Non-Intrusive Load Monitoring System

Group Members

Muhammad Akmal	(2019-EE-510)
Sharjeel Munawar	(2019-EE-511)
Syed Sameer Hussain	(2019-EE-529)

Supervised by

Dr. Haroon Farooq

Department of Electrical Engineering (RCET)

University of Engineering and Technology Lahore

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Dr. Haroon Farooq

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Department of Electrical Engineering

Rachna College of Engineering and Technology (RCET) Gujranwala

University of Engineering and Technology Lahore

Non-Intrusive Load Monitoring System

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Supervisor **External Examiner**

____

Chairman

Electrical Engineering Department

(RCET)

Department of Electrical Engineering

Rachna College of Engineering and Technology (RCET) Gujranwala

University of Engineering and Technology Lahore

Declaration

We Hereby Declare That This Project Report Entitled “NON-INTRUSIVE LOAD MONITORING SYSTEM” submitted to the “Department of Electrical Engineering (RCET)”, is a record of an original work done by us under the guidance of Supervisor “DR. HAROON FAROOQ” and that no part has been plagiarized without citations. Also, this project work is submitted in the partial fulfillment of the requirements for the degree of Bachelor of Science in Electrical Engineering.

Group Members	Signature	Date
Muhammad Akmal		
Sharjeel Munawar		
Syed Sameer Hussain		

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Muhammad Akmal

Sharjeel Munawar

Syed Sameer Hussain

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List of Abbreviations

AC	Alternating Current
AI	Artificial Intelligence
CT	Current Transformer
DAQ	Data Acquisition
DSM	Demand Side Management
GUI	Graphical User Interface
HEMS	Home Energy Management System
ILM	Intrusive Load Monitoring
KNN	K Nearest Neighbors
ML	Machine Learning
NI	National Instruments
NILM	Non-Intrusive Load Monitoring
PT	Potential Transformer
RMS	Root Mean Square
THD	Total Harmonic Distortion
UN	United Nations

Abstract

It is now challenging to identify a location without access to power due to the substantial rise in global electricity use over the past few decades. Load shedding is used to control demand response during peak hours in places where electricity output falls short of the necessary threshold. In every energy management system, load monitoring is essential to ensuring efficient control of demand response in line with power generation. However, the most popular load monitoring techniques, intrusive load monitoring (ILM) and home energy management system (HEMS), have drawbacks like the need to install sensors for each load, which is not cost-effective, and the fact that they monitor the system as a whole rather than at the appliance level. Monitoring every device in a system is crucial to improving load management and overcoming the difficulties of load shedding and demand-side management. Non-intrusive load monitoring (NILM) technology, which is easy to install and doesn't require a different sensor for each load, can be used to do this. NILM allows load observation from a point beyond the user's zone, as its name implies. The project involved utilizing the NI USB 6008 to gather electrical data from appliances such as bulb, laptop, adapter, and fan, with the goal of identifying them through the analysis of their distinct signatures, which were based on electrical properties like Total Harmonic Distortion, Displacement Power Factor, True Power Factor, and True Power. Real-time data was processed using machine learning algorithm for identification of appliances in use, ultimately optimizing energy usage through Demand Side Management (DSM) strategies. A key advantage of NILM was its cost-effectiveness, as it required only a single set of sensors. Appliances were examined based on their on/off patterns to differentiate their energy consumption behaviors. During peak hours, DSM measures were implemented, including the use of LED bulbs, setting laptops to power-saving mode, and reducing fan speeds, all aimed at conserving energy. NILM's potential extended to predicting billing patterns and notifying users of instances of excessive power consumption.

Chapter 1

Introduction

Electricity, a significant form of energy, has played a crucial role in urban areas for several decades. Its introduction initially caused unrest among the public [1]. However, the development of transformers revolutionized the power system design, allowing for the quiet production of energy outside urban regions [2], [3]. This shift minimized disturbances while still incurring expenses for maintenance, production, and personnel wages. To ensure accurate billing and provide customers with insight into their electricity consumption, meters have become an indispensable component of the power distribution process [4].

In the modern industrial era, energy consumption is rapidly increasing. Meeting this demand often requires measures such as increasing power generation, extending transmission lines, adding grids and feeders, and augmenting the workforce [5]. However, effective load control techniques can help mitigate excessive demand, potentially avoiding the need for these measures [6], [7].

Monitoring the power networks for sudden fluctuations and harmonics has become crucial, even in residential areas, due to the proliferation of active and non-linear loads stemming from advancements in power electronics [8]. These loads adversely impact system efficiency, increase losses, and degrade power quality. Controlling harmonics by measuring the Total Harmonic Distortion (THD) of each appliance and imposing fines for excessive usage of non-linear loads in residential areas can help address these issues [9], [10].

Non-intrusive load monitoring (NILM) has gained prominence as a more efficient and cost-effective method for load monitoring in smart homes. In the past, Intrusive Load Monitoring (ILM) was commonly used, necessitating the installation of voltage and current sensors at each load point, enabling homeowners to manage and monitor their electricity consumption. However, this approach raised privacy concerns as it intruded into the building's loads. NILM technology has revolutionized load monitoring by introducing a more discreet approach. It only requires a single set of sensors to be installed at the primary electrical entry point, eliminating the need for intrusive installations at individual load points. This non-intrusive setup preserves the privacy of residents while still providing valuable insights into energy consumption patterns [11], [12].

In the context of Home Energy Management Systems (HEMS), NILM plays a pivotal role in optimizing energy consumption. HEMS integrates various smart devices and appliances within a home to achieve better energy efficiency and cost savings. By incorporating NILM into HEMS, homeowners can access real-time and historical data about their energy usage, enabling them to make informed decisions to reduce energy waste and optimize their electricity consumption. Overall, NILM, coupled with HEMS, represents a powerful and sustainable solution for load monitoring and energy management in smart homes. It empowers homeowners to take control of their energy consumption, leading to reduced energy bills, lower environmental impact, and a more efficient use of electrical resources [13].

Energy supply providers may monitor non-linear loads and record the demand response from each load by permitting bidirectional communication. This enables them to manage their energy supply more effectively and modify their tactics to suit the demands of their clients [14].

Effective energy management is crucial to preventing the depletion of essential natural resources like coal, water, and other fossil fuels while also meeting the world’s growing energy needs. Its importance cannot be emphasized. Imports may be decreased, exports can be raised, and the economy of a nation can be enhanced through minimizing energy waste and increasing effective use of resources on small to big sizes. Additionally, this will lessen air pollution brought on by excessive energy production [15].

Engineers and scientists have benefited greatly from the developments in artificial intelligence and machine learning, which have facilitated research and advanced technological development. Consumer AI devices have made home automation convenient, and when combined with appliances, they greatly simplify cleaning and household upkeep.

Machine Learning (ML) is becoming more widely used as a result of the proliferation of smartphones and the development of sensor, data transfer, and data storage technologies. ML, which is categorized under Artificial Intelligence (AI), makes use of statistical methods to help computers learn from acquired data. As a result, this increase in resources has made it possible to conduct more thorough studies, which has increased the precision of predictions and projections [16].

1.1 Motivation

The world's population is expanding quickly, which is driving up demand for power. Sadly, the resources needed to generate electric energy are running out at an alarming rate and may soon become extinct. The fact that heavy machinery-using companies require a lot of power just makes the situation worse. In light of this, it is crucial to both create new strategies for producing power on a bigger scale and to promote consumer energy efficiency.

Researchers have created a brand-new idea called NILM to control demand side efficiently. Electricity companies may efficiently monitor their customers' patterns of energy usage with this method, even down to the level of individual appliances. The NILM system is a more advanced, efficient, and cost-effective alternative to prior monitoring systems like ILM and HEMS. It allows for more thorough daily or even hourly monitoring of energy use with very little cost.

Unlike the ILM system, which requires specialized sensors to be installed for each load, NILM enables the monitoring of every device in a building or home. Researchers have become interested in further developing this method as a result.

Both in home and commercial settings, smart meters that use the ILM approach are gaining popularity. However, in order to monitor and automate each appliance, this calls for numerous pairs of sensors. The use of NILM technology in smart meters, which can monitor a whole building with only one set of sensors, is a more efficient choice for monitoring buildings while respecting user privacy.

Modern ML technologies have the benefit of high processing capacity, which makes it possible to automate decision-making and build expert systems. These systems can effectively make complicated judgements, with the main expenditure being the time needed for data collection, error eradication, and algorithm assessment to choose the best one. ML technologies may be used to automate and optimize decision-making due to the ease of access to processing capacity, even on a temporary basis, and the general familiarity with popular techniques [17].

