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Except where explicitly stated all work in this report, including the appendices, is my own

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Abstract

The aim of this thesis is to develop a Non-Intrusive Load Monitoring in order to help homeowners acquire a detailed understanding of their power consumption at an appliance level. This is achieved by choosing 3 appliances namely fridge, coffee machine and electric kettle and creating an equivalent circuit. The appliances are combined in 8 different ways and a CT sensor used to record compound waveforms. The waveforms are analyzed and features such as minimum current, maximum current, mean current, median current and standard deviation extracted. The features are used to train SVM and k-NNR classification models to identify the appliances in each combination. k-NNR model achieves an accuracy of 98% and is thus used in testing. Two tests, remote and live are done to verify the performance of the NILM system. In remote test, the classification model is stored locally while in live test the classification model is stored online. The system performs better when the model is locally stored as transmission delays in the system prevents the system form identifying the appliances in real-time. Lastly, the system is presented with a case study scenario where it successfully identifies the appliances, calculates the electricity bill based on the consumption and generates a power consumption report. The key findings from this project are that the NILM system works better when the appliances are in steady state and for future work, whenever inductive loads are used, all the power consumption states should be considered.

Keywords: NILM, kNNR, CT sensor, Label binarization

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Table of Abbreviations

CT sensor- Current Transformer. Used interchangeably with current clamp meter.
HEMS – Refers to Home Energy Management System
KCL- Kirchhoff's Current Law
NILM - Non-intrusive load monitoring
NILM system **–** refers to measuring device (Arduino Uno and CT sensor), feature extraction model and k-NNR classification model.

1 Introduction

This section reviews the electricity status in Kenya and highlights the major challenge that this project aims to solve.

1.1 Electricity status in Kenya

Over the last decade, Kenya has been leading in Africa with the highest rate of increase in the number of households with access to electricity. This number has increased from 27% in 2013 to 73.42% in 2018 [1]. Moreover, electricity access among rural households increased from 7.17% in 2010 to 48.39% and from 58.2% to 77.6% among urban households within the same time period [2]. Despite the progress made, the electricity sector in Kenya still faces some threats.

In rural areas, many of the households remain without access to electricity especially in the Northern part of Kenya. The electricity consumption is low among those that are connected. Mostly, electricity is used for lighting while activities such as cooking is done using firewood in rural areas and portable gas cylinders in urban areas. Electricity supply is unreliable and of poor quality. This is because power outages are very frequent and happen without notice especially during rainy season.

A recent study cited publication of overly rosy projections, which drive over-investment in generation ignoring distribution and transmission [3]. Another issue cited was corruption at Kenya Power (major electricity distribution body). Further the government was accused of being slow in reforming the energy sector as updated energy legislation drafted in 2015 are still being held up in parliament.

Moreover, over the last 5 years, there has been frequent backlash from consumers citing overpricing electricity. The power distribution company has made efforts to reform the billing system by eliminating fixed tariffs and introducing a tariff harmonization plan [4]. This has had a negative impact as the increased variable tariff has led to more backlash from consumers. Moreover, the power distribution company distanced itself from allegations of overpricing of electricity. In order to proof whether the company indeed overcharges electricity, consumers need to have a detailed understanding of their power consumption at an appliance level and use the tariffs that have been made public by the power company to calculate their bills and compare them with what the power company charges. This way both parties can clear any doubts and lay any form of misunderstanding to rest.

2 Background

This section covers a brief introduction to parallel circuit analysis, an overview of existing solutions (energy management systems) and introduces the objectives of this work. In the introduction to circuit analysis, the application of Kirchhoff's Current Law in parallel circuit analysis is described while in energy management systems, the concept of energy management systems and its application in households is discussed. In objectives, the proposed solution is introduced, and the objectives of this work outlined.

2.1 Parallel Circuit Analysis

Kirchhoff's Current Law states that the algebraic sum of all currents entering and leaving a node must be equal to zero. This law has been used in circuit analysis. The circuit in Figure 1 shows a simple application of the law in the analysis of parallel circuits.

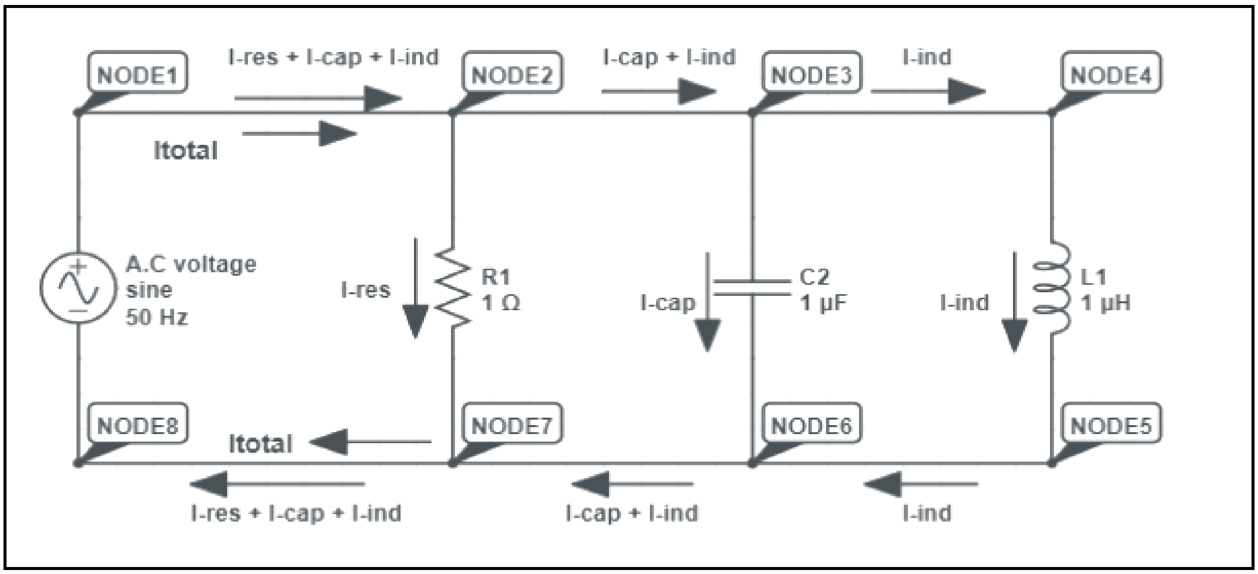


Figure 1: Application of KCL in circuit analysis.

Circuit Analysis.
At any given node, the sum of all the currents entering and leaving the node is equal to 0. + shows currents entering the node while – shows the currents leaving the node. For instance, In Node 2:

The current entering the node is $I\_total(I\_res + I\_cap + I\_ind)$
The currents leaving the node are I_res and $(I\_cap + I\_ind)$
The sum is equal to $I\_res + I\_cap + I\_ind - I\_res - (I\_cap + I\_ind) = 0$

All the different currents entering and leaving all the other nodes are clearly shown in Figure 1. The concept described above has been used in the design of energy management systems. This is because the electrical wiring in households is like parallel circuits with the mains supply as a voltage source and the different loads connected in parallel.

2.2 Energy Management Systems.

Energy management systems (EMS) are described as automatic systems that collect energy data such as electricity and gas and avail it to users using graphics, online monitoring tools and energy quality analyzers hence enabling the management of energy resources under measurement [32].

The key steps in energy management systems include:

- Determining a monitoring point
    - Essentially a point that allows the system to monitor/have access to the entire network.
- Setting up a data acquisition system to collect and transmit the data to a control center through a communication system
    - Data acquisition systems contain measuring instruments such as electric power metering systems.
    - And communication systems such as Bluetooth, WIFI etc. for data transmission.
- Using computational tools such as state estimation (SE) to process the raw data and forward it to other EMS applications.
    - SEs act as filters. They smooth out small errors and suppress gross errors arising from the data acquisition system.

Based on the area of application, there are 3 types of EMS. They include Building Energy Management Systems (BEMS) which are energy management systems used to monitor, control and optimize the energy consumption needs of a building, Home Energy Management System (HEMS) which are EMS used to monitor daily energy consumption in households and Industrial Energy Management System (IEMS) used to monitor energy consumption in industries and factories.

2.2.1 Home Energy Management Systems.

They consist of software and hardware linked together to monitor energy usage in households. The software and the hardware components are linked together by a network. An example of a HEMS is a smart meter.

A smart meter is a device that measures the total amount of electricity and gas used. They have inbuilt A.C voltage and A.C current sensors which measure voltage $(Vtotal)$ and current $(Itotal)$ at the point of entry, equivalent to Node 1 in Figure 1. They use the values to calculate the total power. Smart meters provide real-time information on total consumption and cost. Each installation of a smart meter includes an energy monitoring device, an in-Home Display as shown in Figure 2 and a website portal account or mobile application. The in-Home Display shows the total electricity and gas used so far while the portal and application show how much electricity is used per day, per week, per month, or per year.

Figure 2: Smart meter with an in-Home display unit [40]

Smart meters allow users to have more visibility over their energy consumption. This has made them more popular. In recent years, there has been an increase in the number of home energy management systems installed in households in countries like the United Kingdom and the United States of America as shown in Figure 3. This shows that more homeowners are embracing HEMS and the visibility given to them over their energy use has been useful in reducing energy consumption costs.

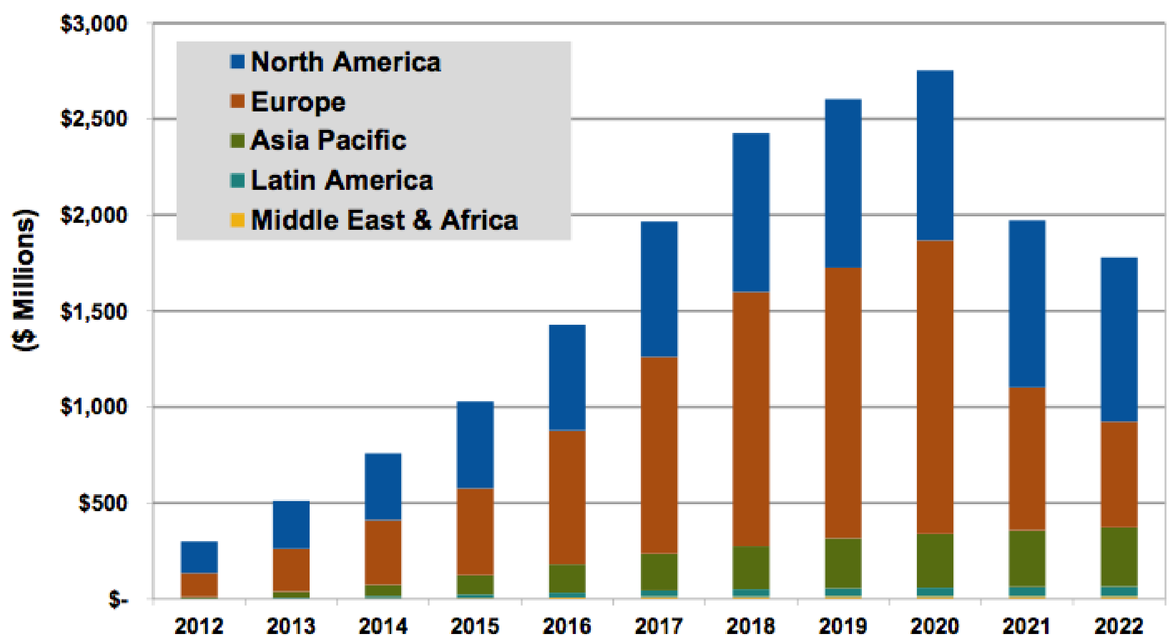


Figure 3: Recent trends and projections of home energy management systems [39]

Despite this visibility, users remain in the dark as they are not able to pinpoint the appliances that are consuming a lot of energy or pinpoint sources of electricity wastage using a single smart meter. In order to have a detailed understanding of per appliance energy consumption, some users have been forced to buy smart meters for every appliance which has led to the installation of many smart meters per household.

This approach is costly as users also must pay for meter installation and system integration depending on the number of appliances in a household. According to [27] - [29], this initial cost ranges from 33 to 253 Euros. Moreover, besides the initial expenses, users also incur operational expenses which include data transmission charges, meter maintenance, training and billing. The operational costs are estimated between 11 and 34 Euros [27],[28]. Furthermore, research has shown as the number of smart meters installed increases, the reliability of the system decreases [30].

2.3 Objectives

In order to improve the reliability and financial burden of Home Energy Management Systems and to help consumers understand their consumption at appliance level, this report proposes a system that uses a single device for load monitoring. The proposed solution is made up of a single energy measuring device mounted at the point of entry (mains supply) and a display system which can either be a mobile application, an in-home display unit or a web portal. When connected, the device can detect all the appliances switched on at a given time and provide a per appliance power consumption breakdown. Further, the system is incorporated with up to date tariff charges charged by power companies enabling it to present a projected monthly electricity bill at any given time. The main advantage of this system is that it constantly updates the user about their power consumption and by being aware of their electricity consumption, consumers can make decisions such as reducing some load operations to fit their budgets.

In reference to the circuit in Figure 1, the device measures I_total (which is a compound waveform) and uses machine learning to break it down to its constituents I_res , I_cap and I_ind .It further identifies the loads $R1$,$C2$ and $L1$.The loads are equivalent to the appliances switched on at the time.

Unlike traditional smart meters, all the display systems of the system should contain the same set of data. The system should show the total electricity consumed, use machine learning to identify the appliances that are on and the amount of power consumed by each per day, per week, per month, or per year. Further, it should also show the cost of the electricity consumed monthly based on current electricity tariffs.

The objectives of this project are:

- To identify a suitable load signature that can clearly show the uniqueness of how different appliances consume power.
- To identify 3 common household appliances.
- To build a circuit that represents a household with the 3 appliances connected.
- To switch on individual appliances, followed by any two appliances and lastly all the appliances and use a suitable measurement device to obtain compound waveforms.
- To analyze the compound waveforms and extract features from the waveforms.
- To use these features to train a model that can identify loads in operation at a time.
- To create a test to verify the efficiency of the model.

- To create a case study scenario and use the model to identify the appliances, calculate the bill and generate consumption report.

2.4 Report Structure

This report is divided into 6 main sections. Literature Review, Methodology, Conclusion, Future Work and Recommendations, Appendices and References. In Literature Review existing journals on load monitoring and NILM system design are reviewed and summarized while Methodology covers all the steps taken in creating the solution proposed in the objectives right from design, implementation and testing. In the Conclusion, the project is critically reviewed to identify the objectives that have been achieved and those that have not, whether the assumptions made when solving the problem were appropriate and the overall strengths and weaknesses of the project. In Future Work and Recommendations, suggestions on how to improve the project are made. Appendices contains the codes used and screenshots of the results obtained in the object during testing. All the resources (journals, books and websites) referred during this project are listed in the Reference section.

3 Literature Review

This literature reviews load monitoring and NILM system design. In load monitoring, intrusive load monitoring methods (ILM) and non-intrusive load monitoring (NILM) methods are defined and their merits and demerits highlighted. NILM system design covers all the stages necessary in developing a NILM energy monitoring system that is, from data acquisition to load identification.

3.1 Load Monitoring

Load monitoring is the process of collecting and identifying load measurements such as current and voltage [6]. The collected measurements are used to determine the power consumption and the operating conditions of the individual loads in operation within the power system. As appliances largely contribute to the electricity bill, load monitoring has become more common in residential and commercial buildings [5]. In the context of residential buildings, load monitoring is often referred to as Appliance Load Monitoring (ALM) [6]. Appliance Load monitoring can be achieved by using intrusive or non-intrusive methods. Intrusive load monitoring (ILM) methods involve the installation of a measurement device on every appliance being monitored while Non-intrusive load monitoring (NILM) methods involve a single measuring device being introduced upstream (often at the meter box) to obtain a single mixed-signal that is disaggregated into constituent signals representative of the appliances in use at the time.

3.1.1 Intrusive Load Monitoring (ILM) Method

In the context of load monitoring, intrusive generally means that the measurement device is close to the appliance being monitored while invasive means that the measurement device is added to the power system and considered as one of the loads. When using ILM methods, the measurement devices can either be intrusive or non-intrusive (low-end sensors externally attached to the appliances). The measurement devices are installed on each appliance of interest and the measurements are transferred to a central monitoring system. This is illustrated in Figure 4. Access to individual appliances is necessary in order to install the sensors.

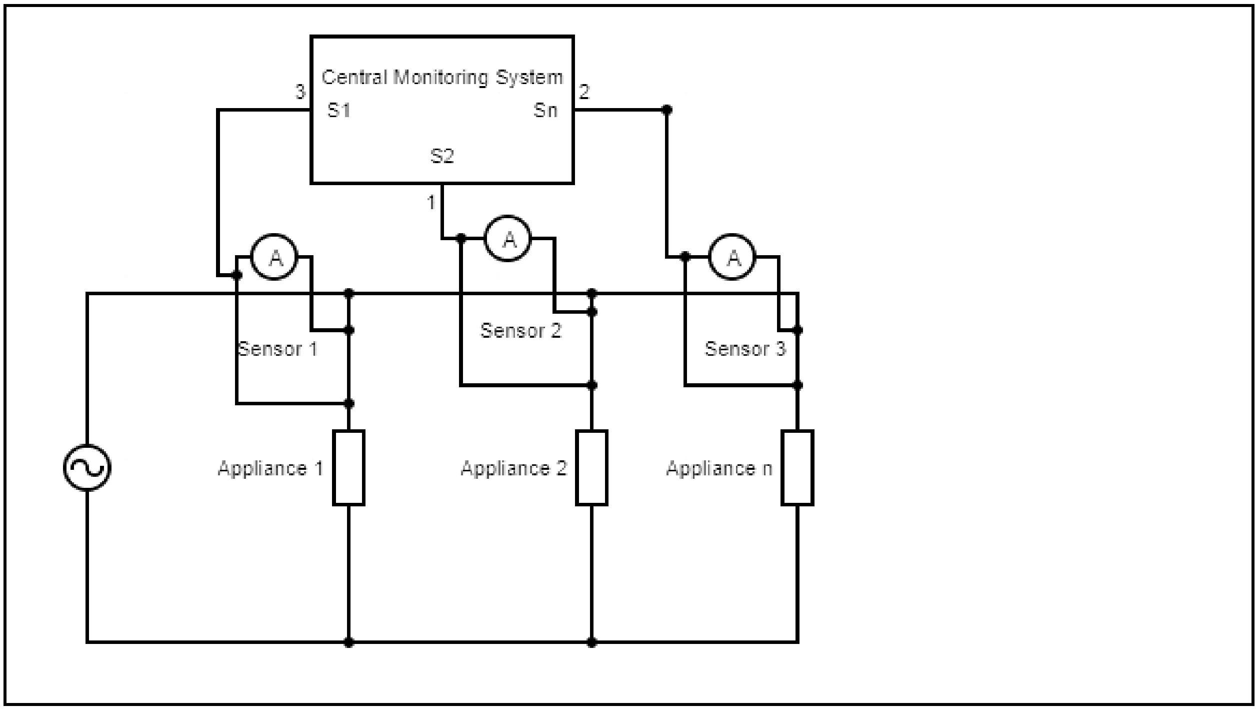


Figure 4: ILM system

The extent of the intrusiveness in ILM systems varies depending on the number of appliances attached to a set of sensors. Based on these variations, [6] classified intrusive load monitoring systems into three subdomains:

- Smart plugs - where the appliances are grouped, each group is connected to a plug and a single meter is used to monitor each plug.
- Submetering systems- where a single meter is connected to a zone of appliances without a plug.
- Smart appliances - each appliance is monitored by a single meter.

The framework of ILM involves three stages namely:

- Single Appliance Detection: Sensors detect whether appliances are ON or OFF and their location.
- Middleware Phase: Software that interprets the readings from the sensors.
- Appliance Status Phase: shows the status of the appliances.

The main advantage of ILM is that sensors are installed on each appliance which makes the process of load identification more accurate as they can identify low power appliances and appliances in stand-by [7]. ILM methods are more accurate when used to identify devices which have multiple consumption states like fridges and microwaves and those that continuously draw variable energy like laptops and mobile phones. However, ILM methods are expensive as each appliance requires a sensor attached to it. Further, users also incur other costs such as the cost of installation, maintenance and management of the systems. This is because the system requires occasional checks to ensure that the measuring devices do not have any impact on the normal functioning of the power system. Another disadvantage is that the presence of all these numerous measuring devices makes the system more complex.

3.1.2 Non-Intrusive Load Monitoring (NILM) Method

NILM was first proposed in the 1980s by Hart to manage the economy and practicability concerns raised with the use of intrusive load monitoring methods [8]. Unlike intrusive load monitoring systems, NILM methods do not require the hardware device to be installed on each load, rather a single hardware device is installed mostly at the mains supply. The single signal obtained is treated as a compound signal and analyzed to obtain individual signals that represent the individual loads in operation [9]. The system is illustrated in Figure 5.

