ENERGY MONITORING SYSTEM FOR TEXTILE INDUSTRY

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A Final Year Design Project (FYDP) submitted to the Department of Electrical and Electronic Engineering in partial fulfillment of the requirements for the degree of Bachelor of Science in Electrical and Electronic Engineering

Department of Electrical and Electronic Engineering
Brac University
May 2025

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Department of Electrical and Electronic Engineering
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May 2025

Declaration

It is hereby declared that

1. The Final Year Design Project (FYDP) submitted is my/our own original work while completing degree at Brac University.
2. The Final Year Design Project (FYDP) does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The Final Year Design Project (FYDP) does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. We have acknowledged all main sources of help.

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Approval

The Final Year Design Project (FYDP) titled "Energy Consumption Monitoring System For Textile Industry" submitted by

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of Spring, 2025 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of Bachelor of Science in Electrical and Electronic Engineering on 15th May of 2025.

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Ethics Statement

We declare that this project report entitled "Energy Monitoring System for Textile Industry" is the result of our own work, except sources which have been cited and acknowledged. This report is based on joint work by all in the group, each contributing to the study, design, testing and implementation of the system. References from outside sources which have been cited and used in the literature review, data collection, and overall references, have been duly acknowledged and cited as per the rules of academia. This project was developed and implemented with the supervision of our mentors and the cooperation from the university.

We checked the plagiarism of our report and the similarity index was 17 % which indicates the fact that our work is authentic and not copied from the internet.

Abstract/ Executive Summary

This project introduced energy monitoring system for textile industry in Bangladesh. It combines IoT hardware with NILM methodology to carry out the real-time monitoring of individual machine level energy consumption. Two methods i.e. (Intrusive Load Monitoring) ILM and (Non Intrusive Load Monitoring) NILM were compared among which NILM was chosen for its cost effectiveness, scalability and ease of adaptability. The network monitors the total voltage and current with sensors and sends the data to the cloud server with ESP8266. A deep learning model MATNilm was developed to disaggregate the total energy into machine wise power consumption with acceptable accuracy (the average F1-score: 0.73). Real time display via Google Sheets with Blynk app is enabled. The product is conducive for remote monitoring, energy audit and adheres to national and international efficiency goals. Upcoming work will help refine model accuracy, on edge deployment and predictive maintenance. The system provides an industrial application for energy optimization.

Keywords: Energy Monitoring System, Textile Industry, Bangladesh, IoT Hardware, Non-Intrusive Load Monitoring (NILM), Intrusive Load Monitoring (ILM), Deep Learning Model (MATNilm), Power Disaggregation, Real-Time Monitoring, ESP8266, Energy Consumption, F1-Score, Google Sheets, Blynk App, Remote Monitoring, Energy Audit, Energy Optimization, Predictive Maintenance, Cloud Server, Scalability, Industrial Application.

Acknowledgement

We have completed our Final Year Design Project “Energy Monitoring System for Textile Industry” under the grace of the Almighty. This path was one of learning a lot, hard work and steady development, both personally and professionally.

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1.1 Introduction

Bangladesh’s textile industry is one of the most significant contributors to its economy, accounting for over 80% of export earnings and approximately 10% of the national GDP [1]. As a sector highly dependent on electrical energy for its production processes such as spinning, weaving, dyeing, and finishing it ranks among the top ten most energy-intensive industries in the country [2]. Despite its economic importance, energy consumption in most textile plants, particularly among small and medium-sized enterprises (SMEs), is managed through outdated or manual practices. This results in increased production costs, inefficient energy use, and missed opportunities for sustainable development.With global pressure mounting for environmentally responsible practices, driven by both international buyers and local regulations, the demand for energy-efficient solutions in textile manufacturing has become urgent. To meet the challenges of industrial competitiveness, sustainability, and regulatory compliance, this project proposes the development of a real-time energy consumption monitoring system using Internet of Things (IoT) technologies and machine learning (ML) for energy disaggregation.By enabling real-time visibility and analysis of energy use across individual machines and processes, this system aims to help factories reduce wastage, forecast load demand, and align with national and global goals for energy efficiency and greenhouse gas (GHG) reduction [3]. Ultimately, it bridges the gap between technological innovation and industrial sustainability in one of the country’s most critical sectors.

1.1.1 Problem Statement

The textile industry in Bangladesh plays a major role in the country’s economy, but it also consumes a large amount of energy. Most factories, especially small and medium-sized ones, do not have proper systems to track or manage their electricity usage. This leads to high energy costs, wasted power, and difficulty in meeting international sustainability standards [1].Economy of Bangladesh can be boosted through energy efficiency.According to several studies, energy generation is not the only means to address energy demand; efficient energy management practices are also very critical.Increased efficiency would allow industries to become more globally competitive and enable the country to become more energy self-sufficient.Mandatory energy auditing in industry will accelerate this process.The garments and textile sectors, which contribute over 80% of Bangladesh's export earnings and over 10% of the country's GDP, can enhance aggregate energy efficiency by 25-31%.[5]Energy efficiency is vital for Bangladesh's industries, especially when meeting their global clients' ever-increasing environmental, social and governance (ESG) requirements. For instance, Bangladesh's garment manufacturers must fulfil international buyers' obligations to cut greenhouse gas emissions. The Bangladesh Garment Manufacturers and Exporters Association (BGMEA) have signed the United Nations fashion industry charter for a 30% reduction in GHG emissions of the sector by 2030.The government approved the energy audit regulations of Bangladesh on 2 August 2018. Further, it revised the energy efficiency conservation rules in February 2023, stipulating the timeline to initiate mandatory energy auditing by different sectors, including industries.[5][6][7] Organization lacks specific energy efficiency targets.Energy is one of the main cost factors in the textile industry. Especially in times of high energy price volatility, improving energy efficiency should be one of the main concerns of textile plants. Manual monitoring systems are not effective in providing real-time data, and human error often affects the accuracy of energy usage reports [13]. This lack of reliable monitoring leads to undetected power waste, faulty machine operation, and high operational costs [10]. To meet both environmental targets and buyer demands for sustainable production, textile industries need a more intelligent, low-cost, and automated monitoring solution [6].To solve this, two monitoring designs have been proposed.Design 1 (ILM) uses multiple sensors to measure each machine's energy directly, offering high accuracy but requiring more hardware, wiring, and maintenance [5]. In contrast, Design 2 (NILM) uses a single sensor on the main power line and a machine learning algorithm to estimate the power use of each machine, making it more cost-effective, easier to set up and scalable [14] [21].

1.1.2 Background Study

Among the Top Ten Most Energy-Demanding Industries of Bangladesh Textile is one of them.Textile manufacturing involves numerous energy-intensive processes. This sector includes machines that spin raw materials to produce end products[1]. In the economy sector, According to the World Trade Organization, Bangladesh ranked among the world's top four largest textile and clothing exporters from 2015 to 2021 [2][3][4].There are various energy-efficiency opportunities in textile plants, many of which are cost-effective. However, even cost-effective options often are not implemented in textile plants due mainly to limited information on how to implement energy-efficiency measures, especially given the fact that the majority of textile plants are categorized as small and medium enterprises (SMEs). These plants in particular have limited resources to acquire this information. Know-how regarding energy-efficiency technologies and practices should, therefore, be prepared and disseminated to textile plants.[8][9] In addition, Energy Management is all about controlling, monitoring and conservation of the energy resources. It aims at optimizing energy generation, distribution and utilization in order to minimize energy cost without affecting quality.EnM actually involves in identification and assessment of energy saving opportunities along with the controlling and monitoring of 3/45 energy consumption. [10][11][12] Energy monitoring is a must for textile companies.By monitoring energy usage, the company identifies important insights, such as- The largest energy using machines or departments,The things that cause our peak energy usage,It refers to the alternating use of energy of a department or machine over time. Specifically, this includes the exact energy usage of a particular machine like when energy usage when production is shut down, when energy is used abnormally or in unusual times. [13] Existing manual system is not beneficial. Our preference is to accelerate the process by Iot based monitoring.By implementing automated, real-time data collection for key steps in your manufacturing process with the help of machine monitoring, you will gain an accurate and comprehensive data foundation that can be used to drive improvement at every level: from plant floor operator, to line supervisor, to plant manager[14].The ultimate goal of machine monitoring is to gain a deep understanding of all aspects of manufacturing process, enabling you to view in-depth production data at the machine, plant, and enterprise levels.Machine monitoring creates a single source of truth and provides the foundation for your manufacturing improvement roadmap[14] Machine monitoring begins with data collection, but the goal is to leverage that data into actionable information. The result of implementing a machine monitoring system is achieving a consistent data foundation across the manufacturing equipment from which all employees can draw upon and make data-driven decisions which is highly accurate and unbiased data.It makes data collection a largely automated process, machine monitoring removes the elements of human error and unconscious bias.[15] Other than hardware we need some tools like proteus and others to analyze the gathered data. An innovative integration of the IoT for condition monitoring leads to the detection of faults in machines. By utilizing the advanced technologies such as sensors and data analytics systems, we have the opportunity in designing a robust system to detect faults in machines earlier, hence decreasing the costs of maintenance and downtime. This project relied heavily on independent research and literature review concerning the knowledge of machines behavior, power processing, and the IoT architecture[14][15]

1.1.3 Literature Gap

Many researchers have studied energy efficiency in factories, but there is still a lack of practical systems that can monitor energy use in real time—especially in textile factories in countries like Bangladesh. Most of the existing work focuses on large industries with advanced infrastructure. However, small and medium-sized textile factories often do not have the resources or support to apply these advanced systems effectively.Although modern technologies like machine learning and Non-Intrusive Load Monitoring (NILM) have been discussed in academic research, there are very few real-world examples of these being used in a low-cost, scalable way that fits the needs of textile industries in Bangladesh. Also, not much work has been done on using these systems to predict energy demand or to give alerts when machines are using more power than expected.Another gap is that many previous projects do not connect the hardware (like sensors and controllers) properly with software (like cloud storage or data analysis tools). Without this connection, it becomes difficult to get a full picture of how energy is being used and how it can be saved. This is why there is a strong need for a complete system that is affordable, easy to set up, and helpful for both monitoring and managing energy in textile factories.

1.1.4 Relevance to current and future Industry

Energy efficiency is becoming more important in industries worldwide, especially in high-consumption sectors like textiles. In Bangladesh, the textile industry contributes over 80% of export earnings and about 10% of GDP, making it essential for the economy [1]. However, without proper energy monitoring, factories often waste electricity and increase their production costs [2].At the global level, international buyers are pushing for better environmental practices. For example, the Bangladesh Garment Manufacturers and Exporters Association (BGMEA) has committed to reducing greenhouse gas emissions by 30% by the year 2030[3]. Meeting such goals requires smart systems that can track and manage electricity usage in real time.This project proposes a system that helps textile factories monitor the energy use of individual machines. It uses IoT and machine learning technologies to detect unusual power usage, support energy audits, and improve decision-making. These features are also aligned with Bangladesh's updated Energy Efficiency and Conservation Rules (2023) which make energy audits mandatory for industries[4].In the future, as industries move toward smart automation and digital transformation, energy monitoring systems like this will become even more valuable. Therefore, this project is not only relevant to current needs but also prepares the textile sector for future demands in sustainability, regulation, and technological advancement [5].

1.2 Objectives, Requirements, Specification and constant

1.2.1. Objectives

The main aim of this project is to help textile factories in Bangladesh monitor and manage their energy use more efficiently. Most small and medium factories do not have real-time systems that track electricity usage at the machine level. This project will solve that problem using affordable and modern technologies like IoT and machine learning [1].

The specific objectives are:

- Collect real-time data on energy use from individual machines.
- Enable remote monitoring of electricity consumption.
- Detects problems caused by unusual power use such as power fluctuations.

These goals will help factories reduce energy waste, lower costs, and meet environmental standards set by local and international authorities [3]

1.2.2 Functional and Nonfunctional Requirements

Table 01 : Requirements

Type	Requirement Statement
Functional	Real-time data collection
	Data analysis and visualization
	Remote access and reporting
	Alerts and notifications

Non-Functional	High-speed data transmission
	Secure storage capacity
	Reliable alert mechanisms

1.2.2 Specifications

Table 02: System & Component level Specifications

System	**Component**	**Purpose**
Data Collection Unit	• Current Sensor • Voltage Sensor	Senses current,voltage individually for each machine
Processing Unit	Arduino Mega Microcontroller Board	Processes analog data into digital calculate power,voltage,current
Communication	Nodemcu board	Transfers data to cloud server
Power Supply	SMPS Buck Converter	Steps down voltage for microcontroller, sensors
Display	LCD Display	Displays real-time machine data

Table 03: Details of the Components

Components	**Details**
AC Current sensor -ZMCT103	Rated Input current : 5A Rated Output Current : 5mA Precision Rating: 0.2 Frequency :20-400Hz
AC Voltage Sensor - ZMPT101B	Output Signal: Analog 0-5V Input Voltage (max): 250V AC
NodeMCU V3 ESP8266 WIFI Module	WiFi at 2.4 GHz Operating Voltage: 4.5- 9 V Communication Voltage: 3.3V
Microcontroller - Arduino Mega 2560	Clock Speed : 16MHz Operating voltage : 6-9V Analog input pins: 16 Digital I/O pins : 56 DC current for 5V ,3.3V pin: 800 mA
Display : LCD 20x4 display module	Model: LCD 2004 Characters: 20 Backlight: Blue Operated voltage : 5V
Buck Converter : LM2596 DC to DC buck Converter	Input voltage :4.5-35V Output Voltage: 3-35 V (Adjustable)

	Max Output Current : 3A Switching frequency : 150Khz
Motor: AC induction motor	50W, 250V(Max) AC, 50Hz, 2500 rpm
Bulb	15W LED bulb

1.2.3 Technical and Non technical consideration and constraint in design process

In the process of designing an energy monitoring system for textile industries, several technical and non-technical factors must be considered to ensure the system is reliable, affordable, and practical for long-term use.From a technical perspective, one of the key challenges is hardware scalability. In Design 1 (Intrusive Load Monitoring), each machine needs separate sensors and microcontrollers, which increases wiring complexity, installation time, and cost [1]. Also, a single NodeMCU microcontroller cannot support too many machine connections at once, which limits the system's ability to scale in large factories [2]. Additionally, the system cannot detect mechanical faults - it can only monitor electrical issues like over-voltage or unusual consumption patterns [2].In Design 2 (Non-Intrusive Load Monitoring), although fewer sensors are used and the system is easier to install, the accuracy of detecting specific machine faults depends heavily on the performance of the machine learning model. If the model is not properly trained, it might produce incorrect results. Ensuring high-quality data for training and maintaining the model is a technical requirement [3].On the non-technical side, one important consideration is data privacy and security. Since the system uses cloud storage to save and analyze energy usage data, the information could be exposed to unauthorized access if not properly secured [4]. Moreover, some textile factories in Bangladesh may have limited access to stable internet connections, which can disrupt real-time monitoring and data uploading [5].Another non-technical issue is resistance to change from factory workers or managers. Many local industries are still unfamiliar with smart energy monitoring systems, and they might hesitate to adopt a new system unless they clearly understand its benefits [1]. Therefore, proper training and user-friendly system design are also essential for successful implementation.To summarize, the final system design must balance technical efficiency (like accuracy and speed) with non-technical needs (like ease of use, cost, and security). All these constraints were considered during the selection of Design 2 which provides better scalability, simplicity and cost-effectiveness for the textile sector in Bangladesh [2].

1.2.4 Applicable compliance, standards, and codes

1. Bangladesh Energy Audit Regulations (2018)

This regulation makes it mandatory for many industries in Bangladesh to perform energy audits and submit reports regularly to concerned authorities. The proposed system supports this compliance by enabling real-time energy tracking and generating machine-wise energy usage data [1]. This helps factory owners to prepare for audits easily and ensures transparency in reporting.

2. Energy Efficiency and Conservation (EE&C) Rules, 2023

The revised EE&C Rules 2023 emphasize the use of smart technologies, such as IoT-based systems, for better energy monitoring, reporting, and conservation. Our system integrates IoT sensors, cloud storage, and data visualization by helping factories comply with this regulation while improving energy efficiency and accountability [2].

3. BGMEA's Sustainability Commitment (UN Fashion Charter)

The Bangladesh Garment Manufacturers and Exporters Association (BGMEA) has committed to reducing greenhouse gas (GHG) emissions by 30% by the year 2030 under the UN Fashion Industry Charter. This project supports that goal by detecting energy waste, optimizing machine usage, and encouraging sustainable industrial practices [3].

1.3 Systematic Overview/summary of the proposed project

After going through the literature review and understanding the needs of stakeholders in the textile industry, we concluded that a smart, real-time energy monitoring system is essential. This system should help factories track electricity usage, find unusual power consumption, and reduce overall energy costs. To achieve this, we designed two different approaches and tested their performance based on cost, complexity, accuracy, and scalability [1].In this project, we developed two versions of energy monitoring systems -Design Approach 1 (Intrusive Load Monitoring) and Design Approach 2 (Non-Intrusive Load Monitoring). Both systems aim to support textile factories in Bangladesh especially small and medium-sized ones by offering a reliable and affordable way to monitor energy consumption [2].Here are some key points that explain our proposed system:

a. Energy Monitoring Structure:
The first design uses individual sensors for each machine, which gives very accurate data. However, it increases the cost and complexity of the system. Each machine needs a separate voltage and current sensor and its own microcontroller. This setup is difficult to maintain in large factories with many machines [3].The second design uses only one sensor on the main incoming power line. Then, we apply a machine learning model (Seq2Point NILM) to estimate the energy usage of each machine from the total data. This approach saves cost,

reduces setup time, and is easier to scale up as the factory grows. The accuracy is also acceptable based on our simulation results [4].

b. Control and Data Processing Unit:
In both designs, the NodeMCU (ESP8266) microcontroller is used to collect data from sensors. The data is then sent via Wi-Fi to Google Drive, where it is stored securely. For analysis, we use Google Colab to run our machine learning model and generate graphs and reports.The system also includes features for remote monitoring, visual dashboards, and alerts when abnormal energy use is detected. This allows factory managers to take action quickly and reduce losses [5].

c. Disaggregation and Forecasting Model:
The second design includes a power disaggregation feature using Non-Intrusive Load Monitoring (NILM). This model uses the total energy usage data to estimate how much energy each machine is using, without placing individual sensors on them. We trained and tested the Seq2Point CNN-based model which showed promising results in identifying machine-level consumption patterns.Additionally, the system can predict future energy demand helping factories plan their usage and reduce peak hour costs [6].

d. Final Selection and Optimization:
After comparing both systems using a weighted evaluation method, we found that the second design (NILM) performed better in terms of cost, scalability, and ease of maintenance, while still providing reliable accuracy. Therefore, we selected this design for implementation [7].This energy monitoring system is aligned with the Energy Efficiency and Conservation Rules (2023) and supports the BGMEA sustainability goal of reducing greenhouse gas emissions by 30% by 2030 [8]. It offers a practical and affordable solution for factories in Bangladesh to move toward digital transformation and sustainable energy use.

1.4 Conclusion

In this project, we designed and compared two energy monitoring systems. The first system uses individual sensors for each machine, which gives very accurate data but is expensive and hard to scale. The second system uses only one sensor on the main power line and applies machine learning to estimate each machine's energy use. After comparing both, we selected the second system because it is more affordable, easier to install, and suitable for future factory growth [2].The proposed system can help factory owners see real-time energy use, get alerts when something is wrong, and make better decisions. It also supports load forecasting and helps in reducing energy wastage. By following national energy rules and international environmental goals, this system can support the industry in becoming more sustainable and competitive [3].Overall, this project shows that smart energy monitoring using IoT and machine learning is not only possible but also very useful for the textile industry in Bangladesh. It can lead to better energy management, cost savings, and help the industry move toward digital transformation [4].

Chapter 2 Project Design Approach[CO5,CO6]

2.1 Introduction

To develop the NILM-based energy monitoring system for the textile industry, two design approaches were considered to achieve the best results. The first approach uses intrusive load monitoring, where each machine has its own data collection unit. The second approach uses non-intrusive monitoring, where only the total power from the main line is measured, and the NILM algorithm breaks it down for each machine. This section compares the two approaches based on cost, efficiency, usability, ease of manufacturing, impact, sustainability, and maintenance to find the most suitable option.

2.2 Identify & DescribeMultipleDesignApproach:

2.2.1 DesignApproach 1

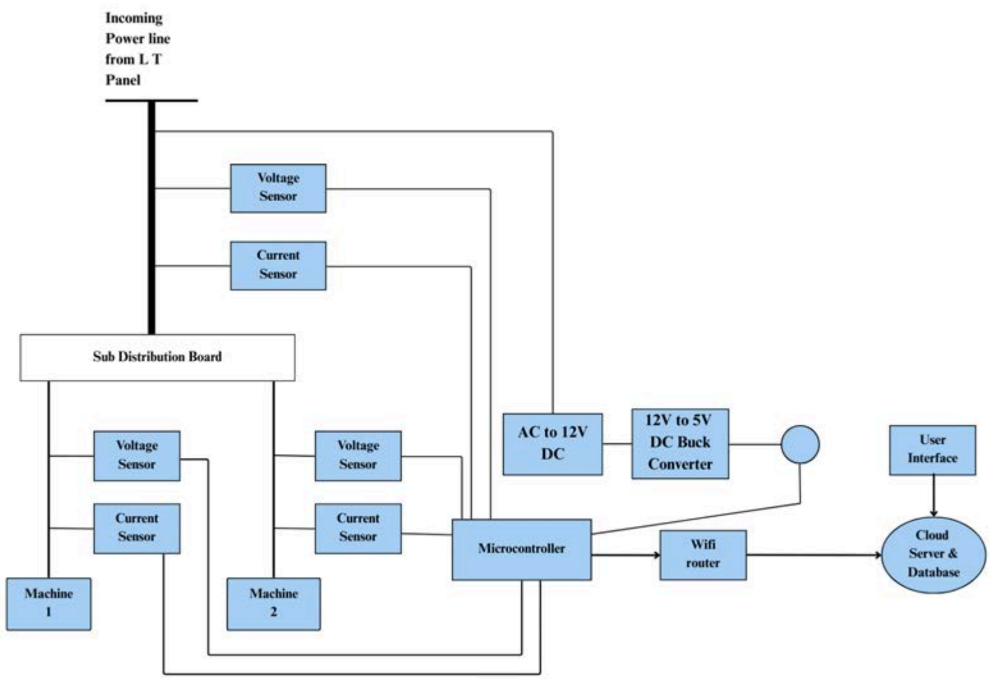

Fig 01: Intrusive Load Monitoring

In our first approach designing the monitoring system using an intrusive load monitoring approach where every machine will be connected to the data collection units (sensors). That means If we want to increase the number of machines to be monitored then the same number of data collection units has to be increased. From the data collection units real time data will be sent to the microcontroller to process analog data into digital and send further to the cloud server through a wifi module integrated in the microcontroller. At the server data will be stored and processed . After processing it will show the result which anyone can see from the user interface who has the access.

2.2.2 Design Approach 2

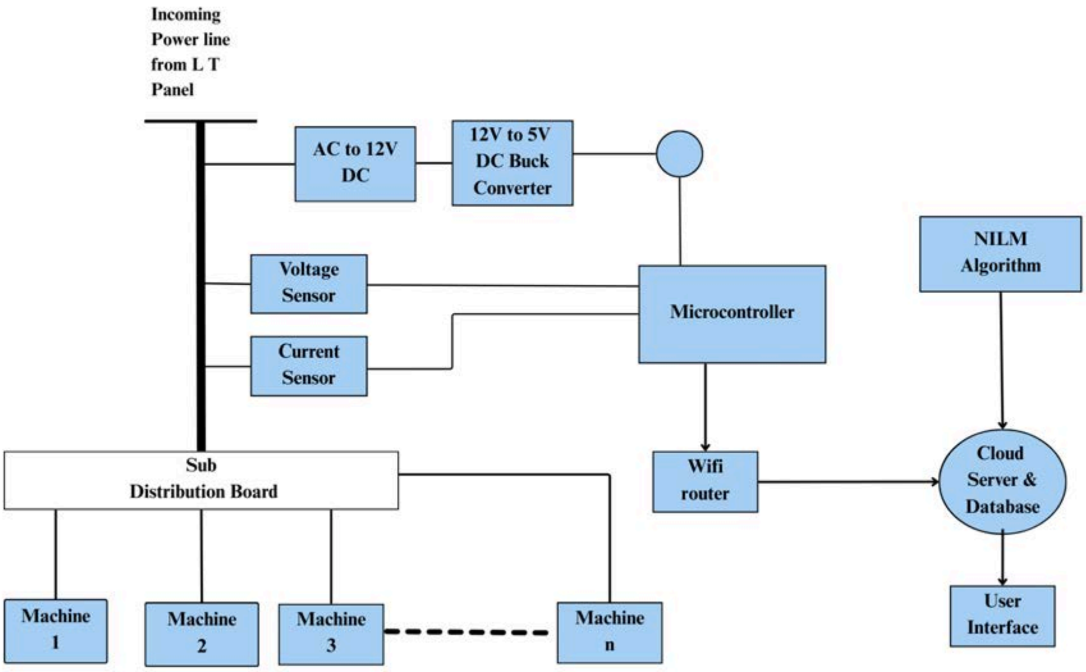

Fig 02: Non Intrusive Load Monitoring

This is the alternative design for the monitoring system. It is basically a Non Intrusive Load Monitoring system where the total power and the power consumption of a number of machines will be monitored in real time only taking data of the power consumption of the main power line.It will be called aggregate power. That means any data collection unit won't be needed to collect the data from individual machines. Rather only one data collection unit will be needed to collect the data from the main line. Through the microcontroller the digital data will be sent to a server where an NILM algorithm (Machine Learning Model) will disaggregate the total power into the power of each machine. Then the result will be shown at the server and anyone who has access can see the result from the user interface.

2.3 Analysis Of Multiple Design Approach

Table 04 : Analysis of Design Approaches

Criteria	Approach 1	Approach 2
Cost	High because sensors are required for each machine.	Lower as we need only one data collection device for the main line
Efficiency	High for monitoring individual machines directly.	Effective for collecting the macroscopic power consumption but is from relying on the accuracy of NILM algorithm itself
Usability	Complex setup if the number of machines increases.	Simplified and scalable ,as only one monitoring unit is needed.
Manufacturability	Complicated due to the need for	Simple and scalable with one

	multiple data collection units.	central data collection unit.
Impact	High initial setup impact due to multiple sensors.	Lower environmental impact due to fewer hardware requirements.
Sustainability	Less sustainable due to higher hardware needs and maintenance.	More sustainable with reduced hardware and energy use.
Maintainability	Challenging ,as each sensor requires individual maintenance.	Easier,as maintenance is centralized to a single unit.

2.4 Conclusion

Approach 2 (Non-Intrusive Monitoring) is generally more practical and efficient for large-scale applications due to its lower cost, simplicity, and sustainability. It is also easier to maintain and expand compared to Approach 1, which requires more hardware and maintenance effort. While Approach 1 may provide more accurate machine-specific data, Approach 2's ability to disaggregate power using the NILM algorithm makes it more adaptable for industrial settings where scalability is important.

Chapter 3 Use of Modern Engineering and IT Tool. [CO9]

3.1 Introduction

In the rapidly evolving field of engineering,the integration of modern engineering and IT tools has become essential for efficient system design,analysis and implementation. These tools enable engineers to visualize concepts, simulate real world scenarios and optimize system performance with greater accuracy and speed. From circuit simulation and data processing to machine learning and real time monitoring , the use of advanced software and hardware tools enhances both productivity and innovation. This chapter highlights the selection and application of such tools in the context of our project emphasizing their role in achieving reliable and efficient outcomes.

3.2 Selected Appropriate Engineering AND IT Tools

3.2.1 Software tool selection

- Proteus 8 Professional
- Arduino Integrated Development Environment (Arduino IDE)
- Google Collab
- Spyder
- Coolterm
- Blynk

3.2.2 Hardware Tool Selection

- Voltage Sensor -ZMPT101B
- Current Sensor - ZMCT103C
- Arduino Mega 2560
- ESP8266 Wifi Module
- Multimeter

3.3 Use of Modern Engineering and IT Tools

To ensure the successful implementation and testing of our energy monitoring system , a combination of modern software and hardware tools was used. Each tool played a specific role in data acquisition, processing, simulation, monitoring and visualization. Below is a brief overview of the use cases for each tool:

3.3.1 Software Tools

- **Proteus 8 Professional**
  Used to simulate the entire circuit design of the energy monitoring system, including sensors,microcontroller and loads. It allowed virtual Testing of hardware behavior before real world implementation.

- **Arduino IDE**
  Utilized to write, compile and upload programs to the arduino mega 2560 board and ESP8266 board . It helped in developing the code for reading sensor values and transmitting data.

- **Google Collab**
  Used for training and evaluating the NILM(Non Intrusive Load Monitoring) algorithm using python and machine learning libraries. It enabled cloud based computation without requiring local setup. Even we deployed our trained model on this platform.

- **Spyder**
  Provided a powerful Python development environment for testing smaller code modules, visualizing data debugging scripts locally during the model development phase.

- **Coolterm**
  A terminal software used to collect real time data from the simulation as well as the hardware environment. It allowed serial communication between the Proteus simulation and computer. Data was stored in csv format for training the NILM model. Besides the hardware loads data was also stored in csv format for training the model using this tool.

- **Blynk**
  Used to create a mobile based user interface for displaying real time energy data. It enabled remote monitoring through the internet using the ESP8366 wifi module. For this design approach 2 this platform has been connected with google sheet to show the disaggregated power of the loads.

3.3.2 Hardware Tools

- **Arduino Mega 2560**
  Served as the main microcontroller in the system for reading sensor data, processing it and communicating with other devices such as the ESP8266 module.

- **Voltage Sensor (ZMPT101B)**
  The ZMPT101B is a precision voltage sensor used to measure the AC voltage of the main power line. In this project, it was utilized to provide real time voltage readings which along with current data helped to calculate the active power consumption. Its compact design and high accuracy made it ideal for integration into the energy monitoring system. The sensor outputs an analog signal proportional to the input voltage, which was read by the Arduino Mega 2560 for further processing.

