Predictive Maintenance in Industry 4.0

by

Muhammad Osama Asghar (02-3-1-048-2019)

Burhanuddin Ali Asghar (02-3-1-013-2019)

Ahad Qasim Dar (02-3-1-002-2019)

Project Report

Thesis is submitted to Faculty of Engineering at PIEAS in partial fulfillment of Degree of B.S/M.S. Electrical Engineering

Pakistan Institute of Engineering and Applied Sciences, Nilore, Islamabad, Pakistan.

December 2022

Declaration of Originality

.

We hereby declare that the work confined in this thesis and the design related content of this thesis are creation of our own study work. This thesis has not been earlier published in any form nor does it contain any verbatim of the published resources which could be treated as intrusion of the international copyright law. We also declare that we do understand the terms copyright and plagiarism, and that in case of any copyright violation or plagiarism found in this work, for any such violation we would held fully responsible.

Signature ________________

Name: Muhammad Osama Asghar

Signature ________________

Name: Burhanuddin Ali Asghar

Signature ________________

Name: Ahad Qasim

Date: Jan 2022

Place: PIEAS

Certificate of Approval

This is to certify that the work contained in this thesis entitled

"Design of a 400A Current Source Power Supply for a DC Plasma Torch"

Was carried out by

Muhammad Osama Asghar

Burhanuddin Ali Asghar

Ahad Qasim

Under our supervision and that in our opinion, it is fully adequate, in scope and quality, for the degree of M.S. Electrical Engineering from Pakistan Institute of Engineering and Applied Sciences (PIEAS).

Approved by:

Signature: ______________________

Supervisor: Dr. Ghulam Mustafa

Signature: ________________

Co-Supervisor: Dr. Abdul Qayyum Khan

Verified by:

Signature: ___________________

Head, Department of Electrical Engineering

Stamp:

To my loving and caring family.

Acknowledgement

First, all praise to ALLAH for bestowing us with knowledge and blessings. All respect to Prophet Muhammad (peace be upon him) for their kindness to this world and hereafter. This Thesis wouldn’t have been possible with the assistance, support, and supervision of many people. For keeping us focused, believing in us, and offering the project in the first place, we are very thankful to our supervisor, Dr. Ghulam Mustafa, who always kept us motivated and provided firm support for carrying this project. We express our sincere gratitude to Dr. Ghulam Mustafa for helping us understand the basic concepts and theory of Industrial Internet of Things. We also express our sincere gratitude to our co-supervisor, Dr. Abdul Qayyum Khan, for his guidance and support throughout the project. Further, we gratitude to our parents and siblings who have always been a source of inspiration and motivation for us during our studies.

Contents

ABSTRACT: .... *XI*

1. INTRODUCTION *1*

1.1. BACKGROUND AND MOTIVATION **2**

1.2. GOALS AND OBJECTIVES **2**

1.3. APPLICATIONS **3**

1.4. SCOPE AND DELIVERABLES **4**

1.5. APPROACH AND METHODOLOGY **5**

1.6. OVERVIEW OF REMAINDER OF THESIS **5**

2. LITERATURE REVIEW ***6***

2.1. INTRODUCTION TO IIOT **6**

2.2. MAINTENANCE **7**

2.3. METHODOLOGIES **8**

2.3.1. Breakdown Maintenance *8*

2.3.2. Scheduled Maintenance *8*

2.3.3. Predictive Maintenance *9*

2.4. CONDITIONAL MONITORING **9**

2.4.1. Infrared Thermography *10*

2.4.2. Radiography *11*

2.4.3. MCSA *12*

2.4.4. Vibration Analysis *13*

2.5. FEATURE EXTRACTION TECHNIQUE **14**

2.5.1. Kurtosis *14*

2.5.2. Skewness *15*

2.5.3. Clearance *15*

2.5.4. Fast Fourier Transform *15*

2.6. KALMAN FILTER **16**

2.7. MACHINE LEARNING APPROACH **16**

2.7.1. Unsupervised Learning *17*

2.7.2. Supervised Learning *17*

2.7.3. Reinforcement *17*

2.7.4. Artificial Neural Network *18*

2.8. SOAP **19**

3. THE HARDWARE DESIGN: *19*
3.1. WORKFLOW DIAGRAM **20**
3.2. MACHINE FAULT SIMULATOR DESIGN: **21**
3.2.1. Motor *22*
3.2.2. Coupling *23*
3.2.3. Shaft *24*
3.2.4. Bearings *25*
3.2.5. Bearing Housings *26*
3.2.6. Flywheel *27*
3.2.7. Belt and pulleys *27*
3.2.8. Gearbox *28*
3.2.9. Base *29*
3.2.10. Control box *30*
3.3. SENSOR **32**
3.3.1. ADC Module *32*
3.3.2. Accelerometer *33*
3.4. DEPLOYMENT AND INTERFACING OF SENSORS **33**
3.4.1. Raspberry PI 3B+ *33*
3.4.2. ADS1115: ANALOG TO DIGITAL CONVERTER *34*
3.4.3. ADS1115: ANALOG TO DIGITAL CONVERTER *35*
4. PRELIMINARY WORK AND PROGRESS *36*
4.1. NGROK **36**
4.2. DJANGO **37**
4.3. NODE.JS **37**
4.4. PREVIOUS WORKING **37**
4.5. THE PROBLEM AT HAND **38**
4.6. PROGRESS **38**
4.6.1. Modbus Protocol *39*
4.6.2. Pymodbus *40*
4.6.3. SCADA System *41*
4.6.4. Interfacing ScadaBR *43*
4.6.5. Output Display on SCADABR: *45*
4.6.6. ANN *45*
4.6.7. Objects Used For Training ANN Model *47*

5. CONCLUSION 48
6. REFERENCES 50

Table of Figures

Figure 2-1: Infrared thermography 11

Figure 2-2: Infrared Radiography 12

Figure 2-3: Motor Current Signature Analysis 13

Figure 2-4: Vibration Analysis 14

Figure 2-5: Hierarchy of ML approach 18

Figure 3-1:Workflow Diagram 21

Figure 3-2: CAD Model of MFS 23

Figure 3-3: Three Phase Induction Motor 23

Figure 3-4:Coupling 24

Figure 3-5: Main Shaft of the Machine 25

Figure 3-6: Bearing (image courtesy rsdelivers) 25

Figure 3-7: Bearing Housing .... **Error! Bookmark not defined.**

Figure 3-8:Flywheels (a) Without Unbalance (b) With Unbalance 27

Figure 3-9: Pulley and Belt 28

Figure 3-10: Gearbox 29

Figure 3-11: Assembled Machine 29

Figure 3-12: Design of Control Box 30

Figure 3-13: Variable Frequency Driver, Model: Yaskawa J-1000 31

Figure 3-14: Raspberry Pi 3B+ by Raspberry Pi 32

Figure 3-15: ADC sensor, Model ADS1115 by makestorein 32

Figure 3-16: Accelerometer, Model ADXL335; Picture from circuits-diy 33

Figure 3-17; Raspberry Pi 3B+ Pin Configuration by Community.elements 34

Figure 4-1: Dataflow Illustration 38

Figure 4-2: Modbus and OSI Model 39

Figure 4-3: Modbus Protocol Working 40

Figure 4-4: Client-Server Model 41

Figure 4-5: SCADA Systems 42

Figure 4-6: SCADABR data sources 43

Figure 4-7: Modbus IP Properties 44

Figure 4-8: Adding Data Points 44

Figure 4-9: X axis readings 45

Figure 4-10: Y-axis Readings 45

Figure 4-11: Basic Structure of ANN 46

Figure 4-12: Sigmoid Function (ANN).. 47
Table 1: Component rating and model used in power supply design **Error! Bookmark not defined.**

Abstract:

IIOT refers to an industrial adoption of internet of things. When we talk about industrial application, IOT includes the use of smart sensors, real time processing, application of ML algorithms to yield meaningful data. This data has powerful implications, such as it can be used to predict the health of a machine to aid in formulating a better maintenance schedule. Therefore, in this thesis we will explore a prototype setup of predictive maintenance for rotating machine using AI algorithms. Bearing vibration data is collected using vibration sensors and a Raspberry PI then passed on to a Modbus client. PI acts as a server that constantly updates data on the holding registers and responds to client requests. The client hosts a SCADABR server that generates timely data acquisition requests. The server responds and the data is updated in real time on a SCADA based UI. An ANN algorithm that is trained on data processed through statistical measures such as kurtosis, communicates with SCADA using JAVA API. The AI algorithm extracts the data, operates on it, and then uploads the result again on the SCADA system. This output gives an insight on the health of the machine in the runtime.

1. Introduction

Machines are a part of life, and after the substantial growth of machine use, we find ourselves in a swarm of machinery. Some makes our life easier, while others carry the burden of whole production lines in several industries. Regardless of machines we are referring to, machinery breakdown is a major inconvenience to say the least. In industries where machinery manage a wide array of operation, a slight breakdown can cause production line to halt leading to a substantial financial loss.

Therefore, maintenance is a critical part of industrial processes, where a new technological era marks the entry of improved and sustainable maintenance protocols. The fourth industrial revolution dubbed as the Industry 4.0 has drawn interest on a global scale. Predictive maintenance is one of the ideas that emerged along with this new revolution.

The original method of industrial automation has undergone significant alterations with the advent of Industry 4.0. Cyberphysical System (CPS) and Internet of Things (IoT) technologies play important roles in this context by introducing cognitive automation and subsequently putting the idea of intelligent production into practice, resulting in smart products and services.

Artificial intelligence is **the simulation of human intelligence processes by machines, especially computer systems**. AI is being deployed by great many applications such as expert systems, natural language processing, speech recognition and machine vision. However, the use of AI is expending to an interesting new frontier predictive maintenance.

The use of AI techniques in the predictive maintenance will make the process more efficient and cost-effective. AI system can continuously monitor a system for anomalies. Training these systems are easy and can be done with a few data sets. Moreover, with the increasing computing power deployment of advanced AI techniques wont be an issue.

.

1.1. Background and Motivation

Predictive maintenance utilizes indicators that relay the health of the machine surveyed. These variables vary from machine to machine, but here is a list of commonly measured variables: Torque, speed, and voltage current, temperature, Vibration, humidity, Acceleration.

Applying these variables to relevant data processing or machine learning techniques can yield an accurate prognosis of machine's health and predict future failures.

Predictive Maintenance begins with selecting the appropriate set of data points, interacting with the machine to obtain real-time data, and enhancing the data quality through live monitoring of machine faults. The most important inputs for any prediction model are data preparation and data quality. The prediction model will perform more accurately the more high-quality data we can feed it.

Motivation behind this work is to:

Help improve productivity.

Reduce system faults

Minimize unplanned downtime

Increase efficient utilization of financial and human resources.

Help managers to optimize the planning of maintenance interventions

1.2. Goals and Objectives

Objectives should be quantifiable in a way that they should describe a particular path to move forward. The goals we are setting should be realistic, achievable, and measurable. Another aspect that impacts the fulfillment of our goals is a suitable time frame. Hence, after considering all of the above parameters, we can frame conclusive objectives. Our objectives for this project are as follows:

Expand the communication on a more secured local area network, primarily comprising of modbus tcp protocol and a scada server.

Increase the types of sensors to acquire a variety of data. Considering the inclusion of a current sensor for motor fault detection.

Improve the scope of the already used sensors. Explicitly using higher frequency vibration sensors.

Extract Data sets of both healthy and faulty operations.

Develop a neural network and train it using the acquired data set.

Develop a UI that will display the real time data and machine status.

1.3. Applications

It's not difficult to foresee the future of predictive maintenance as more and more industries will rush to take shelter under its protective canopy. Common industrial maintenance practice includes two strategies:

- Reactive Maintenance: Run the machine to exhaustion or failure and starts repair or replacement to get everything back on track. This strategy may be suitable to inexpensive disposable assets such as light bulbs. For expensive and critical machinery, the unplanned downtime can be quite costly. For an industry working on full pistons like a soap manufacturing plant, the loss of production can soar up to 30% due to unplanned failures and downtime.
- Preventive Maintenance: Involves maintaining an asset on regular intervals regardless of the condition. This strategy applies to majority of the assets in possession. However, on the downside this strategy can drain finances, time, and materials.

