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The Implementation of Nonlinear Signal Techniques for Enhanced Monitoring of Marine Propulsion Systems

Iradiratu Diah Prahmana Karyatanti[1], Istiyo Winarno [2], Belly Yan Dewantara [3], Anggo Suryo Wibisono[4]
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***Abstract*— The propulsion motor is essential to a ship's propulsion system, enabling effective maritime operations by converting energy into motion. The system's performance can be negatively impacted by dynamic factors such as load fluctuations, speed variations, and difficult marine conditions. This study presents a real-time condition monitoring system specifically designed for ship propulsion motors., utilizing non-invasive analysis of nonlinear acoustic signals to assess their performance. These signals are processed through the Short-Time Fourier Transform (STFT) to extract frequency-domain features that are indicative of the motor's condition. A significant advancement in this research is the optimisation of acoustic sensor placement, achieved through a Completely Randomised Design (CRD) approach, which has been validated using Tukey's test. Sensors were assessed at distances between 10 cm and 210 cm, with the most effective positioning identified at 110 cm. This placement achieved 100% accuracy in detecting faults such as cracks and uneven wear in motor bearings. This methodology effectively addresses challenges associated with nonlinear signal analysis and external noise interference, providing a precise, reliable, and cost-effective monitoring solution. The system improves the reliability and efficiency of marine propulsion motors by enabling early fault detection. This results in lower maintenance costs and decreased operational downtime, which is crucial for both marine and industrial applications.**

Keywords— *Accuracy; Bearing; Completely Randomised Design; Frequency; Sound signal; Spectrum.*

I. INTRODUCTION

The propulsion motor is a fundamental component of a vessel's propulsion system, responsible for converting energy into motion to ensure operational performance. As the primary driver of the vessel, its proper functioning is essential not only for propulsion but also for the operation of auxiliary systems that rely on stable power delivery. The functionality of propulsion motors is influenced by various dynamic conditions, including load fluctuations, rotational speed variations, and environmental factors such as waves, currents, and wind [1]. These conditions create complex operational environments that require the motor to consistently adapt to varying demands, increasing the risk of wear and failure over time. Without effective monitoring and maintenance, minor issues in the propulsion motor can escalate into critical failures that may result in costly repairs or even operational downtime. These factors subject the propulsion motor to stresses that can compromise its performance and, if left undetected, lead to operational failures. The potential consequences of propulsion motor failures extend beyond mere financial losses; they also pose significant risks to the safety of the vessel and its crew. Consequently, developing robust condition monitoring systems for propulsion motors is imperative to maintain their reliability and efficiency [2]. Such systems play a crucial role in ensuring the long-term operational viability of vessels by enabling early fault detection and facilitating proactive maintenance interventions. Moreover, advancements in condition monitoring technology offer opportunities to enhance energy efficiency, reduce environmental impact, and optimize overall vessel performance [3]. Condition monitoring entails the continuous assessment of the motor's operational performance to enable timely maintenance interventions. This systematic approach ensures that anomalies in motor behavior are detected early, reducing the likelihood of unexpected failures that could disrupt operations. Data collected from condition monitoring provides predictive insights into potential failures, thereby mitigating risks of severe damage, optimizing maintenance schedules, and enhancing overall equipment longevity [4]. These insights allow operators to prioritize repairs and allocate resources more efficiently, minimizing downtime and enhancing operational productivity. Such proactive maintenance practices not only improve system reliability but also reduce costs and prevent collateral damage to interconnected machinery components, such as gearboxes and pumps, which are often impacted by motor failures. Monitoring can be conducted through periodic or continuous methods, depending on the operational criticality of the motor and the available monitoring infrastructure. Periodic monitoring involves scheduled inspections, which may miss early-stage issues, while continuous monitoring offers real-time

