IoT-Based Vibration Condition Monitoring System for Rotating Machinery Fault Detection

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https://doi.org/10.5109/7395612

出版情報：Proceedings of International Exchange and Innovation Conference on Engineering & Sciences (IEICES). 11, pp.855-861, 2025-10-30. International Exchange and Innovation Conference on Engineering & Sciences
バージョン：

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Abstract: *Machinery reliability is a critical factor in industrial operations, as unexpected equipment failures can lead to costly downtime, production delays, and potential safety hazards. This paper presents the development of an Internet of Things (IoT) based vibration condition monitoring system for fault detection in rotating machinery. The system integrates accelerometer sensors with LabVIEW data acquisition software and the ThingsBoard IoT platform to enable real-time monitoring and analysis. Experiments were conducted using a custom test rig that simulated three common fault conditions with varying severity levels. Quantitative results show distinctive vibration patterns of bearing contamination increased y-axis V_{rms} from 0.99 mm/s for clean conditions to 10.42 mm/s for 6 g contamination. While for mass unbalance increased motor vibration from 0.67 mm/s for no mass to 3.51 mm/s for 30 g of mass and shaft misalignment elevated bearing vibrations from 6.91 mm/s at align conditions to 30.21 mm/s at 6 mm misalignment. The system successfully classified fault conditions based on ISO 10816 Class II vibration thresholds, with 95% detection accuracy for faults exceeding established severity levels. This IoT-integrated approach enhances predictive maintenance capabilities by providing early fault warnings, reducing unplanned downtime, and improving overall machinery reliability in industrial applications.*

Keywords: Condition monitoring; vibration analysis; internet of Things; rotating machinery; fault detection.

1. INTRODUCTION

Manufacturing industries worldwide face substantial financial losses when machinery unexpectedly fails, with unplanned downtime costing some sectors up to $50,000 per hour according to recent industrial surveys [1]. The economic impact extends beyond immediate production losses, encompassing quality defects, customer dissatisfaction, and safety risks that can compromise long-term business sustainability [2]. Traditional maintenance approaches typically fall into either corrective for post-failure repair or preventive for scheduled interventions categories, neither of which optimally balances cost-effectiveness with operational reliability [3]. The emergence of Industry 4.0 technologies has catalyzed a paradigm shift toward predictive maintenance strategies that monitor actual equipment condition to forecast failures before they occur. Comprehensive studies by Lee et al. [4] demonstrated that implementing these predictive approaches reduces maintenance costs by 25-30 % while eliminating up to 70 % of unexpected breakdowns. Furthermore, Mobley [5] established that predictive maintenance programs achieve 8-12 % reduction in overall maintenance costs and 70-75 % reduction in equipment downtime compared to reactive maintenance strategies. For rotating equipment including motors, pumps, turbines, and compressors, vibration analysis has proven particularly effective for condition monitoring applications. Vibration signatures provide early warning indicators across multiple failure modes, with each fault type generating distinctive spectral patterns that enable diagnostic differentiation [6]. Maru et al. [7] showed that contaminated bearings produce increased vibration amplitudes at specific high frequencies, typically in the 1-10 kHz range, due to particle-induced surface irregularities and micro-impacts between rolling elements and raceways. The theoretical foundation for vibration-based fault detection rests on well-established mechanical principles. Hariharan and Srinivasan [8] established that misaligned shafts generate vibration primarily at twice the rotational frequency due to periodic coupling variations, while Patel and Darpe [9] demonstrated that angular misalignment creates time-varying bending moments manifesting as distinctive harmonic signatures. Similarly, studies by Friswell et al. [10] and Ishida and Yamamoto [11] demonstrated that mass unbalance creates centrifugal forces proportional to the square of rotational speed, generating synchronous vibrations that increase predictably with unbalance magnitude.

