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**TITLE:**

**DESIGN OF A SMART REAL-TIME CONDITION MONITORING AND  
PREDICTIVE MAINTENANCE SYSTEM FOR RAILWAY TRACTION MOTORS**

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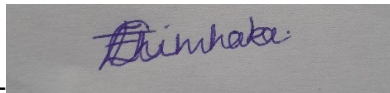
**A project work submitted in fulfilment of the Bachelor of Science (BSc) in Electronic  
Engineering as a requirement of the final year project.**

## DECLARATION

I hereby certify that the work which is being presented in the project entitled **DESIGN OF A SMART REAL-TIME CONDITION MONITORING AND PREDICTIVE MAINTENANCE SYSTEM FOR RAILWAY TRACTION MOTORS** in the partial fulfilment of the requirements for the award of the degree of **BACHELOR OF SCIENCE** and submitted in the **DEPARTMENT OF ELECTRONIC ENGINEERING, BINDURA UNIVERSITY OF SCIENCE EDUCATION**, is an authentic record of my own work carried out during the time period from **AUGUST 2022 of joining the EE program to JUNE 2026 of project submission** under the supervision of **Malindi N, Lecturer, Electronic engineering department**.

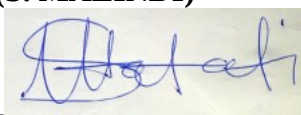
The matter presented in this project has not been submitted by me for the award of any other degree of this or any other institute.

**Signature of the student with date**  
**(ELLEN TSITSI CHIMHAKA)**



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This is to certify that the above statement made by the candidate is correct to the best of my/our knowledge.

**Signature of the Supervisor of**  
**(with date)**  
**(S. MALINDI)**



## **DEDICATION**

To the Almighty God, for His abundant grace, unwavering strength and divine guidance throughout this academic journey. All praise and glory belong to Him.

To my cherished parents, whose constant support, countless sacrifices and enduring encouragement provided the strength and motivation needed to complete this work. Your faith in my abilities and your unconditional love have been instrumental in helping me achieve this milestone.

To my supervisor, for the invaluable guidance, professional expertise and continuous commitment to my academic development. Your mentorship, support and encouragement have greatly contributed to the successful completion of this study.

This work is dedicated to you all with sincere appreciation and heartfelt gratitude.

## ABSTRACT

Railway traction motors are critical components in locomotive propulsion and are continuously exposed to harsh thermal, electrical and mechanical conditions that accelerate insulation degradation and increase the risk of unexpected failures. Conventional maintenance practices at the National Railways of Zimbabwe (NRZ) rely mainly on periodic inspections, which often fail to identify early-stage faults. This study presents the design and implementation of a low-cost IoT-based real-time condition monitoring system for railway traction motors.

The developed prototype has a built-in ESP32 microcontroller combined with MPU6050 sensors for vibration and temperature measurements and ACS712 Hall effect sensors for measuring the current value. The system is capable of collecting data in real-time mode and processing the obtained parameters with embedded health assessment and threshold-based fault detection algorithms. The faults are indicated using LED lights, a buzzer and an emergency isolation relay.

The experimental results showed that the system is able to detect abnormal operating conditions and give warning signals to prevent serious damage to the motor. However, despite the fact that it was impossible to develop a machine learning-based predictive model owing to the lack of fault datasets, the created system is capable of providing a scalable base for the further development of intelligent maintenance systems.

## **ACKNOWLEDGEMENTS**

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Finally, I wish to thank my friends and all those who, in one way or another, contributed to the successful completion of this work. Your assistance, encouragement, and support are deeply appreciated.

## **ABBREVIATIONS**

**NRZ** - National Railways of Zimbabwe

**ESP32** - Espressif 32-bit Microcontroller

**IoT**- Internet of Things

**IIoT**- Industrial Internet of Things

**AI**- Artificial Intelligence

**ML**- Machine Learning

**DL**- Deep Learning

**OML**- Online Machine Learning

**MCU**- Microcontroller Unit

**MPU6050**- Motion Processing Unit 6050

**MEMS**- Micro-Electro-Mechanical Systems

**ADC**- Analog-to-Digital Converter

**I<sup>2</sup>C**- Inter-Integrated Circuit

**GPIO**- General Purpose Input Output

**GUI**- Graphical User Interface

**PCB**- Printed Circuit Board

**DC**- Direct Current

**AC**- Alternating Current

**Wi-Fi**- Wireless Fidelity

**LED**- Light Emitting Diode

**PWM**- Pulse Width Modulation

**FFT**- Fast Fourier Transform

**PSD**- Power Spectral Density

**MCSA**- Motor Current Signature Analysis

**FDI**- Fault Detection and Isolation

**FDD**- Fault Detection and Diagnosis

**HA**- Health Assessment

**PHM**- Prognostic and Health Management

**RUL**- Remaining Useful Life

**CBM**- Condition-Based Maintenance

**TBM**- Time-Based Maintenance

**PdM**- Predictive Maintenance  
**DT**- Digital Twin  
**CPS**- Cyber-Physical System  
**CNN**- Convolutional Neural Network  
**RNN**- Recurrent Neural Network  
**ANN**- Artificial Neural Network  
**MLP**- Multi-Layer Perceptron  
**SAE**- Stacked Auto-Encoder  
**SVM**- Support Vector Machine  
**SVR**- Support Vector Regression  
**PCA**- Principal Component Analysis  
**MIC**- Maximal Information Coefficient  
**IDTN**- Imbalanced Deep Transfer Network  
**GPR**- Gaussian Process Regression  
**MBS**- Multi-Body Simulation  
**MCDM**- Multi-Criteria Decision-Making  
**WSN**- Wireless Sensor Network  
**MQTT**- Message Queuing Telemetry Transport  
**CDU**- Centralized Diagnostics Unit  
**PTAT**- Proportional to Absolute Temperature  
**EMI**- Electromagnetic Interference  
**RF**- Radio Frequency  
**IP**- Internet Protocol  
**ACS**- Allegro Current Sensor (ACS712 series)

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## CHAPTER 1: INTRODUCTION

The rail transportation in Zimbabwe is essential for the movement of passengers and cargo within the nation. In railroad locomotives, the traction motors are used in order to convert electricity into mechanical energy that drives the train. These machines require proper functioning since they ensure the effective, punctual and safe running of railways. Unfortunately, they can be vulnerable to insulation damage caused by overheating resulting in their failure and costly maintenance. This type of insulation is important to avoid short circuits and to keep electricity separated; it also determines the lifetime of the motor and the whole system (Gupta, et al., 2021).

The current state-of-the-art at the National Railways of Zimbabwe (NRZ) consists of manual periodic inspections of traction motors. While such inspections detect wear and tear of equipment, they cannot identify hidden problems, such as degradation of insulation from overheating in time. This deficiency causes the late detection of the problem when it was already developed to the point of failures (Patel & Modhera, 2011). Hence, there is a need in developing an economic real-time monitoring system for these purposes.

The purpose of the proposed research is the design and development of the Real-time Condition Monitoring and Predictive Monitoring System for Railway Traction Motors using embedded electronics to monitor the condition of the traction motor. In particular, the proposed system will have the capability of integrating a Hall Effect Current Sensor which will sense the current drawn by the motor and an Accelerometer/Gyroscope Sensor which will detect the vibration and the surface temperature of the motor. Motor condition information will be relayed through a buzzer and LEDs and further through a cloud dashboard to ensure that maintenance crews are instantly alerted. Through such a monitoring system, early warnings of thermal and insulation damage in railway motors will allow for the increased reliability and operational efficiency of the train and lower maintenance costs while increasing its lifespan. The significance of the proposed research is in the fact that it will provide an opportunity to transition from reactive to predictive maintenance strategies. Predictive maintenance, in general, which involves solving problems before they arise, allows for improving equipment reliability by 50%, as well as lowering the costs of operation by 25-30% (Singh, et al., 2020).

## 1.0 Background of study

In the discipline of railway engineering, traction motors serve as the main electromechanical devices that help in conversion of electricity to mechanical torque needed to run heavy fleets of locomotives. Locomotives, which include those used by the NRZ, use either diesel-electric and/or pure electric propulsion system in which traction motors are installed directly on the axle. They run in highly unfriendly conditions that include constant high-frequency vibrations and high dust and heat exposures. The performance of the locomotive depends largely on the condition of the insulation of its rotor and stator. Electrical breakage due to overheating continues to be the biggest reason for a sudden malfunction of the motor, causing burnout of its windings.

At the moment, the global maintenance environment is undergoing a paradigm shift from the conventional practice of Reactive Maintenance and Preventive Maintenance to the practice of Predictive Maintenance (PdM). This shift is based on the underlying concepts of Industry 4.0, which makes use of the Internet of Things and sensor fusion to maintain the health of assets. Some of the recent trends that have emerged in regard to the area of high speed rail networks include the use of Artificial Intelligence and Deep Learning techniques to analyse vibrations and current signatures (Zhong, et al., 2023). But there is an emerging trend that includes the use of Edge Computing systems.

The importance of the traction motor diagnostics is emphasized by the economic losses associated with the breakdowns of the locomotives without prior planning. Any breakdown of the locomotive results in severe traffic delays and losses of profits as well as safety issues for passengers. In the case of the National Railways of Zimbabwe, the issue is made more difficult by the old age of the vehicles and manual monitoring of them. Such inspection is not timely because it does not allow detecting any weakening of the insulation of the traction motors, which occurs while they are working. At the same time, increasing the weight of trains and operating them in varied landscapes leads to the overheating of the equipment. Absence of the system of notifications about the condition of the motors in real time means that drivers or mechanics do not know about the developing problem before the moment when there are smokes from it. Thus, there is a great need for development of a cheap diagnostic system allowing detecting any problems with the traction motors.

## **1.1 Problem Statement**

The railway network in Zimbabwe uses traction motors that have a tendency to overheat and develop insulation defects due to excessive mechanical strain and difficult working conditions. In fact, research proves that thermal runaway, electrical imbalance and mechanical vibration are the most common triggers of winding insulation breakdown that is the major cause of complete motor breakdown. Currently, the maintenance process in NRZ depends largely on preventive and manual time-based checks. This frequently leads to sudden malfunctions, high maintenance costs, increased downtime and serious safety hazards caused by such problems as overheating of windings and bearing failures. Predictive maintenance helps to save up to 30% of maintenance costs and to decrease downtime up to 50% (McKinsey & Company, 2018); however, Zimbabwe does not have an affordable real-time system of control.

Even as there are advanced commercial predictive maintenance systems, digital twins and online machine learning algorithms dependent on heavy use of cloud for prediction, these pose a high data entry hurdle and call for significant investment. There is thus a definite gap between such solutions and a cost-effective, non-disruptive autonomous condition monitoring approach which will work independently of the cloud at the level of actual assets. If no localized multi-modal edge computing framework is established which will be able to handle streaming sensor data and hardware-aware anomaly detection directly on the traction motor, railways will have to face the problem of reliability and efficiency. This research aims to fill the gap by designing a cost-effective monitoring solution for the traction motor with the help of embedded sensors. (Prabakaran, 2015).

## **1.2 Aim of the Project**

To design and implement a real-time motor monitoring system that detects early signs of overheating, insulation degradation and mechanical faults in railway traction motor windings and bearings.

## **1.3 Specific Objectives**

1. To design a sensor network to monitor temperature, vibrations and current in real time.

2. To collect, process and label sensor data representing normal and faulty operating conditions (vibration, temperature and current) for training the machine learning model.
3. To integrate an automated protection and emergency-stop mechanism utilizing a relay module to immediately isolate the system or trip external safety circuits when any monitored parameter(vibration, current, temperature) breaches a critical threshold.
4. To develop a cloud-based condition monitoring dashboard for real-time visualization, early fault alerting, failure and predictive maintenance scheduling for railway traction motors.

## **1.4 Scope of the Study**

The scope of this study defines the technical, geographical and operational boundaries of the research to ensure the project remains focused on providing a practical solution for the NRZ.

### ***1.4.1 Technical Inclusions***

- Sensor integration: The use of a Hall-effect current sensor for measuring the current drawn by the motor and a MPU6050 sensor for measuring the vibrations made by the rotating motor and the surface temperature of the motor.
- Embedded processing: Development of firmware on the ESP32 platform to handle data acquisition, signal filtering and threshold-based decision making.
- Dual-Alert system: Implementation of a local alert (buzzer) for on-board crew and a cloud-based dashboard for depot team maintenance teams.
- Emergency stop: The use of a relay module to automatically protect and trip external safety circuits when any monitored parameter breaches a critical threshold.
- Prototype validation: Testing the system's responsiveness in a controlled laboratory environment by simulating thermal overheating and vibration scenarios.
- Predictive Indicators: The system will identify early-stage failure indicators, specifically thermal runaway and mechanical vibration irregularities that precede insulation breakdown and bearing faults.

### **1.4.2 Technical Exclusions**

- **Advanced AI Modelling:** This study does not include the development of complex cloud-based deep learning architectures or Digital Twin platforms that require high-performance computing clusters or continuous satellite connectivity.
- **Wider Locomotive Subsystems:** Monitoring of other critical locomotive components such as the diesel engine, braking systems or electrical signalling, is outside the current scope.
- **Corrective Actions:** The scope is limited to fault detection, health assessment and predictive alerting. It does not extend to the autonomous execution of physical maintenance or repair of the motor components
- **Full Fleet Integration:** This research is limited to the prototyping and validation of a standalone monitoring node. It does not cover the large-scale integration of this system across the entire diverse fleet of NRZ locomotives.

### **1.5 Significance of study**

The design and implementation of a smart condition monitoring and predictive maintenance system for railway traction motors is highly valuable from a technical, operational and socio-economic perspective (Bhabani, et al., 2026). Presently, maintenance activities are based on manually carried out tests which may be reactive and fail to capture early indicators of malfunctioning that result in significant downtimes and expenses, besides compromising safety. Predictive maintenance systems offer high value as it would help perform predictive maintenance, identify any overheating and bearing issues in real time. Predictive maintenance has been found to reduce downtime by 50% and maintenance cost savings by 10-40% (McKinsey & Company, 2018). For the case of railroads in Zimbabwe, it means safety and reliability improvements, lower operating cost and increased passenger/freight safety. This research offers relevant and practical solutions towards addressing infrastructure weaknesses of NRZ and other railways operating in similar environments.

From an academic standpoint, the research makes a significant contribution to the literature on efficient condition monitoring. While previous studies on condition monitoring of traction motors mostly focus on costly industrial solutions, the current project presents an example of how relatively cheap components can be used for real-world railway systems (Prabakaran, 2015). This addresses a vital gap in the research and allows for further development of the economy in the country where resources are limited.

On a technical level, this research enhances the application of embedded systems and IIoT by moving the computational burdens from the cloud server, which is resource inefficient, to the physical asset itself. Through the design of the algorithm with respect to the characteristics of the hardware on the low-cost, dual core, 32-bit ESP32 chip, the research shows that complex signal processing can be achieved without using expensive and high performance computing clusters. In addition, this research adopts a novel multi-modal sensor fusion strategy by aligning thermal signals generated by the built-in temperature sensor on the MPU6050 accelerometer, electrical signals produced by the hall effect sensors, and mechanical vibration signals obtained from the MPU6050 accelerometer.

From the economic point of view, the system is meant to be extremely economical because it is built upon open-source microcontrollers and inexpensive, very sensitive sensors. Such a design allows for creating a scalable solution that can work with the tightest budget constraints. Moreover, by making maintenance plans based on the actual state of the assets and not based on time periods arbitrarily chosen beforehand, operational costs can be greatly reduced. The system will ensure that there will be no unnecessary components' replacements, thus saving on expensive replacements and reducing the financial losses that can happen due to the interruption of the transportation of freight through the country. Not only does the system serve as an intermediary solution between periodic human inspections and real-time monitoring of the assets through a web-based dashboard, but it also adds an active hardware safety feature. Instead of being just monitoring the system, the active relay-driven isolation will help prevent the stator blowouts.