The advent of Industry 4.0 and predictive maintenance can provide an escape from all the hassle by maintaining optimum machine working while saving valuable resources and time. The whole concept of predictive maintenance is centric to finding the optimal time of maintenance. This lucrative option appeals to many industries, who will eventually adopt predictive maintenance. Here is a list of leading industries that can benefit the most from the implementation of predictive maintenance.

Oil and Gas Industry: This prominent industry will feel that predictive maintenance is more of a compulsion than an option. Predictive maintenance will allow managers to remotely monitor the equipment, and promptly repairing any faulty equipment. This will mitigate the risk of a machinery failure that may lead to environmental disaster.

Food And Beverages: Machinery used in food and beverages sectors have an impact on the life of people. Produces of a broken or failing machine can't comply to the strict food and health laws. Spoiled food supplies, and tarnished company reputation can be the bitter aftermath of unplanned downtime and sudden machine failure. Hence, to allude such a bitter end, food and beverages industry can opt for predictive maintenance.

IT Industry: Every institute employs large data centers and central computer to automate the data flow and ease the operation. By using predictive maintenance to predict the health of computer, the IT industry can abate any unsightly breakdown and ensure smooth operation of many dependent institutes.

Power And Energy Sector: This industry also cannot suffer machine breakdown otherwise the related grid will suffer from an energy outage. Hence, to avoid such events from occurring power and energy sector is keen towards the adoption of predictive maintenance.

1.4. Scope and Deliverables

Scope of this project is to setup an IIOT platform that can interact with the hardware, collect relevant data, use machine learning algorithms and display results using a SCADA software. Close loop motor control or equilibrium controller along with detection of faults not covered by current and vibration sensors are beyond the scope of this project. This project delivers a complete IIOT setup, health monitoring display and results with discussion. It provides suggestions regarding the extension of fault detection methodologies in future.

1.5. Approach and Methodology

This project consists of two parts: setting up a communication protocol that is on par with industrial standards. The communication medium should be secure yet fast. Hence, data transfer over ethernet is preferred using the modbus protocol. For greater connectivity we will upload the SCADA software on the cloud. Secondly, we will implement machine learning algorithms to detect faults. These will help in efficient and timely detection of several faults. Data for AI algorithms will be collected by deployment of sensors.

1.6. Overview of Remainder of Thesis

Later part of the thesis contains six chapters. In chapter 2, we have discussed different maintenance techniques currently employed in industry, and statistical analysis measures. In chapter 3, we discussed our approach and methodology.

2. Literature Review

2.1. Introduction To IIOT

IIOT is an extension of internet of things to the industry. Integrating OT into the industry helps improve the efficiency, production, security, and performance of several industrial components. It harnesses the data churned out by several industrial units and utilizes them using machine learning algorithms to detect changes and interact accordingly in a way human cannot.

There are some core fundamentals to an IIOT factory which include superior connectivity, smart sensors, real time data transfer, and machine learning algorithms. All of this combined play a revolutionary role in how an industry operate. IIoT can improve operational efficiencies, paving the path for the development of whole new business models.

An industry thrives on a secure environment, where data breaches can be fatal to some extent. Therefore, the concern over security poses a threat to widespread use of IIOT because IIOT makes extensive use of internet connectivity to relay data.

IIoT systems that are not secure can result in a range of negative consequences, including operational disruptions, financial losses, and other serious issues. As more devices and systems are connected to networks, the potential for security vulnerabilities increases, including the risk of:

- Devices and systems that are connected to the internet and are easily searchable by anyone.
- Threats such as hacking, targeted attacks, and data breaches.

- The potential for system manipulation, which could lead to operational disruptions (e.g. product recalls) or sabotage (e.g. production line stoppages).
- System failures that can cause damage to devices and physical facilities, as well as harm to operators or people nearby.
- The possibility of IT systems being held for ransom as a result of compromise to the OT environment. "

As we adapt our setup for industrial use, it’s empirical that we consider the security concern and come forward with a setup that’s not only secure but also scalable.

2.2. Maintenance

Modern world demands efficiency and industries today are looking after designing the most suitable and economical system which demands technical enhancement. Most of the factories today are getting rid of inventory and working on JIT (Just-in-time) model to cut down the workforce, this new inception in today’s world upbrings an issue of machine maintenance to a whole new scale and therefore it needs to be addressed effectively. Under 10 % of industrial equipment are bound to wear out because of their old age, the way machine deteriorate is not our concern but when it will be needed to replace is what we have to address and some of them are swift while other take time, it all depends upon various environmental and equipment factor but all rotary machine have some signature hidden under their working which can be resourceful for detecting the particular error and hence a maintenance process is eased by the aid of some signal marks as shown by [1].

2.3. Methodologies

In industries, following three techniques are in practice for industrial maintenance:

- Breakdown maintenance
- Scheduled or preventive maintenance
- Predictive maintenance

2.3.1. Breakdown Maintenance

Breakdown maintenance refers to changing the equipment when it is worn out. Maintenance of this type saves the cost of maintenance system but there are few factors which have to be kept in mind as this kind of maintenance do come up with major risks. If there is a small scale production facility with limited amount of products to be delivered in ample time and the machinery being used have separate part and misfunctioning of one sector does not relate to other, here we can implement breakdown maintenance and there is no need to inject maintenance system her but in corporate world, we have tightly scheduled production facility and even delay of an hour can be bit problematic and some misfunction left unaddressed can lead to extensive repairing than could have been needed before so in these system, we have to look for different approach.

2.3.2. Scheduled Maintenance

Breakdown A type of maintenance where periodic inspection of machine is performed and machine is dismantled and assessed, all the worn-out part or event entire machinery is replaced after certain period but this approach have several drawbacks.

Inspection and tracing the defects is cost inefficient and scheduling it at regular intervals worsen it in making financially effective. Moreover, shutting down the machine for its testing adds more to the problem.

This approach can be effective only if the anticipated span of machine's wear and tear is accurately predicted and there is no significant financial risk incurred in its inspection but there are better alternatives to it as discussed below.

2.3.3. Predictive Maintenance

Breakdown The name itself suggests the crux of this technique. We have different parameter which are non-linearly related to the motor working, these parameter like temperature, vibration and current have their particular signatures which are largely influenced by any change in motor working condition and therefore differences in their signature will lead us to further analysis of fault detection and predicting the estimated life of a motor.

In predictive maintenance unlike scheduled, we don't have to parse the entire system and look for the fault rather we just detect the fault and predict how much and upto which extent system can bear and then we scheduled its repairing according to our comfort hence avoiding sudden repairing which is the case in breakdown maintenance.

In industries, now a days, predictive maintenance is being deployed as it reduced the cost which is incurred by scheduling maintenance, and it also emits the issue like production inefficiency and time mismanagement which are imposed via breakdown maintenance.

2.4. Conditional Monitoring

Modern Faultier machine exhibit nuances in their different parameters which can be processed down to detect the fault. There are several parameters like vibration, current, temperature etc., considered while estimating the machine status by deploying data analysis technique on fetched data set. We can directly detect the fault by looking at the output signal of a sensor in some cases while in most cases, we have to rely on statistical analysis technique on fetched packet of data set from Raspberry PI as noted in [7].

2.4.1. Infrared Thermography

Every object above absolute zero emit thermal radiation which can't be seen by bare eyes but there are instrument to observe it and *Thermograms* are used to plot the object temperature,

Specific to plant maintenance and condition monitoring, infrared thermography is used in applications such as:

- Monitoring the electrical and mechanical conditions of a motor
- Bearing inspections (abnormal bearing friction)
- Monitoring refractory insulation
- Locating gas, liquids and sludge levels

Abnormal heat pattern can be indicator of the fault as machines hear signature do vary if there is any noise in it but to analyze and pinpoint the fault you have to carefully understand radiometry and heat transfer analysis on it.

Some technique includes

- Spot infrared thermometers
- Infrared thermal-imaging cameras
- Infrared scanner systems.

Figure 2-1: Infrared thermography

2.4.2. Radiography

This method uses radiation imaging to identify internal hardware and component flaws. Applications include inspecting castings, sintered parts, and weldments. One of the most thorough non-destructive testing methodologies is this one.

The method is based on calculating the differential radiation assimilation into the part or material, which may be measured and studied. Internal corrosion and flaws absorb various amounts of radiation.

Techniques include:

- Neutron backscatter
- Computed radiography
- Computed tomography (CT)
- Direct radiography

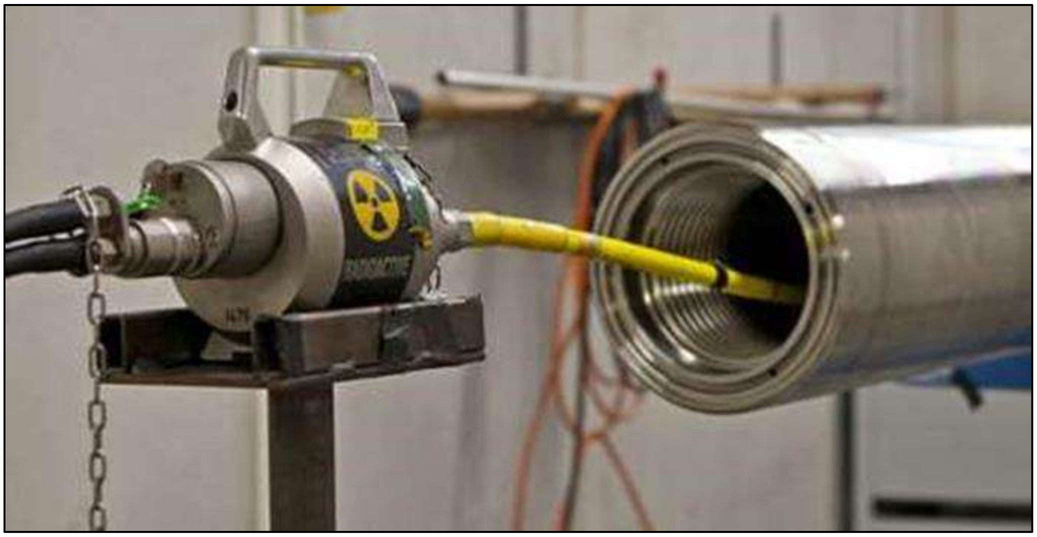


Figure 2-2: Infrared Radiography

2.4.3. MCSA

Motor current signature analysis is another critical analysis technique used to detect faults like:

- Broken rotor bars
- Shorted turn in stator winding
- Airgap nonconcentric

In MCSA, current sensors are used to detect current of armature winding and other components involved to extract the signature of motor, healthy motor will definitely depict the different output than unhealthy one and then further feature extracted coupled with ML approach will detect which error to suspect.

Figure 2-3: Motor Current Signature Analysis

2.4.4. *Vibration Analysis*

Many components in machine exhibit vibration and their pattern are distinctive. When there is fault like

- Nonconcentric air gap
- Damaged Weld/Bolts
- Broken Gear Tooths

There will be change in pattern which can be sensed through a sensor and crew member know that different fault leads to different pattern and these patterns can be used to perform vibration analysis.