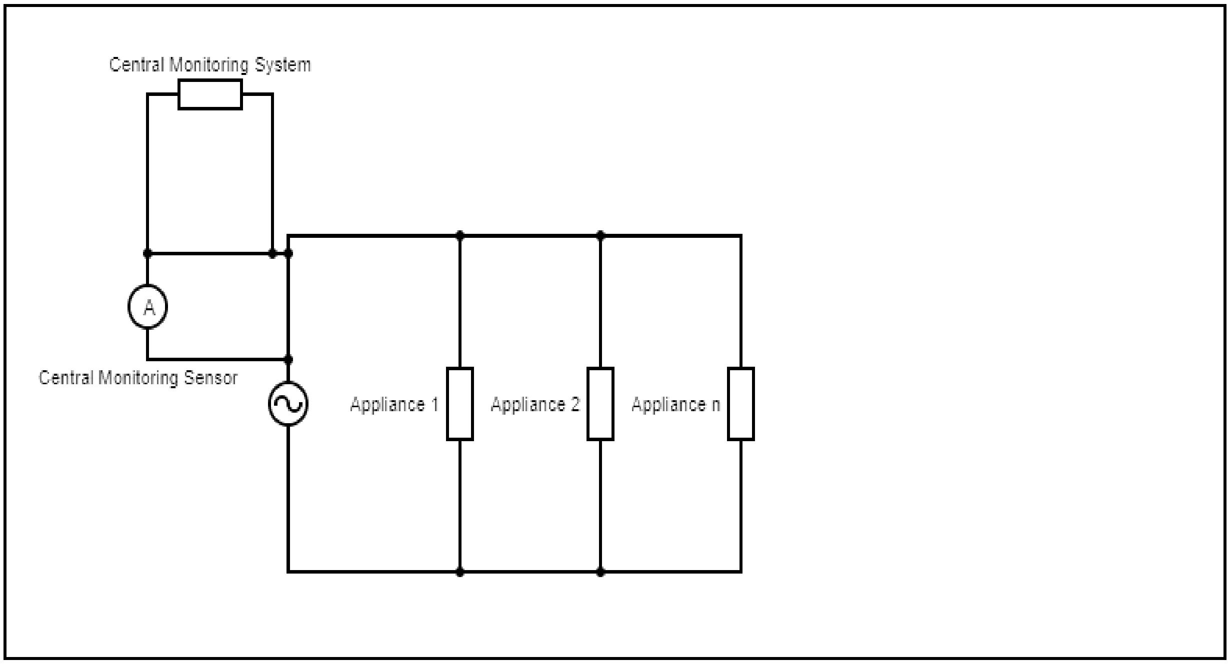


Figure 5: NILM system

During the analysis process of the compound signal, current and voltage waveforms measured at the mains supply are analyzed to come up with features which give more information about the operational characteristics of the appliances. The general approach in a NILM system can be summarized as shown in Figure 6.

Figure 6: Summary of NILM approach [7].

NILM methods require the installation of a single sensor which makes data collection simple and easy. When used to identify devices that have multiple consumption states like fridges and microwaves and those that continuously draw variable energy like laptops and mobile phones, NILM devices are less accurate. Moreover, NILM accuracy is heavily dependent on the sampling rate. The more the sample, the higher the chances of correctly identifying the appliances. This is because the load identification models depend on pre-recorded data to identify appliances.

3.1.3 Conclusion

NILM methods have more merits as compared to ILM methods. For instance, NILM requires the installation of a single hardware device at the mains supply while ILM requires sensors to be installed in every appliance which is quite expensive. NILM enables users to save on device costs. Also, since no access to individual appliances is needed to install the sensor, NILM systems are convenient. Lastly, NILM hardware devices are easy to install and do not require technical skills for installation and set-up. This report focuses on the NILM approach.

3.2 NILM System Design

This subsection covers Load signatures and the three stages involved in NILM energy monitoring systems that is, data acquisition, feature extraction and load identification.

3.2.1 Load Signatures

Load signatures can be defined as unique patterns that show how each electrical appliance consumes energy [8]. They are an integral part of load monitoring and identification. Further, for effective load monitoring, they must be clearly considered. This is because the signature chosen informs the choice of measuring equipment and the technique of extracting and analyzing the compound waveform.

Different energy monitoring systems are based on different load signatures. In his work, [8] Hart divided load signatures into two distinct groups, intrusive and non-intrusive signatures. He described nonintrusive signatures as signatures that could be measured passively by observing the normal operation of the load. Nonintrusive signatures were further divided based on whether the information on the load state continuously present thus steady-state signatures is or present only when there is a state transition (transient signatures) i.e. ON to OFF or OFF to ON.

Intrusive signatures, on the other hand, require physical or electrical intrusion. Physical intrusion involves the construction of devices that are linked to the appliances such that whenever the appliance uses power, the device generates certain current harmonics or radio frequency signals which are then injected into the power system [8]. The injected radio frequency signals or current harmonics are then used to identify appliances on or off. Electrical intrusion involves injecting voltage harmonics or transients into the mains supply. By tracking the change of the current waveform, the appliances on can be identified.

Intrusive signatures are less common as they involve the injection of signals into the power system lines which were not accounted for during the design of the system protection.

3.2.1.1 Load Signatures in previous works

Hart [8] proposed a load signature clustering algorithm that is based on active power and reactive power. Each appliance is turned on and off for some time. The duration and the appliance are recorded, and a measuring instrument used to measure the power (active and reactive power). The key point is the use of a step detector. The step detector measures the change in power when the appliance is on or off. This change is recorded alongside the appliance in a database.

The key steps in load monitoring are summarized as follows;

- A measuring instrument is used to measure total power,
- A step detector used to detect the change in power
- The values are then compared with those pre-recorded to identify the appliances.

In [10], a complex signal is recorded at the mains and current, voltage, active power and reactive power waveforms are extracted. These samples are transformed from time domain to frequency domain and used as signatures. A Self-Organizing Feature-Mapping Neural Network (SOFMNN) is used to extract features from the signatures. SOFMNN is used at this stage because the components of the frequency spectrum are not equally important. Some are more important thus carrying more weight while the less important ones carry less weight and can be easily ignored.

Furthermore, the signature topological structures have to be arranged before training the neural network to identify the loads- it's not possible to use a supervised neural network to arrange these structures. The extracted features are forwarded to a two-layer supervised neural network.

In [11] the load signature used is shape that is, wave-shape features. The wave-shape features used are based on V-I trajectory. V-I trajectory refers to the mutual trajectory of instantaneous voltage and current waveforms [11]. Four algorithms, artificial feed-forward neural networks (ANN), hybrid neural networks, support vector machine (SVM) with a Gaussian kernel function and adaptive boost (AdaBoost) for one-dimensional decision stumps are trained to identify appliances.

In [12] odd-order harmonic current vectors are used to determine the load signature of different appliances. The amplitude and the phase angle of each harmonic order are considered. However, the harmonics considered are up to 3rd order as above that, the amplitude measured does not represent the sum of individual amplitudes of the individual loads. This is because, in higher-order harmonics, the harmonic current vectors of the individual loads are not in phase [13]. The current vectors are converted from 2-dimension to 1-dimension by using vector projection onto the x-axis. FFT analysis is applied to the filtered current signal to identify the loads. Based on the examples given above, fundamental frequency signatures are widely used. This is because the utility fundamental frequency and line voltages in different countries are known; 60Hz frequency and 120V line voltage in the U.S and 50 Hz frequency and 240V line voltage in most African countries. This makes them convenient and easy to use in identifying loads.

3.2.1.2 Conclusion

This report uses current as load signature. The extracted current waveform in the time domain gives detailed information about the load behavior [14]. The signal usually has a high resolution meaning it is easy to identify the distinct appliances. Further in [15], a study on the most commonly used load signatures showed that some of the loads used in households have unique current waveforms. This cemented the use of the current spectrum in load monitoring. The distinct current waveforms of some of the most commonly used appliances like a water heater, air conditioner, TV and an induction cooker are summarized in Figure 7. By visual observation of the current waveform, appliances can be identified. This is because they all have unique amplitudes.

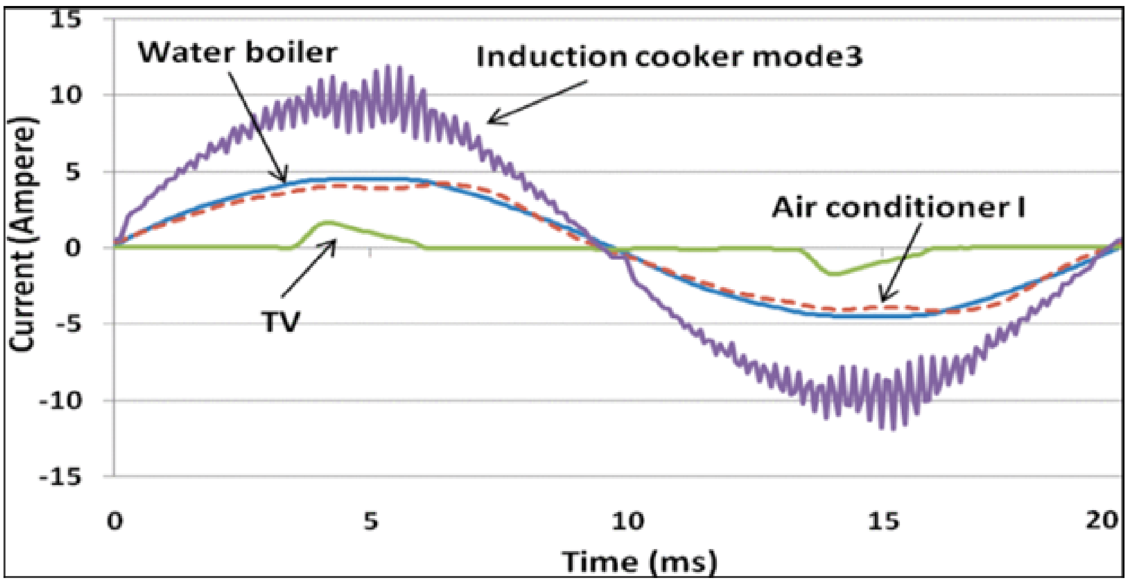


Figure 7: The current waveform of the most commonly used household appliances [14].

The same study [15], found out that active and reactive power-based load signatures to be ideal in distinguishing resistive loads from capacitive, inductive and nonlinear loads. These signatures will be used to further distinguish loads with similar properties. For instance, in Figure 7, the active and reactive power-based load signature would be used to differentiate the water boiler and the air conditioner.

3.2.2 Data Acquisition

The data acquisition process is designed to measure electrical properties such as current, voltage or power. The measured signals are used to extract features such as current and voltage waveforms which are used to identify the different loads. The load signature used in this report is current. In order to get a current waveform, the data acquisition process involves the measurement of current. The subsection below covers current measurement and transmission of the measured current to the model for feature extraction and load identification.

3.2.2.1 Current Measurement

Current measurement can be done using invasive or non-invasive methods. Invasive current measuring, also direct sensing is based on Ohm's law ($V = IR$). It involves the connection of a shunt resistor in series with the load as shown in Figure 8. This way, the current that flows through the resistor is directly proportional to the ratio of the applied voltage to shunt resistor value ($I = V/R$). This technique is said to be invasive since the power dissipated at the shunt resistor is added to the system.

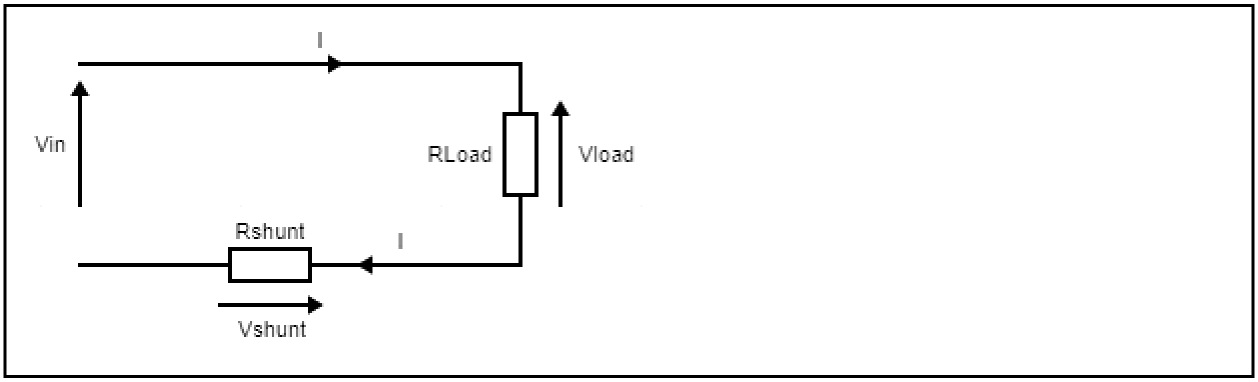


Figure 8: Invasive current measurement using a shunt resistor

Non-invasive current measurement also referred to as indirect sensing is based on Ampere law which relates the magnetic field along a closed loop to the current passing through the loop and Faraday law of induction which relates the rate of change of magnetic flux through a loop to the induced emf in the loop. Indirect sensing involves placing a coil around a current-carrying conductor as shown in Figure 9. This leads to a voltage being induced across the coil. The induced voltage is proportional to the current. In this method, the current being measured is isolated from the load.

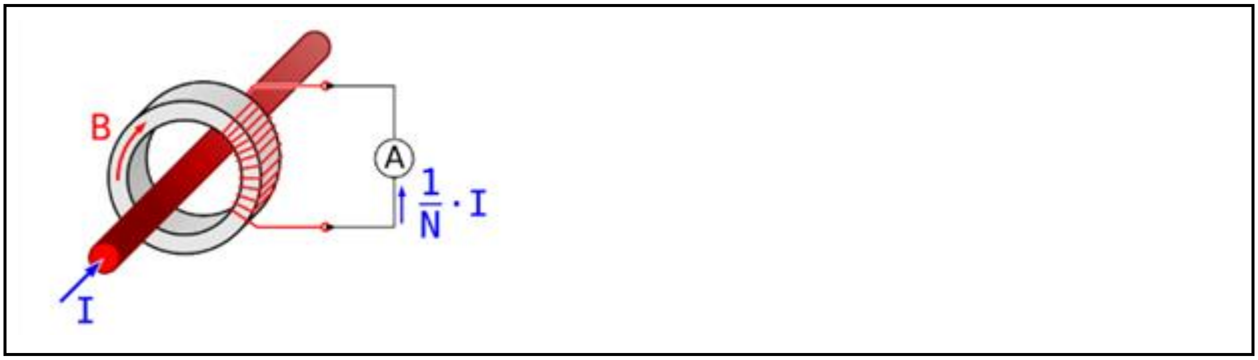


Figure 9: Indirect sensing: Coil around a current-carrying conductor [38]

Non-invasive methods are more commonly used with NILM methods. This is because non-invasive AC Current sensors do not affect the current being measured and are easy to install.

Current sensors have current transformers that step down any large AC current to a small current reading that is easily converted to a voltage using a built-in resistor. This voltage is measured and used to infer the AC current value.

3.2.3 Feature Extraction

Feature extraction refers to the process of reducing data rate by selecting a few features that are more relevant and informative from a large dataset [16]. The extracted features, mostly current, voltage or power, are referred to as load signatures. Feature extraction can be done locally or externally in which case the choice of communication method is crucial. The first subsection analyses the different communication methods that can be used.

3.2.3.1 Data Transfer

Communication between devices allows data transfer. The communication channel can be wired -involving the use of cables to connect the devices like ethernet cables used to transfer data between PCs or wireless meaning communication is over the air. Wireless communication is preferred in load monitoring as it is flexible and less complex especially when many devices are used, compared to wired communication [17]. Wireless networks include Bluetooth, Infrared, WIFI, Zigbee, LORA and other local wireless area networks (WLAN).

The factors that inform the choice of the wireless network technology include battery life, range of coverage, power requirements, data transmission rate and the operating frequency. Figure 10 summarizes the comparison between the different technologies.

Wireless Network	**Zigbee**	**Bluetooth**	**WIFI**	**Infrared**	**LoRa**
Range	10–100 m	10 m	50 – 100 m	<10 m (line of sight)	20 km
Power consumption	Very low	High	High	Low	Very low
Data transmission rate	20, 40 & 50 Kbit/s	1 Mbit/s	54 Mbit/s	20–140 Kbit/s, 115 Kbit/s, 4 & 16 Mbit/s	0.3-50 Kbit/s
Operating frequency	900–928 MHz	2.4 GHz	2.4 & 5 GHz	300 GHz to 430 THz	<1 GHz

Figure 10: A comparison of the different wireless technologies [17].

When designing an energy management system, researchers always aim to create a system that utilizes as little power as possible to guarantee long battery life [17].

3.2.3.2 Features extracted

Different variables can be extracted from the current waveform. These variables are unique to every waveform and can be used in load identification.[31] Some of the variables include:

- $I_{Intensity}$: The current intensity per cycle
- $\Delta I_{\ Intensity}$: The variation of the current intensity
- $I'_{\ Intensity}$: Intensity of a differential current waveform per cycle
- $\Delta I'_{\ Intensity}$: Rate of change of the intensity
- I_{peak} : maximum value of an acquired transient current waveform
- I_{avg} : average value of an acquired transient current waveform
- I_{RMS} : the root-mean-square value of an acquired transient current waveform.
- I_{min} : minimum value of an acquired transient current waveform
- I_{median} : median value of an acquired transient current waveform
- I_{stdev} : standard deviation value of an acquired transient current waveform
- E_t : overall transient period

The variables are obtained from the current signal using the equations shown in the figures below.

Current intensity:

$$I_{intensity} = \frac{\sum_{j=1}^{N} |i(j) - mean(i)|}{N}$$

Figure 11: Equation for current intensity.

$i(j)$represents the j-th load current sampling point, N is the total number of sampling points per cycle and $mean(i)$ indicates the average current for each cycle.

Variation of the current intensity:

$$\Delta I_{intensity} = (I_{intensity})_{s+1} - (I_{intensity})_s$$

Figure 12: Equation for variation in current intensity [s denotes the s-th cycle]

If the change in current intensity is positive and higher than a pre-assigned threshold α, it is assumed that an appliance has been switched on. The threshold α is used for detecting the turn-on of an appliance. The maximum current in the system when all the appliances are switched off can be used as the threshold which means whenever a current higher than the threshold is detected, the assumption is an appliance has been switched on.

Detection of the 'switch on' triggers the measurement of the transient period. The time when the measurement starts is saved as TR_{start}. This will be different as different appliances are switched on or off at different instances. When the measurement of the transient period is ongoing, a differential procedure is performed for each cycle after 'switch on'. The differential procedure is based on the fundamental property of superposition. A differential waveform $i'(j)$ is extracted for every cycle.

The intensity of the differential current waveform per cycle:

$$I'_{intensity} = \log\left(\left(\sum_{j=1}^{N}(i'(j) - mean(i'))^2\right)^{\varepsilon}\right)$$

Figure 13: Equation for the intensity differential current waveform per cycle

[$i'(j)$ is the differential waveform while ε is a sensitivity constant that influences the rate of change in the intensity of the differential waveform]

Rate of change in intensity:

$$\Delta I'_{intensity} = |(I'_{intensity})_{s+1} - (I'_{intensity})_s|$$

Figure 14: Equation for the rate of change of the intensity

If the $\Delta I'_{Intensity}$ is less than a pre-assigned threshold $\gamma$for δ cycles, the measurement of transient period ends, and the termination instance saved as TR_{end}. The assigned threshold γin resistive loads may be equal to αas the assumption is the current in the system increases when they are switched on and decreases to a value equal to the maximum current in the system when all appliances are switched off.

When dealing with inductive loads (appliances with electrical motors and convert current into a magnetic field) like fans, washing machines, blenders, air conditioner, fridge etc., the threshold γ may have 2 values. In case one of the appliances is a fridge, one threshold value is used to detect the change from a normal operating state to switch off while the other threshold is used to detect the change from 'compressor startup state' to a normal operating state. Compressor startup state refers to the period when the fridge draws a lot of current in order to get the motors and other internal components of the compressor running. Normal operating state refers to the period when the fridge draws current equivalent to the rated current to operate in a continuous mode.

The overall transient period is given by:

$$E_t = TR_{\text{end}} - TR_{\text{start}} - \delta(16.67\ \text{ms/cycle})$$

Figure 15: Equation for overall transient period.

After extracting all the variables listed above, a transient waveform $I_{aq}(t)$, denoting the switch-on period and switch-off period is created.

