

Spectral Acoustic Characterisation for Bearing Fault Detection in Marine Propulsion Motors

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ABSTRACT

Damage to the bearings of a ship's propulsion motor represents a significant reason why ships experience operational disruptions. Therefore, it is important to detect and diagnose early on problems related to the bearings of a propulsion motor early on to reduce maintenance costs and prevent potential maritime accidents. Additionally, since bearings subjected to variable loading and speed in dynamic environments have the possibility for various types of damage to occur, an accurate, non-destructive detection method is required to allow for early indication of damage to bearings. A condition monitoring system based on acoustic signals was developed within this study to be able to monitor the health of the bearings of a propulsion motor without damaging them. A method called

Short Time Fourier Transform (STFT) was used to analyse the time vs frequency characteristics of the acoustic signal generated by the motor during various operating conditions. The STFT analysis revealed unique spectral patterns that identified different forms of bearing damage, i.e., failure of the inner-race, outer-race, ball of the bearing, and cage. Testing of the system was conducted with a variety of combinations of speed and load to identify the reaction of the system to variations in operational conditions. Monitoring ship propulsion motors using the

ARTICLE INFO

Article history:

Received: 28 October 2025

Accepted: 26 December 2025

Published: 30 April 2026

DOI: <https://doi.org/10.47836/pjst.34.2.22>

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STFT algorithm has been proven to be suitable for processing non-linear data with a high accuracy of 97.5%. Development of this system will provide a safe and environmentally friendly way to monitor the operation of equipment at sea.

Keywords: Acoustic signals, bearing fault detection, ship propulsion motor, spectral analysis, STFT

INTRODUCTION

The motor bearing is a critical part of the propulsion system on a ship. It performs a key function in providing navigational safety and operational efficiency. Therefore, it is extremely important that the motor bearing is reliable as it affects continuity of operations, fuel consumption, and the overall safety of the vessel. An integral part of the motor bearing is the bearing itself, which assists in reducing friction between moving parts and provides rotational load support (Wu et al., 2025). Damage to the bearing may cause increased friction, higher than normal energy use, total system failure, and large amounts of repairs, which can create significant unplanned downtime for the vessel (Abbasi et al., 2025). Historically, ship propulsion motor bearings were maintained using two types of corrective maintenance. The first type was a reactive maintenance method. Maintenance was performed after the component failed. The primary drawback of this type of maintenance was the costly and unplanned vessel downtime. The second type of maintenance historically used was predictive or time-based maintenance. Maintenance was performed at a set time based on when the maintenance interval was reached, regardless of the actual condition of the bearing being assessed. The main drawback of this type of maintenance was unnecessary maintenance on components that were operating satisfactorily and thus producing high cost, and additional waste from the industry. To improve on these previous types of maintenance, designers and engineers developed and continued to implement intelligent and real-time monitoring systems to provide the capability to continuously monitor the condition of the bearings during operation (Karatuž et al., 2023).

The utilisation of vibration data, current, and flux to predict the failure of bearings is an established means of predictive maintenance because it does not require disassembly of the machine and can be performed while the machine is running with no interruption in production. All three methods have their own unique disadvantages. Some of the most obvious disadvantages of using a vibration-based method of failure prediction include the high susceptibility of this type of method to external influences (i.e., adjacent equipment), which can create noise that will reduce the reliability of the analysis. A disadvantage of this type of method is the necessity of installing accelerometer sensors directly onto the bearing housing. The installation of accelerometers onto the bearing housing is often difficult to accomplish in closed systems or when machines are operated in extremely hostile environments (Chu et al., 2024).

In terms of costs, sensors, and associated equipment for collecting sensor data are also somewhat expensive. Additionally, with slow-rotating machines, the amplitudes of vibration produced will be low; therefore, detecting defects during their initial development phases will be extremely difficult. On the other hand, the method of fault diagnosis via current signature analysis has several benefits. The first is that no additional sensors need to be attached to the machine, as the diagnosis process uses the existing stator current of the induction motor (Niu et al., 2023). However, the diagnostic technique suffers from a lack of specificity. Several possible causes exist which could produce fluctuations in the currents, including changes in loads, voltage imbalance, or other types of electrical system disturbance. Therefore, determining that the cause of these fluctuations was due to a defective bearing would be very difficult. Typically, an increase in current levels occurs when significant damage has occurred to the bearing. At the initial stages of damage, the bearing condition may not have resulted in a noticeable increase in the current pattern. As a result, the current signature method alone will typically not provide sufficient information to diagnose early-stage bearing damage. Advanced signal processing techniques will likely be required, such as Wavelet Transform, Short Time Fourier Transform (STFT), or Fast Fourier Transform (FFT) (Kumar & Anand, 2024).

The monitoring of bearing conditions based on magnetic flux (Flux Signal Analysis) is an infrequently used method and still appears to be in the research and development phase in several different branches of industry. The measured magnetic flux signals exhibit very weak amplitudes and are sensitive to electromagnetic noise from the environment. Earlier damage in the bearings will usually produce only very slight changes in the flux signals, making them difficult to correct from the normal signals. In addition, the flux depends strongly on operating conditions of the motor, e.g., voltage, current, temperature, etc., and is thus quite complicated to analyse and requires the use of mathematical models or intelligent algorithms for correct interpretation (Čulić et al., 2005). Disregarding the shortcomings of the other methods, however, the most effective method of bearing condition monitoring is by using the simultaneous integration of several data sources by sensor fusion techniques or multi-domain integration methods. Thus, the accuracy of the detection of bearing damage is improved, and the availability of timely maintenance decisions is assured.

Monitoring bearings using acoustic data is beneficial for several reasons. It is often possible to detect early signs of damage using acoustic data before detecting damage through vibration or electrical currents (Lu et al., 2025). Acoustic sensors can be mounted externally; therefore, they offer less complexity than vibration sensors. In addition, acoustic signals contain high-frequency information; thus, they enable the detection of subtle symptoms such as micro-friction or small crack formation (Shuai et al., 2023). Moreover, the digitalised signal processing enables

the detection and classification of damage in real-time through the acoustic signals. Characteristic sound patterns are emitted by anomalies in the operation of motors such as bearing wear, rotor imbalance, misalignment, and abnormal friction (Suman et al., 2022). The acoustic signals are measured with high-precision microphones placed at a certain distance to provide operator safety while enhancing the detection capability of the system (Karyatanti et al., 2025).

Damage to the bearings of a ship's propulsion motor is one of the most critical factors that can affect the reliability of a ship's propulsion system. Several condition monitoring techniques have been developed that include those based on vibration, current, and magnetic flux. Each of these techniques has some disadvantages, including the requirement for invasive sensors and issues with environmental noise levels, as well as lower accuracy during the early stages of damage or when there are changes in load and speed. To address these shortcomings, the study proposes a novel condition monitoring technique for bearings based on acoustic signals. The proposed condition monitoring technique is non-invasive, real-time, and adaptive to allow adjustments to variations in the operating conditions of the ship's motor regarding load and speed. The ability to utilise acoustic signals provides for high sensitivity in the early detection of damage, even when the disturbance level is at a micro-level and cannot be detected by traditional methods.