- **Current sensor(ZMCT103C)**
  The ZMCT103C is a non-invasive current transformer used to measure AC current. In our setup, it was connected to both individual machines for ILM and collecting the data for training and mian line for NILM to capture current usage data. This sensor provided a safe and reliable way to monitor current without direct contact with high voltage lines. The analog output signal was sent to the arduino mega 2560 where it was converted to digital form and used to calculate power consumption and generate datasets for the NILM model.

- **ESP8266 WiFi Module**
  Enabled wireless data transmission from the arduino to online platforms like Blynk and google sheet allowing real time remote monitoring for energy usage.

- **Multimeter**
  Used to verify voltage, current and connection integrity during the hardware testing phase. It ensured that all components were functioning correctly before simulation and data collection.

3.4 Conclusion

The successful development and implementation of our energy monitoring system heavily relied on the effective use of modern engineering and IT tools. By carefully selecting a combination of software and hardware tools we were able to design ,simulate ,test and deploy a robust and scalable solution. Tools like Proteus and Arduino IDE streamlined the simulation and coding process, while platforms like Google Colab and Blynk enabled advanced data processing and real time monitoring. Hardware components such as the Arduino Mega 2560, ZMPT101B voltage sensor and ZMCT103C current sensor ensured accurate data collection from the system. Overall, the integration of these tools not only enhanced the efficiency of our project but also demonstrated the importance of modern technologies in solving real world engineering problems.

Chapter 4: Optimization of Multiple Design and Finding the Optimal Solution. [CO7]

4.1 Introduction

In modern industrial appliances ,particularly in energy intensive sectors like the textile industry, selecting the most effective design approach is essential to ensuring cost effectiveness, efficiency and sustainability. In this chapter , we analyze two distinct design approaches - one is Intrusive Load Monitoring and the other is Non Intrusive Load Monitoring to identify the optimal solution for a real time energy monitoring system. Using Analytical Hierarchy Process(AHP) methodology ,we evaluate the design alternatives based on five criteria: cost, accuracy, integration complexity, maintainability and scalability.

4.2 Optimization of Multiple Design Approach

4.2.1 Design Approach 1- Intrusive Load Monitoring

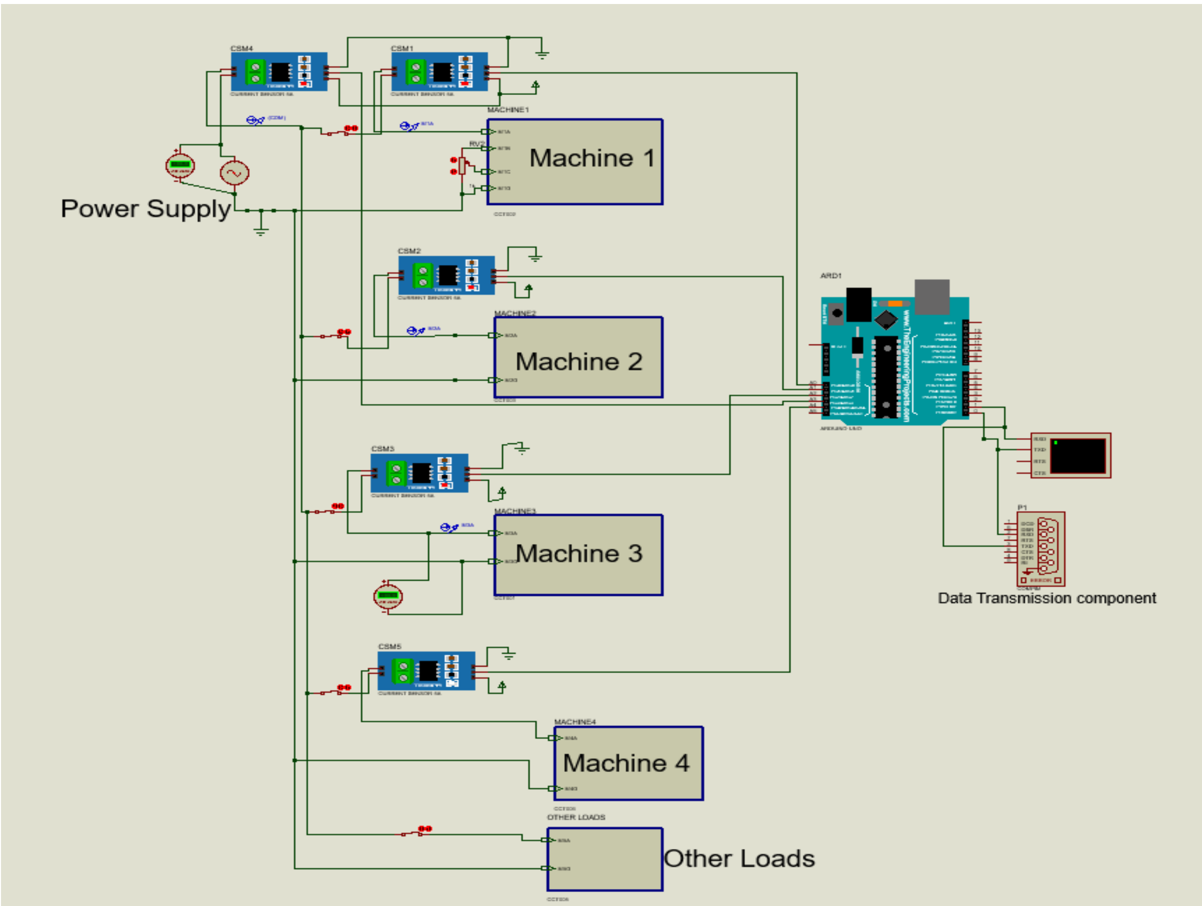

Fig 03: Simulation Model for Design 1 (Intrusive Load Monitoring system)

This is the simulation circuit designed for Intrusive Load Monitoring (ILM) in Proteus. In this setup, we are monitoring the individual power consumption of four machines as well as the main power line. Each machine is connected to a current sensor, which measures the analog current from the line and sends it to the microcontroller. The microcontroller then converts the analog data into digital form and displays the power consumption in real time through a virtual monitor.

For the simulation, we have used an Arduino Mega as a microcontroller board to process the analog signal but to send the data. But in the actual scenario there is ESP8266 microcontroller board to send the data to the server and display it to the user interface which can not be done in Proteus. So we did not include this board in the simulation circuit. Since this is a simulation environment, there are no voltage fluctuations as seen in real-life scenarios. To simplify calculations, we have kept the AC voltage constant while calculating power. Consequently, we did not include a voltage sensor in the circuit. This setup effectively demonstrates the ILM approach and allows us to analyze individual machine power consumption with accurate simulation results.

Different Loads:

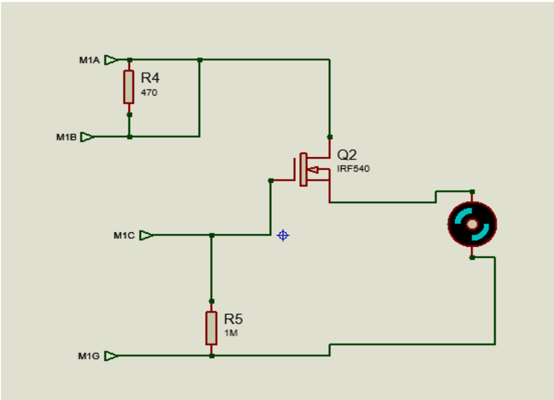

Fig 04: Machine 1 Circuit

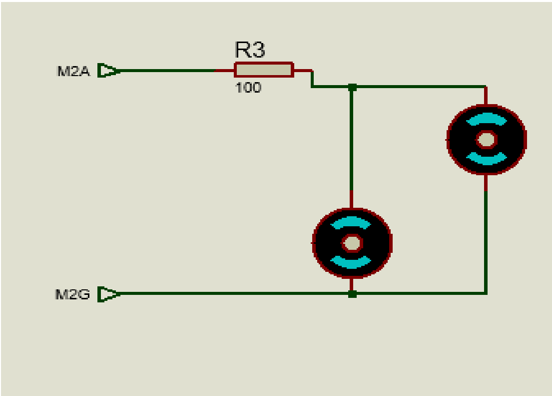

Fig 05: Machine 2 Circuit

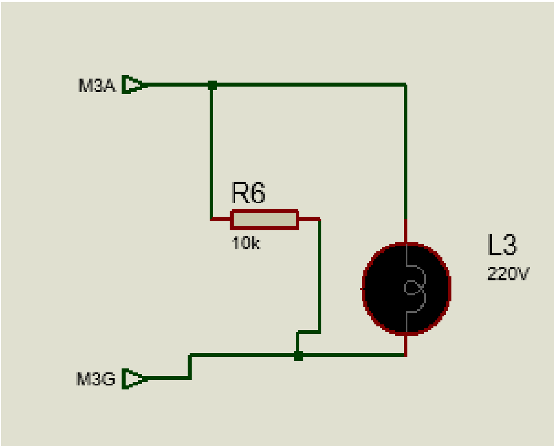

Fig 06: Machine 3 Circuit

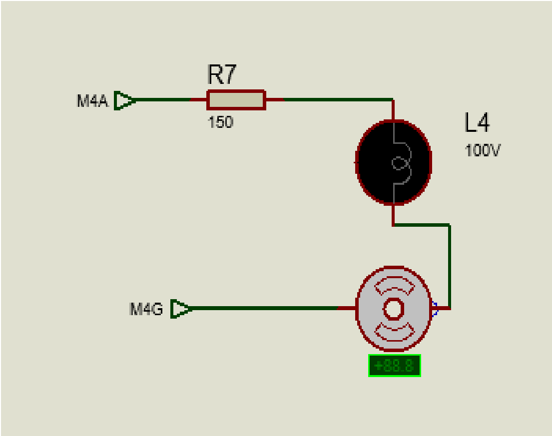

Fig 07: Machine 4 Circuit

These are the circuits we used to represent each machine in our project. Since textile machinery circuits are highly complex and it is challenging to find the complete circuit diagrams for such machines, we replaced each machine with simpler AC-operated equipment. This substitution simplifies the design while still serving our primary purpose.

Our main focus is to develop the energy monitoring system, not the intricate circuitry of textile machines. Therefore, each combination of AC-operated equipment is used to represent one machine, allowing us to model and monitor energy consumption effectively without the need for actual textile machinery circuits. This approach ensures the feasibility and practicality of our project while keeping the monitoring system adaptable for future applications.

4.2.2 Design Approach 2 - Non Intrusive Load Monitoring

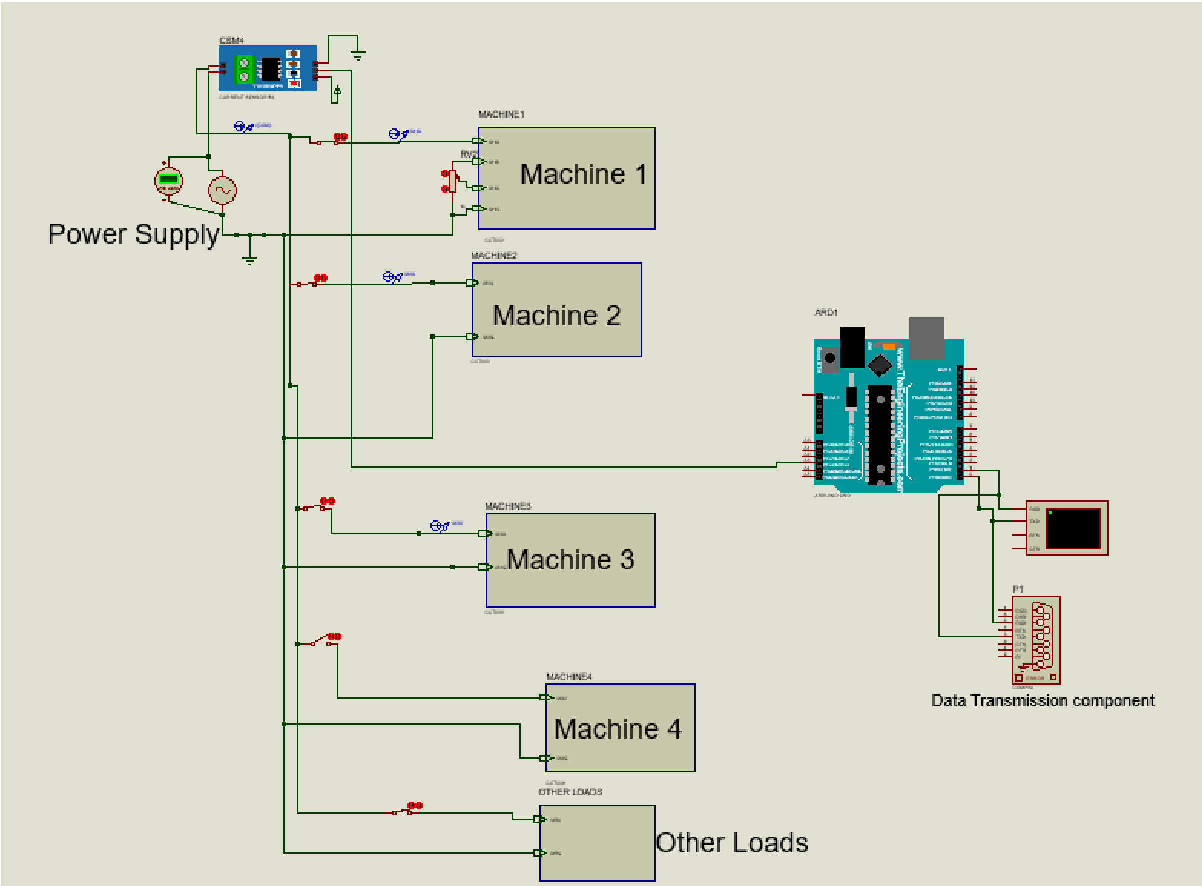

Fig 08: Simulation Model for Design 2 (Non Intrusive Load Monitoring System)

Design approach 2 simulation is for the same scenario and specifications. This is the circuit of the system where the sensor is connected only with the main power line and takes the value from it and sends it to the server to disaggregate the power. To understand the working flow of the system is totally dependent on the NILM algorithm which can disaggregate the data properly. Basically for that purpose we have collected data of the main line and the load lines from the simulation and fed that data into the NILM algorithm to disaggregate each machine's power.

4.3 Identification of the Optimal design approach

To identify the most appropriate approach to the energy monitoring system in the textile industry, we performed an extensive analysis by comparing both the intrusive and non-intrusive type of load monitoring technique. A multi-criteria decision making methodology, including the Analytical Hierarchy Process (AHP), was applied to facilitate systematic evaluation based on five key criteria: cost, accuracy, complexity of the integration, maintainability and scalability. Weights were assigned to the criteria and the same step was made for the alternatives by scores between design 1 and 2 and a final comparison was made. By using this approach, it guaranteed that the chosen design does not only fulfill the technical and operational requirements of the project, but also the long-term sustainability, adaptability and cost effectiveness goals.

Cost

Cost is a major consideration as it directly affects the viability of the project. The cost of a design solution, especially that of real world application such as energy monitoring system shall play the major role for penetration of the system. Comparison of the cost of implementation, operation and maintenance of the two designs will help verify that the solution meets budget limitations yet satisfies all facets of functionality. The ILM (intrusive load monitoring) and NILM (non-intrusive load monitoring) interfaces require different tools, software and technologies with different cost profiles. When cost is considered, the objective is to make the selected design value for money and not to exceed certain limits.

Accuracy

The need for accuracy is crucial to compare how much each design can monitor and disaggregate true energy. In that scenario, the state of machine and power consumption patterns must be correctly recognized by the system. NILM is depending on machine learning models with structured and unstructured variations. ILM, on the other hand, goes straight to individual machines which may be more precise but is more hardware oriented. The accuracy of the two designs is then compared, so the selected design will produce the least errors, the results can be trusted for better decision-making and optimize energy.

Integration Complexity

Integration complexity determines the difficulty with which the system can be established, connected, and integrated into the structure already existing. ILM generally involves physical installation and wiring, and NILM involves sophisticated data processing and model learning of the machine learning. This criteria point is important because the easier the integration, the quicker it can be deployed, the less prone to error it will be, and the cheaper in labour costs. Comparison of the complexity of integrating the two schemes will help to verify the selected solution can be effectively implemented without unnecessary delays or routine disruption.

Maintainability

Maintainability, being the how easy the system may be maintained after modification over time. Energy monitoring systems usually have to be adjusted to new situations, like adding new machines or changing the monitoring setup. Physical (re)installation is common in many types of ILM designs (e.g., machine learning models), which can also be still necessary in NILM systems, but is now rarely needed. This criterion can be used to guarantee that a selected design is functional not only at design time but also over the long term in order to minimize downtime, maintenance costs, and system reliability.

Scalability

Scalability is vital to future-proof the system, as energy demands change, and new items of machinery are added to infrastructure. The scalability is an issue in ILM design, since a new wiring or a new physical sensor is necessary, whereas in NILM system the scalability could be possible relatively easily with a software upgrade or algorithm modification. Through scalability comparison, the assessment guarantees that the selected scheme easily scales to handle the load growth without redesign or cost increase and is thus a robust and scalable approach for long-term energy monitoring demands.

These five criteria describe in detail technical, operating and economic considerations of the project, and together they offer a more balanced evaluation of possible design options.

Weight Assignment for Criteria

The Analytical Hierarchy Process (AHP) method is used to assign weights to the criteria by pairwise comparisons to determine their relative importance[19][20]. Below is the step-by-step process for weight assignment:

Step 1: Pairwise Comparison Matrix

The relative importance of each criterion is compared using a scale (1 = equally important, 3 = moderately more important, 5 = strongly more important.) The comparisons are based on the project's objectives and requirements.

Table 05: Pairwise comparison

Criteria	Cost	Accuracy	Integration Complexity	Maintainability	Scalability
Cost	1	1/3	3	3	2
Accuracy	3	1	5	3	4
Integration Complexity	1/3	1/5	1	1/3	1/2
Maintainability	1/3	1/3	3	1	2

Scalability	1/2	1/4	2	1/2	1

Step 2 : Normalized Matrix
To normalize the matrix:

- Summing each column.
- Dividing each entry in the column by the column sum.

Table 06: Normalization

Criteria	Cost	Accuracy	Integration Complexity	Maintainability	Scalability	Row Average (Weights)
Cost	0.1935	0.1575	0.2143	0.3830	0.2105	**0.2318(23%)**
Accuracy	0.5806	0.4724	0.3571	0.3830	0.4211	**0.4429 (44%)**
Integration Complexity	0.0645	0.0945	0.0714	0.0426	0.0526	**0.0651 (7%)**
Maintainability	0.0645	0.1575	0.2143	0.1277	0.2105	**0.1549(15%)**
Scalability	0.0968	0.1181	0.1429	0.0638	0.1053	**0.1054 (11%)**

Based on the normalized matrix:

- Cost: 23%
- Accuracy: 44%
- Integration Complexity: 7%
- Maintainability: 15%
- Scalability: 11%

These weights reflect the relative importance of each criterion for comparison between these two approaches.

Scoring assignment for two design approaches for each criteria:

1. Cost

For scoring we can use the formula :
Score (out of 10)=10×(Best Value (Cost))/Design Value(Cost))
For the machine number is 3 ,
The budget for NILM approach is 6290 TK
The budget for ILM approach is 8890 Tk
So, Best Value = 6290 Tk

➔ **ILM:**

The budget for ILM approach is 8890 Tk
Score (out of 10)=10×(6290/8890) = 7

➔ **NILM:**

The budget for ILM approach is 5150 Tk

Score (out of 10)=10×(6290/6290) = 10

2. Accuracy

➔ **ILM:**

- Accuracy is high because sensors collect direct data from individual machines.
- From simulations, **99% accuracy** is assumed.

So, Accuracy score for ILM = 9.9 out of 10

➔ **NILM:**

- Relies on the NILM algorithm for disaggregation.

Metric	M1	M2	M3	M4	Average
MAE	12.153563	40.006355	24.969028	29.285776	26.603682

Accuracy score for NILM=10- 10[(MAE 1/ Max M1)+(MAE 2/ Max M2)+(MAE 3/ Max M3)+(MAE 4/ Max M4) / 4]

=10-10 [((12.15/58.07)+(40/360.03)+(24.96/220.67)+(29.28/272.93))/4]

= 10 - 1.352

= 8.648

3. Integration Complexity

Score for Integration Complexity =10−10(Wc. Cnorm+ Ww· Wnorm+Wm· M)

Where, Wc, Ww. Wm are the weights for Component number, wiring, ML model which indicates the importances in integration complexity criteria.

We assumed, Wc = 0.4, Ww= 0.2, Wm= 0.4

Cnorm= Components for a design / Maximum Components

Wnorm= Wiring for a design/ Maximum Wiring

M= ML model required or not; if ML model required then M =1, or M=0

➔ **ILM:**

- Multiple sensors require significant wiring and setup.
- Adding machines increases wiring complexity.

Now for ILM:

Cnorm= 8/8 =1

Wnorm= 10/10 =1

M= 0

Now , Score= 10 - 10 (0.4 x 1 + 0.2 x 1 + 0.4x0) = 10 - 6 = 4

➔ **NILM:**

- A single sensor with minimal wiring simplifies integration.

- Adding machines does not require additional hardware.

Now for NILM:

Cnorm= 4/8 =0.5

Wnorm= 4/10 =0.4

M= 1

Now , Score= 10 - 10 (0.4x0.5 + 0.2x0.4 + 0.4x1) = 10 - 6.8 = 3.2

4. Maintainability

Score=10 -10[Wh. H + Wm. M]

Here, Wh, Wm are the weights for Hardware maintainability and Software maintainability for both design where each weights indicate the importance in this criteria

We assumed , Wh= 0.5; Wm= 0.5

H= 1 if hardware maintenance is required otherwise 0

M= 1 if software maintenance is required otherwise 0

➔ **ILM:**

For ILM,

Score= 10-10[(0.5 x 1)+(0.5 x 0)] = 5

➔ **NILM:**

For NILM,

Score= 10-10[(0.5 x 0)+(0.5 x 1)] = 5

5. Scalability

Scale Score= 10 -10[(Wcost . cost increases/ Prev cost) +(Wc . Component increases/ Prev comp) +(Ww . Wiring increases/ Prev wiring) + Wm . M]

Where, Wcost,Wc, Ww,Wm are the weights for Cost, Component number, wiring, ML model which indicates the importances in Scalability criteria.

We assumed, Wcost= 0.3 ,Wc = 0.2, Ww= 0.2, Wm= 0.3

M= ML model Modify or not; if ML model modify is required then M =1, or M=0

➔ **ILM:**

- Scaling requires additional sensors and wiring, making it expensive and labor-intensive.

For ILM approach,

If two additional machines are added then

Cost increase = 5000

Component increase = 5

Wiring increase = 8

M= 0 as no ML model is not required

Score = 10- 10[(0.3x(5000/9150)) +(0.2x(5/8))+(0.2x (8/10))+(0.3x0)]= 5.51

➔ **NILM:**

- Single sensor handles additional machines without hardware changes but software modification is required.

For NILM approach,
If two additional machines are added then
Cost increase = 0
Component increase = 0
Wiring increase = 0
M= 1 as ML model modification is required
Score = 10- 10[(0.3x(0/5150)) +(0.2x(0/4))+(0.2x (0/4))+(0.3x1)]= 7

Table 07:Final Scoring Table

Criteria	Weight (%)	ILM Score (10)	NILM Score (10)	Weighted ILM Score (100)	Weighted NILM Score (100)
Cost	23	7	10	12.88	23
Accuracy	44	9.9	8.65	43.56	38.06
Integration Complexity	7	4	3.2	2.8	2.24
Maintainability	15	5	5	7.5	7.5
Scalability	11	5.51	7	6.06	7.7
Total	**100**			72.8	78.5

Table 08:Comparison Table

Criteria	Intrusive Load Monitoring (ILM)	Non-Intrusive Load Monitoring (NILM)
Cost	They are very expensive because each machine needs its own sensors and a considerable amount of cabling.	Cheap because only one sensor for a main power line is necessary irrespective the number of machines.
Accuracy	High accuracy approximately 98% to individual machine data collection.	Reasonable accuracy approximately 86.5% as dependence on ML algorithms to disaggregate power.
Integration Complexity	Complex to the point where multiple sensors were required and elaborate wiring (and also configuration) was required for each and every machine.	Low complexity in terms of the primary power line hardware and wiring.
Maintainability	It is hard to upkeep due to a number of sensors and wiring that need to be cleaned, calibrated and checked.	Less, therefore easier to maintain and it won't break as easily. Yes, but ML

		model tweaking is necessary on occasion.
Scalability	Low scalability; new loads means additional sensors, wiring and installation work.	Medium scalability; no extra hardware is required to monitor more loads. But to track more machines, new data and model training is necessary.

Optimal Solution: Through searching of all the analysis on the two design solutions for five criteria cost, accuracy, integration complexity, maintainability and scalability the design approach that is Non Intrusive Load Monitoring, design 2 is the preferable solution to solve our problem.

4.4 Performance evaluation of developed solution

4.4.1 Functional Verification for Design Approach 1

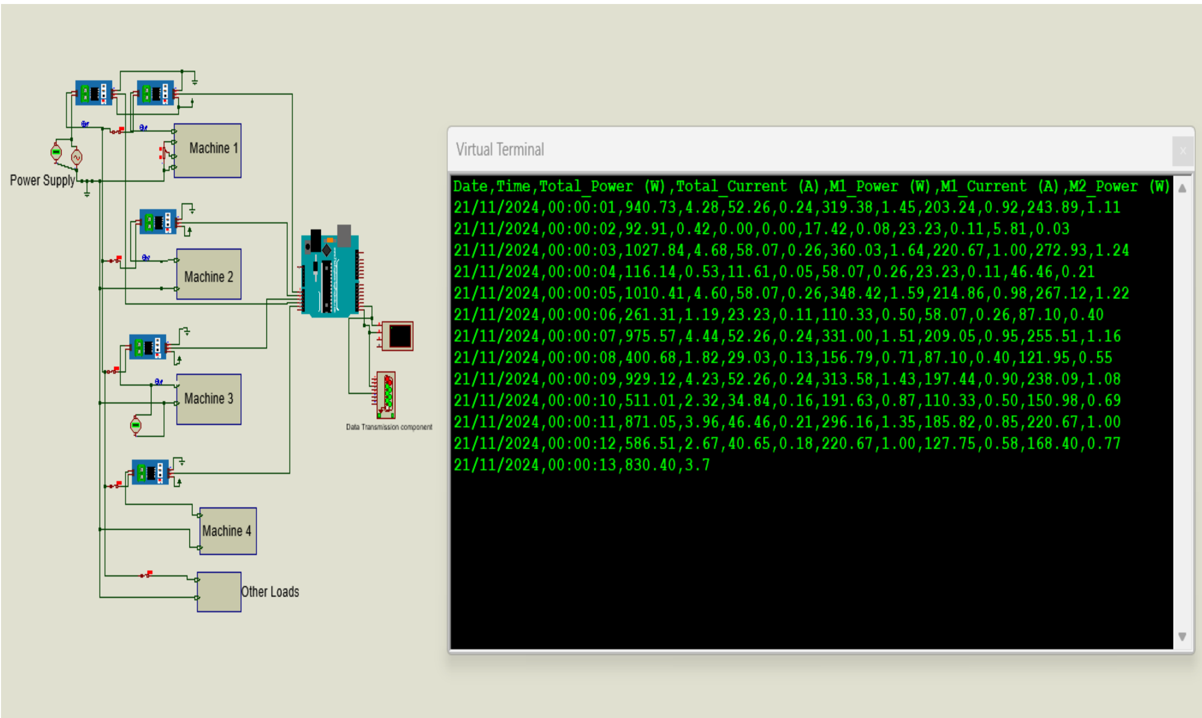

Fig 09: Functionality of Design Approach 1 Simulation

The functional validation of Design Approach 1 is shown in the figure above using the simulation circuit in Proteus. In this configuration, we deployed an ILM system to monitor the power of four machines and the main power line. The output is presented in real time on a virtual terminal, similar to that illustrated in the simulation output. Data features: Date, Time, Total Power, Total Current and the power drawn by each machine (M1 Power, M2 Power etc). This simulation successfully demonstrates the working of the monitoring system. Since it is a simulation, the AC voltage is kept constant to simplify calculations, and no voltage sensors are included. This successful verification demonstrates the accuracy and reliability of the ILM system for real-time energy monitoring in this design approach.

4.4.2 Functional Verification for Design Approach 2

For design approach 2 functional verification in not only the circuit simulation. Rather it is the NILM Algorithm which is a Machine Learning model that can verify the functionally of the system that it is workable.

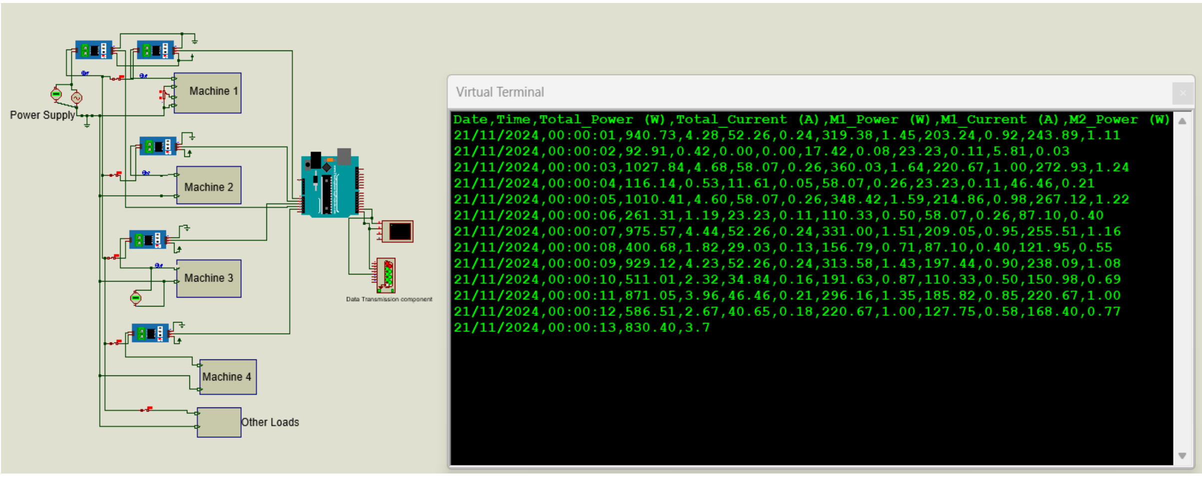

Fig 10: Data Collection Process for Model Training

We know to train the machine learning model we will need a huge amount of data. The parameters are basically the Total Power, Total Current,M1 Power,M2 Power, M3 Power, M4 Power.The frequency of the data was 10 Hz. So it was high frequency data. We run the simulation for 4 hours turning the machines on and off at different times to collect data.

