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Bearing Fault Analysis Utilizing Fuzzy Logic Methodology for Enhanced Diagnostic Accuracy

***Abstract**. This research aims to design a tool that can be used to detect damage or malfunctions in induction motors, especially in the bearing part which is the main driving component. Using the MPU 6050 accelerometer sensor and sound sensor module with the Arduino Nano microcontroller and the HC 05 Bluetooth module as a medium for sending and acquiring signal data. The signal data obtained in the form of a datalog with the extension .txt is then processed further with Matlab software to find out information on the characteristics of sound signals and vibration signals generated by induction motor bearings. Using a cut-off signal filter low pass filter for voice signal filter processing and fast Fourier transform (FFT) to convert the time domain signal into a signal frequency domain to determine the frequency characteristics arising from the signal. From the sound and vibration signal input data obtained, the Fuzzy logic method is used to determine the bearing condition output. The developed system is capable of detecting bearings in three conditions, namely good, damaged, and alert.*

***Streszczenie.** Celem badań jest zaprojektowanie narzędzia, które będzie można wykorzystać do wykrywania uszkodzeń lub usterek w silnikach indukcyjnych, zwłaszcza w części łożyskowej będącej głównym elementem napędowym. Wykorzystanie czujnika akcelerometru i modułu czujnika dźwięku MPU 6050 z mikrokontrolerem Arduino Nano i modułem Bluetooth HC 05 jako medium do przesyłania i pozyskiwania danych sygnałowych. Uzyskane dane sygnałowe w postaci datalogu z rozszerzeniem .txt są następnie przetwarzane w programie Matlab w celu uzyskania informacji o charakterystyce sygnałów dźwiękowych i sygnałów wibracyjnych generowanych przez łożyska silników indukcyjnych. Zastosowanie filtra dolnoprzepustowego filtra sygnału odcinającego do przetwarzania filtra sygnału głosowego i szybkiej transformaty Fouriera (FFT) w celu konwersji sygnału w dziedzinie czasu na dziedzinę częstotliwości sygnału w celu określenia charakterystyk częstotliwości wynikających z sygnału. Na podstawie uzyskanych danych wejściowych sygnałów dźwiękowych i wibracyjnych metoda Fuzzy logic służy do określenia wyjściowego stanu łożyska. Opracowany system jest w stanie wykryć łożyska w trzech stanach: dobre, uszkodzone i czujne. (**Analiza uszkodzeń łożysk wykorzystująca metodologię logiki rozmytej w celu zwiększenia dokładności diagnostyki**)*

Keywords: Sensor, Sound Sensor, Bearing, Fault, Fuzzy Logic
Słowa kluczowe: Czujnik, czujnik dźwięku, łożysko, usterka, logika rozmyta.

Introduction

Bearing is a machine element that supports a shaft that has a load, so that the rotation or alternating movement can take place smoothly, safely and has a long life. Bearings must be rigid enough to allow the shaft and other machine elements to operate properly. If the bearing is not functioning properly then the performance of the entire system cannot work properly[1]–[5].

Bearing detection is expected to reduce the level of bearing damage that is not detected by the human senses[1]–[10]. This research aims to make a bearing condition detection module on a motor using a sound sensor and accelerometer sensor connected to the Arduino Nano microcontroller. The sound sensor is used to measure the level of noise or noise generated when the motor is moving and the accelerometer sensor detects vibrations generated by the motor[6]–[10]. Furthermore, the sound and vibration signal data obtained will be examined, and compared and accuracy level analyzed using Matlab software to determine the signal from the bearing condition that is damaged, rough, or still good[11]–[13].

Bearing or rolling bearing is an important element or driving part of a tool or object that rotates on its axis. It consists of a ball that is in a cage or cage that is between the inner ring and the outer ring, the way it works is to separate the movement of objects attached to the inner ring and the outer ring to maximize movement and minimize friction[14]–[16].

