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# Inner and Outer Races Bearing Damage Detection using Low-cost Fault Detecting Sensors

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**Abstract:- Bearings are small components of a machine used in various industries. However, bearings have an important role in transferring energy from the main motor to other parts. Therefore, monitoring the condition of the bearings is very necessary to keep the production process running smoothly. The study provides a new perspective that bearing damages were analyzed by low-cost sensors, namely the Accelerometer sensor (ADXL-335) and Arduino Uno. The results showed that the low-cost sensor developed in this study was able to detect damage to the ball bearing. The Fast Fourier Transform (FFT) signal processing tool works compatible with the low-cost sensor and could be used to determine the type of damage to the bearing by analyzing the signal frequency spectrum. In this process, there were several frequencies that appear with characteristics related to the condition of the bearing. The working frequency of the shaft rotation on the bearing with normal conditions was 10 Hz, the frequency with damage to the inner race of the bearing was 55.52 Hz, and the bearing with damage to the outer race included a frequency of 34.47 Hz.**

***Keywords:-*** *Bearing Condition Monitoring, Low-Cost Sensor Detection, Vibration, FFT.*

## I. INTRODUCTION

Induction motors are electromechanical devices used in various industrial applications to convert electrical energy into mechanical energy. Induction motors are equipment that plays a very important role in industry. This is because so many operational processes in industry use induction motors as their main drive. The main reason is because induction motors have high reliability and relatively lower costs. Almost 70% [1,2] of industrial processes use induction motors as their main drive components. Some processes that usually use induction motors include pumps, compressors, and become the main drive of several other industrial machines.

Although it has a strong construction, it does not mean that the induction motor will not experience damage. There are times when the induction motor is damaged and must be stopped operating. This will certainly be very detrimental because it affects the process in the industry. In addition, damage to the induction motor can endanger workers around it. The solution to overcome this is to carry out routine monitoring so that the condition of the induction motor can continue to be observed. Bearing damage is one of the biggest types of damage that is often found in induction motors. Around 41-44% of induction motor damage occurs due to damage to the bearings [3,4]. Bearings are components of an induction motor that help the rotor move freely. Bearing damage can cause vibration, noise, increased working temperature, and sparks that can damage other parts of the induction motor [5,6].

Several studies have found ways to detect bearing damage. Yao, et al. [7] identified bearing damage using the LCD-MPE and ELM-AdaBoost methods. Hastie, et al. [8] observed bearing damage using Multi-class AdaBoost. However, they mostly use very expensive measuring sensors and data acquisition instruments, such as accelerometers, oscilloscopes, and various other data acquisitions [9-14].

This study will analyze vibration characteristics using a fast Fourier transform (FFT) signal processing tool applied to an induction motor to detect bearing damage. In this study, several experiments will be carried out in the form of varying bearing damage to determine the performance of the proposed damage detection method. Experiments are carried out using several test equipment made of low-cost sensors. This instrument is then connected to the open software Octave to analyze the data. Bearing damage considered includes damage to the outer race and inner race and balls.

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## II. RESEARCH METHOD

➢ *Data Collection*

At this stage, data is collected in the form of vibration signals from various conditions of the tested bearing components. Depending on the nature of the bearing component damage, there are several requirements for the data collection process. Figure 1 shows a schematic diagram of experimental data collection using a test-rig. Based on the image, a low-cost sensor to detect bearing damage is used. These instruments include the Accelerometer sensor (ADXL-335) and Arduino Uno. The ADXL-335 sensor is placed on the bearing housing, whether the bearing is in normal condition, inner race damage, or outer race damage. The data collection process with the bearing operating condition is connected to the motor at a rotation speed of 600 rpm. Vibration signal data is recorded and stored on a laptop in CSV file format. The raw data is then analyzed using a Fast Fourier Transform (FFT) signal processing tool.