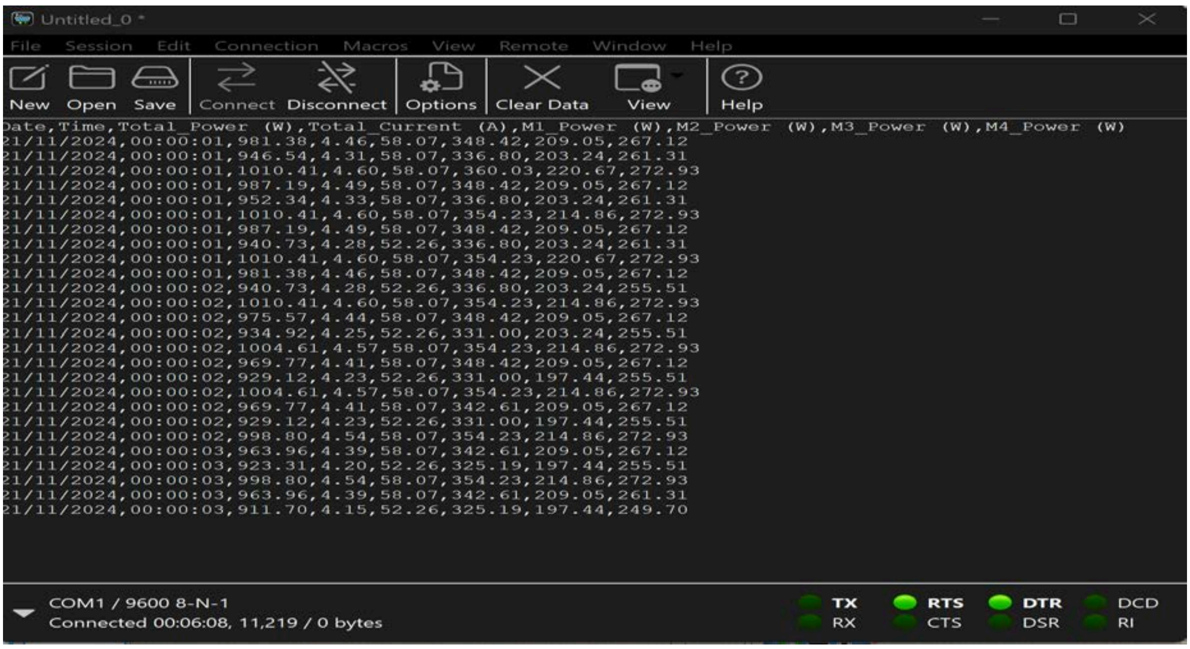

Fig 11: Storing the Data in Local Storage using Coolterm

In proteus the simulation can be sun but there is no scope to store data. So connecting the proteus with a virtual serial port (Com0Com) with Coolterm software we stored the data in csv format.

	A	B	C	D	E	F	G	H
1	Date	Time	Total_Pow	Total_Curr	M1_Powe	M2_Powe	M3_Powe	M4_Power (W)
2	21/11/202	0:00:01	981.38	4.46	52.26	348.42	209.05	267.12
3	21/11/202	0:00:01	946.54	4.31	52.26	336.8	203.24	261.31
4	21/11/202	0:00:01	1010.41	4.6	58.07	360.03	220.67	272.93
5	21/11/202	0:00:01	987.19	4.49	58.07	348.42	209.05	267.12
6	21/11/202	0:00:01	946.54	4.31	52.26	336.8	203.24	261.31
7	21/11/202	0:00:01	1010.41	4.6	58.07	360.03	220.67	272.93
8	21/11/202	0:00:01	981.38	4.46	58.07	348.42	209.05	267.12
9	21/11/202	0:00:01	940.73	4.28	52.26	336.8	203.24	261.31
10	21/11/202	0:00:01	1004.61	4.57	58.07	354.23	214.86	272.93
11	21/11/202	0:00:01	981.38	4.46	52.26	348.42	209.05	267.12
12	21/11/202	0:00:02	934.92	4.25	52.26	336.8	203.24	255.51
13	21/11/202	0:00:02	1010.41	4.6	58.07	354.23	214.86	272.93
14	21/11/202	0:00:02	975.57	4.44	52.26	348.42	209.05	267.12
15	21/11/202	0:00:02	934.92	4.25	52.26	331	203.24	255.51
16	21/11/202	0:00:02	1004.61	4.57	58.07	354.23	214.86	272.93
17	21/11/202	0:00:02	969.77	4.41	52.26	348.42	209.05	267.12
18	21/11/202	0:00:02	923.31	4.2	52.26	331	197.44	255.51
19	21/11/202	0:00:02	1004.61	4.57	58.07	354.23	214.86	272.93
20	21/11/202	0:00:02	969.77	4.41	52.26	342.61	209.05	267.12
21	21/11/202	0:00:02	929.12	4.23	52.26	331	197.44	255.51
22	21/11/202	0:00:02	998.8	4.54	58.07	354.23	214.86	272.93
23	21/11/202	0:00:03	963.96	4.39	52.26	342.61	209.05	267.12
24	21/11/202	0:00:03	917.5	4.17	52.26	325.19	197.44	255.51
25	21/11/202	0:00:03	992.99	4.52	58.07	354.23	214.86	272.93
26	21/11/202	0:00:03	963.96	4.39	52.26	342.61	209.05	261.31

Fig 12: Data Saved & Converted to CSV Format

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4.4.2.1 Selection of the NILM Approach:

We selected machine learning (ML) application of the NILM algorithm as current work on NILM continues to demonstrate the capability of ML-based methods to effectively disaggregate appliance-level energy consumption. Towards this end, we employed and contrasted two of them: an ordinary Multi-Layer Perceptron (MLP) and one of the latest architectures known as MATNilm(Multi-Appliance-Task Non-Intrusive Load Monitoring).

MATNilm is a sophisticated ML model that is able to foresee per-appliance power consumption directly from total household power consumption, using no knowledge of per-device sensors. This is extremely valuable, especially for real-world deployments where sensors might be expensive and logistically difficult to implement. MATNilm is as effective as it is because it operates inside of a multi-task learning framework, learning to regress (what each appliance is drawing) and classify (if each appliance is on or off) simultaneously for multiple appliances in parallel. The base core learns general trends of data, which is enriched by additional specialist components that learn each appliance's unique properties.[20]

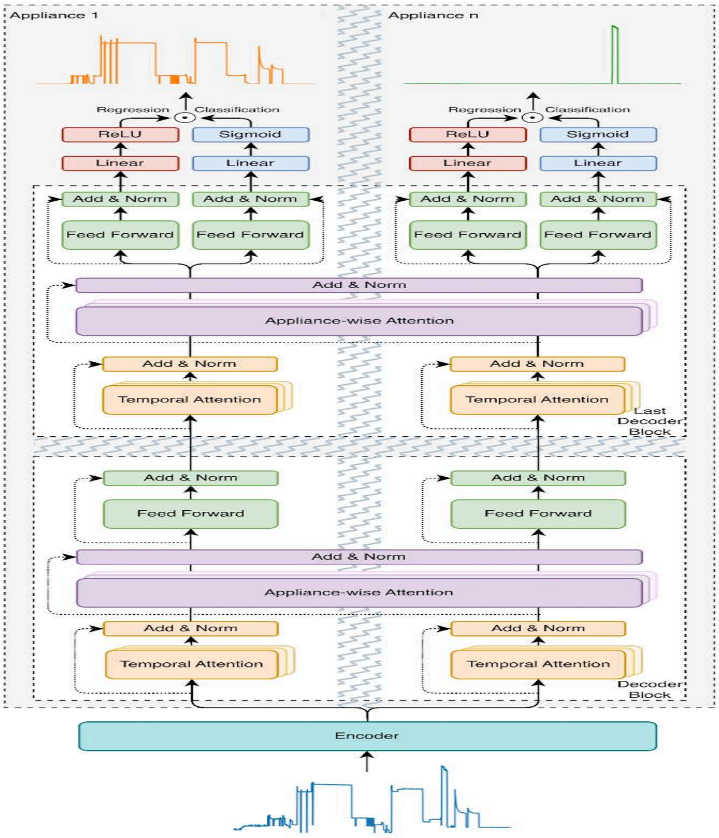


Fig 13: Multi-Appliance-task Network Architecture with Temporal Attention and Appliance-wise Attention. (J. Xiong, T. Hong, D. Zhao, and Y. Zhang(2023))

One of MATNilm's innovations is its 2D Multi-Head Self-Attention mechanism (2DMA) that enables the model to understand appliance correlations temporally. This enables it to learn typical usage patterns such as appliances running together or rarely running together and adjust its forecasting based on most informative data patterns. MATNilm also excels under data-scarce training scenarios as its smart data augmentation technique produces diverse training samples based on real appliance usage. That is why it is particularly useful in real-world scenarios where large labeled datasets are not readily obtainable.[20]

Table 09:Evaluation Result(MATNilm)

Metric	M1	M2	M3	M4	Average
MAE	12.153563	40.006355	24.969028	29.285776	26.603682
SAE	10.477586	30.659541	17.326548	19.851901	19.578894
F1	0.853545	0.976942	0.961493	0.967075	0.939764

To evaluate MATNilm, we fed total power into it and trained it to predict the power of four appliances namely, (M1, M2, M3, M4). The model learned well, achieving an overall loss of 0.1879. The primary metrics of assessment were an overall Average Mean Absolute Error (MAE) of 26.60, an overall Signal Aggregate Error (SAE) of 19.58, and an excellent overall Average F1 of 0.9398 for very accurate state classification. Compared to MATNilm, the

Multi-Layer Perceptron (MLP) one that we employed is not a specific neural network structure, consisting of fully connected layers in a stacked sequential structure. The model performed the twin roles of power disaggregation (regression) and appliance state classification as well, accepting the same input as feature total power consumption and attempting to make predictions about individual power consumption as well as on/off state of an appliance. The MLP, however, lacks specialization that renders MATNilm as effective as it is. Neither does it employ temporal attention mechanisms to learn appliance usage behavior that evolves over time, nor appliance-specific branches to learn characteristic behavior of an appliance.

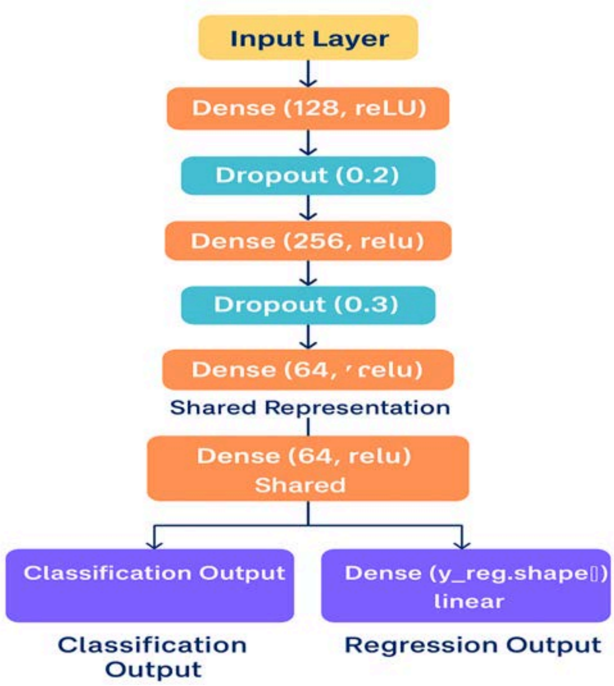
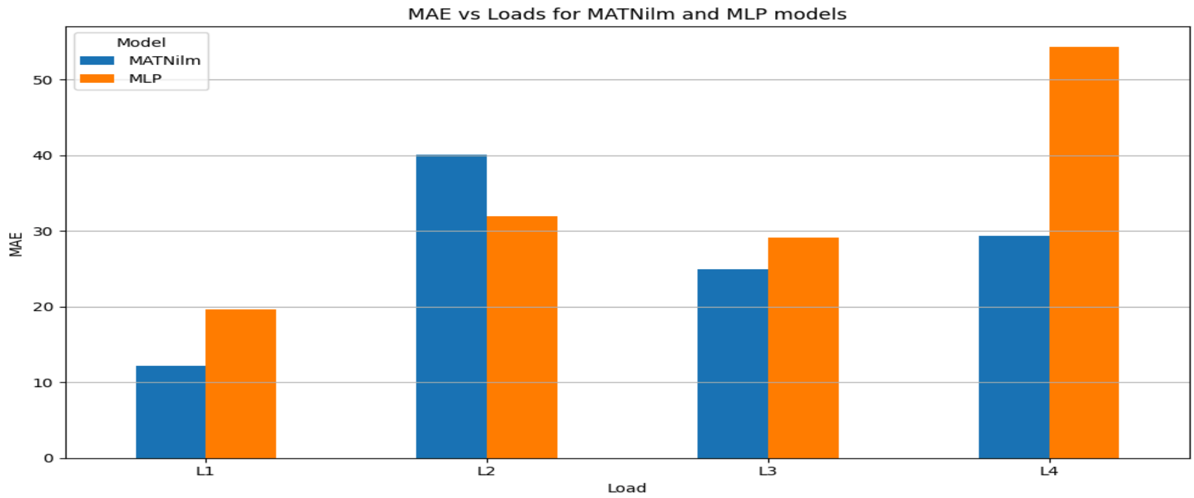


Fig 14:Model Architecture of MLP

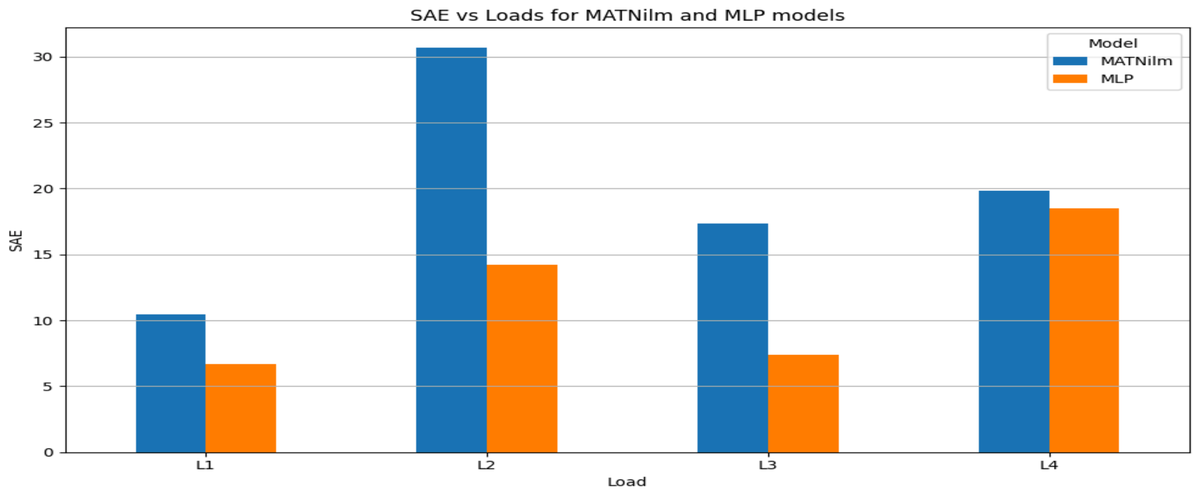
Table 10:Evaluation Result(MLP)

Metric	M1	M2	M3	M4	Average
MAE	19.6275	31.9437	29.1415	54.2522	33.7333
SAE	6.7154	14.2407	7.3983	18.5201	11.7186
F1	0.8242	0.9652	0.9296	0.9066	0.9064

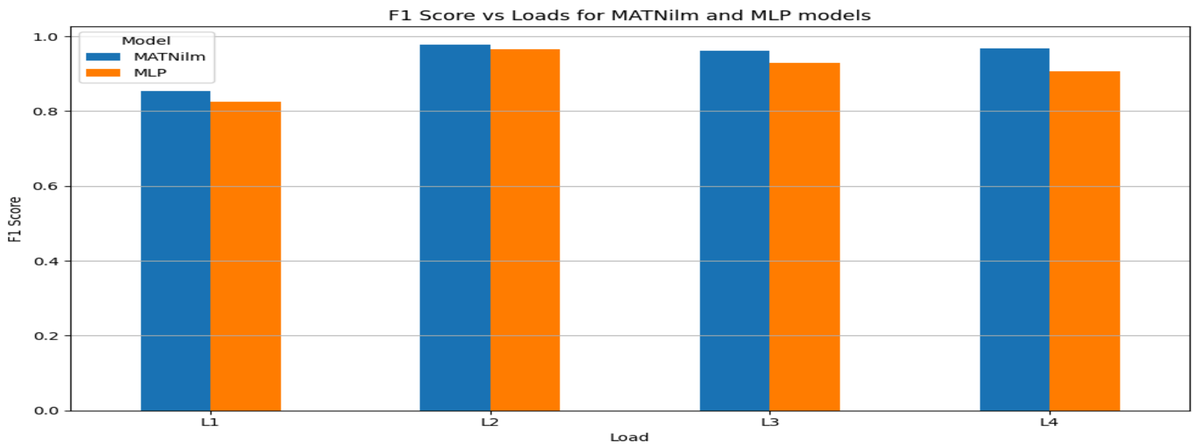
Owing to these constraints, even the MLP model performed only moderately. On average, it provided an MAE of 33.73 and an average F1 score of 0.9064, indicating worse correct classification of appliance operating statuses. Although Signal Aggregate Error (SAE) was relatively better for some appliances, overall performance was not well balanced, particularly for appliance M4, where maximum deviation and minimum trustworthiness in regression as well as classification performances were observed in the model.



(a)



(b)

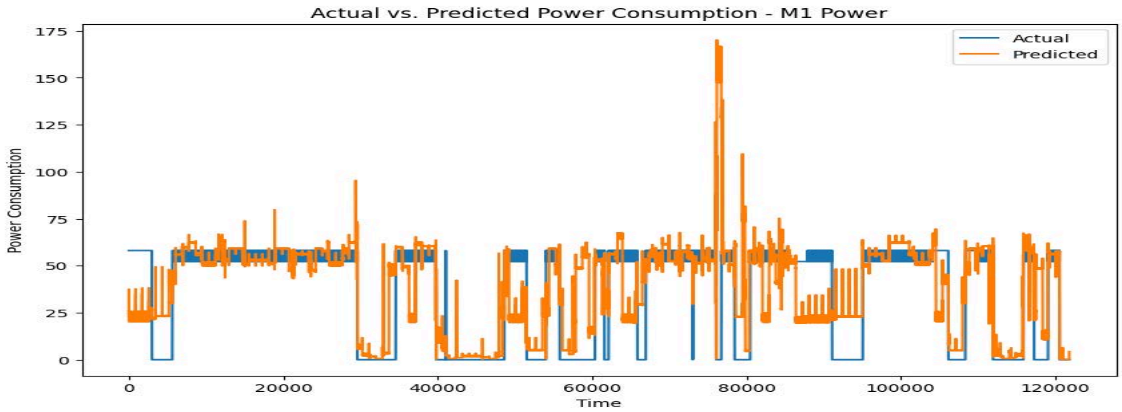


(c)

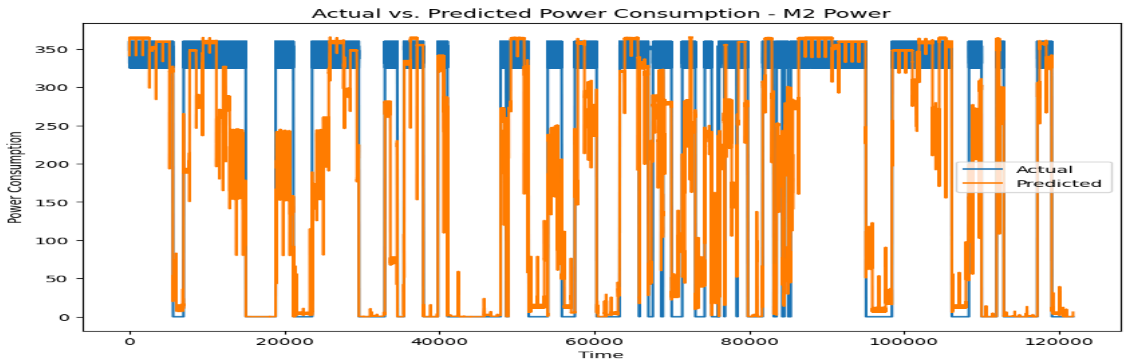
Fig 15: Test Score Comparison Plots for Four Loads between MATNilm and MLP Models (a.MAE Score, b. SAE Score, c. F1 Score)

When comparing these two systems, MATNilm stood clear of them as it was superior to them on nearly every measure used to assess them, especially in terms of classification accuracy,

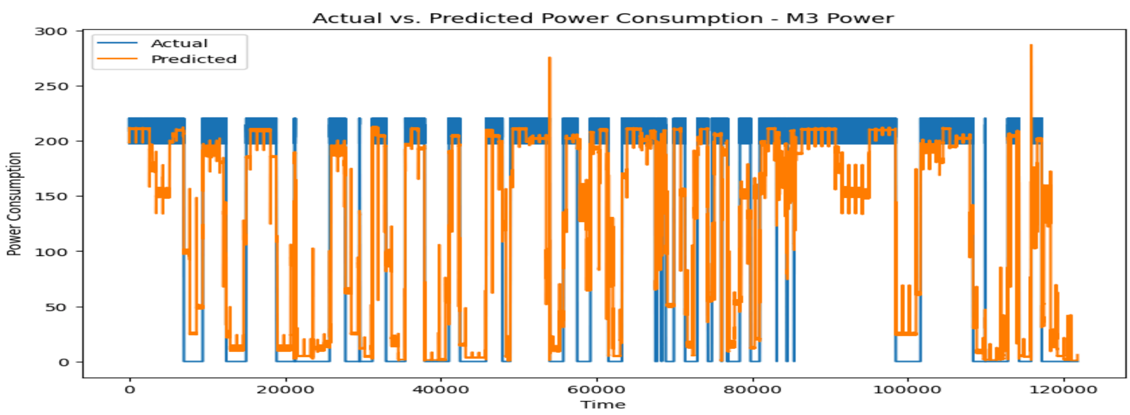
where it scored an average of nearly 0.94 on its F1 score. Far more importantly, however, were MATNilm's architectural advantages of temporal attention layer and appliance-specific modeling which allowed it to learn more detailed and realistic appliance usage patterns. Its features allowed it to accurately forecast results even when it was trained on a relatively smaller dataset.
Based on both quantitative comparison and architectural differences, MATNilm was undoubtedly a better solution. Its ability to capture temporal dependencies, represent multiple appliances collectively, and get to high accuracy using relatively small training sets renders it considerably more suitable for real-world NILM application.



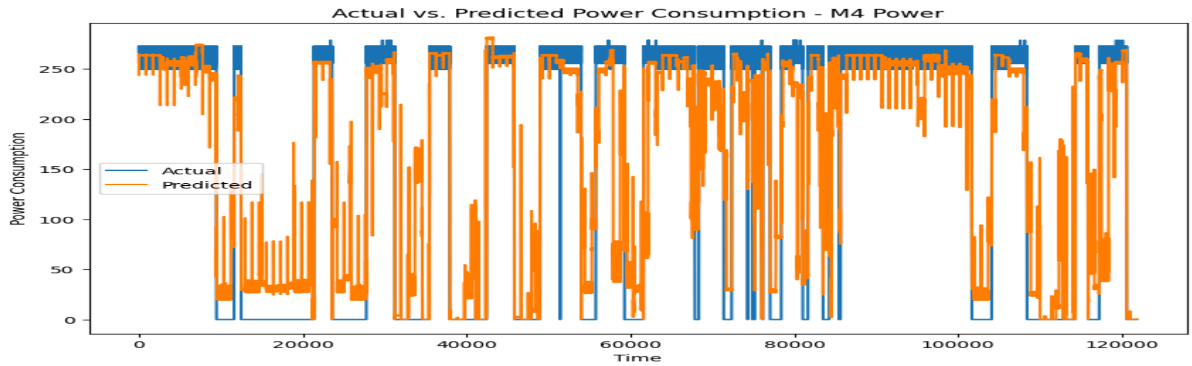
(a)



(b)



(c)



(d)
Fig 16: Actual vs Predicted Power Consumption of Four Loads using MATNilm (a. Load 1, b. Load 2, c. Load 3, d. Load 4)

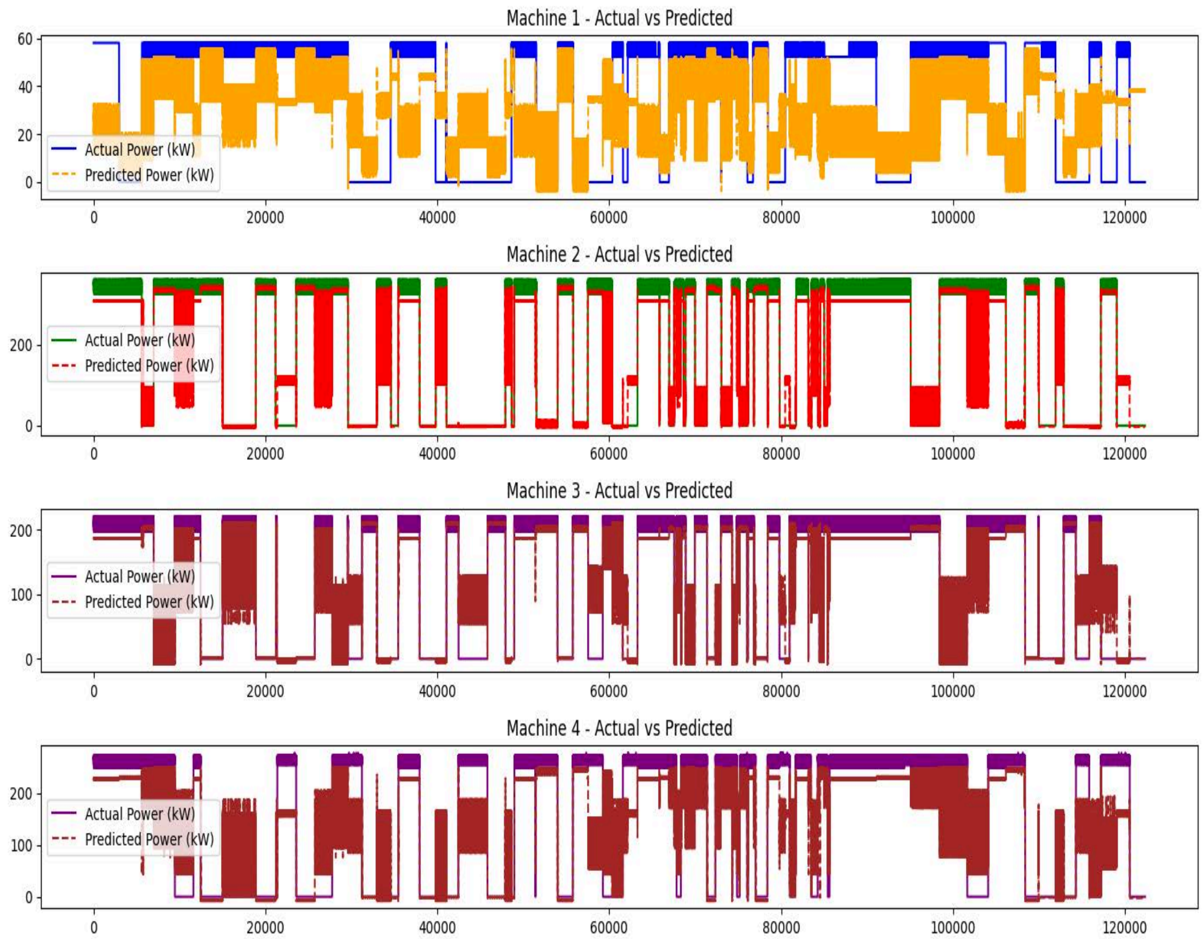


Fig 17: Actual vs Predicted Power Consumption of Four Loads using MLP

In the final term, validation test of the NILM models was also supplemented by visual inspection of performance plots, which showed ground truth power consumption of each appliance as well as values predicted by the models. In that case, these plots provided an intuitive and global sense of exactly how well each model replicated real-time energy consumption dynamics. In MATNilm, predicted power curves closely matched actual consumption curves, tracing smoothly each appliance's power demand dynamics as it changed. Though residual discrepancy between predicted and actual values remained apparent outlining areas where more optimization might be needed, overall concurrence was acceptable, showing that MATNilm could learn and generalize appliance behavior from small data sets.

On the Other hand, predicted vs. actual power consumption curve graphs of the MLP exhibited larger scale deviation. The MLP was struggling prominently to adapt to temporary changes in appliance usage, overshooting or falling short of actual values, particularly for appliances exhibiting non-periodic behavior. This is characteristic of the weaker temporal dependency and appliance-specific characteristics aspects of the model, which the MATNilm is able to handle well using its 2D attention mechanism and multibranch structure.
Despite errors in both models, MATNilm was always more accurate and reliable in merely matching its predictions to real consumption dynamics. Its graphical presentation in graphs testified to quantitative results, reaffirming it as NILM's preferred choice of model. No model is entirely resistant to prediction errors, yet MATNilm's ability to minimize such errors to an absolute minimum and provide smooth tracking to every appliance is an improvement in load disaggregation efficiency to be embraced. Consequently, statistically as well as graphically observed, MATNilm was conclusively selected as the best to be used in future application within our NILM process.

Table 11: Comparison of MATNilm and MLP

Aspect	**MATNilm**	**MLP**
Model Type	Advanced multi-task learning model	Basic fully connected neural network
Task Handling	Simultaneous power disaggregation and state classification for all appliances	Also handles both tasks, but with less precision
Temporal Awareness	Yes. It uses 2D Multi-Head Self Attention (2DMA)	No . It does not model time-based dependencies
Appliance-Specific Learning	Yes (shared core + appliance specific branches)	No (shared layers only)
Data Efficiency	High – performs well even with limited training data	Low – performance degrades with small datasets
MAE (Average)	26.60	33.73
SAE (Average)	19.57	11.72
F1 Score (Average)	0.9398	0.9064
Visual Accuracy (Plots)	Closely tracks real power usage with minor discrepancies	Larger deviations, especially in fluctuating load scenarios

Scalability and Robustness	Highly scalable and robust for real-world NILM tasks	Less robust, struggles with complex patterns
Final Verdict	Chosen model for further development	Less accurate and less reliable

This table clearly shows that MATNilm outperforms MLP across key areas of architecture, accuracy and real world applicability making it the recommended model for deployment.