The features extracted from the acquired transient current waveform include the maximum, minimum, average and RMS values of the current waveform with the overall transient period. The transient periods give more information when certain appliances are switched on and switched off. All of this is crucial in load identification. The equations in the figures below show how the features are obtained from the waveform.

$$I_{avg} = \frac{\sum_{idx=1}^{N_{tot}} i_{aq}(idx)}{N_{tot}}$$

Figure 16: The equation for the average value of the acquired transient current waveform

$$I_{peak} = \max_{idx=1,2,...,N_{tot}} |i_{aq}(idx)|$$

Figure 17: The equation for the peak current of the acquired transient current waveform

$$I_{min} = \min_{idx=1,2,...,N_{tot}} |i_{aq}(idx)|$$

Figure 18: The equation for the minimum current of the acquired transient current waveform

$$I_{rms} = \sqrt{\frac{\sum_{idx=1}^{N_{tot}} i_{aq}^2(idx)}{N_{tot}}}$$

Figure 19: The equation for the RMS current of an acquired transient current waveform

$$I_{median} = \underset{idx=1,2,...,N_{tot}}{\text{median}} |i_{aq}(idx)|$$

Figure 20: The equation for the median current of the acquired transient current waveform

$$I_{stdev} = \sqrt{\frac{1}{N_{tot}} \sum_{idx=1}^{N_{tot}} (i_{aq}(idx) - I_{avg})^2}$$

Figure 21: The equation for the standard deviation of each current value in the acquired transient current waveform

[$I_{aq}(t)$is the acquired transient current waveform and N_{tot} is the total number of samples of $I_{aq}(t)$.]

3.2.4 Appliance/Load Identification

Load identification is the last step in the NILM method. It relies heavily on conducting a pre-experiment and recording the load signature waveforms in a database [9]. The extracted load signatures are then compared with those from the database. Identification is based on the similarity of the signatures and the accuracy of the identification depends on the number of pre-recorded load signatures. The more the pre-recorded load signature sample of the same load, the more accurate identification is.

Some more accurate techniques have been proposed over the years. They are classified as supervised, semi-supervised and unsupervised learning [18]. Semi-supervised learning as used in [19] and [20] involves the use of unlabeled load signature waveforms to predict the appliances. In supervised learning, algorithms capable of recognizing patterns are trained using a series of waveforms with specific features and already identified loads. Such algorithms include Artificial Neural Networks used in [16] where an accuracy of 86.087% is recorded, hybrid Support Vector Machines(SVM) and GMM used in [21]- accuracy of 90%, k-Nearest Neighbor Rule (k-NNR) and Back-Propagation Artificial Neural Network (BP-ANN) both used in [22] where an accuracy of around 95% is recorded and Naive Bayes used in [23] where an accuracy of 91.34% is recorded.

In [23] the identification is done through Bayesian algorithm or Naïve Bayes classification. The load identification process starts with the training of a model using existing load signatures. The model is then used to identify/classify the specific loads that represent electric equipment. Naive Bayes classification is based on the theory of probability and uses all the features of the data as evidence in the probability.

The algorithm requires an initial probability of individual loads and the power rating of the available load to be known. The accuracy of Naive Bayes is dependent on the number of features used. Increase in the number of features leads to an increase in the accuracy of identifying loads as proved in this [23] study where 4 features give an accuracy of 55.76% while 7 features give an accuracy of 91.34%.

Unlike supervised learning, unsupervised learning does not require pre-recorded appliance load signatures. Instead, the model is registered using the aggregate load without user influence. Algorithms proposed include Four Hidden Markov Models (FHMMs), Graph Signal Processing (GSP) and Deep Learning. FHMM [24] uses a low-frequency real power feature and assumes that the appliances can either be on or off. It is however limited to a few appliances; all appliances require manual labelling after disaggregation and suffers from high computational complexity which means it cannot be used for real-time applications [25]. GSP extends classical signal processing and analysis to data that has been indexed by a graph. It is still a new field [26].

4 Methodology

This section is divided into 3 parts; model training, testing and model application in bill calculation and generation of reports. Model training covers data collection, feature extraction and training of different models to identify the loads while testing covers verification of the performance of the model with the highest prediction accuracy using two tests namely remote and live testing. Lastly, in model application, a case study is presented and the NILM system used to identify the appliances, calculate the bill and generate power usage report.

4.1 Model Training

In this section, the NILM system design, data collection, feature extraction and model training are discussed in detail.

4.1.1 Data Collection

This subsection covers the design of the NILM system and its use in collecting current readings.

4.1.2 Device design

As mentioned in
Current Measurement, non-invasive methods are more ideal in measuring AC current. An example of a non-invasive device is the current transformer (CT). A CT has primary winding, a magnetic core, and a secondary winding. When AC current flows through the primary winding, it produces a magnetic field in the magnetic core which induces a current in the secondary winding. The induced current is proportional to the current flowing through the primary winding. CTs are used together with burden resistors as they complete the secondary circuit by providing a voltage proportional to the current in the secondary circuit. The value of the burden resistor should however be low enough to avoid saturation of the CT's core. The CT is connected to a microcontroller.

The microcontroller is used to control the reading of AC current and initiate a connection to the data transmission system. Arduino Uno board is used as it's already designed and contains microcontroller (AT mega 328), analogue to digital converters (ADCs) which can sense voltages (useful in current measurement), PWM outputs, digital and analogue pins and power supply. It also comes with an IDE which makes it easy to program and has a wide range of libraries. The connection between the CT and the Arduino Uno is shown in Figure 22.

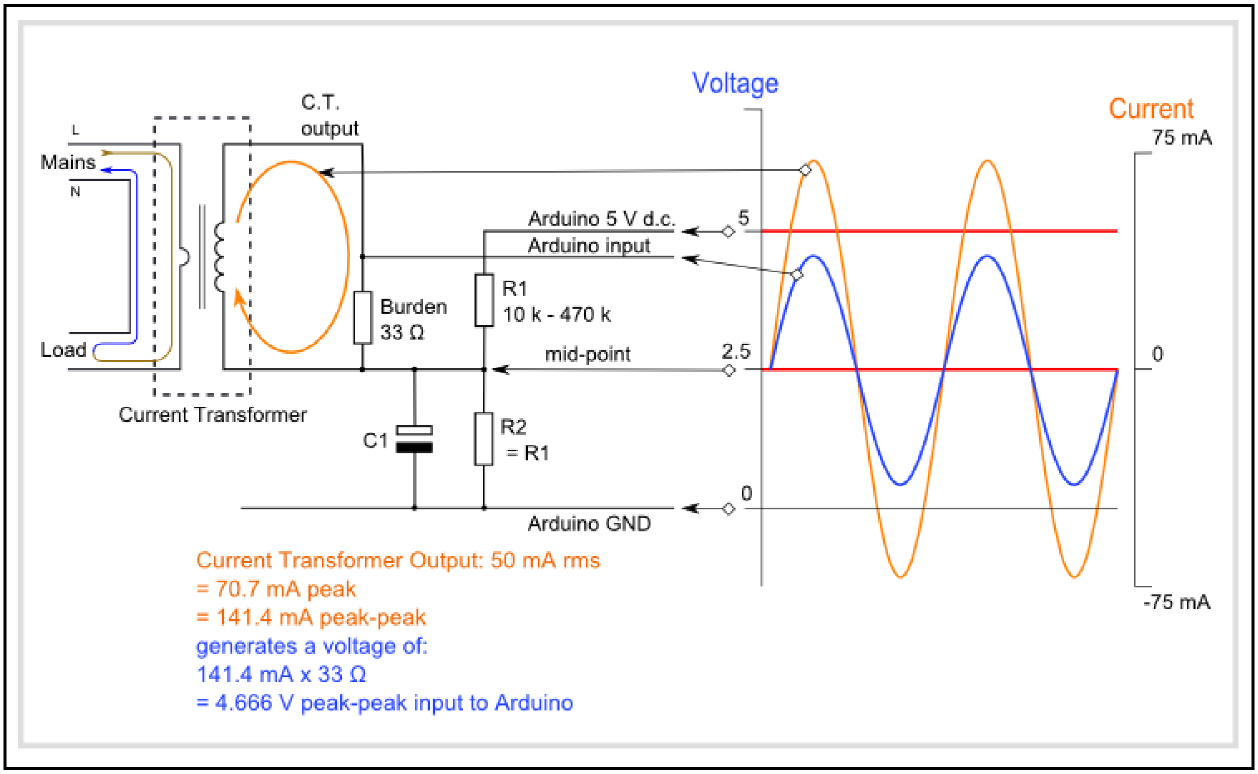


Figure 22: Schematic diagram of the connection between the CT and the Arduino Uno [36]

Arduino Uno requires analog inputs with positive voltages between 0 V and ADC reference voltage. The output from the CT sensor is however lower than this and needs to be conditioned. This is done by adding a burden resistor and a biasing voltage divider. These are calculated as shown below.

4.1.2.1 Burden resistor sizing

$primary\ peak\ current\ =\ RMS\ current\ \times\ \sqrt{2}\ \ldots\ldots$ (eq 1)

The RMS current is equal to the rating of the CT sensor, in this case $\mathbf{100\ A}$

$100\ A\ \times \sqrt{2} = 141.42\ A\ \ldots\ldots$ (eq 2)

$secondary\ peak\ current\ =\ primary\ peak\ current\ /\ no. of\ turns\ \ldots\ldots$ (eq 3)

No. of turns are given in the datasheet and are equal to $\mathbf{2000}$

$141.4\ A\ /2000\ \ = 0.07071\ A\ \ldots\ldots$ (eq 4)

Thus, the ideal burden resistor is given by:

$Burden\ resistor\ =\ (AREF/2)\ /\ secondary\ peak\ current\ \ldots\ldots$ (eq 5)

AREF is the Arduino analog reference voltage is 5V as stated in the datasheet for Arduino Uno.

$(5/2)\ V\ /\ 0.07071\ A\ \ = 35.4\ \Omega\ \ldots\ldots$ (eq 6)

Since a $35.4\ \Omega$ resistor does not exist, the nearest resistor value $\mathbf{33\ \Omega}$ is selected. This is because a larger resistor in this case $39\ \Omega$ will create a current larger than 5 V in the secondary circuit.

4.1.2.2 Choosing a DC Bias

When one of the CT wires is connected to the Arduino ground directly, the voltage in the second wire varies from negative values to positive values. As stated before, Arduino only accepts input values between $0\,V$ and $5\,V$.In order to limit the voltage to only positive values, that is values above and below $2.5\,V$, the CT wire is connected to the ground at half the supply voltage as shown in Figure 22.

The two resistors $R_1$and R_2 act as a voltage divider and provide the 2.5 volts required to limit the CT voltage. According to the CT datasheet, the capacitor C_1(function is to provide an alternative path for the alternating current to bypass the resistor, R_2) should be equal to **10 μF** for $100\,A$ CT sensors.

Further, R_1 and R_2 should be high to lower energy consumption, thus $10\,k\Omega$ or $470\,k\Omega$ resistors are ideal. The latter is used when the circuit is battery powered as it further lowers power consumption while the former is used when the circuit is powered by mains supply. In this experiment, the $\boldsymbol{10\,k\Omega}$ resistor is used.

4.1.2.3 Circuit connection

The raw electrical signal is measured by the current sensor and the inbuilt ADC of the Arduino Uno converts it into a digital signal. The pin connection between the SCT013 current sensor and the Arduino Uno is shown in Figure 23.

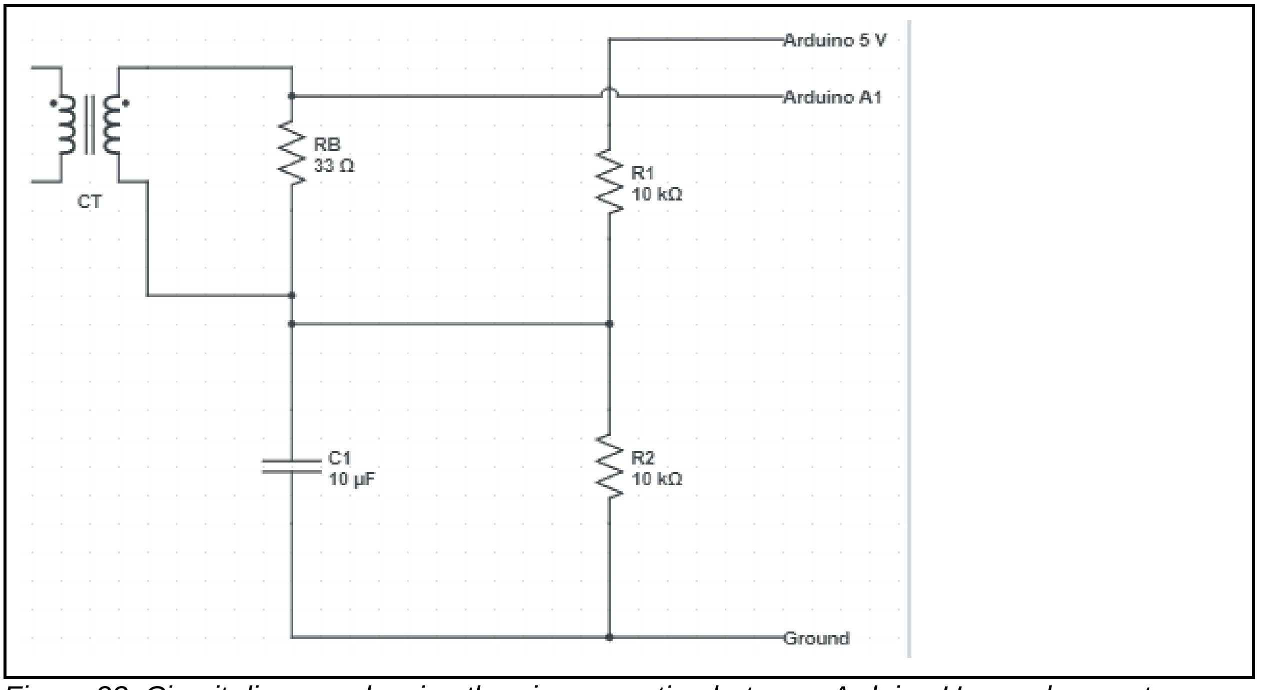


Figure 23: Circuit diagram showing the pin connection between Arduino Uno and current sensor

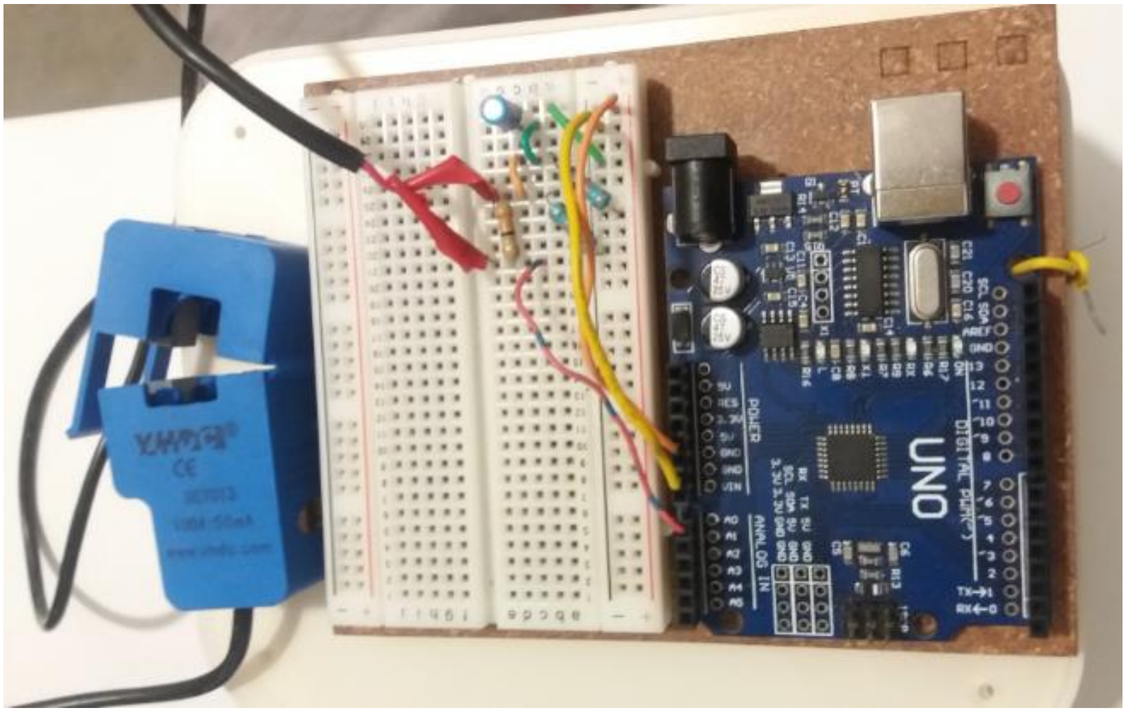


Figure 24: Actual circuit built for this project

4.1.3 System set-up

In order to get the current readings, a household equivalent system was simulated in the lab. This is because the system needs to be flexible, safe and easy to access. In order to collect data, different appliances are to be switched on and off which should be done at any time without inconveniencing the users. Moreover, easy access would allow the measuring device to be connected or disconnected at will, especially in cases where data collection must be repeated.

In setting up the household equivalent, 3 readily available appliances namely fridge, coffee machine and electric kettle were chosen. The three appliances selected were connected to an extension power cable. This is because the ports in an extension cable are connected in parallel making it a parallel circuit which is like the electrical wiring in households. The extension power cable was connected to a 240 A.C. supply. The household equivalent system set-up design was as shown in Figure 25 while Figure 26 shows the actual circuit created.

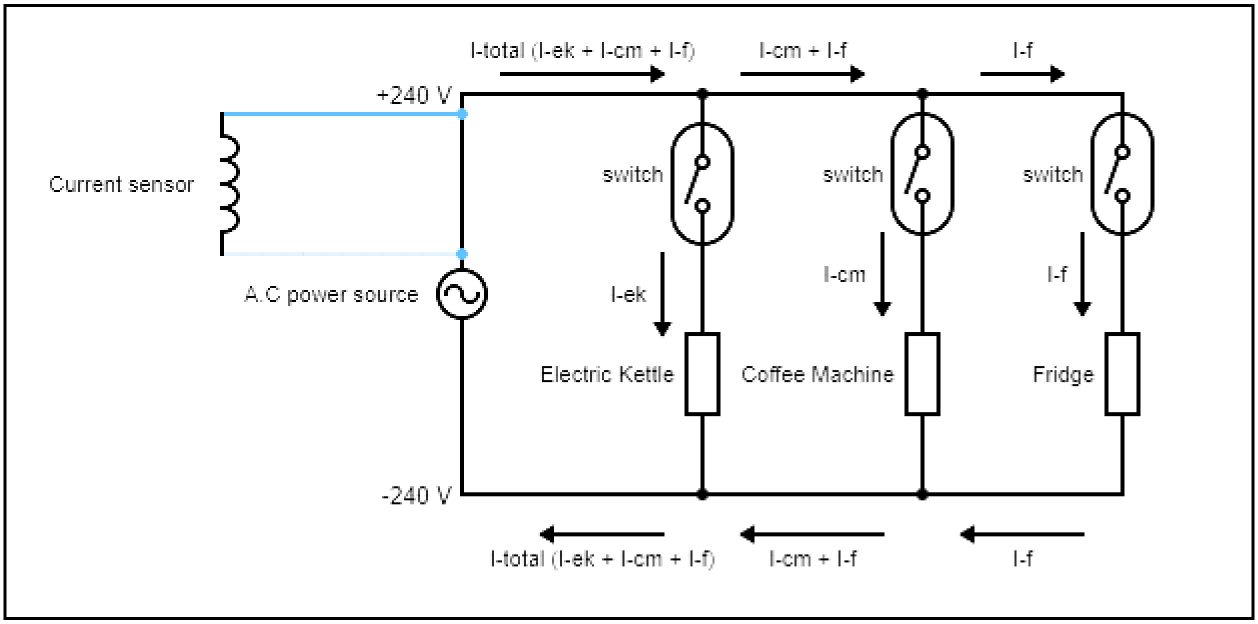


Figure 25: Household system circuit design

Figure 26: Implementation of the household system design circuit

4.1.4 Data Collection

In order to get current reading for the different appliances and their combinations, different scenarios were simulated. The sets are as shown in Table 1.

Table 1: List of appliances switched on at a time

Fridge	Coffee Machine	Electric Kettle + Fridge	Coffee Machine + Fridge
Electric Kettle	All appliances off	Coffee Machine + Electric Kettle	Coffee Machine + Electric Kettle + Fridge

In all scenarios, the recording of current readings started at, $TR_{start} = 0\ s$ and ended at $TR_{end} = 60\ s$ thus for each set, the current readings are recorded for a duration of 60 s per cycle for 15 cycles.

The fridge has 2 operating/power consumption states that is compressor state and normal operating state. Current readings are only recorded when the fridge is in its normal operating state. Like the fridge, the coffee machine has two cycles brewing cycle and warm plate cycle. The two cycles consume different amounts of power and last for different durations. The brewing cycle is shorter but requires a significant amount of power while the warm plate cycle lasts up to 4 hrs. and requires less power. During the 60s, in all cycles, the coffee machine remained in the brewing cycle.

4.1.5 Feature Extraction

The raw data collected using the current sensor is used for feature extraction. The current readings are plotted against time for each appliance and by visual inspection, the key differences are identified and used to determine the appropriate features.

