TALLINN UNIVERSITY OF TECHNOLOGY
SCHOOL OF ENGINEERING
Department of Electrical Power Engineering and Mechatronics

CONDITION MONITORING AND BEARING FAULT DIAGNOSIS OF THREE PHASE BLDC MOTOR BY ELECTRICAL SIGNATURE USING IOT AND MACHINE LEARNING

KOLMEFAASILISE HARJAVABA ALALISVOOLUMOOTORI SEISUNDISEIRE JA LAAGRIRIKETE DIAGNOSTIKA KASUTADES ELEKTRILISI SIGNAALE, ASJADE INTERNETTI JA MASINÕPET

MASTER THESIS

Student: Hardik Vinod Raval

Student code: 194358 MAHM

Supervisor: Hadi Ashraf Raja
(Early stage researcher)

Co-supervisor:
Toomas Vaimann
Senior Researcher

Tallinn 2021 - 22

(*On the reverse side of title page*)

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Author: Hardik Raval
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Department of Electrical Power Engineering and Mechatronics

THESIS TASK

Student: Hardik Vinod Raval, 194358MAHM
Study programme MAHM02/19, - Mechatronics
main specialty: Mechatronics
Supervisor: Hadi Ashraf Raja, Early-stage researcher
(Department of Electrical Power Engineering and Mechatronics)
Co-supervisor: Toomas Vaimann, Senior researcher
(Energy Conversion and Control Systems)

Thesis topic:
(in English) Condition monitoring and bearing fault diagnosis of three-phase BLDC motor by electrical signature using IoT and machine learning

(in Estonian) Kolmefaasilise harjavaba alalisvoolumootori seisundiseire ja laagririkete diagnostika kasutades elektrilisi signaale, asjade internetti ja masinõpet

Thesis main objectives:

1. Perform Background research of IoT 4.0
2. Develop hardware & software type for IoT framework.
3. Discuss the source of faults in the BLDC machine.
4. Comparison of healthy & faulty bearing current spectrum in offline analysis & real-time FFT

Thesis tasks and schedule:

No	Task description	Deadline
1.	Literature review and introduction	May-Sep 2021
2.	Implementing & developing IoT framework and hardware	Oct- Nov 2021
3.	Developing Machine learning model	Nov 2021
4	Writing Discussion and conclusion	Dec 2021

Language: English **Deadline for submission of thesis:** ″20‟ Dec 2021

Student: Hardik Vinod raval ’’20‟ Dec 2021

/signature/

Supervisor: Hadi Ashraf Raja, Early-stage researcher “20” Dec .2021

/signature/

Co supervisor: Toomas Vaimannn, Senior researcher “20” Dec.2021

/signature/

Head of study programme: Anton Rassõlkin ’’20‟ Dec 2021

/signature/

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PREFACE

Brushless DC motors have been utilized in electric vehicles, medical, military, and industry. The bearing is one of the most critical components of a BLDC motor. With the increasing popularity of brushless DC motors, an unforeseen failure of a vital component like a bearing may have enormous financial repercussions. Existing industrial monitoring systems such as SCADA are very costly. An early failure of the bearing of a BLDC motor can cost millions of losses to the industry. The introduction of Industry 4.0 drives new approaches, and research industries are maintenance.

Condition maintenance and fault diagnosis bearings of BLDC motors check the motor's bearing health and diagnose any irregularities in its functioning. The author presents an overview of the condition maintenance of paths in general, what can be done in the era of IoT 4.0, and the steps for conducting fault detection in approaches and diagnosis in real-time and offline.

The project goal concerns designing an IoT system for condition maintenance & fault diagnosis of 3 phase BLDC motor using the current sensor & identifying which machine learning method will be more accurate for future perspective. Follow up, research case study, where an experiment is carried out with 3 phase BLDC motor 48 v, healthy & faulty bearings, three ACS 712 current which helps for data acquisition from an individual phase of motor and esp32 which push data on my SQL Xampp server. Visualizes them on the line chart, stores them in the MySQL database of the Xampp web server domain. Extract data and performs offline spectrum analysis on MATLAB to check current signature analysis of respected bearing and online real-time monitoring & FFT fault diagnosis. At last, Train the machine learning model and perform a competitive analysis model for diagnosis signal.

A particular thanks to my supervisor, Hadi Ashraf Raja, who believed in the author and helped him fulfill the thesis's main goal in every manner possible. Also, I would like to thank Toomas Vaimann for his support & encouragement.

LIST OF ABBREVIATIONS AND SYMBOLS

SCADA - Supervisory Control and Data Acquisition

IoT - Internet of Things

IIoT - Industrial Internet of Things

CPS - Cyber-Physical System

KPI - Key Performance Indicators

PWM - Pulse Width Modulation

MCSA - Motor Current Signature Analysis

DC - Direct Current

BLDC - Brushless Direct Current

BDC - Brushed DC motor

HTML - HyperText Markup Language

PHP - Personal Home Page

REST - Representational State Transfer

MQTT - Message Queuing Telemetry Transport

HTTP - HyperText Transfer Protocol

FFT - Fast Forium Transform

DT - Decision tree

RF - Random Forest

SVM - Space Vector Module

TP - True Positive

TN - True Negative

FP - False Positive

FN - False Negative

1. INTRODUCTION

Brushless Direct Current motors have been utilized in electric vehicles and industry for decades. BLDC motors are now widely employed in medical, military, and aerospace applications due to their ease of speed and position control. As BLDC motors are used more, excellent dependability and safety are required. These plants cannot tolerate any BLDC motor failure. Plant engineers should thus frequently inspect the entire system, including BLDC motors. These repeated checks add to the expenses, but people may never predict such failure[1], [2].

BLDC motors are also used in medical, military, and aerospace applications to regulate speed and position. Because operational circumstances are more demanding in such areas, excellent dependability and safety are required. It is difficult to determine if any of the modules in such systems will fail without frequently testing. Thus, specialists can provide periodic maintenance and repair; maintenance expenditures range from 15% to 40% of overall production costs. The primary loss of supply lies in the sudden breakdown of electrical machines, which block industry production. An early study can cost millions of losses to the industry. Therefore, an innovative & automatic condition monitoring system is required[3], [4].

Adding additional modules for emergency usage is one technique to improve dependability and safety. Each key component can be designed as a redundant module. While replacing minor applications with standard features with more details might be appropriate, it increases total cost, volume, and complexity for more advanced systems. Adding additional BLDC motors to systems is challenging since replacing a damaged motor necessitates mechanical and electrical adjustments. The automatic system detects 40-50% of the issues. A sophisticated mechanism may be necessary. This technology increases maintenance and repair requirements for the replacement mechanism, reducing overall system dependability. It may be beneficial to continually monitor or test a BLDC motor's status to detect failure before it causes system or human health damage[5]–[7].

Existing industrial monitoring systems such as Programming Logical Control & Supervisory Control and Data Acquisition etc., are very costly. As it system very complex & only cooperates with specific software & hardware. SCADA provides a limited amount of data. Also, it is expensive to add sensors & make changes in the SCADA system[8].

Therefore, it is not surprising that with the advent of Industry 4.0, which is expected to be the fourth industrial revolution, one of the sectors where many investments are being made and in which the research is very active is precisely that of maintenance[9]. Condition monitoring and fault diagnosis of BLDC motors checks the motor's health and diagnose any irregularities in its functioning. BLDC monitoring applies to practically any electrical or mechanical component. Online condition maintenance through IoT system and fault diagnosis through FFT spectrum in MATLAB software and real-time in Xampp server. These concepts have remained popular among researchers who aim to apply new approaches to new motors to obtain more accurate and reliable diagnostics and categorization of faults that may arise in BLDC motors.

Objectives

The thesis aims to identify the current spectrum of different bearings in the era of IoT 4.0. for that study, relevant literature of IoT 4.0 & faults in BLDC. Experiment with different bearings. Following problems can be resolved.

- What is IoT 4.0?
- How does the current frequency spectrum for a healthy motor look like?
- What are the sources of faults in brushless DC Motor motors?
- What are the characteristics of the different faults of BLDC bearing?
- How are fault detection and diagnosis can be done today?
- How is the current frequency spectrum affected by different faults in the bearing?
- Does faults can be detected at the early stage?
- Which machine learning algorithm performs better accuracy for bearing faults?

Scope of work

- Description about IoT 4.0 & Smart maintenance
- An overview of the working principle of the BLDC motor and its application in the industry.
- A presentation of the different fault sources and the resulting fault in the BLDC motor. Their consequence and signature are also presented.
- An overview of condition monitoring in general, what can be done in the industry today, and the different steps for conducting fault detection and diagnosis.
- Evaluate the frequency current spectrum of the bearings.
- Competitive analysis of different machine learning methods.

2. LITERATURE REVIEW

The industry branch of the economy deals with material assets mechanically. Technology innovation has led to significant and rapid changes in the industrial sector, resulting in revolutions. "Industry 4.0" refers to the current industrial revolution. Three initial industrial processes preceded this one in human history. The first industrial revolution, which spanned from the mid-18th century until the mid-19th, brought mechanized production. The second industrial revolution began in the 1870s with electrification and division of labor. The third industrial revolution started in the 1970s as electronics and computer technology developments permitted more production automation. Like mass-production techniques in the early twentieth century, this age of automation began with the automobile industry but spread to other sectors. Industrial businesses could now establish predictable, repeatable, and managed production processes that did not require constant human interaction, allowing output to exceed past staff limitations. The benefits of automatic method management have been realized in practically all business fields with increased computer power and microprocessors. SCADA (Supervisory Control and Data Acquisition) systems helped firms better inform processes using features in networked structures, allowing visibility throughout the plant. The foundations of the third business revolution were a virtual age and large-scale computers[9]–[11].

In 2011, a group of business, political, and academic leaders embraced the concept of "Industry 4.0" to improve Germany's manufacturing industry's competitiveness[12]. Industry 4.0 will "fundamentally improve industrial processes involved in the production, engineering, material consumption, supply chain, and life cycle management," say proponents.

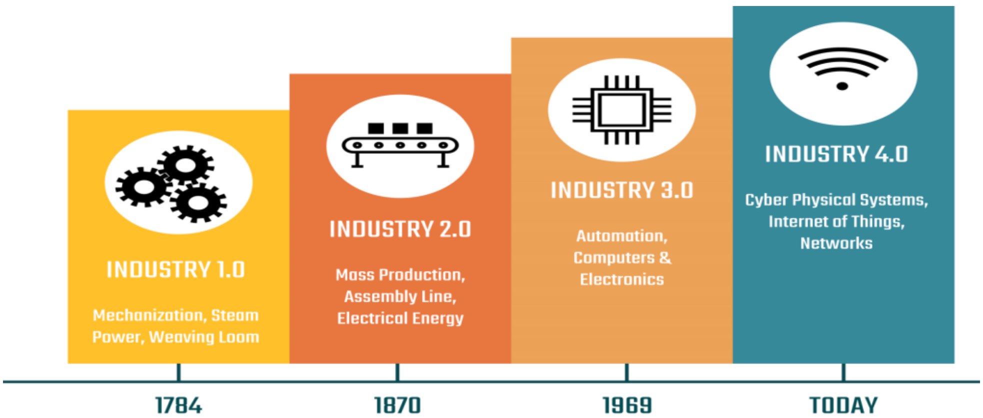


Figure 2.1.1 Industry trend[13]

The fourth industrial revolution shifts manufacturing processes from centrally controlled to autonomous, enabling connectivity between people, machines, and resources. Innovative products actively steer themselves through the manufacturing process by telling motors to finish critical manufacturing tasks and ordering conveyors to move to the next production stage.

To define Industry 4.0, both the enabling technology and the primary benefits are discussed here.

Cyber-Physical System: It includes computation, networking, and physical processes. Embedded computers and networks monitor and govern physical processes, using positive and negative feedback loops where analyses alter physical processes. Advanced man-machine communication interfaces allow oral, visual, and haptic iterations[11].

Internet of things: The Internet of Things (IoT) connects things, functions, and settings to the Internet. Those "connected" things collect, send, or both. A gadget linked to the Internet can send and receive data. Sending and receiving data makes things smarter. Super storage or a supercomputer are not required to be clever. Instead, cloud storage or supercomputers are needed[10]–[12].

Industrial Internet of Things (IIoT): IIoT focuses on industrial applications such as transportation, manufacturing, energy, and agriculture. However, due to its increased complexity, interoperability, and security requirements. Incorporating artificial intelligence and CPS functions into an autonomous gathering and transmitting data about the physical environment is feasible[11], [12].

Cloud Computing: It is commonly used to define data centers accessible over the Internet. Due to the lack of a human interface, it is renowned for data storage and computing power. In addition, it allows organizations to avoid or reduce upfront IT infrastructure costs. It will also help organizations update their apps faster, with less maintenance. As a result, IT teams will quickly shift resources to changing demand[11], [12].

Big Data: A relational database cannot handle a vast, rapid, and diverse data set. Activity, sensor values, and machine status are examples. We look for unknown links between variables and events when studying data. Data become information that helps decision-making in the study. Massive data needs cloud-based solutions[11], [12].

2.1 Smart Management System

In this new era of the 21^{st} century, the system developed with the help of the Internet of things. It is called a smart management system. It is a system that helps identify and detect the motors' faults to reduce maintenance costs. Data acquisition, Data manipulation, diagnostics, key performance indicator, and optimization are major modules of the smart management system using IoT[9], [10].

Data acquisition: It is the initial step towards an intelligent system. In this step, sensors are chosen and mounted on the machine to generate the best output signal for the equipment's state. Real-time data is captured and stored in the cloud. It is then turned into a domain that contains maximum data regarding the equipment's condition[10], [12].

Data manipulation: Multiple sensor data are not readily available for analytics. It lacks noise, redundant data, and inaccurate sensor readings. Before processing, the raw data must be sorted, filtered, and prioritized. Pre-processing and signal conditioning increase signal quality. Many strategies are employed to reduce noise and enhance the signal-to-noise ratio. Essential elements from the pre-processed signal are retrieved to highlight impending failure. We can remove features from the time domain, frequency domain, and time-frequency domain[8], [14].

Diagnostics: Signal identified in the data manipulation section is used to identify equipment faults. Diagnostics focus on detection, isolation, and identification of a spot.

Key performance indicators: Component degradation is shown graphically by a radar/spider chart or danger chart. Severity, criticality, business rules, and safety are used to rank KPIs. These charts help operators visualize component conditions. Most equipment failures are caused by human error. Technicians should reschedule maintenance at an ideal period to reduce common equipment failure and maximize performance and reliability. The figure illustrates the relationship between loss, reliability, and maintenance costs.