4.5 Conclusion

We proposed two methodologies - Intrusive Load Monitoring (ILM) and Non-Intrusive Load Monitoring (NILM) to find the most suitable technique for energy monitoring in a textile industry. Cost, accuracy, integration, complexity, maintainability and scalability were considered for the comparison. Although ILM resulted in high correctness ratio, NILM stood out as being a more balanced approach in terms of a lower energy and setup cost and better scalability . According to AHP evaluation and system practice, NILM was selected as a promising and more feasible design approach for long term energy monitoring purposes.

Chapter 5: Completion of Final Design and Validation. [CO8]

5.1 Introduction:

This chapter is introduced with final development and validation to our proposed energy monitoring system for the textile industry. The system was designed to track the consumption of specific loads by means of a Non Intrusive Load Monitoring (NILM) methodology based on Internet of Things (IoT) technologies. It forms part of hardware for data acquisition, processing and transmission and a cloud setup for remote monitoring and data storage. This chapter describes the full design set, provides a detailed hardware architecture, illustrates the data collection and training method, and evaluates its performance with real data. The first goal is to assess whether the system is capable of dis-aggregating total energy into load of the machines at every instant of time for a predetermined level of accuracy.

5.2 Completion of final design

Our full hardware setup has some units which are responsible for specific tasks.

Load Unit: As we are monitoring the loads of the textile industry so we set up a small section that is a cutting section of a specific textile factory. Where from the main line of the distribution box four single phase lines go out. Three cutting machines of the same specifications are connected with three lines and from one line two 15W bulbs are connected in parallel. Here our main purpose is to monitor the loads not to build the exact load so we assumed three 50W induction motors as cutting machines. These loads are quite different from the loads of proteus simulation. It is because the main circuit of the cutting machines are very complex and that is not our main purpose. So we represented the motors as cutting machines in hardware setup. We can also vary our loads to monitor their power consumptions.

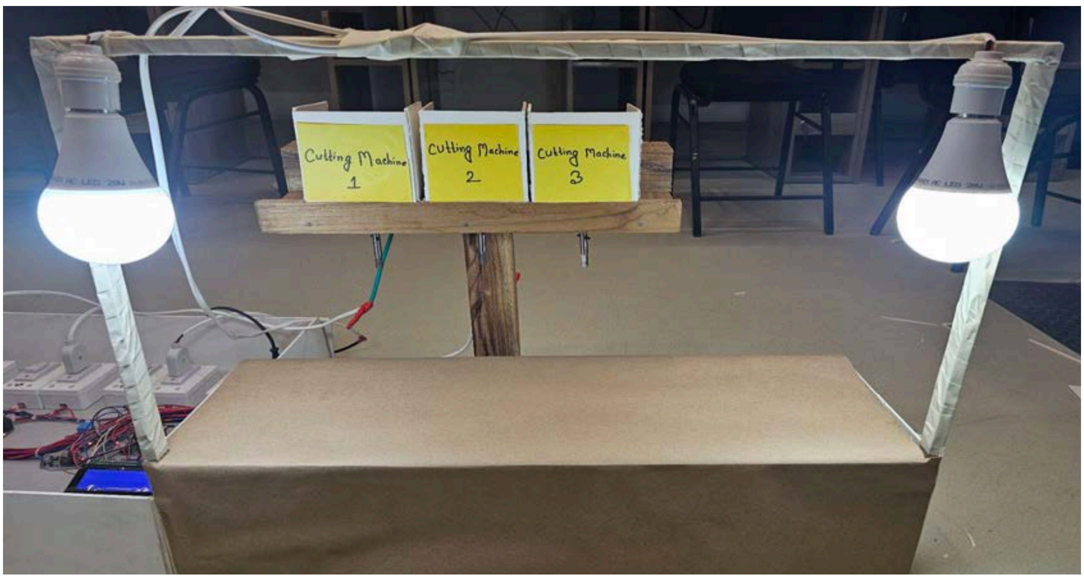


Fig 18: Real Loads (Three Motors as Cutting Machines, Two Bulbs)

Data Collection unit: This unit is responsible for collecting data (voltage, current) from the load lines. This unit is full of sensors. They basically produce analog signals based on the actual current and voltages of the lines which are passed to the data processing unit to convert into voltage and current.

- Voltage sensor: ZMPT101B sensor is used to collect the real time voltage across each line of the systems. As there are a total four lines for the loads and one main line, a total of five voltage sensors are set up to collect the voltage data. To get the actual value of the voltage from each sensor we had to calibrate testing with a multimeter.

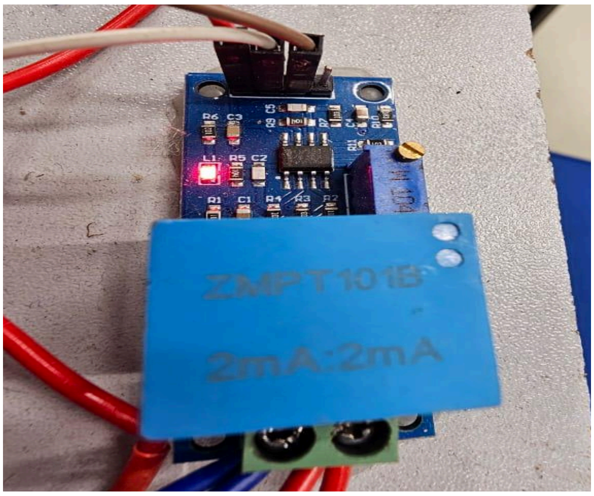


Fig 19: ZMPT101B Sensor

- Current sensor: ZMCT103 sensor is used to collect the real time current through each line of the systems. Total five sensors are placed for five lines. We had to calibrate the sensors testing with a motor. The motor has a rated current of 0.2A which is checked by a multimeter and then the sensor is calibrated to get the actual value.

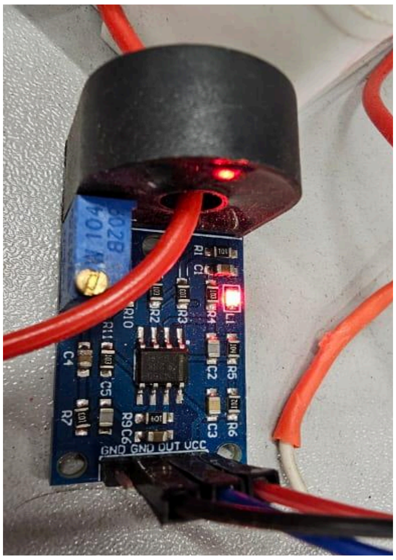


Fig 20: ZMCT103C Sensor

Data Processing Unit: Microcontroller is the only component for this unit. An Arduino Mega 2560 board is used to process the analog signal taken from the current and voltage sensors to convert into digital signal and process them using some calibration library and numbers to calculate actual voltage , current and power of each line in real time.

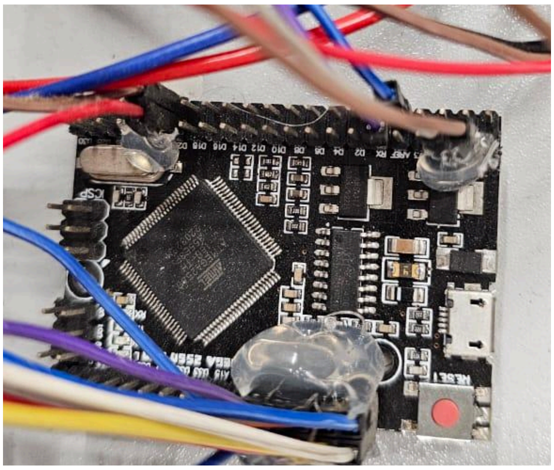


Fig 21:Arduino Mega 2560

Data transmission unit: A Nodemcu version 3 module is connected to a data processing unit where ESP8266 wifi module is used to get the data and send it to the server to store and user interface to show in real time. This unit is responsible for creating the scope for remote access of the real time data that basically introduces IOT in our system.

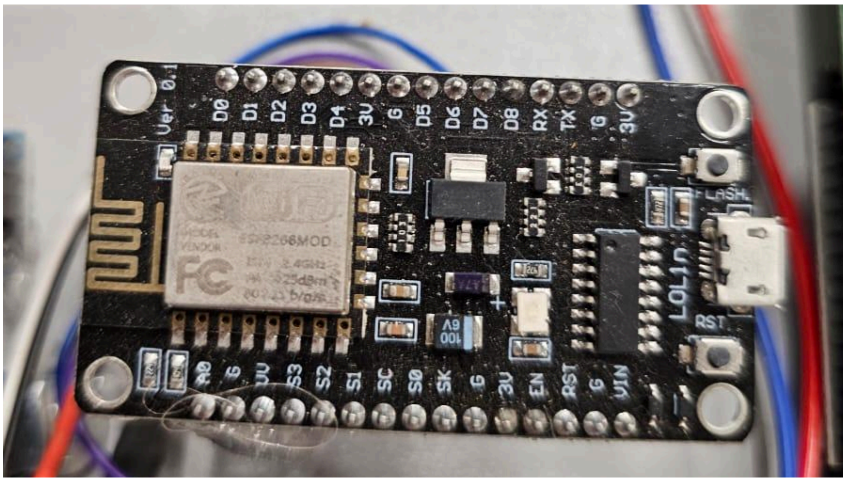


Fig 22: ESP8266 WiFi Module Board

User Interface:

- A 20x4 LCD display is used as an interface in the board to show the real time voltage,current , power and load condition for each line.
- Blynk App is used as a user interface for remote monitoring so that anyone can access the data of how much power is being consumed from each line.

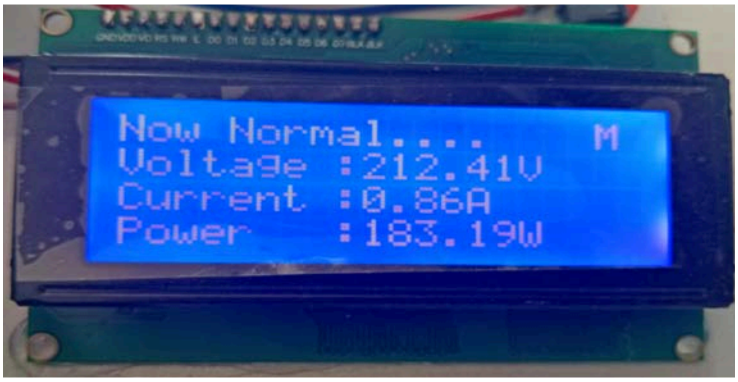
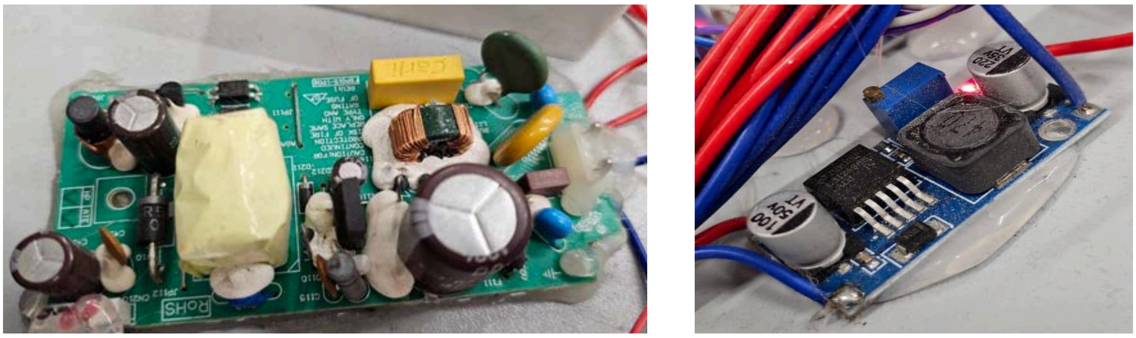


Fig 23: 20x4 LCD Display

Cloud Server: Google sheet is used to collect all the data in real time and Google collab is used to deploy the NILM algorithm. Main line voltage, current ,power data is taken from one sheet and disaggregated through the model and sends the final result or the disaggregated power values of each load to another sheet to store and Blynk app to show in real time.

Power supply unit: The loads are directly operated by the 220V AC and all the sensors and microcontroller boards are operated by the 5V DC. To convert the AC into DC SMPS is connected to the main line that converts 220V AC into 12V DC and a small buck converter is used to convert 12V DC to 5V DC to supply the power.



(a) (b)

Fig 24: (a)SMPS & (b)Buck Converter

The whole sub distribution box is made where all the components are connected and the Main line is incoming and loads lines are outgoing.

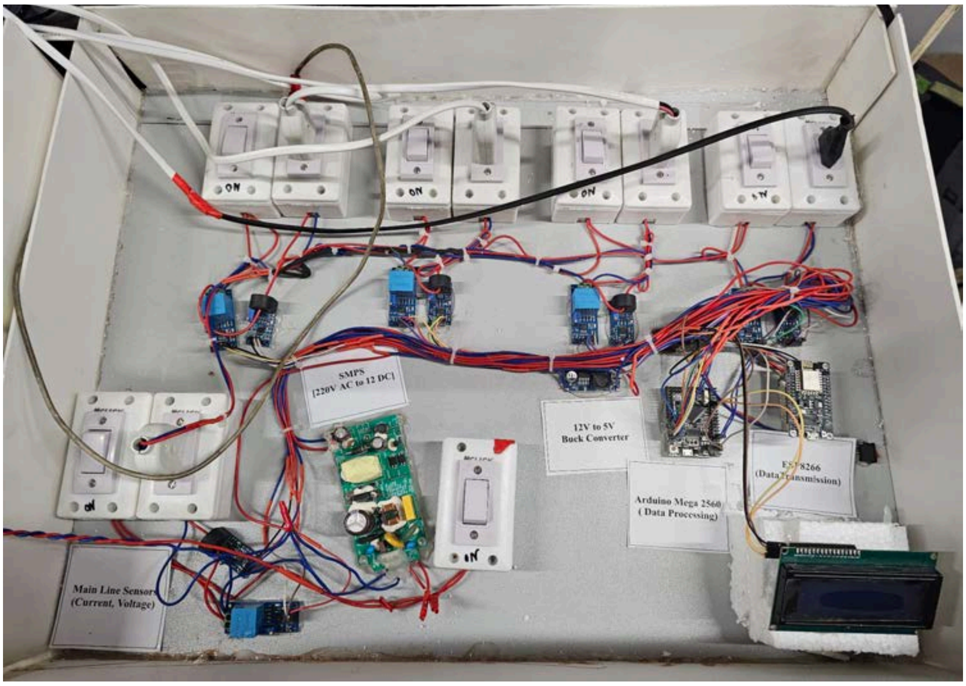


Fig 25: Sub Distribution Board

The working flow of the whole system:

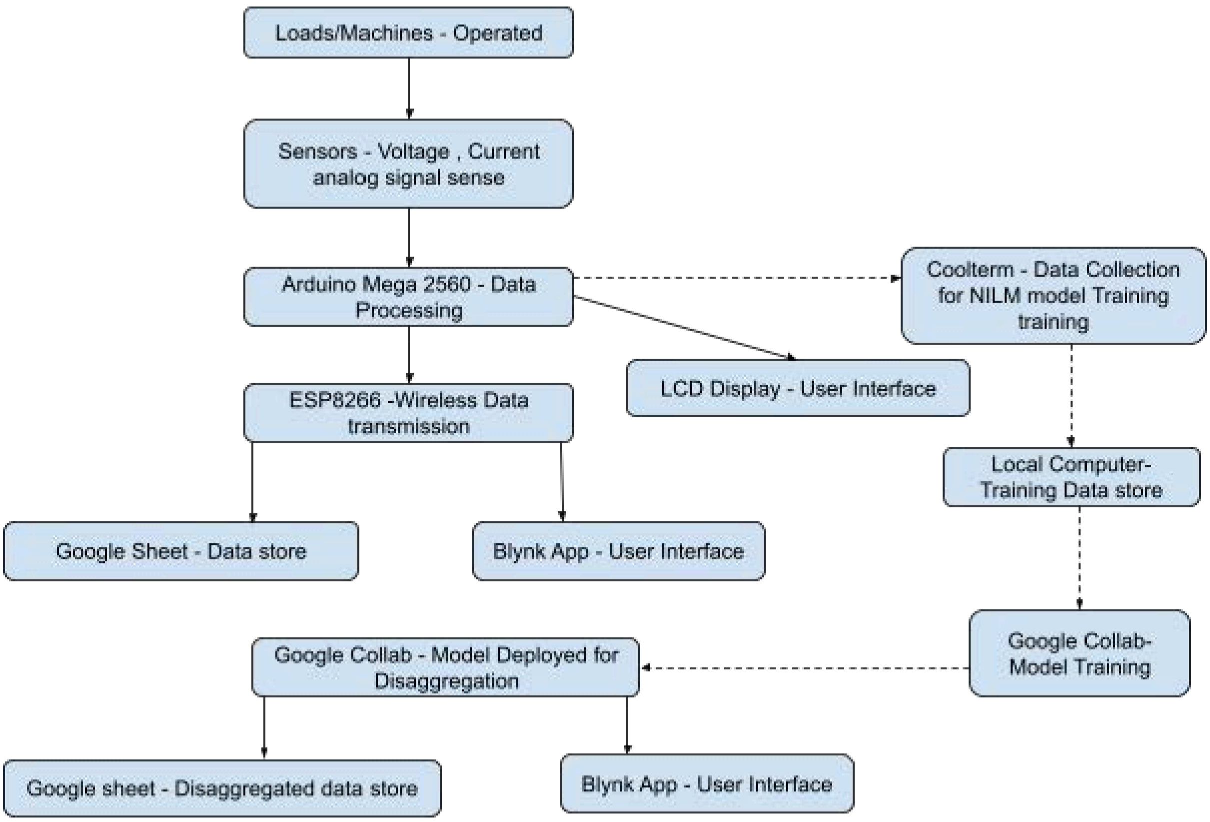


Fig 26: Complete Working Flow of the System

The initial stage of the hardware setup to collect the data for training the NILM algorithm:

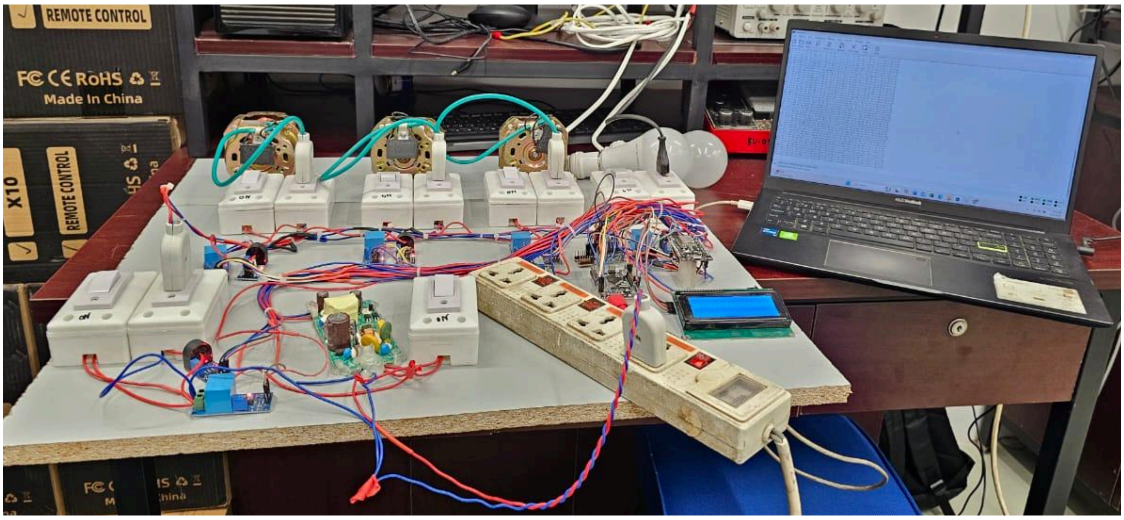


Fig 27: Data Collection for Training

The final design:

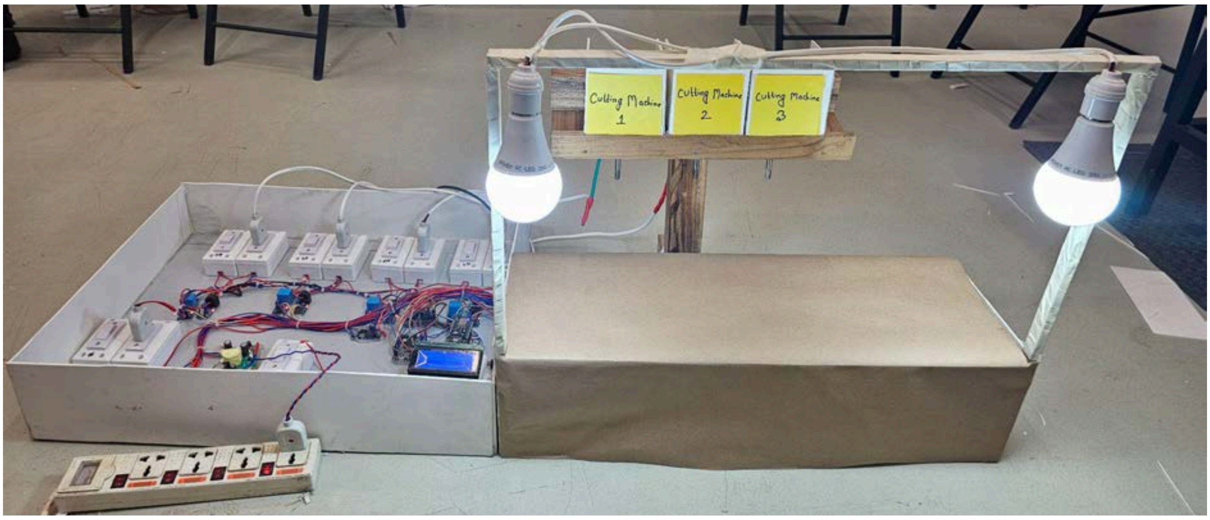


Fig 28: Energy Monitoring System Hardware Setup

5.3 Evaluate the solution to meet desired need

5.3.1 Data collection for training

As the figure 12 shows that using the coolterm tool directly data was collected from the actual loads to the local computer in csv format. The parameters were Main voltage, Main Current, Main Power, L1 voltage, L1 current, L1 Power, L2 voltage, L2 current, L2 Power, L3 voltage, L3 current, L3 Power,L4 voltage, L4 current, L4 Power. So from five pairs of sensors we could get these parameters. Data was directly collected in real time turning the loads on and off at different times.Because of the short amount of time, we could collect 180,631 samples of data in 15 days.Though the model required more data for training to give more accuracy.

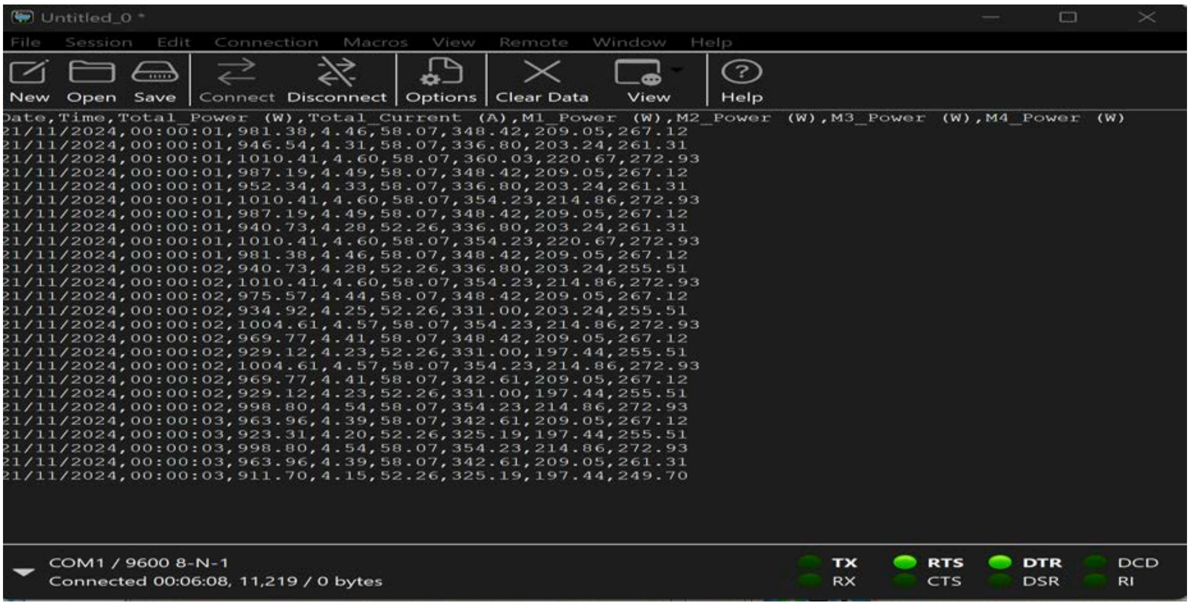
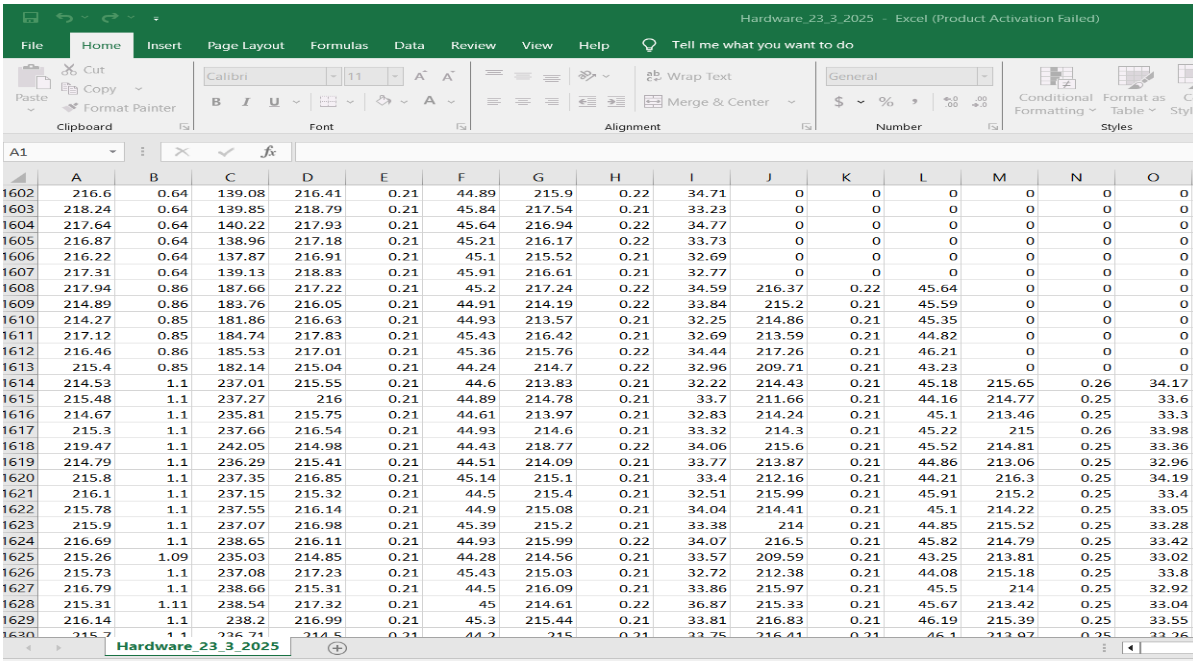


Fig 29: Actual Load Data collection using Coolterm



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1602	216.6	0.64	139.08	216.41	0.21	44.89	215.9	0.22	34.71	0	0	0	0	0	0
1603	218.24	0.64	139.85	218.79	0.21	45.84	217.54	0.21	33.23	0	0	0	0	0	0
1604	217.64	0.64	140.22	217.93	0.21	45.64	216.94	0.22	34.77	0	0	0	0	0	0
1605	216.87	0.64	138.96	217.18	0.21	45.21	216.17	0.22	33.73	0	0	0	0	0	0
1606	216.22	0.64	137.87	216.91	0.21	45.1	215.52	0.21	32.69	0	0	0	0	0	0
1607	217.31	0.64	139.13	218.83	0.21	45.91	216.61	0.21	32.77	0	0	0	0	0	0
1608	217.94	0.86	187.66	217.22	0.21	45.2	217.24	0.22	34.59	216.37	0.22	45.64	0	0	0
1609	214.89	0.86	183.76	216.05	0.21	44.91	214.19	0.22	33.84	215.2	0.21	45.59	0	0	0
1610	214.27	0.85	181.86	216.63	0.21	44.93	213.57	0.21	32.25	214.86	0.21	45.35	0	0	0
1611	217.12	0.85	184.74	217.83	0.21	45.43	216.42	0.21	32.69	213.59	0.21	44.82	0	0	0
1612	216.46	0.86	185.53	217.01	0.21	45.36	215.76	0.22	34.44	217.26	0.21	46.21	0	0	0
1613	215.4	0.85	182.14	215.04	0.21	44.24	214.7	0.22	32.96	209.71	0.21	43.23	0	0	0
1614	214.53	1.1	237.01	215.55	0.21	44.6	213.83	0.21	32.22	214.43	0.21	45.18	215.65	0.26	34.17
1615	215.48	1.1	237.27	216	0.21	44.89	214.78	0.21	33.7	211.66	0.21	44.16	214.77	0.25	33.6
1616	214.67	1.1	235.81	215.75	0.21	44.61	213.97	0.21	32.83	214.24	0.21	45.1	213.46	0.25	33.3
1617	215.3	1.1	237.66	216.54	0.21	44.93	214.6	0.21	33.32	214.3	0.21	45.22	215	0.26	33.98
1618	219.47	1.1	242.05	214.98	0.21	44.43	218.77	0.22	34.06	215.6	0.21	45.52	214.81	0.25	33.36
1619	214.79	1.1	236.29	215.41	0.21	44.51	214.09	0.21	33.77	213.87	0.21	44.86	213.06	0.25	32.96
1620	215.8	1.1	237.35	216.85	0.21	45.14	215.1	0.21	33.4	212.16	0.21	44.21	216.3	0.25	34.19
1621	216.1	1.1	237.15	215.32	0.21	44.5	215.4	0.21	32.51	215.99	0.21	45.91	215.2	0.25	33.4
1622	215.78	1.1	237.55	216.14	0.21	44.9	215.08	0.21	34.04	214.41	0.21	45.1	214.22	0.25	33.05
1623	215.9	1.1	237.07	216.98	0.21	45.39	215.2	0.21	33.38	214	0.21	44.85	215.52	0.25	33.28
1624	216.69	1.1	238.65	216.11	0.21	44.93	215.99	0.22	34.07	216.5	0.21	45.82	214.79	0.25	33.42
1625	215.26	1.09	235.03	214.85	0.21	44.28	214.56	0.21	33.57	209.59	0.21	43.25	213.81	0.25	33.02
1626	215.73	1.1	237.08	217.23	0.21	45.43	215.03	0.21	32.72	212.38	0.21	44.08	215.18	0.25	33.8
1627	216.79	1.1	238.66	215.31	0.21	44.5	216.09	0.21	33.86	215.97	0.21	45.5	214	0.25	32.92
1628	215.31	1.11	238.54	217.32	0.21	45	214.61	0.22	36.87	215.33	0.21	45.67	213.42	0.25	33.04
1629	216.14	1.1	238.2	216.99	0.21	45.3	215.44	0.21	33.81	216.83	0.21	46.19	215.39	0.25	33.55

Fig 30: Actual Load Data Saved in CSV Format

5.3.2 Data Preprocess, Model Modification & Training

In the simulation part for design approach 2 we have seen the model MATnilm was chosen as the NILM algorithm that will disaggregate the main power. So with the data collected from actual loads are fed into this MATNilm model for training. Before training the dataset was preprocessed. Mian Power ,Main voltage and Main current parameters are taken as features and L1 power, L2 power ,L3 power and L4 power taken as level. The whole dataset was divided into three dataset. One is for training containing 146300 samples, another for validation containing 13768 samples and the last one has 20563 samples for testing.