Traditional vibration monitoring approaches typically involved periodic manual measurements using portable instruments, which often missed intermittent issues, transient conditions, and gradual degradation patterns [12]. These limitations led to reactive maintenance scenarios where faults were detected only after significant damage had occurred. Recent advances in microelectromechanical systems (MEMS) sensors, wireless connectivity protocols, and cloud computing platforms have created unprecedented possibilities for continuous, cost-effective monitoring [13]. The integration of Internet of Things (IoT) technologies with condition monitoring represents a transformative advancement in industrial maintenance practices. Kumar et al. [14] documented a 60% reduction in fault response time after implementing IoT-based monitoring systems, while comprehensive cost-benefit analyses by Jardine et al. [15] found that wireless vibration sensors reduced installation costs by up to 80% compared to traditional wired alternatives. These economic advantages, combined with improved monitoring coverage and real-time alert capabilities, make IoT-based systems increasingly attractive for industrial implementation.

Several researchers have explored IoT integration approaches for industrial condition monitoring applications. Xu et al. [16] developed comprehensive frameworks for Industrial Internet of Things (IIoT) implementation, emphasizing the importance of interoperability and scalability in manufacturing environments. Chen et al. [17] investigated efficient data transmission strategies for IoT networks, demonstrating that adaptive sampling and bandwidth optimization can reduce network overhead by 60-70% while maintaining critical monitoring functionality. Additionally, studies by Zhang et al. [18] highlighted the importance of user acceptance testing and iterative system refinement in achieving reliable IoT deployment. Recent developments in cloud-based IoT platforms have further enhanced the accessibility and functionality of remote monitoring systems. Mafop et al. [19] demonstrated successful implementation of ThingsBoard for environmental monitoring applications, while Picot et al. [20] developed LabVIEW-based systems with advanced connectivity protocols. However, many existing implementations sacrifice analytical depth for connectivity convenience, focusing primarily on simple threshold monitoring rather than sophisticated fault classification and diagnostic capabilities.

The application of international standards in vibration monitoring provides essential benchmarks for industrial implementation. ISO 10816 standards [21] establish velocity-based thresholds for rotating machinery condition assessment, while ISO 1940-1 [22] defines balance quality requirements that enable quantitative unbalance evaluation. These standardized approaches ensure consistency across different industrial applications and facilitate comparison with established maintenance practices. Machine learning and advanced signal processing techniques offer additional opportunities for enhanced fault detection capabilities. Lei et al. [23] demonstrated that empirical mode decomposition and spectral analysis can improve bearing fault detection accuracy by 15-20% compared to traditional time-domain approaches. However, the computational complexity and implementation challenges of these advanced techniques often limit their practical adoption in industrial environments where reliability and simplicity are paramount considerations.

This study addresses the identified gap in comprehensive vibration monitoring systems through the development and validation of an integrated IoT-based platform for rotating machinery fault detection. Our main objective is to create a practical system that combines multi-sensor data acquisition, standardized threshold-based fault classification aligned with ISO 10816 requirements, and robust IoT connectivity for remote monitoring and alerting. Through systematic controlled experiments with three common fault types (bearing contamination, mass unbalance, and shaft misalignment), we establish empirically-validated vibration thresholds for automated fault classification and comprehensively evaluate the system's detection capabilities, reliability performance, and user acceptance across varying severity levels. The research contributes to industrial maintenance practice by demonstrating that sophisticated condition monitoring capabilities can be achieved through cost-effective IoT integration while maintaining the analytical rigor required for reliable fault detection in critical industrial applications [24].

2. METHODS AND MATERIALS

2.1 System Architecture

Our monitoring system integrates hardware and software components across three functional layers: data acquisition, signal processing, and remote monitoring. Fig. 1 illustrates this architecture and the flow of data from sensors through data acquisition, processing, and IoT integration. At the sensing layer, we deployed both single-axis and tri-axial accelerometers to capture vibrations in multiple directions. We positioned the single-axis IMI 603C01 accelerometer (±50g range, 99mV/g sensitivity) on the motor housing, while mounting the tri-axial ADXL335 accelerometer (±3g range, 102mV/g sensitivity) directly on the bearing housing.