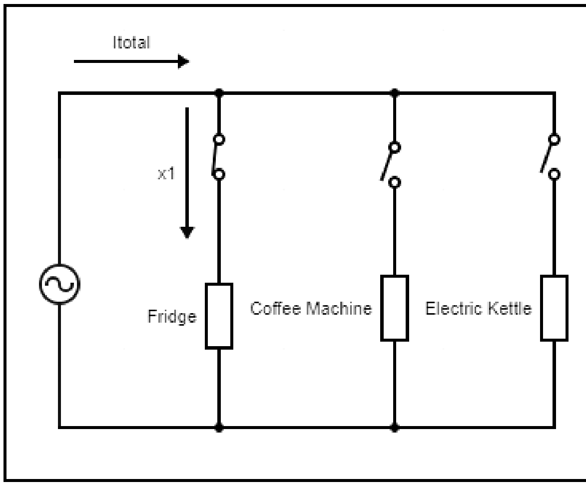
4.1.6 Load Identification

As shown in Table 1, the 3 appliances can be combined in 8 different ways. The labels are binarized in order to retain as much information as possible.

4.1.6.1 Label binarization

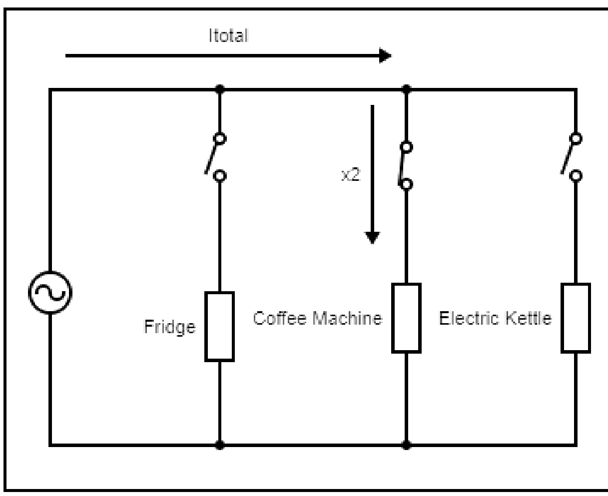
Assuming that the current through the fridge is x_1, current through the coffee machine is x_2,current through the electric kettle is x_3 and 0 depicts off status while 1 depicts on state:

1. When all 3 appliances are switched on individually at a time, the total current is equal to the current through each appliance depending on which one was switched on. This can be represented using the equations shown next to the circuit diagrams in Figure 27: Circuit diagram and equivalent equation when the fridge is on.Figure 27-Figure 29.



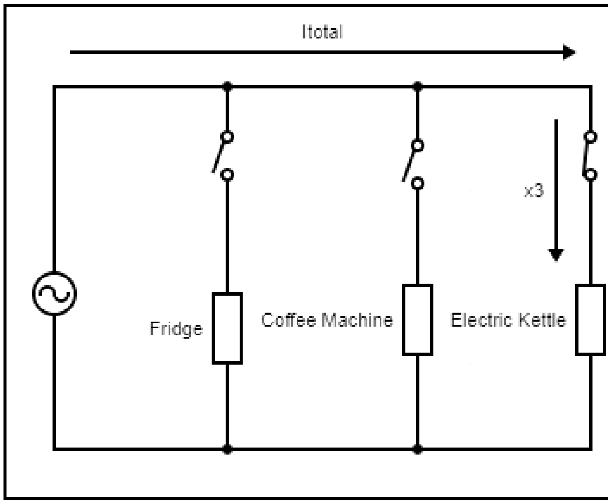
$$I_{total} = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} x1 \\ x2 \\ x3 \end{bmatrix} = x_1$$

Figure 27: Circuit diagram and equivalent equation when the fridge is on.



$$I_{total} = \begin{bmatrix} 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} x1 \\ x2 \\ x3 \end{bmatrix} = x_2$$

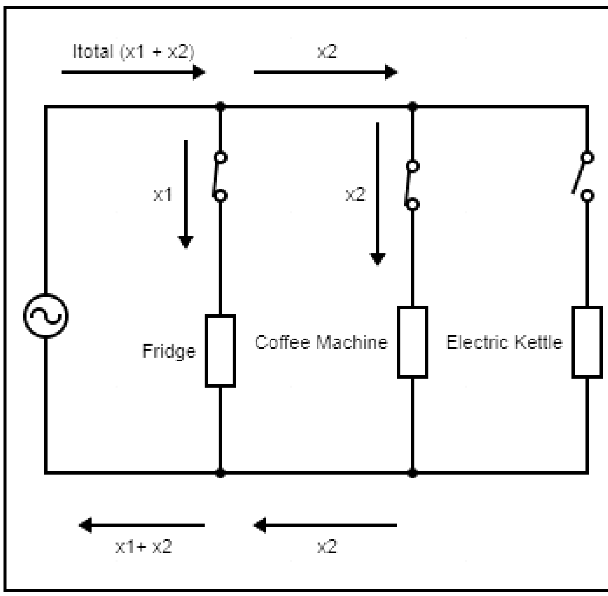
Figure 28: Circuit diagram and equivalent equation when the coffee machine is on.



$$I_{total} = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x1 \\ x2 \\ x3 \end{bmatrix} = x_3$$

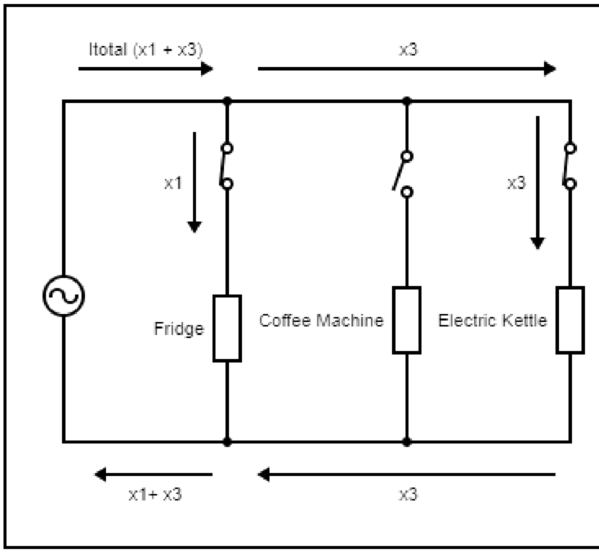
Figure 29: Circuit diagram and equivalent equation when the electric kettle is on.

2. When two appliances are switched on, the total current is equal to the sum of currents through both appliances. This can be represented using the equations shown next to the circuit diagrams in Figure 27: Circuit diagram and equivalent equation when the fridge is on.Figure 27-Figure 29.



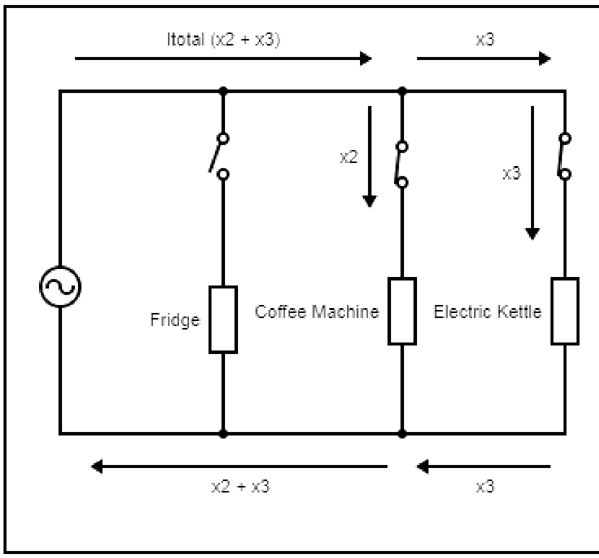
$$I_{total} = \begin{bmatrix} 1 & 1 & 0 \end{bmatrix} \begin{bmatrix} x1 \\ x2 \\ x3 \end{bmatrix} = x_1 + x_2$$

Figure 30: Circuit diagram and equivalent equation when the fridge and coffee machine are on.



$$I_{total} = \begin{bmatrix} 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} x1 \\ x2 \\ x3 \end{bmatrix} = x_1 + x_3$$

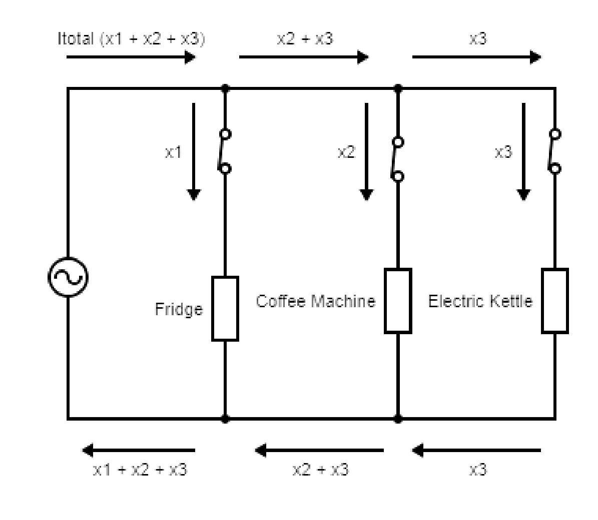
Figure 31: Circuit diagram and equivalent equation when both the fridge and electric kettle are on.



$$I_{total} = \begin{bmatrix} 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} x1 \\ x2 \\ x3 \end{bmatrix} = x_2 + x_3$$

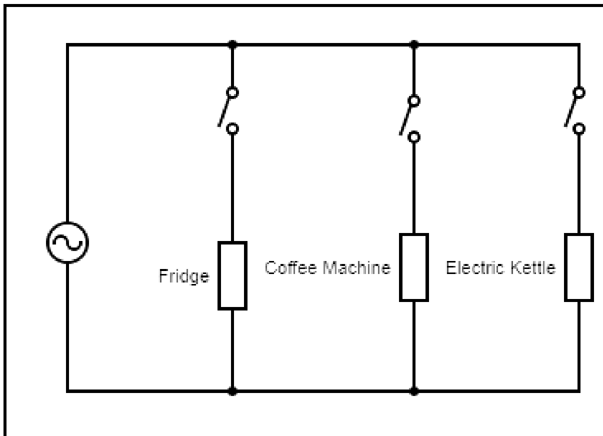
Figure 32: Circuit diagram and equivalent equation when both the electric kettle and coffee machine are on.

3. When all the appliances are switched on or off, the total current is equal to the sum of current through all appliances. This can be represented using the equations shown next to the circuit diagrams in Figure 33 and Figure 34.



$$I_{total} = \begin{bmatrix}1 & 1 & 1\end{bmatrix} \begin{bmatrix} x1 \\ x2 \\ x3 \end{bmatrix} = x_1 + x_2 + x_3$$

Figure 33: Circuit diagram and equivalent equation when all appliances are on



$$I_{total} = \begin{bmatrix}0 & 0 & 0\end{bmatrix} \begin{bmatrix} x1 \\ x2 \\ x3 \end{bmatrix} = 0$$

Figure 34: Circuit diagram and equivalent equation when all appliances are off

The vectors $[0\ 0\ 1]$, $[1\ 1\ 1]$, $[1\ 1\ 0]$ are used to show the status (on or off) of all the connected appliances at a time. They are thus called state vectors. This process is called label multi-binarization.

4.1.6.2 Load Identification

After label multi-binarization load identification follows. This is achieved by using k-Nearest Neighbor Rule (k-NNR) and Support Vector Machine in conjunction with One vs Rest multiclass Classifier classification algorithms. The algorithm with the highest accuracy score is used in system testing.

4.1.7 Results and Analysis

In this section, the results obtained from the steps above are presented, key observations noted and discussed.

4.1.7.1 Data Collection

The raw current readings for all the appliances in all 15 cycles are plotted in Figure 35 - Figure 42