1.2 Problem Statement

The creation of effective energy monitoring systems is necessary given the rising global demand for energy, the rising price of electricity, and the necessity for sustainable resource management.

The current methods of production are not enough to keep up with the rising demand for energy, especially electric power, due to the expanding global population and the depletion of fossil resources. The International Electro-Technical Commission (IEC) emphasizes the necessity of utilizing electricity wisely and economically as the fundamental remedy to the present energy crisis to address this issue [18].

By delivering real-time energy consumption analysis and appliance detection without the requirement for intrusive hardware installations, NILM systems present a possible option. The precise disaggregation of aggregated energy data, reliable appliance identification, and managing the dynamic nature of appliance usage patterns are some of the issues that still plague the field of NILM. These difficulties obstruct the general deployment of NILM systems and necessitate additional study and invention to improve their precision, dependability, and usability. The requirement for an improved NILM system that takes on these problems by utilizing cutting-edge methods like machine learning, signal processing, and data analytics to optimize energy use, enabling exact appliance-level energy monitoring, and provide users with useful information for efficient energy management. This project aims to create and assess such a non-intrusive load monitoring system, advancing energy monitoring technologies and laying the foundation for a future that is sustainable and energy-efficient.

1.3 Objectives

The objectives of our project are as under:

- Development of hardware module to be utilized to log the current, voltage, power factor and harmonic distortion profile of the consumers.
- Development of a machine learning based algorithm to analyze the current signature to identify the appliance being used by the consumer.
- Utilizing the results to develop demand side management algorithm to optimize the energy usage to achieve sustainable development goals set forth by UN.

1.4 Chapter Outline

This thesis is divided into five chapters from introduction to conclusion of this work. After the introduction (Chapter 1), the review of literature work and prior work on non-intrusive load monitoring is included in Chapter 2. Methodology and design are elaborated in Chapter 3. Results and different parameters are discussed in Chapter 4 followed by Chapter 5 which will cover conclusions and future work.

Chapter 2

Literature Review

A type of energy called electrical energy results from the motion of charged particles in an electrical circuit. Because it indicates the amount of energy that can be released or changed when a charged particle is moved or an electrical circuit is finished, this sort of energy is referred to as potential energy [19].

Calculating electrical energy uses the following formula [20]:

$$E = P * t \tag{2.1}$$

Where,

P = Power in watts (W)

E = Electrical energy in joules (J)

t = Time in seconds (s)

This calculation makes the assumption that the power stays constant during time t. Calculus may be used to integrate the power over time to calculate the electrical energy, but, if the power swings over time.

Lighting, heating, and the powering of technological equipment are just a few examples of the many uses for electricity. It may be produced using many different types of energy, including renewable energy sources like wind and solar power as well as non-renewable energy sources like fossil fuels and nuclear power. The effective and sustainable use of electrical energy depends on the management and control of its production, distribution, and consumption.

2.1 Components of AC Power

AC (alternating current) power consists of two main components:

- Voltage.
- Current.

Three different forms of power result from the combination of the voltage and current components of AC electricity:

- Real or Active power.
- Reactive power.
- Apparent power.

2.1.1 Active Power

Active power, also known as real power, is the power that is really consumed by a load or produced by a generator in an AC circuit and converted into useful work like mechanical motion, heat, or light. The letter P stands for active power, which is expressed in watts (W), kilowatts (kW), or megawatts (MW) [21].

In a single-phase AC circuit, active power is calculated using the following formula [20]:

$$P = V_{rms} * I_{rms} * \cos(\theta) \tag{2.2}$$

Where,

P = Active power in watts (W), kilowatts (kW), or megawatts (MW)

V_{rms} = RMS voltage in volts (V)

I_{rms} = RMS current in amperes (A)

$\cos(\theta)$ = Power factor of the circuit

In a three-phase AC circuit, active power is calculated using the following formula [20]:

$$P = \sqrt{3} * V_{L-L} * I_{L-L} * \cos(\theta) \tag{2.3}$$

Where,

P = Active power in watts (W), kilowatts (kW), or megawatts (MW)

V_{L-L} = Line to Line voltage in volts (V)

I_{L-L} = Line to Line current in amperes (A)

$\cos(\theta)$ = Power factor of the circuit

Since active power reflects the actual work being done by the circuit, it is an important consideration when designing and analyzing AC circuits. A circuit's power factor is also important since it affects the circuit's effectiveness and overall performance. Low power factors imply energy waste, whereas high power factors show effective use of the given power.

2.1.2 Reactive Power

The power in an AC circuit known as reactive power, is the power that is required to create and maintain the magnetic and electric fields in the circuit but does not contribute to the beneficial work that the circuit does. Reactive power is denoted by the letter Q and is measured in volt-amperes reactive (VAR), kilovolt-amperes reactive (kVAR), or megavolt-amperes reactive (MVAR) [21].

In a single-phase AC circuit, imaginary power is calculated using the following formula [20]:

$$Q = V_{rms} * I_{rms} * \sin(\theta) \qquad (2.4)$$

Where,

Q = Imaginary power in VAR, kVAR, or MVAR

V_{rms} = RMS voltage in volts (V)

I_{rms} = RMS current in amperes (A)

$\sin(\theta)$ = Reactive power angle

In a three-phase AC circuit, active power is calculated using the following formula [20]:

$$Q = \sqrt{3} * V_{L-L} * I_{L-L} * \sin(\theta) \qquad (2.5)$$

Where,

Q = Imaginary power in VAR, kVAR, or MVAR

V_{L-L} = Line to Line voltage in volts (V)

I_{L-L} = Line to Line current in amperes (A)

$\sin(\theta)$ = Reactive power angle

A key consideration in the design and analysis of AC circuits is imaginary power since it affects the effectiveness and performance of the circuit. Low levels of imaginary power indicate effective use of the circuit's available power, whereas high levels suggest poor use.

2.1.3 Apparent Power

The AC circuit's entire power, including reactive and real power, is denoted by the letter S, which stands for apparent power. Volt-amperes (VA), kilovolt-amperes (kVA), and megavolt-amperes (MVA) are used to measure it [21].

In a single-phase AC circuit, apparent power is calculated using the following formula [20]:

$$S = V_{rms} * I_{rms} \tag{2.6}$$

Where,

S = Apparent power in VA, kVA, or MVA

V_{rms} = RMS voltage in volts (V)

I_{rms} = RMS current in amperes (A)

In a three-phase AC circuit, imaginary power is calculated using the following formula [20]:

$$S = \sqrt{3} * V_{rms} * I_{rms} \tag{2.7}$$

Where,

S = Apparent power in VA, kVA, or MVA

V_{rms} = RMS voltage in volts (V)

I_{rms} = RMS current in amperes (A)

Since it dictates the size of the components needed to handle power inside the circuit, such as transmission lines, transformers, and generators, apparent power is crucial in the design and analysis of AC circuits. It is advantageous to calculate the power factor because it shows how well a circuit converts electrical power into productive work. The ratio of real power to apparent power is used to calculate the power factor.

2.2 Harmonics

A harmonic is a wave or signal whose frequency is integer multiple of fundamental frequency. An increase in non-linear loads brought on by the development of power electronics technology results in a current waveform that deviates from sinusoidal shape and contains harmonics [22]. The following are a few examples of non-linear loads that generate harmonics:

- Motors.
- Computers.
- Fluorescent lighting.
- Compressed air systems.

2.2.1 Total Harmonic Distortion (THD)

A metric called THD measures how much harmonic distortion is present in a signal or system. It is calculated by dividing the RMS value of the harmonic components of the signal or system by the RMS value of the fundamental frequency [23].

THD is frequently used in power systems to gauge the caliber of the power supply. A high THD value can destroy equipment and result in energy waste and power quality issues. THD is a statistic that measures the amount of harmonic distortion in a power supply. THD levels must be kept low in order to ensure a high-quality power supply.

In power systems, THD may be calculated for both current and voltage. The harmonic distortion present in the current waveform is measured by the Total Harmonic Distortion of Current (THDi), whereas the harmonic distortion present in the voltage waveform is measured by the Total Harmonic Distortion of Voltage (THDv) [22].

Low power factor is a characteristic of inductive load-bearing electrical equipment like electric motors and generators. As a result, efficiency problems may arise since they require more power to function properly. More energy is wasted as a result, which raises power costs [24].

