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Sound-Based Health Monitoring of Induction Motor Considering Load and Measuring Distance Variations Using Frequency Calculation and Statistical Analysis

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ABSTRACT

Bearing is an important part of the induction motor, whose function is to help the rotor spin. It contributes the highest percentage of damage compared to other parts. When operated in this condition, it causes overheating, imbalance in the rotation of the rotor shaft, sparks, and noise pollution to the environment. A bearing monitoring system must be implemented and developed to avoid further damage. Furthermore, a non-invasive technique through sound signals was developed in this study. A sound signal is easy to overlap with the noise from other sources. Environmental noise is unavoidable during data collection, affecting health monitoring accuracy (HM). Therefore, this study aims to develop an HM method for sound-based induction motors based on measurement differences, load variation, frequency calculations, and statistics. The distance measured was used as an independent variable of the non-machine noise. The load variations were also applied as required, and the operation of the motor varies according to users' needs. In an effort to prevent negative environmental impacts, noise monitoring was carried out from the motor operation, and the results showed an HM of accuracy of 83.09%. The best distance for performing HM conditions is 100 cm and 83.59 dB(A). The noise value does not exceed the industrial worker threshold. Therefore, close surveillance of the motor's condition tends to be conducted with or without a load. It is because the load variation does not affect the accuracy of health monitoring.

Keywords: Fault detection, health monitoring, machine condition diagnosis, sound

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INTRODUCTION

The induction motor is called an 'asynchronous motor' because it operates at speed less than the synchronous and is one of the most important components of a spinning rotor. A survey by the Electric Power Research Institute (EPRI) shows that the percentage of damage to motor parts in bearings, stators, and rotors is 41%, 36%, and 9%, respectively (Barusu & Deivasigamani, 2020). Bearing is a motor component whose function is to help the rotor spin, and the relative motion between the outer and inner races makes it susceptible to damage. Small damage to the bearing causes more severe deterioration of other parts (Das & Ray, 2020). In addition to mechanical factors, bearing damage is caused by external factors such as contamination, corrosion, brinelling, installation, and lubrication errors. Brinelling is a phenomenon that gives rise to the formation of indentations in the race bearings due to excessive load, while Installation errors occur due to incorrect set-up of the bearing on the shaft. Furthermore, lubrication errors are caused by insufficient or excessive lubricant application, leading to overheating and accelerating the process of bearing damage (He et al., 2020).

The negative effect of damage to motor parts should be avoided as early as possible by providing proper maintenance. Therefore, Health Monitoring (HM) and Fault Diagnosis (FD) of industrial driving machines are important for maintenance actions and should be conducted regularly and routinely. Further action should be taken to effect restoration when the tool is operating abnormally. In addition, the advantages of the HM system include predicting early damage, more optimal maintenance actions, minimizing surveillance costs, and increasing industrial productivity and motor reliability (Amanuel et al., 2021).

The general stages in conducting HM include data acquisition, namely collecting information from the instrument used (current, vibration, thermal, and sound). The second stage is data processing, which includes several methods, such as time domain data analysis, Fast Fourier Transform (FFT), Wavelet Transform (WT), Hilbert-Huang Transform (HHT), and Soft Time Fourier Transform (STFT). The third stage is making decisions regarding the treatment based on diagnostic and prognostic methods (Goyal et al., 2021). HM has the advantage of a microphone as a low-cost sound sensor and does not require contact with the diagnosed engine part. However, the drawback is that the sound signal easily overlaps with other sources and sometimes does not change when there is a change in the rotation of the engine components (AlShorman et al., 2021).

Because it has the advantages of a low price and simple application, HM, through sound regulation, began to be developed further. Sound signals are superior to HM using vibrations, indicated by a significant spike in amplitude when the motor part is abnormal (Nirwan & Ramani, 2022). Accuracy is needed to follow up the maintenance phase. The effect of placing the microphone as sound data acquisition needs to be considered, hence, as not to cause the capture of noise signals originating from background sound as HM data is susceptible to environmental noise. Consequently, placing the microphone 30 cm from the rotor avoids overlapping sound signals from other sources (Glowacz et al., 2018). With the same consideration, several studies placed the microphone 50 cm from the machine body (Zhong et al., 2018). The importance of sound signal distance on accuracy results promotes this research regarding HM bearing and induction motor noise calculation at various measuring distances and loads. Load variations are tested as an approach to be operated on, with different loads according to the user requirements. HM was developed by processing sound signals using the FFT algorithm. Band-pass filtering was used to determine the frequency of failure as a diagnosis of bearing conditions. The result of the test was presented in the form of a percentage of detection accuracy. The best measurement distance was determined by considering the highest HM accuracy and noise that does not exceed the threshold that harms the environment. Statistical analysis was used to analyze the proposed hypothesis. This study greatly contributes to the development of HM bearings with non-invasive techniques through sound signals, followed by an analysis of the effect of variations in distance and load on the accuracy of HM bearings. The proposed method offers solutions that are considered by comparing similar studies. Statistical analysis provides the benefit of avoiding excessive noise by not neglecting the main importance of HM accuracy. Therefore, the proposed method is an effective, simple, inexpensive alternative to HM and minimizes noise exposure for industrial workers, especially machine operators.