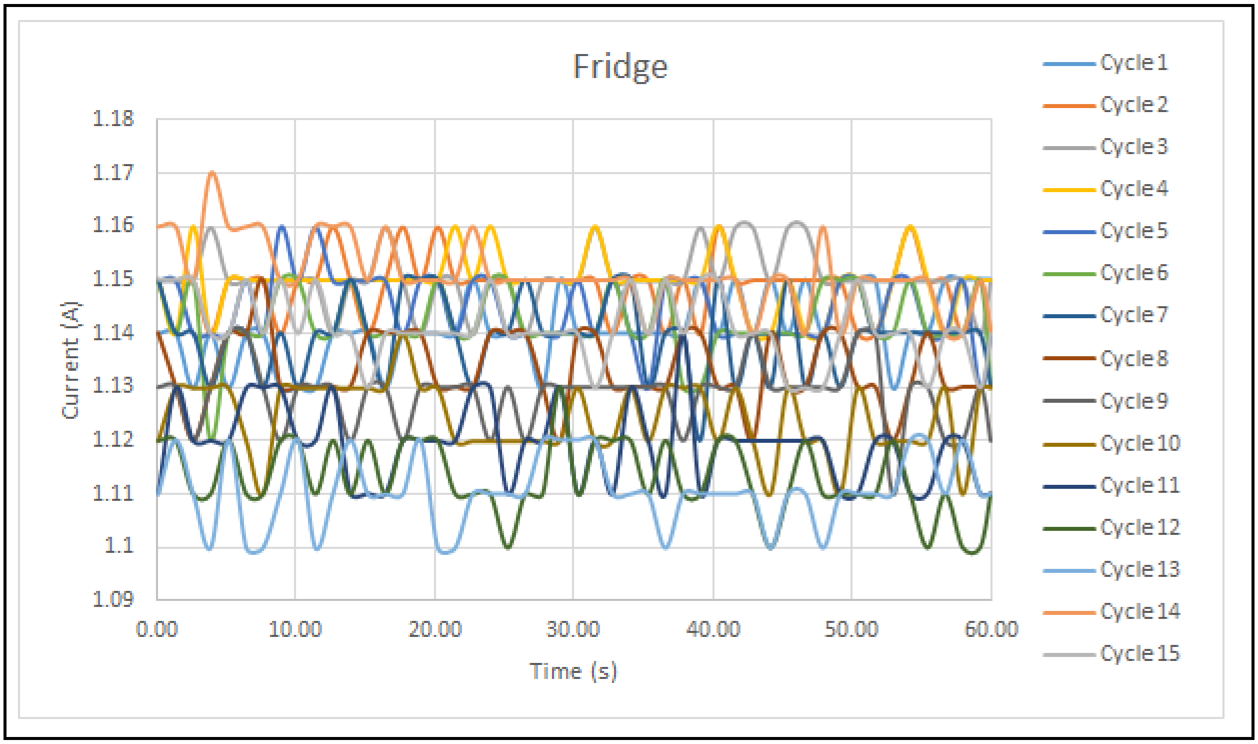


Figure 35: Current reading when the Fridge is switched on

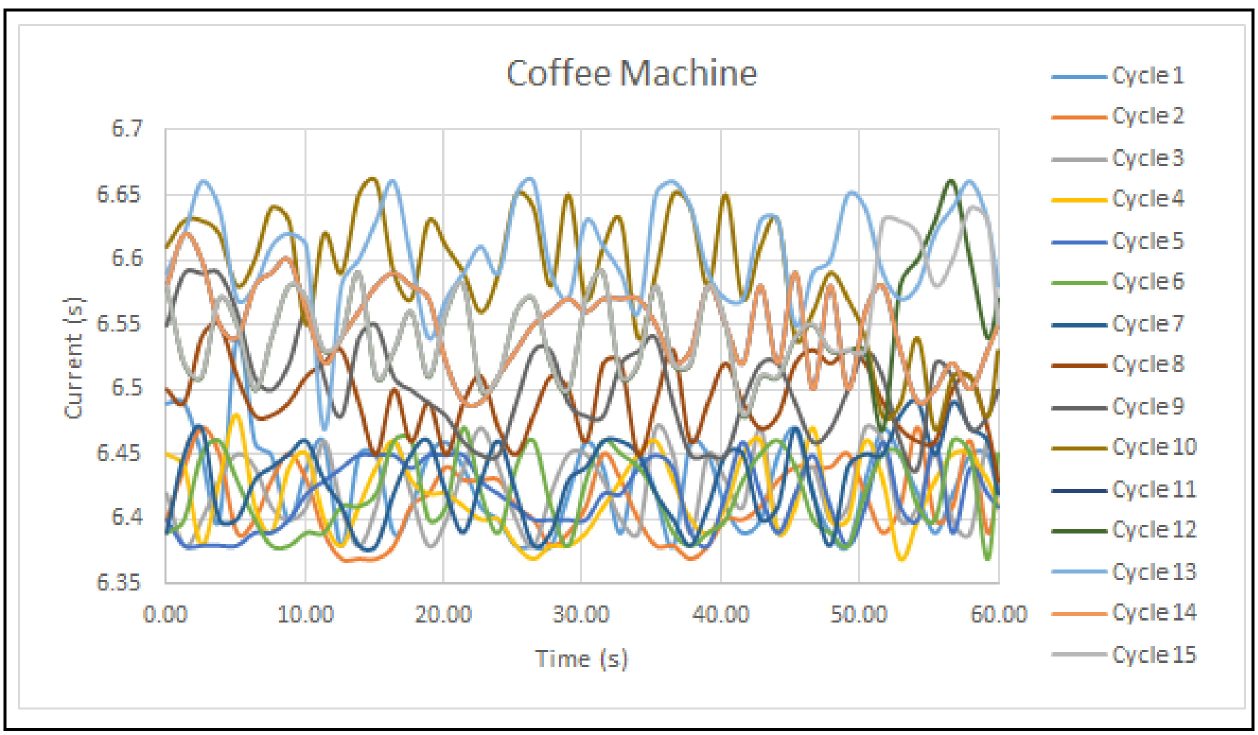


Figure 36: Current reading when the Coffee machine is switched on

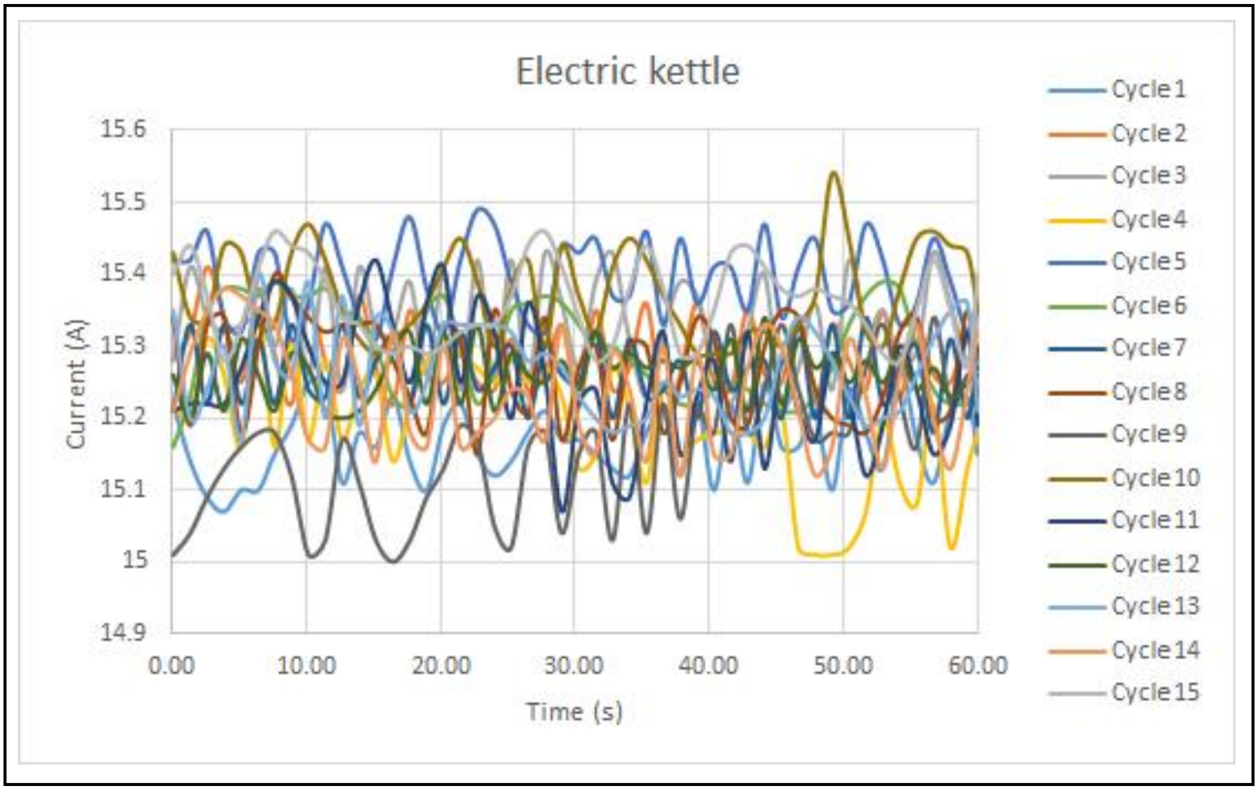


Figure 37: Current reading when the Electric kettle is switched on

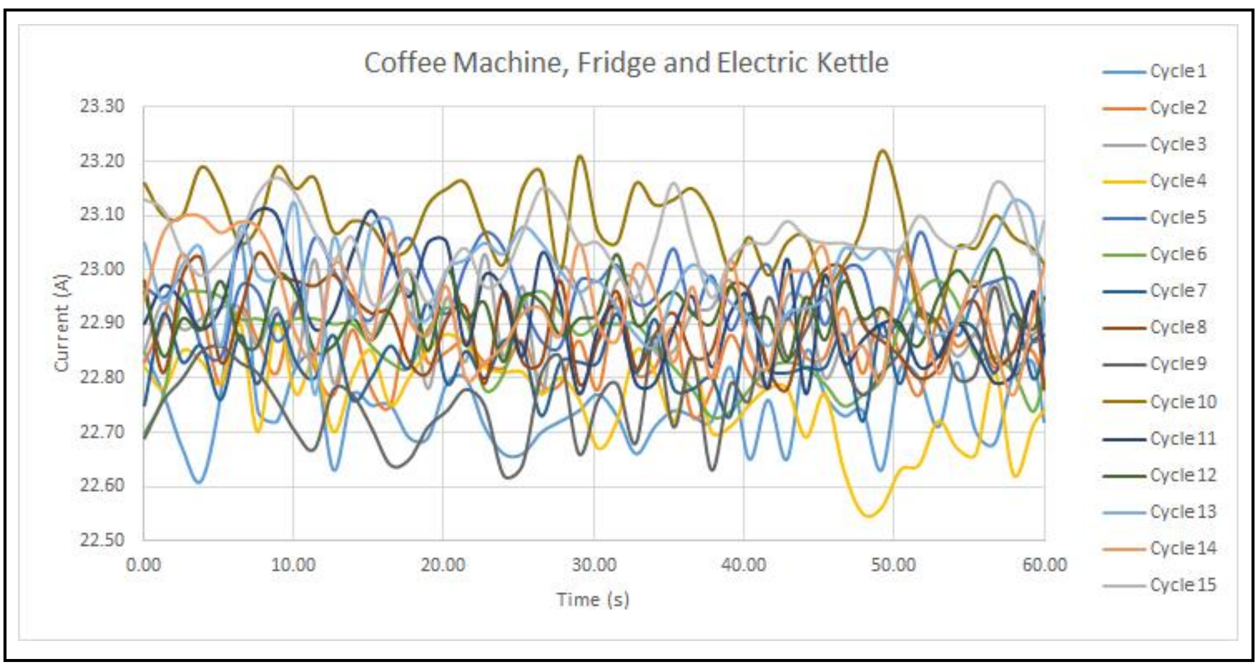


Figure 38 : Current reading when all 3 appliances are switched on

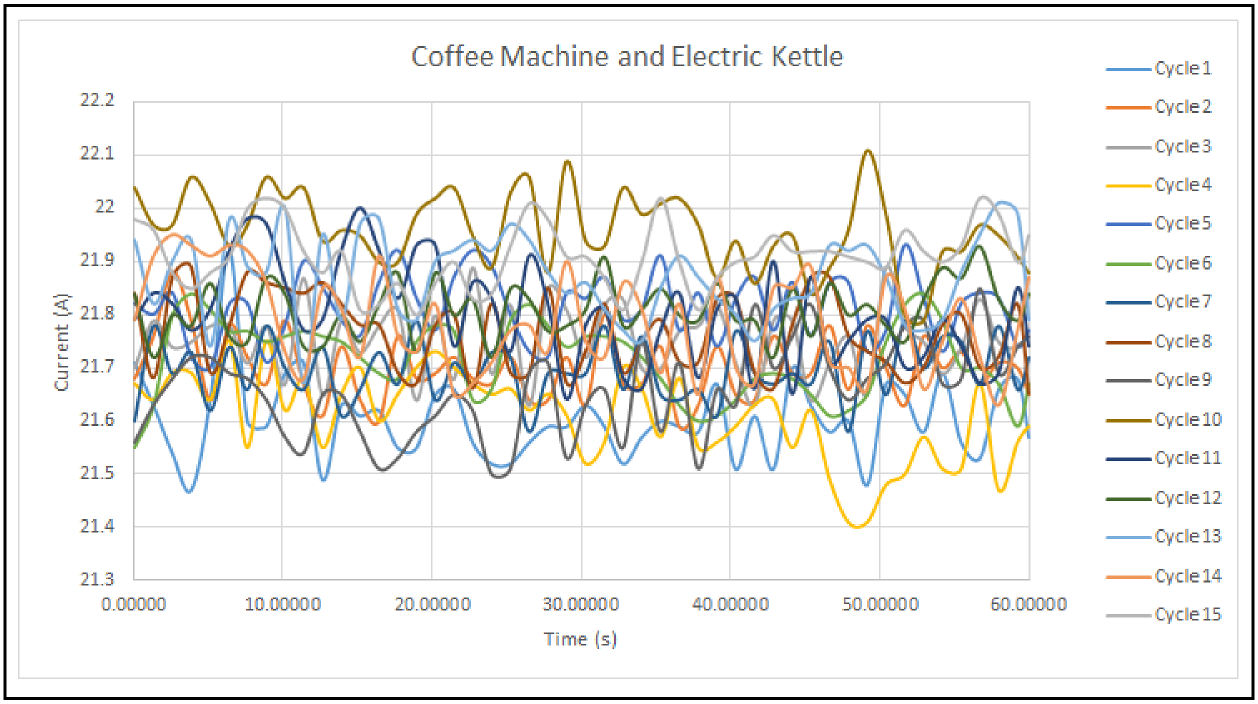


Figure 39: Current reading when the Coffee machine and the Electric kettle are switched on

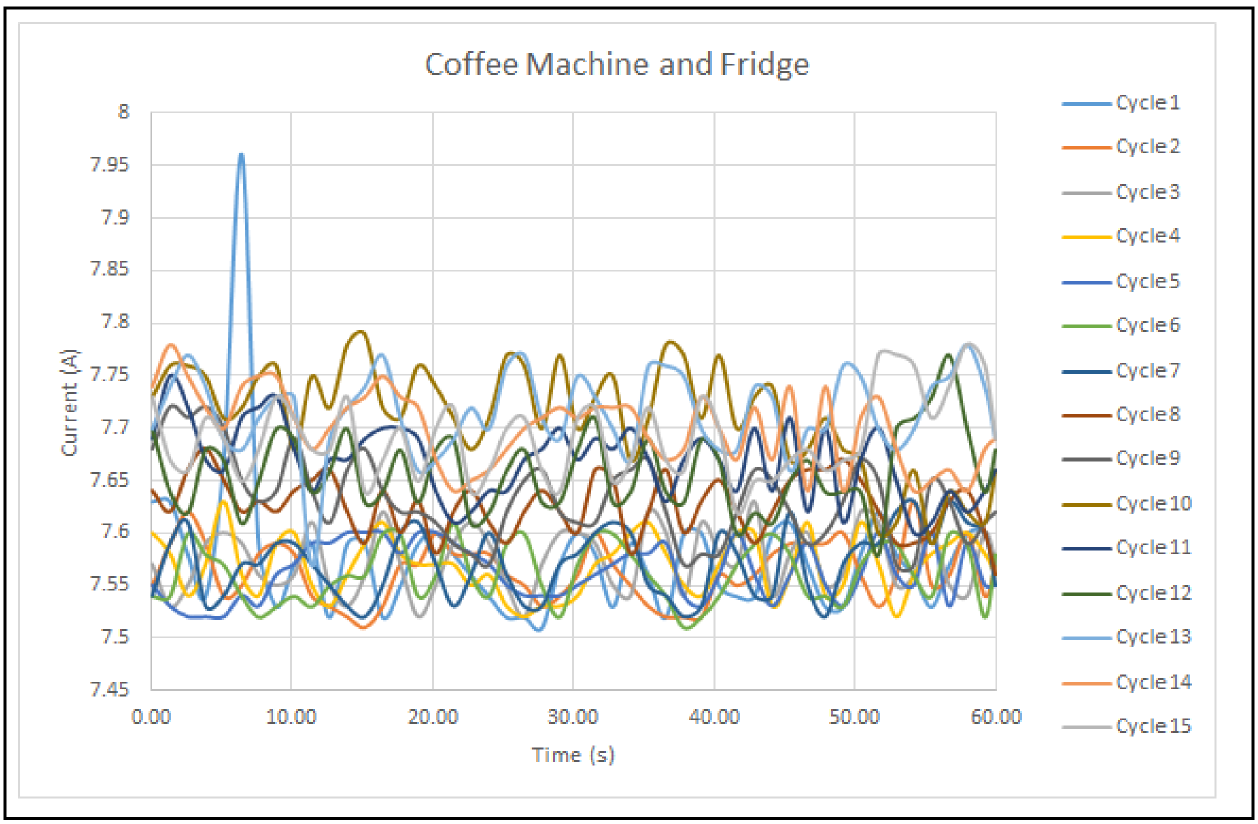


Figure 40:Current reading when the Coffee machine and the Fridge are switched on

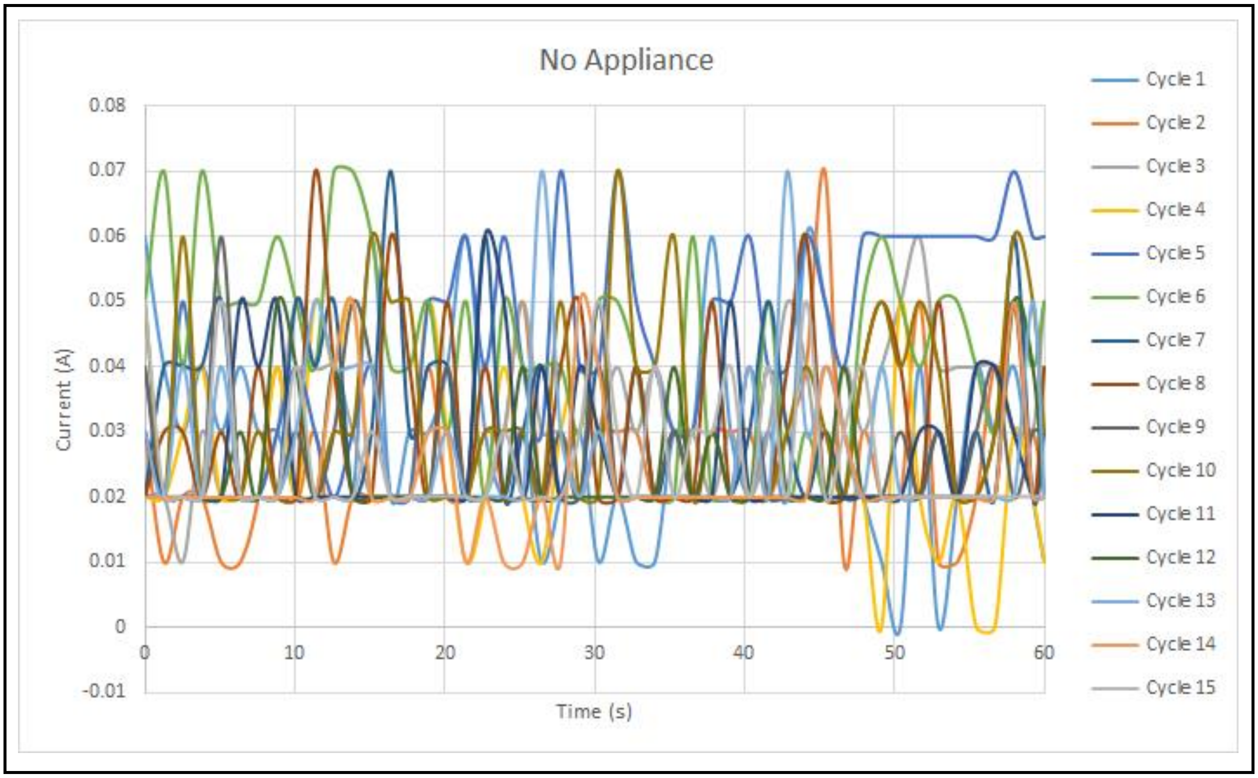


Figure 41: Current reading when all 3 appliances are switched on

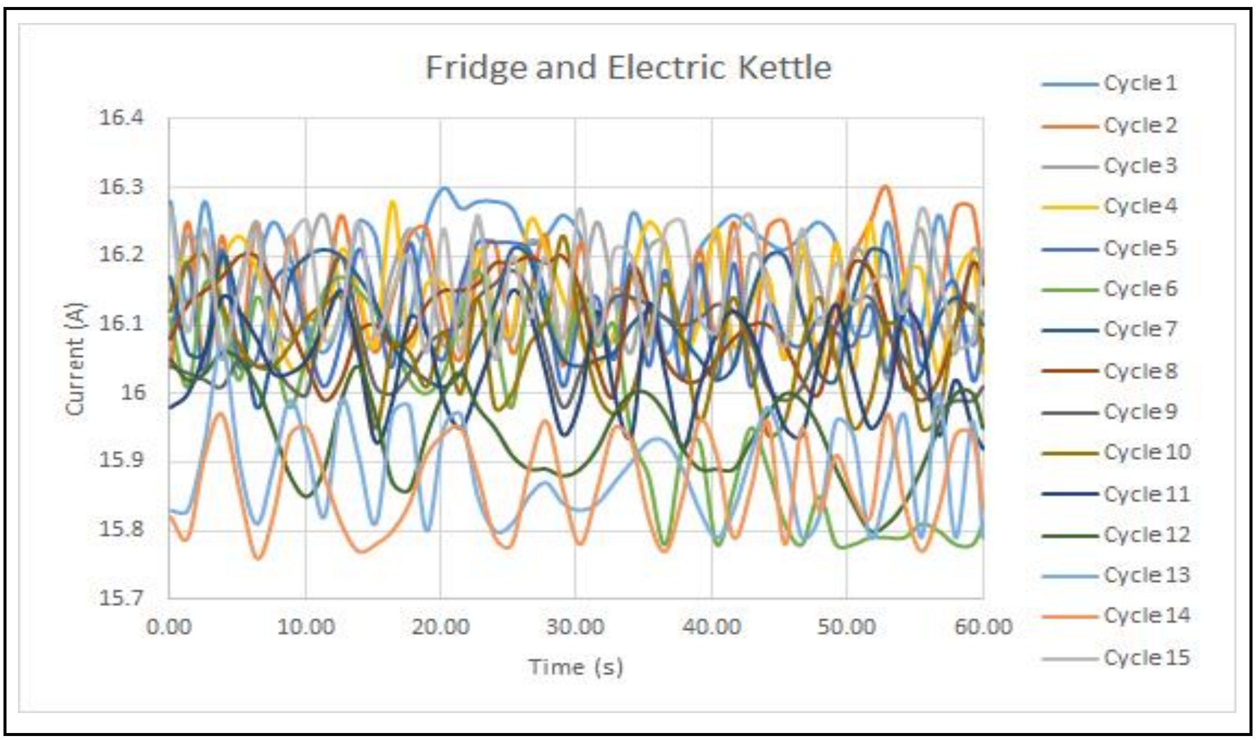


Figure 42: Current reading when the Fridge and the Electric kettle are switched on

4.1.7.1.1 Observations

- The peak current differs in all eight states as summarized in Table 2.

Table 2 : Peak currents from all 8 states

Appliances	No Appliance	Coffee Machine	Electric Kettle	Fridge
Peak Current	0 to 0.07 A	6.37 A to 6.66 A	15 A to 15.5 A	1.1 A to 1.7 A
Rated Current	-	5.83 A	12.5 A	1.1 A
Combination	Coffee Machine + Electric Kettle	Coffee Machine + Fridge	Electric Kettle + Fridge	All Appliances
Actual Peak Current	21.4 A to 22.1 A	7.5 A to 7.96 A	15.75 A to 16.3 A	22.55 A to 23.22 A
Theoretical Peak Current	21.37 A to 22.16 A	7.47 A to 8.36 A	16.1 A to 17.2 A	22.47 A to 23.86 A

- The peak current varies in all cycles in each state.

4.1.7.1.2 Analysis

According to Kirchhoff's Current Law (KCL), when only one appliance is on, the total current is equal to the current through the appliance. And when two or more appliances are on, the total current is equal to the sum of currents through the individual circuits. In Table 2, the recorded peak current values are shown against the expected theoretical values. In all the 4 combinations, the total current is within the expected ranges. This verifies the application of KCL in the load monitoring circuit analysis. The peak currents for individual appliances are slightly higher than their rated currents. This can be attributed to under sizing of the burden resistor. The current readings are recorded 15 times for each combination. The result is that the peak current differs in all the cycles but the peak current stays within ± 5 % of each other.

4.1.7.2 Feature Extraction

Based on the observations stated in the section above, the following features are extracted using the formulas shown in Figure 16 - Figure 21.

- Maximum current
- Average current
- Median current
- Standard deviation
- Minimum current

In Figure 43 to Figure 47 below, for each feature, the 8 vector states are compared against each other.

