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Intelligent Condition Monitoring of a Ball Roller Bearing

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Abstract: A bearing itself is one of the essential components that allow constrained relative motion between two or more parts, typically motion or linear movement. It is cylindrical in shape and contains small metal balls and has caused various problems in machineries. Common roller bearings use cylinders of slightly greater length than diameter. Roller bearings are therefore the earliest known type of rolling element bearing. Maintenance of rotary machinery is very essential in all walks of different industries and recently has attracted great attention. Methods of detecting and diagnosing the defective rolling element bearing. Numerous methods have been developed based on intelligent condition monitoring and in this case artificial neural networks, fuzzy expert system, condition based reasoning, vibration measurements, temperature measurements, shock pulse method have been applied and measured. Acceleration sensor was applied on a roller bearing with a charge amplifier to measure acoustic emissions. Analogue-Digital converter was used to produce signal pre-processing which lead to feature extraction. Time and frequency domains were used to show signals change over time and analysis of mathematical functions of signals respectively. Artificial Neural Networks and pattern recognition identifies defects. The computer uses mathematical laboratory software (MATLAB) for command plots of inputs and output signals and indicates a normal or a failing bearing..

Keywords: Accelerometer, Artificial Neural Networks, charge amplifier, Fast Fourier Transform, frequency domain, time domain, signal processing and intelligent condition monitoring.

INTRODUCTION

This is a modern online spectral condition monitoring condition monitoring and recent equipment is used in order to improve the operational availability of machinery for example sensors, data processing; AlShorman (2020) and Liu et al, (2022). Condition monitoring is the continuous process assessment of a parameter of condition in machinery such that a significant change is indicative of a developing failure. Various sensors are used in condition monitoring and in this case a piezo electric sensor was engaged. The bearing is one of the most sensitive components which usually give problems in various engineering sectors. Purpose of monitoring the ball bearing is to establish status and trends of machinery and avoids series of damages; to allow maintenance to be scheduled, other actions to be taken to avoid consequences of failure before damage occurs; to reduce costs by reduced repairs because if there is planned repair so it is likely to be of better quality than that was done at short notice; to avoid revenue losses and to improves safety assurance and reduces personnel risks. The noise coming from the bearing could be concluded for good and bad bearing. For the good bearing it was sound and for the bad one the noise was irritating you could tell that something was wrong through sense of hearing. The defective bearing produced certain frequencies that depend on bearing geometry and its side bands rise in a spectrum graph. Spectral analysis is therefore a predictive maintenance tool. When a bearing reaches an advanced stage, high frequency amplitude levels often decrease due to it peening. If the vibration monitoring is applied within regular selected periods, capable instrumentation and if vibration analysis is performed by experienced personnel, implementing failures can be easily detected.

LITERATURE REVIEW OF CONDITION MONITORING TECHNIQUES

There are various researchers who have engaged on articles of recent condition monitoring of a roller bearing. A bearing itself is one of the essential components that allow constrained relative motion between two or more parts, typically motion or linear movement. Numerous methods of detecting and diagnosing the defective element bearing have been developed based on intelligent condition monitoring, systems such as artificial neural networks, fuzzy expert system, condition based reasoning, random forest and many more; Casoul-Guisande et al, (2022) and Pimenov et al, (2022).

A comparison of some condition monitoring techniques for the detection of defect in induction motor roller bearing have been looked at. Piezo electric transducer was used and it works in shock pulse method (SPM); Beganovic and Soffker (2016) and Kubic et al, (2022). For treatment of original signal, a test rig was used and it consisted of 1,1kW/1440rpm single phase induction motor driving the v-belt drive. Alternating power supply provided the drive to the induction motor.