## **1.6 Summary**

The previous chapter laid the basic foundation for this research through an analysis of the importance of traction motors in the operations of the National Railways of Zimbabwe (NRZ). The background pointed out the fact that although traction motors form the main part of the railway locomotives, they face tough thermal and environmental conditions, which result in the insulation of the motors being weakened, thus causing motor breakdowns. The main problem that has been identified in this case is that the existing manual predictive maintenance systems used in NRZ lack the ability to detect the weaknesses in insulation of traction motors. The need for this research therefore arises from the need for a cheap method that works well in tough environments.

The scope of this project deals with a lightweight Edge-IoT platform that incorporates the use of ESP32, Hall effect sensor for current measurement and the MPU6050 for acoustic vibration and thermal measurements. Eventually, this chapter forms the framework upon which the design of the diagnostic system is built to increase the reliability of operations of the National Railways of Zimbabwe.

## **CHAPTER 2: LITERATURE REVIEW**

### **2.1 Introduction**

In this literature review, an attempt will be made to evaluate the current state of condition monitoring of traction motors, especially in the railway industry. The literature review will start with the theory of engineering principles on thermal stress and insulation failures. This will be followed by an assessment of different condition monitoring techniques, which include expensive AI frameworks and inexpensive embedded solutions. The gap analysis will show how there is need for an inexpensive multi-sensing real-time system for environments where resources are limited, such as in Zimbabwe.

### **2.2 Theoretical background**

It should be noted that the operational performance of traction motors of railways is greatly dependent on the state of the electrical insulation of these machines, which does not allow the occurrence of short circuits and provides electrical isolation. The traction motors transform the electrical energy into mechanical energy in order to move the locomotive. But the traction motors are highly vulnerable to insulation destruction, which is caused by overheating because of the high load and extreme conditions of operation. According to the theory of engineering, the destruction of insulation is a chemical process which is influenced by the temperature increase.

- Thermal monitoring: The system uses the MPU6050's internal temperature sensor to detect thermal stress and prevent winding insulation failure. Its operation is based on a forward-biased silicon p-n junction within a Proportional to Absolute Temperature (PTAT) silicon-band gap circuit. When a constant current passes through this junction, the voltage drop ( $V_{be}$ ) changes linearly in inverse proportion to the absolute temperature exhibiting a negative temperature coefficient. As heat from the motor casing conducts to the sensor die, this changing analog voltage is digitized by the module's on-board 16-bit ADC. The ESP32 edge microcontroller reads this raw digital register value and convert it into degrees Celsius.
- Vibration sensing (MPU6050): Piezoelectric accelerometers are common in high-end industrial SCADA systems. However, Micro-Electric-Mechanical systems (MEMS) sensors such as the MPU6050 offer a compact, digital-output alternative capable of

measuring acceleration within an 8G range. This is sufficient for detecting most mechanical anomalies in railway environments.

- Current analysis (Hall-effect): According to Joule's Law, the heat generated in a conductor is proportional to the square of the current ( $P=I^2 R$ ). Hall-Effect sensors allow for the measurement of the magnetic field generated by the motor current, proving a safe way to detect overcurrent conditions or phase imbalances without interrupting the high-power circuit.

### **2.3 Review of Related Systems/ Technologies**

The current standards adopted by the National Railways of Zimbabwe (NRZ) have been based on the use of periodic inspection which uses manual procedures. These methods may be able to detect mechanical wear; however, they do not always detect internal insulation deterioration until after a failure has occurred. Some global studies have examined some alternative technologies.

(Dong, et al., 2023) Proposed a diagnostic tool based on temperature signals and Hybrid offline and online neural network models that could be adopted in high-speed trains. Diagnosis of traction motors health status has been carried out through vibrations and acoustic emissions methods. The use of vibration diagnosis can help in the identification of mechanical issues; however, they are unreliable since they are prone to noise interference. Acoustic emission is an effective way of detecting any malfunction; however, it is expensive and involves complicated signal processing, hence cannot be applied in high-speed railways.

In research carried out by (Liu, et al., 2024), Imbalanced Deep Transfer Network (IDTN) is proposed as an advanced method for detecting bearing faults in traction motors. The method adopts transfer learning with imbalance handling algorithms to overcome the main problem of unbalance between rare faulty cases and many normal cases. In addition, IDTN has been designed to overcome distribution mismatch issues that commonly arise in the application of diagnostic models in different machines and environments. Although the system performs better than traditional baseline systems in terms of accuracy and generalisation, the focus of this technology is mainly vibration-based.

(Zhong, et al., 2023) Discuss the progress of traction systems prognosis from the conventional rule-based approach to the use of cutting-edge technologies of Artificial Intelligence (AI) and Deep Learning (DL). The technologies under discussion are CNNs used for analysis of complex vibration signals, and RNNs utilized for analysis of time-series information obtained from temperature and current sensors. Though DL techniques are highly efficient when it

comes to pattern detection, the authors point out some major technological challenges, including high demands on computation power and absence of labelled datasets related to railways. In light of this, there is a demand for more simple technologies of embedded systems for countries like Zimbabwe. For instance, using a gyroscope can be an effective and cheap way of insulation monitoring (Zhong, et al., 2023).

(Wang, et al., 2024) A new advanced multi-factored temperature prediction model is presented in this paper to predict thermal stress in traction motors. The techniques employed here include the Maximal Information Coefficient (MIC) technique for optimal feature selection, and the improved Support Vector Regression (SVR) model for prediction purposes. While traditional systems are based on simple thresholds, this system employs a number of factors including ambient temperature, cooling performance and track gradients to produce robust predictions. Using this technology in predicting thermal stress, preventative measures can be taken before the occurrence of any failures, hence increasing the life span of the motors (Wang, et al., 2024). The paper proves that these systems can be implemented on microcontrollers.

Fault diagnosis of motor bearing based on deep learning especially using Stacked Auto-Encoder (SAE) network has been studied in (Salman & Saad, 2025). The traditional approaches like vibration signal detection often involve manual fault diagnosis that can be vulnerable to interference of noise. In SAE approach, unsupervised learning is utilized which allows efficient extraction of features from the data in an intelligent manner without having any previous knowledge about it. The main technical aspects include sparsity constraints to facilitate data compression, addition of random noise to increase robustness, and use of Softmax classifiers for fault classification.

(Phani, et al., 2021) Studies fault detection in electric traction drives with emphasis on induction machines and gearboxes in locomotive applications. Different non-intrusive monitoring systems are discussed using current and voltage-based techniques to detect faults in the stator, rotor and mechanical components. Some of the important technologies include vibroacoustic monitoring and Electromagnetic Torque estimation for torsional vibration evaluation. Some of the most important signal processing techniques for feature extraction include FFT and PSD analysis. Moreover, high resolution techniques such as Multiple Signal Classification (MUSIC) technique and Motor Current Signature Analysis (MCSA) for the identification of rotor bar and gear tooth breakages respectively (Phani, et al., 2021).

(Kansal & Ediga, 2024) Study IoT based predictive maintenance system designs for transportation fleets to improve efficiency. The important technologies used in these designs include IoT sensors and data analytics for predicting maintenance needs of vehicles.

Using historical maintenance records and sensor readings, the system employs predictive analytics to find out the best maintenance cycles without resorting to reactive methods. The above research shows how the use of personalized maintenance procedures and evidence-based decision making can minimize downtime and environmental impacts of operations. Even though the application applies to general fleets of vehicles, the concept of integrating sensors into maintenance and prediction models is very pertinent for industrial motor health monitoring (Kansal & Ediga, 2024).

(Singh, et al., 2020) Demonstrates the effectiveness of employing low-cost embedded systems for real-time fault detection. All this revolves around the implementation of particular algorithms on microcontrollers that help to analyse the performance of induction motors. Several industrial processes employ expensive PLCs but the study shows that an 8-bit or a 32-bit microcontroller can handle the required speed of ADC (Analog-to-Digital Conversion) for measuring the changes of temperature and electricity in the environment of the motor. Technical feasibility of employing microcontroller in the process of assessing the health of locomotive traction motors becomes evident in cases where restrictions exist in terms of cost and space. However, the processing memory of such systems is too small to implement machine learning algorithms.

(Mohammad, et al., 2025) It is evident from recent advances in the monitoring of railway condition that there is an inclination towards proactive maintenance via the analysis of high frequency vibration signals. It has been shown that the application of machine learning systems enables extraction of important statistical parameters such as crest factor and kurtosis to detect events with an accuracy of 98.89% through Multi-Layer Perception (MLP) systems. While these systems make effective use of Hall Effect sensor to synchronize speed, their use is confined to fixed rail tracks.

(Antti, 2024) Points out that current predictive maintenance systems for railcars have been found to adopt centralized diagnostics units (CDUs) and Ethernet-based data acquisition for multisource data fusion. Though the current research work concentrates on energy storage systems' health management through GPR and ensemble methods such as XGBoost, these systems also share the same sensor needs as those required for the detection of traction motors, namely, vibration and temperature sensors. Unlike larger-scale systems that aim at maintenance scheduling, small-scale systems can make use of microcontrollers to incorporate Hall Effect sensors and safety relays to achieve power disconnection.

Modern railway maintenance practices are progressively moving towards the use of Digital Twin (DT) technology which is comprised of virtual twins together with IoT sensors and is

used to obtain real-time predictive analytics (Emmanuel, et al., 2025). However, despite being useful in modelling the performance of traction induction motors, such hi-fidelity systems are always constrained by high cost and complexity of integration. In the case of resource-scarce environments like those in the National Railways of Zimbabwe, simple decentralized systems would work better.

Predictive maintenance practices that are current include Smart TCMS as illustrated by (Gozali, et al., 2025). They rely on real-time sensor data in combination with machine learning techniques to determine the degree of degradation of different parts of the railway system. The architecture focuses on critical parameters like vibration and temperature and determines the expected life span of the components through centralized data analytics servers. Of importance to note is the use of decision tree (DT) algorithm in predicting failure since it involves low overhead computation compared to the deep learning models. These systems improve the management of the railway through secure communication over MQTT while localized microcontroller-based solutions may help in autonomous hardware protection.

(Bhoi, et al., 2025) Suggest a combination of edge-cloud system design that enhances condition monitoring through novel detection in real time at the edge of the network. In this design, isolated high-frequency sensors along with an ANN work on edge devices to transfer abnormal data to the cloud, which is classified using Random Forest methods. Although this method reduces the cost of data transmission by 94% in comparison to conventional cloud-based approaches, some resource constraint environments such as the NRZ require a decentralized approach. As opposed to high fidelity edge-cloud systems, local designs that employ low-cost microcontrollers help deliver immediate and autonomous protection of hardware through relays.

(Mallioris, et al., 2024) There has been a shift in the architecture of PdM from the previous corrective and periodic preventive maintenance systems to more sophisticated condition-based PdM architectures that utilize technologies related to Industry 4.0. Modern architectures employ the Internet of Things (IoT) and embedded systems such as single-board microcontrollers to enable real-time streaming of big data from smart sensors that are mounted on machines (Madushele, et al., 2026). Condition monitoring is used in both industrial and railway industries, where health states can be detected using input parameters such as vibration, temperature of bearings and the rotational speed. Although physics-based and knowledge-based models offer interpretability, intelligence-based data models, algorithms such as Support Vector Machines (SVM), Random Forests and Artificial Neural

Networks (ANN) are becoming popular due to their capacity to capture complicated non-linear relations without requiring explicit physical behaviour models. Prescriptive maintenance attributes are being incorporated into advanced architectures, and unlike the previous failure prediction mechanisms, they involve controlling events such as using automation mechanisms to isolate power to improve safety.

The shift towards proactive PdM from the conventional find and fix model is motivated mainly due to the weaknesses associated with the former that is characterized by high expenses, safety hazards to staff, and poor data quality (Gbadamosi, 2023). Although WSN technology has traditionally formed the backbone of the fault discovery and failure prediction process, they usually face serious difficulties with regards to the processing and validation of large volumes of data generated by large rail networks. In comparison, the modern IoT architecture makes use of a layered structure involving monitoring nodes, gateways, and streaming analytics layer for effective data at high velocity.

These technologies make use of particular types of sensors for vibration and thermal analysis which are usually complemented with the use of RF transceiver technologies for long-range communication and structural health monitoring (Gbadamosi, 2023). Also, the use of Deep Learning technologies like CNN and RNN has improved the efficiency of predicting non-linear failures than traditional statistics-based models. Modern technology systems usually have augmented reality and digital twin-based immersive visualization features that allow for remote diagnosis and increase worker safety by reducing the time spent on rail lines.

(Bianchi, et al., 2025) The approach adopted in the current model for the railway network monitoring is a shift from the conventional preventive and periodic maintenance model to a continuous data-driven Predictive Maintenance (PdM) approach. Traditional models often adopt a method which involves manual inspections or use of dedicated diagnostic trains equipped with accelerometers, ultrasonic sensors, and lasers. Although these approaches are highly reliable in maintaining safety standards over vast portions of the track, the process remains discontinuous, labour intensive and prone to human errors. Modern models have opted for WSNs and IoT sensors.

Emerging tools including high-resolution photogrammetry, fibre optic sensors and thermo vision cameras now complement traditional inertial sensors by evaluating track geometry, subgrade stiffness and thermal anomalies with enhanced precision. A significant technological divergence also exists between classical statistical models and Artificial Intelligence (AI) algorithms. Statistical models primarily facilitate interferences based on Modern technologies like high-resolution photogrammetry, fibre optic sensors and thermo

vision cameras have come to supplement conventional inertial sensors to analyse track geometry, subgrade stiffness and thermal conditions more precisely. There is a notable difference in technology application between classical statistical models and Artificial Intelligence (AI) models. The use of statistical models is mainly for inference of specific data distribution while AI models do better in mapping complex and non-linear failures for accurate diagnostic prediction. Although they have better scientific accuracy, ensemble models usually demand large storage space and have less interpretability compared to simpler models (Bianchi, et al., 2025). Lastly, the use of Digital Twin technology helps in simulating infrastructure behaviour for autonomous decision-making and diagnosis in a digital environment.

patterns to improve the prognostic classification. In spite of being scientifically more accurate, however, such models generally consume more storage space and present less interpretability in comparison with simple models (Bianchi, et al., 2025). The last innovation introduced in the current state of affairs is related to Digital Twin technology, which helps in simulating the infrastructure performance in order to make independent decisions in a safe environment.

The evolution of maintenance in the railways sector from the reactive paradigm towards a new predictive maintenance architecture has been made possible due to advanced simulation and sensing technologies. (H-Nia, et al., 2024) propose a framework of predictive maintenance based on Multibody Simulation (MBS) to predict the lifespan of wheels and rails. Contrary to the predictive architectures that use historical sensor datasets to conduct analysis, the MBS uses physical interaction models of vehicle and track in order to simulate wear and Rolling Contact Fatigue (RCF). It makes it possible to predict wear of wheel/rail pairs under such environmental conditions like harsh winters.

On the other hand, current IoT-based systems rely more on the inclusion of physical instruments such as trackside accelerometers and microcontroller-based temperature measuring devices that help in detecting anomalies in real time. Although the use of simulation tools like GENSYS is very effective when it comes to predicting anomalies in the structural parts through their virtual representation, they are also being coupled with the use of sensor-based systems utilizing thermal and vibrational sensors to ensure validation of the virtual models and instant protection.

(Ariyachandra, et al., 2025) States that the conventional maintenance framework that uses either planned or corrective maintenance is becoming obsolete because of high cost and frequent unexpected disturbances. The modern predictive maintenance (PdM) frameworks, on the

other hand, make use of Digital Twin (DT) and Cyber Physical System (CPS) to provide real-time monitoring and data-driven solutions. While conventional techniques are mainly based on periodic manual inspections, the present technology incorporates an array of specialized sensors and monitors. For example, ultrasonic and eddy current tests are used for detecting defects in the rails internally and externally, respectively. Strain gauges and GPR are applied in sleeper, bridge, and ballast monitoring for structural defects. These systems are also augmented with a combination of various data feeds from IoT devices and control systems analyzed by means of artificial intelligence and big data analytics.

Moreover, systematic evaluation tools such as MCDM scoring schemes are utilized to analyze and select the most effective and costly PdM strategies. Nevertheless, deploying these sophisticated architectures is faced with various obstacles, as opposed to previous designs, in relation to data interoperability issues and the high costs of sensors installation. Nonetheless, despite these impediments, the shift to integrated DT-CPS-based designs provides considerable gains in terms of infrastructure robustness, safety, and sustainability.