MATERIALS AND METHODS

The developed HM bearing considers noise, non-engine noise variables, and load variations. The conceptual framework of the study is shown in Figure 1. The induction motor tested has specifications of 1.5 kW, 380 V, 3.68 A, 3 phases, and 4 poles. The treatment to determine the effect of non-machine sound is carried out by recording and diagnosing bearing conditions from sound signals with distances of 0cm (S1), 50cm (S2), 100cm

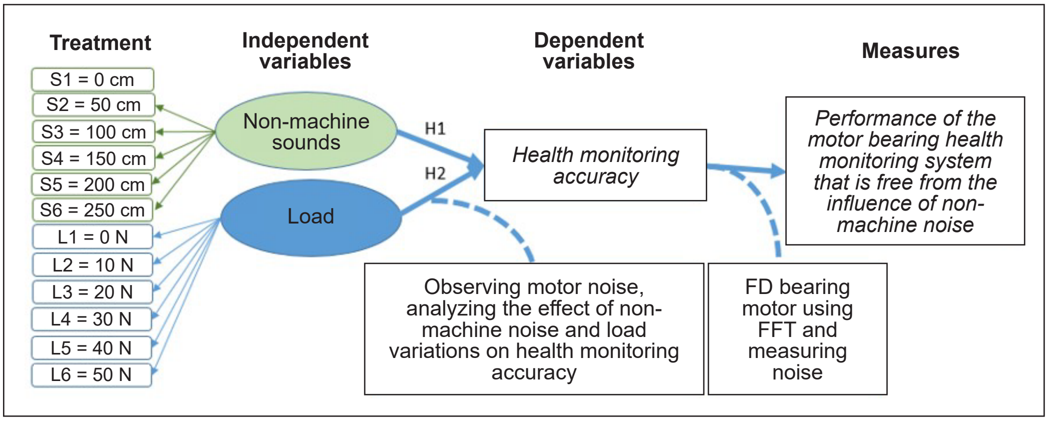


Figure 1. Study conceptual framework

(S3), 150cm (S4), 200cm (S5), and 250cm (S6). In addition, the effect of the load value variable is tested on the HM system with a value of 0 Newton (L1), 10 Newton (L2), 20 Newton (L3), 30 Newton (L4), 40 Newton (L5), and 50 Newton (L6). The noise in all tests is observed as information and warning of the sound level generated by the motor to avoid negative environmental impacts early. The hypotheses obtained include whether the non-machine noise and the load variation variable affect the accuracy of bearing health monitoring. From this, it is known that the performance of the induction motor health monitoring system is free from the influence of non-engine noise. The flowchart of this study is depicted in Figure 2.

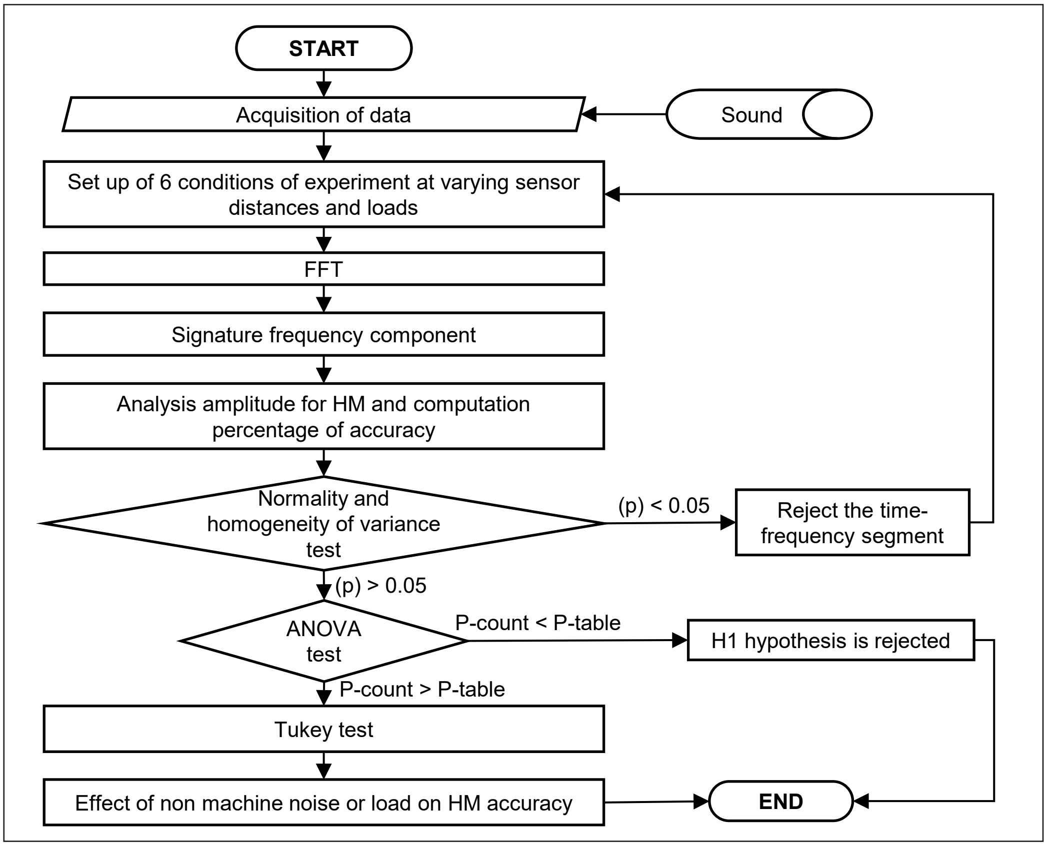


Figure 2. Flowchart of the study

Figure 3 shows the configuration of the HM being tested. The sound amplitude value in the frequency domain is used for the FD bearing. The time sound signal obtained from the microphone is transformed into the frequency domain. The sound signal transformation algorithm applied is Fast Fourier Transform (FFT). It is an algorithm derived from the Discrete Fourier Transform (DFT) calculation. Mathematically, the FFT of a discrete signal is X_n using N points (Karyatanti et al., 2019) (Equation 1).

$$X_n = \sum_{n=0}^{N-1} x_n e^{-i2\pi \frac{k}{N} n} \qquad k = 0,1,2,\ldots,(N\text{-}1) \tag{1}$$

In one cycle, a signal is sampled several N and is grouped into 2, namely odd and even. Then, each group is divided into 2 continuously until 2 samples are left. Each group is subjected to DFT per 2 samples. In radix-2 FFT, the DFT process is conducted by dividing the sample N DFT by a number to the power of two, enabling many steps as p, which is determined by $2^p = N$.

Each sound source has its frequency, and to determine the specific sound produced by motor bearing, this study proposed using a band-pass filter. The frequency value is unique and used as the FD observation point. When the bearing is damaged, it causes the induction motor to produce different harmonic frequencies. It is because the flux density in the air gap becomes asymmetrical and affects the inductance in the stator. Signals carrying harmonic information describe defective or non-ideal conditions that occur in them (Nirwan & Ramani, 2022).

