REAL-TIME ENERGY CONSUMPTION MONITORING USING ARTIFICIAL INTELLIGENCE BASED NON-INTRUSIVE LOAD MANAGEMENT SYSTEM

Group Members:

MUHAMMAD MOIN DILDAR	**(211201)**
MUHAMMAD MAHMOOD GHAURI	**(211265)**
MUHAMMAD SALMAN	**(211291)**

BE MECHATRONICS (Session 2021-2025)

Project Supervisor

Engr. Umer Farooq

Lecturer

DEPARTMENT OF MECHATRONICS & BIOMEDICAL ENGINEERING

FACULTY OF ENGINEERING

AIR UNIVERSITY, ISLAMABAD

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FINAL YEAR PROJECT REPORT

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Submitted By:

MUHAMMAD MOIN DILDAR (211201)

MUHAMMAD MAHMOOD GHAURI (211265)

MUHAMMAD SALMAN (211291)

Project Supervisor

Engr. Umer Farooq

Lecturer

Chair Department

Dr. Noman Naseer

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Abstract

Nonintrusive load monitoring (NILM) systems serve to uncover the energy usage patterns of individual devices within an electrical system, yet expanding their market reach poses a significant hurdle. A novel approach to NILM, utilizing edge processing, is introduced, wherein energy consumption data undergo processing directly on the device installed within the monitored facility. Specifically, a neural network implemented on an Arm CortexM7 microcontroller is employed for this purpose. The NILM system is slated for installation on four everyday appliances in real-world scenarios. This report outlines a promising configuration aimed at facilitating the widespread adoption of NILM frameworks by reducing their implementation costs and complexity, while also addressing privacy concerns associated with cloud-based data processing. The outcomes of real-world testing in this endeavor are expected to provide compelling evidence of the potential of the proposed NILM framework across various applications, including smart homes, building automation, and industrial energy management..

Nomenclature

Symbol	*Abbreviation*
A	Unit of Current
AI	Artificial Intelligence
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
DL	Deep Learning
FHMM	Factorial Hidden Markov Model
f_{lin}	Linear Frequency
HMM_s	Hidden Markov Models
Hz	Unit of Frequency
ILM	Intrusive Load Monitoring
I_{max}	Maximum Current
I_{nom}	Normal Current
NILM	Non-Intrusive Load Monitoring
NN	Neural Network
RMS	Root Mean Square
V	Unit of Voltage
V_{nom}	Normal Voltage
V_{max}	Maximum Voltage

Table of Contents

List of Figuress

List of Tables

1 Introduction

Energy management is a critical aspect of modern society, with increasing demands for efficient utilization of resources and sustainable practices. In response to this need, this project focuses on developing an AI-based energy monitoring embedded system. This system integrates advanced technologies such as Non-Intrusive Load Monitoring (NILM), Neural Networks (NN), and hardware components like the STM32 microcontroller and ARM processor. Today, it's really important for businesses and homes to keep an eye on how much energy they use. This project is all about helping with that. This project tends to create a smart system that can track energy use in real-time. In a world where everything costs money and resources are precious, it's really useful to know where the energy is consumed. This project isn't just about looking at numbers; it's about helping user to make better choices about how they use energy. With this system, user can see exactly where energy is being used, find ways to use less, and save money on energy bills. When humans use energy more carefully, pollution can be reduced and make the world a cleaner, healthier place for everyone.

1.1 Background and Motivation

1.1.1 Sustainable Development Goals

Today's world is using more energy than ever, and it's hurting the environment. That's why we need smarter ways to track how much energy we're using.

The old way of monitoring energy was **Intrusive Load Monitoring (ILM)** which needs each monitoring device to be installed on every appliances, which could be challenging sometimes to be implemented practically. This project tackles that problem with an approach called **Non-Intrusive Load Monitoring (NILM)**. In which a system can analyze overall energy usage and figure out how much each appliance is using by analyzing the input AC voltage signal, all without installing each monitoring device on each appliance.

