Journal Geuthee of Engineering and Energy (JOGE)
Vol. 5, No. 1, May 2026, pp. 24 - 32
ISSN: 2964-2655, DOI: 10.52626/joge.v5i1.69

Application of fourier transform for early detection of bearing failures in electric motors

Giovanni Dimas Prenata[1], Muhammad Alif Sofi Syariffudin[2], Reza Sarwo Widagdo[3]
[1,2,3]Department of Electrical Engineering, Universitas 17 Agustus 1945 Surabaya, Indonesia

**Corresponding Author: gprenata@untag-sby.ac.id*

ABSTRACT
This study presents an analysis of bearing fault conditions in electric motors through stator current measurements and their transformation into the frequency domain. Measurements were conducted under two main bearing conditions: normal and damaged, each tested with three load variations (no load, generator load, and generator load with one lamp). The time-domain current waveforms showed minimal visual distinction between normal and damaged bearing conditions, making classification difficult. Therefore, the current data were transformed into the frequency domain using the Discrete Fourier Transform (DFT). The frequency domain analysis revealed that in normal bearing conditions, the frequency magnitude distribution was relatively stable and symmetrical, with low fluctuation in the frequency index range k = 0 to k = 10. In contrast, damaged bearing conditions exhibited larger and irregular fluctuations in frequency magnitude across different load levels, indicating a distinct signature of bearing failure. Consequently, frequency domain analysis proves to be an effective approach for detecting bearing faults based on the spectral characteristics of motor current signals.

Keywords: Current, Time Domain, DFT, Frequency Domain, Normal Bearing, Damaged Bearing

ABSTRAK
Penelitian ini menyajikan analisis kondisi gangguan bearing pada motor listrik melalui pengukuran arus stator dan transformasinya ke dalam domain frekuensi. Pengukuran dilakukan pada dua kondisi utama bearing, yaitu kondisi normal dan kondisi rusak, yang masing-masing diuji pada tiga variasi pembebanan (tanpa beban, beban generator, dan beban generator dengan satu lampu).Berdasarkan hasil pengamatan pada domain waktu, bentuk gelombang arus tidak menunjukkan perbedaan visual yang signifikan antara kondisi bearing normal dan rusak, sehingga proses klasifikasi menjadi sulit dilakukan. Oleh karena itu, data arus kemudian ditransformasikan ke domain frekuensi menggunakan Discrete Fourier Transform (DFT). Hasil analisis pada domain frekuensi menunjukkan bahwa pada kondisi bearing normal, distribusi magnitudo frekuensi cenderung stabil dan simetris, dengan fluktuasi yang relatif kecil pada rentang indeks frekuensi k = 0 hingga k = 10. Sebaliknya, pada kondisi bearing rusak, terlihat fluktuasi magnitudo frekuensi yang lebih besar dan tidak beraturan pada berbagai tingkat pembebanan, yang mengindikasikan adanya karakteristik khas (signature) dari gangguan bearing. Dengan demikian, analisis domain frekuensi terbukti menjadi pendekatan yang efektif untuk mendeteksi gangguan bearing berdasarkan karakteristik spektral sinyal arus motor.

Kata kunci: Arus, Domain Waktu, DFT, Domain Frekuensi, Bearing normal, Bearing Rusak

Manuscript received 19 April. 2026; revised 30 April. 2026; accepted 3 May. 2026.
Journal Geuthee of Engineering and Energy is licensed under a Creative Commons Attribution-Share Alike 4.0 International License.

1. INTRODUCTION

Three-phase induction motors are essential components frequently used in industry. As drivers for various types of loads, induction motors are easily assembled into essential devices to support industrial efficiency. However, when implemented incorrectly, damage often occurs. To prevent this, it is necessary to analyze and observe the relationship between motor damage and vibration levels or current consumption. Extensive research has been conducted on the correlation between motor damage and vibration levels and current consumption. By analyzing waveforms in the frequency domain, it is possible to predict the level of damage in three-phase induction motors.