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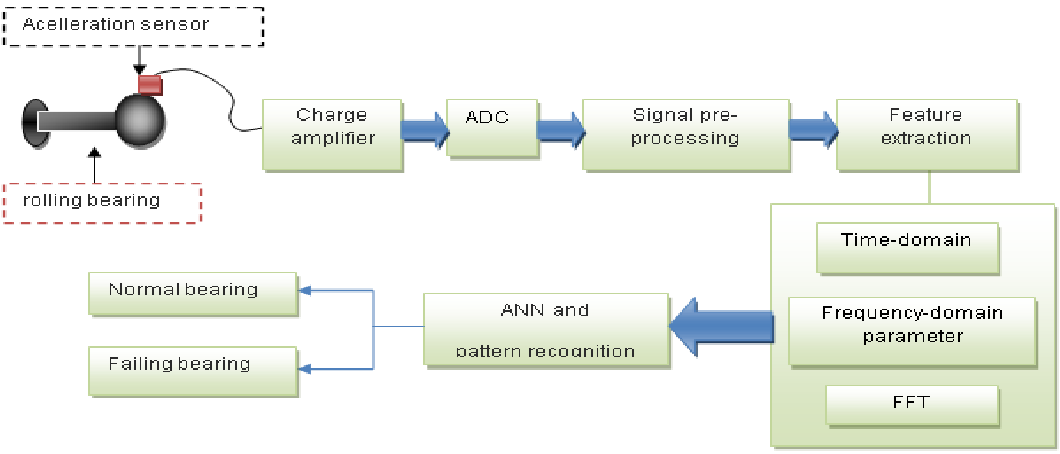
A piezo electric accelerometer was used to measure vibrations. Fast Fourier analyzer was used in filtering and the output from the current sensor fed to it. Frequency span of the Fast Fourier transform was 500 and 20 kHz for frequency spectrum analysis. Acoustic emission technology corporation (AET), model AETAc35L transducer with resonance frequency of 375 kHz, a preamplifier with 60dB gain and a filter (AET FL25x) with a pass band of 250-500 kHz was used to measure AE. The pre-amplifier used +/-12VDC supply and the output was fed to Tektronix TDS210 digital real time oscilloscope to give frequency spectrum. Measurements carried out from no load to full load (27kg) for induction motor bearing with an increment of 5kg. The motor was run at constant speed of 1440rpm. And a good bearing was used and vibration velocity, stator current signals and acoustic emission monitoring was done. The vibration a stator current signal measurements were successful in detecting simulated defects in the outer race of the bearing. The current harmonics for the bearing outer race defect vibration frequency increased in the current spectrum for maximum size of defect. As for the AE and SPM measurements were very good in detecting the bearing defect. It is therefore seen that AE peak amplitude and shock pulse value increased more than other techniques as defect size increases. This was found to be the best in AE monitoring.

Application of Empirical Mode Decomposition (EMD) method and Hilbert spectrum to the fault diagnosis of roller bearing views condition and monitoring of a roller in another way; Kedudouche *et al.* (2016); & Ni *et al.* (2022). FFT method is the spectrum analysis of envelope signals as it regards harmonic signals as basic components which will lead to emerge leakage and cause lower accuracy. For accuracy EMD and Hilbert spectrum are combined for fault diagnosis of defective roller bearing. The pulse force modulated the high frequency vibration amplitude of operating roller bearing. So as to obtain fault characteristic, frequencies the vibration signals of roller bearing had to be demodulated. The time domain waveform of an acceleration signal picked up from a bearing has rotating frequency of 25Hz, sample frequency is 4096Hz and the characteristic frequency of roller bearing with outer race fault was 76Hz.The load marginal spectrum of signal of outraces fault had a double frequency of 152Hz.

The envelope of signal of the same data by Hilbert envelope analytic method with pass band (1000, 2000) Hz showed no spectrum line at the characteristic frequency of roller bearing with outrace fault this was same for band filtering pass band (1500, 2000) Hz. Local marginal spectrum can be obtained from EMD and Hilbert transform when applied to the envelope signal from diagnosis and therefore fault pattern can also be identified. This shows that the method is excellent in obtaining fault characteristics of the roller bearing.

EXPERIMENTAL SET UP DEVICE



For the experiment the rig used was for a small vehicle racing car ramp or stand for checking the braking system.