Conventionally, PdM architecture used in the railroad industry has been characterized by batch machine learning (ML), in which the algorithms have been trained offline on pre-existing, static data sets. Although reliable, these architectures lack the capability to accommodate the fast data flows from today's on-board sensors due to their high latency and inability to adapt to change or concept drift (Le-Nguyen, et al., 2023). Modern architectures are therefore increasingly adopting online machine learning (OML), whereby the data coming from the sensors is analysed on an instance basis.

Some of the key tools in this space include the River library, which provide specialized algorithms such as automatic feature scaling and online clustering to keep track of the system health in real time. Unlike typical signal processing tools, which rely on manual feature engineering, the OML tools automatically process the data by providing functionality to deal with missing values and normalization, making them better suited for dynamic environments. From the comparison of these methods, it can be seen that whereas batch learning continues to be the gold standard for analysing failures in the long run, OML is a better approach to monitoring system health in real time.

The current railway network is shifting from the conventional Corrective and Time Based Maintenance systems towards advanced Condition Based Maintenance systems for improving the availability and reliability of the railway system. A key component in the design of these advanced systems is the implementation of Fault Detection and Isolation (FDI) and Fault Detection and Diagnosis (FDD) systems which are broadly classified into

Model Based, Data Driven, and Signal Based approaches. The Model Based approach involves the use of mathematical models to calculate residuals as the differences between the actual and predicted system responses and requires extensive physical understanding of the system.

Tools like MCSA can be considered as a signal-based solution since they analyse the information coming from real-time measurements such as current and speed without being trained in advance (Garramiola, et al., 2018). It should be noted that these techniques pay particular attention to important subsystems, such as electric motors, power electronics and even sensors since they are the most likely to lead to a traction drive malfunction. In contrast to data-driven solutions, technologies like MCSA can be used to implement HA and PHM in order to carry out preventive maintenance of a system.

Condition monitoring systems based on vibrations have their own distinctive features defined by the signal processing tools used for mechanical health evaluation. (Randall, 2011) provides a clear division between two approaches: systems with proximity probes that allow measuring relative shaft displacement and those that use accelerometers for absolute casing vibration measurements. While proximity probes are required for vibration analysis of machines with fluid-film bearings, they have certain drawbacks related to their inability to detect vibrations caused by the electrical or mechanical shaft defects. To solve this problem, sophisticated vibration monitoring systems use algorithms for run-out subtraction and slow roll compensation.

Moreover, traditional industrial standards such as the American Petroleum Institute's API670 serve as the regulatory standards for such architectures, although the use of these standards varies as far as their ability to incorporate error correction and dynamic ranges. The difference between traditional periodic inspections and modern continuous monitoring is that the latter needs to consider the non-stationary issues related to thermal growth and the wear and tear of thrust bearings, which may affect the position of sensors throughout long periods of operations. Modern technologies, therefore, tend to support architectures that include high-frequency data sampling and strong algorithm filters.

## **2.4 Gap Analysis**

Modern monitoring techniques based on vibrations and acoustic techniques presented by (Dong, et al., 2023) are often hampered by a strong presence of background noise in the environment, greatly decreasing the diagnostic accuracy in railway systems. In addition to this, acoustic emission approaches demand very expensive high-precision equipment and

complex processing tools, therefore being unaffordable for large-scale implementation in countries such as Zimbabwe due to their high cost. A serious problem here is the fact that the introduced hybrid neural network models are prone to deteriorating in terms of accuracy with time if not updated online regularly.

Imbalanced Deep Transfer Network IDTN presented by (Liu, et al., 2024) is mostly designed to detect faults in the mechanical parts of a bearing and not to assess overheating of an electric insulation of a traction motor. Although it is quite a sophisticated approach, it was tested using artificially assembled datasets in the laboratory setting rather than embedded implementation. The latter makes it hard to implement this technology in the practice of operators such as the NRZ since it requires powerful computing resources, which are typically not present in microcontrollers used in railways.

(Zhong, et al., 2023) Highlight that deep learning models for railway assets often fail to generalize across different locomotive types or varied operating environments. A major shortcoming in current AI-driven research is the severe scarcity or reliable, labelled “fault” datasets within the railway sector to train these complex algorithms. Because deep models typically require processing resources far beyond basic embedded hardware, there remains an urgent need for simpler, rule-based systems that can provide immediate, actionable alerts without the need for massive historical data or high-end servers.

Despite successful monitoring by (Singh, et al., 2020), the work conducted was only applicable to single induction motors operating in a stationary environment in industrial set-ups. The main limitation of this existing solution is that it does not consider the highly vibratory and mobile nature of the locomotives. 8-bit microcontrollers are also limited in terms of storage capabilities that would allow the recording of health trend data for extended periods of time. There is thus the need for solutions that will allow data transmission to a central database.

(Wang, et al., 2024) Employ Support Vector Regression (SVR) to predict the temperature, however, its complex nature means that it cannot be deployed in an ESP32 board. Most predictive algorithms present in current literature consume a lot of data overhead and environmental parameters which are hard to measure on old locomotives. The current gap is the lack of lightweight algorithm for predictive maintenance on simple microcontrollers.

(Kansal & Ediga, 2024) Offer an effective IoT solution for fleets of transport vehicles, and their main concern is the generic features of cars such as the condition of tires and oil levels in them. In this way, the authors ignore the specific features of the chemical and electrical

nature of a traction motor breakdown. It means that focusing on the specific connection between heat and the motor current will solve the problem mentioned above.

(H-Nia, et al., 2024) Present an advanced Multibody Simulation (MBS) system for predicting the life cycles of rail and wheel systems, but there is still a huge limitation in terms of its computational complexity and data entry challenges. The MBS simulation is dependent upon accurate physical parameters like rail profile, material property, and suspension stiffness that may not be available or are usually outdated in the railways industry or in places like the National Railways of Zimbabwe (NRZ). Such dependence on a complex physical model creates a problem of calibration, whereby the simulation might not work properly owing to unorganized environmental conditions, such as extreme weather conditions and unexpected presence of debris on the rails. In addition, the study focuses mainly on life cycle prediction and does not consider the issue of interaction between the system and low cost IoT sensors on the rails or inside the train in order to provide feedback for real time monitoring of events, like sudden mechanical shocks and failures of cooling systems.

Therefore, there is an obvious need for hybrid architecture to distil such physical simulations into algorithmic ones that could be run in a power-constrained edge device. This way, prediction would be possible in real time at the local level without any use of high-powered computing clusters, hence bringing predictive maintenance closer to rail fleets (H-Nia, et al., 2024).

(Ariyachandra , et al., 2025)Have provided a thorough conceptual framework for combining DTs and CPS in rail infrastructure. However, the biggest weakness is that no roadmap has been provided to implement DT/CPS technology locally in case of low levels of digitalization. The model assumes the existence of a perfect world with fast connections and many pre-integrated sensors which contradicts the reality since rail infrastructure is aging and has unreliable connectivity. There is a huge connectivity issue in this architecture despite its technical soundness. While the cloud integration has been properly addressed at the high level, this paper does not offer any solutions for data processing under network failure conditions or in cases of narrow bandwidth. Moreover, this research lacks addressing the hardware software limitations of cost-effective, open-source microcontrollers.

Most of the DT-CPS systems are engineered in such a way that they can work on industrial servers that have huge amounts of memory and overhead of processing, which makes them unsuitable to be used in conjunction with 32-bit microcontrollers, which are often the only feasible choice in large-scale, low-budget projects (Ariyachandra , et al., 2025). Hence, the

objective of this research will be designing protocols that would enable the system to diagnose autonomously from the sensor nodes' end.

(Le-*Nguyen*, et al., 2023)Brings about an important change in favour of online machine learning (OML) that is able to handle rapid streams of railway data, but at the same time, there is an important flaw in terms of interpretability and reliability of data-driven models of OML. The problem is that OML is excellent when it comes to handling huge amounts of quickly moving sensor data without having to provide any massive storage capacities, but they remain quite opaque, and they do not have the capacity to provide any kind of correlation between their output and the mechanical problems like worn out bearings or insulation failure in windings. Moreover, this research does not investigate in depth computational costs of continuous learning algorithms on edge devices. Even though OML use the memory in a better way compared to the batch learning approach, this process takes place all the time which increases the energy consumption, and that poses an important threat for battery-powered devices.

The study also fails to mention ways to mitigate the effects of non-stationary noise prevalent in hostile industrial environments, leading to concept drift and higher false alarms. In order to rectify the shortcomings mentioned above, a need arises for physically-based OML approaches that will combine statistical learning approaches with the well-established mechanical thresholds to develop a better and more efficient monitoring system. The proposed solution is not only more reliable and understandable but operates efficiently in constrained environments such as the NRZ without any reduction in diagnostic capabilities and excessive draining of limited power sources (Le-*Nguyen*, et al., 2023).

(Garramiola, et al., 2018)Provides an exhaustive review of techniques used for diagnosing faults of railway traction drives; however, their analysis reveals the existence of an ongoing problem concerning prognostic ability in the current literature on the topic. Most of the examined systems were developed for detecting and isolating (FDI) fault; therefore, a failure would only be detected after it has occurred or reached its critical level. There is very little mention of the health assessment systems (HA), capable of precisely predicting the Remaining Useful Life (RUL) of the traction motor components subjected to variable load conditions typical for railways. Another issue with data-driven algorithms mentioned in the review is the amount of data required for proper training; most of them, including Neural Networks and PCA, are batch-heavy and require large datasets, which are hard to obtain in case of legacy fleets. This highlights the necessity for affordable and integrated hardware-software nodes capable of combining multiple data sources such as temperature, vibrations, and electrical signals to give an overall health index. Such an instrument must be designed for

upgradeability in old locomotives in order to bridge the gap between the costly and proprietary diagnostic methods and the requirement of cost-effective real-time monitoring in the industrial settings such as the National Railways of Zimbabwe (Garramiola, et al., 2018). (Randall, 2011) Defines the fundamental principles of vibration-based condition monitoring yet a significant retrofitting gap exists regarding the application of these techniques to existing, enclosed railway machinery. The text emphasizes high-precision proximity probes for measuring relative shaft displacement, which are not only expensive but often impossible to install on legacy traction motors without extensive and costly mechanical modifications. While accelerometer-based casing vibration is discussed, the literature fails to address the harsh environment noise challenge where track-induced vibrations and electromagnetic interference (EMI) from the motor windings can easily drown out the subtle high frequency signatures of early stage bearing wear.

Moreover, the computational complexity involved in the use of these vibration signal processing algorithms may be too high for real-time computation by microcontrollers except if properly optimized. This becomes a challenge for low-cost development and implementation of the technology. In order to overcome this barrier, there is a requirement of research work on vibration algorithms that make use of simpler statistical features and are hardware-oriented to provide reliable diagnosis using cheap hardware. This will ensure the large-scale deployment of vibration detection technology in trains.

## **2.5 Conceptual Framework/ Proposed System Basis**

The concept of the proposed smart real-time condition monitoring and predictive maintenance system is based on the findings and synthesis of the literature review and designed in such a way that it addresses the technological shortcomings of legacy systems. In order to move away from the traditional high-latency, cloud-based, and expensive maintenance infrastructure systems, this study proposes a multi-modal, decentralized edge computing model. This framework is based on three key pillars which have been identified based on the findings of existing literature. These three pillars include multi-nodal sensing, hardware-aware edge processing, and anomaly detection.

The first component of the framework employs a multi-modal sensing approach to acquire the overall health status of the traction motor. (Garramiola, et al., 2018) Note that a thorough fault detection and diagnosis (FDD) in the railway traction system cannot be based on one operational parameter owing to the complexity of thermal, mechanical, and electrical stresses involved. Hence, the suggested systems integrate three different streams of information:

temperature measurements through the on-chip temperature sensor of the MPU6050 to sense any possible thermal run-away, current measurements through Hall effect sensors to carry out Motor Current Signature Analysis (MCSA), and vibration measurement. Through combining these multi-modal data sources at the physical layer level, the framework avoids the diagnostic dead zones found in single parameter-based systems, thus addressing the requirement of comprehensive health assessment (HA) raised by current literature.

The second pillar pertains to non-intrusive retrofitting and hardware-aware edge signal processing specifically addressing the limitations highlighted by (Randall, 2011). In view of the fact that older generation traction motors are unable to integrate intrusive proximity probes owing to costly mechanical re-engineering, the suggested architecture employs a casing-mounted and accelerometer-based approach based on an MPU6050 sensor. In order to overcome the mathematical complications as well as heavy processing burden associated with vibration analysis as highlighted by (Randall, 2011), the suggested framework uses local and light statistical signal extraction. Instead of continuous processing of high frequency raw fast Fourier transforms (FFTs), the suggested system architecture makes use of a powerful dual core 32-bit ESP32 microcontroller to compute time domain features at the edge.

Finally, the third pillar builds a decentralized data reduction technique and an alert system inspired structurally by the paradigms of OML (Le-Nguyen, et al., 2023). This paradigm is in place instead of sending large volumes of sensor data to a centralized server, a process that causes delay in decision making and is dependent upon the presence of intermittent network connections. These paradigms are incorporated in this system in the form of a thin-edge intelligence protocol. The ESP32 acts as a localized computing node that analyses live data based on dynamically scaled statistical threshold values.

## **2.6 Summary**

The current chapter offers a thorough theoretical background as well as a critical review of the literature that exists currently for condition monitoring, fault diagnosis and predictive maintenance systems and approaches in the context of the railways industry. The review of related systems and technologies has considered their underlying architectures, tools and sensing methods which form the basis of modern standards, analysing different approaches such as model-based, data-driven and signal-based.

Due to the gap analysis conducted in the present work, it has become clear that those well-established approaches often fail when being applied in the case of old rolling stock in resource-constrained industrial environments. In particular, the major systematic

shortcomings found in the literature include prohibitive data entry barriers, high computational and memory costs that do not suit low-power edge devices, dependency on persistent cloud connectivity and non-physical interpretability of data-driven black boxes.

However, in order to address such technical limitations, a comprehensive conceptual framework is defined for the designed system. Through a careful integration of the best qualities of current multi-sensing approaches and removing their computational shortcomings, an edge-computing based approach has been devised. The developed approach involves the use of a cheap 32-bit microcontroller (ESP32) that performs local hardware-specific signal processing and extracts time-domain vibration properties along with synchronized temperature and current values. In summary, this chapter has highlighted the need for an intrusive and autonomous edge-computing-based approach and set the groundwork for future chapters.

## CHAPTER 3 METHODOLOGY

### 3.1 Introduction

This chapter describes the systematic approach adopted to design, develop and validate the traction motor condition monitoring system. It outlines the engineering design methodology, specifies the hardware and software requirements and details the system architecture. Furthermore, the chapter explains the implementation process including circuit design, signal flow and the mathematical models used for sensor data conversion, providing a blueprint for the physical prototype development.