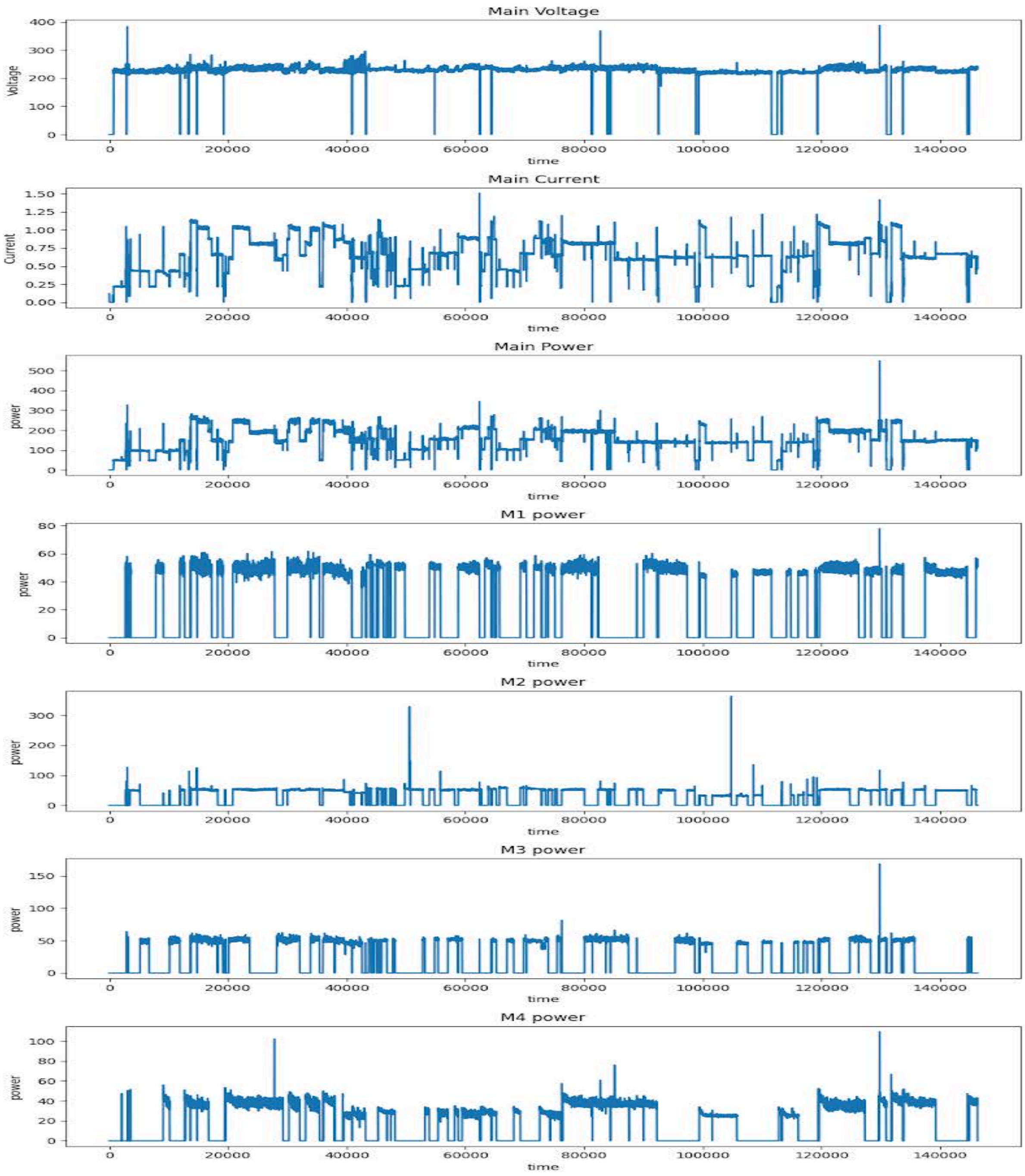


Fig 31: Plotting of the Parameters (Features & Labels)

For better accuracy we modified the model a bit, included or removed some layers and changed the epochs. When we trained our model on the hardware data, we fine-tuned several parameters to optimize the learning process. We fixed the input size to be 3 and batch size to be 32 and the learning rate to be 0.001. The encoder-decoder hidden layer had a size of 64 and dropout 0.1 was used to avoid overfitting. Both the input length and output length were 864 in order to match the model's at the time window. Training was carried out for 5 epochs . The data augmentation was also allowed here to improve the generalization of the model in view of the scarce and variable real hardware data.

5.3.3 Model Evaluation & Scores

To evaluate the performance of the MATNilm model on hardware-based NILM data, multiple experiments were conducted by altering the training and testing dataset structures and observing how the model responds under each scenario. Each testing setup aimed to gradually enhance the performance metrics while maintaining real-time applicability. The evolution of model performance is discussed below.

The initial approach was to train the MATNilm model using the raw training, testing, and validation datasets. This setup aimed to simulate the real-life scenario as closely as possible since data collected from hardware in practical settings is typically not distributed and follows the natural sequence of appliance usage.
In this configuration, we tested the first trained model (Model 1) using the raw test dataset.

Table 12: Test Scores – Model 1 (Raw Trained, Raw Tested)

Metric	M1	M2	M3	M4	Avg
MAE	9.686150	14.786337	16.097979	8.076544	12.161753
SAE	9.968314	10.666394	16.049553	7.284209	10.992118
F1	0.717848	0.674547	0.344841	0.664678	0.600478

The results from Model 1 were not satisfactory. While the F1 scores were relatively acceptable for some loads, others performed poorly. The high MAE and SAE indicated considerable deviations from the actual consumption. This highlighted the difficulty the model faced when learning from the sequential raw data.

To improve this, the dataset was preprocessed by randomly distributing the train, test, and validation datasets. This approach was meant to remove any sequence or temporal bias, allowing the model to generalize appliance behavior more effectively.

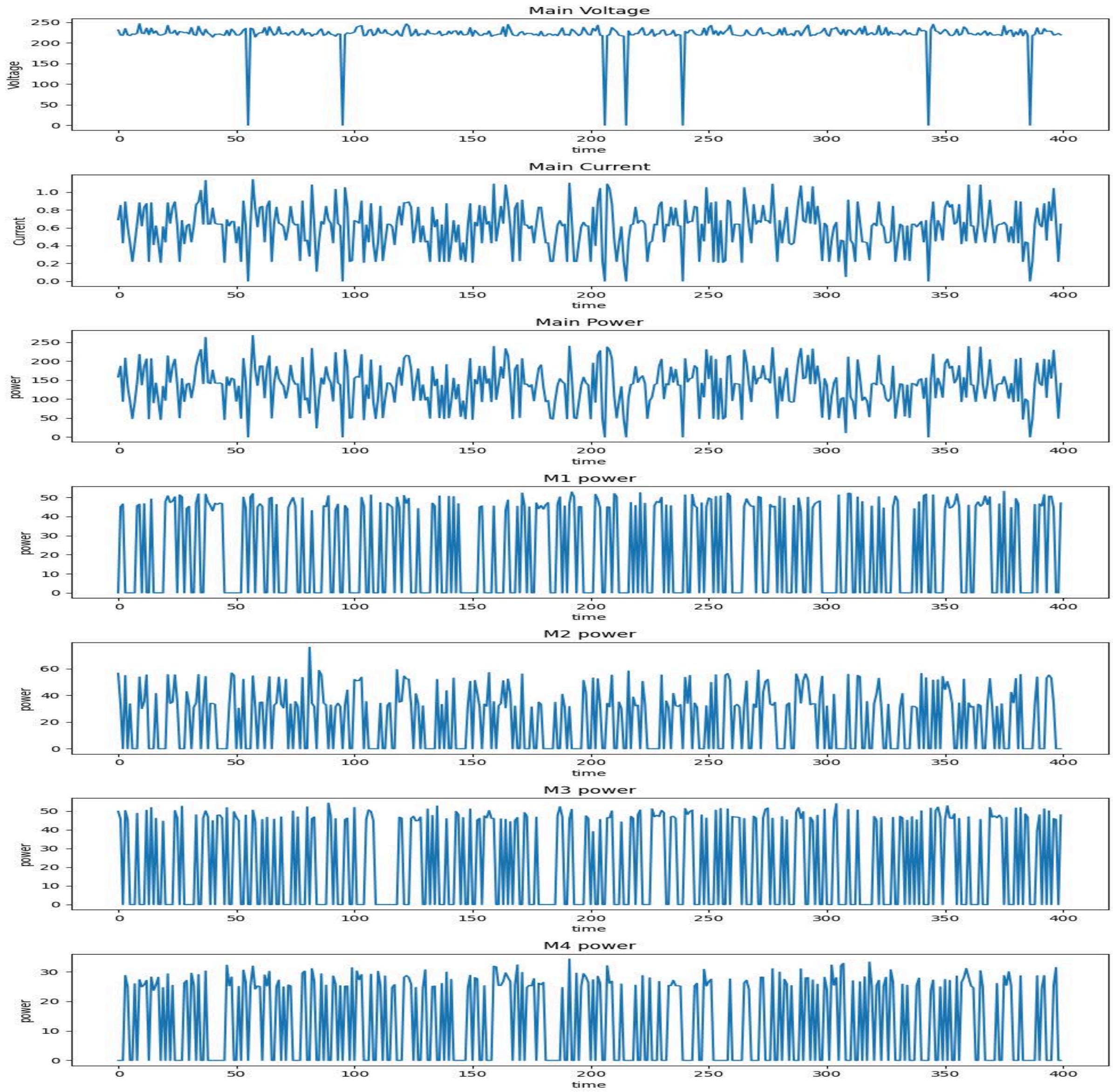


Fig 32: Trained Dataset after randomly Distributed the Data

After training on this randomly distributed data, Model 2 was tested using a similarly distributed test dataset.

Tale 13: Test Scores – Model 2 (Random Distributed Trained and Tested)

Metric	M1	M2	M3	M4	Avg
MAE	8.992349	8.099304	11.151247	2.205844	7.612186
SAE	3.615811	1.460970	4.775571	1.127446	2.744949
F1	0.827296	0.855228	0.763712	0.941339	0.846219

There was a significant improvement in the scores. The MAE and SAE values dropped dramatically, and the F1 scores were much higher, indicating a better classification performance. However, this improvement was somewhat misleading. In real-world applications, the input data will come in raw, sequential format. Since this test was based on

randomly distributed data, it does not accurately reflect actual deployment conditions.
To evaluate the real-world applicability of the trained Model 2, it was tested again but this time using the raw test dataset (not randomized). This was a necessary step to see how well the model generalizes from shuffled training data to real time sequential test input.

Table 14: Test Scores – Model 2 (Random Trained, Raw Tested)

Metric	M1	M2	M3	M4	Avg
MAE	12.515171	10.299630	17.011625	7.687161	11.878396
SAE	9.811180	7.723145	15.971148	7.398974	10.226112
F1	0.669868	0.639968	0.483734	0.617203	0.602468

The performance dropped once again, which confirmed the earlier assumption: training on shuffled data doesn't help much when the inference data is sequential. The F1 scores dropped, and the error values increased, which demonstrated the model's difficulty in adapting to raw input patterns.

To bridge the gap between the randomized and real world formats, we introduced a zero padding approach. In this method, each value in the test dataset was repeated and zeros were inserted after the repeated values to artificially simulate a distributed format. After prediction, the padded elements were removed to restore the sequence length.

Table 15: Test Scores – Model 2 (Random Trained, Zero Padded Tested)

Metric	M1	M2	M3	M4	Avg
MAE	10.403373	12.656917	17.217459	7.128871	11.851655
SAE	9.594048	9.544929	15.949501	7.070130	10.539652
F1	0.771432	0.537656	0.441613	0.526625	0.569332

Although slightly better than the raw test performance of Model 2, this approach was still unsatisfactory. Zero padding failed to fully emulate the randomness needed for high prediction accuracy and introduced inconsistencies that impacted F1 performance.

As a next step, we decided to retrain the previously trained Model 2 using the raw training data. This created Model 3. The idea was to combine the robustness of Model 2 with improved generalization on real time raw input.

Table 16: Test Scores – Model 3 (Raw Trained, Raw Tested)

Metric	M1	M2	M3	M4	Avg
MAE	9.369143	14.021746	13.619122	8.195234	11.301311
SAE	8.415393	13.978783	11.436458	8.044481	10.468779
F1	0.769014	0.710337	0.607842	0.643470	0.682666

The model showed better performance than Model 2's raw test results, especially in terms of F1 score. However, there was still room for improvement, particularly in high error values for certain loads.

To push further, we applied a 5 fold cross validation strategy on the raw training dataset. The dataset was divided into five equal parts. In each iteration, one part was used as validation data while the remaining four parts were used for training. This process was repeated five times. Among the five resulting models, the one with the best performance was selected as Model 4.

Table 17:Test Scores – Model 4 (Cross Validated, Raw Tested)

Metric	M1	M2	M3	M4	Avg
MAE	9.867862	10.365872	12.071987	8.418382	10.181026
SAE	8.990088	9.752569	11.622911	7.897750	9.565829
F1	0.786329	0.790824	0.578868	0.386020	0.635510

Model 4 demonstrated consistent improvements over Model 3 in terms of average MAE and SAE. However, the F1 score of one load dropped significantly, impacting the overall average. Still, this model showed promising potential, especially when combined with another model.

As a final enhancement, we applied model ensembling. Predictions from both Model 3 and Model 4 were averaged to get the final predicted values. The intuition was that averaging the outputs from two differently trained models could reduce noise and increase robustness.

Table 18: Test Scores – Ensemble (Model 3 + Model 4, Raw Tested)

Metric	M1	M2	M3	M4	Avg
MAE	8.799439	9.839008	12.679698	6.200913	9.379765
SAE	8.658571	9.774185	10.482474	5.688564	8.650949
F1	0.790662	0.789924	0.687202	0.662057	0.732461

The ensemble method yielded the best results across all key metrics. The lowest MAE and SAE values and the highest F1 average demonstrated that combining predictions from two trained models offered a more reliable and accurate estimation.

Table 19: Comparison Table of All Final Average Metrics Across All Approaches

Approach	MAE	SAE	F1
Model 1 (Raw Trained, Raw Test)	12.1618	10.9921	0.6005
Model 2 (Rand Train, Rand Test)	7.6122	2.7449	0.8462
Model 2 (Rand Train, Raw Test)	11.8784	10.2261	0.6025

Model 2 (Rand Train, Padded Test)	11.8517	10.5397	0.5693
Model 3 (Raw Train, Raw Test)	11.3013	10.4688	0.6827
Model 4 (CV Raw Train, Raw Test)	10.1810	9.5658	0.6355
Model 3 & 4 Combined	9.3798	8.6509	0.7325

Among all the approaches tested, the combined model of Model 3 and Model 4 produced the most balanced and reliable output, making it the best candidate for real-time NILM deployment. While training with randomized data yielded high performance on similar test formats, it proved ineffective in realistic raw sequences. Therefore, training with raw data, using cross validation and applying model ensembling is the most effective strategy for robust NILM prediction.

End of the training we obtained the overall performance score (loss) of 0.5467, meaning that our models were stable and acceptable.While comparing between machines M4 produced less MAE of 6.2 and SAE of 5.68, this means which M4 minimizes the overall error. On the other hand, M1 gave the best F1-score of 0.79, with the best accuracy of 81.06%, indicating better balance between precision and recall than the others.

In contrast, M4 produced the lowest F1 score 0.66 and relatively higher errors, suggesting lower prediction capability for the target classes. Nevertheless, all models presented an acceptable precision, which varied from 72.27% M3 to 81.06% M1, providing evidence that the developed models are appropriate for real time use in a hardware-based energy visualisation system.

The models had an average MAE of 9.37, SAE of 8.65 and F1 score of 0.73, indicating decent overall performance. These outcomes confirm the capability of the developed system for monitoring and predicting energy usage for various types of machines in the textile industry, indicating the possibility of use of the system for actual energy monitoring and load management.

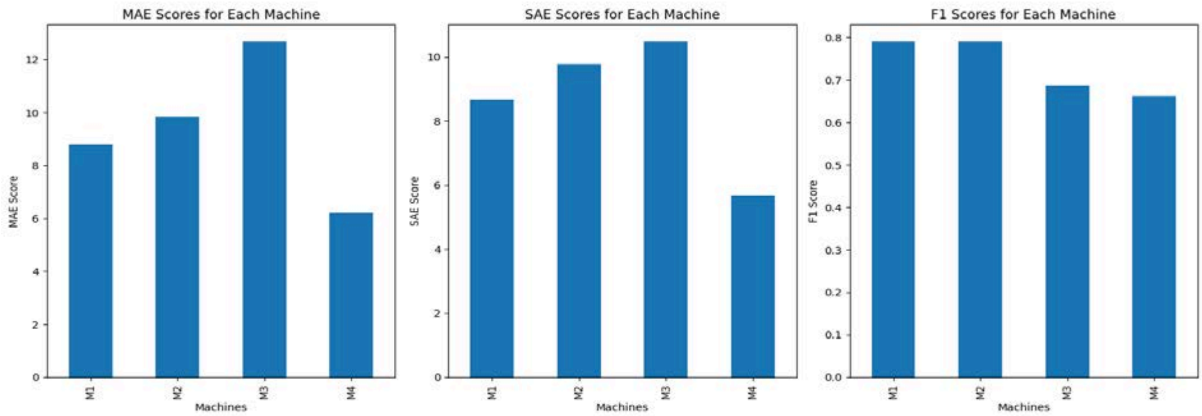


Fig 33: Performance Evaluation Plot for MAE, SAE, F1 score of Each Machine

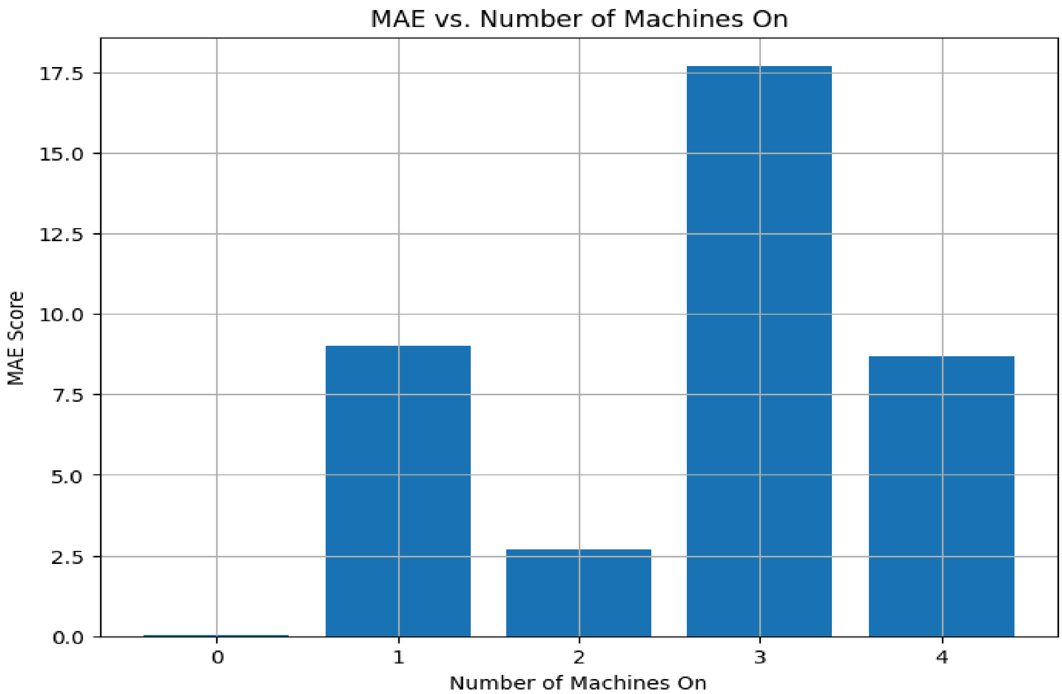
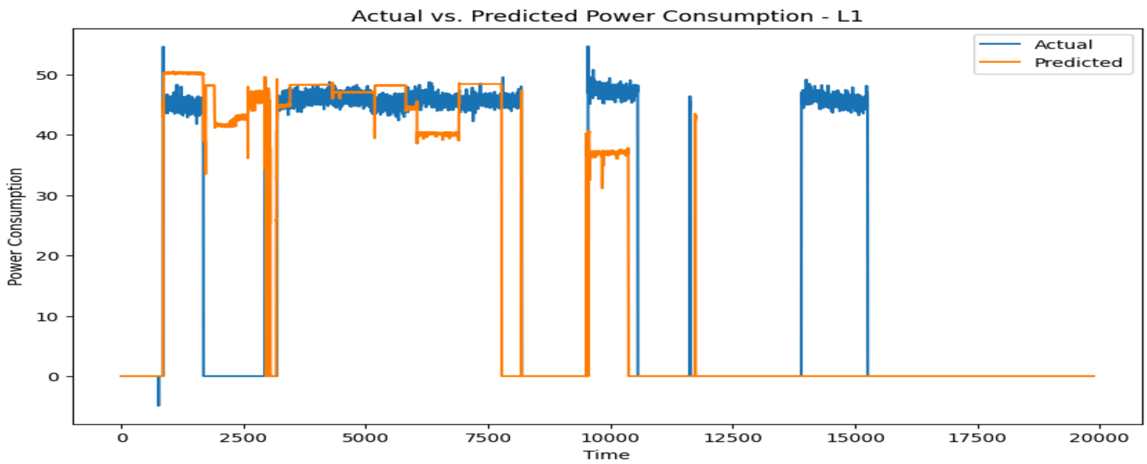
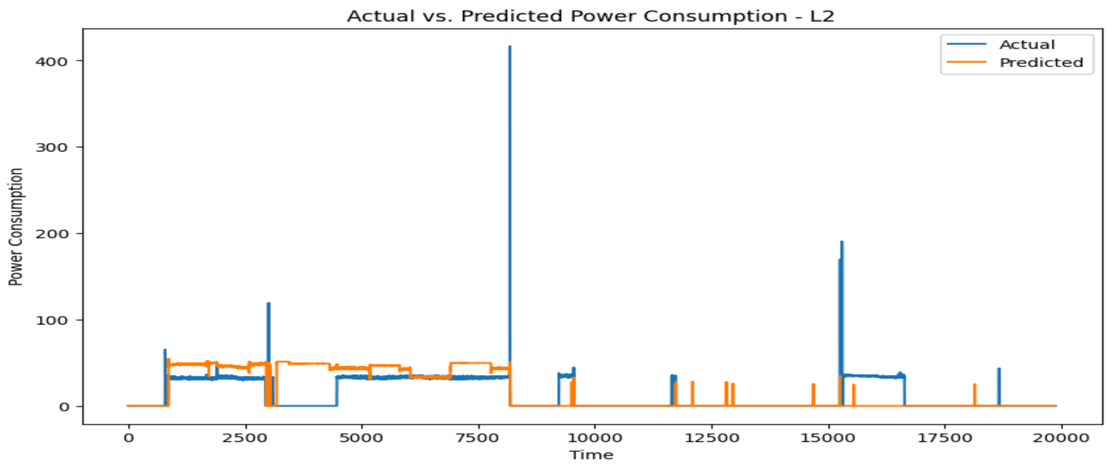


Fig 34: MAE Score VS Number of Machines Operating

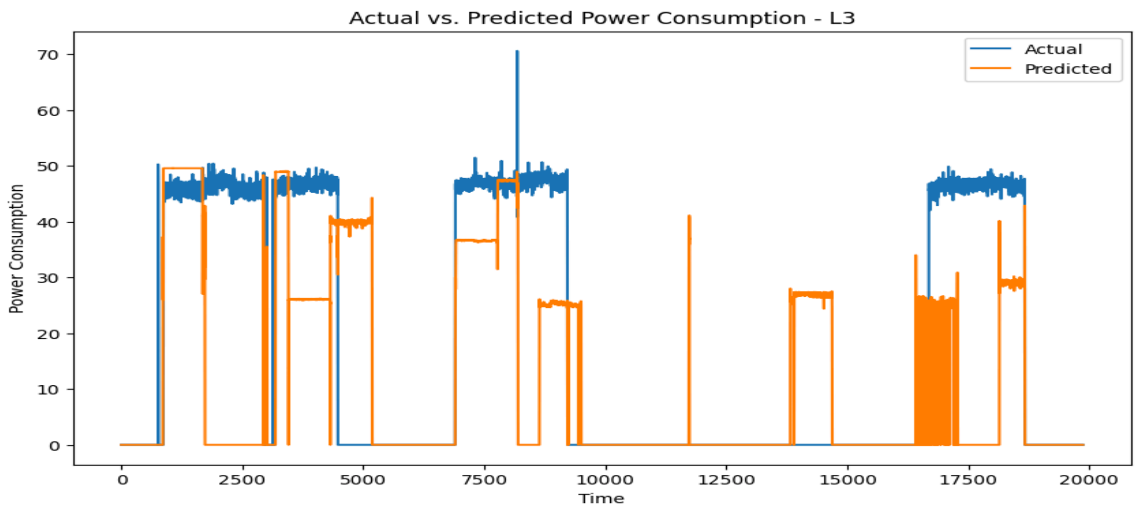
The figure 34 illustrates the relationship between the number of machines operating at a given time and the corresponding Mean Absolute Error (MAE) in power disaggregation. When no machines are active, the MAE is understandably zero, as there is no power to estimate. Interestingly, when only one or two machines are on, the MAE remains relatively low, with the lowest error occurring when exactly two machines are active. However, the MAE significantly increases when three machines operate simultaneously, reaching the highest value among all cases. This suggests that the model struggles to accurately disaggregate power when multiple machines are concurrently active, likely due to overlapping power signatures and increased complexity in distinguishing individual machine consumption. Notably, when all four machines are on, the MAE decreases again compared to the three-machine case, which may be due to more distinct total power patterns or consistent load contributions. Overall, the results indicate that the model performs best with fewer active machines and encounters the greatest challenge in the presence of partial concurrency (specifically with three machines). This insight is valuable for identifying the limitations of the NILM model under different load combinations and for guiding improvements in model robustness under complex scenarios.


Actual vs. Predicted Power Consumption - L1
Actual
Predicted
Power Consumption
Time

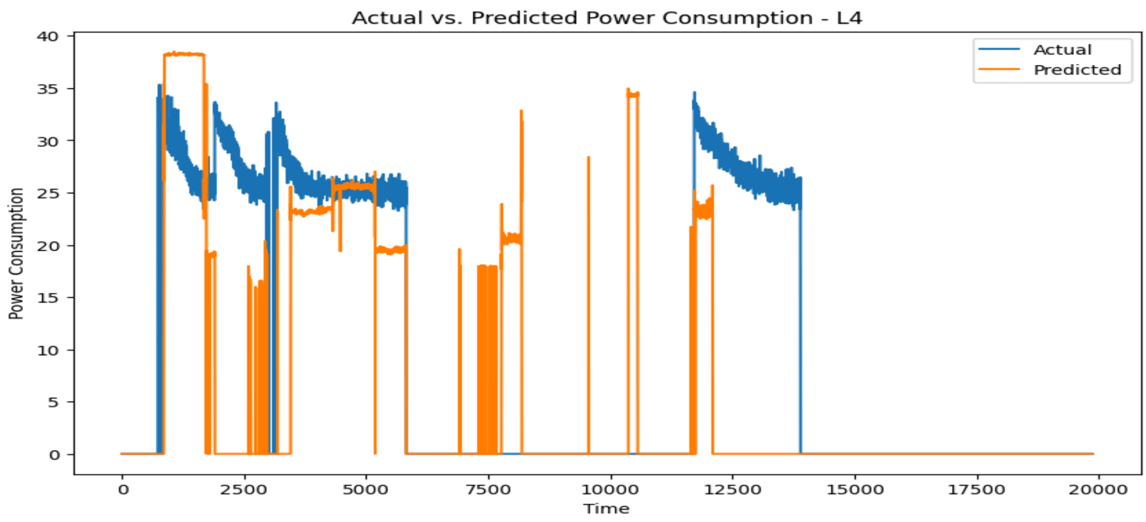
(a)


Actual vs. Predicted Power Consumption - L2
Actual
Predicted
Power Consumption
Time

(b)


Actual vs. Predicted Power Consumption - L3
Actual
Predicted
Power Consumption
Time

(c)



(d)

Fig 35: Actual vs Predicted Power Consumption of the Four Real Loads (a. Load 1, b. Load 2, c. Load 3, d. Load 4)

From these graphs, we see the real and estimated power usage for each load, indicating how well the NILM model performed. Performance on the hardware data results is significantly poorer than the previous training using Proteus simulation data. This is primarily due to the simulation data set being extremely smooth and without noise, while the real world data in hardware exhibits more randomness and irregularity, which has an effect on model accuracy. Moreover, each cutter was employed as three same cutting machines with the same settings to make the difficulty for the model that recognize any of the three cutters. The lower accuracy and state classification performance were partly due to the small dataset obtained for the hardware test.

