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SMART MULTI-SENSOR CONDITION MONITORING SYSTEM FOR PREDICTIVE MAINTENANCE OF ROTARY DRIVE ASSEMBLIES

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Abstract

The rapid growth of Industry 4.0 has increased the demand for intelligent condition monitoring systems that can continuously evaluate the health of industrial machinery and reduce unexpected failures. Rotary drive assemblies are widely used in manufacturing industries, where faults such as bearing wear, shaft misalignment, excessive vibration, overheating, and speed fluctuations can significantly affect machine performance and maintenance costs. Conventional maintenance methods are generally based on periodic inspection or manual observation, making early fault detection difficult. This research presents the development of a Smart Multi-Sensor Based Condition Monitoring System for rotary drive assemblies. The proposed system integrates four sensing technologies, including a Hall Effect Sensor for rotational speed (RPM) measurement, a 10k NTC Thermistor for bearing temperature monitoring, an MPU6050 Accelerometer and Gyroscope for three-axis vibration measurement (AX, AY, and AZ), and two HC-SR04 Ultrasonic Sensors for shaft alignment monitoring. Two Arduino microcontrollers are employed for efficient sensor interfacing and real-time data acquisition. A Python-based monitoring dashboard was developed using Visual Studio Code to receive live sensor data, display real-time values, generate automatic graphs, and store measurement records in Microsoft Excel files. Signal processing techniques, including Fast Fourier Transform (FFT) and digital filtering methods, were applied to analyze vibration signals and improve fault detection accuracy.

1. Introduction

The rapid advancement of Industry 4.0 has transformed traditional industrial maintenance into intelligent, automated, and data-driven systems. Modern industries are increasingly adopting smart technologies to improve machine reliability, reduce operational costs, and minimize unexpected equipment failures. Rotary drive assemblies, which consist of components such as motors, shafts, and bearings, are widely used in manufacturing plants, power generation systems, conveyors, pumps, and various industrial machines. Since these components operate continuously under different mechanical loads and environmental conditions, they are highly susceptible to faults such as bearing wear, shaft misalignment, excessive vibration, overheating, and speed fluctuations.[1]

If these faults remain undetected, they can lead to severe equipment damage, production downtime, increased maintenance costs, and safety risks. Traditional maintenance strategies mainly rely on reactive maintenance (repair after failure) or preventive maintenance (scheduled maintenance). Although these approaches are commonly used, they cannot accurately predict the actual condition of machinery and often result in unnecessary maintenance activities or unexpected machine breakdowns. Therefore, industries are moving towards predictive maintenance, where machine health is continuously monitored using smart sensors and real-time data analysis to detect faults before catastrophic failure occurs. To address these challenges, this research presents a Smart Multi-Sensor Based Condition Monitoring System for Rotary Drive Assemblies. The proposed system integrates four different sensing technologies to monitor multiple machine parameters simultaneously.[2] A Hall Effect Sensor is used to measure shaft rotational speed (RPM), a 10k NTC Thermistor continuously monitors the bearing temperature, an MPU6050 Accelerometer and Gyroscope measures vibration along the X, Y, and Z axes, and two HC-SR04 Ultrasonic Sensors measure the left and right distances of the shaft to monitor alignment conditions. Unlike conventional monitoring systems that rely on a single sensor, the proposed multi-sensor approach provides a more comprehensive and accurate assessment of machine health. The hardware system is built using two Arduino microcontrollers, where one Arduino acquires RPM and temperature data while the second Arduino handles vibration and shaft alignment measurements. The collected sensor data is transmitted to a Python-based monitoring dashboard developed in Visual Studio Code, where live sensor readings are displayed, real-time graphs are generated, and all monitoring data is automatically stored in Microsoft Excel files for maintenance documentation. In addition, Fast Fourier Transform (FFT) and digital filtering techniques are applied to vibration signals to analyze frequency components, remove unwanted noise, and improve fault detection accuracy. Whenever abnormal operating conditions are detected, the system activates a buzzer alarm to immediately notify the operator. The proposed system offers a low-cost, reliable, and smart solution for industrial condition monitoring by combining real-time sensing, automated data acquisition, graphical visualization, signal processing, and digital maintenance record generation. The integration of multiple sensors with intelligent software significantly reduces human intervention, improves fault diagnosis, and supports predictive maintenance strategies aligned with the principles of Industry 4.0. The developed system demonstrates that smart monitoring technologies can enhance machine reliability, increase operational efficiency, reduce maintenance costs, and contribute to the development of intelligent industrial automation systems.[3]. Main Objectives of this research work are:

- To develop a smart multi-sensor condition monitoring system for rotary drive assemblies using RPM, temperature, vibration, and alignment sensors.
- To perform real-time monitoring, automatic data logging, graph visualization, and vibration analysis using Arduino and Python.
- To detect machine faults at an early stage using FFT and signal processing techniques for predictive maintenance.
- To improve machine reliability, reduce manual inspection, and support Industry 4.0-based intelligent maintenance.

This paper is organized into four main sections. The first section presents the literature review and discusses recent advancements in fault diagnosis, predictive maintenance, and Industry 4.0 technologies. The second section explains the proposed methodology, including the hardware configuration, software implementation, multi-sensor integration, and signal processing techniques. The third section presents the experimental results and discussion, demonstrating the performance of the proposed system through real-time monitoring, vibration analysis, FFT, and automatic data logging. The final section concludes the research and provides recommendations for future improvements.

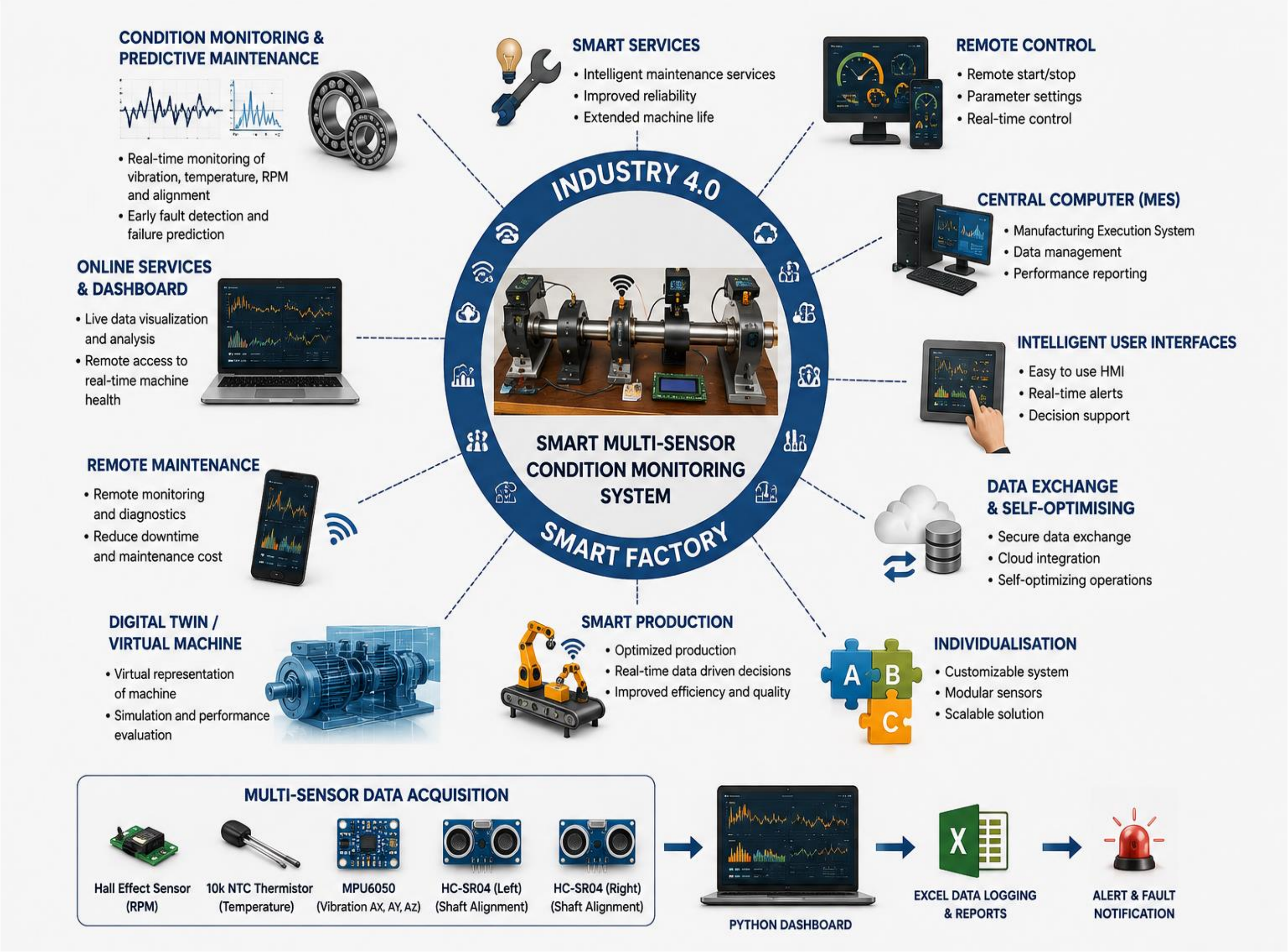


Figure 1: Industry 4.0 Revolution

2. Literature Review

Fault diagnosis of rotating machinery has become an important research area due to the rapid adoption of Industry 4.0, Industrial Internet of Things (IIoT), and predictive maintenance. Traditional maintenance methods rely on periodic inspections, which often fail to detect faults at an early stage and may lead to unexpected machine failures. Therefore, modern industries are shifting toward intelligent condition monitoring systems that continuously monitor machine health using multiple sensors and advanced data analysis techniques. Among various fault diagnosis methods, vibration analysis is the most widely used technique because vibration signals contain valuable information about bearing defects, shaft misalignment, imbalance, and mechanical wear. Recent studies have combined vibration analysis with Fast Fourier Transform (FFT), digital signal processing, and multi-sensor data fusion to improve fault detection accuracy under different operating conditions.[4]

The increasing demand for sustainable energy solutions has accelerated research efforts in diverse yet interconnected domains, including Zero Energy Buildings (ZEBs) [23], [24], [25], nano-energy harvesting technologies [19], vibration signal processing and active control methodologies [20], [21], and emission control systems [22].

Recent research during 2024–2026 has focused on integrating Artificial Intelligence (AI), Deep Learning, Digital Twins, and cloud-based IIoT platforms for automatic fault diagnosis and predictive maintenance. Technologies such as

Convolutional Neural Networks (CNNs), Transformer models, and digital twin frameworks enable real-time monitoring, automatic fault classification, and Remaining Useful Life (RUL) prediction, making maintenance systems more intelligent and reliable. Based on these developments, this research proposes a Smart Multi-Sensor Based Condition Monitoring System that integrates a Hall Effect Sensor, 10k NTC Thermistor, MPU6050, and dual HC-SR04 Ultrasonic Sensors. The system uses Arduino and a Python-based dashboard to perform real-time monitoring, automatic graph generation, Excel data logging, FFT-based vibration analysis, and buzzer alerts. Compared with many existing systems, the proposed approach offers a low-cost, real-time, and multi-sensor solution suitable for predictive maintenance and Industry 4.0 applications.[5]

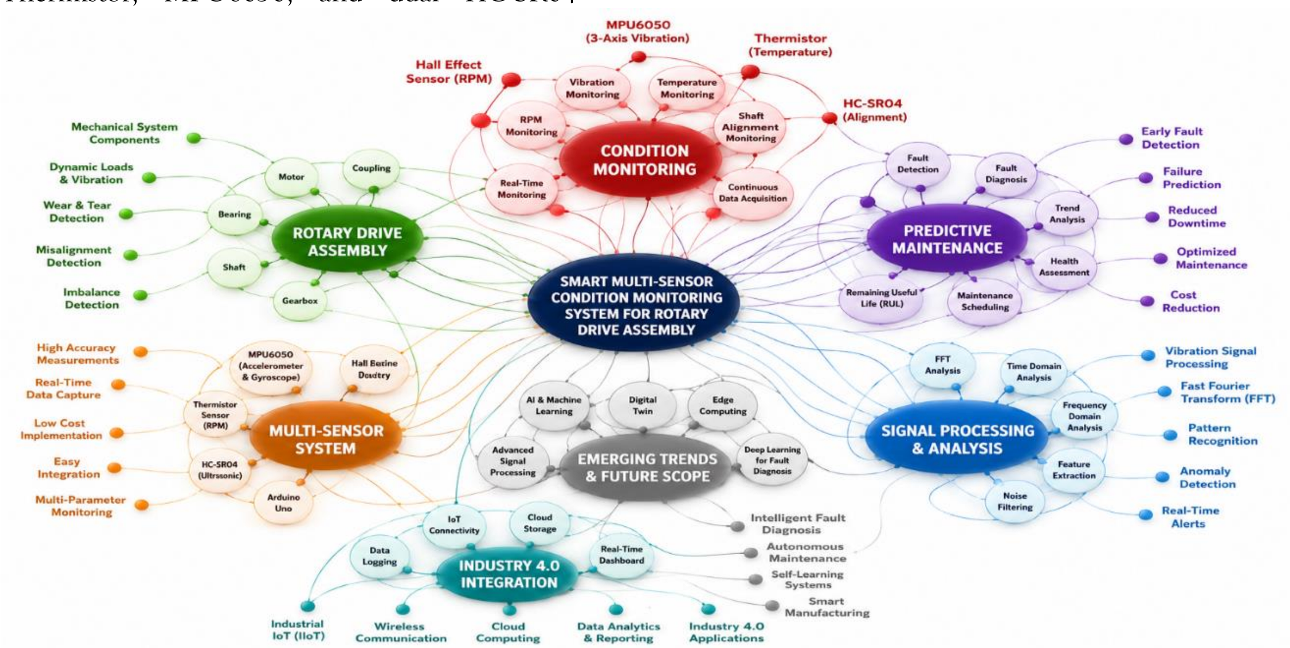


Figure 2. Conceptual framework of the proposed smart multi-sensor condition monitoring system for rotary drive assemblies.