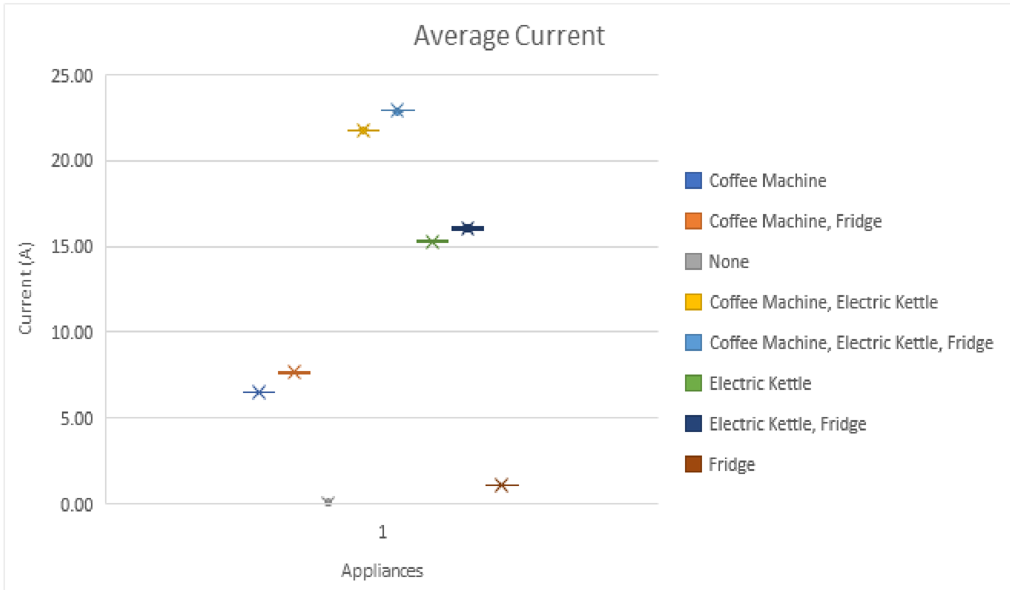


Figure 43: Feature extraction: Average current

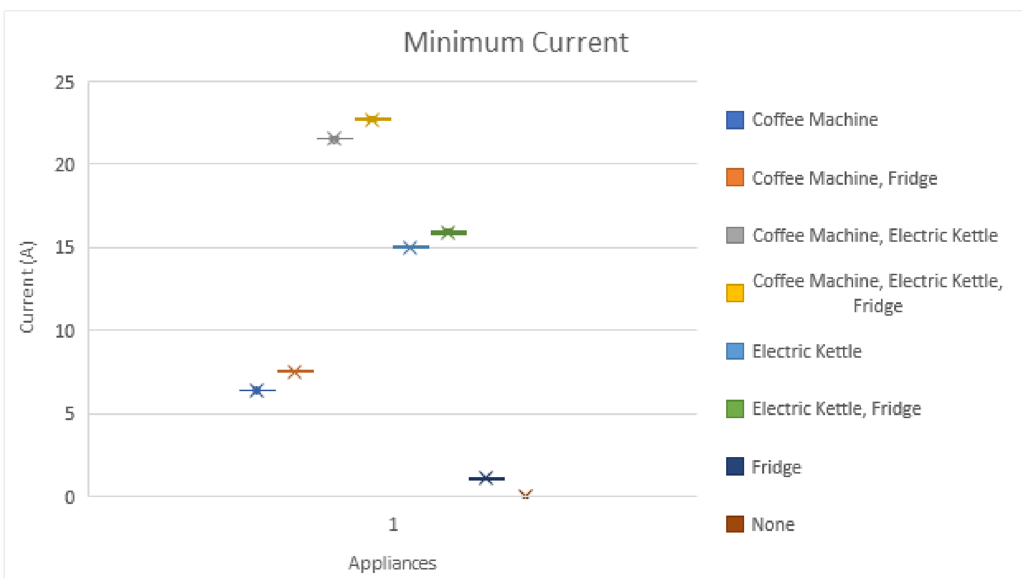


Figure 44: Feature extraction: Minimum current

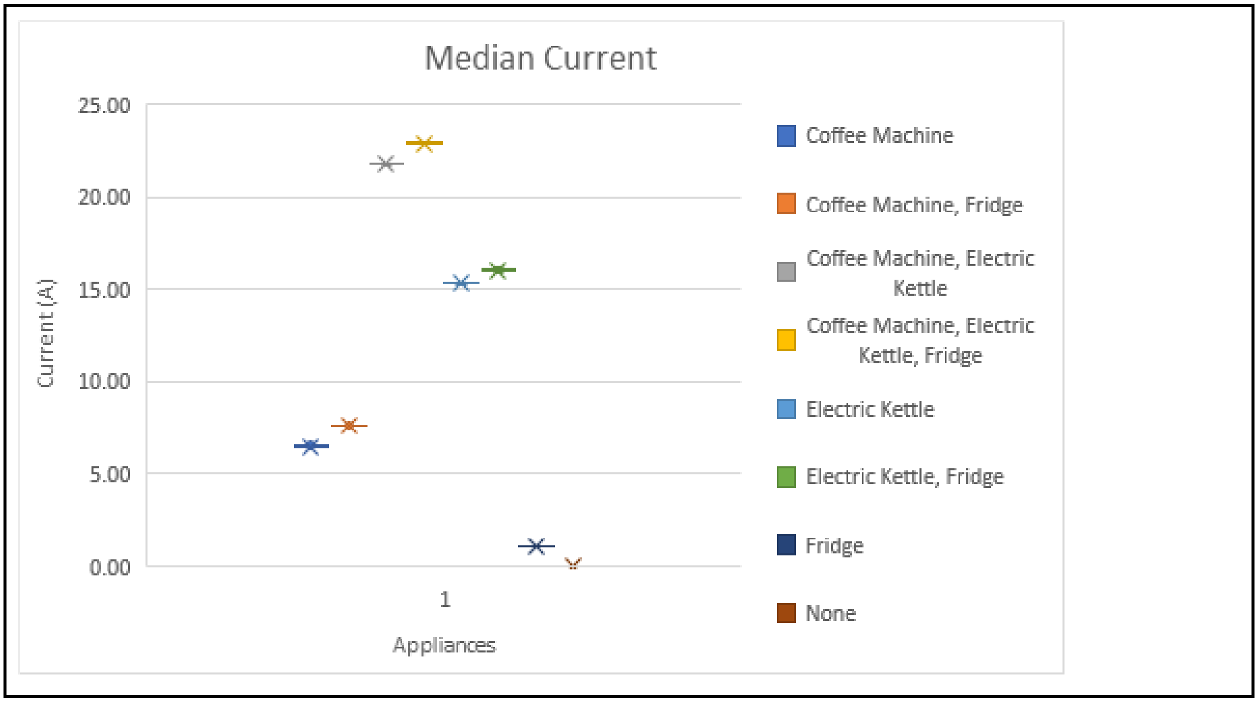


Figure 45: Feature extraction: Median current

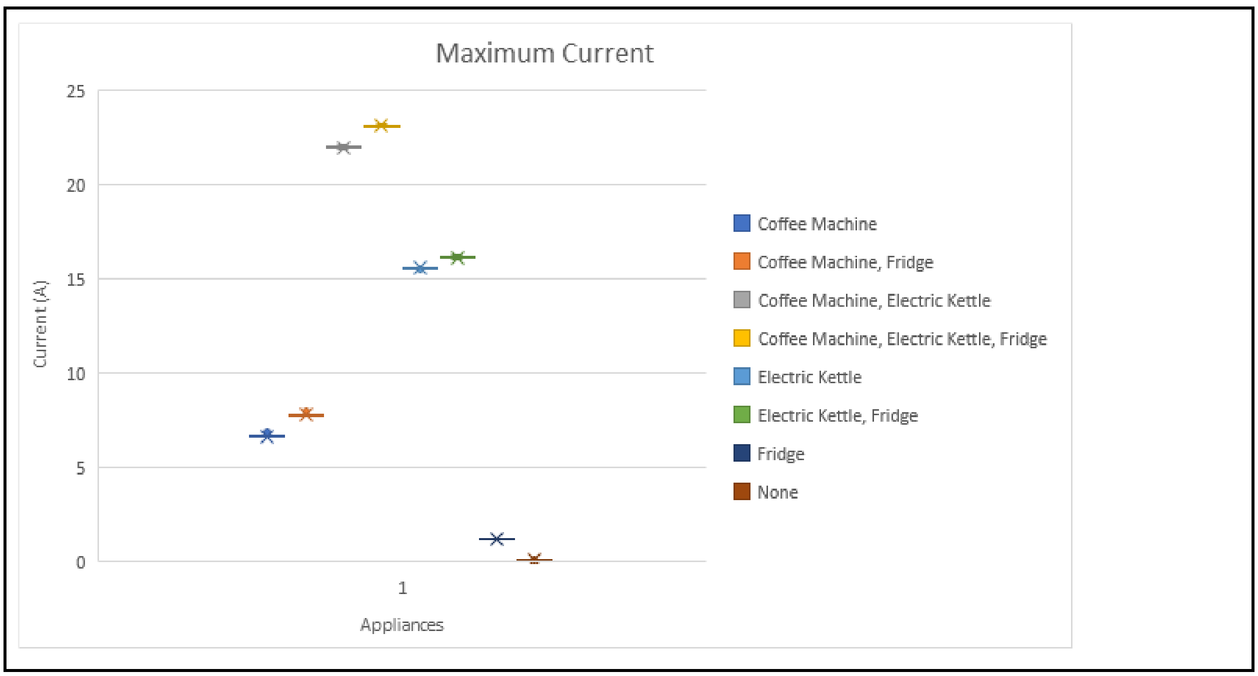


Figure 46: Feature extraction: Maximum current

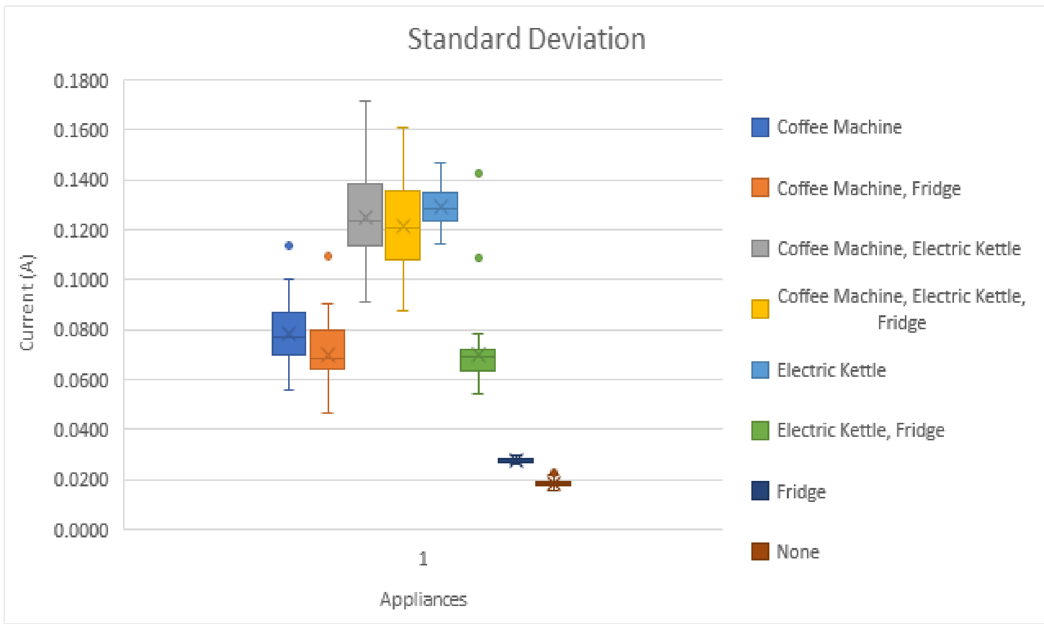


Figure 47: Feature extraction: Standard deviation

4.1.7.2.1 Observations

For the average current, median current, maximum current and minimum current, the current values;

- When all appliances are off and when the fridge is on are very close.
- When the electric kettle is on and when both the electric kettle and fridge are on are also very close.
- When all appliances are on and when both the coffee machine and electric kettle are on are also very close.
- When the coffee machine is on and when both the coffee machine and fridge are on are very close.

For standard deviation, the current values;

- When all appliances are off and when the fridge is on are very close.
- When the coffee machine is on, when both the coffee machine and fridge are on and when both the electric kettle and fridge are on are also very close.
- When all appliances are on, when both the coffee machine and electric kettle are on and when the electric kettle is on are also very close.

4.1.7.2.2 Analysis

In all features, the current values for different appliance combinations are very close and could easily be mistaken for each other. As a result, none of the features can be used alone as the load identification accuracy would be low. Therefore, in order to achieve a higher accuracy, all features should be used together as they collectively make the waveforms for the different appliances and their combinations unique and easy to identify.

Also, the maximum and minimum currents set the boundaries for current values for each vector state. More like the maximum current values and minimum current values that can be obtained for a given state vector.

The median and mean current values shows the average and most common current values for a given vector state. Lastly, the standard deviation informs the allowable variation of the current values from the average current for each state vector. This can be summarized as shown in Figure 48.

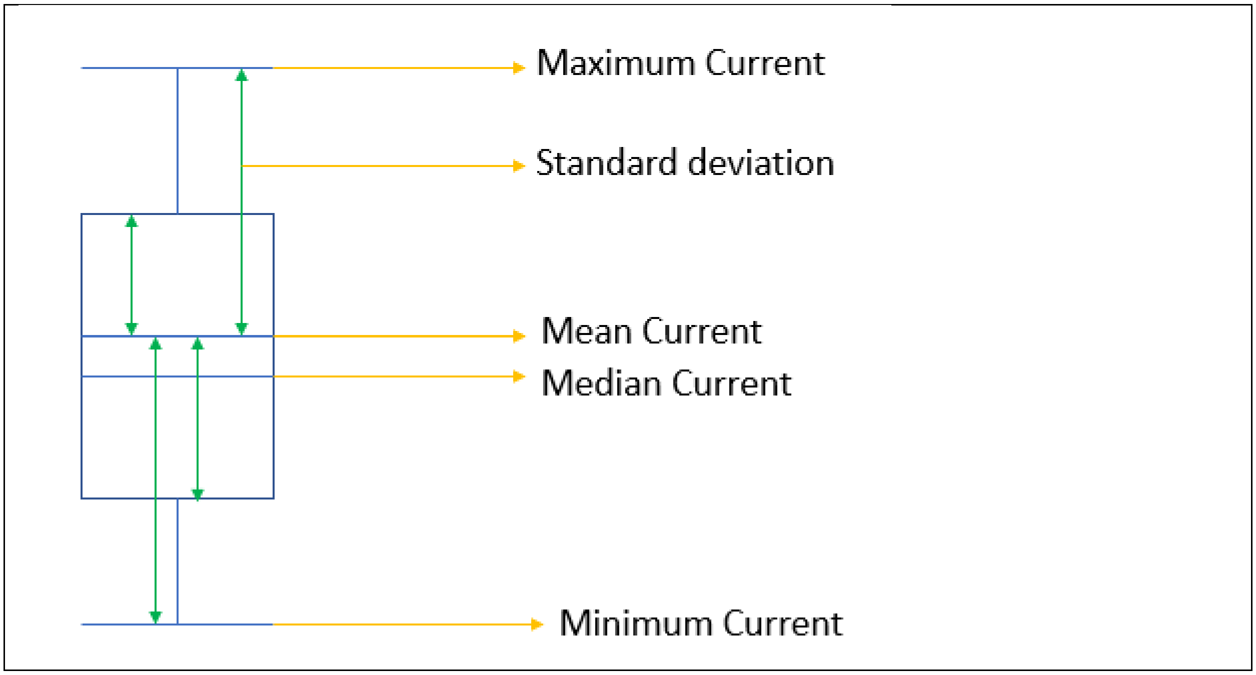


Figure 48: Role of each feature in appliance identification

4.1.7.3 Load Identification

The dataset with the extracted features is divided into 2, training and testing data in the ratio 3:2 respectively. The training dataset is used to train the two classification models. The models are then used to predict the labels for the remaining testing data. The predicted labels are compared with the actual labels and the accuracy score calculated. The accuracy scores are shown in Table 3.

Table 3: Accuracy score for the classification models

Classification model	Accuracy (%)
k-Nearest Neighbor Rule (k-NNR)	98.75
Support Vector Machine	45

4.1.7.3.1 Observation

The k-NNR model records the highest accuracy.

4.1.7.3.2 Analysis

KNN-R model worked way better than the SVM in load identification. This could be because when all the five features are put together, they make the current waveforms for the different appliances and their combinations easy to differentiate. In cases where two or more appliances have similar power consumption patterns, the model would have difficulties in differentiating them. However, increasing the number of features extracted would improve the performance of the model.

4.1.8 Conclusion

As k-NNR has the highest accuracy, it is used to test the performance of the NILM system.
The NILM system is made up of a measuring device, feature extraction model and k-NNR classification model.

4.2 Testing

This section focuses on verifying the performance of the system by carrying out two tests; remote and live tests.

4.2.1 Test 1: Remote test

This involves switching on and off different appliances to check whether the k-Nearest Neighbor Rule (k-NNR) model is able to identify the different appliances. The classification model is stored locally in the laptop.

The appliances are switched on and off in the following sequence:

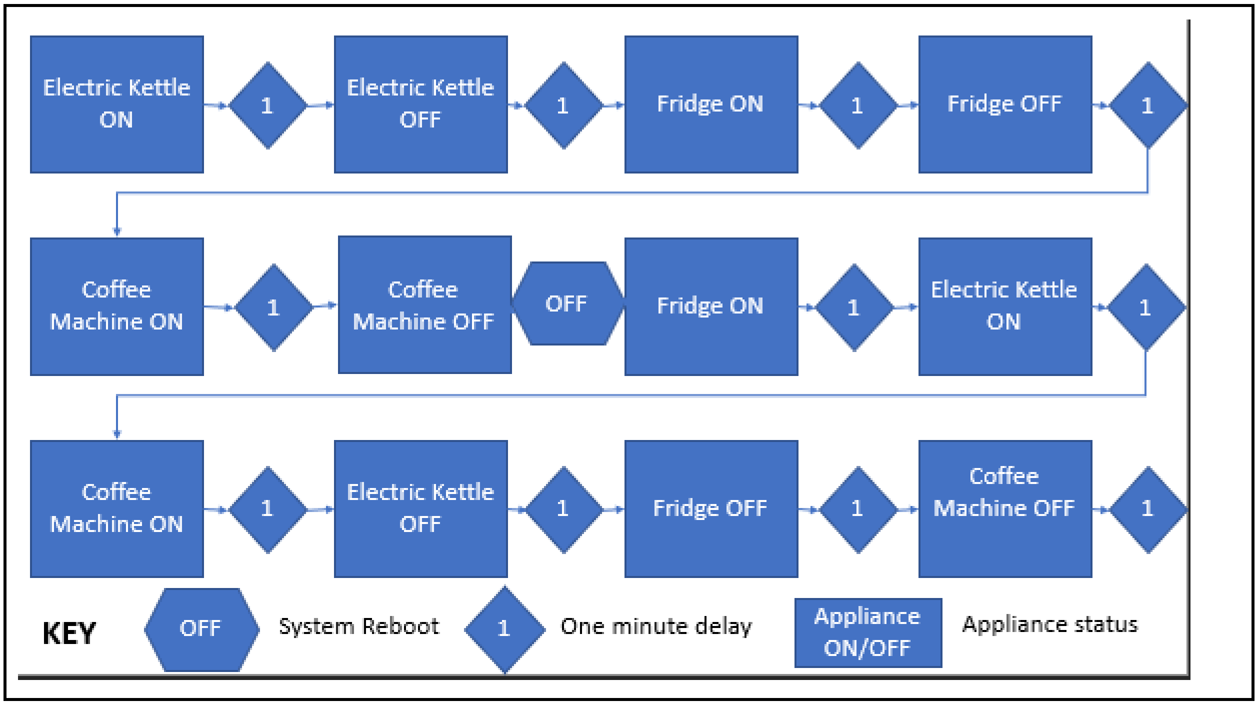


Figure 49: Sequence used to test the performance of the model

4.2.1.1 Data collection

The measuring device made up of a CT sensor, Arduino and a USB cable is used to collect current readings. The current readings are forwarded to local storage for feature extraction and load identification. The USB cable enables serial port communication between the Arduino and the laptop. During the training phase of the classification model, current readings were collected for 15 cycles before features were extracted. Similarly, feature extraction is done on every 15 current data readings. Further, the same features are extracted. They include: Minimum current, Maximum current, Average current, Median current and Standard deviation. The extracted features are used as inputs in k-Nearest Neighbor Rule (k-NNR) classification model which then attempts to identify the appliances using their state vectors, for instance $[0\ 0\ 1]$ represents the fridge. This procedure is summarized in Figure 50 while the system set-up is shown in Figure 51.

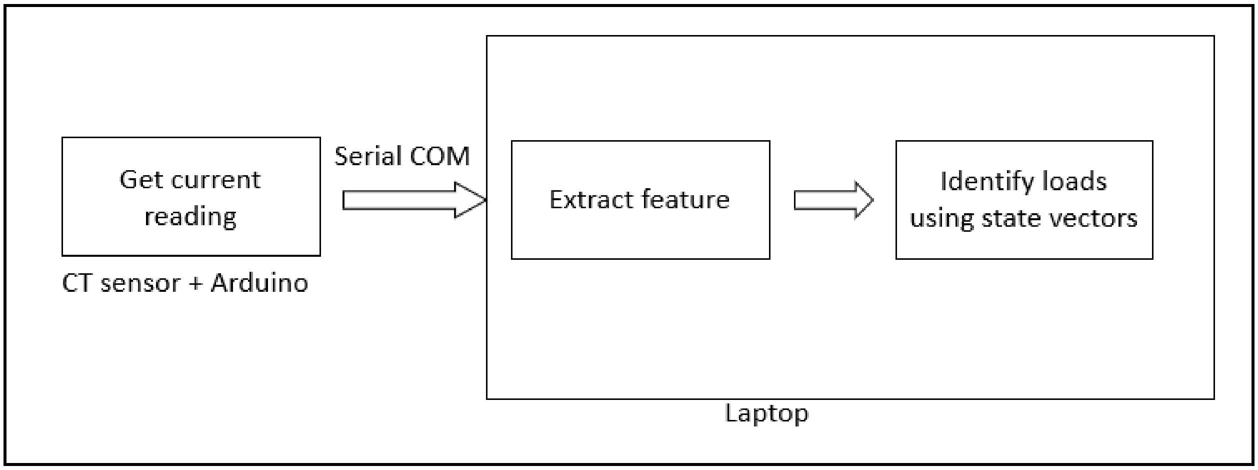


Figure 50: Summary of system functions and components

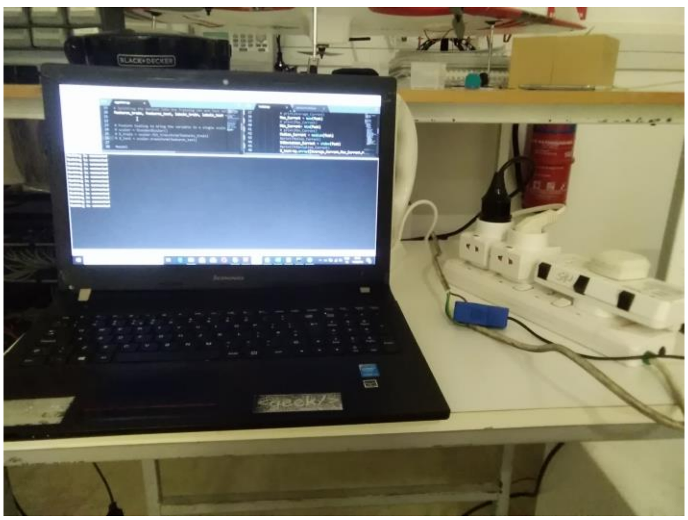


Figure 51: Image of the actual system set-up

4.2.2 Test 2: Live test

In the live test, the classification model, k-Nearest Neighbor Rule (k-NNR), is stored on a cloud-based server. Thus, feature extraction and load identification happen externally. The appliances are switched on and off following the sequence used in Remote test (see Figure 49).

As the model is online, the following tasks are performed:

1. Get current reading using CT sensor
2. Forward the data to the server using LoRa
3. Extract the following features using the equations shown in Figure 52 – Figure 21 from current waveform: Minimum current, Maximum current, Average current, Median current and Standard deviation.

4. Use the extracted features to identify the loads using k-Nearest Neighbor Rule (k-NNR) classification model.

The step by step tasks are summarized in Figure 52.