Numerous methods, including harmonic filters, passive and active power factor correction, and improved transformer design and operation, are available to lower the degree of harmonic distortion in power systems. These solutions can aid in enhancing the dependability and efficiency of electrical systems and devices, as well as the quality of the power being delivered.

2.2.2 Disadvantages of Harmonics

Harmonics may have a substantial negative effect on how well power systems operate, leading to a number of losses, some of which are listed below [25]:

- Due to higher resistance brought on by harmonic currents that exceed typical values, the system experiences more losses.
- Resonance in the power system brought on by harmonics can result in higher voltage and current losses.
- Harmonics can result in voltage distortion, which raises losses by lowering power factor.
- Equipment in a power system may prematurely break due to harmonics, increasing the cost of maintenance and replacement.
- Harmonics can interrupt operations and increase expenses by interfering with other systems, such telecommunication and control systems.

2.3 Machine Learning

In the field of artificial intelligence known as machine learning, algorithms and statistical models are developed to help computers learn from their experiences and get better over time without explicit programming. The main goal is to create models and algorithms that make it easier to learn from data, spot patterns, and base choices on those patterns. Furthermore, predictive models that anticipate future events may be created using machine learning approaches.

2.4 Supervised and Unsupervised Machine Learning

Unsupervised learning and supervised learning are the two main subcategories of machine learning.

2.4.1 Supervised Learning

Supervised learning is a method which involves training a model using data that has already been labelled with known inputs and related outputs. The main goal is to gain understanding of a function that can link inputs and outputs, enabling precise predictions to be produced on brand-new data. This category includes regression and classification methods, which have significant applications in a wide range of sectors, including banking, healthcare, natural language processing, and image identification [26].

2.4.2 Unsupervised Learning

Unsupervised learning is a method of machine learning that entails building a model from raw data without any preconceived goals or results. This method’s main goal is to identify correlations, structures, and patterns in the data without any prior knowledge of what to look for. Clustering, dimensionality reduction, and association rule mining are frequently used in this procedure. Unsupervised learning is often used in a variety of industries, including recommendation systems, consumer segmentation, anomaly detection, and picture and text clustering [26].

2.5 Demand Side Management (DSM)

Demand Side Management (DSM) is a set of techniques that can be used to modify the consumption pattern of the end users of electricity over time. DSM methods encourage the users to optimize their energy usage and focus on reducing the energy cost and improving the efficiency [27].

NILM can be used for a variety of demand side management (DSM) applications, such as:

- Peak load reduction: NILM can be used to identify appliances that are responsible for peak loads and then implement strategies to reduce their energy consumption during peak hours.
- Demand response: NILM can be used to create demand response programs that incentivize consumers to reduce their energy consumption during times of high demand.
- Energy efficiency: NILM can be used to identify appliances that are inefficient and then provide consumers with information about how to improve their energy efficiency.

NILM is a powerful tool for DSM, but it is not without its challenges. One challenge is that NILM algorithms can be computationally expensive, so they may not be suitable for all applications. Another challenge is that NILM algorithms can be sensitive to noise in the power signal, so they may not be able to accurately identify all appliances.

Despite these challenges, NILM is a promising technology for DSM. As NILM algorithms continue to improve, they will become more widely used to help consumers and utilities manage energy demand.

Here are some additional benefits of using NILM for demand side management:

- It can help to improve grid reliability by reducing peak loads.
- It can help to reduce greenhouse gas emissions by reducing energy consumption.

- It can help to save consumers money on their energy bills.

NILM is a valuable tool for demand side management, and it is becoming increasingly important as the world transitions to a more sustainable energy future.

2.6 Research Gap

Compared to studies on the issue done elsewhere, non-intrusive load monitoring has not received much attention in Pakistan.

1. Limited Appliance Recognition Accuracy: Previous studies [28] have shown that existing appliance recognition algorithms based on current signatures exhibit lower accuracy in distinguishing between similar appliances with overlapping consumption patterns, such as laptops and desktop computers.
2. Inadequate Harmonic Distortion Analysis: Research by [29] highlighted the lack of comprehensive harmonic distortion analysis in consumer-level energy monitoring systems, preventing accurate assessment of power quality issues caused by nonlinear loads.
3. Scalability Challenges: Earlier work [30] faced scalability challenges when attempting to monitor a larger number of appliances simultaneously, limiting the applicability of their demand-side management strategies to smaller settings.
4. Absence of Sustainable Development Integration: Prior efforts [31] in demand-side management often lacked direct integration with sustainable development goals, neglecting the potential for holistic energy optimization aligned with the United Nations' targets.
5. Non-Real-Time Analysis: Some research [32] used batch processing for appliance recognition, leading to delays in identifying appliance changes and hindering prompt demand-side adjustments.
6. Lack of User Interaction: Previous projects [33] lacked user-friendly interfaces, hindering consumers’ ability to actively engage in energy management and make informed choices.
7. Single-Appliance Analysis: While some studies [34] focused on individual appliance analysis, the lack of multi-appliance recognition hindered the development of comprehensive demand-side management strategies.
8. Limited Consumer Feedback: Earlier work [35] lacked mechanisms for incorporating consumer feedback into demand-side algorithms, potentially leading to suboptimal energy-saving recommendations.

9. Non-Adaptive Algorithms: Previous machine learning algorithms [36] lacked adaptability to changes in appliance usage patterns over time, limiting the long-term effectiveness of demand-side management.

This project addresses these research gaps in several significant ways:

1. Enhanced Appliance Recognition: The project employs a K-Nearest Neighbors (KNN) algorithm to analyze comprehensive data encompassing current, voltage, power factor, and harmonic distortion. This approach significantly enhances accuracy in distinguishing between various appliances.
2. Comprehensive Power Quality Analysis: A distinctive feature of this research is the integration of thorough harmonic distortion analysis into the framework. These addresses limitations identified in previous studies and enables the detection and mitigation of power quality issues stemming from nonlinear loads.
3. Scalable and Holistic Approach: The project's design emphasizes scalability, allowing for the simultaneous monitoring of a larger number of appliances. This capability facilitates effective demand-side management across diverse settings.
4. Direct Alignment with Sustainable Goals: Unlike prior efforts, the demand-side management algorithm is intentionally aligned with UN sustainable development goals. This integration ensures not only energy optimization but also the promotion of sustainable practices.
5. Real-Time Analysis and User Interaction: The research introduces real-time appliance recognition and a user-friendly interface to address the shortcomings associated with delayed analysis and limited user interaction. This empowers consumers to proactively engage in energy management.
6. Multi-Appliance Recognition: In contrast to studies focused solely on individual appliances, the project's algorithm excels at recognizing and managing multiple appliances concurrently. This comprehensive approach leads to a more effective demand-side strategy.
7. Consumer-Centric Feedback Integration: Mechanisms for consumer feedback are integrated into the project, ensuring that energy-saving recommendations are responsive to user preferences and requirements. This user-centered approach enhances the overall effectiveness of energy management.
8. Adaptive Learning Algorithms: The project incorporates adaptive machine learning algorithms capable of accommodating changes in appliance usage patterns. This

adaptability ensures the sustained effectiveness of demand-side management over the long term.

Despite these advancements, this project acknowledges a few limitations:

1. Hardware Complexity: Developing the hardware module for comprehensive data collection may introduce cost and complexity, potentially limiting widespread adoption.
2. Training Data Diversity: The accuracy of our KNN algorithm heavily relies on diverse and extensive training data, which could be challenging to gather for all possible appliance combinations.
3. Appliance Identification Limits: There may still be scenarios where appliances with similar consumption profiles are challenging to distinguish accurately.
4. User Engagement: While our user-friendly interface promotes user engagement, the success of the demand-side management strategy still depends on consistent user participation.
5. Initial Calibration: Initial calibration and setup of the system might require technical expertise, potentially deterring some users.
6. Network Dependence: Real-time analysis and remote interaction rely on stable network connectivity, which could hinder functionality in areas with poor network coverage.
7. Algorithm Optimization: The performance of the KNN algorithm may degrade as the number of monitored appliances increases, necessitating ongoing algorithm optimization efforts.

This project addresses several research gaps left by previous work, offering improved accuracy, comprehensive analysis, scalability, sustainability alignment, user-friendliness, and adaptability. However, it does come with its own set of limitations, emphasizing the need for ongoing refinement and user support.