This condition monitoring system uses time-frequency analysis using the Short-Time Fourier Transform (STFT) method to extract the spectral characteristics associated with different types of bearing damage, i.e., the inner-race, outer-race, ball of the bearing, and cage. The primary innovation of this study is the development of an acoustic-based condition monitoring system for ship propulsion motor bearings that operates under dynamic conditions, particularly where the load and/or speed of the motor are changing. Unlike many previous studies, which evaluated systems at static loads or at constant speed, this study evaluates systems during variable loads and/or speeds, which is common in actual maritime environments. The system can identify and localise the type and location of bearing damage (i.e., inner-race, outer-race, ball of the bearing, and cage) based on spectral characteristics extracted from STFT analyses of acoustic signals. Additionally, the use of acoustic sensors as the primary data source provides a cost-effective and non-invasive condition monitoring system compared to vibration or electrical current monitoring systems, which require expensive contact sensors and complicated installation procedures. The system is also reliable in non-linear signal conditions and noisy maritime environments due to the transformation of the signal to the time-frequency domain, which permits precise identification of localised changes. It is expected that the effectiveness of predictive maintenance for ship propulsion systems will be improved, and the risk of unexpected failures that affect safety and operational performance will be reduced.

MATERIALS AND METHODS

An extensive experimental testing methodology is needed to create a dependable acoustic condition monitoring system that will work successfully in a dynamic operational environment. This testing methodology includes the effects of load, motor speed, and the non-linear acoustic signal characteristics from acoustic sources. The propulsion motor is being simulated with several forms of controlled bearing damage simulating real-world operational conditions in maritime operations. All the acoustic data collected was then analysed with the STFT algorithm to transform the signals from the time domain to the time-frequency domain, providing a better illustration of anomaly patterns produced by mechanical damage. The spectrum features developed from this were utilised to determine the type and location of damage. Each step of the testing process was developed to test the dependability of the acoustic-based monitoring system under the various load and speed conditions, as well as to test how well the method works in terms of environmental disturbances and dynamic variations within the ship's propulsion system. Induction motors were chosen as the type of motor used for the propulsion system, and the bearings are artificially damaged in specific locations to simulate real-world damage conditions.

The angular speed of the motor and amount of load applied to the shaft in the propulsion system of the ship could affect the characteristics of the signals produced by the mechanical components. Thus, the effects of load and speed must be examined in this study to test the reliability of the acoustic condition monitoring system. When the motor is running at lower speeds, the acoustic signals that are produced have lower energy and a smaller range of frequencies. Under these conditions, it may be more difficult to see the effects of bearing damage since the intensity of the acoustic signals is still within the range of what is considered normal. Conversely, when the motor is running at higher speeds, the effect of bearing damage produces a significant increase in the energy of the acoustic signals, which are spread out over a larger range of frequencies, thus making it easier to see the effects of bearing damage through spectral analysis.

The amount of load also affects the dynamic response of the system. Increased loads result in greater compressive forces between the bearing components, therefore producing louder and more consistent sounds because of mechanical defects. In addition, when the system is under increased load, the symptoms of damage will produce a distinct and repeated sound pattern that can be recognised through time-frequency analysis utilising STFT. Conversely, under decreased loads, minor damage may not produce enough acoustic disturbance to be recognised.

Therefore, the goal of this research is to incorporate various speeds and loads into the testing to evaluate the sensitivity and robustness of the acoustic monitoring system to changes in operational conditions. It is essential to establish that the system can function

in an adaptive manner in dynamic maritime environments, while continuously producing accurate diagnostic results across all modes of operation of the ship's engines.

Figure 1 is a block diagram of a bearing condition monitoring system within a ship's propulsion system, which uses acoustic signals to make non-invasive damage detections. The ship's propulsion system utilises a motor to drive the shaft and propeller. The bearing components support the shaft and facilitate the smooth rotation of the shaft and are the focal point of the monitoring because failure of the bearings can cause severe disruption to the propulsion performance. The system identifies signs of bearing damage by employing acoustic sensors in the form of high-precision microphones located near the bearing components. The microphones capture the sounds produced during the operation of the motor at various speeds and loads. The acoustic signals captured are non-linear and complex; therefore, they must be preprocessed through time-frequency conversion (i.e., STFT) to create a visual display of the sound spectrum in the form of a spectrogram. A diagram of the configuration of this block diagram is depicted in Figure 2.

Once the spectrum data has been generated, it is sent to a processing unit (based on a Raspberry Pi). Not only does this system detect the presence of damage, but it also identifies the position where damage to the bearing occurs (whether it occurs on the inner-race, outer-race, ball of the bearing, or cage). The analytical results are displayed on a monitor screen in the form of a colored spectrogram illustrating the energy intensity over time across various frequencies.

The test-bearing used in the study was a rolling-element bearing whose physical condition was illustrated in Figure 3. It was shown how the bearing exhibited different types of damage to its raceways (the circular surface where the balls run). There were three types of damage shown: in Figure 3(a), the bearing had cracks on its outer race (minor defects); in Figure 3(b), the bearing had similar minor defects on the inside raceway (inner race); and in Figure 3(c), the bearing had more serious damage to the outer race. These types of damage were artificially created to simulate typical failures experienced in marine propulsion systems (e.g., through wear, excessive loading, or imbalanced operation of the motor).

These artificial failures in the bearing were used as the test object for assessing the accuracy of an acoustic signal-based condition monitoring system to identify and classify both the location and type of damage occurring to the bearing races. The acoustic signal generated by the rotating motor with a damaged bearing has distinguishable spectral features relative to the signal generated by a normal condition. A machine learning-based classification technique and time-frequency transformation were used to predict the ability of the system to accurately determine whether the damage was in either the outer or the inner race. Testing with the perforated bearing object in the validation phase of the system will allow for comparison of the performance of the system in identifying damage (both in terms of magnitude and location) in both a healthy condition and a damaged condition.

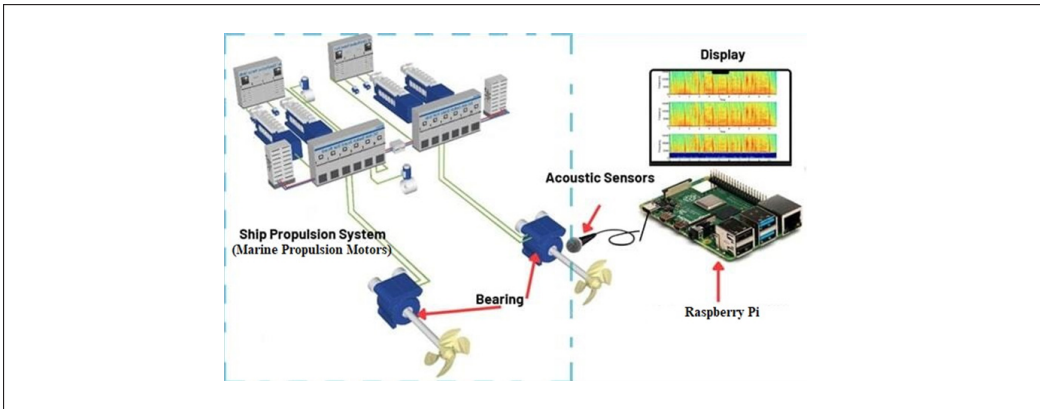


Figure 1. Scheme of the monitoring system for the condition of ship propulsion engines