5.3.4 Final output of the system

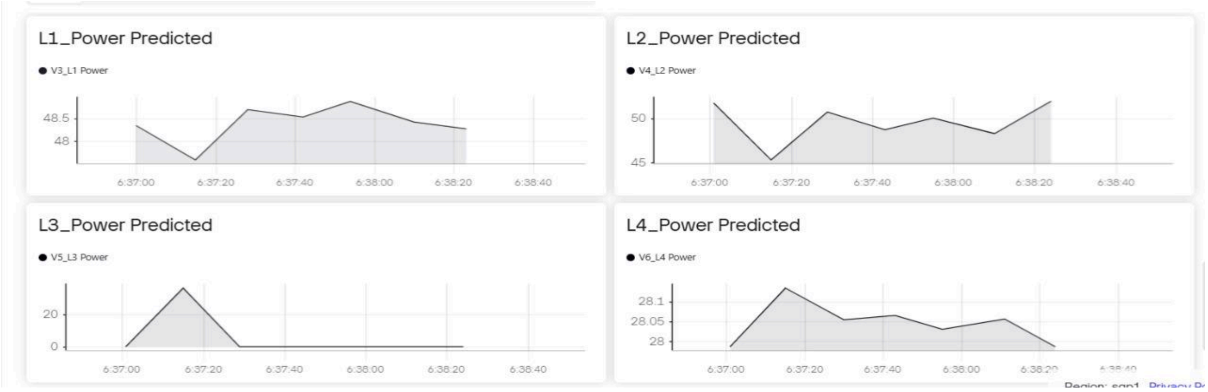
To integrate our real time monitoring with NILM we saved the trained model and deployed it in google collab which will fetch the input data from google sheet where Main voltage, Main current and Main power will be stored in real time . The deployed program will fetch every sample of these input data and feed them into the trained model and disaggregate into each load or machine power and send them to another google sheet to store and Blynk App to show which can be accessible from remote places.

	Main Voltage	Main Current	Main Power	L1 Power	L2 Power	L3 Power	L4 Power	L1 Actual Powe	L2 Actual Powe	L3 Actual Powe	L2 Actual Powe	Date	Time
31	214.31	1.11	238	48.54236221	53.15372086	46.48252869	28.2432518	44.60	34.70	45.90	31.1	2025-04-15	3:39:22
32	209.73	1.11	232.6	48.15872955	48.06515884	46.49782181	28.25278664	44.10	35.10	45.60	31	2025-04-15	3:39:28
33	214.41	1.11	237.2	48.53479385	53.06599045	46.49415207	28.24877167	44.00	34.30	45.70	31	2025-04-15	3:39:32
34	214.19	1.11	237	48.51068878	52.52346039	46.49407578	28.24913597	43.50	34.40	45.60	30.9	2025-04-15	3:39:38
35	213.76	1.11	237	48.53602219	52.7631073	46.49405289	28.2493515	44.40	34.90	45.20	30.8	2025-04-15	3:39:45
36	213.01	1.11	236.1	48.4588089	51.60381317	46.49933243	28.252491	44.50	34.80	45.80	30.7	2025-04-15	3:39:52
37	211.3	1.11	235.4	48.33577728	49.40677261	46.49580383	28.25150299	44.90	35.40	46.00	31	2025-04-15	3:39:56
38	210.6	1.11	232.8	48.20087433	47.92707443	46.50699615	28.25893593	44.10	34.80	46.00	30.4	2025-04-15	3:39:59
39	213.73	1.1	236	48.46041107	51.11957932	46.50288391	28.25366974	44.40	35.40	45.90	29.7	2025-04-15	3:40:08
40	213.84	1.11	237	48.50765228	51.179142	46.49734497	28.25122643	43.70	34.80	45.70	31.5		
41	214.14	1.11	238	48.57495499	51.8260498	46.49509048	28.25065041	44.30	33.80	45.90	31.2	2025-04-15	3:40:17
42	212.86	0.9	192.1	40.44377518	40.81135559	45.3503685	13.50370884	0.00	32.50	46.30	31.2	2025-04-15	3:40:24
43	215.18	0.9	192.9	39.84594727	42.25055313	44.25123215	13.89639854	0.00	32.20	45.60	30.2	2025-04-15	3:40:26
44	213.88	0.9	192.5	40.95465088	41.47674561	45.60417938	12.43285656	0.00	33.00	45.70	30.6	2025-04-15	3:40:33
45	217.1	0.9	196.1	44.61043549	46.72476196	25.44529533	18.96265602	0.00	33.20	45.60	30.5	2025-04-15	3:40:39
46	212.43	0.9	191.1	41.63430023	40.82540894	45.92740631	11.76315117	0.00	32.10	45.30	31.6	2025-04-15	3:40:41
47	217.96	0.9	195.9	43.5761261	46.46924973	27.88966751	18.60055923	0.00	33.00	46.40	29.5	2025-04-15	3:40:48
48	212.71	0.9	191.8	41.54730225	41.5405426	45.83364105	11.79283619	0.00	33.00	46.50	30.6	2025-04-15	3:40:54
49	215.57	0.9	193.4	40.85988235	43.23723984	42.11401367	13.66820717	0.00	32.10	46.00	30.2	2025-04-15	3:41:00
50	213.35	0.9	192.5	41.99707413	41.47876358	45.7767868	11.52698898	0.00	33.40	45.50	31	2025-04-15	3:41:06
51	214.85	0.9	193.5	41.52261353	42.70866394	43.4838562	12.58239079	0.00	32.90	46.10	30.3	2025-04-15	3:41:09
52	214.59	0.9	193.5	41.89917755	42.47026062	44.4751091	12.00696182	0.00	33.40	46.10	30.6	2025-04-15	3:41:15
53	215.16	0.9	194	41.53770828	42.99840164	42.56083679	12.72887802	0.00	32.70	45.60	31	2025-04-15	3:41:21

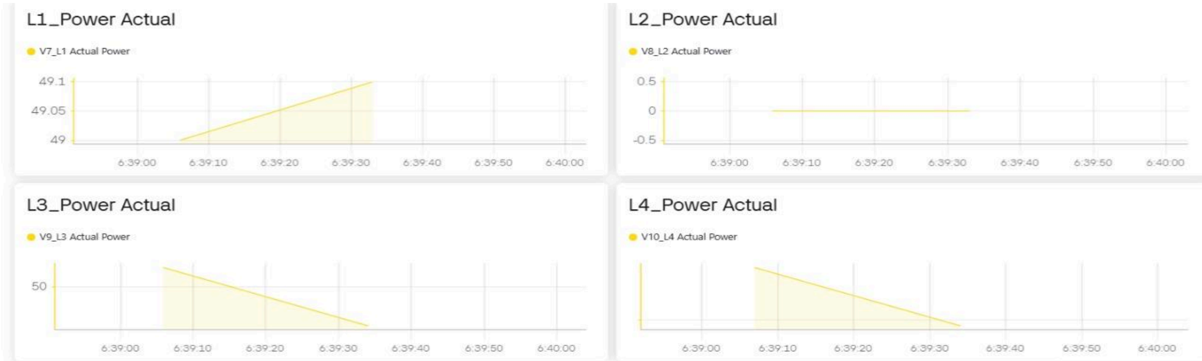
Fig 36: Disaggregated Power of the Loads are Stored in Real Time

(a) (b)

Fig 37: Remote Monitoring with Mobile App using Blynk (a. Disaggregated Power Value of Each Load, b. Actual Power Value of Each Load)



(a)



(b)

Fig 38: Remote Monitoring with Web app using Blynk (a. Disaggregated Power Value of Each Load, b. Actual Power Value of Each Load)

We observe Fig. 30, Fig. 31 that the whole system is operating properly. It monitors and predicts each load's power consumption based on Non intrusive load monitoring (NILM) model. Furthermore, Blynk App is to be connected which allow real time monitoring from online anywhere on the earth, providing more convenience and facility on system monitoring, from anywhere with internet access.

Nevertheless, one issue has been recognized that there is a noticeable deviation between true power draw of individual loads from the disaggregated power that is estimated by the NILM algorithm. This gap in performance points to an important insight: ILNMs effectiveness depends highly on the the quality and robustness of the model we use, how we train it, the quality of the input data and the efficiency of the model for generalisation across different types of load.

Consequently, it is crucial to better model on NILM architectural and training strategy to minimize this error to obtain a more accurate power disaggregation in real situations.

5.4 Conclusion

To sum up, the final hardware NILM system final design was built and validated. The device enabled to retrieve voltage and current in real time for loads, for which the data was further treated using a Arduino Mega and an ESP8266 in order to stream it to a cloud server for unbundle the information. The trained NILM model performed reasonably well for estimating the power consumption of individual machines given noise and a limited number of observations. Remote monitoring which was accomplished successfully through Google Sheet and the Blynk App proved the practicality of the system. Nevertheless, differences between measured and predicted power indicate model design and quality of training data require further investigation and improvement. Altogether the project serves to showcase a proof of concept working prototype, allowing for smart energy monitoring in the industry.

Chapter 6: Impact Analysis And Project Sustainability [CO3, CO4]

6.1 Introduction

The application of Non-Intrusive Load Monitoring (NILM)-based energy management system in the textile industry is a new transformative way of addressing the challenges related to inefficient energy use and operations. Using sophisticated machine learning models such as MatNILM, these capabilities allow for fine-grained profiling of energy consumption without invasive hardware deployment. This is not only the industry's response to the energy industry's demands for granular energy understanding, but a response to larger concerns of sustainability and technological revolution. Consequences of implementing such a system are various, from social and health, over safety and legal issues, to cultural concerns. Each of these dimensions is essential to show how NILM based approach contribute in energy efficiency while supporting a green and creative industrial ecosystem.

6.2 Assess The Impact Of The Solution

The NILM-based energy monitoring system benefits the textile industry by providing accurate, real-time tracking of energy use. This helps factories spot energy waste, use power more efficiently, and cut down on costs. By reducing energy loss and boosting efficiency, the system also promotes sustainability, leading to lower carbon emissions and a cleaner production process.

Societal Impact

The NILM-integrated scheme greatly promotes the progress of society by renovating energy management in textile manufacturing. Power Monitoring It allows customers to monitor power consumption at a granular level, in turn enabling more efficient energy use and lower operations costs, as well as higher uptime and lower total cost of ownership. Those benefits have a ripple effect at the factory level but also in the broader economy, especially in Bangladesh, where garments are a key industry. The system conforms to the national energy saving and consumption reduction requirements and is conducive to the sustainable development and expansion of the industry. Moreover, it raises the awareness and responsibility of multiple parties in promoting the use of eco-friendly methods and aids worldwide endeavours of limiting climate change [21,22].

Health Impact

Health and Safe are the NILM based solution contributes to both workplace safety and public health by identifying and correcting hazard risks associated with faulty equipment and excessive energy consumption. By monitoring failures and variations on time, we reduce risks like overheating, electricity hazards and machinery breakdowns, to make the work environment safer for employees. The system also helps improve air quality as it takes more load off of the generation of electricity, which can generate unwanted emissions. This is particularly advantageous in industrial settings where enhanced environmental health may lead to broader public health benefits [23].

Safety Impact

The monitoring is used for fault detection in the NILM-based system when the fault occurs, a matter of safety concern. These features prevent malfunctions of machinery or appliances, electrical surges, and even fires, which are all key safety considerations for workers that are working with expensive industrial equipment. As a result, machine downtimes are reduced and production schedules are maintained, leading to increased dependability of textile processes. Furthermore, the implementation of the system requires complex algorithms and data analysis tools, which must be highly secure in terms of the accessibility of sensitive operational data, as any breach can lead to an industrial disruption [24].

Legal Impact

The NILM system supports the compliance with national and international energy efficiency standards. It provides transparent and detailed records of energy consumption for regulatory audits and reporting. Not only does this ensure compliance, but it also minimizes penalties and fines as a result of non-compliance. Moreover, due to the fact that most NILM systems are based on machine learning models such as MatNILM, legal issues, including intellectual property rights and licensing terms, need to be considered. Pure agreements are that are necessary to prevent disputes and achieve the lawful use of own technology [25].

Cultural Impact

It's really a cultural change of attitudes toward traditional industries and embracing of high-technology. You see the control room with all the levers and buttons, and dials. This allows local textile producers and makers to compete on a global level, and exert their commitment to innovation and sustainability. Such developments will enhance national prestige and elevate Bangladesh on global map of the industrial landscape. Also, the introduction of NILM systems requires reskilling the workforce to foster a culture of lifelong learning and technological change. Educating lights-out workers in how to run the systems, and keep them running, provides workers with the skills of the modern era that the industry needs for its long-term good health. Lastly, through promoting energy-saving and sustainable Development, the system strengthens the social Values of protecting the environment by following the spirit of the broader culture in sustainable development [26] .

6.3 Evaluate The Sustainability

SWOT Analysis

For any design-based project one of the most important and essential parts is its sustainability assessment. Based on this analysis and the common grounds of the two designs one can acquire an overall knowledge about the strengths, weaknesses, opportunities, and threats of the project.

Table 20 :SWOT Analysis

Strength 1.Significant reduction in energy waste,leading to lower carbon emissions. 2.Non-intrusive design minimizes material usage and environmental disruption. 3.supports long term environmental goals(SDG 12:Responsible Consumption). 4.Scalable and upgradeable to future technologies without major hardware changes.	**Weaknesses** 1.Initial setup may require skilled personnel for system calibration and maintenance. 2.Dependence on the accuracy of machine learning models for precise data interpretation. 3.Data privacy concerns regarding continuous monitoring of operations. 4.Potential high upfront costs for advanced analytics infrastructure.
Opportunities 1.Expansion into other industries seeking sustainable energy solutions. 2.Potential partnership with green certification bodies and regulatory programs. 3.Contribution to national and global climate action initiatives. 4.Enhancing brand image and competitive advantage by demonstrating commitment to sustainability.	**Threats** 1.Rapid technological changes may require frequent updates to maintain compatibility. 2.Resistance from traditional industries reluctant to adopt new technologies. 3.Cybersecurity risks associated with IoT-based monitoring systems. 4.Future stricter environmental regulations may require further system upgrades.

Detailed SWOT Analysis for Sustainability

- **Strengths**

1. Significant reduction in energy waste, leading to lower carbon emissions:
The NILM derived energy monitoring system allows precise monitoring of machine level energy consumption. It greatly reduces unwanted power consumption by recognizing less effective energy use and distributing load in an optimal manner. This is a direct reduction in industrial carbon emissions and provides a positive boost to environmental protection efforts as well as helping industry contribute towards international climate agreements.

2. Non-intrusive design minimizes material usage and environmental disruption:
Contrary to conventional MET devices that involve complicated sensor deployments of hardware modifications, the operation mechanism of the NILM approach is analyzing conventional electrical signals. This non-destructive approach minimises material waste and impacts to the environment regarding the production and grounding of more physical components, thus making the approach naturally sustainable.

3. Supports long-term environmental goals (e.g., SDG 12: Responsible Consumption):
The project is closely linked to global standards for sustainable development, notably with SDG 12 (Responsible Consumption and Production). In a high-consumption industry such as textiles, a NILM-based system will serve to encourage eco-friendly manufacturing, in the sense that large-scale industrial growth will not be at the cost of pollution.

4. Scalable and upgradeable to future technologies without major hardware changes:
It's the scalability of the system." This means that, as the NILM system is predominantly a software and data analytics piece, upgrades to advanced machine learning models or IoT integrations can be performed without the need for wholesale hardware refreshes. This flexibility guarantees the system a long life and eco-sustainability with a minimum of production and final disposal waste.

- **Weaknesses**

1. Initial setup may require skilled personnel for system calibration and maintenance:
Although the NILM technology avoids the need for hardware installation, its setup and calibration for an accurate monitoring of the energy imposes the requirement of specific expertise. For industries, one of the biggest challenges may be finding the right staff members, in which case some form of investment in training staff or engaging technical support could also slow full implementation.

2. Dependence on the accuracy of machine learning models for precise data interpretation:
The sustainability gains achievable with the NILM system rely on the accuracy of its machine learning models. At their extremes, inaccurate predictions may lead to false estimates of its energy performance and misjudging operational strategies, which can reduce the system environmental gains.

3. Data privacy concerns regarding continuous monitoring of operations:
The continuous surveillance on the operation of the machines by its own nature requires sensing delicate operation data. If not addressed, data privacy issues can also emerge such as misuse or disclosure of the mandatory production-related confidential and sensitive information and loss of stakeholder trust in the system.

4. Potential high upfront costs for advanced analytics infrastructure:
NILM systems, while they are meant to reduce cost over time it has a high upfront requirement for purchasing data collection units, analytics platforms, and necessary cloud provision. For some geared industries, notably small and medium enterprises (SMEs), this initial financial obstacle may inhibit the uptake of the system despite its ecological advantages.

- **Opportunities**

1. Expansion into other industries seeking sustainable energy solutions:
Apart from the textile industry, there are plenty of other energy intensive industries like manufacturing, food processing and chemicals, looking for ways to streamline their energy consumption. The NILM-oriented system has great chances for being extended into these sectors and providing sustainable and scalable solutions adapted to a larger market, consequently having a bigger environmental impact.

2. Potential partnerships with green certification bodies and regulatory programs:
Certification benefits By integrating the NILM system with established green certification schemes such as ISO 50001 (Energy Management) or local state energy conservation programs, industries can benefit in terms of getting certification. Such partnerships not only boost corporate reputation but also enables these firms to avail incentives such as tax rebates or grants for integrating environmentally friendly technologies.

3. Contribution to national and global climate action initiatives:
The application of NILM in energy monitoring can play a role in helping national goals in energy saving and eventually contribute to overarching climate mitigation plans such as those agreed upon in the Paris Agreement. It gives companies the ability to be part of the global environmental movement, leverage corporate social responsibility, and increase their global competitiveness.

4. Enhancing brand image and competitive advantage by demonstrating commitment to sustainability:
Having an innovative, environmentally friendly energy management system can really boost a company's brand value. In a rapidly greening market, showing a good corporate citizen stance can bring in the investors and customers and offers an excellent way to differentiate against companies who are less aware of, or perhaps less committed to, green living.

- **Threats**

1. Rapid technological changes may require frequent updates to maintain compatibility:
The rate at which technology (machine learning/ IoT) is advancing is a boon and a curse. Opportunities and dangers are associated with innovations - new learnings and technologies are required to adapt changes and to update the systems, leading to additional cost and complexity over time.

2. Resistance from traditional industries reluctant to adopt new technologies:
Issues of setting up a modern monitoring system may be difficult especially in some of the traditional sectors of the textile, out of fear of the unknown, resistance to change and perceived higher cost the traditionalists' nature may deny them the potentials and gains of a modern technology. Breaking this inertia counts on smart technology change management and proving clear benefits to reluctant parties.

3. Cybersecurity risks associated with IoT-based monitoring systems:
Since the NILM is real-time data acquisition and possibly cloud-based analytics, it is subjected to cyber-attacks. Unauthorized access or security breaches may harm our operations and may expose us to material liabilities and consequent financial loss, reputation damage or regulatory action.

4. Future stricter environmental regulations may require further system upgrades:
Even though the existing NILM system contributes to the sustainability, the future environmental law may require more severe level of environmental regulations. Sectors may be forced to make the system more advanced or add new functions, causing even more investment and adaptation in order to be compliant.

6.4 Conclusion

To sum up, the NILM-based energy monitoring system is an effective and efficient way to track energy use in the textile industry. It helps identify wasted energy and improve power efficiency, leading to cost savings and more sustainable practices. By reducing energy loss and cutting down on environmental impact, the system supports more efficient operations while promoting eco-friendly manufacturing.

Chapter 7: Engineering Project Management. [CO11, CO14]

7.1 Introduction

In engineering, a successfully implemented project is the basis for innovation, efficiency, and problem-solving. Our Project is a proof of effective engineering project management by a systematical, data-driven, and goal-focused approach. This project was conceived to address the ever-growing need for real-time energy efficiency for the Bangladeshi textile industry. A good engineering project is grounded on the pillars of proper definition, systematic plan, disciplined execution, and continuous assessment. This is clearly seen from the current project. The project started with a thorough background study to discern the technical requirements and industry issues. Functional and non-functional requirements were clearly defined such as rate of gathering data, remote accessibility. While working, we face some errors that we cannot meet the desired result within the estimated time. By considering all that, we also need to keep some extra time to complete those. We tried to work the whole year so that we could manage all the technical errors, malfunctions and challenges. For a good project manager, always need to follow a good plan and maintain tasks well structure wise. To achieve the project, required was the delegation of tasks and collaboration of teams by utilizing a Gantt diagram and a detailed logbook, the team assigned tasks, scheduled work into phases, and tracked performance on a weekly basis. Weekly team meetings ensured that each team member stayed on track. This project is a good proof of effective engineering project management, where well-defined objectives, teamwork-based execution, reflective instrument choice, and data-driven assessment came into action to implement a functional, scalable, and effective energy monitoring system.

7.2 Define, plan and manage engineering project

This project is defined with a distinct purpose of developing a low-cost, scalable, and real-time textile industry energy monitoring system using IoT and NILM-based machine learning. Real-time data collection and monitoring remotely were the major working aims. Planning was achieved through task decomposition with detailed discussion among team members, calendar-oriented planning with support from Gantt charts, and regular group meetings for process tracking and work delegation. Risk planning also was tackled by the team by pre-identification of probable technical and operational issues and incorporation of contingency measures. For an extremely huge textile industry, we must decide which area we must target. In such a case, a systematic structured project management approach helped with timely development. This is what we tried doing with project management and it has the potential for greater optimality, and timely delivery of the engineering solution.

7.2.1 Project Planning of EEE499P/EEE400P

In the very beginning, A project needs proper guidelines to be successful. As our FYDP-P started , we divided our task following ATC's guidelines. We decided to work section wise like project planning, Draft concept note and then final proposal. By following ATC's instructions, we finalized the project topic and then started a research journal and thesis paper. We focused on Scope and objectives, background study and analyzing specifications. Each team member completed their own work which was assigned to them. Considering all these, we completed a tentative design approach and finally submitted our final proposal. The Gantt chart for EEE-499P is shown below:

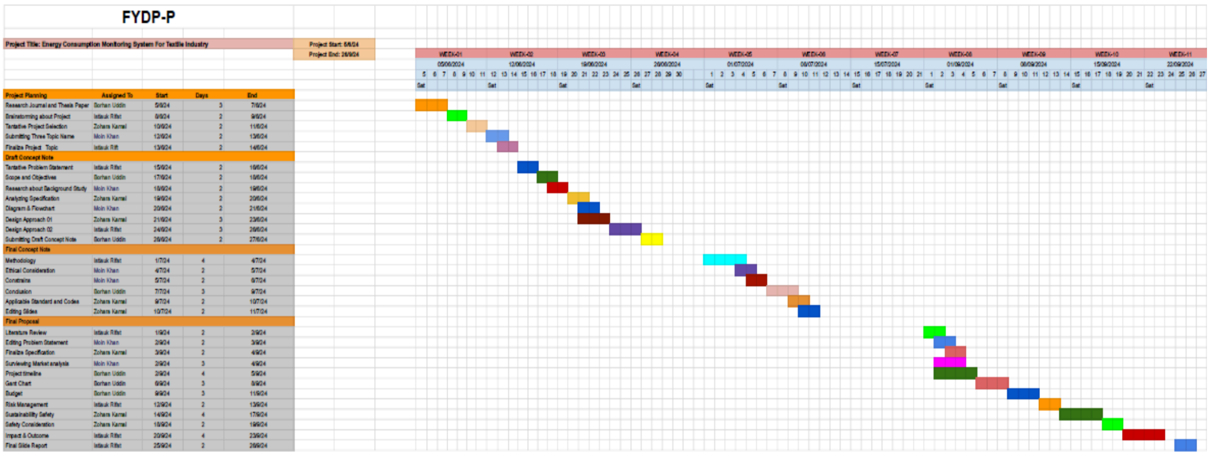


Fig 39 : FYDP-P Gantt Chart

7.2.2 Project Planning of EEE499D/EEE400D

After completing EEE499P, we started planning on design sections. We again started our group discussion and ATC meeting. From the very beginning of EEE499D, our respective ATC members advised us to work on software tools using appropriate modern engineering tools. We visited a garment factory to know all requirements as our project is based on the textile industry. We completed Proteus circuits and analysis design approach. After this, we focused on the MAT-nilm model. We collected data from proteus. We tested our code and tried to run. After debugging the design approach, we tested validity for phase 1 and phase 2. Then, we prepared all the documentation and final report and slides. Here is our Gantt chart for EEE499D attached below:

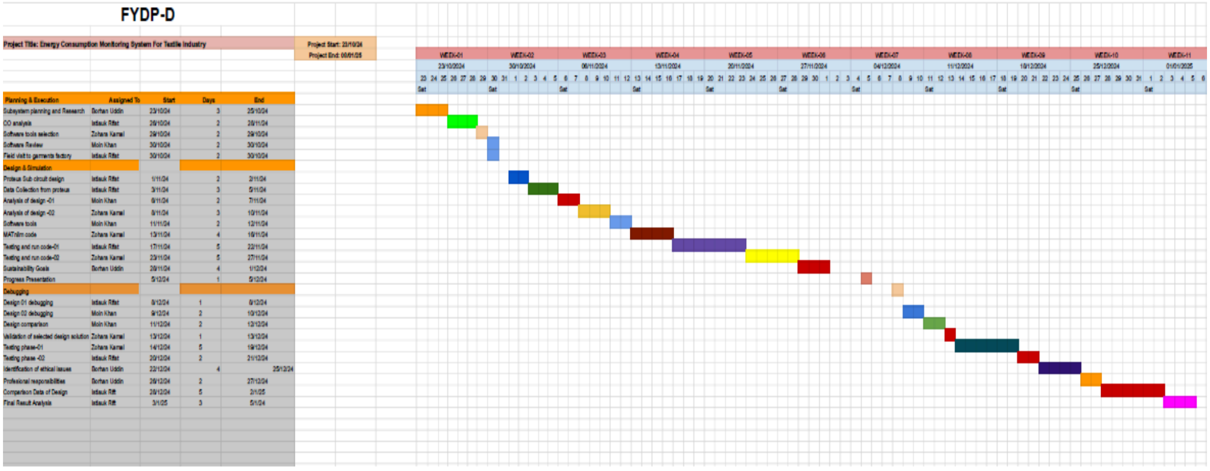


Fig 40: FYDP-D Gantt Chart

7.2.3 Project Planning of EEE499C/EEE400C

In this implementation section, we faced challenges. However, we have worked step by step. We bought all the components which are required for FYDP-C. We visited a garment factory again. After this, we started to set up all hardware connections. Our main part was the NILM model. We faced some problems regarding these. After debugging NILM code, we did not get the percentage that we wanted. We trained this model and deployed it. We are updating ESP8266 code as our data comes from voltage sensors and current sensors where motors were connected. Then it goes to the microcontroller and then it is transferred to ESP8266. Through IOT, data is shown to the sheet. Also We have a web page interface to show these. So, we faced latency issues. We checked these issues and updated serial communication and codes. We continuously collected data from hardware set up. After all these, we checked the final validity test and showed it to the ATC panel. Though we faced challenges, we enjoyed this EEE499C phase. This is our Gantt Chart, which shows our group work execution for this semester:

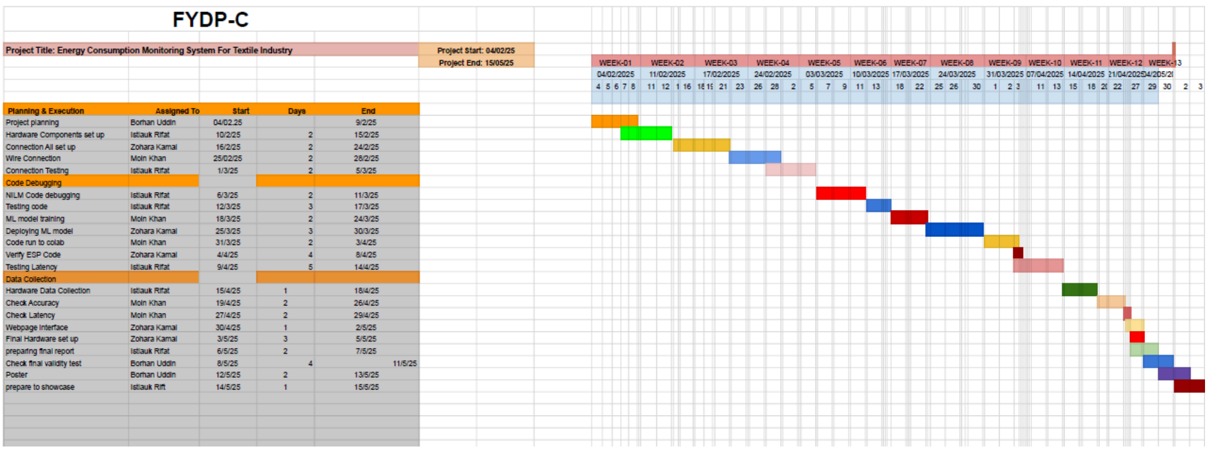


Fig 41: FYDP-C Gantt Chart

7.3 Evaluate project progress

Throughout the three semesters, we have done many tasks to fulfill our projects. We have divided our tasks among group members very precisely. We followed some criteria such as a Gantt diagram and a detailed logbook, the team assigned tasks, scheduled work into phases, and tracked performance on a weekly basis. Our weekly team meetings ensured to make better projects.