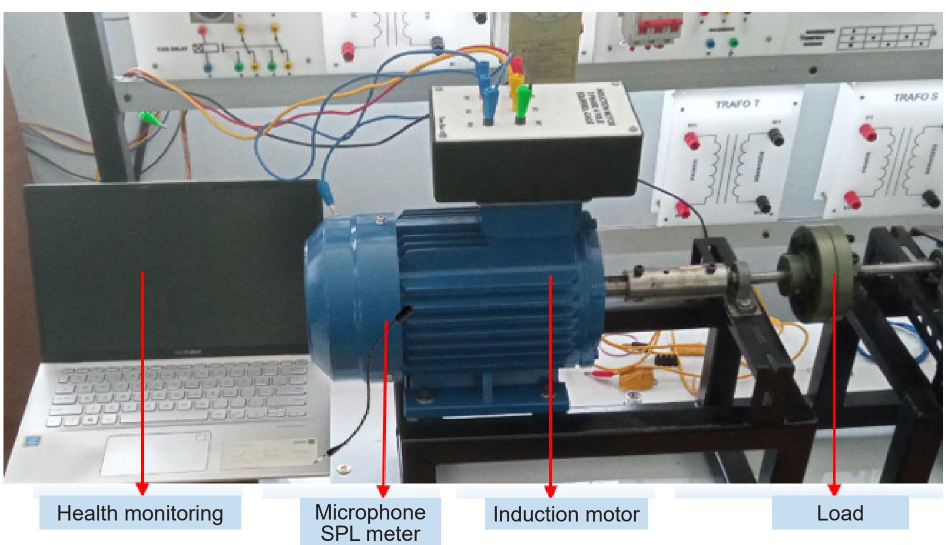


Figure 3. HM bearing configuration

Figure 4 shows the bearing section based on calculating frequency characteristics and tested bearing conditions. Where ω = angular velocity, N= number of ball bearings, d = diameter of ball bearings, D_p = diameter of pitch, and Θ= contact angle. A spike in amplitude occurs when the bearing rotates, and a ball defect occurs (Ewert et al., 2020). The frequency of the ball bearing is formulated as Ball Spin Frequency (BSF) as in Equation 2:

$$f_{BSF} = \frac{N}{2d}\omega\left[1-\left(\frac{d\cos\theta}{D_p}\right)^2\right] \quad (2)$$

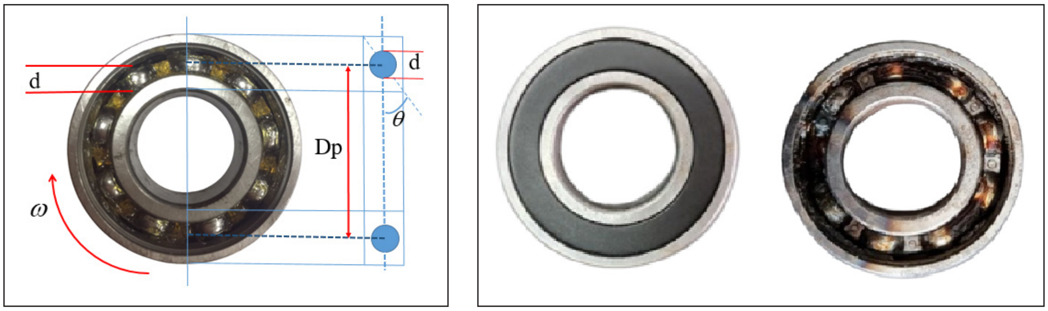
The f_{BSF} harmonic frequency is obtained from Equation 3. Where f_p is the harmonic frequency, f_v s is the frequency of the bearing component of Equation 2, and k is the constant k=1,2,3,...

$$f_p = |k.f_v| \quad (3)$$

Statistical testing for the effect of distance and load variation on HM accuracy using a Completely Randomized Design (CRD) approach. The CRD Equation 4 is as below:

$$Y_{ij} = \pi + \tau_i + \varepsilon_{ij} \quad (4)$$

with
Y_{ij} = observations on treatment i and repetition j, π = general average, τ_i = effect of treatment i, ε_{ij} = random effect on treatment i, repetition j, $i = 1,2, \dots, t$ and $j = 1,2, \dots, r$



(a) (b)

Figure 4. Bearing (a) front view; and (b) healthy and damage bearing

RESULTS AND DISCUSSION

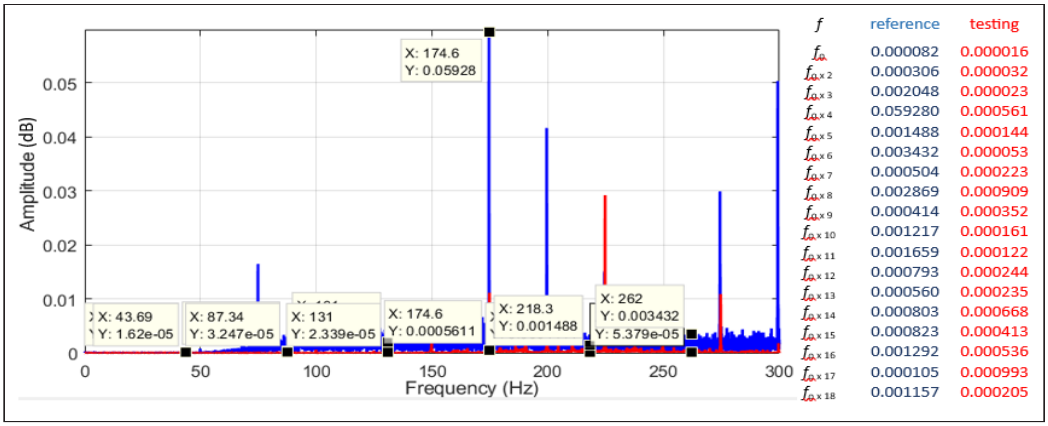
The sound characteristics tend to change when the motor is loaded. The value of the load greatly affects the rotational speed of the motor and gives the effect of changing the sound. Tests were conducted when the motor was not loaded and was measured in comparison with the initial conditions of the motor. The noise measurements in the healthy and the damaged motor at various distances and loads are shown in Table 1. The data retrieval was conducted for 30 seconds by recording. Table 1 shows that the farther the distance from the sound source, the lower the noise level. Various noise levels were produced both in healthy and damaged conditions. When the motor operates under damaged and loaded bearing conditions, there is an increase in noise. The noise threshold value in the industrial environment is 85 dB(A) (Aminian et al., 2021). Motors as industrial propulsion tools operate mostly under high load conditions. Hence, the noise level does not get worse, and because of this, monitoring is needed. From this test, noise measurement is not recommendable as a parameter to determine motor conditions. Although the damage caused increased noise, the location of the faulty part is usually unknown. Therefore, the HM system is needed as a bearing monitoring system.