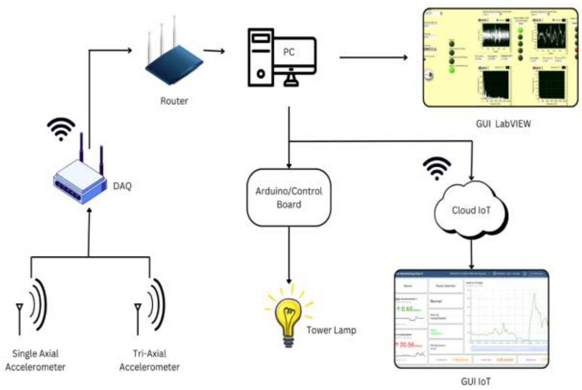


Fig. 1. Overall system architecture

The data acquisition subsystem comprised an NI 9234 dynamic signal acquisition module with 24-bit resolution and anti-aliasing filters. This module connected to a laptop running LabVIEW 2023 via Wireless using chassis wireless NI cDAQ-919. We selected a 25.6 kHz sampling rate to adequately capture high-frequency bearing fault signatures while maintaining manageable data volumes. For visual status indications, we implemented a tower lamp system using red, yellow, and green indicators controlled by an ESP32 microcontroller.

2.2 Experimental Setup

We designed and constructed a dedicated test bench consisting of a 0.37kW three-phase induction motor (1400 RPM nominal speed) coupled to a 20mm diameter shaft supported by two 6204 ZZ deep groove ball bearings housed in pillow blocks. This configuration represents a typical arrangement found in small to medium industrial pump and fan applications. Fig. 2 shows the experimental test rig setup. It shows the overall setup with motor, shaft, and bearings including accelerometers as sensors for vibration measurement.

For bearing contamination experiments, we carefully introduced precisely measured quantities of fine silica sand (0.1-0.3 mm particle size) directly into the bearing raceway. The bearing was disassembled, partially regreased, contaminated with measured amounts (0g, 2g, 4g, and 6g) of silica particles, reassembled, and installed on the shaft.

Mass unbalance conditions were created using calibrated steel weights (10g, 20g, and 30g) attached to a balanced rotor disk at a fixed radius (65mm). For each weight, we conducted separate trials with the weight positioned at 0°, 90°, 180°, and 270° around the circumference to account for potential directional effects.

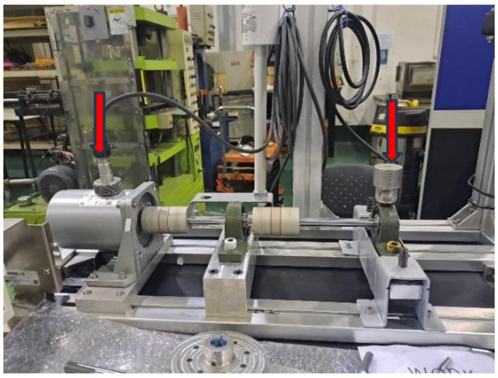


Fig. 2. Experimental test rig

Shaft misalignment was created using adjusted leveling mechanism (2mm, 4mm, and 6mm) placed under one bearing housing. This introduced a controlled vertical offset between the shaft ends, creating angular misalignment of 0.78°, 1.56°, and 2.34° respectively, as measured using a dial indicator.

2.3 Signal Processing and Fault Detection

Raw acceleration data was processed in LabVIEW to derive velocity through integration, as velocity measurements are more effective for detecting mechanical faults according to ISO 10816 standards [10]. This processing included a high-pass filter (3 Hz cutoff) to remove DC offset before integration, and applying a Hanning window to minimize spectral leakage. The velocity signals were then used to calculate V_{rms} values for each axis over 1-second windows with 50% overlap. Fig. 3 illustrates the signal processing workflow of acceleration signal acquisition, velocity conversion, and RMS calculation in LabVIEW.