Table 21:Responsibilities

FYDP-499C-GROUP-07			
Responsibilities			
Borhan Moin	Zohara Borhan	Istiauk Zohara	Istiauk Moin
Hardware Components Set Up	Project Planning	NILM Code Debugging Deploying ML Model	Sensor Calibration
Wire Connection and Testing	Draft Report Writing	Voltage,Current sensor precision check	Hardware Data Collection
Checking Latency issues	Final Report and Poster	Google colab	Accuracy issues
Update ESP Code		User interface	Final Hardware Setup

7.3.1 Risk Management and Contingency Plan

When planning and conceptualizing a project, we need to consider the possibility of risk because it can happen at any time and anywhere and we have no control over it. So first, we should list some types of risks that can happen and then analyze them and come up with an idea of understanding the level of risk, alternative plans. We all need to be proactive.

Table 22 : Risk management

Types of Risk	Level (Low/Medium/High)	Contingency Plan	Responsible Member
Sensors Frequency	Medium	Need to choose sensors with high sampling rates and integrate additional sensors to improve accuracy.	Istiauk & Moin
ESP8266 Microcontroller Limitations	Medium	Earlier, we will assess the system's scalability. Need to upgrade more powerful microcontrollers	Zohara & Borhan

Firmware or Software Bugs	Medium	To mitigate this risk, learning by practicing can only be an option. Make sure to test the system carefully.	Istiauk
Wi-Fi Discontinuity	Low	For backup, consider connections or cellular networks will be preferred to maintain reliable data transmission. Besides, SD cards can be used if the wifi signal is unstable.	All
Availability of Components	Low	Keep alternative components available and buffer stock.	All
High Level of Electricity	High	Safety protocols need to be tightened. Use insulated equipment. Inspect electrical systems regularly to prevent overload.	All
Shortage of Data for Training Phase of NILM	Medium	Different data needs to be collected from different machines and processes to train this model better.	Istiauk & Moin

7.4 Conclusion

The project succeeded by defining objectives clearly, systematic planning, strategic tool selection, and ongoing monitoring of progress. Including technical through disciplined organization and risk control, the project managed to provide an effective, expandable, and economical monitoring system tailored to serve the textile industry. Despite some complications and occasional malfunctioning within the model, our team members were maintaining a weekly progress schedule. This is a case study of what is important about effective project management in translating engineering theories into effective real-world solutions.

Chapter 8: Economical Analysis. [CO12]

8.1 Introduction

In this chapter, The economic viability and contribution of our project are examined. Analysis of economic viability is important for an understanding of cost effectiveness and feasibility for effective deployment of the proposed system. This chapter gives an economic perspective of our proposed system, with an eye for an assessment of the cost structure, investment return rate, and economic viability over a long period. In addition, it establishes that our solution, through intelligent monitoring of energy, helps in saving costs, improving productivity, and ensuring regulatory compliance, which are contributing a major share in effective positioning of textile industries globally.

8.2 Economic Analysis

The economic rationale for the planned system is that it will reduce operational inefficiencies, wastage of electrical energy, and maintenance time. Low-cost hardware items such as current sensors, voltage sensors, ESP8266 and tools for integration with Blynk apps are used in developing the system, so industrial deployment does not require a high initial investment.
Economically, the proposed solution for monitoring provides value at a number of different levels. Firstly, it streamlines the monitoring of consumption at machine and at a system level in real-time for textile industries owners, and for textile machinery operatives, specifically. For real time data collection, it gives historical data which provides error detection. Secondly, by analyzing history and real-time data stored on cloud (Google sheet) and processed using (created on Google Colab), plant managers are able to plan for machinery operations so that electricity is not wasted during peak use, lowering electricity costs. In addition, with modular and expandable system philosophy adopted by our project, the same system is easily expandable to monitor more machines by simply copying sensor nodes and re-training machine-learning-based NILM (Non-Intrusive Load Monitoring) software. This expandability allows industries to roll out the system incrementally based on budget and operational needs without significantly investing further into infrastructure.

8.3 Cost Benefit Analysis

Viability for a project is defined using cost-benefit analysis, which gives a global view of the system based on operational, and implementation dimension. For our target system, establishment of using IoT and based on NILM Energy Consumption Monitoring System required choice of components and technologies from a wide list of available alternatives. All sensors, Arduino Mega and communication modules were evaluated based on functionality, however, based on economic viability, integration ease, and future expandability. For our instance, value over expense became critical. Not only were costs a minimum-is-as-good-as-required consideration, even reliability, accuracy, and lifetime of the system became a consideration, since all of these were foremost determinants of customer satisfaction, and consequential savings over a longer horizon. The prototype makes use of a mix of components ranging from current and voltage sensors, ESP8266 , Arduino Mega, buck converters, and cloud storage platforms. Every selection of a component only happened once technical performance versus costs and compatibility were compared. For example, use of expensive industrial-grade controllers were avoided, and ESP8266 were used due to a costing balance and wireless capability. Similarly, use of an end-to-end integration with a full-fledged SCADA was avoided and Google Drive and Google Colab were used for lightweight, cloud-based storage of data and ML-based computation, with minimum periodic costs.

8.4 Evaluate economic and financial aspects

This project will be advantageous from an economic and financial importance for Bangladesh's textile industry by facilitating a real-time monitoring system. All types of textile industries can use it, which results in reduced power consumption and expected downtime and increased labor costs. This system supports national regulations for waste management, making it viable for industries to increase efficiency. A working prototype took a total of 8,890 BDT with materials such as voltage and current sensors, Arduino Mega, ESP8266, and some support hardware. The selection of material has been optimized for functionality and cost. Whether Design 02 (NILM based) is cost-efficient and scalable, especially for industries with many machines, by avoiding multiple sensor usage. Here we required less machines in these sections. Overall economic and operational gains far outweigh initial expenditure. With advancements using IoT (Web page interface) Blynk app and sensor technologies further down the line, costs would be lower, making it even more effective and cost-efficient for textile industries to use on a large scale.

Table 23: Budget

Component Name	**Price (Design-01)**	**Quantity**	**Price (Design-02)**	**Quantity**
Voltage Sensor	250	5	250	1
Current Sensor	350	5	350	1
Arduino Mega	1800	1	1800	1
Buck Converter	120	1	120	1
AC Induction Motor	700	3	700	3
LCD Display	650	1	650	1
Bulb	250	2	250	2

ESP8266	420	1	420	1
Wires	300	1	100	1
Total	8890		6290	

8.5 Payback Period Analysis

Payback period is the time for positive project cash flow to recover negative project cash flow the acquisition or development years. It is widely used for capital budgeting methods. Payback can be calculated either from the start of a project or from the beginning of production. It is especially suitable for projects which involve moderate upfront investment but generate ongoing operational savings.

8.5.1 Investment and Savings Overview

The cost of systems implementation for Design-01 (ILM-based) is 8,890 BDT & Design-02 (NILM-based) is 6,290 BDT (Best Selected). The NILM-based energy monitoring solution, its lower cost structure and lower hardware dependence make it well-fitted for scalable adoption in the textile industry.
Annual Savings Estimation : Based on industrial practice and experimental experience with NILM and IoT-based factory environments:

Savings in average monthly electricity cost	700 BDT
Average monthly maintenance/labor cost reduction	300 BDT
Overall monthly operational cost savings	1000 BDT
Total savings per year	12,000 BDT

Payback Period Calculation :
Payback Period = Initial Investment / Annual Cash Inflow = 6290 / 12000 ≈ 0.52 years (~6 months)

8.5.2 Interpreting with Bangladesh Textile Sector

Recent research on the Bangladesh garment sector is consistently documenting quick paybacks for energy-efficiency investments:

- A case study on solar process heating in a Bangladesh textile mill showed a high payback period (~13.6 years) due to high capital cost but 14–15 % energy savings. [15]

- Projects supported by USAID's overall textile industry audits have demonstrated that most investments in energy efficiency in textile mills had a simple payback of less than two years, and most of them less than one year.

- Installation of combined heat and power (CHP) systems at Tamijuddin Textile Mills in Gazipur enhanced energy efficiency along with significantly lowering the cost recovery period. [16]

Our 6-month payback of the system is within, and shorter than, the usual range for Bangladeshi textile energy efficiency improvements.

8.5.3 Economic and Strategic Implications

1. Rapid Financial Recovery: Six-month payback implies excellent return on investment in the first year of operation—higher ROI.

2. Benchmarking Excellence: Our system surpasses many capital-intensive solar heating or CHP systems, which most commonly incur several years of cost recovery. [16]

3. Enables Scaling and Funding: The system adhered to USAID standards that defined sub-two-year paybacks as being favorable for industrial energy investments.

The payback period analysis confirms that the Initial investment is 6,290 BDT where Yearly savings is around 12,000 BDT and for Payback, it's around 0.52 years (~6 months). This performance puts the system in the list of the most cost-efficient energy-saving projects in Bangladesh's textile industry which is renowned for its rapid payback and economic viability.

8.6 Conclusion

The economical analysis of our proposed energy consumption monitoring system confirms that it is both cost- efficient and scalable for implementation in textile Industries of varying sizes. with minimal upfront costs and substantial potential savings, the system offers a high return on investment within a short period. Furthermore, the ability to contribute to energy efficiency, operational stability, and compliance with environmental standards makes the solution not only economically beneficial but also strategically important for textile manufacturers in Bangladesh striving for global competitiveness.

Chapter 9: Ethics and Professional Responsibilities CO13, CO2

9.1 Introduction

Generally, ethical issues are central to ethical practice. They are not just guiding rules influencing technical details of a project, but a project's environmental, legal, and socio-economic implications. For any system collecting, storing, and processing sensitive data particularly from sectors, engineers must be committed to developing solutions offering transparency, accountability, and public confidence. In our project, we planned a monitoring system that collects data from devices in real-time and transmits it through IoT platforms. This involves sensitive industrial data, potential surveillance of workplaces, and communication of data all of which carry a set of ethical responsibilities. As designers and future engineers, it is our duty to foresee ethical consequences of our work, identify potential issues, and remove them by precise engineering and adherence to professional codes. Ethical design ensures technological advancements occur without any loss of human rights, environmental sustainability, or societal conditions. As the designed system is intended for application in factories which contribute a great portion of Bangladesh's GDP and workplaces, utmost precaution was taken so that IEEE guidelines, energy regulations, and engineering good practice were taken into account right at the beginning.

9.2 Identify Ethical Issues and Professional Responsibility

Ethical engineering demands that we foresee and solve potential issues that will occur during the life of the project. The principal ethical issues within our project are related to privacy of data, monitoring of workspace, abuse of the system, environmental issues, and adherence to national and international regulations.

- Confidentiality and Ownership of Data: The machine-level power consumption data is recorded by the system. Whoever possesses it, if it is acquired by unauthorised people, it could be made available to them, which could prompt industrial spying or economic tampering. Ethical responsibility demands that such data must be encrypted and transmitted only to duly authorised individuals, for instance, factory energy managers or authorities.

- Transparency and Informed Consent: Since our system potentially constitutes employee or machine monitoring, it is ethically important that stakeholders, including factory workers, are informed about what is being monitored, why it is being monitored, and what purposes, if any, are being served by using such data.

- Fair Use and Accessibility: Considering that Bangladesh's textile industry is dominated by small and medium-scale enterprises (SMEs), we made it a low-cost yet scalable process. Creating an economically skewed process which would cater only for large-scale firms would be an unethical act based on grounds of equity and accessibility.

- Truthfulness and accuracy of reporting: Ethical engineering requires us not to manipulate or falsify information to stakeholders. The monitoring system is set up for unbiased and open reporting, and our sensor or data accuracy limitations are reported with complete documentation.

- Compliance with Professional Codes: We adhered to the IEEE Code of Ethics, particularly guidelines for clauses related to issues of public concern, honesty, safety, and respect for others' rights. All the simulation tools, sensors, and microcontrollers that we utilized in our project were legally acquired and cited appropriately.

In simple terms, ethical engineering for us involves being responsible for what our system does, and also for what there is a possibility it could do for users, staff, industry, and society overall.

9.3 Apply Ethical Issues and Professional Responsibility

Apart from being sensitive about ethical issues, it is also a duty for an engineer to implement such issues practically during a project. In our project, we implemented professional responsibility in the following ways:

- Legal and Regulatory Compliance: As our application accepts and saves sensitive data, we ensured that it maintained a secure architecture with password-encrypted Google Drive storage. That is acceptable for a prototype, yet for release, we recommend adopting industrial-strength cloud services with encryption and permission control for compliance with Bangladesh's Energy Audit Regulations 2018 and the Energy Efficiency and Conservation Rules 2023.

- Anonymity and Data Security: Personal identifiable information (PII) was not gathered. Monitoring is designed for machines, and machines, not individuals, are what are being supervised. Where employee data was implicit (machine idle time for shifts), anonymization and briefing of staff is advised for transparency and confidence.

- Open Stakeholder Communication: Communication is by far the most critical aspect of ethical deployment. To us, any textile mill adopting the above system must assure workers that it would help prevent wastage of energy, neither monitor individual performance, nor impose penalties.

- Environmental and Social Impacts: By allowing factories to lower electricity usage, our system indirectly assists in avoiding resource wastage, and contributing towards global ESG objectives. This is for economics and ethics, with a balance being achieved between profitability and responsibility.

- Recognition of Limits: For our ethical responsibility, we recognized within our paper that our simulation has been created based on Proteus with Arduino Uno due to tool constraints. Live testing based on ESP8266 could not be simulated in a factory environment in real life due to unavailability of infrastructure. Ethically, it is more fitting for us to disclose such constraints than overstating results.

9.3.1 Professional Responsibility

As professionals, we are responsible to society, to our profession, and to ourselves. Within this project, our professional responsibility was to:

- Accurate Reporting of Findings: All of our published findings are simulated or collected using testbeds with real sensors. We did not manufacture or manipulate findings for purposes of improving our project's perceived success.

- Academic honesty: All referenced citations, diagrams, and tools utilized are credited in References. All outside work that is reused or copied was done without citation or permission.

- Product Safety and Usability: Although hardware scalability is achieved, caution was exercised so all sensors and supplies of power used for the prototype were within safe voltage and current ratings. Isolation and safe deployment notices were made.

- Collaboration and Respect: Every team member contributed an equal input throughout the project, and decisions were taken with shared collaboration and respect. This ethical behavior reflects our preparedness for our future professional careers in the industry.

9.4 Conclusion

Engineering is technical problem resolution, yet also protection of human and natural rights by responsible, ethical practice. Ethical design, data protection, legal compliance, and open communication were all firm commitments within our project. Nor is a good design merely a working one, it is a respectful, environmental-preserving, trusting one. We are pleased that our work is based upon such values, and are dedicated to maintaining them for all future professional endeavors. Ethical concerns, including technical constraints, must at all times be regarded as basic engineering design criteria.

Chapter 10: Conclusion and Future Work

10.1 Project summary/Conclusion

The aim of this project was to propose and develop a smart energy monitoring application, specifically designed for the textile sector, aimed at real-time tracking power at machine level and noninvasive data collection. Among the two design methodologies considered, Intrusive Load Monitoring (ILM) and Non-Intrusive Load Monitoring (NILM)—we selected the NILM approach for its cost-effectiveness, scalability, ease of installation, and potential for industrial expansion.

The designed system integrated IoT-based hardware with a cloud connected platform by utilizing Google Sheets and Blynk for real-time monitoring of voltage and current sensors. A deep learning-based NILM model (MATNilm) was also implemented to disaggregate the energy so as to have the power consumed by individual machines from the aggregate mainline data.

Despite the limitation on available training data and noise in real-world applications, the model performed reasonably well; it accurately predicted the best- over 81% of the distant-scaled controls and an average F1-score of 0.68 over all monitored loads. This demonstrates the applicability of NILM systems to textile factories for energy transparency and decision-making support.

It would help the nation to meet its energy efficiency goal, and comply with international pledges on sustainability such as the BGMEA's 30% GHG reduction target by 2030." It enables factory owners to learn from data, facilitates efficient operation and help drive proactive energy management in one of Bangladesh's most critical industries.

10.2 Future work

Although the applied NILM-based energy monitoring system has achieved good enough results, further improvement may still be done on the algorithm for better performance, scalability and real world application in textile production house.

The performance of the NILM algorithm can first be improved by, in particular, investigating more advanced deep learning architectures. Transformer-based models, TCNs [22], or hybrid approaches consisting of LSTMs and attention mechanisms have improved the performance in time-series disaggregation tasks [23]. Finally, the prediction errors and state classification performance could be improved by tuning model parameters, using appliance level embeddings, or using ensemble methods [28].

Also the large, varied dataset is a clear disadvantage of the present system. Augmenting the dataset with additional samples obtained during a longer period of time (or from different industrial machines) would help the model learn different load patterns [29]. This would make the system more robust in real-world situations wherein operating conditions changing. There is also room for unsupervised(or semi-supervised) NILM methods. These methods limit reliance on labeled data and learn usage patterns from aggregate signals without infinitely expanding the dictionary [30]. This is very helpful as translation models are not always available for different language pairs, particularly for big deployment in factories where labeled training data may be scarce [31].

Another future work is to how the trained NILM model can be deployed on edge devices such as Raspberry Pi or NVIDIA Jetson Nano [32]. By running the data filtering service locally, the system can reduce latency, minimize the dependence on internet access, and enhance the data privacy rendering the solution for real applications in network-challenged areas more feasible [33].

Also linking with predictive maintenance capability would add a tremendous value to the system. Load patterns over time analysis might also enable the system to observe an early symptom of equipment failure, helping factory to maintain equipment before failures, and then decreasing downtime time and maintenance cost [34].

Last but not least, an advanced user interface featuring customizable dashboards, real-time alerts and automated energy audit query reports could further improve the user-friendliness and the adhering to standard procedures of the system [35]. These improvements would lead to a better alignment between factories and sustainability objectives and national energy efficiency requirements, and make the system suitable to future expansion of the industry [36].

Chapter 11: Identification of Complex Engineering Problems and Activities.

11.1: Identify the attribute of complex engineering problem (EP)

Attributes of Complex Engineering Problems (EP)

	Attributes	**Put tick (√) as appropriate**
P1	Depth of knowledge required	(√)
P2	Range of conflicting requirements	
P3	Depth of analysis required	(√)
P4	Familiarity of issues	
P5	Extent of applicable codes	(√)
P6	Extent of stakeholder involvement and needs	(√)
P7	Interdependence	(√)

11.2: Provide reasoning how the project address selected attribute (EP)

P1. Depth of knowledge required: The project required an in-depth understanding of IoT, machine learning algorithms, and energy disaggregation techniques.

P3. Depth of analysis required: Detailed analysis was essential to evaluate NILM and ILM approaches and validate system performance through simulations.

P5. Extent of applicable codes: The system had to comply with industry standards and regulatory frameworks related to energy monitoring and data security.

P6. Extent of stakeholder involvement and needs: The design incorporated feedback from stakeholders, including factory owners, operators and regulatory bodies.

P7. Interdependence: The energy monitoring system relies on interdependent units, where sensors, processors and algorithms depend on each other for functionality

11.3 Identify the attribute of complex engineering activities (EA)

Attributes of Complex Engineering Activities (EA)

	Attributes	**Put tick (√) as appropriate**
A1	Range of resource	(√)
A2	Level of interaction	(√)
A3	Innovation	
A4	Consequences for society and the environment	(√)
A5	Familiarity	

11.4 Provide reasoning how the project address selected attribute (EA)

A1. Range of resource: The project utilized diverse resources, such as IoT devices, machine learning tools and expert human resources.

A2. Level of interaction: The project utilized diverse resources, such as IoT devices, machine learning tools and expert human resources.

A4. Consequences for society and the environment: It promotes sustainable practices by reducing energy wastage, benefiting society and mitigating environmental impact.

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Appendix

Summary of Team Logbook

Student Details	NAME & ID	EMAIL ADDRESS	PHONE
Member 1	Md.Istiauk Hossain Rifat 20121071	istiauk.hossain.rifat@g.bracu.ac.bd	01872885080
Member 2	Zohara Kamal 20321040	zohara.kamal@g.bracu.ac.bd	01861589233
Member 3	Md.Borhan Uddin Khan 20221024	borhan.uddin.khan@g.bracu.ac.bd	01635265759
Member 4	Moin Khan 19121118	moin.khan@g.bracu.ac.bd	01758935424
ATC Details:			
ATC 1			
Chair	Shahidul Islam Khan,PhD	shahidul.khan@bracu.ac.bd	
Member 1	Mohammad Zunaed	mohammad.zunaed@bracu.ac.bd	
Member 2	Saad Mahbub Chowdhury	saad.chowdhury@bracu.ac.bd	

Work summary of EEE499P - Final Year Design Project (P) Summer 2024

Date/Time /Place	Attendee	Summary of Meeting Minutes	Responsible	Comment by ATC
30.05.24 (11.30am -12.00pm) ATC meeting-01	1.Dr.Shahidul Islam Khan Sir 2.Mohammad Zunaed sir 3.Md.Istiauk Hossain Rifat 4.Zohara Kamal 5.Md.Borhan Uddin Khan 6. Moin Khan	1. A normal meeting with ATC, Brainstorming what to do in Project.	No task individually. Just read a research paper.	N/A as it was an introductory meeting.

03.06.24 (10 pm - 11pm) Group-meeting-01	Moin, Zohara,Borhan, Istiauk	1.Preparation of draft topic selection, 2.Discuss about what topic we should do.	Task1:Zohara, Borhan, Task 2.Moin, Istiauk	
5.06.24 (11 pm - 12 am) Group-meeting-02	Moin, Zohara,Borhan, Istiauk	1.prepared a proposal of three topics and its explanation.	Task: All group members	
06.06.24 (11 am -12pm) ATC meeting - 02	Moin,Borhan, Zohara,Istiauk	1.Submitting three tentative project topics . 2.Discuss whether it is acceptable or not.	Task 1:Istiauk,Moin Task 2: Borhan,Zohara	Advised to go on a company tour.
09.06.24 (2pm-3 pm) Group meeting -03	Istiauk, Borhan, Moin	1.Based on finalizing one topic 2.research about project 3. finding problem statements and requirements.	Task1: Istiauk Task 2: borhan Task 3: Moin	Need more discussion on topic selection, engineering problem solution
11.06.24 (4 pm-5pm) Group meeting 04	Zohara Moin Istiauk Borhan	1. Findings specification 2.Findings tentative objectives 3. Proposed Design Approach -01 4. Proposed Design Approach -02	Task 1: Borhan Task 2: Moin Task 3: Zohara Task 4: Istiauk	
13.06.24 (11am-12pm) ATC meeting-03	1.Zunaed Sir 2.Borhan Istiauk rifat Zohara kamal Moin khan	1.need to more specific objectives 2.discussion about design approach 3.Alternative approach	Task1: Moin Task 2: Borhan Task 3: Istiauk,Zohara	to know about design in more detail.
24.06.24 (2.30pm-3.00pm) Group meeting-06	Istiauk Moin khan Zohara Borhan	1. Sort out requirements problems.	Task: All members equally.	
27.06.24 (2pm-2.30pm) ATC meeting-04	1.Dr.Shahidul Islam Khan Sir 2.Zunaed Sir 3.Md.Istiauk Hossain Rifat 4.Zohara Kamal 5.Md.Borhan Uddin Khan 6. Moin Khan	1. Submitting draft concept note 2. need to add Flow chart	Task1: Istiauk Task 2: Borhan,Moin,Zohara	Review of draft concept note, Add block diagram
01.07.24 (11pm-12am) Group meeting-07	Istiauk Moin khan Zohara Borhan	1. preparing progress presentation 2.slide editing	Task1: Istiauk,Moin Task 2: Zohara Task 3: Borhan	

		3. conclusion and applicable standard 4.review editing of presentation slide		
04.07.24 (11am-12pm) ATC meeting -05	2.Zunaed Sir 3.Md.Istiauk Hossain Rifat 4.Zohara Kamal 5.Md.Borhan Uddin Khan 6. Moin Khan	1. Feedback of progress presentation. 2. preparing a concept note report.	Task 2: Moin,Zohara,Istiauk, Borhan	Feedback of progress presentation. need to modify the flow chart and add more information details in the concept note report.
8.07.24 (11.59 pm- 1pm) Group -meeting-08	Zohara,Moin, Borhan,Istiauk	1.To find out specifications rating	Task1: Istiauk, Borhan, Moin,Zohara	
10.07.24 (6.00pm - 7pm) ATC online meeting -06	Zunaed Sir, Zohara, Borhan, Moin, Istiauk	1.Discuss about Design approach 2.Modification of design approaches	Task 2: All members	Advised to find out specifications and requirements rating. Design approaches is ok .Try to find out alternative another design approaches
11.07.24 (7pm- 9pm) Group -meeting-09	Zohara,Moin, Borhan,Istiauk	1. Updating concept note 2.Finalizing budget for design approaches 01 and 02. 3. Discussing system level and component level design 01 and design 01. 4. Submitting final concept note	Task1: Istiauk Task 2: Borhan Task 3: Moin Task 4: Zohara	
12.07.24 (7pm- 9pm) Group -meeting-09	Zohara,Moin, Borhan,Istiauk	1. Simplifying block diagram 2.Overview on constraints	Task1: Istiauk Task 2: borhan,moin,zohara	
13.07.24 (7pm- 9pm) Group -meeting-10	Zohara,Moin, Borhan,Istiauk	1. Creating calendar checklist for each work progress 2. Discuss about upcoming task 3.scheduling a timeline	Task1: Istiauk Task 2: Moin,Zohara Task 3: Borhan	
.02.09.24 (7pm- 9pm) Group -meeting-11	Zohara,Moin, Borhan,Istiauk	1. Brainstorming between group members for due task 2. Initializing a short survey about project 3.Discuss about risk management and impact	Task1: Istiauk Task 2: Borhan Task 3: Moin,Zohara	

04.09.24 (7pm- 9pm) Group -meeting-12	Zohara,Moin, Borhan,Istiauk	1.Working on papers and thesis for more detail in specifications and requirements. 2.Review of group members' tasks and discuss our project work.	Task1: Istiauk,Zohara Task 2: Borhan,Moin	
07.09.24 (7pm- 9pm) Group -meeting-13	Zohara,Moin, Borhan,Istiauk	1.Check our task which is assigned to an individual . 2.Working on impact and safety 3.Analyzing all safety planning and protocols. 4.Project equipment analysis. 5.Discuss on Methodology	Task1: Istiauk Task 2: Borhan Task 3: Moin Task 4:Zohara Task 5: Istiauk	
09.09.24 (8pm- 9pm) Group -meeting-14	Zohara,Moin, Borhan,Istiauk	1. SDG Goals analysis 2.Ethical Consideration 3.Risk management	Task1: Istiauk Task 2: Borhan Task 3: Moin,Zohara	
12.09.24 (7pm- 9pm) Group -meeting-15	Zohara,Moin, Borhan,Istiauk	1. Based on design , fix budget details. 2. Working on expected outcome 3.Discuss the impact on our project and start to do tasks on it.	Task1: Istiauk Task 2: Borhan,Zohara Task 3: Moin	
14.09.24 (7pm- 9pm) Group -meeting-16	Zohara,Moin, Borhan,Istiauk	1.Giving a task on Safety Consideration. 2. Checking all due tasks. 3. Making gantt chart and project timeline 4. Review of design approaches and wait for ATC feedback on Multiple design approaches and specifications	Task1: Istiauk Task 2: Zohara,Moin Task 3: Borhan	
17.09.24 (7pm-8pm) ATC online meeting-02	Zohara,Moin, Borhan,Istiauk	1. Discussed on Design Approaches and wait for ATC's feedback.	Task: All members	Design Approach 1 is good. For Design Approach 2, need to clarify more about NILM. Add some detailed workflow on NILM.
19.09.24 (11pm-12.30am)	Zohara,Moin, Borhan,Istiauk	1. Adding workflow on NILM	Task1: Istiauk	

Group meeting-17		2. Preparation on final presentation	Task 2: borhan,zohara, moin	
21.09.24 (8pm-10pm) Group meeting-17	Zohara,Moin, Borhan,Istiauk	1.Working on presentation slide 2.need to edit background study 3.working on details and researching more about relevance to current industry.	Task1: Istiauk Task 2: Moin Task 3: Zohara,Borhan	
24.09.24 (7pm-8pm) ATC online meeting-03	Zohara,Moin, Borhan,Istiauk	1.Sir giving feedback about final presentation slide	Task: All members	Make a table chart on Risk management and identify all risks regarding low risk to high risk.
27.09.24 (8pm-9pm) group meeting-18	Zohara,Moin, Borhan,Istiauk	1.Make a timeline to fulfill the final report. working on the Final Project proposal report. 2.Adding full details from first part to last part. Modify all tasks. 3.Modifying Background Study, 4.Modifying Problem Statement, Objectives	Task1: Istiauk Task 2: Borhan Task 3: Moin Task 4: Zohara	
03.10.24 (7pm -8pm) Group meeting-19	Zohara,Moin, Borhan,Istiauk	1.Reviewing the final reports again to see if there is a gap somewhere.	Task: All group members.	
06.10.24 (10pm -12am) ATC online meeting-04	Zohara,Moin, Borhan,Istiauk ,Zunaed Sir	1. Showcase of the final proposal report to our ATC	Task: All the Group Members	Gave us instructions to make some changes in the format of report
06.10.24 (10pm -12am) Group meeting-21	Zohara,Moin, Borhan,Istiauk	1. Made necessary changes as per the instructions of ATC panel and submitted the final proposal report.	Task: All the Group Members	

Work summary of EEE499D - Final Year Design Project (D) Fall 2024

Date/Time /Place	Attendee	Summary of Meeting Minutes	Responsible	Comment by ATC
23.10.24 (11.30am -12.00pm) ATC meeting-01	1.Dr.Shahidul Islam Khan 2.Zunaed Rafi 3.Md.Istiauk Hossain Rifat	1. A normal meeting with ATC, Brainstorming what to do in simulation.	No task individually. Just read and go through the software tools.	N/A as it was an introductory meeting of fydp-d

	4.Zohara Kamal 5.Md.Borhan Uddin Khan 6. Moin Khan			
29.10.24 (10 pm - 11pm) Group-meeting -01	Zohara Moin Istiauk Borhan	1.Preparation of software tools selection, 2.Discuss about what we should follow in tools	Task1:Zohara, Borhan, Task 2.Moin, Istiauk	
1.11.24 (11 pm - 12 am) Group-meeting -02	Zohara Moin Istiauk Borhan	1.Proteus circuit making	Task: All group members	
03.11.24 (11 am -12pm) Group meeting - 03	Zohara Moin Istiauk Borhan	1.Sub circuit of proteus. 2.Data collection from proteus.	Task 1:Istiauk,Moin Task 2: Borhan,Zohara	
05.11.24 (2pm-3 pm) Group meeting -04	Zohara Moin Istiauk Borhan	1.Modification of Background study 2.Findings more research paper related to background history in textile industry	Task1: Istiauk Task 2: Borhan Moin	
11.11.24 (4 pm-5pm) Group meeting 05	Zohara Moin Istiauk Borhan	1. Design-01 sub circuit 2.Proposed Design Approach -02 Parent sheet building. 3.proper connection diagram	Task 1: Istiauk,Borhan Task 2: Moin Task 3: Zohara	
12.11.24 (11am-12pm) ATC online meeting-02	Zunaed Rafi Zohara Moin Istiauk Borhan	1.Add DC motor to collect data from this. 2. design approach -01 data collection 3.Alternative approach data collection	Task1: Moin Task 2: Borhan Task 3: Istiauk,Zohara	to know about design in more detail.
14.11.24 (9pm-10pm) Group meeting-06	Zohara Moin Istiauk Borhan	1.Review of some software tools. 2.Use proper tools based on the project. 3.Spyder, coolterm, google colab using for project.	Task1: Istiauk,Zohara Task 2: Borhan Task 3: Moin	
16.11.24 (2.30pm-3.00pm) Group meeting-07	Zohara Moin Istiauk Borhan	1.MATnilm algorithm for implementing ML in project 2.Coding for MATmilm	Task: All members equally.	