Table 1
Average motor operating noise under conditions of healthy and damaged bearings

Treatment	Noise healthy bearing db(A)	Noise Damaged bearing db(A)
S1	87.92	88.42
S2	80.97	85.24
S3	76.31	83.59
S4	72.31	82.03
S5	70.24	80.36
S6	72.50	79.85
L1	82.91	85.24
L2	87.81	89.03
L3	86.96	87.09
L4	85.86	89.00
L5	86.27	86.96
L6	85.96	89.50

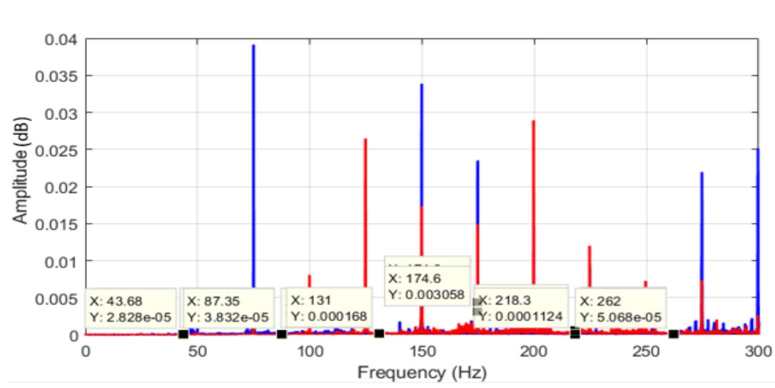
Effect of Non-Machine Noise on HM Bearing Accuracy

The sound signal from the microphone is processed by FFT, band-pass filtering and the motor bearing condition is analyzed. By applying Equations 3 and 4, the amplitude of each frequency is observed to determine the bearing condition. It is declared defective when the test amplitude exceeds the healthy value. The HM results are accurate when each harmonic frequency states many damaged conditions because the bearing test reconstructed the defective condition. Figure 5 shows the HM results of the sound signal in the frequency domain by testing different sound measurement distances. The blue sound graph is the signal for the healthy motor condition, and the red color is the test signal.



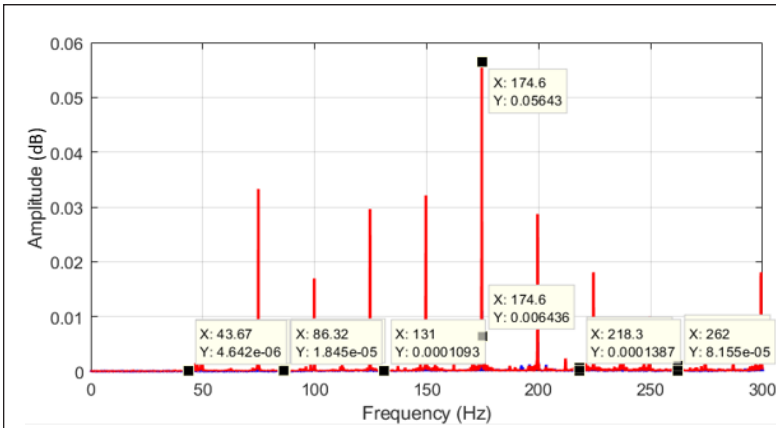
(a)

Figure 5. Sound signal in the frequency domain in bearing damage test with various measurement distances: (a) Treatment S1



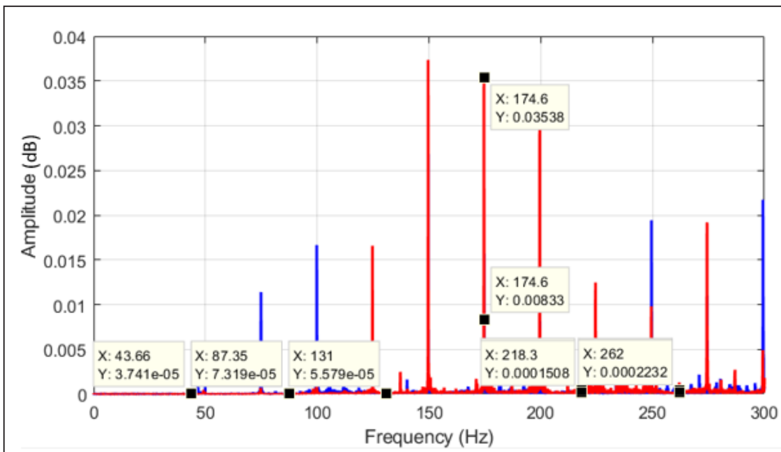
f	reference	testing
f_o	0.000068	0.000028
$f_{o\times 2}$	0.000121	0.000038
$f_{o\times 3}$	0.000168	0.000071
$f_{o\times 4}$	0.003058	0.004393
$f_{o\times 5}$	0.000112	0.000557
$f_{o\times 6}$	0.000050	0.000178
$f_{o\times 7}$	0.000193	0.000099
$f_{o\times 8}$	0.000177	0.010100
$f_{o\times 9}$	0.000462	0.000158
$f_{o\times 10}$	0.000104	0.000445
$f_{o\times 11}$	0.000100	0.000270
$f_{o\times 12}$	0.001007	0.001136
$f_{o\times 13}$	0.000135	0.000461
$f_{o\times 14}$	0.000115	0.000317
$f_{o\times 15}$	0.000115	0.000164
$f_{o\times 16}$	0.001664	0.002156
$f_{o\times 17}$	0.000042	0.001944
$f_{o\times 18}$	0.000204	0.000412