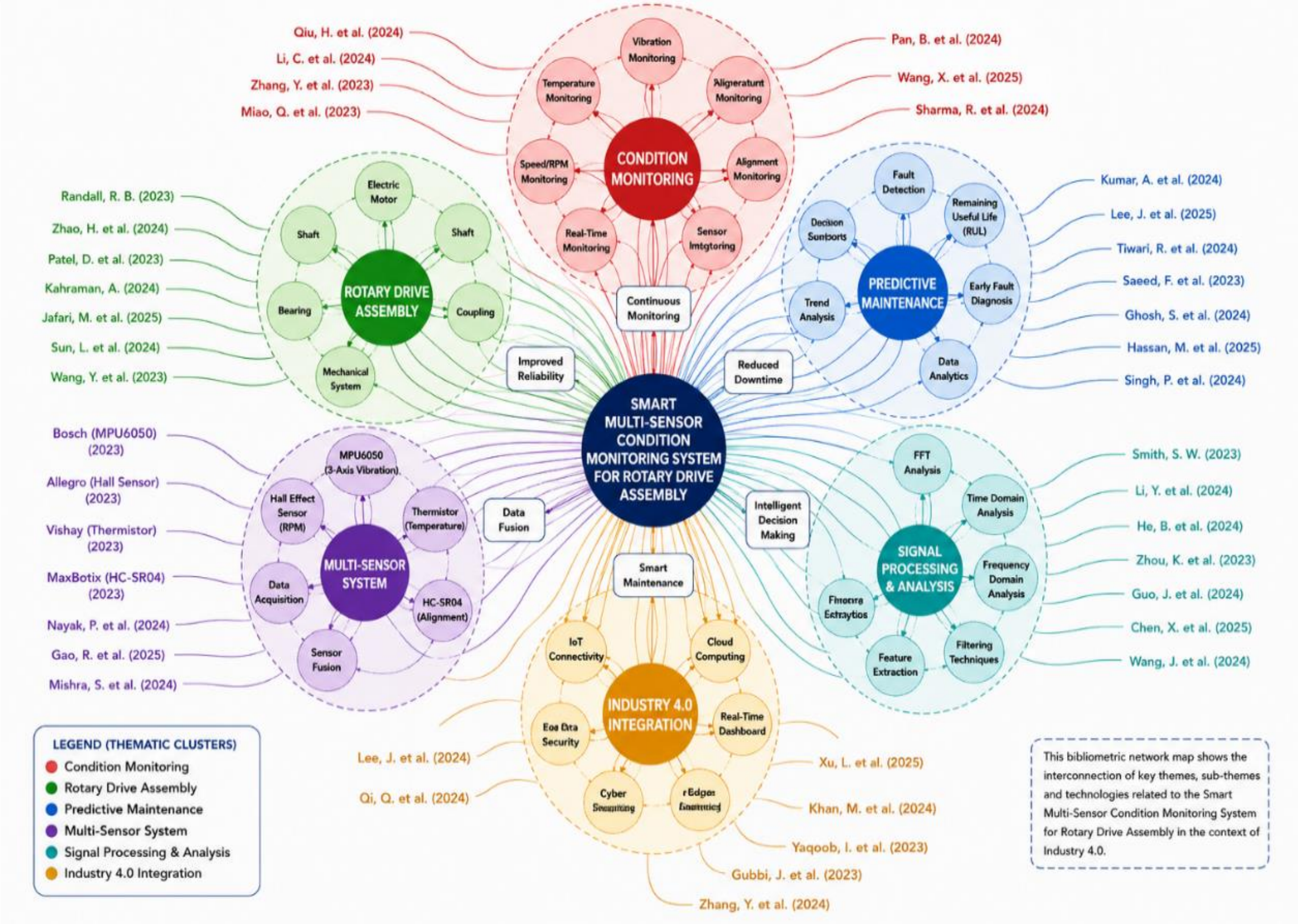
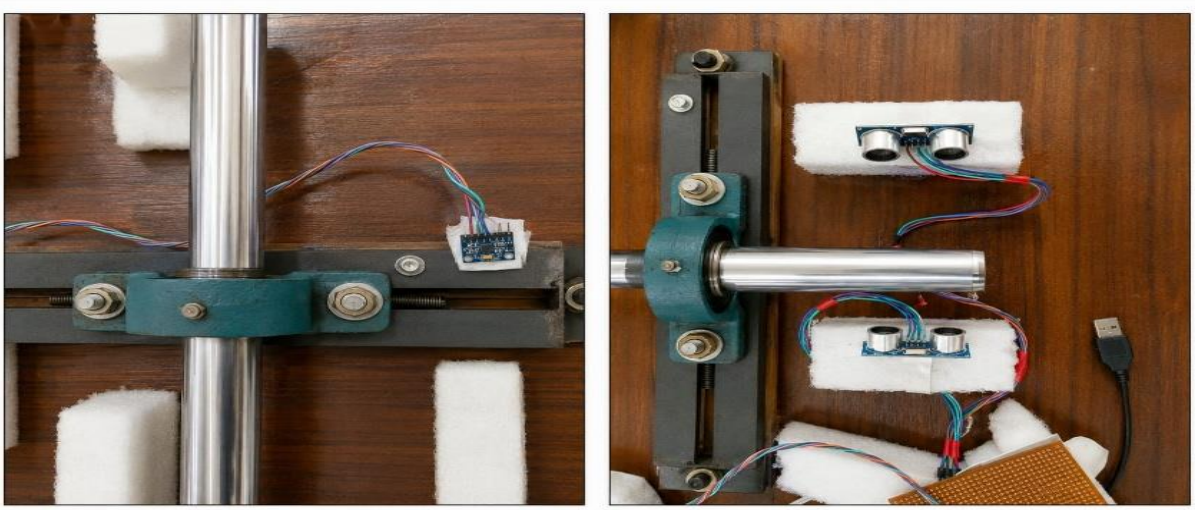
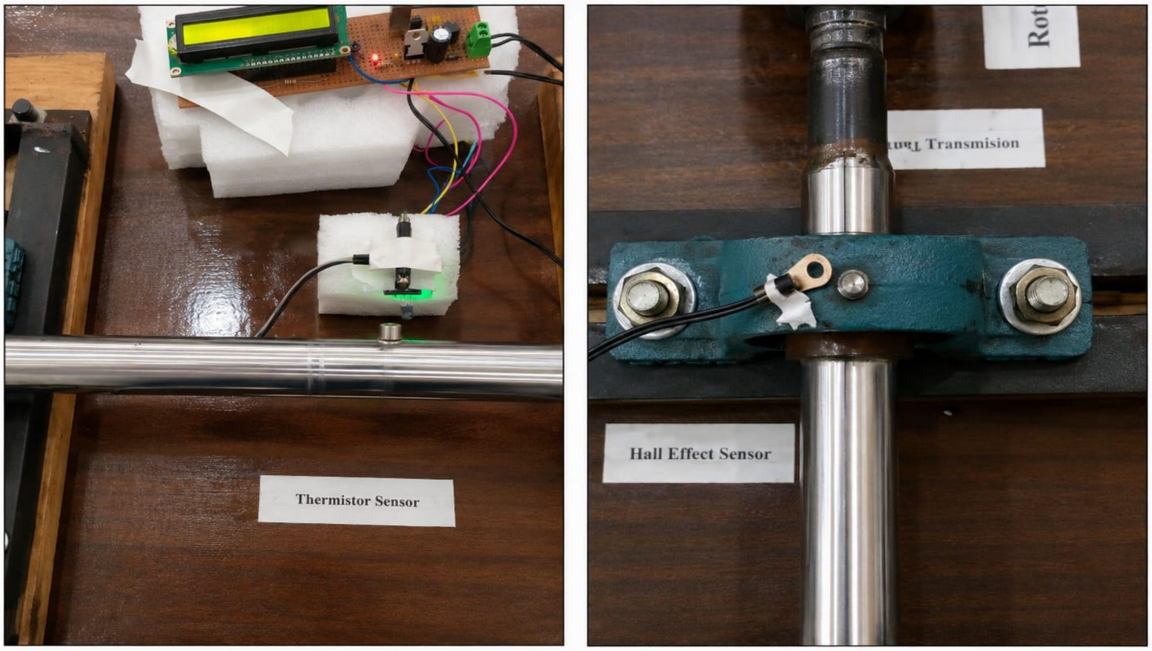


Figure 3. Evolution of smart condition monitoring from traditional maintenance to Industry 4.0.



(a) MPU6050 sensor mounted on the rigid base

(b) HC-SR04 ultrasonic sensors mounted on both sides of the shaft



(a) 10K thermistor temperature sensor mounted near the shaft

(b) Hall effect sensor mounted on the shaft

Figure 4: Mounting Sensors

3. Methodology

a. System Overview

The proposed Smart Multi-Sensor Based Condition Monitoring System was developed to continuously monitor the health condition of rotary drive assemblies under real-time operating conditions. The system integrates multiple sensors with embedded hardware and a Python-based monitoring dashboard to collect, process, visualize, and store machine operating parameters automatically. The methodology consists of four major stages: data acquisition, data transmission, signal processing, and fault detection. Initially, four different sensors were installed on the rotary drive assembly to monitor critical machine parameters. A Hall Effect Sensor measures shaft rotational speed (RPM), a 10k NTC Thermistor monitors the bearing temperature, an MPU6050 Accelerometer and Gyroscope measures vibration along the X, Y, and Z directions, while two HC-SR04 Ultrasonic Sensors measure the left and right shaft distances to detect shaft misalignment. Two Arduino Uno boards are used for efficient data acquisition. The first Arduino interfaces with the Hall Effect Sensor and Thermistor Sensor and displays RPM and temperature values on a 16×2 LCD. The second Arduino interfaces with the MPU6050 sensor and dual HC-SR04 sensors and displays vibration and alignment data on another 16×2 LCD. Both microcontrollers continuously collect sensor readings and transmit the data to a computer through serial communication.[6]

A Python-based monitoring dashboard developed in Visual Studio Code receives the incoming data from both Arduino boards. The dashboard continuously updates the live sensor readings, generates real-time graphs, performs vibration analysis using Fast Fourier Transform (FFT), and automatically stores all measured values into Microsoft Excel files for future maintenance analysis. To improve vibration signal quality, digital filtering techniques including Butterworth, Chebyshev, Gaussian, and Savitzky–Golay filters are applied before frequency-domain analysis. These filters remove unwanted noise and improve fault detection accuracy. Whenever abnormal operating conditions such as excessive vibration, high temperature, abnormal RPM, or shaft misalignment are detected, the system immediately activates a buzzer alarm and warning indication. The complete methodology provides an intelligent, automated, and low-cost solution for predictive maintenance while minimizing human intervention.[7]

b. System Architecture

Table 1: Hardware Components of the Proposed System

Component	Quantity	Purpose
Arduino Uno Controller	2	Data acquisition and sensor interfacing
Hall Effect Sensor	1	Measures shaft rotational speed (RPM)
10 kΩ NTC Thermistor	1	Monitors bearing temperature
MPU6050(Accelerometer & Gyroscope)	1	Measures vibration along X, Y, and Z axes
HC-SR04 Ultrasonic Sensor	2	Measures left and right shaft distance for alignment
16×2 LCD Display	2	Displays real-time sensor readings
Buzzer	1	Generates audible fault warning
Red LED	1	Indicates abnormal operating conditions
DC Motor & Shaft	1	Experimental rotary drive test setup
Laptop (Python Dashboard)	1	Real-time monitoring, graph generation, and Excel data logging

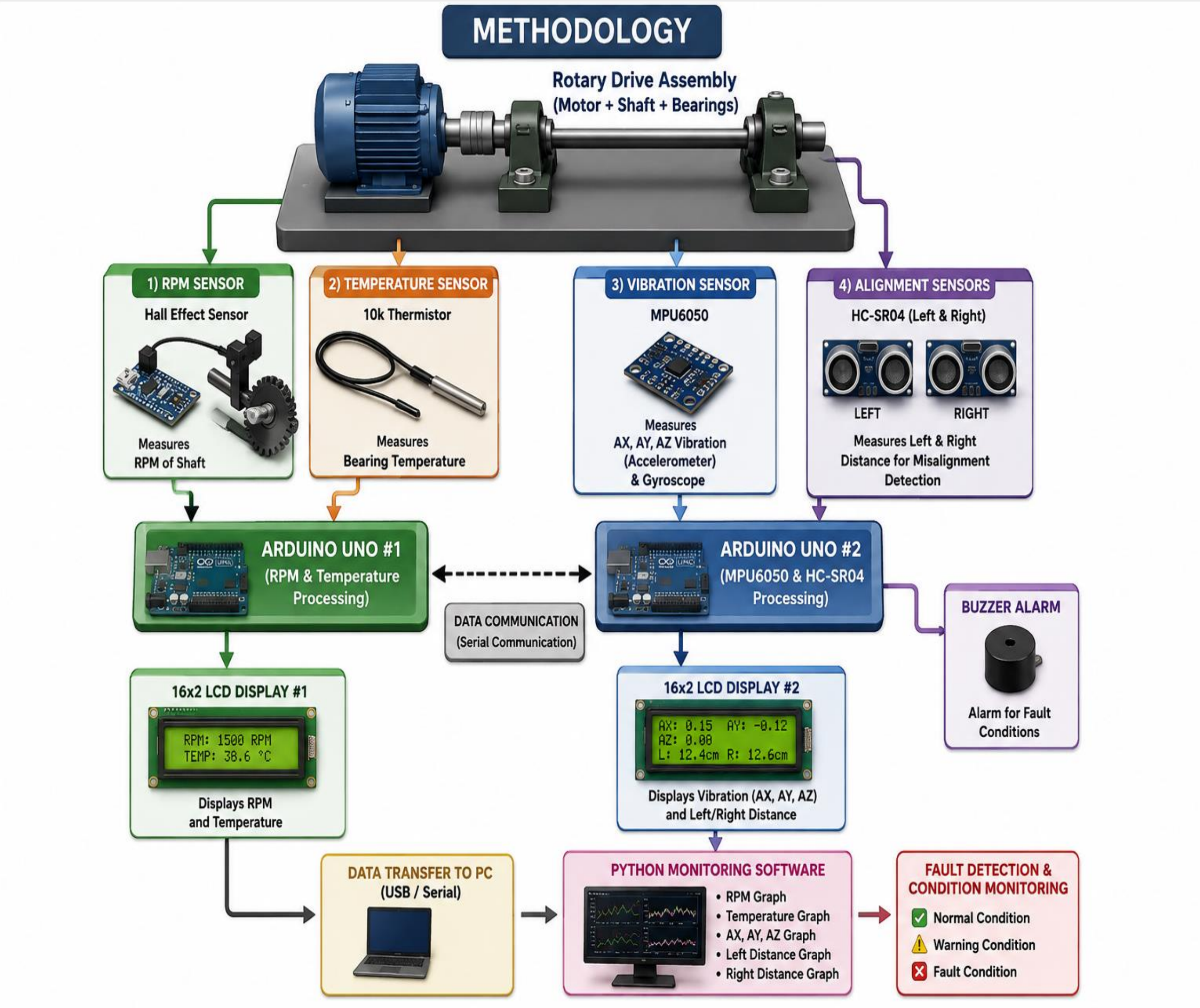


Figure 5: Research Methodology

c. Data Acquisition

Real-time data acquisition was carried out using four different sensors installed on the rotary shaft assembly. The Hall Effect sensor measured the rotational speed (RPM) by counting magnetic pulses generated during shaft rotation. The 10 kΩ thermistor continuously sensed the bearing temperature to monitor thermal variations caused by friction or bearing wear. The MPU6050 sensor recorded vibration data along the X, Y, and Z axes by measuring linear acceleration and angular motion. In addition, two HC-SR04 ultrasonic sensors measured the left and right distances from the rotating shaft to detect shaft misalignment based on distance differences. Sensor data were continuously collected and transmitted to two Arduino Nano/UNO boards through analog and digital interfaces.[8] The processed measurements were simultaneously displayed on two LCD displays and transmitted to the computer through serial communication for further monitoring.

The acquired sensor signals were processed individually according to their respective measurement parameters. The Hall Effect sensor pulses were converted into shaft RPM using pulse-counting algorithms. The analog voltage obtained from the thermistor was converted into temperature values using the thermistor calibration equation. Raw acceleration values obtained from the MPU6050 sensor were converted into vibration values for the X, Y, and Z axes. The resultant vibration magnitude was calculated to evaluate the overall vibration level of the shaft. The distance measurements from the left and right HC-SR04 sensors were compared to determine shaft alignment conditions. The processed sensor values were continuously updated on the LCD displays and transmitted to the Python monitoring dashboard, where real-time numerical values, graphical plots, and historical data logging were performed.

d. Fault Detection Algorithm

A threshold-based fault detection algorithm was developed to continuously evaluate the health condition of the rotary shaft assembly. The measured RPM, bearing temperature, vibration levels, and shaft misalignment values were compared with predefined threshold limits established during system calibration. If all measured parameters remained within their allowable operating ranges, the system indicated a normal operating condition. However, if excessive vibration, abnormal temperature, excessive shaft misalignment, or abnormal RPM variation was detected, the monitoring system immediately classified the machine as operating under a fault condition. In such cases, a buzzer alarm and red LED indicator were activated to alert the operator, while the Python dashboard displayed a warning message for predictive maintenance purposes.[9]

e. System Integration

The proposed monitoring system integrates four sensing modules, two Arduino Nano/UNO microcontrollers, two 16×2 LCD displays, a buzzer, a red LED indicator, and a Python-based monitoring dashboard into a unified condition monitoring platform. The first Arduino board was dedicated to processing RPM and temperature measurements obtained from the Hall Effect sensor and thermistor. The second Arduino board processed vibration data from the MPU6050 sensor and shaft alignment data from the dual HC-SR04 ultrasonic sensors. Both Arduino boards communicated with the computer through USB serial communication, allowing the Python dashboard to display real-time graphs of RPM, temperature, vibration (X, Y, and Z axes), and left/right shaft distances. The integrated architecture enabled continuous machine health monitoring and early fault detection.[10]

f. Testing and Evaluation

The developed system was experimentally evaluated under both normal and simulated fault conditions to verify its performance and reliability. Several operating scenarios, including normal shaft operation, increased bearing temperature, excessive vibration, shaft misalignment, and abnormal RPM conditions, were intentionally introduced during testing. The accuracy of each sensor was verified by comparing measured values with reference readings. The response of the buzzer, red LED indicator, LCD displays, and Python dashboard was also evaluated under different fault conditions. Experimental results demonstrated that the proposed system successfully detected abnormal operating conditions before potential machine failure, thereby validating its effectiveness as a low-cost predictive maintenance solution for rotary drive assemblies.[11]

g. Real-Time Monitoring and Data Logging

The processed sensor data is continuously displayed on the Python dashboard. Real-time graphs for RPM, temperature, vibration, and shaft alignment are generated automatically. Simultaneously, all sensor readings are stored in Microsoft Excel files with timestamps to create a digital maintenance record. This automatic data logging enables engineers to review historical machine performance and perform trend analysis for predictive maintenance.[12]