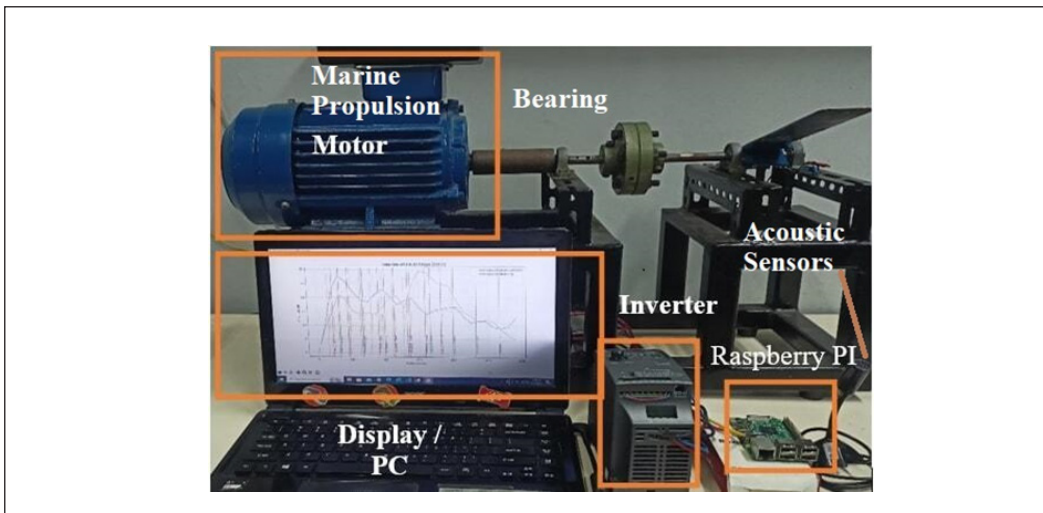


Figure 2. Implementation of a test system for monitoring the condition of ship propulsion engines

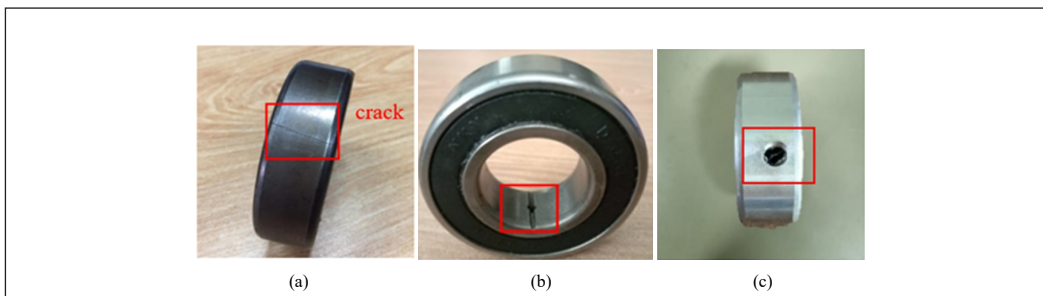


Figure 3. Test bearings for ship propulsion motors: (a) outer race minor defect; (b) inner race minor defect; (c) outer race serious damage

In addition, this will enable assessment of the sensitivity of the acoustic sensor and the associated signal processing algorithms to noise caused by damage located at different positions within the bearing.

Experimental tests are important to demonstrate the ability of the monitoring system to carry out real-time damage detection within the dynamic operating environment of a vessel. One of the more common methods of analysing the acoustic signals generated from a motor in terms of research work carried out regarding the use of acoustic signals for condition monitoring of propulsion motor bearings is the STFT method. This method is in some part popular because the acoustic signals generated from a motor are non-stationary (especially if there are present mechanical faults). A signal is classified as being non-stationary if the frequency contents are changing with time. Therefore, it will be appreciated that a Fourier Transformation will not give sufficient information about the local alterations in the frequency contents due to mechanical faults, giving only the global frequency contents of the signal. The STFT overcomes this disadvantage through time-frequency analysis of signals, allowing the study of spectral changes developed as the motor turns. The STFT enables this to be done because it divides the long length of the signal into small segments, which are considered as being locally stationary, and a window function is applied to each section to reduce the effect of spectral leakage. After the preceding procedures are put into practice, a Fast Fourier Transform (FFT) is employed. The result is a time-frequency spectrum or spectrogram, which shows signal energy distribution on both parameters, both in time and frequency. The formulation of STFT is provided below (Geraei et al., 2024).

$$STFT\{x(t)\}(t, \omega) = \int_{-\infty}^{\infty} x(\tau) \cdot \omega(\tau - t) \cdot e^{-j\omega\tau} d\tau$$

where:

$x(\tau)$ = original signal in the time domain (motor sound signal)

$\omega(\tau - t)$ = window function, which is shifted over time

$e^{-j\omega\tau}$ = exponential basis of the Fourier transform

ω = angular frequency (rad/s)

t = centre of the window

An expression for the Discrete STFT is described below:

$$STFT\left[[x[n]]\right](m, \omega) = \sum_{-\infty}^{\infty} x[n] \cdot \omega(n - m) \cdot e^{-j\omega n} d\tau$$

$x[n]$ = discrete signal (sampled from a microphone)
 $\omega(n - m)$ = fixed-length window function shifted to index m

The results of the Short-Time Fourier Transform are usually displayed as a spectrogram, which is a two-dimensional graph of energy amplitude in time and frequency.

When a bearing is damaged, the spectral characteristics of the acoustic signal generated will display a particular frequency pattern that is a strong indicator of mechanical defects. When a bearing element is damaged (for example, cracked, worn or holed), the repeated collision of the bearing element with other parts of the bearing produces mechanical impulses that are recorded as non-stationary signals. As previously stated, these impulses can be identified via spectrum analysis as amplitude spikes at certain frequencies known as the bearing characteristic frequencies.

Damage to a bearing could cause an increase in the magnitude of the vibrations at the harmonic frequencies generated by an induction motor. Due to the asymmetry of the flux intensity in the air gap, the inductance of the stator changes as well. The acoustic signals contain information about the status of defects or anomalies found in the motor (Wu et al., 2022). Bearing frequency is determined from the calculation of kinematical parameters, geometrical parameters, and the rotational speed of the bearing. When the bearing rotates along a path, the parameters include V = linear velocity, ω = angular velocity, r = distance, d = diameter of the ball bearing, θ = contact angle, D_p = pitch diameter, dan N = number of ball bearings. The linear velocity of the bearing within the cage V_c is expressed in Equation 1:

$$V_c = \frac{V_i + V_o}{2} = \frac{\omega_i r_i + \omega_o r_o}{2} \quad [1]$$

with $V_c = \omega_c r_c = \omega_c \left(\frac{D_p}{2}\right)$ where $r_c = \frac{D_p}{2}$. Bysubstituting the relationship between angular and linear velocity, the cage angular velocity ω_c can be derived, as shown in Equation 2.

$$\omega_c = \left(\frac{2V_c}{D_p}\right) = \left(\frac{2}{D_p}\right) \cdot V_c = \left(\frac{2}{D_p}\right) \left(\frac{\omega_i r_i + \omega_o r_o}{2}\right) = \frac{\omega_i r_i + \omega_o r_o}{D_p} \quad [2]$$