Accelerometer sensor

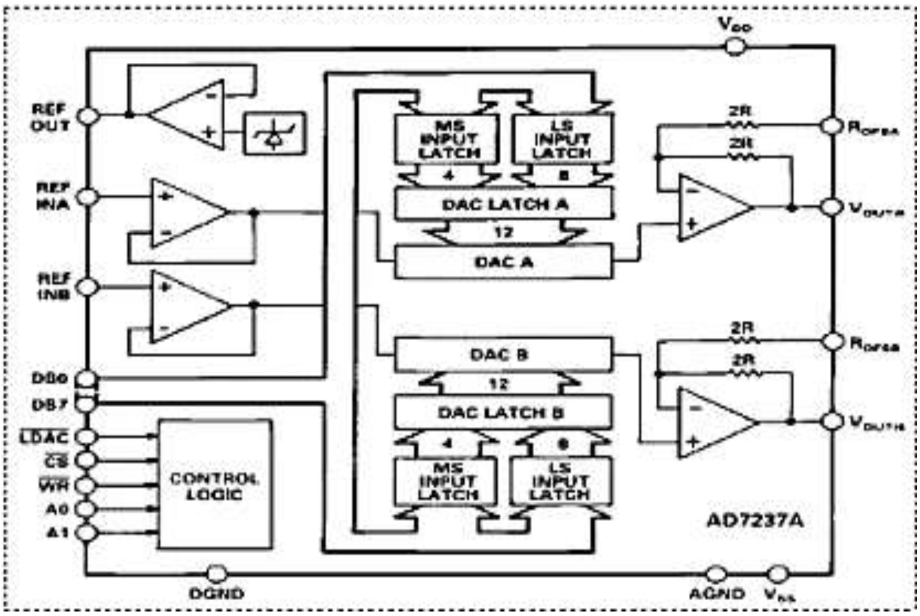
As a sensing technology piezo-electric transducer accelerometer was used together with shock pulse method. Alternating power supply provided drive to the induction motor. An accelerometer was mounted on the ramp and the ramp had a good and bad bearings. This ramp system is linked or networked to the management center which is the database large storage analysis with a PC. The sensor used was an accelerometer (CSI 350) with a sensitivity of 0,1V/EU. In the experiment a mechanical sensor was used to sense vibration and an accelerometer piezo electrical was used to offer a wide range and rank among the optimal choices for vibration monitoring apparatus. The accelerometer is for sensing vibration of the two bearings and in transferring the signal for conditioning which was analogue so it could be converted to digital, Satira *et al.* (2022); & Wang *et al.* (2022). The PC machine had a software product to provide advanced digital signal processing (DSP); intelligent user interfaces, decision assistance and alarm functions. The machine could sense and indicate the state of bearing. For good bearing a green light emitting diode was shown whereas for a bad one a red light emitting diode.

Charge Amplifier

A pre-amplifier with 60dBgain was also used to measure acoustic emission and was +/-12VDC. Output was fed to Tektronix TDS210 digital real time oscilloscope to give frequency spectrum motor bearing increment of 5kg, Tandon (2007). The sensor is configured as a four element bridge. The sensor requires voltage excitation. The full swing output of the sensor is small (tens of milli volts) differential signal that most appropriately is gained by an operational amplifier structure that also converts the differential output of the sensor to a single ended analog signal. One the converter digitizes the voltage presented at its input, the digital code is sent to a micro controller. The micro controller then performs tasks such as calibration corrections and linearization. A two channel memory oscilloscope and a multiple measuring station with function generator and power supply are used. For input and output of the audio signals, a USB and a loudspeaker are used.

Analogue Digital Converter

The following indicates the structure and principles of Analog/Digital board



An analog/digital converter (ADC, A/D or A TO D) is a device that converts a continuous quantity to a discrete digital number, Avina-Corral *et al.* (2022); & Mushafa & Khushnood (2022). It is an electronic device that converts an input analog voltage or current to a digital number proportional to the magnitude of the voltage or current. The power supply is supplied with voltages +15V, 0V and -15V through connectors. In voltage part, +6V, +5V, -1V and -5V will be additionally generated from these power supplies. While the conversion procedure takes place, the AD converter gives a low active busy signal. If the signal is set, the digital value will be saved, the seven segment display is properly installed before the latch, so that the conversion process can be visually traced. Once this is done the results are sent to the LCD display.

SIGNAL PROCESSING

This generally involves two steps; the 1st step usually is called signal preprocessing and is intended to enhance the signal characteristics that eventually may facilitate the efficient extraction of useful information that is the indicators of the condition of a failing component or subsystem. The tools used include filtering. Fast Fourier Transform and data validation. The classic image-recognition and the signal processing paradigm of data→information→knowledge becomes most relevant and takes central stage in the fault diagnosis case particularly because such operations must be performed on line in a real-time environment, Scheeren *et al.* (2022); &Wang *et al.* (2021).

FEATURE EXTRACTION

In feature extraction, time domain; frequency domain and FFT is involved. In filtering a filter is an electronic device that passes certain frequencies (pass-band) but block other frequencies (stop-band). It is therefore classified as low-pass (high-stop) and high-pass (low-stop), band- pass or band-stop. A filter used in the experiment as an AETFL25x with pass band of 250-500Hz which is used to measure acoustic emission.

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On the second article, a central frequency of filter is determined with experience and the band pass is 1k;2kHz and 1,5k; 2kHz, Blanco et al, (2021). The piezo was used and it's based on resonance frequency of 32kHz and for other instruments the resonance was 100kHz. Band pass filter technique was processed in the time domain low frequency vibrations in machine generated by sources as for the rolling bearings were electronically filtered out. In another research, the band pass filter performs sampling together with analogue/digital converter which is 150-1kHz, consisted in envelope method. It focuses on ranges of frequency which must be wide to include the resonance frequency, Altaf *et al.* (2022); & Hasan *et al.* (2022).