Sandi and Sofian used FFT and ANN for the design and simulation of bearing damage detection in 3-phase induction motors [1]. This study produced 100% accuracy in detecting damage to the outer race by using vibration signals generated by 3-phase induction motors. Further research was conducted by Iradiratu, Belly and Achmad using FFT-based Motor Current Signature Analysis (MCSA) to detect damage to the inner race bearing [2]. This study took current data based on 5 levels of motor loading percentage. For 25% loading, the damage detection accuracy was 22.22%, 75% loading resulted in 29.63% damage detection accuracy and for 100% loading, the damage detection accuracy was 37.04%.

Romdhoni, Mardiansyah and Heri detected bearing failure using the wavelet method simulated in Labview [3]. The results of the study showed that bearing damage in the cage section had the highest level with data of 2,668 dB with a value of 90% to 100% damage to the bearing when given a load of 50 - 250 volts. Furthermore, Noer, Hilmy, Syaiful, Fadil and Mahkuta identified induction motor bearing defects based on stator current and torque at motor rotation speed using FFT [4]. The results of the waveform analysis, for normal conditions the amplitude is smoother and there is no fluctuation, but when the condition is damaged the fluctuation tends to be more so that it looks like a sawtooth.

In this study, researchers analyzed the current value absorbed by a 3-phase induction motor. Data in the time domain was converted using FFT into data in the frequency domain. Waveforms in the frequency domain will be compared for normal and damaged bearing conditions to obtain patterns. However, the analysis still does not involve AI to accelerate the conversion of data from the time domain to the frequency domain. Unlike Prenata's research which has used AI (KNN [5]) to categorize conditions in transformers. So operators do not need to monitor the transformer temperature periodically, but it has been replaced by a system that will report periodically to the operator. However, if an emergency condition occurs, reporting to the operator will be done directly. Likewise, the implementation of KNN [6] and SVM [7] to determine the level of reliability of the electrical network.

2. RESEARCH METHOD

2.1. Discreet Fourier Transform

In continuous measurement systems, such as temperature or voltage monitoring, the recorded signal data often contains two main components: an information signal and a noise signal. The information signal is an idealized representation of the physical quantity being observed, while the noise can originate from external influences such as electromagnetic interference, unstable sensors, or other random fluctuations.

When a signal is analyzed only in the time domain, it is not easy to separate the information signal from the noise [8]. Therefore, transforming the signal to the frequency domain is very important to identify the dominant frequencies that may originate from noise. This transformation can be done using the Discrete Fourier Transform (DFT) method, which functions to decompose a discrete signal into frequency-based signal components. The general form of the DFT formula is [9][10]:

$$X_k = \sum_{n=0}^{N-1} x[n].e^{-j.2\pi.\frac{kn}{N}} \quad , k=0,1,.., n-1 \qquad (1)$$

Where:
x[n] = signal value at time n
N = total number of signal samples
X_k = complex coefficient indicating the kth frequency component
j = imaginary number (j^2 -1)

To find the frequency value of each X_k, use the following formula:

$$f_k = \frac{k}{N} . f_a \quad (2)$$

where fa is the sampling frequency. While the magnitude of the signal in the frequency domain is obtained from [11][12]:

$$|X_k| = \sqrt{[Re(X_k)]^2 + [Im(X_k)]^2} \quad (3)$$

By observing the |Xk| value, we can identify the dominant frequency components in the signal. If there are certain frequency components that do not originate from the information signal (for example, signals at high frequencies originating from noise), then a digital filter can be designed such as a low-pass filter or a notch filter to remove these frequencies. This transformation is very helpful in clarifying the spectral structure of the signal, and is a basic method in digital signal processing systems, both for analysis and noise removal.

This is a new paragraph. It does not need additional space between paragraphs (before or after) in same subsection. Additional space is required for new section or subsection.