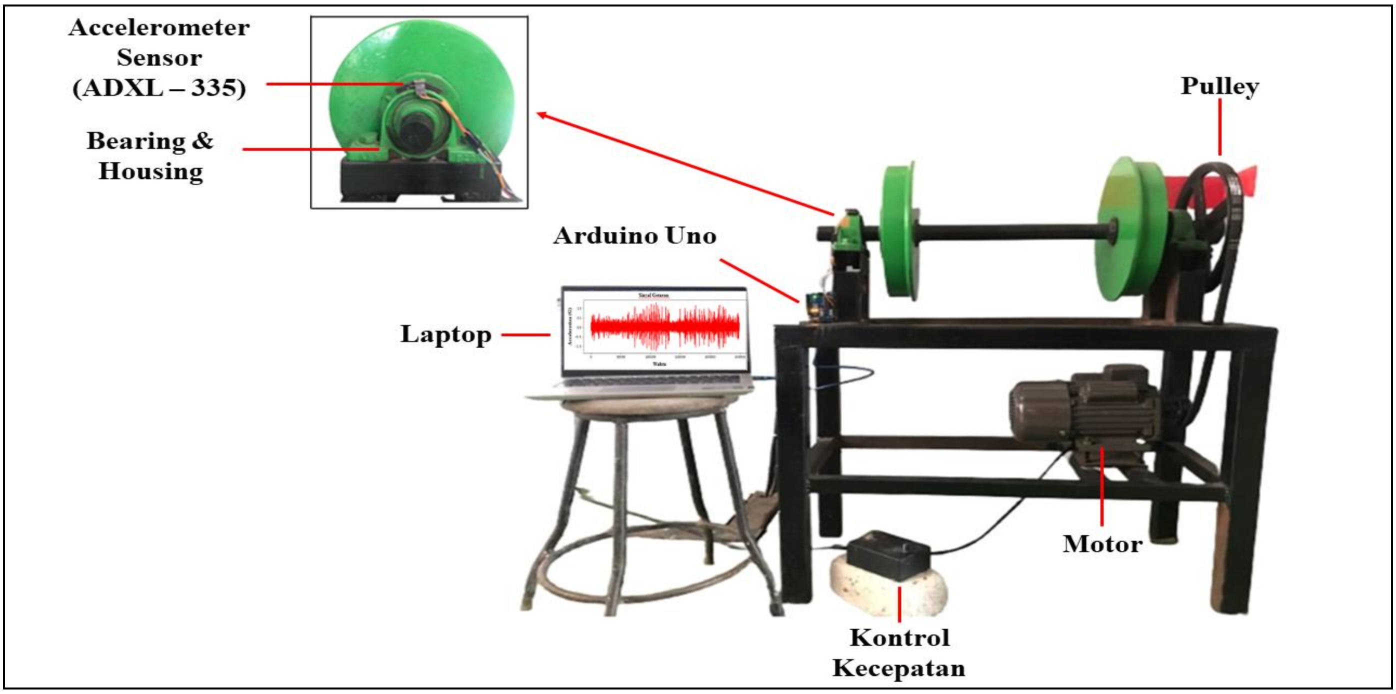


Fig 1 Set-Up Experiment for Data Acquisition

The bearings used in this study are shown in Figure 2 and the specifications are the FK UCP208-24 ball bearing type with an outer diameter of 80 mm, an inner diameter of 38 mm, and a pillow block bearing housing type.


Fig 2 Ball Bearings and Bearing Housing used in the Study

Three bearings with different types of conditions that will be analyzed in this study as shown in Figure 3.

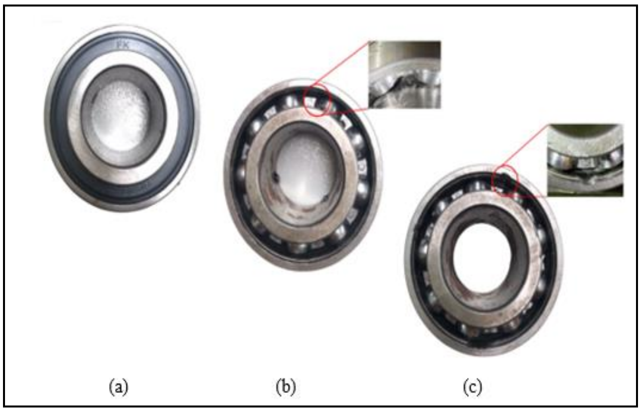


Fig 3 Three Bearing Conditions During Data Collection; (a) Bearing without Damage, (b) Bearing with Inner Race Damage, (c) Bearing with Outer Race Damage

## III. RESULTS AND DISCUSSIONS

Based on the use of bearing test rig as a research tool and the application of predetermined bearing parameters, data collection was carried out which produced a signal in the time domain as shown in Figure 4. This signal represents changes and characteristics of the bearing condition on the machine or equipment being observed.