Types of damage to bearings can be distinguished as follows and are expressed in the equation as follows.
Local Defects in *the Inner Race*

(1) $BPFI = \frac{Nb}{2}\ x\ f_r\ x\ \left(1 + \frac{Bd}{Pd}\ x\ \cos\alpha\right)$

Local defects in *the Outer Race*

(2) $BPFO = \frac{Nb}{2} x\ f_r\ x\ \left(1 - \frac{Bd}{Pd}\ x\ \cos\alpha\right)$

Local defects on *the rolling element* or ball

(3) $BSF = \frac{Nb}{2Bd}\ x\ f_r\ x\ \left(1 - \left(\frac{Bd}{Pd}\ x\ \cos\alpha\right)^2\right)$

Local defects on *Cage*

(4) $FTF = \frac{f_r}{2}\ x\ \left(1 - \frac{Bd}{Pd}\ x\ \cos\alpha\right)$

However, if in the case of only the number of balls and the rotational speed of the machine, the following formula can be used

(5) $FTF = f_r\ x\ \left(\frac{1}{2} - \frac{1{,}2}{Nb}\right)$
(6) $BPFI = f_r\ x\ \left(\frac{Nb}{2} + 1{,}2\right)$
(7) $BPFO = f_r\ x\ \left(\frac{Nb}{2} - 1{,}2\right)$

Where: Nb = Number of balls (*Number of balls*); Fr = Rotation frequency (Hz); Bd = Ball diameter (mm); Pd = Pitch Diameter (mm); α = contact angle in degrees (0^{0} for bearing series 6xxx)

Vibration is the oscillatory movement of an object from rest. The vibrations that appear can cause vibration signals which are commonly called waveforms. In vibration analysis, certain motor conditions will be identified through the vibration signal spectrum because certain conditions or defects in the bearing will produce a different vibration signal spectrum[17]–[23].

The induction motor will also produce sound signals from vibrations when the motor is rotating or working.

Sound signals will produce information about the condition of the induction motor. irregularities and damage to the bearings is information that can be obtained from the condition of the sound signal frequency[24]–[33].

Method

The process begins on the motor that is used as a research object that has been conditioned for research. To record the signal, sound sensors and accelerometer sensors are used to retrieve data. There are 2 types of signal data obtained, namely from the sound sensor and vibration sensor which are used at the same time and position of the motor.

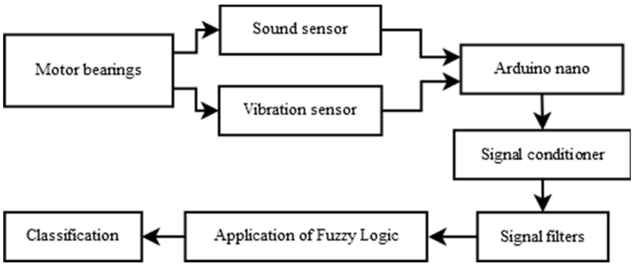

Fig. 1. Bearing condition system

Arduino as a microcontroller will process signal data from sensors and send serial signal data via the Bluetooth module. After the signal data is obtained, it will be processed using Matlab software, in this process signal processing will be carried out. Then proceed with a fuzzy logic process from 2 signal data to determine bearing conditions. The last process is the process of analyzing and comparing the results of fuzzy logic with the actual condition of the bearings on existing motors[17], [34]–[38].

Hardware Design

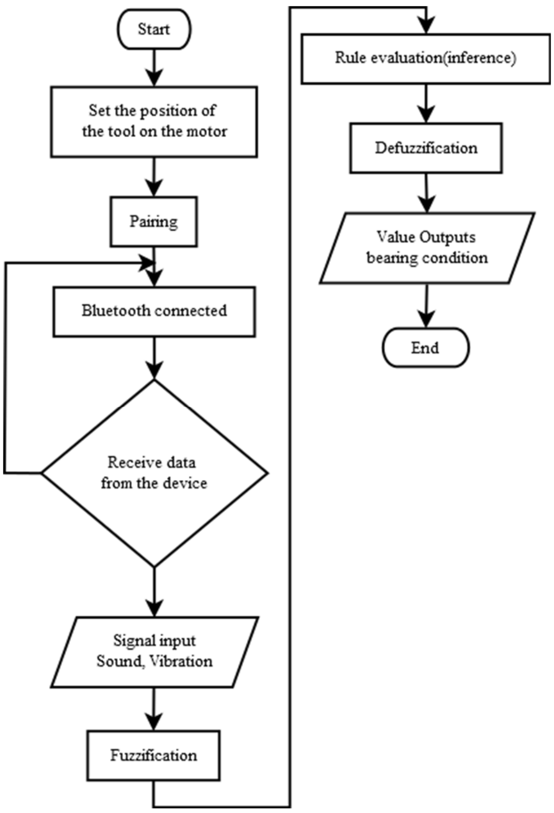

Fig. 2. Bearing monitoring system Flowchart

The Bearing Signal Detector consists of an Arduino Nano microcontroller equipped with a sound sensor to detect sound signal waves and an MPU 6050 accelerometer sensor to detect vibration signal , and for communication[39]–[41]. uses the HC-05 Bluetooth module to send signal data from a signal detector to a computer or an Android mobile device in datalog form[42]–[46]. For the power supply, this tool uses a 9v battery connected to a step-down dc to dc converter (mini buck 360 DC converter) to lower the 9v to 5v voltage. The hardware design works can be seen in fig 2.