Distances of *inner-race* (r_i) and *outer-race* (r_o) are:

$$r_i = \frac{D_p}{2} - \frac{d \cos \theta}{2} \quad \text{and} \quad r_o = \frac{D_p}{2} + \frac{d \cos \theta}{2}$$

Considering the geometrical relationships of the inner and outer race radii, the expression is further expanded into Equation 3.

$$\omega_c = \frac{\omega_i \left(\frac{D_p}{2} - \frac{d \cos \theta}{2} \right) + \omega_o \left(\frac{D_p}{2} + \frac{d \cos \theta}{2} \right)}{D_p} = \frac{1}{2} \left[\omega_i \left(1 - \frac{d \cos \theta}{D_p} \right) + \omega_o \left(1 + \frac{d \cos \theta}{D_p} \right) \right] \quad [3]$$

By converting angular velocity into frequency form using $\omega = 2\pi f$, then the cage frequency is obtained as given in Equation 4:

$$f_c = \frac{1}{2} \left[f_i \left(1 - \frac{d \cos \theta}{D_p} \right) + f_o \left(1 + \frac{d \cos \theta}{D_p} \right) \right] \quad [4]$$

The frequency of the outer-race bearing rotation, also called the Ball Pass Frequency of Outer Race (BPFO), is defined in Equation 5:

$$\begin{aligned} f_{BPFO} &= N(\omega_c - \omega_o) \\ &= N \left\{ \frac{1}{2} \left[f_i \left(1 - \frac{d \cos \theta}{D_p} \right) + f_o \left(1 + \frac{d \cos \theta}{D_p} \right) \right] - f_o \right\} \\ &= \frac{N}{2} (f_i - f_o) \cdot \left(1 - \frac{d \cos \theta}{D_p} \right) \end{aligned} \quad [5]$$

The outer-race bearing frequency is assumed to be zero, since it is fixed in place outside of the motor case. Therefore, the inner-race frequency is equivalent to the frequency of the motor rotor shaft ($f_i = f_s$). It follows the simplified BPFO expression in Equation 6:

$$f_{BPFO} = \frac{N}{2} f_s \left(1 - \frac{d \cos \theta}{D_p} \right) \quad [6]$$

Therefore, if calculated in the same way, the Ball Pass Frequency of the Inner Race (BPFI) could be expressed as in Equation 7:

$$\begin{aligned} f_{BPFI} &= N(\omega_i - \omega_c) \\ &= N \left\{ f_i - \frac{1}{2} \left[f_i \left(1 - \frac{d \cos \theta}{D_p} \right) + f_o \left(1 + \frac{d \cos \theta}{D_p} \right) \right] \right\} \\ &= \frac{N}{2} (f_i - f_o) \left(1 + \frac{d \cos \theta}{D_p} \right) \\ f_{BPFI} &= \frac{N}{2} f_s \left(1 + \frac{d \cos \theta}{D_p} \right) \end{aligned} \quad [7]$$

The value of the ball bearing frequency, known as Ball Spin Frequency (BSF), is calculated as presented in Equation 8:

$$\begin{aligned}\omega_r &= \frac{V_r}{r_r} = \frac{(\omega_i - \omega_c)r_i}{r_r} = \frac{\left(\omega_i - \left\{\frac{1}{2}\left[\omega_i\left(1 - \frac{d \cos \theta}{D_p}\right) + \omega_i\left(1 + \frac{d \cos \theta}{D_p}\right)\right]\right\}\right) \cdot r_i}{r_r} \\ \omega_r &= \frac{D_p}{2d}(\omega_i - \omega_o) \left[1 - \left(\frac{d \cos \theta}{D_p}\right)^2\right] f_r = \frac{D_p}{2d}(f_i - f_o) \left[1 - \left(\frac{d \cos \theta}{D_p}\right)^2\right] \\ f_{BSF} &= \frac{D_p}{2d} f_s \left[1 - \left(\frac{d \cos \theta}{D_p}\right)^2\right]\end{aligned}\quad [8]$$

Acoustic characteristics of the acoustic signals created by a ship's propulsion motor will clearly indicate the state of the bearings by detecting certain frequencies, specifically BPFO, BPFI, BSF, and FTF. Each of the above-mentioned frequencies relates to the damage of bearings to individual bearing parts. Under normal bearing conditions, the amplitudes of the signals at these frequencies remain relatively small and steady. However, when there is some type of damage, such as spalling, wear or cracking, the amplitude of the signal at one or more of the characteristic frequencies will significantly rise. The rise in the amplitude of the signal represents a good indicator of the damage to the bearing part associated with the respective frequency.

Time-frequency transformation methods used in conducting spectral analysis enable the visualisation of patterns of acoustic energy over multiple frequencies. If the amplitude exceeds the threshold established under the bearing being free of defects, then the system will immediately report the existence of a defect in the bearing. Moreover, the sound signal related to the fault contains harmonic components formed based on the fundamental frequency of the bearing. These harmonic components develop from the nonlinear interaction between the mechanical defects and the dynamic forces existing within the rotating system. The relationship between the harmonic frequencies and the characteristic frequencies of the bearing may be represented as Equation 9:

$$f_p = |k \cdot f_v| \quad [9]$$

where f_p is the component of the harmonic, f_v is the frequency of bearing, and k is a constant $k=1,2, 3, \dots$

When the harmonic peaks emerge in the spectrum, they enhance the diagnosis of damage and represent the degree of mechanical disturbances occurring.

Therefore, the observation of the amplitude and distribution of the harmonic components from the acoustic signals at the characteristic frequencies of bearings provides the fundamental basis for acoustic-based damage diagnostic systems.

RESULTS AND DISCUSSION

In this chapter, the results of an investigation regarding how effectively a spectral-based technique could detect bearing problems in ship propulsion motors are described and analysed using acoustic signals recorded under regulated running conditions (both from bearings that were healthy and those that had failed).

A harmonic frequency is a measure of the relationship between the RPM of a ship's propulsion motor and acoustic characteristics created by defects in the bearings. When the bearing elements pass over a fault, they produce impulse signals. The Bearing Pitch Frequency Outer (BPFO) and Bearing Pitch Frequency Inner (BPFI) are characteristic frequencies produced by impulses at the bearing pitch frequency when the elements pass over a fault. Equation 5 and 6 were used to calculate the harmonic frequencies of the outer and inner raceways of the test motor bearing with diameter $d = 7.25\text{mm}$, $\cos \alpha = 0^\circ = 1$, $D_p = 38.5\text{mm}$, and $N = 9$ (Table 1). The presence of impulses at each frequency within the acoustic harmonic spectrum serves as a symptom that there may be some damage. The variations in amplitude values at harmonic frequencies, as well as the distribution of energy in the resulting spectrum and spectrogram, are used to determine the acoustic characteristics that signify what kind of damage is present. Loaded tests were performed on this investigation since it simulates real world conditions more accurately than unloaded tests; therefore, the data presented in this paper should provide a more realistic and more accurate diagnostic capability.