Iradiratu Diah Prahmana Karyatanti, Department of Electrical Engineering, Hang Tuah University, Surabaya, 60111 Indonesia. E-mail: iradiratu@hangtuah.ac.id
Istiyo Winarno, Department of Electrical Engineering, Hang Tuah University, Surabaya, 60111, Indonesia. E-mail: istiyo.winarno@hangtuah.ac.id
Belly Yan Dewantara, Department of Electrical Engineering, Hang Tuah University, Surabaya, 60111, Indonesia. E-mail: bellyyandewantara@hangtuah.ac.id
Anggo Suryo Wibisono, Department of Electrical Engineering, Hang Tuah University, Surabaya, 60111, Indonesia. E-mail: suryoanggo@gmail.com

data, enabling immediate responses to emerging problems. Addressing both mechanical and electrical failures is critical, as each presents unique challenges. Common mechanical issues include shaft imbalance, uneven air gaps, and bearing damage, whereas electrical failures typically involve stator and rotor malfunctions [5]. Mechanical issues, such as bearing damage, not only affect the motor's capacity to handle loads but can also create secondary effects like misalignment and excessive vibrations that further degrade performance. Among the various types of failures identified, bearing failures are the most common, representing 41% of induction motor failures. This is followed by issues related to stator windings, which account for 37%. Rotor problems contribute to 10% of failures, while other sources of failure make up the remaining 12% [6]. Bearing damage can significantly impact motor performance, leading to elevated operating temperatures, sparking, decreased efficiency, and rotor shaft deformation, which manifest as vibrations and noise. These symptoms, if left unaddressed, can result in complete motor failure, necessitating costly repairs or replacements and potentially causing extended operational disruptions. By utilising advanced monitoring technologies, operators are able to proactively address these risks, thereby ensuring the long-term reliability and efficiency of motor systems [7].

Despite these advances, several challenges persist in propulsion motor condition monitoring. Traditional linear signal analysis methods are insufficient for detecting early-stage faults or irregular condition changes in non-linear dynamic systems, such as marine propulsion motors. These methods struggle to capture the complexities of signals influenced by varying operational and environmental factors, limiting their effectiveness in dynamic maritime conditions. Moreover, invasive monitoring techniques often require direct interaction with motor elements, which complicates their application in dynamic environments and increases maintenance costs [8]. Such techniques can also introduce additional risks, such as potential damage to motor components during sensor installation or maintenance activities. Acoustic-based non-invasive methods, while promising, are hindered by overlapping noise and the complex non-linear nature of the signals, leading to reduced diagnostic accuracy [9].

Environmental noise, vibrations from other machinery, and variations in operational conditions can mask critical fault indicators, making accurate diagnosis challenging [10]. Additionally, the lack of standardized procedures for sensor placement and signal processing further complicates the implementation of non-invasive monitoring systems. These issues highlight the necessity for innovative strategies to improve the reliability and efficiency of condition monitoring systems [11].

Developing advanced algorithms capable of isolating and analyzing fault-specific signal features within noisy and non-linear datasets is a key research priority. Furthermore, optimizing sensor placement and leveraging real-time data processing technologies can significantly improve the accuracy and practicality of condition monitoring systems for propulsion motors [12]. The second phase focused on health monitoring in a rotor winding short circuit. Both phases utilised invasive techniques, which have inherent limitations, particularly the difficulty of installing sensors on moving motor parts [13]. This necessitated the development of health monitoring through non-invasive techniques. The health monitoring system was further developed by utilising flux signals generated during motor operation as monitoring data [14]. Additionally, the operational efficiency of the motor was investigated to assess the extent of energy loss when the bearing operates under faulty conditions [15]. Further advancements in motor monitoring, with an emphasis on bearings, were pursued using non-invasive techniques based on acoustic analysis, given that this method is simpler and more cost-effective compared to others. However, challenges arise due to the overlapping nature of acoustic signals with surrounding noise, which significantly affects the accuracy of diagnostic results, as these acoustic signals are inherently non-linear [16-19]. Traditional monitoring technologies generally utilise linear methods, which are constrained in their capacity to accurately capture the intricate signal patterns associated with non-linear dynamic systems, such as marine propulsion motors. Nevertheless, advancements in non-linear signal analysis methods have made it possible to accurately depict the behaviour of more complex systems.