Velocity signals were band pass filtered using a 4^{th} order Butterworth filter in MATLAB program. Ratio of rms and kurtosis values increased the filter velocity signal and also in the 2,5k-5kHz frequency band and ration of crest factor increased by 0-2,5kHz frequency band. Also cited is the use of band pass and low filtering involved in amplitude demodulation which provides mechanism for extracting defect rolling frequency from extraneous noise present in the signal. Kalman filter was used to obtain signals. Presented is a research showing signals being low filtered at 9 kHz and Hilbert transform. The scaling function having a low pass and wavelet function having a high pass form. Basically filtering in this section shows ranges from 0-5kHz frequency band which I think was conducive for the experiments undertaken.

Time-domain Features Extraction

This shows how signals change over time and in fault diagnosis.

It is sensitive to the impact fault of gear and bearing and when a command is inputted then this brings up the G201's time-domain features.

Assuming x_i is vibration signal series acquired. i =1,2,…,N. Time-domain has some features as follow:

A. Mean Value $\overline{X}$: $\overline{X} = \frac{1}{N}\sum_{i-1}^{N} x_i$

The advantage of mean value being used for fault diagnosis is to detect peak stability.

B. Variance σ^2: $\sigma^2 = \frac{\sum_{i=1}^{N}(x_i-\bar{X})^2}{N}$

The variance σ^2 describes distribution of random process around mean value; it is dynamic component of random process.

C. Root-mean-square Value: $X_{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$

The root-mean-square value reflects with respect to zero signal x (t)'s fluctuation, it is the average energy. It considers experience process of vibration time changed, also expresses the amount of mechanical vibrating energy.

D. Peak: $X_{peak} = \frac{1}{2}(\max(x_i) - \min(x_i))$

The peak is the biggest instantaneous amplitude of signal, reflecting the signal's strength.

E. Crest Factor: $C_f = \frac{X_{peak}}{X_{RMS}}$

The peak factor expresses whether there is the index of impact.

F. Kurtosis Factor: $K_v = \frac{\sum_{i=1}^{N} x_i^4}{NX_{RMS}^4}$

The kurtosis factor expresses the probability for the large amplitude pulse being formed by fault. It is sensitive to early faults on the bearing. The bearing once appears faults, the kurtosis factor will increase.

G. Shape Factor: $S = \frac{X_{RMS}}{\frac{1}{N}\sum_{i=1}^{N}|x_i|}$

The shape factor is the ratio of the root-mean-square value to absolute mean value.

H. Impulse Factor: $I_f = \frac{X_{Peak}}{\frac{1}{N}\sum_{i=1}^{N}|x_i|}$

The impulse factor is the ratio of the peak value to absolute mean value..

I. Clearance Factor: $CL_f = \frac{X_{Peak}}{(\frac{1}{N}\sum_{i=1}^{N}\sqrt{|x_i|})^2}$

Frequency Domain Feature Extraction

This describes the domain of analysis of mathematical functions or signals with respect to frequency. It shows a signal lies within each frequency band over a range of frequencies. The frequency spectrum of time signals is computed using the discrete Fourier Transformation form (DFT)>Frequency-domain Feature Extraction.

The major of frequency-domain parameter has centre frequency FC, mean-square frequency MSF, and variance frequency VF. Each value can be calculated by the following formula:

A. Centre Frequency $FC = \frac{\sum_{i=1}^{N} f_i p_i}{\sum_{i=1}^{N} p_i}$

The centre frequency reflects the variation of spectrum centre position.

B. Variance Frequency $VF = \frac{\sum_{i=1}^{N}(f_i - fc)^2 p_i}{\sum_{i=1}^{N} p_i}$

The variance frequency reflects the dispersion degree of spectral energy distribution.

C. Mean-square Frequency $MSF = \frac{\sum_{i=1}^{N} f_i^2 p_i}{\sum_{i=1}^{N} p_i}$

The mean-square frequency describes the changing position of Power spectrum fundamental frequencies.

Type : f_i is the frequency value responding to power spectrum at time i .p_i is the amplitude of power spectrum at time i.