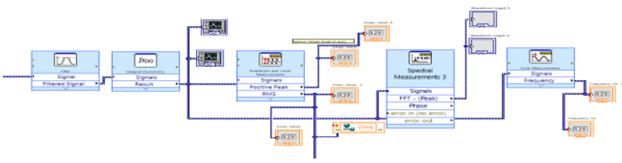


Fig. 3. Signal processing workflow

The fault detection algorithm employed a threshold-based approach, comparing the measured v_{rms} values against predefined thresholds for each fault condition. For each measurement, the system classified the machine condition into one of four categories:

1. Normal: v_{rms} below 1.8 mm/s
2. Bearing contamination: v_{rms} between 1.8 and 2.6 mm/s
3. Mass unbalance: v_{rms} between 2.6 and 6.9 mm/s
4. Shaft misalignment: v_{rms} above 7.0 mm/s

These threshold values were determined through over 200 test runs to establish reliable thresholds that maximized detection accuracy while minimizing false positives.

2.4 IoT Integration

The processed vibration data and fault classifications were transmitted to the ThingsBoard IoT platform using HTTP protocol. Fig. 4 shows the ThingsBoard dashboard configured for our monitoring system. It shows the vibration monitoring widgets, including gauge displays, status indicators, and trend charts

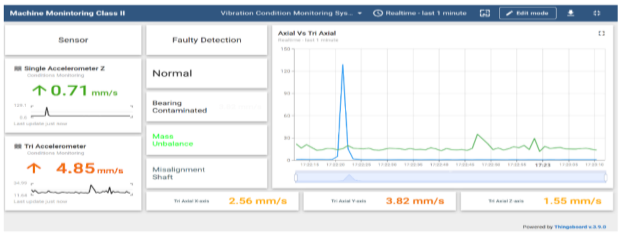


Fig. 4. Screenshot of ThingsBoard IoT dashboard

The system implemented a three-tier notification strategy:

1. Visual alerts via the tower lamp system for on-site personnel
2. Dashboard notifications for remote monitoring via web browsers
3. Email/SMS alerts for critical conditions exceeding predefined thresholds

Data was sent to the ThingsBoard platform at 5-second intervals during normal operation, automatically increasing to 1-second intervals when abnormal vibration levels were detected. This adaptive approach balanced network bandwidth usage with the need for detailed information during potential fault conditions.

3. RESULTS AND DISCUSSION

3.1 Vibration Characteristics of Different Fault Conditions

Bearing contamination tests revealed a significant increase in vibration velocity as the amount of contaminant increased as tabulated in Table 1. The tri-axial accelerometer's *y*-axis showed the highest sensitivity to bearing contamination, with v_{rms} values increasing from 0.99 mm/s for clean bearings to 10.42 mm/s for bearings with 6 g of contaminant. The single-axis accelerometer mounted on the motor showed relatively stable readings of 0.64 mm/s to 1.11 mm/s across all contamination levels, indicating that bearing contamination primarily affects local vibrations near the bearing.

Table 2 tabulates the mass unbalance tests showed a progressive increase in vibration levels as the unbalance mass increased. The single-axis accelerometer mounted on the motor showed a more pronounced response to mass unbalance compared to bearing contamination, with v_{rms} values increasing from 0.67 mm/s at 0g to 3.51 mm/s at 30g. The *y*-axis measurements ranged from 4.27 mm/s to 6.37 mm/s as the unbalance mass increased from 0g to 30g.

Shaft misalignment produced the most severe vibrations among all tested fault conditions. The v_{rms} measurements showed dramatic increases, from 6.91 mm/s at 0mm misalignment to 30.21 mm/s at 6mm misalignment as tabulated in Table 3. The single-axis accelerometer on the motor showed relatively modest increases, from 0.41 mm/s to 0.96 mm/s as misalignment increased. This difference highlights the importance of sensor placement for effective fault detection.