(b)



f	reference	testing
f_o	0.000004	0.000137
$f_{o\times 2}$	0.000018	0.000288
$f_{o\times 3}$	0.000032	0.000109
$f_{o\times 4}$	0.006436	0.056430
$f_{o\times 5}$	0.000138	0.000599
$f_{o\times 6}$	0.000081	0.001001
$f_{o\times 7}$	0.000124	0.000135
$f_{o\times 8}$	0.001174	0.001672
$f_{o\times 9}$	0.000096	0.000110
$f_{o\times 10}$	0.000411	0.000848
$f_{o\times 11}$	0.000030	0.000073
$f_{o\times 12}$	0.001464	0.000462
$f_{o\times 13}$	0.000079	0.000136
$f_{o\times 14}$	0.000078	0.000128
$f_{o\times 15}$	0.000112	0.000275
$f_{o\times 16}$	0.001557	0.000875
$f_{o\times 17}$	0.000263	0.000858
$f_{o\times 18}$	0.000239	0.000548

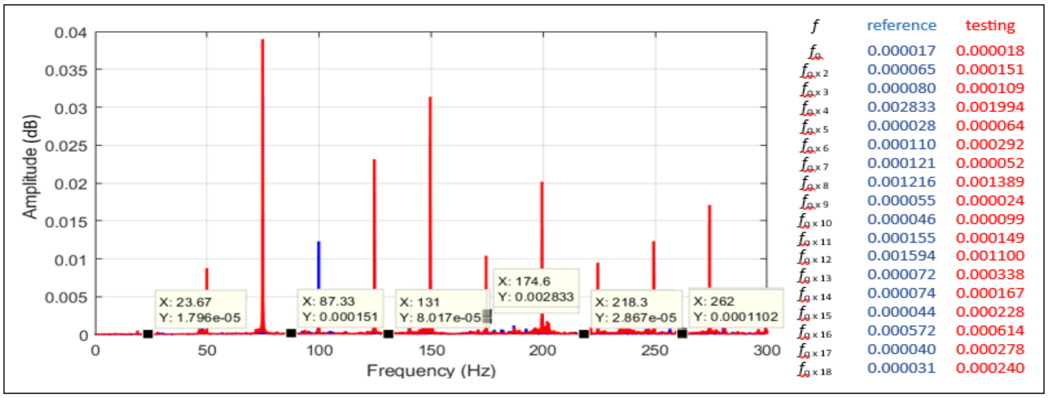
(c)



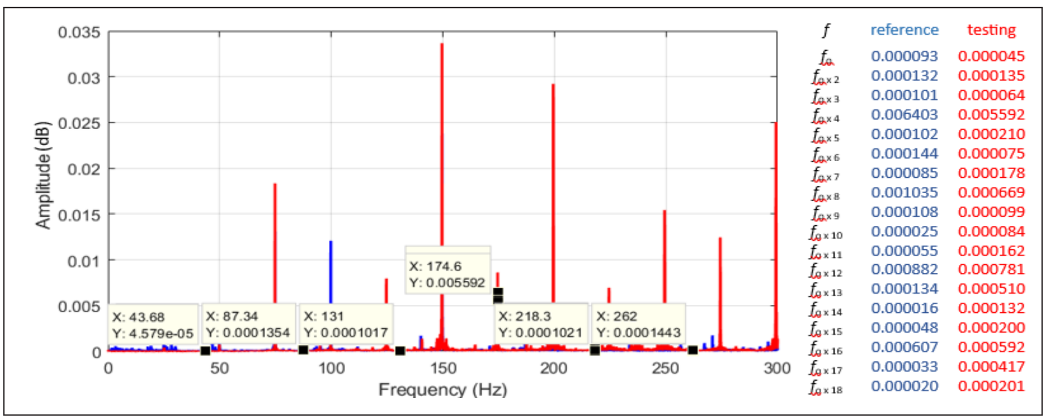
f	reference	testing
f_o	0.000037	0.000012
$f_{o\times 2}$	0.000037	0.000073
$f_{o\times 3}$	0.000055	0.000067
$f_{o\times 4}$	0.008330	0.035380
$f_{o\times 5}$	0.000150	0.000396
$f_{o\times 6}$	0.000223	0.000404
$f_{o\times 7}$	0.000174	0.000083
$f_{o\times 8}$	0.000722	0.000570
$f_{o\times 9}$	0.000145	0.000201
$f_{o\times 10}$	0.000214	0.000745
$f_{o\times 11}$	0.000177	0.000051
$f_{o\times 12}$	0.003871	0.000768
$f_{o\times 13}$	0.000077	0.000132
$f_{o\times 14}$	0.000161	0.000215
$f_{o\times 15}$	0.000008	0.000062
$f_{o\times 16}$	0.000654	0.000585
$f_{o\times 17}$	0.000046	0.000272
$f_{o\times 18}$	0.000024	0.000053

(d)

Figure 5 (continue). Sound signal in the frequency domain in bearing damage test with various measurement distances:(a) Treatment S1; (b) Treatment S2; (c) Treatment S3; and (d) Treatment S4



(e)



(f)

Figure 5 (continue). Sound signal in the frequency domain in bearing damage test with various measurement distances:(e) Treatment S5; and (f) Treatment S6

Each condition is tested four times; the results represent the actual situation. Figure 5 shows the sound signal from the first test data (r1). At the measurement distance of 0 cm, the first data found that all harmonic frequencies had a lower amplitude than the reference. Therefore, they did not detect damage. This result is a detection error because the bearing is damaged. When presented, the detection accuracy in testing data 1 is 0%.

At the measurement distance of 50 cm, it was found that in the r1 data, five harmonic frequencies did not detect the bearing damage. Hence the HM accuracy is 72.22%. The test is conducted on all conditions of the measurement distance variation with four repetitions. Table 2 shows the tabulation of the influence of non-machine noise on the accuracy of HM bearings.