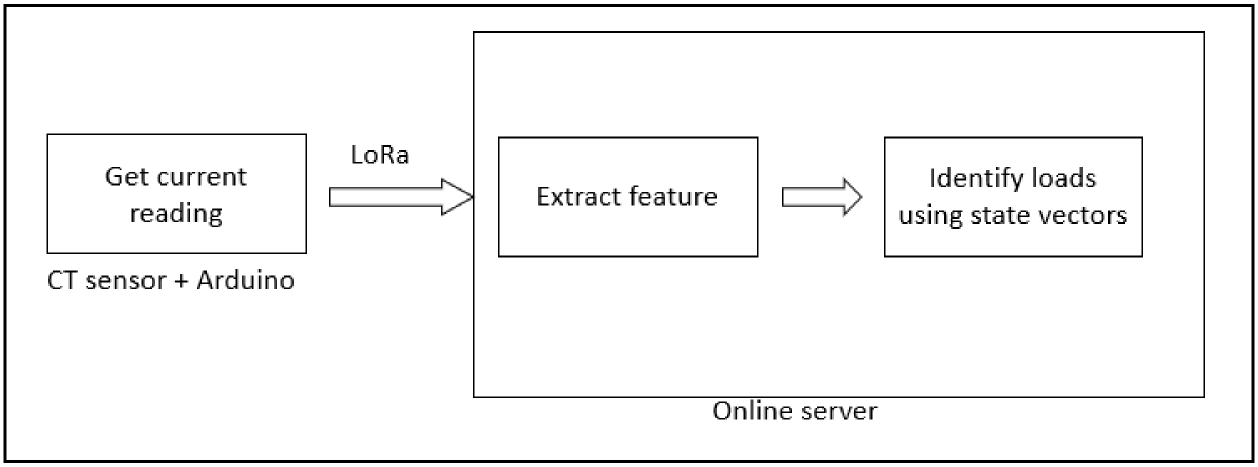


Figure 52: Summary of tasks and components

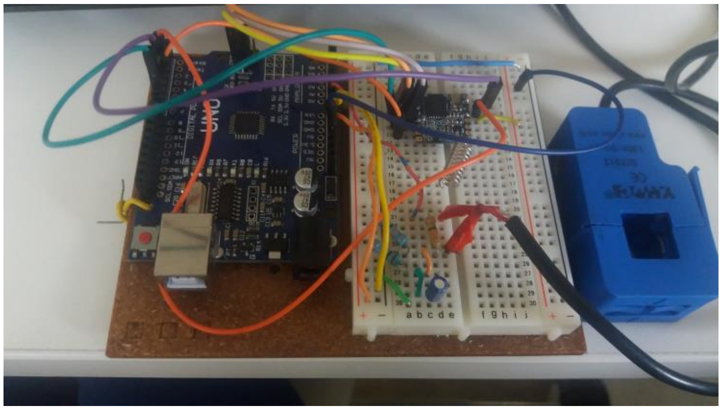
The NILM system is modified to include a communication module. The system modification and set-up are discussed below.

4.2.2.1 Communication module set-up

As the model is online, a good communication module is required to forward the real-time data from the Arduino Uno to the online server. Based on Figure 10, LoRa offers a combination of advantages such as low power consumption, strong in-door coverage, bi-directional secure data transmission and since it uses spread spectrum technology, the adjacent transmitters do not interfere with each other's transmission.

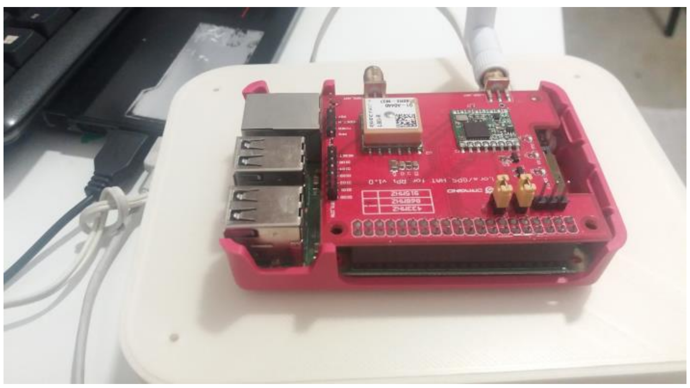
To transmit the measured data, a radio module (transceiver) is interfaced with the Arduino Uno to form a LoRa node while Lora Gateway is set up using LoRa/GPS HAT and raspberry pi. Arduino is used to read the data from the sensor and sends it through the transceiver. This data is then picked up by LoRa Gateway. LoRa Gateway also has a transceiver and a microprocessor. The transceiver receives the data and the microprocessor sends it to the host server The Things Network. This is achieved by setting up a Single Channel LoRaWAN Gateway on the Raspberry Pi. The purpose of the channel is to receive LoRa packets (data received) from the LoRa node and send them to The Things Network.

The pin connection between the Arduino Uno, CT sensor and the LoRa transceiver module (SX1276) is shown in Figure 53 while Figure 54 shows the pin set up between the LoRa/GPS HAT and raspberry pi to create a LoRa Gateway.



LoRa SX1276 Module	Arduino UNO Board
VCC	3.3V
Gnd	Gnd
NSS	D10
DIO0	D2
DIO1	D3
SCK	SCK
MISO	MISO
MOSI	MOSI
RST	D5

Figure 53: Arduino Uno and LoRa module connection



LoRa GPS HAT	Raspberry pi 2B
3.3 V	3.3 V
5 V	5 V
GND	GND
D100	GPIO7
RX	GPIO15/TX
TX	GPIO16/RX
RESET	GPIO0
NSS	GPIO6
MISO	GPIO13/MISO
MOSI	GPIO12/MOSI
SCK	GPIO14/SCK

Figure 54: LoRa HAT and Raspberry pi pin connection

After the connections are done, the Gateway is registered in The Things Network as shown in Figure 55.

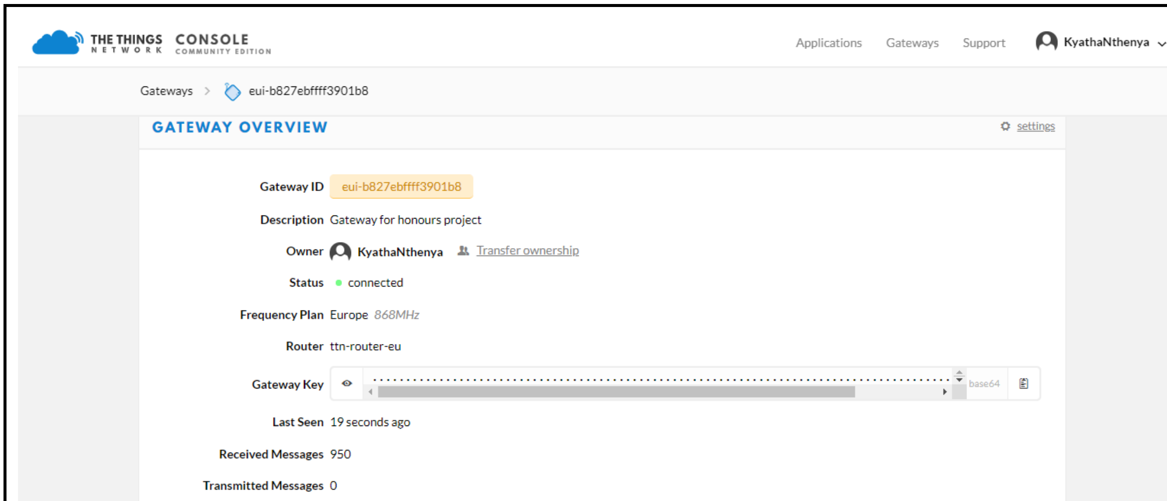


Figure 55: The Things Network LoRa Gateway registration

4.2.2.2 Configuration

The Things Network offers limited storage space and does not allow real-time plotting of the data, its integrated system allows data transfer to other platforms like [Ubidots] and [ThingSpeak] with larger storage limits for Educational projects.

In this report, the ThingSpeak platform is used as it offers a wide range of data analytics tools. Once an account has been created, a channel is created to store the data received from The Things Network. The raw current waveform can be visualized using the chart option as in Figure 56.

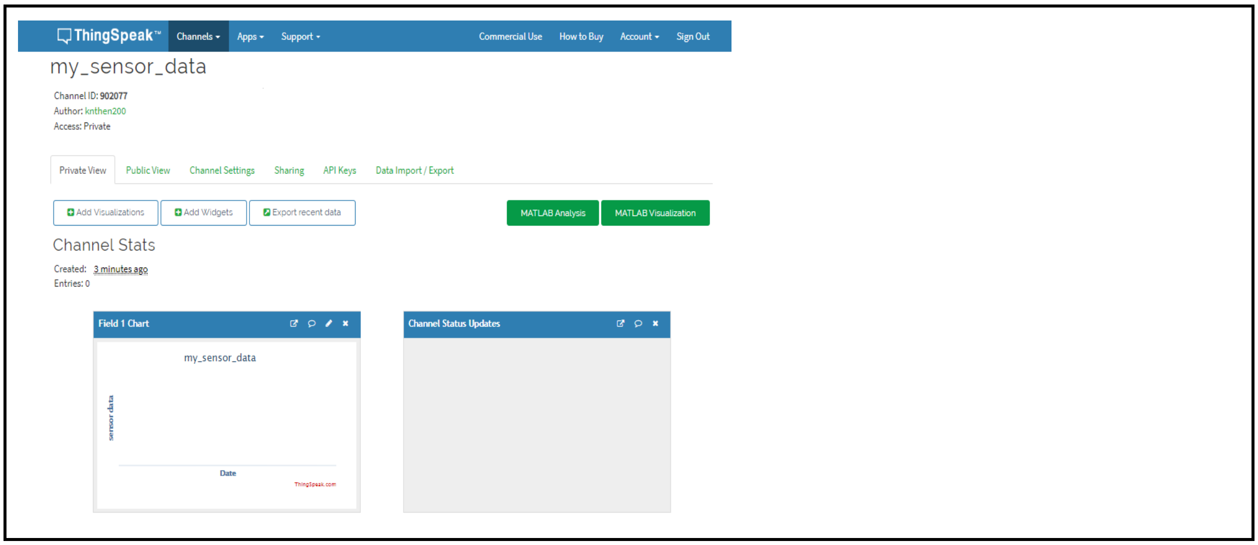


Figure 56: ThingSpeak channel set-up

4.2.3 Results

Section presents the results obtained from both tests and highlights key observations noted from the results.

4.2.4 Remote Test

The performance of the model is evaluated against the expected output. The results were summarized in Table 4.

Table 4: Summary of Remote test system evaluation results

State	Expected output	Actual Output	Evaluation
Electric Kettle on	[0 1 0]	[0 1 0]	Correct
Electric Kettle off	[0 0 0]	[0 0 0]	Correct
Fridge on	[1 0 0]	[1 0 0]	Correct
Fridge off	[0 0 0]	[0 0 0]	Correct
Coffee machine on	[0 0 1]	[0 0 1]	Correct
Coffee machine off	[0 0 0]	[0 0 0]	Correct
Fridge on	[1 0 0]	[1 0 0]	Correct
Electric kettle	[1 1 0]	[1 1 0]	Correct
Coffee machine	[1 1 1]	[1 1 1]	Correct
Electric kettle off	[1 0 1]	[1 0 1]	Correct
Fridge off	[0 0 1]	[0 0 1]	Correct
Coffee machine off	[0 0 0]	[0 0 0]	Correct

4.2.4.1 Observations

After rebooting the system, the fridge is switched on followed by the electric kettle. This means the state vector changes from $[0\ 0\ 1]$ to$[0\ 1\ 1]$. The device is able to detect this change instantly. Similar instant load identification is experienced when reverting from $[1\ 0\ 1]$(coffee machine and fridge) to $[1\ 0\ 0]$(coffee machine).

Later in the testing sequence, the electric kettle and the fridge stay on for a minute and then the coffee machine is switched on. The expectation is that the state vector should instantly change from $[0\ 1\ 1]$to $[1\ 1\ 1]$.Figure x shows the system output during this transition. As it can be seen in the highlighted section, the system response is delayed as the output is still $[0\ 1\ 1]$ instead of $[1\ 1\ 1]$. This error is corrected after 2s. The same error (see Figure 57) is experienced when the electric kettle is switched off to have $[1\ 0\ 1]$.

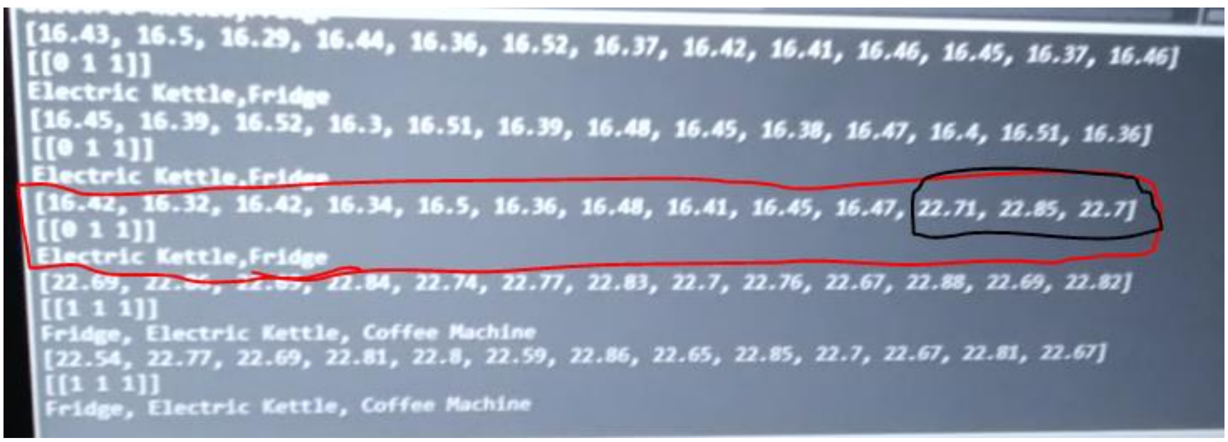


Figure 57: Transient state error

4.2.4.2 Analysis

The NILM system was able to identify the appliances in a steady state without any challenges. During the transient state, the system was able to identify some of the appliances but struggled to identify others. This is because the data collection window was set to a limit of 15 data points before feature extraction. It follows that during the transient period (moving from one state to the other), the list of 15 data points collected includes values from the previous state and values from the current state. This decreases the accuracy of feature extraction especially the maximum current, minimum current, average current and standard deviation. Features are used as unique identifiers of different loads, hence once they are miscalculated, the state vectors change and so do the labels. One way of correcting this is by reducing the data collection window from 15 but the downside of this is that the features are affected. They increase or decrease depending on the appliances which can lead to misidentification.

4.2.5 Live Test

The performance of the model is evaluated against the expected outcome. The results were summarized in Table 5.

Table 5: Summary of live test system evaluation results

State	Expected output	Actual Output	Evaluation
Electric Kettle on	[0 1 0]	-	Incorrect
Electric Kettle off	[0 0 0]	-	Incorrect
Fridge on	[1 0 0]	-	Incorrect
Fridge off	[0 0 0]	-	Incorrect
Coffee machine on	[0 0 1]	-	Incorrect
Coffee machine off	[0 0 1]	-	Incorrect
Fridge on	[1 0 0]	-	Incorrect
Electric kettle	[1 1 0]	-	Incorrect
Coffee machine	[1 1 1]	-	Incorrect
Electric kettle off	[1 0 1]	-	Incorrect
Fridge off	[0 0 1]	-	Incorrect
Coffee machine off	[0 0 0]	-	Incorrect

4.2.5.1 Observations

- The system is not able to identify any of the appliances.
- When the current readings are forwarded to ThingSpeak, the results are shown in Figure 58.

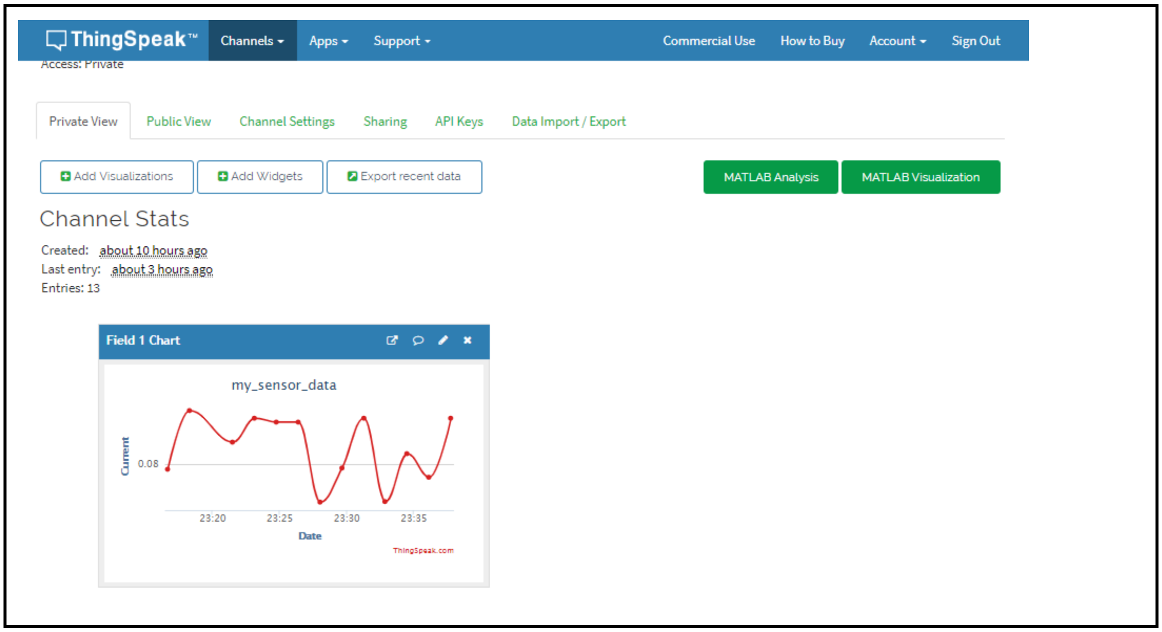


Figure 58: Current readings as recorded in ThingSpeak

  - From the graph, ThingSpeak receives only 13 data points in 25 minutes. This shows that it takes approximately 2 minutes to send one data point from The Things Network to ThingSpeak.

- The time taken to send current readings from the CT sensor to other parts of the system is summarized below.
  - It takes 2 seconds for the Arduino to get a single data point from the CT sensor and convert it into bytes.
  - It takes 3.5 seconds to send a single current reading from Arduino to LoRa Gateway.
  - It takes 10 seconds for the current value to be reflected in The Things Network gateway.
  - The data received by the TTN gateway server is decoded from bytes to float and saved in connected devices within a minute.

- Overall, it takes 3 minutes and 16 seconds for a single data value to be sent from the Arduino to ThingSpeak network. This is visually summarized in Figure 59 below.

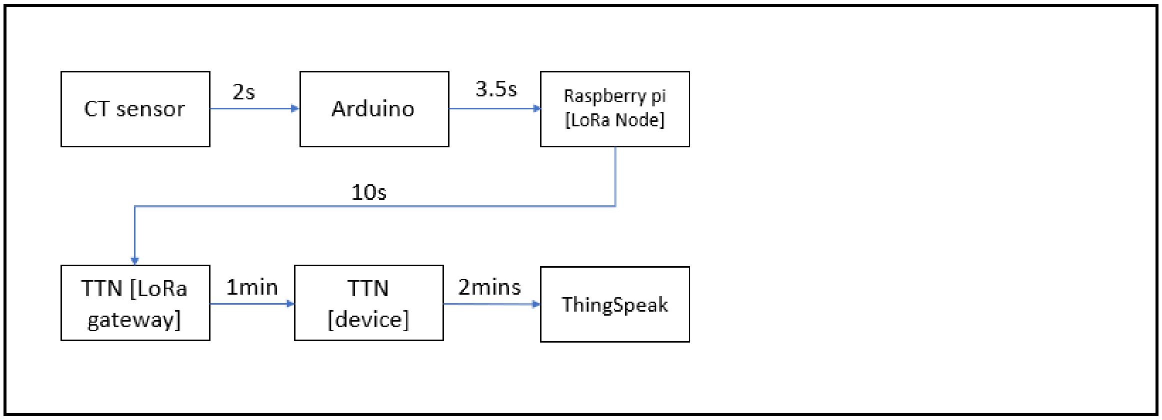


Figure 59: Visual representation of the delays experienced in the different components

The test runs for 12 minutes. This shows that only 3 data points were forwarded. As feature extraction and load identification starts after 15 data points, there was no output recorded at the end of the designated testing period.

4.2.5.2 Analysis

Overall, when conducting the live test, the process was filled with delays right from data collection to load identification. These delays affected the ability of the NILM system to process the data in real-time. Thus, it was not able to identify any of the appliances during the testing period. One of the major contributors to this delay was the LoRa module. LoRa is less popular due to its slow transmission rate. This makes it unsuitable for real-time data processing. The forwarding of data from one server to the other made the process slower. One way to reduce the delay would be to use a single custom server to host the gateway, decode the data, perform feature extraction and load identification.

4.2.6 Conclusion

In conclusion, when feature extraction and load identification are to be done externally, the data transmission method selected should have a fast data transmission rate to allow the NILM system to process data in real-time. Also, when feature extraction and load identification are to be done locally, the data collection window should be small enough to avoid system error when identifying loads during transient period and have no effect on feature extraction.