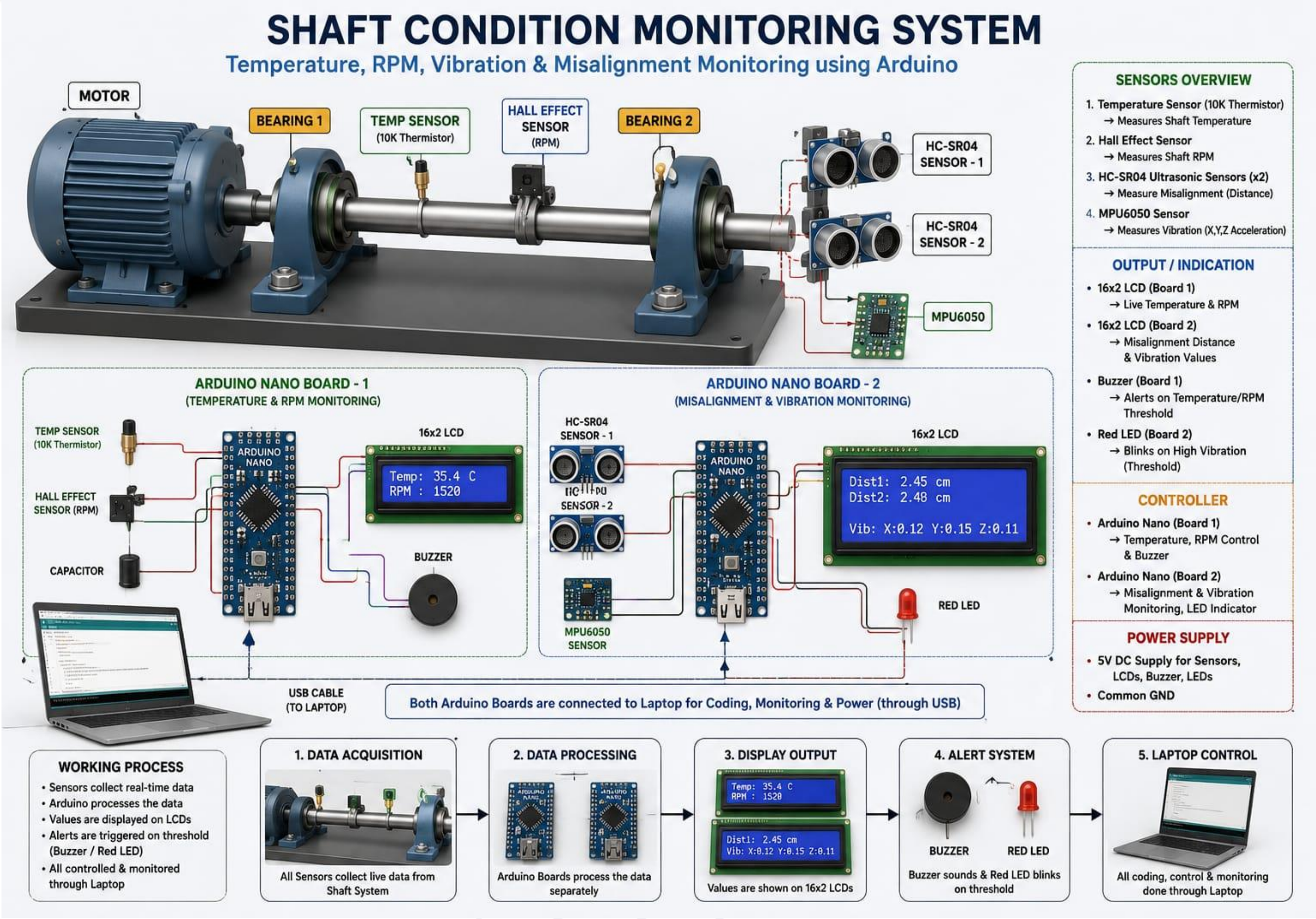
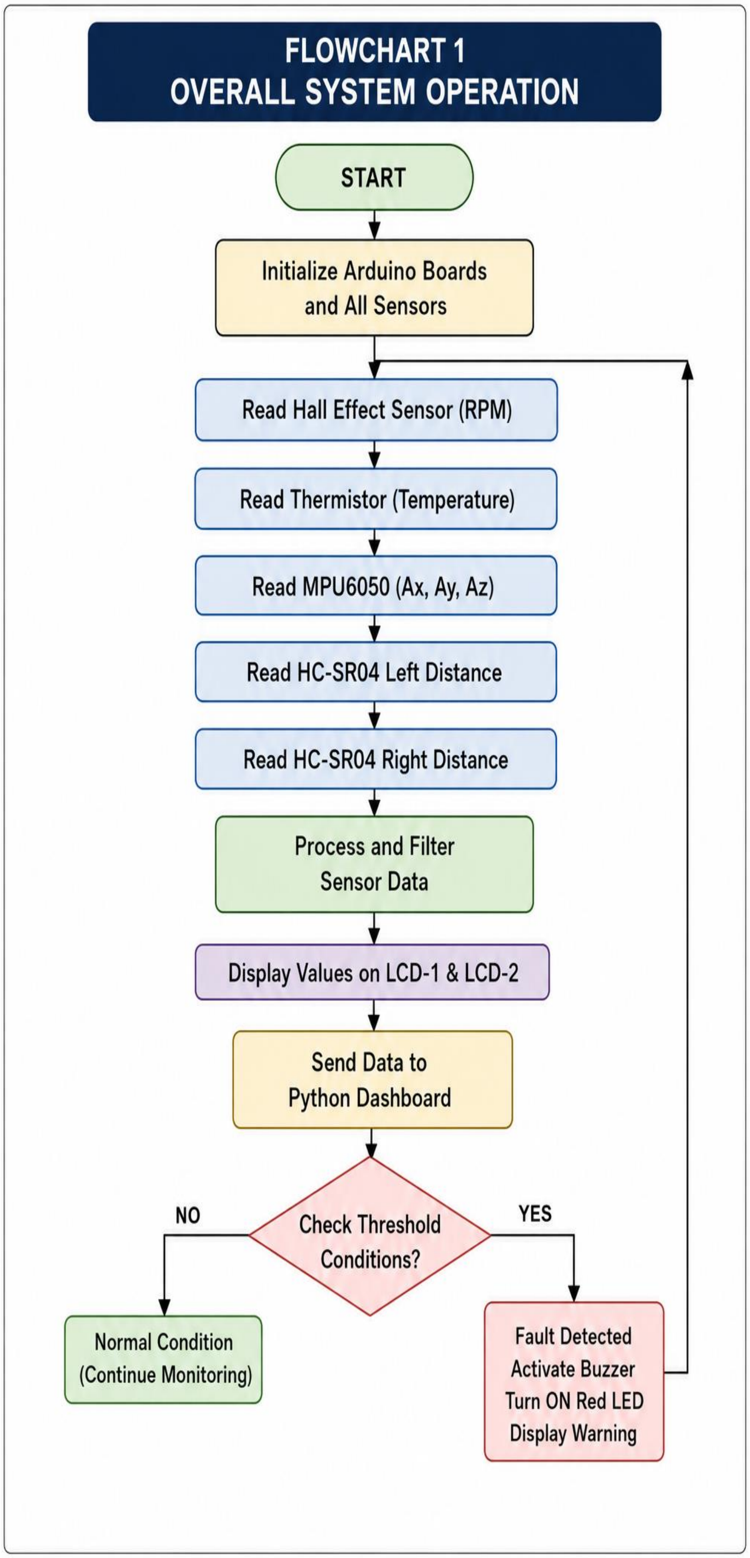
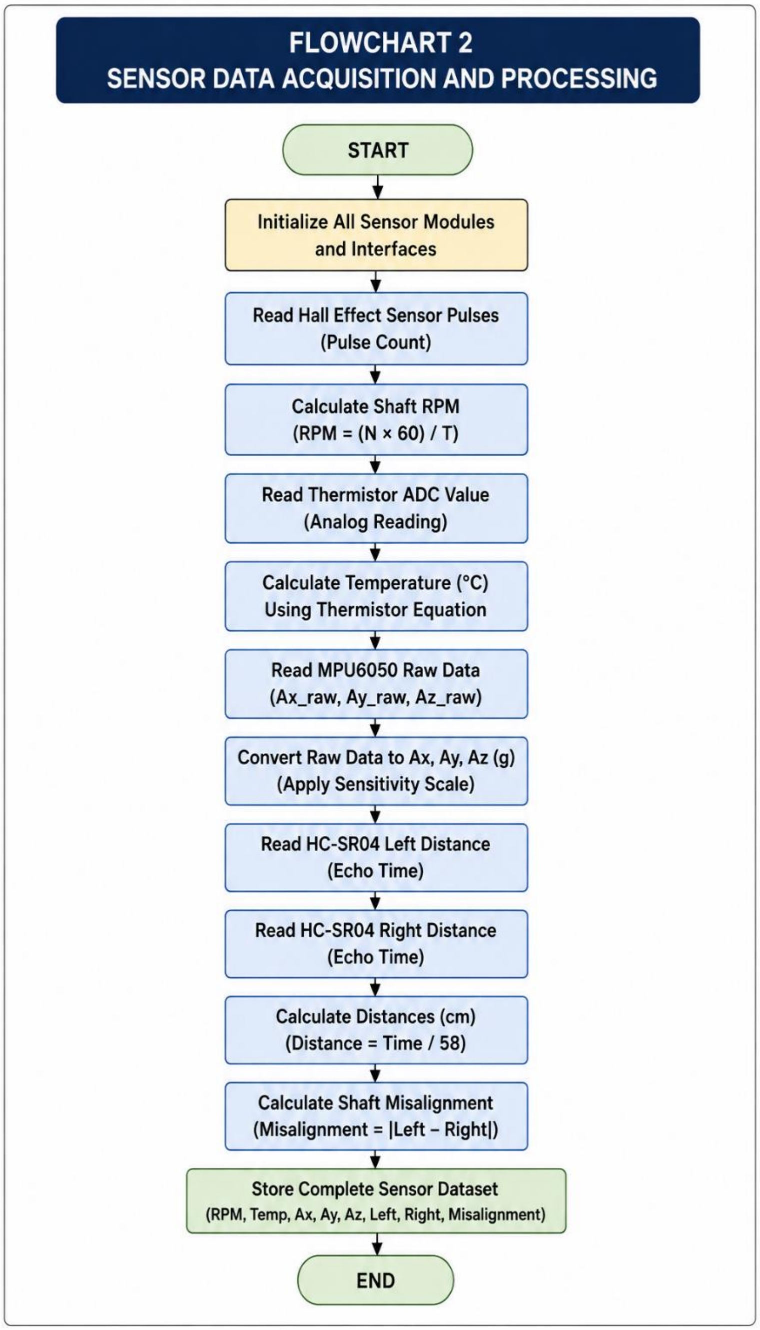


Figure 6: Working Principal


FLOWCHART 1
OVERALL SYSTEM OPERATION
START
Initialize Arduino Boards and All Sensors
Read Hall Effect Sensor (RPM)
Read Thermistor (Temperature)
Read MPU6050 (Ax, Ay, Az)
Read HC-SR04 Left Distance
Read HC-SR04 Right Distance
Process and Filter Sensor Data
Display Values on LCD-1 & LCD-2
Send Data to Python Dashboard
Check Threshold Conditions?
NO
YES
Normal Condition (Continue Monitoring)
Fault Detected Activate Buzzer Turn ON Red LED Display Warning



The monitoring process consists of five stages:

Stage 1: Data Acquisition

All sensors continuously collect real-time operational data from the rotating shaft system.

Stage 2: Signal Processing

The collected sensor data is processed using two Arduino controllers. One controller handles RPM and temperature measurements, while the second controller processes vibration and misalignment data.

Stage 3: Display Output

The first LCD displays:

- RPM and Temperature

The second LCD displays:

- X-axis, Y-axis, Z-axis vibration and Left sensor distance, Right sensor distance

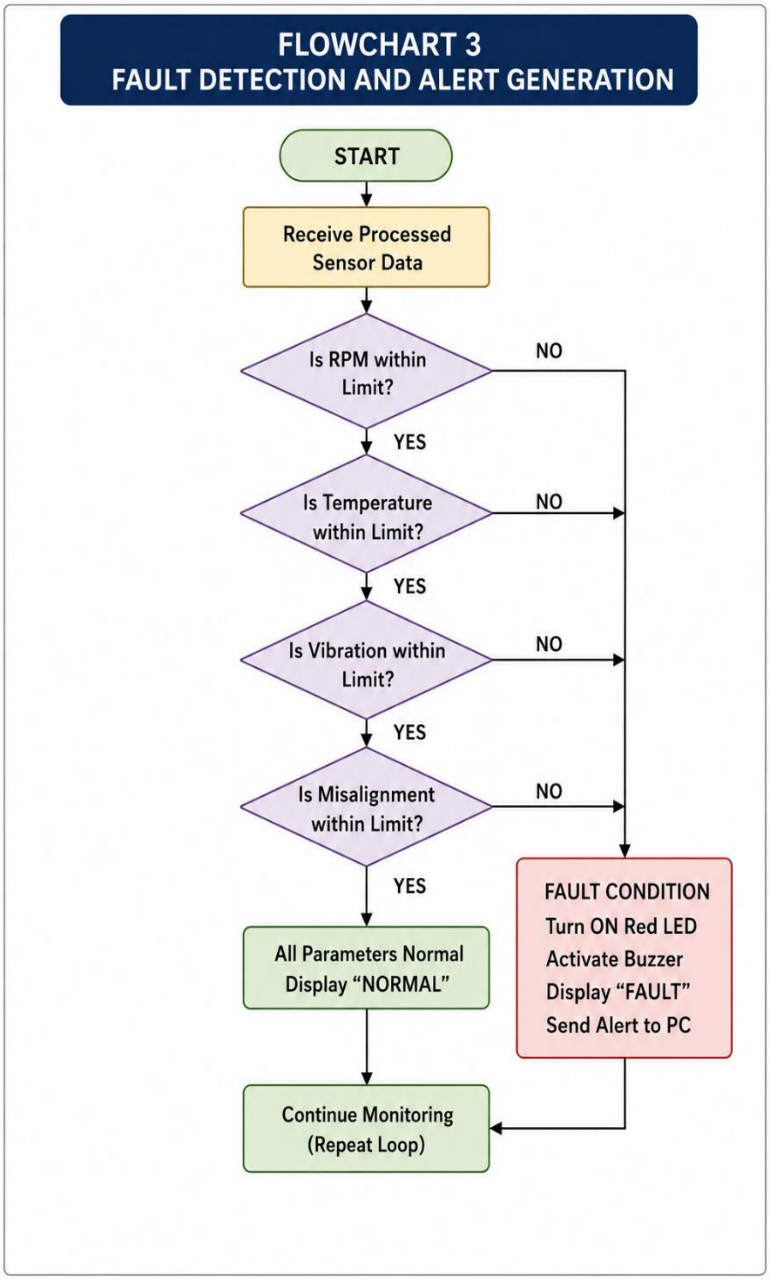
Stage 4: Fault Detection

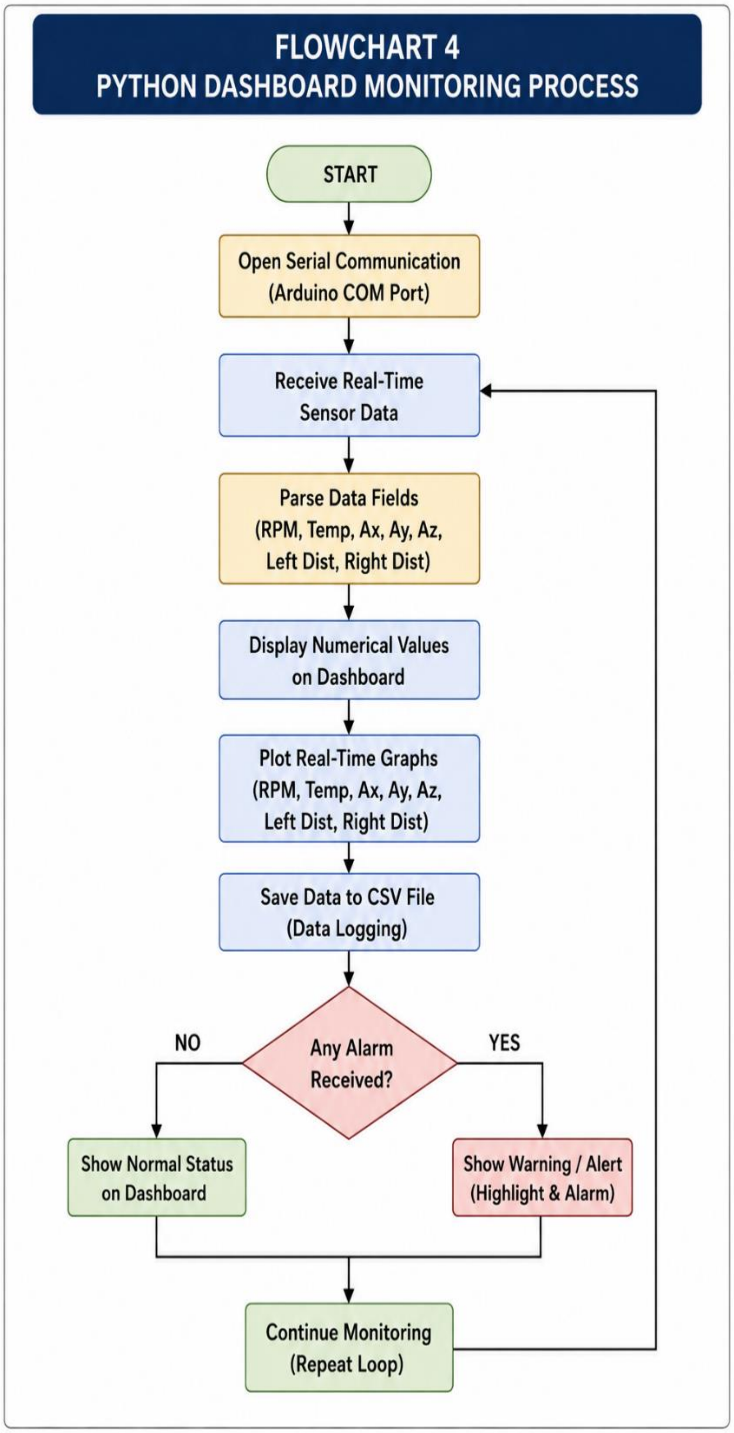
Measured values are compared against predefined threshold values. Any abnormal condition triggers warning mechanisms.