Chapter 3

Methodology and Design

For electrical systems to operate at their best, energy management is essential. Monitoring the energy use of certain appliances, however, can be difficult, particularly if they are concealed behind cabinets or walls. NILM is useful in this situation. Without the requirement for physical installation on each appliance, NILM systems can track the electrical signals of an entire home or building to determine how much energy is used by certain appliances. Now, this study demonstrates how to use a NILM system to achieve the following outcomes:

- In order to learn more about the application of NILM systems for appliance identification, a literature review was first carried out. This study aims to comprehend the current methods and algorithms utilized in NILM systems and how they may be enhanced for greater precision and effectiveness. In order to gather valuable data for the survey, at least 20 items were read, including pertinent research papers, articles, and books.
- The project's equipment will then be chosen after this. Based on the information acquired during the literature review, the equipment will be chosen.
- For data acquisition, an NI USB 6008 DAQ Card, a CT and PT bridge rectifier circuit, and LabVIEW software will be chosen. The equipment will be chosen based on its capacity to precisely record the electrical signals from the power cables without interfering with the appliances' regular operation.
- To determine the specific appliance's trends of energy usage, a machine learning algorithm is created. The algorithm is tuned for increased precision and effectiveness using the electrical signals recorded by the NILM device as training data. The program can identify the appliances that use the most energy and suggest ways to save it by examining the patterns of energy use.
- Utilizing NILM systems for energy management may improve the efficiency of the electrical system and offer useful insights into how much energy is used by certain appliances. The system's energy efficiency may be increased, resulting in lower energy bills and a more sustainable future, by using a machine learning algorithm for appliance recognition and energy consumption analysis.

3.1 Block Diagram of NILM

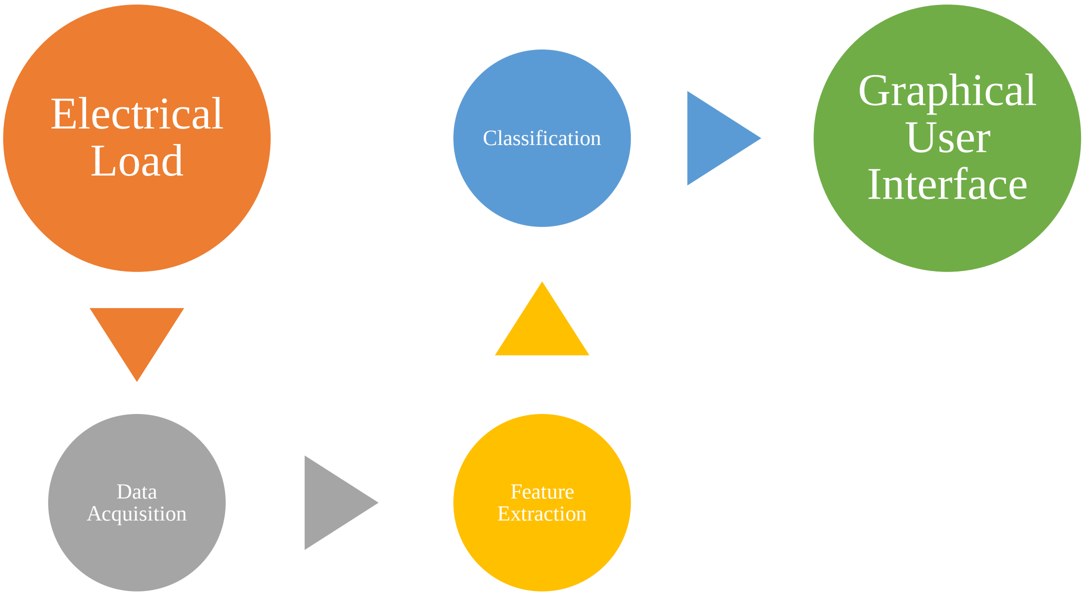

Figure 3-1: Block Diagram.

A NILM system consists of three main parts.

- Data Acquisition.
- Feature Extraction.
- Classification.

According to the block diagram, the initial step is to gather data from the appliances using CT and PT sensors linked to a NI USB 6008 DAQ card. While the PT sensor measures voltage and the CT sensor measures current. It is necessary to transform the analogue raw data from the sensors into a digital signal. This conversion is carried out by the DAQ card, which then delivers the digital signal to the computer for additional processing.

Extraction of traits that can distinguish between several appliances comes after data acquisition. Different methods, such as time-domain, frequency-domain, or time-frequency analysis, can be used to extract the characteristics. The characteristics chosen for this particular situation are Total Harmonic Distortion, Displacement Power Factor, True Power Factor, and True Power. The observed current and voltage data may be used to compute these properties.

The next step is to differentiate the appliances using the machine learning algorithm based on their features that were retrieved. The KNN method is applied here to do classification. A supervised machine learning algorithm called the KNN can categorize data points depending on how far off they are from their nearest neighbors. Based on the majority class of the chosen neighbors, the algorithm chooses K nearest neighbors and provides a class label to the data point.

The KNN method is trained with labelled data and then applied to detect appliances. The KNN method will process the measured features of appliance like as true power, displacement power factor, true power factor, and THDi, and the algorithm will differentiate the appliance label depending on the characteristics that are chosen.

3.2 Proposed Solution

Through encouraging positive changes in consumer behavior, NILM is a strategy that can increase the effectiveness of home energy usage. By using sophisticated data processing techniques on data gathered from a single point, often at the utility service entrance, it enables the monitoring of energy use at the appliance level. Due to its low cost, ease of data collecting, and simplicity of installation, this technology is a prominent trend in contemporary energy management systems, especially with the advent of smart meter devices. The main service utility entrance's two sensors are all that are needed in the NILM system's suggested technique to extract characteristics from the recorded voltage and current values. The ultimate objective of this project is to create a system that is less expensive than ILM systems and is capable of detecting and monitoring appliances with the fewest possible sensors. For regulating, controlling, and lowering energy costs and use in homes, workplaces, and public and private organizations, energy monitoring is essential.

3.3 Hardware Modules

This project made use of both significant and insignificant hardware components. The following were the main elements:

- NI USB 6008.
- Current Transformer.
- Potential Transformer.
- Bridge Rectifier.
- Switch Board.
- Four appliances used in this project, namely a bulb, pedestal fan, laptop, and travel adapter.

Appliances with particular ratings were employed in this project. The four appliances that were utilized received the following ratings:

- Bulb (60W, 220V, 50Hz).
- Laptop (65W, 220V, 50Hz).
- Travel Adapter (33W, 220V, 50Hz).
- Pedestal Fan (200W, 220V, 50Hz).

3.3.1 NI USB 6008

National Instruments (NI) has created a low-cost data gathering tool called the NI USB 6008. Users may connect to and interact with a variety of sensors, signals, and devices with this little gadget. LabVIEW software, a graphical programming language frequently used for data collecting and control applications, is designed to interact flawlessly with the device.

Eight analogue input channels with 12-bit resolution, two analogue output channels with 12-bit resolution, and 12 digital input/output channels are all included in the NI USB 6008. The analogue output channels can sample at a maximum of 1 kS/s, whereas the analogue input channels can sample at a maximum of 10 kS/s. There is no need for an extra power source because the gadget is fueled through USB [37].

Numerous applications, such as data logging, process control, and test and measurement, frequently employ the NI USB 6008. It is especially helpful for applications with low costs and few channels, where higher-end data gathering devices would not be economically viable.

Figure 3-2: NI USB-6008.

3.3.2 Current Transformer

In order to assess the electrical system's current, Current Transformers (CTs) are frequently employed in NILM systems. CTs can be used to clamp around the current-carrying wire and generate a voltage signal corresponding to the current through the wire. To determine the energy usage of certain appliances, the voltage signal from the CT is then monitored using a data gathering system, such as the NI USB 6008. Because they are less invasive than other measuring techniques, are simple to install, and are more affordable, CTs are favored in NILM systems. Furthermore, CTs offer a very exact assessment of the current flow, which makes them perfect for identifying minute variations in the current waveform brought on by the operation of certain appliances [38].

3.3.3 Potential Transformer

A potential transformer (PT) is a type of instrument transformer used to reduce the high voltage of an AC power supply to a level that is safe for measurement equipment. It is utilized in the NILM system together with the CT to non-intrusively measure the voltage and current of the power supply. The PT measures the voltage across the load, steps it down to a lower value, and then applies that voltage to the bridge rectifier circuit. A pulsing DC voltage that is proportionate to the voltage across the load is the output of the bridge rectifier circuit [38].

The potential transformer utilized in this project was a step-down from 230V mains to 12 V.

Figure 3-3: Potential Transformer.