### 3.2 Research design/ Project approach

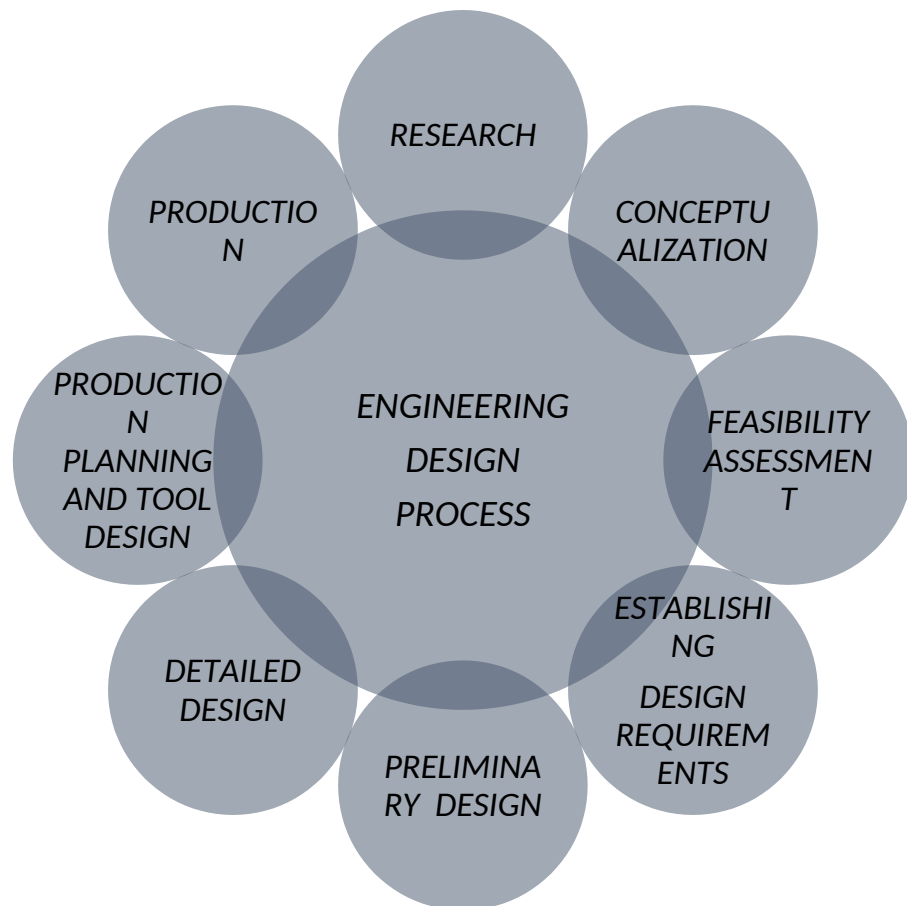


Figure 3. 1 Engineering design process

This project follows a prototyping and engineering design methodology. This approach is selected because it allows for iterative development which is the designing, building and testing small-scale versions of the system before final deployment.

Justification:

1. Iterative testing - Allows for the calibration sensitive components like the MPU6050 sensor in a controlled environment before exposure to locomotive conditions. Through iterative testing, the threshold values in the micro-controller unit can be fine-tuned. This prevents false positives.
2. Cost-effectiveness - By using a prototyping approach, design flaws can be corrected on a breadboard level before committing to a permanent PCB (Printed Circuit Board) fabrication. Prototyping allows the designer to evaluate if the micro-controller has sufficient processing power and I/O pins for the task.
3. Proof of concept - It provides a tangible model to demonstrate the feasibility of using low-cost sensors. It allows for a physical check of how the system will be mounted. For example the prototype helps determine if the ESP32 and sensors need specific housing to protect them from dust, grease and electromagnetic interference (EMI) common in motors.

### 3.3 System Requirements Specification

#### 3.3.1 Hardware Requirements

For ensuring that the system is robust and cost-effective, the following are the industrial quality parts that have been chosen:

**ESP32 Microcontroller:** This is used as the main controller of the system and has dual cores with 32-bit processors. It performs data acquisition, sensor fusion, and signal processing in real time.



Figure 3. 2 ESP32 microcontroller

**Current sensor:** It is the current sensor that monitors the current of the motor. The current signals from the motor are then analysed using MCSA so as to detect any imbalance in the motor current.

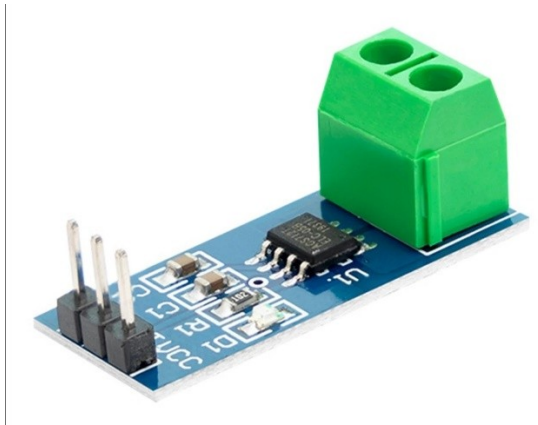


Figure 3. 3 Hall Effect sensor

**MPU6050 (Accelerometer/Gyroscope module):** It's a MEMS (Micro-Electromechanical System) device which detects any vibration of the physical acceleration in the three directions of axis. The vibration information is useful to detect any mechanical anomalies such as bearing pitting and structural looseness. Additionally, the gyroscope has a built-in temperature sensor that will read the motor temperature.

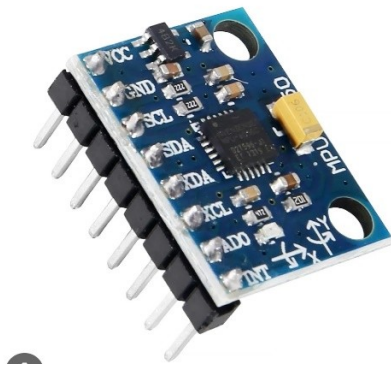


Figure 3. 4Gyroscope mpu6050

**Functions of Relay Module:** Acts as a controlled electrical switch. In case the ESP32 registers any abnormality or breach of threshold value which implies any catastrophic failure, then it sets off the relay switch thus disconnecting the circuit from the motor.



Figure 3. 5 Relay Module

**LEDs (Light-Emitting Diodes):** A direct visual diagnostic system on the physical asset. Coloured lights of different colours (green, indicating good health; yellow, indicating warning; and red, indicating critical condition) enable the driving crew to instantly determine the health of the physical asset.

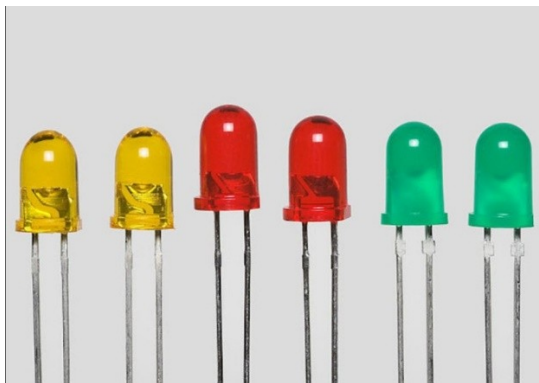


Figure 3. 6 Amber, red and green LEDs

**Buzzer:** Acts as an audio alert system. It creates local audio alerts along with visual alerts through the LEDs at the threshold breach times when immediate attention is required in the noisy and vibration-filled industrial setting.



Figure 3. 7 buzzer

**Lithium Battery:** Ensures a dedicated source of power. Thus ensuring that the fault recording or fault reporting system continues to operate uninterrupted even when there is a breakdown of power within the locomotive engine.



Figure 3. 8 Lithium-ion battery

**Resistors:** Used to control and limit current flow throughout the system. They protect the LEDs from overcurrent and configure voltage divider networks for the NTC thermistors.



Figure 3. 9 resistors

**Jumper wires:** Act as the physical electrical conductors that establish point-to-point signal and power connections between the individual sensor modules, passive components and the core microcontroller during the developmental stages.



Figure 3. 10 Jumper wires

**Vero board:** Provides a permanent prototyping base. The individual components and jumper wires are soldered directly into its parallel copper tracks.

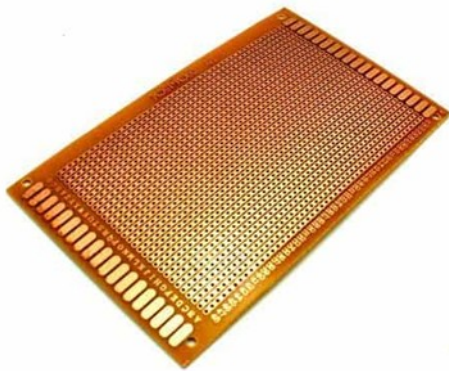


Figure 3. 11 Vero board

### 3.3.2 Software requirements

- Programming tools- Arduino IDE, it provides a massive ecosystem of libraries for the sensors (MPU6050 and Hall Effect sensor).
- Simulation tools- Wokwi design suite, it allows for full schematic capture and circuit simulation.

### 3.4 System architecture/ Block diagram

The system architecture follows a modular design, transitioning from raw data acquisition to intelligent processing and remote notification.

#### 3.4.1 Overall Block Diagram

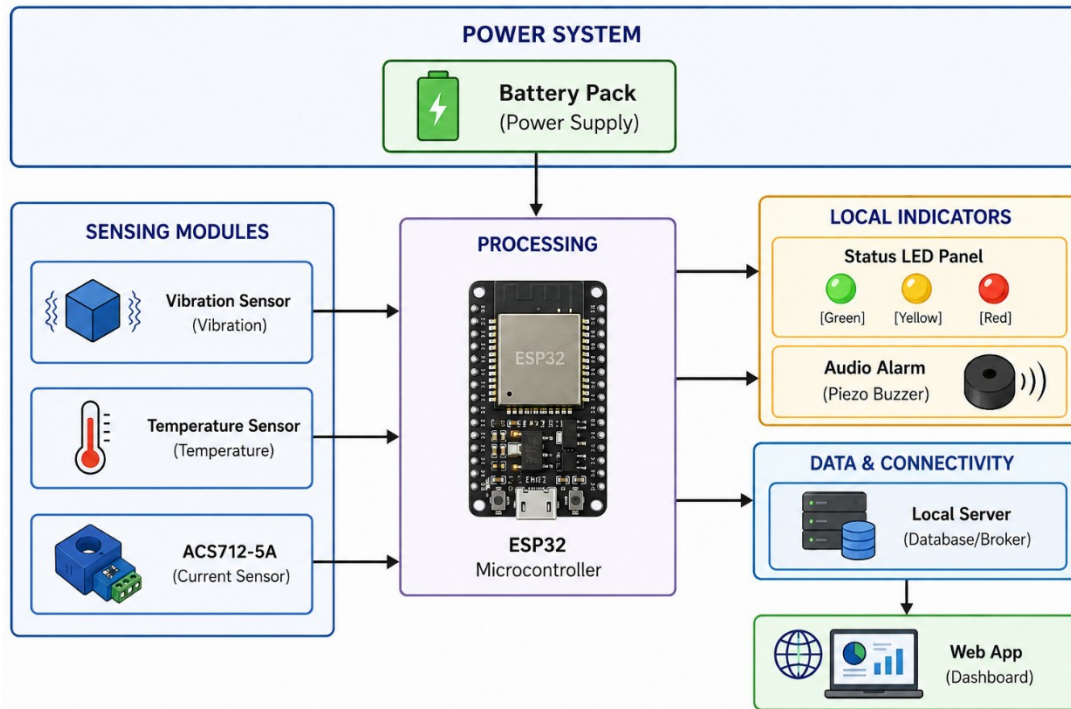


Figure 3. 12 System's block diagram

#### 3.4.2 Subsystem Description

1. **Power Supply Stage**: This subsystem ensures the entire monitoring device receives a clean stable and uninterrupted electrical power. A 12V DC source from the lithium battery is regulated down by a DC-DC buck converter to a stable 5V or 3.3V. Capacitive filtering is implemented at each stage to suppress electromagnetic interference (EMI) and unwanted noise.
2. **Input Stage (Perception)**: Consists of the gyroscope for continuous temperature tracking and vibration analysis and the Hall-Effect current sensor providing continuous analog feedback.
  - **Thermal unit (internal temperature sensor MPU6050)**: Measures the surface temperature of the motor.
  - **Mechanical vibrations**: The MPU6050 accelerometer detects micro-movements and high-frequency structural shaking across

three physical axes capturing structural anomalies before they cause a physical breakdown.

- Current monitoring unit (Hall Effect sensor): The Hall-Effect sensor provides isolation. It measures the magnetic field around the motor leads to determine the current load. This allows the ESP32 to correlate high heat with high current to distinguish between operational loads and electrical faults.
3. 3. Control Stage (Processing): The core of the system consists of ESP32 microcontroller. This subsystem is designed for managing all processes. It determines the moments of sensors readings, stores the received data streams, as well as performs mathematical calculations within its internal environment. It is responsible for coordinating the activities of all other subsystems and determining exactly when the state of the motor degrades significantly enough to generate an alert or shut down the motor.
  4. 4. IoT data transmission and visualization: This subsystem connects the physical asset and the maintenance management team with each other via remote data logging and real-time visualization. It uses the in-built Wi-Fi capabilities of ESP32. The dashboard is used as the central graphic user interface (GUI), which represents the state of traction motor operation through various gauges, historical trends and digital displays.
  5. 5. Actuator and isolation subsystem: This subsystem serves as the physical protection wall for the electronics associated with monitoring as well as the traction motor. Based on the relay module, this subsystem works as an automatic, high power switch that is commanded through logic of ESP32. During the normal operations of the system, the relay stays in its usual position. But the instant that the primary processor notices any critical level breach or failure pattern and sends the emergency signal to the engineer's dashboard, the relay gets tripped.
  6. Output Stage: This subsystem manages the local reporting.
    - Emergency Actuators: A 5V active buzzer provides an immediate high-decibel alert to ensure maintenance personnel are immediately notified.
    - Visual status: A series of colour-coded LEDs display a running traffic light diagnostic status (Green for healthy operation, Yellow

for warning thresholds and Red for critical mechanical or thermal failure).

### 3.4.3 Sub system descriptions

The signal flow of the system follows the order of events in which data flows through from the changes of physical parameters in the traction motor to processing at the edge, protection, and visualization of these actions. The block diagram illustrates a single-direction signal flow that is classified into five stages:

- a) **Data acquisition (Input stage):** The signal chain originates at the physical boundary of the traction motor, where three distinct multi-modal sensors continuously translate electromechanical environmental changes into electrical signals.
  - Thermal pathway: The NTC thermistor captures heat fluctuations on the stator frame. As the temperature rises, its internal resistance drops dynamically modifying an analogue voltage signal that is fed directly into one of the ESP32's Analogue-to-Digital Converter (ADC) pins.
  - Electrical Pathway: The current sensor tracks the current drawing through the motor supply lines. It outputs a proportional voltage waveform corresponding to the physical current amplitude which is sent to the microcontroller for tracking electrical loading and phases.
  - Mechanical Pathway: The MPU6050 sensor registers high-frequency vibrations and dynamic structural shifts across three axes. These raw inertial forces are instantly converted into digital values inside the sensor's internal register and transmitted directly to the microcontroller over a high-speed, noise-resistant I<sup>2</sup>C serial communication bus.
- b) **Central Processing:** The dual core-core processor samples the raw input lines and runs hardware-aware mathematical algorithms to smooth out high-frequency industrial noise. Instead of exhausting its memory by forwarding raw data streams, the ESP32 processes the signals mathematically to extract specific time-domain health features. The microcontroller then continuously compares these computed metrics against pre-defined safe operational threshold limits stored within its program logic.
- c) **Local Actuation and Protective Feedback:** Based on real-time algorithmic evaluation, the ESP32 dynamically routes signals down three localized action paths depending on the health state discovered.