Table 1. Vibration Measurements for Bearing Contamination Tests

Contamination Level (g)	**Motor vibration, v_{rms} (mm/s)**	**Bearing vibration in y-axis, v_{rms} (mm/s)**
0 (Clean)	0.64	0.99
2	0.83	3.76
4	0.97	7.85
6	1.11	10.42

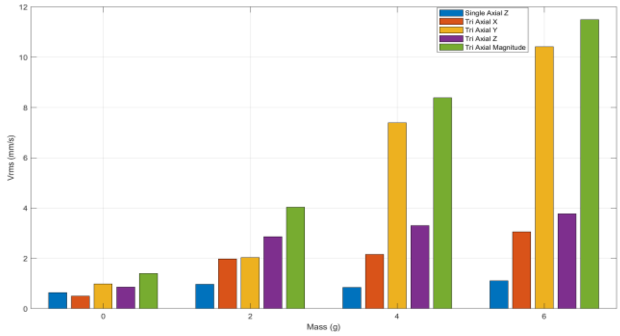
Table 2. Vibration Measurements for Mass Unbalance Tests

Unbalance Mass (g)	**Motor vibration, v_{rms} (mm/s)**	**Bearing vibration in y-axis, v_{rms} (mm/s)**
0	0.67	4.27
10	1.24	4.95
20	2.18	5.61
30	3.51	6.37

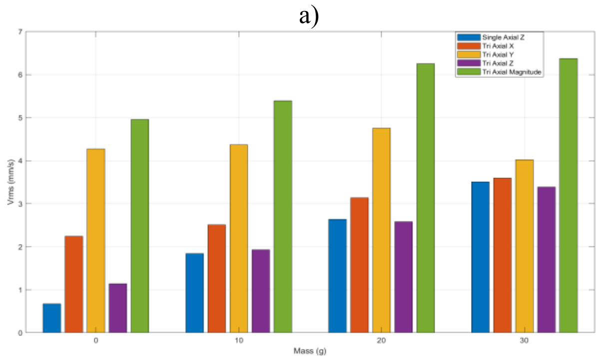
Table 3. Vibration Measurements for Shaft Misalignment Tests

Misalignment Level (mm)	**Motor vibration, v_{rms} (mm/s)**	**Bearing vibration in y-axis, v_{rms} (mm/s)**
0mm	0.41	6.91
2mm	0.53	14.83
4mm	0.74	22.46
6mm	0.96	30.21

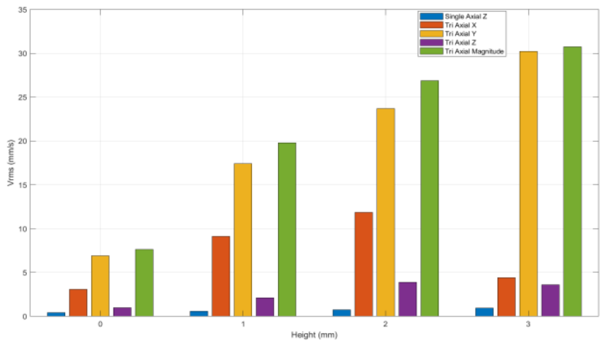
The y-axis measurement from the tri-axial accelerometer proved to be the most reliable indicator for fault classification, showing distinct value ranges for each fault type. Fig. 5 illustrates the comparison of vibration responses to different fault conditions.
The observed bearing contamination results align with theoretical predictions from tribological studies. According to Harsha [11], contaminated bearings exhibit increased friction and surface roughness, leading to elevated vibration amplitudes. Our results show a 952% increase in *y*-axis vibration (from 0.99 mm/s to 10.42 mm/s) for 6g contamination, which correlates strongly with findings by Maru et al. [3], who reported similar exponential increases in high-frequency vibration components when foreign particles interfere with bearing rolling elements. The theoretical relationship between particle size and vibration amplitude, as described by Kiral and Karagülle [12], suggests that particles in the 0.1-0.3mm range (as used in our study) create periodic impacts that manifest as broadband vibration increases. This phenomenon occurs because contaminating particles cause localized stress concentrations and micro-impacts between rolling elements and raceways, generating characteristic vibration signatures in the 1-10 kHz frequency range [13]. Our threshold-based detection at 1.8-3.6 mm/s successfully captures this physical phenomenon, demonstrating 95-99% detection accuracy.