NILM uses artificial intelligence (AI) to become a super-powered detective for energy usage. It can analyze energy usage in real-time, helping user understand where user can save money and be kinder to the environment. This project dives into the world of AI-powered NILM, exploring its potential to revolutionize how we manage energy

1.2 Literature Review

Since Hart [1] introduced the primary NILM framework during the 1980s, there have been huge progressions in the field. All through the accompanying twenty years, research basically centered around finding novel marks prepared to do precisely recognizing gadgets and creating classifiers to decipher these marks. This approach frequently involves recognizing occasions prior to classifying them. When an occasion is distinguished, the related machine's elements (and accordingly its mark) are separated. This technique can be broken down into three key stages: occasion recognition, include extraction, and burden ID. These procedures are normally sorted inside an occasion based structure, where an "occasion" alludes to any adjustment of the electrical boundaries of the total sign..

Dong et al. [2]proposed a framework focused on distinguishing power signal occasions and their connected boundaries, including dynamic power range, receptive power range, consonant substance range, presence of spikes, number of stages, and occasion search time. The recognized occasions are then connected with machine functional cycles utilizing a bunching calculation. In[3], a comparative methodology is taken, connecting identified power signal occasions to machines by limiting contrasts across different boundaries, for example, successful voltage, compelling current, dynamic power, receptive power, obvious power, power factor, complete symphonious bending, and voltage-current direction. Over the long haul, endeavors have been pointed toward recognizing highlights extractable from occasions that empower exact machine separation while preferably staying predictable across various working circumstances. Thus, Teshome et al[4] disintegrated the total current into two symmetrical parts and characterized V-I directions comparative with every part.

Gupta et al. [5], further investigated this road by ceaselessly observing the electromagnetic obstruction impacts created by machines during their initiation or deactivation. Their framework processes the voltage estimated at a family attachment progressively to get its Fourier change. Post-handling uncovers a striking expansion in symphonic substance following machine exchanging occasions. Recognizable proof of the machine liable for the noticed symphonic substance is accomplished through a k-closest neighbor classifier.. Essentially, in [6],the effect of turning procedure on the retained current sign was surveyed to create galvanically detached estimation frameworks. Be that as it may, these strategies share a few limits: Right off the bat, the adequacy of occasion location calculations is tested by the trouble in adjusting bogus up-sides and misleading negatives. Commotion in total power flags frequently clouds the distinguishing proof of minor burdens. While recently proposed occasion based frameworks show remarkable execution because of precisely quantifiable post-occasion highlights, for example, those referenced prior, they display unfortunate speculation abilities, particularly when sent in concealed families or when prepared on information from different homes [7]. Furthermore, a considerable lot of these frameworks face computational difficulties that raise essentially with the quantity of burdens to be dis-collected, delivering them unrealistic for true applications [4].

Lastly, while many of these systems can detect appliance activities, they often lack the ability to provide quantitative insights into energy consumption. Non-intrusive acquisition of information regarding the status of various appliances holds significance in numerous applications where NILM systems find utility, including smart home automation and ambient assisted living. NILM systems serve to delineate the energy consumption patterns of individual appliances, potentially facilitating the development of recommendation systems.

Around 2010, a prominent shift arose in the domain of NILM frameworks research: the ascent of frameworks that sidestep the underlying occasion discovery stage. These frameworks work on a ceaseless stream of total sign examples (basically time-series information), handling them without hanging tight for explicit occasions. Named non-occasion based frameworks, they take out the requirement for elements or marks, depending rather on the total power signal itself. Kolter et al.. [8] were among the trailblazers in this field, presenting frameworks in light of discriminative meager coding for energy disaggregation. This technique includes preparing discriminative models for various machine classes, with individual energy utilization determined as a mix of essential capabilities increased by initiations.