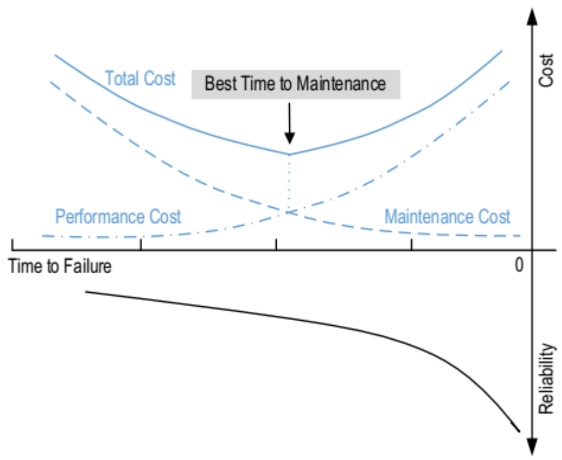


Figure 2.1.1 Relationship between failure time, cost & realibility[10]

2.2 Maintenance in IoT 4.0

Management systems are critical to the maintenance information system. It is a platform for systematic maintenance planning, implementation, and control. It manages human and capital resources efficiently. The figure below shows the resources that an enterprise must address. As seen in the illustration, maintenance is a sub-system of enterprise and production. Both rely on maintenance systems. Facilitates the management of resources such as labor and spare parts. These inputs result in output, availability, maintenance, and asset safety[8], [10], [12], [14].

Sensors: They are installed on the machines to perform measurements regarding the physical parameters of interest.

Communication: It is important to transmit the data collected to an aggregation center.

Storage: It keeps the history of the sensor values and possibly integrates it with a list of events and activities.

Analysis: It is used to extrapolate correlations between variables and machine states to recognize and predict failure.

2.3 Development Trend

This section discusses the research and development trend relating to condition-monitoring techniques and methods for marine propulsion systems. It is important to note that most techniques and methods are generic and used in other industries. Condition monitoring and fault diagnosis of electrical machines has always been a topic of interest and importance in industry and academia. In recent years, there has been extensive research activity towards developing smart maintenance systems. Electrical machines are increasingly used in new applications and are often critical systems.

Several studies have been conducted on fault diagnosis and health monitoring of BLDC of rolling bearings[7], [15]. BLDC bearing issues are investigated. The study approach compares the vibration signal of excellent and unhealthy bearings utilizing specific vibration frequencies with the help of accelerometers[16]. Later, Vivek Kumar Sharma and Bharat Raj purohit et al. used surface force densities and force distribution for Modal and Harmonic-Response based analysis were used by For mechanical vibration analysis of a BLDC motor[6]. After, Computations were performed using the finite element method using the program Ansys by J. Podhajecki et al. [3]. Again, Vivek Shart et al. proved that each vibration spectrum component is affected by the change in machine quantity[17]. Also, L. Cui et al.'s Paper provides a nonlinear vibration model for quantitative bearing fault diagnosis[18]. R. Pindoriya et al. research examine the vibration and acoustic noise generated by BLDC motor[4]. The motor was driven experimentally using digital pulse width modulation (PWM) to analyze vibration and noise[4]. Moreover, X.wang proved that Vibration signal analysis was used to discover variable-speed motor bearing difficulties.

When it comes to BLDC motor stator coils, the most prevalent fault is related to the windings. High temperatures, inadequate insulation, age due to the operation, contamination, and other factors are the primary causes of wind faults [4].

Multiple investigations into the identification of faults and condition monitoring of BLDC motor stator-related difficulties have been carried out in the past[1], [2], [19]–[21].

Among the techniques used to diagnose stator defects in motors, MCSA is the most widely used. The current flowing through the motor conveys critical information regarding the precision with which the stator windings are operated [1], [2], [19]–[21].

A large number of experiments have demonstrated that by examining the current signature, it is feasible to discover defects in the winding at the earliest possible moment. Stator current frequency analysis was proposed by J. K. Park et al. [18]. In addition, input impedance monitoring for BLDC motor inter-turn failures has been proposed.

A technique developed by S. Rajagopalan et al. For detecting rotor-related problems in nonstationary situations was based on the Wigner-Vile Distribution of motor currents[2]. Following that, S. T. Lee et al. used the study of third harmonic components of motor current to find defects connected to the stator[1], which was later confirmed. Online defect detection was proposed by O. Moseler et al, who developed a model-based parameter estimation technique[22].

These methods have a solid theoretical background, and performance is validated using several machinery data such as rolling-element bearing, stator winding, inter-turn winding, rotor gearbox, etc. However, a detailed study on the brushless DC motor's bearing fault diagnosis using FFT with the help of the current sensor has not been reported to date despite having an excellent cyclostationary behavior. In literature, most studies on BLDC motor fault diagnosis deal with vibration sensors with mechanical properties. In practice, a motor serves different purposes with unique operational complexity and environmental influence. It is understood that a higher load will cause the motor to draw a more significant amount of current from the source than usual. Motor speed and torque can also get affected under particular stress and load. And it will increase the current for a motor, and it will depend on the system where it is operating. Therefore,

only monitoring will not be sufficient to conclude the motor health state. Moreover, the same fault can exhibit unique characteristics for different bearing conditions. All the parameters do not show similar deviations from normal behavior simultaneously.

Bearing condition maintainnce[23] & fault identification using MCSA technique with the help of the Esp32 module had been proposed. The thesis study motivated to establish a prototype & well-defined fault diagnostic framework using a current sensor that will detect the fault of mechanical characteristics such as bearing faults—also, a train machine learning model on different methodologies to recognize specific current patterns. FFT Signal processing analyses the stored measurement signals in the data acquisition process. Traditional time-domain analysis computes statistical variables describing machine health, such as peak, root means square, mean, kurtosis, and skewness. The frequency-domain analysis is based on the frequency-domain converted signal. The benefit of frequency-domain research over time-domain analysis is that it breaks the original signal down into a series of frequency components.

3. ELECTRIC MOTOR

Electric motors are used in almost every industry. There are several types of electric motors available. Engineers can choose these motors based on voltage and application. Field winding and armature winding are essential in every motor. The field winding is responsible for creating the fixed magnetic field, whereas armature winding appears to be a conductor within the magnetic field. The armature winding uses energy to create torque to turn the motor shaft. Induction and DC motors are the two most common types of motors. The rotor of an AC induction motor is made up of laminations and windings, not magnets. 3 phase power creates a revolving magnetic field in the motor's stator. The magnetic field drives the rotor's current. That current creates its magnet, which interacts with the stator field to produce torque[23].

This benefit is lost when variable speed is required, as in many pump applications, because a variable frequency drive (VFD) must be installed between the AC supply and the motor.

A BLDC motor, on the other hand, uses permanent magnets instead of rotor windings. The magnets' magnetic field interacts with the stator's field to generate torque. Unlike a 3-phase motor, a BLDC motor's magnetic field must be carefully controlled and aligned with the rotor position and fixed magnets. Its full torque is available at zero speed. The motors are usually smaller and lighter than equivalent induction motors. This allows a BLDC motor to respond to changing load circumstances significantly faster. The following specification has been compared in table 3.1.

Table 1 Difference between AC and DC motor

Specifications	**Induction motor**	**BLDC motor**
Speed/torque characteristics	Nonlinear	linear
Output power	Average	Extreme
Rotor inertia	Low	High
Controller	Not required	Needed
slip	existed	Absent

Improved efficiency, precise torque and speed control, lower rotor inertia, and a compact structure are advantages of BLDC motors over induction motors.

3.1 BLDC motor

Low maintenance requirements and energy efficiency have allowed brushless DC motors to gain noticeable attention in domestic and industrial applications such as renewable energy, household, aeronautics, and industrial automation. In addition, the transport and automotive industries have specifically found significant use cases for DC motors[24].

DC motors can be divided according to structure into the following two types.

- Brushless DC motors (BLDC)
- Brushed DC motors (BDC)

The simplest motor is a DC brushless motor. A brushed DC motor has a commutator, brushes, stator, and rotor. Brushed DC motors are excellent for a wide range of applications due to their simple design and low cost. The main downside of brushed DC motors is the use of brushes, which reduce motor life and produce noise. So, these brushes need to be replaced regularly[16].

Brushless DC motors were created to replace brushes. Brushes are not used to transport or convert current here. These brushless motors do not produce sparks. They are also electronically commutated, which is useful in areas where sparks can cause problems, such as gas applications.

Brush removal minimizes electrical erosion and mechanical friction. Brushless DC motors can also produce more power than brushed motors due to permanent magnets and power electronics. The same power output as brushed DC motors, but smaller and lighter. Thus, brushless DC motors gain significant value in applications where weight and size are crucial.

Economic and environmental factors drive urban vehicle efficiency and sustainability. Self-driving automobiles, electric and hybrid cars, electric scooters, etc. will all benefit from brushless DC motors. Electric scooters are an ongoing market trend requiring high starting torque and power density, varying range of speed, reduced noise, reliability, and low maintenance. BLDC motors easily fit these requirements[3], [25].

Drones are another aviation trend that is catching up in the market. Drones need to have a powerful yet lightweight motor, which BLDC motors are suited for. BLDC motors can easily regulate current and voltage, which, therefore, helps in controlling speed. This is an essential requirement for moving drones from one place to another[16].

BLDC motors, in addition to transport and logistics, are also used in several industrial applications. Since these motors do not have brushes, they do not create any sparks, which are highly suited for oil and gas. In the oil and gas industry, sparks can be extremely dangerous. For instance, electric submersible pumps make use of BLDC motors for oil production[4], [15].

Mentioned below are the advantages that brushless DC motors possess over brushed DC motors[16], [23].

- Smaller size
- Minimum engine gauge
- Minimum rotor vibration on motor operation
- Lesser weight
- Greater reliability
- Improved efficiency
- Greater lifespan
- Reduced noise
- A wider range of speed
- Enhanced speed-torque ratios

3.1.1 Design & working principle of the BLDC motor

In the case of design, brushless DC motors are quite similar to permanent magnet synchronous motors. The magnetic fields of the stator and rotor have the same frequency of rotation. The stator has a correlating number of windings when it comes to phase configuration. A brushless DC motor can be three-phase, two-phase, or one-phase, out of which the three-phase DC motor is most widely used. The thesis focuses on three-phase brushless DC motors, which can be seen in Figure 3.1.1.

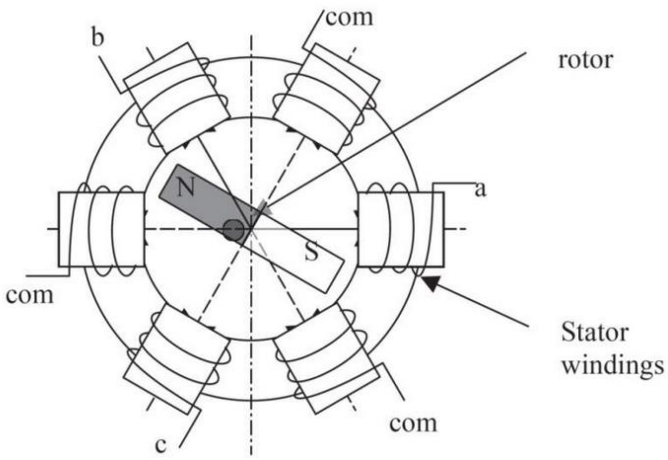


Figure 3.1. 1 three-phase of BLDC motor[26]

The rotor is usually underneath the motor, whereas the stator is in front. The rotor has coil field winding driven by DC, while the stator has either electromagnets or magnetic field winding[23].

3.1.2 Rotor

Brushless DC motor rotors comprise a hub with permanent magnets and a shaft, two to eight pairs of poles, with alternating north and south poles. The utilization of permanent-magnet electric machines is trending while the market, in the recent past, has portrayed an increase in demand for such materials. The right magnetic material is chosen for the rotor according to the magnetic field required by the rotor density. In recent years, four magnetic materials have been used in different applications[23].

Figure 3.1.1 Projected demand for the materials in recent years[27]

As of today, that ferrite magnets dominate the global permanent-magnet industry. The cost-efficiency of ferrite materials is its primary advantage, primarily due to the low manufacturing costs. Additionally, the electrical resistance of ferrite is also very high, with good corrosion resistance and a long lifespan. However, ferrite is not the preferred magnetic material for high-power density applications due to the material's low-residual inductance[17], [23].

AlNiCo materials undergo demagnetization as they possess low coercivity. While this material possesses excellent corrosion resistance and elevated temperature properties, the maximum energy density is 1/5th of SmCo materials. Rare earth permanent-magnet electric motors find an application in automotive electric motors as these provide high performance over a wide range of temperatures. SmCo magnets possess greater thermal demagnetization resistance, high corrosion resistance, and high coercivity. The disadvantages of these magnets are their high cost and brittle nature. On the other hand, NdFeB magnets aren't as brittle and possess poor corrosion resistance and thermal properties[22]–[24], [28].

Rare earth alloys have recently been preferred within the industry for applications in electrical machinery. NdFeb alloys are specifically used in applications that require high power density, whereas SmCo alloys are preferred in wide temperature range applications. When it comes to brushless DC motors, rotor magnet cross-sections varied configurations are utilized. The primary options are portrayed below in Figure 3.1.2 Cross-sections of the magnets on the rotor: (a) Surface-mounted magnets, (b) tangential magnets mounted inside the rotor, (c) radial magnets mounted

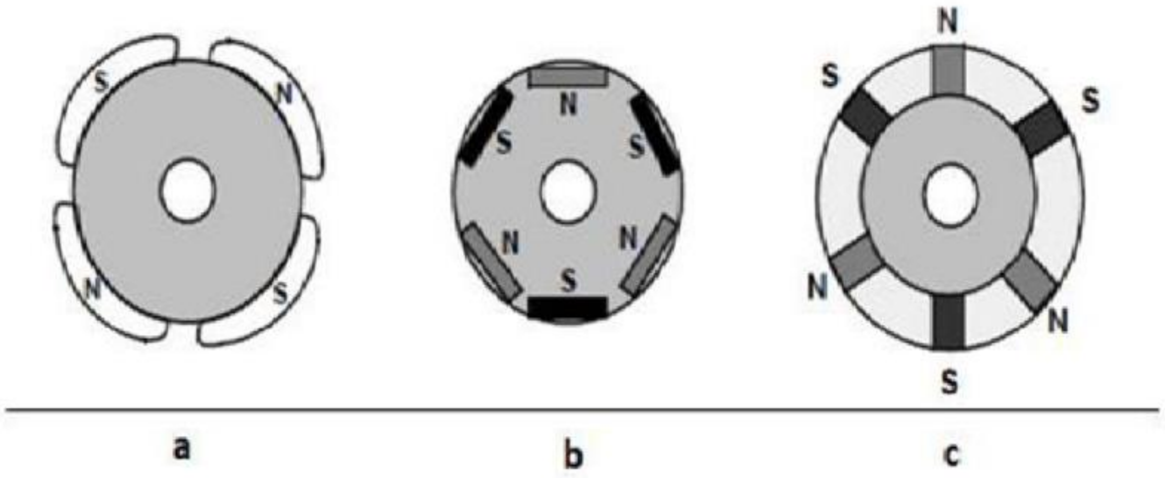


Figure 3.1.2 Cross-sections of the magnets on the rotor: (a) Surface-mounted magnets, (b) tangential magnets mounted inside the rotor, (c) radial magnets mounted

The magnets shall be placed on the surface of the rotor, as shown in Figure 3.1.2.2a, The magnets are placed in the slots of the rotor, as shown in Figure 3.1.2.2 b, c. In the case of an engine where the magnets are placed on the rotor surface (Figure 3.1.3 a), the engine design becomes simpler compared to other arrangements. However, surface-mounted magnets may reduce the reliability of the electrical machine. There are also possibilities for placing magnets inside the rotor (Figures 3.1.3 b, c). Depending on the reason, different placements can be used. In this case, the rotor design becomes more complex. The advantage of internal placement is that it eliminates the possibility of peeling or breakage in the event of centrifugal forces or failure[22]–[24], [28].