Table 1
Harmonic frequency bearing

The Ship's Propulsion Motor Speed				
BPFO	1495.3 RPM	1560.3 RPM	1618.7 RPM	1676.1 RPM
<i>f_o</i>	91.02 Hz	94.98 Hz	98.53 Hz	102.03 Hz
<i>f_{ox2}</i>	182.05 Hz	189.97 Hz	197.07 Hz	204.07 Hz
<i>f_{ox3}</i>	273.07 Hz	284.95 Hz	295.61 Hz	306.10 Hz
<i>f_{ox4}</i>	364.10 Hz	379.94 Hz	394.15 Hz	408.14 Hz
<i>f_{ox5}</i>	455.13 Hz	474.92 Hz	492.69 Hz	510.17 Hz
BPFI	1495.3 RPM	1560.3 RPM	1618.7 RPM	1676.1 RPM
<i>f_o</i>	133.26 Hz	139.05 Hz	144.26 Hz	149.37 Hz
<i>f_{ox2}</i>	266.52 Hz	278.11 Hz	288.52 Hz	298.75 Hz
<i>f_{ox3}</i>	399.78 Hz	417.17 Hz	432.78 Hz	448.13 Hz
<i>f_{ox4}</i>	533.05 Hz	556.23 Hz	577.04 Hz	597.51 Hz
<i>f_{ox5}</i>	666.31 Hz	695.29 Hz	721.31 Hz	746.89 Hz

Two different conditions of a ship's propulsion motor are illustrated in Figure 4: a reference signal (healthy) and test signal (damaged). Comparing these two signals will help us determine whether the reference signal (representing the healthy motor) stayed within a steady state amplitude and was not subject to extreme fluctuations. The fluctuations in amplitude indicate that the acoustic vibration caused by all the motor components functioned properly, and there was no physical interference. Although it may appear to be so at first glance, the test signal (from the damaged motor) has many characteristics that are identical to the reference signal. However, as stated previously; to properly identify and diagnose any underlying damage, these signals cannot be solely evaluated in the time domain, as depicted in Figure 4. The next critical step is to convert the signals into the frequency domain using the STFT method. This conversion enables the separation and evaluation of each frequency component contained within the signals. As such, it will allow for the identification of the specific frequencies that may be associated with bearing damage.

A time-frequency map, also known as a spectrogram, is the graphical representation of the results obtained after converting a time-domain signal into a frequency-time image. A spectrogram displays the square magnitude $[X(\tau, f)]^2$ in a two-dimensional image format. The horizontal axis in the graph represents time (τ) while the vertical axis represents frequency (f) (Figure 5).

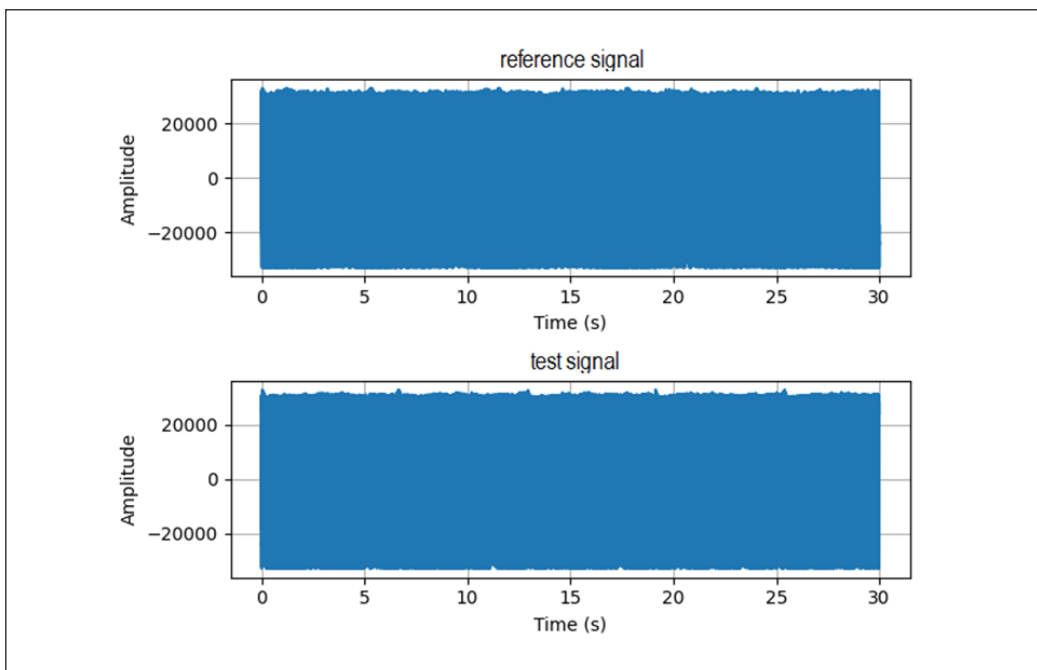


Figure 4. Reference sound signal and test sound signal under load conditions

The colours within the spectrogram illustrate the energy level of the signal, where red represents high energy levels, and blue represents low energy levels. Energy distribution is consistent and even in a healthy motor, which is representative of normal operation. Conversely, in a motor where the bearing has failed, there is a significant increase in energy level at frequencies, specifically in the low-to-mid frequency range, which is an indicator of abnormal conditions caused by bearing failure. The difference in the characteristics illustrated above serves as an important indicator that bearing damage can be identified by analysing the frequency content of acoustic signals.

Figure 6 illustrates the window amplitude of the STFT for both acoustic signals, namely the reference signal and test signal. In the context of the analysis of the condition of bearings, selecting a proper window amplitude minimises leakage; thus, it allows for the peaks of the BPFO and their harmonics to appear clearly in the spectrum. Therefore, if a window amplitude not suitable for the application is chosen, the energy of other frequencies will leak into the BPFO and BPF1 frequency bands and lead to a false diagnosis. For the reference signal window, it is seen that the amplitude of the window is concentrated primarily in the low frequency range (approximately 0-1000 Hz), with the largest peak occurring approximately 14,000 magnitude units. Following this, the amplitude of the window decreased significantly, eventually reaching near-zero magnitudes at higher frequencies. This pattern illustrates that the acoustic signal from the motor, when it is in a healthy condition, is typically clean, stable, and devoid of harmonic disturbances or abnormal frequencies.

In addition to the characteristics mentioned above, the signal test window graph shows greater amplitude peaks (about 17,500 units of magnitude) and a less stable amplitude profile, characterised by the occurrence of several amplitude spikes in the mid-high frequency range (from 1000 to 10,000 Hz). The existence of these supplementary frequency components, therefore, constitutes a clear sign of anomaly or damage to a bearing that produces additional acoustic phenomena at specific frequencies. In other words, the test signal displays spectral anomalies that do not appear in the reference signal; therefore, the STFT method is demonstrated to be effective in identifying localised damage (for example, in the inner or outer races of a bearing) through the differences in the patterns of amplitude spectra in the frequency domain.

Figure 7 to 10 show the results of sound signal extraction using the STFT method to identify frequency characteristics related to the condition of the bearings in the ship's propulsion motor. These graphs show a comparison between two signal conditions, namely the average reference amplitude (blue line) as the normal bearing condition and the average test amplitude (orange line) as the tested bearing condition or one that is indicated to be damaged. The tests were conducted at several different speeds: 1495.3 rpm (Figure 7), 1560.3 rpm (Figure 8), 1618.7 rpm (Figure 9), and 1676.1 rpm (Figure 10).