Stage 5: Monitoring and Visualization

Sensor data is transmitted to a computer through serial communication where a Python dashboard displays real-time graphs for:

- RPM
- Temperature
- X-axis, Y-axis and Z-axis vibration
- Left and Right distance





h. Hardware Components and Sensor Specifications

Table 2: Comparison between the Proposed Shaft Condition Monitoring System and Conventional Monitoring Methods

Feature	Proposed Shaft Condition Monitoring System	Conventional Monitoring Method

Monitoring Technique	Real-time multi-sensor monitoring	Manual periodic inspection
RPM Measurement	Hall Effect Sensor	Handheld Tachometer
Temperature Monitoring	10 kΩ Thermistor	Infrared Thermometer
Vibration Monitoring	MPU6050 (3-Axis Accelerometer)	Portable Vibration Meter
Shaft Misalignment	Dual HC-SR04 Ultrasonic Sensors	Dial Indicator / Laser Alignment
Processing Unit	Dual Arduino Nano Boards	No centralized processing
Display	Dual 16×2 LCD Displays	External Measuring Instruments
Data Logging	Python Dashboard with Serial Communication	Manual Record Keeping
Alert System	Buzzer + Red LED + Dashboard Warning	Manual Observation
Maintenance Strategy	Predictive Maintenance	Preventive / Corrective Maintenance
Cost	Low Cost	High Cost
Suitability	Educational, Laboratory & Small Industries	Industrial Maintenance Only

Table 3: Sensor Specifications

Sensor	Measured Parameter	Specifications
Hall Effect Sensor	Shaft Speed (RPM)	Operating Voltage: 5 V, Digital Output, Magnetic Pulse Detection
10 kΩ Thermistor	Bearing Temperature	Resistance: 10 kΩ, Beta ≈ 3950 K, Range: −40 °C to 125 °C
MPU6050	Shaft Vibration	3-Axis Accelerometer & Gyroscope, 16-bit ADC, ±2g, ±4g, ±8g, ±16g, I2C Interface
HC-SR04 (Left)	Left Shaft Distance	Range: 2–400 cm, Accuracy: ±3 mm, Operating Voltage: 5 V
HC-SR04 (Right)	Right Shaft Distance	Range: 2–400 cm, Accuracy: ±3 mm, Operating Voltage: 5 V
16×2 LCD	Data Display	Displays RPM, Temperature, Vibration and Distance Values
Buzzer	Fault Alarm	Audible Warning at Threshold Condition
Red LED	Fault Indication	Visual Fault Indicator

4. Results and Discussion

Vibration Analysis

In this section Time-domain signals and frequency spectrums by using FFT and HHT have been shown for experimental conditions at frequencies of 20, 30, 40 and 50 Hz.