3.1.3 Stator

Brushless DC motors have stators similar to stators of asynchronous motors, where the primary difference is the distribution of the windings. For example, portrayed below in Figure 3.1.3.1 is a three-phase brushless DC motor stator.

Brushless DC motor stators comprise ordered steel laminates and windings arranged in slots that are present in the inner edge of the laminate. These motors utilize a three-star-connected winding, with the possibility of a triangular connection. Star connections provide higher output torque, whereas has the triangle connection provides a higher rotational speed[27], [29].

Figure 3.1.3 BLDC motor stator

3.1.4 Rotor detection sensors

Brushless DC motors, unlike brushed DC motors, are controlled electronically. Stator windings are energized in series to achieve continuous rotor rotation. It is also important to know the rotor position to apply the correct voltage to the right winding. Hall sensors are built into the stator to detect rotor position, as displayed in Figure 3.1.4.1 Hall sensors are also known as position sensors or rotor detection sensors[27], [29].

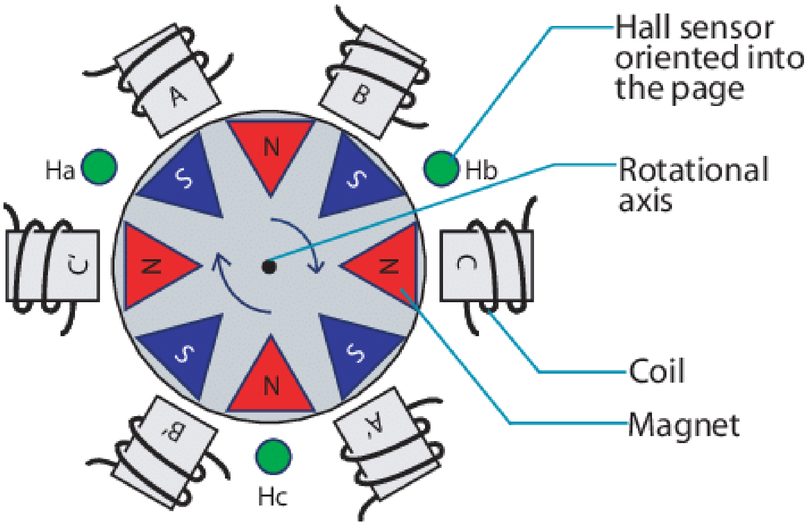


Figure 3.1.4 Hall sensors or rotor detection sensors [26]

Hall sensors are incorporated into the stator of brushless DC motors. Putting the Hall sensors on the stator is a pain. Any misalignment of the Hall sensor with the rotor magnets will cause rotor positioning failure. Some motors include Hall sensor magnets in the rotor and primary rotor magnets to make installation easier. When the magnetic pole passes the sensor, it detects the north or south pole. The controller then determines which stator winding to activate. The sensor's signal can also detect permanent magnet failures such as breaking or demagnetization

.

3.2 Brushless DC Motor Working

Motors can also be classified by counter-electromotive force, which can also be defined as the method that drives them. Contrary to synchronous motors that comprise permanent magnets, brushless DC motors use sinusoidal or trapezoidal commutation. As per the name, sinus[23]oidal commutation provides the sinusoidal counter-electromotive force, whereas trapezoidal commutation provides the trapezoidal counter-electromotive force[3], [4], [17], [23], [25]. This is shown in figure 3.2.1 & figure 3.2.2.

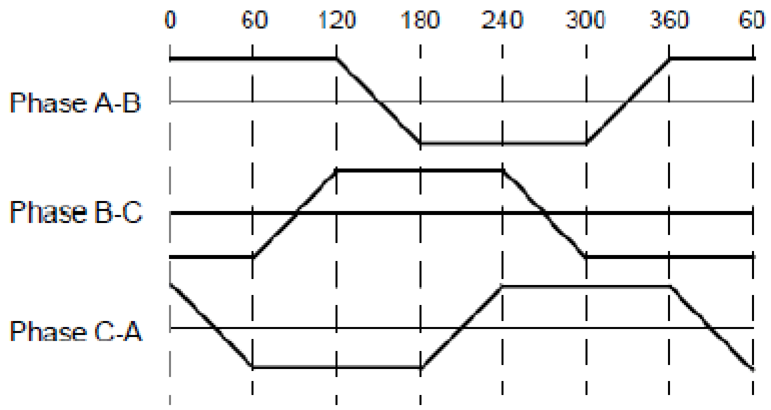


Figure 3.2.1 Trapezoidal electromotive force[23]

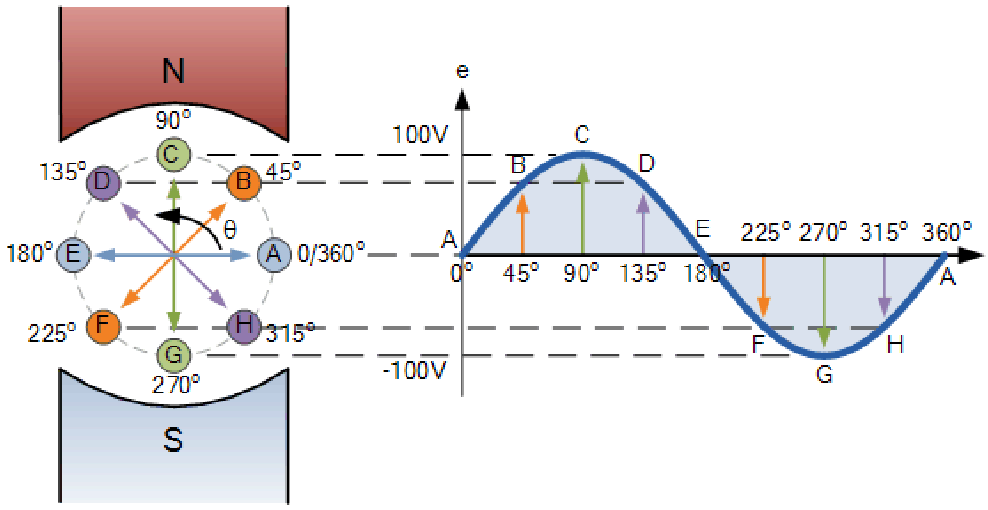


Figure 3.2.2 Sinusoidal electromotive force[23]

Fig. 3.2.1 & 3.2.2 types of counter elective force

Depending on motor type, phase currents can also be classified as sinusoidal or trapezoidal. Motors that are sinusoidal make the torque smoother than trapezoidal motors. However, sinusoidal motors aren't as cost-effective as they comprise additional stator connections due to winding distribution, increasing copper usage. Applying a direct current to the coil gives off energy and becomes an electromagnet. The brushless DC motor works based on the interaction between a permanent magnet and an electromagnet. Figure 1.7 shows that when winding A is energized, the opposite poles of the rotor and stator are attracted. As the rotor approaches winding A, winding B is energized. On the other hand, as the rotor approaches winding B, winding C tensions. After this, they were winding A is energized with the opposite polarity. This process repeats, and the rotor continues to rotate[3], [4], [17], [23], [25].

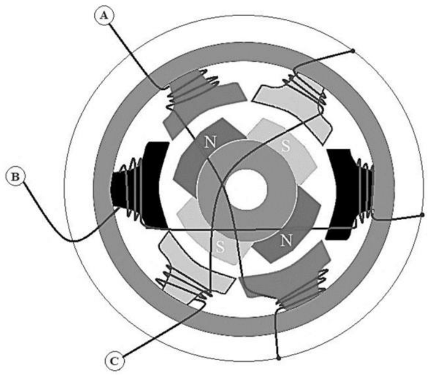


Figure 3.2.3 BLDC motor working

3.3 Disadvantages Of BLDC Motor

During operation, BLDC motors can suffer from a wide variety of faults. A variety of factors can cause electrical machinery failures. BLDC motor failures can be categorized into the following three groups.

1. Magnetic failures (i.e., permanent magnet demagnetization)

2. Electrical faults (winding faults)

3. Mechanical failures (bearing failures and eccentricity)

Electrical machinery operates in a range of conditions over long periods of operating time, which makes breakdowns a certainty; thus, creating a correlation between the three categories of failures mentioned above.

3.3.1 Electrical faults

Electrical imbalance occurs when the magnetic attraction between the stator and rotor is unevenly distributed over the motor. Deflection of the shaft causes mechanical unbalance. BLDC motors have field coils that are regularly shorted due to the open stator or rotor windings. Uneven air gap generated by badly worn sleeve bearings causes electrical imbalance[16], [23].

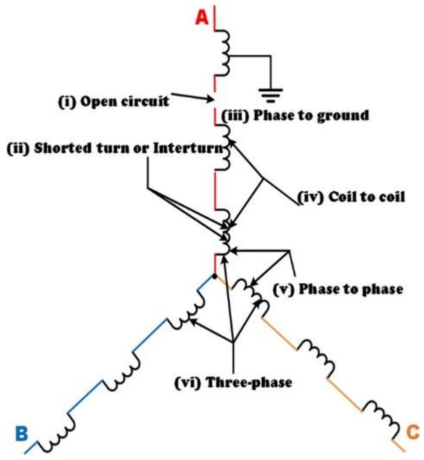


Figure 3.3.1.1 Electrical faults[16]

Open Circuit: An open circuit can occur due to a component failure, a break in the conductor, or a manual interruption.

Phase to the ground: Low resistance is the most prevalent cause of motor failure and, arguably, the most difficult to overcome. Wind insulation deterioration causes low resistance due to overheating, corrosion, or physical damage.

Coil to coil: When current flows through a wire coil, it transforms into an electromagnet, when an electromagnet interacts with a permanent magnet, the coil spins.

Phase to phase: it caused by the broken wire. Unrecognized phase loss can quickly lead to dangerous circumstances, equipment breakdowns, and costly downtime.

Uneven air gap: An air gap distortion might occur if the motor is not properly mounted to its bedplate. A loose or missing bolt permits the motor's mounting foot to slide during frame thermal expansion. This shifting over time could result in frame distortion and possibly stator bore distortion.

3.3.2 Magnetic Faults

In BLDC motors, demagnetization is the most common permanent magnet failure. Demagnetization is the partial or total loss of magnetization. Conditions in electric machines that cause permanent magnet demagnetization are as follows.

- High operating temperatures
- Production defects
- Overloading machines
- Short circuits

Permanent magnets demagnetize due to overloading and overheating. High-temperature electrical machine operation without adequate cooling increases permanent magnet demagnetization danger. Another common cause of permanent magnet demagnetization is short circuits, particularly phase-to-phase short circuits. Corrosion also decreases the material's magnetic characteristics. Permanent magnets are widely used in many industries and have high magnetic capabilities, but their resilience in harsh environments is limited. Two strategies to improve corrosion resistance are using metallic or non-metallic coatings and changing the magnet microstructure (by adding components).

3.3.3 Mechanical faults

Almost 50% of all brushless DC motor failures are related to mechanical failures. Such errors usually indicate eccentricity and bearing faults in most machines. One of the mechanical failures that occur in brushless DC motors is eccentricity. Eccentricity failures cause an uneven air gap between the rotor and stator. It is mainly caused by incorrect installation, lack of bolts, shaft misalignment, or rotor imbalance. There are three main types of eccentricity: static eccentricity, dynamic eccentricity, and elliptic eccentricity[16], [23].

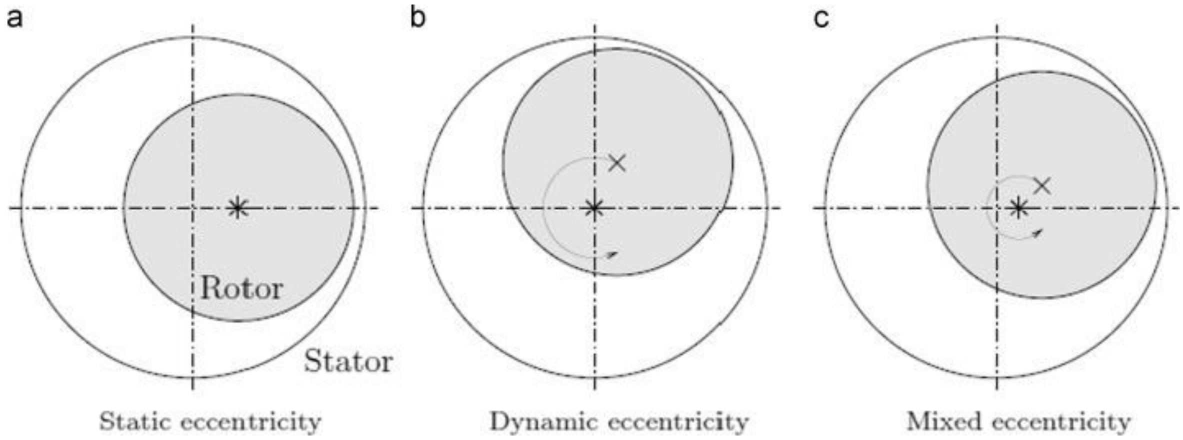


Figure 3.3.2 Types of eccentricity[16]

Static eccentricity: In this case, the rotor spinning axis is the same as the symmetrical stator axis. The rotor's air gap distribution is not uniform, but it is not time-dependent. During routine maintenance, increased static eccentricity is caused by improper motor mounting or misalignment of the stator and rotor centers.

Dynamic eccentricity: The rotor's angular position governs the minimal air gap length—misalignment or curvature of the rotor axis. The imbalanced magnetic force from static eccentricity creates dynamic eccentricity.

The stator symmetry axis and the rotor rotation axis are the same with this eccentricity, but the rotor symmetry axis has been shown. The air gap around the rotor is non-uniform and fluctuates. An angled rotor shaft, worn bearings, mechanical resonance at critical speed, and other factors might produce this misalignment.

A mixed eccentricity has both static and dynamic oddities. In this case, the rotor's rotation axis and symmetry axes are shifted due to mixing static and dynamic transfer vectors.

3.3.3.1 Bearing

An electric machine's key components are bearings. As a result, bearings have received much attention in recent decades. Bearings are made in compliance with bearing quality standards. They are one of the most precise mechanical engineering products available. The main components of rolling bearings are as follows,

- The Inner Ring,
- The Outer Ring,

- o The Rolling Elements,
- o The Cage

Figure 3.3.3 Bearing structure[16]

Its inner ring is usually mounted on a rotating shaft, and its outer ring is fastened to the housing. Rolling elements can be balls or rollers. It is a ball bearing with a small surface (preferably, point contact). Its load-carrying capability is lower than that of a roller bearing, where the rollers transfer the weight by line contact. The cage keeps the rolling components from clashing. It also helps prevent inadequate lubrication and retains the Bearing together while handling it.