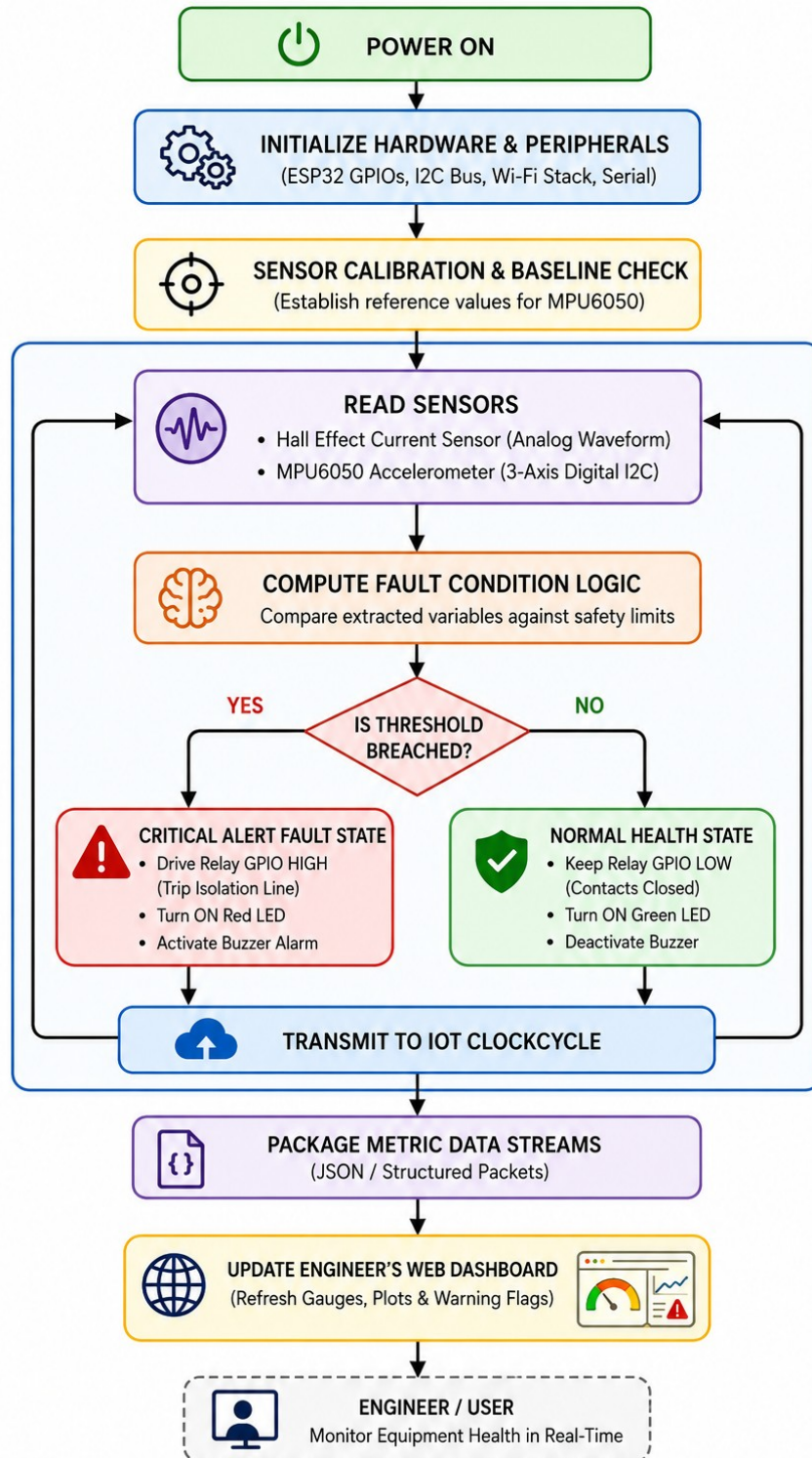
### **Safety Isolation**

In case the extracted parameters reach a threshold that points to serious problems like overheating of the winding and damage to the bearings, ESP32 will trigger the GPIO pin to go high, which triggers the relay circuit to activate its coil and thus open its contacts, resulting in the interruption of control lines or isolation of vulnerable parts of the circuits of the locomotive.

### **Local Alarm**

In case of any abnormalities with the train, ESP32 will switch the GPIO lines to the local alarm cluster. While everything is fine, green LED will light up. When approaching a threshold, yellow LED will turn on and when there are serious problems, the red LED will turn on as well as a PWM signal for the buzzer to produce a loud acoustic signal.

d) Remote Visualisation (Transmission IoT via Internet): While the local hardware responds, the processed health data is inputted into the network stack of the ESP32. These are packaged as the essential performance data of the system in data packets, including the maximum current drawn and the vibration levels. These data packets are then transmitted wirelessly via the IP network to a web-based dashboard. Through this process, the raw physical forces exerted on the motor have been converted to live updating gauges and trend lines on a web page.



System

Figure 3.13 System's flowchart

Firstly, it begins by switching on the ESP32 and initialization of all hardware devices like the sensors, Wi-Fi module, etc. Further, the process includes calibration of the sensors and continuous acquisition of the temperature signal (from MPU6050), current signal (from Hall effect sensor), and vibration signal (from MPU6050). The obtained signals are filtered and

conditioned, and some of their parameter values are considered for assessing the condition monitoring of the motor. The values are compared with some threshold values to detect whether the motor is in a healthy state or not. In case the motor is unhealthy, then the relay, buzzer, and red LED are turned on, otherwise, everything works normally and green LED is on.

### 3.5 System design and implementation

#### 3.6.1 Hardware design

MPU6050 was interfaced with the ESP32 using the I<sup>2</sup>C communication protocol through GPIO21 (SDA) and GPIO22 (SCL), which runs on 3.3 V voltage rails. In the case of the current sensor (ACS712), its outer two pins were connected with 3.3 V and GND. On the other hand, GPIO26 controlled the relay module for switching off the motor in fault condition, whereas the active buzzer was interfaced with GPIO27. There were three LEDs connected; one green (GPIO13) and red (GPIO12).

Table 3. 1 Pin out allocation summary

| Component    | Interface        | ESP32 GPIO | Purpose                      |
|--------------|------------------|------------|------------------------------|
| MPU6050 SDA  | I <sup>2</sup> C | GPIO21     | Vibration / temperature data |
| MPU6050 SCL  | I <sup>2</sup> C | GPIO22     | I <sup>2</sup> C clock       |
| Green LED    | Digital OUT      | GPIO13     | NORMAL status indicator      |
| Red LED      | Digital OUT      | GPIO12     | CRITICAL status indicator    |
| Buzzer       | Digital OUT      | GPIO14     | Acoustic alert               |
| Relay module | Digital OUT      | GPIO26     | Motor emergency cut-off      |

#### i. Interface of the current sensor and the ESP32

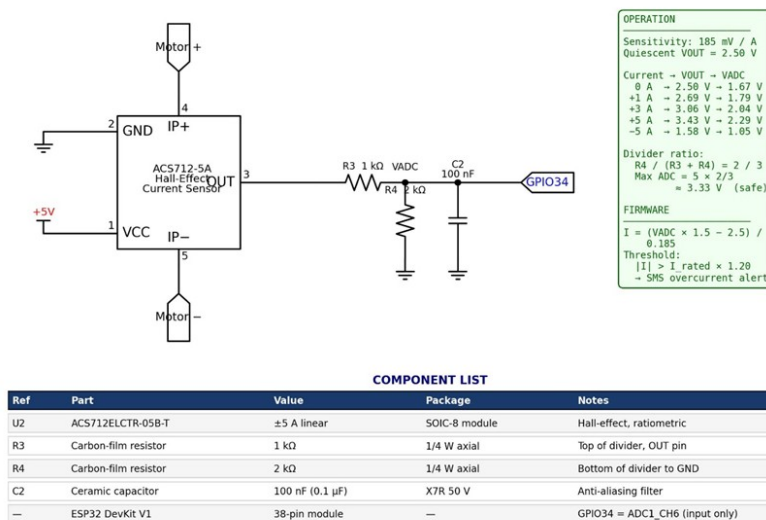


Figure 3.18 Interface between a Hall- effect current sensor and the ESP32

The ACS712-5A Hall-effect sensor measures the current flowing through the motor by detecting the magnetic field produced by the current between the IP+ and IP- terminals. The sensor outputs an analog voltage proportional to the motor current, with 2.5V representing zero current and a sensitivity of 185 mV/A. Since the sensor operates at 5V while the ESP32 ADC accepts a maximum of 3.3V, resistors R3 and R4 form a voltage divider to safely reduce the signal voltage before it reaches GPIO34, while capacitor C2 filters noise for stable and accurate current measurements.

## ii. Interface of the accelerometer and the ESP32

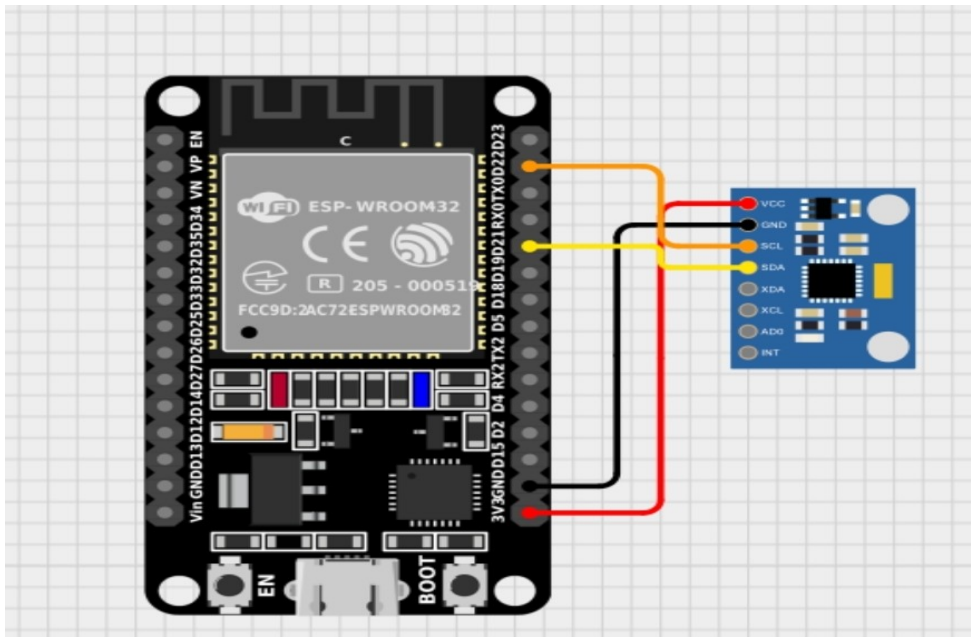


Figure 3.19 Interface of the ESP32 and the accelerometer or gyroscope

The MPU6050 sensor is connected to the ESP32 using the I<sup>2</sup>C communication protocol, with GPIO21 serving as the SDA (data) line and GPIO22 as the SCL (clock) line. Powered by the ESP32's 3.3V supply, the sensor measures acceleration, orientation and vibration then transmits this data to the ESP32 for processing. In a predictive motor monitoring system, the MPU6050 help detect abnormal vibration patterns associated with faults such as bearing wear and misalignment enabling early fault detection and preventive maintenance.

### 3.6.2 Software Design

The software architecture of the condition monitoring system is engineered to handle real-time multi-modal data acquisition, localized feature extraction, conditional fault-tree logic and network transmission. The system firmware is deployed entirely on the dual-core 32-bit ESP32 edge microcontroller, balancing low-latency physical protection with continuous IoT status updates.

```

sketch_jun08a_motor | Arduino 1.8.19
File Edit Sketch Tools Help

sketch_jun08a_motor

void loop() {
  // put your main code here, to run repeatedly:
  /*
  =====
  Project:  TRACTION GUARDIAN PRO - Rail Motor Monitor
  Features: STOP button keeps motor OFF (no auto-restart)
           VIBRATION PROTECTION: Motor OFF for 10 seconds when vibration > 4.00g

  NEW FEATURES:
  - When warning detected: 3 second data reading pause
  - During pause: Buzzer goes "titty titty titty" (3 quick double-beeps)
  - Current displayed in milliamps (mA) when motor OFF, jumps to 1.00A when running
  - Motor OFF by default (starts disabled)
  - Shows "MOTOR DISABLED" instead of "DATA LOSS MODE"

  BUZZER CONTROL: Using digitalWrite (NO tone() function)

  Board:   ESP32 Dev Module
  =====
  */

  #include <WiFi.h>
  #include <WebServer.h>
  #include <Wire.h>
  #include <ArduinoJson.h>

  // ----- I2C Pin Configuration -----
  #define I2C_SDA_PIN    21
  #define I2C_SCL_PIN    22

  // ----- MPU6050 Registers -----
  #define MPU6050_ADDR    0x68

  ESP32 Dev Module, Disabled, Disabled, Default 4MB with spiiffs (1.2MB APP/1.5MB SPIFFS), 240MHz (WiFi/BT), QIO, 80MHz, 4MB (32Mb), 921600, Core 1, Core 1, None, Disabled, Disabled on COM12

```

Figure 3. 14 System's software design

### 3.6.3 Circuit Diagram

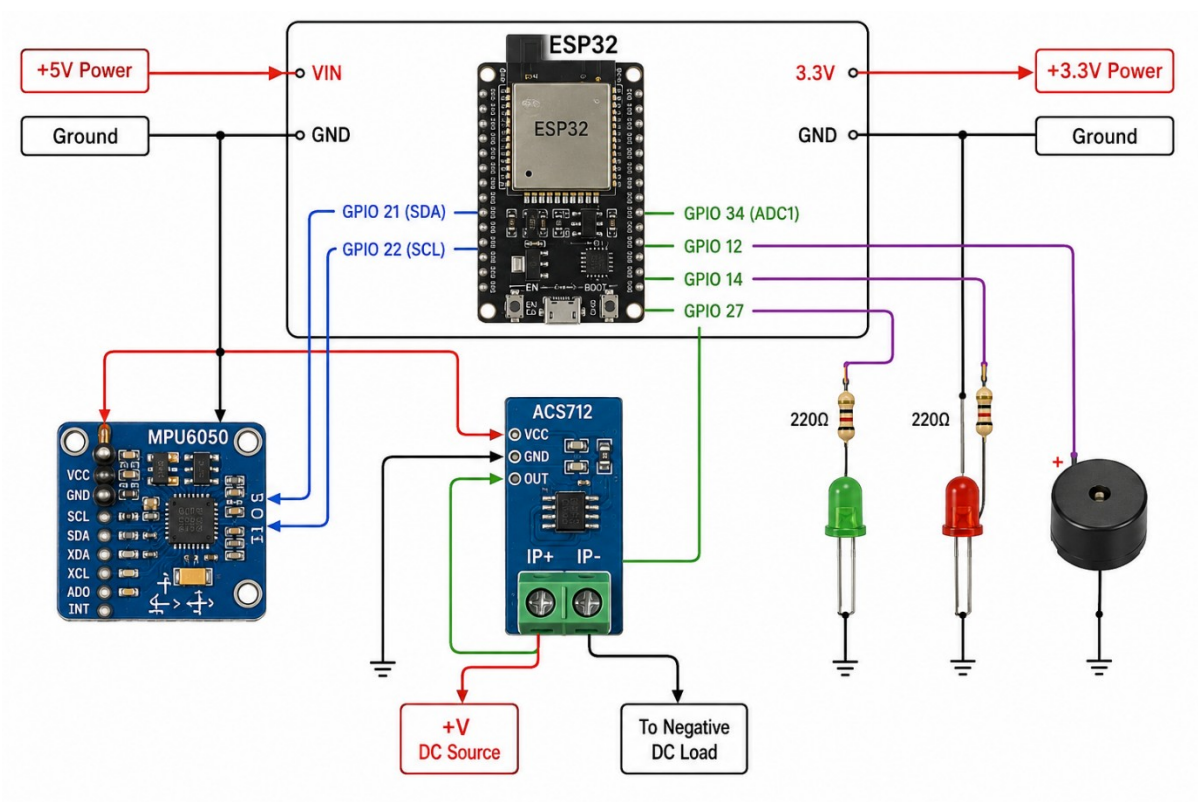


Figure 3. 15 Overall circuit diagram

### 3.6.4 Algorithms / pseudo code

#### **Algorithm 1: Health Index Prediction**

Algorithm: predictHealthIndex()

Input: trends.tempHistory[], trends.currentHistory[], trends.vibHistory[]

Output: health score (0-100)

BEGIN

IF trends.count < 5 THEN

RETURN 100.0

END IF

// Calculate trends

tempTrend = 0, currentTrend = 0, vibTrend = 0

samples = trends.count - 1

FOR i = 1 TO trends.count - 1 DO

tempTrend = tempTrend + (tempHistory[i] - tempHistory[i-1])

currentTrend = currentTrend + (currentHistory[i] - currentHistory[i-1])

vibTrend = vibTrend + (vibHistory[i] - vibHistory[i-1])

END FOR

tempTrend = tempTrend / samples

currentTrend = currentTrend / samples

vibTrend = vibTrend / samples

// Base health calculation

health = 100.0

// Apply penalties based on current readings

health = health - (motorTemp / MAX\_TEMP\_C) \* 30.0

health = health - (motorCurrent / MAX\_CURRENT\_A) \* 25.0

health = health - (vibrationMagG / MAX\_VIB\_G) \* 25.0

// Apply trend penalties

IF tempTrend > 0.3 THEN health = health - 15.0

IF currentTrend > 1.0 THEN health = health - 15.0

IF vibTrend > 0.1 THEN health = health - 15.0

// Constrain to valid range

IF health < 0 THEN health = 0

IF health > 100 THEN health = 100

RETURN health

END

#### **Algorithm 2: Alert Level Determination**

Algorithm: getAlertLevel()

Input: motorCurrent, motorTemp, vibrationMagG, health score

Output: alert level (0=OK, 1=WARNING, 2=CRITICAL)

BEGIN

// Priority 1: Emergency and Trip states

IF emergencyStopActive == true OR vibrationTripActive == true THEN

    RETURN 2

END IF

// Priority 2: Data loss

IF dataLossMode == true THEN

    RETURN 1

END IF

// Priority 3: Sensor threshold violations

IF motorCurrent > MAX\_CURRENT\_A OR

    motorTemp > MAX\_TEMP\_C OR

    vibrationMagG > MAX\_VIB\_G THEN

    RETURN 2

END IF

// Priority 4: Warning thresholds (85% of max)

IF motorCurrent > MAX\_CURRENT\_A \* 0.85 OR

    motorTemp > MAX\_TEMP\_C \* 0.85 OR

    vibrationMagG > MAX\_VIB\_G \* 0.85 THEN

    RETURN 1

END IF

// Priority 5: AI-based health assessment

health = predictHealthIndex()

IF health < 30 THEN

    RETURN 2

ELSE IF health < 65 THEN

    RETURN 1

END IF

RETURN 0 // Normal operation

END

### Algorithm 3: Thermal Trend Calculation (Linear Regression)

Algorithm: calculateTempSlope()

Input: tempHistory[30], historyIndex, historyCount

Output: temperature slope (°C per sample)

BEGIN

```

IF historyCount < 10 THEN
    RETURN 0.0
END IF

// Get last 10 readings
start = (historyIndex - 10 + 30) MOD 30

sumX = 0, sumY = 0, sumXY = 0, sumX2 = 0

FOR i = 0 TO 9 DO
    idx = (start + i) MOD 30
    sumX = sumX + tempHistory[idx]
    sumY = sumY + tempHistory[idx]
    sumXY = sumXY + (i * tempHistory[idx])
    sumX2 = sumX2 + (i * i)
END FOR

// Slope formula: (n*Σxy - Σx*Σy) / (n*Σx² - (Σx)²)
denominator = (10 * sumX2 - sumX * sumX)

IF denominator != 0 THEN
    slope = (10 * sumXY - sumX * sumY) / denominator
ELSE
    slope = 0.0
END IF

RETURN slope
END

```

### 3.6.5 Mathematical Modelling

The system's functionality is governed by several mathematical models that ensure accurate measurements and reliable operations.