While purchasing sensor for vibration analysis, we have to keep in notice the frequency range of sensors as uncertainty can be dealt with sensor fusion technique but there is no way to deal with frequency range once it is purchased. All this have been covered in [2][5]

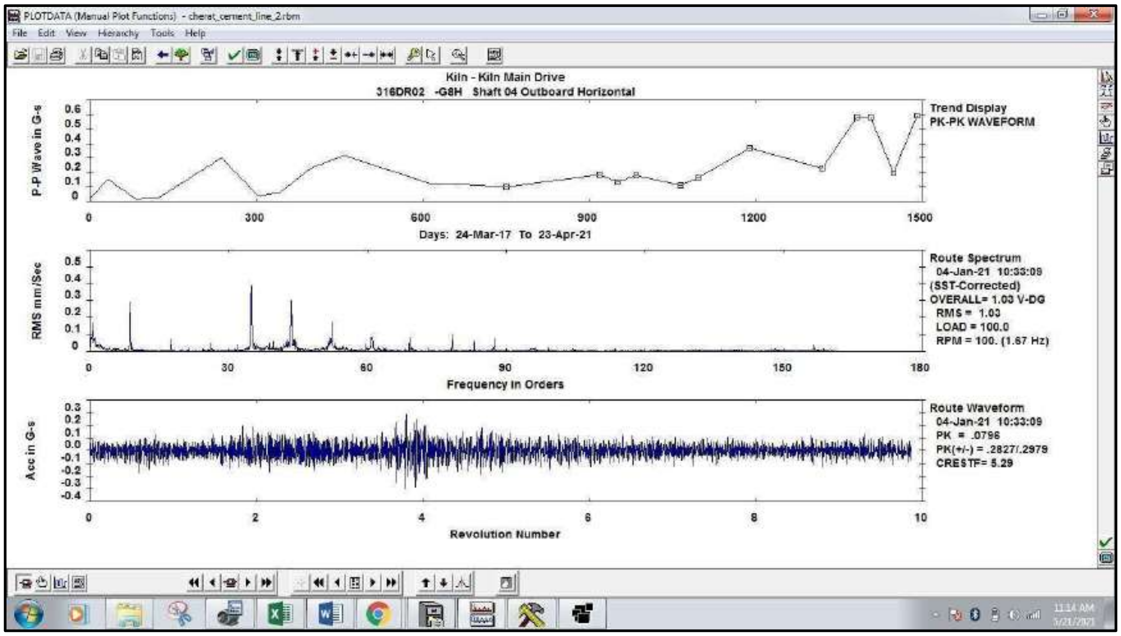


Figure 2-4: Vibration Analysis

2.5. Feature Extraction Technique

Modern Feature extraction techniques are applied on raw signal most probably in time domain to extract the certain feature of signal out of it which are proportional to the changes in consideration thus making ease in designing a model of system.

2.5.1. Kurtosis

Breakdown The fourth normalised core statistical moment is kurtosis. It is a measurement of the peak value of the input vibration signal via its PDF. It determines whether the peak is higher or lower than the peak of the distribution corresponding to the normal state of the vibration signal [11].

$$\boxed{x = \sum_{i=1}^{N} \frac{(x_i - x)^4}{N\sigma^4}}$$

2.5.2. Skewness

Breakdown Skewness is a measurement of the asymmetrical behaviour of the vibration signal based on its probability density function, also known as the third normalised central statistical moment (PDF). In actuality, it establishes whether the vibration signal deviates to the left or right of the distribution of the normal condition.

$$\boxed{x = \sum_{i=1}^{N} \frac{(x_i - x)^3}{N * \sigma^3}}$$

2.5.3. Clearance

Breakdown Clearance factor is defined as the ratio of the input vibration signal's peak value to the mean square root of the absolute value of the signal.

$$\boxed{x = \frac{x_{max}}{\left(\left(\frac{1}{N}\right) \sum_{i=1}^{N} \sqrt{|x|}\right)^2}}$$

2.5.4. Fast Fourier Transform

Breakdown The Fast Fourier Transform (FFT) allows for the efficient computation of DFT of stationary time signals. FFT is used in a variety of practical applications. It reduces the complexity to significant units. In FFT, the complex multiplication is reduced from N2 in DFT to Nlog2(N). In general, a discrete time signal of length N (usually a power of 2) is used to calculate its FFT. The signal is split into two equal parts, odd and even. Both Xeven and Xodd have half of the sampled size, i.e., N/2. The Fourier Transform is used separately before combining the two. The expression can be written as follows [10]:

$$
\boxed{X(k) = \sum_{n-even=0}^{N-2} x(n)\, W_N^{nk} + \sum_{n-odd=0}^{N-1} x(n)\, W_N^{nk}}
$$

2.6. Kalman Filter

"Also known as linear quadrative estimation is an algorithm that use series of input along with a signal noise and accuracies and predict the output estimate better than that of single measurement alone"

Sensor for collecting data of signal do possess some in accuracies which are preferable to be removed for better model design. These uncertainties in reading can be decreased significantly by using sensor fusion via Kalman filtering as studied in Li, Q. *et al.* [8].

Kalman filtering can be used for different purpose in different application but in our context, we will be only referring to it for lessening the uncertainties in our sensor by influencing the calculated value by the prediction which is actually made via other sensor values. Details of it will be explained separately.

2.7. Machine Learning Approach

Sensor Designing a system which can learn and train to extract information from statistical data and draw pattern out of it is what is known as Machine learning. Different models are proposed and there are used keeping in view the application we are plugging in.

There are three different types of learning technique used:

- Supervised
- Unsupervised
- Reinforcement Learning

2.7.1. Unsupervised Learning

This approach is used when dataset are unlabeled and machine itself would derive relation between different elements in data set. Here external interference is not involved and unlike supervised learning, we don't train model knowing in advance output of dataset.

2.7.2. Supervised Learning

Standing quite in contrast to Unsupervised approach, we deal with labelled data set in this class, and we train models by using already tested dataset with define output. In our case, this approach seems reasonable as we have to inject fault by ourselves in first place and then we will testify our data.

2.7.3. Reinforcement

Reinforcement learning is somewhat different to that of supervised in a sense that we will reward some behaviors of data set and we will punish some behaviors to train our model. It is used when we want to perceive our environment and learn through trial-and-error approach.

Several models of all three-training approach have been devised. Mathematical models are different statistical technique used to calculate the output. Figure2.1 summarize the whole discussion.

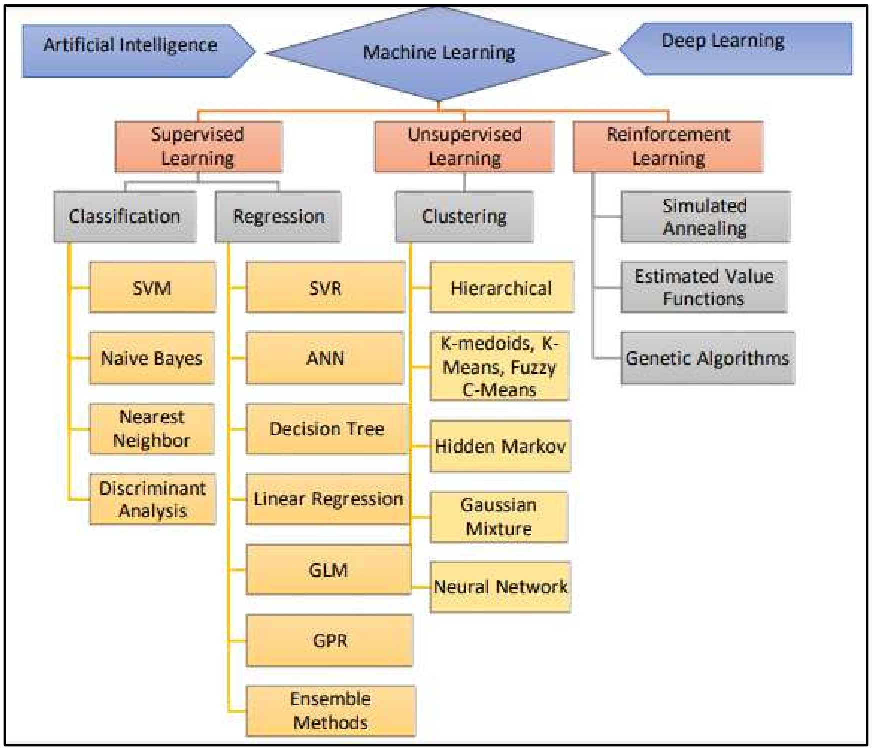


Figure 2-5: Hierarchy of ML approach

2.7.4. Artificial Neural Network

Breakdown Last year, our apparatus was modelled using logistic regression approach where two different sensors were used to capture two bearing vibration signatures but the drawback of logistic regression is that it gives output in form of pass / fail and this year,we will inject more faults into our system which will become a bit problematic therefore we have to move on to a more advance technique called ANN.

There is a lot to discuss about this technique, but we will stick to its general overview.

ANN is composed of multiple layers. Each layer corresponds to particular pattern of the output and as we move further in to the layers, we are drawing close to the output pattern. Each layer contains nodes which contain weights, each weight can either be constant value or function which is limited to value between 0 and 1 using sigmoid function and biases are also further added.

So, ANN modelling comprises of multiple datasets which will adjust all the weight and biases to conform with given output. One more interesting thing to discuss is that sometimes we obtain multiple outputs instead of one and here cost function comes into play which act as output layer on all the calculations discussed before.

In context to our FYP, input to model will be processed signal and output will be an error out of many suspected.

$$\overset{\text{Sigmoid}}{\sigma}\left(w_1a_1 + w_2a_2 + w_3a_3 + \cdots + w_na_n \underbrace{\boxed{-10}}_{\text{“bias”}}\right)$$

2.8. SOAP

Sensor Acronym for Simple Object Access Protocol is a message protocol widely used for communication between element of network. It can be based on HTTP and SMTP etc. The communication between different element is established via API written in SOAP (usually using extensible markup language XML). It can also serve the purpose of inter language communication via SOAP API which we have done in our project too where JAVA based application is set to communicate and exchange data with Python.

WSDL (Webservice Description Language): A file written in XML with tags which can work as a link to exchange data between two different software. A ScadaBR generate its WSDL file which will be utilized to set Datapoint and fetch information from Data points.[9]

3. The Hardware Design:

This section discusses:

1. The complete workflow of the project
2. The design of machine fault simulator and its control box

3. The selection of microcontroller and sensors

4. Interfacing of sensors with microcontroller

3.1. Workflow Diagram

The workflow diagram, shown in Figure 3.1, includes the following steps:

1. Vibration signals are sent to the ADC module, where analog outputs sensed by the accelerometer are converted to digital signals.

2. ADC is connected with Raspberry Pi through an SDA pin and transfers the data for further processing. Pi acts as a server and sends the data to the SCADABR on request.

3. The database of organized such that features are extracted from raw vibration data andsaved in a particular file using JAVA API.

4. Then kurtosis and further data-driven approaches are applied to the features, after whichit is ready for fault prediction.

5. The Kurtosis applied data points are then fed into the ANN trained model. The training occurred with an extensive data set of both faulty and non-faulty data. For training our data sets included up to 60,000 points. However, 90% of the data was used for training while 10% was used to compute the confusion matrix. Our final accuracy soared above 90%.

6. Model returned two output points, 1 and 0. Output of 1 denotes a faulty machine in runtime, and a output of 0 indicates otherwise.

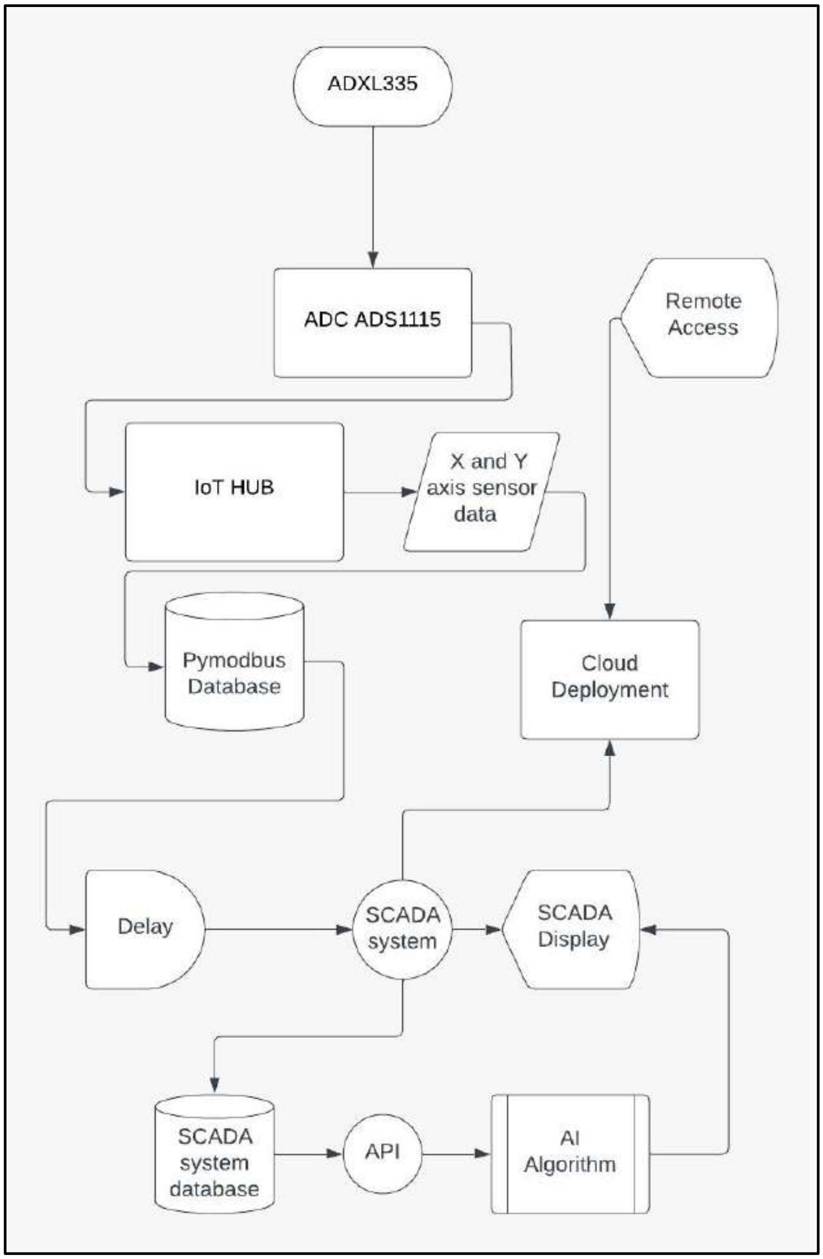


Figure 3-1:Workflow Diagram

3.2. Machine Fault Simulator Design:

Figure 3.2, shows the setup under consideration for predictive maintenance. It consists of a 3-phase induction motor, followed by a coupler. 3-phase motors handle larger loads than single phase motors.