Secret Markov models (Gee) have turned into a staple in non-occasion based NILM frameworks. Kim et al. [9] were early defenders, presenting a factorial Well (FHMM) where every machine's way of behaving is displayed freely. Following a preparation stage, the FHMM can gather machine states from the total utilization signal, empowering individual utilization division. In [10],Well are coordinated into a Bayesian structure, amalgamating different machine models into an exhaustive machine model. Bonfigli et al. [11] proposed a bivariate FHMM utilizing both active and reactive power consumption data. Additionally, Paradiso et al. [12] exhibited that consolidating advantageous data like house inhabitance and machine use times can upgrade disaggregation results.

In 2015, Kelly and Knottenbelt [13]inpresented the utilization of profound learning (DL) in non-occasion based NILM frameworks. While fake brain organizations (ANNs) had been used beforehand in NILM research, they were ordinarily utilized as classifiers in occasion based frameworks' heap recognizable proof stages. [13]for the initial time, the total power signal was handled through an ANN utilizing moving-window handling, regarding the issue as a visually impaired source partition task. The creators exhibited that such designs beat combinatorial streamlining[8] and FHMM models [9], [10].DL algorithms offer the benefit of computerizing highlight extraction, learning undertakings, for example, individual apparatus utilization, on-off state advances, and functional lengths straightforwardly from the information utilizing ANNs.

[14]Sense tracks your home's energy, it starts to perceive most apparatuses and different gadgets that utilization in excess of 60 watts. Normally the Sense screen identifies 12 gadgets in the principal month after it's introduced and 25-30 gadgets following a year. Each house is unique, notwithstanding, so the quantity of recognized gadgets might be sequential. Sense is intended for fast establishment and consistent improvement. The screen utilizes sensors that read the electrical flow north of 1 million times each second, while AI utilizes that information to figure out what gadgets are here and there.

[15] In this study, a Nonintrusive Load Monitoring (NILM) system leveraging edge processing is introduced, meaning to observe the energy utilization ways of behaving of individual gadgets inside an electrical arrangement. The proposed framework conducts energy utilization information handling straightforwardly on the gadget introduced inside the observed office. In particular, it embraces a succession to-point approach utilizing a convolutional brain network executed on an Arm CortexM7 microcontroller. Moreover, the paper presents discoveries from a broad year testing stage. The NILM framework was conveyed in two genuine homes in focal Italy to survey its down to earth sending and likely utility in true settings. This exploration offers a promising arrangement ready to work with the far reaching reception of NILM frameworks, tending to worries in regards to execution expenses, intricacy, and protection related with cloud-based information handling. The results of true testing highlight the proposed NILM framework's possible across different spaces, including brilliant homes, building computerization, and modern energy the board.

1.3 Problem Statement

The current landscape of energy consumption monitoring lacks efficient real-time capabilities, often relying on intrusive hardware installations but that could be challenging to practically implement. To address this, there is a critical need for a non-intrusive load management system (NILM) powered by artificial intelligence (AI) that can accurately monitor energy consumption in real-time, including individual appliance energy usage.

1.4 Objectives of the Project

- Identification of Energy consumption by individual appliance of limited set of daily use appliances.
- Real Time Data collection and analyze to predict the possible power consumption by a specific appliance.
- Implementing AI algorithm in Microcontroller.

1.5 Cost Analysis

Table 1: Cost Estimation

Item	No. of Items	Price
STM32 Nucleo Board	1	16,000
ESP 32	5	6,000
Sensors	5	13,000
Storage Device	1	20,000
Display & Other miscellaneous items		5,000
Total		**60,000**