This study introduces a novel methodology that addresses these limitations by leveraging non-linear signal processing techniques to monitor marine propulsion motors under dynamic conditions. The proposed approach emphasizes the analysis of non-linear acoustic signals to capture complex behaviors, offering improved diagnostic capabilities compared to traditional methods. Furthermore, this research highlights the critical importance of sensor placement in achieving accurate monitoring results. By employing Short-Time Fourier Transform (STFT) for feature extraction and utilizing statistical methods such as Completely Randomized Design (CRD) and the Tukey test, the study optimizes sensor placement to enhance diagnostic precision.

A key contribution of this research is the integration of non-linear signal analysis with real-time implementation using a Raspberry Pi platform. This innovative approach enables efficient monitoring of induction motor bearings, even in challenging maritime environments, by addressing both signal complexity and noise interference. Additionally, the proposed system offers a cost-effective and practical solution for improving the reliability and operational efficiency of marine propulsion systems.

II. Method

A. System Monitoring

The configuration of the monitoring system for the ship's propulsion motor, along with the development of an optimal sensor placement strategy, is illustrated in Figure 1. The monitoring system requires several supporting components to represent the propulsion motor, including the motor itself, a microphone, a

Raspberry Pi programmed with Python, sound sensors, and an LCD for presenting graphs and monitoring results. The focus of the research is on the bearings of the ship's propulsion motor, specifically monitoring the outer race, inner race, and ball-bearing elements. The placement of the sensors is a variable that significantly influences the accuracy of the monitoring process. The experimental conditions for the placement of the sound sensors are set at distances of 10 cm, 60 cm, 110 cm, 160 cm, and 210 cm from the motor's body.

The microphone, functioning as a sound sensor, records the operational sounds of the motor. Subsequently, the audio signals are processed for diagnosing the condition of the bearings, with the central processing carried out on a Raspberry Pi. The results of this monitoring are displayed on an LCD screen. Figure 2 illustrates the research flow, demonstrating how the research objectives are achieved. Once the software and hardware have been developed, data collection commences. The initial audio data collected pertains to sound from the source under normal conditions, with variations in the placement of the sound sensor at specific distances, which serves as a reference signal. The non-linear audio signals are processed using Short-Time Fourier Transform (STFT), enabling the extraction of unique signal characteristics that reflect the condition of the ship's drive motor components. Different sensor placements create opportunities for the test audio signals to overlap with external noise. Consequently, this research implements an optimal sensor placement strategy, employing the statistical technique of Completely Randomised Design (CRD). Should the placement of the sensors significantly influence the accuracy of monitoring, the next step will involve determining the optimal sensor placement, to achieve high monitoring accuracy.

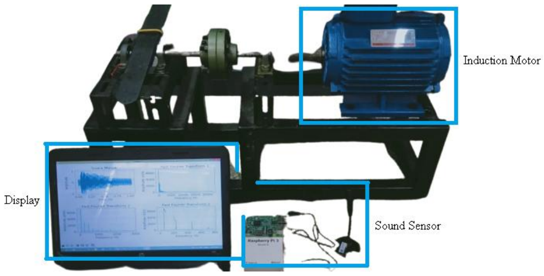

Figure. 1. Configuration of motor monitoring system.

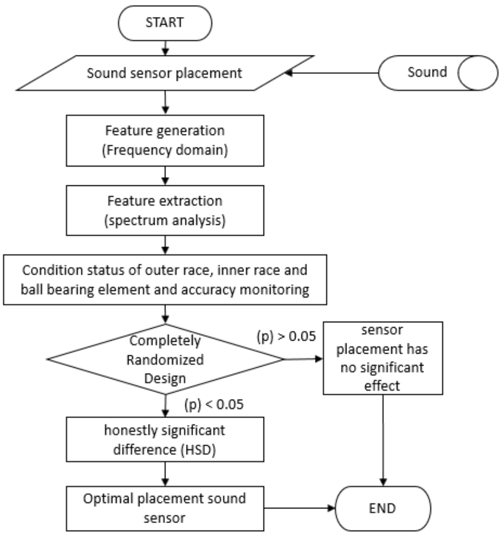

Figure. 2. Flowchart of motor condition monitoring with the development of optimal sensor placement strategy