The validity of the data for CRD analysis is tested for homogeneity and is carried out with Levene's test. The significance value (p) > 0.05 is said to be homogeneous, while if (p) < 0.05, hence the data is not homogeneous. HM data with the measurement

Table 2
Data tabulation of the effect of non-machine noise on the accuracy of HM bearing

Non-machine sound	Repetition (r)				Average
	1	2	3	4	
S1	0	5.55	0	0	1.3875
S2	72.22	66.66	61.11	66.66	66.6625
S3	83.33	83.33	88.88	88.88	86.105
S4	66.66	61.11	61.11	61.11	62.4975
S5	72.22	72.22	77.77	77.77	74.995
S6	55.55	55.55	61.11	61.11	85.33

distance variations get a calculated value of 0.831. When the value is greater than 0.05, homogeneity is achieved. Parametric statistical analysis requires data with a normal distribution; therefore, carrying out the Anderson-Darling normality test is necessary. The results showed that the P-value is 0.196, which means it is greater than the value of 0.05. Hence, it is stated that the HM data is normally distributed.

Hypothesis testing using CRD with the calculation of the analysis of variance is shown in Table 3. From the ANOVA, the effect of distance measurement as a treatment of non-machine noise factor on the accuracy of HM gets an F-count value greater than the F-table. Hence the hypothesis (H1) is accepted. It means that there is an effect of distance measurement, as a non-machine sound factor, on the accuracy of HM. When analyzed through the coefficient of determination (R Square), the influence of non-machine sound on the accuracy of HM contributes 98.87%. At the same time, other factors cause the remaining 1.13%. The R square value of 0.75, 0.50, and 0.25 belongs to the strong, moderate, and weak categories, respectively (Gouda et al., 2020). The results found that non-machine sound is a strong category.

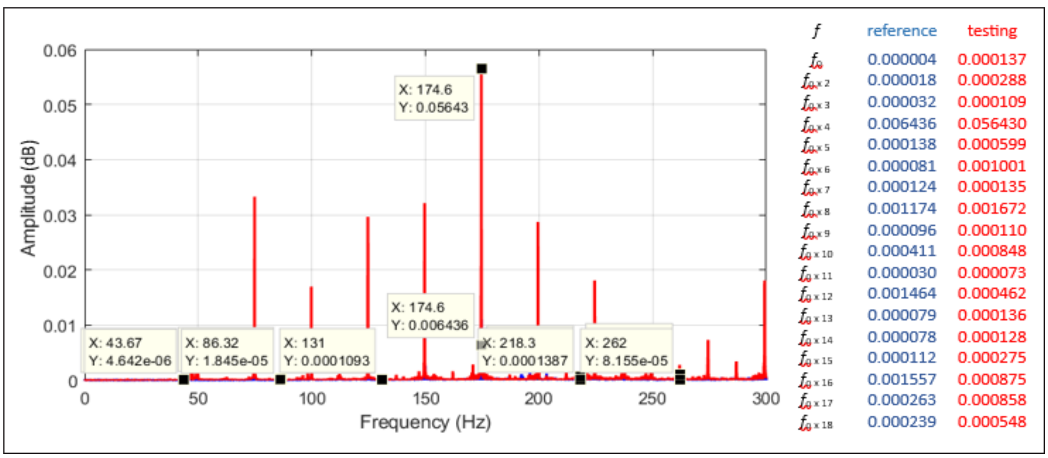
Table 3
Analysis of variance on the effect of non-machine sound on the accuracy of HM

Source of Diversity	Free Degrees	Sum of squares	Middle square	F-count	F-table
Treatment	5	17513.7	3502.74	314.56	2.77
Galat	18	200.4	11.14		
Total	23	17714.1			

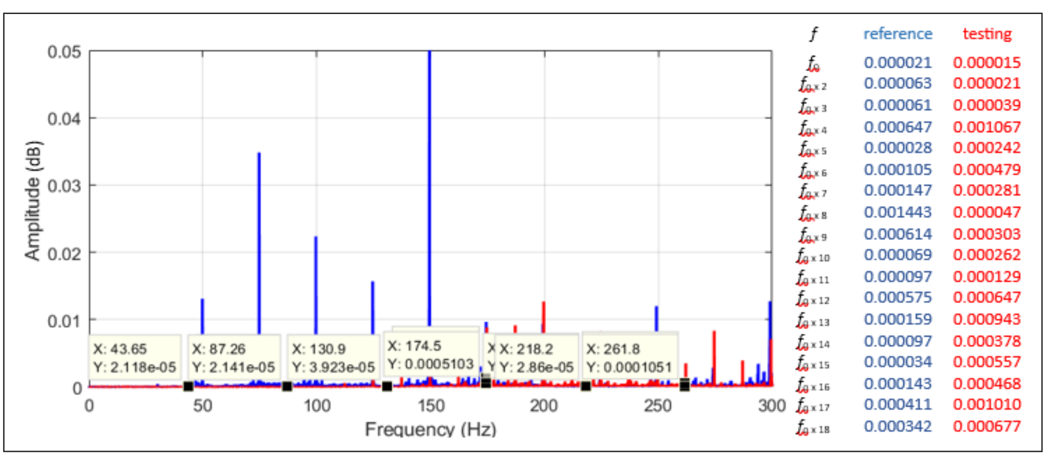
Further analyses use the Tukey test or Honest Significance Difference (HSD) to discover the best measurement distance. Tukey's test is used to compare all treatment pairs after the analysis of variance was performed. The principle is to compare the difference between each average with a critical value (w). When the absolute value of the average difference being compared is more than or equal to the critical value, it is stated that the two averages are significantly different (Priyastama, 2020). The follow-up tests showed that HM produces the best accuracy with a measuring distance of 100 cm and the largest average of 86.10. The noise experienced by industrial machine maintenance operators when sound data is taken at 100 cm from the machine body is contaminated with the noise of 83.59dB(A). This value is still below the specified noise permit (85 db(A)).