Use of Fast Fourier Transform (FFT) is a popular computer method used to shift data from the time domain to the frequency domain. It is used in extensive applications that require fast response times like vibration and shock transient analysis. They reduce the amount of calculations for which you just input the system and then observe and record results. Merits of FT method has various merits like having a multiplex function, high accuracy and reproducibility of frequency measurements, high controlled resolution function and computerization is used to get the signals. FFT analyzer was used and current sensor output fed to it. The frequency of the FFT was 500 and 20 kHz. In the research FFT was used in spectral analysis of the envelope signals and it regarded the harmonic signals as basic components, Li (2021. Time and frequency domain were used to measure overall root means square (rms) level and the crest factor for detection of localized defects. Frequency domain or spectral analysis was widely used for defect detection. FFT plots of some test signals showed deviations from models at low and high frequency. The time frequency provides tools for a more systematic band pass filtering at whole range of possible oscillation frequencies. Based on the other citation on time domain analysis and the defect was located on the outer ring between nodes at 225 and 229, 5 degrees. The FFT of enveloped signal included the outer ring defect frequency. Also high frequency resonance technique (HFRT) was employed in the frequency domain analysis.

The piezoelectric transducer has a resonant frequency of 32 kHz and other instruments being resonant frequency around 100kHz.On frequency domain approach the modern FFT analyzer has made it easier to obtain narrowband spectra. For normal speeds defect frequencies lie in low frequency range of less than 500Hz. Sound intensity, sound pressure and acoustic emission measurements have been used successfully for detecting defects in roller bearings. MATLAB was used to evaluate combinations of different methods and best performing methods were evaluated that is misclassification rate, false alarm rate and miss rate. For each test 150-10kHz band pass filter was applied and demodulation. Envelopes were then added before computing the FFT. It was then found that methods in MATLAB are fully automatic.

ANN AND PATTERN RECOGNITION

Artificial Intelligent has uses that outweigh its demerits. Among the 1st merits or use we recognize the reduced knowledge-acquisition task, flexibility in knowledge modeling, Fallahian *et al.* (2022); & Olsulluvan *et al.* (2022). Also reasoning in domains that have not been fully understood, defined, or modeled. It is also good in learning overtime, providing an explanation module. It also makes use of both qualitative (textual descriptions) and quantitative (measurements) information. Its demerits include large processing time to find similar cases, large storage space, and the best or optimal solution is not guaranteed, among others, Zhang *et al.* (2022); & Zhen *et al.* (2022).

The user can select function to show raw data, filtering, FFT and output signal waveforms. An automated procedure for detection and identification of roller bearing damage using multivariate statistics and pattern recognition is used to recognize between signals from a healthy bearing and to select which are defective. For the experiment four signals were considered that is health bearing, inner race fault, outer race fault and rolling element fault signals. To manifest faults in a bearing impulses are created when a defect on a rolling surface impacts with another surface. And each time the defect comes into contact with another surface it makes the bearing vibrate at its natural frequency. To reduce dimensionality of a signal in time and frequency domain while retaining most of the variance present in data principal component analysis is used. An accelerometer is used to measure vibrations. Original signals for the categories of bearing were different but impossible to be recognized. To clear the indication of this type frequency domain was used. The PCA is applied on the filtered high frequency content signals which contain the information about the presence of a fault. The suggested method is therefore automatic and appropriate for potential applications.

The research is based on data acquisition for different faulty and faultless gear and bearing conditions, processing using wavelet packet for feature extraction, design of an appropriate neural network. Test rig at this was set up and consisted of four speed motorcycle gearbox, an electrical motor, a triaxial accelerometer, tachometer and four shock absorbers. One good bearing and three faulty bearings were used. An ANN was presented for fault detection using vector extracted from standard deviation of wavelet packet coefficients of vibration signals. It has been proved that this approach has a 100% perfect accuracy and performance to identify and detect bearing defects. The ANNs are best performs especially when used with accelerator assisted or specialized parallel chip boards, they substitute a non-available expert as it is also quick. It is a very powerful data modeling capturing tool like a brain and it processes information. It is a non-linear mathematical model or computational model that is inspired by the structure of functional aspects of biological neural networks.

DATA PROCESSING RESULTS

In this we look at the information got from the signals and the principle of Fourier Transformation (FT) is in operation. It performs transformations from one complex valued function of a real variable into another. In applications as signal processing, the domain of the original function is typically time and is accordingly called the time domain. The domain of the new function itself is called the frequency domain representation of original function. The FT decomposes a function into oscillating functions. The machine uses MATLAB which is mathematical laboratory software for command plots of inputs and output signals. Finally, the output is a normal or a failing bearing. Then we can obtain the time-domain features of from G201 to G205 and from Z201 to Z205. From the results find is the table as follows