1.6 Timeline of the Project

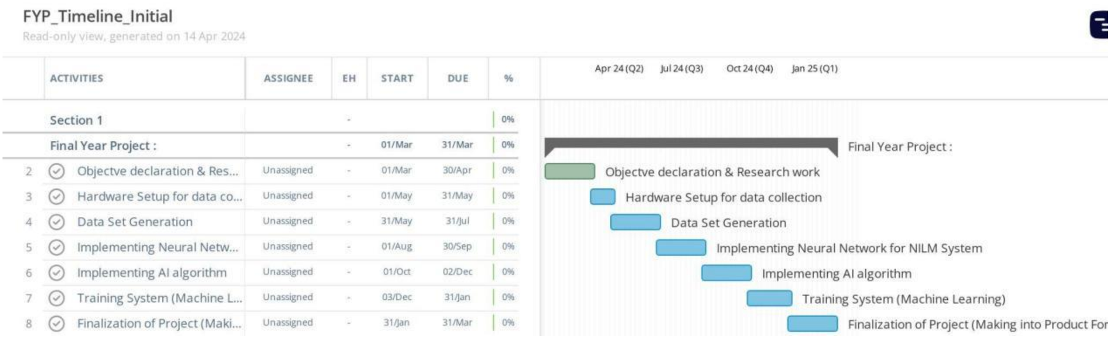

Figure 1: Timeline of Project

1.7 Work Division

- Research work and theoretical background will be carried out by MUHAMMAD SALMAN.
- Code implementation (Neural Network & AI Algorithms) will be performed by MUHAMMAD MAHMOOD GHAURI.
- PCB designing, hardware design and implementation will be performed by MUHAMMAD MOIN DILDAR.

1.8 Organization of Report

In Chapter 1, an introduction is presented and discusses the background motivation to perform this project. Also mentioned the previous work done on technologies used in this project. Chapter 1 discusses why today's world needs it and what objectives are to be achieved. Also what cost and timeline required to do this project.

Chapter 2 discusses the final product specifications and approach used to achieve the above mentioned objectives.

2 Description

Chapter 1, the background, motivations, and already research related to AI-powered energy management systems had been studied, In Chapter 2, further searched on the project. Here, a detailed description of the system itself, outlining the methodology behind its development, product specifications, and a preliminary schematic diagram. And also delve into the design considerations and initial calculations that will guide the project's implementation.

2.1 Description of the Project

This project aims to monitor energy consumption using smart technology called Non-Intrusive Load Monitoring (NILM) Using Artificial Intelligence (AI). The main goal of this device is to help businesses and households to keep track of their energy usage in a simple and efficient way. The project consists of several components, including the design of the monitoring system, the integration of NILM and AI technologies using STM32 Nucleo board (NUCLEO-H743ZI2), ESP 32, sensors (EVALSTPM32) and Display. The device works by analyzing overall energy consumption data to identify patterns associated with specific appliances or behaviors, without the need for intrusive methods like installing sensors on individual devices. It helps businesses and homes to save money by finding ways to reduce their energy usage and to protect the environment by promoting energy-saving practices that reduce pollution and save resources and it makes energy monitoring easier for everyone, so more people can manage their energy usage better.

