the highest values (6.0–6.8) and is the most readily detected.
3. The inner-race fault gives larger feature ratios than the outer-race fault, consistent with the inner-race defect rotating with the shaft.
4. The calculated fault frequencies (6.5–106.8 Hz at 1000–1500 RPM) lie inside the sensor bandwidth, so the low-cost MEMS chain is adequate for this bearing and speed range. Every healthy value is below every single-fault value for RMS, kurtosis and crest factor, so provisional limits can be set in the gaps.
5. The impulse bench gives a repeatable response on new bearings: over 200 impacts on four bearings the coefficient of variation of the impact amplitude was 0.4–3.7 % within a bearing, with isolated outliers accounting for the largest values. Baseline amplitude differs between bearings by about 7 %, so limits must be set per bearing.
6. A CUSUM chart on impact amplitude responds to isolated outlier impacts in healthy bearings; a persistence rule or a pooled σ is needed for routine use.

Future work should extend the tests to many more bearings of each health state, add healthy replicates, test the CUSUM chart on the faulty conditions with sample-level data, trace the ten-impact periodicity in the power-spectrum values, and evaluate a classifier on the enlarged dataset.

Nomenclature

RMS – Root mean square; σ , SD – Standard deviation; K – Kurtosis; Cf – Crest factor; SH, SL – Upper and lower one-sided cumulative sum (CUSUM); k – Reference (allowance) value; UCL, LCL – Upper and lower control limits; h – Decision-limit multiplier; Z – Number of balls; d, D – Ball diameter and pitch diameter, respectively; α – Contact angle; fr – Shaft rotation frequency; BPFO, BPFI – Ball-pass frequency of the outer race and inner race, respectively; BSF, FTF – Ball-spin frequency and fundamental train (cage) frequency, respectively.

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