4.3 Model Application

In this section a case study is presented and the NILM system used to measure the current, extract features, identify the appliances, calculate the bill using current tariffs obtained from the Kenya Power and Lighting Company website and generate power usage report. Feature extraction and load identification are done locally (feature extraction and k-NNR models are stored in the laptop).

4.3.1 Case study scenario

- A homeowner with a NILM system installed at their house owns a drip coffee machine, an electric kettle and a fridge.
- They leave the fridge on for 24 hrs.
- Every day at 7 am, they use the coffee machine to brew coffee, takes only 2 cups and leaves the rest. The brewing cycle lasts for 30 minutes while the warm plate cycle (to keep the coffee warm) restarts every 4 hrs.
- In the evening at 7.10 pm, they use an electric kettle to boil water for noodles. The electric kettle takes 15 minutes to boil the water.

Since the voltage in the mains supply is known (240 V), the total power consumed is calculated as shown in Figure 60.

$$P = \sum_{k=0}^{\infty} P_k = \sum_{k=0}^{\infty} V_k I_k \cos(\phi_k)$$

Figure 60: Power equation.

[where V and I represent the magnitude of voltage and current, ϕ is the phase angle between voltage and current while k is the harmonic order]

Prior research has been done to identify fixed charges and the different tariffs used by the Kenya Power and Lighting Company based on power consumption. This information is summarized in **Error! Reference source not found.**.

Table 6: Electricity charges and tariffs for domestic electric usage [37]

Billing concept	Amount
Cost (ksh/kWh) for 0-100 units per month	10
Cost (ksh/kWh) for more than 100 units per month	15
Other charges	**Amount**
Balance Brought Forward (ksh)	0
Fixed charges (ksh)	240
Fuel cost charge (cents /kWh)	519
Forex Adjustment (ksh)	0.0
Inflation Adjustment	62.01
Water Resource Management Authority (WARMA) Levy (cents /kWh)	5
Energy Regulatory Commission (ERC) Levy (cents/kWh)	3
Rural Electrification Authority (REA) Levy (% cost of the units consumed)	5 %
VAT (applicable to Fixed Charge, Consumption, Fuel Cost Charge and Forex Adjustment)	16%

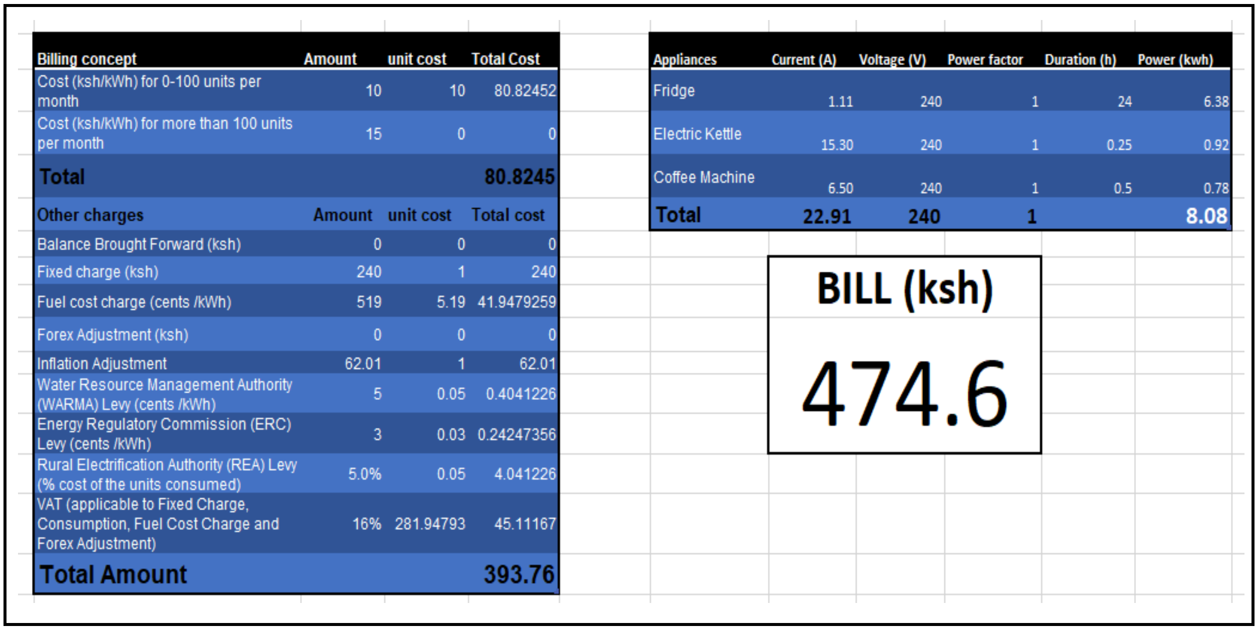
Depending on the value of the total power consumed, the relevant tariffs are considered, and the bill calculated. The tariffs inform the cost of power per kwh and other charges payable. The bill is calculated using the equations in Figure 61 .

$$\boxed{Bill\ = Other\ charges\ + Cost\ of\ power\ consumed}$$

Figure 61: Bill formula

4.3.2 Results and Analysis

The power consumption and the bill displayed is shown in Figure 62.



Billing concept	Amount	unit cost	Total Cost
Cost (ksh/kWh) for 0-100 units per month	10	10	80.82452
Cost (ksh/kWh) for more than 100 units per month	15	0	0
Total			**80.8245**
Other charges	**Amount**	**unit cost**	**Total cost**
Balance Brought Forward (ksh)	0	0	0
Fixed charge (ksh)	240	1	240
Fuel cost charge (cents /kWh)	519	5.19	41.9479259
Forex Adjustment (ksh)	0	0	0
Inflation Adjustment	62.01	1	62.01
Water Resource Management Authority (WARMA) Levy (cents /kWh)	5	0.05	0.4041226
Energy Regulatory Commission (ERC) Levy (cents /kWh)	3	0.03	0.24247356
Rural Electrification Authority (REA) Levy (% cost of the units consumed)	5.0%	0.05	4.041226
VAT (applicable to Fixed Charge, Consumption, Fuel Cost Charge and Forex Adjustment)	16%	281.94793	45.11167
Total Amount			**393.76**

Appliances	Current (A)	Voltage (V)	Power factor	Duration (h)	Power (kwh)
Fridge	1.11	240	1	24	6.38
Electric Kettle	15.30	240	1	0.25	0.92
Coffee Machine	6.50	240	1	0.5	0.78
Total	**22.91**	**240**	**1**		**8.08**

BILL (ksh)

474.6

Figure 62: Amount payable based on consumption

After load identification, the power values for each load are plotted against time highlighting the exact time they were switched on and switched off as shown in the daily usage report in Figure 63.

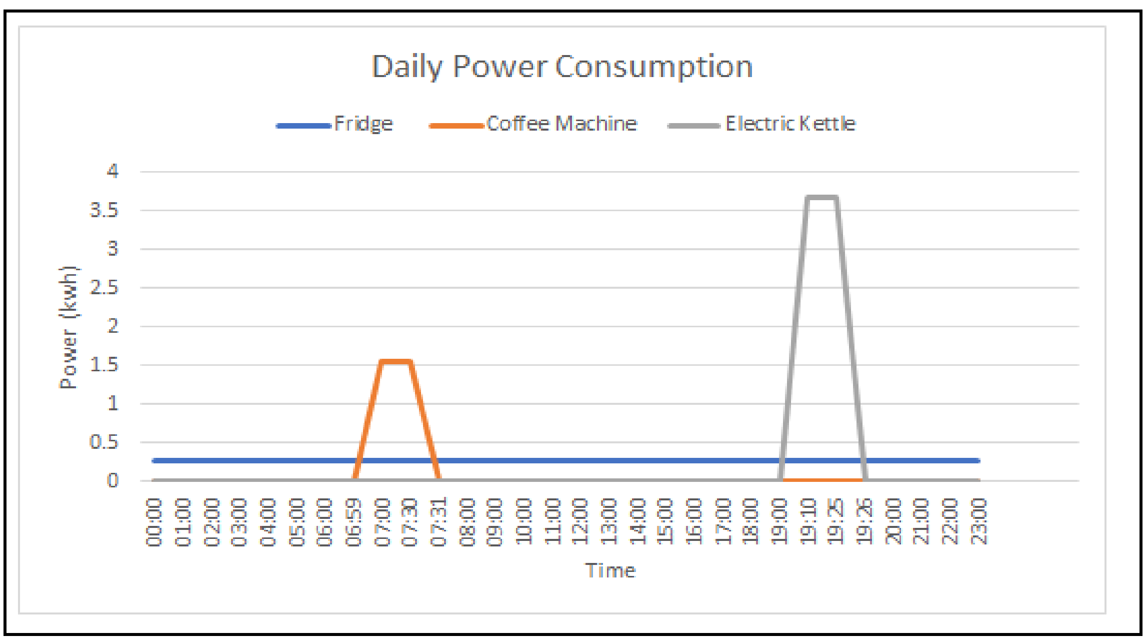


Figure 63: Power usage report generated

4.3.2.1 Observation

- The power consumed by the fridge remains constant.
- The coffee machine only stays on for 30 minutes while the electric kettle stays on for 15 minutes.

4.3.2.2 Analysis

Based on the calculated bill and the usage report, the NILM system only takes into consideration the normal operating state of the fridge and ignores compressor start-up state. Further, for the coffee machine, only the brewing cycle is considered. During the warm plate cycle and the compressor start-up state, the two appliances consume a considerable amount of power. The fridge consumes 792 watts (3 times the rated power) during compressor state [34] while the coffee machine consumes 100 watts during warm plate cycle [35]. Hence ignoring the two phases leads to underestimation of the total amount payable.

5 Conclusion

The objectives of this project were to identify a suitable load signature, choose 3 common household appliances, build a circuit that represents a household with the 3 appliances connected, switch on individual appliances and combine them with each other and using a suitable measurement device obtain compound waveforms. The compound waveforms would then be analyzed, and features extracted. The features would then be used to train a model that can identify the appliances switched on at a given time. After creating the model, an appropriate test would then be carried out to verify the performance of the model before using the model to identify appliances, calculate the bill and generate consumption reports of a case study scenario.

In the course of this project, current was used as the load signature and three appliances namely fridge, electric kettle and coffee machine selected for data collection. The three appliances were connected in an extension cable. Each appliance was individually switched on for 60 seconds and a compound waveform was obtained. Next, any two appliances were switched on simultaneously for 60 seconds and compound waveforms obtained. Later, all three were switched on and off for 60 seconds and waveforms obtained again. This process was repeated 15 times. The compound waveforms were obtained using a CT sensor integrated with Arduino Uno.

All the compound waveforms were analyzed, and the following features extracted; Minimum current, Maximum current, Average current, Median current and Standard deviation. These features were used to train two classification models k-Nearest Neighbor Rule (k-NNR) and Support Vector Machine in conjunction with One vs Rest multiclass Classifier. k-NNR had the highest accuracy and was thus used in testing. The two tests carried out were a remote test where the model was stored locally in the laptop and a live test where the model was stored in an online server. In the remote testing, the model was able to identify the appliances in real-time while in live testing, the data transmission took longer thus the model was not able to identify any of the appliances in real-time. Local testing achieved better results and was thus used in the case scenario to identify appliances, calculate bills and generate usage reports.

Despite the system being able to identify the appliances in real-time, calculate electricity bill and generate usage reports in real-time, the process was not as smooth. The model worked well when identifying appliances in a steady-state but faced some challenges when the appliances were in a transient state. Thus, the system is well suited for steady-state and not transient-state. Another challenge encountered was that the waveforms were collected when the fridge was in the normal operating state and the coffee machine in brewing state. This made it impossible for the model to identify the fridge whenever it is in a compressor start-up state and the coffee machine is in a warm plate state. The result of this was the underestimation of the bill payable.

6 Future Work and Recommendations

A lot was done in developing the NILM system. However, further work would improve the system. One way of improving it would be to consider all the power consumption states when dealing with inductive loads like the fridge and the coffee machine. Also, reducing the length of data collection window when using the system to identify loads in households to get rid of transient state error.

If applied on a large scale, this project could be useful in energy forecasting at a national level. The knowledge of load consumption patterns from household level can be used to project the load growth at a national level. Moreover, energy forecasts are useful when laying out future infrastructure expansion plans and setting up appropriate financing schemes for the energy sector.

7 Appendices

Appendix A: Codes used

```
from sklearn.svm import SVC
from sklearn.multiclass import OneVsRestClassifier
import numpy as np
from sklearn.svm import LinearSVC
from sklearn import preprocessing
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

#Spliting the dataset in independent and dependent variables
X = df.iloc[:,:5].values
Y = df.iloc[:,5:8].values
#print(X.shape)
#print(Y.shape)

# Splitting the dataset into the Training set and Test set
features_train, features_test, labels_train, labels_test = train_test_split (X, Y, test_size=0.20, random_state=0)

# Feature Scaling to bring the variable in a single scale
scaler = StandardScaler()
X_train = scaler.fit_transform(features_train)
X_test = scaler.transform(features_test)

#train
clf= OneVsRestClassifier(LinearSVC(random_state=0))

clf.fit(X_train, labels_train)
predicted = clf.predict(X_test)

#test
y_pred = clf.predict(X_test)
#print(y_pred)

#accuracy
acc = accuracy_score(y_pred, labels_test)
print(acc)

0.45
```

Figure 64: SVM classification model code

```python
from sklearn.neighbors import KNeighborsClassifier
import numpy as np
from sklearn import preprocessing
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

#Spliting the dataset in independent and dependent variables
X = df.iloc[:,:5].values
Y = df.iloc[:,5:8].values
#print(X.shape)
#print(Y.shape)

# Splitting the dataset into the Training set and Test set
features_train, features_test, labels_train, labels_test = train_test_split (X, Y, test_size=0.20, random_state=0)

# Feature Scaling to bring the variable in a single scale
scaler = StandardScaler()
X_train = scaler.fit_transform(features_train)
X_test = scaler.transform(features_test)

clf = KNeighborsClassifier(n_neighbors=3)

#train
clf.fit(X_train, labels_train)


#test
y_pred = clf.predict(X_test)
#print(y_pred)

#accuracy
acc = accuracy_score(y_pred, labels_test)
print(acc)
```

```
0.9875
```

Figure 65: k-NNR classification model code

```cpp
#include <EmonLib.h>
EnergyMonitor emon1;

void setup() {

  Serial.begin(9600);

  emon1.current(A0, 111.1);

}

void loop() {

   float Irms = emon1.calcIrms(1480);


  Serial.println(Irms);

  delay(2000); //add a delay
```

Figure 66: Arduino Uno- CT sensor code

Appendix B: Testing Results screenshots

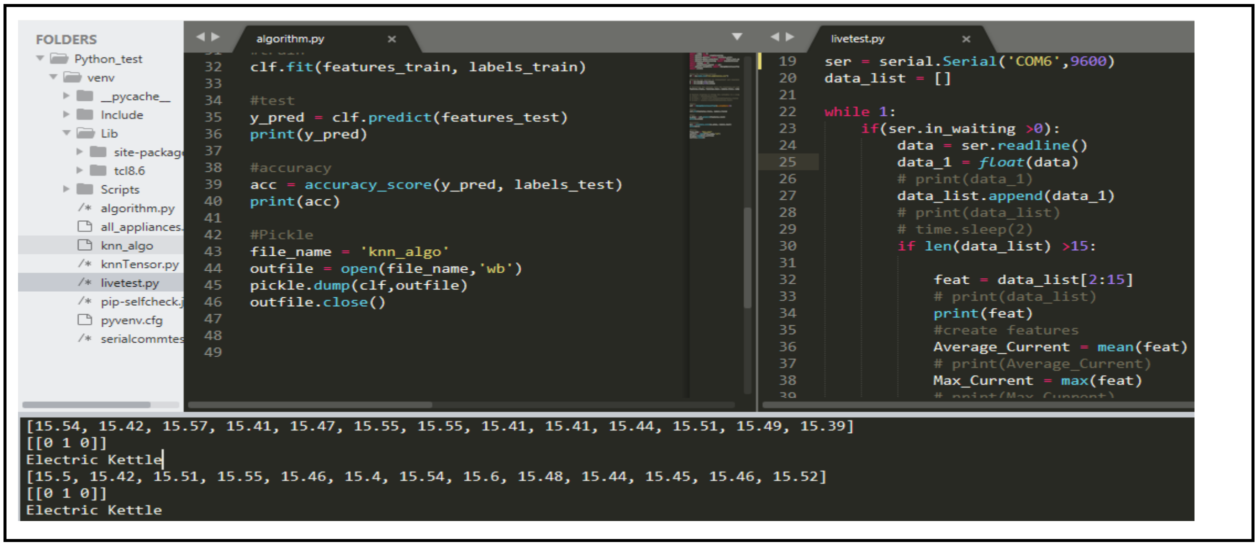


Figure 67: Load identification test: Electric kettle

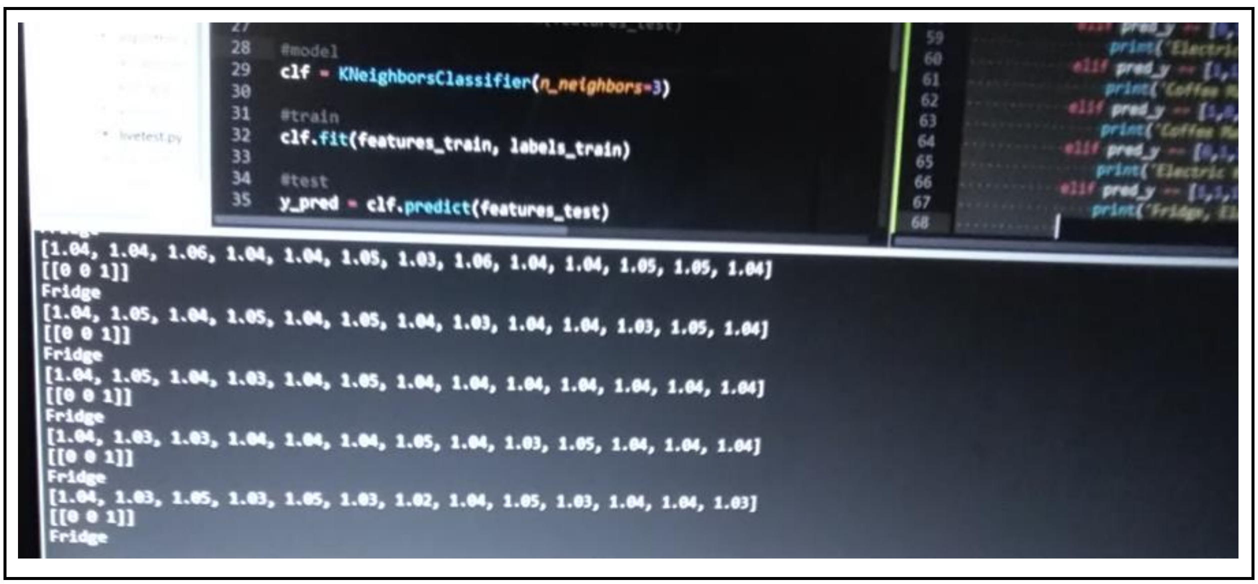


Figure 68: Load identification test: Fridge

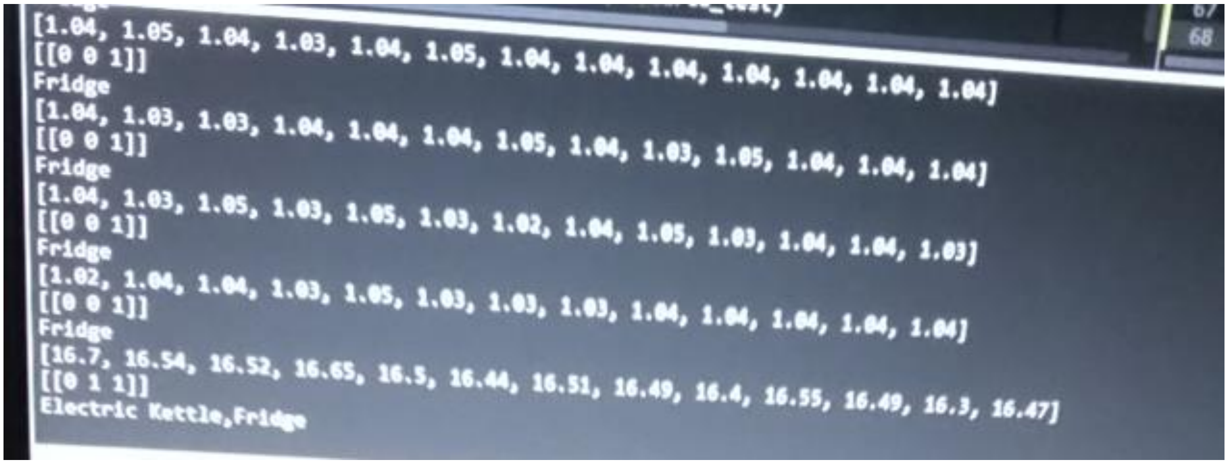


Figure 69: Load identification test: Electric Kettle and Fridge

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