Choosing such a motor allowed to simulate a system which is closer to an industrial environment. Following the coupler is a bearing, and a flywheel along a shaft. At the other end of the flywheel, there is another bearing and then a belt mechanism. The belt finally drives a gearbox, representing a load connected to the machine.

This system is termed as ‘Machine Fault Simulator’ or MFS. Since all common machines consists of bearings, induction motors, shafts, and other components of our system, we can study common machinery faults without compromising production schedules or profits of the industry. Furthermore, it allows us to introduce different types of faults in a controlled environment. In this way, the behavior, and faults of common industrial machines, can be properly simulated, without having to go there.

The following section covers the basic calculations involved in the manufacturing of MFS. The basic steps involved in the mechanical design are mentioned discussed below.

3.2.1. Motor

A three-phase induction motor, shown in Figure 3.3, rated at 250W, was chosen to drive the machine. The main purpose to use a three-phase motor was to replicate an industrial

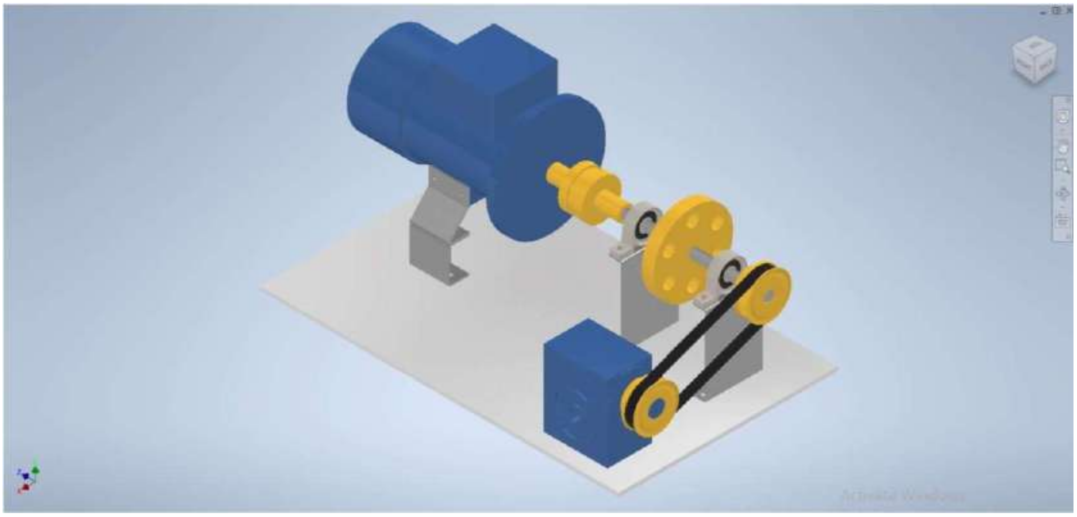


Figure 3-2: CAD Model of MFS

Figure 3-3: Three Phase Induction Motor

machine as closely as possible. This way the vibration signature produced by the motor can be studied, and the information can be useful later when working with industrial machines.

3.2.2. Coupling

The rotor was connected to the shaft using a coupling, as shown in Figure 3.4. An aluminum coupling was chosen to reduce the weight of the total machine and make it moremobile. The rotor has a diameter of 11mm, whereas the shaft used has a diameter of 12mm.The two sides of the couplings were bored accordingly to accommodate each of the elements connected to it.

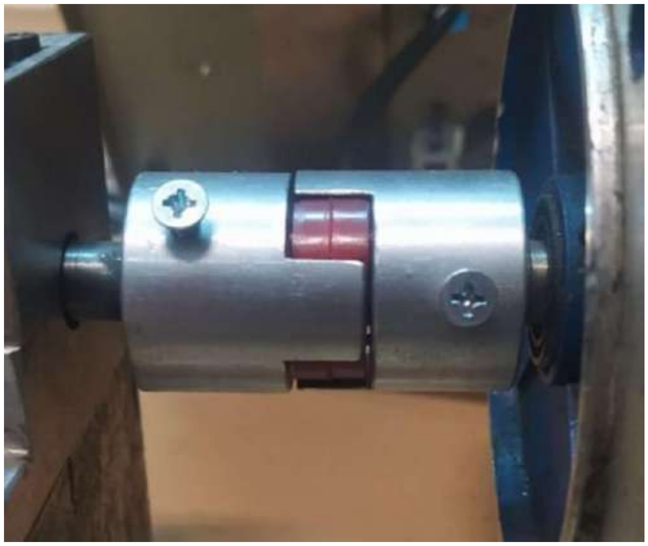


Figure 3-4:Coupling

3.2.3. Shaft

A 300mm long aluminum shaft, with a diameter of 12mm, as shown in Figure 3.5, was used. Aluminum was used to reduce the weight of the machine. One end of the shaft was connected to the coupling, which in turn connected it to the motor. The other end had a pulley connected to it, which was used to drive a gearbox, using a belt. The shaft also hastwo bearings mounted on it, along with a flywheel. The first bearing is located around 75mm away from the coupling end, and the second bearing is located at around 225mm away from the coupling end. This left a 150mm distance between the two bearings. The flywheel is located between the two bearings, at the center of the shaft, around 150mm from the coupling end. The substantial distance between the two bearings, allowed the shaft to swing a considerable amount when introduced to small unbalance. This created greater vibration amplitudes and allowed easy detection.

3.2.4. Bearings

The 6001-2Z deep groove ball bearings, shown in Figure 3.6, were used in this machine. The bearing has an inner diameter of 12mm, and an outer diameter of 28mm. The width ofthe bearing is 8mm. The bearing has a static load rating of 2360N and a dynamic load rating of 5400N, both of which are far greater than the expected loads in this machine.

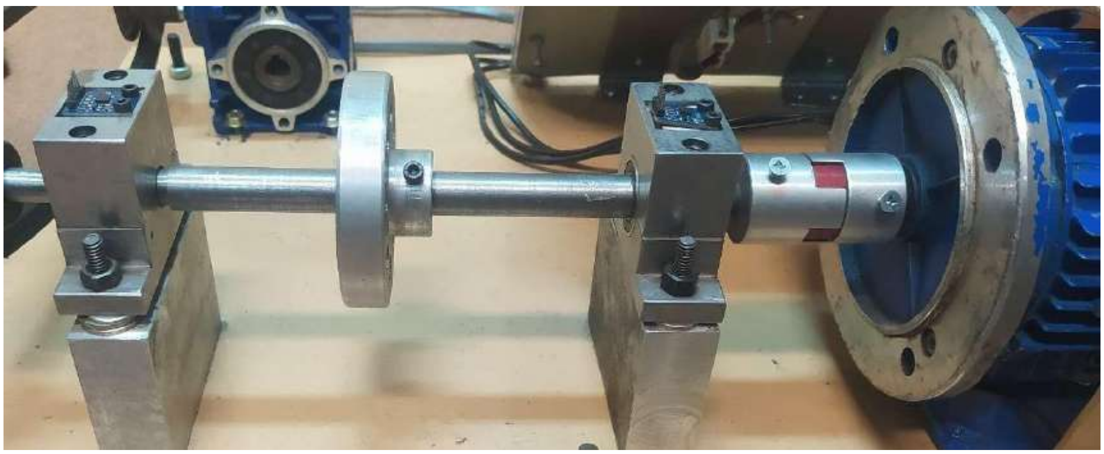


Figure 3-5: Main Shaft of the Machine

Figure 3-6: Bearing (image courtesy rsdelivers)

The healthy bearings can be replaced with bearings with known faults. The specific vibration signatures corresponding to each type of fault in the bearing, can be collected andstudied for development of algorithms to identify these faults.

3.2.5. Bearing Housings

The housings for these bearings, shown in Figure 3.7, were machined with customized designs. This was necessary as housings with a flat body was required to properly mount accelerometers. The housings are made from mild steel to provide strength and a long life, since they cannot be easily replaced. The housings' have two parts: top and bottom. The bottom parts are mounted to the base using some supports, which were also custom designed to align the bearings with the motor and shaft. The bottom parts are tightly fastened with large screws and double nuts, as they are not meant to be removed. The top part of the housings is designed to be easily removed. The important part of their design is to allow easy installation and removal of shafts, without removing any other components, besides the top parts of the bearing housings. The top part of each housing also has a cavity at the top, for easy installation of accelerometers.

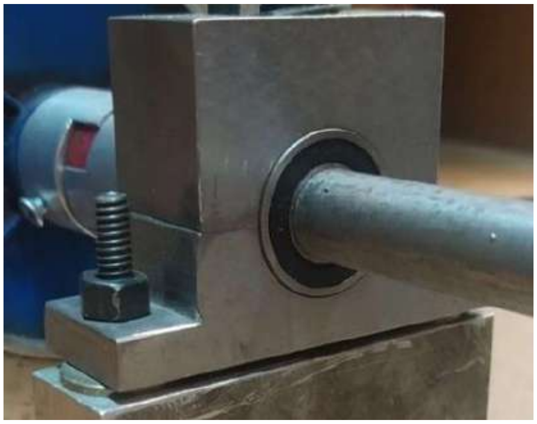
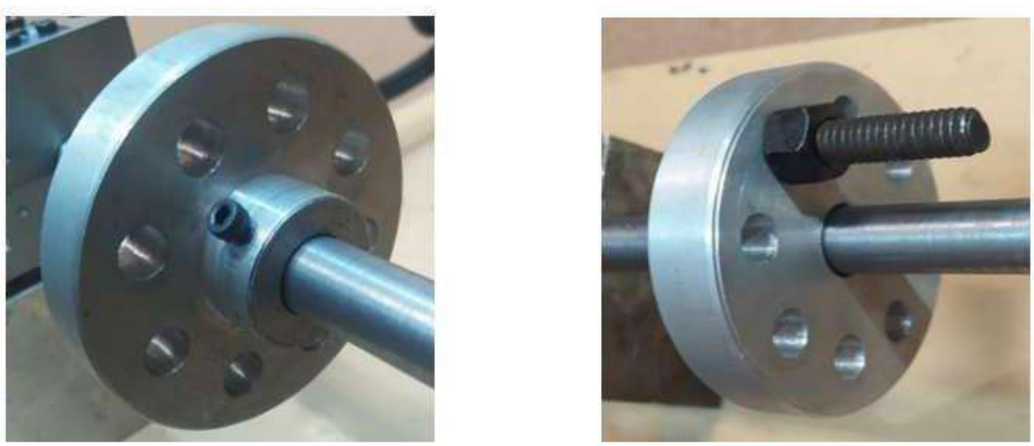


Figure 3-7: Bearing Housing

3.2.6. Flywheel

A flywheel was made from aluminum, as shown in Figure 3.8 (a), to save weight. It has anouter diameter of 100mm, and a bore of 12mm. The flywheel has 6 12mm holes drilled on it, which are radially symmetric. Usually, a flywheel is used to reduce jerks in an operating machine, which can be a result of imperfect operation of the motion and smooth the overallmotion. However, in this machine, the flywheel is used to do quite the opposite. The flywheel in this machine is used to simulate an unbalance fault, which commonly occurs in industrial machines. One of few of the holes of the flywheel can be tied a weight to, as shown in Figure 3.8 (b), to shift the center of gravity of the flywheel from the axial center.This will in turn produce an unbalance of load on the shaft, producing vibrations. The specific vibration signature from this fault can be studied, to create algorithms to detect it.