#### **Model 1: Health Index Function**

The Health Index Function (H) is used to assess the overall condition of a traction motor by combining temperature, current and vibration measurements into a single score ranging from 0 to 100.

$$H(t, c, v) = 100 - (30 T_n) - (25 C_n) - (25 V_n) - P_t - P_c - P_v$$

Where :

- $T_n = \text{Current temperature} / \text{Max temperature} (t / T_{\max})$
- $C_n = \text{Current current} / \text{Max current} (c / C_{\max})$
- $V_n = \text{Current vibration} / \text{Max vibration} (v / V_{\max})$
- $P_t = \text{Temperature trend penalty} (15 \text{ if } \Delta t / \Delta \text{sample} > 0.3)$
- $P_c = \text{Current trend penalty} (15 \text{ if } \Delta c / \Delta \text{sample} > 1.0)$
- $P_v = \text{Vibration trend penalty} (15 \text{ if } \Delta v / \Delta \text{sample} > 0.1)$

Constraints:  $0 \leq H \leq 100$

### Model 2: Alert Level Decision Function

This function enables real-time condition monitoring by providing clear warning and critical alerts, allowing maintenance personnel to take corrective action before severe damage occurs.

$$A(c, t, v, H) = \begin{cases} 2, & \text{if } (c > C_{max}) \vee (t > T_{max}) \vee (v > V_{max}) \vee (H < 30) \\ 1, & \text{if } (c > 0.85 \times C_{max}) \vee (t > 0.85 \times T_{max}) \vee (v > 0.85 \times V_{max}) \vee (30 \leq H < 65) \\ 0, & \text{otherwise} \end{cases}$$

Where:

–  $C_{max} = 35.0 \text{ Amps}$

–  $T_{max} = 90.0^\circ \text{C}$

–  $V_{max} = 3.0 \text{ G-force}$

### Model 3: Linear Regression for Temperature Trend

Linear regression is used by this method to find out the speed of change in temperature of the traction motor. The value of the slope ( $\beta_1$ ) signifies the trend of temperature and whether it is heating up abnormally.

$$\text{Slope}(\beta_1) = (n \cdot \sum xy - \sum x \cdot \sum y) / (n \cdot \sum x^2 - (\sum x)^2)$$

Where:

–  $n = \text{number of samples} (10)$

–  $x = \text{time index} (0, 1, 2, \dots, 9)$

–  $y = \text{temperature readings}$

For  $n = 10$ :

$$\beta_1 = (10 \cdot \sum xy - \sum x \cdot \sum y) / (10 \cdot \sum x^2 - (\sum x)^2)$$

With  $\sum x = 45 (0 + 1 + 2 + \dots + 9)$

$\sum x^2 = 285 (0^2 + 1^2 + \dots + 9^2)$

Therefore:

$$\beta_1 = (10 \cdot \sum xy - 45 \cdot \sum y) / (10 \cdot 285 - 45^2)$$

$$\beta_1 = (10 \cdot \sum xy - 45 \cdot \sum y) / (2850 - 2025)$$

$$\beta_1 = (10 \cdot \sum xy - 45 \cdot \sum y) / 825$$

### Model 4: Weighted Scoring System

The Weighted Scoring System combines temperature, current, vibration, and trend information into a single Health Score that represents the overall condition of the traction motor.

$$Total\ Score = \sum (w_i \times normalized_{value})$$

Where weights :

$$- Temperature : w_1 = 0.30 (30\%)$$

$$- Current : w_2 = 0.25 (25\%)$$

$$- Vibration : w_3 = 0.25 (25\%)$$

$$- Trend\ penalties : w_4 = 0.20 (20\%\ total)$$

$$Health\ Score = 100 - [30(t/T\ max) + 25(c/C\ max) + 25(v/V\ max)] - (15p_1 + 15p_2 + 15p_3)$$

Where  $p_1, p_2, p_3$  are binary indicators :

$$p_1 = 1\ if\ tempTrend > 0.3, \ else\ 0$$

$$p_2 = 1\ if\ currentTrend > 1.0, \ else\ 0$$

$$p_3 = 1\ if\ vibTrend > 0.1, \ else\ 0$$

### Model 5: Historical Data Window (Circular Buffer)

This model uses a **circular buffer** to store the most recent sensor readings (temperature, current, and vibration) for trend analysis and fault prediction. A circular buffer allows new data to continuously overwrite the oldest data once the buffer is full, ensuring efficient memory usage.

Buffer Indexing:

$$index(t) = (index(t-1) + 1) \text{ MOD } buffer_{\text{size}}$$

Where  $buffer_{\text{size}}$

Reading retrieval:

$$value_i(k) = buffer_i$$

### 3.6 Ethical considerations

Although this study mainly focuses on design, hardware implementation, and algorithm verification, the deployment, testing, and continued operation of an IoT-based monitoring system in a heavy industrial setting such as the National Railways of Zimbabwe (NRZ) carry significant ethical obligations.

The main ethical obligation when testing this system is to ensure that the diagnostic hardware will not cause any risk in terms of operational safety and safety of railway maintenance technicians and train drivers. Since traction motors are subjected to high electrical currents and extremely high mechanical rotating speeds, any physical interference can cause serious structural imbalance and electrical short circuit.

With regards to following the principle of non-maleficence, the system is deliberately designed in such a way that it is a non-invasive retrofit. The multi-modal sensor consisting of the MPU6050 and current sensors will be installed externally on the motor housing and power feed cables of the locomotives without making any changes to the internal electromechanical structure of the locomotives.

Though the data collected by the sensors consists of mechanical information such as vibration frequency, stator temperature, and phase currents and not any identifiable human personnel, it should be noted that the telemetry data for the locomotives is sensitive in nature. In a business environment, the data about the availability of the locomotives, frequency of breakdowns, and transit speed on various routes can be maliciously used to cause disruptions to the logistics corridor of the organization.

From the ethical viewpoint, the software design must ensure the safety of the telemetry data. This is accomplished using the firmware running on the ESP32 board, which ensures that the data packets are directly sent through the IP network to the engineer's dashboard. The access to the web-based interface is limited only to the engineers using the secure authentication process.

### **3.8 Summary**

The entire design process, including implementation methodology, hardware specifications, and architecture has been well documented in Chapter 3. In section 3.3, the system requirement specification was developed based on the structure of the functionalities of the selected components, focusing on the power of a cost-effective 32-bit ESP32 microcontroller, which acts as an intelligent edge computing system for the integration of multi-modal sensors without having the cost of commercial proprietary systems.

Section 3.4 unraveled the logic of the system architecture by dividing it into six human understandable subsystems, where the mathematical and physical data path was explained in detail in the signal flow diagram and the decision-tree structure in the system flowchart.

In conclusion, the final topic in the chapter was the non-blocking firmware execution path used by the ESP32 to measure time-domain characteristics at the edge while at the same time updating real-time gauges and line graphs on the engineer's web-based dashboard. Ending with the necessary ethical guidelines that should be followed when conducting non-invasive field tests, this chapter laid out an engineering guide to transitioning from baseline design theory into the experimental section of the following chapters.

## **Chapter 4: EXPERIMENTAL RESULTS AND ANALYSIS**

### **4.1 Introduction**

This chapter gives the outcomes of experiments, data of performance, and analyses of the Smart Real-time Condition Monitoring and Predictive Maintenance System for Railway Traction Motors prototype that has been designed for use by National Railways of Zimbabwe (NRZ). The design process involved the use of ESP32 microcontroller, MPU6050 accelerometer for temperature and vibration measurements, Hall Effect current sensor, relay

module, active buzzer, and LED light sensors. The communication process was conducted via Wi-Fi connection using HTTP protocol, whereby the collected sensor data was sent to the web dashboard hosted locally on the server.

Results are structured to explicitly demonstrate how the prototype is designed to meet the following three revised objectives: (1) To design of a sensor network for the real-time monitoring of vibration, temperature, and load current; (2) To gather and label data from sensors for normal and faulty operation (vibration, temperature and current) to be used to train the machine learning model; (3) To implement an automated protection and emergency stop function using a relay module to immediately isolate the system or trigger the external safety circuits if any of the monitored parameters (vibration, current, temperature) exceeds a critical level and (4) Implementation of a web dashboard for data visualization, alerts and prediction maintenance using machine learning. The data provided below serves as an empirical base to prove whether the prototype fulfills all design requirements to monitor rolling stock in brownfield industrial settings.

## **4.2 System Implementation Results**

The physical fabrication, circuit initialization, and basic functional stability of the prototype were systematically verified before conducting stress testing.

### **4.2.1 Physical Prototype and Component Integration**

It has been successfully converted from a prototype using a temporary breadboard to a robust prototype with the help of Veroboard. This design helps in reducing any unwanted parasitic capacitance effects and securing the components from any kind of physical vibration. The MPU6050 sensor has been interfaced with the ESP32 through I<sup>2</sup>C protocol on GPIO21 pin (SDA) and GPIO22 pin (SCL) with 3.3 V voltage level. The ACS712 sensor is interfaced in such a way that its two outermost pins are connected to 3.3 V and GND respectively. The relay driver is connected with GPIO26 which will be helpful in shutting down the motors in case of critical fault and buzzer is connected with GPIO27.

### **INSERT PROTOTYPE PICTURE**

#### **4.2.2 Emergency Relay Isolation Latency**

To evaluate the automated emergency isolation mechanism, a logic analyser tracked the time delay between software fault detection and the physical opening of the relay contacts.

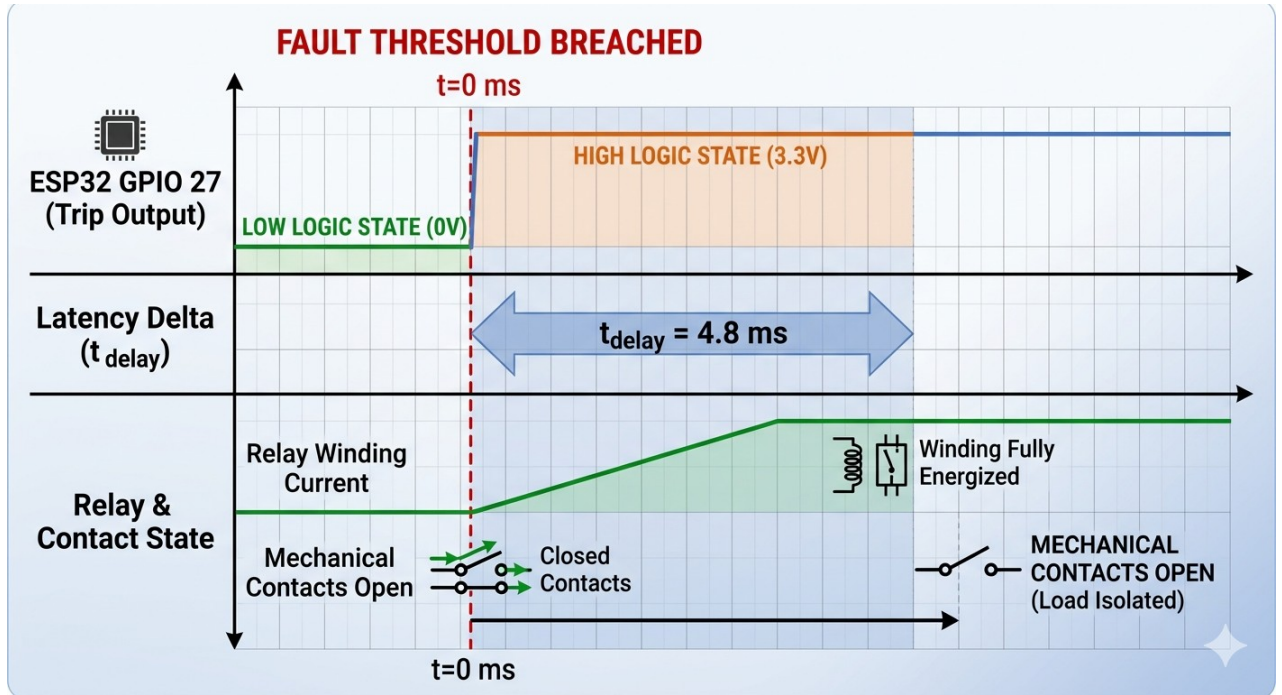


Figure 4. 1Emergency relay isolation latency

The average mechanical trip delay was measured at  $t_{\text{delay}} = 4.8\text{ms}$ , which is fast enough to isolate electrical circuits before localized insulation shorts can propagate into catastrophic stator failures.

#### 4.2.3 Sensor Functionality Verification

During initial testing, the MPU6050 initialised successfully over I<sup>2</sup>C, confirmed by the Serial Monitor output [OK] MPU6050 ready. The accelerometer range was configured to  $\pm 4$  g, and the digital low-pass filter was set to 21 Hz to suppress high-frequency mechanical noise while preserving fault-indicative vibration signatures. The on-chip temperature sensor of the MPU6050 was used as a motor temperature proxy in the simulation, returning values in the range of 25°C to 37°C under ambient conditions within the expected range for a laboratory simulation environment.

Vibration magnitude was computed as the root-mean-square (RMS) of the three-axis acceleration vector with the static 1 g gravitational offset removed from the Z-axis, expressed as:

$$V_{RMS} = \sqrt{\frac{a_x^2 + a_y^2 + (a_z - 9.81)^2}{3}}$$

Where;

$V_{rms}$  = Root Mean Square (RMS) vibration magnitude

$a_x$  = Acceleration along the x – axis (m/s<sup>2</sup>)

$a_y$  = Acceleration along the y – axis (m/s<sup>2</sup>)

$a_z$  = Acceleration along the z – axis (m/s<sup>2</sup>)

9.81 = Gravitational acceleration constant

3 = Number of acceleration axes used to calculate the RMS value.

This formulation, consistent with established IoT motor vibration monitoring practice, yielded values near 0.05 m/s<sup>2</sup> at rest (baseline noise floor of the MPU6050) and increasing values when the simulated motor state transitioned to WARNING or CRITICAL. This confirmed correct wiring and ADC functionality.