2.2 Methodology

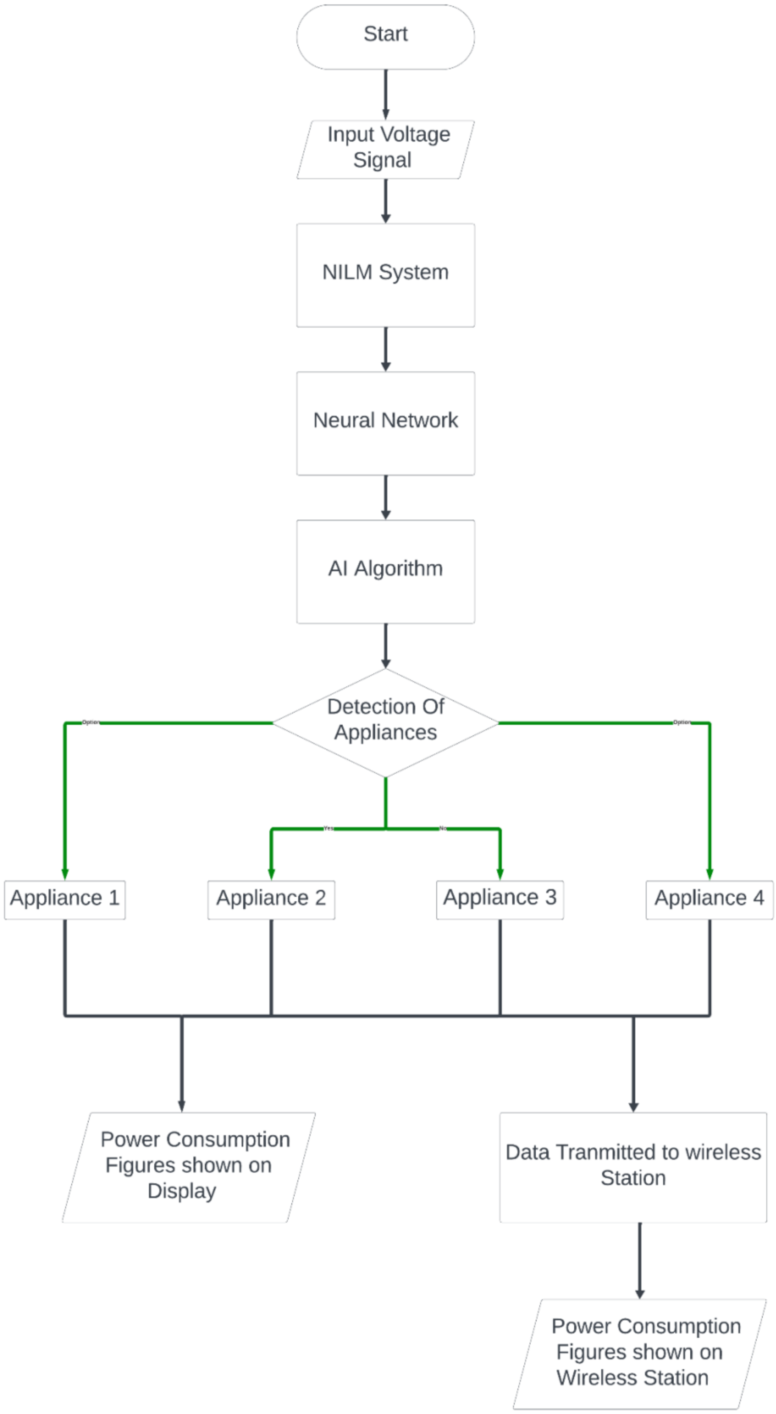

Figure 2: Code Flow inform of Flow Chart

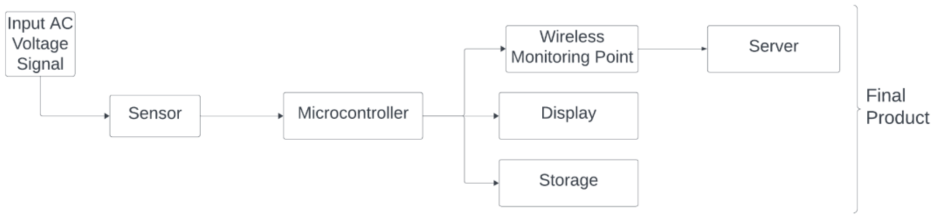

Figure 3: Block Diagram of NILM system

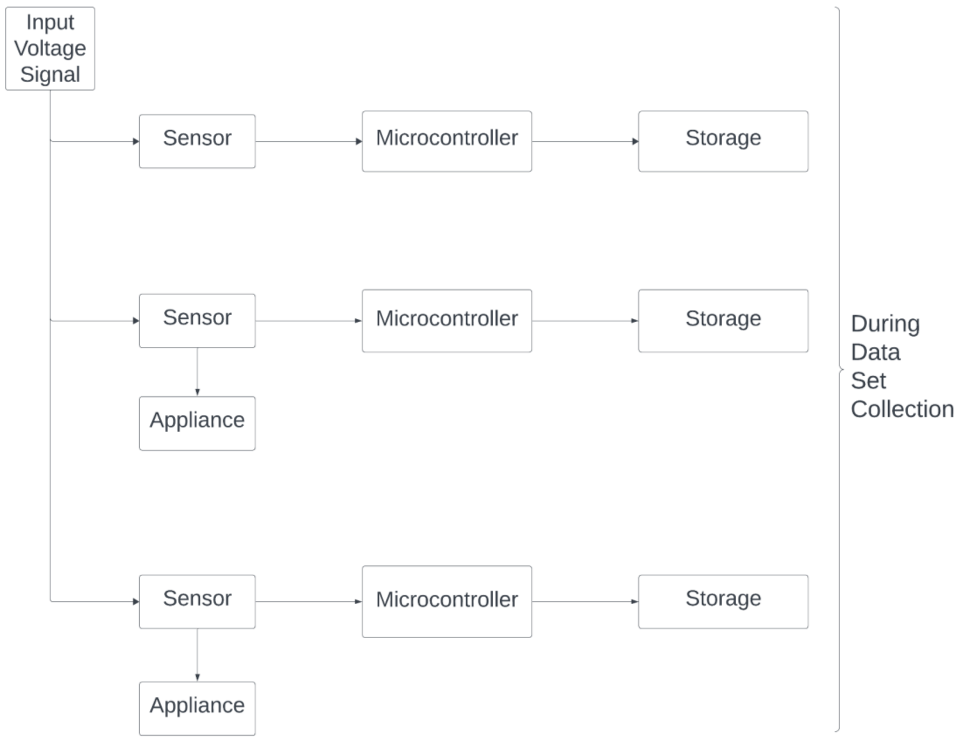

Figure 4: Block Diagram of System during Data Set collection phase

In Figure 2, flow of code is represented in the form of flowchart. The system will start and real-time signals will be passed through the neural network and artificial intelligence will detect which appliance is consuming energy and the results will be shown on display. Also results will be transmitted to wireless monitoring station.

In Figure 4, the system is shown in block diagram form during data set generation where the system will act as an intrusive load monitoring system in which signal from each appliance will be stored in a storage device and overall signal of combined load of input will be analyzed and stored.

In Figure 3, the final product is shown on block diagram level in which system will be Non-Intrusive Load Monitoring system. The system will only analyze input signals and through Energy Disaggregation technique, energy consumption by each load will be detected.

2.3 Product Specifications

Here, the list of features and operational specifications of our project is mentioned.

1) **Real-Time Monitoring:** The device provides up-to-date information on energy consumption, permitting users to path usage patterns as they occur.
2) **Non-Intrusive Operation:** Using Non-Intrusive Load Monitoring (NILM) technology, the system analyzes overall power consumption without the need for intrusive hardware installation.
3) **AI Integration:** By including Artificial Intelligence, the device can identify individual appliance usage patterns and provide insights for monitor and display.
4) **User-Friendly Interface**: The device features a simple interface that permits users to easily access and illuminate energy usage data.
5) **Environmental Sustainability**: It helps protect the environment by promoting energy-saving practices that reduce pollution and save resources and it makes energy monitoring easier for everyone, so more people can manage their energy use better