(a) (b)

Figure 3-8:Flywheels (a) Without Unbalance (b) With Unbalance

3.2.7. Belt and pulleys

A standard pulley made from casted iron was used to drive the gearbox using a belt, as shown in Figure 3.9. One of the pulleys was mounted on the end of the main shaft.

A 12mmbore was drilled out in this pulley to make this possible. The other pulley was mounted onthe shaft of the gearbox. A 10mm bored was drilled in this pulley to match the diameter ofthe shaft of the gearbox. An A-25 belt was used, to drive the pulleys. It has a 1-inch width, and a 25-inch circumference.

Figure 3-9: Pulley and Belt

3.2.8. Gearbox

The gearbox, shown in Figure 3.10, consists of a worm gear, connected to a spur gear. Thecombination of these gears produces a gear reduction of 10:1. The pulley is connected to ashaft, which is in turn connected to the worm gear. The spur gear is not connected to any shaft currently. However, this can be changed in future, is the gearbox is desired to drive something.

The gearbox in this machine, is used to act as a load, and induce stresses on the shaft, alongwith the rest of the components. This is necessary, as the study of a freely moving shaft, will provide inaccurate information, when compared to industrial machines. The gearbox can be further studied by replacing the healthy gears with known faulty gears. The vibration signatures of those gears can be studied to develop an algorithm for fault detection in thosegears.

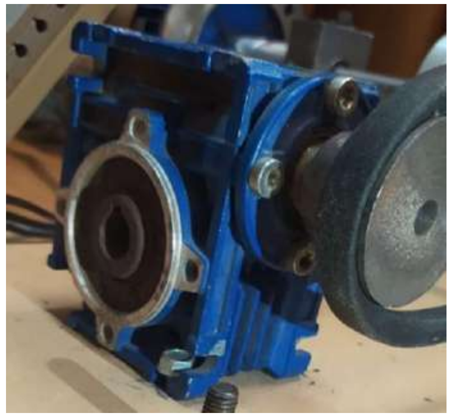


Figure 3-10: Gearbox

3.2.9. Base

The base of the machine was built from a 5mm thick mild steel plate, measuring 500mm x350mm. The steel provides sufficient strength to support the heavy components, mountedon it, without any sorts of deformation. The base has 6 rubber supports attached to the bottom of it to elevate it from the ground. The rubber supports provides a fine grip with the surface, which is necessary to keep a vibrating machine in place.

Figure 3.11 shows the assembled machine.

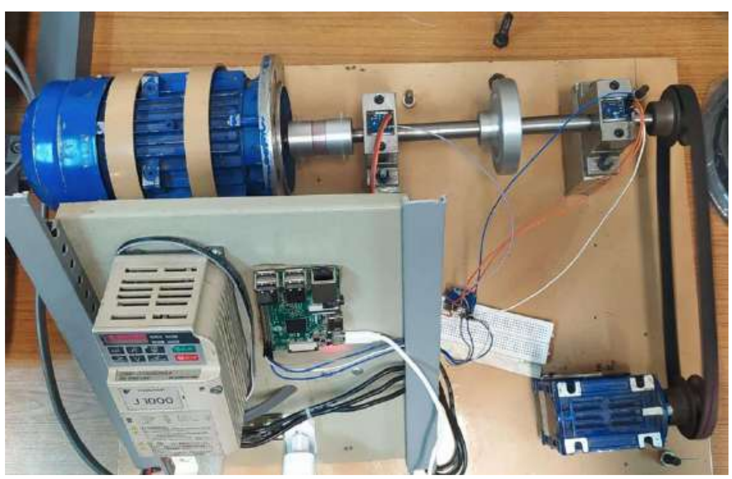


Figure 3-11: Assembled Machine

3.2.10. Control box

Control box was designed to provide power to the sensors and motor. Figure 3.12 shows the design of control box. It contains a VFD, which powers the motor, along with the microcontroller which is responsible to power and collect data from the sensors, and thentransmitting it over the cloud. A number of supporting elements are used, such as a circuitbreaker to protect the equipment from surges. The control box also uses wire ducts and dinrails to neatly organize all the wires and elements mounted on it.

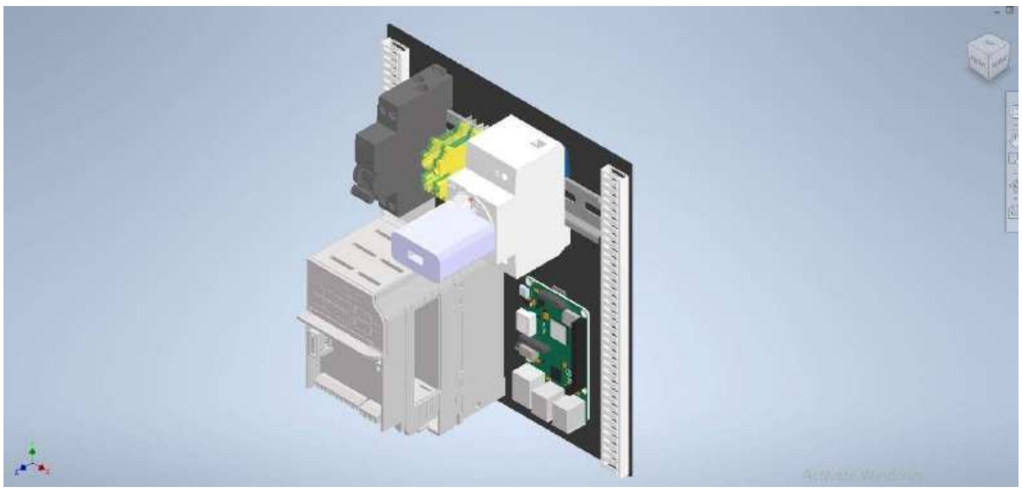


Figure 3-12: Design of Control Box

3.2.10.1. Variable Frequency Drive (VFD)

The CIMR-JUBA0002BAA in the Yaskawa J-1000 series, shown in Figure 3.13, was selected to drive the three-phase induction motor since its rated power is 0.25 Horsepower,which converts to almost 200W. The VFD takes a single-phase AC input, and outputs a three phase AC output. Its maximum frequency is 400Hz which is far greater than the 50Hz AC output required. Its maximum current output is 1.6A, which is sufficient to drive the motor. This VFD also allows to control the speed of the motor by varying its output frequency [3].

Figure 3-13: Variable Frequency Driver, Model: Yaskawa J-1000

3.2.10.2. Microcontroller

As a microcontroller platform, Raspberry PI 3B+, as shown in Figure 3.14, was used. Raspberry Pi is a low cost, modular, credit-card sized computers that support HDMI and USB connections. It provides a set of GPIO pins, using which one can control electronic components for physical computing and explore the Internet of Things (IOT). Raspberry Pi 3 is utilized in this study because it has a highly integrated and miniaturized Ha-Low Wi-Fi module. This module has a low-bandwidth, long-range, low power and massive IoT applications that supports 802.11 ah communication standards. Since communication withthe server is over the internet protocol of CoAP, this Wi-Fi module is extremely beneficialin this regard. Furthermore, a local database was needed to run on the microcontroller, which includes all the data for pre-processing. The memory and RAM capacity ofRaspberry PI facilitates this and reduces the load over server, ultimately leading to a fasterprocess.

Figure 3-14: Raspberry Pi 3B+ by Raspberry Pi

3.3. Sensor

3.3.1. ADC Module

ADS1115, shown in Figure 3.15, is used as an Analog to Digital converter. It has 16 bits resolution with sample rate of 860 samples/second. In this project, data from ADC is transferred to Raspberry Pi in batch mode. The sample rate of ADC The power required by ADS1115 ranges from 2.0V to 5.5V. It communicates through I2C protocol using SDApin. A0-A4 pins are used as digital data output pins [24].

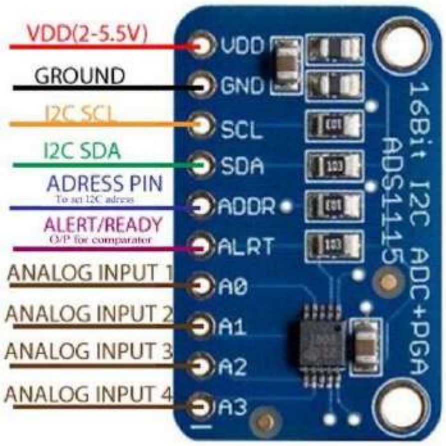


Figure 3-15: ADC sensor, Model ADS1115 by makestorein

3.3.2. Accelerometer

The ADXL335, shown in Figure 3.16, is a low power accelerometer used to sense vibrations in a machine. It is 3-axis accelerometer with ±3 g sensitivity. It encodes the vibration in voltages ranging from -3V to 3.3V. ADXL335 can sense dynamic accelerations, shocks, and vibrations. The bandwidth is adjustable with X and Y output pins can having maximum of 1600Hz bandwidth while Z-axis bandwidth ranges from 0-550Hz. Maximum bandwidth possible is used in this project.

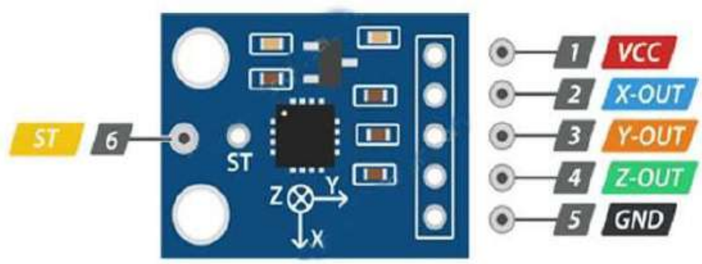


Figure 3-16: Accelerometer, Model ADXL335;
Picture from circuits-diy

3.4. Deployment and Interfacing of sensors

Components used:

- Raspberry Pi 3B+
- ADXL335 3-axis accelerometer
- ADS1115 Analog to digital converter Following is the schematic diagram of interfacing.

3.4.1. Raspberry PI 3B+

The pin configuration of the Raspberry Pi 3B+ is shown in Figure 3.17.