2.2. Motor Current Signature Analysis (MCSA)

Air gap eccentricity is a condition where the rotor of an induction motor is not centered on the stator, causing an imbalance in the air gap between the rotor and stator. This imbalance results in an uneven distribution of magnetic flux, leading to the generation of additional harmonics in the stator current. This condition can accelerate power losses, increase local temperatures, and accelerate thermal failure of the stator insulation, known as thermal failure stress. One effective and non-invasive method for detecting air gap eccentricity is Motor Current Signature Analysis (MCSA). MCSA analyzes the motor's stator current to identify typical signs of various internal faults, including eccentricity. In this approach, the measured current signal is transformed from the time domain to the frequency domain using the Fast Fourier Transform (FFT) method. This transformation allows the separation of dominant frequency components and harmonics caused by damage.

Eccentricity, whether static or dynamic, will give rise to characteristic harmonic components around the supply frequency. These frequencies can be calculated using the following formula [13]:

$$f_e = \left(1 \pm \frac{n(1-s)}{p}\right) . f_s \quad (4)$$

Where:
fe = harmonic frequency due to eccentricity
n = harmonic index (usually 1 or 2)
a = motor slip
I = number of pole pairs
fs = supply frequency

2.3. Method

The researcher determined the research stages as follows:

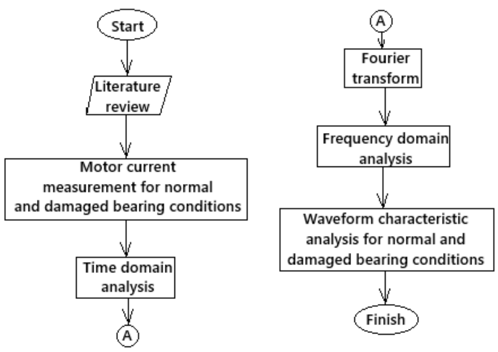

Figure 1. research methods

The motor used in this study is a three-phase induction motor with the following specifications: rated power of 1.5 kW (2 HP), rated voltage of 380 V, rated current of 3.6 A, frequency of 50 Hz, and rotational speed of 1400 rpm. The motor operates under continuous duty (S1) with insulation class F. These specifications ensure stable operation during testing under various loading conditions.

It begins with an exploration of related references such as Fourier transforms, frequency domain waveform analysis, and the concept of Motor Current Signature Analysis (MCSA). This is followed by motor current measurements for normal and abnormal conditions/damaged bearings. Each of these conditions is broken down into unloaded motor conditions, generator-loaded motor conditions, and generator-loaded motor conditions plus one lamp. This study presents a total of six current data collection scenarios.

Current measurements were carried out using an ammeter (AC clamp power meter CM3286) to capture the stator current signal under different operating conditions. The rotational speed of the motor was measured using a tachometer to ensure consistent operating conditions during testing. The measurement process was conducted under three loading conditions: no load, generator load, and generator load with an additional lamp. The current signal was recorded in the time domain and then processed using Discrete Fourier Transform (DFT) for frequency domain analysis.

The six data sets will focus on single-wave data, which will be processed by the Fourier transform. Single-wave data for six data collection scenarios, resulting in six Fourier-transformed data sets to be analyzed in the frequency domain. The data will then be plotted graphically, using only magnitude data. Before plotting the waveforms, the data must first be converted to phasor form. This is because the Fourier transform results are complex numbers consisting of real and imaginary numbers. After plotting the magnitude values converted to phasors, analysis will be performed to identify specific characteristics for normal and damaged bearings under various loading conditions.

The current signal was sampled with a total of N = 11 data points over one cycle, with a sampling interval of approximately 1.95 ms, resulting in a sampling frequency of approximately 512 Hz. This sampling configuration is sufficient to capture the fundamental frequency characteristics of the motor current signal.

3. RESULTS AND DISCUSSION

Current measurements were performed for both normal and damaged bearing conditions. The following are the measurement results.