Fuzzy Design

The initial process of fuzzy logic begins with determining and forming fuzzy sets[36], [47]–[49]. The determination of the variables and the universe of speakers or the range of variables is obtained from existing previous research and the data can be seen in the table.

Table 1. Fuzzy set function

Function	Name Variable	Universe of Talks	Information
Inputs	Voice	Smooth, alert, rough	Sound signal frequency in Hz
	Vibration	Smooth, alert, rough	The pulse signal frequency is in Hz
output	bearings	Fine, alert, broken	bearing condition

The data in the table above are the input and output data that have been obtained along with the linguistic value or universe of discussion of each variable[48], [50]–[52]. Voice Input has a universe of speech in the form of a crisp value (crisp) 0 to 500. This value is obtained from the signal frequency from the sound sensor. The assertive values are converted into fuzzy sets, namely Smooth, Alert and Rough with the following picture.

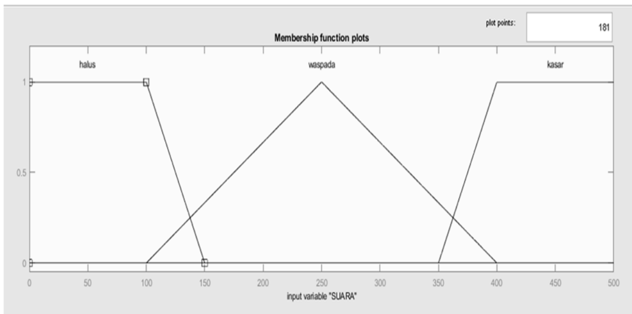

Fig. 3. Voice Input Membership Function

The vibration input has a universe of speech in the form of a crisp value 0 to 500. This value is obtained from the frequency of the vibration signal from the acceleration sensor MPU 6050. The strict value is converted into fuzzy sets, namely Smooth, Alert and Rough with the following picture

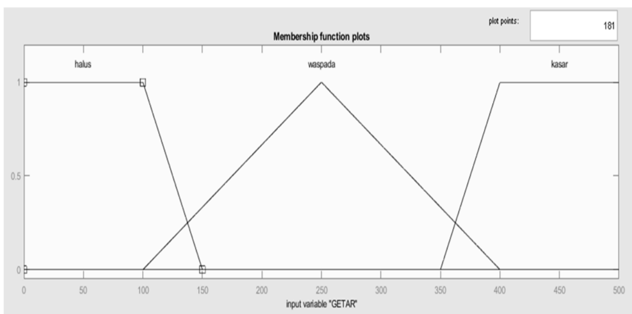

Fig. 4. Vibration Input Membership Function

Output bearings are in the form of crisp values 0 and 1 which are used to indicate the condition of the bearing. The assertive value is converted into good, alert, damaged and fuzzy output sets.

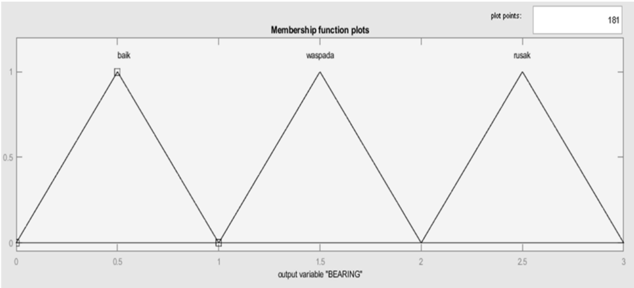

Fig. 5. Membership Functions of Output Bearings Condition

Decision making is based on input values, differences in input values obtained from sound and vibration signal data which will influence decisions on output. The determination of the desired rules is built according to simple reasoning obtained from design knowledge and sources existing from references.