2.3.1 Schematic Diagram

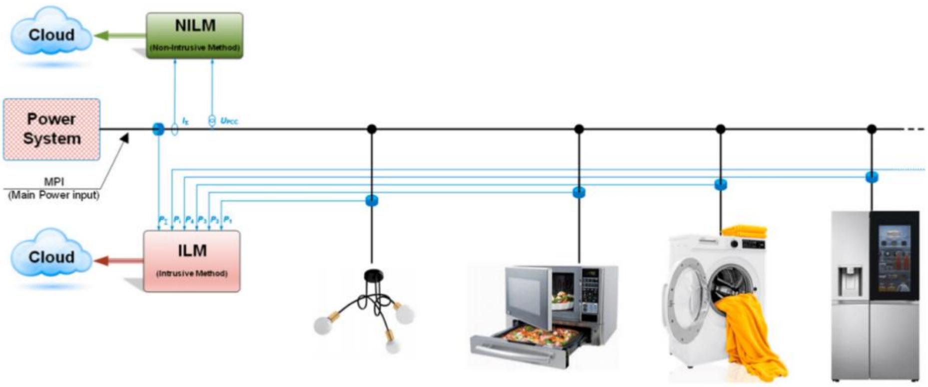

Figure 5: Schematic Diagram of System

During Data set collection phase ILM System will be implemented and In final product NILM system will be implemented.

2.4 Preliminary Design and Calculations

- 0.2% accuracy single-phase meter
- Vnom(RMS) = 140 to 300 V
- Inom/Imax(RMS) = 5/100 A
- flin = 50/60 Hz ± 10%

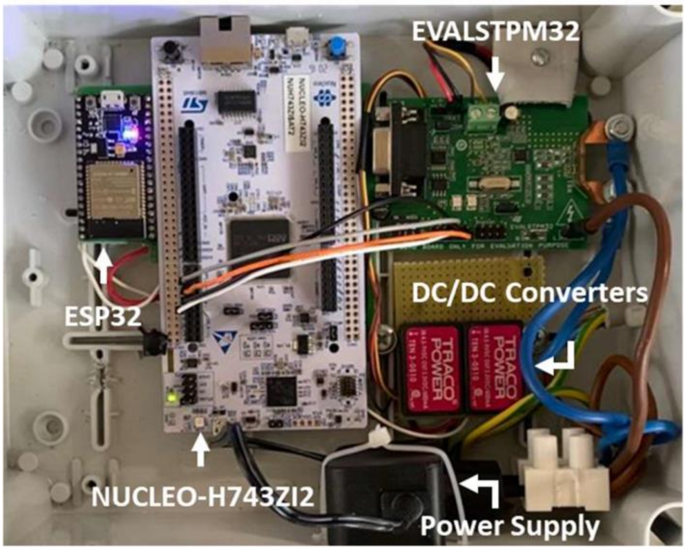

Figure 6: Possible Hardware Circuit of NILM System [15]

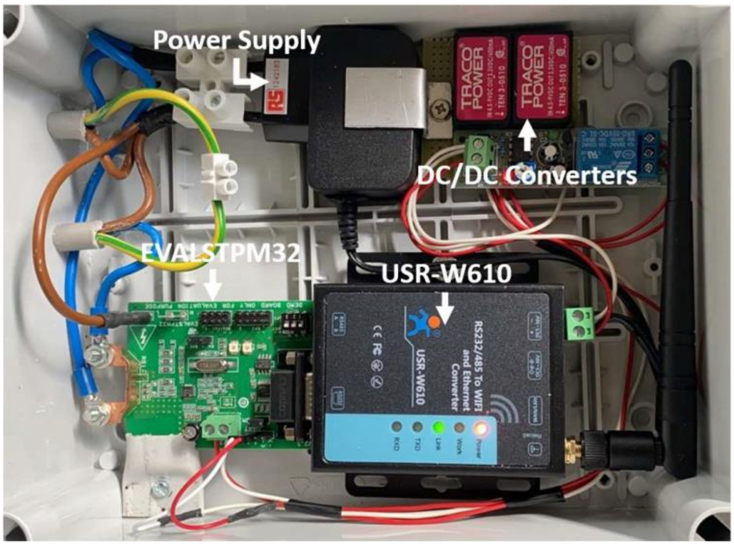

Figure 7: Possible Hardware Circuit of system installed on each appliance to generate data set [15]

Figure 8: Preliminary Design of Final Product

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