B. Ship Propulsion Motor Rotation Frequency

Detecting damage in bearings is crucial, as any deterioration can adversely affect the reliability of induction motors. When bearings fail, they can cause the rotor to become misaligned with the stator, resulting in noise emanating from the rotor. If a bearing operates under damaged conditions, it generates periodic impulses at specific frequencies. These impulses are referred to as characteristic defect frequencies. Equations (1)-(3) provide the calculations for the frequencies of bearing elements, where Nb represents the number of balls, nm denotes the rotational speed, db indicates the ball diameter, Dp signifies the pitch diameter, and $\propto$ is the contact angle of the balls [20].

$$\text{Outer race bearing } f_o = \left(\frac{Nb}{2} \times nm\right)\left(1 - \frac{db}{Dp} \times \cos\propto\right) \quad (1)$$

$$\text{Inner race bearing } f_i = \left(\frac{Nb}{2} \times nm\right)\left(1 + \frac{db}{Dp} \times \cos\propto\right) \quad (2)$$

$$\text{Ball Bearing} \qquad f_b = \left(\frac{Dp}{2db}\, x\; nm\right)\left(1 - \left(\frac{db}{Dp}\right)^2 \cos^2\propto\right) \quad (3)$$

The frequency of the bearing is repeated across each of its harmonic components as the constant increases [21]. The periodic frequency of the bearing is denoted as f_p , while the characteristic frequency of the bearing elements is represented by f_v, according to equations (1)-(3), and constants $k = 1,2,3,4 \ldots$ Consequently, the harmonic frequency components of the bearing elements can be expressed as follows :

$$f_p = |k \; x \; f_v| \quad (4)$$

The repetition of treatments is employed to ensure a high level of accuracy. Data collection was repeated five times for each case and variation in sensor placement.

The testing of the ship's propulsion motor components, specifically the inner, outer, and ball bearings, has revealed significant damage (see Figure 3). The deterioration of the bearings typically begins with minor issues, such as scratches; however, if these are not addressed promptly, the bearings can sustain severe damage. Figure 3 illustrates three distinct faults: Fault#1, which involves a crack in the outer race bearing; Fault#2, characterised by a hole in the inner race bearing; and Fault#3, where the ball bearing has fractured. The reconstruction of the ship's propulsion motor bearings aims to evaluate the effectiveness of the monitoring system in detecting such faults. Should the designed monitoring system successfully identify the actual condition of the bearings as being faulty, it will indicate that the monitoring results are accurate.

Figure. 3. Bearing in damaged condition as testing

III. Results and Discussion

3.1. Non-linear signal analysis

The monitoring system for the condition of ship propulsion motors in real-time, specifically addressing failures in the outer race, inner race, and ball bearings, involves the strategic placement of acoustic sensors at distances of 10 cm, 60 cm, 110 cm, 160 cm, and 210 cm from the motor body. By employing Short-Time Fourier Transform (STFT) analysis on the nonlinear signals, valuable insights regarding the condition of the motor bearings can be obtained. The analysis entails comparing the amplitude of harmonic frequencies from the test bearing with the amplitude of a reference sound signal. Figure 4 illustrates the results from the testing and processing of the bearing condition monitoring at a distance of 10 cm, with the reference signal derived from recordings of a healthy bearing, while the test signal corresponds to a bearing in a state of disrepair. The nonlinear characteristics of the recorded sound signal do not yield clear information regarding the condition of the ship propulsion motor, as there are no significant differences between the reference and test signals. This highlights the critical role of STFT in providing accurate information about the condition of the motor bearings. Figure 5 presents the processed signal from the STFT, depicted as a spectrogram that illustrates the relationship between time and frequency, along with colour intensity representing amplitude levels. An analysis of the spectrum is then conducted by comparing the amplitudes of the reference bearing against those of the test bearing, as shown in Figure 6. Observing the signal patterns allows for the determination of the bearing condition. Notably, the average amplitude of the test signal is higher than that of the reference signal. Specifically, the outer frequency at 91.27 Hz exceeds the reference amplitude of 80.19, while its periodic frequency of 182.54 Hz reaches 66.48. Such patterns are expected to recur at other outer race frequencies. This spectral analysis indicates the presence of damage within the outer race bearing.