3.3.4 Bridge Rectifier

An effective circuit for converting alternating current (AC) voltage to direct current (DC) voltage is a bridge rectifier shown in Figure 3-4. In this project, the CT and PT sensors are employed with a bridge rectifier to transform the AC voltage and current readings into DC signals that can be processed and analyzed by the data collecting system [39].

The positive and negative components of the AC signal may be transformed to a continuous DC signal by applying an AC voltage to the circuit, which causes the diodes to conduct in a particular order. A capacitor is used to filter the pulsing DC voltage produced by the bridge rectifier, which results in a smooth DC voltage.

This project uses a bridge rectifier in combination with CT and PT sensors to accurately measure voltage and current, which is necessary for the NILM system to operate properly.

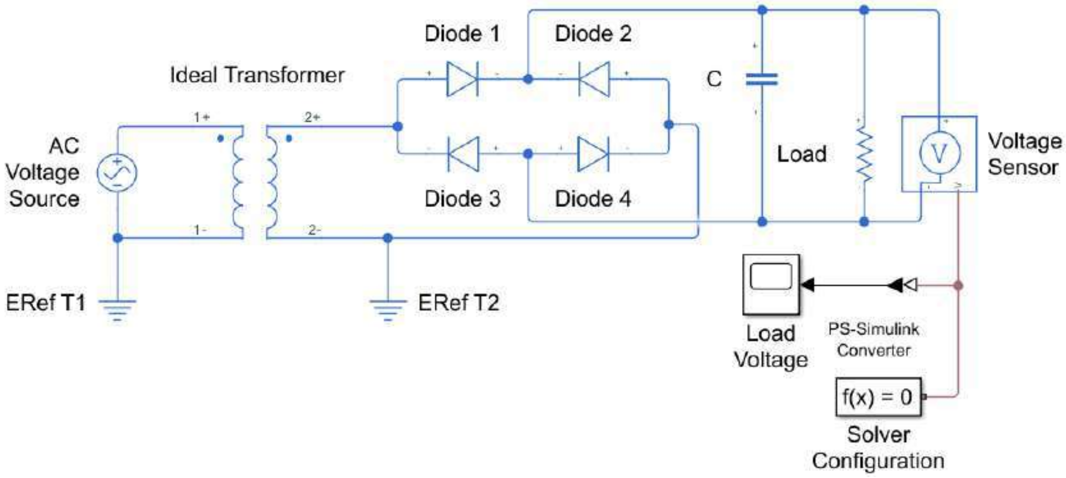

Figure 3-4: Bridge Rectifier Circuit.

3.4 Detailed System Design

3.4.1 Data Aquisition

In a NILM system, many actions must be completed in order to collect data for each device. To begin with, each appliance has to be wired into a bridge rectifier circuit so that we can collect its voltage and current.

The NI USB 6008 DAQ card may be attached to measure the voltage and current of each appliance once the appliances are linked to the bridge rectifier circuit and CT sensors. A USB cable should be used to link this DAQ card to the computer. The voltage and current data from the DAQ card may be obtained using the LabVIEW VI. To assure the correctness of the data, the sampling rate of the DAQ card should be established, and the VI should be set up to gather the data for a certain amount of time.

The LabVIEW VI may be used to obtain the voltage and current data for each appliance independently after being configured. After then, the collected data may be saved to a file for further study. These processes allow us to gather the voltage and current information for each appliance, which we can use to recognize each device based on its own load signature. In this instance, a bulb, pedestal fan, laptop, and travel adapter are the appliances being used.

3.4.2 Feature Extraction

The feature extraction procedure in the context of the NI USB 6008 and LabVIEW entails the extraction of distinctive characteristics, or signatures, from the obtained voltage and current data. To do this, properties like true power, displacement power factor, true power factor, and THDi are calculated using the digital values of current and voltage.

The definition of numerous signatures aims to guarantee proper appliance categorization. To distinguish between appliances with identical active and reactive power, current THD is measured in addition to active and reactive power.

The machine learning method may use the retrieved parameters, such as true power, displacement power factor, true power factor, and THDi, to identify the appliances based on their distinctive signatures.

3.4.2.1 Measurement of True Power

In a single-phase AC circuit, active power is calculated using the following formula [20]:

$$P = V_{rms} * I_{rms} * \cos(\theta) \tag{3.1}$$

Where,

P = Active power in watts (W), kilowatts (kW), or megawatts (MW)

V_{rms} = RMS voltage in volts (V)

I_{rms} = RMS current in amperes (A)

$\cos(\theta)$ = Power factor of the circuit

3.4.2.2 Measurement of Displacement Power Factor

In a single-phase AC circuit, displacement power factor is calculated using the following formula [20]:

$$S = V_{rms} * I_{rms} \tag{3.2}$$

$$P = S * \cos(\theta) \tag{3.3}$$

Where,

S = Apparent power in VA, kVA, or MVA

V_{rms} = RMS voltage in volts (V)

I_{rms} = RMS current in amperes (A)

cos (θ) = Power factor of the circuit

3.4.2.3 Measurement of True Power Factor

The phase difference between the voltage and current waveforms is referred to as power factor. Harmonics are a significant element that must be taken into account in power factor estimates for non-linear loads, though. Power factor may be computed by multiplying the displacement factor by the distortion factor, which is a standard definition of power factor as the proportion of useable power to total power.

In a single-phase AC circuit, true power factor is calculated using the following formula [40]:

$$PF_{true} = PF_{displacement} \times PF_{distortion} \tag{3.4}$$

$$PF_{displacement} = \cos(\theta) \tag{3.5}$$

$$PF_{distortion} = \frac{1}{\sqrt{1+THDi^2}} \tag{3.6}$$

Where,

cos (θ) = Power factor of the circuit

$THDi$ = Total harmonic distortion of the current

3.4.2.4 Measurement of Total Harmonic Distortion of Current

The amount of harmonic content in a current signal is quantified by the term “THD”. It measures how far the waveform deviates from the desired sinusoidal behaviour.

In a single-phase AC circuit, total harmonic distortion of current is calculated using the following formula [23]:

$$THDi = \frac{\sqrt{\sum_{k=2}^{n} I_k^2}}{I_1} \times 100\% \tag{3.7}$$

Where,

I_k^2 = RMS current of the kth harmonic

3.4.3 Classification

A NILM system's classification step involves identifying specific devices such as bulb, pedestal fan, laptop, and travel adapter by analyzing the attributes that were derived from the aggregated load data. Electrical signatures that are specific to each electrical equipment can be utilized to identify it with accuracy.

Machine learning techniques may now be used for appliance recognition because to ongoing developments in artificial intelligence and machine learning. These methods are highly beneficial since they can find patterns in data and extrapolate information to devices that are not yet known. In order to monitor appliances, the data of each power load must be isolated from the aggregated power data. The NILM system must have prior knowledge of the physical characteristics of each appliance's power data in order to do this. These factors are influenced by a device's internal electrical characteristics, such as its voltage, current, phase angle, power factor, frequency, and THDi of the appliance's power patterns. External factors that affect the power characteristics include external disturbances and user usage behaviors of appliances, such as usage time, frequency, and duration. These properties play a significant role in the machine learning techniques used to categories appliances.

In order to train a model utilizing the gathered data, each appliance's individual and collective load signatures must be recorded. These load signatures are then utilized in a dis-aggregation technique to separate the appliances running at a given moment. A supervised machine learning approach is used with well-defined data to categories appliances. For this aim, several algorithms have been created, and the selection of algorithm relies on the particular problem. Several algorithms were tested using MATLAB classifier tool and the algorithm with higher accuracy were selected. By splitting the original data set into 30% test data and 70% training data, the test data set was constructed in this case, and KNN produced the greatest accuracy of about 95.79 percent. Here is a quick summary of the KNN machine learning algorithm.

3.4.3.1 K-nearest neighbors (KNN)

KNN, short for k-nearest neighbors, is a machine learning algorithm used for both classification and regression tasks. It is a non-parametric algorithm that makes predictions based on the similarity of a new instance to its k nearest neighbors in the training dataset.

Here's how the KNN algorithm works [41]:

1. Training Phase: During the training phase, the algorithm stores the feature vectors and their corresponding labels or target values from the training dataset.
2. Prediction Phase: When a new instance (unlabeled data point) needs to be classified or predicted, the KNN algorithm calculates the distance between the new instance and all the instances in the training dataset. The distance metric can be Euclidean distance, Manhattan distance, or any other distance measure.
3. Finding Neighbors: The algorithm selects the k nearest neighbors (the data points with the smallest distances) to the new instance. The value of k is a hyperparameter that needs to be specified before training the model.
4. Voting or Averaging: For classification tasks, the algorithm assigns the class label to the new instance based on the majority vote of the k nearest neighbors. Each neighbor gets a vote, and the class with the most votes is assigned to the new instance.