Bearing – Normal Condition at 20 Hz

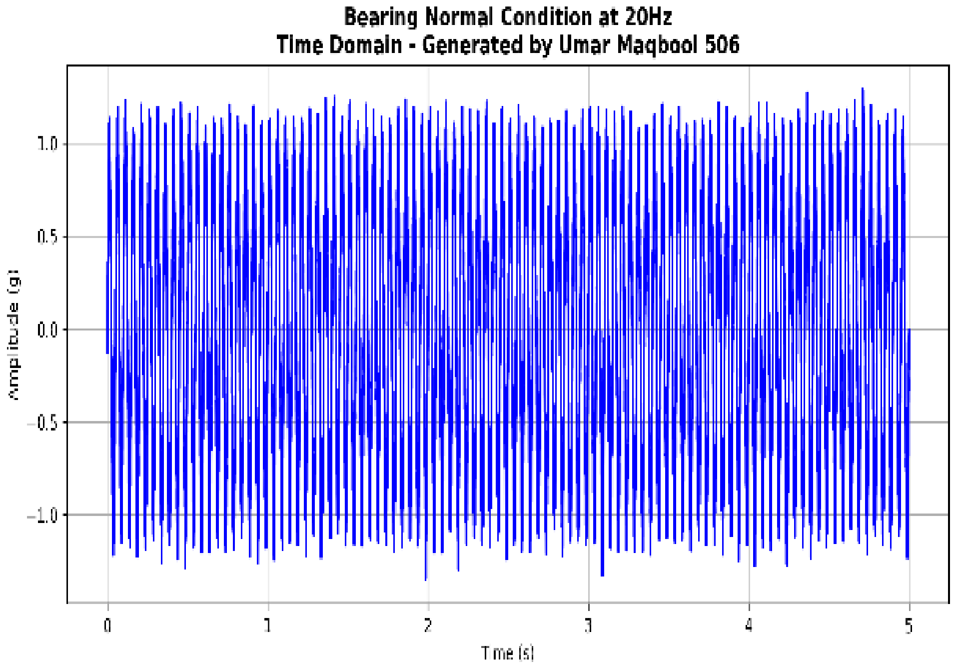


Figure 8: Time Domain Graph on 20Hz

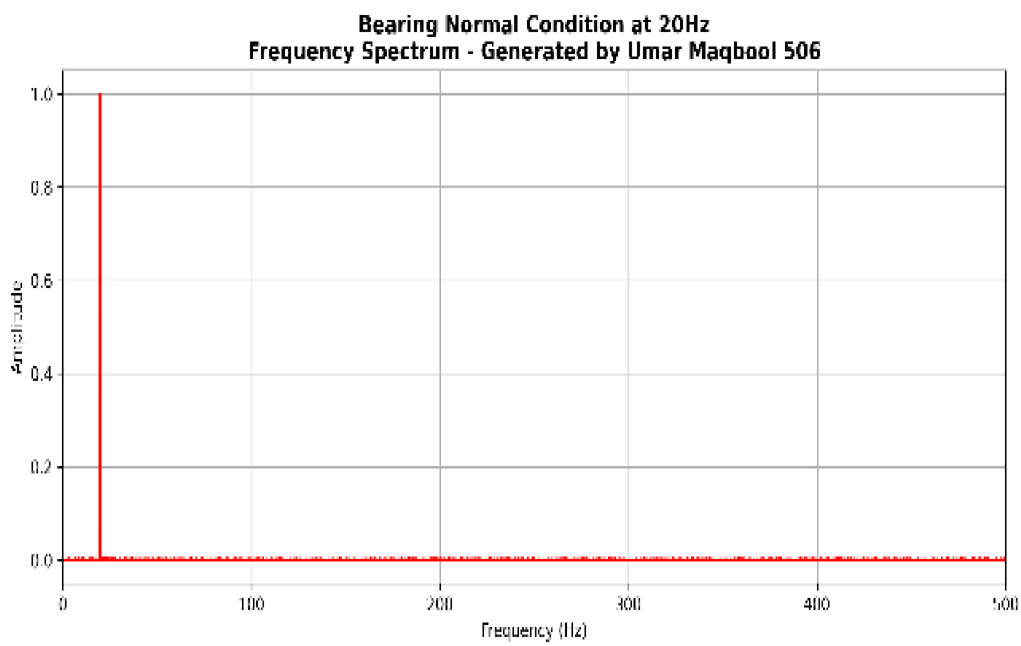


Figure 9:Frequency Spectrum on 20Hz

Bearing – Normal Condition at 30 Hz

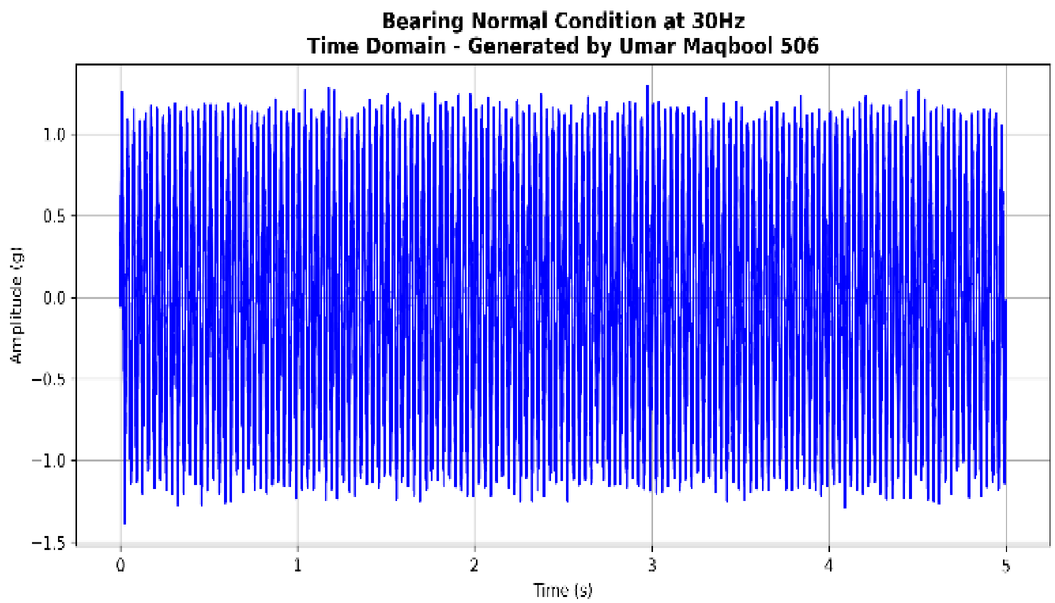


Figure 10: Time Domain Graph on 30Hz

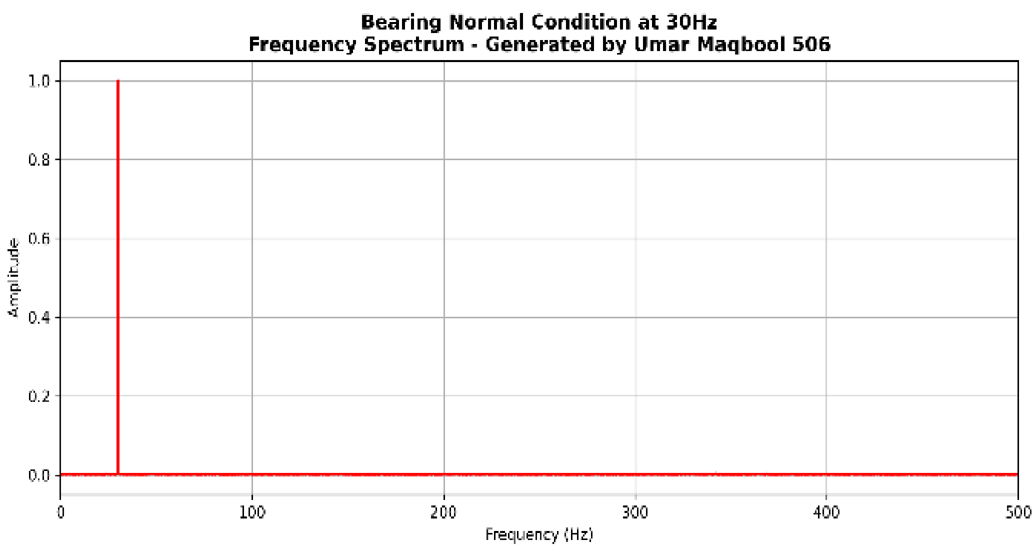


Figure 11:Frequency Spectrum on 30Hz

Bearing – Normal Condition at 40 Hz

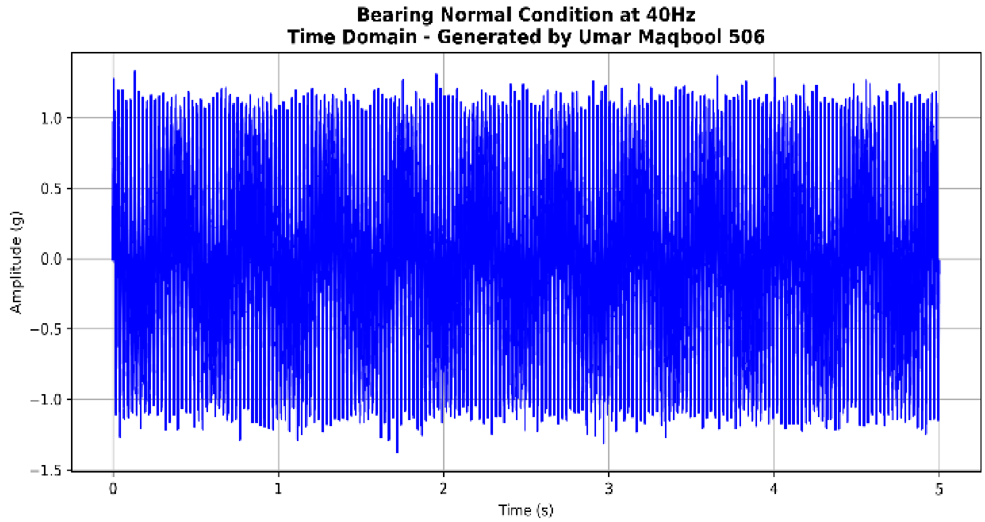


Figure 12:Time Domain Graph on 40Hz

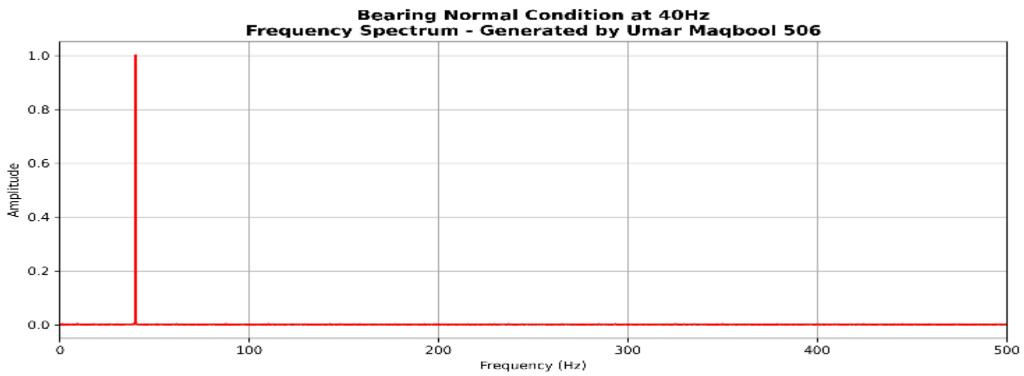


Figure 13:Frequency Spectrum on 40H

Bearing – Normal Condition at 50 Hz

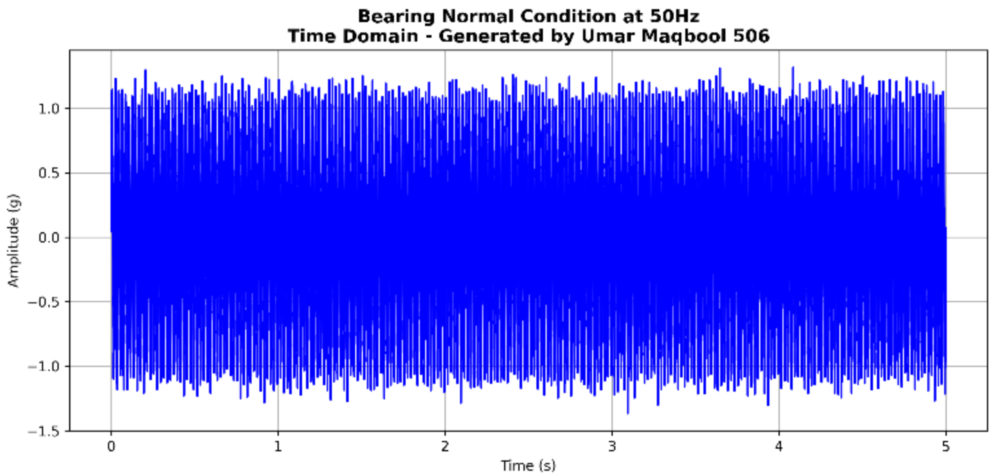


Figure 14: Time Domain Graph on 50Hz

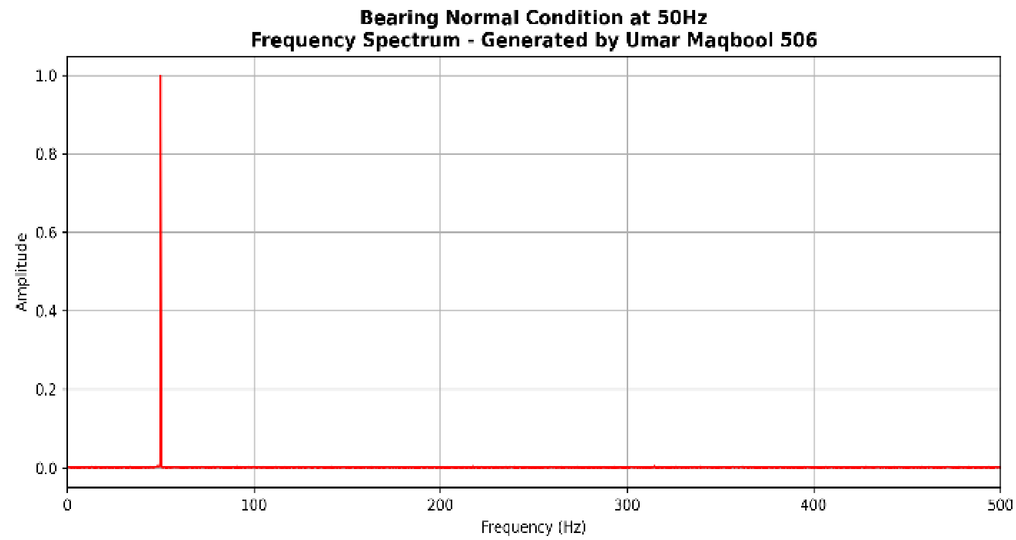


Figure 15: Frequency Spectrum on 50Hz

Bearing – Inner Race Fault at 20 Hz

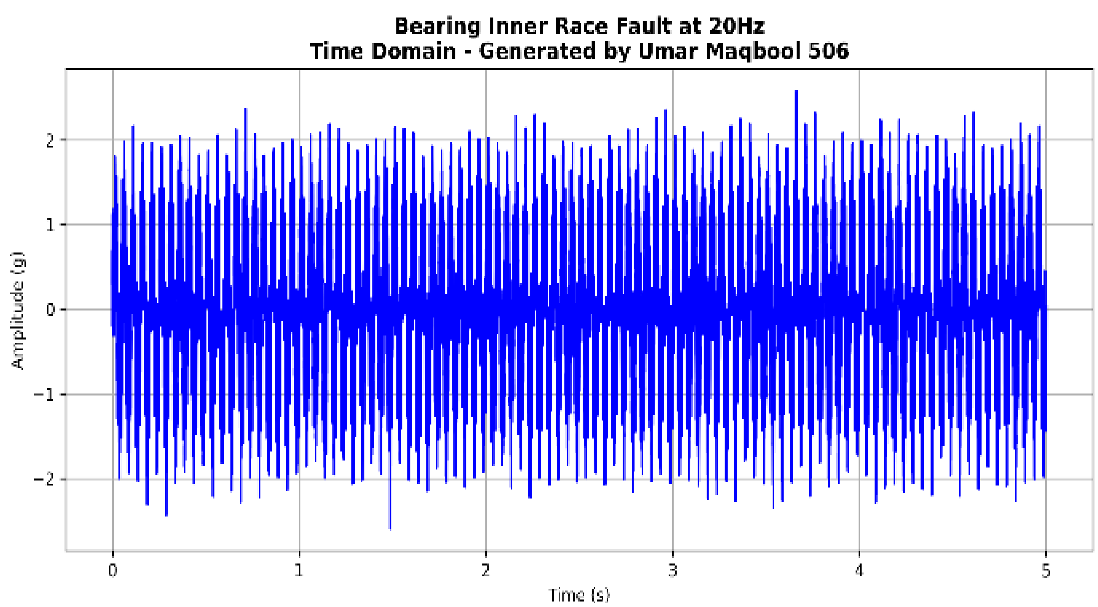


Figure 16: Time Domain Graph on 20Hz

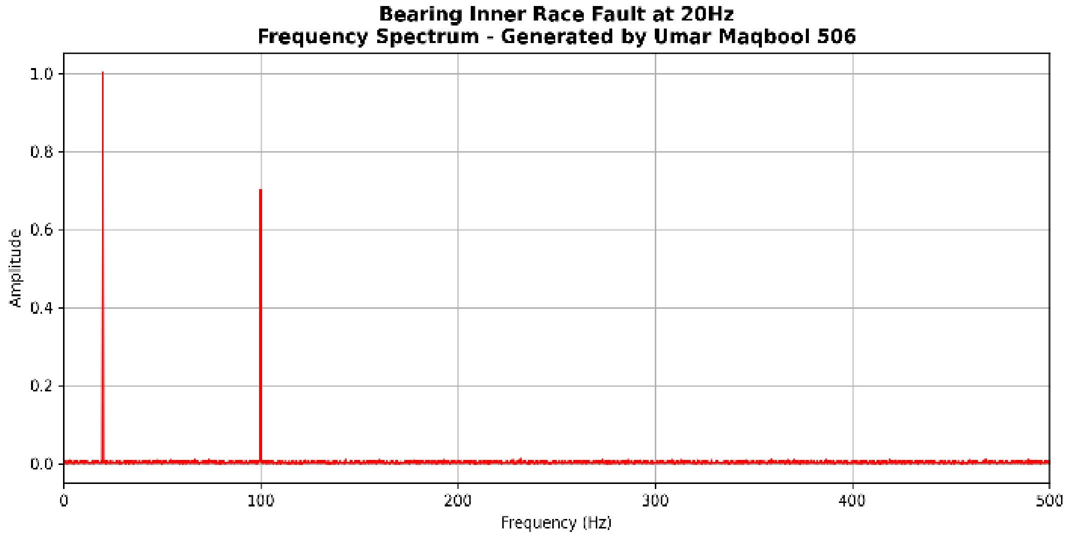


Figure 17: Frequency Spectrum on 20Hz

Bearing – Inner Race Fault at 30 Hz