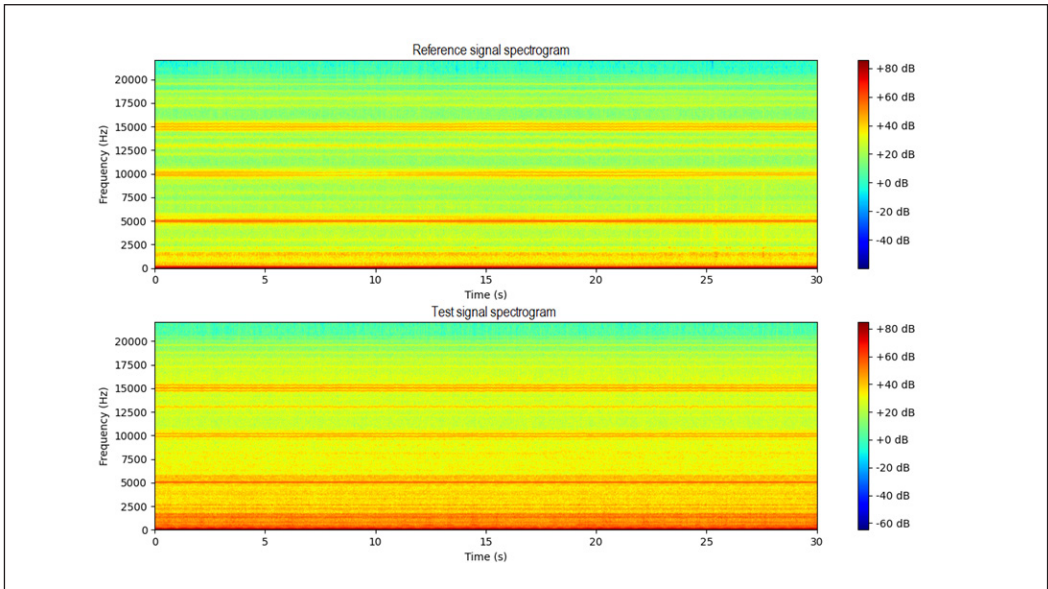


Figure 5. Spectrogram of sound signals in testing the outer race and inner race conditions of propulsion motors