The bearing type should be determined by the load direction and nature, the Bearing lattice fixation rate, and the operating environment. Failure of a bearing isn't always Bearings are usually replaced due to typical bearing material fatigue (natural bearing wear). A well-chosen and used Bearing can outlive a machine. In general, Bearing types can be divided into the following groups,

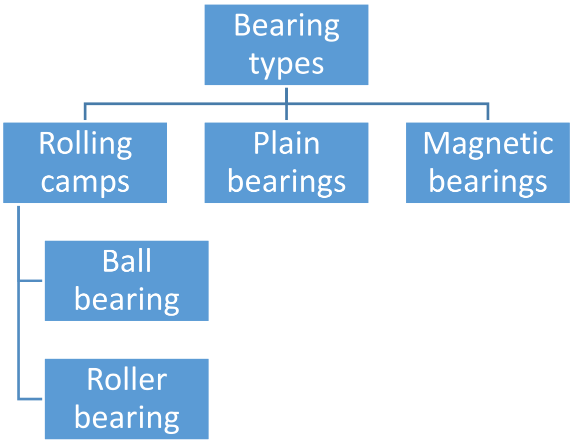


Figure 3.3.4 Types of bearing

Rolling element bearings, such as ball bearings, have three primary functions: carrying loads, minimizing friction, and positioning mechanical parts in motion. Especially, Ball bearings are the most widely used bearing types, which are also used in brushless DC motors. As driving conditions are rarely ideal, the potential resource of bearings is seldom fully realized. In general, the life of a bearing depends on the level of production technology, storage conditions, correct bearing selection, and use. Proper mounting, high-quality lubrication, and sealing are also necessary. Bearings are usually components that are smaller than other major engine components. At the same time, they are subject to a wide range of forces, making them particularly vulnerable to damage and wear[16], [23]. The reasons behind bearing faults are as follows,

1. Material fatigue
2. Semi lubrication
3. Incorrect installation
4. Pollution
5. Waterways

These reasons are possible because of the environmental & production factors. Bearing damage can be significantly reduced by monitoring bearing performance, measuring noise and vibration, and periodically analyzing lubricant quality.

4. IOT ARCHITECTURE

In general, to execute or design an efficient IoT system design, the architecture of IoT is required to be considered primarily. Figure 4 is the pictorial representation of the four main stages in IoT architecture

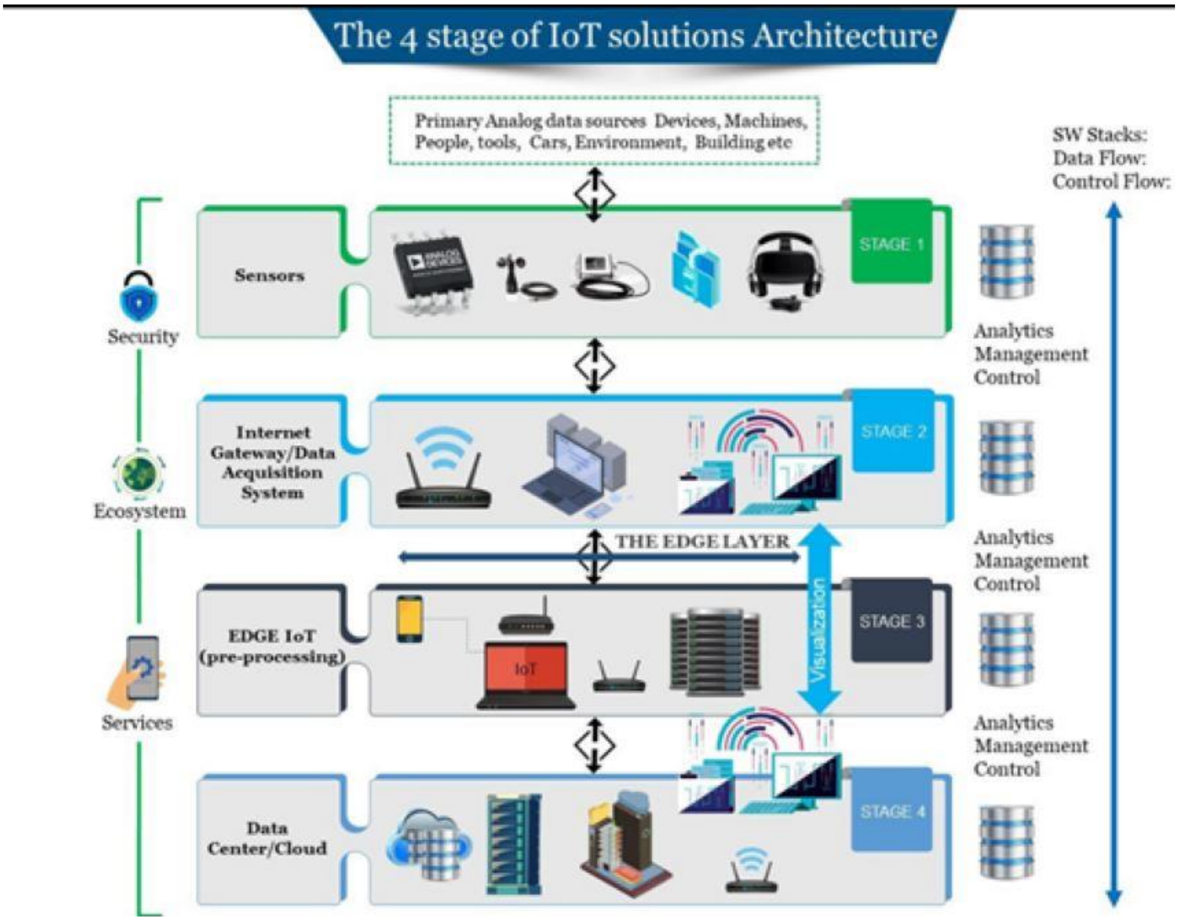


Figure 3.3.1 IoT architecture[30]

Sensors collect data from electrical impulses, and actuators operate automatically based on that data. These devices collect data from diverse areas and deliver it to the next IoT tier. Current, Voltage, temperature, pressure, and RFID tags are popular IoT sensors. They sent data via Wi-Fi, ZigBee, and Bluetooth to the server. IoT gateway must translate wireless protocols to assure sensor and electrical device interoperability. The gateway also secures data transmission from one system to another. In other words, it ensures data is delivered to the cloud. This acquisition system must move data from the edge to cloud-based infrastructure—incorporated circuit boards. During the edge computing stage, sensors send a lot of data to the IoT Cloud. Before sending data to the cloud, the edge system evaluates it. It reduces bandwidth usage, traffic delays, and system response times. Consider connection, adaptability, and flexibility when choosing an IoT edge system[31].

The device-cloud link Security requires that employees be assigned responsibilities based on their job functions. Also, IoT data is secure, and only certain people can access it. IoT systems can use symmetric and asymmetric cryptography techniques. Data visualization comes after data preparation. Many IoT devices create data that is difficult to control. So, Data visualization helps firms discover hidden patterns and current monitoring[31].

4.1 Microcontroller

4.1.1 Arduino UNO

The Ivrea Interaction Institute designed this board for students with no prior experience in electronics. Electronics hobbyists and students flocked to it. The most common Arduino boards are the Uno (ATmega328) and Mega (ATmega2560). The Arduino IDE accepts C or C++ programming and has Arduino-specific capabilities. These are the main advantages of adopting Arduino and its ecosystem. The Arduino is relatively cheap compared to other microcontrollers, with an Arduino Uno costing about €20 and a Mega costing under €35[31].

Table 2 Advantages & Disadvantages of Arduino UNO[31]

Advantages	**Disadvantages**
Simple to use.	Wi-FI, Bluetooth connectivity is not included.
Large no. Variety of libraries available.	Arduino microcontrollers are not well suited for battery operation.
Code written for one board can use for another board.	Arduino boards have less computational power.

Esp Family

In addition to Wi-Fi, the ESP8266 has Bluetooth. Espressif's first microprocessor to gain traction in IoT projects. However, it is still less expensive than the ESP32 and hence a feasible solution for IoT applications that do not require the extra capability of the

ESP32. The ESP32 replaces the ESP8266. The Esp8266 has a two-core microprocessor and supports Bluetooth Low Energy (BLE). Is a more secure gadget with enhanced safety features like secure boot and flash encryption that the ESP8266 lacked.

Table 3 Compersion between Arduino Uno & esp32[31]

Specification	**Arduino Uno**	**Esp 32**
Internal memory	8 kb SRAM, 4k EEPROM	520KB RAM
Connectivity	None	Wifi 802.11 b/g/n (HT20),Bluetooth,
External memory	256 kb	Upto 16MB SPI flash & Upto 4b SPI RAM
Periherals Supports	GPIO(14), ADC(6)	GPIO(34),ADC(12),DAC(8),SPI(4),UART(3)
Security Features	None	Secure boot, Flash encryption 1024 bit OTP
Operating Voltage	5V	3 to 3.6 V
Cost	20 euro	12 euro

Table 4.1.1.2 shows that the Arduino and ESP32 boards differ significantly. Rather than an IoT device, Arduino was intended to be a low-cost prototyping tool. Several Arduinos have appeared over time, but the Arduino Uno remains the most popular. Arduino is significantly inferior to Esp boards in terms of computing power and lacks native Wi-Fi connectivity, making it unsuitable for IoT applications. Regardless, it is a good tool for teaching electronics and prototyping[31].

4.1.2 Esp32

AVR Esp32 This thesis focuses on the DOIT board, a single IoT kit for beginners. Low power and seamless integration are the board's highlights.

In IoT and other wearable electronic mobile applications, the ESP32 is extensively used. The duty cycle has been decreased to save energy. Its adjustable output can also offer an appropriate trade-off between communication range, data rate, and power consumption. The ESP32 datasheet specifies a 3.0V supply voltage. One of ESP32's exterior components is an antenna switch. ESP32 features a high integration solution, especially in Wi-Fi and Bluetooth. ESP32 enables software that transforms a computer into a router or wireless access point, among other critical functions.

Espressif 32-bit LX6 dual-core microprocessor, 240 MHz (in the DOIT development board) has 448KB ROM, 520KB SRAM, and 4MB program memory. The microcontroller's CPU controls and communicates with other electronic components. But this core needs further elements to work. Other components on the breadboard include relays, motor controllers, keypads, 7-segment screens, electronic and electrical sensors. The pin diagram of the ESP32 is one of the most critical factors to consider when programming it.

Table 4 Esp32 pin no. list

Types Of Pins	No. Of Pins
Digital input/Output pins	25
Analog Input pins	6
Analog output pins	2
UARTs	3
SPIs	2

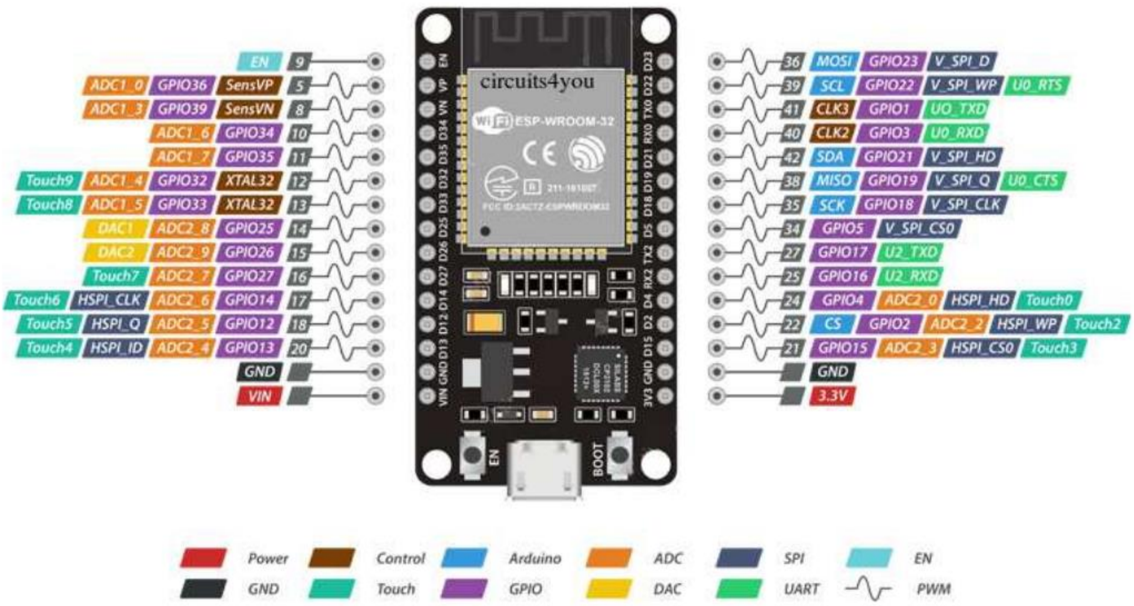


Figure 4.1.1 Esp32 pinout[31]

4.2 ACS 712 Hall Effect Current Sensor

ACS 712 Hall Effect Current Sensor is a low-cost, fully integrated linear current sensor IC with 2.1 kV RMS isolation and a low-resistance current conductor. Analog signal path, 5 V single supply, 66-185 mV/A output sensitivity, and almost negligible magnetic hysteresis. The applied current generates a magnetic field, which the Hall IC translates into a proportionate output voltage. The output voltage varies with the observed AC or DC currents. The 30 A module measures the direct current from a 3 phase BLDC motor. This module measures currents from 0 to 30 A. Also, with this module, 0 A equals 2.5 V and 30 A equals 5 V. The ESP32-Arduino code to measure the PV current with the sensor takes these settings into account and the ESP32 Thing ADC Pin parameters.

Regarding wired connections, the step-down resistors configuration mentioned in "Sensors" above is utilized to match the Current Sensor's 5V signal demand to the ESP32 Thing ADC Pins' 3.3 V signal capacity. The figure shows the step-down resistors set up with the sensor connected to the ESP32 Thing, and Equation shows the voltage divider equation. As can be seen, the VCC pin is powered by the Breadboard's 5 V supply, the OUT pin is connected to the Analog pin 32 on the ESP32 Thing microcontroller via a step-down resistor and its ground pin is connected to the GND pin on the Breadboard. In contrast, the two Input pins are connected in series to the BLDC system to measure the DC flowing through the system & it follows the same for the other two sensors[31].