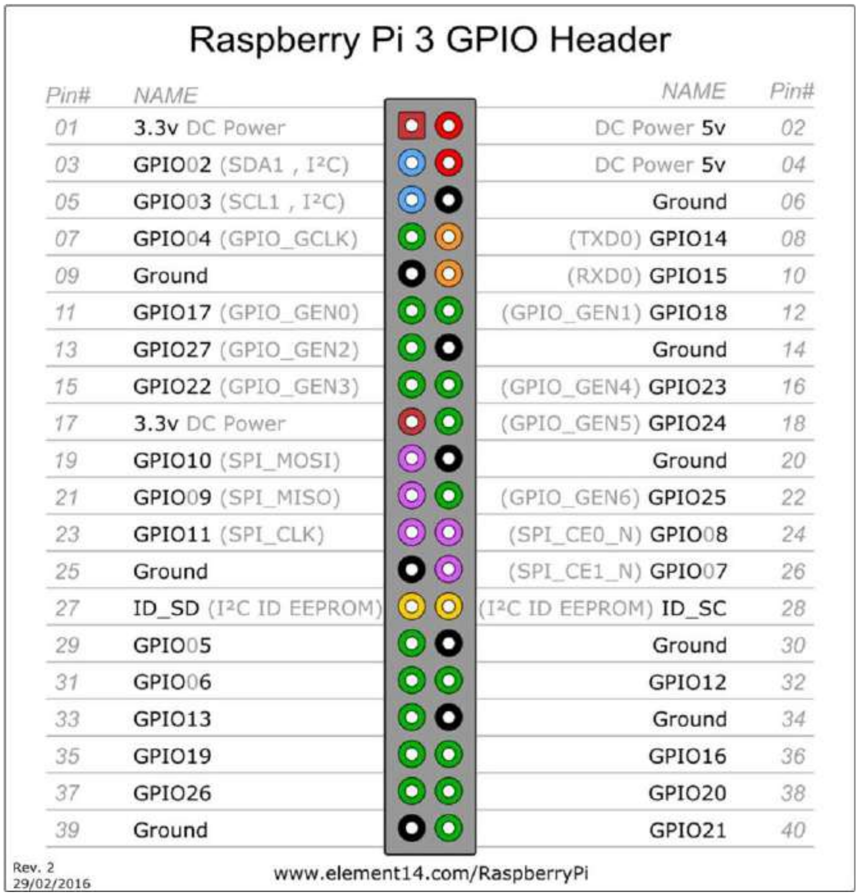


Figure 3-17; Raspberry Pi 3B+ Pin Configuration by Community.elements

Raspberry Pi is powered with an adapter on the control box. Pi is also acting as a power source for the sensors. The accelerometer and the ADC is powered through pin 01 (3.3V)of pi. Similarly pin 03 is used for ground to complete the connection. Pin 03, and pin 05 are connected to the SDA and SCL port of ADS115 respectively.

3.4.2. ADS1115: ANALOG TO DIGITAL CONVERTER

ADS115 is used to convert the analog output of accelerometer to digital signal. As explained earlier, ADS115 is powered by Raspberry Pi. It communicates with Pi through SDA and SDL pins. A_0 and A_1 are connected with the x and y-axis of one accelerometer. A_2 and A_3 are connected with the x and y-axis of second accelerometer. Two accelerometers are used for separately detecting faults of the two bearings.

3.4.3. ADS1115: ANALOG TO DIGITAL CONVERTER

V_{cc} and Ground of ADXL335 are connected with pi. The x and y pin are used for monitoring the vibrations of bearing. These pins are connected to the ADS1115 analog input pins.

4. Preliminary work and progress

We have to look into what previous progress has been made therefore to conclude that what were the drawbacks in those system and how to improve them, let us start off with general overview of a work which was already done. **In a nutshell,** the server which was already being deployed exist on Django and it was linked to, the data was extracted via ADXL335 sensor mounted on the top of bearings and 'x' & 'y' value of these sensors were fed to the 16-bit ADC, data is fetched in raspberry via I2C protocol.

4.1. Ngrok

Ngrok is a tool that allows developers to expose a local web server to the internet. It is commonly used for testing and debugging web applications during development, as it allows developers to access the web application from a remote location as if it were running locally. a cross-platform application that allows developers to easily expose a local development server to the Internet. The software makes your locally hosted web server appear to be hosted on a subdomain of ngrok.com, which eliminates the need for a public IP address or domain name on the local machine.

For example, suppose you have a web application running on your local machine on port 8080. You can use ngrok to expose this web application to the internet by running the following command:

ngrok http 8080

This will start a tunnel and give you a public URL, such as http://abcdefg.ngrok.io, which you can use to access your local web application from the internet. When you visit this URL, the traffic will be forwarded through the ngrok servers to your local machine, and your web application will be served to the client as if it were running on a public server. In this way, ngrok can be used to expose a local web server to the internet and make it accessible from the cloud or anywhere else.

4.2. Django

Django is a Python web framework that allows for the rapid development of secure and maintainable websites. Django, which was created by experienced developers, takes care of much of the hassle of web development, allowing you to focus on writing your app instead of reinventing the wheel. It is free and open source, has a thriving and active community, excellent documentation, and numerous free and paid-for support options.

4.3. Node.js

Node.js is a runtime environment that allows developers to execute JavaScript code outside of a web browser. It enables the creation of server-side applications with JavaScript and includes a library of modules for various functions such as accessing databases, reading and writing files, and building web applications. Node.js is cross-platform and open-source, and is often used for real-time, high-concurrency applications and server-side components of web applications. It is supported by a large community of developers and has many available libraries and frameworks. Node.js is known for its high performance and scalability. Node.js is commonly used to build back-end components of web applications, and is particularly well-suited for building real-time, high-concurrency applications. It is also used to build command-line tools and other standalone applications.

4.4. Previous Working

Modern Feature extraction techniques are applied on raw signal most probably in time domain to extract the certain feature of signal out of it which are proportional to the changes in consideration thus making ease in designing a model of system.

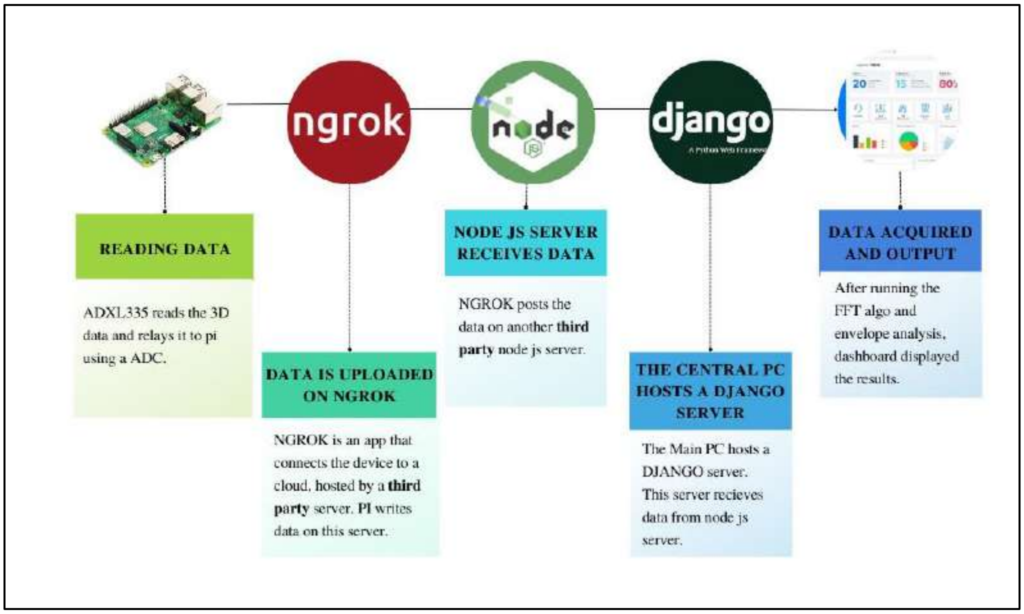


Figure 4-1: Dataflow Illustration

4.5. The Problem at Hand

At a glance, the data flow looks fine, but there is a critical flaw in the flow that defies industrial standards because it involves two third party servers. This makes the system unsecure and vulnerable to data breaches. Therefore, our first concern is to improve the security by moving the data transfer on a local network like Modbus protocol. Using the Scada systems we can display the data stream, and then upload the SCADA system on private hosted cloud.

Secondly, algorithms used were based on linear regression that couldn't model a nonlinear rotating motor adequately. As a result, we need to move ahead on neural network models like ANN that are computationally intensive but yield an accurate result.

4.6. Progress

Modern Feature extraction techniques are applied on raw signal most probably in time domain to extract the certain feature of signal out of it which are proportional to the changes in consideration thus making ease in designing a model of system

4.6.1. Modbus Protocol

Modicon created Modbus, a data communications protocol, in 1979. It was primarily created to be used with PLCs. Gradually Modbus evolved in a common industrial communication protocol, widely used for linking electrical devices.

The Modbus protocol is widely used in industrial settings due to its open and royalty-free nature. It was designed specifically for industrial applications and is easy to deploy and maintain compared to other standards. It imposes few constraints on the format of data being transferred. As a transport layer, Modbus can use character serial communication lines, Ethernet, or the internet protocol suite. Modbus enables communication between multiple devices that are connected to the same cable or Ethernet network. In SCADA systems, it is often used to connect a supervisory computer to a remote terminal unit (RTU).

The modbus protocol supports a hierarchal structure of devices with the controlling unit known as master and subunit, which receives data from PLC, known as slave. The master-slave and client-server notation can be used interchangeably. However, for communication over TCP/IP using Ethernet we shall stick to the notation of Client-Server[25].

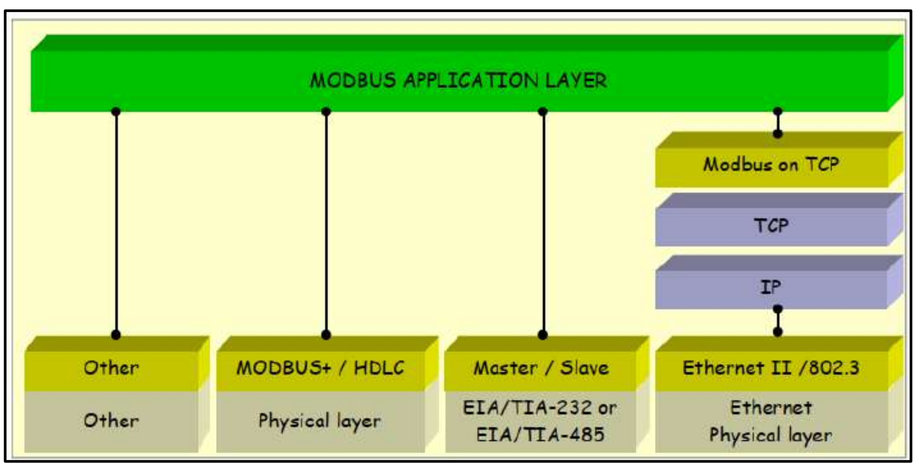


Figure 4-2: Modbus and OSI Model

The following object types may be provided by a Modbus server to a Modbus client device. The addresses are representative of the original Modicon specification. Under the current standard the address can be 0 - 65535 with the object type identified by the command used to read or write the coil or register approach.

Object	Access	Size	Address Space
Coil	Read-write	1 bit	00001 – 09999
Discrete input	Read-only	1 bit	10001 – 19999
Input register	Read-only	16 bits	30001 – 39999
Holding register	Read-write	16 bits	40001 – 49999

4.6.2. Pymodbus

Pymodbus is a python supported full modbus protocol implementation using synchronous and asynchronous core. Modbus communication modes supported include: tcp, rtu-over-tcp, udp, serial, and tls. Pymodbus is a relatively lightweight project that has no third-party dependencies (apart from pyserial).

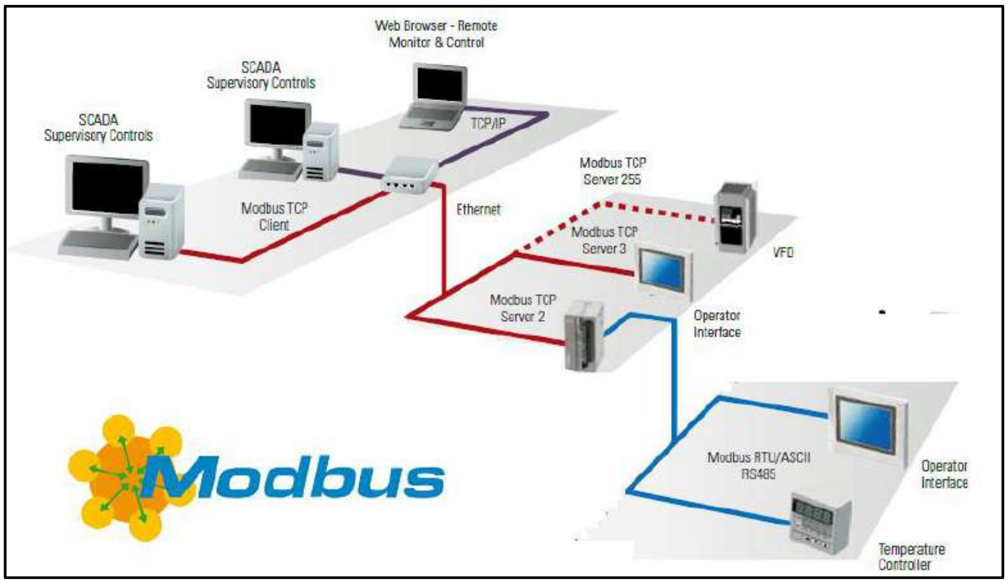


Figure 4-3: Modbus Protocol Working

In our setup, the raspberry PI collects data from vibration sensors. The data is converted into the digital using the ADS ADC. The PI acts as a server and uploads the sensor information on the Holding register. Holding register is an ideal choice for our database because it allows a 16 bit data upload on the Address Space from where the client can read. To maintain the integrity and preserve the accuracy of data, we removed the floating point yet preserved its decimal accuracy by multiplying each value to 1000. This is transformation is reverted on the client end. Our client hosts the SCADA BR setup, and timely reads the relevant address spaces to update the sensor value. Using the JAVA API function, the SCADA communicates with the machine learning algorithms.