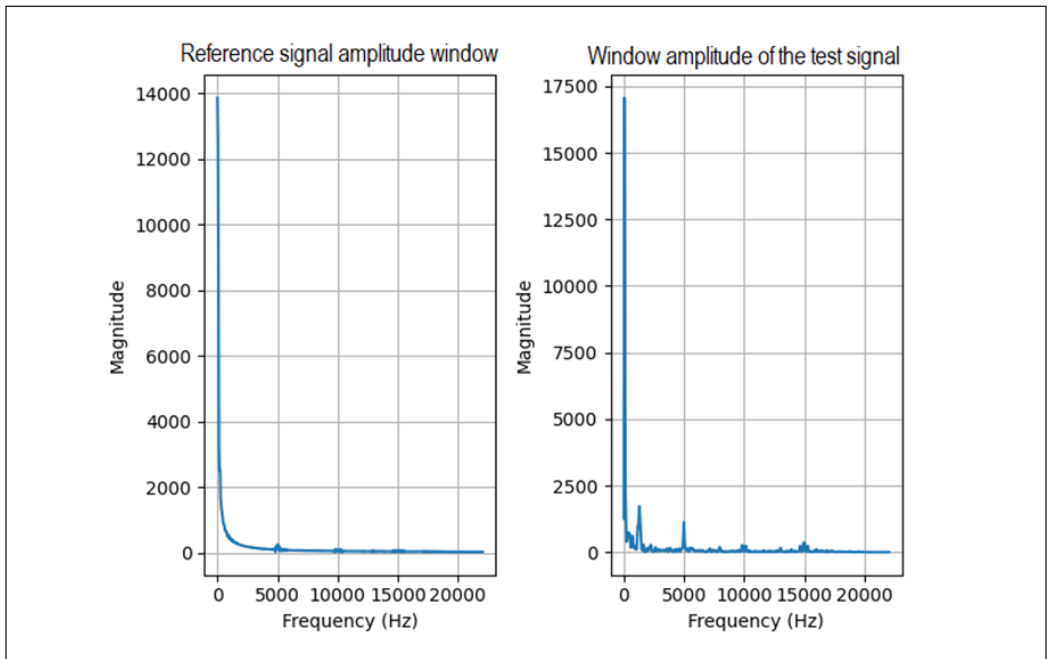


Figure 6. Acoustic signal window from the STFT process

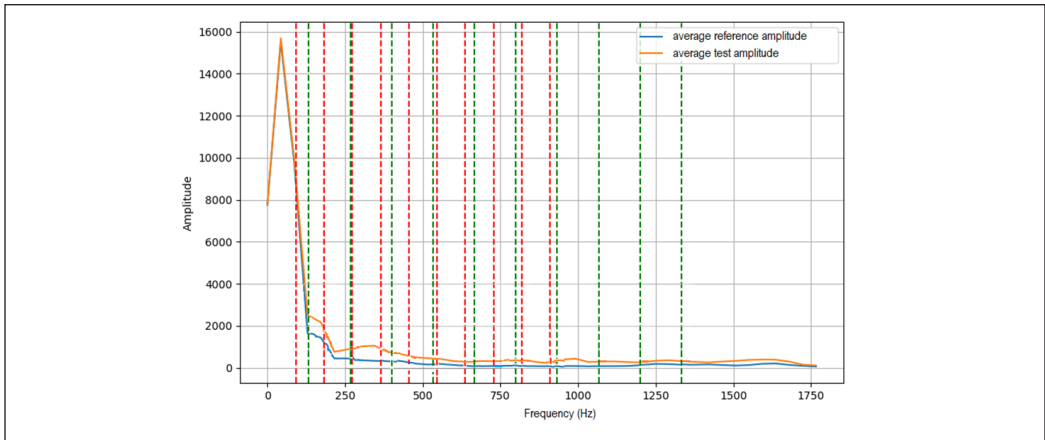


Figure 7. Average amplitude graph, motor with a speed of 1495.3 rpm

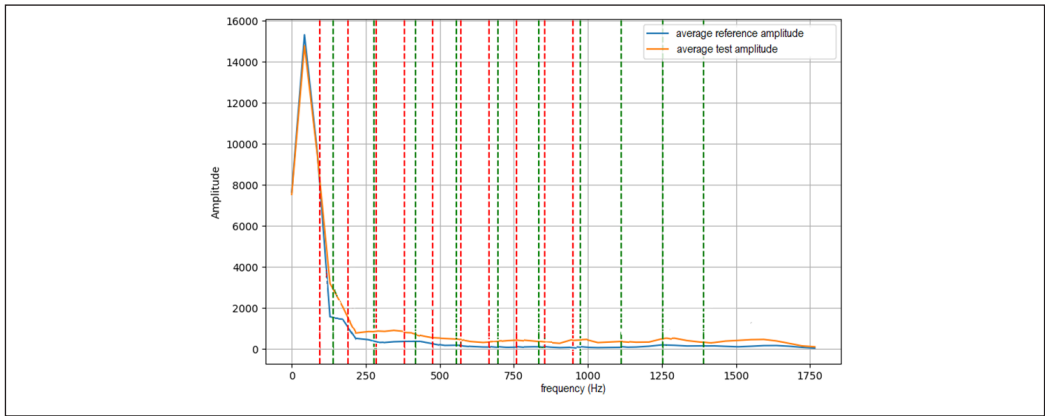


Figure 8. Average amplitude graph at a speed variation of 1560.3 rpm

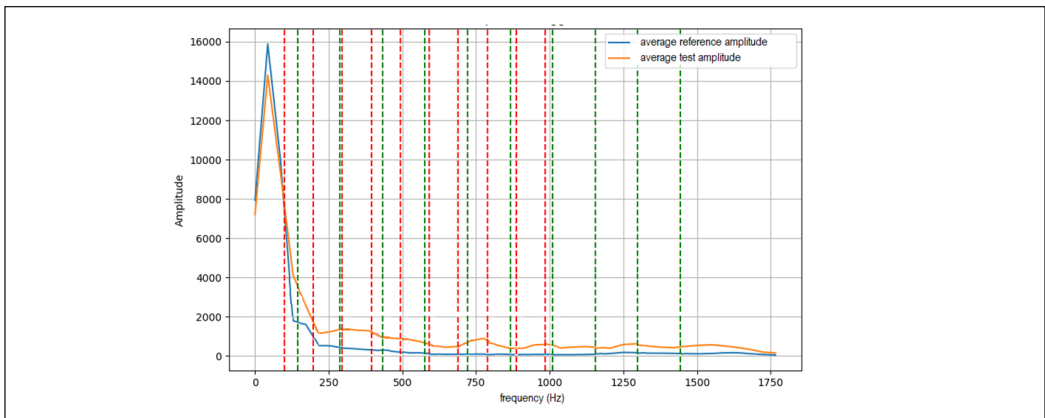


Figure 9. Average amplitude graph of the motor at a speed of 1618.7 rpm

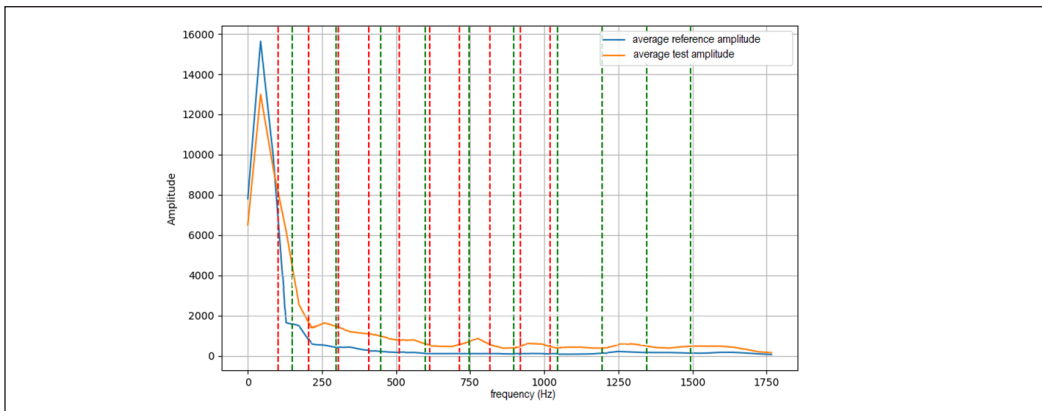


Figure 10. Average amplitude graph of the motor at a speed of 1676.1 rpm

The graph is the basis for spectrum analysis to determine whether the bearing is damaged or still in normal condition. Observations are focussed on the amplitude at the bearing harmonic frequency according to Table 1. When the test signal has an increase in amplitude at the inner-race or outer-race frequency, this indicates damage. Under load conditions, the sound signals produced by the motor contain more information due to the increased compressive force applied to the bearing components, which, in the event of defects or wear, will produce vibrations or sounds that are more pronounced and clearer.

Table 2 shows the results of the accuracy recap of the bearing condition monitoring performed on the propulsion motor of the vessel, about the detection of defects in the outer race (BPFO) and inner race (BPF1) bearings, at a range of motor speeds, from 1495.3 rpm to 1676.1 rpm. The reference value (Ref) corresponds to the acoustic amplitude measured under healthy bearing conditions, whereas the test value represents the amplitude recorded during the evaluation of the bearing (as presented in Figure 7 to 10). According to the validation principle (Val) adopted, when the amplitude of the test value exceeds the reference value, the bearing is considered defective (Val = 1). This is consistent with the reality of the situation, and therefore receives a notation of 1, indicating correct monitoring (Val = 1). On the contrary, when the test value does not exceed the reference value, or does not match the actual situation, it is considered incorrect (Val = 0). As an example of a case from Table 2 regarding the BPFO at a speed of 1618.7 rpm at the third harmonic frequency (fox3) is studied. Under normal conditions (Ref), the amplitude of vibration for fox3 was recorded at 59.84. In turn, the test results of the analysed bearing (Uji) showed an amplitude of 61.79. Since the test value exceeded the reference, it met the criteria for declaring the outer race bearing as damaged. The findings are consistent with the actual field conditions and therefore resulted in a column (Val) equal to 1, which indicates a correct detection result. This example also demonstrates that the monitoring system retains

Table 2

Recapitulation of the accuracy of outer race and inner race bearing monitoring

BPFO	1495,3 Rpm			1560,3 Rpm			1618,7 Rpm			1676,1 Rpm		
	Ref	Test	Val	Ref	Test	Val	Ref	Test	Val	Ref	Test	Val
<i>fo</i>	79.78	79.92	1	79.35	79.67	1	79.99	79.05	0	79.30	78.58	1
<i>fox2</i>	62.55	65.72	1	62.49	65.3	1	53.32	59.85	1	53.55	61.07	1
<i>fox3</i>	52.13	57.58	1	48.44	57.16	1	50.84	61.79	1	50.48	61.89	1
<i>fox4</i>	49.11	59	1	50.26	57.35	1	48.64	60.98	1	47.79	59.82	1
<i>fox5</i>	44.83	52.49	1	47.15	53.46	1	45.56	57.54	1	42.22	56.1	1
FBFI												
<i>fo</i>	63.24	66.72	1	63.02	68.7	1	64.01	71.11	1	63.35	75.16	1
<i>fox2</i>	52.13	57.58	1	52.28	57.24	1	50.84	61.79	1	50.48	61.89	1
<i>fox3</i>	48.34	56.25	1	50.09	55.33	1	47.97	57.97	1	45.89	59.09	1
<i>fox4</i>	42.48	51.83	1	44.33	52.33	1	43.03	55.79	1	39.38	53.61	1
<i>fox5</i>	37.85	47.56	1	38.63	49.91	1	39.04	56.31	1	39.34	54.45	1

Note. Val = validation; 0 = inaccurate; 1 = accurate

its sensitivity to distinguish between healthy and damaged states, although the increase in amplitude is only 1.95 units, and particularly at specific harmonic frequencies. Such sensitivity is necessary for early detection, since slight variations in amplitude at the typical BPFO frequency can represent early warning signs of potential failure of the outer race of the bearing. Therefore, overall, the monitoring system used during the tests under different load conditions provided an accuracy of 97.5%.

Highly reliable fault detection was achieved through the high accuracy rate of the Bearing Monitoring System at 97.5%. It shows that almost all the amplitude measurement results at the characteristic frequencies of the bearings (both fundamental and harmonic frequencies) were verified against the true field conditions. Therefore, there will be fewer than 2.5% of cases where the detection results will not match, indicating an extremely low error rate for the system.