The analysis of the inner race condition is observed at a frequency of 133.62 Hz, where the amplitude reaches 66.77. At a frequency of 267.24 Hz, the amplitude measures 56.36. These amplitude values exceed their respective reference levels of 65.92 and 55.26. The observations were conducted across ten periodic frequencies for each sound signal sample. The testing involved varying the placement distance of the sound source, as this would influence the analytical results; an increased measurement distance raises the likelihood of the motor sound overlapping with non-motor sounds. Monitoring was repeated five times for each treatment condition.

Table 1 presents the overall results of the tests conducted. The validity percentage obtained from the monitoring system indicates its capability to identify the actual condition of the test bearing. In this testing display, both the outer race and inner race are observed to be in a state of cracking.

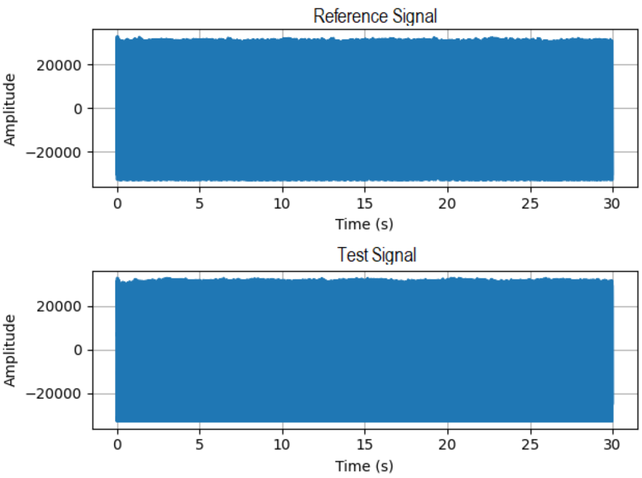

Figure. 4. Non-linear reference and test signals

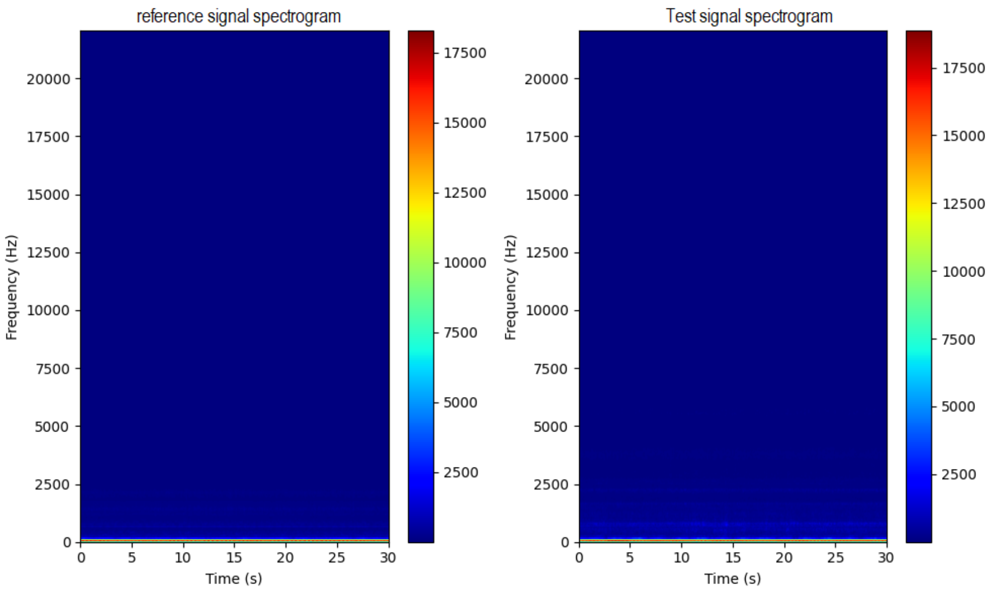

Figure. 5. STFT spectrograms of reference and test signals

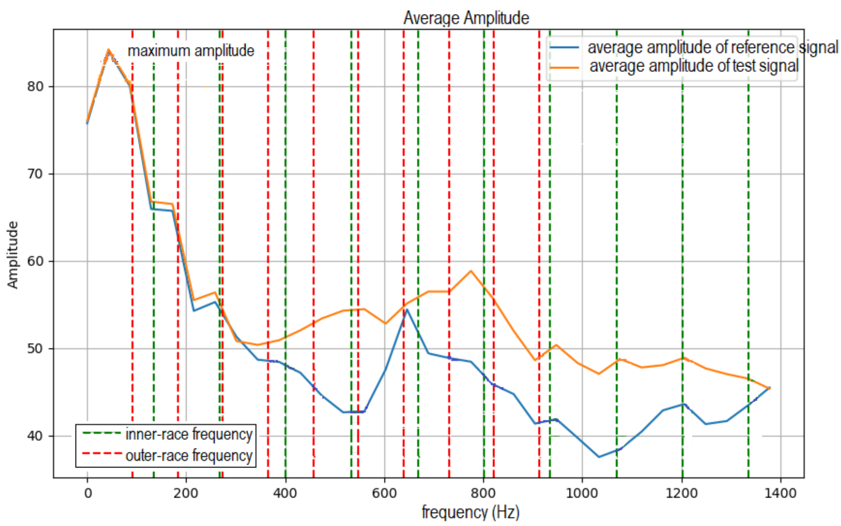

Figure. 6. Monitoring system display

3.2. Sensor Placement Strategy

The accuracy tabulation for monitoring the placement of sensors will be tested using a Completely Randomised Design (CRD) approach. In the normality test, a p-value of 0.220 was obtained, indicating that the errors or residuals are normally distributed, as this p-value exceeds 0.05. This can be observed in Figure 6. For the homogeneity test, a p-value of 0.458 was recorded, suggesting that the data variance is homogeneous, as this value is also greater than 0.05, as illustrated in Figure 8. Consequently, the validity of the data for hypothesis testing analysis has been established.