Table 2. Fuzzy Rules

No	Fuzzy Rules
1	If (Sound is Smooth) and (Vibration is Smooth) then (Bearing is Good)
2	If (Sound is Alert) and (Vibration is Soft) then (Bearing is Diesel Good)
3	If (Sound is Coarse) and (Vibration is Soft) then (Bearing is Solar Alert)
4	If (Sound is Smooth) and (Vibrate is Alert) then (Bearing is Good)
5	If (Sound is Alert) and (Vibration is Alert) then (Bearing is Alert)
6	If (Sound is Rough) and (Vibrate is Alert) then (Bearing is Damaged)
7	If (Sound is Soft) and (Vibration is Coarse) then (Bearing is Damaged)
8	If (Sound is Alert) and (Vibration is Rough) then (Bearing is Damaged)
9	If (Sound is Rough) and (Vibration is Rough) then (Bearing is Damaged)

Signal Data

The process of taking the signal is carried out by placing the finished bearing tester on the motor to be tested, trying and to position it close to the position of the bearing on the motor[21], [25], [53]–[57].

Table 3. Research Motor Specification Data

No	Motor Name	Type	Year	Motor Power	Work Cycle
1	CSD 125	Compressor Screw Motors	2019	75Kw	2982rpm
2	CSD 125	Compressor Screw Motors	2017	75Kw	2982rpm
3	CSD 125	Compressor Screw Motors	2013	75Kw	2978rpm

Result and Discussions

Research Data

The research data used uses a screw compressor drive motor on 3 machines that have the same specifications but have different manufacturing years, for bearings in 2013 according to the machine history data obtained, new bearings have been replaced because the machine's service life has exceeded the hours of use and the condition use starts from the beginning, so according to historical data the bearings on the 2013 engine are in the best condition among the others. Later conditions will certainly have different results. The data for the tool test materials are as follows.

Signal Result

Signals that are still in the form of .txt datalog files are then processed with the Matlab application, data that are still in the form of numbers in the .txt file will be imported using the import data menu. Signal data will be displayed in the form of signal plotting in a figure in the time domain, then the signal will be filtered with a low pass filter in the domain, after that the signal will be processed by FFT to change the display from the time do the main to the frequency domain[20], [58]–[62].

The signals obtained from the csd125 motor in 2013, 2017, and 2019 show signals under different conditions to see more clearly, from the signal graphic data it can be seen that the vibrations caused by the csd125 years are smoother with the result that the frequency tends to be sloping and there are no frequency spikes, different with csd 125 in 2017 there was a spike in the highest frequency of 370 Hz and a small spike before the high spike which indicated the bearing was experiencing symptoms of damage or roughness, for bearing csd125 in 2019 there was a spike in the frequency of 370 Hz but there was no high spike before the spike in the frequency of 370 Hz. The comparison results can be seen in figure 6, 7, 8 below shows a graphic image of the signal before it is filtered in the time domain.