Achievement of this high accuracy rate, using the STFT signal analysis method employed, confirms that the method can distinguish between undamaged and damaged bearing conditions. The system has a high sensitivity, allowing the detection of small changes in amplitudes between reference conditions and test conditions, thus allowing the early diagnosis of damage. High accuracy indicates that the system produces consistent results under different operating conditions (i.e., varying motor speeds). In practice, an accuracy rate of 97.5% suggests that the system would provide sufficient reliability to be used as a real-time monitoring tool for propulsion motor systems on ships. Reliability is essential in the prevention of sudden failure and the reduction of risks associated with potential major damage and unanticipated maintenance costs. As such, the system can

become an important component in predictive maintenance strategies and therefore ensure that the operation of the vessels remains safe and efficient.

As demonstrated by the review of literature, regarding the variety of subject areas examined in research focused on monitoring of ship propulsion systems, the number of subject areas is very large and diverse. Subject areas include driving motors, both PMSM and IM, and the corresponding gearbox shafts, bearings, propulsion shafts, and vibrational-acoustic properties of parallel propulsion systems. Differences among subject areas directly affect the type of sensor(s) employed. For example, research on motors commonly uses measurements of currents, voltages, vibrations and temperatures, whereas research on bearings typically relies on measurements made with vibration or acoustic sensors. The signal processing methods applied in this area of research also differ because researchers attempt to tailor their analytical procedures to the nature of the measured data and the difficulties posed by the marine environment. For example, time-frequency domain analyses, such as STFT, Hilbert envelope analysis, chaotic analysis and phase space reconstruction are commonly used to capture the dynamic features of the signals caused by variations in speed and load. Also, signal decomposition methods, such as VMD, optimised using meta-heuristics such as GWO or WOA, are often applied to separate signal components from the noise.

Many studies have reported good accuracy rates, ranging from 97.5% to 100%, during laboratory experiments or simulations. Nevertheless, it is expected that the accuracy in real-world scenarios could be affected by the variability of the load, variation of the speed, and the complexity of environmental disturbances. In general, the trend in the research appears to be toward the development of intelligent diagnostic systems that are multi-sensorial, adaptable and able to perform real-time analysis. These systems combine the analysis of the domain in both time and frequency, signal decomposition, and machine learning to enable early detection and high-reliability prediction of potential failures. Accordingly, the future direction of the development will be the creation of integrated platforms that allow for monitoring the health of the entire propulsion system of a ship (engine, motors, gearboxes, shafts, and propeller) through non-invasive methods with high precision.

Compared to previous studies listed in Table 3, there are three major advantages of this method: The first advantage is that this proposed method utilises acoustic data to measure the condition of bearings of ship propulsion motors. Since this method uses a non-invasive technique to measure vibrations, it does not require direct attachment of vibration sensors to rotating components, which will make it easier to install these sensors, reduce the amount of money spent on vibration sensor maintenance and cause minimal disruptions to vessel operation. Most of the prior studies utilising vibration measurements, however, do require physical access to the rotating components and therefore, can be difficult to implement on ships at sea. The second major advantage of the proposed method is that it was designed

Table 3
Similar research on ship component monitoring

Works	Monitoring Objects	Highlight
(Anitha et al., 2024)	ship propulsion engine	Early detection of damage and real-time maintenance scheduling are achieved through data analysis involving temperature, pressure, vibration, current, or other operational parameters
(Park & Oh, 2023)	ship propulsion engine	Monitoring cylinder exhaust gas temperature (CET) and maximum cylinder combustion pressure (CCP)
(Marey & Ali, 2023)	bearings on a ship's gearbox shaft	This study monitors the condition of ship generator shaft gearbox bearings using an adaptive signal approach and deep learning models. The data used is vibration data
(Lv et al., 2025)	propulsion engines, gearboxes, and other ship propulsion components	The combination of simulation data and real data (vibration) within the Digital Twin framework effectively overcomes the limitations of damage data, while opening opportunities for the implementation of more practical and precise intelligent diagnosis systems in the maritime industry
(Lu et al., 2025)	ship propulsion shafting	This study shows that vibration signals—when analysed through chaos theory and phase space reconstruction—can be an effective method for detecting early changes in the alignment of a ship's propulsion shaft. This technique provides a strong theoretical basis for the development of real-time shaft alignment monitoring systems in the shipping industry
(Xu et al., 2024)	acoustic vibration characteristics of the ship's parallel propulsion system, namely vibration (lateral, torsional, axial)	Acoustic vibration data from the test platform is used in conjunction with an RBF neural network model to accurately predict and optimise system performance even with limited samples
(Ma et al., 2023)	Permanent Magnet Synchronous Machine (PMSM)	Specifically, the detection of inter-turn short circuits in ship propulsion motors (simulation using Simulink models)
(Kato & Otaka, 2025)	induction motor in ship propulsion	The ship propulsion motor system uses envelope processing based on the Hilbert transform to extract the characteristic fault frequency of the bearing (BPFO)
Proposed method	ship propulsion motor bearings	Monitoring ship propulsion motor bearings using acoustic data, which is non-linear data, STFT has proven to be suitable for processing non-linear data with a high sensitivity 97.5%

to work with nonlinear data; STFT was shown to provide excellent extraction of frequency information from complicated acoustic waveforms. This method also has a very high degree of detection sensitivity (97.5%), allowing it to detect small changes in the bearing condition when operates in an environment of environmental noise generated by the ship. A few alternative methods have demonstrated similar levels of accuracy using simulated or laboratory data, but none of these alternatives was tested using the nonlinear acoustic data commonly found in marine environments. The third major advantage of the proposed method is that it provides the opportunity to integrate the acoustic measurement method with existing real-time monitoring systems without requiring expensive additional sensor systems. Overall, the primary advantages of the proposed method include its ease of use, low cost, and ability to accurately perform under adverse signal conditions, all of which make it a better choice than many other methods that were developed and tested using simulated data and/or special-purpose sensors.

CONCLUSION

A monitoring system for the condition of ship propulsion motor bearings was successfully designed and tested using acoustic signal analysis based on the STFT. These test results clearly show that this method has great potential for detecting changes in bearing condition and shown a great level of sensitivity at an accuracy rate of 97.5%, even though the data from the bearing conditions were nonlinear and affected by both the ambient noise from the vessel and variability in the rotational speeds of the motor. An additional benefit of this acoustic methodology is that it is noninvasive, which will enable easy implementation into vessels' operating environments without disruption or requiring sensors directly installed onto rotating components. Therefore, given the low cost and ability to be used in real time, this method provides a viable solution for developing real-time monitoring systems for use onboard ships while improving operational reliability, preventing catastrophic failures, and optimising maintenance scheduling. Additionally, the success of this method opens the door to the integration of the Internet of Things (IoT) and digital twin technologies to enhance predictive analytics in the maritime industry.

ACKNOWLEDGEMENT

This research was funded by the Direktorat Penelitian dan Pengabdian kepada Masyarakat, Direktorat Jenderal Riset dan Pengembangan, Kementerian Pendidikan Tinggi, Sains, and Teknologi Republik Indonesia for the year 2025 contract number 128/C3/DT.05.00/PL/2025; 039/LL7/DT.05.00/PL/2025, B/15/DT.05.00/PL/UHT.C7/V/2025.

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