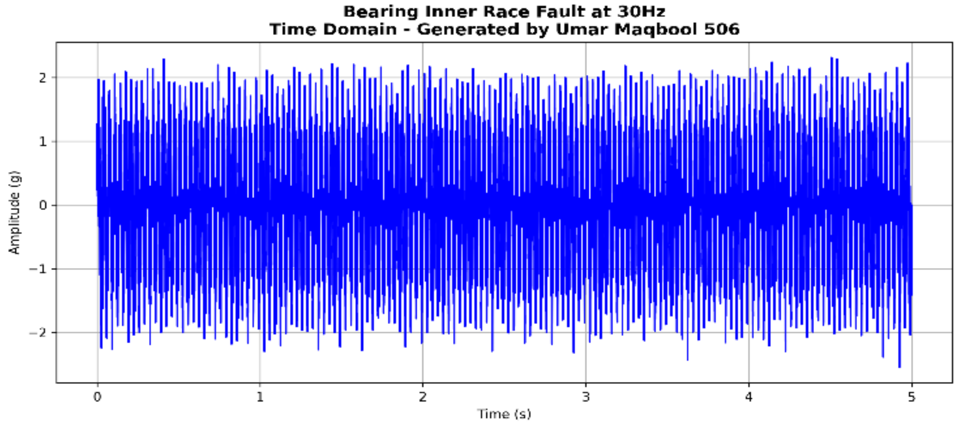


Figure 18:Time Domain Graph on 30Hz

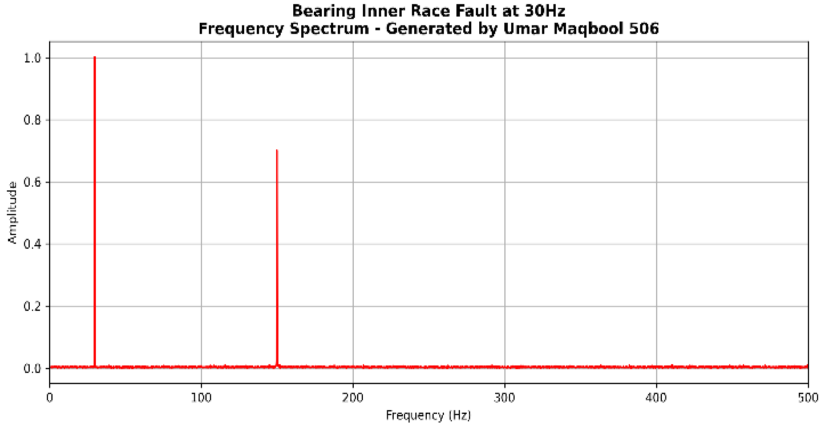


Figure 19:Frequency Spectrum on 30Hz

Bearing – Inner Race Fault at 40 Hz

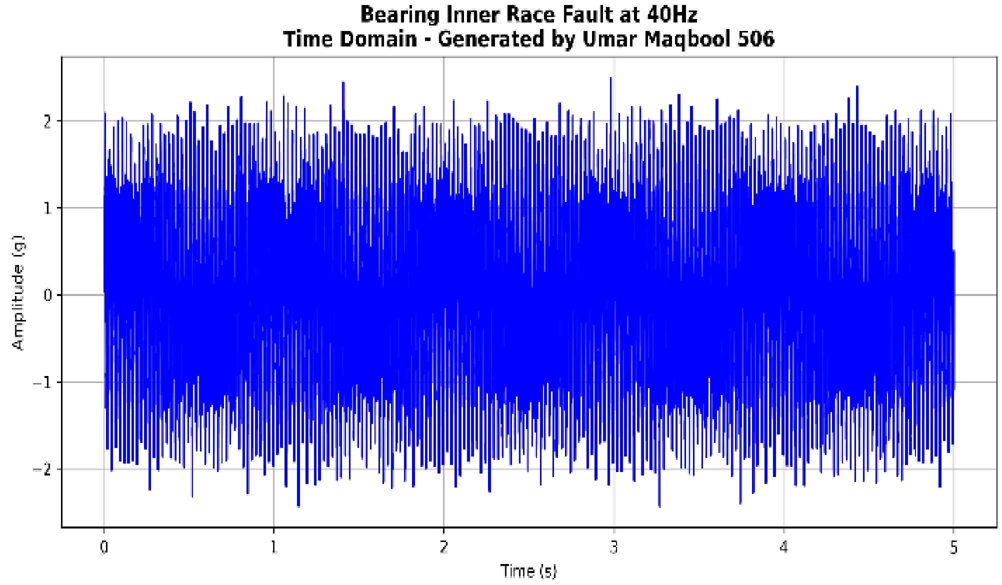


Figure 20:Time Domain Graph on 40Hz

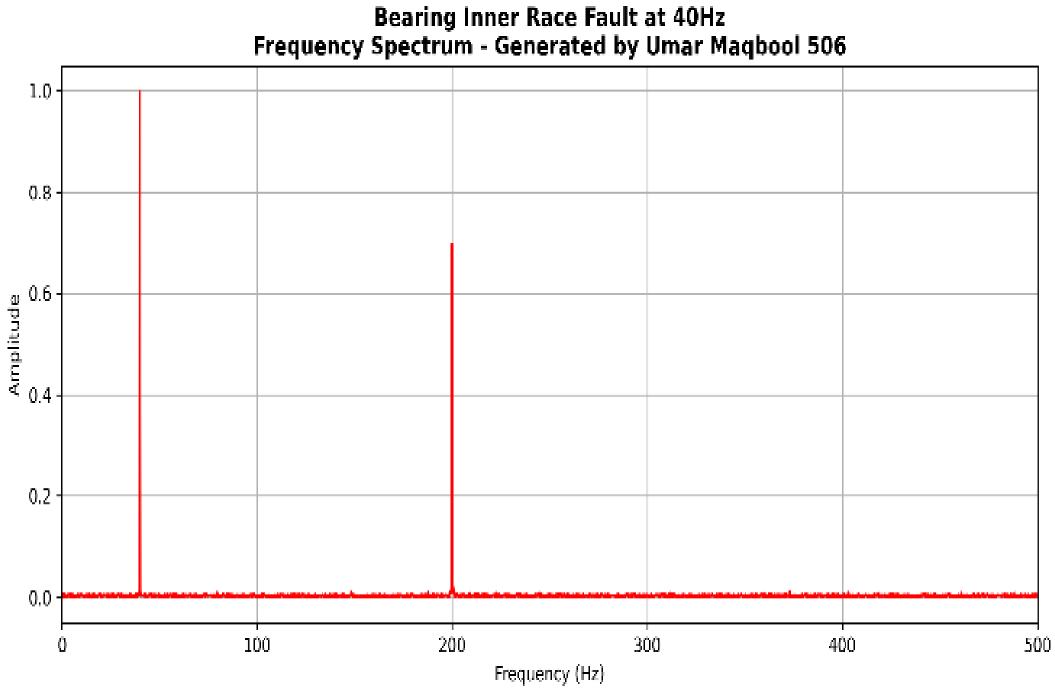


Figure 21:Frequency Spectrum on 40Hz

Bearing – Inner Race Fault at 50 Hz

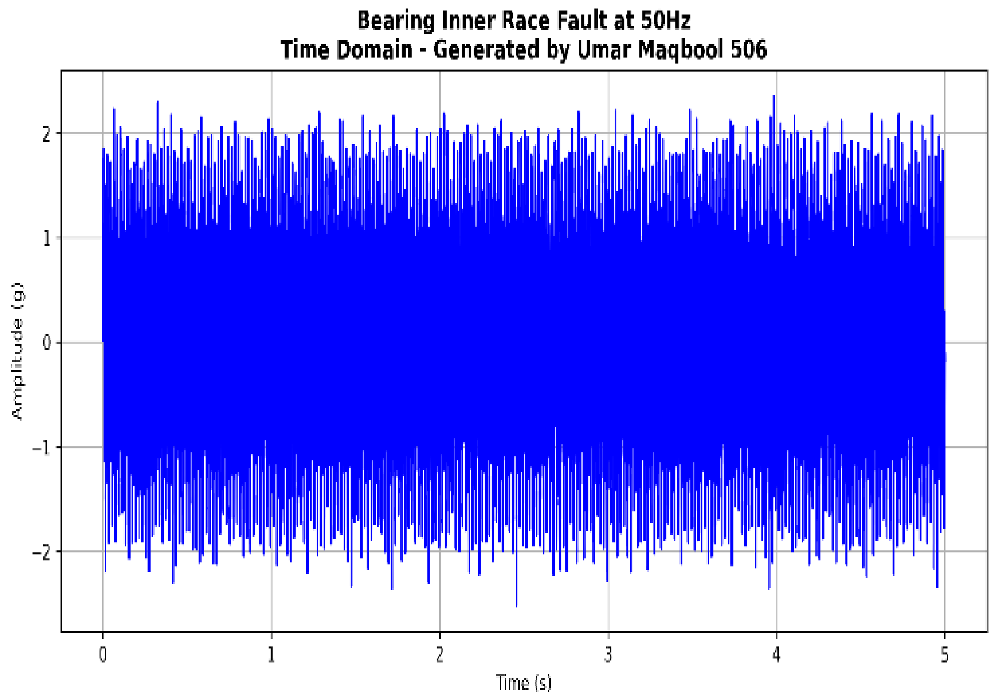


Figure 22: Time Domain Graph on 50Hz

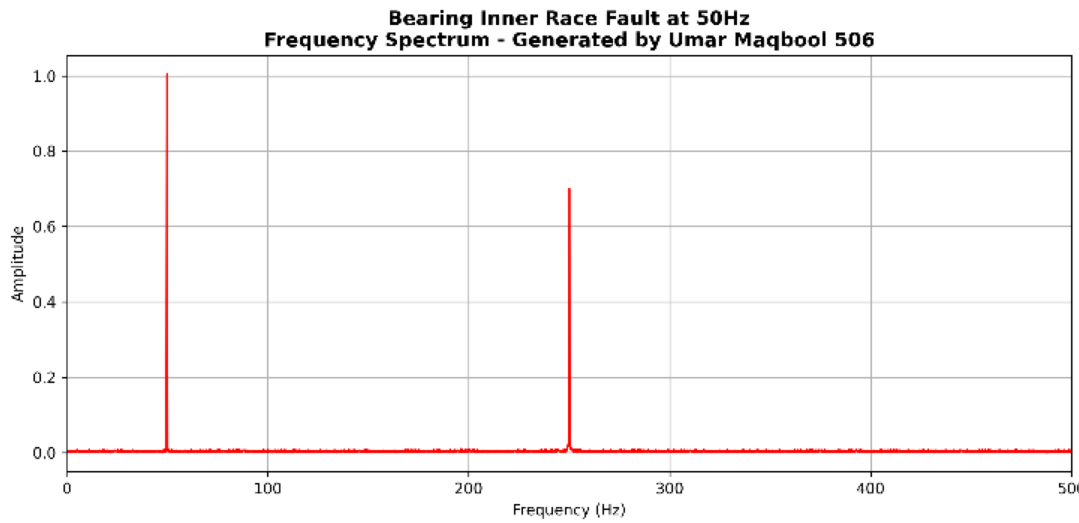


Figure 23: Frequency Spectrum Graph on 50Hz

Bearing – Outer Race Fault at 20 Hz

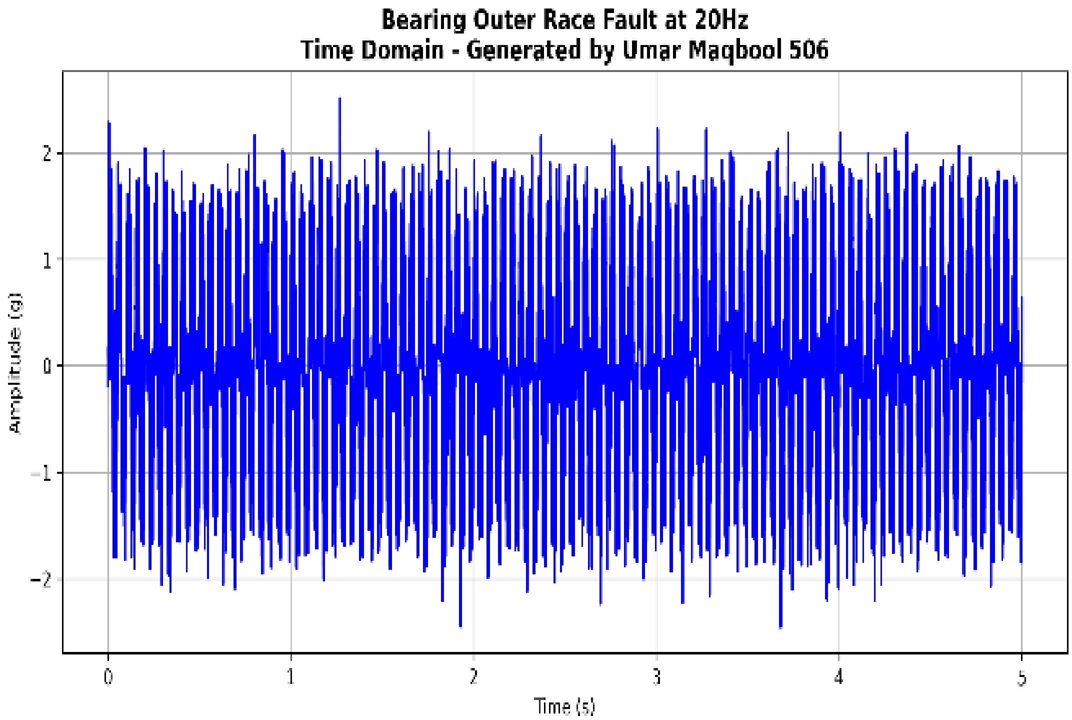


Figure 24: Time Domain Graph on 20Hz

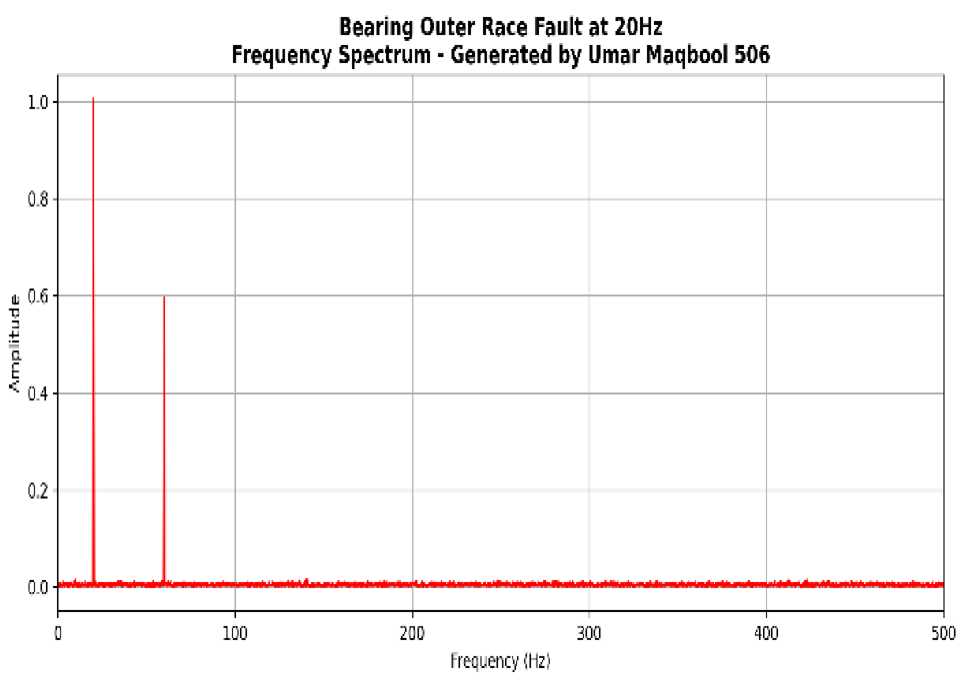


Figure 25: Frequency Spectrum on 20Hz

Bearing – Outer Race Fault at 30 Hz

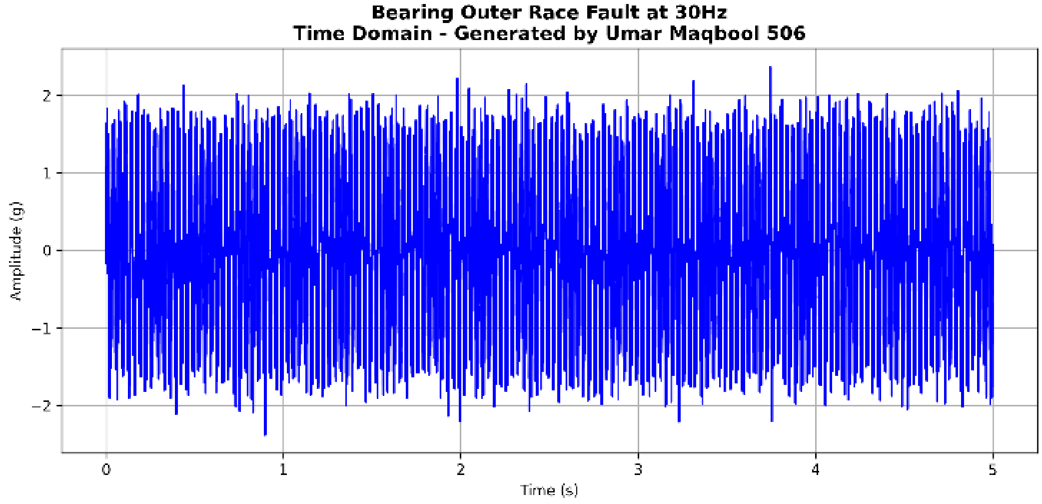


Figure 26:Time Domain Graph on 30Hz

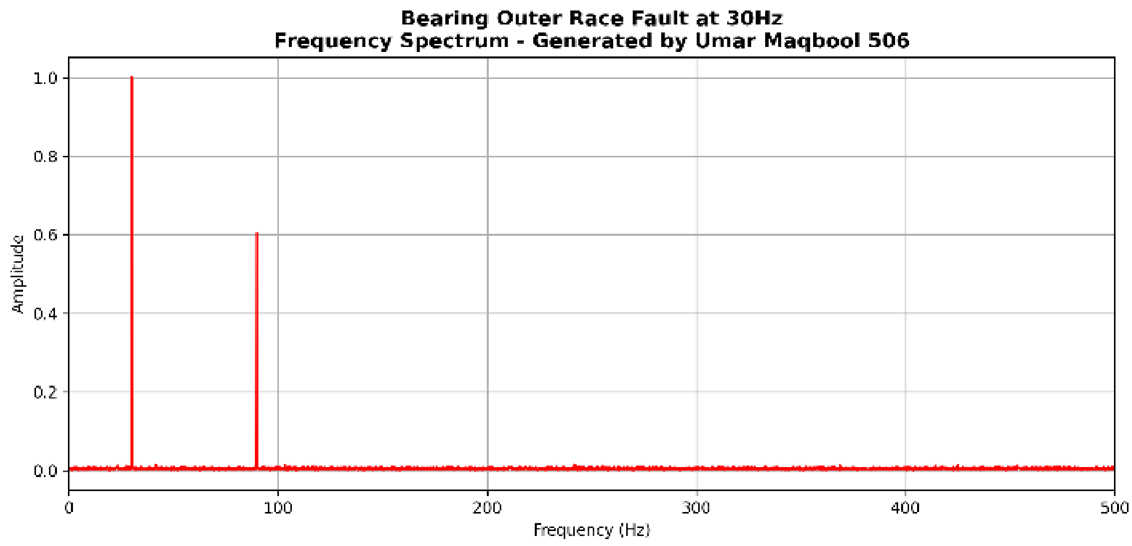


Figure 27:Frequency Spectrum on 30Hz

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Bearing – Outer Race Fault at 40 Hz