Condition	Sample	Time-domain features								
		Mean Value（$\times 10^{-7}$	Variance	RMS	peak	Kurtosis Factor	Crest Factor	Clearance Factor	Impulse Factor	Shape Factor
Failure bearing	G201	6.8522	2340.8	0.3421	2.2701	13.3234	6.6357	18.2259	12.465	1.8785
	G202	22.345	2605.74	0.361	2.3549	14.217	6.5242	18.8212	12.628	1.9355
	G203	-32.385	2902.36	0.3809	2.4886	13.532	6.5326	18.9323	12.636	1.9343
	G204	15.329	2630.68	0.3627	2.4803	13.8756	6.8388	19.0288	12.964	1.8957
	G205	15.894	2510.69	0.3543	2.3379	13.2632	6.5985	18.574	12.527	1.8985
Normal bearing	Z201	5.2419	1940.06	0.3115	1.585	4.3203	5.0889	8.1828	6.7397	1.3244
	Z202	27.718	1805.18	0.3004	1.503	4.4684	5.0027	8.0612	6.6351	1.3263
	Z203	-23.982	1698.73	0.2914	1.3764	4.6255	4.7228	7.7033	6.3155	1.3372
	Z204	2.5821	1677.68	0.2896	1.7399	4.8859	6.0073	9.6808	7.977	1.3279
	Z205	3.4274	1890.52	0.3075	1.5231	4.5035	4.9539	7.9403	6.5522	1.3226

From these time-domain features we can find that there are obvious differences at variance, peak, kurtosis factor, clearance factor, impulse factor, and shape factor and other features are not obvious. Input a command and this brings up the G201's frequency-domain features. Then we can obtain the frequency-domain features of from G201 to G205 and from Z201 to Z205 as reflected on the table as follows :

Condition	Sample	Frequency-domain parameter features		
		Centre Frequency	Variance Frequency	Mean-square Frequency
Failure bearing	G201	727.439	768683.09	1297850.575
	G202	732.7359	755254.2402	1292156.146
	G203	783.7554	830793.7149	1445066.288
	G204	772.6559	858228.7434	1455225.833
	G205	708.5887	743009.3845	1245107.368
Normal bearing	Z201	1947.7204	6177234.382	9970849.154
	Z202	2063.4476	6752047.59	11009863.56
	Z203	2124.7889	6969666.444	11484394.4
	Z204	2129.9819	7038297.662	11575120.48
	Z205	2049.5272	6681185.6	10881747.31

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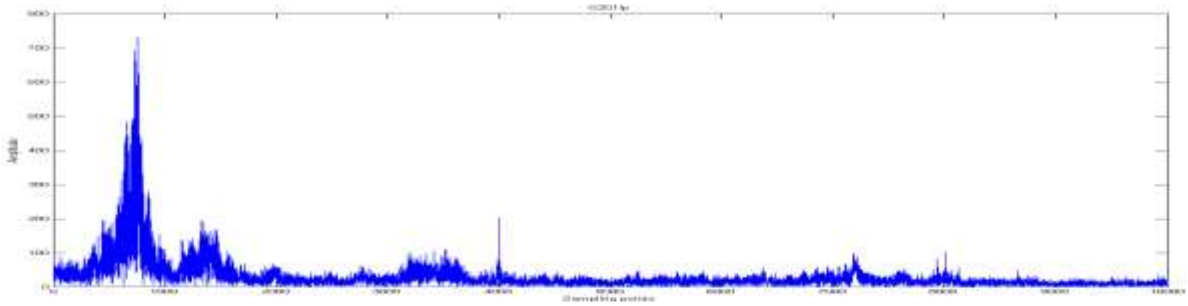
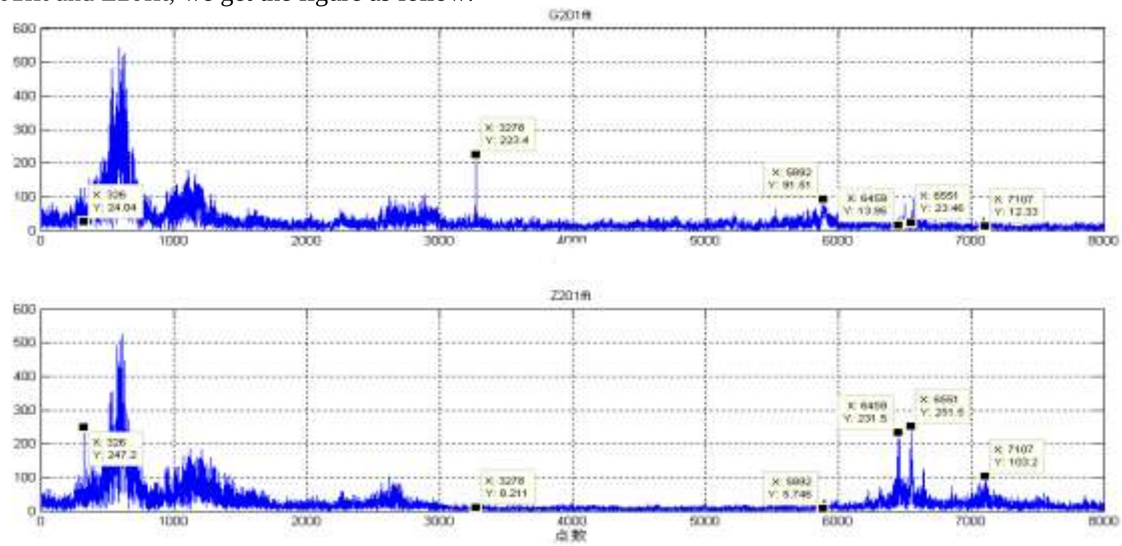
From the above table it can be seen that the repeatability and diversity of frequency-domain parameter are good.