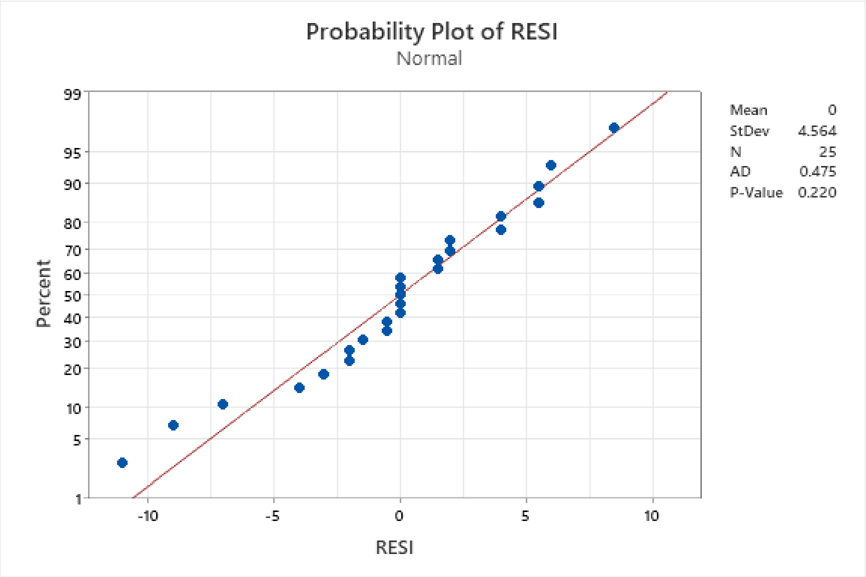

Figure. 7. Normality test

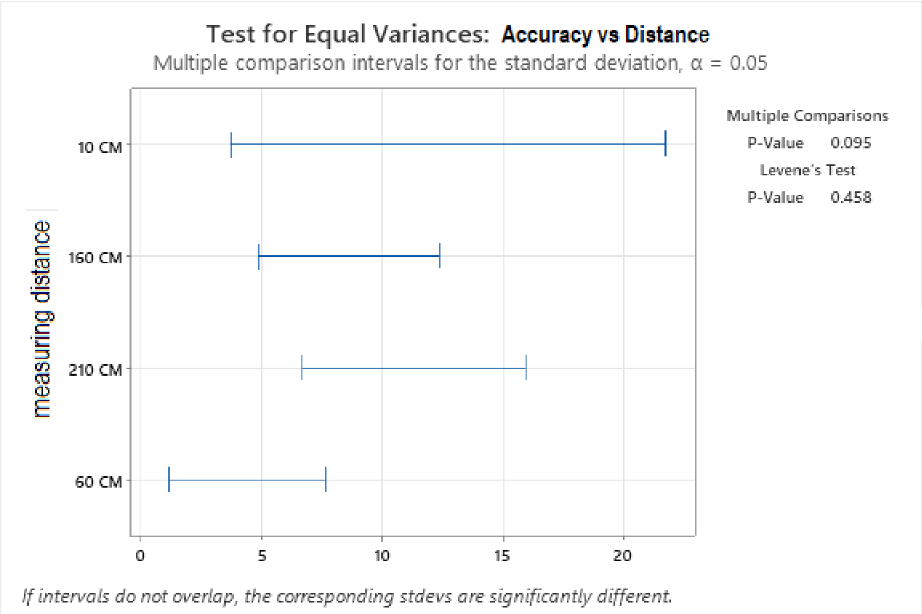

Figure. 8. Homogeneity test

The CRD test indicates that the calculated F-value exceeds the critical F-value of 2.76, leading to the acceptance of the alternative hypothesis (H1). This suggests that there is a significant impact on the accuracy of the bearing condition monitoring system based on sensor placement. The results of the test reveal that the positioning of the sensor, with varying distances, significantly affects monitoring accuracy. It is noteworthy that the bearing test indicated corrosion damage in the outer race and uneven wear in the inner race, which can be classified as non-severe damage. These findings reinforce the evidence that sensor placement significantly influences monitoring accuracy.

This underscores the importance of careful sensor placement to prevent diagnostic and prognostic errors.

The placement of sensors in different locations will result in variations in sensitivity, thereby affecting the accuracy of the monitoring system for the condition of induction motor bearings. The analysis of optimal sensor placement strategies in this study employs the Tukey test, also known as the Honest Significance Difference (HSD) method. The Tukey test compares all pairs of treatment means following an analysis of variance. The fundamental principle of this test involves comparing the differences between each mean against a specific critical value. If the absolute difference between the means is greater than or equal to this critical value, it can be concluded that the two means differ significantly. The application of the Tukey test for developing an effective sensor placement strategy is outlined as follows :