Effect of Motor Load Variation on HM Bearing Accuracy

The operation of electric motors in the industry is always under load conditions. The load varies depending on the desired production capacity and is used as the basis for all tests on electrical machine systems. Figure 6 shows a sound signal in the frequency domain transformed by the FFT algorithm in testing the condition of the motor under load. The bearing conditions are known by comparing the amplitude values for each harmonic

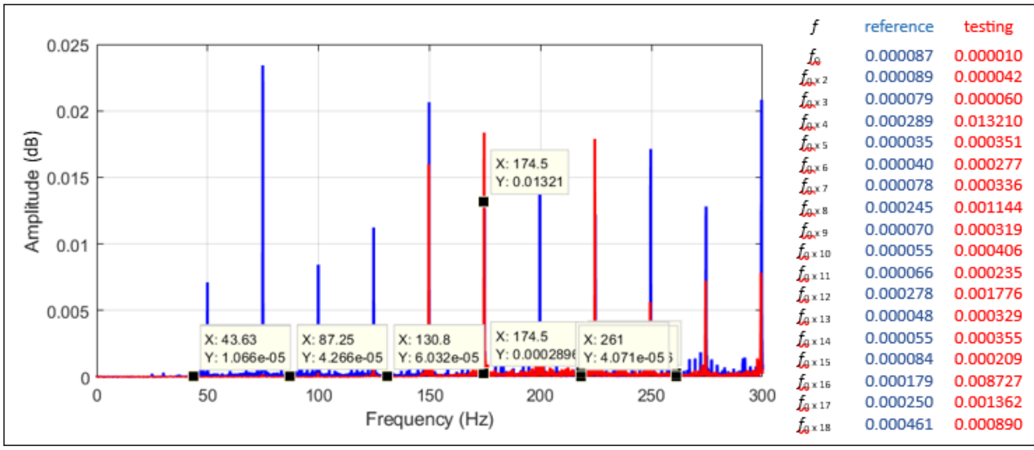


(a)

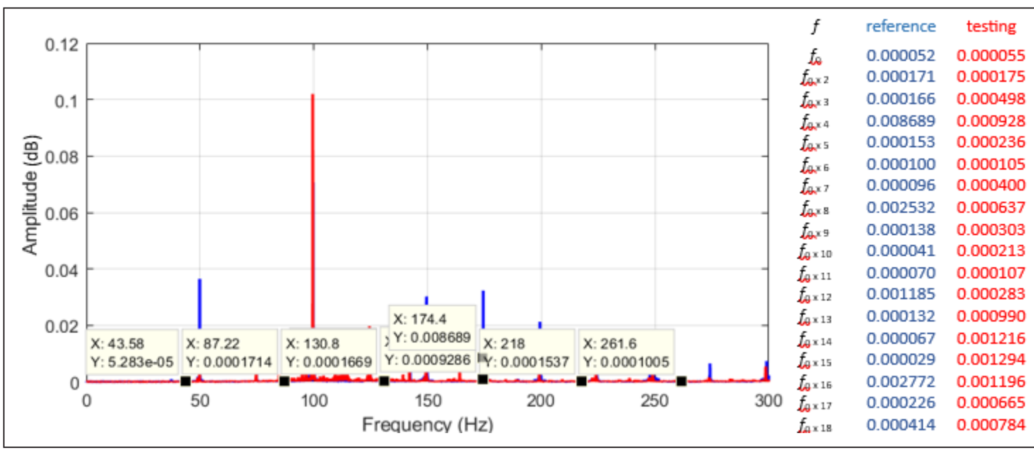


(b)

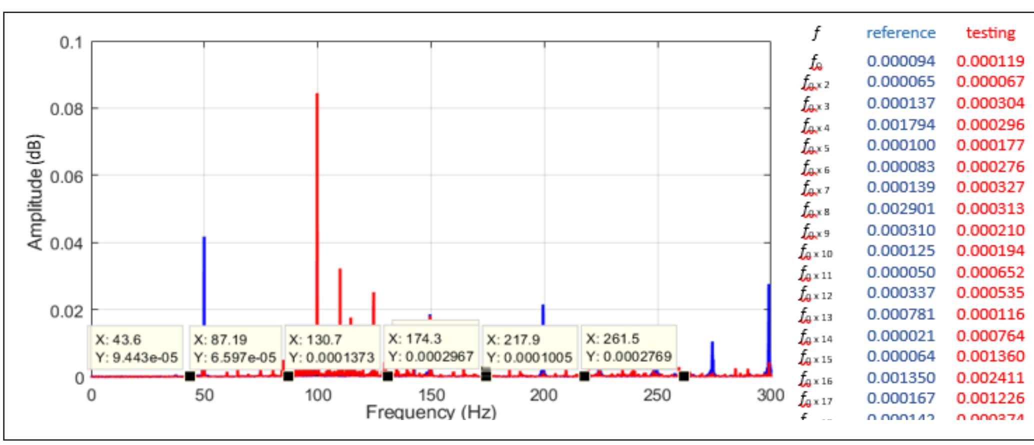
Figure 6. Frequency domain sound signal under: (a) Treatment L1 with 0N load; and (b) Treatment L2 with 10N load



(c)

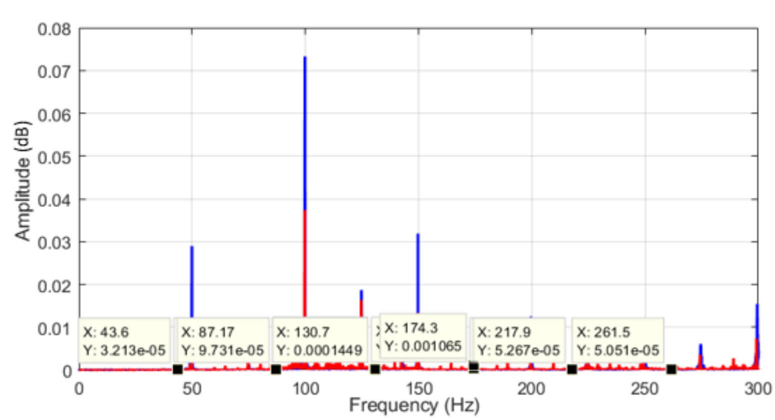


(d)