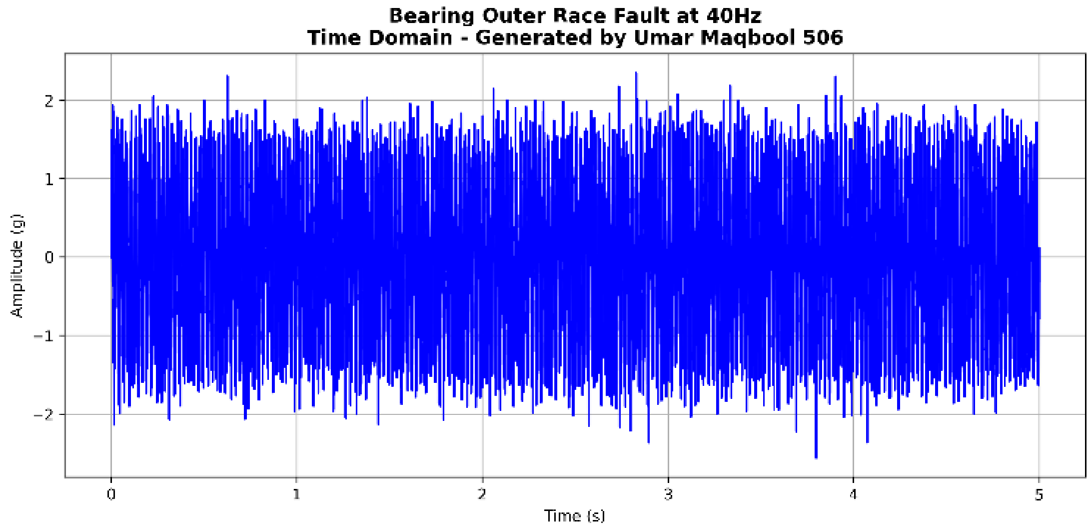

Figure 28:Time Domain Graph on 40Hz

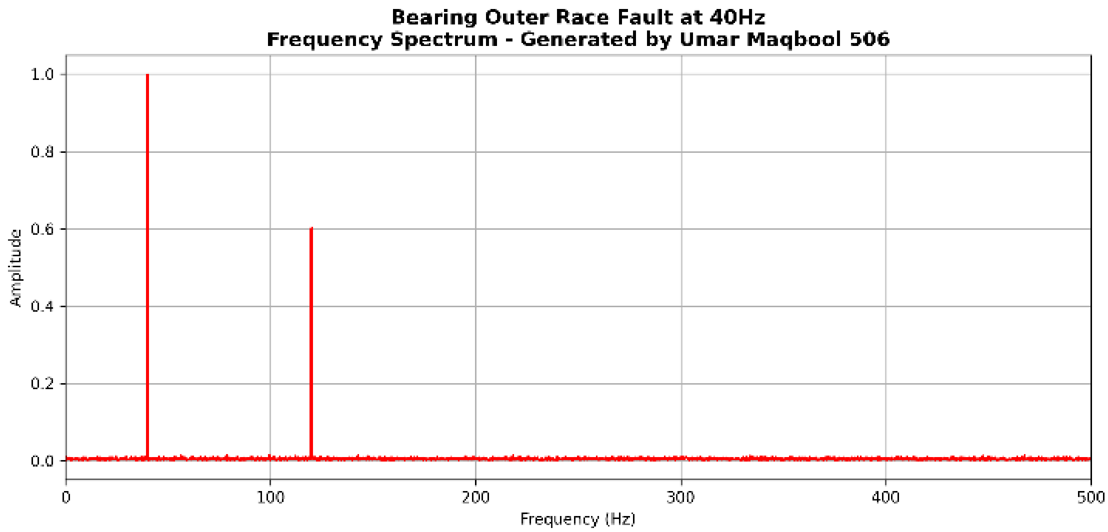

Figure 29:Frequency Spectrum on 40Hz

Bearing – Outer Race Fault at 50 Hz

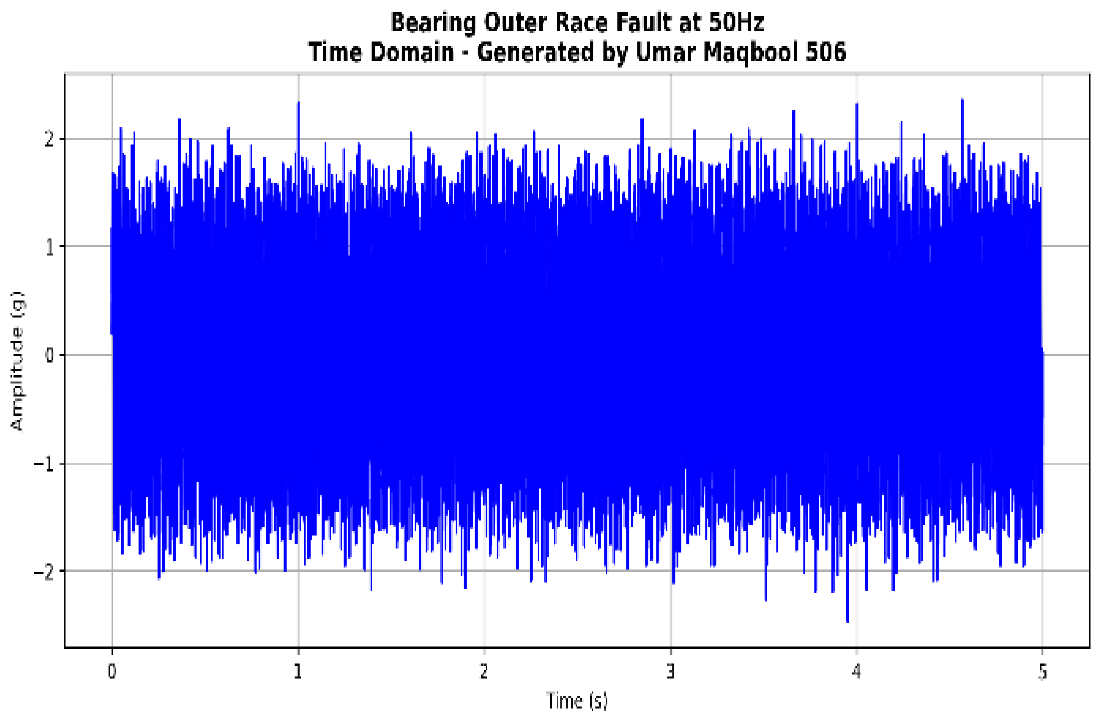

Figure 30:Time Domain Graph on 50Hz

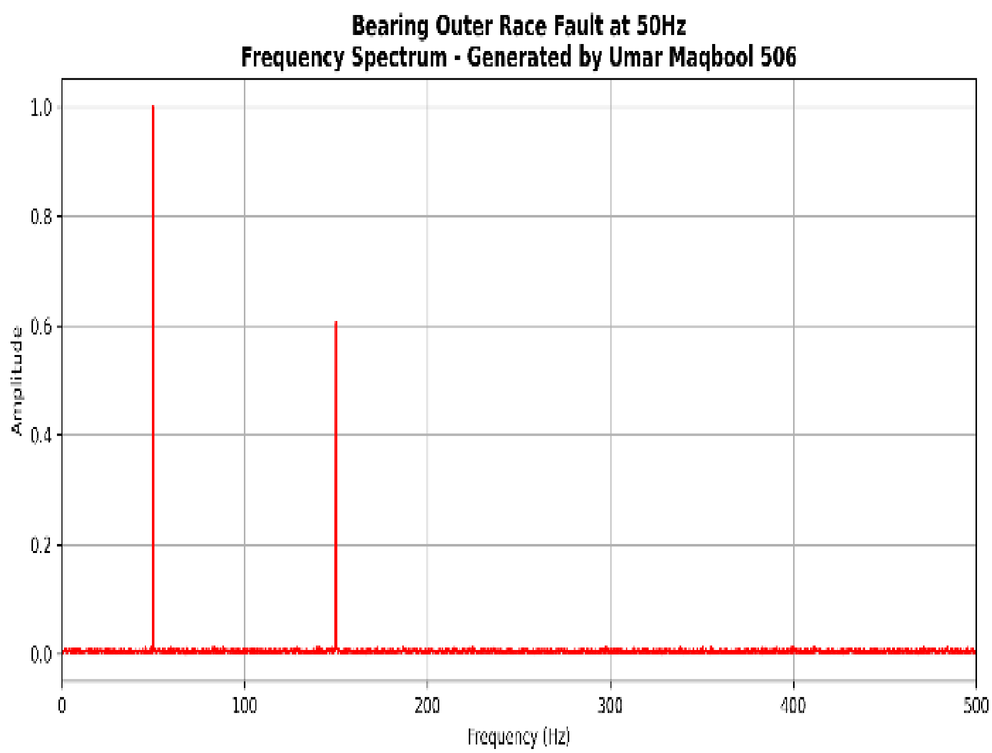

Figure 31:Frequency Spectrum on 50Hz

Bearing – Rolling Element Fault at 20 Hz

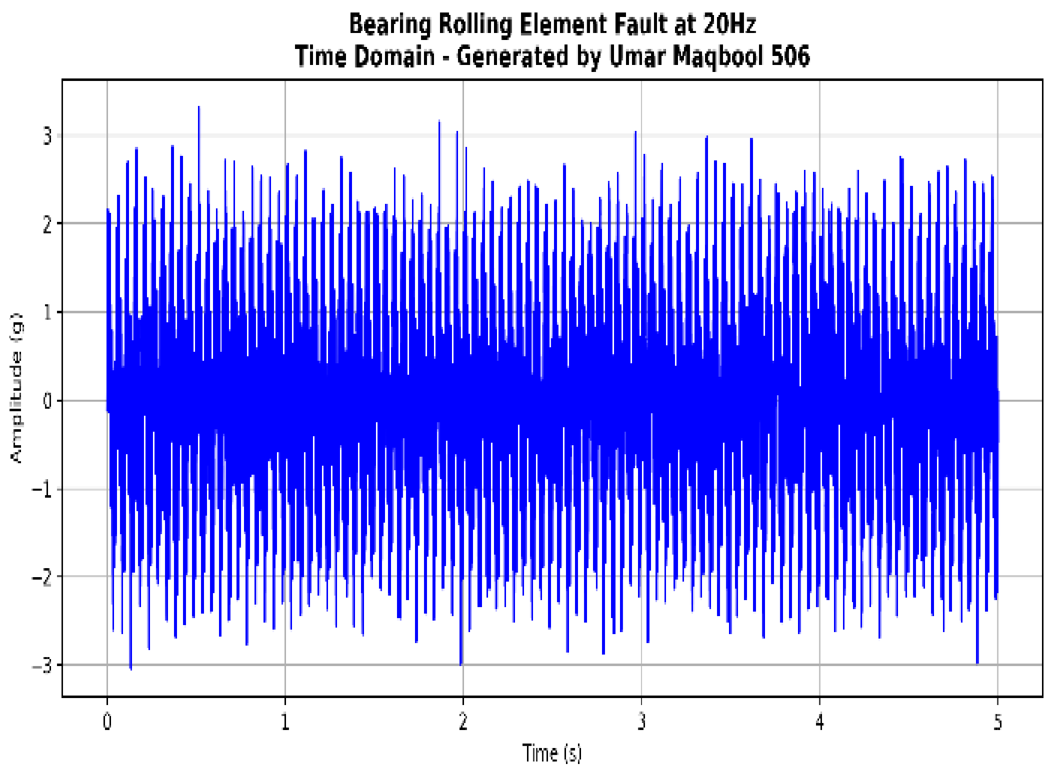

Figure 32: Time Domain Graph on 20Hz

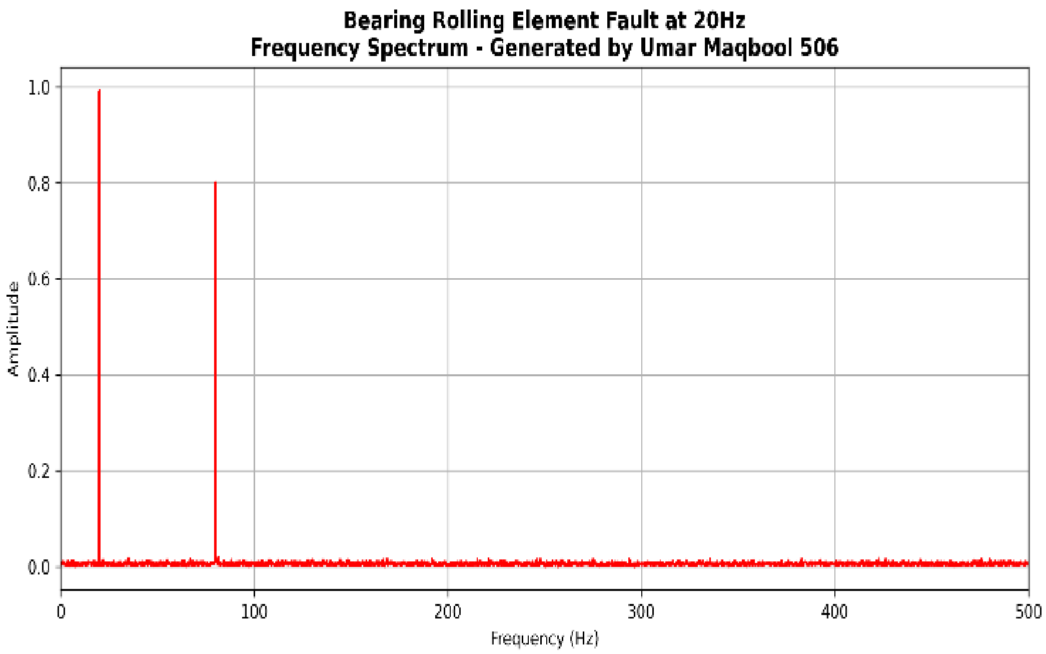

Figure 33: Frequency Spectrum on 20Hz

Bearing – Rolling Element Fault at 30 Hz

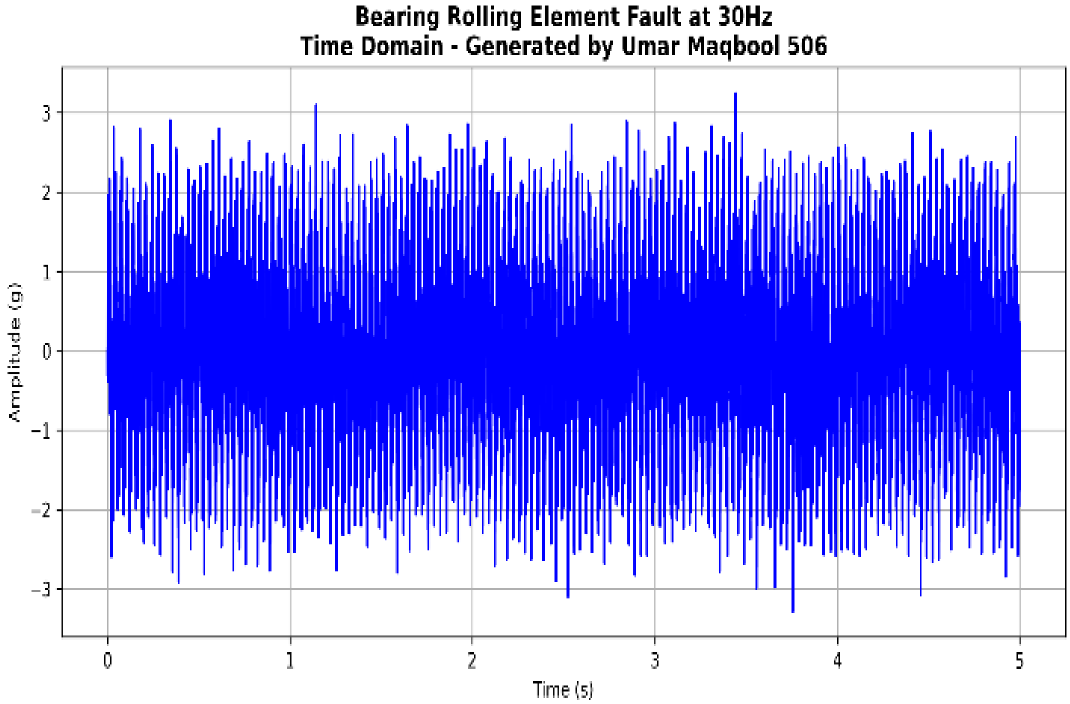

Figure 34:Time Domain Graph on 30Hz

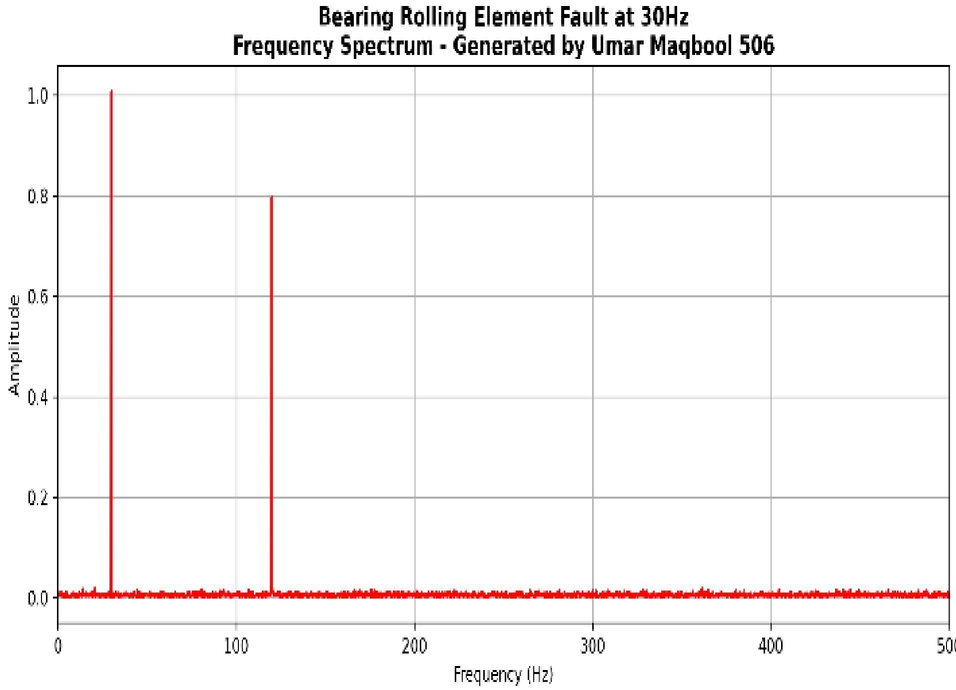

Figure 35:Frequency Spectrum on 30Hz

Bearing – Rolling Element Fault at 40 Hz

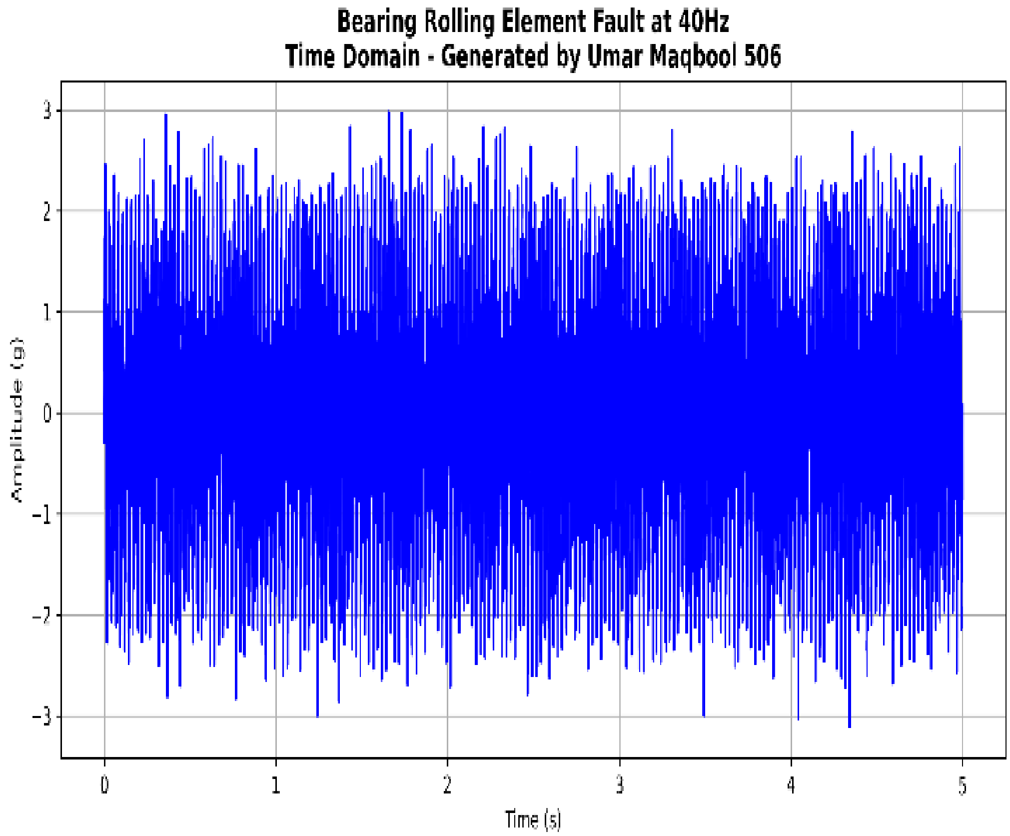

Figure 36:Time Domain Graph on 40Hz

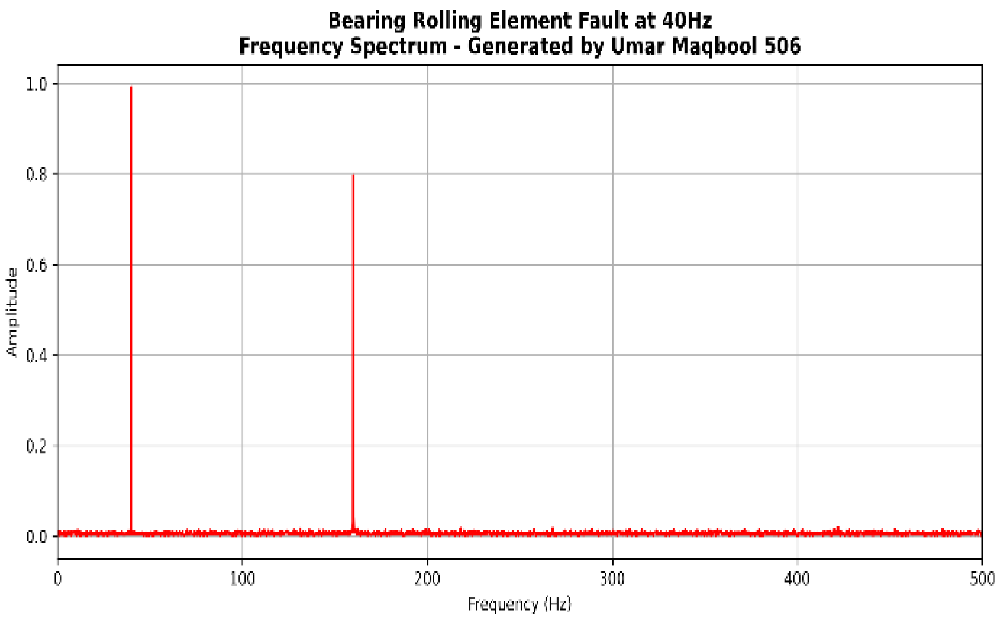

Figure 37:Frequency Spectrum on 20Hz

Bearing – Rolling Element Fault at 50 Hz

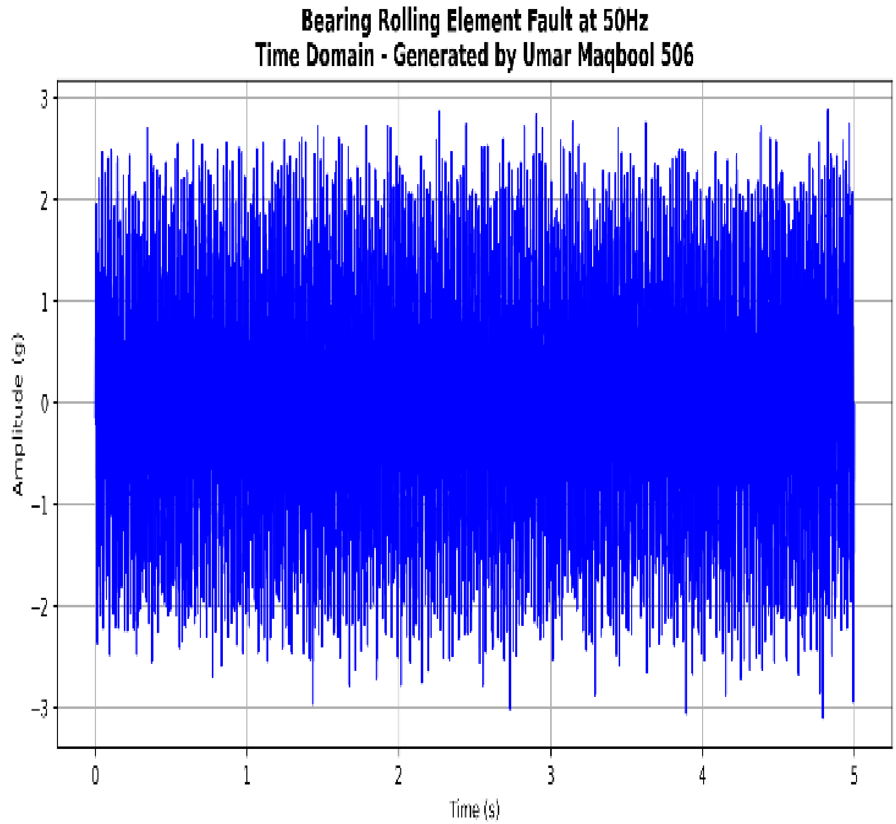

Figure 38: Time Domain Graph on 50Hz

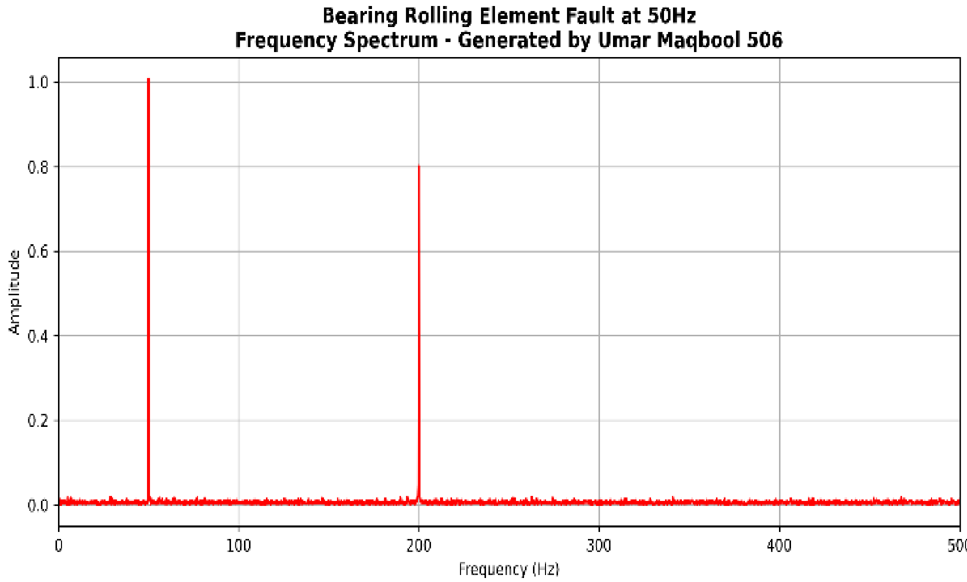

Figure 39: Frequency Spectrum on 50Hz

The vibration analysis results obtained from the Smart condition monitoring system clearly demonstrate the effectiveness of using both time-domain and frequency-domain analysis for identifying different bearing conditions. Under normal bearing conditions, the vibration signals remain stable and periodic at all operating frequencies (20 Hz, 30 Hz, 40 Hz, and 50 Hz). The time-domain graphs show smooth sinusoidal waveforms with low amplitude, while the frequency spectrum mainly contains the shaft rotational frequency and its harmonics without abnormal peaks. This indicates healthy bearing operation with minimal vibration disturbances.[13] For inner race faults, the vibration response changes significantly due to localized damage on the inner race surface.