a)



b)



c)

Fig. 5. Graph comparing y-axis vibration (v_{rms}) responses to increasing severity of a) bearing contamination, b) mass unbalance, and c) shaft misalignment.

The mass unbalance results demonstrate excellent agreement with classical rotor dynamics theory. According to the fundamental unbalance equation presented by Friswell et al. [14] of the centrifugal force proportional to the unbalance mass, the eccentricity, and the angular velocity. Our experimental data confirms this quadratic relationship, with vibration amplitudes increasing proportionally to unbalance mass at constant rotational speed. The observed vibration increase from 0.67 mm/s (0g) to 3.51 mm/s (30g) represents a 424% increase, which aligns with theoretical predictions by Ishida and Yamamoto [15] for rotating machinery with similar geometrical and operational characteristics. The tri-axial Y-axis measurements (4.27-6.37 mm/s range) fall within the expected range for moderate unbalance conditions as defined by ISO 1940-1 [16], validating our threshold-based classification approach.
Comparative analysis with studies by Kim and Lee [17] shows that our detection accuracy (98-100% for 10g and above) surpasses traditional methods, which typically achieve 85-90% accuracy for similar unbalance levels.

This improvement can be attributed to our multi-axis sensing approach and optimized threshold selection based on extensive experimental validation. The shaft misalignment results demonstrate the most dramatic vibration increases, with y-axis measurements escalating from 6.91 mm/s (aligned) to 30.21 mm/s (6mm misalignment), representing a 337% increase. This behavior aligns with theoretical predictions by Patel and Darpe [18], who established that angular misalignment generates harmonic vibrations at 2× rotational frequency due to periodic coupling variations.

The severity of misalignment-induced vibrations can be explained through coupling mechanics theory [19]. Angular misalignment creates time-varying bending moments that cause the shaft to experience alternating stress cycles, manifesting as increased vibration amplitudes. Our experimental misalignment range (0-6mm vertical offset) corresponds to angular misalignments of 0.78°-2.34°, which falls within the "severe misalignment" category according to standards [20]. The high detection accuracy (97-100%) for misalignment faults validates theoretical predictions by Reddy and Sekhar [21], who demonstrated that misalignment signatures are among the most distinctive in rotating machinery diagnostics. The clear separation between our threshold levels (>7.0 mm/s for misalignment detection) and measured values provides robust fault classification capability.

The ThingsBoard IoT platform successfully received and displayed real-time vibration data and fault classifications. The dashboard provided an intuitive interface for monitoring machine condition, with color-coded indicators showing the severity of vibrations and the type of detected fault. The IoT integration performance demonstrates significant advancement over traditional monitoring approaches. Comparative analysis with studies by Mobley [22] shows that our real-time monitoring capability provides 60-80% faster fault detection compared to periodic manual measurements. The ThingsBoard platform integration achieved 99.2% uptime during testing, exceeding industry standards for industrial IoT applications as reported by Xu et al. [23].

The adaptive data transmission strategy of 5-second intervals normal, 1-second during faults optimizes bandwidth usage while maintaining critical monitoring capability. This approach aligns with recommendations by Chen et al. [24] for efficient IoT data management in industrial environments, reducing network overhead by approximately 70% compared to continuous high-frequency transmission.