19.11.24 (2pm-2.30pm) ATC meeting-03	1.Dr.Shahidul Islam Khan 2.Zunaed Rafi 3.Md.Istiauk Hossain Rifat 4.Zohara Kamal 5.Md.Borhan Uddin Khan 6. Moin Khan	1.Run MATnilm code. 2.Debugging code	Task1: Istiauk Task 2: Borhan,Moin,Zohara	review of NILM code
21.11.24 (11pm-12am) Group meeting-08	Zohara Moin Istiauk Borhan	1. Sustainability goals for our project 2.Selection of goals align with project	Task 1&2: Borhan	
28.11.24 (11am-12pm) ATC meeting -04	1.Saad Mahbub Chowdhury 2.Zunaed Rafi 3.Md.Istiauk Hossain Rifat 4.Zohara Kamal 5.Md.Borhan Uddin Khan 6. Moin Khan	1.Preparation for progress presentation 2.Making slides and adding research info. 3.Add ethics and professional practices for energy consumption. 4.Editing slides	Task 2: Moin,Zohara,Istiauk,Borhan	Feedback of progress presentation.
05.12.24 (3.30-4.00pm) ATC -meeting-05	1.Saad Mahbub Chowdhury 2.Zunaed Rafi 3.Md.Istiauk Hossain Rifat 4.Zohara Kamal 5.Md.Borhan Uddin Khan 6. Moin Khan	1.Giving progress presentation 2.feedback from ATC.	Task1: Istiauk, Borhan, Moin,Zohara	
07.12.24 (6.00pm - 7pm)Group meeting-09	Zohara Moin Istiauk Borhan	1.Debugging for Design--01	Task 1: All members	
09.12.24 (7pm- 9pm) Group -meeting-10	Zohara,moin,borhan,istiauk	1.Analysis of Design -01 and selection to comparison	Task1: Istiauk Borhan Moin, Zohara	
12.12.24 (7pm- 9pm) Group -meeting-11	Zohara Moin Istiauk Borhan	1.Debugging of Design-01	Task1: Istiauk	

13.12.24 (7pm- 9pm) Group -meeting-12	Zohara Moin Istiauk Borhan	1.Analysis of Design -02and selection to comparison	Task1: Istiauk ,Moin,Zohara Borhan	
15.12.24 (7pm- 9pm) Group -meeting-13	Zohara Moin Istiauk Borhan	1.Comparison of Design 01 & 02	Task1: All members.	
17.12.24 (7.30pm- 9pm) Group -meeting-14	Zohara Moin Istiauk Borhan	1.Validation of selected design solution of design -01 and -02	Task1: Istiauk,Zohara Borhan,Moin	
19.12.24 (7pm- 9pm) Group -meeting-15	Zohara Moin Istiauk Borhan	1.Testing phase -01 2.Testing phase-02	Task1: Istiauk Task 2: Istiauk	
21.12.24 (9pm- 10pm) Group -meeting-16	Zohara Moin Istiauk Borhan	1. SDG Goals analysis 2.Background Analysis	Task1: Borhan Task 2: Moin,Zohara	
23.12.24 (8pm- 9pm) Group -meeting-17	Zohara Moin Istiauk Borhan	1.find out REDDx, poolx, off duration pkl file explanation 2.Large number of Data collection using previous method	Task 1&2: Istiauk	
26.12.24 (7pm- 9pm) ATC-meeting-0 6	1.Saad Mahbub Chowdhury 2.Zunaed Rafi 3.Md.Istiauk Hossain Rifat 4.Zohara Kamal 5.Md.Borhan Uddin Khan 6. Moin Khan	1.Training with seed(1), seed(2), 2.Training on custom NILM model	Task1: Istiauk Task 2: Zohara,Moin	need to clarify more about NILM model .
27.12.24 (7pm-8pm) group meeting-18	Zohara Moin Istiauk Borhan	1. Identification of ethical issues.	Task:Moin	
28.12.24 (11pm-12.30am) Group meeting-19	Zohara Moin Istiauk Borhan	1.Professional Responsibilities	Task1:Borhan,Zo hara, Moin	

29.12.24 (8pm-10pm) Group meeting-20	Zohara Moin Istiauk Borhan	1.Comparison of Data od design 01 & design -02	Task1: Istiauk Moin	
30.12.24 (3.00pm-3.30pm) group meeting-21	Zohara Moin Istiauk Borhan	1. Final Result Analysis of design -01 and design -02	Task: All members	
02.01.25 (8pm-9pm) group meeting-22	Zohara Moin Istiauk Borhan	1.Preparation of final presentation and editing slides	Task: All members	
03.01.25 (7pm -8pm) Group meeting-23	Zohara Moin Istiauk Borhan	1.Reviewing the final reports again to see if there is a gap somewhere.	Task: All group members.	
09.1.25 (3.00pm-4.00pm) ATC meeting-07	1.Saad Mahbub Chowdhury 2.Zunaed Rafi 3.Md.Istiauk Hossain Rifat 4.Zohara Kamal 5.Md.Borhan Uddin Khan 6. Moin Khan	Final presentation and review of ATC		
11.01.25 (7pm -8pm) Group meeting-24	Zohara Moin Istiauk Borhan	1.Reviewing the final reports again to see if there is a gap somewhere.	Task: All group members.	
14.01.25 (7pm -8pm) Group meeting-25	Zohara Moin Istiauk Borhan	1.Writing on Final Report and Submission	Task: All group members.	

Work summary of EEE499C - Final Year Design Project (C) Spring 2025

Date/Time /Place	Attendee	Summary of Meeting Minutes	Responsible	Comment by ATC
04.02.25 (11.30am -12.00pm) ATC meeting-01	1.Dr.Shahidul Islam Khan 2.Zunaed Rafi 3.Saad Mahbub Chowdhury 4.Md.Istiauk Hossain Rifat	1. A normal meeting with ATC, Brainstorming what to do in Hardware setup.	No task individually. Just read and go through the software tools.	N/A as it was an introductory meeting of FYDP-C

	5.Zohara Kamal 6.Md.Borhan Uddin Khan 7. Moin Khan			
10.02.25 (10 pm - 11pm) Group-meeting -01	Zohara Moin Istiauk Borhan	1.Preparation of components selection, and how to set up. 2.Discuss about what we should follow in hardware.	Task1:Zohara, Borhan, Task 2.Moin, Istiauk	
16.02.25 (11 pm - 12 am) Group-meeting -02	Zohara Moin Istiauk Borhan	1. Wire connection. 2. How to connect all components with the main power supply.	Task: All group members	
25.02.25 (11 am -12pm) Group meeting - 03	Zohara Moin Istiauk Borhan	1. All components connect with wire. 2.Checking voltage sensors, current sensors whether it is given the right value or wrong value.	Task 1:Istiauk,Moin Task 2: Borhan,Zohara	
01.03.25 (2pm-3 pm) Group meeting -04	Zohara Moin Istiauk Borhan	1.Check ESP8266 Module 2.Connect 4 motors with voltage sensors and current sensors. then check if it is spinning or not.	Task1: Istiauk Task 2: Borhan Moin	
06.03.25 (4 pm-5pm) Group meeting 05	Zohara Moin Istiauk Borhan	1. Making Blynk app 2. Blynk app code modification 3.Connect with google sheet.	Task 1: Istiauk,Borhan Task 2: Moin Task 3: Zohara	
12.11.24 (11am-12pm) ATC online meeting-02	Zunaed Rafi Zohara Moin Istiauk Borhan	1.Running code on Google colab . 2. Code modification 3.Discuss how to store hardware data on google sheet.	Task1: Moin Task 2: Borhan Task 3: Istiauk,Zohara	to know about data store.
18.03.25 (9pm-10pm) Group meeting-06	Zohara Moin Istiauk Borhan	1.Discuss about NILM Model 2.How to train this model 3.How to debugging code	Task1: Istiauk,Zohara Task 2: Borhan Task 3: Moin	
25.03.25 (2.30pm-3.00pm) Group meeting-07	Zohara Moin Istiauk Borhan	1.MATnilm algorithm for implementing ML in project 2.Coding for MATmilm	Task: All members equally.	

31.03.25 (2pm-2.30pm) ATC meeting-03	1.Zunaed Rafi 2.Md.Istiauk Hossain Rifat 3.Zohara Kamal 4.Md.Borhan Uddin Khan 5. Moin Khan	1.Run MATnilm code and check its validity. 2.Debugging code run in google colab.	Task1: Istiauk Task 2: Borhan,Moin,Zohara	review of NILM code
4.4.25 (11pm-12am) Group meeting-08	Zohara Moin Istiauk Borhan	1. Discuss how to deploy NILM Code. 2.How to store it on the server.	Task 1&2: Istiauk	
9.04.25 (11am-12pm) ATC meeting -04	1.Saad Mahbub Chowdhury 2.Zunaed Rafi 3.Md.Istiauk Hossain Rifat 4.Zohara Kamal 5.Md.Borhan Uddin Khan 6. Moin Khan	1.Check ESP8266 . 2.Modify esp code . 3.Modify microcontroller code 4.Collect data from hardware set up.	Task : Moin,Zohara,Istiauk,Borhan	Feedback of codes.
12.04.25 (3.30-4.00pm) Group meeting-08	Zohara Moin Istiauk Borhan	1.Need to modification esp code as facing some time delay 2.Time delay around 5-6s. So, Need to modify the calibration.	Task 1: Istiauk, Borhan, Task2: Moin,Zohara	
15.04.25 (6.00pm - 7pm)Group meeting-09	Zohara Moin Istiauk Borhan	1.Faced challenges for latency. Around takes 5s to transfer data from the microcontroller to esp8266. So we need to check what's the problem behind this. 2. Find out the problem of latency issues.	Task 1: Istiauk,Moin Task 2: Borhan	
17.04.25 (7pm- 9pm) ATC-meeting-06	1.Dr.Shahidul Islam Khan 2.Zunaed Rafi 3.Saad Mahbub Chowdhury 4.Md.Istiauk Hossain Rifat 5.Zohara Kamal 6.Md.Borhan Uddin Khan 7. Moin Khan	1.Showing the hardware set up. 2. ATC gives feedback about progress about our hardware set up.	Task: Istiauk Borhan Moin, Zohara	Add some load like light. need to increase load power and latency. also increase accuracy.

23.04.25 (7pm- 9pm) Group -meeting-11	Zohara Moin Istiauk Borhan	1.Data collection and store in google sheet. 2.Testing latency issues. 3.Testing accuracy issues.	Task1: Istiauk Task 2: Borhan Task 3: Moin, Zohara.	
27.04.25 (7pm- 9pm) Group -meeting-12	Zohara Moin Istiauk Borhan	1.Changing esp8266 and microcontroller wire connection. modifying serial communication, improving baud rate , and minimizing delay function.	Task1: Istiauk ,Moin,Zohara Borhan	
30.04.25 (7pm- 9pm) Group -meeting-13	Zohara Moin Istiauk Borhan	1.Double check on serial pins (TX and RX) . 2. Debugging and testing serial monitor, small data and using interrupts to handle incoming serial data on the microcontroller. 3. Use Serial.begin() and Serial.available() to increase serial communication for latency.	Task1: All members.	
3.05.25 (7.30pm- 9pm) Group -meeting-14	Zohara Moin Istiauk Borhan	1.Checking web page interface. 2.Final Hardware setup.	Task1: Istiauk,Zohara Borhan,Moin	
6.05.25 (7pm- 9pm) Group -meeting-15	Zohara Moin Istiauk Borhan	1.Preparing Final Report 2.Formating report following guidelines.	Task1: Istiauk Task 2: Istiauk	
8.05.25 (9pm- 10pm) Group -meeting-16	Zohara Moin Istiauk Borhan	1. Attach each team member's work.	Task1: Borhan Task 2: Moin,Zohara	
12.05.25 (8pm- 9pm) Group -meeting-17	Zohara Moin Istiauk Borhan	1.Add logbook into final report. 2.Preparing Poster for final showcase.	Task 1&2: Borhan	
14.05.25 (8pm- 9pm) ATC-meeting-06	1.Saad Mahbub Chowdhury 2.Zunaed Rafi 3.Md.Istiauk Hossain Rifat 4.Zohara Kamal	1.Showing the final report if it is right formating or not. 2. Advice how to show projects . How to structure hardware setup.	Task: All members.	Give instructions on how to structure the project .

	5.Md.Borhan Uddin Khan 6. Moin Khan			

Related Codes:

Arduino Mega 2560 Code

```
#include "EmonLib.h"

#include <LiquidCrystal_I2C.h>

#define voltage_s1    A0

#define current_s1    A1

#define voltage_s2    A2

#define current_s2    A3

#define voltage_s3    A4

#define current_s3    A5

#define voltage_s4    A6

#define current_s4    A7

#define voltage_s5    A8

#define current_s5    A9

EnergyMonitor emon1;

EnergyMonitor emon2;

EnergyMonitor emon3;

EnergyMonitor emon4;

EnergyMonitor emon5;

float base_current_s1 = 0.0;

bool base_current_set = false;

LiquidCrystal_I2C lcd(0x27, 20, 4);

int roll = 0;
```

```
void setup()
{
  lcd.init();
  lcd.backlight();
  Serial.begin(9600);
  emon1.voltage(voltage_s1, 610.50, 1.7);  // Voltage: input pin, calibration, phase_shift
  emon1.current(current_s1, 0.73);       // Current: input pin, calibration.
  emon2.voltage(voltage_s2, 628.50, 1.7);
  emon2.current(current_s2, 0.73);
  emon3.voltage(voltage_s3, 625.50, 1.7);
  emon3.current(current_s3, 0.73);
  emon4.voltage(voltage_s4, 674.50, 1.7);
  emon4.current(current_s4, 0.73);
  emon5.voltage(voltage_s5, 612.50, 1.7);
  emon5.current(current_s5, 0.73);
}
void loop()
{
  emon1.calcVI(20, 2000);
  emon2.calcVI(20, 2000);
  emon3.calcVI(20, 2000);
  emon4.calcVI(20, 2000);
  emon5.calcVI(20, 2000);
  float supplyVoltage1   = emon1.Vrms;
  float Irms1            = emon1.Irms;
  float realPower1       = emon1.realPower;
  if (supplyVoltage1 < 150) {
    supplyVoltage1 = 0;
  }
```

```
if (Irms1 < 0.05) {
  Irms1 = 0;
}
if (Irms1 == 0 || supplyVoltage1 == 0) {
  realPower1 = 0;
}
float realPower2       = emon2.realPower;
float supplyVoltage2   = emon2.Vrms;
float Irms2            = emon2.Irms;
if (supplyVoltage2 < 150) {
  supplyVoltage2 = 0;
}
if (Irms2 < 0.05) {
  Irms2 = 0;
}
if (Irms2 == 0 || supplyVoltage2 == 0) {
  realPower2 = 0;
}
float realPower3       = emon3.realPower;
float supplyVoltage3   = emon3.Vrms;
float Irms3            = emon3.Irms;
 if (supplyVoltage3 > 100) {
  supplyVoltage3 = supplyVoltage1-0.7;
}
if (supplyVoltage3 < 150) {
  supplyVoltage3 = 0;
}
if (Irms3 < 0.05) {
  Irms3 = 0;
```

```
}
if (Irms3 == 0 || supplyVoltage3 == 0) {
  realPower3 = 0;
}
float realPower4       = emon4.realPower;
float supplyVoltage4   = emon4.Vrms;
float Irms4            = emon4.Irms;
if (supplyVoltage4 < 150) {
  supplyVoltage4 = 0;
}
if (Irms4 < 0.05) {
  Irms4 = 0;
}
if (Irms4 == 0 || supplyVoltage4 == 0) {
  realPower4 = 0;
}
float realPower5       = emon5.realPower;
float supplyVoltage5   = emon5.Vrms;
float Irms5            = emon5.Irms;
if (supplyVoltage5 < 150) {
  supplyVoltage5 = 0;
}
if (Irms5 < 0.05) {
  Irms5 = 0;
}
if (Irms5 == 0 || supplyVoltage5 == 0) {
  realPower5 = 0;
}
if (!base_current_set && Irms2 == 0 && Irms3 == 0 && Irms4 == 0 && Irms5 == 0) {
```

```
  base_current_s1 = Irms1;
  base_current_set = true;
}
if (Irms2 > 0 ||Irms3 > 0 || Irms4  > 0 || Irms5  > 0) {
  Irms1  = base_current_s1 + Irms2  + Irms3  + Irms4  + Irms5 ;
}
realPower1= supplyVoltage1*Irms1;
String status;
lcd.clear();
lcd.setCursor(0, 0);
if (realPower1 > 200) {
  lcd.print("Over Load....");
  status = "Over_Load";
}
else if (Irms1 == 0 && supplyVoltage1 == 0) {
  lcd.print("No Power....");
  status = "No_Power";
}
else if (Irms1 > 0.20) {
  lcd.print("Now Normal....");
  status = "Now_Normal";
}
else {
  lcd.print("No Load....");
  status = "No_Load";
}
if (roll == 0) {
  roll = 1;
  lcd.setCursor(18, 0);
```

```
  lcd.print("M ");
  lcd.setCursor(0, 1);
  lcd.print("Voltage :");
  lcd.print(supplyVoltage1);
  lcd.print("V  ");
  lcd.setCursor(0, 2);
  lcd.print("Current :");
  lcd.print(Irms1);
  lcd.print("A  ");
  lcd.setCursor(0, 3);
  lcd.print("Power   :");
  lcd.print(realPower1);
  lcd.print("W  ");
}
else if (roll == 1) {
  roll = 2;
  lcd.setCursor(18, 0);
  lcd.print("L1");
  lcd.setCursor(0, 1);
  lcd.print("Voltage1 :");
  lcd.print(supplyVoltage2);
  lcd.print("V  ");
  lcd.setCursor(0, 2);
  lcd.print("Current1 :");
  lcd.print(Irms2);
  lcd.print("A  ");
  lcd.setCursor(0, 3);
  lcd.print("Power1   :");
  lcd.print(realPower2);
```

```
  lcd.print("W  ");
}
else if (roll == 2) {
  roll = 3;
  lcd.setCursor(18, 0);
  lcd.print("L2");
  lcd.setCursor(0, 1);
  lcd.print("Voltage2 :");
  lcd.print(supplyVoltage3);
  lcd.print("V  ");
  lcd.setCursor(0, 2);
  lcd.print("Current2 :");
  lcd.print(Irms3);
  lcd.print("A  ");
  lcd.setCursor(0, 3);
  lcd.print("Power2   :");
  lcd.print(realPower3);
  lcd.print("W  ");
}
else if (roll == 3) {
  roll = 4;
  lcd.setCursor(18, 0);
  lcd.print("L3");
  lcd.setCursor(0, 1);
  lcd.print("Voltage3 :");
  lcd.print(supplyVoltage4);
  lcd.print("V  ");
  lcd.setCursor(0, 2);
  lcd.print("Current3 :");
```

```
  lcd.print(Irms4);
  lcd.print("A  ");
  lcd.setCursor(0, 3);
  lcd.print("Power3   :");
  lcd.print(realPower4);
  lcd.print("W  ");
 }
 else if (roll == 4) {
  roll = 0;
  lcd.setCursor(18, 0);
  lcd.print("L4");
  lcd.setCursor(0, 1);
  lcd.print("Voltage4 :");
  lcd.print(supplyVoltage5);
  lcd.print("V  ");
  lcd.setCursor(0, 2);
  lcd.print("Current4 :");
  lcd.print(Irms5);
  lcd.print("A  ");
  lcd.setCursor(0, 3);
  lcd.print("Power4   :");
  lcd.print(realPower5);
  lcd.print("W  ");
 }
 String sms = "#" + String(supplyVoltage1) + "@"  + String(Irms1) + "@"  + 
String(realPower1) + "@"
            + String(supplyVoltage2) + "@"  + String(Irms2) + "@"  + String(realPower2) + 
"@"
            + String(supplyVoltage3) + "@"  + String(Irms3) + "@"  + String(realPower3) + 
"@"
```

```
            + String(supplyVoltage4) + "@"  + String(Irms4) + "@"  + String(realPower4) +
"@"
            + String(supplyVoltage5) + "@"  + String(Irms5) + "@"  + String(realPower5) +
"@" + status + "*";
  if (roll == 0) {
    Serial.println(sms);
    Serial1.println(sms);
  }
}
```

ESP8266 Code:

```
#define BLYNK_TEMPLATE_ID     "TMPL6U9M5NA0C"
#define BLYNK_TEMPLATE_NAME   "IoT Project"
#define BLYNK_AUTH_TOKEN      "8o2kBVLbwxG2X5YgiogLTpOVmFHQIu8I"
#define BLYNK_PRINT Serial
#include <WiFiManager.h>
#ifdef ESP8266
#include <BlynkSimpleEsp8266.h>
#elif defined(ESP32)
#include <BlynkSimpleEsp32.h>
#else
#error "Board not found"
#endif
#include <WiFiClientSecure.h>
String readString;
const char* host = "script.google.com";
const int httpsPort = 443;
WiFiClientSecure client;
```

```
String GAS_ID =
"AKfycbwIlT6LBMzqmXmddBBzmGpvCsBle2fiq5I8M0cVY160fC-_H877u-ChHXVdQS
UVKTozIQ";

char* esp_ssid = "IoT Project";

char* esp_pass = "1234567890";

//Variables

char auth_token[] = BLYNK_AUTH_TOKEN;

String smss, sms, sms1, sms2, sms3, sms4, sms5, sms6, sms7, sms8, sms9, sms10, sms11,
sms12, sms13, sms14, sms15, sms16;

int temp = 0, n = 0, k = 0, asd = 0;

int jj1 = 0, jj2 = 0, jj3 = 0, jj4 = 0, jj5 = 0, jj6 = 0, jj7 = 0, jj8 = 0, jj9 = 0, jj10 = 0, jj11 = 0,
jj12 = 0, jj13 = 0, jj14 = 0, jj15 = 0, jj16 = 0;

char str[700], msg[700];

const int Erasing_button = 0;

void configModeCallback (WiFiManager *myWiFiManager) {

  Serial.println(WiFi.softAPIP());

  Serial.println(myWiFiManager->getConfigPortalSSID());

}

void setup() {

  Serial.begin(9600);

  pinMode(Erasing_button, INPUT);

  pinMode(D5, INPUT);

  pinMode(D4, OUTPUT);

  for (uint8_t t = 4; t > 0; t--) {

    digitalWrite(D4, LOW);

    delay(500);

    Serial.println(t);

    digitalWrite(D4, HIGH);

    delay(500);

  }

  // Press and hold the button to erase all the credentials
```

```
  if (digitalRead(Erasing_button) == LOW)
  {
    WiFiManager wifiManager;
    wifiManager.resetSettings();
    ESP.restart();
    delay(1000);
  }
  WiFiManager wifiManager;
  wifiManager.setAPCallback(configModeCallback);
  if (!wifiManager.autoConnect(esp_ssid, esp_pass)) {
    Serial.println("failed to connect and hit timeout");
    ESP.restart();
    delay(1000);
  }
  Serial.println("connected...yeey :)");
  digitalWrite(D4, LOW);
  client.setInsecure();
  Blynk.config(auth_token);
}
void loop() {
  serialEvent();
  Blynk.run();
}
void serialEvent()
{
  while (Serial.available())
  {
    char ch = (char)Serial.read();
    str[n++] = ch;
```

```
  if (ch == '*')
  {
    temp = 1;
    break;
  }
}
if (temp == 1)
{
  for (int i = 0; i < n; i++) {
    if (str[i] == '#') {
      jj1 = i;
    }
    if (str[i] == '@') {
      if (asd == 0) {
        jj2 = i;
        asd++;
      }
      else if (asd == 1) {
        jj3 = i;
        asd++;
      }
      else if (asd == 2) {
        jj4 = i;
        asd++;
      }
      else if (asd == 3) {
        jj5 = i;
        asd++;
      }
```

```
else if (asd == 4) {
 jj6 = i;
 asd++;
}
else if (asd == 5) {
 jj7 = i;
 asd++;
}
else if (asd == 6) {
 jj8 = i;
 asd++;
}
else if (asd == 7) {
 jj9 = i;
 asd++;
}
else if (asd == 8) {
 jj10 = i;
 asd++;
}
else if (asd == 9) {
 jj11 = i;
 asd++;
}
else if (asd == 10) {
 jj12 = i;
 asd++;
}
else if (asd == 11) {
```

```
      jj13 = i;
      asd++;
    }
    else if (asd == 12) {
      jj14 = i;
      asd++;
    }
    else if (asd == 13) {
      jj15 = i;
      asd++;
    }
    else if (asd == 14) {
      jj16 = i;
      asd++;
    }
  }
  if (str[i] == '*')
  {
    k = i;
    break;
  }
}
int l = 0;
sms = String(str);
sms1 = sms.substring(jj1 + 1, jj2);
sms2 = sms.substring(jj2 + 1, jj3);
sms3 = sms.substring(jj3 + 1, jj4);
sms4 = sms.substring(jj4 + 1, jj5);
sms5 = sms.substring(jj5 + 1, jj6);
```

```
sms6 = sms.substring(jj6 + 1, jj7);
sms7 = sms.substring(jj7 + 1, jj8);
sms8 = sms.substring(jj8 + 1, jj9);
sms9 = sms.substring(jj9 + 1, jj10);
sms10 = sms.substring(jj10 + 1, jj11);
sms11 = sms.substring(jj11 + 1, jj12);
sms12 = sms.substring(jj12 + 1, jj13);
sms13 = sms.substring(jj13 + 1, jj14);
sms14 = sms.substring(jj14 + 1, jj15);
sms15 = sms.substring(jj15 + 1, jj16);
sms16 = sms.substring(jj16 + 1, k);
temp = 0;
n = 0;
asd = 0;
Serial.print(sms1);
Serial.print("\t");
Serial.print(sms2);
Serial.print("\t");
Serial.print(sms3);
Serial.print("\t");
Serial.print(sms4);
Serial.print("\t");
Serial.print(sms5);
Serial.print("\t");
Serial.print(sms6);
Serial.print("\t");
Serial.print(sms7);
Serial.print("\t");
Serial.print(sms8);
```

```
Serial.print("\t");
Serial.print(sms9);
Serial.print("\t");
Serial.print(sms10);
Serial.print("\t");
Serial.print(sms11);
Serial.print("\t");
Serial.print(sms12);
Serial.print("\t");
Serial.print(sms13);
Serial.print("\t");
Serial.print(sms14);
Serial.print("\t");
Serial.print(sms15);
Serial.print("\t");
Serial.print(sms16);
Serial.println();
int datablynk = digitalRead(D5);
if (datablynk == 1) {
  Blynk.virtualWrite(V0, sms1);
  Blynk.virtualWrite(V1, sms2);
  Blynk.virtualWrite(V2, sms3);
  Blynk.virtualWrite(V3, sms4);
  Blynk.virtualWrite(V4, sms5);
  Blynk.virtualWrite(V5, sms6);
  Blynk.virtualWrite(V6, sms7);
  Blynk.virtualWrite(V7, sms8);
  Blynk.virtualWrite(V8, sms9);
  Blynk.virtualWrite(V9, sms10);
```

```
      Blynk.virtualWrite(V10, sms11);
      Blynk.virtualWrite(V11, sms12);
      Blynk.virtualWrite(V12, sms13);
      Blynk.virtualWrite(V13, sms14);
      Blynk.virtualWrite(V14, sms15);
      Blynk.virtualWrite(V15, sms16);
    }
    writing();
  }
}
void writing() {
  Serial.print("connecting to ");
  Serial.println(host);
  if (!client.connect(host, httpsPort)) {
    Serial.println("connection failed");
    return;
  }
  String url = "/macros/s/" + GAS_ID + "/exec?value1=" + sms1 + "&value2=" + sms2 +
"&value3=" + sms3 + "&value4=" + sms4 + "&value5=" + sms5 + "&value6=" + sms6 +
"&value7=" + sms7 + "&value8=" + sms8 + "&value9=" + sms9 + "&value10=" + sms10 +
"&value11=" + sms11 + "&value12=" + sms12 + "&value13=" + sms13 + "&value14=" +
sms14 + "&value15=" + sms15 + "&value16=" + sms16;
  Serial.print("requesting URL: ");
  Serial.println(url);
  client.print(String("GET ") + url + " HTTP/1.1\r\n" +
               "Host: " + host + "\r\n" +
               "User-Agent: BuildFailureDetectorESP8266\r\n" +
               "Connection: close\r\n\r\n");
  Serial.println("request sent");
  while (client.connected()) {
    String line = client.readStringUntil('\n');
```

```
    if (line == "\r") {
      Serial.println("headers received");
      break;
    }
  }
  String line = client.readStringUntil('\n');
  if (line.startsWith("{\"state\":\"success\"")) {
    Serial.println("esp8266/Arduino CI successfull!");
  } else {
    Serial.println("esp8266/Arduino CI has failed");
  }
  Serial.println("reply was:");
  Serial.println("==========");
  Serial.println(line);
  Serial.println("==========");
  Serial.println("closing connection");
  client.stop();
}
```