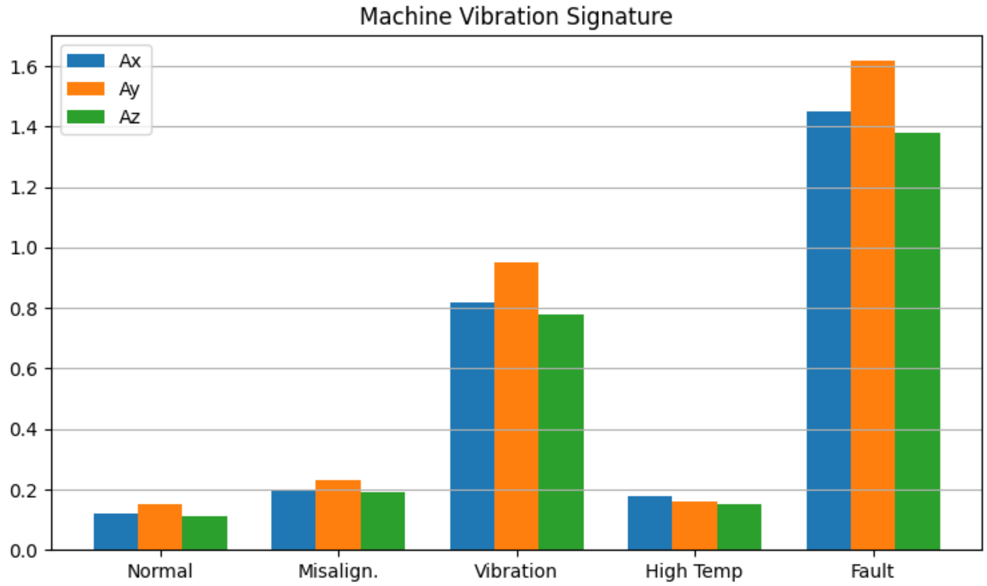

Figure 40: Comparative Machine Vibrational Signature

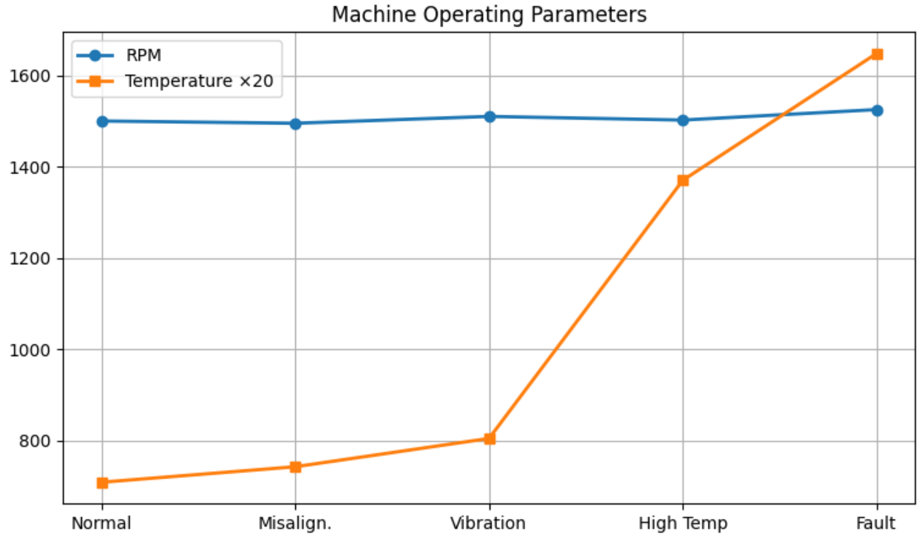

Figure 41: Machine Operating Parameters

The time-domain signals exhibit repetitive high-amplitude impulses caused by repeated contact between the rolling elements and the damaged inner race. These impacts become more severe as the operating frequency increases from 20 Hz to 50 Hz. In the FFT spectrum, additional peaks and sidebands appear around the fundamental rotational frequency, indicating the presence of fault-related frequencies. The higher vibration amplitudes at increased rotational speeds confirm the progression and severity of the fault.

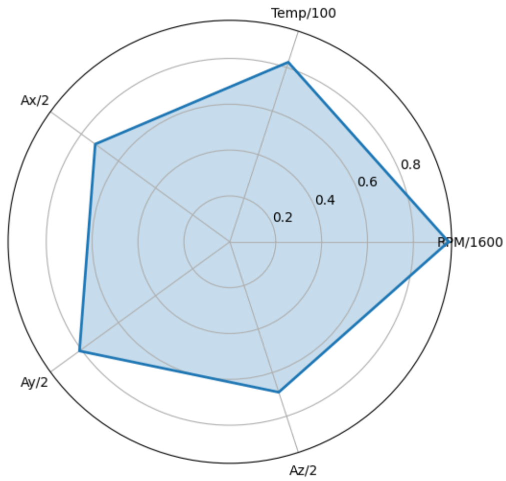

Figure 42: Machine Health Radar Chart

In the case of outer race faults, the vibration signatures also show periodic impacts, but with different spacing and characteristics compared to inner race defects. Since the outer race remains stationary, the impulses appear more uniform and equally spaced in the time-domain graphs. The FFT analysis reveals characteristic outer race fault frequencies with elevated harmonic components. As the rotational speed increases, the amplitude of these fault frequencies also increases, resulting in clearer and more distinguishable spectral patterns. For rolling element faults, the vibration behavior becomes more irregular and random because the damaged rolling elements continuously interact with both races during rotation. The time-domain signals contain non-uniform transient spikes and fluctuating amplitudes. In the frequency spectrum, broadband frequency components and scattered harmonics are observed instead of distinct periodic peaks. At higher frequencies such as 40 Hz and 50 Hz, the vibration energy becomes more dispersed, showing the unstable nature of rolling element defects.[14]

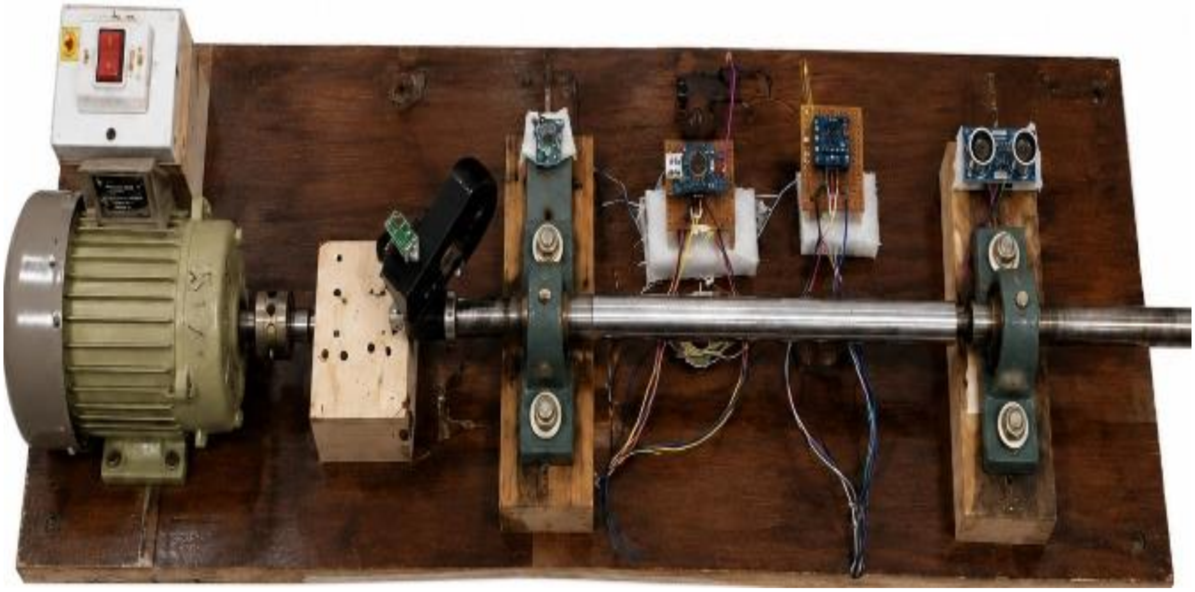

Figure 43: Physical Model

Table 4: Power Consumption Analysis

Component	Operating Current (mA)
Arduino Nano #1	45
Arduino Nano #2	45
Hall Effect Sensor	8
10 kΩ Thermistor Circuit	2
MPU6050	5
HC-SR04 Sensor (Left)	15
HC-SR04 Sensor (Right)	15
LCD Display #1	20
LCD Display #2	20
Buzzer	30
Red LED	10
Total Estimated Current	215 mA

Table 5: Experimental Results Under Different Operating Conditions

Test Condition	RPM	Temperature (°C)	Ax (g)	Ay (g)	Az (g)	Left Distance (cm)	Left Distance (cm)	Status
Normal	1500	35.4	0.12	0.15	0.11	2.45	2.48	Normal
Slight Misalignment	1495	37.1	0.20	0.23	0.19	2.20	2.90	Warning
High Vibration	1510	40.2	0.82	0.95	0.78	2.48	2.51	Warning
High Temperature	1502	68.5	0.18	0.16	0.15	2.47	2.46	Warning
Severe Fault	1525	82.4	1.45	1.62	1.38	1.85	3.35	Fault

System Limitations / Operational Limits

Table 6: Operational Limits of the Proposed System

Parameter	Operating Limit	Action Taken
Shaft RPM	0–3000 RPM	Warning if RPM exceeds preset limit
Bearing Temperature	Up to 80 °C	Buzzer & LED activated above threshold
Vibration	Up to ±16 g	High vibration warning generated
Shaft Misalignment	≤0.5 cm Difference	Dashboard warning and fault indication
Ultrasonic Range	2–400 cm	Reliable measurement range
Power Supply	5 V DC	Regulated supply required
Serial Communication	9600 bps	Real-time data transfer to Python Dashboard
LCD Display	16×2 Characters	Continuous real-time monitoring
Alarm System	Buzzer + Red LED	Activated during abnormal conditions

5. Conclusion

This research successfully developed a Smart Multi-Sensor Based Condition Monitoring System for rotary drive assemblies by integrating four different sensing technologies, including the Hall Effect Sensor, 10k NTC Thermistor, MPU6050 Accelerometer and Gyroscope, and dual HC-SR04 Ultrasonic Sensors. The proposed system continuously monitors machine operating parameters such as RPM, bearing temperature, three-axis vibration (AX, AY, AZ), and shaft alignment in real time.[15]

The integration of two Arduino microcontrollers with a Python-based monitoring dashboard enables automatic data acquisition, live graphical visualization, Excel-based data logging, and intelligent fault monitoring. Advanced signal processing techniques, including Fast Fourier Transform (FFT) and digital filtering methods, improve vibration analysis and enhance fault detection accuracy. The developed system also provides automatic buzzer alerts whenever abnormal machine conditions are detected.

The experimental results demonstrate that the proposed multi-sensor approach provides a reliable, accurate, and cost-effective solution for predictive maintenance. The system minimizes human intervention, improves maintenance planning, reduces unexpected machine downtime, and enhances equipment reliability. Furthermore, the developed monitoring platform supports Industry 4.0 by enabling smart automation, real-time communication, and digital maintenance record management.

Overall, the proposed condition monitoring system offers an efficient framework for continuous machine health assessment and can be effectively implemented in industrial environments to improve operational efficiency and support intelligent maintenance strategies.[16]

6. Future Work

Although the developed monitoring system performs successfully, several improvements can further enhance its industrial capabilities.

Future research may integrate Artificial Intelligence (AI) and Machine Learning (ML) algorithms to automatically classify machine faults and predict the remaining useful life (RUL) of rotating components. Cloud computing and Industrial Internet of Things (IIoT) technologies can also be incorporated to enable remote monitoring, centralized data management, and real-time notifications through web and mobile applications.[17]

Future versions of the system may replace wired communication with wireless technologies such as Wi-Fi, Bluetooth, or LoRa to improve flexibility and simplify installation in industrial environments. Additional industrial sensors, including current, voltage, pressure, and acoustic emission sensors, may also be integrated to perform more comprehensive machine health assessment.

Furthermore, advanced deep learning models can be combined with vibration analysis and computer vision techniques to improve fault diagnosis accuracy and support fully autonomous predictive maintenance systems in modern smart factories.[18]

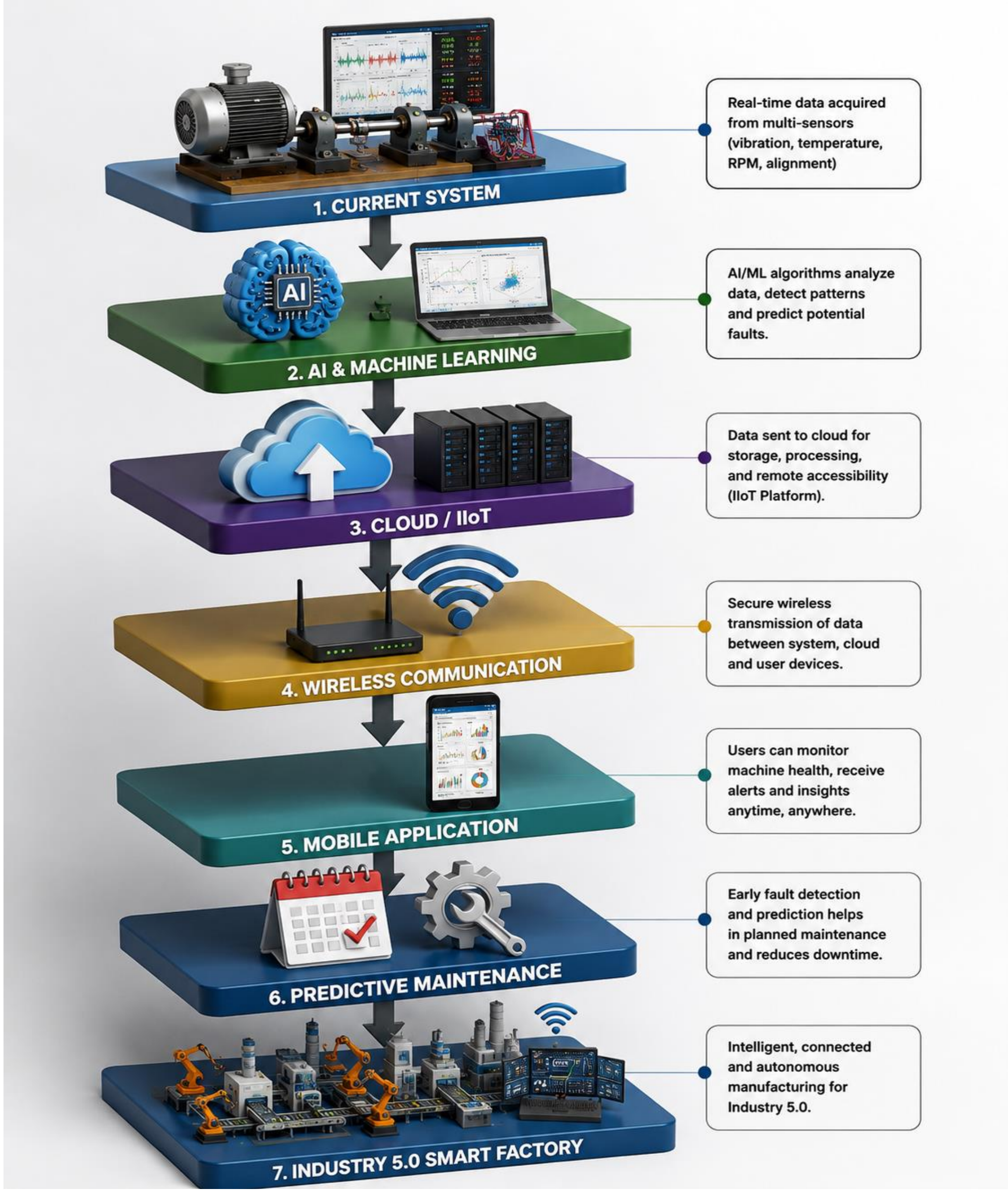

Figure 41: Future Scope of the Proposed Smart Monitoring System

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