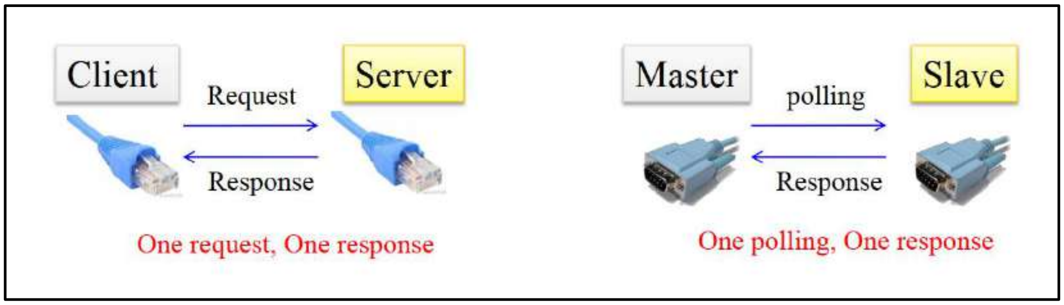


Figure 4-4: Client-Server Model

4.6.3. SCADA System

SCADA (supervisory control and data acquisition) systems are computer-based systems that are used to monitor and control industrial processes and infrastructure. They are commonly used in a wide range of industries, including manufacturing, power generation and distribution, water and wastewater treatment, oil and gas production, transportation, and telecommunications.

SCADA systems typically consist of three main components:

Sensors and actuators: These are devices that are used to measure and control various aspects of the process or infrastructure being monitored. Sensors can include devices such as temperature probes, flow meters, and pressure sensors, while actuators can include devices such as valve controllers and motors.

Remote terminal units (RTUs): These are devices that are located at remote sites and are used to collect data from the sensors and actuators and send it back to the central control room. RTUs are typically connected to the sensors and actuators via a network of communication channels, such as telephone lines, radio, or satellite.

Central control room: This is the central location where the SCADA system is operated and monitored. It is typically equipped with a computer system that is used to collect, process, and display data from the sensors and actuators. The control room is also where operators can interact with the system and make changes to the process or infrastructure being monitored. SCADA systems are used to monitor and control a wide range of processes and infrastructure, including power plants, water treatment plants, pipelines, transportation systems, and manufacturing plants. They allow operators to monitor and control the processes remotely, and to quickly identify and respond to problems that may arise. In addition, SCADA systems can be programmed to automatically take certain actions in response to certain conditions, such as shutting down a process if a sensor detects a dangerous condition.

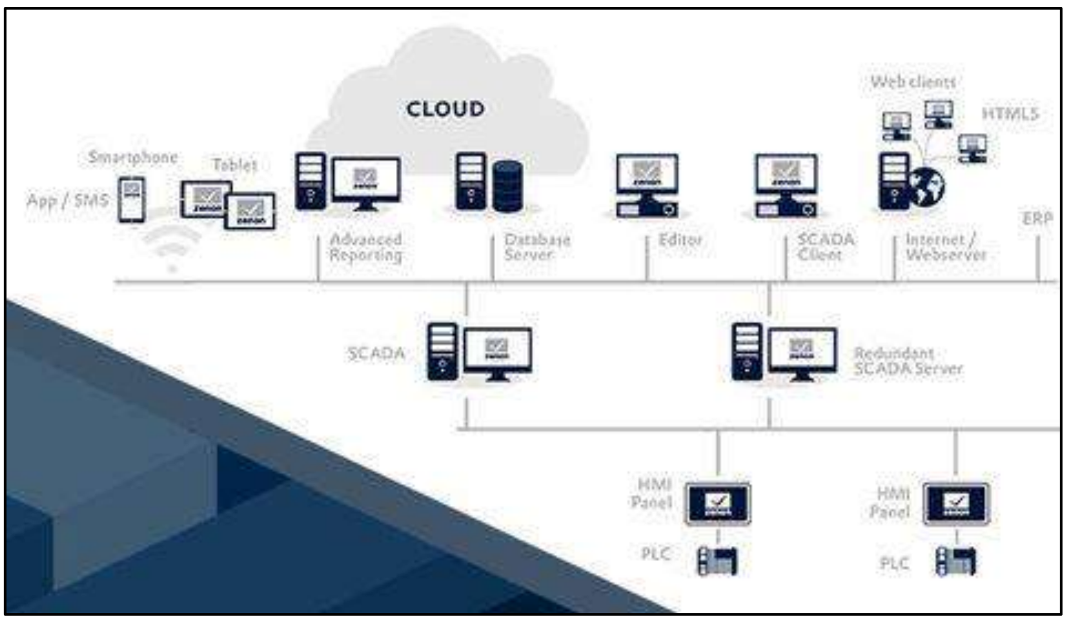


Figure 4-5: SCADA Systems

Overall, SCADA systems are an important tool for ensuring the safety and efficiency of industrial processes and infrastructure. They allow operators to monitor and control processes remotely, and to quickly identify and respond to problems as they arise.

We used SCADABR system to collect data from the sensors and display them using a variety of GUI option provided by the software.

4.6.4. Interfacing ScadaBR

1) Modicon After installing and launching SCADABR, access its web app using the url.

2) Click on Data sources and in the resulting interface chose Modbus IP from the drop-down menu.

Figure 4-6: SCADABR data sources

3) Click on add Data Source.

4) In the resulting window, make a few changes, such as timeout, retries, update period, and host IP. Figure, shows the configuration we use to interface with PI.

5) Save the data source.

6) Proceed to add a data point in the pointer locator test. Configure as required. We were writing our data after an off-set of 1000. Hence, we enter "1000" in the offset slot. Modbus data type is another mandatory slot to be filled appropriately. As holding register offers 16 bit data, we selected, "unsigned 2 byte data." Finalize everything by clicking Add-point.

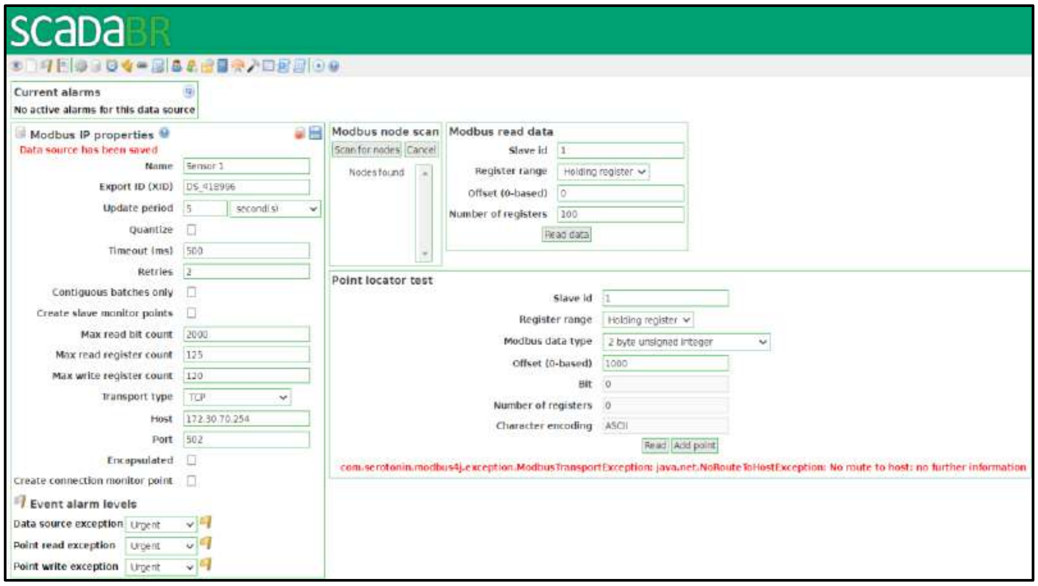


Figure 4-7: Modbus IP Properties

s

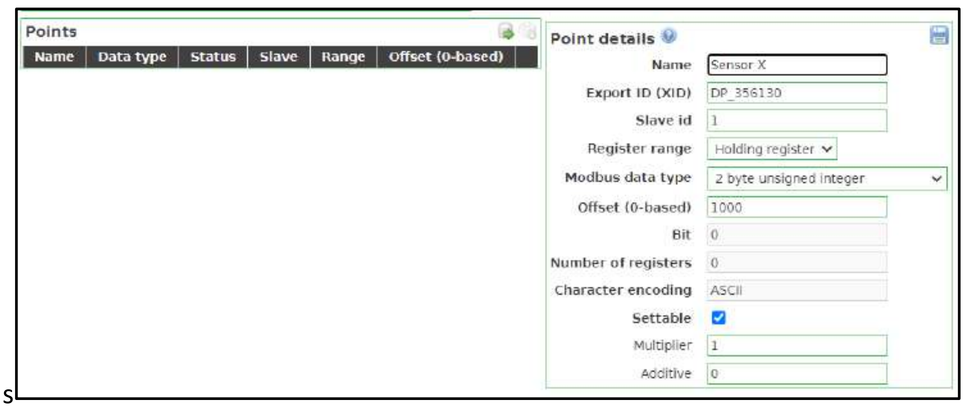


Figure 4-8: Adding Data Points

7) To create more point repeat step 6 and 7.

4.6.5. Output Display on SCADABR:

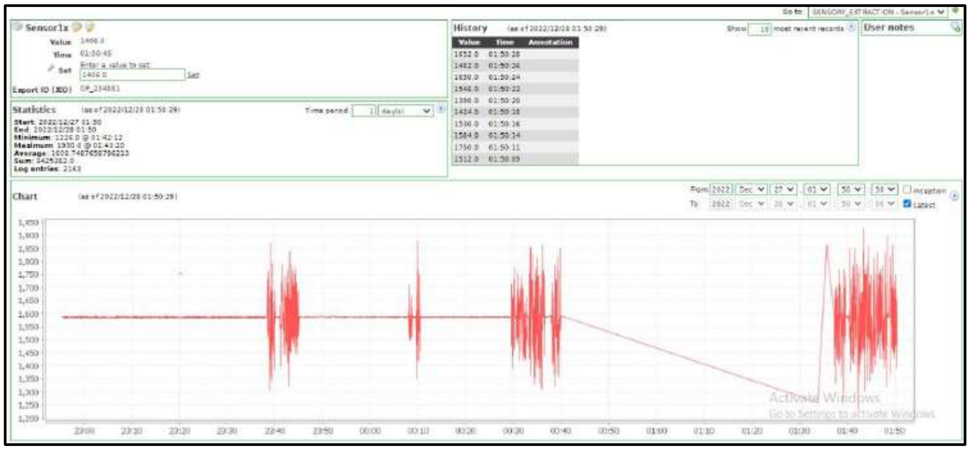


Figure 4-9: X axis readings

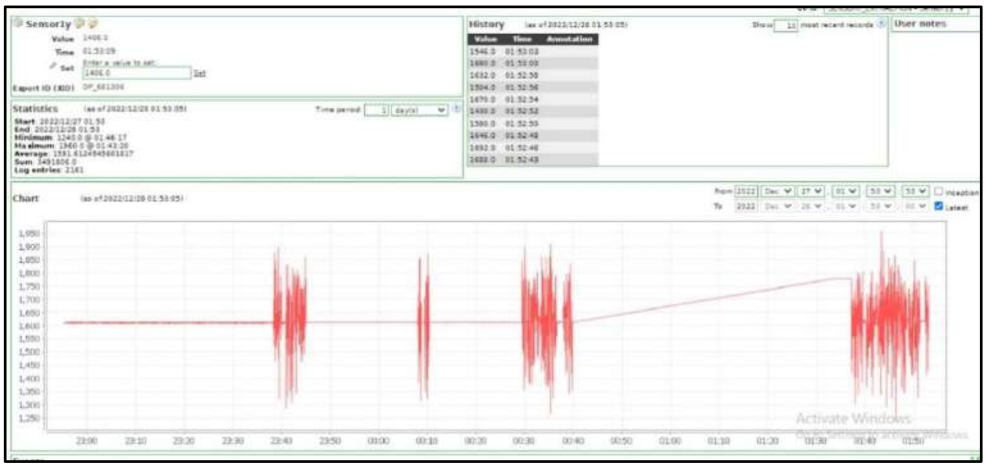


Figure 4-10: Y-axis Readings

These two figures are a part of SCADA GUI that displays the graph of incoming data stream.