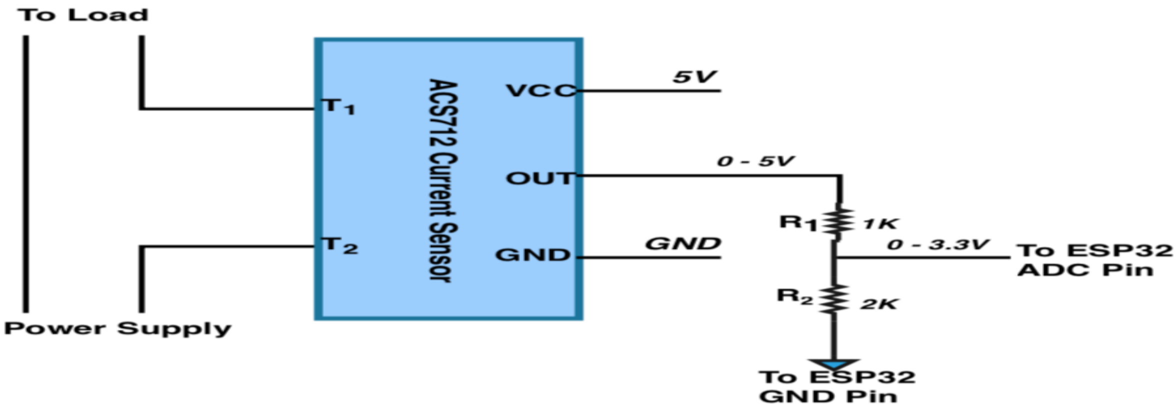


Figure 4.2.1 Schematic of ACS712 current sensor[31]

Figure 4.2.2 Acs 712[31] sensor pic

5. SOFTWARE

5.1 Xampp

Xampp is Cross-Platform, Apache, MySQL, PHP, and Perl. It is a minimal Apache distribution that allows developers to set up a local web server for testing. Installation of a web server (Apache), database (MySQL), and programming language (PHP). PHP is a commonly used open-source scripting language. The server runs PHP scripts. PHP files contain text, HTML, CSS, JavaScript, and PHP code. To link Apache, MySQL, and PHP, go to the Xampp control panel and start "Apache" and "MySQL". Apache uses port 80, while MySQL uses port 3306. The Xampp user interface is shown below[31].

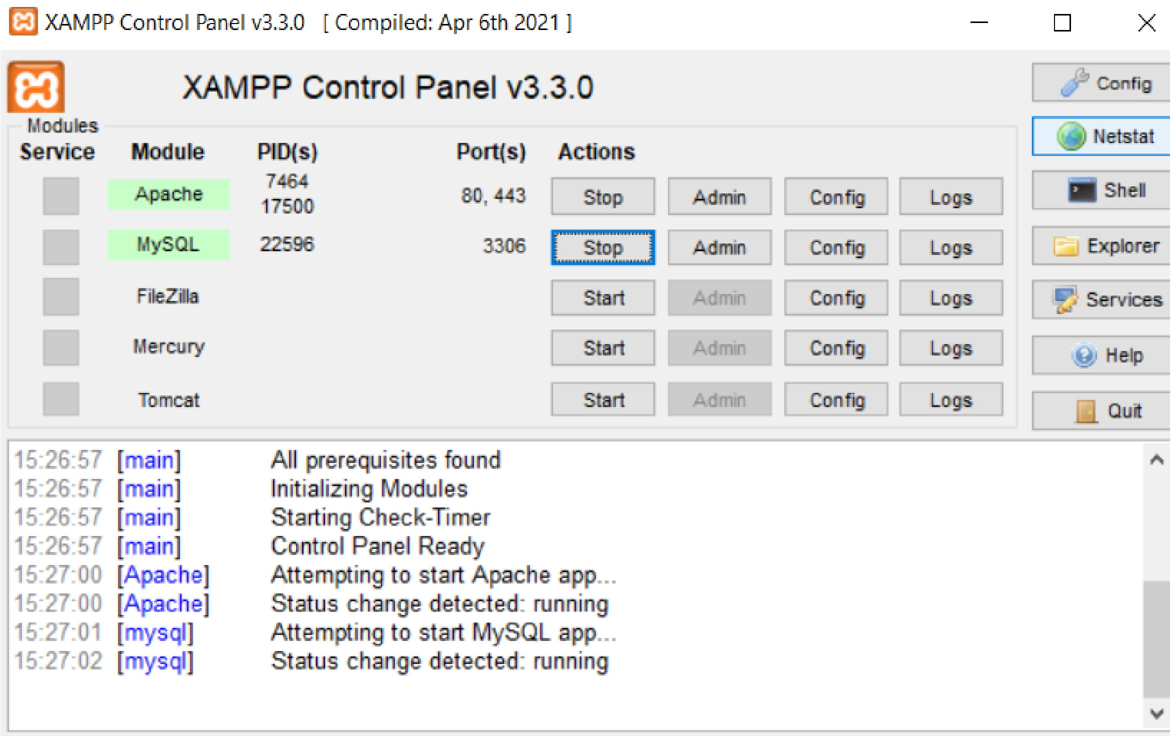


Figure 5.1.1 Xampp server[32]

Apache, HTML, PHP, PHP my admin are subfunctions of the Xampp. Due to its multi-platform and security, Apache is the most widely used open-source web server software. It's fast and reliable. HTML is a programming language used to develop web page interfaces. As the name implies, hypertext pages can contain images, links, music, applications, and other non-text elements. Hypertext markup language has two parts:

the "head" and the "body," where the "head" provides information about the web page and the "body" contains its content. A popular web scripting language is PHP. Using cached PHP code speeds up response times. In some cases, this can result in a 2-5x speedup. The server saves time reading files from the hard drive for each new request by caching code. There are more requests. An opcode cache helps[31].

The database allows users to update data. These apps and databases collect data from users. The DBMS also handles the database's logical structure and engine (which provides data access, locking, and update). The database also offers security and standard administration. Existing Today, SQL and NoSQL are widely used (Not Only SQL). Unlike SQL-based systems, NoSQL data storage and retrieval differ. But not usually. SQL is a database query and update language for DB2, SQL Server, and Oracle. SQL is an RDBMS. MySQL is an Oracle relational database management system. MySQL is well-known. Most online apps use MySQL. Tables in relational databases increase speed and versatility. MySQL uses SQL, the most popular database access language. MySQL software is tiny, fast, and has a low total cost of ownership. PHP and Apache should work. SQL is a query language. It varies by database. PHPMyAdmin is a free database management tool[31].

phpMyAdmin is a free PHP program for managing MySQL databases. This web interface may be superior when dealing with large amounts of data. A MySQL database can be created, modified, or deleted remotely using phpMyAdmin.

5.1.1 Comparison with other IoT open platform

The author compared the IoT features of Xampp with other open-source IoT platforms. The table shows the results of analyzing the Xampp server's supported platforms. The elements considered were communication protocols, hardware boards, data retention time, and communication patterns. Because REST and MQTT are the most widely used protocols in IoT, every platform supports them. Also, Novus-io, Xampp server, and Thinger.io provide HTTP Streaming for video broadcasting. Users like this feature since it lets them watch the device's movements. Any evaluated IoT platform can easily add Raspberry Pi and Arduino boards as supporting hardware. It confirms their appeal for IoT applications[8]. An API for Novus-io & Xampp server allows embedded systems, particularly those based on the Microchip PIC24 microcontroller, to be easily enhanced with IoT capability.

In contrast to current IoT open-source platforms (free versions), the Xampp server was built with no data retention limits.

Finally, all platforms support monitoring and triggering communication patterns, but only a handful support control action. Control actions allow users to alter and engage directly with the IoT application's decisions. Thinger.IO and Adafruit IO do not offer this capability to keep the platforms simple. The stream data pattern gives rare video streaming functionality on IoT platforms. Overall, the Xampp server and Thinger.io provide the most relevant communication patterns.

Table 5 Comparison with open IoT platform

Types of platform	**Protocoals**	**Hardware**	**Data retention**	**Communication Patterns**
Thingspeak	REST, MQTT	Esp82, Esp32, Arduino Uno, Raspberry Pi	120 days	Monitor, Control, Analysis, trigger
Adafruit IO	REST,MQTT, HTTP	Esp82,Esp32, Arduino Uno, Raspberry Pi	30 days	Monitor,Trigger
Thinger.IO	REST,MQTT, HTTP, Websockets	Esp82,Esp32, Arduino Uno, Raspberry Pi,Arm controller	30 days	Monitor, Stream, Trigger
Things Board	REST,MQTT, CoAP	Esp82,Esp32, Arduino Uno, Raspberry Pi	30 days	Monitor, Control,Trigger
Xampp server	REST, MQTT, HTTP, CoaP	Esp82, Esp32, Arduino Uno, Raspberry Pi, Arm controller	Unlimited	Monitor, Control, Analysis, trigger, Stream

5.2 Arduino IDE

While hardware is the backbone of an IoT system, the software is vital for hardware to communicate with itself. Microcontroller programming software is required. A database is needed to collect data. Following data collection, data analysis allows data to be used.

The Arduino IDE streamlines code creation and device uploading. It runs on Windows, Mac OS X, and Linux. An integrated development environment (IDE) consists of a simple I/O board and a programming environment. The IDE can develop interactive objects or link to computer applications. The program code in the IDE tells the Esp32 circuit board what to do. The Arduino esp32 coding language refers to the Arduino esp32 library, including APIs and C or C++.

5.3 MATLAB

MATLAB is commercial mathematic software developed by a U.S. company named MathWorks. It is a highly technical computing language and interactive environment used for algorithm development, data visualization, data analysis, and numeric computation.

5.4 Google collab

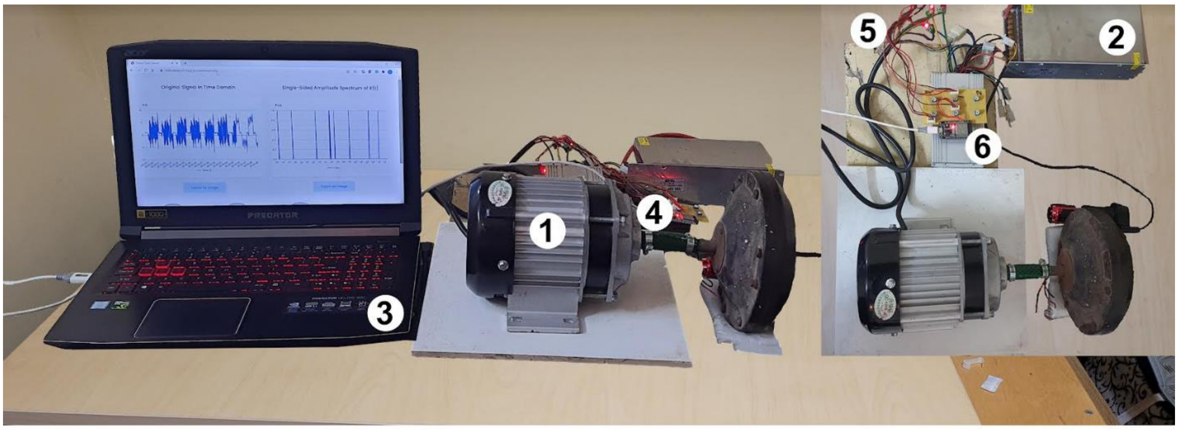
Colab is a Google Research product that allows anyone to create and execute arbitrary Python code in the browser. It is particularly well suited to machine learning, data analysis, and education. Colab is a hosted Jupyter notebook service that requires no setup and provides free access to computer resources such as GPUs.

6. EXPERIMENTAL SETUP

In implementing the proposed low-cost, open-source IOT solution, the analog ACS 712 current sensors are connected with each phase of 3 phase BLDC 48 V motor. The first step was attaching the 48 V power supply with 3 phase BLDC motor. The second essential component was the motor driver. It has inputs for hall sensor power and provides a connection motor forward and reverse. Thirdly, an essential element was ACS 712 analog sensors. These analog sensors, voltage divider circuit & esp32 microcontroller, are connected. The 3.3 V voltage signal needed for the current sensor to match the 3.3 V requirement of the ESP32 ADC pins is acquired from the voltage divider circuit with the pull-down resistors arrangement shown.

In contrast, the 5 V power supply for the ESP32 Thing board is provided using a 5 V USB power supply. Esp32 microcontroller burns written program. It is programmed in the Arduino IDE software to receive data from current sensors. It will display them on a serial monitor. Afterward, it sends them via the locally configured Wi-Fi network to the locally installed MySQL Xampp server. Above, the procedure follows for healthy inner & outer bearing testing.

Where the Mysql Xampp server act as an IoT monitoring platform. On MySQL local Xampp server web platform, the author has developed an HMI dashboard interface where users have access to data visualization.



1. BLDC motor
2. Power supply
3. Laptop
4. ESP32 (Black Color)
5. Current Sensor
6. Motor Controller

Figure 5.4.1 Hardware setup of the prototype

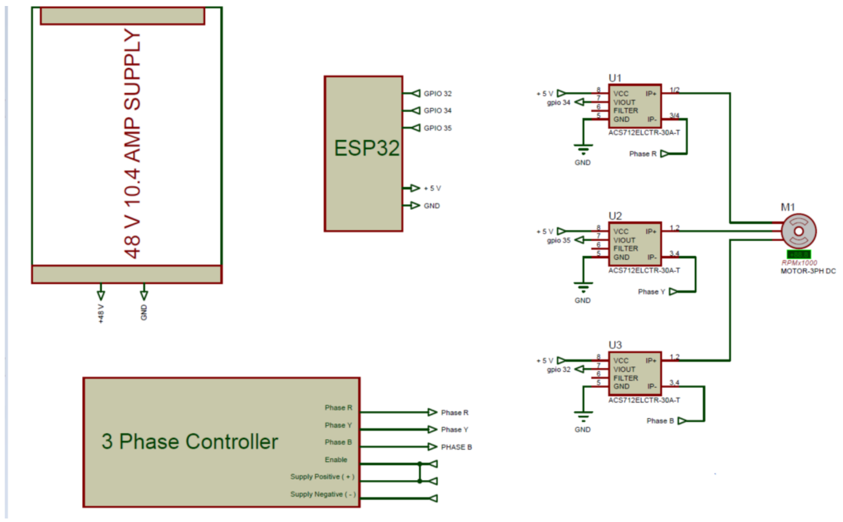


Figure 5.4.2 Block diagram

For executing the monitoring & fault diagnosis system must complete these procedures for the Arduino IDE software burns program to successfully transport data from the ESP32 to the web server domain. Once the ESP32 has been configured to connect to the Internet, the system must provide it with a network user id and password. Then, using array pointers, it can be specified where it should send all its readings, in this case, "http://localhost/bldc/sensordata/BLDC.php," for the device to communicate with the website. Second, this code would generate a random and characteristic string variable apiKeyValue, which would serve as the security key to prevent the SQL database from being read and written by other anonymous users who were not authorized to do so.

```
Read Sensor values on analog pins 32, 34 and 35 and perform ADC;
Display the above values on arduino IDE seiral monitor;
Connect to local Wi-Fi Network with Wi- FI name and Password;
Connect to my SQl Xampp server with IP address;
Identify the specified Xampp server account name, device ID & Credentials;
Post Sensor data to the specified Xampp server location;
while Xampp server Acknowledge data receipts do
  Display sensor data on cloud database
  Display "OK" on arduino serial monitor
  if NO Data Receipt acknowledge from Xampp server then
     Display error message on IDE serial monitor;
  else
     GO to Step 1;
  End
End
```

Figure 5.4.3 Data acquisition algorithm

Third, three PHP script files were necessary to be stored in the web's file managers to send the HTTP request to save the data of a three-phase BLDC motor from the ESP32 to the specified columns of the web's database, which was the protocol used to make the HTTP request. In specifically, one file is responsible for connecting to and storing the data sent from the Arduino program (which is connected to the ESP32) into the specific database of the server.