For regression tasks, the algorithm assigns the average value of the target variable in the k nearest neighbors to the new instance.

KNN is a simple yet effective algorithm. However, it has some limitations. One limitation is that it can be computationally expensive, especially when dealing with large datasets, as it requires calculating distances for all instances. Additionally, KNN assumes that all features are equally important, so it may not perform well if some features are more relevant than others.

To use the KNN algorithm effectively, it is important to preprocess the data, handle missing values, scale features if necessary, and choose an appropriate value for k. Cross-validation can be used to evaluate the performance of the KNN model and tune the hyperparameters.

3.4.3.1.1 Implementation

The datasets utilized in the analysis contained 3500 samples for combinations of appliances and 13685 samples for each individual appliance. There were four features in the dataset:

- True Power.
- Displacement Power Factor.
- True Power Factor.
- THDi.

The dataset was then divided into two subsets, with 30% of the data used for model testing and 70% of the data used for model training. The KNN model was trained using the training data, and its accuracy was then determined using the test data. 90.84% was found to be the model's accuracy when applied to the test data. The accuracy was determined by comparing the predicted labels from the model to the actual labels in the test set using the metrics function from the sklearn package using the following formula [42]:

$$accuracy\ (y, \hat{y}) = \frac{1}{n_{samples}} \sum_{i=0}^{n_{samples}-1} 1(\hat{y} = y_i) \tag{3.8}$$

The datasets confusion matrix is displayed below:

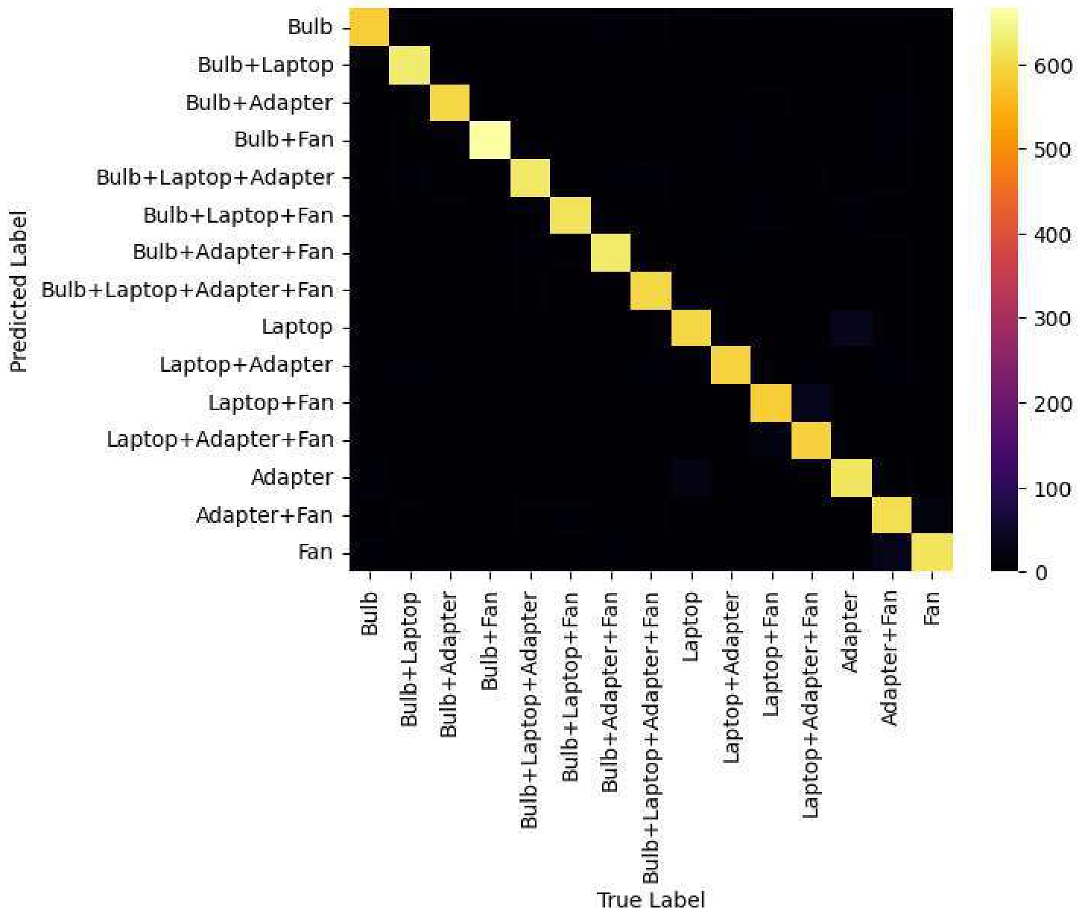

Figure 3-5: Confusion Matrix.

3.4.4 Load Management

Here's an explanation of the design behind the demand side management (DSM) strategy for the appliances used in this project:

1. Prioritizing Essential Tasks: The strategy starts by identifying the essential tasks that need to be performed during the peak hours, such as studying, working on a laptop, or using

the fan for comfort. By prioritizing these tasks, energy consumption can be focused on activities that are necessary during the peak period.

2. Energy-efficient Lighting: The strategy emphasizes replacing the 60W bulb with an energy-efficient LED bulb with a lower wattage (e.g., 9-12W). LED bulbs are known for their energy efficiency, providing similar or better lighting output while consuming significantly less power. By utilizing LED lighting, the strategy aims to reduce energy consumption without compromising on the quality of illumination.
3. Optimal Laptop Usage: The strategy focuses on optimizing the energy consumption of laptops. By utilizing power-saving features such as sleep mode, screen brightness adjustments, and power-saving adapters, the laptop's energy usage can be significantly reduced. These features ensure that the laptop operates efficiently while minimizing unnecessary power consumption.
4. Smart Charging Strategy: The strategy suggests charging the laptop and travel adapter during off-peak hours to avoid adding to the peak demand. By charging these devices when the overall electricity demand is lower, it helps to balance the load on the grid and reduce strain during peak hours.
5. Fan Utilization: To optimize energy consumption, the strategy recommends adjusting the fan speed to a lower setting or utilizing a timer function. By reducing the fan speed or running it intermittently, energy usage can be reduced while still providing a comfortable level of airflow and cooling.

By combining these elements, the DSM strategy aims to manage and reduce energy consumption during peak hours while ensuring essential tasks are fulfilled. The strategy promotes the use of energy-efficient appliances, optimization of usage patterns, and behavioral changes to achieve effective demand side management and contribute to overall energy conservation efforts.

Chapter 4

Results and Discussion

This project contains following hardware setup shown below.

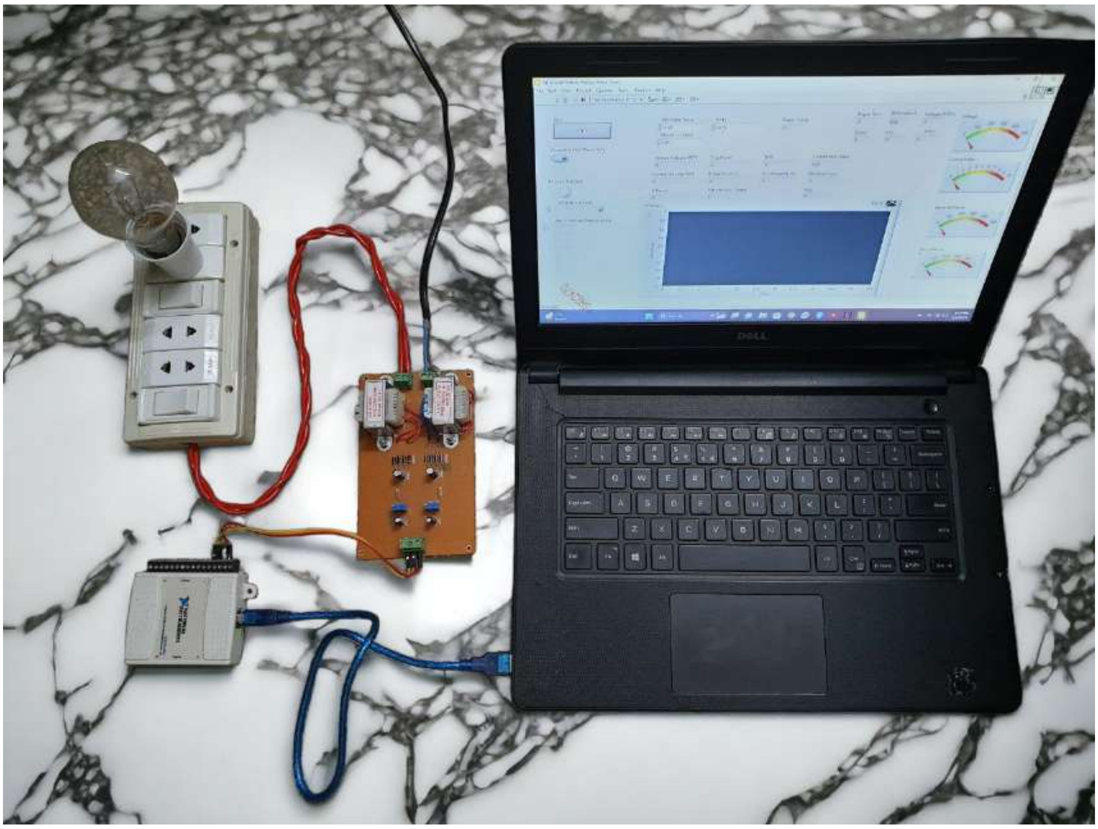

Figure 4-1: Hardware Setup.