(e)

Figure 6 (continue). Frequency domain sound signal under: (c) Treatment L3 with 20N load; (d) Treatment L4 with 30N load; and (e) Treatment L5 with 40N load



f	reference	testing
f_0	0.000032	0.000040
$f_0 \times 2$	0.000101	0.000097
$f_0 \times 3$	0.000144	0.000283
$f_0 \times 4$	0.001065	0.000261
$f_0 \times 5$	0.000052	0.000102
$f_0 \times 6$	0.000050	0.000059
$f_0 \times 7$	0.000843	0.000212
$f_0 \times 8$	0.001812	0.000583
$f_0 \times 9$	0.000851	0.000473
$f_0 \times 10$	0.000066	0.000945
$f_0 \times 11$	0.000064	0.000929
$f_0 \times 12$	0.000246	0.001250
$f_0 \times 13$	0.000146	0.000438
$f_0 \times 14$	0.000077	0.000423
$f_0 \times 15$	0.000029	0.001160
$f_0 \times 16$	0.000554	0.001627
$f_0 \times 17$	0.000096	0.001747
$f_0 \times 18$	0.000167	0.000823

(f)

Figure 6 (continue). Frequency domain sound signal under: (f) Treatment L6 with 50N load

frequency. Each sound signal is observed up to the 18th harmonic frequency with the sound signal for 30 seconds. Table 4 shows the results of HM accuracy by conducting four tests repeatedly until it is observed that all HM results get a high percentage of accuracy.

The CRD variance analysis showed that the F-count (0.06) was smaller than the F-table (2.77). Hence, the H1 hypothesis is rejected. It means that loading does not affect the accuracy of HM. The analysis of R Square showed a value of 14.29%. Hence, the independent variable (load variation) is categorized as weakly affecting the accuracy of HM. Therefore, HM bearings are performed on the motor operating without or with different load values.

Table 4
Tabulation of the effect of load variations on the accuracy of HM

Load Variation	**Repetition (r)**				**Average**
	1	2	3	4	
L1	83.33	83.33	88.88	88.88	86.105
L2	72.22	88.88	88.88	77.77	81.9375
L3	77.77	83.33	83.33	77.77	80.55
L4	77.77	83.33	88.88	77.77	80.55
L5	83.33	83.33	88.88	77.77	82.3275
L6	88.88	83.33	88.88	77.77	84.715
General average					82.86417

Some previous research was discussed to develop the HM system further. Table 5 presents the differences between the previous research and the proposed development. It shows the differences in data input, signal processing techniques, noise measurement, the effect of non-machine variables on HM accuracy, and load variations. One of the health monitoring systems that must be developed is to examine the effect of environmental noise on the accuracy of HM (AlShorman et al., 2020). The proposed method contributes to the development of bearings by considering noise, measuring distance, and load variations. Using non-invasive techniques, FFT signal processing, and band-pass filtering, the bearing approach provides promising diagnostic results. It is necessary to consider the backfill distance when performing motor monitoring actions to obtain low noise and good HM accuracy.

Table 5
Similar HM research

Works	HM Data	Signal processing technique	Noise Monitoring	Non-machine Sound Effect	Motor load variation
Elasha et al. (2017)	Vibration	FFT	No	No discussion on measuring distance	Yes
Daraz et al. (2018)	Sound signal, vibration	FFT	No	No discussion on measuring distance	No
Nirwan and Ramani (2022)	Sound signal, vibration	FFT	No	No discussion on measuring distance	Yes
Lucena-Junior et al. (2020)	Sound signal	signal analysis based on chaos using a density of maxima (SAC-DM)	No	No discussion on measuring distance	Yes
Glowacs et al. (2018)	Sound signal	MSAF-20-MULTIEXPANDED	No	Fixed measuring distance of 30 cm	Yes
Zhong et al. (2018)	Sound signal	Ensemble empirical mode decomposition	No	Fixed measuring distance of 50 cm	No
AlShorman et al. (2020)	Review	Artificial Intelligence Methods		provide future challenges and trends for the next researcher to discuss the effect of environmental noise	
AlShorman et al. (2021)	Sound signal	Review all technique		Review, challenges and future trends are also discussed	
Proposed method	Sound signal	FFT	Yes	Best measurement distance analysis on HM accuracy and noise	Yes

CONCLUSION

With non-invasive techniques through motor sound and signal processing using the FFT algorithm, the HM system produces an average accuracy of 83.09%. Therefore, this technique is recommendable as an alternative to HM in preventing negative environmental impact. When the results of the HM state that the bearing is in a damaged condition, maintenance actions should be conducted to prevent damage to other motor parts. The operation of faulty motor parts increases the noise level. According to the analysis data, the noise of the damaged bearing conditions is above the threshold intensity of 85dB(A). Hence, it needs to be maintained for the safety of industrial workers. Sound data retrieval for HM is influenced by non-engine noise and variations in motor loading. The sound of the engine easily overlaps with that of the non-machine or the vibration from the engine body. The CRD statistical analysis showed that hypothesis (H1) was accepted. It means that the measurement distance, an independent variable of non-machine sound, affects the accuracy of the HM. The Tukey test indicated that the best HM accuracy was obtained at 100 cm with the noise level not exceeding the intensity value of 83.59 dB(A). The effect of loading on the motor does not affect the accuracy of the HM. Hence the condition of the motor part is diagnosed with or without load. Therefore, as negative environmental prevention, HM is conducted at any time and periodically when the motor operates with or without load.

The proposed HM provides the advantages of a simple and inexpensive technique. Hence it is recommendable as an alternative for monitoring the condition of other motor parts, for example, the rotor bar, stator, and shaft balance. Further research needs to be conducted on the severity of bearing damage. The reliability of the HM does not need to be doubted when tested with minor damage. The signal processing technique could be developed using deep learning methods and signal to filter for noise reduction, affecting HM accuracy. The weakness of the proposed method is that changes strongly influence the determination of the bearing frequency in motor speed. Therefore, speed measurement accuracy is needed to prevent errors in conducting FD bearings.

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