4.6.6. ANN

Artificial neural networks (ANNs) are a type of machine learning algorithm that is inspired by the way the human brain works. They consist of multiple interconnected "neurons" that process and transmit information. ANNs have the ability to learn and adapt based on the data they receive, and they have been effective in a variety of applications, including image and speech recognition, natural language processing, and even playing games.

There are many different types of neural networks, but they all have a few basic components in common:

1. Input layer: This is the layer where the neural network receives input data.
2. Hidden layers: These are the layers in between the input and output layers. They are called "hidden" because they are not directly visible to the outside world.
3. Output layer: This is the layer where the neural network produces its output, based on the input it received and the information it has learned through the hidden layers.

Artificial neural networks (ANNs) are a type of machine learning algorithm that is inspired by the way the human brain works. They consist of multiple interconnected "neurons" that process and transmit information. ANNs have the ability to learn and adapt based on the data they receive, and they have

ANNs are trained using a process called backpropagation, which involves adjusting the weights and biases of the connections between the neurons in order to minimize the error between the predicted output and the actual output.

ANNs have proven to be very effective at solving complex problems, but they do have some limitations. For example, they can be difficult to design and tune, and they require a large amount of data in order to learn effectively.

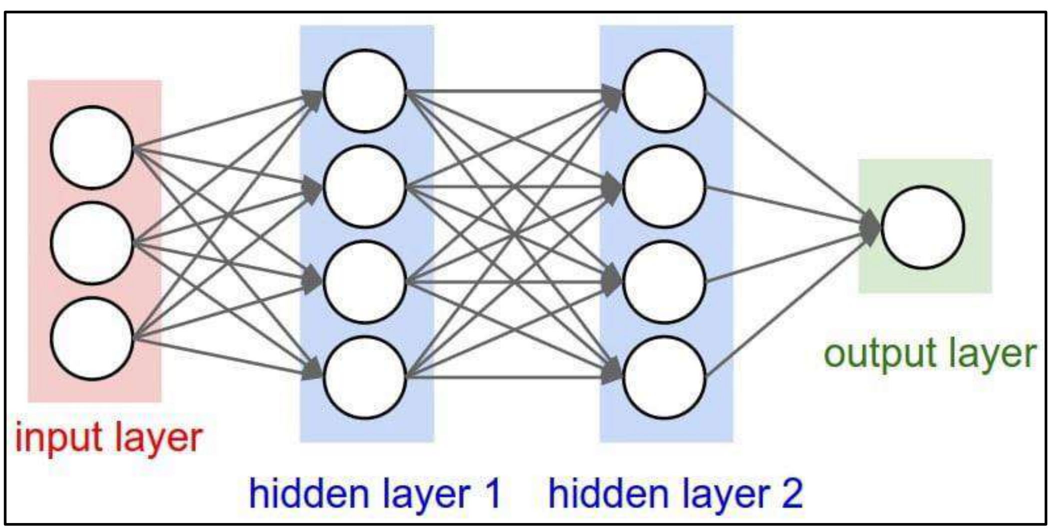


Figure 4-11: Basic Structure of ANN

4.6.7. Objects Used For Training ANN Model

Artificial We primarily used sigmoid function and Adam optimizer for training the ANN algorithm.

4.6.7.1. Sigmoid Function:

The sigmoid function is a common tool in artificial neural networks (ANNs) and other machine learning algorithms. It is used as an activation function to map input data to a range of 0 to 1, which makes it useful for predicting probabilities in binary classification tasks. The sigmoid function has a smooth curve with a range of 0 to 1 and is differentiable, meaning it has a derivative that can be calculated. This property is useful for training neural networks using techniques such as backpropagation. The sigmoid function also has a smooth transition between the two output values, which can aid the model in converging more quickly during training. It is defined as

f(x) = 1 / (1 + e^(-x)),

where x is the input value and e is the base of the natural logarithm.

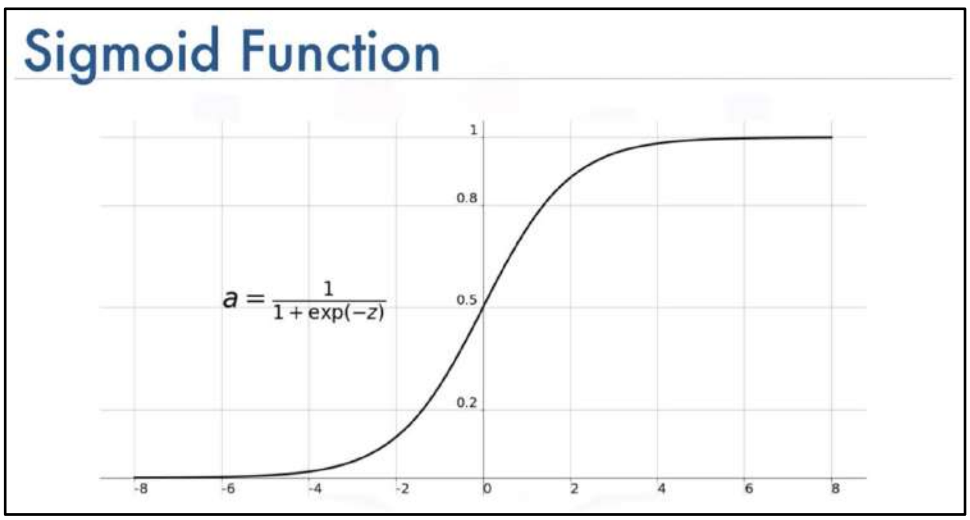


Figure 4-12: Sigmoid Function (ANN)

4.6.7.2. *Adam Optimizer:*

Adam, or Adaptive Moment Estimation, is a popular optimization algorithm used in deep learning and machine learning to update model parameters during training. It combines elements of two other optimization algorithms, Root Mean Square Propagation (RMSprop) and momentum, and is a variant of stochastic gradient descent. Adam uses exponentially weighted moving averages of gradients and squares of gradients to adapt learning rates in a computationally efficient way that helps the model converge more quickly. It is efficient in terms of computational resources and has good convergence properties, making it a popular choice for many deep learning frameworks such as TensorFlow and PyTorch. Adam is often the default optimization algorithm for training neural networks.

5. Conclusion

The objective we have set to achieve were finally met and we have successfully installed an updated version of the system. Unbalanced load fault was put under the test and detected. The workflow starts with extracting vibration data from sensors and a Raspberry PI which is then passed on to a Modbus client. PI acts as a server and data is being fetched by ScadaBR hosting itself as server and displaying the data being collected on a Modbus holding register. The AI algorithm is designed to take batch of 200 datapoints at regular interval being set by us and then it will proceed by making the prediction. Datapoints has been communicated to python using APIs and the information is then processed through statistical analysis technique, converting consecutive 200 points as a single batch and applying kurtosis on it and then predict it using ANN. All the operation being performed finally leads to machine status which is then updated to ScadaBR. The sensor used for extraction are mounted on bearing and accuracy achieved even by using a single sensor exceeds 90%. The shortcoming in the previous setup were addressed and we will further work on designing it more efficiently and up to the industrial standard. Our goals for next semester are to integrate MCSA technique assisting us in detection of various other faults , working on Kalman filter to increase the certainty of signal and controlling the induction motor via Scada system.

6. References

[1] R. Visintini, "Rectifiers," Elettra Synchrotron Light Laboratory, Trieste, Italy.

[2] K. C. Meher, "Study of thermal, electrical and fluid dynamic," Bhabha Atomic Research Centre, Mumbai, April, 2015.

[3] “J1000 Drive - Yaskawa,” www.yaskawa.com. https://www.yaskawa.com/products/drives/industrial-ac-drives/microdrives/j1000-drive

[4] B. M. I, "Thermal Plasma Processing," *IEEE Transactions on Plasma Science,* pp. Vol.-19, No.-6, pp.-1078-1089, 1991.

[5] D. M. Robert W. Erickson, Fundamentals of Power Electronics, 2nd Edition, New York: KLUWER ACADEMIC PUBLISHERS, 2004.

[6] N. F. J. B. P. W. Jitendra Solanki, "Comparison of Thyristor-Rectifier with Hybrid Filter and ChopperRectifier for High-Power, High-Current Application," *PCIM,* p. 8, 2013.

[7] W. V. D. Merwe, "PWM Converter for a Highly Non-Linear Plasma Load," University of Stellenbosch, Stellenbosch, 2005.

[8] M. H. Rashid, Power Electronics, New York, Boston,Londan, Sydney: Academic Press, 2001.

[9] S. &. H. S. &. H. M. &. C. T. Lopa, "Design and Simulation of DC-DC Converters," *International Research Journal of Engineering and Technology.,* vol. 3, pp. 62-70, 2016.

[10] M. &. N. J. &. B. M. Villablanca, "A 12-Pulse AC–DC Rectifier With High-Quality Input/Output Waveforms," *Power Electronics, IEEE Transactions,* vol. TPEL.2007.904185., p. 22, 2007.

[11] R. &. B. I. Alves, " Analysis and Implementation of a Hybrid High-Power-Factor Three-Phase Unidirectional Rectifier," *IEEE Transactions,* vol. TPEL.2008.2010219, p. 24, 2009.

[12] S. &. L. S. Bai, "New Method to Achieve AC Harmonic Elimination and Energy Storage Integration for 12-Pulse Diode Rectifiers," *Industrial Electronics, IEEE Transactions,* vol. TIE.2012.2196903., p. 60, 2013.

[13] Z. &. O. J. &. Z. J. &. S. K. &. Y. W. Wang, "Resonant power electronic transformer for power grid.," *IEEE Energy Conversion Congress and Exposition,* vol. ECCE.2014.6954021., p. 10, 2014.

[14] W.-Y. S. B. K. L. Geun Wan, "Comparison and Design of Resonant Network Considering the Characteristics of a Plasma Generator," *Energies,* Vols. 1996-1073/12/16/3156, p. 10, 2019.

[15] G. &. H. C. Hinow, "Analysis of a series resonant inverter," vol. EPE.2005.219682, 2005.

[16] S. &. X. H. Pan, "A resonant inverter and its soft switching boundary conditions analysis," *2012 7th International Power Electronics and Motion Control Conference,* vol. IPEMC.2012.6258919., p. 10, 2012.

[17] C.-C. &. C. H.-J. Huang, "A PWM switch model of isolated full-bridge converter," *Conference,* vol. IGBSG.2018.8393523., p. 10, 2018.

[18] G. &. J. K. Conway, "Harmonic currents produced by variable speed drives with uncontrolled rectifier inputs," *conference,* pp. 4/1 - 4/5, 1993.

[19] D.-H. &. Y. P. Zhang, "Study of the series resonant capacitor charging power supply with sinusoidal analysis," *conference paper,* vol. 33, pp. 201-204, 2007.

[20] &. T. D. Harik, "Average value analysis of single-phase uncontrolled rectifier," *conference paper,* 2019.

[21] &. T. D. Harik, "Average value analysis of single-phase uncontrolled rectifier," *conference paper,* 2019.

[22] J. Lazar, "Analysis of single phase rectifier circuits," 1997.

[23] M. &. F. P. &. P. E. Boulos, "DC Plasma Torch Design and Performance.," 2017, p. 10.

[24] “ADS1115,” Ti.com, 2019. https://www.ti.com/product/ADS1115

[25] “pymodbus: A fully featured modbus protocol stack in python,” PyPI. https://pypi.org/project/pymodbus/ (accessed Dec. 28, 2022).