Table 1. Current measurements are carried out for normal bearing conditions and damaged bearings

Condition	n	Time (ms)	Current (A)	Load
Normal Bearings	0	0	0	No Load
	1	1,95	2,3	
	2	3,9	4,17	
	3	5,85	3,9	
	4	7,8	2,5	
	5	9,75	0	
	6	11,7	-2,3	
	7	13,65	-4,18	
	8	15,6	-4,15	
	9	17,55	-2,8	
	10	19,5	0	
	0	0	0	Generator Load
	1	1,95	2,6	
	2	3,9	4	

	3	5,85	4,43	
	4	7,8	2,61	
	5	9,75	0	
	6	11,7	-2,6	
	7	13,65	-4,2	
	8	15,6	-4,53	
	9	17,55	-2,79	
	10	19,5	0	
	0	0	0	Generator Load + 1 Lamp
	1	1,95	2,8	
	2	3,9	4	
	3	5,85	4,47	
	4	7,8	2,85	
	5	9,75	0	
	6	11,7	-2,5	
	7	13,65	-4,24	
	8	15,6	-4,48	
	9	17,55	-2,72	
	10	19,5	0	
Broken Bearing	0	0	0	No Load
	1	1,95	2,5	
	2	3,9	4,27	
	3	5,85	4,7	
	4	7,8	2,7	
	5	9,75	0	
	6	11,7	-2,53	
	7	13,65	-4,39	
	8	15,6	-4,15	
	9	17,55	-2,28	
	10	19,5	0	
	0	0	0	Generator Load
	1	1,95	2,4	
	2	3,9	4	
	3	5,85	4,65	
	4	7,8	3	
	5	9,75	0	
	6	11,7	-1,9	
	7	13,65	-3,5	
	8	15,6	-4,3	
	9	17,55	-2,7	
	10	19,5	0	
	0	0.00	0.00	Generator Load + 1 Lamp
	1	1.95	2.60	
	2	3.90	4.24	
	3	5.85	4.42	
	4	7.80	2.66	
	5	9.75	0.00	
	6	11.70	-2.55	
	7	13.65	-4.20	
	8	15.60	-4.49	

	9	17.55	-2.80	
	10	19,5	0	

When analyzing the above data, no difference could be found between the bearing in normal condition and the bearing in a broken state. Therefore, it was necessary to convert it to the frequency domain using a Fourier transform. The following shows the results of the data transformation in the frequency domain.

Table 2. Normal Bearing Frequency Domain Data (k = 0 to k = 10)

n	X[n].cos(theta)	X[n].sin(theta)	Magnitude	Condition
0	-0.560	0.000	0.56	No Load
1	5.86	-21.25	22.04	
2	-1.404	2.769	3.10	
3	-1.66	1.66	2.35	
4	-1.259	1.017	1.62	
5	-1.26	0.83	1.51	
6	-1.26	-0.84	1.51	
7	-1.25	-1.02	1.61	
8	-1.64	-1.66	2.33	
9	-1.37	-2.74	3.06	
10	5.73	21.27	22.03	
0	-0.48	0.00	0.48	Generator Load
1	6.25	-22.33	23.19	
2	-1.58	3.18	3.55	
3	-1.21	1.84	2.21	
4	-1.52	0.36	1.56	
5	-1.70	-0.22	1.72	
6	-1.70	0.21	1.71	
7	-1.51	-0.36	1.55	
8	-1.19	-1.84	2.19	
9	-1.54	-3.15	3.51	
10	6.12	22.36	23.18	
0	0.18	0.00	0.18	Generator Load + 1 Lamp
1	6.21	-22.55	23.38	
2	-1.58	3.27	3.63	
3	-1.17	1.54	1.93	
4	-1.73	-0.03	1.73	
5	-1.83	0.05	1.83	
6	-1.82	-0.06	1.82	
7	-1.72	0.02	1.73	
8	-1.15	-1.54	1.92	
9	-1.54	-3.24	3.59	
10	6.07	22.57	23.38	

The data above is data for a normal bearing condition, the X[n].cos(theta) and X[n].sin(theta) values are obtained using the Fourier transform (DFT) formula and the magnitude value is obtained by changing the shape into a phasor. The X[n].cos(theta) and X[n].sin(theta) values represent rectangular numbers. The data will be plotted in a Cartesian diagram as follows.