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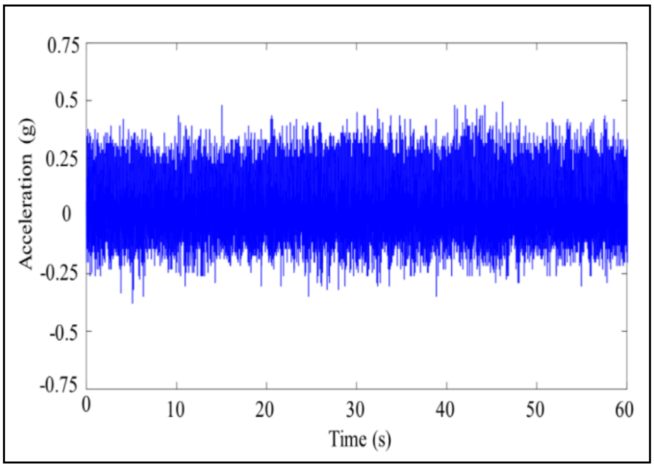
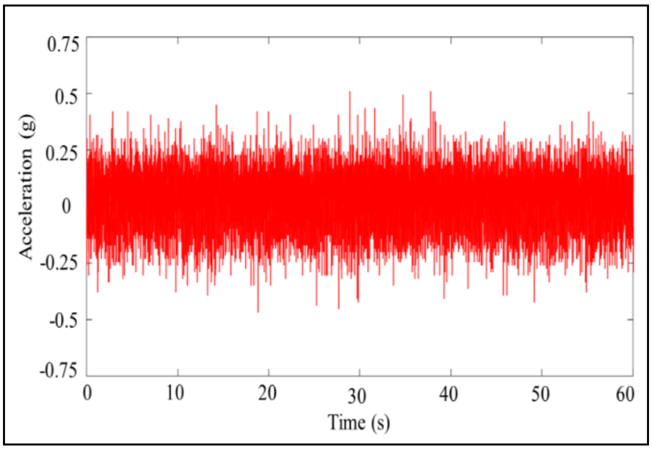
**Figure 4** is a signal that has been acquired based on experiments on bearing vibrations in conditions; (a) normal, (b) damaged inner race, (c) damaged outer race. It can be seen that the signal generated by bearing vibrations in normal conditions is a completely modulated or constant amplitude, and the signal duration can be calculated from start to finish. It can be seen that the time domain displays a range of acceleration amplitude values between -0.75 to 0.75 (g) and a time range between 0 to 60 (s). In addition, the signal obtained from normal bearing vibrations has a constant signal and has the highest amplitude value of 0.4 (g).

The signal generated by bearing vibrations in damaged conditions on the inner race is a signal in the time domain showing changes, namely irregular and inconsistent patterns compared to signals from normal bearing vibrations. This pattern change indicates instability due to vibrations in damaged conditions on the inner race. It can be seen that the time domain displays a range of acceleration amplitude values between -1.25 to 1.25 (g) and a time range between 0 to 60 (s). This can be observed from the high change in acceleration amplitude values, seen with the highest value reaching 0.5 (g).