A connected load's voltage and current levels are measured using the NI USB 6008. To extract distinctive characteristics, or signatures, such as real power, displacement power factor, true power factor, and THDi, the voltage and current data are analyzed in LabVIEW and displayed on a GUI. Digital current and voltage data are used in the calculation of these characteristics. Appliance classification using a KNN supervised machine learning algorithm is the next stage. A graphical user interface (GUI) is used to present the findings, which include a list of the powered on/off appliances shown below:

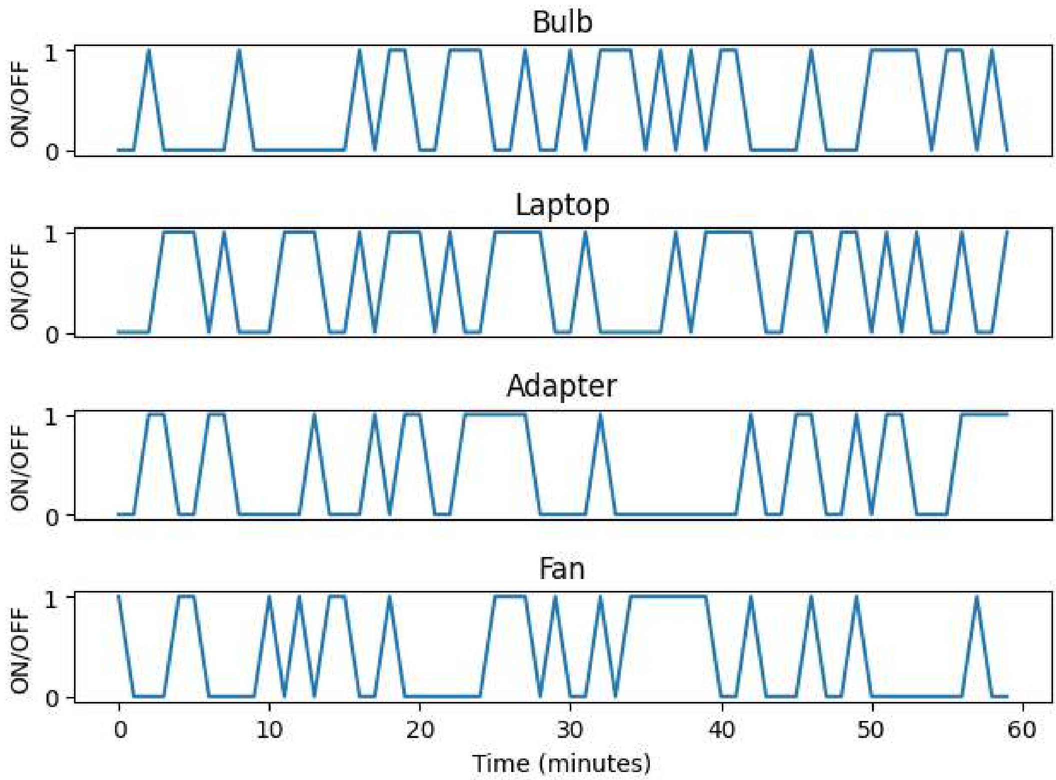

Figure 4-2: Disaggregated Data.

Let's break down the results of analyzing on/off patterns for the appliances:

1. Bulb: Analyzing the on/off patterns of a bulb involves studying the frequency and duration of its cycles. A typical incandescent bulb will have a clear on/off pattern where it consumes energy when it's on and consumes zero energy when it's off. However, for more modern energy-efficient bulbs like LED or CFL, the on/off pattern might not be as distinct due to their lower power consumption and quicker response times.
2. Laptop: The on/off pattern of a laptop can reveal its usage patterns. When the laptop is on, it consumes energy for its various components (CPU, screen, memory, etc.). During periods of inactivity or sleep mode, the energy consumption might be lower, but not zero, as some components remain active. These varying energy levels during different usage states can help in distinguishing between active use and idle times.
3. Adapter: The adapter (charger) of a device, such as a smartphone, can also exhibit distinct on/off patterns. When the device is charging, the adapter will consume energy. When the device is fully charged or unplugged, the adapter might still consume a small amount of standby power. Analyzing the adapter's on/off pattern can provide insights into the charging behavior of the associated device.

4. Fan: The on/off pattern of a fan is characterized by its cycling between being turned on and off to maintain the desired level of ventilation or cooling. The energy consumption of a fan is generally higher when it’s on compared to when it’s off. The duration and frequency of these on/off cycles can help in estimating the energy consumption of the fan over a specific period.

In a NILM system, these on/off patterns are analyzed using signal processing techniques and machine learning algorithms to identify and separate the energy consumption of individual appliances from the overall energy consumption of a household. The system might use algorithms to distinguish between different appliances based on the distinctive energy consumption patterns and the timings of their on/off cycles.

It's worth noting that while NILM can provide valuable insights into appliance-level energy consumption without the need for additional hardware, it might not always achieve perfect accuracy due to the complexity of appliance behaviors, variations in energy usage, and potential overlaps in energy patterns.

The results of implementing DSM strategy can be observed in the load profile comparison show below:

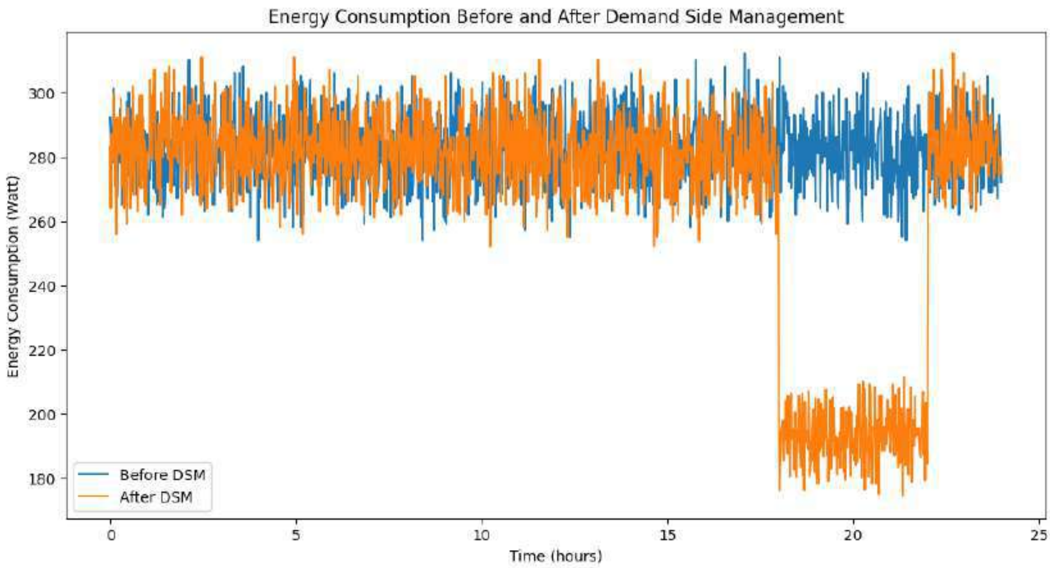

Figure 4-3: Load Profile Comparison.