For FFT Input of a command like

N=20000; %sampling points
fs=10000; %sampling frequency
G201fft=abs (fft(G201l)); %FFT,G201fft is the result of G201l making FFT G201fft=G201fft (1: N/2,1);



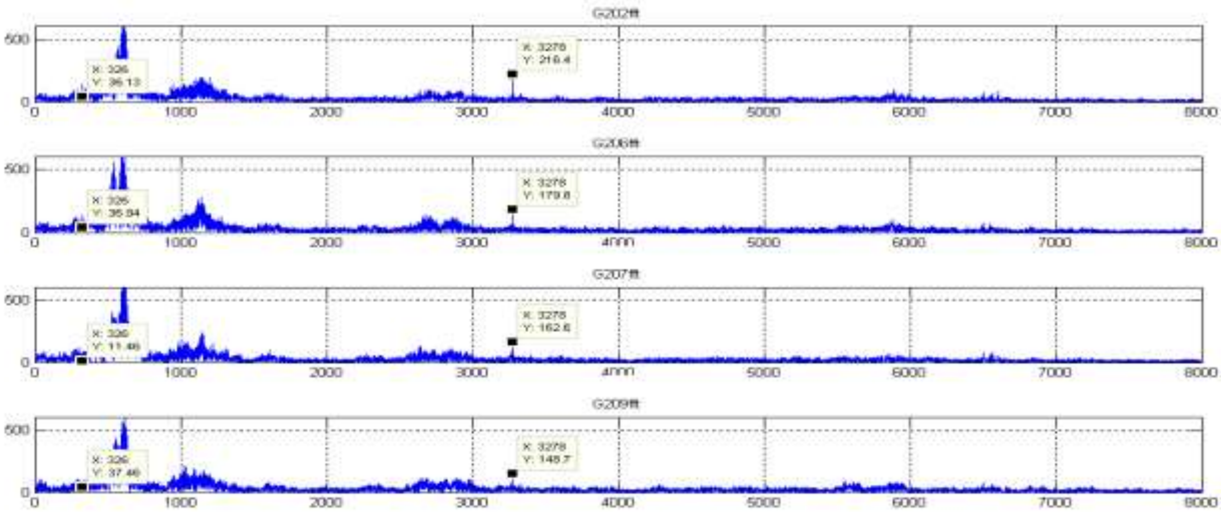
Plot G201fft and Z20fft, we get the figure as follow:



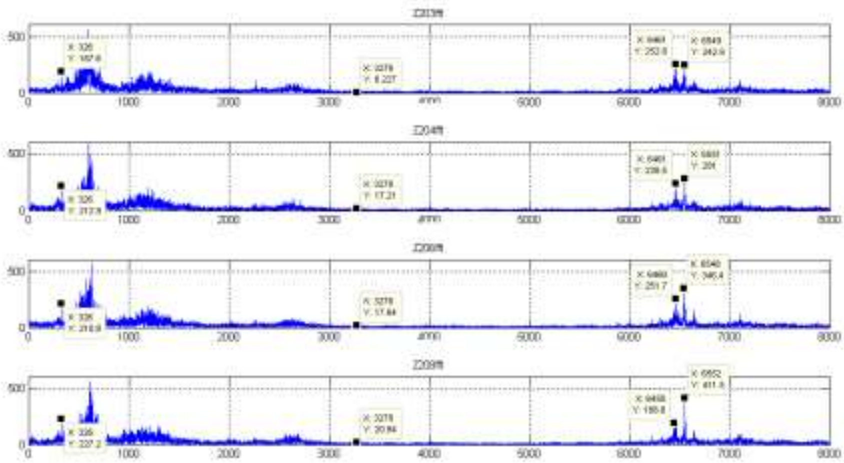
So we can get the areas or points which can distinguish between two conditions: point (326,1)and (3278,1),area(2560 to 3000),(6310 to 6646) and (6850 to 7300). Marked with 

.