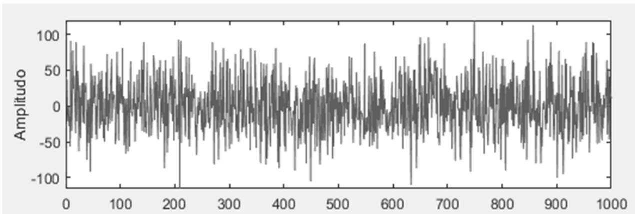

Fig. 6. Sound Signal Before CSD Filter in 2013

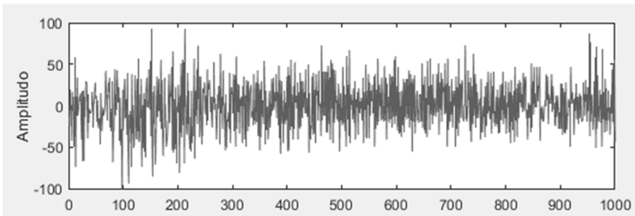

Fig. 7. Sound Signals Before the 2017 CSD Filter

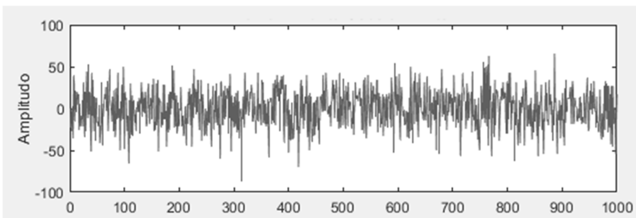

Fig. 8. Sound Signals Before the 2019 CSD Filter

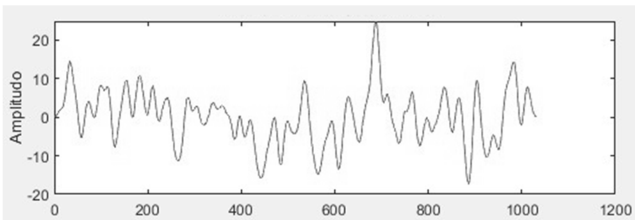

Fig. 9. Sound Signal After CSD Filter in 2013

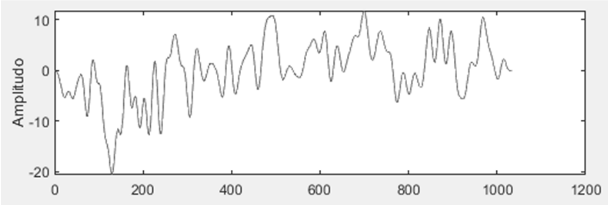

Fig. 10. Sound Signal After CSD Filter in 2017

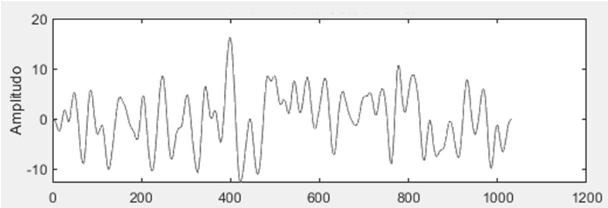

Fig. 11. Sound Signal After the 2019 CSD Filter

After a low pass filter is performed with the time domain in Matlab. Figure 9, 10, 11 below shows a graphic image of the signal before it is filtered in the frequency domain.

Figure 12, 13 below shows a comparison of vibration signals between CSD 125 in 2013, 2017, 2019 in the frequency domain.

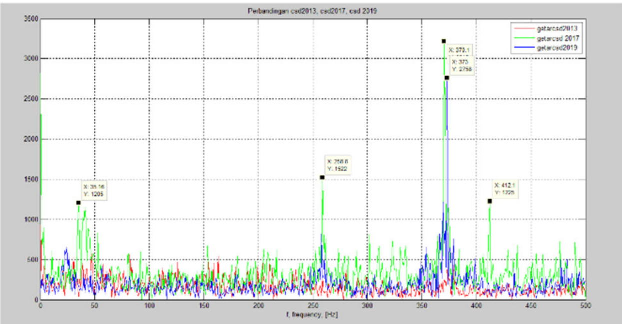

Fig. 12. Comparison of the csd 125 motor vibration signals in one plot

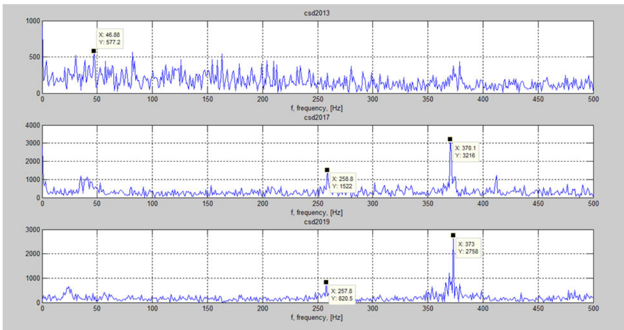

Fig. 13. CSD 125 motor vibration signal frequency 2013, 2017 & 2019

From the data obtained and the discussion above, it can be concluded that the results are as follows:

Table 4. Results Vibration frequency and sound

No.	Motor	Sound signal frequency	Vibration signal frequency
1	csd 125 2013	225	45
2	csd 125 2017	417	370
3	csd 125 2019	383	370

The condition of the bearings on the 2017 csd125 motor shows abnormal symptoms or the bearing is damaged, in the vibration signal there is a spike at a frequency of 370 Hz and other spikes before and after the main surge, this is also amplified in a high amplitude arising sound signal at a frequency of 417 Hz. The condition of the bearings on the csd125 motor in 2019 shows alert symptoms with a spike at a frequency of 370 Hz but there are no other spikes before and after the main spike in the vibration signal which indicates an alert level of, the sound signal appears at a frequency of 383 Hz which is still in the alert category. The condition of the bearings on the csd125 motor in 2013 showed normal or good bearing symptoms by showing no significant spikes in the 45 Hz frequency vibration signal which was in the good category, while the 225 Hz frequency signal indicated an alert level.

Table 5. Final results of bearing condition

No.	Motorcycle	Inputs		Output
		voice	shakes	bearings
1	csd 125 2013	alert	fine	Good
2	csd 125 2017	Rough	alert	damaged
3	csd 125 2019	alert	alert	alert

Conclusions

In this study, the system is able to detect bearing damage in 3 phase induction motors. Future research can focus on sound signal processing and signal filtering so that it can be more sensitive and can reduce unwanted noise by using a Kalman filter or other filter methods. For subsequent development classification using machine learning and other classification methods. The next stage is the delivery of the resulting information can be monitored in real time through the android application.

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