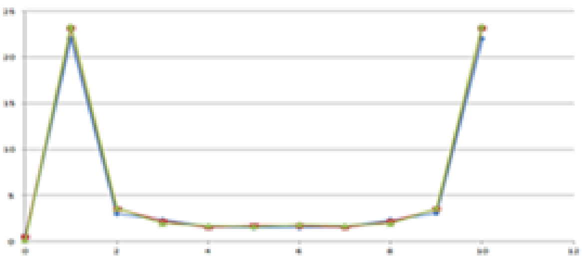

Figure 2. Waves for various types of loads under normal bearing conditions

In contrast to the previous plotting results, the image above tends to exhibit greater fluctuation and greater non-uniformity. This is characteristic of bearing failure conditions, with high fluctuations regardless of the loading conditions. There is no consistent data across load levels for bearing failure conditions.

Table 3. Broken Bearing Frequency Domain Data (k = 0 to k = 10)

n	X[n].cos(theta)	X[n].sin(theta)	Magnitude	Condition
0	0.82	0.00	0.82	No Load
1	6.40	-22.14	23.04	
2	-2.69	3.66	4.54	
3	-1.81	1.67	2.46	
4	-0.89	0.11	0.90	
5	-1.43	0.09	1.43	
6	-1.43	-0.10	1.43	
7	-0.88	-0.12	0.89	
8	-1.79	-1.68	2.45	
9	-2.64	-3.64	4.50	
10	6.27	22.17	23.04	
0	1.65	0.00	1.65	Generator Load
1	4.67	-21.70	22.19	
2	-1.72	2.74	3.24	
3	-0.63	2.70	2.78	
4	-1.77	-0.13	1.78	
5	-1.38	0.21	1.39	
6	-1.37	-0.22	1.39	
7	-1.77	0.12	1.77	
8	-0.60	-2.70	2.77	
9	-1.69	-2.71	3.20	
10	4.54	21.72	22.19	
0	-0.12	0.00	0.12	Generator Load + 1 Lamp
1	6.26	-22.53	23.38	
2	-1.73	3.00	3.46	
3	-1.41	1.88	2.35	
4	-1.55	0.57	1.65	
5	-1.52	0.05	1.52	
6	-1.51	-0.06	1.51	
7	-1.54	-0.58	1.65	
8	-1.39	-1.88	2.34	
9	-1.69	-2.97	3.42	
10	6.13	22.56	23.38	

The data above is data for a broken bearing condition, the X[n].cos(theta) and X[n].sin(theta) values are obtained using the Fourier transform (DFT) formula and the magnitude value is obtained by changing the shape into a phasor. The X[n].cos(theta) and X[n].sin(theta) values represent rectangular numbers. The data will be plotted in a Cartesian diagram as follows.

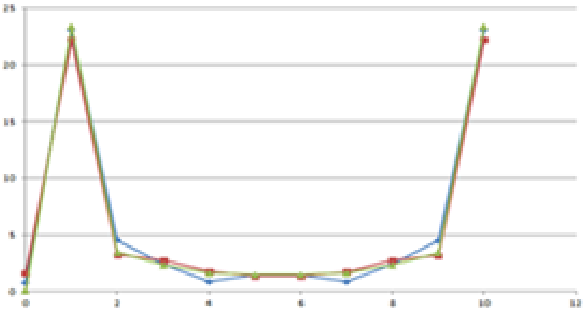

Figure 3. Waves for various types of loads under broken bearing conditions

In contrast to the previous plotting results, the image above tends to exhibit greater fluctuation and greater non-uniformity. This is characteristic of bearing failure conditions, with high fluctuations regardless of the loading conditions. There is no consistent data across load levels for bearing failure conditions.

4. CONCLUSION

The current conditions under normal and ruptured bearings in the frequency domain are significantly different. However, when analysis and observations are conducted in the time domain, the conditions under normal and ruptured bearings are identical. Therefore, further study is needed to identify the differences or characteristics between normal and ruptured bearings. For ruptured bearings, analysis in the frequency domain shows an unstable and fluctuating state. Meanwhile, under normal bearing conditions, the waveforms in the frequency domain tend to be identical, with no fluctuations for the three types of loading (no load, generator, and generator + lamp).