In contrast, the other files are responsible for showing that data in the table and line chart forms. The third step is to run FFT analysis on the SQL database results obtained in step two. The fourth stage involves collaborating with the webserver domain to establish a database, table, and three PHP scripts to save the data from the Arduino code to the database and view all of the sensor information in a table and line chart. The final step is to flash the program created in the IDE to the main breadboard and then start the Internet of Things system by the Xampp server on the laptop.

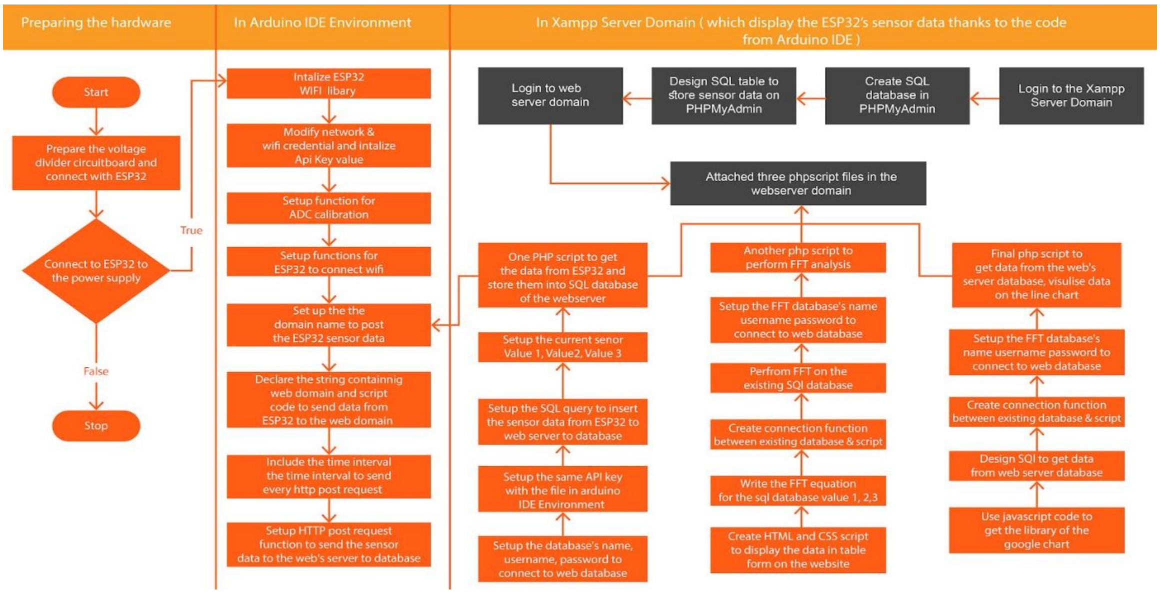


Figure 5.4.4 Prototype working flowchart

6.1 Matlab Programming

For the offline analysis, The data has been collected in CSV file format from the SQL database of the Xampp server. Afterward, data has sorted & filtered out in a readable manner for the MATLAB program. The author has aimed to compare the spectrum result of healthy bearings & faulty bearing. With the help of their respected development, the author can identify the signature current spectrum of individual bearing. Overthere, The raw data of each bearing current signal compute into the FFT.

FFT is a fast Fourier transform signal processing technique that transforms a time-domain signal into a frequency domain signal. This diagnostic technique is effortless compared to many other signal processing techniques. This technique requires less computing power, but the high-speed Fourier transform has several drawbacks and limitations. Firstly, a low discrete frequency can cause signal distortion. Second, the time limit of the signal can cause spectral leakage. Spectral leakage is the energy leakage of the fundamental frequency component—Matlab program's flowchart as follows.

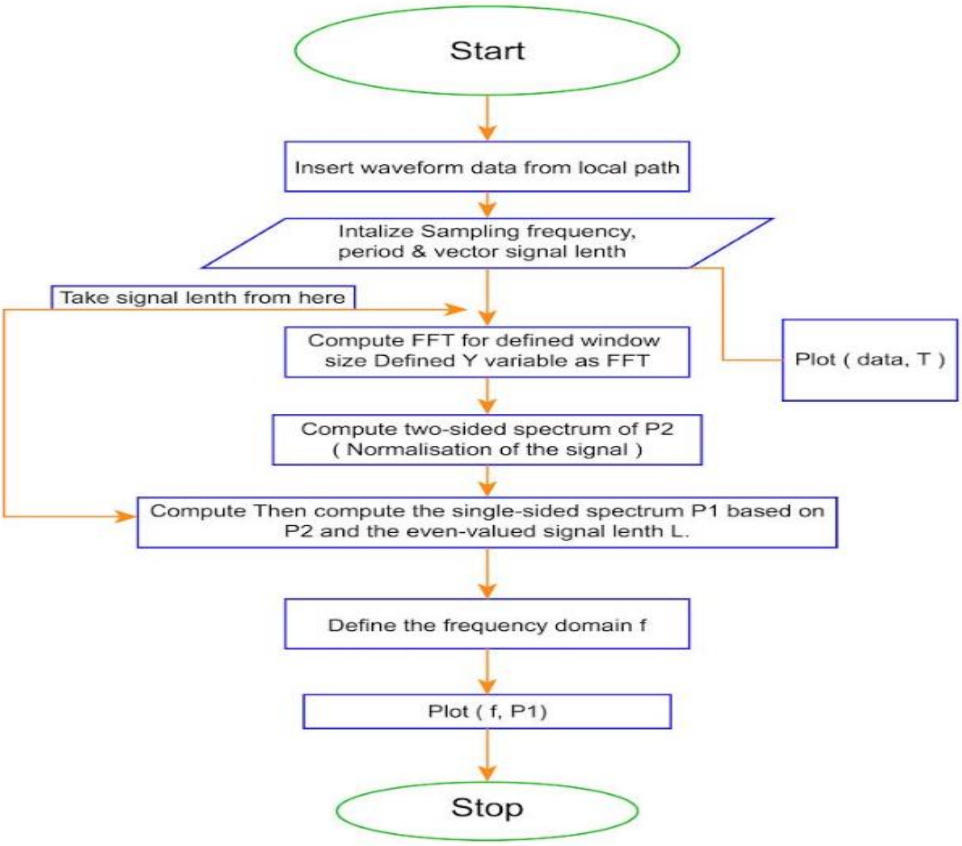


Figure 6.1.1 FFT flowchart

6.2 Machine learning

Matlab offline analysis has its challenges. It is more dependent on humans as well as a software tool analysis. It constantly requires human interaction first to diagnose the system's problem. Secondly, the support of software tools is also undeniable. one has to look after software up-gradation & installation procedure every time.

The proposed Xampp IoT server with real-time fault diagnosis has overcome Matlab challenges. It shows signal health status simultaneously with its monitoring which reduces the time for analysis procedure. However, this IoT platform has its limitations. First of all, it can not predict future maintenance one has to keep looking at graphs or historical data to define maintenance time. As data increases, the system performance will slowly start to degrade.

To overcome these issues, the author has proposed a solution of the machine learning technique. Machine learning has grown in importance in industrial IOT due to data collection and storage simplicity. The amount of data collected makes manual analysis impractical. In this instance, machine learning is crucial. Machine learning's growing attractiveness is also due to lower processing costs. Machine learning approaches have become more efficient in time and money, notably for failure type diagnosis and predictive maintenance. Machine learning has the potential to accelerate data processing and analysis, making it useful for predictive analytics. Machine learning techniques will give the system the following benefits: integration, Interoperability, decision making, individualized production & better collaboration.

First of all, The integration of operations throughout the production chain allows for digitization and optimization of activities from internal logistics to sales. Secondly, Interoperability between systems or organizations allows for the construction of a network that connects and simplifies information exchange between all partners involved in producing a given asset. Thirdly, the Capacity to gather and retain data on every machine and production aspect while allowing operators and managers to access it at any time aids decision-making. Methods of analysis and artificial intelligence provide additional information collected from the data. Fourth, Automation and digitization provide high config functionality and modularity. These features make it easier to meet particular consumer needs. Individualized production could well be done quickly. At last, it provides better collaboration between cyber-physical systems and human interface, assisting operators in their various jobs.

Machine learning algorithms are engineered to adapt and improve as they process more data. Once trained on clean, high-quality data, a machine learning algorithm can be applied to messy data. Condition-based maintenance is the analysis of the trend and the construction of a model for the evolution of the state based on previous research or previous historical data.

6.2.1 Model development using machine learning

Solving machine learning problems First and foremost, we require raw data since we cannot solve machine learning challenges without it. The raw data was obtained from a cloud database.

The second phase after collecting data is data analysis, and the author will cover an extra item here: data cleaning. Data cleaning entails either removing or using the imputer function for null values. The program identified no null values in the dataset because data has taken from a real-time machine. The dataset has then been ready for training.

After cleaning the data, we examine it to determine which machine learning approach is ideal for that data set and determine the relationship of features, which indicates whether the data is suitable for linear regression, logistic regression, clustering, or other methods.

The third step is to divide the data so that about 80 percent of the data is for training and 20 percent is for testing. It is a basic rule in machine learning. In constructing the model, training data has been a vital component of the system. The validation of training data is the initial step in this training process. Training data sets will provide either overfitting or underfitting difficulties, resulting in false positive or negative output. The data from the training set are not included in the test (validation) set. In each iteration, a data set is often separated into a training set, a validation set (some people use 'test set' instead), or divided into a training set, a validation set, and a test set. During the testing step, we use cross-validation to determine whether the model is working correctly or not. After training, model selection of the algorithm comes in the program. The author has selected four different methods of machine algorithm, which are as follows,

Decision Tree - The DT algorithm provides a quick training procedure and requires less memory. During the training phase of the program, The values of the root attribute are first compared to the actual dataset attribute to estimate the class of a given dataset. The algorithm continues to go forward by comparing the attribute value with the other sub-nodes in the following node. Finally, the procedure reaches the tree's leaf node.

Randon Forest Tree - Numerous decision trees are combined in the random forest method. However, each decision tree in the forest is now constructed using a random subset of characteristics and trained on an arbitrary portion of the training data set. The random forest model is then predicted using an average vote from each decision tree. As a result, the RF algorithm can reduce overfitting in decision trees.

Space Vector Module - To properly separate two or more independent clauses in a classification task, a support vector machine finds an ideal separation line termed a 'hyperplane.' The aim is to identify the best hyperplane separation by training the SVM algorithm on linearly separable data.

K nearest - A straightforward algorithm saves all existing examples and classifies new ones using a similarity metric (e.g., distance functions). A case is categorized by a majority vote of its neighbors, with the point being assigned to the class that has the most prevalence among the case's K nearest neighbors as defined by a distance function. After multiple attempts, ve neighbors are chosen because of their superior performance;

After training the model, a new dataset has been applied to the trained model to predict unseen data. After that, the confusion matrix will tell how successful the model has been prepared.

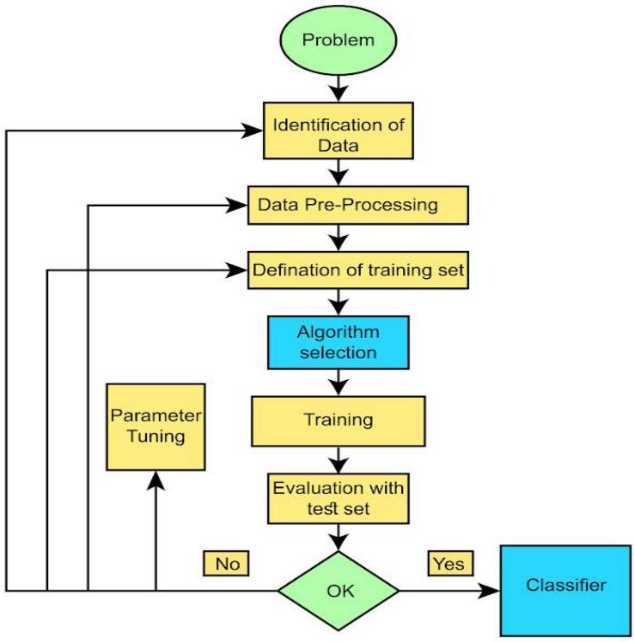


Figure 6.2.1.1 machine learning algorithm

The performance will be measured using accuracy, precision, recall, and f1 scores. To calculate these measurements, four terms must be introduced: true-positive (TP), true-negative (TN), false-positive (FP), and false-negative (FN).

Table 6 Parameter description

Types	Decription	Equation
Accuracy	It is the percentage of correct predictions made by model.	$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$
Precision	Ratio of the true positives (TP) and sum of true positive & false positives (FP).	$Precision = \frac{TP}{TP + FP}$
Recall	ratio between the examples which are actually positive and the examples which are predicted as negative, but actually positive.	$Recall = \frac{TP}{TP + FN}$
F1-Score	It is a weighted harmonic mean of precision and recall with a highest score of 1.0 and a lowest score of 0.0.	$F1 - Score = \frac{2 * (Precision * Recall)}{(Precision * Recall)}$

7. RESULT & ANALYSIS

This chapter discusses offline analysis through Matlab, IoT platform GUI dashboard, & competitive analysis of the accuracy of machine learning model results.

7.1 Offline analysis

The signal is stationary, and the loaded motor was operating at a medium constant speed. Data of 3 phase BLDC motor current signals analyzed by FFT method. It was also possible to use waveform conversion or some advanced technique for more accurate data processing, but this would lead to complex mathematical models and complicate the process. As discussed in the previous chapter, Matlab offline analysis aimed to compare healthy & faulty bearing spectrum. Figure 7.1.1, 7.1.2, 7.1.3 shows the bearing current signals of 3 phase BLDC motor recorded simultaneously from three current sensors in three different axes. Those three axes represent X1(t), X2(t), X3(t). Below fig is the time domain signal of three bearings. Where X-axis represents time and Y-axis represents current. There is a noticeable change in the Y-axis of faulty bearings compared to healthy bearing graphs. However, it is difficult to identify the order of specific harmonic signals.