a. The results of the CRD test indicate a rejection of the hypothesis H_0, demonstrating that the placement of the sensor has a significant impact on the accuracy of the monitoring system for the condition of the ship's propulsion motor bearings.
b. Determining the Tukey value at a significance level of 5%.
c. The criteria for testing involve comparing the absolute values of the differences in the averages of two groups (see Figure 9).
d. The treatment at 110 cm (sensor placement at 110 cm) demonstrated a significant difference compared to the other treatment groups and achieved the highest average accuracy in monitoring.

TABLE 1.
ACCURACY OF BEARING CONDITION MONITORING IN ALL TESTS

Sensor Placement	Repetition of monitoring accuracy tests				
	1	2	3	4	5
10 cm	95%	95%	80%	95%	90%
60 cm	100%	100%	85%	90%	90%
110 cm	100%	100%	100%	100%	100%
160 cm	80%	90%	80%	90%	90%
210 cm	95%	85%	80%	95%	75%

TABLE 2.
VARIANCE ANALYSIS OF PLACEMENT SENSORS

Source of Diversity	Degrees Free	Sum of squares	Middle square	F-Value	P-Value
Treatment	4	600	150	6	0.002
Galat	20	500	25		
Total	24	1100			

Tukey Simultaneous Tests for Differences of Means

Difference of Levels	Difference of Means	SE of Difference	95% CI	T-Value	Adjusted P-Value
110 CM - 10 CM	9.00	3.16	(-0.46, 18.46)	2.85	0.067
160 CM - 10 CM	-4.00	3.16	(-13.46, 5.46)	-1.26	0.715
210 CM - 10 CM	-4.50	3.16	(-13.96, 4.96)	-1.42	0.621
60 CM - 10 CM	2.00	3.16	(-7.46, 11.46)	0.63	0.968
160 CM - 110 CM	-13.00	3.16	(-22.46, -3.54)	-4.11	0.004
210 CM - 110 CM	-13.50	3.16	(-22.96, -4.04)	-4.27	0.003
60 CM - 110 CM	-7.00	3.16	(-16.46, 2.46)	-2.21	0.215
210 CM - 160 CM	-0.50	3.16	(-9.96, 8.96)	-0.16	1.000
60 CM - 160 CM	6.00	3.16	(-3.46, 15.46)	1.90	0.350
60 CM - 210 CM	6.50	3.16	(-2.96, 15.96)	2.06	0.277