Before implementing the DSM strategy, the energy consumption of the appliances follows their regular usage patterns. The 60W bulb, 65W laptop, 33W travel adapter, and 200W pedestal fan consume power independently throughout the day. The total energy consumption is the sum of the random power values drawn from the respective power ranges for each appliance at different time intervals. During the peak hours of 6 pm to 10 pm, the appliances operate without any specific adjustments or energy-saving measures.

After implementing the DSM strategy, several changes are made to optimize energy consumption during the peak hours. Firstly, the 60W bulb is replaced with an energy-efficient LED bulb, which reduces its power consumption by approximately 80%. This modification significantly lowers the energy usage for lighting while maintaining adequate illumination. Secondly, the laptop is set to power-saving mode, reducing its energy consumption by approximately 40%. By enabling power-saving features such as adjusting the CPU performance and screen brightness, the laptop operates more efficiently during the peak hours. Thirdly, the pedestal fan is operated at 80% speed during the peak hours, reducing its power consumption while still providing a reasonable level of airflow and cooling.

By implementing these DSM measures during the peak hours, the overall energy consumption is effectively managed and reduced compared to the baseline scenario. The modifications aim to prioritize essential tasks, utilize energy-efficient appliances, and optimize the usage patterns to align with the peak demand period. These strategies not only contribute to energy conservation but also help to mitigate the strain on the electricity grid during high-demand periods.

Here are the specific reasons behind the modifications:

1. LED Bulb Reduces Consumption by 80%: The reason for reducing the energy consumption of the LED bulb by 80% is based on the assumption that an energy-efficient LED bulb is used as a replacement for the 60W bulb. LED bulbs are known to be much more energy-efficient compared to traditional incandescent bulbs. On average, LED bulbs consume around 80% less energy while providing the same or even better lighting output. Hence, the reduction in consumption is an estimation based on the assumption of using an LED bulb.
2. Laptop Power-Saving Mode Reduces Consumption by 40%: Power-saving mode on laptops is designed to reduce energy consumption by optimizing various components and functionalities. It typically involves lowering the CPU performance, reducing the screen brightness, and managing power distribution to different hardware components. The 40% reduction in energy consumption is an estimation based on the assumption that the laptop is set to power-saving mode, which is a common feature available on many laptops.
3. Fan Runs at 80% Speed During Peak Hours: The strategy of running the fan at 80% speed during peak hours is aimed at reducing energy consumption while still providing a

comfortable airflow. By running the fan at a slightly lower speed, it consumes less power compared to its maximum speed while still providing a reasonable level of cooling. This reduction in fan speed helps to lower energy usage during peak hours without compromising significantly on the cooling effect.

These specific modifications were made to demonstrate the implementation of energy-saving measures and demand side management techniques for the appliances during peak hours. The actual energy savings achieved may vary based on the specific models and settings of the appliances used.

Chapter 5

Conclusions and Future Work

5.1 Conclusions

In recent times, significant advancements in the field of electronics have brought about transformative changes in people’s lives. Traditional technologies have rapidly evolved, giving way to the rise of smart homes equipped with automated controls and intelligent appliances. This shift has created a demand for simpler and more cost-effective load monitoring solutions, such as NILM based energy meters.

The NILM approach offered a more streamlined and economical alternative compared to conventional ILM systems. By utilizing a single set of sensors, the system extracted essential properties like true power, displacement power factor, true power factor, and THD from voltage and current data of individual appliances and their combinations. Employing the KNN machine learning technique, the system effectively analyzed aggregated load data characteristics to accurately identify each appliance type.

With successful appliance identification in place, DSM strategy were implemented to optimize energy consumption patterns. These strategies encompassed redistributing energy usage of appliances to off-peak hours, thus reducing overall energy demand during peak periods. The outcome was tangible energy savings.

Furthermore, the system demonstrated the potential to evolve into a comprehensive solution for tracking, estimating, and calculating billing for individual appliances within a household or other structures. This technology also found applications in the industrial sector, enabling efficient wireless monitoring and control of individual units.

The initiative achieved significant milestones by successfully identifying appliances through advanced NILM technique and implementing DSM strategy that yielded substantial energy savings. These accomplishments mark a significant step towards revolutionizing smart energy metering, catering to the evolving needs of modern households and industries.

5.2 Future work

Even if we were able to apply this concept successfully, there is always space for improvement. We were unable to expand the project's functionality due to time limitations. However, as part of continuous developments, these functionalities might be created in the future.

This project has a number of possible areas for advancement. The following are some of the things that can be completed soon.

5.2.1 More Appliances should be used

In this project, the focus is on NILM technology, which aims to revolutionize the way households manage their energy consumption. The current scope covers four vital household loads: bulb, laptop, travel adapter, and pedestal fan. However, to truly unleash the potential of this endeavor, the integration of more appliances is paramount. By expanding the monitoring spectrum to include appliances like refrigerator, air conditioner, washing machine, electric oven/stove, water heater, television and entertainment systems, microwave, dishwasher, electric iron, and ceiling fans, the project's reach will extend far beyond its current boundaries. With such comprehensive data at their disposal, users can gain deep insights into their energy usage patterns and take informed actions to optimize efficiency, reduce wastage, and pave the way for a greener and more sustainable future.

5.2.2 Apply More Accurate Classification Technique

The accuracy of the classifier may deteriorate as a system's number of appliances rises and the number of potential combinations of these appliances expands. Therefore, it's crucial to investigate improved categorization methods that might lead to more hopeful outcomes. Future objectives should include making sure the system operates as efficiently as possible.

5.2.3 Extending DSM: Applying Energy-Saving Strategies to More Devices for a Sustainable Future

The DSM strategy is an effective approach to optimize energy consumption during peak hours. While the specific modifications were applied to a 60W bulb, 65W laptop, and 200W pedestal fan, similar strategies can be applied to other loads and appliances to achieve energy savings and demand reduction. Here are some potential applications and ways to apply the same strategy to other loads in the future:

1. Air Conditioners: During peak hours, air conditioners contribute significantly to the overall energy demand. Implementing DSM measures, such as setting the temperature slightly higher or utilizing smart thermostats to optimize cooling cycles, can lead to substantial energy savings without compromising comfort.
2. Refrigerators: Refrigerators are always on and can be a major contributor to energy consumption. Future DSM strategies might involve using more energy-efficient refrigerator models or implementing techniques like thermal storage to optimize cooling cycles and reduce energy usage during peak hours.
3. Water Heaters: DSM strategies can be applied to water heaters by scheduling their operation during off-peak hours or utilizing energy-efficient water heaters that consume less power while maintaining a steady supply of hot water.
4. Electric Vehicle Charging: With the increasing adoption of electric vehicles (EVs), their charging can strain the grid during peak hours. DSM can be applied by encouraging EV owners to charge their vehicles during off-peak hours through incentives or dynamic pricing.
5. Industrial Loads: Industrial processes often have flexible operating schedules. DSM can be employed in industries by adjusting production schedules or using energy-efficient equipment to reduce energy consumption during peak hours.
6. Home Appliances: Beyond the specific examples mentioned earlier, other home appliances like washing machines, dishwashers, and microwaves can also be integrated into DSM programs to optimize their energy usage during peak hours.
7. Energy Storage Integration: Energy storage systems, such as batteries, can play a vital role in DSM. These systems can be charged during off-peak hours when energy is abundant and inexpensive, and discharged during peak hours to offset the demand on the grid.
8. Smart Grid Technologies: The future holds immense potential for smart grid technologies that enable real-time communication between appliances and the grid. These technologies can facilitate automated DSM measures based on electricity pricing and demand patterns.
9. Behavioral Changes: DSM strategies can also involve raising awareness and encouraging energy-efficient behaviors among consumers, such as turning off lights and appliances when not in use, using natural ventilation when possible, and reducing overall energy consumption during peak hours.
10. Integration of Renewable Energy Sources: DSM can be complemented with the integration of renewable energy sources like solar and wind power. Consumers can be

encouraged to use more electricity from renewables during peak hours when the demand on conventional power plants is high.

In the future, advancements in technology, increasing focus on sustainability, and the drive to reduce carbon footprints will likely lead to further development and widespread implementation of demand-side management strategies across various sectors. These efforts will not only result in significant energy savings and cost reductions for consumers but also contribute to a more stable and resilient electricity grid.

5.2.4 Android Application

A smartphone app might be a useful addition to this project given the rising popularity of Android applications for mobile devices. The major objective of the app may be to give a thorough overview of each load connected to the system. Additionally, there are a number of extra features that can be added to the app, including information on the current billing for each load in real-time, a forecasted bill, and the ability to automate control of the entire system down to the level of individual appliances.

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