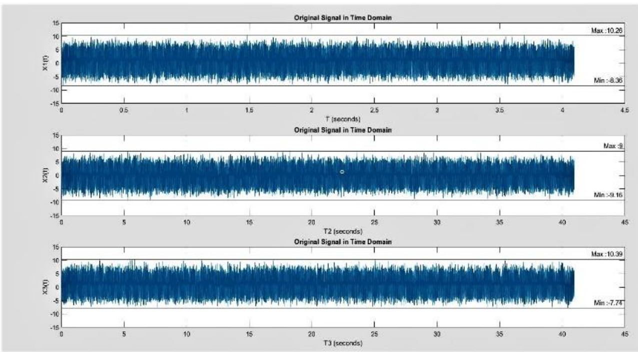


Figure 7.1.1 Healthy bearing time-domain signal

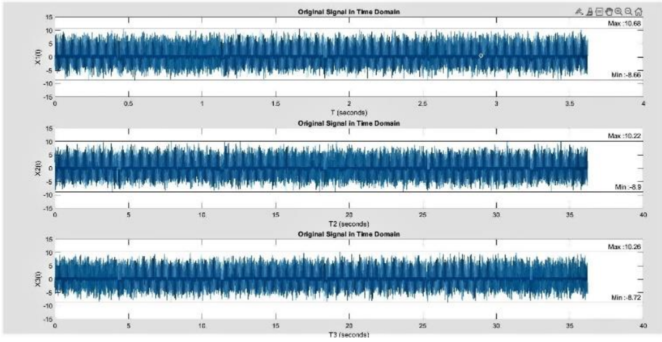


Figure 7.1.2 Inner fault time-domain signal

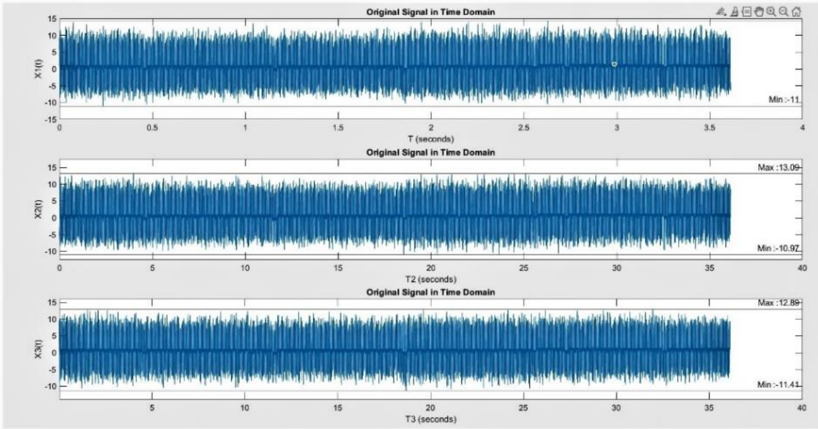


Figure 7.1.3 Outer fault bearing time-domain signal

On the other hand, the following figure7.1.4, 7.1.5, 7.1.6 result shows the frequency domain of 3 phase BLDC motor where P1, P3, and P5 represent the individual axis of the motor. The below picture shows a noticeable frequency peak in all three bearing plot results. It allows accurate identification of the existence of the defect, especially when the frequency spectrum is presented on a logarithmic scale.

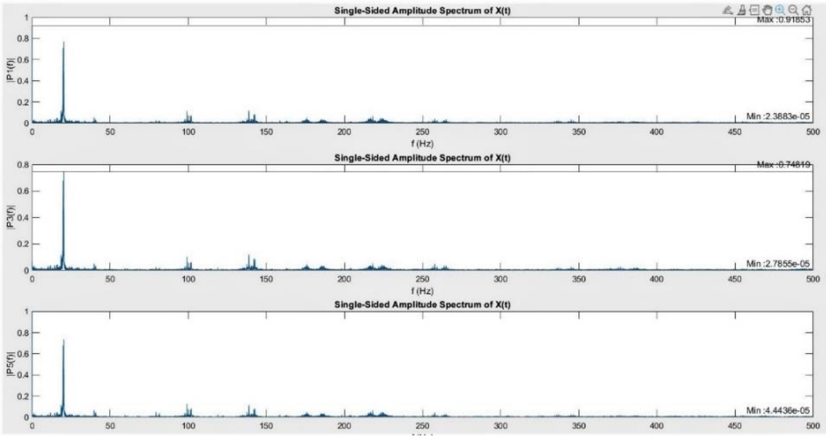


Figure 7.1.4 Frequency domain signal of 3 phase BLDC motor

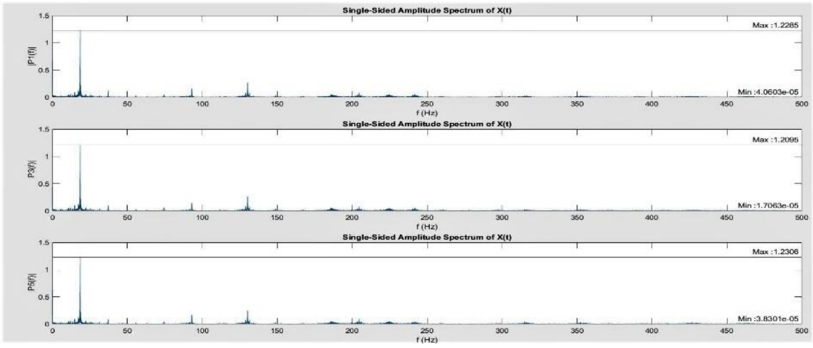


Figure 7.1.5 Inner fault frequency domain

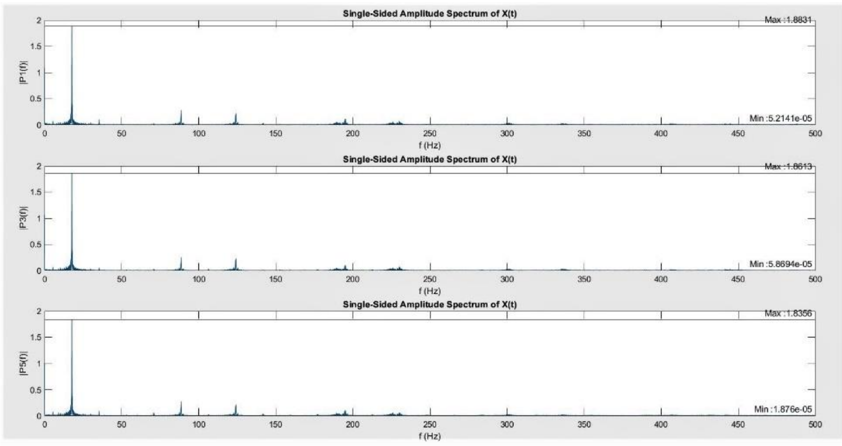


Figure 7.1.6 outer fault frequency signal

The main diagnostic feature is a specific manifestation of bearing defects in the spectrum of current signals. The signs of the defect appear in the spectrum when it grows to such a level that the energy released by it becomes relatively noticeable in the total current power of the bearing and will be presented on the spectrum. In the first stages of defect development, a prominent frequency peak appears, as seen in the case of contaminated bearing in the given research. It makes it possible to identify the defective element accurately, mainly if the harmonic amplitude is represented on a logarithmic scale. The following, figure shows that the frequency spectrum amplitude of healthy bearing is smaller compared to the faulty bearings. Also, it can be seen that outer bearing fault frequency amplitudes are higher than the other two bearings. Moreover, it can be seen that the main peak of the frequency amplitudes comes in between 10 Hz to 25 Hz.

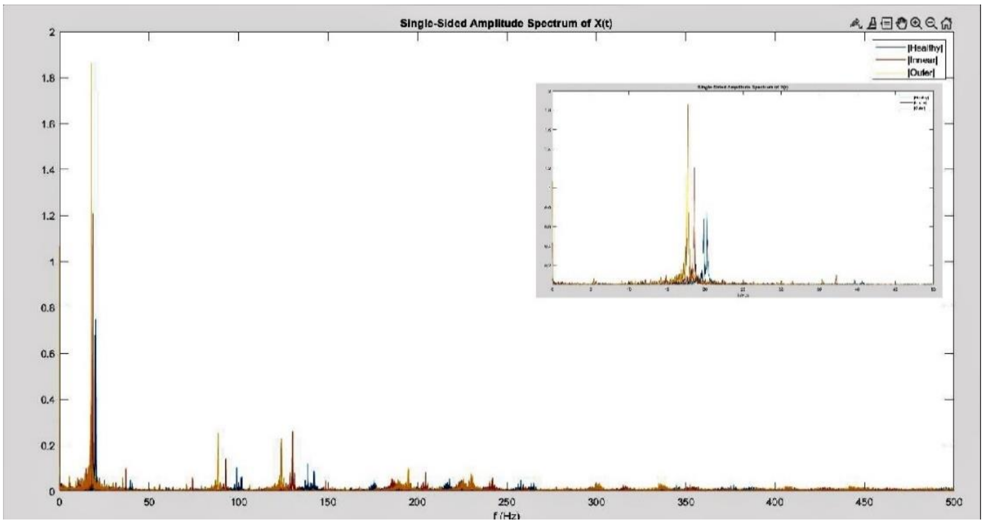


Figure 7.1.7 Frequency spectrum of all bearing

In figure 7.1.7 last stage above, the bearing has already degraded and ceased to fulfill its functions. However, after applying a high pass filter in the signal, there is a clearer understating of harmonics order. The figure shows that the outer bearing fault has the highest no. of harmonics order compared to other bearings.

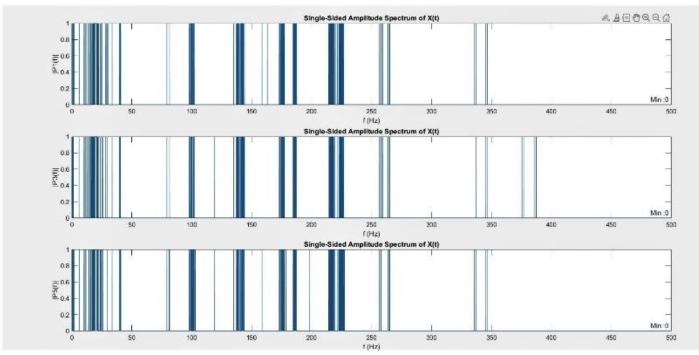


Figure 7.1.8 Filter frequency of healthy bearing

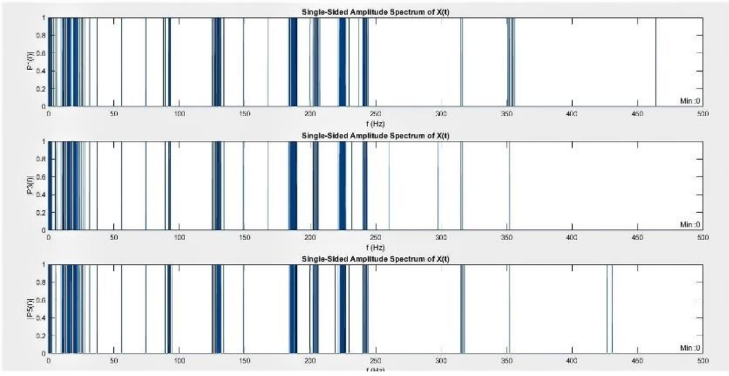


Figure 7.1.9 filter frequency of inner fault bearing

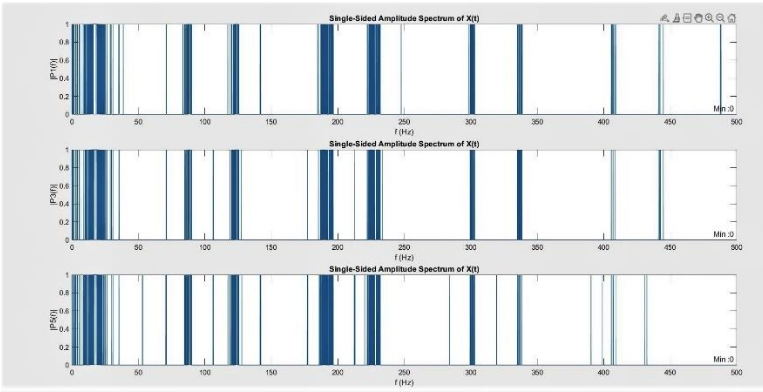


Figure 7.1.10 filter frequency of outer bearing fault

7.2 IoT GUI dashboard

As previously mentioned in the chapter, offline analysis has been a time-consuming & dependency-oriented methodology. The author has developed an IoT Gui interface to overcome that challenge, as shown below in figure 7.2.1. It will continuously display the health progression of the bearing of the motor. The two different bearing results were presented in the Gui for the testing purpose. IoT local Xampp server Gui offers additional features to the user. First of all, it will allow the user to interact with the system's graphical interface. Secondly, it provides access to look into previous databases & results. Furthermore, it has two line charts available in the Gui. The first line chart indicates the current signal of individual bearing. Where X represents time and Y-axis represents current. & the second line chart describes the real-time FFT of that respective signal where the X-axis represents frequency components and the Y-axis represents amplitude value. Thirdly, there is no need to install any external software to save the result of monitoring & analysis. Fourth, it has a dialogue box of the bearing which will indicate the availability of signal in their bearing. For example, the dialogue box of the inner fault shows 100%, which means the signal is entirely faulty. The signal availability status is proportional to the percentage of their respected dialogue box.

The following figures describe the dashboard of the IoT platform of condition monitoring & fault diagnosis. It is seen that the inner fault-bearing FFT analysis plot has more noise availability compare to the healthy bearing FFT. The author was comparing incoming signals with previously saved signals in real-time to assess if there is a likelihood that a defect would develop; the similarity criterion was set at 70% or higher for comparable signals. The probability of a fault occurring increases if the similarity criteria are in the range of 70 – 80 percent between the two pieces of information. A high possibility exists that the defect has begun to manifest when the percentage falls between 80 and 90 percent. If the ratio is greater than 90 percent, a technician must evaluate the machine for a specific defect or maintenance that needs to be performed. With help of real-time FFT, the diagnosis author identifies frequency components & compare individual signal of bearing.