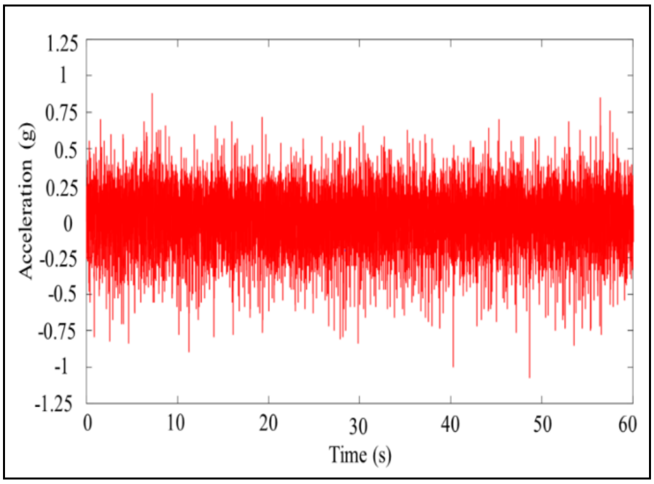
The signal generated by bearing vibrations in damaged conditions on the outer race is a signal in the time domain showing changes similar to damaged conditions on the inner race, namely an irregular and inconsistent pattern compared to the signal from normal bearing vibrations. This pattern change indicates instability due to vibrations in damaged conditions on the inner race. It can be seen that the time domain displays a range of acceleration amplitude values between -0.75 to 0.75 (g) and a time range between 0 to 60 (s). This can be observed from the high change in acceleration amplitude values, seen with the highest value reaching 0.9 (g). These signals are then analyzed using Fast Fourier Transform (FFT) signal processing.




(a) Signal Obtained in Experiment using Bearing in Normal Condition




(b) Signal Obtained in Experiment using Bearing in Inner-Race Fault Condition

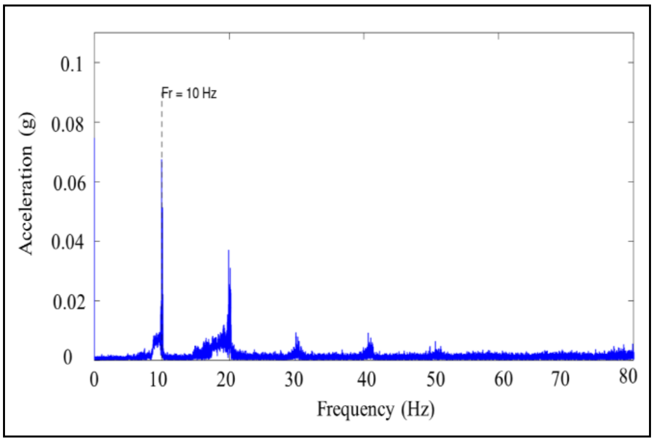



(c) Signal Obtained in Experiment using Bearing in Outer-Race Fault Condition

Fig 4 Signals in the Time Domain Acquired from Experiments with Various Bearing Conditions

- *Frequency Analysis*

The results of the FFT spectrum that correspond to the calculation data with normal variations and 2 types of damage, namely inner race damage and outer race damage, are shown in the following figure.




(a) Frequency Spectrum of Bearing Vibrations Associated with Normal Bearing Condition

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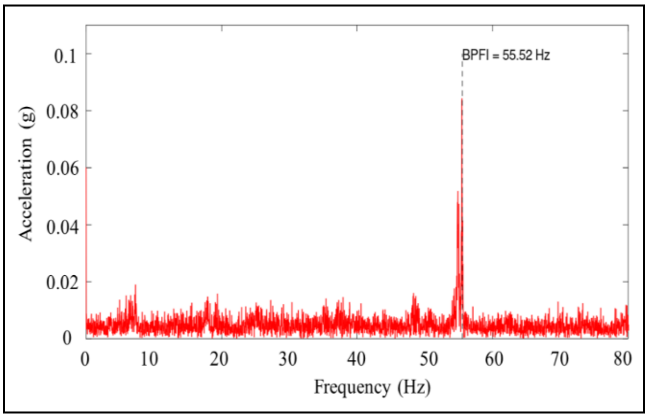
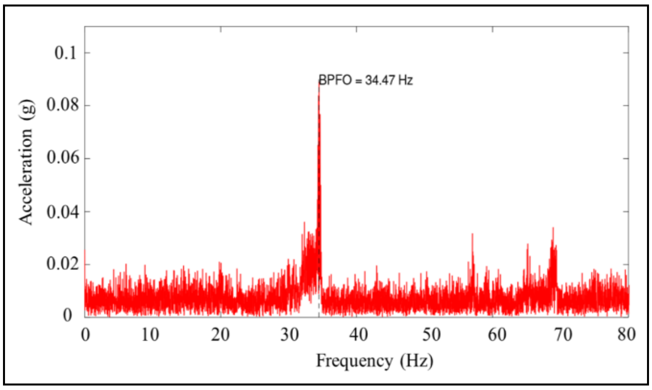