Plotting data of a failing bearing gives the following:



From the above figure it can be seen that the repeatability of each feature is good. Plotting data of normal bearing gives the following:



From the above figure it can be seen that the repeatability of each feature is good. Using the below command to extract the points and areas of FFT features which from G201 to G205 and from Z201 to Z205.

G201ffttz=[G201lp(326,1),sum(G201lp(2560:3000,1)), G201lp(3278,1),sum(G201lp(6310:6646,1)), sum(G201lp(6850:7300,1))];%G201ffttz is the features which G201 is made FFT. Then we establish the table:

Condition	Sample	FFT features				
		（326，1）	（2560：3000，1）	（3278，1）	（6310：6646，1）	（6850：7300，1）
Failure bearing	G201	24.037	16457.4591	223.4111	5511.6023	5070.6419
	G202	36.1318	15337.1272	216.3505	5283.4564	5046.534
	G203	28.2671	18178.6398	213.6201	5642.9205	5046.534
	G204	11.1246	18178.6398	163.9869	5662.4984	5687.772
	G205	114.0399	16154.9008	168.2039	5562.4298	5151.0799
Normal bearing	Z201	247.1716	10356.3888	8.211	15539.7691	11057.7255
	Z202	179.1598	10083.4336	27.4943	14772.372	10632.8833
	Z203	187.5852	10018.7181	6.2269	15396.4913	10692.6573
	Z204	212.9235	9502.5877	17.2084	15035.7169	10475.6605
	Z205	132.3277	10125.0714	18.6699	15691.3139	11033.852

Features Normalization

Because of the different values of feature, it is not convenient to compare the same feature between different samples and extract features. Considering the input values of neural network, this article normalizes all features in interval [0, 1]. Linear transformation is expressed as follow:

y=(x-MinValue)/ (MaxValue-MinValue)

Explanation：x and y is respectively the valve of before and after transformation, Max Value and Min Value is respectively the maximum and minimum value of the samples.

Input a command like this:
for i=1:17
for j=1:10
gy(i,j)=(tz(i,j)-min(tz(i,:)))/(max(tz(i,:))-min(tz(i,:)));%
The tz is original feature matrix, the gy is the feature matrix after normalization. The 17 is the number of original feature and the 10 is the number of samples.

Then we get the below tables：

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	Failure bearing G201~G205				
	0.6453	0.9	0	0.7847	0.794
	0.5671	0.7713	1	0.7906	0.6981
	0.6025	0.7961	1	0.8135	0.7275
Time-domain features	0.8123	0.8851	1	0.9929	0.8705
	0.9131	1	0.9334	0.9668	0.9073
	0.8999	0.8516	0.8552	0.988	0.8838
	0.8736	0.9208	0.9296	0.9373	0.9012
	0.8881	0.9103	0.9115	0.9563	0.8966
	0.9091	1	0.9981	0.9366	0.941
Frequency-domain parameter	0.0128	0.0164	0.051	0.0435	0
	0.004	0.0019	0.0136	0.0178	0
	0.0049	0.0044	0.0186	0.0196	0
FFT features	0.0547	0.1059	0.0726	0	0.436
	0.6313	0.5296	0.7875	0.7875	0.6038
	1	0.9675	0.9549	0.7264	0.7458
	0.0219	0	0.0345	0.0364	0.0268
	0.0039	0	0	0.1041	0.017

CONCLUSION

Various researchers have been reviewed on modern conditioning monitoring of a roller bearing. Therefore, these are put into use in our industry so as to avoid machinery damage, production losses and personnel injury caused by these rotating machineries that are in daily use. The maintenance department must in turn present these failures when they are in the initial stages before something goes wrong. For a good condition monitoring there must be involvement of sensors, filtering, FFTs, ANNs and many others above all the pattern recognition classification to give or output the end results. ANNs are usually applied in image processing like identifying hand written characters, matching of good and bad bearing, performing data compression on the image with minimal loss of content. Outputs and inputs and algorithms must be understood in great detail. This is very important and if some critical inputs are emitted then the network will fail to converge on a solution. Due to these technological changes thank you to intelligent conditioning monitoring which will save various industries as they are into production.

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