Individual confidence level = 99.28%

Figure. 9. Tukey Simultaneous

Grouping Information Using the Tukey Method and 95% Confidence

Distance	N	Mean	Grouping	
110 CM	5	100.0	A	
60 CM	5	93.000	A	B
10 CM	5	91.00	A	B
160 CM	5	87.00		B
210 CM	5	86.50		B

Means that do not share a letter are significantly different.

Figure. 10. Grouping Tukey Test

The Tukey test revealed that the accuracy of the bearing condition monitoring system achieved optimal results with the placement of the sensor at a distance of 110 cm from the motor body. According to the Minitab software analysis, this sensor placement of 110 cm from the motor body represented the highest average compared to other treatments, as illustrated in Figure 10.

Based on the analysis and calculations derived from the Tukey test, it was found that the bearing condition monitoring system, which employed sensor placement testing at varying distances of 10 cm, 60 cm, 110 cm, 160 cm, and 210 cm from the motor body using the Short-Time Fourier Transform (STFT) method in real-time, demonstrated a high level of success, with damage detection results exceeding 70%. The average accuracy percentage of monitoring results for both unloaded and loaded motor conditions for each sensor placement distance was as follows: 91% at 10 cm, 93% at 60 cm, 100% at 110 cm, 87% at 160 cm, and 86.5% at 210 cm. The strategy of placing the sensor at a distance of 110 cm from the motor body was identified as the optimal distance, as the monitoring system achieved an accuracy of 100%.

Table 3 presents a comparison of similar studies, focusing on the impact of sensor placement for motor condition monitoring. Several researchers have employed multisensor approaches to gather extensive information, albeit without discussing optimal strategies. In contrast, the findings of this study contribute to the development of a monitoring system that is cost-effective, straightforward, and offers promising accuracy in monitoring.

TABLE 3.
SIMILAR STUDIES

Works	Signal Measurement	Signal Processing Technique	Fault Identified	Highlight
Nirwan, N. W. [20]	Sound signal, vibration	FFT	Outer race, inner race, ball bearing	No
Lucena-Junior, et al [22]	Sound signal	signal analysis based on chaos using density of maxima (SAC-DM	Outer race, inner race	No
Vanraj, et al, [23]	Sound signal	No discussion	Bearing	MSAF-20-MULTIEXPANDED
Glowacs et al, [24]	Sound signal	MSAF-20-MULTIEXPANDED	Bearing	MSAF-20-MULTIEXPANDED
Zhong, J.H, et all [25]	Sound signal	Ensemble empirical mode decomposition	Bearing	Placement sensor fixed 50cm
Goyal et al, [26]	Vibration signal	FFT	NC-OSP strategy	-
Proposed method	Sound signal	FFT	Bearing in marine ship engine systems	Strategi placement sensor = 110cm, monitoring accuracy = 100%

IV. CONCLUSION

This research addresses the monitoring of the bearing condition of ship propulsion motors through the development of an optimal sensor placement strategy. The monitoring system has been designed to operate in real-time, ensuring that diagnosis is conducted efficiently without significant delays. By employing the Short-Time Fourier Transform (STFT) approach for non-linear signals and spectrum analysis, it has been established that the monitoring system is capable of reliably detecting the condition of motor elements. The placement of sensors significantly impacts the accuracy of monitoring. The study demonstrates a decline in accuracy when sound sensors are positioned too far from the motor. It was found that placing the sensor at a distance of 110 cm from the motor body is optimal, resulting in a monitoring system accuracy of 100%. Such high monitoring accuracy is invaluable for the diagnostic and prognostic assessment of motor conditions, enabling the prevention of severe damage and the avoidance of operational downtime.

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