REFERENCES

[1] Sandi Hardiansyah and Sofian Yahya, "Perancangan dan Simulasi Deteksi Kerusakan Bearing Pada Motor Induksi Tiga Fasa Menggunakan FFT dan ANN," *Pros. Ind. Res. Work. Natl. Semin.*, vol. 15, no. 1, pp. 412–419, 2024, doi: 10.35313/irwns.v15i1.6231.

[2] I. DPK, B. Y. Dewantara, and A. M. Janudin, "Deteksi Kerusakan Inner Race Bearing Menggunakan Motor Current Signature Analysis Berbasis Fast Fourier Transform," *J. Tek. Elektro dan Komput. TRIAC*, vol. 6, no. 1, pp. 6–9, 2019, doi: 10.21107/triac.v6i1.5145.

[3] Romdhoni, Mardiansyah, and H. Kusnadi, "Bearing Fault Detection Menggunakan Metode Wavelet Berbasis Labview," *Techné J. Ilm. Elektrotek.*, vol. 22, no. 1, pp. 49–58, 2023, doi: 10.31358/techne.v22i1.340.

[4] M. P. Darmawan and N. S. Soedjarwanto, "Analisis Identifikasi Kecacatan Bearing Motor Induksi Berdasarkan Arus Stator Dan Torsi Pada Rpm Berbasis Fast Fourier Transform," *J. Inform. dan Tek. Elektro Terap.*, vol. 11, no. 3, pp. 303–310, 2023, doi: 10.23960/jitet.v11i3.3071.

[5] G. D. Prenata *et al.*, "TEMPERATURE CLASSIFICATION IN HIGH VOLTAGE ELECTRICAL EQUIPMENT USING K-NEAREST NEIGHBOR KLASIFIKASI SUHU PADA PERALATAN LISTRIK TEGANGAN TINGGI MENGGUNAKAN K-NEAREST NEIGHBOR buatan dalam klasifikasi keandalan sistem tenaga listrik dapat memberikan hasil," vol. 27, no. 1, pp. 40–49, 2025.

[6] G. D. Prenata, "Klasifikasi Keandalan Sistim Distrbusi Tenaga Listrik Di Pt. Pln (Persero) Up3 Surabaya Selatan Menggunakan Metode K-Nearest Neighbor (Knn)," *J. Inform. dan*

Tek. Elektro Terap., vol. 11, no. 3s1, 2023, doi: 10.23960/jitet.v11i3s1.3397.
[7] J. Vocational, T. Elektronika, A. Kehandalan, F. Modes, and E. Analysis, "VoteTEKNIKA," vol. 12, no. 1, 2024.
[8] J. G. Proakis and D. G. Monolakis, "Digital signal processing: principles, algorithms, and applications," *Pentice Hall*, pp. 1–42, 1996.
[9] P. Heckbert, "Fourier Transforms and the Fast Fourier Transform (FFT) Algorithm," *Notes Comput. Graph.*, vol. 3, no. 2, pp. 15–463, 1995.
[10] E. K. Wati, *Teori Pengolahan Sinyal Digital Oleh: Erna Kusuma Wati*. 2020.
[11] B. McHenry and J. McHenry, "Practice Exercises," *What Ther. Say Why They Say It*, vol. 1, no. 1, pp. 181–191, 2021, doi: 10.4324/9781315764085-20.
[12] D. Ford, "Transforming polar equations to rectangular form," *Math 140 Lecture Notes, Cerritos College, Norwalk, CA, USA*. [Online]. Available: https://www.cerritos.edu/dford/SitePages/Math_140/Math140Lecture19.pdf
[13] Zuhal, Dasar Teknik Tenaga Listrik dan Elektronika Daya. Jakarta, Indonesia: *PT Gramedia Pustaka Utama*, 2000.
[14] I. Nurhadi, A. I. Muhyuddin, and M. Ahamrudin, "Ciri getaran mekanik dan arus catu pada motor listrik induksi 3-fasa akibat eksentrisitas celah udara," *MESIN*, vol. XVI, no. 1, pp. 18–22, 200X.
[15] W. T. Thomson and M. Fenger, "Current signature analysis to detect induction motor faults," *IEEE Industry Applications Magazine*, vol. 7, no. 4, pp. 26–34, Jul./Aug. 2001.