Figure 7.2.1 Gui sample 1

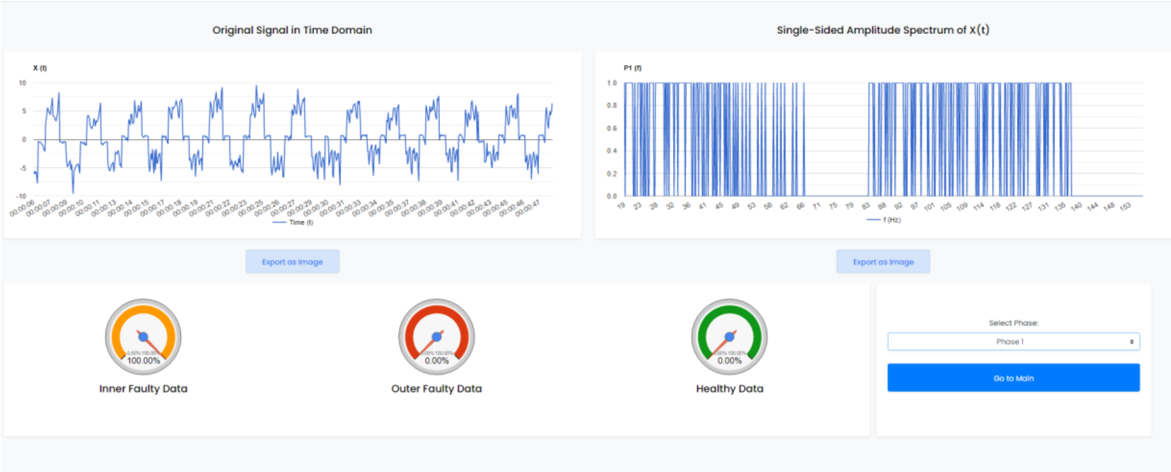
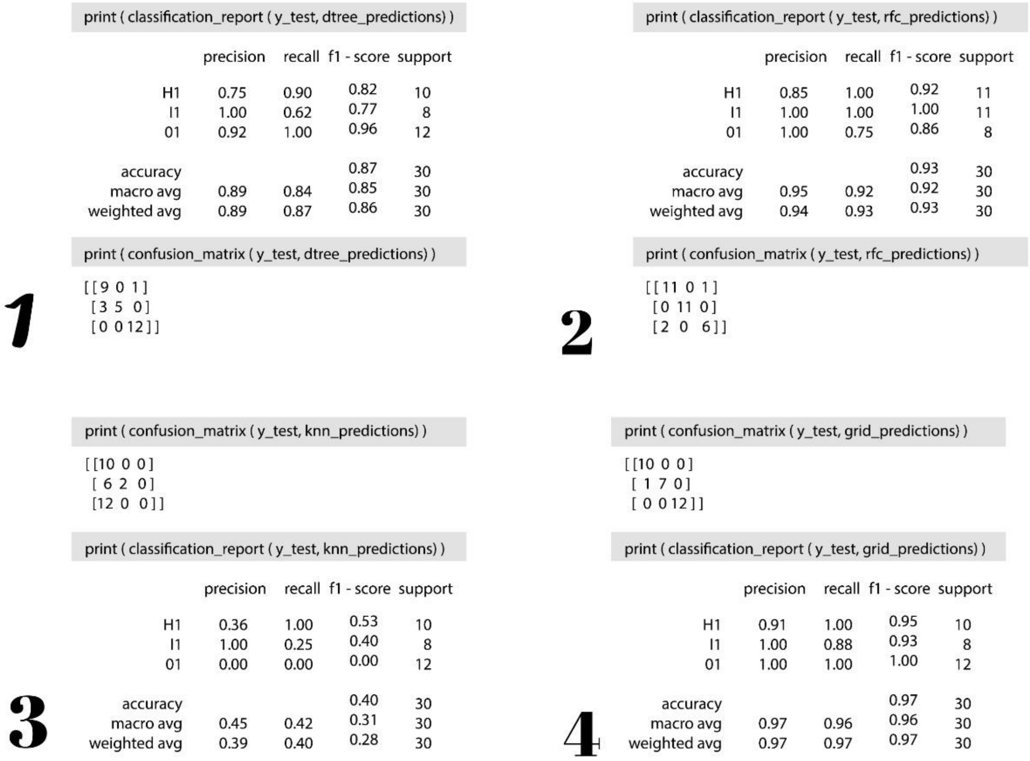


Figure 7.2.2 Gui sample 2

7.3 Machine learning results

After sorting data, the data has classified in three terms namely healthy, inner and outer fault. The dataset has trained in four machine learning algorithms namely, Decision tree, random forest method, super vector model, and k nearest neighbor. Each machine learning module classification and confusion matrix were as per below figure 7.3.1. where 1 is the decision tree, 2 is the random forest tree, 3 is the super vector model, 4th is k nearest neighbor classification and confusion matrix models.



1

```
print ( classification_report ( y_test, dtree_predictions) )

              precision    recall  f1 - score   support

          H1       0.75      0.90      0.82        10
          I1       1.00      0.62      0.77         8
          01       0.92      1.00      0.96        12

    accuracy                           0.87        30
   macro avg       0.89      0.84      0.85        30
weighted avg       0.89      0.87      0.86        30

print ( confusion_matrix ( y_test, dtree_predictions) )

[[9 0 1]
 [3 5 0]
 [0 0 12]]
```

2

```
print ( classification_report ( y_test, rfc_predictions) )

              precision    recall  f1 - score   support

          H1       0.85      1.00      0.92        11
          I1       1.00      1.00      1.00        11
          01       1.00      0.75      0.86         8

    accuracy                           0.93        30
   macro avg       0.95      0.92      0.92        30
weighted avg       0.94      0.93      0.93        30

print ( confusion_matrix ( y_test, rfc_predictions) )

[[11 0 1]
 [0 11 0]
 [2 0 6]]
```

3

```
print ( confusion_matrix ( y_test, knn_predictions) )

[[10 0 0]
 [ 6 2 0]
 [12 0 0]]

print ( classification_report ( y_test, knn_predictions) )

              precision    recall  f1 - score   support

          H1       0.36      1.00      0.53        10
          I1       1.00      0.25      0.40         8
          01       0.00      0.00      0.00        12

    accuracy                           0.40        30
   macro avg       0.45      0.42      0.31        30
weighted avg       0.39      0.40      0.28        30
```

4

```
print ( confusion_matrix ( y_test, grid_predictions) )

[[10 0 0]
 [ 1 7 0]
 [ 0 0 12]]

print ( classification_report ( y_test, grid_predictions) )

              precision    recall  f1 - score   support

          H1       0.91      1.00      0.95        10
          I1       1.00      0.88      0.93         8
          01       1.00      1.00      1.00        12

    accuracy                           0.97        30
   macro avg       0.97      0.96      0.96        30
weighted avg       0.97      0.97      0.97        30
```

Figure 7.3.1 Confusion matrix and classification

From the above figure, 7.3.1 author concluded the machine learning algorithm's success & error rate. The following table describes it.

Tabel 7.3.1 Machine learning algorithm's success & error rate

Type of algorithm	Success rate	Error rate
Decision tree	87 %	13 %
Random forest tree	93 %	7 %
Super vector control	97 %	3 %
K nearest neighbor	40 %	60 %

Following figure 7.3.2 indicates about classification model of accuracy with filter signal dataset. The X-axis of the figure indicates types of machine learning techniques while on the Y-axis it indicates the percentage of the result. In the figure DEC refers to the Decision tree, RFC refers to random forecast tee, SVM refers to space vector module, KNN refers to K nearest neighbor. In the array, it is showing the mean, mid and max value of the result. The array list result follows a decision tree, random forest, space vector module, and k nearest neighbor. As per result, the SVM module has the highest percentage of 94%. RFC has the second-highest accuracy of the model. While Knn has the lowest one.

```
classification_Models(X_train,X_test, y_train, y_test)

DEC 0.7971014492753623
RFC 0.8985507246376812
SVM 0.9420289855072465
KNN 0.49275362318840576
[array([0.82608696, 0.73913043, 0.82608696]), array([0.91304348, 0.95652174, 0.82608696]), array([0.95652174, 0.95652174, 0.91304348]), array([0.60869565, 0.39130435, 0.47826087])]
```

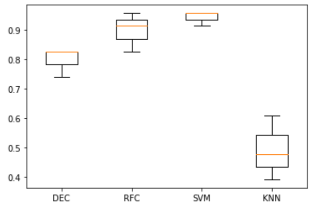


Figure 7.3.2 accuracy with filter signal

The below figure shows the result with original signal dataset accuracy. While comparing the result, it has been proved that SVM is the best approach for this model training.

```
DEC 0.7246376811594203
RFC 0.9130434782608695
SVM 0.927536231884058
KNN 0.5072463768115942
[array([0.86956522, 0.65217391, 0.65217391]), array([0.86956522, 0.91304348, 0.95652174]), array([0.86956522, 0.91304348, 1.        ]), array([0.47826087, 0.56521739, 0.47826087])]
```

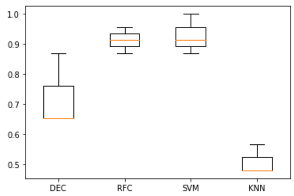


Figure 7.3.3 with an original signal dataset

8. DISCUSSION

The proposed local Xampp server-based IoT framework has several advantages. First of all, the data acquisition system used in the system is low cost compared to existing systems such as PLC and SCADA. The total cost of hardware components of the system was around 50 euro which is cheaper than the existing products. Secondly, the results have proved that it is possible to identify health & frequency components of the signal while monitoring and it saves maintenance time. Moreover, users have access to motor health. Thirdly, users can easily make data log reports from the MySQL database. Also, Xampp server availability and reliability are more than offline spectrum analysis. The web server is installed on the local MySQL Xampp server and self-managed. It gives system authorization freedom to access the system to continuously monitor, manage, and maintain to ensure its continuous availability and reliability. The real-time FFT analysis & monitoring system of the Xampp server helps the user to identify the frequency components of the individual signal. From that, the user can compare the bearing test sample online as well. For now, the author has developed a machine learning model and identified the best method for the deployment model in the future.

Future work can be classified as follows,

- The Xampp server-based IoT framework is an open-source platform. One can easily add more functions or features regarding 3 phase BLDC motor such as vibration, torque, speed, temperature, and so on.
- The real-time FFT analysis can be posted on online platforms such as AWS, Google Cloud, etc.
- In addition, machine learning detection will be deployed to an internet server, and the system will be transferred to the cloud.
- A future author can develop ioS and android app.
- One can use a different protocol such as MQTT, CoAP. Also, raspberry pi can be used instead of Arduino as a data acquisition module.
- Moreover, the machine learning model can be implemented on the web. So, it can predict the upcoming faults in the system.

9. SUMMARY

The thesis aim was condition monitoring & bearing fault diagnosis of BLDC motor by utilizing electrical signature, IoT device & machine learning.

This research topic is relevant and essential because brushless DC motors are used in many domestic and industrial applications abroad and in Estonia. It is also necessary to ensure their reliability because these motors have recently been used extensively in electric vehicles: hybrid and electric cars, electric bicycles, and scooters. The growing number of applications makes monitoring these motor conditions essential to avoid fault consequences. The primary reason behind fault occurrence is bearing faults. Existing systems such as PLC & SCADA systems are costly & time-consuming. Therefore, the advent of Industry 4.0, which is expected to be the fourth industrial revolution, is not surprising.

The literature review gave insight into IoT 4.0, smart maintenance, and existing methodology about the problem. Afterward, differences between electric motor & BLDC motor was explained with their electrical & mechanical faults. Later, the author explained the architecture of IoT components required for building the system.

The experiment is carried out in the university environment with healthy & faulty bearing of the motor in the IoT web framework. Different bearing results have been compared. The result of condition maintenance monitoring of current signal shows that there has been a fluctuation in the time domain signal of healthy & faulty current. However, it is difficult to identify the order of the harmonic signal as there is so much noise available in the time domain signal. To overcome this issue of the time domain, FFT spectrum implementation was used with MATLAB software. The Matlab spectrum analysis identified that every bearing signal has a different spectrum of frequency components availability. Applying a high pass filter on the bearing signals gives a better and clear understanding of it. The Xampp (webserver) runs FFT analysis of the signal in real-time & also visualizes it in real-time, from where the user can check on the health of the signal of every bearing. Among all classification techniques, the space vector module better identifies the signal for the trained model.

Limitations of the thesis are that the testing & real-time analysis has been done on the local server. Also, for IoT, the framework has been developed for testing individual bearing. Also, it describes only one parameter of the motor fault diagnosis in solution. As far as thesis difficulties are concerned, a few challenges came across while getting a solution. First, the author has thought about the ideal module for the data acquisition part. Second, selecting the best IoT platform for the testing purpose. Third, developing an environment for real-time FFT analysis. In future work, machine learning detection will be deployed to an internet server, and the system can be transferred to the cloud with additional monitoring features.

The author successfully achieved the offline and real-time fault diagnosis of a three-phase BLDC bearing motor utilizing electrical signature by IoT and machine learning in the thesis.

10. KOKKUVÕTE

Lõputöö eesmärk oli BLDC-mootori seisundi jälgimine ja laagrivigade diagnoosimine, kasutades elektrilist allkirja, asjade interneti seadet ja masinõpet.

Antud uurimisteema on aktuaalne ja oluline, kuna harjadeta alalisvoolumootoreid kasutatakse paljudes kodumaistes ja tööstuslikes rakendustes välismaal ja Eestis. Samuti on vaja tagada nende töökindlus, sest neid mootoreid kasutatakse viimasel ajal laialdaselt elektrisõidukites: hübriid- ja elektriautodes, elektrijalgratastel ja -mootorites. Kasvav rakenduste arv muudab nende mootorite seisundi jälgimise hädavajalikuks, et vältida rikete tagajärgi. Peamine põhjus rikete tekkimiseks on laagrivigade tekkimine. Olemasolevad süsteemid, näiteks PLC- ja SCADA-süsteemid, on kulukad ja aeganõudvad. Seetõttu ei ole tööstus 4.0, mis on eeldatavasti neljas tööstusrevolutsioon, tulek üllatav.

Kirjanduse ülevaade andis ülevaate IoT 4.0, aruka hoolduse ja olemasoleva metoodika kohta probleemi kohta. Seejärel selgitati erinevusi elektrimootori & BLDC-mootori vahel koos nende elektriliste ja mehaaniliste vigadega. Hiljem selgitas autor süsteemi ehitamiseks vajalike IoT-komponentide arhitektuuri.

Eksperiment viiakse läbi ülikooli keskkonnas koos mootori terve & vigase laagriga IoT veebiraamistikus. Võrreldi erinevaid laagri tulemusi. Praeguse signaali seisundi jälgimise tulemus näitab, et terve & vigase voolu ajalises domeenisignaalis on olnud kõikumine. Harmoonilise signaali järjekorda on siiski raske kindlaks teha, kuna ajadomeenisignaalis on nii palju müra. Selle ajadomeeni probleemi lahendamiseks kasutati FFT spektri rakendamist MATLABi tarkvaraga. Matlab'i spektrianalüüsiga tuvastati, et igal laagrisignaalil on erinev spektri sageduslike komponentide kättesaadavus. Laagrisignaalidele kõrgpääsufiltri rakendamine annab sellest parema ja selgema ülevaate. Xampp (veebiserver) teostab signaali FFT-analüüsi reaalajas ja visualiseerib seda ka reaalajas, kust kasutaja saab kontrollida iga laagri signaali seisundit. Kõigist klassifitseerimistehnikatest tuvastab ruumivektori moodul paremini signaali koolitatud mudeli jaoks.

Lõputöö piirangud seisnevad selles, et testimine ja reaalajas analüüs on tehtud kohalikus serveris. Samuti on IoT jaoks välja töötatud raamistik üksikute laagrite testimiseks. Samuti kirjeldab see ainult ühe parameetri mootori vea diagnoosimise lahendust. Mis puutub lõputöö raskustesse, siis lahenduse saamisel tuli ette mõned probleemid. Esiteks on autor mõelnud ideaalse mooduli kohta andmete kogumise osa jaoks. Teiseks, parima IoT-platvormi valimine testimise eesmärgil. Kolmandaks, reaalajas FFT analüüsi keskkonna väljatöötamine. n tulevases töös võetakse masinõppe tuvastamine kasutusele internetiserveris ja süsteemi saab viia pilve koos täiendavate seirefunktsioonidega.

Doktoritöös saavutas autor edukalt kolmefaasilise BLDC-laagermootori offline- ja reaalajas vea diagnoosimise, kasutades elektrilist allkirja IoT ja masinõppe abil.

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APPENDIX

https://github.com/Hardik096/-CONDITION-MONOTORING-BEARING-FAULT-DIAGNOSIS-OF-3-PHASE-BLDC-MOTOR-BY-ELECTRICAL-SIGNATURE-USING-.git