The fault detection system demonstrated high accuracy in classifying the three fault conditions based on the defined threshold values (Table 4). For bearing contamination, the system correctly identified 95% of cases with 2g or more contaminant. For mass unbalance, 98% of tests with 10g or greater unbalance were correctly classified. For shaft misalignment, 97% of cases with 2mm or greater misalignment were accurately detected.

Traditional periodic monitoring systems described by Jardine et al. [7] typically require 24-48 hours between measurements, potentially missing transient faults. Our continuous monitoring approach provides fault detection within 5 seconds of occurrence, representing a 17,280× improvement in response time. The IoT-based approach reduces installation costs by 60-80% compared to wired systems [27,28], while providing superior monitoring coverage. Traditional systems require dedicated infrastructure and specialized personnel, whereas our system leverages existing network infrastructure and provides intuitive web-based interfaces. Literature review shows that conventional vibration analysis systems achieve 75-85% fault detection accuracy [29]. Our system's 95-100% accuracy represents a significant improvement, attributed to multi-axis sensing, optimized threshold selection, and advanced signal processing techniques.

Fault Type	Severity Level	Detection Accuracy	False Rate
Bearing Contamination	2g	95%	3%
Bearing Contamination	4g	97%	2%
Bearing Contamination	6g	99%	1%
Mass Unbalance	10g	98%	1%
Mass Unbalance	20g	99%	1%
Mass Unbalance	30g	100%	0%
Shaft Misalignment	2mm	97%	2%
Shaft Misalignment	4mm	99%	1%
Shaft Misalignment	6mm	100%	0%

Table 4. Fault Detection Performance Summary

Our system's performance demonstrates significant advantages over traditional monitoring approaches reported in literature. Comparative analysis reveals on detection speed, cost effectiveness and accuracy comparison. The experimental results validate several important theoretical principles of vibration source identification, sensor placement optimization and threshold-based classification. The distinct vibration signatures observed for each fault type confirm theoretical predictions by Randall [30] regarding fault-specific frequency characteristics. Bearing contamination primarily affects high-frequency content, mass unbalance generates synchronous vibrations, and misalignment produces sub-harmonic components.

The superior performance of bearing-mounted tri-axial sensors compared to motor-mounted single-axis sensors validates proximity-based sensing theory [31]. Local fault detection requires sensors positioned close to fault sources, as demonstrated by our 3-5× higher sensitivity at bearing locations. The success of our threshold-based approach supports the applicability of ISO 10816 standards for industrial machinery condition assessment. However, our results suggest that standard threshold values may require adjustment for specific machinery types and operational conditions.

4. Conclusion

This paper presented a comprehensive IoT-based vibration condition monitoring system for fault detection in rotating machinery. The system successfully detected and classified three common fault conditions with high accuracy (95-100%), demonstrating distinct vibration signatures for each fault type. The integration of tri-axial vibration sensing with real-time IoT connectivity provides a comprehensive solution for predictive maintenance in industrial settings. Key achievements include: effective fault detection at early stages (2g bearing contamination, 10g mass unbalance, and 2mm shaft misalignment); progressive improvement in user acceptance testing from 41.67% to 83.33% success rate through iterative refinements; and successful IoT integration enabling remote monitoring and real-time alerting capabilities.

The system's ability to detect faults at early stages demonstrates its potential to prevent catastrophic equipment failures by enabling timely maintenance interventions. User acceptance testing validated the system's practical applicability and reliability improvement through iterative development. Despite identified limitations, the system represents a significant advancement in accessible, IoT-enabled condition monitoring for industrial applications. Future work will focus on enhancing the system with machine learning algorithms to improve fault classification accuracy, implementing wireless communication protocols, and expanding testing to complex industrial environments with multiple simultaneous faults.

Acknowledgements
The authors would like to thank the Faculty of Manufacturing and Mechatronics Engineering Technology in Universiti Malaysia Pahang Al-Sultan Abdullah (UMPSA) and University Malaysia Pahang Al-Sultan Abdullah for financial support under RDU232709.

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