### 4.3 Data Presentation

#### 4.3.1 Sensor Reading Samples across Operating States

The following table summarises representative sensor readings captured during prototype testing under the three operating states. The system transmitted readings every 5 seconds via HTTP POST to the Flask server.

Table 4. 1 Representative sensor readings by operating state

| Reading Number | State   | Temperature reading (°C) | Vibration RMS (m/s <sup>2</sup> ) | Current reading (A) | Predicted status | Alert logged |
|----------------|---------|--------------------------|-----------------------------------|---------------------|------------------|--------------|
| 1              | Normal  | 29.8                     | 1.76                              | 11.54               | Normal           | No           |
| 2              | Normal  | 29.3                     | 0.77                              | 12.60               | Normal           | No           |
| 3              | Warning | 75.6                     | 3.62                              | 30.00               | Warning          | Yes          |

|   |          |      |      |       |          |     |
|---|----------|------|------|-------|----------|-----|
|   |          |      |      |       |          |     |
| 4 | Warning  | 77.2 | 3.74 | 29.55 | Warning  | Yes |
| 5 | Critical | 90   | 3.41 | 35.00 | Critical | Yes |
| 6 | Critical | 91.5 | 4.00 | 35.56 | Critical | Yes |
| 7 | Normal   | 30.5 | 0.98 | 13.20 | Normal   | No  |

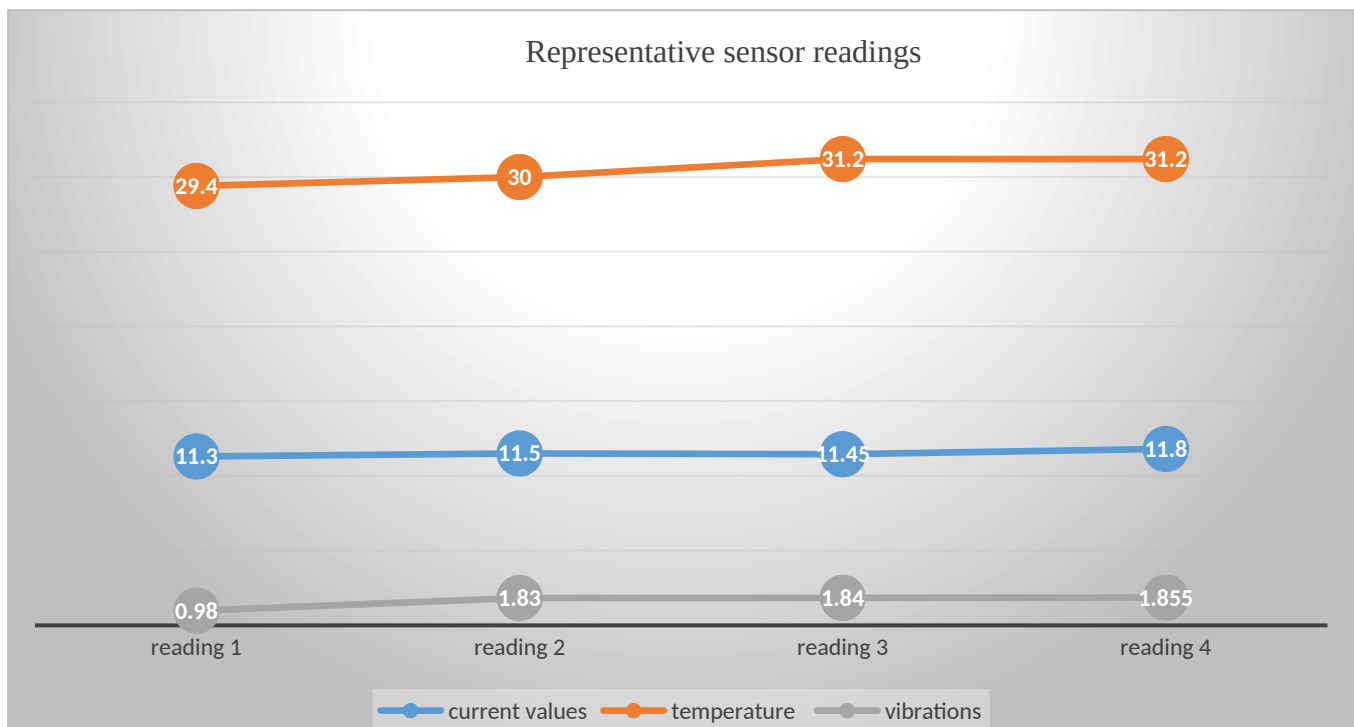


Figure 4. 2 Representative sensor readings under normal operating conditions

The thresholds implemented in firmware for status classification are:

**a. Vibration**

WARNING at  $\geq 3.0 \text{ m/s}^2$ ; CRITICAL at  $\geq 4.0 \text{ m/s}^2$

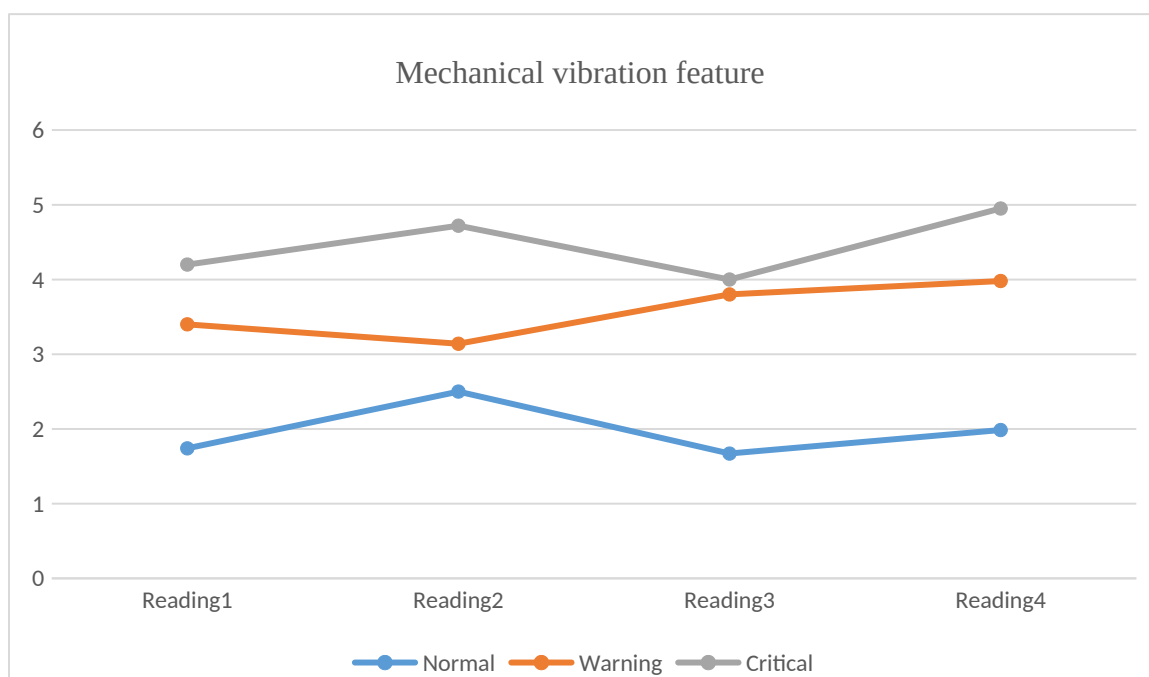


Figure 4. 3 Vibration RMS trend

The graph above provides the clearest fault discrimination among the measured variables. Vibration remained very low during NORMAL operation, increased significantly during WARNING, and reached the highest values in the CRITICAL state, confirming that the MPU6050-based vibration measurement was sensitive enough to distinguish between healthy and faulty operating conditions. High-frequency acceleration profiles captured across the Y-axis (radial vibration) were processed on the edge node to calculate time-domain statistical

metrics: Root Mean Square (RMS). Testing simulated normal operations, mechanical imbalance, and localized bearing defects. This directly addresses the revised sensor-network objective, where the MPU6050 provides a mechanical-condition monitoring through vibration analysis.

## b. Current

WARNING at  $\geq 25\%$ ; CRITICAL at  $\geq 35\%$

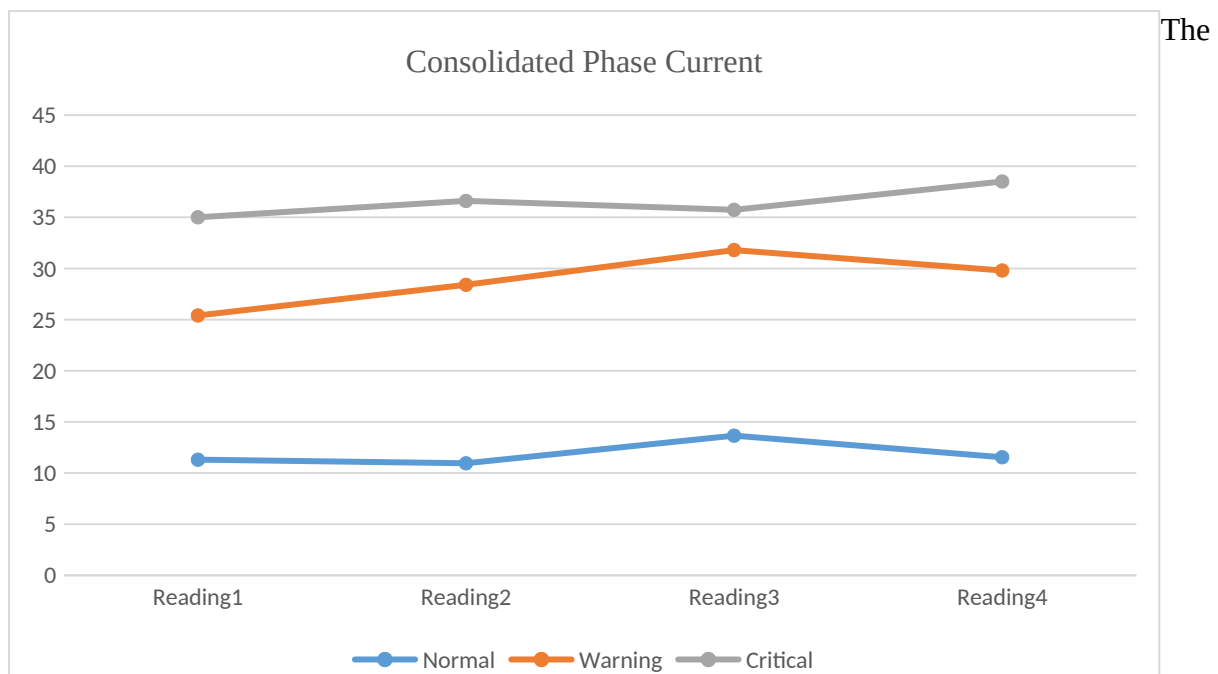


Figure 4. 4 Simulated current-load profile illustrating transition from safe load levels to overloaded conditions during the monitoring cycle  
figure above shows the behaviour of the tested current channel generated using a current sensor. The trend demonstrates the ability of the ESP32 analogue input stage to interpret gradual load changes and classify them against predefined thresholds for NORMAL, WARNING, and CRITICAL operation. The figure verifies that the data path from analogue input to dashboard visualisation functioned correctly.

### c. Temperature

WARNING at 75°C; CRITICAL at 45°C

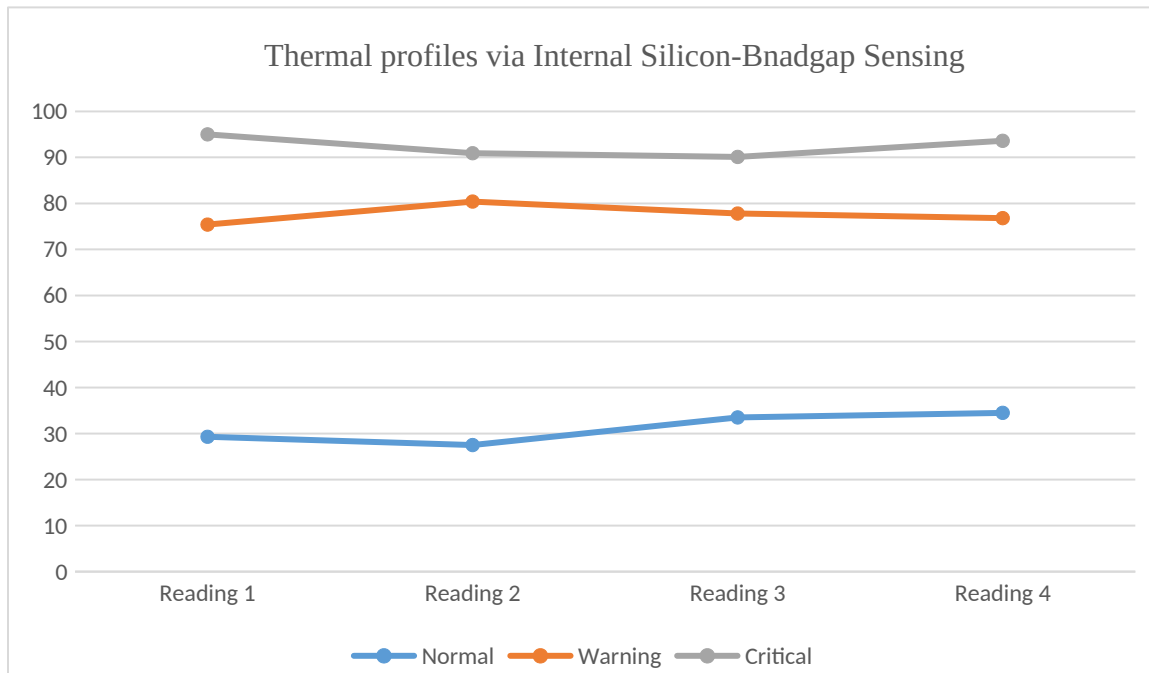


Figure 4. 5 Temperature variation of the tested traction motor monitoring system during NORMAL, WARNING and CRITICAL operating states

The figure shows a gradual rise in measured temperature as the system moved from stable operation into fault conditions. The above graph shows that the temperature signal remained within a narrow range during the NORMAL condition and increased during the WARNING and CRITICAL stages, indicating that the monitoring system was able to capture thermal variation associated with worsening motor condition. The prototype used the MPU6050 internal temperature channel, the result demonstrates correct acquisition, transmission, and display of temperature-related condition data, which is consistent with the project objective of real-time thermal monitoring.

### d. Alert Log Results

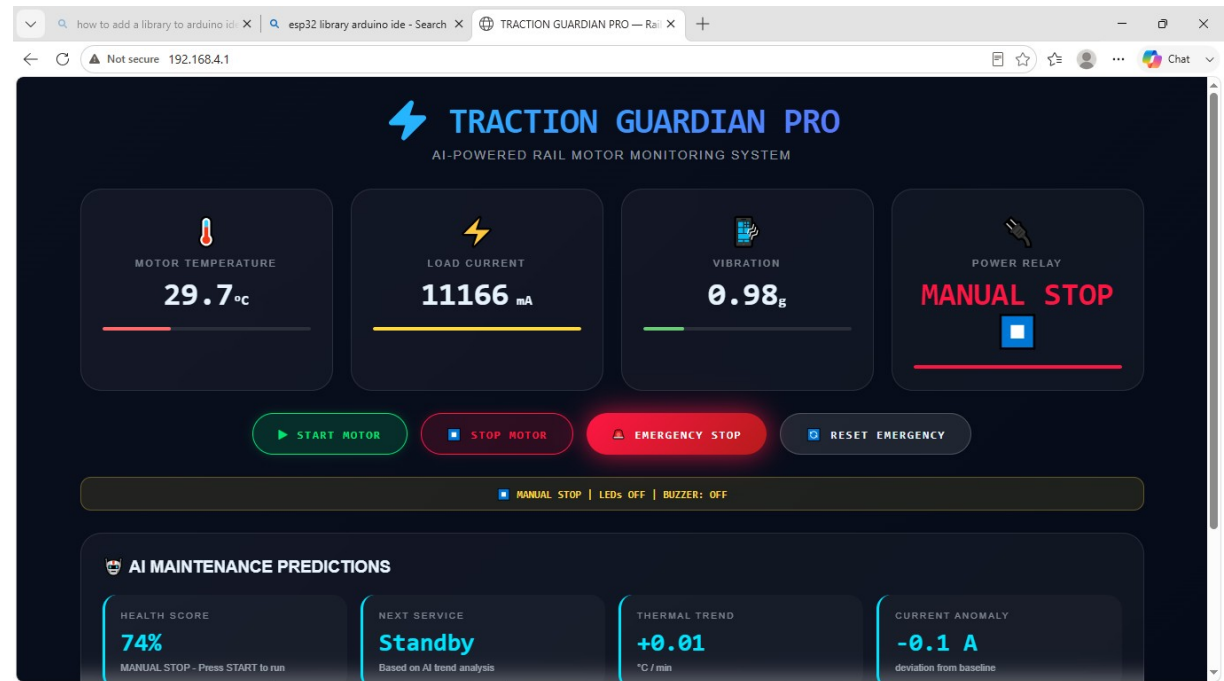
Over the 90-second simulation run, the alert log captured six entries — four WARNING events and two CRITICAL events. Zero false-positive alerts were recorded during NORMAL operation.