(b) Frequency Spectrum of Bearing Vibrations Associated with Inner-Race Fault Bearing Condition




(c) Frequency Spectrum of Bearing Vibrations Associated with Outer-Race Fault Bearing Condition
Fig 5 Frequency Spectrum Calculated using FFT Corresponding to its Time Domain Data

**Figure 5(a)** is a spectrum for bearings in normal condition corresponding to time domain data processed using the Fast Fourier Transform (FFT) signal processing method. The resulting signal is a time domain converted to a frequency domain, so that high amplitude values will be seen. The high amplitude value is the working frequency of the fr shaft rotation of 10 Hz and its harmonic frequency which is a multiple of 10 Hz. The working frequency of the fr shaft rotation = 10 Hz calculated using Equation (1) [11]:

$$\mathrm{fr} = \frac{\omega}{t} \tag{1}$$

Where ω and t are the motor rotation speed (rpm) and time (seconds), respectively.

**Figure 5(b)** is the FFT spectrum for the bearing vibration signal in the inner race damage condition. There is a dominant frequency peak of the Ball Pass Frequency Inner Race (BPFI) of 55.52 Hz in the FFT spectrum, which can be seen from the time domain which is converted into the frequency domain. The difference in characteristics between the FFT spectrum of the bearing in the inner race damage condition and the FFT spectrum of the normal bearing shows a change in the frequency and amplitude parameters of the vibration in the bearing that has experienced inner race damage. The BPFI frequency = 55.52 Hz is calculated using Equation (2) [11]:

$$\mathrm{BPFI} = \frac{\mathrm{Nb}}{2} \times f_r \times \left(1 + \frac{\mathrm{Bd}}{\mathrm{Pd}} \times \cos a\right) \tag{2}$$

**Figure 5(c)** is the FFT spectrum of bearing vibrations in outer race damage conditions. There is a dominant frequency peak Ball Pass Frequency Outer Race (BPFO) of 34.47 Hz in the spectrum. This frequency indicates damage to the outer race of the bearing. This frequency is calculated using Equation (3) [11]:

$$\mathrm{BPFO} = \frac{\mathrm{Nb}}{2} \times f_r \times \left(1 - \frac{\mathrm{Bd}}{\mathrm{Pd}} \times \cos a\right) \tag{3}$$

Signal processing tools are techniques used to analyze, manipulate, and process signals in order to obtain useful information. The following are the advantages and disadvantages of signal processing methods and signal processing using FFT. FFT displays a frequency spectrum that can display information in the form of a frequency domain. The frequencies that appear are clearly visible and are able to detect bearing damage and frequency values according to the results of the equation, namely ($fr$) of 10 Hz, BPFI of 55.52 Hz, and BPFO of 34.47 Hz. However, the disadvantage of FFT is the assumption that the signal is stationary, that is, the signal does not change over time. If the signal is non-stationary or has a frequency component that varies over time, then FFT does not provide accurate results.

## IV. CONCLUSIONS

The study provides a new perspective on that bearing damage analysis can be done with low-cost sensors, namely the Accelerometer sensor (ADXL-335) and Arduino Uno. Based on data analysis and discussion, it can be said that the low-cost sensor developed in this study is able to detect damage to ball bearings. Fast Fourier Transform (FFT) signal processing tools work compatible with these low-cost sensors and can be used to determine the type of damage to the bearing by analyzing the signal frequency spectrum. In this process, there are several frequencies that appear characteristics related to the condition of the bearing. The frequency of the working rotation of the shaft on the bearing with normal conditions is 10 Hz, the frequency with damage to the inner race of the bearing is 55.52 Hz, and the bearing with damage to the outer race has a frequency of 34.47 Hz.

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