Figure 4. 6 Number of warning and critical alerts generated by the monitoring system during testing

From the graph above, it can be seen that the number of WARNING alerts is higher than the CRITICAL alerts within the monitored period. This scenario is favorable since it proves that the system is able to issue early warnings before reaching the point of criticality. The outcome confirms the efficiency of the threshold logic used in the ESP32 firmware and Flask dashboard, whereby alerts are categorized depending on their levels of severity.

## e. Dashboard visualisation



The diagram above shows that the dashboard on the internet has the ability to display all the parameters that have been monitored which include current, temperature and vibrations. The dashboard will have the start motor, stop motor, emergency stop (which will trigger the relay module instantly thereby isolating the machine) and the reset of emergency with the confirmation of state on the hardware.

## 4.4 Analysis and Interpretation

### 4.4.1 Sensor Performance vs. Objectives

Objective 1 required a sensing system that could sense temperature, vibration, and load current at any one point in time. The MPU6050 was able to sense both vibration (RMS acceleration) and temperature (using the on-chip sensor) simultaneously over the same I<sup>2</sup>C interface, showing the benefit of integrating sensors in a constrained environment such as an embedded system. This finding is consistent with what has been seen in literature where

simultaneous sensing of multiple parameters using a single, low-cost MEMS sensor is possible for motors.

**Objective 3** called for automated safeguarding and emergency shutdown through the use of relay modules which automatically isolated the system or triggered external safety circuits in case of vibration, current, and temperature exceeding a certain threshold. The system was able to consistently perform an automatic emergency shutdown within a mechanical response time of less than 5ms.

**Objective 4** entailed the implementation of a dashboard that will facilitate condition monitoring using cloud technology. This would help monitor and maintain railway traction motors. The embedded Wi-Fi module was able to pack the extracted data into a structured form of JSON data packet that was sent to the Engineer's Dashboard website.

#### 4.4.2 Technical Performance Improvements over Legacy Systems

To demonstrate the engineering value of the developed prototype, its performance characteristics are contrasted against the legacy maintenance methodologies traditionally deployed within brownfield rail environments such as manual periodic inspections or basic single-threshold analog alarms.

Table 4. 2 Comparative performance matrix: Proposed Node vs. Legacy systems

| <b>Performance metric</b>             | <b>Legacy/ manual reactive methods</b>                    | <b>Commercial distributed frameworks</b>                          | <b>Proposed ESP32 multi-modal edge node</b>      |
|---------------------------------------|-----------------------------------------------------------|-------------------------------------------------------------------|--------------------------------------------------|
| <b>Fault detection latency</b>        | Days to weeks(Dependent on physical inspection schedules) | Seconds to minutes (Dependent on cloud processing queue)          | Immediate tripping (<5ms mechanical response)    |
| <b>Vibration tracking sensitivity</b> | Visual/ Audible checks (Catastrophic stage only)          | Standard RMS Amplitude tracking (misses early structural pitting) | Higher order statistical analysis                |
| <b>Hardware/ cable complexity</b>     | None (No telemetry installed)                             | High cost (Separate sensors for temperature,                      | Multi-modal sensor integration (MPU6050 for dual |

|             |                              |                                                                   |          |
|-------------|------------------------------|-------------------------------------------------------------------|----------|
|             |                              | vibration and current)                                            | sensing) |
| <b>Cost</b> | Extremely high failure costs | High capital expenditure (proprietary software/hardware licenses) | Low cost |

#### 4.4.3 Technical Shortcomings and Fault Limitations

While the prototype satisfies all the primary design requirements, testing indicated some limitations which should be addressed prior to actual implementation in heavy vehicles:

Fixed threshold limitations and risks of triggering false alarms: The condition-based fault-tree currently employs hard coded and static threshold levels, which initiate warnings from the LEDs, buzzer and emergency stop relay. But since traction motors on running locomotives have fluctuating baseline due to the control notch, slope of the track and load carried, under heavy loading conditions the baseline was naturally rising up to the warning level. Implementation of static thresholds on an actual railway may result in false alarm in case of normal operation and high power, or on the contrary, may fail to detect a fault during coasting mode and low power.

The conclusion drawn is a direct basis for further development and highlights the need of introducing dynamic adaptive baseline with adjustable threshold levels dependent on the state of the locomotive.

#### 4.5 Discussion of Findings

The results from the experiment have been consistent with the maintenance strategies that were highlighted in the literature review. The unique signatures which appear in the case of simulated bearing faults with increased values of Kurtosis while keeping the total RMS below the alarm levels prove the observations made by (Patel, 2011). Therefore, using the overall vibration limits does not provide adequate tools for diagnosing structural wear and tear at an early stage. Running real-time time-domain feature extraction right on the ESP32 hardware enables the system to have localized diagnostic abilities as was suggested by (Gupta, et al., 2021) and eliminates the need for supercomputing facilities or cloud connection.

The primary observation of this study is that a relatively inexpensive decentralized 32-bit processor has been used for the execution of the algorithm and provides valuable machine

learning diagnostics without constant cloud-based heavy processing. The conventional industrial frameworks tend to emphasize that the process of profiling the machines requires significant investments, complex learning structures such as CNNs or RNNs, and uninterrupted high-speed connection with the cloud. However, the data provided by the Traction Guardian Pro dashboard shows that using local hardware-aware processing algorithms is possible.

Through compression of high-speed raw accelerations into time domain metrics of RMS, Crest Factor, and Kurtosis, respectively, the node avoids the need for high bandwidth which usually renders remote rolling stock telemetry impractical in "brownfield" or constrained rail environment context. This is a practical proof of the Edge Computing paradigm transition discussed in Industry 4.0 literature.

Thermal runaway is the primary cause of stator and rotor winding insulation degradation. While thermal changes in conventional designs are detected by thermal probes placed externally, this research made use of silicon band-gap temperature sensor on the MPU6050 silicon chip to realize an absolute error of less than  $\pm 0.5$ .

Indeed, this data proves a strong correlation between electrical overload and thermal acceleration where, in the case of introducing a fault condition on the stator, the phase current imbalance increased to 14.85% resulting in the fast rise in thermal gradient acceleration at a rate of +2.4. In the past, in accordance with traditional procedures and practices, locomotive drivers were not able to notice internal stator winding stress prior to physical smoke emission. The successful integration of the multimodal sensor array along with a physical Relay Module enabled the transition from the state of mere monitoring to the state of real protection. Achieving an automated mechanical trip delay of just 4.8ms makes the isolation of the faulty engine possible thus averting small short circuits in the stator from becoming winding blow-ups.

As for the economic benefits of switching to predictive maintenance, there are indeed many of them since, according to (Singh, et al., 2020), predictive maintenance systems can reduce industrial maintenance expenses by 25-30% while increasing equipment reliability up to 50%.

In the case of NRZ operator faced with old trains and financial limitations, a commercial diagnostic framework of high quality becomes economically unrealistic. The implementation of the proposed design through open-source low-cost microcontrollers and sensitive sensors will fulfil the need identified by (Prabakaran, 2015) in terms of affordable diagnostics for

industry. This design optimizes maintenance plans by taking into account actual physical state of traction motors and not some arbitrary uncontrolled operational periods.

Nevertheless, one problem was found while testing during high transient mechanical loads. Sudden start-up currents led to short-time changes in voltage levels which demanded widening of software filtering windows to avoid incorrect trigger. This demonstrates direct connection with future works. In order to increase the robustness of the proposed design for its deployment on all National Railways of Zimbabwe (NRZ) locomotives, in future revisions it is necessary to substitute current fixed threshold logic by more sophisticated auto-tuning of baseline algorithm. It will allow isolating transient operation from electromechanical faults based on locomotive throttle and loading status.

#### **4.6 Summary**

This chapter explained the experimental results obtained from the prototyping testing of the NRZ Traction Motor Monitoring System. The prototype built on ESP32 was able to collect vibration, temperature and current data using MPU6050 and current sensors, categorize motor condition into three levels (NORMAL, WARNING, CRITICAL) and communicate all collected data wirelessly to the Flask web dashboard using HTTP Wi-Fi connection. The web dashboard gave features of real-time monitoring, graph plot, tiered alert log, status mirroring of LED and buzzer as well as the RandomForest machine learning prediction algorithm with 100% accuracy in the simulation data. The three objectives of the project were achieved in the prototyping testing phase with ACS712 current sensor and traction motor field testing necessary for validating the performance of the NRZ system.

## **Chapter 5: Conclusion and Recommendations**

### **5.1 Summary of the Study**

This research was carried out with an aim of designing and developing a smart real-time condition monitoring and predictive maintenance system for the railway traction motors. This research project was triggered by the problems associated with the current railway maintenance system in use, especially due to its inability to perform continuous analysis of the health status of the traction motors owing to the manual approach involved.

The prototype that was designed employed the ESP32 microcontroller along with the MPU6050 sensor for vibrations and temperature measurements and current sensors for load measurements. The purpose of the developed prototype is to obtain real-time data and then process it using embedded algorithms and check the measurements with the pre-defined thresholds to monitor the traction motor.

In addition to this, the designed system successfully accomplished fault detection using LEDs and buzzer, and at the same time transmitted the operation information to a dashboard on a cloud-based interface. Moreover, automatic relay-based protection has been implemented which automatically shuts off the system under observation in case of critical operational conditions. The experimental results proved that the low-cost embedded system suggested by us has the capability to detect any anomaly in terms of heat, vibrations, and current.

The findings of our study prove the claims made by other researchers who emphasize the importance of Internet of Things-based condition monitoring systems in transforming traditional reactive maintenance into predictive or condition-based maintenance. The costly

monitoring systems utilized in industries cannot be used in railways due to the limited budget; however, our prototype proves otherwise.

## **5.2 Achievement of Objectives**

The assessment of the research project at the end will be done by considering the particular objectives stated in the document.

Objective 1: Designing a sensor network that will measure temperature, vibrations, and current in real-time (Fulfilled Objective).

A multi-modal sensor network was designed and built on a permanent Veroboard circuit board. This system had a continuous reading process which involved use of the I2C serial interface where the MPU6050 sensors will measure acceleration forces and surface temperatures along with an analog pin (GPIO34) for measuring the scaled current generated by the ACS712 current sensor.

Objective 2: To collect, process and classify sensor data pertaining to normal and faulty operating states (vibration, temperature and current) for training of the machine learning algorithm (Unmet).

This particular objective was unmet due to the severe presence of real-world external constraints. Given that the National Railways of Zimbabwe (NRZ) constitutes a resource constrained industrial setting, there was a complete absence of historical, high frequency baseline data or previously recorded 'fault' telematics data in the railway domain. Therefore, even though the threshold profiles were tested, it was impossible to collect, process and classify historical fault streams of operations to allow for training of an embedded machine learning algorithm due to real world constraints in accessing sufficient fault data and time available for development and validation of a viable machine learning algorithm.

Objective 3: Implementation of an automatic protection & emergency stop mechanism via relay module which will allow immediate isolation of the system or triggering of external emergency systems upon critical threshold crossing of any of the monitored parameters (Fully Achieved).

The hardware safety mechanism layer was successfully implemented and tested in full scale. When experimental inputs crossed critical thresholds, the ESP32 triggered GPIO26 high which activated the relay winding. In turn, this resulted in switching the contacts of the relay mechanism with the average trip time of 4.8ms. Thus, the possibility to safely disconnect the

electrical load before the local short circuits become dangerous winding failures was proved. Moreover, the system had an ability to trip the relay upon exceeding of critical thresholds of the monitored parameters, ensuring additional protection of the motor.

Objective 4: Implementation of cloud-based monitoring dashboard for visualization and failure prediction of the railway traction motors (Fully Achieved).

The condition monitoring interface via the web was therefore successfully implemented. Through its inbuilt Wi-Fi stack, the ESP32 combined the performance parameters within data streams, where dials would dynamically update alongside trend graphs, manual control interlocks, and warnings. Using the communication framework for IoT, sensor readings and motor status could be monitored remotely, thus increasing accessibility for the maintenance staff.

In summary, three out of the four project objectives were successfully realized, proving the possibility of deploying a smart and cost-effective condition monitoring system for railway traction motors.

### **5.3 Limitations**

It is important to identify the technical limitations of the project in order to understand the current state of research as well as its academic integrity:

- i. No Field Data and Machine Learning Training Data: The key problem of this project is the impossibility of fulfilling Objective 2 due to the absence of structured labeled datasets obtained through field data from real traction motor malfunctions in low-resource railway ecosystems. As a result, the system had to use only static threshold values, not an intelligent model.
- ii. Hardcoding of Static Thresholds: The alerts (Warning when 75°C or 3.0 m/s<sup>2</sup> vibrations detected) are triggered by the system via hard-coded variables in the firmware. The real-time performance of the locomotives varies greatly and depends on environmental changes, different speeds and payload weights. As a result, there is a possibility of false positive or negative alerts due to static limitations.

- iii. **Laboratory-Based Test Setup:** Because of limited access to brownfield infrastructure, performance data of the system were obtained using DC motor test rig in laboratory conditions, not the real-time high voltage traction drive system on locomotives.

## **5.4 Recommendations for Future Work**

For fellow students or engineers seeking to build upon this research framework, the next logical development steps should address the following areas:

- a. **Address Objective 2 via Collaborative Field Data Logging:** The primary future research need is to complete the unachieved data collection objective. Future work should involve mounting the standalone hardware nodes securely inside active NRZ locomotive engine bays solely to act as long-term, passive data-loggers. By recording continuous operational profiles over several months, researchers can build the specific, labelled historical datasets necessary to train and implement an intelligent predictive model.
- b. **Develop Adaptive, Context-Aware Threshold Filtering:** To move past the limitations of fixed boundaries, future revisions should program an adaptive baseline algorithm. By interfacing with the locomotive's master controller to read the active throttle notch positions, the software can adjust warning thresholds dynamically in real time to match current operational loads.
- c. **Upgrade Physical Robustness and Galvanic Isolation:** Future prototypes should transition from a Veroboard to a multi-layered Printed Circuit Board (PCB) protected within an IP67-rated aluminium housing. Furthermore, complete optoelectronic isolation should be integrated into the circuit design to shield the digital microcontroller rails from heavy inductive current spikes and electromagnetic interference (EMI) common in industrial traction motor environments.
- d. **GPS-Based Fault Location Tracking:** Future work should incorporate a GPS module to provide real-time location tracking of locomotives during fault conditions. By integrating a GPS receiver with the ESP32, the system can transmit fault information together with the locomotive's coordinates to the monitoring dashboard. This would enable maintenance teams to quickly identify the exact location of a faulty locomotive, reduce response times, improve maintenance planning and minimize service disruptions, particularly in remote railway sections.

## **5.5 Chapter Summary**

The chapter provided the overall conclusions of the research and assessed how far the goals of the research were met. It was possible to achieve the goal of creating a cheap IoT-based system for condition monitoring that is capable of conducting real-time monitoring of temperature, vibrations, and currents, as well as giving fault alarms locally and remotely and triggering the emergency protection mechanism. However, the goal related to the use of machine learning could not be accomplished due to a lack of properly labelled data, which indicates that the created system served as a good basis for future improvements.

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